Welcome to MCQMC 2016 at Stanford University

We are pleased to welcome you to Stanford University for the 12th International Conference on Monte Carlo and Quasi-Monte Carlo Methods in Scientific Computing, MCQMC 2016. This conference series is the major event for researchers in the Monte Carlo and Quasi-Monte Carlo community. Our scientific committee identified ten extraordinary researchers to give plenary talks. The broader community of researchers submitted an astonishing variety of talks in minisymposia, special sessions and contributed sessions. We have a full schedule, and you will often find yourself wishing to be at more than one talk at a time.

We hope that you are able to take some time to explore our corner of the world. We are pleased to bring MCQMC back to the United States, back to California, and for the first time, to the San Francisco Bay Area. The conference takes place on the campus of Stanford University, which is celebrating its 125th anniversary this year. The main venue is the Li Ka Shing Center (LKSC) in the School of Medicine. From here you are a short distance from Pacific Ocean beaches, from the city of San Francisco and from the head offices of our local industry, commonly called Silicon Valley. If you extend your stay some days, you may see the wine country to the North, the Sierra mountains to the East, or the Monterey peninsula to the South.

We wish you a pleasant and productive week,

Art B. Owen, Peter W. Glynn, Wing H. Wong, Kay Giesecke
MCQMC 2016 Conference Organizers
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The MCQMC Conference Series

History

The MCQMC conference series is a biennial meeting focused on Monte Carlo (MC) and quasi-Monte Carlo (QMC) methods in scientific computing. The conference typically attracts between 150 and 200 participants. This year we are just over 200. Its aim is to provide a forum where leading researchers and users can exchange information on the latest theoretical developments and important applications of these methods.

Recent conferences have attracted researchers in Markov chain Monte Carlo (MCMC). In a nutshell, MC methods study complex systems by simulations fed by computer-generated pseudorandom numbers. QMC methods replace these random numbers by more evenly distributed (carefully selected) numbers to improve their effectiveness. A large variety of special techniques are developed and used to make these methods more effective in terms of speed and accuracy. The conference focuses primarily on the mathematical study of these techniques, their implementation and adaptation for concrete applications, and their empirical assessment.

This conference series was initiated by Harald Niederreiter. He co-chaired the first seven conferences. In 2006 Harald Niederreiter announced his wish to step down from the organizational role and a Steering Committee was formed to ensure and oversee the continuation of the conference series. The locations of the first 12 conferences are set out below.

<table>
<thead>
<tr>
<th>Year</th>
<th>Location</th>
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</thead>
<tbody>
<tr>
<td>1994</td>
<td>Las Vegas, NV USA</td>
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<tr>
<td>1996</td>
<td>Salzburg, Austria</td>
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<tr>
<td>1998</td>
<td>Claremont, CA USA</td>
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<tr>
<td>2000</td>
<td>Hong Kong</td>
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<td>2002</td>
<td>Singapore</td>
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<td>2004</td>
<td>Juan-Les-Pins, France</td>
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<tr>
<td>2006</td>
<td>Ulm, Germany</td>
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<td>2008</td>
<td>Montréal, Canada</td>
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<tr>
<td>2010</td>
<td>Warsaw, Poland</td>
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<tr>
<td>2012</td>
<td>Sydney, Australia</td>
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<tr>
<td>2014</td>
<td>KU Leuven, Belgium</td>
</tr>
<tr>
<td>2016</td>
<td>Stanford, CA USA</td>
</tr>
<tr>
<td>2018</td>
<td>????, ????</td>
</tr>
</tbody>
</table>

Steering Committee

The MCQMC steering committee consists of:

Stefan Heinrich (Germany) (chair)
Fred J. Hickernell (USA)
Alexander Keller (Germany)
Frances Y. Kuo (Australia)
Pierre L’Ecuyer (Canada)
Art B. Owen (USA)
Friedrich Pillichshammer (Austria)
MCQMC 2016 Scientific Committee

The scientific committee members nominates plenary speakers, and are active in organizing special sessions and minisymposia as well as refereeing proceedings submissions. It consists of the local organizers, the MCQMC Steering Committee and the following researchers:

Dmitriy Bilyk (USA, Minnesota)  
Nicolas Chopin (France, ENSAE)  
Ronald Cools (Belgium, KU Leuven)  
Josef Dick (Australia, UNSW)  
Arnaud Doucet (UK, Oxford)  
Henri Faure (France, Marseille)  
Mike Giles (UK, Oxford)  
Paul Glasserman (USA, Columbia)  
Michael Gnewuch (Germany, Kiel)  
Aicke Hinrichs (Austria, JKU Linz)  
Christophe Hery (USA, Pixar)  
Wenzel Jakob (Switzerland, ETH and Disney)  
Dirk Kroese (Australia, U Queensland)  
Erich Novak (Germany, Friedrich Schiller University, Jena)  
Gareth Peters (UK, University College London)  
Dirk Nuyens (Belgium, KU Leuven)  
Aneta Karaivanova (Bulgaria, Bulgarian Academy of Sciences)  
Faming Liang (USA, U Florida, Gainesville)  
Gerhard Larcher (Austria, JKU Linz)  
Christiane Lemieux (Canada, Waterloo)  
Makoto Matsumoto (Japan, Hiroshima)  
Thomas Mueller-Gronbach (Germany, Passau)  
Harald Niederreiter (Austria, Austrian Academy of Sciences)  
Klaus Ritter (Germany, Kaiserslauten)  
Wolfgang Schmid (Austria, Salzburg)  
Steve Scott (USA, Google Inc)  
Xiaoqun Wang (China, Tsinghua)  
Yazhen Wang (USA, Wisconsin)  
Grzegorz Wasilkowski (USA, U Kentucky)  
Dawn Woodard (USA, Uber)  
Henryk Wozniakowski (USA, Columbia and Poland, Warsaw)  
Qing Zhou (USA, UCLA)
Acknowledgments

The local organizing committee would like to acknowledge the many organizations and people who have supported or contributed to MCQMC 2016.

Sponsors

We are very grateful for the financial support from the following sponsors:
- Stanford Statistics Department,
- SAMSI,
- Google Inc.,
- Yi Zhou (PhD 1998) and Brice Rosenzweig,
- Intel,
- Two Sigma, and
- Uber.

Promotional

The following kindly helped to promote MCQMC 2016:
- SIAM,
- The Institute of Mathematical Statistics, and
- Xian’s Og.

MCQMC Community

Previous organizers helped this conference by offering their advice and even LaTeX source files. Among them are Fred Hickernell, Pierre L’Ecuyer, Dirk Nuyens, Ronald Cools and Frances Kuo. The Scientific Committee and others too, contributed talks and sessions and agreed to introduce speakers. Michael Giles and Ian Sloan reported some website issues very early on and that was super helpful. Some of the prose in this booklet describing the MCQMC conference has been handed down from meeting to meeting and we acknowledge their wording.

Stanford Statistics Department

We have had considerable help from the Statistics department here at Stanford. The following people have been instrumental:
- Ellen van Stone,
- Emily Lauderdale,
- Heather Murthy,
- Joanna Yu,
- Amir Sepehri,
- Keli Liu, and
- Zeyu Zheng (actually MS&E).

We are very grateful to Gunther Walther for his strong support when this project was being conceived.

Stanford Conference Services

It is a pleasure to acknowledge the hard work done on our behalf by Stanford Conference Services. They are tireless, cheerful and professional, and we could not have organized it without their help:
- Brigid Neff (team lead),
- Suzette Escobar,
- Meredith Noe,
- John Ventrella, and
- Dixee Kimball.
Practical Information

Wireless

Most of the practical information you need, gathered from all those emails we sent you, is online at mcqmc2016.stanford.edu. That website contains numerous links to Google maps of the Stanford campus and surrounding areas. So the primary practical information is about how to connect to wireless.

Stanford participates in Eduroam so you should have access from them if you have joined. Alternatively you can connect to one of Stanford’s wireless networks, called Stanford Visitor. The access is free and you do not have to log in. You do have to accept their terms and conditions.

Venue

Our primary venue is the Li Ka Shing Center (LKSC) in the medical school. The lecture rooms we will use are on the first and second floors. Berg Hall A, B and C are also known as rooms LK 230, LK 240 and LK 250.

On Wednesday morning, the medical school needs the space we are using for plenary talks. So for that talk only, we will be in room 200 of the Hewlett Learning Center, about a five minute walk from LKSC.

Registration

The registration desk is on the second floor of LKSC. It will be staffed throughout the entire meeting including Sunday afternoon during the tutorial sessions.

Hotel to venue and back

It is about a 30 minute walk to LKSC from downtown Palo Alto where the closest hotels are. This may be a nice walk, but it could also be hot. We have chartered some shuttles from the Cardinal Hotel to LKSC each morning and back each afternoon. You do not have to be a hotel guest to use those shuttles.

The website also has a link to a bicycle rental shop on campus.

Finally, if you are in a car, and have pre-purchased parking, information about how to use your parking pass is given in the conference website.

Tutorials

We have QMC tutorials on Sunday afternoon from 2pm to 6pm.

Audiovisual

In case of any difficulty, there is an A/V technician in the building. The people at the registration desk can locate the technician for you. Here is a description of our A/V setup:

• Each LKSC meeting room has a projector and projection screen.
• The control panel is connected to a Mac. Presentations should be brought on a flash drive to use with the existing Mac. Your file name should be titled with the following information, “PresentationDay,LastName,FirstName” (e.g. Tuesday,Smith,Jane). Please don’t bring a file called stanford.pdf!
• In an effort to reduce set-up time and avoid taking time away from any of the talks, speakers are strongly encouraged to use the existing Mac.
• For speakers whose presentations were created on a PC and who plan to use the existing Mac, presentations should make sure to use standard fonts. As a back-up, it’s suggested to also bring a version in PDF format, with any slide animations or embedded video removed.

• Presenters bringing their own computer are required to bring along their own adapter. The venue has adapters only for Thunderbolt/DVI (Mac) and VGA (PC). The venue cannot accommodate HDMI at this time.

• In order to load and test the presentations, presenters should visit the podium of the room you are presenting one half hour before the program begins for the day or at any of the breaks prior to their scheduled talk. Also, you may ask your room moderator for assistance with loading your presentations, if needed.

Welcome reception

There will be a welcome reception on the LKSC lawn on Monday evening. It will include drinks and light food. Partners are welcome to join.

Plenary lectures

Most plenary lectures are held in Berg Hall, on the second floor of LKSC. The one exception is Wednesday morning’s 9 AM lecture by Jose Blanchet in Hewlett 200. These lectures are in 60 minute time slots. The talks should last for 50 minutes to leave adequate time for discussion, questions and answers.

Regular lectures

The other lectures from minisymposia, special sessions and contributed talks all take place in 30 minute time slots. The talks should last 25 minutes. This allows time for questions, as well as speaker transitions. Many audience members will want to move between sessions. It is therefore essential to start and stop on time.

Coffee

The coffee breaks include light snacks. They will be served in Berg Hall of the LKSC. On Wednesday morning there will be a coffee service at the Hewlett building just ahead of the plenary talk there.

Lunch

Lunch is not provided. There are a number of cafeterias very close to LKSC and they know that we are coming. No single one of them is large enough to handle our conference, but if we disperse among them we should be fine. The conference takes place the week after summer quarter final exams and so there should be fewer students. The website has some maps and descriptions.

Dinner

There are lots of interesting restaurants on University Drive in Palo Alto. The website has a map showing directions there. It also describes dining at Stanford shopping center, or in Mountain View and it gives a short list of local grocery stores.

Wednesday group photo

On Wednesday we finish a little earlier than usual. We will have a group photo on or near the steps of LKSC at about 5pm.

Reception and banquet

On Wednesday we will have a reception and banquet at the Arrillaga Alumni Center. The reception starts at 6pm. The banquet starts at 7pm. After the group photo, we have one hour to walk to Arrillaga. The conference web page contains maps for three routes that take you past different campus sights.

Your conference ID badge is your ticket to the banquet. Guests need a ticket to attend the banquet. If you have paid for such a ticket when you registered, then you will get your ticket along with your ID badge from the desk.

There will be two surprises at the banquet. One of them is the announcement of the location of MCQMC 2018. What the other surprise will be, is a surprise.
Steering Committee Meeting

The MCQMC Steering Committee will have a closed meeting on Thursday evening. If you are interested in organizing a future MCQMC conference please approach any member of the committee prior to their meeting.

Emergency

In case of any life threatening emergency, call 911. The LKSC is adjacent to Stanford University Hospital. It is prudent to ensure that your insurance covers events here.

Conference Close

On the last day, Friday, there will be a brief presentation in the morning from the MCQMC 2018 organizers. In the afternoon there will be some brief closing remarks.

Conference Statistics

<table>
<thead>
<tr>
<th>Category</th>
<th>Count</th>
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<tbody>
<tr>
<td>Registrants</td>
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<tr>
<td>Tutorials</td>
<td>3</td>
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<tr>
<td>Plenary Lectures</td>
<td>10</td>
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<td>Talks</td>
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<td>Special and Minisymposium</td>
<td>115</td>
</tr>
<tr>
<td>Contributed</td>
<td>54</td>
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</tbody>
</table>

Return to SFO

If you are flying home, departing from San Francisco International Airport, then the conference web page has a link to their ground transportation web site. It is also possible to get there on Uber.

Miscellaneous

If you have additional questions or need any special local information please ask at the reception desk.
<table>
<thead>
<tr>
<th>Time</th>
<th>Event</th>
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<tbody>
<tr>
<td>1:30–5:00</td>
<td>Registration desk is open</td>
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<tr>
<td>2:00–3:00</td>
<td>Pierre L’Ecuyer</td>
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<tr>
<td></td>
<td>QMC Tutorial I: Introduction to (Randomized) Quasi-Monte Carlo Methods</td>
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<tr>
<td>3:00–3:20</td>
<td>Break</td>
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<td>3:20–4:20</td>
<td>Fred J. Hickernell</td>
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<td>QMC Tutorial II: Error Analysis for Quasi-Monte Carlo Methods</td>
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<tr>
<td>4:20–4:40</td>
<td>Break</td>
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<tr>
<td>4:40–5:00</td>
<td>Richard Smith: Introduction to SAMSI</td>
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<td>4:50–5:50</td>
<td>Frances Y. Kuo</td>
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<td>QMC Tutorial III: Application of QMC to PDEs with Random Coefficients</td>
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<tr>
<td></td>
<td>– a Survey of Analysis and Implementation</td>
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<tr>
<td>5:50–6:00</td>
<td>Ilse Ipsen: Vision for the 2017-18 SAMSI QMC Program</td>
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<td>Time</td>
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<tr>
<td>8:55-9:00</td>
<td>Opening Ceremony</td>
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<tr>
<td>9:00-10:00</td>
<td>Plenary Lecture</td>
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<td></td>
<td>Lattice Rules and Beyond</td>
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<tr>
<td>10:00-10:25</td>
<td>Coffee</td>
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<td></td>
<td>Special session</td>
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<td>Hamiltonian Monte Carlo</td>
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<td>Chair: Wing Wong</td>
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<td>Special session</td>
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<td>Hamiltonian Monte Carlo</td>
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<tr>
<td>10:25-10:55</td>
<td>Michael Betancourt</td>
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<td></td>
<td>Stefan Heinrich</td>
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<tr>
<td></td>
<td>A Coercivity-Type Condition for SPDEs with Additive White Noise</td>
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<tr>
<td>10:55-11:25</td>
<td>Andria Dawson</td>
</tr>
<tr>
<td></td>
<td>Efficient Computation of Uncertainty in Spatio-Temporal Forest Composition Inferred from Fossil Pollen Records</td>
</tr>
<tr>
<td>11:25-11:55</td>
<td>David Rubin</td>
</tr>
<tr>
<td></td>
<td>Confronting Supernova Cosmology’s Statistical and Systematic Uncertainties with Hamiltonian Monte Carlo</td>
</tr>
<tr>
<td>11:55-12:15</td>
<td>Lunch</td>
</tr>
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</table>
### Monday early PM, August 15

**11:15 – 11:45**

**Plenary Lecture**  Berg BC  
_Michael I. Jordan_  
_A Variational Perspective on Accelerated Methods in Optimization_  p. 30  
Chair: Lester Mackey

<table>
<thead>
<tr>
<th>Room separators close</th>
<th>Berg A</th>
<th>Berg B</th>
<th>Berg C</th>
<th>LK 120</th>
<th>LK 101</th>
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</thead>
<tbody>
<tr>
<td><strong>Mini-symposium</strong></td>
<td><strong>Multilevel Monte Carlo II</strong></td>
<td><strong>Mini-symposium</strong></td>
<td><strong>Mini-symposium</strong></td>
<td><strong>Contributed session</strong></td>
<td><strong>Contributed session</strong></td>
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<tr>
<td><strong>Chair:</strong> Michael Giles</td>
<td><strong>Chair:</strong> Stefan Heinrich</td>
<td><strong>Chair:</strong> Alex Keller</td>
<td><strong>Chair:</strong> Steve Scott</td>
<td><strong>Chair:</strong> Yahzen Wang</td>
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<tr>
<td><strong>2:25 – 2:55</strong></td>
<td>Alexander Gilbert</td>
<td>Andreas Neuenkirch</td>
<td>Christophe Hery &amp; Ryusuke Villemin</td>
<td>David Draper</td>
<td>Ying Yang-Jun</td>
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<tr>
<td><strong>The Multivariate Decomposition Method</strong></td>
<td><strong>The Order Barrier for Strong Approximation of Rough Volatility Models</strong></td>
<td><strong>On MCQMC Issues in Production Rendering</strong></td>
<td><strong>Fast Bayesian Non-Parametric Inference, Prediction and Decision-Making at Big-Data Scale</strong></td>
<td><strong>Progress in Simulation of Stochastic Neutron Dynamics</strong></td>
<td></td>
</tr>
<tr>
<td><strong>p. 48</strong></td>
<td><strong>p. 60</strong></td>
<td><strong>p. 43</strong></td>
<td><strong>p. 105</strong></td>
<td><strong>p. 106</strong></td>
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<tr>
<td><strong>2:55 – 3:25</strong></td>
<td>Aretha Teckentrup</td>
<td>Mario Hefter</td>
<td>Leonid Pekelis</td>
<td>Cyril Chimisov</td>
<td>DanHua ShangGuan</td>
</tr>
<tr>
<td><strong>Quasi and Multilevel Monte Carlo Methods for Bayesian Inverse Problems</strong></td>
<td><strong>Strong Convergence Rates for Cox-Ingersoll-Ross Processes: Full Parameter Range</strong></td>
<td><strong>Data-Driven Light Scattering Models: An Application to Rendering Hair</strong></td>
<td><strong>Adapting the Gibbs Sampler</strong></td>
<td><strong>Detailed Comparison of Uniform Tally Density Algorithm and Uniform Fission Site Algorithm</strong></td>
<td></td>
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<tr>
<td><strong>p. 48</strong></td>
<td><strong>p. 60</strong></td>
<td><strong>p. 43</strong></td>
<td><strong>p. 105</strong></td>
<td><strong>p. 106</strong></td>
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</tr>
<tr>
<td><strong>3:25 – 3:50</strong></td>
<td>Coffee</td>
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## Monday late PM, August 15

<table>
<thead>
<tr>
<th>Time</th>
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<th>Session</th>
<th>Chair/Authors</th>
<th>Title/Abstract</th>
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<tr>
<td>3:00–4:20</td>
<td>Berg A</td>
<td>Special session</td>
<td>Markus Weimar</td>
<td>Josef Dick</td>
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<tr>
<td>4:20–5:40</td>
<td>Berg B</td>
<td>Mini-symposium</td>
<td>Denis Belomestny</td>
<td>Lukasz Szpruch</td>
</tr>
<tr>
<td>4:50–6:10</td>
<td>Berg C</td>
<td>Special session</td>
<td>Tino Ullrich</td>
<td>Thomas Kühn</td>
</tr>
<tr>
<td>6:00–7:30</td>
<td>Welcome reception</td>
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</table>

NB: The only seminar rooms we have past 5pm are Berg A,B,C. Please do not linger in the others after the last sessions end. We may use the lobby area outside of Berg A,B,C past 5pm.
<table>
<thead>
<tr>
<th>Time</th>
<th>Event</th>
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</thead>
</table>
| 9:00–10:00 | Plenary Lecture Berg BC  
**Christiane Lemieux**  
Dependence Sampling and Quasi-Random Numbers p. 31  
Chair: Pierre L’Ecuyer |
| 10:00–10:25 | Coffee |
| 10:25–11:00 | Berg A  
**Special session**  
Approximate Bayesian Computation  
Chair: Christian Robert |
| 10:25–11:25 | Berg B  
**Special session**  
Combinatorial Discrepancy  
Chair: Kunal Talwar |
| 10:25–11:25 | Berg C  
**Special session**  
Quadrature Constructions  
Chair: Kosuke Suzuki |
| 10:25–11:00 | LK 120  
**Special session**  
Systemic Risks and Financial Networks  
Chair: Paul Glasserman |
| 10:25–11:00 | LK 203/4  
**Contributed session**  
Diffusions  
Chair: Kryzstof Latuszynski |
| 11:00–11:25 | Coffee |
| 11:25–11:55 | LK 203/4  
**Contributed session**  
Lunch |

**Tuesday AM, August 16**

**9:00–10:00**
- Plenary Lecture Berg BC  
  **Christiane Lemieux**  
  Dependence Sampling and Quasi-Random Numbers p. 31  
  Chair: Pierre L’Ecuyer

**10:00–10:25**
- Coffee

**10:25–11:00**
- Berg A  
  **Special session**  
  Approximate Bayesian Computation  
  Chair: Christian Robert
- Berg B  
  **Special session**  
  Combinatorial Discrepancy  
  Chair: Kunal Talwar
- Berg C  
  **Special session**  
  Quadrature Constructions  
  Chair: Kosuke Suzuki

**10:25–11:25**
- LK 120  
  **Special session**  
  Systemic Risks and Financial Networks  
  Chair: Paul Glasserman
- LK 203/4  
  **Contributed session**  
  Diffusions  
  Chair: Kryzstof Latuszynski

**11:00–11:25**
- Coffee

**11:25–11:55**
- Lunch
<table>
<thead>
<tr>
<th>Time</th>
<th>Session</th>
</tr>
</thead>
</table>
| 115–215 | **Plenary Lecture**  Berg BC  
*Nicolas Chopin*  
**Sequential Quasi-Monte Carlo in Infinite Dimension**  p. 32  
**Chair:** Wing Wong |
| 25–255 | **Berg A**  
**Mini-symposium**  
**Multilevel Monte Carlo III**  
**Chair:** Michael Giles  
*Lukas Herrmann*  
**QMC for Parametric, Elliptic PDEs**  p. 49  
*Sotirios Sabanis*  
**A new Generation of Explicit Numerical Schemes for SDEs with Superlinear Coefficients**  p. 61  
*Peter Shirley*  
**Monte Carlo for Light Transport Including Linear Polarization**  p. 44  
*James M. Hyman*  
**High Accuracy Algorithms for Integrating Multivariate Functions Defined at Scattered Data Points**  p. 111  
*Lester Mackey*  
**Measuring Sample Quality with Stein’s Method**  p. 112  |
| 255–325 | **Berg B**  
**Mini-symposium**  
**Stochastic Computation and Complexity III**  
**Chair:** Pawel Przybyłowicz  
*Jerome Spanier*  
**Towards Real Time Monte Carlo Simulations for Biomedicine**  p. 44  
*Simon Mak*  
**Support points**  p. 111  
*Dootika Vats*  
**Multivariate Output Analysis for Markov Chain Monte Carlo**  p. 112  |
| 325–350 | **Berg C**  
**Mini-symposium**  
**Graphics and Transport II**  
**Chair:** Alex Keller  
*Pieterjan Robbe*  
**A Multi-Index Quasi-Monte Carlo Algorithm for Lognormal Diffusion Problems**  p. 49  
*Larisa Yaroslavtseva*  
**On Non-Polynomial Lower Error Bounds for Adaptive Strong Approximation of SDEs with Bounded $C^{\infty}$-Coefficients**  p. 61  |
| 255–350 | **LK 120**  
**Contributed session**  
**Quadrature at non-QMC points**  
**Chair:** Kinjal Basu  
*Lukas Herrmann*  
**A Multi-Index Quasi-Monte Carlo Algorithm for Lognormal Diffusion Problems**  p. 49  |
| 325–350 | **LK 203/4**  
**Contributed session**  
**MCMC Output Analysis**  
**Chair:** Michael Betancourt  
*Lukas Herrmann*  
**A Multi-Index Quasi-Monte Carlo Algorithm for Lognormal Diffusion Problems**  p. 49  |

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<tr>
<th>Time</th>
<th>Room</th>
<th>Session Type</th>
<th>Title</th>
<th>Authors</th>
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<tr>
<td>3:50-4:20</td>
<td>Berg A</td>
<td>Special session</td>
<td>Higher Order QMC</td>
<td>Takehito Yoshiki</td>
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<td>4:20-5:00</td>
<td>Berg B</td>
<td>Contributed session</td>
<td>Probability</td>
<td>Jens Oettershagen</td>
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<td>5:00-5:20</td>
<td>Berg C</td>
<td>Special session</td>
<td>Multi-modal MC/MCMC</td>
<td>Christopher Kacwin</td>
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<td>5:20-6:00</td>
<td>LK 120</td>
<td>Contributed session</td>
<td>Uncertainty Quantification</td>
<td>Dong T. P. Nguyen</td>
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Adjourn
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<th>Time</th>
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| 0900–1000 | **Plenary Lecture**  
**Hewlett 200**  
*Jose H. Blanchet*  
Efficient Monte Carlo Methods for Spatial Extremes  
Chair: Peter Glynn |
| 1000–1005 | **Walk from Hewlett to LKSC**                                          |
| 1005–1025 | **Coffee (at LKSC)**                                                  |
| 1025–1055 | **Berg A**  
**Mini-symposium**  
Graphics and Transport III  
Chair: Christophe Hery |
| 1025–1055 | **Berg B**  
**Special session**  
Importance Sampling Chair: Nicolas Chopin |
| 1025–1055 | **Berg C**  
**Special session**  
Quantum Computing Chair: Christiane Lemieux |
| 1025–1055 | **LK 203/4**  
**Special session**  
Financial Sensitivity Analysis Chair: Kay Giesecke |
| 1025–1055 | **LK 205/6**  
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Nonlinear Monte Carlo II Chair: Lukasz Szpruch |
| 1025–1055 | **Alexander Keller**  
Learning Light Transport the Reinforced Way p. 45 |
| 1025–1055 | **Víctor Elvira**  
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| 1025–1055 | **Yahzen Wang**  
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| 1025–1055 | **Michael Fu**  
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| 1025–1055 | **Emmanuel Gobet**  
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| 1055–1125 | **Tzu-Mao Li**  
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| 1055–1125 | **Sourav Chatterjee**  
The Sample Size Required in Importance Sampling p. 65 |
| 1055–1125 | **Eric R. Johnston**  
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| 1055–1125 | **Jong Mun Lee**  
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| 1055–1125 | **Denis Belomestny**  
Variance Reduction Technique for Nonlinear Monte Carlo Problems p. 55 |
| 1125–1155 | **Anton Kaplanyan**  
Choosing the Path Integral Domain for MCMC Integration p. 45 |
| 1125–1155 | **Krzysztof Latuszynski**  
Continuous Time Importance Sampling for Jump Diffusions with Application to Maximum Likelihood Estimation p. 66 |
| 1125–1155 | **Faming Liang**  
An Imputation-Consistency Algorithm for High-Dimensional Missing Data Problems p. 98 |
| 1125–1155 | **Nan Chen**  
Monte Carlo Applications in Stochastic Dynamic Programming p. 90 |
| 1155–1155 | **Lunch** |
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<th>Time</th>
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| 1:15–2:15 | Plenary Lecture Berg BC  
Frances Y. Kuo  
Hot New Directions for QMC Research in Step with Applications p. 34  
Chair: Fred Hickernell |
|   | Room separators close                                                  |

#### Berg A  
**Mini-symposium**  
QMC on the Sphere and Other Manifolds I  
Chair: Josef Dick

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<thead>
<tr>
<th>Time</th>
<th>Speaker</th>
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</table>
| 2:25–2:55 | Johann S. Brauchart  
Spherical Lattices: Explicit Construction of Low-Discrepancy Point Sets on the 2-Sphere p. 56 |
| 2:55–3:25 | Wöden Kusner  
Configurations of Points with Respect to Discrepancy and Uniform Distribution p. 56 |

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<tr>
<th>Time</th>
<th>Speaker</th>
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</table>
| 2:25–2:55 | Andreas Rößler  
A Derivative-Free Milstein Scheme for SPDEs with Commutative Noise p. 62 |
| 2:55–3:25 | Paweł Przybyłowicz  
Minimal Asymptotic Errors for Strong Global Approximation of SDEs Driven by Poisson and Wiener Processes p. 62 |

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<tr>
<th>Time</th>
<th>Speaker</th>
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| 2:25–2:55 | Kun Yang  
Density Estimation via Discrepancy p. 118 |
| 2:55–3:25 | Antonio Dalessandro  
Multivariate Concordance Measures and Copulas via Tensor Approximation of Generalized Correlated Diffusions p. 118 |

#### Berg B  
**Mini-symposium**  
Stochastic Computation and Complexity IV  
Chair: Thomas Mueller-Gronbach

#### Berg C  
**Contributed session**  
Statistical  
Chair: Mac Hyman

#### LK 203/4  
**Contributed session**  
QMC-Simulation of Piecewise Deterministic Markov Processes p. 119  
Chair: Christian Bender

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<th>Time</th>
<th>Speaker</th>
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| 2:25–2:55 | Gunther Leobacher  
QMC-Simulation of Piecewise Deterministic Markov Processes p. 119 |
| 2:55–3:25 | Michaela Szölgyenyi  
A Numerical Method for Multidimensional SDEs with Discontinuous Drift and Degenerate Diffusion p. 119 |

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<tr>
<td>3:25–3:50</td>
<td>Coffee</td>
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<td>Time</td>
<td>Event Description</td>
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</tbody>
</table>
| 3:50–4:20 | **Berg A**  
Contributed session  
Discrepancy  
Chair: Dimitriy Bilyk  
Mario Neumüller  
Probabilistic Star Discrepancy Bounds for Digital Kronecker-Sequences  
p. 120 |  
**Berg B**  
Mini-symposium  
Multilevel Monte Carlo IV  
Chair: Raul Tempone  
Chiheb Ben Hammouda  
Multilevel Hybrid Split Step Implicit Tau-Leap for Stochastic Reaction Networks  
p. 50 |  
**Berg C**  
Contributed session  
Processes for Finance IV  
Chair: Osnat Stramer  
Alex Kreinin  
Forward and Backward Simulation of Correlated Poisson Processes  
p. 121 |  
**LK 203/4**  
Contributed session  
Chair: Jon Cockayne  
Anna Zaremba  
Non-Parameteric Gaussian Process Vector Valued Time Series Models and Testing For Causality  
p. 122 |
| 4:20–4:50 | **Florian Puchhammer**  
Sharp General and Metric Bounds for the Star Discrepancy of Perturbed Halton-Kronecker-Sequences  
p. 120 |  
**Klaus Ritter**  
Multilevel Monte Carlo for SDEs with Random Bits  
p. 50 |  
**Adam Kolkiewicz**  
Efficient Simulation For Diffusion Processes Using Integrated Gaussian Bridges  
p. 121 |  
**Hiroshi Haramoto**  
A Method to Compute an Appropriate Sample Size of the Two-Level Test of NIST Test Suite for Frequency and Binary Matrix Rank Test  
p. 122 |
| 5:00 | Group Photo at LKSC |  |  |
| 5:10–6:00 | Walk to Arrillaga Alumni Center |  |  |
| 6:00–7:00 | Reception at Arrillaga Alumni Center |  |  |
| 7:00–10:30 | Banquet at Arrillaga Alumni Center |  |  |

**Location of MCQMC 2018 Announced**
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<thead>
<tr>
<th>Time</th>
<th>Event</th>
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<tbody>
<tr>
<td>900–1000</td>
<td>Plenary Lecture Berg BC</td>
<td>Berg BC</td>
<td>Christoph Aistleitner: One Hundred Years of Uniform Distribution Theory: Hermann Weyl's Seminal Paper of 1916  p. 35 Chair: Josef Dick</td>
</tr>
<tr>
<td>1000–1025</td>
<td>Coffee</td>
<td>Berg A</td>
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<tr>
<td>1025–1055</td>
<td>Special session Mini-symposium Stochastic Maps</td>
<td>Berg B</td>
<td>Robert N. Gantner: Multilevel Higher-Order Quasi-Monte Carlo for Bayesian Inverse Problems  p. 40 Chair: Christoph Schwab</td>
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<td>Berg C</td>
<td>Chang-Han Rhee: Unbiased MLMC for Rare Event Simulation of Equilibrium Distributions of Stochastic Recurrence Equations  p. 50 Chair: Mike Giles</td>
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<td>LK 101</td>
<td>Peter Glynn: Randomized MLMC for Markov Chains  p. 77 Chair: Jose Blanchet</td>
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<td>LK 102</td>
<td>James Johndrow: Approximations of Markov Chains and Bayesian Inference  p. 123</td>
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<tr>
<td>1155–1215</td>
<td>Lunch</td>
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<tr>
<th>Time</th>
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<tbody>
<tr>
<td>1:15</td>
<td><strong>Plenary Lecture</strong> Berg BC</td>
<td>Andrew M. Stuart&lt;br&gt;Hierarchical Bayesian Methods for the Solution of Inverse Problems p. 36&lt;br&gt;Chair: Frances Kuo</td>
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<tr>
<td>2:55</td>
<td>Mini-symposium Berg A&lt;br&gt;Multilevel Monte Carlo VI&lt;br&gt;Chair: Michael Giles</td>
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<tr>
<td></td>
<td><strong>Mini-symposium Berg B</strong></td>
<td>Paweł Morkisz&lt;br&gt;Optimal Pointwise Solution of Stochastic Differential Equations in Presence of Informational Noise p. 63</td>
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<tr>
<td></td>
<td><strong>Mini-symposium Berg C</strong></td>
<td>Toshiya Hachisuka&lt;br&gt;Rise of the Machines in Monte Carlo Integration for Rendering p. 46</td>
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<td></td>
<td><strong>Contributed session LK 101</strong></td>
<td>Osnat Stramer&lt;br&gt;Bayesian Inference for Heston-STAR Models p. 124</td>
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<tr>
<td>3:25</td>
<td><strong>Contributed session LK 101</strong></td>
<td>Jennifer Nguyen&lt;br&gt;Perturbation Monte Carlo-Based Methods for Characterization of Micro-Architectural Changes in Tissue p. 46</td>
</tr>
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<td><strong>Contributed session LK 101</strong></td>
<td>Jan Pospíšil&lt;br&gt;Novel Approach to Calibration of Stochastic Volatility Models using Quasi Evolutionary Algorithm with Local Search Optimization p. 124</td>
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<td>3:50</td>
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<td>Time</td>
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<td>Berg A</td>
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<td>4:50-5:20</td>
<td>Berg C</td>
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<td>LK 203/4</td>
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<td>1:50–4:50</td>
<td>LK 205/6</td>
<td>Contributed session</td>
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<td>Suryanarayana</td>
<td>Rules to Extremal Lattices</td>
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<td>5:20–5:50</td>
<td>David</td>
<td>Rank 1 Lattice Rules for</td>
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</table>
| 9:00–10:00 | Plenary Lecture Berg BC  
*Arnaud Doucet*  
On Pseudo-Marginal Methods for Bayesian Inference in Latent Variable Models  
p. 37 | Berg BC    | *TBA*                                                                          |       |                                            |
| 10:00–10:05 | Presentation on MCQMC 2018                                         | Berg BC    |                                                                                |       |                                            |
| 10:05–10:25 | Coffee                                                                   | Berg A     |                                                                                |       |                                            |
|          | **Mini-symposium** Berg A                                             | Berg B     | **Special session** BERG C  
Intractable Normalizing Constants  
Chair: Krzysztof Latuszynski | Berg B |                                            |
|          | **Special session** Berg C                                             | Berg C     | **Special session** BERG C  
Function Space  
Embeddings for High Dimensional Problems  
Chair: Aicke Hinrichs | LK 101 | **Contributed session** BERG C  
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Chair: Bruno Tuffin |
| 10:25–10:55 | Tan Bui-Thanh  
Particle-based Approximate Monte Carlo Approaches for Large-Scale Bayesian Inverse Problems  
p. 42 | Berg A     | Youssef Marzouk  
Accelerating Metropolis Algorithms via Measure Transport  
p. 42 | Berg B |                                            |
|          | Hani Doss  
An MCMC Approach to Empirical Bayes  
Inference and Bayesian Sensitivity Analysis via Empirical Processes  
p. 69 | Berg B     | Ick Hoon Jin  
A Bayesian Hierarchical Spatial Model for Dental Caries Assessment Using Non-Gaussian Markov Random Fields  
p. 69 | Berg C | Michael Gnewuch  
High-Dimensional Problems: On the Universality of Weighted Anchored and ANOVA Spaces  
p. 82 | LK 101 | Zdravko Botev  
Reliability Estimation for Networks with Minimal Flow Demand and Random Link Capacities  
p. 127 |
|          | Tino Ullrich  
Sparse Approximation with Respect to the Faber-Schauder System  
p. 81 | Berg C     | Peter Kritzler  
Integration in Weighted Anchored and ANOVA Spaces  
p. 82 | LK 101 | Paul Russell  
Parallel Adaptive Importance Sampling  
p. 127 |
| 10:55–11:25 | Oliver Ernst  
Analysis of the Ensemble and Polynomial Chaos Kalman Filters in Bayesian Inverse Problems  
p. 42 | Berg A     | Qianyun Li  
A Latent Potts model for Cancer Pathological Data Analysis  
p. 70 | Berg B |                                            |
|          | Beef Tallow                                                                 | Berg B     |                                                                                |       |                                            |
|          | Tino Ullrich  
Sparse Approximation with Respect to the Faber-Schauder System  
p. 81 | Berg C     |                                                                                |       |                                            |
| 11:25–11:55 | LK 101                                                                 | Berg B     |                                                                                |       |                                            |
| 11:55–12:15 | Lunch                                                                       | Berg C     |                                                                                |       |                                            |
Friday early PM, August 19

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<th>Location</th>
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<tr>
<td>1:15-2:15</td>
<td>Plenary Lecture Berg BC  &lt;br&gt; <em>Peter Frazier</em>  &lt;br&gt; Bayesian Optimization in the Tech Sector: Experiences at Uber, Yelp, and SigOpt  &lt;br&gt; Chair: Dawn Woodard</td>
<td>Berg BC</td>
<td>p. 38</td>
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<tr>
<td>2:15-2:20</td>
<td>MCQMC 2016 Closing Remarks</td>
<td>Berg A</td>
<td>Room separators close</td>
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<tr>
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<td>Berg A  &lt;br&gt; <strong>Contributed session</strong>  &lt;br&gt; Rank One Lattices  &lt;br&gt; Chair: Dirk Nuyens</td>
<td>Berg B</td>
<td>Berg C  &lt;br&gt; <strong>Contributed session</strong>  &lt;br&gt; Chair: Alex Kreinin</td>
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<tr>
<td>2:30-3:00</td>
<td>Toni Volkmer  &lt;br&gt; Sparse High-Dimensional FFT Based on Rank-1 Lattice Sampling  &lt;br&gt; p. 128</td>
<td>Berg B</td>
<td>Art Owen  &lt;br&gt; Permutation p-value  &lt;br&gt; Approximation via Generalized Stolarsky Invariance  &lt;br&gt; p. 130</td>
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<td>Lluís Antoni Jiménez  &lt;br&gt; <em>Rugama</em>  &lt;br&gt; Adaptive Quasi-Monte Carlo Where Each Integrand Value Depends on All Data Sites: the American Option Case  &lt;br&gt; p. 129</td>
<td>Berg B</td>
<td>Art Owen  &lt;br&gt; Permutation p-value  &lt;br&gt; Approximation via Generalized Stolarsky Invariance  &lt;br&gt; p. 130</td>
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<tr>
<td>3:00-3:30</td>
<td>Helene Laimer  &lt;br&gt; On Combined Component-by-Component Constructions of Lattice Point Sets  &lt;br&gt; p. 128</td>
<td>Berg C</td>
<td>Michael Feischl  &lt;br&gt; Fast Random Field  &lt;br&gt; Generation with H-Matrices  &lt;br&gt; p. 130</td>
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<td>Shin Harase  &lt;br&gt; A Comparison Study of Sobol’ Sequences in Financial Derivatives  &lt;br&gt; p. 129</td>
<td>Berg C</td>
<td>Michael Feischl  &lt;br&gt; Fast Random Field  &lt;br&gt; Generation with H-Matrices  &lt;br&gt; p. 130</td>
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<tr>
<td>3:30</td>
<td>Adjourn until 2018</td>
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<tr>
<td>3:30-4:30</td>
<td>Light refreshments for anybody who chooses to linger before heading home</td>
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Tutorials

At this MCQMC we have a series of tutorials on quasi-Monte Carlo (QMC) methods to introduce QMC to attendees who are new to it. We have three members of the MCQMC steering committee giving these tutorials.

Pierre L’Ecuyer and Fred Hickernell will describe the basics of QMC but we can also expect some of their personal views on important future directions.

The Statistical and Applied Mathematical Sciences Institute (SAMSI) is planning a year on quasi-Monte Carlo and probabilistic numerics for 2017/18. We will hear from Richard Smith and Ilse Ipsen of SAMSI in the third session. That is also where Frances Kuo will speak on her work applying QMC methods to PDEs with random coefficients.
Sunday August 14. 2^{00}–3^{00}, Berg Hall

QMC Tutorial I: Introduction to (Randomized) Quasi-Monte Carlo Methods

Pierre L’Ecuyer
Université de Montréal
lecuyer@iro.umontreal.ca

Monte Carlo (MC) methods are ubiquitous in many areas of science, engineering, management, entertainment, etc. MC is commonly used to estimate mathematical expectations viewed as integrals over the unit hypercube \([0,1)^s\) in \(s\) dimensions, by averaging samples of the integrand taken at \(n\) independent random points in \([0,1)^s\). Quasi-Monte Carlo (QMC) replaces these points by a deterministic set of \(n\) points that covers the space more evenly, to reduce the integration error. Randomized QMC (RQMC) randomizes the \(n\) QMC points in a way that they retain their high uniformity while each point has a uniform distribution over \([0,1)^s\). This provides an unbiased estimator which, under appropriate conditions, has much lower variance than with MC. Variants of QMC and RQMC have also been designed for the simulation of Markov chains, for function approximation and optimization, for solving partial differential equations, etc. Highly successful applications are found in computational finance, statistics, physics, and computer graphics, for example. Huge variance reductions occur mostly when the integrand can be well approximated by a sum of low-dimensional functions, often after a clever (problem-dependent) multivariate change of variable.

In this tutorial, we summarize the main ideas and some basic results on QMC and RQMC methods, discuss their practical aspects, and give several examples and numerical illustrations. Key issues to be discussed include: How good QMC point sets and sequences can be constructed and randomized, and how should we measure their uniformity? How can these methods work for high-dimensional integrals? Can they work in the context of simulating Markov chains over a large number of steps? Can they be used to estimate an entire distribution instead of just an expectation? How can we extend point sets on the fly by adding new points or new coordinates? What about computing confidence intervals?

This tutorial will emphasize ideas, intuition, and examples. A follow-up tutorial by F. Hickernell will go more deeply into the theory.
QMC Tutorial II: Error Analysis for Quasi-Monte Carlo Methods

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Quasi-Monte Carlo methods can provide accurate approximations to high dimensional integrals, \( \mu = \int_X f(x) \nu(dx) \), in terms of (weighted) sample means of the integrand values at well chosen sites, \( \hat{\mu} = \sum_{i=1}^{n} w_i f(x_i) \). Such integrals arise in a variety of applications, including finance, statistical physics, sensitivity analysis, and Bayesian inference. The cubature error, \( |\mu - \hat{\mu}| \), depends on properties of the integrand \( f \), and how well the sampling measure, \( \hat{\nu} = \sum_{i=1}^{n} w_i \delta_{x_i} \), approximates the probability measure \( \nu \).

This tutorial highlights some of the major approaches to analyzing and reducing the cubature error that the conference presentations will develop in great detail. There are deterministic, randomized, and Bayesian ways of viewing cubature error, each making different assumptions about the integrand, \( f \), and the sampling measure, \( \hat{\nu} \). When the integrands lie in a Hilbert space or can be modeled as instances of a Gaussian process, the error analysis is particularly elegant. Some strategies for increasing efficiency are described. We also show how the dimension of the integration domain may affect the error analysis. In some cases this leads to a curse of dimensionality, while in other cases the computational cost does not explode as the dimension becomes arbitrarily large. Finally, we discuss progress in developing data-based error bounds, which can be used to determine the sample size, \( n \), required to meet a desired error tolerance.

This talk builds upon the preceding tutorial by Pierre L’Ecuyer, which describes how quasi-Monte Carlo point sets are constructed and employed in a variety of situations. Afterwards, Frances Kuo provides a tutorial on quasi-Monte Carlo methods for solving partial differential equations with random coefficients.
Sunday August 14. 4\(^{50}\)–5\(^{50}\), Berg Hall

QMC Tutorial III: Application of QMC to PDEs with Random Coefficients – a Survey of Analysis and Implementation

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Many physical, biological or geological models involve spatially varying input data which may be subject to uncertainty. This induces a corresponding uncertainty in the outputs of the model and in any physical quantities of interest which may be derived from these outputs. A common way to deal with these uncertainties is by considering the input data to be a random field, in which case the derived quantity of interest will in general also be a random variable or a random field. The computational goal is usually to find the expected value, higher order moments or other statistics of these derived quantities. A prime example is the flow of water through a disordered porous medium.

In this tutorial I will provide a survey of recent research efforts on the application of quasi-Monte Carlo (QMC) methods to elliptic partial differential equations (PDEs) with random diffusion coefficients. As motivated above, such PDE problems occur in the area of uncertainty quantification. There is a huge body of literature on this topic using a variety of methods. QMC methods are relatively new to this application area. The aim of this tutorial is twofold:

- to introduce this interesting new application area to QMC experts, outlining the remaining theoretical difficulties and encouraging more QMC research in this direction; and

- to demonstrate to PDE analysts and practitioners how to tap into the contemporary QMC theory for the error analysis and how to apply the software to their problems.

The tutorial will be loosely based on my survey with Dirk Nuyens from KU Leuven. The survey and the accompanying software package are available from


The survey covers my recent joint works with Ivan Graham and Robert Scheichl from Bath, Dirk Nuyens from KU Leuven, Christoph Schwab from ETH Zurich, Elizabeth Ullmann from TU Munich, and Josef Dick, Thong Le Gia, James Nichols and Ian Sloan from UNSW Australia.
Here is our roster of plenary lectures. Their abstracts are on the following pages. Note that Jose Blanchet’s Wednesday talk is in Hewlett 200. The others are in Berg Hall at LKSC. The AM plenary lectures are at 9:00 and the PM plenary lectures are at 11:15.

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In this talk I will show the beautiful simplicity of approximating high-dimensional integrals using lattice rules. In current engineering applications it is relatively easy to come up with very high and ultra high dimensional integrals, which might be expectations, that depend on hundreds, thousands, or even an infinite number of variables. As the minimal non-trivial tensor product rule, constructed from a 2-point rule, in 100 dimensions already uses $2^{100} = 1267650600228229401496703205376 \approx 10^{30}$ function evaluations—which would take $10^{24}$ seconds at 1 function evaluation per microsecond and we remember the age of the universe to be only approximately $10^{17}$ seconds—we all know why to use Monte Carlo or quasi-Monte Carlo methods where we can freely choose the number of function evaluations independent of the number of dimensions.

While plain vanilla Monte Carlo methods are very robust and easy to apply, in the case of quasi-Monte Carlo methods a lot more details can pop up. I will first introduce the most elegant—in my biased opinion, which I will defend—of all quasi-Monte Carlo methods: the rank-1 lattice rule. This method is defined by one single integer generating vector together with the total number of points in the rule. Approximating a multivariate integral by this method can be done in one line of Matlab code! As one is often interested in successive approximations I will next introduce a rank-1 lattice sequence. Maybe surprisingly, also here, one simple line of Matlab code is sufficient to calculate a segment of a lattice sequence (with a special property).

While for Monte Carlo integration the usual assumption is $L_2$ integrability, leading to an error bound of $O(N^{-1/2})$. For quasi-Monte Carlo methods we generally work with more involved function space settings, leading to error bounds of the form $O(N^{-\alpha})$ with $\alpha \geq 1/2$. I will show the standard function space settings and dive into the weighted function spaces which are being used in current theory to be able to make the error bounds independent of the number of dimensions. We will gloss over the Korobov space of periodic smooth functions, the unanchored Sobolev space with first mixed derivatives, and the cosine space which is a special space of smooth non-periodic functions. All of which are spaces of so-called mixed dominating smoothness, which in terms of mixed derivatives would mean $\partial^{k_1+\cdots+k_s}/(\partial x_1^{k_1} \cdots \partial x_s^{k_s})$ exists for all $(k_1, \ldots, k_s) \leq (\alpha, \ldots, \alpha)$. For non-periodic function spaces lattice rules and sequences can only reach $O(N^{-1})$ convergence.

To arrive at higher-order convergence of $O(N^{-\alpha})$ for non-periodic functions we dive into higher-order Sobolev spaces (of mixed dominating smoothness) in combination with digital nets, but here disguised as a lattice rule, namely polynomial lattice rules. Here, all arithmetic is over a finite field (we will choose the one of order 2) and our lattice rules now take the form of a lattice of polynomials which we map back to points in the unit cube. Higher order can now be obtained by means of the interlacing method from Josef Dick. Although more complicated, again, given the generating matrices of the digital net (as a bunch of integers), and two lines for a magical de Bruijn sequence, we can approximate an integral by such a digital sequence with a single line of (complicated) Matlab code.

While Matlab/Octave one-liners might be fun, and somehow instructive, I will also point you to my online resources where code is available to (a) construct good lattice rules, lattice sequences and polynomial lattice rules (for product, order-dependent, product-and-order-dependent aka POD, and smoothness-driven product-and-order dependent aka SPOD) weighted spaces, and (b) generate points given the generating vector or matrices. Armed with this software you will be able to attack your own problems in no time.

This talk is based upon the results of collaborations with many colleagues.
A Variational Perspective on Accelerated Methods in Optimization

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Accelerated gradient methods play a central role in optimization, achieving optimal rates in many settings. While many generalizations and extensions of Nesterov’s original acceleration method have been proposed, it is not yet clear what is the natural scope of the acceleration concept. In this paper, we study accelerated methods from a continuous-time perspective. We show that there is a Lagrangian functional that we call the Bregman Lagrangian which generates a large class of accelerated methods in continuous time, including (but not limited to) accelerated gradient descent, its non-Euclidean extension, and accelerated higher-order gradient methods. We show that the continuous-time limit of all of these methods correspond to traveling the same curve in spacetime at different speeds. From this perspective, Nesterov’s technique and many of its generalizations can be viewed as a systematic way to go from the continuous-time curves generated by the Bregman Lagrangian to a family of discrete-time accelerated algorithms.

Joint work with Andre Wibisono and Ashia Wilson.
In this talk we will discuss two topics related to the combination of dependence sampling with quasi-random numbers. In the first part of the talk, we will present some recent results where quasi-random numbers are used to sample from copula models, which are a popular way to model dependence in several application areas including risk management and insurance. Both theoretical and numerical results will be presented, and ongoing work on the topic of successfully combining this approach with importance sampling will be discussed as well. In the second part of the talk, we will present a new approach to study randomized quasi-Monte Carlo methods that makes use of dependence concepts to analyze the variance of the corresponding estimators. A generalization of Hoeffding’s lemma will be presented, along with a covariance decomposition result that makes use of this lemma, and allows for the derivation of conditions under which this variance is guaranteed to be smaller than for the Monte Carlo method. The specific case of scrambled nets and their variance will also be discussed.

Joint work with Mathieu Cambou (Ecole Polytechnique Fédérale de Lausanne, Switzerland), Marius Hofert (U. Waterloo, Canada) and Yoshihiro Taniguchi (U. Waterloo, Canada).
Sequential Quasi-Monte Carlo in Infinite Dimension

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The objective of this talk is twofold. First, I would like to present SQMC (Sequential quasi-Monte Carlo), a class of algorithms that merges particle filtering and QMC. Contrary to previous presentations, I will not assume prior knowledge from the audience of particle filtering, state-space modelling and Feynman-Kac representations. I will thus take to introduce these notions and the motivation to perform particle filtering.

Second, I would like to discuss some recent extensions and applications of SQMC, in particular to partly observed diffusion models, which are infinitely-dimensional. QMC techniques, and particularly SQMC, tend to suffer from a curse of dimensionality: their performance gain, relative to Monte Carlo tends to vanish for large-dimensional problems. However, by exploiting well-known properties of partly observed diffusion models, we are able to implement SQMC so that it outperforms significantly standard particle filtering.

Joint work with Mathieu Gerber (Harvard University).
Wednesday August 17. 9^{00}–10^{00}, Hewlett 200

Efficient Monte Carlo Methods for Spatial Extremes

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The main result in univariate EVT says that if the maximum, $Z_n$, of $n$ independent and identically distributed (iid) observations can be approximated by a linear model of the form $a_n M + b_n$ (where $\{a_n, b_n\}$ are deterministic sequences), then $M$ must be a max-stable distribution (having a simple parametric density). The term max-stable is justified by the fact that if $M_1, \ldots, M_n$ are iid copies of $M$, then, in distribution, $M = (\max_{i=1}^n M_i - a_n)/b_n$.

The linear model of extrapolation postulated by EVT turns out to be applicable to virtually all of the parametric univariate distributions which arise in applied statistics (e.g. Gaussian, exponential, gamma, Pareto, log-normal, etc.). Consequently, EVT provides a flexible and, yet, parsimonious way of extrapolating univariate extreme statistics.

Now, many applications, including modeling extreme weather events, naturally call for extrapolation techniques of extremes with spatial dependence. A natural starting point is to build models with max-stable marginal distributions. Therefore it is natural to consider random fields, $\{M(t) : t \in T\}$ ($T$ may represent a geographical region), satisfying the max-stable property by definition. That is, if $\{M_i(\cdot)\}_{i=1}^n$ are iid copies of $M(\cdot)$ then there is a sequence of functions $\{a_n(t), b_n(t)\}$ satisfying the equality in distribution $M(\cdot) = \max_{i=1}^n (M_i(\cdot) - a_n(\cdot))/b_n(\cdot)$. It turns out that if $M(\cdot)$ is a max-stable random field then (after applying a simple transformation) $M(\cdot)$ must admit a representation of the form

$$M(t) = \max_{n=1}^\infty \{-\log(A_n) + X_n(t)\},$$

where $A_n$ is the $n$-th arrival of a Poisson process and $X_n(\cdot)$ is an iid sequence of random fields (typically Gaussian) independent of the $A_n$s. The goal of this talk is to discuss efficient Monte Carlo techniques for max-stable random fields. In particular, we study the following questions:

a) Is it possible to simulate $\{M(t_1), \ldots, M(t_d)\}$ exactly (i.e. without bias)?

b) Can exact simulation be performed optimally as $d$ grows to infinity?

c) Can conditional simulation also be done efficiently and without bias?

We share surprising good news in response to these questions using ideas borrowed from recent exact simulation algorithms, rare-event simulation, and multilevel Monte Carlo.

Joint work with Zhipeng Liu (Columbia University), Ton Dieker (Columbia University) and Thomas Mikosch (University of Copenhagen).
High dimensional computation is a new frontier in scientific computing, with applications ranging from financial mathematics such as option pricing or risk management, to groundwater flow, heat transport, and wave propagation. This talk will begin with a contemporary review of quasi-Monte Carlo (QMC) methods for approximating high dimensional integrals. I will highlight some recent developments on “lattice rules” and “higher order digital nets”. One key element is the “fast component-by-component construction” which yields QMC methods with a prescribed rate of convergence for sufficiently smooth functions. Another key element is the careful selection of parameters called “weights” to ensure that the worst case errors in an appropriately weighted function space are bounded independently of the dimension.

I will outline recent research efforts on the application of QMC methods to PDEs with random coefficients. (For background motivation see the abstract for my Sunday tutorial.) I will then showcase some current collaborations in progress, including the analysis and implementation of “multi-level methods” and “multivariate decomposition methods” for PDE applications; the development of QMC theory for PDE eigenvalue problems; fast QMC matrix vector multiplication method; a preintegration smoothing technique to tackle high dimensional integration of kinks and jumps; circulant embedding and $H$-matrix techniques for generating lognormal random fields using QMC. The defining characteristic of these projects is that the theory and methods for high dimensional computation are developed not in isolation, but in close connection with applications.
One Hundred Years of Uniform Distribution Theory: Hermann Weyl’s Seminal Paper of 1916

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Hermann Weyl’s seminal paper “Über die Gleichverteilung von Zahlen mod. Eins” appeared in the Mathematische Annalen one hundred years ago, in 1916. This paper established the theory of uniform distribution modulo one as a proper mathematical discipline and connected it with various other mathematical topics, including Fourier analysis, number theory, numerical analysis and probability theory. This paper formed the cornerstone for the later development of uniform distribution theory, discrepancy theory and the theory of Quasi–Monte Carlo integration, and it is amazing to see to which extent later developments were already anticipated in Weyl’s paper and how far he went beyond previous work.

In this talk, we narrate the evolution of Weyl’s paper and present its content. We show how it initiated subsequent developments, and we discuss some of the most important results in the field as well as some of the most important open problems.
Hierarchical Bayesian Methods for the Solution of Inverse Problems

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The last decade has seen the development of a theory of infinite dimensional Bayesian inversion, leading to new MCMC algorithms for statistical inversion which converge at rates independent of the dimension of the state-space; for problems arising in the physical sciences, for example, the state-space may be infinite dimensional, and in practice of very high dimension when represented on a computer. At the same the time machine learning community has made enormous advances in the development of predictive algorithms which learn from data, and do not use mechanistic models. A key idea to emerge from this work in machine learning is that hierarchical modelling is a very effective and flexible way of representing complex prior knowledge. This talk is concerned with the use of hierarchical Bayesian methods for the solution of inverse problems, and in particular the interaction of hierarchical methodologies with the construction of effective MCMC algorithms for problems in high or infinite dimensional state spaces.
On Pseudo-Marginal Methods for Bayesian Inference in Latent Variable Models

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The pseudo-marginal algorithm is a popular variant of the Metropolis–Hastings scheme which allows us to sample asymptotically from a target probability density when we are only able to estimate unbiasedly an un-normalized version of it. It has found numerous applications in Bayesian statistics as there are many latent variable models where the likelihood function is intractable but can be estimated unbiasedly using Monte Carlo samples. In this talk, we will first review the pseudomarginal algorithm and show that its computational cost is for many common applications quadratic in the number of observations at each iteration. We will then present a simple modification of this methodology which can reduce very substantially this cost. A large sample analysis of this novel pseudo-marginal scheme will be presented.
Bayesian Optimization in the Tech Sector: Experiences at Uber, Yelp, and SigOpt

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We discuss Bayesian optimization, a class of methods for optimization of expensive functions and optimization via simulation, in which Monte Carlo simulation is playing an increasingly critical role. We describe optimization as a decision-making task (“where should I sample next?”), in which we use decision theory supported by Monte Carlo methods to reduce the number of expensive function evaluations required to find approximate optima. We discuss these methods in the context of applications from the tech sector: optimizing e-commerce systems, real-time economic markets, mobile apps, and hyperparameters in machine learning algorithms. We conclude with examples of the impact of these methods, from the speaker’s experiences working with Yelp, Uber, and the Bayesian Optimization startup company, SigOpt.
Mini symposia

Mini-symposia are collections of related talks spanning two or more special sessions. We have six of them:

- MC and QMC Methods for Bayesian Inverse Problems
- MCQMC in Graphics and Computational Transport
- Multilevel Monte Carlo
- Nonlinear Monte Carlo Methods
- Quadrature on the Sphere and Other Manifolds
- Stochastic Computation and Complexity

They are described on the next pages.
MC and QMC Methods for Bayesian Inverse Problems

Organizers: Christoph Schwab, SAM ETH Zurich and Andrew Stuart, University of Warwick.

Inverse problems are of enormous importance in the numerous applications in the sciences and engineering where there is a combination of both sophisticated mathematical model and access to large data. The Bayesian formulation of such problems opens substantial research challenges at the intersection of the fields “data science” and “uncertainty quantification”. For problems with “distributed uncertain input” parameter, Bayesian inverse problems can be reduced under rather general hypotheses to essentially computing infinite-dimensional integrals in which the data and model are combined to define the integrand. Widely used methodologies to deal with these problems are MCMC, Ensemble Kalman Filtering methods (EnKF), and their variants. Being based on Monte-Carlo techniques, these methods feature convergence rates of order 1/2 in terms of the number of “forward” solves of the underlying model. Application of QMC to Bayesian inverse problems does open the possibility of methods which improve upon this convergence rate, offering for problems with costly forward solves the perspective of massive performance gains. The session will present new theoretical advances on MC and QMC in this broad and dynamic field.

Bayes Inverse, Part I: Thursday August 18. 10:25–11:55, Berg B

Multilevel Higher-Order Quasi-Monte Carlo for Bayesian Inverse Problems

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We consider Bayesian inversion of partial differential equations with distributed uncertain inputs, which reduces to the computation of high-dimensional integrals. Under certain sparsity conditions on the parameteric input, the resulting integrands fulfill the same conditions, implying applicability of recently developed higher-order QMC methods. We focus in this talk on computational aspects of this problem, including fast CBC construction of interlaced polynomial lattice rules achieving higher order convergence rates, as well as single and multilevel formulations of the discretized Bayesian inverse problem. Numerical results showing improvements of the time-to-solution compared to traditional, Monte Carlo-based approaches are presented. We also comment briefly on a repository of generating vectors for such problems, and an open-source software package to aid in the application of such methods.

This work was supported by CPU time from the Swiss National Supercomputing Centre (CSCS) under project ID d41, by the Swiss National Science Foundation (SNF) under Grant No. SNF149819.

Joint work with Christoph Schwab (ETH Zurich, Switzerland), Josef Dick (UNSW, Australia) and Quoc Thong Le Gia (UNSW, Australia).


Multilevel Markov Chain Monte Carlo Methods for Bayesian Inversion of Partial Differential Equations

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The Bayesian approach to inverse problems, in which the posterior probability distribution on an unknown field is sampled for the purposes of computing posterior expectations of quantities of interest, is starting to become computationally feasible for partial differential equation (PDE) inverse problems. Balancing the sources of error arising from finite-dimensional approximation of the unknown field, the PDE forward solution map and the sampling of the probability space under the posterior distribution are essential for the design of efficient computational Bayesian methods for PDE inverse problems. We study Bayesian inversion for a model elliptic PDE with an unknown diffusion coefficient. We consider both the case where the PDE is uniformly elliptic with respect to all the realizations, and the case where uniform ellipticity does not hold, i.e. the coefficient can get arbitrarily close to 0 and arbitrarily large as in the log-normal model. We provide complexity analysis of Markov chain Monte Carlo (MCMC) methods for numerical evaluation of expectations under the Bayesian posterior distribution given data, in particular bounds on the overall work required to achieve a prescribed error level. We first bound the computational complexity of the plain MCMC, based on combining MCMC sampling with linear complexity multi-level solvers for elliptic PDEs. The work versus accuracy bounds show that the complexity of this approach can be quite prohibitive. We then present a novel multi-level Markov chain Monte Carlo strategy which utilizes sampling from a multi-level discretization of the posterior and the forward PDE. The strategy achieves an essentially optimal complexity level that is essentially equal to that for performing only one step on the plain MCMC. The essentially optimal accuracy and complexity of the method are mathematically rigorously proven. Numerical results confirm our analysis.

This is joint work with Jia Hao Quek (NTU, Singapore), Christoph Schwab (ETH, Switzerland) and Andrew Stuart (Warwick, England).

Numerical Analysis of Posterior Concentration in Multilevel QMC Estimators for Bayesian Inverse Problems

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For Bayesian inversion of partial differential equations with high-dimensional parametric, or distributed uncertain inputs, the posterior density may concentrate for small observation noise covariance.

We present an analysis of the posterior concentration, from [3], shedding light on the scaling and geometry of posterior concentration for BIP with formally infinite-dimensional, parametric input.

We address the question of numerical stability of high order, Quasi Monte-Carlo quadratures in the numerical computation of high-dimensional integrals in the case of small observation noise covariance.

Several strategies of building numerical stable, deterministic estimators which are free from the curse of dimension will be discussed: a reparametrization of the posterior density using 2nd order information at the MAP point and a more general strategy using nonlinear reparametrizations. We prove that, under certain nondegeneracy assumptions, these strategies will facilitate deterministic Bayesian estimates with dimension-independent, possibly higher order, convergence rates, with error bounds that are independent of the observation noise covariance as well.

Joint work with Robert Gantner (SAM, ETH Zürich), Youssef Marzouk and Alessio Spantini (MIT).

Work supported by CPU time from the Swiss National Supercomputing Centre (CSCS) under project ID d41, by the Swiss National Science Foundation (SNF) under Grant No. SNF149819.

Bayes Inverse, Part II: Friday

August 19. 10^{25}–11^{55}, Berg A

Particle-based Approximate Monte Carlo Approaches for Large-Scale Bayesian Inverse Problems

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Bayesian inverse problems/UQ are ubiquitous in sciences and engineering. The solution of a Bayesian inverse problem is the posterior in (possibly infinite) high dimensional parameter space. One of the most effective tools to explore the posterior is the Markov chain Monte Carlo (MCMC) framework. However, MCMC is often too computationally extensive, and alternatives are necessary for large-scale problems. In this talk, we present several particle methods to compute (approximate) posterior samples without the need for a Markov chain. We present theory, computational experiments, and comparisons among the methods.

Accelerating Metropolis Algorithms via Measure Transport

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We present a new approach for efficiently characterizing complex probability distributions, using a combination of measure transport and Metropolis corrections. We use continuous transportation to transform typical Metropolis proposal mechanisms into non-Gaussian proposal distributions. Our approach adaptively constructs a Knothe-Rosenblatt rearrangement using information from previous MCMC states, via the solution of convex and separable optimization problems. We then discuss key issues underlying the construction of transport maps in high dimensions, and present ways of exploiting sparsity and certain kinds of near-identity structure.

Joint work with: Matthew Parno (MIT), Alessio Spantini (MIT).

Analysis of the Ensemble and Polynomial Chaos Kalman Filters in Bayesian Inverse Problems

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We analyze the ensemble and polynomial chaos Kalman filters applied to nonlinear stationary Bayesian inverse problems. In a sequential data assimilation setting, such stationary problems arise in each step of either filter. We give a new interpretation of the approximations produced by these two popular filters in the Bayesian context and prove that, in the limit of large ensemble or high polynomial degree, both methods yield approximations which converge to a well-defined random variable termed the analysis random variable. We then show that this analysis variable is more closely related to a specific linear Bayes estimator than to the solution of the associated Bayesian inverse problem given by the posterior measure. This suggests limited or at least guarded use of these generalized Kalman filter methods for the purpose of uncertainty quantification.
MCQMC in Graphics and Computational Transport

Organizers: Alexander Keller, NVIDIA and Christophe Hery, Pixar Animation Studios and Wenzel Jakob, EPFL Switzerland.


On MCQMC Issues in Production Rendering
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Use of MC integration has popularized in the VFX industry, but since it is usually not possible to find one importance sampling that will directly match the whole rendering equation, the common solution is to use MIS. Unfortunately render times increase with the number of techniques to MIS, and sometimes arbitrary (artistic) signals don’t have a good sampling method to begin with. This is why we are looking into MCMC with the hope that it will solve some of the problems. In this talk, we will also show some of the common shortcomings of QMC, in particular in conjunction with the Alias method; and we will explore the biased approaches we still resort to in graphics (such as denoising, photon mapping and mollification), mainly to overcome the “slow” quadratic convergence of pure MC or MCMC.

Data-Driven Light Scattering Models: An Application to Rendering Hair
Leonid Pekelis
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We present an implementation of Adaptive Importance Sampling [1], specialized to fit easily sampled distributions to complicated BCSDFs - light transport equations employed for realistic graphics rendering. Innovations include alternating objective minimization and penalization designed to produce good fit, automatically across a diverse range of cases.

We apply our algorithm to the canonical model [2] for light scattering from hair and fur. The result is novel among importance sampling implementations in that it includes features such as eccentricity for elliptical hair fiber cross-section, azimuthal roughness control, and fiber torsion. It is also fully energy preserving. We compare with two leading implementations in the literature as well as a ground truth, physical model which directly evaluates light-cylinder interactions. Ours well approximates the ground truth, and drastically reduces both computation and artist time compared to the others.

Examples from a recent Pixar animated film, as well as brief discussion of general convergence of the fitting algorithm are included.

Joint work with Christophe Hery (Pixar Animation Studios), Ryusuke Villemin (Pixar Animation Studios), and Junyi Ling (Pixar Animation Studios).


Monte Carlo for Light Transport Including Linear Polarization

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Monte Carlo Ray Tracing (MCRT) is often used for general light transport problems. A variety of open source and commercial packages are available that do this. Few of these packages support light polarization.

A very simple approach to polarized light transport is presented that uses adjoint light particles each tagged with a linear polarization. This results in a very simple algorithm. Because all MC adjoint particles are independent, parallelization is straightforward but also implies the limitation that light phase is not supported.

A series of validation experiments is presented, and the debugging challenges added by polarization are discussed.

Towards Real Time Monte Carlo Simulations for Biomedicine

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Monte Carlo methods provide the “gold standard” computational technique for solving biomedical problems but their widespread use is hindered by the slow convergence of the sample means. An exponential increase in the convergence rate can be obtained by adaptively modifying the sampling and weighting strategy employed. However, if the radiance is represented by a truncated expansion of basis functions, a bias is introduced by the truncation and the geometric acceleration of the convergence rate is partly or entirely offset by the sheer number of expansion coefficients to be estimated in as many as 6 independent variables and in every homogeneous tissue subregion. As well, the (unknown amount of) bias is unacceptable for a gold standard numerical method. Conventional density function estimation methods are widely used in other light transport applications. They avoid the need to represent the radiance in a functional expansion but the need for smoothing parameters also introduces a bias in the density estimator. This precludes convergence to the exact solution and is unacceptable in a gold standard method. We introduce a density estimation methodology that eliminates the bias by constraining the radiance to obey the transport equation. We provide numerical evidence of the superiority of this Transport-Constrained Unbiased Radiance Estimator (T-CURE) in simple problems and indicate its promise for general, heterogeneous problems.

Joint work with Rong Kong, Hyundai Capital America and Shuang Zhao, UCI.
Learning Light Transport the Reinforced Way

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We show that the equations for reinforcement learning and light transport simulation are related integral equations. Based on this correspondence, a scheme to learn importance during sampling path space is derived. The new approach is demonstrated in a consistent light transport simulation algorithm that uses reinforcement learning to progressively learn probability density functions for importance sampling. As the number of paths with non-zero contribution can be dramatically increased, much less noisy images can now be rendered within the same time budget.

This is joint work with Ken Dahm, NVIDIA.

Hessian-Hamiltonian Monte Carlo Rendering

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The simulation of light transport in the presence of multi-bounce glossy effects and motion is challenging because the integrand is high dimensional and areas of high-contribution tend to be narrow and hard to sample. We present a Markov Chain Monte Carlo (MCMC) rendering algorithm that extends Metropolis Light Transport by automatically and explicitly adapting to the local shape of the integrand, thereby increasing the acceptance rate. Our algorithm characterizes the local behavior of throughput in path space using its gradient as well as its Hessian. In particular, the Hessian is able to capture the strong anisotropy of the integrand. We obtain the derivatives using automatic differentiation, which makes our solution general and easy to extend to additional sampling dimensions such as time.

However, the resulting second order Taylor expansion is not a proper distribution and cannot be used directly for importance sampling. Instead, we use ideas from Hamiltonian Monte Carlo and simulate the Hamiltonian dynamics in a flipped version of the Taylor expansion where gravity pulls particles towards the high-contribution region. Whereas such methods usually require numerical integration, we show that our quadratic landscape leads to a closed-form anisotropic Gaussian distribution for the final particle positions, and it results in a standard Metropolis-Hastings algorithm. Our method excels at rendering glossy-to-glossy reflections on small and highly curved surfaces. It is also the first MCMC rendering algorithm that is able to resolve the anisotropy in the time dimension and render difficult moving caustics.

Joint work with Jaakko Lehtinen (Aalto University; NVIDIA), Ravi Ramamoorthi (University of California, San Diego), Wenzel Jakob (ETH Zürich), Frédo Durand (MIT CSAIL).

Choosing the Path Integral Domain for MCMC Integration

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The path integral formulation of light transport is the basis for (Markov chain) Monte Carlo global illumination methods. In this talk we present Half Vector Space Light Transport (HSLT), a novel approach to sampling and integrating light transport paths on surfaces. The key is the transformation of the path space into another domain, where a path is represented by its start and end point constraints and a sequence of halfway vectors. We show that this domain has several benefits. It enables importance sampling of all interactions along paths. Another important characteristic is that the Fourier-domain properties of the path integral can be easily estimated. These can be used to achieve optimal correlation of the MCMC samples due to well-chosen step sizes, leading to more efficient exploration of light transport features.
Rise of the Machines in Monte Carlo Integration for Rendering

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Following the recent success of deep learning, machine learning is getting used to solve various problems in many different fields. While deep learning is often hyped as an emulation of a human brain via a computer, one can see it as a mere parametric model for approximating a (usually hidden) functional relationship between input data and output data. It should then be possible to use machine learning to make general MC/MCMC computation adaptive by learning a hidden, but useful structure of a target problem. This talk summarises our recent attempts to accelerate practical computation via MC/MCMC in computer graphics based on machine learning. Topics covered include an automatic mixture of MC samplers and adaptive MCMC. While the applications are specific to computer graphics, the developed algorithms are general and potentially applicable to other applications.

Perturbation Monte Carlo-Based Methods for Characterization of Micro-Architectural Changes in Tissue

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We present a polarization-sensitive, transport-rigorous perturbation Monte Carlo (pMC) method to model the impact of optical property changes on reflectance measurements within a discrete particle scattering model. The model consists of three log-normally distributed populations of Mie scatterers that approximate biologically relevant subatomic size distributions in cervical tissue. We compare our method’s reflectance estimates for perturbations across wavelength and/or scattering model parameters and conventional Monte Carlo’s reflectance estimates. We then use these comparisons to draw conclusions about the performance of pMC as to accuracy and computational efficiency gains. Finally, we examine the utility of differential Monte Carlo in estimating sensitivities with respect to the parameters of our discrete particle scattering model and with respect to the optimization of parameters of interest. To our knowledge, ours is the first study that takes account of scattering phase function changes, in addition to changes in the parameters of the particle size distributions used for the scattering model. Time permitting, we will illustrate the improvement in the solution of inverse problems engendered by our pMC/dMC methods in identifying microarchitectural changes in cervical tissue.

Joint work with Carole K. Hayakawa (University of California, Irvine), Judith R. Mourant (Los Alamos National Laboratory), Vasan Venugopalan (University of California, Irvine), and Jerome Spanier (University of California, Irvine).
Multilevel Monte Carlo


MLMC Part I: Monday August 15. 10^25–11^55, Berg C

Adaptive Timestepping for SDEs with Non-Globally Lipschitz Drift

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This talk looks at the use of the standard Euler-Maruyama discretisation with adaptive timesteps for SDEs with a drift which is not globally Lipschitz. It is proven that under certain conditions all moments of the numerical solution remain bounded for any finite time interval, and the strong order of convergence is the same as usual, when viewed as accuracy versus expected cost per path. Furthermore, for SDEs which satisfy a certain contraction property, similar results hold over the infinite time interval. The strong convergence results are relevant to the use of this discretisation for Multilevel Monte Carlo simulation.

This is joint work with Mike Giles.

Mean Square Error Adaptive Euler–Maruyama Method with Applications in Multilevel Monte Carlo

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A formal mean square error expansion (MSE) is derived for Euler–Maruyama numerical solutions of stochastic differential equations (SDE). The error expansion is used to construct a pathwise a posteriori adaptive time stepping Euler–Maruyama method for numerical solutions of SDE, and the resulting method is incorporated into a multilevel Monte Carlo (MLMC) method for weak approximations of SDE. This gives an efficient MSE adaptive MLMC method for handling a number of low-regularity approximation problems. In low-regularity numerical example problems, the developed adaptive MLMC method is shown to outperform the uniform time stepping MLMC method by orders of magnitude, producing output whose error with high probability is bounded by $TOL>0$ at the near-optimal MLMC cost rate $O(TOL^{-2}\log(TOL)^4)$.
The Multivariate Decomposition Method

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The Multivariate Decomposition Method (MDM) is an algorithm for approximating the integral of a function $f$ which depends on $\infty$-many variables, $y_1, y_2, \ldots$. It begins by decomposing $f$ into the countable sum of functions which depend only on finitely many variables:

$$f(y_1, y_2, \ldots) = \sum_{|u| < \infty} f_u(y_j : j \in u),$$

where $u \subset \mathbb{N}$ denotes a subset of variables and each $f_u$ only depends on the variables $y_j$ for $j \in u$. The general idea of the MDM algorithm is as follows. First, choose the “active set”, which is a collection of subsets of variables $u$ corresponding to terms $f_u$ which, loosely speaking, contribute most to the total integral. The next step, is to apply separate quadrature rules to each decomposition term $f_u$ for $u$ in the active set. The final approximation of the integral is then the sum of all the quadrature approximations of the terms in the active set.

One such problem where $\infty$-variate integrands arise is a PDE with a random coefficient, where the coefficient can be parametrised by $\infty$-many stochastic variables. Here the quantity of interest is the expected value, with respect to the stochastic parameters, of some linear functional of the PDE solution.

In this talk I will discuss applying the MDM when the integrand is a linear functional the solution of a PDE with a random coefficient. I will briefly introduce the PDE problem, the MDM algorithm, then focus on the two aspects of the implementation: constructing the active set and efficiently constructing the quadrature approximations.

Quasi and Multilevel Monte Carlo Methods for Bayesian Inverse Problems

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The parameters in mathematical models for many physical processes are often impossible to determine fully or accurately, and are hence subject to uncertainty. By modelling the input parameters as stochastic processes, it is possible to quantify the induced uncertainty in the model outputs. Based on available information, a prior distribution is assigned to the input parameters. If in addition some dynamic data (or observations) related to the model outputs are available, a better representation of the parameters can be obtained by conditioning the prior distribution on these data, leading to the posterior distribution in the Bayesian framework.

In most situations, the posterior distribution is intractable in the sense that the normalising constant is unknown and exact sampling is unavailable. Using Bayes’ Theorem, we show that posterior expectations of quantities of interest can be written as the ratio of two prior expectations involving the quantity of interest and the likelihood of the observed data. These prior expectations can then be computed using Quasi-Monte Carlo and multilevel Monte Carlo methods.

In this talk, we give a convergence and complexity analysis of the resulting ratio estimators, and demonstrate their effectiveness on a typical model problem in uncertainty quantification.

This is joint work with Rob Scheichl (University of Bath, UK), Andrew Stuart (California Institute of Technology, USA).
QMC for Parametric, Elliptic PDEs

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Stochastic and parametric PDEs are considered with particular focus on mean field approximations and/or approximations of the expectation of quantities of interest, cp. [3, 2]. We analyze convergence rates of first order quasi Monte-Carlo (QMC) integration with randomly shifted lattice rules and for higher order, interlaced polynomial lattice rules, for a class of countably parametric integrands that result from linear functionals of solutions of linear, elliptic diffusion equations with uncertain coefficient function represented in a system \((\psi_j)_{j\geq 1}\) in a bounded domain \(D\), cp. [2].

Whereas in [4, 1] the functions \((\psi_j)_{j\geq 1}\) stemmed from global basis functions, we allow \((\psi_j)_{j\geq 1}\) to be wavelet systems and investigate consequences for the (multilevel) QMC quadrature as considered in [4, 1]. The QMC weights facilitate work bounds for the fast, component-by-component constructions of [5].

This research is supported in part by the Swiss National Science Foundation (SNSF) under grant SNF 200021_159940/1 and under grant SNF 200021_149819, the European Research Council under ERC AdG 247277, the Knut and Alice Wallenberg foundation, and the Swedish Research Council under Reg. No. 621-2014-3995.

This is joint work with Robert N. Gantner, Christoph Schwab (ETH Zurich, Switzerland), and Annika Lang (Chalmers University of Technology & University of Gothenburg, Sweden).


A Multi-Index Quasi-Monte Carlo Algorithm for Lognormal Diffusion Problems

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We present a Multi-Index Quasi-Monte Carlo method for the solution of elliptic partial differential equations with random coefficients and inputs. By combining the multi-index sampling idea with randomly shifted rank-1 lattice rules, the algorithm constructs an estimator for the expected value of some functional of the solution. The efficiency of this new method is illustrated on a three-dimensional subsurface flow problem with lognormal diffusion coefficient with underlying Matérn covariance function. This example is particularly challenging because of the small correlation length considered, and thus the large number of uncertainties that must be included. We present strong numerical evidence that it is possible to achieve a cost inversely proportional to the requested tolerance on the root-mean-square error.
Multilevel Hybrid Split Step Implicit Tau-Leap for Stochastic Reaction Networks

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This talk focuses on providing, efficiently, accurate estimations of the expected value, \( E[g(X(T))] \), where \( g : \mathbb{R}^d \to \mathbb{R} \) is a given smooth scalar observable of the process \( X \), continuous-time Markov chains called SRN (stochastic Reaction Network). SRNs are employed to describe the time evolution of biochemical reactions, epidemic processes and transcription and translation in genomics, etc.

In biochemically reactive systems with small copy numbers of one or more reactant molecules, the dynamics is dominated by stochastic effects. To approximate those systems, discrete state-space and stochastic simulation approaches have been shown to be more relevant than continuous state-space and deterministic ones. In systems characterized by having simultaneously fast and slow timescales, existing discrete space-state stochastic path simulation methods, such as the stochastic simulation algorithm (SSA) and the explicit tau-leap (Explicit-TL) method, can be very slow. Implicit approximations have been developed to improve numerical stability and provide efficient simulation algorithms for those systems. Here, we propose an efficient Multilevel Monte Carlo (MLMC) method in the spirit of the work by Anderson and Higham (2012). This method uses split-step implicit tau-leap (SSI-TL) at levels where the SSI-TL method is not applicable due to numerical stability issues. We present numerical examples that illustrate the performance of the proposed method.

This is joint work with Alvaro Moraes and Raul Tempone (KAUST, Saudi Arabia).

Multilevel Monte Carlo for SDEs with Random Bits

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Let \( X \) be the solution to a stochastic differential equation (SDE), and let \( \varphi \) be a real-valued functional on the path space. We study the approximation of the expectation of \( \varphi(X) \) by means of randomized algorithms that may only use random bits.

We provide upper and lower bounds on the complexity of the problem. Moreover, we present a new multilevel algorithm with two dimensions of discretization, time and number of bits.

The talk is based on joint work with M. Hefter, L. Mayer, S. Omland (all from Kaiserslautern), and M. Giles (Oxford).

Unbiased MLMC for Rare Event Simulation of Equilibrium Distributions of Stochastic Recurrence Equations

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In this talk, we discuss applications of multi-level ideas to the rare event simulation of stochastic recurrence equations of the form \( Z_{n+1} = A_n Z_n + 1 \) where \( \{A_n\}_{n \in \mathbb{N}} \) is an iid sequence of positive random variables, and \( \log A_i \) is heavy-tailed with negative mean. The equilibrium distribution of such stochastic recursion arise in the analysis of probabilistic algorithms or financial mathematics, where the limit random variable \( Z_\infty \) represents the stochastic perpetuity. If one interprets \( -\log A_n \) as the interest rate at time \( n \), then \( Z_\infty \) is the present value of a bond that generates a unit of money at each time point \( n \). Taking advantage of the close connection between the maximum of random walks and the associated stochastic perpetuities, we construct a strongly efficient simulation estimator for the rare event probability \( P\{Z_\infty > x\} \). The new estimator, however, involves infinite number of random variables, and hence, cannot be computed exactly. We apply the unbiased multi-level technique developed in [1] to construct a computable unbiased estimator, and show that the resulting estimator maintains strong efficiency.
Joint work with Bohan Chen (CWI Amsterdam, The Netherlands) and Bert Zwart (CWI Amsterdam, The Netherlands).


**Multi-index Monte Carlo**

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We describe and analyze the Multi-Index Monte Carlo (MIMC) for computing statistics of the solution of a PDE with random data. MIMC is both a stochastic version of the combination technique introduced by Zenger, Griebel and collaborators and an extension of the Multilevel Monte Carlo (MLMC) method first described by Heinrich and Giles. Instead of using first-order differences as in MLMC, MIMC uses mixed differences to reduce the variance of the hierarchical differences dramatically. These mixed differences yield new and improved complexity results, which are natural generalizations of Giles’s MLMC analysis, and which increase the domain of problem parameters for which we achieve the optimal convergence. We finally show the effectiveness of MIMC in some computational tests, including PDEs with random coefficients and Stochastic Particle Systems.


**Unbiased Estimators and Multilevel Monte Carlo**

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Multilevel Monte Carlo (MLMC) [1, 2] and recently proposed debiasing schemes [3, 4] are closely related methods for scenarios where exact simulation methods are difficult to implement, but biased estimators are available. The talk is based on a recent paper [5] about a new general class of unbiased estimators which admits earlier debiasing schemes of Rhee and Glynn [4] as special cases, and, more importantly, allows new lower variance estimators, which are based on stratification. The stratified schemes behave asymptotically like MLMC, both in terms of variance and cost, under general conditions—essentially those that guarantee canonical square root error rate for MLMC. This suggests that MLMC bias can often be eliminated entirely with a negligible additional cost. The new schemes also admit optimisation criteria which are easy to implement in practice.


The Population Dynamics Algorithm

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A variety of problems in science and engineering, ranging from population and statistical physics models to the study of queueing systems, computer networks and the internet, lead to the analysis of branching distributional equations. The solutions to these equations are not in general analytically tractable, and hence need to be computed numerically. This talk discusses a simulation algorithm known as “Population Dynamics”, which is designed to produce a pool of identically distributed observations having approximately the same law as the endogenous solution in a wide class of branching distributional equations.

The Population Dynamics algorithm repeatedly uses bootstrap to move from one iteration of the branching distributional equation to the next, which dramatically reduces the exponential complexity of the naïve Monte Carlo approach. We present new results guaranteeing the convergence of the Wasserstein distance between the distribution of the pool generated by the algorithm and that of the true endogenous solution, including results on its rate of convergence.

Multilevel Sequential Monte Carlo for Normalizing Constants

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The age of data is upon us, and the importance of its incorporation into estimation schemes cannot be understated. Bayesian inference provides a principled and well-defined approach to the integration of data into an a priori known distribution. The posterior distribution, however, is known only point-wise (possibly with an intractable likelihood) and up to a normalizing constant. Monte Carlo methods have been designed to deal with these cases, such as Markov chain Monte Carlo (MCMC) and sequential Monte Carlo (SMC) samplers. Recently, the multilevel Monte Carlo framework has been extended to some of these cases. This talk will concern the recent development of multilevel SMC (MLSMC) samplers and the resulting estimators for standard quantities of interest [1] as well as normalizing constants [2].

Joint work with Alex Beskos (UCL), Pierre Del Moral (INRIA Bordeaux), Ajay Jasra (NUS), Raul Tempone (KAUST), Yan Zhou (NUS).


Nonlinear Monte Carlo Methods

Organizers: Lukasz Szpruch, University of Edinburgh and Denis Belomestny, Universitat Duisburg-Essen.

In recent years a great progress has been made in expanding applicability of Monte Carlo techniques to nonlinear problems arising in physics, biology and finance. In particular, language of Backward Stochastic Differential Equations (BSDEs) and Stochastic particle systems allowed probabilistic interpretations for semi-linear and fully nonlinear PDEs. In this session we aim to overview the most recent results in the field.

The main topics are: stochastic particle systems, simulation-based techniques for BSDEs, stochastic control and optimal stopping problems.


Multilevel Monte Carlo for McKean-Vlasov SDEs

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Stochastic Interacting Particle System (SIPS) and they limiting stochastic McKean-Vlasov equations offer a very rich and versatile modelling framework. On one hand, interactions allow us to capture complex dependent structure, on the other provide a great challenge for Monte Carlo simulations. The non-linear dependence of the approximation bias on the statistical error makes classical variance reduction techniques fail in this setting. In this talk, we will devise a strategy relying on the fixed point argument, that will allow constructing a novel SIPS with the superior computational properties. In particular, we will establish Multilevel Monte Carlo estimator for SIPS that significantly improves classical Monte Carlo estimators that build on the propagation of chaos results.

Monte Carlo Method for Optimal Management in Energy Markets

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This paper is about the management of a power-grid. The aim of power grid managers is to optimize their expected future profit. The methods of risk management are non-standard because the underlying asset, electricity, cannot be traded. This leads naturally incomplete financial market. Additionally, changing the production strategy incurs costs which one must consider in the risk analysis. We approach this optimal management problem by means of risk measure minimization. It involves a system of reflected backwards differential equations, whose solution determines the optimal management strategy. We present a novel numerical method based on least-squares Monte Carlo in order to determine the management strategy in high dimensions. Unlike other approaches, our system of equations avoids quadratic growth, and therefore leads to a more stable system of equations for numerical methods.

This is joint work with Luciano Campi and Clemence Allasseur.
A Primal-Dual Algorithm for Backward SDEs

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We generalize the primal-dual methodology, which is popular in the pricing of early-exercise options, to a backward dynamic programming equation associated with time discretization schemes of backward stochastic differential equations (BSDEs). Taking as an input some approximate solution of the backward dynamic program, which was pre-computed, e.g., by least-squares Monte Carlo, this methodology enables us to construct a confidence interval for the unknown true solution of the time discretized BSDE. We numerically demonstrate the practical applicability of our method for some multidimensional nonlinear pricing problems where tight price bounds were previously unavailable.

The talk is based on joint work with N. Schweizer, J. Zhuo, and C. Gärtner.

Particle Methods for the Smile Calibration of Cross-Dependent Volatility Models

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In quantitative finance, pricing and hedging multi-asset derivatives requires using multi-asset models and calibrating them to liquid market smiles (e.g., the smiles of stocks and indices). The local volatilities in multi-asset models typically have no cross-asset dependency. In this talk, we propose a general framework for pricing and hedging derivatives in cross-dependent volatility (CDV) models, i.e., multi-asset models in which the volatility of each asset is a function of not only its current or past levels, but also those of the other assets. For instance, CDV models can capture that stock volatilities are driven by an index level, or recent index returns. We explain how to build all the CDV models that are calibrated to all the asset smiles, solving in particular the longstanding smiles calibration problem for the “cross-aware” multidimensional local volatility model. CDV models are rich enough to be simultaneously calibrated to other instruments, such as basket smiles, and we show that the model can fit a basket smile either by means of a correlation skew, like in the classical “cross-blind” multi-asset local volatility model, or using only the cross-dependency of volatilities itself, in a correlation-skew-free model, thus proving that steep basket skews are not necessarily a sign of correlation skew. The calibrated models follow nonlinear stochastic differential equations in the sense of McKean. All the calibration procedures use the particle method, a very robust and efficient Monte Carlo method for calibrating models to given marginal distributions. The calibration of the implied “local in basket” CDV uses a novel fixed point-compound particle method. Numerical results in the case of the FX smile triangle problem illustrate the efficiency of particle methods and the capabilities of CDV models.
Our goal is to solve certain dynamic programming equations associated to a given Markov chain $X$, using a regression-based Monte Carlo algorithm. This type of equation arises when computing price of American options or solving non-linear pricing rules. More specifically, we assume that the model for $X$ is not known in full detail and only a root sample of size $M$ of such process is available. We are investigating a new method that by-passes the calibration step. By a stratification of the space and a suitable choice of a probability measure $\nu$, we design a new resampling scheme that allows to compute local regressions (on basis functions) in each stratum. The combination of the stratification and the resampling allows to compute the solution to the dynamic programming equation (possibly in large dimensions) using only a relatively small set of root paths. To assess the accuracy of the algorithm, we establish non-asymptotic error estimates in $L_2(\nu)$. Our numerical experiments illustrate the good performance, even with $M = 20$–$40$ root paths.

In this talk I present several variance reduction approaches which are applicable to a variety of challenging nonlinear Monte Carlo problems like simulation-based optimal stopping or simulation of McKean-Vlasov-type equations. A distinctive feature of these approaches is that they allow for a significant reduction of the computational complexity not only up to a constant but also in order. A numerical performance of these approaches will also be illustrated.
Quadrature on the Sphere and Other Manifolds

Organizer: Johann Brauchart, Graz University of Technology and Josef Dick, University of New South Wales.

Sphere plus, Part I: Wednesday August 17. 2^{25}–3^{25}, Berg A

Spherical Lattices: Explicit Construction of Low-Discrepancy Point Sets on the 2-Sphere

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The aim of this talk is two-fold: firstly, to provide an introduction into the main theme of ‘quadrature on the sphere and other manifolds’ of this minisymposium, and, specifically, to discuss recent progress in the construction of explicit spherical node sets derived from lattices in the plane.

It can be shown that an \( n \)-point node set with maximal sum of mutual distances has smallest possible spherical cap \( L_2 \)-discrepancy among all \( n \)-point sets on the sphere and is also the best possible choice for a QMC method for functions from a certain Sobolev space over the sphere (Brauchart and Dick, 2013). From a practical point of view, it is not feasible to solve the underlying highly non-linear optimization problem for large \( n \). Indeed, a central unresolved question is to give explicit constructions of node sets on the sphere that have provable good properties regarding numerical integration. One approach considered here is to lift to the sphere well-studied lattice constructions in the square.

Configurations of Points with Respect to Discrepancy and Uniform Distribution

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We would like to find point sets on spheres with low discrepancy, and also of known discrepancy. There are some good algorithms to compute the discrepancy of point sets and a number of candidate point sets work with. For the purposes of applications in low dimensions, we can compare sets of several thousand points using the most naive algorithms in a reasonable amount of time.

We’ll describe some algorithms for explicitly computing discrepancy, analyze some problems in optimizing the quality point sets, and look at some experimental data related to conjectured “good” point sets coming from a brute force implementation.
Sphere plus, Part II: Thursday August 18. 350–550, Berg C

QMC Designs and Determinantal Point Processes

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The concept of quasi-Monte Carlo (QMC) design sequence is introduced by Brauchart et al. [1]. In this talk, we consider probabilistic generations of a sequence of QMC design by using determinantal point processes (DPPs), which are used in a fermion model in quantum mechanics and also studied in probability theory. We show that, the spherical ensemble on the 2-dimensional unit sphere $S^2$, a well-studied DPPs (e.g., [2]), generate on average QMC design sequences for Sobolev space $H^s(S^2)$ with $1 < s < 2$. We also show that, DPPs defined by reproducing kernels for polynomial spaces over the $d$-dimensional unit sphere $S^d$ generate on average a better convergent sequence for $H^s(S^d)$ with $d/2 + 1/2 < s < d/2 + 1$. Moreover, we deal with DPPs defined on other manifolds and related results.


Fast Framelet Transforms on Manifolds

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Data in practical application with some structure can be viewed as sampled from a manifold, for instance, data on graphs and in astrophysics. A smooth and compact Riemannian manifold $\mathcal{M}$, including examples of spheres, tori, cubes and graphs, is an important manifold. In this work, we construct a type of tight framelets using quadrature rules on $\mathcal{M}$ to represent the data (or a function) and to exploit the derived framelets to process the data (for instance, inpainting an image on $\mathcal{M}$).

One critical computation for framelets is to compute, from the framelet coefficients for the input data (which are assumed at the highest level), the framelet coefficients at lower levels, and also to evaluate the function values at new nodes using the framelet representation. We design an efficient computational strategy, said to be fast framelet transform (FMT), to compute the framelet coefficients and to recover the function. Assuming the fast Fourier transform (FFT) on the manifold $\mathcal{M}$, the FMT has the same computational complexity as the FFT. Numerical examples illustrate the efficiency and accuracy of the algorithm for the framelets.

This is joint work with Xiaosheng Zhuang (City U. of Hong Kong, Hong Kong).
Diameter Bounded Equal Measure Partitions of Compact Manifolds

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The algorithm devised by Feige and Schechtman [5] for partitioning higher dimensional spheres into regions of equal measure and small diameter is combined with David and Christ’s construction of dyadic cubes [3, 4] to yield a partition algorithm suitable to any connected Ahlfors regular metric measure space of finite measure. As a particular case, we show the following result.

Theorem 1. Let \( (X, \rho, \mu) \) be a smooth compact connected \( d \)-dimensional Riemannian manifold without boundary. Then there exist positive constants \( c_1 \) and \( c_2 \) such that for every sufficiently large \( N \), there is a partition of \( X \) into \( N \) regions of measure \( \mu(X)/N \), each contained in a ball of radius \( c_1 N^{-1/d} \) and containing a ball of radius \( c_2 N^{-1/d} \).

Several recent results on good quadrature rules on manifolds [1, 2] are based precisely on the possibility of obtaining one such partition.

This is joint work with Paul Leopardi (Australian Bureau of Meteorology).


Covering Radii of Various Point Configurations Distributed over the Unit Sphere

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For a fixed positive integer \( N \) we can place \( N \) independent random points on the unit sphere distributed with respect to its surface measure. Another way is to place \( N \) points that minimize certain discrete energy, or maximize certain discrete polarization (or Chebyshev constant). For these methods we compare how well the obtained \( N \) points cover the sphere. It turns out that, even though some deterministic configurations cover the sphere better than random ones, the difference is not too big.

This is joint work with E. Saff and A. Volberg.
Stochastic Computation and Complexity

Organizers: Stefan Heinrich, University of Kaiserslautern, Germany and Thomas Mueller-Gronbach, University of Passau, Germany and Paweł Przybyłowicz, AGH University of Science and Technology, Krakow, Poland.

SC&C Part I: Monday August 15. 10^{25}–11^{55}, Berg B

Complexity of Parametric Stochastic Integration in Hölder Classes

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We study the complexity of pathwise approximation of the stochastic Ito integral of functions depending on a parameter. We consider functions belonging to Hölder classes, that is, functions that are \( r \)-times differentiable and the highest derivatives satisfy some Hölder condition. This work continues previous investigations on function classes of mixed smoothness. We present multilevel algorithms and analyze their convergence rate, using the interplay between Banach space valued and parametric problems.

The considered classes require more subtle lower bound methods. We discuss this aspect in some detail (along with a brief introduction into lower bound concepts of information-based complexity theory). The results show the order optimality of the proposed algorithm and settle the complexity of the problem.

A Coercivity-Type Condition for SPDEs with Additive White Noise

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In this talk we explain a new explicit, easily implementable, and fully discrete accelerated exponential Euler-type approximation scheme for additive space-time white noise driven stochastic partial differential equations (SPDEs) with possibly non-globally monotone nonlinearities such as stochastic Kuramoto-Sivashinsky equations. The main result proves that the proposed approximation scheme converges strongly and numerically weakly to the solution process of such an SPDE. Key ingredients in the proof of our convergence result are a suitable generalized coercivity-type condition, the specific design of the accelerated exponential Euler-type approximation scheme, and an application of Fernique’s theorem.

The talk is based on joint work with Arnulf Jentzen and Diyora Salimova.

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Adaptive Approximation of the Minimum of Brownian Motion

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We study the $L_p$-error in approximating the minimum of a Brownian motion on the unit interval based on finitely many point evaluations. We construct an algorithm that adaptively chooses the points at which to evaluate the Brownian path. In contrast to the $1/2$ convergence rate of optimal non-adaptive algorithms, the proposed adaptive algorithm converges at an arbitrarily high polynomial rate. The problem of approximating the minimum of a stochastic process naturally arises in the context of numerics for reflected stochastic differential equations. In particular, the proposed algorithm can be applied to the squared Bessel process of dimension 1, which is an instance of a Cox-Ingersoll-Ross process where the boundary point zero is accessible.

This is joint work with James M. Calvin (New Jersey Institute of Technology, USA) and Mario Hefter (TU Kaiserslautern, Germany).

SC&C Part II: Monday August 15. 2^25–3^25, Berg B

The Order Barrier for Strong Approximation of Rough Volatility Models

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We study the strong approximation of a rough volatility model, in which the log-volatility is given by a fractional Ornstein-Uhlenbeck process with Hurst parameter $H < 1/2$. Our methods are based on an equidistant discretization of the volatility process and of the driving Brownian motions, respectively. For the root mean-square error at a single point the optimal rate of convergence that can be achieved by such methods is $n^{-H}$, where $n$ denotes the number of subintervals of the discretization. This rate is in particular obtained by the Euler method and an Euler-trapezoidal type scheme.

This is joint work with Taras Shalaiko (University of Mannheim).

Strong Convergence Rates for Cox-Ingersoll-Ross Processes: Full Parameter Range

Mario Hefter
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In recent years, strong (pathwise) approximation of stochastic differential equations (SDEs) has intensively been studied for SDEs of the form

$$dX_t = (a - bX_t)dt + \sigma \sqrt{X_t}dW_t,$$

with a scalar Brownian motion $W$ and parameters $a, \sigma > 0$, $b \in \mathbb{R}$. These SDEs are used to describe the volatility in the Heston model and the interest rate in the Cox-Ingersoll-Ross model. In the particular case of $b = 0$ and $\sigma = 2$ the solution is a squared Bessel process of dimension $a$.

We propose a tamed Milstein scheme $Y^N_t$, which uses $N \in \mathbb{N}$ values of the driving Brownian motion $W$, and prove positive polynomial convergence rates for all parameter constellations. More precisely, we show that for every $1 \leq p < \infty$ and every $\varepsilon > 0$ there exists a constant $C > 0$ such that

$$\sup_{0 \leq t \leq 1} (E|X_t - Y^N_t|^p)^{1/p} \leq C \cdot \frac{1}{N^{\min(1, \delta)/(2p) - \varepsilon}},$$

for all $N \in \mathbb{N}$, where $\delta = 4a/\sigma^2$.

This is joint work with André Herzwurm (TU Kaiserslautern, Germany).
A new Generation of Explicit Numerical Schemes for SDEs with Superlinear Coefficients

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Convergence results for a new class of explicit, high-order schemes, which approximate stochastic differential equations (SDEs) with super-linear coefficients, will be presented. Theoretical results will be illustrated through the implementation of these algorithms to known non-linear models. Some relevant references are below.

Joint work with Chaman Kumar (Edinburgh U., U.K.).


On Non-Polynomial Lower Error Bounds for Adaptive Strong Approximation of SDEs with Bounded $C^\infty$-Coefficients

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Recently it has been shown in [2] that there exist SDEs with bounded $C^\infty$-coefficients, such that no approximation method based on finitely many observations of the driving Brownian motion at fixed time points converges in absolute mean to the solution with a polynomial rate. This result does not cover methods that may choose the number as well as the location of the evaluation nodes of the driving Brownian motion in a path dependent way, e.g. methods with a sequential step-size control. For SDEs with globally Lipschitz continuous coefficients it is well-known that using a path-dependent step-size control typically does not lead to a better rate of convergence compared to what is best possible for non-adaptive algorithms, see e.g. [3]. However, in the case of the one-dimensional squared Bessel process, which is the solution of an SDE with a non-globally Lipschitz continuous diffusion coefficient, an adaptive method has recently been constructed in [1], which converges to the solution even at a superpolynomial rate, while non-adaptive algorithms achieve rate 1/2 in the best case. In this talk we show that a similar positive result does not hold for the SDEs from [2]. In fact, for these SDEs a polynomial rate of convergence can also not be achieved with any kind of adaptive algorithm.


A Derivative-Free Milstein Scheme for SPDEs with Commutative Noise

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We consider the problem of approximating mild solutions of stochastic partial differential equations (SPDEs) in the mean-square sense. Therefore, an infinite dimensional version of a derivative-free Milstein scheme for the time discretization is proposed. The introduced scheme can be applied to a certain class of semilinear SPDEs in the case of commutative noise. In this case, increments of the driving Q-Wiener process have to approximated only. This makes the numerical scheme easy to implement. As a novelty, the derivative-free Milstein scheme turns out to be also efficiently applicable in the general case of non-multiplicative diffusion operators. Moreover, the order of convergence and the efficiency of the new scheme will be discussed.

This is joint work with Claudine Leonhard.

Minimal Asymptotic Errors for Strong Global Approximation of SDEs Driven by Poisson and Wiener Processes

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We refer our recent results on the strong global approximation of SDEs driven by two independent processes: a nonhomogeneous Poisson process and a Wiener process. We assume that the jump and diffusion coefficients of the underlying SDE satisfy jump commutativity condition. We establish the exact convergence rate of minimal errors that can be achieved by arbitrary algorithms based on a finite number of observations of the Poisson and Wiener processes. We consider classes of methods that use equidistant or nonequidistant sampling of the Poisson and Wiener processes. We provide a construction of optimal methods, based on the classical Milstein scheme, which asymptotically attain the established minimal errors. The analysis implies that methods based on nonequidistant mesh are more efficient than those based on the equidistant mesh. We also discuss methods based on the adaptive stepsize control.
SC&C Part V: Thursday August 18. 2^{25}–3^{25}, Berg B

Optimal Pointwise Solution of Stochastic Differential Equations in Presence of Informational Noise

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We study a pointwise approximation of solutions of systems of stochastic differential equations. We assume that an approximation method can use values of the drift and diffusion coefficients which are perturbed by some deterministic noise. Let $K_1, K_2 \geq 0$ be the precision levels for the drift and the diffusion coefficients, respectively. We give a construction of the randomized Euler scheme and we prove that it has the error $O(n^{-\min\{\varrho, 1/2\}} + K_1 + K_2)$ as $n \to +\infty$, $K_1, K_2 \to 0$, where $n$ is the number of discretization points and $\varrho$ is the Hölder exponent of the diffusion coefficient. We also investigate lower bounds on the error of an arbitrary algorithm and establish optimality of the defined randomized Euler algorithm. Finally, we report some numerical results.

We generalize the results of [1] and [2]. Those papers concern problems for ODEs and SDEs correspondingly when the exact information is available.

Joint work with Paweł Przybyłowicz.


General Multilevel Adaptations for Stochastic Approximation Algorithms

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We present and analyse multilevel adaptations of stochastic approximation algorithms. In contrast to the classical application of multilevel Monte Carlo algorithms we are now dealing with a parameterised family of expectations and we want to find parameters with zero expectation. Our analysis is carried out under mild assumptions with respect to the family of expectations and nearly classical assumptions with respect to the multilevel approach. In particular, we prove upper bounds for the $p$-th mean error of our methods in terms of their computational cost, which coincide with the bounds known for the classical problem of approximating a single expectation with the multilevel approach.

Joint work with Steffen Dereich (University of Münster, Germany).
Special sessions

Special sessions consist of 3 or 4 related talks put together by one or more organizers. These special sessions are described on the following pages:

- Advances in Importance Sampling
- Approximate Bayesian Computation
- Bayesian Computation with Intractable Normalizing Constants
- Combinatorial Discrepancy
- Construction and Error Analysis for Quadrature Rules
- Constructions of Quadrature Rules
- Exact Sampling of Markov Processes
- Experimental Design for Simulation Experiments
- Function Space Embeddings for High Dimensional Problems
- Hamiltonian Monte Carlo in Theory and Practice
- High Dimensional Numerical Integration
- Higher Order Quadrature Rules
- Monte Carlo for Financial Sensitivity Analysis
- Monte Carlo Sampling from Multi-Modal Distributions
- Preasymptotics for Multivariate Approximation
- Probabilistic Numerics
- Quantum Computing and Monte Carlo Simulations
- Stochastic Maps and Transport Approaches for Monte Carlo
- Systematic Risk and Financial Networks
Advances in Importance Sampling

Organizer: Ingmar Schuster, Université de Paris, Dauphine.

Recently, there has been renewed interest in Importance Sampling, with results that go far beyond the state of the art of the early nineties when research focus shifted to MCMC. These results include theoretical advances in the analysis of convergence conditions and convergence assessment on one side. On the other, an overarching Multiple Importance Sampling framework has been proposed as well as IS based on piecewise deterministic processes, which allows, amongst other things, data subsampling and incorporating gradient information.

Wednesday August 17. 10^{25}–11^{55}, Berg B

Generalized Multiple Importance Sampling

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Importance sampling methods are broadly used to approximate posterior distributions or some of their moments. In its standard approach, samples are drawn from a single proposal distribution and weighted properly. However, since the performance depends on the mismatch between the targeted and the proposal distributions, several proposal densities are often employed for the generation of samples. Under this Multiple Importance Sampling (MIS) scenario, many works have addressed the selection or adaptation of the proposal distributions, interpreting the sampling and the weighting steps in different ways. In this paper, we establish a novel general framework for sampling and weighting procedures when more than one proposal is available. The most relevant MIS schemes in the literature are encompassed within the new framework, and, moreover novel valid schemes appear naturally. All the MIS schemes are compared and ranked in terms of the variance of the associated estimators. Finally, we provide illustrative examples which reveal that, even with a good choice of the proposal densities, a careful interpretation of the sampling and weighting procedures can make a significant difference in the performance of the method.

Joint work with L. Martino (University of Valencia), D. Luengo (Universidad Politecnica de Madrid) and M. F. Bugallo (Stony Brook University of New York).

The Sample Size Required in Importance Sampling

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I will talk about a recent result, obtained in a joint work with Persi Diaconis, about the sample size required for importance sampling. If an i.i.d. sample from a probability measure P is used to estimate expectations with respect to a probability measure Q using the importance sampling technology, the result says that the required sample size is \(\exp(K)\), where K is the Kullback-Leibler divergence of P from Q. If the sample size is smaller than this threshold, the importance sampling estimates may be far from the truth, while if the sample size is larger, the estimates are guaranteed to be close to the truth.
Continuous Time Importance Sampling for Jump Diffusions with Application to Maximum Likelihood Estimation

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In the talk I will present a novel algorithm for sampling multidimensional irreducible jump diffusions that, unlike methods based on time discretisation, is unbiased. The algorithm can be used as a building block for maximum likelihood parameter estimation. The approach is illustrated by numerical examples of financial models like the Merton or double-jump model where its efficiency is compared to methods based on the standard Euler discretisation and Multilevel Monte Carlo.

Joint work with Sylvain Le Corff, Paul Fearnhead, Gareth O. Roberts, and Giorgios Sermaidis.
Approximate Bayesian Computation

Organizer: Scott Sisson, University of New South Wales.

Many scientific problems feature intractable likelihoods that cannot be evaluated, complicating the task of Bayesian inference. Approximate Bayesian Computation (ABC) is a computationally intensive alternative that is available when one can simulate from the distribution underlying the likelihood.

**Tuesday August 16. 10^{25}–11^{55}, Berg A**

**Bayesian Synthetic Likelihood**

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Having the ability to work with complex models can be highly beneficial. However, complex models often have intractable likelihoods, so methods that involve evaluation of the likelihood function are infeasible. In these situations, the benefits of working with likelihood-free methods become apparent. One of these methods is called the synthetic likelihood (SL), which uses a multivariate normal approximation of the distribution of a set of summary statistics. This paper explores the accuracy and computational efficiency of the Bayesian version of the synthetic likelihood (BSL) approach in comparison to a competitor known as approximate Bayesian computation (ABC) and its sensitivity to its tuning parameters and assumptions. We relate BSL to pseudo-marginal methods and propose to use an alternative SL that uses an unbiased estimator of the SL, when the summary statistics have a multivariate normal distribution. Several applications of varying complexity are considered to illustrate the findings.

Joint work with Leah Price (Queensland University of Technology, Australia), David Nott (National University of Singapore), and Anthony Lee (University of Warwick, United Kingdom).

**Synthetic Likelihood Variational Bayes**

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Synthetic likelihood is an attractive approach to likelihood-free inference when an approximately Gaussian summary statistic for the data informative for inference about the parameters is available. The synthetic likelihood method uses a plug-in normal density estimate for the summary statistic, with the plug-in mean and covariance matrix obtained by simulation at each parameter value. A pseudo-marginal implementation of Bayesian synthetic likelihood has been introduced recently, where an unbiased estimate of the likelihood is employed. In this setting, if the summary statistic is Gaussian, the distribution targeted by the MCMC scheme does not depend on the number of Monte Carlo samples used to estimate the mean and covariance matrix. However, to obtain satisfactory mixing of the pseudo-marginal algorithm it is important that the likelihood estimate is not too variable, which means that a large number of simulations are still required for each synthetic likelihood evaluation, particularly when the summary statistic is high-dimensional.

Here we consider implementing stochastic gradient variational Bayes methods for posterior approximation with the synthetic likelihood, employing unbiased estimates of the log likelihood. The main interest of this idea is that the stochastic gradient optimization is much more tolerant of noise in the log-likelihood estimate, so that fewer simulations
can be used in each synthetic log-likelihood evaluation compared to the number required in pseudomarginal Bayesian synthetic likelihood. We compare the pseudo-marginal implementation with the synthetic likelihood variational Bayes (SLVB) approach and an existing variational approach to likelihood free inference in the literature in a number of examples.

Joint work with V. Ong, D. Nott, S. Sisson and C. Drovandi.

Inference via Bayesian Synthetic Likelihoods for a Mixed-Effects SDE Model of Tumor Growth and Response Treatment

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We consider parameter inference for a state-space model for repeated measurements obtained on several subjects. We construct a nonlinear mixed-effects model where individual dynamics are expressed by stochastic differential equations (SDE). Nonlinear SDE state-space models are notoriously difficult to fit: however, advancements in parameter estimation using sequential Monte Carlo methods have made the task in principle approachable, if not always straightforward. While each individual (subject specific) contribution to the overall likelihood function for the “population of subjects” can be approximated using sequential Monte Carlo, here we propose a global approximation performed directly on the the entire likelihood function. We use summary statistics to encode information pertaining between-subjects variation, as well as individual variation, and resort to a synthetic likelihood approximation [1]. In particular, we take advantage of the Bayesian (pseudo-marginal) synthetic likelihood approach in [2].

We consider longitudinal data from measurements of tumor volumes in mice. Mice are divided in five groups and administered different treatments. We postulate a two compartments model to represent the fraction of volume pertaining the compartment of tumor cells killed by the treatment and the fraction of cells still alive. The dataset is challenging because of sparse observations. Inference via synthetic likelihoods is then compared with exact Bayesian inference from a standard pseudo-marginal approach. Consistently for both approaches our model is able to identify a specific treatment to be more effective in reducing tumor growth.

Joint work with Julie Lyng Forman (Dept. Biostatistics, University of Copenhagen, Denmark).


Bayesian Computation with Intractable Normalizing Constants

Organizer: Faming Liang, University of Florida.

Friday August 19. 10^{25}−11^{55}, Berg B

An MCMC Approach to Empirical Bayes Inference and Bayesian Sensitivity Analysis via Empirical Processes

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Consider a Bayesian situation in which we observe $Y \sim p_{\theta}$, where $\theta \in \Theta$, and we have a family $\{\nu_{h}, h \in \mathcal{H}\}$ of potential prior distributions on $\Theta$. Let $g$ be a real-valued function of $\theta$, and let $I_{g}(h)$ be the posterior expectation of $g(\theta)$ when the prior is $\nu_{h}$. We are interested in two problems: (i) selecting a particular value of $h$, and (ii) estimating the family of posterior expectations $\{I_{g}(h), h \in \mathcal{H}\}$. Let $m_{y}(h)$ be the marginal likelihood of the hyperparameter $h$: $m_{y}(h) = \int p_{\theta}(y) \nu_{h}(d\theta)$. The empirical Bayes estimate of $h$ is, by definition, the value of $h$ that maximizes $m_{y}(h)$. It turns out that it is typically possible to use Markov chain Monte Carlo to form point estimates for $m_{y}(h)$ and $I_{g}(h)$ for each individual $h$ in a continuum, and also confidence intervals for $m_{y}(h)$ and $I_{g}(h)$ that are valid pointwise. However, we are interested in forming estimates, with confidence statements, of the entire families of integrals $\{m_{y}(h), h \in \mathcal{H}\}$ and $\{I_{g}(h), h \in \mathcal{H}\}$: we need estimates of the first family in order to carry out empirical Bayes inference, and we need estimates of the second family in order to do Bayesian sensitivity analysis. We establish strong consistency and functional central limit theorems for estimates of these families by using tools from empirical process theory. As an application, we consider Latent Dirichlet Allocation, which is heavily used in topic modelling.

The two-dimensional hyperparameter that governs this model has a large impact on inference. We show how our methodology can be used to select it. We also show how to form globally valid “two-dimensional confidence bands” for certain posterior probabilities of interest, and give an illustration on a real data set.

Joint work with Yeonhee Park (MD Anderson Cancer Center).

A Bayesian Hierarchical Spatial Model for Dental Caries Assessment Using Non-Gaussian Markov Random Fields

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Research in dental caries generates data with two levels of hierarchy: that of a tooth overall and that of the different surfaces of the tooth. The outcomes often exhibit spatial referencing among neighboring teeth and surfaces, i.e., the disease status of a tooth or surface might be influenced by the status of a set of proximal teeth/surfaces. Assessments of dental caries (tooth decay) at the tooth level yield binary outcomes indicating the presence/absence of teeth, and trinary outcomes at the surface level indicating healthy, decayed, or filled surfaces. The presence of these mixed discrete responses complicates the data analysis under a unified framework. To mitigate complications, we develop a Bayesian two-level hierarchical model under suitable (spatial) Markov random field assumptions that accommo-
dates the natural hierarchy within the mixed responses. At the first level, we utilize an autologistic model to accommodate the spatial dependence for the tooth-level binary outcomes. For the second level and conditioned on a tooth being non-missing, we utilize a Potts model to accommodate the spatial referencing for the surface-level trinary outcomes. The regression models at both levels were controlled for plausible covariates (risk factors) of caries, and remain connected through shared parameters. To tackle the computational challenges in our Bayesian estimation scheme caused due to the doubly-intractable normalizing constant, we employ a double Metropolis-Hastings sampler. We compare and contrast our model performances to the standard non-spatial (naive) model using a small simulation study, and illustrate via an application to a clinical dataset on dental caries.

A Latent Potts model for Cancer Pathological Data Analysis

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Nowadays, much biological data are acquired via images. In this project, we study the pathological images scanned from 205 lung cancer patients with the goal to find out the relationship between the distribution of different types of cells, including lymphocytes, stroma and tumor cells, and the survival time.

Toward this goal, we model the distribution of different types of cells using a modified Potts model for which the parameters represent interactions between different types of cells, and estimate the parameters of the Potts model using the double Metropolis-Hastings algorithm. The double Metropolis-Hastings algorithm allows us to simulate samples approximately from a distribution with an intractable normalizing constant. Our numerical results indicate that the distribution of different types of cells is significantly related with the patient’s survival time.
Combinatorial Discrepancy

Organizer: Aleksandar Nikolov, University of Toronto and Kunal Talwar, Google Inc.

Combinatorial discrepancy is a quantity associated with finite set systems, and is a discrete analogue of geometric discrepancy. Going back to work of Beck, it is well known that upper bounds on combinatorial discrepancy can be used to construct point sets with small geometric discrepancy. This connection has been used (most notably by Matousek) to give tight bounds on the geometric discrepancy of several natural families of sets, for example halfspaces and Cartesian products of discs. The constructions based on combinatorial discrepancy have the appealing property that they provide upper bounds on geometric discrepancy with respect to essentially any measure, rather than just Lebesgue measure. We propose a special session to cover the basic connection mentioned above, as well as several new developments in combinatorial discrepancy. These include:

- A near-resolution of Tusnady’s problem, which is the combinatorial analogue of the great open problem of determining the star discrepancy in higher dimensions.
- The discovery of efficient algorithms to compute low discrepancy colorings.
- New upper bounds on random bounded degree set systems, which are related to the Beck-Fiala conjecture.

Tuesday August 16. 1025–1155, Berg B

Combinatorial Discrepancy – Introduction
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In this talk I will describe the basics of combinatorial discrepancy theory, some of the important historical results, and connections to geometric discrepancy. I will highlight some methods of proving upper and lower estimates on combinatorial discrepancy. Finally, I will describe the connection between hereditary discrepancy and the \( \gamma_2 \) factorization norm, and how it helps in giving estimates on discrepancy.

Joint work with Kunal Talwar, Google (USA) and Jiří Matoušek (deceased).

Minimizing Discrepancy by Walking on the Edges
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Minimizing the discrepancy of a set system is a fundamental problem in combinatorics. One of the cornerstones in this area is the celebrated six standard deviations result of Spencer (AMS 1985): In any system of \( n \) sets in a universe of size \( n \), there always exists a coloring which achieves discrepancy \( 6\sqrt{n} \). The original proof of Spencer was existential in nature, and did not give an efficient algorithm to find such a coloring. Bansal (FOCS 2010) gave the first efficient algorithm which finds such a coloring. His algorithm is based on an SDP relaxation of the discrepancy problem and a clever rounding procedure. In a follow up work (FOCS 2012) we give a simple randomized algorithm to find a coloring as in
Spencer’s result based on a restricted random walk. Our algorithm and its analysis use only basic linear algebra and is “truly” constructive in that it does not appeal to the existential arguments, giving a new proof of Spencer’s theorem and the partial coloring lemma.

This is joint work with Raghu Meka (UCLA).

An Algorithm for Komlos Conjecture Matching Banaszczyk’s Bound

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The Komlós conjecture and its special case the Beck-Fiala conjecture are challenging open problems in discrepancy theory and convex geometry. The best known bounds on both are due to Banaszczyk from 1998, using a non-constructive convex geometric argument. While there had been a lot of progress in the past few years in algorithms for discrepancy theory, matching Banaszczyk’s bounds algorithmically seemed challenging. I will talk about our recent work which gives an algorithm giving the same bounds as Banaszczyk. I will also talk about the more general theorem proved by Banaszczyk and some of its other applications. Our result uses ingredients from semidefinite programming duality, martingales and convex geometry.

This is based on joint work with Nikhil Bansal and Daniel Dadush.
Construction and Error Analysis for Quadrature Rules

Organizers: Christian Irrgeher, RICAM Linz and Takehito Yoshiki, University of New South Wales.

The analysis of multivariate integration for various classes of functions is of high interest, because for many applications in different areas, like finance, biology or physics, it is necessary to compute high-dimensional integrals in a fast way. There is active research on constructing and studying integration rules which solve the multivariate integration problem efficiently. The aim of this special session is to discuss current progress on the theoretical analysis of efficient quadrature rules for multivariate integration.

**Thursday August 18.** 3:50–5:50, Berg A

**Optimal Order Quasi-Monte Carlo Integration in Sobolev Spaces of Arbitrary Smoothness**

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We investigate quasi-Monte Carlo integration using higher order digital nets in Sobolev spaces of arbitrary fixed smoothness \( \alpha \in \mathbb{N}, \alpha \geq 2 \), defined over the \( s \)-dimensional unit cube. We prove that randomly digitally shifted order \( \beta \) digital nets can achieve the convergence of the root mean square worst-case error of order \( N^{-\alpha}(\log N)^{(s-1)/2} \) when \( \beta \geq 2\alpha \). The exponent of the logarithmic term, i.e., \( (s - 1)/2 \), is improved compared to the known result by Baldeaux and Dick, in which the exponent is \( s\alpha/2 \). Our result implies the existence of a digitally shifted order \( \beta \) digital net achieving the convergence of the worst-case error of order \( N^{-\alpha}(\log N)^{(s-1)/2} \), which matches a lower bound on the convergence rate of the worst-case error for any cubature rule using \( N \) function evaluations and thus is best possible. Further we discuss how we can obtain explicit constructions of point sets which achieve such best possible rate of convergence.

**Construction of Lattice Rules: from K-Optimal Lattices to Extremal Lattices**

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The concept of K-optimal lattices was introduced by Cools and Lyness (2001) to set up searches for lattice rules for multivariate integration with a low number of points for a given trigonometric degree of precision. For more than 3 dimensions no so-called critical lattices are known but we are happy with lattices that are “nearly” critical. The original searches were restricted to 3 and 4 dimensions. Refinements were later made to make the searches possible in 5 and 6 dimensions.

The idea behind K-optimal lattices was later extended in Russia using extremal lattices. One could say that an extremal lattice is a locally critical lattice.

In this talk both approaches to lattice rule construction will be described and a survey of the obtained results will be presented.
Rank 1 Lattice Rules for Integrands with Permutation Invariant Inputs

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We study multivariate integration of functions that are invariant under the permutation (of a subset) of their arguments. We show an upper bound for the “$n$-th” minimal worst case error for such problems, with the highlight that under certain conditions this upper bound only weakly depends on the number of dimensions. We present the use of rank-1 lattice rules in such a setting, and show that “randomly shifted” rank-1 rules can achieve such a bound. We then present a component-by-component algorithm to find the generating vector for a shifted rank-1 lattice rule that obtains a rate of convergence arbitrarily close to the optimal rate of $O(n^\alpha)$, where $\alpha > 1/2$ denotes the smoothness of our function space. We further show numerical experiments to compare and contrast the error convergence in these permutation-invariant spaces and spaces without this special property.

A Universal Algorithm for Multivariate Integration

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I will present a randomized version of Frolov’s algorithm for multivariate integration over cubes. The resulting method is unbiased and has optimal order of convergence (in the randomized sense as well as in the worst case setting) for many function spaces, including Sobolev Hilbert spaces of dominating mixed smoothness $r \in \mathbb{N}$ or isotropic smoothness $s \in \mathbb{N}$ for $s > d/2$. The algorithm is a randomization and enhancement of Frolov’s quadrature rule from 1976.

My talk is based on a joint work with Erich Novak that appeared under the same name in Foundations of Computational Mathematics and on a recent paper by Mario Ullrich, which is yet to be published.

This is joint work with Erich Novak (Jena University, Germany) and Mario Ullrich (Linz University, Austria).
Constructions of Quadrature Rules


The construction of good quadrature rules has been of high interest in numerical integration. Recently, different kinds of quadrature rules, including Frolov rules, (higher order) digital nets, and lattice rules, have been intensively discussed. The aim of this session is to bring experts of these research areas together to discuss recent theoretical and numerical results for the construction of such quadrature rules.

Tuesday August 16. 10^{25}–11^{55}, Berg C

$L_p$-Discrepancy and Beyond of Higher Order Digital Sequences

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The $L_p$-discrepancy is a quantitative measure for the irregularity of distribution modulo one of infinite sequences. In 1986 Proinov proved for all $p > 1$ a lower bound for the $L_p$-discrepancy of general infinite sequences in the $d$-dimensional unit cube, but it remained an open question whether this lower bound is best possible in the order of magnitude until recently. In 2014 Dick and Pillichshammer gave a first construction of an infinite sequence whose order of $L_2$-discrepancy matches the lower bound of Proinov. Here we give a complete solution to this problem for all finite $p > 1$. We consider so-called order 2 digital $(t, d)$-sequences over the finite field with two elements and show that such sequences achieve the optimal order of $L_p$-discrepancy simultaneously for all $p \in (1, \infty)$.

Beyond this result, we estimate the norm of the discrepancy function of those sequences also in the space of bounded mean oscillation, exponential Orlicz spaces, Besov and Triebel-Lizorkin spaces and give some corresponding lower bounds which show that the obtained upper bounds are optimal in the order of magnitude.

The talk is based on joint work with Josef Dick, Lev Markhasin, and Friedrich Pillichshammer.

Antithetic Sampling for Quasi-Monte Carlo Integration using Digital Nets

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Antithetic sampling is one of the well-known variance reduction techniques for Monte Carlo integration. In this talk we discuss its application to deterministic quasi-Monte Carlo (QMC) integration using digital nets. Numerical experiments based on Sobol’ point sets up to dimension 100 indicate that the rate of convergence can be improved for smooth integrands by using antithetic sampling technique. Although such a nice convergence behavior is beyond the reach of our theoretical result obtained so far, we can prove the existence of good polynomial lattice point sets in base 2 with antithetics in weighted Sobolev spaces of smoothness of second order. The result can be extended to the case of an arbitrary prime base by generalizing the notion of antithetic sampling itself.
Successive Coordinate Search and Component-by-Component Construction of Rank-1 Lattice Rules in Weighted RKHS

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The (fast) component-by-component (CBC) algorithm is an efficient tool for the construction of generating vectors for quasi-Monte Carlo rank-one lattice rules in weighted reproducing kernel Hilbert spaces. Even though it was proven in [1] that the CBC algorithm achieves the optimal rate of convergence in the respective function spaces, the generating vector $z$ produced by the CBC method may not yield the smallest possible worst-case error $e_{n,d}(z)$. Therefore, we investigate a generalization of the component-by-component construction that allows for a general successive coordinate search based on an initial generating vector $z^0$. The proposed method admits the same type of worst-case error upper bounds as the CBC algorithm, independent of the choice of the initial vector $z^0$. Moreover, a fast version of our method, based on the fast CBC algorithm as in [2], is available, reducing the computational cost of the algorithm to $O(d n \log(n))$ operations. A practical combination with the classical CBC construction can be performed so that the final results are never worse than the CBC outputs and sometimes significantly better, depending on the weights, with a minor overhead in the runtime. We will report on different test examples and analyze variations of the new method.

Joint work with Hernan Leövey (Humboldt-University Berlin).


Exact Sampling of Markov Processes

Organizer: Sandeep Juneja, Tata Institute of Fundamental Research.

Thursday August 18. 10:25–11:55, LK 101

Randomized MLMC for Markov Chains

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Multi-level Monte Carlo (MLMC) algorithms have been extensively applied in recent years to obtain schemes that often converge at faster rates than corresponding traditional Monte Carlo methods. In this talk, we shall introduce a randomized stratified variant of MLMC, and discuss applications of MLMC to equilibrium computations for Markov chains, computing relative value functions, spectral densities, and sensitivity estimates.

This work is joint with Zeyu Zheng.

“Omnithermal” Perfect Simulation for M/G/c Queues

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The last few years have seen much progress in the area of perfect simulation algorithms for multi-server queueing systems. Sigman [3] first showed how to build a dominated Coupling from the Past (domCFTP) algorithm for the super-stable M/G/c operating under First Come First Served discipline; the dominating process used is an M/G/1 queue under Processor Sharing. This was extended to the stable case by Connor and Kendall [2], who used the M/G/c system under random assignment as an upper bound. More recently, Blanchet, Pei and Sigman [1] have shown how to extend this method to GI/GI/c queues.

In [2] the question was posed of whether it is possible to carry out domCFTP simultaneously for a suitable range of c (the number of servers); what might be described as “omnithermal dominated CFTP”. In this talk I will demonstrate how the domCFTP algorithm of [2] may be adjusted to accomplish this in the M/G/c setting, and will provide an indication of the additional computational complexity involved.


Exact Sampling and Large Deviations for Spatial Birth and Death Processes

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We propose a simple algorithm for exact sampling from the stationary distributions of spatial birth-and-death processes whose invariant measures are absolutely continuous with respect to some Poisson point process. Specifically, we consider systems where Poisson births are marked points on a vector space (such as spheres on a Euclidean space). Each birth is accepted with a probability that depends upon the system state upon its arrival. Every accepted birth stays for an exponentially distributed time. Examples include loss systems, area interaction processes, Strauss processes and Ising models. In contrast to the existing literature, the proposed method does not require construction of auxiliary birth-and-death processes and development of coupling and/or thinning methodologies. We analyze and compare the performance of the proposed algorithm with the existing ones based upon dominated coupling from the past in an asymptotic regime where marked points are spheres in a compact Euclidean space. Here the arrival rate increases to infinity while the sphere diameter reduces to zero at varying rates. We also conduct large deviations analysis of number of spheres in the system in steady state. This is useful to our comparative analysis and may also be of independent interest.
Experimental Design for Simulation Experiments

Organizer: Peter Qian, University of Wisconsin-Madison.

Monday August 15. $10^{25} - 11^{55}$, LK 120

Multi-Level Monte Carlo for Metamodelling of Stochastic Simulations with Discontinuous Output

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The Multi-Level Monte Carlo (MLMC) method for parametric integration has lower computational complexity than standard Monte Carlo, given sufficient conditions. This MLMC method is applicable to metamodelling of stochastic simulations. However, the sufficient conditions established so far require that the integrand/simulation output be continuous in the parameters of the simulation model. We prove that the MLMC method for parametric integration improves computational complexity under novel sets of assumptions on the integrand/simulation output, allowing for discontinuities in it. We also present simulation experiment results showing that the MLMC method can reduce the computational cost of simulation metamodelling by a large factor even when simulation output is discontinuous.

Simulating Probability Distributions Using Minimum Energy Designs

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In this talk, I will explain an experimental design-based method known as minimum energy design ([1]) for simulating complex probability distributions. The method requires fewer evaluations of the probability distribution and therefore, it has an advantage over the usual Monte Carlo or Markov chain Monte Carlo methods when the distribution is expensive to evaluate. I will explain the application of the proposed method in Bayesian computational problems, optimization, and uncertainty quantification.

Joint work with Tirthankar Dasgupta (Harvard University), Rui Tuo (Chinese Academy of Sciences), and C. F. Jeff Wu (Georgia Tech).

Samurai Sudoku-Based Space-Filling Designs for Data Pooling

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Pooling data from multiple sources plays an increasingly vital role in today’s world. By using a popular Sudoku game, we propose a new type of design, called a Samurai Sudoku-based space-filling design to address this issue. Such a design is an orthogonal array based Latin hypercube design with the following attractive properties: (1) the complete design achieves uniformity in both univariate and bivariate margins; (2) it can be divided into groups of subdesigns with overlaps such that each subdesign achieves uniformity in both univariate and bivariate margins; (3) each of the overlaps achieves uniformity in both univariate and bivariate margins. Examples are given to illustrate the properties of the proposed design, and to demonstrate the advantages of using the proposed design for pooling data from multiple sources.
Function Space Embeddings for High Dimensional Problems

Organizers: Michael Gnewuch, Christian-Albrechts-Universität, Kiel and Aicke Hinrichs, JKU Linz.

Results on function space embeddings are valuable tools in complexity studies of numerical problems. For an illustration, consider the following situation: We want to approximate the solution of an s-variate problem with the help of numerical algorithms. On the space $F_s$ of input functions we have two norms; one norm is well suited for the application we are interested in and one norm is well suited for the analysis of the algorithms we want to apply. Assume that the two norms on our function space are equivalent up to a constant $c_s$, i.e., $F_s$ endowed with one norm can be embedded into $F_s$ embedded with the other norm and vice versa, and $c_s$ is an upper bound for the respective embedding constants. Then estimates for errors of algorithms measured with respect to one norm can increase only by a factor $c_s$ if measured with respect to the other norm. This example is a “classical” application of function space embeddings to numerical analysis. In tractability studies of high-dimensional problems the situation gets more involved; instead of dealing with a fixed space $F_s$ of input functions we usually deal with a whole scale $(F_s)_{s \in \mathbb{N}}$ of function spaces. A typical situation would be that $F$ consists of real-valued functions defined on a domain $D^s$, where $D$ is some fixed set. If we have on each of the spaces $F_s$ two equivalent norms, we get two scales of normed spaces. To transfer tractability results from one scale to the other it is essential to keep track of the dependence of the constants $c_s$ on $s$. If $\sup_{s \in \mathbb{N}} c_s$ is finite, then tractability results transfer directly from one scale to the other. If the supremum is not finite, one still may be able to transfer tractability results from one scale to the other; this can be done by using invariance properties and manipulating the norms and function spaces of one scale (e.g., by changing weights that moderate the importance of groups of variables) and proving only suitable embedding results in one direction (and not equivalence) and then doing the same thing the other way around. This kind of application of function space embeddings to tractability studies is a very recent development. In our special session we want to focus on applications of function space embeddings to high-dimensional problems with an emphasis on tractability studies of approximation and integration problems.

Friday August 19. 10^{25}–11^{55}, Berg C

Sparse Approximation with Respect to the Faber-Schauder System

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We consider approximations of multivariate functions using $m$ terms from its tensorized Faber-Schauder expansion. The univariate Faber-Schauder system on $[0,1]$ is given by dyadic dilations and translations (in the wavelet sense) of the $L_\infty$ normalized simple hat function with support $[0,1]$. We obtain a hierarchical basis which will be tensorized over all levels (hyperbolic) to get the dictionary $\mathcal{F}$. The worst-case error with respect to a class of functions $\mathcal{F}$ is measured by the usual best $m$-term widths denoted by $\sigma_m(\mathcal{F},\mathcal{F})$. As a first step we establish the Faber-Schauder characterization for classes of functions with bounded mixed derivative (Sobolev spaces with dominating mixed smoothness) and more general Triebel-Lizorkin spaces, which gives us a sequence space isomorphism. Based on results by
Hansen, Sickel 2009 for the sequence space setting, we are able to compute upper bounds for $\sigma_m$. In particular we prove

$$\sigma_m(H^r \times x, L_\infty) \lesssim m^{-r} (\log m)^{(d-1)(r+1/2)}.$$ 

We emphasize, that the coefficients in the best m-term expansion can be computed from a finite set of function values. In addition, we emphasize that, compared to linear widths in this situation, the main rate improves by $1/2$. Let us also stress on the fact that sparse approximation with respect to the Faber-Schauder system behaves significantly better than sparse approximation with respect to the trigonometric system as dictionary.

This is joint work with my student G. Byrenheid (Bonn).

High-Dimensional Problems: On the Universality of Weighted Anchored and ANOVA Spaces

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Analyzing high-dimensional approximation problems, one often faces the following situation: In some settings (depending on the considered class of input functions, the norm used to measure the approximation error, the admitted class of approximation algorithms, and the way the computational cost is accounted) one can derive good or even optimal error bounds directly. But if one changes the norm, a correspondent direct error analysis can be much more involved and complicated or even seem impossible. The focus of the talk is to discuss new results on function space embeddings of weighted spaces of tensor product structure which allow for an easy transfer of error bounds.

To demonstrate the usefulness of these (rather abstract, functional analytic) embedding theorems, we discuss as example problems multivariate and infinite-dimensional integration problems. In particular, we present new upper and lower error bounds for high- and infinite-dimensional integration. Moreover, we discuss an interesting transfer principle, which holds for weighted reproducing kernel Hilbert spaces of tensor product structure: If you want to establish tractability results on such a space, then it suffices to prove those results for a corresponding space whose norm is induced by an underlying function space decomposition either of anchored or of ANOVA type. In the talk we formulate this transfer principle for the integration problems we present, but we want to emphasize that it can be easily formulated for other approximation problems as, e.g., function recovery.

Joint work with Mario Hefter (TU Kaiserslautern, Germany), Aicke Hinrichs (JKU Linz, Austria), and Klaus Ritter (TU Kaiserslautern, Germany).


Integration in Weighted Anchored and ANOVA Spaces

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We consider the problem of numerical integration (and also function approximation) for weighted anchored and ANOVA Sobolev spaces of $s$-variate functions, where $s$ is large. Under the assumption of sufficiently fast decaying weights, we show in a constructive way that integrals can be approximated by quadratures for functions $f_k$ with only $k$ variables, where $k = k(\varepsilon)$ depends solely on the error demand $\varepsilon$. A crucial tool in the derivation of our results are bounds on the norms of embeddings between weighted anchored and ANOVA spaces.

This talk is based on joint work with F. Pillichshammer (JKU Linz), and G. W. Wasilkowski (University of Kentucky).
Hamiltonian Monte Carlo in Theory and Practice

Organizer: Michael Betancourt, University of Warwick.

Many of the most important problems in modern statistical practice are characterized by complex, high-dimensional models that are extremely challenging to fit. Hamiltonian Monte Carlo, however, has proven a tremendous empirical success in this domain, and aided with computational tools such as probabilistic programming and automatic differentiation, the algorithm has become a powerful tool for advancing the frontiers of applied statistics. This session will consider multiple aspects of Hamiltonian Monte Carlo, from the underlying theory to challenges in robust implementations and innovative scientific applications.

Monday August 15. 10^{25}–11^{55}, Berg A

Scalable Bayesian Inference with Hamiltonian Monte Carlo

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Despite the promise of big data, inferences are often limited not by sample size but rather by systematic effects. Only by carefully modeling these effects can we take full advantage of the data – big data must be complemented with big models and the algorithms that can fit them. One such algorithm is Hamiltonian Monte Carlo, which exploits the inherent geometry of the posterior distribution to admit full Bayesian inference that scales to the complex models of practical interest. In this talk I will discuss the theoretical foundations of Hamiltonian Monte Carlo, elucidating the geometric nature of its scalable performance and stressing the properties critical to a robust implementation.

Efficient Computation of Uncertainty in Spatio-Temporal Forest Composition Inferred from Fossil Pollen Records

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Understanding past compositional changes in vegetation provides insight about ecosystem dynamics in response to changing environments. Past vegetation reconstructions rely predominantly on fossil pollen data from sedimentary lake cores, which acts as a proxy record for the surrounding vegetation. Stratigraphic changes in these pollen records allow us to infer changes in composition and species distributions. Pollen records collected from a network of sites allow us to make inference about the spatio-temporal changes in vegetation over thousands of years. Using a Bayesian hierarchical spatio-temporal model, we first calibrate the pollen vegetation relationship using settlement era data (see below). We then use fossil pollen networks to estimate latent species distributions and relative abundances. To avoid estimating the latent vegetation process for all spatial locations in the domain, we use a predictive process framework which requires that this process be estimated only for a selection of knots. In both the calibration and prediction phases of the
model, we use a modified version of Stan, which provides an efficient implementation of the No-U-Turn Sampler (NUTS). Modifications included the specification of user-defined gradients, and the ability to take advantage of parallel computation. This work highlights the importance of efficient statistical and computational methods in cases such as this where the model is sufficiently complex and the domain of inference is large.

Joint work with C. J. Paciorek (University of California, Berkeley, USA), J. S. McLachlan (University of Notre Dame, USA), S. Goring (University of Wisconsin - Madison, USA), J. W. Williams (University of Wisconsin - Madison, USA), and S. T. Jackson (United States Geological Survey and University of Arizona, USA).

@article{dawson2016quantifying,
title={Quantifying pollen-vegetation relationships to reconstruct ancient forests using 19th-century forest composition and pollen data},
author={Dawson, Andria and Paciorek, Christopher J and McLachlan, Jason S and Goring, Simon and Williams, John W and Jackson, Stephen T},
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Confronting Supernova Cosmology’s Statistical and Systematic Uncertainties with Hamiltonian Monte Carlo

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Cosmology with standard candle (type Ia) supernovae provides our best constraints on the dynamics of the expansion of the universe. I discuss the limitations of current supernova cosmological analyses in treating outliers, selection effects, the nonlinear correlations used for standardization, unexplained dispersion, and heterogeneous observations. I present a new Bayesian hierarchical model, called UNITY (Unified Nonlinear Inference for Type-Ia cosmology), that is an significant step towards a full generative model of the data. UNITY is implemented using the code Stan, which efficiently samples over the required thousands of parameters. I apply the framework to real supernova observations and demonstrate smaller statistical and systematic uncertainties.

High Dimensional Numerical Integration

Organizer: Markus Weimar, University of Siegen, Germany.

In recent years the enormous increase in computer power paved the way for the development of more and more complicated models of multi-parameter real-world phenomena which have to be analyzed and simulated. Thus, motivated by applications from natural sciences, engineering, and finance, the efficient numerical treatment of these models has become an area of increasing importance. Often approximate integration of multivariate or even infinite-dimensional functions is a crucial task in this context. This has led to the development of advanced numerical schemes such as, e.g., (generalized) quasi-Monte Carlo methods.

The talks in this special session aim to address recent progress in the field of cubature rules, as well as applications of related techniques in the context of numerical analysis. Besides theoretical error bounds on spaces of high-dimensional functions, also complexity estimates are discussed.

Monday August 15. 3^50–5^50, Berg A

Quasi-Monte Carlo Methods and PDEs with Random Coefficients

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In this talk we consider quasi-Monte Carlo rules which are based on (higher order) digital nets and their use in approximating expected values of solutions of partial differential equations (PDEs) with random coefficients. In particular, so-called interlaced polynomial lattice rules have attractive properties when approximating such integrals. These are applied for PDEs with uniform random coefficients, but can also be used in Bayesian inversion. In this talk we give an overview of recent results in this area.

Joint work with Frances Y. Kuo (UNSW, Australia), Quoc T. Le Gia (UNSW, Australia), and Christoph Schwab (ETH Zurich, Switzerland).

A Reduced Fast Component-by-Component Construction of Lattice Point Sets with Small Weighted Star Discrepancy

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The weighted star discrepancy is a quantitative measure for the performance of point sets in quasi-Monte Carlo algorithms for numerical integration. In this talk we consider lattice point sets, whose generating vectors can be obtained by a component-by-component construction to ensure a small weighted star discrepancy.

Our aim is to reduce the construction cost of such generating vectors significantly by restricting the set of integers from which we select the components of the vectors.

The research was supported by the Austrian Science Fund (FWF): Project F5509-N26, which is a part of the Special Research Program “Quasi-Monte Carlo Methods: Theory and Applications”.

This talk is based on joint work with Helene Laimer.
High Dimensional Integration of Kinks and Jumps:– Smoothing by Preintegration

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In many applications, including option pricing, integrals of $d$-variate functions with “kinks” or “jumps” are encountered. (Kinks describe simple discontinuities in the derivative, jumps describe simple discontinuities in function values.) The standard analyses of sparse grid or Quasi-Monte Carlo methods fail completely in the presence of kinks or jumps not aligned to the axes, yet the observed performance of these methods can remain reasonable.

In recent joint papers with Michael Griebel and Frances Kuo we sought an explanation by showing that many terms of the ANOVA expansion of a function with kinks can be smooth, because of the smoothing effect of integration. The problem settings have included both the unit cube and $d$-dimensional Euclidean space. The underlying idea is that integration of a non-smooth function with respect to a well chosen variable, say $x_j$, can result in a smooth function of $d-1$ variables.

In the present work we have extended the theoretical results from kinks to jumps, and have turned “preintegration” into a practical method for evaluating integrals of non-smooth functions over $d$-dimensional Euclidean space. In this talk I will explain both the method and the ideas behind “smoothing by preintegration”.

This is joint work with Andreas Griewank (Yachay Tech, Ecuador), Frances Kuo (UNSW Australia), and Hernan Leovey (Humboldt University, Germany).

On the Optimal Order of Integration in Hermite Spaces with Finite Smoothness

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In many different areas, like finance, physics or biology, it is necessary to approximate expected values of functionals depending on $s$ independent and normal distributed random variables efficiently. For that, we study multivariate integration over $\mathbb{R}^s$ with respect to the Gaussian measure in Hermite spaces of finite smoothness. These spaces are reproducing kernel Hilbert spaces of functions with polynomial decaying Hermite coefficients.

In this talk we discuss the multivariate integration problem in the worst-case setting and give upper and lower bounds on the worst-case error. Furthermore, explicit quadrature rules are presented which are of optimal order. The integration nodes of these algorithms are based on higher order nets and the integration weights are chosen according to the Gaussian measure.

Joint work with Gunther Leobacher (JKU Linz, Austria), Friedrich Pillichshammer (JKU Linz, Austria) and Josef Dick (UNSW, Australia).
Higher Order Quadrature Rules

Organizers: Josef Dick, University of New South Wales and Takashi Goda, University of Tokyo

Recently there has been significant interest in the design of quadrature rules which achieve a higher rate of convergence for sufficiently smooth integrands. This session brings together several approaches to obtaining such methods, from Frolov rules, to higher order digital nets, weighted integration rules and lattice rules. Recent theoretical advances and numerical results will be discussed.

Tuesday August 16. 3^{50}–5^{50}, Berg A

Optimal Order Quadrature Error Bounds for Higher Order Digital Sequences

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In this talk we consider construction methods of Quasi-Monte Carlo (QMC) quadrature rules, which achieve the optimal rate of convergence of the worst-case error in Sobolev spaces.

QMC rules using higher order digital nets and sequences have been shown to achieve the almost optimal rate of convergence of the worst-case error in Sobolev spaces of arbitrary fixed smoothness $\alpha \in \mathbb{N}$, $\alpha \geq 2$. In a recent work by the authors, it was proved that randomly-digitally-shifted order $2\alpha$ digital nets can achieve the best possible rate of convergence of the root mean square worst-case error of order $N^{-\alpha}(\log N)^{(s-1)/2}$, where $N$ and $s$ denote the number of points and the dimension, respectively, which implies the existence of an optimal order QMC rule. More recently, the authors provided an explicit construction of such an optimal order QMC rule by using Chen-Skriganov’s digital nets in conjunction with Dick’s dig
terlacing composition.

In this talk we give a more general result on an explicit construction of optimal order QMC rules, that is, we prove that any $s$ dimensional order $2\alpha + 1$ digital sequence can achieve the best possible rate of convergence of the worst-case error of order $N^{-\alpha}(\log N)^{(s-1)/2}$ when $N$ is of the form $b^m$ for any $m$ with a fixed prime base $b$. The explicit construction presented in this talk is not only easy to implement but also extensible in $N$.

This is joint work with Takashi Goda (The University of Tokyo, Japan) and Kosuke Suzuki (The University of New South Wales, Australia).

On Higher Order Monte Carlo Integration

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Classically, plain Monte Carlo (MC) for integration on the unit cube uses the average over $N$ random point evaluations of the integrand. For square-integrable functions this gives a convergence rate of $N^{-1/2}$. But even if higher-order smoothness is present, the MC rate of convergence does not improve.

In this talk we give examples for quadrature rules that also rely on random samples of the integrand but by the choice of certain non-uniform quadrature weights actually ‘see’ higher-order regularity and can achieve convergence rates of type $N^{-r} \log(N)^q$, if the integrand possesses dominating mixed smoothness of order $r$.

This talk is based on joint-work with Michael Griebel, Aicke Hinrichs and Mario Ullrich.
Orthogonality of the Chebychev-Frolov Lattice and its Implementation

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We deal with lattices that are generated by the Vandermonde matrices associated to the roots of Chebyshev-polynomials. If the dimension $d$ of the lattice is a power of two, i.e. $d = 2^m, m \in \mathbb{N}$, the resulting lattice is an admissible lattice in the sense of Skriganov (1994). Those are related to the Frolov cubature formulas, which recently drew attention due to their optimal convergence rates in a broad range of Besov-Lizorkin-Triebel spaces. We prove that the resulting lattices are orthogonal and possess a lattice representation matrix with entries not larger than $2$ (in modulus). This allows for an efficient and stable enumeration of the Frolov cubature nodes in the $d$-cube $[-1/2, 1/2]^d$ up to dimension $d = 16$. Using these results, we are able to compare the Frolov cubature formula to other up-to-date schemes for high-dimensional integration, e.g. the sparse grid method.

This is joint work with Jens Oettershagen and Tino Ullrich.

Integration of Functions in Weighted Korobov Spaces with (Super)-Exponential Rate of Convergence

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We discuss multivariate integration for a weighted Korobov space of functions for which the Fourier coefficients decay (super)-exponentially fast. We construct cubature rules which achieve (super)-exponential rates of convergence, namely $O(n^{-cn^p})$ and $O(\exp(-cn^p))$ for two function spaces which are extensions of the function space of analytic functions introduced in [1, 2]. We also study the dependence of the number of dimensions on the convergence and show some tractability results.

This is joint work with Dirk Nuyens and Ronald Cools (KU Leuven, Belgium).


Monte Carlo for Financial Sensitivity Analysis

Organizer: Nan Chen, City University of Hong Kong.

Sensitivity analysis plays an important role in financial risk management. For instance, derivative price sensitivities, known as Greeks in the market jargon, provide key inputs for a variety of hedging schemes. The second example is quantile-based risk measures that the minimum capital requirement is based on. Their sensitivities will shed key insights on how to change portfolio allocation to improve its return-risk characteristics in response to certain market environment changes. The first speaker, Prof. Michael Fu, will discuss estimating quantile sensitivities via Monte Carlo simulation. His presentation reviews several key techniques on this topic, including both pathwise estimators such as infinitesimal perturbation analysis and measure-valued procedures such as the likelihood ratio method. Then, he will discuss recent research developed to handle various discontinuities that frequently arise in financial applications, such as in the payoff function (e.g., a digital option) and in sample paths (e.g., jump processes).

The second talk primarily focuses on the sensitivities of diffusion models that are widely used in financial applications. Taking advantage of the Beskos-Roberts exact simulation method and applying the Poisson-kernel method, the talk proposes unbiased Monte Carlo estimators of Greeks. The third presentation is about the Monte Carlo application in stochastic dynamic programming, an essential tool in financial decision-making. Combined with the information relaxation based duality, the authors develop a Monte Carlo primal-dual method to solve SDP problems. Optimal trading execution and investment-consumption problems are discussed. The information about optimal policy sensitivities are also important to develop robust controls.

Wednesday August 17. 10^{25}–11^{55}, LK 203/4

Estimating Quantile Sensitivities

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This talk will discuss estimating quantile sensitivities via Monte Carlo simulation. It will review several key techniques on this topic, including both pathwise estimators such as infinitesimal perturbation analysis and measure-valued procedures such as the likelihood ratio method. It will also discuss recent research developed to handle various discontinuities that frequently arise in financial applications, such as in the payoff function (e.g., a digital option) and in sample paths (e.g., jump processes).

Unbiased Estimators of the Greeks for General Diffusion Processes

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Derivative price sensitivities are useful in financial engineering and it is important to compute these quantities accurately and efficiently. When using the general diffusion models as an underlying asset price, discretization methods such as the Euler scheme are conventionally used because of the lack of knowledge to the probability distributions associated with general diffusions. These methods are easily applicable, but cause the discretization bias unavoidably. Taking advantages of Beskos-Roberts
method, which is an exact simulation algorithm of one dimensional SDE, and applying the Poisson-kernel method, we propose unbiased Monte Carlo estimators of greeks. The suggested estimators can be evaluated only with the finite points of the Brownian motion in any model, thus it is quite easy to implement our algorithms. We detail the ideas and the algorithms.

This is joint work with Wanmo Kang.

Monte Carlo Applications in Stochastic Dynamic Programming

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This talk is about the Monte Carlo application in stochastic dynamic programming, an essential tool in financial decision-making. Combined with the information relaxation based duality, we develop a Monte Carlo primal-dual method to solve SDP problems. Optimal trading execution and investment-consumption problems are discussed. The information about optimal policy sensitivities are also important to develop robust controls.
Monte Carlo Sampling from Multi-Modal Distributions

Organizers: David van Dyk, Imperial College London and Xiao-Li Meng, Harvard University.

Tuesday August 16. 350–550, Berg C

Love or Hate: a RAM for Exploring Multi-Modality

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Although the Metropolis algorithm is simple to implement, it often has difficulties exploring a multimodal distribution. We propose a repelling-attracting Metropolis (RAM) algorithm that maintains the simple-to-implement characteristic of a Metropolis algorithm, but is more able to jump between modes. The RAM algorithm is a Metropolis-Hastings algorithm with a proposal that consists of a downhill move in density that aims to make local modes repelling, followed by an uphill move in density that aims to make local modes attracting. The downhill move is achieved via a reciprocal Metropolis ratio so that the algorithm prefers downward movement. The uphill move does the opposite using the standard Metropolis ratio which prefers upward movement. This down-up movement in density increases the probability of a proposed move to a different mode. Because the acceptance probability of the proposal involves a ratio of intractable integrals, we introduce an auxiliary variable which creates a term in the acceptance probability that cancels with the intractable ratio. Using several examples, we demonstrate the potential for the RAM algorithm to explore a multimodal distribution more efficiently than a Metropolis algorithm and with less tuning than is commonly required by tempering-based methods.

This is joint work with Xiao-Li Meng (Harvard University) and David A. van Dyk (Imperial College London).

Wormhole Hamiltonian Monte Carlo

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Statistical inference involving multimodal distributions tends to be quite difficult. This is especially true in high dimensional problems, where most existing algorithms cannot easily move from one mode to another. To address this issue, we propose a novel Bayesian inference approach based on Markov Chain Monte Carlo. Our method can effectively sample from multimodal distributions, especially when the dimension is high and the modes are isolated. To this end, it exploits and modifies the Riemannian geometric properties of the target distribution to create wormholes connecting modes in order to facilitate moving between them. Further, our proposed method uses the regeneration technique in order to adapt the algorithm by identifying new modes and updating the network of wormholes without affecting the stationary distribution. To find new modes, as opposed to rediscovering those previously identified, we employ a novel mode searching algorithm that explores a residual energy function obtained by subtracting an approximate Gaussian mixture density (based on previously discovered modes) from the target density function.
Exploring with Wang-Landau Algorithms and Sequential Monte Carlo

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Among MCMC methods designed to tackle multimodality, Wang-Landau algorithms (and variants thereof) produce non-homogeneous Markov chains, that explore the state space by adaptively avoiding regions that have already been visited. The regions can be defined implicitly by the values of the target density function. Thus, these algorithms scale well with the dimension of the state space, despite the use of a state space partition. The exploratory behavior of Wang-Landau is obtained by recursively estimating penalty terms associated with each region. We show how this estimation can benefit from being performed by multiple interacting chains, leading to a novel algorithm belonging to the class of Sequential Monte Carlo methods. We describe the stability properties of the proposed algorithm, the choice of its tuning parameters and its performance compared to related methods, such as standard SMC samplers, Parallel Adaptive Wang-Landau and Free Energy Sequential Monte Carlo.

This is joint work with Luke Bornn, Pierre Del Moral and Mathieu Gerber.

Folding Markov Chains

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In this talk, we consider the implications of “folding” a Markov chain Monte Carlo algorithm, namely to restrict simulation of a given target distribution to a convex subset of the support of the target via a projection on this subset. We argue that this modification should be implemented in most cases an MCMC algorithm is considered. In particular, we demonstrate improvements in the acceptance rate and in the ergodicity of the resulting Markov chain. We illustrate these improvements on several examples, but insist on the fact that they are universally applicable at a negligible computing cost, independently of the dimension of the problem.

Joint work with Randal Douc (CITI, Telecom SudParis, France) and Gareth Roberts (University of Warwick, UK).
Preasymptotics for Multivariate Approximation

Organizers: Thomas Kühn, University of Leipzig and Tino Ullrich, Hausdorff-Center for Mathematics, Bonn

In the investigation of high-dimensional function approximation or recovery problems gaining control over associated worst-case errors is central in many respects. Such estimates are needed, for instance, in the search for optimal algorithms, for complexity-theoretical considerations (tractability analysis), or practically, to obtain reliable a priori error estimates. Deriving worst-case error bounds requires model assumptions. These narrow down the set of admissible functions, which potentially fit the given data, to a function class $F_d$. The function class could be the unit ball of a smoothness space (e.g., Sobolev, Gevrey, or a class of analytic functions), which is a naturally appearing model assumption in the context of Galerkin methods for PDEs. Another type of model assumption are structured dependencies. The idea to allow only specific functional dependencies is very prominent in statistics and machine learning to mitigate the burden of high-dimensionality. Classically, people were interested in the correct asymptotical behavior of worst-case errors. Those investigations are, of course, important for determining optimal algorithms. However, the obtained asymptotical error bounds are often useless for practical implementations since they are only relevant for very large numbers $n$ which is, related to the amount of data an algorithm uses, beyond the range a computer is able to process. Moreover, asymptotical error bounds often hide dependencies on the ambient dimension $d$ in the constants, which makes a rigorous tractability analysis impossible. Controlling the dependence of the underlying constants is a first step to improve on the classical error estimates. But this does not automatically provide preasymptotic error guarantees, that is, error guarantees for algorithms using smaller amounts of data.

The goal of this minisymposium is to present recent progress in the direction of finding reliable preasymptotic error estimates and corresponding algorithms. It turned out, that this problem is mathematically rather challenging and connected to deep problems in Banach space geometry. Some recent findings highlight and elaborate a connection to metric entropy and present a generic tool how to obtain preasymptotics for several classes of functions $F_d$ when dealing with general linear information. This rather new viewpoint opens several research directions such that we are already faced with a huge list of open problems.

Monday August 15. 350–550, Berg C

Preasymptotic Estimates for Approximation in Periodic Function Spaces

Thomas Kühn
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In this talk I will give a survey on some recent results on preasymptotic estimates for approximation in multivariate periodic function spaces, including a motivation for this type of problems.

For embeddings of classical Sobolev spaces the exact rate of approximation numbers has been known for many years. However, almost all asymptotic estimates in the literature involve unspecified constants which depend on the parameters of the spaces, in particular on the dimension $d$ of the un-
derlying domain, and on the chosen norm. Often the asymptotic rate can only be seen after "waiting exponentially long".

In high-dimensional numerical problems, as they appear e.g. in financial mathematics, this might be beyond the capacity of computational methods. Therefore one needs additional information on the $d$-dependence of these constants, and also on the behaviour in the so-called preasymptotic range, i.e. before the asymptotic rate becomes visible.

I will discuss these problems for the classical isotropic Sobolev spaces, Sobolev spaces of dominating mixed smoothness, and for periodic Gevrey spaces. The latter have a long history, they consist of $C^\infty$-functions and have been used in numerous problems related to partial differential equations.

Preasymptotics via Entropy

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I will present an abstract characterization result which allows to readily derive preasymptotic error bounds for approximation numbers of certain Sobolev type spaces from the well-known entropy numbers of the embedding $I : \ell_p \to \ell_\infty$.

Point Distributions on the Sphere, Almost Isometric Embeddings, One-Bit Sensing, and Energy Optimization

*Dmitriy Bilyk*

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We shall consider various versions and applications of questions of equidistribution of points on the sphere. First we address the question of uniform tessellation of the sphere $S^d$ (or its subsets) by hyperplanes, or equivalently, almost isometric embeddings of subsets of the sphere into the Hamming cube. We find that in the general case this problem is equivalent to the study of discrepancy with respect to certain spherical "wedges", which behaves very similarly to the well-studied situation of the spherical cap discrepancy. In particular, asymptotically the so-called "jittered sampling" yields better results than random selection of points.

However, in one-bit compressed sensing (which is closely related to this problem), one is interested in the preasymptotic case, where the number of points (measurements) is small relative to the dimension. We address this issue and obtain a series of results, which may be roughly summarized as: Theoretically, one-bit compressed sensing is just as good as the standard compressed sensing. In particular, we prove direct one-bit analogs of several classical compressed sensing results (including the famous Johnson-Lindenstrauss Lemma).

Finally, we obtain several different analogs of the Stolarsky principle, which states that minimizing the $L^2$ spherical cap discrepancy is equivalent to maximizing the sum of pairwise Euclidean distances between the points. These results bring up some interesting connections with frame theory and energy optimization. In particular, we show that geodesic energy integrals yield surprisingly different behavior from their Euclidean counterparts.

Parts of this work have been done in collaboration with Michael Lacey and Feng Dai.

Non-Optimality of Rank-1 Lattice Sampling in Spaces of Mixed Smoothness

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We consider the approximation of functions with mixed smoothness by algorithms using $m$ nodes on a rank-1 lattice

$$\Lambda(z, m) := \left\{ \frac{k}{m} z : k = 0, \ldots, m - 1 \right\}, \quad z \in \mathbb{Z}^d.$$  

We prove upper and lower bounds for the sampling rates with respect to the number of lattice points in various situations and achieve improvements in the main error rate compared to earlier contributions to the subject. This main rate (without logarithmic factors) is half the optimal main rate coming for instance from sparse grid sampling and surprisingly turns out to be best possible among all algorithms taking samples on rank-1 lattices.

This is joint work with Lutz Kämmerer (TU Chemnitz, Germany), Tino Ullrich (HCM Bonn, Germany) and Toni Volkmer (TU Chemnitz, Germany).
Probabilistic Numerics

Organizer: Mark Girolami, University of Warwick.

Probabilistic Numerics (PN) is an emerging theme of research that straddles the disciplines of mathematical analysis, statistical science and numerical computation. This nascent field takes its inspiration from early work in the mid 80s by Diaconis and O’Hagan, who posited that numerical computation should be viewed as a problem of statistical inference. The progress in the intervening years has focused on algorithm design for the probabilistic solution of ordinary differential equations and numerical quadrature, suggesting empirically that an enhanced performance of e.g. numerical quadrature routines can be achieved via an appropriate statistical formulation. However there has been little theoretical analysis to understand the mathematical principles underlying PN that deliver these improvements.

This mini-symposium seeks to bring the area of PN to the MCQMC research community, to present recent mathematical analysis which elucidates the relationship between PN schemes, functional regression and QMC.

Thursday August 18. 350–550, Berg B

Probabilistic Numerical Computation: A New Concept?
Mark Girolami
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The vast amounts of data in many different forms becoming available to politicians, policy makers, technologists, and scientists of every hue presents tantalising opportunities for making advances never before considered feasible.

Yet with these apparent opportunities has come an increase in the complexity of the mathematics required to exploit this data. These sophisticated mathematical representations are much more challenging to analyse, and more and more computationally expensive to evaluate. This is a particularly acute problem for many tasks of interest such as making predictions since these will require the extensive use of numerical solvers for linear algebra, optimization, integration or differential equations. These methods will tend to be slow, due to the complexity of the models, and this will potentially lead to solutions with high levels of uncertainty.

This talk will introduce our contributions to an emerging area of research defining a nexus of applied mathematics, statistical science and computer science, called “probabilistic numerics”. The aim is to consider numerical problems from a statistical viewpoint, and as such provide numerical methods for which numerical error can be quantified and controlled in a probabilistic manner. This philosophy will be illustrated on problems ranging from predictive policing via crime modelling to computer vision, where probabilistic numerical methods provide a rich and essential quantification of the uncertainty associated with such models and their computation.

Probabilistic Integration: A Role for Statisticians in Numerical Analysis?
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One of the current active branches of the field of probabilistic numerics focuses on numerical integration. We will study such a probabilistic integration method called Bayesian quadrature, which provides solutions in the form of probability distribu-
tions (rather than point estimates) whose structure can provide additional insight into the uncertainty emanating from the finite number of evaluations of the integrand [1]. Strong mathematical guarantees will then be provided in the form of convergence and contraction rates in the number of function evaluations. Finally, we will compare Bayesian quadrature with non-probabilistic methods including Monte Carlo and Quasi-Monte Carlo methods, and illustrate its performance on applications ranging from computer graphics to oil field simulation.


Probabilistic Integration and Intractable Distributions

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This talk will build on the theme of Probabilistic Integration, with particular focus on distributions that are intractable, such as posterior distributions in Bayesian statistics. In this context we will discuss a novel approach to estimate posterior expectations using Markov chains [1,2]. This is shown, under regularity conditions, to produce Monte Carlo quadrature rules that converge as

$$\left| \sum_{i=1}^{n} w_i f(x_i) - \int f(x)p(dx) \right| = \mathcal{O}(n^{-\frac{1}{2} - \frac{2a}{a + b} + \epsilon})$$

at a cost that is cubic in $n$, where $p$ (the posterior density) has $2a + 1$ derivatives, the integrand $f$ has $a \wedge b$ derivatives and $\epsilon > 0$ can be arbitrarily small.


Probabilistic Meshless Methods for Partial Differential Equations and Bayesian Inverse Problems

Jon Cockayne
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Partial differential equations (PDEs) are a challenging class of problems which rarely admit closed-form solutions, forcing us to resort to numerical methods which discretise the problem to construct an approximate solution. We seek to phrase solution of PDEs as a statistical inference problem, and construct probability measures which quantify the epistemic uncertainty in the solution resulting from the discretisation [1]. We explore construction of probability measures for the strong formulation of elliptic PDEs, and the connection between this and “meshless” methods.

We seek to apply these probability measures in Bayesian inverse problems, parameter inference problems whose dynamics are often constrained by a system of PDEs. Sampling from parameter posteriors in such problems often involves replacing an exact likelihood involving the unknown solution of the system with an approximate one, in which a numerical approximation is used. Such approximations have been shown to produce biased and overconfident posteriors when error in the forward solver is not tightly controlled. We show how the uncertainty from a probabilistic forward solver can be propagated into the parameter posteriors, thus permitting the use of coarser discretisations which still produce valid statistical inferences.

Joint work with Chris Oates (University of Technology, Sydney), Tim Sullivan (Free University of Berlin, Germany), and Mark Girolami (University of Warwick, UK and The Alan Turing Institute for Data Science, UK).

Quantum Computing and Monte Carlo Simulations

Organizer: Yazhen Wang, University of Wisconsin-Madison.

Wednesday August 17. 10:25–11:55, Berg C

Quantum Computing Based on Quantum Annealing and Monte Carlo Simulations

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This talk introduces quantum annealing to solve optimization problems and describe D-Wave computing devices to implement quantum annealing. We illustrate implementations of quantum annealing using Markov chain Monte Carlo (MCMC) simulations carried out by classical computers. Computing experiments have been conducted to generate data and compare quantum annealing with classical annealing. We propose statistical methodologies to analyze computing experimental data from a D-Wave device and simulated data from the MCMC based annealing methods and provide Monte Carlo based statistical analysis to explain possible sources for the data patterns.

Quantum Supersampling

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With a focus on practical use of near-future quantum logic devices in computer graphics, we implement a qubit-based supersampling technique with advantages over Monte Carlo estimation, designed for physical fabrication as an integrated silicon photonic device.

Intended for an audience new to quantum computation, this talk provides a live demonstration and a visual walk-through of the development and implementation of a qubit-based image supersampling technique, with comparison of output images. Though still experimental, the surprising noise redistribution properties of this technique have potential applications in ray tracing, as well as other types of computer imaging.

During this talk, an online quantum computation simulator (QCEngine) is used to provide an intuitive visual demonstration of the QSS method.
Beyond simulation, the increasing sophistication of silicon-based quantum photonic devices allows a very limited version of QSS to be run on actual hardware, using circuit designs which allow it to scale up as better hardware becomes available. Recent developments of this ongoing work will be shown, in addition to results from implementation and testing on a 5-qubit superconducting quantum computation device.

An Imputation- Consistency Algorithm for High-Dimensional Missing Data Problems

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Missing data problems are frequently encountered in high-dimensional data analysis, but they are usually difficult to solve using the standard algorithms, such as the EM and Monte Carlo EM algorithms, as the E-step involves high dimensional integrations. We propose an attractive solution to this problem, which iterates between an imputation step and a consistency step. At the imputation-step, the missing data are imputed given the observed data and a current estimate of the parameters; and at the consistency-step, a consistent estimate of the parameters is computed based on the pseudo-complete data. The consistency of the averaged estimator over iterations can be established under mild conditions. The proposed algorithm is illustrated with high dimensional Gaussian graphical models.
Stochastic Maps and Transport Approaches for Monte Carlo

Organizers: Youssef Marzouk, MIT and Xiao-Li Meng, Harvard University.

Transformations of random variables have broad utility in Monte Carlo simulation. They can be used to improve the estimation of normalizing constants, to increase the efficiency of importance sampling or MCMC, to approximate the conditioning step in nonlinear filtering, and even as a mechanism for density estimation from samples. Specific examples include bridge sampling and its generalizations from deterministic to stochastic maps; ensemble transform methods in data assimilation; and the numerical approximation of various canonical couplings (e.g., the Knothe-Rosenblatt rearrangement) for stochastic simulation. Many of these approaches can be understood and analyzed using ideas from optimal transportation. This session will present talks that describe how to construct useful maps/transports between probability distributions, how to understand the structure of these transports in high dimensions, and how to use them to tackle a variety of challenging sampling problems.

Thursday August 18. 10^{25}–11^{55}, Berg A

Warp Bridge Sampling: the Next Generation

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Bridge sampling is an effective Monte Carlo method for estimating the ratio of normalizing constants of two probability densities, a routine computational problem in likelihood and Bayesian inferences, as well as in physics, chemistry, etc. The Monte Carlo error of the bridge sampling estimator is determined by the amount of overlap between the two densities. Complementing and generalizing the Warp-I, II, and III transformations (Meng and Schilling, 2002, JCGS), which are most effective for increasing the overlap between two (essentially) uni-modal densities, we introduce Warp-U transformations that aim to transform multi-modal densities into Uni-modal ones but without altering their normalizing constants. The construction of Warp-U transformation starts with a Gaussian (or other convenient) mixture distribution \( \phi_{\text{mix}} \) that has a reasonable overlap with a target density \( p \) underlying the unknown normalizing constant. The stochastic transformation that maps \( \phi_{\text{mix}} \) back to its generating distribution \( N(0,1) \) is then applied to \( p \), resulting its Warp-U transformation \( \tilde{p} \). The overlap between \( \tilde{p} \) and \( N(0,1) \) is theoretically guaranteed to be no less than the overlap between \( p \) and \( \phi_{\text{mix}} \), as measured by any \( f \)-divergence, leading to statistically more efficient bridge sampling estimators. We propose a computationally efficient method to find an appropriate \( \phi_{\text{mix}} \), and use simulations to explore various estimation strategies and the choices of tuning parameters, with the aim to achieve statistical efficiency without unduly losing computational efficiency. We illustrate our findings using 10-50 dimensional highly irregular multi-modal densities.

This is joint work with Lazhi Wang.
Measure Transport, Variational Inference, and Low-Dimensional Maps

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Measure transport is a useful tool for characterizing difficult and non-Gaussian probability measures, such as those arising in Bayesian inference. In this setting, we seek a deterministic transport map between an easy-to-sample reference distribution (e.g., a Gaussian) and the desired target distribution (e.g., the posterior), via optimization. As a result, one can easily obtain samples from the target distribution by pushing forward reference samples through the map. In the same spirit, one can also leverage quadrature rules for the reference measure to induce a new set of quadrature rules for the target distribution.

In this talk, we address the computation of the transport map in high dimensions. In particular, we show how the Markov structure of the target measure induces low-dimensional parameterizations of the transport map in terms of sparsity and decomposability. The results of our analysis will not only enable the characterization of a large class of high-dimensional and intractable distributions, but will also suggest new approaches to classical statistical problems such as the modeling of non-Gaussian random fields, as well as Bayesian filtering, smoothing, and joint parameter and state estimation.

Joint work with Daniele Bigoni (MIT, USA) and Youssef Marzouk (MIT, USA).

What the Collapse of the Ensemble Kalman Filter Tells us About Localization of Particle Filters

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Suppose you have a mathematical model for the weather and that you want to use it to make a forecast. If the model calls for rain but you wake up to sunshine, then you should recalibrate your model to this observation before you make a prediction for the next day. This is an example of Bayesian inference, also called “data assimilation” in geophysics. The ensemble Kalman filter (EnKF) is used routinely and daily in numerical weather prediction (NWP) for solving such a data assimilation problem. Particle filters (PF) are sequential Monte Carlo methods and are in principle applicable to this problem as well. However, PF are never used in operational NWP because a linear analysis shows that the computational requirements of PF scale exponentially with the dimension of the problem. In this talk I will show that a similar analysis applies to EnKF, i.e., “in theory” EnKF’s computational requirements also scale poorly with the dimension. Thus, there is a dramatic contradiction between theory and practice. I will explain that this contradiction arises from different assessments of errors (local vs. global). I will also offer an explanation of why EnKF can work reliably with a very small ensemble (typically 50), and what these findings imply for the applicability of PF to high-dimensional estimation problems.

Joint work with Daniel Hodyss (Naval Research Laboratory), and Chris Snyder (National Center for Atmospheric Research).
Systemic Risk and Financial Networks

Organizer: Paul Glasserman, Columbia University.

This session will address simulation problems arising in the modeling and analysis of systemic risk, financial networks, and credit risk.

Tuesday August 16. 10:25–11:55, LK 120

**Importance Sampling for Default Timing Models**

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In credit risk management and other applications, one is often interested in estimating the likelihood of large losses in a portfolio of positions exposed to default risk. A serious challenge to the application of importance sampling (IS) methods in this setting is the computation of the transform of the loss on the portfolio. This transform is intractable for many models of interest, limiting the scope of standard IS algorithms. We develop, analyze and numerically test an IS estimator of large-loss probabilities that does not require a transform to be computed. The resulting IS algorithm is implementable for any reduced form model of name-by-name default timing that is amenable to simulation.

We state conditions for asymptotic optimality of the estimator, and characterize its performance when these conditions are not met. In the process, we develop a novel technique for analyzing the optimality properties of importance sampling estimators. Our methods are based on the weak convergence approach to large deviations theory. In particular, it is observed that the efficiency of an estimator may be analyzed only along convergent subsequences of a sufficiently large compact set. Characterizing the behavior of the estimator on each such subsequence is simpler than using the traditional methods in the literature. We sketch the potential of this approach for applications outside of credit risk including queuing, insurance and system reliability.

Joint work with Kay Giesecke, Stanford.

**Revisiting Eisenberg-Noe: A Dual Perspective**

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We consider the Eisenberg-Noe framework for systemic risk with random shocks. Using duality, we characterize the amount of shock amplification due to the network structure and find the region for the shock vector that makes a specific bank default. These results enable us to improve our understanding of the default probability of a specific bank. More importantly, we propose efficient simulation schemes for the systemic risk measurement based on the characterization, of which effectiveness is illustrated via several examples.
How Informative is Eigenvector Centrality?

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Financial networks have attracted attention as models of systemic risk. In practice, public data on interconnections between financial firms is limited to aggregate obligations by firm, with specific obligations between firms remaining confidential. Reconstructing the network becomes a problem of inferring the entries of a matrix from its row and column sums, a problem that has been studied through random sampling in other contexts. We investigate the additional information provided by eigenvector centrality (a standard network measure) in reducing the number or volume of feasible networks given firm-level information. When row sums are normalized to one, the problem becomes one of estimating the volume of Markov chains with a given stationary distribution. We develop sampling procedures and find that centrality can be surprisingly informative. For example, numerical results suggest that most Markov chains have rare stationary distributions.

Joint work with Paul Glasserman.
Contributed talks

We received numerous contributed abstracts. The ones listed here were accepted. In most cases we were able to find enough similarities among pairs or triples of contributed talks to form them into sessions with a common theme. NB: each talk may contain more than just that theme.

Non-cubical QMC
Monday August 15. 10:25–11:55, LK 101

$L^p$ Results for the Discrepancy Associated to a Large Convex Body

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Let $\Omega \subset \mathbb{R}^d$ ($d > 1$) be a convex body with measure $|\Omega|$, and let $R \geq 2$. The problem of estimating the discrepancy

$$D_{R\Omega} := \text{card} \left( \mathbb{Z}^d \cap R\Omega \right) - R^d |\Omega|$$

carries a long history, particularly when $\Omega$ is the ball $B_d := \{ t \in \mathbb{R}^d : |t| \leq 1 \}$ (the case of $B_2$ is Gauss’ circle problem) or a polyhedron.

$L^2$ means of $D$ have been studied for a long time. G. Hardy proved that

$$\left\{ R^{-1} \int_0^R D_{R^2 B_2}^2 \, dr \right\}^{1/2} \leq c \, R^{1/2+\varepsilon}$$

and conjectured that $|D_{RB_2}| \leq c \, R^{1/2+\varepsilon}$.

D. Kendall, A. Podkorytov et al. proved that, for every convex body $\Omega \subset \mathbb{R}^d$,

$$\|D_{R\Omega}\|_{L^2(SO(d) \times T^d)} := \left\{ \int_{SO(d)} \int_{T^d} |D_{\sigma(R\Omega)+x}|^2 \, dx \, d\sigma \right\}^{1/2} \leq c R^{(d-1)/2} .$$

We present several $L^p$ estimates which depend on the geometry of $\Omega$ and on the dimension $d$.


The Variance Lower Bound and Asymptotic Normality of the Scrambled Geometric Net Estimator

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In a very recent work, Basu and Owen [1] propose the use of scrambled geometric nets in numerical integration when the domain is a product of arbitrary spaces of dimension $d$ having a certain partitioning constraint. It was shown that for a class of smooth functions, the integral estimate has variance $O(n^{-1-2/d}(\log n)^{s-1})$ for scrambled geometric nets, compared to $O(n^{-1})$ for ordinary Monte Carlo.

In this talk, we shall show a matching lower bound for the variance and develop on the work by Loh [2], to show that the scrambled geometric net estimate has an asymptotic normal distribution for certain smooth functions defined on products of suitable subsets of $\mathbb{R}^d$.

Joint work with Rajarshi Mukherjee (Stanford University, USA).


Generating Mixture Quasirandom Points with Geometric Consideration

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This work proposes a quasi-Monte Carlo implementation to generate a point set which follows a mixture distribution. While Monte Carlo method, i.e. using pseudorandom numbers, is commonly used for generating a sample from mixture distribution, our method makes use of quasirandom numbers in hope of generating as faithful points from a given mixture distribution as possible. Special attention is focused on mimicking the adjacency of points in the Euclidean space where the sample points are scattered. To this end, our method uses a computational geometric tool, more specifically, we make the Delaunay diagram of sample points to find the adjacency of them, and partition the space of mixing probability with keeping the adjacency. One feature of the method is that it is fully implemented with quasirandom numbers. We divide the coordinates of quasirandom point into two parts, then the first several coordinates are employed for the mixing probability and the latter are for generating a point from the chosen probability distribution.

Whereas we are at work on the theoretical investigation of the error estimation of our method, we tested the performance of the method by some application problems. The result of computational experiments in particle filtering and stochastic optimization is reported with comparison to existing QMC methods as well as traditional MC methods. Although our method still has a drawback in computational time, it shows a good performance in the computational experiments.
Gibbs Sampling
Monday August 15. 2^{25}–3^{25}, LK 120

Fast Bayesian Non-Parametric Inference, Prediction and Decision-Making at Big-Data Scale

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Bayesian non-parametric (BNP) methods provide an approach to what may be termed “optimal Bayesian model specification”, by which I mean a specification approach that (a) makes full use of all available contextual and data information, and (b) does not make use of “information” not implied by problem context. However, traditional (MCMC) BNP computational methods do not scale well with sample size or dimensionality of the vector of unknowns. In this talk, I will present a case study from data science in eCommerce — on the topic of “A/B testing,” which is the data science term for randomized controlled trials — in which optimal BNP inference can be performed in a highly accurate manner, on a laptop computer in minutes or seconds, with sample sizes in each of the A (treatment) and B (control) groups on the order of tens of millions. I will conclude the talk with a method, based on optimal BNP inference, with which information from a number of control groups, judged similar to the B group in the actual A/B test, may be combined to increase accuracy of the A/B comparison; this method permits the analysis of O(100,000,000) observations on a laptop computer in minutes or seconds.

Joint work with Alex Terenin (University of California, Santa Cruz, and eBay, inc).

Adapting the Gibbs Sampler

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The popularity of Adaptive MCMC has been fueled on the one hand by its success in applications, and on the other hand, by mathematically appealing and computationally straightforward optimisation criteria for the Metropolis algorithm acceptance rate (and, equivalently, proposal scale). Similarly principled and operational criteria for optimising the selection probabilities of the Random Scan Gibbs Sampler have not been devised to date.

In the present work we close this gap and develop a general purpose Adaptive Random Scan Gibbs Sampler that adapts the selection probabilities. The adaptation is guided by optimising the L^2—spectral gap for the target’s Gaussian analogue [1,3], gradually, as target’s global covariance is learned by the sampler. The additional computational cost of the adaptation represents a small fraction of the total simulation effort.

We present a number of moderately- and high-dimensional examples, including Truncated Normals, Bayesian Hierarchical Models and Hidden Markov Models, where significant computational gains are empirically observed for both, Adaptive Gibbs, and Adaptive Metropolis within Adaptive Gibbs version of the algorithm, and where formal convergence is guaranteed by [2]. We argue that Adaptive Random Scan Gibbs Samplers can be routinely implemented and substantial computational gains will be observed across many typical Gibbs sampling problems.

Joint work with Krys Latuszynski and Gareth O. Roberts (Department of Statistics, University of Warwick, UK).


Progress in Simulation of Stochastic Neutron Dynamics

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Stochastic behavior of neutron dynamics is very important in nuclear power plant design and nuclear reactor safety. Based on the stochastic character of neutron reactions, simulation method for the stochastic neutron dynamics proposed by one of the authors which is made in generalized semi-Markov process is introduced. The multiplicities of fission neutrons are one of the main sources of reactor noise. Based on the description equation of the neutron fluctuation and its solution, the stochastic theory and simulation code of zero power and power reactor noise is evolved. It is a distinct progress in stochastic neutron kinetic process simulation, which reveals inherent law of neutron initiation experiments in pulse reactor. The simulation results agree with the experiments very well on the probability distribution of burst waiting time. So it can be used as a tool to implement quantitative analysis of problems related to stochastic neutron dynamics.

Joint work with Xiao Gang.

Detailed Comparison of Uniform Tally Density Algorithm and Uniform Fission Site Algorithm

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Because of the non-uniform power distribution in reactor core and the fact that relative uncertainties of local tallies tend to be large in low-power regions and small in higher-power regions, reducing the largest uncertainties to an acceptable level simply by running a large number of neutron histories is often prohibitively expensive when doing global tallying in Monte Carlo criticality calculation. The uniform tally density algorithm and uniform fission site algorithm are two different methods to increase the efficiency of global tallying. They have been compared carefully using the global volume averaged cell flux and energy deposition tally of the Dayawan reactor pin-by-pin model. But, because it is unfair to use the same parameters of survival bias method for these two algorithms, this popular method for reducing the fluctuation of particle weight has not been used in former works. In this paper, the same strategy for producing the parameters of survival bias method for these two algorithms, this popular method for reducing the fluctuation of particle weight has not been used in former works. In this paper, the same strategy for producing the parameters of survival bias method has been combined with these two algorithms and the efficiencies have been compared carefully still using the two global tallies of the Dayawan pin-by-pin model mentioned above.

Joint work with Gang Li, BaoYin Zhang, Li Deng of the Institute of Applied Physics and Computational Mathematics of Beijing and Rui Li and YuanGuan Fu of CAEP Software Center of High Performance Numerical Simulation.
Hamiltonian MCMC  
Monday August 15. 3\(^{50}\)–4\(^{50}\), LK 120

A Markov Jump Process for More Efficient Hamiltonian Monte Carlo

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Discrete-time Markov Chain Monte Carlo sampling methods are limited by the fact that transition rates between states must be less than or equal to one. The popular Metropolis-Hastings acceptance rule works well because it maximizes the transition rate between a pair of states subject to this constraint. Yet it discards information about the distribution in the sense that the acceptance rate is the same for all states of higher probability relative to the current state.

On the other hand, the transition rates of Markov Jump processes, which make transitions between discrete sets of states in continuous time, are only constrained to be non-negative. Our primary contribution is a Hamiltonian Monte Carlo sampling algorithm that is a continuous time Markov Jump process. One advantage of using Hamiltonian Monte Carlo is that only a small number of transitions need to be considered from each state - our algorithm takes advantage of Markov Jump process dynamics while retaining approximately the same computational cost per sample as standard Hamiltonian Monte Carlo.

In this talk we present our algorithm, Markov Jump Hamiltonian Monte Carlo (MJHMC), and some experimental results. Exact comparison of the spectral gap of the Markov operators corresponding to MJHMC and standard HMC on a toy problem and autocorrelation analysis on a challenging high-dimensional distribution suggest that MJHMC mixes faster than standard HMC on a wide-range of distributions.

Additionally, we provide some intuition for the improved performance of the method through connection to importance sampling. It is the duality between a Markov Jump process and its embedded Markov Chain (the discretely indexed sequence of transitions) that provides this connection.

Joint work with Mayur Mudigonda (UC Berkeley, USA), Michael DeWeese (UC Berkeley, USA), and Jascha Sohl-Dickstein (Google Research, USA).

Hamiltonian Monte Carlo without Detailed Balance

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We present a method for performing Hamiltonian Monte Carlo that largely eliminates sample rejection for typical hyperparameters. In situations that would normally lead to rejection, instead a longer trajectory is computed until a new state is reached that can be accepted. This is achieved using Markov chain transitions that satisfy the fixed point equation, but do not satisfy detailed balance. The resulting algorithm significantly suppresses the random walk behavior and wasted function evaluations that are typically the consequence of update rejection. We demonstrate a greater than factor of two improvement in mixing time on three test problems. We release the source code as Python and MATLAB packages.

Joint work with Jascha Sohl-Dickstein (Google Brain) and Michael R. DeWeese(UC Berkeley)
Sohl-Dickstein, Mudigonda, DeWeese, Hamiltonian Monte Carlo Without Detailed Balance, International Conference of Machine Learning, 2014
Strong Law of Large Numbers for Interval-Valued Gradual Random Variables

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Financial problems can be analyzed by several ways. One of them is based on simulation of scenarios that might happen. In the standard case, we assume that a given financial quantity in question is a stochastic (or random) variable, i.e., it follows some probability distribution and its possible states can get prescribed particular probabilities. The analysis is basically related to the Law of Large Numbers, which allows one to show that as the number of scenarios approaches to infinity, the modelled results should approach the reality. However, in real-world modelling it can appear that a precise estimation of parameters of such models (e.g., volatility of financial returns) is not feasible. By contrast, if one decides to apply Monte Carlo simulation to analyze a given problem with values expressed by imprecisely defined numbers, it is important to show that such variables with imprecisely defined numbers satisfy the strong law of large numbers, as well. Otherwise such approach would have no sense. In this research we extend our previous results in the field to interval-valued gradual variables. The strong law of large numbers for fuzzy random variables is standardly proved with help of alpa-cut decomposition of fuzzy numbers (or more general fuzzy relations), where each alpha-cut is a compact set (see, [1],[2]). During last few years, an interesting generalisation of fuzzy numbers appeared, namely, intervals of gradual numbers are considered instead of fuzzy numbers, where a gradual number is a function from a scale (usually a finite subset of the unit interval) into the set of real numbers (see, [3],[4]). In the presentation, we design random variables in such a way that their values are interpreted by means of intervals of gradual numbers (special functions) and discuss the strong law of large numbers for such kind of random variables.


Green Simulation for Repeated Experiments

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In many financial, actuarial, industrial applications, simulation models are often run repeatedly to perform the same task with different inputs due to changing market conditions or system states. We introduce a new paradigm in simulation experiment design and analysis, called “green simulation,” that aims to increase computational efficiency in the setting of repeated experiments. Green simulation means recycling and reusing outputs from previous experiments to answer the question being asked of the current simulation model.

As a first method for green simulation, we propose estimators that reuse outputs from previous experiments by weighting them with likelihood ratios, when parameters of distributions in the simulation model differ across experiments. We analyze convergence of these green simulation estimators as more experiments are repeated, while a stochastic process changes the parameters used in each experiment. We find that green simulation reduces variance by more than an order of magnitude in examples involving catastrophe bond pricing and credit risk evaluation.

Joint work with Jeremy Staum.
Diffusions
Tuesday August 16. 10^{25}–11^55, LK 203/4

Second Order Langevin Markov Chain Monte Carlo

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Dynamical systems approaches to Markov Chain Monte Carlo (MCMC) have become very popular as the dimension and complexity of Bayesian inference problems has increased. These approaches like Hamiltonian Monte Carlo (HMC) and Stochastic Gradient MCMC (SGMCMC) allow samplers to achieve much higher acceptance rates and effective sample sizes compared to standard MCMC methods because they are able to better exploit the structure of the posterior distribution to explore areas of high probability. In this work, we present a stochastic dynamical system based upon the damped second-order Langevin stochastic differential equation (SDE) whose stationary distribution is an arbitrary posterior. We can simulate this SDE to effectively generate samples from the posterior by using an integrator derived from the Metropolis Adjusted Geometric Langevin Algorithm (MAGLA).

In the limit of no damping this sampler is deterministic and samples constant likelihood contours as in HMC. When it has large damping, it samples like random walk Metropolis-Hastings. Further, like HMC and SGMCMC, this SDE can be adapted using a Riemannian metric to develop a sampler that better exploits the local structure of the posterior.

Since this method is based upon an auxiliary dynamical system, we can apply ideas from dynamics and control theory to optimize the performance of our sampler. When the system is linear, as is the case for a Gaussian posterior, we can derive the optimal structure for the damping matrix to speed up convergence to the stationary distribution. We then discuss a control strategy to minimize a cost that weighs both the sample correlation and the energy correlation. This is related to balancing the effective sample size for the mean and covariance estimate of the posterior. Finally we apply this method to several challenging Bayesian inference problem and compare its performance to other methods.

Joint work with James L. Beck (California Institute of Technology).

MCMC for Estimation of Incompletely Discretely Observed Diffusions

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Suppose \( X \) is a multidimensional diffusion taking values in \( \mathbb{R}^d \) with time dependent drift \( b \) and time dependent dispersion coefficient \( \sigma \) governed by the stochastic differential equation (SDE)

\[
dX_t = b(t, X_t) dt + \sigma(t, X_t) dW_t.
\]

The process \( W \) is a vector valued process consisting of independent Brownian motions. Denote observation times by \( 0 = t_0 < t_1 < \cdots < t_n \). Assume observations

\[
V_i = L_i X_{t_i} + \eta_i, \quad i = 0, \ldots, n,
\]

where \( L_i \) is a \( m_i \times d \)-matrix. The random variables \( \eta_1, \ldots, \eta_n \) are independent random variables, independent of the diffusion process \( X \). We equip the parameter \( \theta \) with a prior and are interested in drawing from the posterior (Cf.[5]).

In case of full observations (\( L_i = I \) for all \( i \)), it well known that this can be done using a data-augmentation algorithm, in which the latent paths of the diffusion in between observations are treated as missing data. One then iteratively samples diffusion bridges on all segments and next conditional on the obtained “full” diffusion path samples from the posterior. A direct implementation of this approach will fail if the parameter \( \theta \) is present in the diffusion coefficient (Cf.[1]). We present a non-centred parametrisation and prove that it yields an irreducible Markov chain that samples from the posterior. We assume that diffusion bridges are simulated using a Metropolis-Hastings algorithm with diffusion bridge proposals generated from the SDE

\[
dX^\circ_t = b_\circ(t, X^\circ_t) dt + \sigma(t, X^\circ_t) dW_t.
\]

Here the drift \( b_\circ \) is chosen to ensure the process \( X^\circ \) ends up in the right endpoint of the bridge. Specific
constructions of $b^b_\theta$ are detailed in [2] and [3]. It turns out that this framework can be directly extended to the case of incomplete discrete observations.

Joint work with Moritz Schauer (Leiden University, The Netherlands).


Optimal diffusion for stochastic Bayesian Particle Flow

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We derive the optimal covariance matrix of the diffusion in stochastic particle flow for nonlinear filters, Bayesian decisions, Bayesian learning and transport. Particle filters generally suffer from the curse of dimensionality owing to particle degeneracy. The purpose of particle flow is to mitigate the problem of particle degeneracy in particle filters. Particle flow moves the particles to the correct region in state space corresponding to BayesÂÄ” rule. The flow is from the prior probability density to the posterior probability density. Particle flow is similar to Monge-Kantorovich transport, but it is much simpler and much faster to compute in real time, because we avoid solving a variational problem. Our transport of particles is not optimal in any sense, but rather it is designed to provide good estimation accuracy and good UQ for a given computational complexity. In contrast to almost all papers on transport theory, we use non-zero diffusion in our particle flow corresponding to BayesÂÄ” rule. This talk shows how to compute the best covariance matrix for such diffusion, using several optimization criteria (most stable flow, least stiff flow, robust UQ, best estimation accuracy, etc.). We derive a simple explicit formula for the optimal diffusion matrix. We show numerical experiments that compare our stochastic particle flow with state-of-the-art MCMC algorithms (Hamiltonian Monte Carlo, MALA, auxiliary particle filters, regularized particle filters, etc.); our stochastic particle flow beats such MCMC algorithms by orders of magnitude in computation time for the same accuracy for difficult nonlinear non-Gaussian high dimensional problems. The computational complexity of particle filters for optimal estimation accuracy generally depends on the dimension of the state vector, coupling between components of the state vector, stability of the plant model, initial uncertainty in the state vector, measurement accuracy, geometry of the probability densities (e.g., log-concave), ill-conditioning of the Fisher information matrix in a given coordinate system, stiffness of the flow in a given coordinate system, Lipschitz constants of the log-densities, etc. Our flow is designed by solving a linear highly underdetermined PDE similar to the Gauss law in electrodynamics. We have several dozen distinct solutions of this PDE using different methods to pick a unique solution. The best flows avoid explicit normalization of the posterior probability density. It turns out that particle flows are extremely sensitive to errors in computing the normalization, and hence it is best to avoid this completely. This phenomenon is known in other applications of transport; e.g., in adaptive integration for numerical weather prediction the normalization must be computed to machine precision!
Quadrature at Non-QMC points
Tuesday August 16. $2^{25} - 3^{25}$, LK 120

High Accuracy Algorithms for Integrating Multivariate Functions Defined at Scattered Data Points

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We will describe a class of accurate and efficient algorithms for estimating the integral of multidimensional functions defined at a small set of very sparse samples in high dimensions. These situations arise when the function values are computationally expensive to evaluate, experimentally difficult to obtain, or just unavailable. The methods are based on deriving a weighted quadrature rule specially for a given set of sample points that is exact for a class of sparse multivariate orthogonal polynomials. We will compare the convergence rate of the method on smooth and discontinuous functions defined on both low discrepancy quasi-Monte Carlo distributions of samples, as well as for sample distributions that are far from uniformly distributed. We observe that although the approach does not change the error convergence rate, the constant multiplicative factor in the error is often reduced by a factor of over 100 or more.

Joint with Jeremy Dewar (Tulane U, USA) and Mu Tian (Stony Brook U, USA).

Support points

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In this talk, we present a new method for compacting any continuous distribution $F$ into a set of optimal representative points called support points. Support points can have many useful applications in statistics, engineering and operations research. Two applications will be highlighted here: (1) as a way to optimally allocate experimental runs for stochastic simulations, and (2) as an improved alternative to MCMC thinning in Bayesian computation. For numerical integration, we will also show the improved performance of support points over Monte Carlo (MC) and quasi-Monte Carlo (qMC) methods using several simulation studies.

On a technical level, support points differ from existing qMC methods on two fronts. The latter often assumes integration on the unit hypercube to obtain a closed-form expression for discrepancy, and employs number-theoretic methods to generate sampling points (see, e.g., Dick-Kuo-Sloan, 2013). Support points, on the other hand, are obtained from the energy goodness-of-fit statistic (Székely and Rizzo, 2013), which can be efficiently optimized using subsampling methods, despite having no closed-form expression. As a result, these points can be generated for any distribution from which a random sample can be obtained. We will present a Koksma-Hlawka-like bound connecting integration error to the energy statistic, and establish an existence result for error convergence rate using support points. A quick blockwise coordinate-descent algorithm is then proposed for generating support points, with time-complexity scaling linearly in both sample space dimension and number of desired points.

Joint work with V. Roshan Joseph (Georgia Institute of Technology, USA).
Measuring Sample Quality with Stein’s Method

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To improve the efficiency of Monte Carlo estimation, practitioners are turning to biased Markov chain Monte Carlo procedures that trade off asymptotic exactness for computational speed. The reasoning is sound: a reduction in variance due to more rapid sampling can outweigh the bias introduced. However, the inexactness creates new challenges for sampler and parameter selection, since standard measures of sample quality like effective sample size do not account for asymptotic bias. To address these challenges, we introduce a new computable quality measure based on Stein’s method that quantifies the maximum discrepancy between sample and target expectations over a large class of test functions. We use our tool to compare exact, biased, and deterministic sample sequences and illustrate applications to hyperparameter selection, convergence rate assessment, and quantifying bias-variance tradeoffs in posterior inference.

Joint work with Jackson Gorham (Stanford University, USA).

Multivariate Output Analysis for Markov Chain Monte Carlo

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Markov chain Monte Carlo (MCMC) is a method of producing a correlated sample in order to estimate expectations with respect to a target distribution. A fundamental question is when should sampling stop so that we have good estimates of the desired quantities? The key to answering these questions lies in assessing the Monte Carlo error through a multivariate Markov chain central limit theorem. However, the multivariate nature of this Monte Carlo error has been ignored in the MCMC literature. I will give conditions for consistently estimating the asymptotic covariance matrix. Based on these theoretical results I present a relative standard deviation fixed volume sequential stopping rule for deciding when to terminate the simulation. This stopping rule is then connected to the notion of effective sample size, giving an intuitive, and theoretically justified approach to implementing the proposed method. The finite sample properties of the proposed method are then demonstrated in examples.

Joint work with James Flegal (UC, Riverside) and Galin Jones (U of Minnesota).
Estimating Orthant Probabilities of High Dimensional Gaussian Vectors with an Application to Set Estimation

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The computation of Gaussian orthant probabilities has been extensively studied for low dimensional vectors. Here we focus on the high dimensional case and we present a two step procedure relying on both deterministic and stochastic techniques.

The proposed estimator relies indeed on splitting the probability into a low dimensional term and a remainder. While the low dimensional probability can be estimated by fast and accurate quadrature, see e.g. [1], the remainder requires Monte Carlo sampling. We show that an estimator obtained with this technique has higher efficiency than standard Monte Carlo methods. We further refine the estimation by using a novel asymmetric nested Monte Carlo algorithm for the remainder and we highlight cases where this approximation brings substantial efficiency gains.

Finally this method is applied to derive conservative estimates of excursion sets of expensive to evaluate deterministic functions under a Gaussian random field prior without requiring a Markov assumption.

This is joint work with David Ginsbourger (Idiap Research Institute, Switzerland and University of Bern, Switzerland).


Monte Carlo with User-Specified Relative Error

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Monte Carlo data has properties that are very different from data obtained from other sources. In particular, the number of data points is typically not fixed, but can vary randomly as needed by the user.

Compared to classical estimators which usually use a fixed number of data points, this allows for extra flexibility in estimation of parameters derived from Monte Carlo data. In this talk, I will describe two new estimators for the means of Bernoulli and Poisson distributed output designed with Monte Carlo output in mind. These estimators have the remarkable property that the relative error in the distribution is determined by the user ahead of time: it does not depend on the quantity being estimated in any way.

Applications of these estimators include construction of randomized approximation schemes (also known as exact confidence intervals) for normalizing constants of posterior distributions and for approximating the value of other high dimensional integrals.

Tail Probabilities of Infinite Sums of Random Variables – Exact and Efficient Simulation

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In addition to arising naturally in the study of linear processes and recurrence equations, infinite sums of random variables form a main building block in various stochastic risk models. In this talk, we present an exact algorithm for estimating tail probabilities of such infinite sums with uniformly bounded computational effort.

The problem considered is challenging because any algorithm that stops after generating only finitely many summands is likely to introduce bias. Apart from the task of eliminating bias, we are faced with an additional challenge of estimating the rare tail probabilities just with bounded computational budget. Assuming that the individual summands in the infinite series possess regularly varying tails, we use multi-level randomization techniques and heavy-tailed heuristics to arrive at a simulation algorithm that efficiently estimates such tail probabilities without any bias.
Joint work with Henrik Hult (KTH, Stockholm) and Sandeep Juneja (TIFR, Mumbai).

**Faster Monte Carlo with Determinantal Point Processes**

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In this talk, we show that repulsive point processes can yield Monte Carlo methods that converge faster than the vanilla Monte Carlo rate [1]. More precisely, we build estimators of integrals, the variance of which decreases as \( N^{-1-1/d} \), where \( N \) is the number of integrand evaluations, and \( d \) is the ambient dimension. We rely on stochastic numerical quadratures involving determinantal point processes (DPPs; [2]) associated to multivariate orthogonal polynomials.

The proposed method can be seen as a stochastic version of Gaussian quadrature, where samples from a determinantal point process replace zeros of orthogonal polynomials. Furthermore, integration with DPPs is close in spirit to randomized quasi-Monte Carlo methods such as scrambled nets [3], with the advantage of letting the user specify a non-uniform target measure, and most importantly tailoring repulsiveness to the integration problem at hand. This results in a central-limit theorem with an easy-to-interpret asymptotic variance.

DPPs are the kernel machines of point processes, and as such they come with computational limitations. In particular, sampling is \( \Theta(N^3) \) in most cases, and further requires rejection sampling. Targeted applications so far are thus integration tasks where the bottleneck is the cost of evaluating the integrand.

Joint work with Adrien Hardy (Univ. Lille, France).


Global sensitivity analysis (GSA) is used to identify key parameters whose uncertainty most affects the output. This information can be used to rank variables, fix or eliminate unessential variables and thus decrease problem dimensionality. Among different approaches to GSA variance-based Sobol’ sensitivity indices (SI) are most frequently used in practice owing to their efficiency and ease of interpretation [1].

Most existing techniques for GSA were designed under the hypothesis that model inputs are independent. However, in many cases there are dependences among inputs, which may have significant impact on the results. Such dependences in a form of correlations have been considered in the generalised Sobol’ GSA framework developed by Kucherenko et al. [2].

There is an even wider class of models involving inequality constraints (which naturally leads to the term ‘constrained GSA’ or cGSA) imposing structural dependences between model variables. It implies that the parameter space may no longer be considered to be an $n$-dimensional hypercube as in existing GSA methods, but may assume any shape. This class of problems encompasses a wide range of situations encountered in engineering, economics and finances where model variables are subject to certain limitations imposed e.g. by conservation laws, geometry, costs, quality constraints etc.

The development of efficient computational methods for cGSA requires the development of special Monte Carlo or quasi-Monte Carlo sampling techniques and methods for computing sensitivity indices. Consider a model $f(x_1, ..., x_n)$ defined in a non-rectangular domain $\Omega^n$, an arbitrary subset of variables $y = (x_{i_1},...,x_{i_s})$, $1 \leq s < n$ and a complementary subset $z = (x_{i_{s+1}},...,x_{i_n})$, so that $y = (x_1,...,x_n) = (y,z)$. Then formulas for the main effect and total Sobol’ SI have the following form:

$$S_y = \frac{1}{D} \int_{\Omega^n} f(y',z') p^{\Omega}(y',z') dy' dz' \left( \int_{\Omega^{n-s}} f(y', z) p^{\Omega}(y', z) dy' dz - \int_{\Omega^n} f(y, z) p^{\Omega}(y, z) dy dz \right)$$

$$S^T_y = \frac{1}{2D} \int_{\Omega^n} \int_{\Omega^n} (f(y, z) - f(y', z))^2 p^{\Omega}(y, z) p^{\Omega}(y', z) dy' dz$$

Here $p^{\Omega}(y,z)$ is a joint probability distribution function and $p^{\Omega}(y)$ is a marginal distribution. Both distributions are defined in $\Omega^n$. We propose two methods for the estimation of Sobol’ SI: 1) quadrature integration method, and 2) MC/QMC estimates based on the acceptance-rejection sampling method. Several model test functions with constraints for which we found analytical solutions were considered. These solutions were used as benchmarks for verifying the developed integration methods. The method is shown to be general and efficient.

Joing work with Oleksiy V. Klymenko and Nilay Shah (Imperial College London, UK).


Uncertainty quantification in Multi-Phase Cloud Cavitation Collapse using Multi-Level Monte Carlo

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Cloud cavitation collapse pertains to the erosion of liquid-fuel injectors, hydropower turbines, ship propellers, and is harnessed in shock wave lithotripsy. To assess the development of extreme pressure spots, we performed numerical two-phase flow simulations of cloud cavitation collapse containing 50’000 bubbles using up to 1 trillion cells using petascale high performance code CUBISM-MPCF on up to half a million cores.

To quantify the uncertainties in the collapsing clouds under random initial conditions, we investigate a novel non-intrusive multi-level Monte Carlo methodology, which accelerates the plain Monte Carlo sampling. Highly complex cloud cavitation collapse phenomenon was observed to possess reduced statistical correlations across multiple discretization levels, severely limiting the variance reduction potential of the standard multi-level methodology.

Newly proposed optimal control variate coefficients for each resolution level of the multi-level Monte Carlo estimator overcomes such limitations and delivers significant variance reduction improvements, leading to an order of magnitude in computational speedup. Conducted numerical experiments reveal that uncertain locations of equally sized cavities in vapor clouds lead to significant uncertainties in the location and magnitude of the peak pressure pulse, emphasizing the relevance of the uncertainty quantification in cavitating flows.

This is joint work with Panagiotis Hadjidoukas, Diego Rossinelli, Ursula Rasthofer, Fabian Werfelinger, and Petros Koumoutsakos all of (ETH Zurich, Switzerland).
Faster Gibbs  
Tuesday August 16. 350–450, LK 203/4

Using Low Discrepancy Sequences in Grid based Bayesian Methods

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Computational Bayesian methods are dominated by Markov Chain Monte Carlo (MCMC) based methods. While versatile, for many complex problems these methods can become computationally very expensive. For certain types of models, grid based alternatives have been proposed. However, use of grids limits their accuracy as well as computational efficiency.

We view this as a numerical integration problem and make three unique contributions. First, we explore the space using low discrepancy point sets instead of a grid. This allows for accurate estimation of marginals of any shape at a much lower computational cost than a grid based approach and thus makes it possible to extend the computational benefit to a parameter space with higher dimensionality (10 or more). Second, we propose a new, quick and easy method to estimate the marginal using a least squares polynomial and prove the conditions under which this polynomial will converge to the true marginal. Our results are valid for a wide range of point sets including grids, random points and low discrepancy points. Third, we show that further accuracy and efficiency can be gained by taking into consideration the functional decomposition of the integrand and illustrate how this can be done using anchored f-ANOVA on weighted spaces.

Joint work with Paul T. Brown and Stephen Joe (University of Waikato, New Zealand).

Asynchronous Gibbs Sampling

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Gibbs sampling is a widely used Markov Chain Monte Carlo method for numerically approximating integrals of interest in Bayesian statistics and other mathematical sciences. It is widely believed that MCMC methods do not extend easily to parallel implementations, as their inherently sequential nature incurs a large synchronization cost.

We present a novel scheme - Asynchronous Gibbs sampling - that allows us to parallelize Gibbs sampling in a way that involves no synchronization or locking, avoiding typical performance bottlenecks of parallel algorithms. We present two variants: an exact algorithm that converges to the correct target distribution, and an approximate algorithm that makes the same moves with probability close to 1 and possesses better scaling properties.

Asynchronous Gibbs sampling is well-suited for cluster computing, and latent variable models where problem dimensionality grows with data size. We illustrate the algorithm on a number of applied examples.

Joint work with Dan Simpson (University of Bath, UK) and David Draper (University of California, Santa Cruz).
Density Estimation via Discrepancy
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Given i.i.d samples from some unknown continuous density on hyper-rectangle \([0, 1]^d\), we attempt to learn a piecewise constant function that approximates this underlying density nonparametrically. Our density estimate is defined on a binary split of \([0, 1]^d\) and built up sequentially according to discrepancy criteria; the key ingredient is to control the discrepancy adaptively in each sub-rectangle to achieve overall bound. We prove that the estimate, even though simple as it appears, preserves most of the estimation power. By exploiting its structure, it can be directly applied to some important pattern recognition tasks such as mode seeking and density landscape exploration. We demonstrate its applicability through simulations and examples: (1) mode seeking application in Flow Cytometry Analysis; (2) level set based multivariate data visualization; (3) improve k-means and neural network training and accuracy.

Joint work with Dagna Li and Wing H. Wong of Stanford University.

Multivariate Concordance Measures and Copulas via Tensor Approximation of Generalized Correlated Diffusions
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There is now an increasingly large number of proposed concordance measures available to capture, measure and quantify different notions of dependence in stochastic processes. These can include concepts such as multivariate upper negative (positive) dependence, lower negative (positive) dependence, negative (positive) quadrant dependence; multivariate association, comonotonicity, stochastic ordering; regression dependence negative (positive) and extreme dependence, asymptotic tail dependence and intermediate tail dependence; as well as other concepts such as directional dependence. In addition, there is an increasing number of copula models aimed at modelling dependence, however in many cases there is no clear and intuitive correspondence between the magnitude of a copula’s parameters and the dependence structure they create. In addition, evaluation of these concordance measures for different copula models can be very difficult. Therefore, we propose a class of new methods to overcome these two challenges, by developing a highly accurate and computationally efficient procedure to evaluate concordance measures for a given copula. In addition, this then allows us to reconstruct maps of concordance measures locally in all regions of the state space for any range of copula parameters. We believe this technique will be highly important for modellers and practitioners.

To achieve this, we developed a new class of techniques that takes a copula function and quantifies the dependence properties through a localized coefficient of dependence. Effectively we develop a numerical procedure to map any copula function to a generalized Gaussian copula function. This allows us to visualize a copula’s characteristics. The copula mapping is entirely based on tensor algebra and is part of a new modelling framework we also propose consisting of the tensor approximation of the infinitesimal generator associated to multidimensional correlated diffusions. This new result provides the representation in a tensor space of both correlated diffusive transition densities and generalized copula densities. We demonstrate the simplicity and intuition behind the copula mapping through illustrative examples and all the copula functions mapping results are exact up to the tensor space local discretization error.
QMC-Simulation of Piecewise Deterministic Markov Processes

**Gunther Leobacher**
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A piecewise deterministic Markov process (PDMP) is a Markov process whose paths follow ordinary differential equations between random jumps. Applications arise, among other topics, in mathematics of insurance and financial mathematics.

We propose a PDMP model for catastrophe indices and show how it can be simulated efficiently using low discrepancy sequence. We investigate the efficiency of pricing CAT derivatives and profit loss distribution.

Joint work with A. Eichler (JKU Linz), M. Szölgyenyi (WU Vienna).

A Numerical Method for Multidimensional SDEs with Discontinuous Drift and Degenerate Diffusion

**Michaela Szölgyenyi**
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When solving certain stochastic optimization problems, e.g., in mathematical finance, the optimal control policy is of threshold type, meaning that it depends on the controlled process in a discontinuous way. The stochastic differential equations (SDEs) modeling the underlying process then typically have discontinuous drift and degenerate diffusion parameter. This motivates the study of a more general class of such SDEs.

We prove an existence and uniqueness result, based on certain a transformation of the state space by which the drift is “made continuous”.

As a consequence the transform becomes useful for the construction of a numerical method. The resulting scheme is proven to converge with strong order $1/2$. This is the first result of that kind for such a general class of SDEs.

We will first present the one-dimensional case and subsequently show how the ideas can be generalized to higher dimensions. We discuss the necessity of the geometric conditions we pose, and finally present an example, for which the drift of the SDE is discontinuous on the unit circle.

Joint work with G. Leobacher (JKU Linz).
Discrepancy
Wednesday August 17. 3^{50}–4^{50}, Berg A

Probabilistic Star Discrepancy Bounds for Digital Kronecker-Sequences

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By a well known result of Heinrich, Novak, Wasilkowski and Woźniakowski there exists for any positive integers $N$ and $d$ a set of $N$ points $P \subset [0,1)^d$ such that the star-discrepancy of $P$ satisfies $D^*_N(P) \leq c \sqrt{d/N}$ for some constant $c>0$. It is not known how to construct such a point set in general.

In this talk we consider certain subsequences of digital Kronecker-sequences $S(f) = (x_n)_{n \geq 1}$ in the unit cube $[0,1)^d$ whose construction is based on the field of formal Laurent series over the finite field $\mathbb{F}_q$ of prime order $q$. More detailed, for $f = (f_1,\ldots,f_d) \in (\mathbb{F}_q((t^{-1})))^d$ we define $x_n = (\{t^{n-1}f_1\}_{t=q}, \ldots, \{t^{n-1}f_d\}_{t=q})$. Then we prove for a uniformly distributed $f$ that

$$D^*_N(S(f)) \leq C(\varepsilon) \sqrt{d \log d \over N}$$

with probability $1-\varepsilon$ and $C(\varepsilon)$ is independent of $N$ and $d$ and is of order $C(\varepsilon) \asymp \log \varepsilon^{-1}$. Similar results for classical Kronecker sequences have been recently shown by Th. Löbbe.

This is joint work with Friedrich Pillichshammer.

Sharp General and Metric Bounds for the Star Discrepancy of Perturbed Halton-Kronecker-Sequences

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We consider distribution properties of two-dimensional hybrid sequences $(z_k)_k$ of the form $z_k = (\{k\alpha\},y_k)$, where $\alpha \in (0,1)$ is irrational and $(y_k)_k$ denotes a digital Niederreiter-sequence. By definition, the construction of the sequence $(y_k)_k$ relies on an infinite matrix $C$ over $\mathbb{Z}_2$. Two special cases of such matrices were studied by G. Larcher in 2013 and by C. Aistleitner, R. Hofer, and G. Larcher in 2016. On the one hand, taking the identity in place of $C$ (so-called Halton-Kronecker-sequence) yields an optimal metric discrepancy estimate. On the other hand, taking $C$ as the identity again, but filling its first row entirely with an infinite sequence of 1’s (related to the so-called Evil-Kronecker-sequence) worsens the metrical behavior of $(z_k)_k$ significantly. We are interested in what happens in between these two cases. In particular, we consider Halton-Kronecker-sequences, where the first row of $C$ is exchanged by a periodic perturbation of blocks of length $n$ of the form $(1,0,\ldots,0)$. In this case, we witness the following phenomenon: While, from a metrical point of view, the star discrepancy becomes essentially optimal in the limiting case $n \to \infty$, it surprisingly worsens for more general $\alpha$, as the density of 1’s decreases.

Joint work with Roswitha Hofer (Johannes Kepler University Linz, Austria),
Forward and Backward Simulation of Correlated Poisson Processes

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Backward simulation of the multivariate Poisson processes (BS) was recently proposed in [1], [2]. The idea of the BS is to utilize the conditional distribution property of the arrival moments: conditional on the number of arrivals at the end of time horizon the arrival moments form a uniformly distributed random set.

We propose a pure probabilistic method for the computation of the joint probabilities, describing the extreme measures, based on the Strong Law of Large Numbers. Thus, we can describe all extreme measures given marginal distributions of the multivariate Poisson process. Taking convex combination of these measures one can construct an admissible joint distribution of the multivariate process.

We also compare the backward simulation approach with the forward simulation. We demonstrate that the range of correlations attainable under BS approach is different from that obtained using the forward simulation.

The BS approach allows us to consider in a general framework both Gaussian and Poisson processes. In particular, the correlation boundaries can be computed in closed form in the case of the process \((W_t, N_t)\) having the Wiener and Poisson components.

This is joint work with Ken Jackson and Michael Chiu.


Efficient Simulation For Diffusion Processes Using Integrated Gaussian Bridges

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In this talk we present an extension of a recently proposed method of sampling Brownian paths based on integrated bridges [1]. By combining the Brownian bridge construction with conditioning on integrals along paths of the process, the method turns out to be a very effective way of capturing important dimensions in problems that involve integral functionals of Brownian motions.

In this paper we first show that by conditioning on more general integrated Gaussian bridges, combined with a proper change of measure, we can reduce the dimension of integral functionals that depend on squared Brownian motion. We then demonstrate how this result can be used to construct efficient integration methods for problems that involve functionals of diffusion processes. We illustrate the method using some examples from finance.

Non-Parameteric Gaussian Process Vector Valued Time Series Models and Testing For Causality

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In this work we are developing new classes of multivariate time-series models based on Gaussian process functional non-parametric relationships between current vector of observations and the lagged history of each marginal time series. Then within these new classes of non-parameter time series model we consider several families of causality testing that can be used to identify the conditional dependence relationships that may arise in the non-parametric time series structures. This can include structural causality relationships in the mean function, covariance function and higher order information.

Our main goal is to study the ability to detect causality in such time series models, whilst allowing for very general non-linear causal relationships not often considered in classical parametric time-series models.

To perform the testing for such features we develop compound tests that first require estimation/calibration of the mean and covariance functions parameterizing the non-parametric vector valued time series.

We then provide a generic framework that can be applied to a variety of different problem classes and produce a number of examples to illustrate the ideas developed.

Joint work with Gareth W. Peters.

A Method to Compute an Appropriate Sample Size of the Two-Level Test of NIST Test Suite for Frequency and Binary Matrix Rank Test

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The National Institute of Standards and Technology (NIST) has implemented a test suite for random number generators (RNGs) and pseudo random number generators (PRNGs). NIST test suite consists of 15 statistical tests, each of which measures uniform randomness and returns p-values (called the one-level tests). NIST test suite also offers a two-level test, which measures the discrepancy between the uniform distribution $U(0,1)$ and the empirical distribution of p-values which are provided by a one-level test by $\chi^2$ goodness of fit test.

Two-level tests are widely used, however, it sometimes yields a false rejection because the p-value of a one-level test is often obtained by an approximated computation, then these p-values may defect the accuracy of the two-level. Therefore we need to measure the defect of the numerical error in one-level tests.

In this talk, we introduce a method to compute an appropriate sample size of the two-level test when we adopt Frequency test and Binary Matrix Rank test as the one-level test. This method is based on the $\delta$-discrepancy

$$\delta = \sum_{i=0}^{\nu} \left( \frac{q_i}{p_i} - 1 \right)^2,$$

which measures the differences between two probability distributions $\{p_i\}$ and $\{q_i\}$ [2].

For example, when we use Frequency test with the sample size $10^6$, the appropriate sample size of the two-level test is approximately 125000, and the dangerous sample size (which means that the average p-value becomes 0.9999) is 1300000. Some experiments show the estimations of the two-level sample size above are plausible.

Joint work with Makoto Matsumoto (Hiroshima U., Japan).


Approximations of Markov Chains and Bayesian Inference

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The Markov Chain Monte Carlo method is the dominant paradigm for posterior computation in Bayesian analysis. It has long been common to control computation time by making approximations to the Markov transition kernel. Comparatively little attention has been paid to convergence and estimation error in these approximating Markov Chains. We propose a framework for assessing when to use approximations in MCMC algorithms, and how much error in the transition kernel should be tolerated to obtain optimal estimation performance with respect to a specified loss function and computational budget. The results require only ergodicity of the exact kernel and control of the kernel approximation accuracy. The theoretical framework is applied to approximations based on random subsets of data, low-rank approximations of Gaussian processes, and a novel approximating Markov chain for discrete mixture models.

This is joint work with Jonathan C. Mattingly, Sayan Mukherjee, and David B. Dunson

Function Mixing Times and Concentration away from Equilibrium

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Slow mixing is the central hurdle when working with Markov chains, especially those used for Monte Carlo approximations (MCMC). In many applications, it is only of interest to estimate the stationary expectations of a small set of functions, and so the usual definition of mixing based on total variation convergence may be too conservative. Accordingly, we introduce function-specific analogs of mixing times and spectral gaps, and use them to prove Hoeffding-like function-specific concentration inequalities. These results show that it is possible for empirical expectations of functions to concentrate long before the underlying chain has mixed in the classical sense. We use our techniques to derive confidence intervals that are sharper than those implied by both classical Markov chain Hoeffding bounds and Berry-Esseen-corrected CLT bounds. For applications that require testing, rather than point estimation, we show similar improvements over recent sequential testing results for MCMC. We conclude by applying our framework to real data examples of MCMC, providing evidence that our theory is both accurate and relevant to practice.

This is joint work with Maxim Rabinovich, Michael I. Jordan and Martin J. Wainwright of UC Berkeley.

BAIS+L: An Adaptive MCMC Approach to Sampling from Probability Distributions with Many Modes

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Probability distributions with multiple modes play an important role in many applications. For example, the “rough energy landscapes” of spin glass and protein folding configurations can be modelled by multimodal probability distributions. Optimisation problems also require the exploration of such rough functions in order to find maxima or minima. Unfortunately, we often do not know the positions, sizes or number of the modes in these distributions, so sampling from them becomes difficult.

Here we introduce a Metropolis-Hastings-like Markov chain Monte Carlo sampler designed to address these issues. The new sampler, which we call the Bayesian Adaptive Independence Sampler with Latent variables (BAIS+L) is an extension of an earlier sampler by Keith, Kroese and Sofronov [1], called the Bayesian Adaptive Independence Sampler (BAIS). BAIS+L extends BAIS by replacing its single-component Gaussian proposal distribution with a mixture of Gaussian distributions. This produces a multimodal proposal distribution, which should allow a better approximation to a multimodal target distribution, for more efficient sampling.
BAIS+L involves an acceptance ratio that is impractical to calculate, so we use an approximate acceptance ratio instead. We show, using a criterion from Meyn and Tweedie [2] and certain conditions on the proposal and target, that, even with this approximation, BAIS+L is still uniformly ergodic. We close this introduction to BAIS+L with a brief illustration of its implementation.


**Stochastic Volatility**

**Thursday August 18. 2^{25}–3^{25}, LK 101**

**Bayesian Inference for Heston-STAR Models**

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The Heston-STAR model is a new class of stochastic volatility models defined by generalizing the Heston model to allow the volatility of the volatility process as well as the correlation between asset log-returns and variance shocks to change across different regimes via smooth transition autoregressive (STAR) functions. The form of the STAR functions is very flexible, much more so than the functions introduced in Jones (2003), and provides the framework for a wide range of stochastic volatility models. A Bayesian inference approach using data augmentation techniques is used for the parameters of our model. We also explore goodness of fit of our Heston-STAR model. Our analysis of the S&P 500 and VIX index demonstrates that the Heston-STAR model is more capable of dealing with large market fluctuations (such as in 2008) compared to the standard Heston model.

Joint work with Xiaoyu Shen and Matthew Bognar, (University of Iowa, USA).

**Novel Approach to Calibration of Stochastic Volatility Models using Quasi Evolutionary Algorithm with Local Search Optimization**

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Stochastic volatility (SV) models are widely used in mathematical finance to evaluate derivative securities, such as options. Optimization techniques for calibration of SV models to real market data have been investigated; recently, global optimization based on evolutionary algorithms (EA) have attracted particular attention. For the calibration tasks without having a good knowledge of the market (e.g. a suitable initial model parameters) an approach of combining local and global optimizers seems to be crucial. The aim of this talk is to evaluate thoroughly the performance of calibration process under different EA setting. We propose a novel approach to evolutionary algorithms with local search optimization together with the quasi-random initial population generation. Proposed approach is superior to existing methods especially in terms of speed.
Adaptive Multi-Level Monte-Carlo Method for Stochastic Variational Inequalities
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In this work we focus on a variation of MLMC method for elliptic variational inequalities with stochastic input data. Adaptive Multi-Level Monte-Carlo Finite Element method combines the ideas of Multi-Level Monte-Carlo Finite Element (MLMC-FE) method and a posteriori error estimation for adaptive solution of deterministic spatial problems. Whereas the classical MLMC-FE method is based on a hierarchy of uniform meshes, in the adaptive version of the method we use meshes generated by adaptive mesh refinement of an initially given mesh. Generation of meshes in the method is based on a posteriori error estimation. In contrast to MLMC-FE method, there is no given notion of mesh size anymore and levels are characterized by a hierarchy of FE-error tolerances. Under suitable assumptions on the problem, convergence of adaptive MLMC-FE method is shown and upper bounds for it’s computational cost are obtained. We illustrate our theoretical findings by applying the method to a model stochastic elliptic inequality. Our numerical experiments show a reduction in the computational cost of adaptive MLMC-FE method compared to standard MLMC-FE method. In the end we apply the method to a practically relevant stochastic contact problem with an application in biomechanical investigations of human knee implants. Although we focus on elliptic variational inequalities, the method can be used for solution of other problems containing partial derivatives.

Joint work with Ralf Kornhuber (Freie Universität Berlin, Germany).

Enhancing Morphological Categorization via Monte Carlo Methods
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Quantifying shape variation within a group of individuals, identifying morphological contrasts between populations and categorizing these groups according to morphological similarities and dissimilarities are central problems in developmental evolutionary biology and genetics.

In this talk, we will present an approach to optimal shape categorization through the use of a new family of metrics for shapes represented by a finite collection of landmarks. We develop a technique to identify metrics that optimally differentiate and categorize shapes using Monte Carlo based optimization methods. We discuss the theory and the practice of the methods and apply them to the classification of multiple species of fruit flies based on the shape of their wings.

Joint work with Giray Okten and Washington Mio (Florida State University).
Robustness of Short Rate Models

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Short rate models are a popular means of pricing interest rate-dependent financial products. These models attempt to capture the dynamics of the short rate, a mathematical concept that is readily transformed into prices. Bond prices obtained from different models are quite similar, yet some models demonstrate instability under perturbations to their parameters.

We introduce a notion of robustness of a model, by applying Sobol’ global sensitivity analysis, where the input parameters of the sensitivity analysis are the means and variances of the input parameters of the model in question, obtained via calibration, and the output is the Sobol’ sensitivity indices. We regard a model to be more robust if its sensitivity to parameters is more balanced. We use quasi-Monte Carlo to evaluate the Sobol’ sensitivity indices of the short rate models, after the models are calibrated to recent U.S. Treasury yields, and compare them with respect to their robustness.

Joint work with Giray Ökten.

Dynamic State Space Panel Regression Models for Yield Curves

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In this study we develop a novel class of dimension reduction stochastic multi-factor panel regression based state-space models for the modelling of dynamic yield curves. This includes consideration of Principle Component Analysis (PCA), Independent Component Analysis (ICA) in both vector and function space settings. We embed these rank reduction formulations of multi-curve interest rate dynamics into a stochastic representation for state-space models and compare the results to classical multi-factor dynamic Nelson-Seigal state-space models. We introduce new class of filter to study these models and we also introduce new approaches to the extraction of the independent components via generalisations of the classical ICA methods.

This leads to important new representations of yield curve models that can be practically important for addressing questions of financial stress testing and monetary policy interventions. We will illustrate our results on data for multi-curve Libor interest rates in multiple countries.

This is joint work with Gareth W. Peters.
Rare events and importance sampling
Friday August 19. 10^{25}–11^{55}, LK 101

Reliability Estimation for Networks with Minimal Flow Demand and Random Link Capacities

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We consider a network whose links have random capacities and in which a certain target amount of flow must be carried from a source node to a destination node. The destination node has a fixed demand that must be satisfied and the source node has a given supply. We wish to estimate the unreliability of the network, defined as the probability that the network cannot meet the flow demand. We describe a novel Monte Carlo estimator to estimate this typically small probability and explain how this estimation approach can be applied to estimation problems in finance and Bayesian statistics with similar mathematical structure.

Joint work with P. L'Ecuyer, R. Shah, and B. Tuffin.

Convex Optimization for Monte Carlo: Stochastic Optimization for Importance Sampling

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In many applications, variance reduction is essential for a Monte Carlo simulation to converge within a practical amount of computation time. Variance reduction is an optimization problem. However, numerical optimization has been used sparingly for this problem, and convex optimization more so.

In this talk, we explore how to use convex optimization for Monte Carlo simulations and, in particular, how to use stochastic convex optimization for importance sampling. We propose a principled framework for using convex optimization for several variations of importance sampling: adaptive importance sampling, self-normalized importance sampling, and what-if simulations. The resulting algorithms are simple, conceptually and computationally, and have convergence guarantees due to convexity.

Parallel Adaptive Importance Sampling

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It is frequently of interest to solve data assimilation problems of the form $D = G(u) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \Sigma)$ where the data D is a noisy observation of the system $G(u)$. We assume knowledge of the observation operator $G$, and the covariance operator for the noise, $\Sigma$, and try to recover the parameter $u$ which best satisfies the equation. Viewing the problem from a Bayesian perspective and assuming prior knowledge of $u \sim \mathcal{N}(0, T)$ we can construct a posterior distribution, $\mu_Y$, and use Markov Chain Monte Carlo (MCMC) to produce a sample from this distribution. I will demonstrate that commonly used serial MCMC methods do not take full advantage of modern computer architecture, and that designing parallel algorithms can lead to a large reduction in computational costs. We will compare the performance of our novel algorithm with other recent developments in the parallelisation of the Metropolis-Hastings algorithm for low dimensional inverse problems. I will then discuss extensions to the algorithm which take into account local information about the posterior when building the proposal distribution.

This is joint work with Colin Cotter and Simon Cotter of University of Manchester.
Sparse High-Dimensional FFT Based on Rank-1 Lattice Sampling

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We consider the (approximate) reconstruction of a high-dimensional (e.g. \(d = 10\)) periodic signal from samples using a trigonometric polynomial \(p_I : \mathbb{T}^d \simeq [0,1)^d \to \mathbb{C},\)

\[ p_I(x) := \sum_{k \in I} \hat{p}_k e^{2\pi i k \cdot x}, \quad \hat{p}_k \in \mathbb{C}, \]

where \(I \subset \mathbb{Z}^d\) is a suitable and unknown frequency index set. For this setting, we present a method which adaptively constructs the index set \(I\) of frequencies belonging to the non-zero or (approximately) largest Fourier coefficients in a dimension incremental way. This method computes projected Fourier coefficients from samples along suitable rank-1 lattices and then determines the frequency locations. For the computation, only one-dimensional fast Fourier transforms (FFTs) and simple index transforms are used.

This method can be transfereed to the non-periodic case, where we consider the (approximate) reconstruction of a multi-dimensional signal restricted to the domain \([-1,1]^d\) using an algebraic polynomial \(a_I : [-1,1]^d \to \mathbb{R}\) in Chebyshev basis,

\[ a_I(x) := \sum_{k \in I} \hat{a}_k T_k(x) = \sum_{k \in I} \hat{a}_k \prod_{i=1}^d T_{k_i}(x_i), \quad \hat{a}_k \in \mathbb{R}, \]

where \(I \subset \mathbb{N}_0^d, \ x := (x_1, \ldots, x_d)^\top \in [-1,1]^d, \ k := (k_1, \ldots, k_d)^\top \in \mathbb{N}_0^d\) and \(T_k(x) := \cos(k \arccos x)\) for \(k \in \mathbb{N}_0\). Here, we sample along suitable rank-1 Chebyshev lattices and again only use one-dimensional FFTs / discrete cosine transforms as well as simple index transforms.

Finally, we compare the dimension incremental method with an alternative method in the periodic case which uses algorithms from spectral estimation. This method is based on shifted sampling in combination with a divide-and-conquer technique for the ESPRIT (Estimation of Signal Parameters via Rotational Invariance Technique) algorithm.

Joint work with Daniel Potts (Technische Universität Chemnitz, Germany), and Manfred Tasche (University of Rostock, Germany).


On Combined Component-by-Component Constructions of Lattice Point Sets

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Lattice point sets are for example used as sample points in quasi-Monte Carlo algorithms for numerical integration. Properties of the point sets used can influence the quality of the approximation that is obtained by the algorithm. Thus the goal is to find good lattice point sets.

The standard method for constructing generating vectors for good lattice point sets is the component-by-component construction. Numerical experiments have shown that the generating vectors found by these constructions sometimes tend to have recurring components, which can lead to the problem of having projections with all lattice points lying on the main diagonal.

We combine methods of Dick and Kritzer to avoid this problem with a reduced fast component-by-component construction. That is, we give a variation of the standard component-by-component construction which avoids repeated components and simultaneously results in a considerable speed-up in comparison to the standard construction.
The research was supported by the Austrian Science Fund (FWF): Projects F5506-N26 and F5508-N26, which are part of the Special Research Program “Quasi-Monte Carlo Methods: Theory and Applications”.

QMC for finance
Friday August 19. 2^{30}–3^{30}, Berg B

Adaptive Quasi-Monte Carlo Where Each Integrand Value Depends on All Data Sites: the American Option Case

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The theory of quasi-Monte Carlo cubature assumes that one is approximating \( \mu = \mathbb{E}(Y) \) where \( Y = f(X) \), \( X \sim U[0,1]^d \) by the sample mean \( \hat{\mu}_n = n^{-1} \sum_{i=0}^{n-1} y_i \) with \( y_i = f(x_i) \) for an evenly distributed sequence of data sites \( \{x_i\}_{i=0}^{\infty} \). Recent adaptive integration Sobol’ rules [2] and lattice rules [3] choose \( n \) automatically to ensure that \( |\mu - \hat{\mu}_n| \leq \varepsilon \) for a user-specified error tolerance, \( \varepsilon \).

However in some practical settings, such as valuation of American options via the Longstaff and Schwartz method [4], the quantity \( y_j \) depends not only on \( x_j \) but on all \( \{x_i\}_{i=0}^{\infty} \). This dependence arises because the value \( y \) is a function of the exercise boundary which is in turn estimated from the full set of sample paths. We present a modification of [2] and [3] that handles this problem. In addition, we discuss alternative Brownian motion path generation and control variates that improve the integration efficiency.

Joint work with Da Li and Fred J. Hickernell of Illinois Institute of Technology.


A Comparison Study of Sobol’ Sequences in Financial Derivatives

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Monte Carlo simulation is the primary method for pricing complex financial derivatives. Under certain assumptions, the prices of derivatives can be represented as expected values that correspond to high-dimensional integrals, and it is well-known that quasi-Monte Carlo methods are significantly effective. Sobol’ sequences are widely used quasi-Monte Carlo sequences in applications.

Here, there are several implementations of Sobol’ sequences with distinct parameter sets (so-called direction numbers). Joe and Kuo [2] constructed Sobol’ sequences with good two-dimensional projections. Their motivation is due to the observation that integrands for some problems in finance can be well approximated by a sum of functions with each depending on only a small number of variables at a time (i.e., low effective dimension in terms of the ANOVA decomposition).

To the best of our knowledge, the comprehensive investigation of superiority of the above implementation in practice still seems to remain.

In this talk, we show and analyze when Sobol’ sequences in [2] are superior to other Sobol’ sequences (e.g., [3, 1]) for various numerical examples in finance, such as option pricing and interest rate derivatives. In addition, we explore the possibility of better choices for direction numbers of Sobol’ sequences.

Joint work with: Tomooki Yuasa (Ritsumeikan University, Japan).

Permutation p-value Approximation via Generalized Stolarsky Invariance

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It is really expensive to get a tiny $p$-value via permutations. For linear test statistics, the permutation $p$-value is the fraction of permuted data vectors in a given spherical cap. Stolarsky’s invariance principle from quasi-Monte Carlo sampling gives the root mean squared discrepancy between the observed and expected proportions of points in spherical caps. We use and extend this principle to develop approximate $p$ values with small relative errors. Their accuracy is competitive with saddlepoint approximations, but they come with an error estimate.

This is joint work with Hera He, Kinjal Basu and Qingyuan Zhao.

Fast Random Field Generation with $H$-Matrices

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We use the $H$-matrix technology to compute the approximate square root of a covariance matrix in linear complexity. This allows us to generate normal and log-normal random fields on general finite point sets with optimal complexity. We derive rigorous error estimates, which show that particularly for short correlation length, this new method outperforms the standard method of truncating the Karhunen-Loève expansion. Besides getting rid of the log-factor in the complexity estimate, the method requires only mild assumptions on the covariance function and on the point set. Therefore, it might also be an alternative to circulant embedding, which is well-defined only for regular grids and stationary covariance functions.

This is joint work with Frances Kuo and Ian H. Sloan, both of UNSW.
# List of Session Chairs

## Monday

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