SIAM ACTIVITY GROUP

Financial Mathematics and Engineering

Newsletter

Autumn 2017

Contents

CHAIR'S WELCOME —

With many University fall semesters well on their way, the SIAG executive thought it is high time to send out another informative newsletter!

One of the most important messages we have is that due to the overwhelming response in favor of moving the SIAG FME meetings into odd years, the SIAG executive has done just that. The next FM meeting will be in summer 2019. The exact location and date is not yet set, but you can pencil in late May / early June in your calendars.

In other news, the SIAG executive is aiming to make the newsletter a little more exciting than simply reporting news. In this issue you will find two very interesting interviews one with Prof. Damir Filipovic (Swiss Finance Institute, EPFL) and the other with Dr. Harvey Stein (Bloomberg) giving their perspective on a number of issues that are relevant to our members.

Continuing with the goal of breathing more life into the newsletter, we are soliciting op-ed pieces from our members. If you have a topic that you feel would be of wide appeal, and are interested in putting together a non-technical 1-2page article on it, please do contact us! Ideally we would like to have two such pieces in every newsletter.

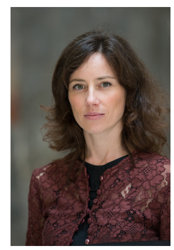
With that, I would like to wish everyone a productive semester!

Sincerely,

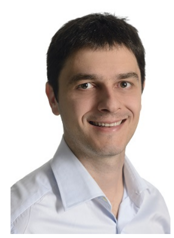
Sebastian Jaimungal,
Chair SIAG FME

Sebastian Jaimungal,
University of Toronto, Canada
Chair

Tim Leung,
University of Washington, USA
Vice Chair



Francesca Biagini,
University of Munich, Germany
Secretary



Agostino Capponi,
Columbia University, USA
Program Director

1 Members' News

Dear SIAG-FME members,
We are delighted to share two articles from our field which have been published in **SIAM News** in June 2017.

Electricity Demand Response and Optimal Contract Theory, by René Aïd, Dylan Possamaï, and Nizar Touzi.

and

Deep Learning Models in Finance, by Justin Sirignano.

2 Conference Report

Conference on Mathematical Modeling in Finance (MMF 2017), Imperial College London, UK, 31.08 - 02.09, 2017.

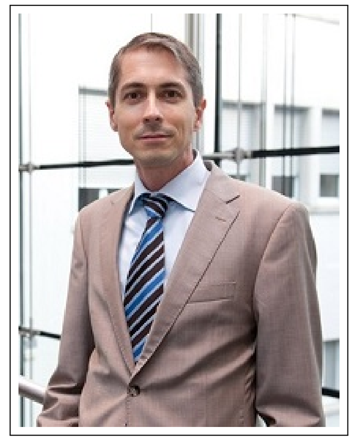
The Conference was organized by SIAG FME as part of our international outreach activities and was co-sponsored by SIAM and London Mathematical Society. It was hosted in London, UK by the CFM-Imperial Institute of Quantitative Finance, taking place in the heart of the Kensington campus. The meeting was a great success, attracting more than 120 participants over 2.5 days of talks. Attendees included academics from the numerous London-area universities, graduate students from many countries (partially supported by SIAM for travel from North America and LMS for travel from EU), as well as a strong contingent of practitioners. Especially popular was a Minisymposium on machine learning for algorithmic trading, organized by Paul Bilokon, that featured a mix of academic and industry speakers. Another highlight was a panel on "Mathematical Modeling in Finance: Where is it All Headed?" moderated by Mark Davis, who was also the opening keynote speaker. In answering the above question, panelists noted the significant shifts in FME research foci that took place over the past decade, such as renewed emphasis on model risk, and analysis of the interactions among (many) agents. Among notable themes addressed by the speakers one may mention network models for systemic risk (including both static and dynamic interacting-particle systems) and stochastic/rough volatility.

– Reported by Mike Ludkovski, University of California Santa Barbara

3 Interviews

The SIAG executive is excited to have had the opportunity to interview two leading financial mathematicians: one academic and one practitioner! It was listening to the response quite fun and we trust that you will find them informative and intriguing.

3.1 Prof. Damir Filipovic – Swissquote Chair in Quantitative Finance, Swiss Finance Institute, EPFL



Where do you think the field of financial mathematics will be going in the forthcoming years?
The demand side will drive research. Currently, there is a high interest in FinTech related research from the industry side. This leads to several interesting problems in financial mathematics. Computational challenges, not only related to big data analytics, arise. The financial industry is calling for expertise from computer scientists and data scientists (machine learning, artificial intelligence, data security and privacy, game theory, fault tolerance). I foresee the synergy of these disciplines to play a pivotal role in the future of financial mathematics.

What advice would you give young researchers to assist them in thinking beyond the "craft" of research, but also think about the "art" of research itself?
Research should come with innovation. My advice to young researchers is to stay open, head out, think out of the box, and look into some disciplines that are close to what you call financial mathematics today, because they may become part of financial mathematics tomorrow. I believe financial mathematics is not a closed discipline. To advance financial mathematics, you should interact with neighboring disciplines, including computer science, statistics, and finance. This is how you innovate when new concepts emerge. So far, I spoke from the point of view of the disciplines. On the other hand, financial mathematics is also an applied field: you should be driven by what the industry and the economy need. A good example is the 2008 financial crisis: it provided strong stimulus for interesting research directions such as systemic risk, and led us to take a macro-perspective, looking from a different angle than we used to in the past. Excellent research has emerged in the past ten years from an academic point of view, and this research has also proved to be useful in the real world, beyond academia.

How can I provide a fresh look at a prominent area of financial mathematics?
In financial mathematics, much of the literature has taken a price taker point of view for a long time when solving portfolio optimization or asset pricing problems. While this is a reasonable assumption if we think of small traders, whose actions have no impact on the market, it may fail to adequately capture reality if we consider a large trader. His actions can have a strong feedback effect from the market, and this has been taken into account in earlier studies (e.g. optimal portfolio choice with transaction costs and price impact). But, I believe one can go further, and there are a lot of interesting avenues to explore. Portfolio liquidation has been studied for quite a while, but the type of interactions rarely take into account strategic aspects. Currently, we only have several partial approaches to the problem. The reason why this problem can now be looked in a way that no one has done before is because of the data availability. And taking this data into account, I believe, can lead to some innovative insights.

Which research questions, if any, are researchers overlooking that you think they should be investigated?
Human behavior seems particularly hard to formally model. In a reduced form, some studies have considered S-shaped utility functions, but can we really rationalize them? Researchers have looked at human behavior from an aggregate point of view, using mean-field games, interacting particle systems. The strategic component is often lost when these approximations are made. I would like to make a parallel with what happens in computer science disciplines such as signal processing.

We are seeing a revival of deep learning and other statistical methods, enabling self-driving cars. Can we leverage on these techniques and use them to model agents in the financial market? As we speak, we can be certain that some of the technical hedge funds have been using such technologies for decades. The challenges for any mathematician is to understand why this works. Many statistical learning methods usually come without rigorous mathematical proofs behind.

Can you comment on whether computational skills will become as important as mathematical skills in the era of big data and artificial intelligence-driven financial technology?
Absolutely, as I said earlier, financial mathematics is not a closed discipline. Some of the closest and hottest neighboring disciplines are computational science, statistics, and finance. These are all very exciting domains to be explored.

What are the next/most important mathematical challenges you foresee in financial mathematics?
Give a rigorous foundation to data analytics applied to finance. We have to keep up-to-date with the developments in computer science. We see self-driving cars, block-chains, and other distributed ledger technologies. These developments will affect the financial industry too. The mathematical challenges we are facing are different from what we used to face in the past. Financial mathematics is a continuously emerging field, which grew out from the financial industry side. There is no reason to stand still.

What parts of your training have you found the most valuable in your research career?
A solid mathematical education is certainly core. Computational skills acquired and exposure to the industry also turned out to be very valuable on a day-to-day basis in my career.

What separates what you view as a great paper from those that are just good?
A good paper has to be well written and correct. This is a necessity. For instance, a paper that generalizes a seminal finance paper from a mathematical perspective is a good paper. A great paper on top of being good has to convey a message; it should contain great ideas and be innovative. Great ideas do not necessarily have to come with complicated mathematics. It is often useful if a great paper addresses a specific problem.

To a non-mathematician, how would you frame the social value of what we do?
We contribute to the functioning of financial services that include financial transactions, wealth management, portfolio management, financial risk management. We quantify risk, and we help to manage risk through, e.g., hedging derivatives. We help designing insurance contracts for protecting people against existence-threatening losses from, e.g., natural disasters. We help to grow the economy (e.g. pooling credit risk is very important). The emphasis is on the quantitative aspect. We do not necessarily provide infrastructure. With the FinTech evolution and digitalization of financial services, the social value of what we do will depend on how we move our field. There are many challenges going forward that will require synergistic efforts with the computer science discipline, including those related to decentralized ledger technologies, trust, and data security and privacy. We can contribute to what data science does for the financial industry. Again, let me re-emphasize that interdisciplinary efforts will play a key role.

– interviewed by Agostino Capponi, Columbia University, USA

3.2 Dr. Harvey Stein – Head, Quantitative Risk Analytics, Bloomberg LP

What made you choose industry over academia?
Popular literature on the subject of career choice encourages pursuing your passion and you dreams. I think this is short-sighted and overly romantic. When choosing a career, a person must take many other factors into account, like their skills, the needs of others, their desired lifestyle, and the value and demand of their skills in different markets. Those who try to travel the road to success by focusing solely on their passion and dreams are unlikely to arrive at their destination.
In my case, when I graduated (in 1991), the academic job market was extremely tight. This was due to some of the repercussions of two of the major political events of the late 1980s, namely Tiananmen Square and Perestroika. After Tiananmen Square, the number of Chinese graduate students applying for US postdoctoral positions shot through the roof. Mathematics departments were inundated with applications. Where they used to get at most a dozen applications for an opening, they were now getting a hundred or more. This caused the entire system of processing applications to collapse. Instead of trying to process all of the applications, the system reverted to what amounted to an old-boy network - positions were filled by professors calling their friends to place their students.
On top of that, with Glasnost and Perestroika, Russian mathematicians were able to leave the Soviet Union much more easily than before. So, while mathematics departments were being flooded with applications for postgraduate positions, they were eliminating such positions to pool together enough money to hire the famous Russian mathematicians who were now able to leave. This didn't leave many openings for newly minted PhDs, and many left academia immediately.
None the less, I was still able to find a postdoctoral research position. But it was a 1 year position, so by the time I started, I had to start looking for my next position. And when I found it, I would have had to start looking for my third position. With so much job hunting, I was doing very little research. This made an academic career somewhat pointless, and after doing it twice, I didn't want to go through it a third time, so I started looking for jobs in industry.

What challenges did you come across in industry that you were not prepared for?
In my case, I had worked in industry for 3 years before going to grad school. I also supported myself as a computer consultant while getting my PhD in pure math. So there weren't any particular on the job surprises. It was more a matter of going back to industry than diving into a new endeavor. The biggest surprise was more the difficulty of finding a job to begin with. I was living in Israel and looking for a job there, and my Hebrew was terrible. The big hurdle was convincing a tech firm that they wanted to hire a math PhD with computer experience instead of a CS BS. Also, being in Israel and not in NYC, I didn't know about the mass migration of math and physics PhDs into the financial sector. So I was lucky to find someone in Tel Aviv looking for math and physics PhDs with computer experience to build a quant team.

What do you enjoy the most/least about being in industry compared to academia?
The great part about being in industry is solving problems that matter to other people. In academia, research can be quite obscure and inaccessible. Interest in and understanding of one's research is often limited to a handful of people. This can be quite lonely. In industry, you are solving problems that are important to people.
Another aspect of the difference is in finding problems. In academia, it's hard to find the right problems to work on, namely interesting unsolved problems that you can make progress on. In industry, there are lots and lots of problems to be solved. Some are easier, and some are more difficult. You don't have to spend time finding problems, they knock on your door.
The nature of problems and solutions are also different. Problems aren't usually unsolved problems, they're just unsolved at your company. Sometimes, a solution can be found in the literature, or in common practice. And a solution doesn't have to be a new way of doing things. It can be applying a known methodology, or tuning an approach. Often, one finds that methodologies that are better in theory turn out to be worse in practice. In industry, what's important is the practice, so often the problem is to take something that works in theory and either make it work in practice or replace it.

Another difference is that in industry, you don't have the option of pursuing these problems, you are tasked with them. You generally don't have the freedom to choose your problems, and often you don't have the time to attack them at the depth that you'd like to. To pursue your own research, or to go deeper, you may have to pursue that on your own time.
Another issue is time. It's hard not to envy the free time that people have in academia. The flip side is that in industry you're paid well for giving up your free time. The difference in pay can be as much as a factor of 5 to 10, so giving up free time yields other sorts of freedoms.

What key skill(s) make a PhD student successful in industry?
Flexibility, broad interests, willingness to dig into problems and find a solution that works even if it isn't a new and different approach. Being able to quickly learn new things. As a quant in finance, this means marrying software engineering, numerical methods and mathematical finance, not to mention statistics.
There's also a general issue of being numerically minded. The most successful quants have not just a mathematical understanding of the models, but a feeling for the numbers and how the models behave.
Communication skills are more important in industry than they are in academia. In academia, you largely communicate with your peers. In industry, you have to communicate with people who don't have the technical background that you have. And much more time is spent on communication because projects in industry involve many more people than projects in academia.

How can academics increase the impact of their research beyond the academic community? How can academics engage industry practitioners into research problems?
The more academics engage practitioners, the bigger the impact of their research beyond the academic community, so let's focus on the second question. Academics need to be willing to collaborate with practitioners, learn what the important problems are in industry, and be willing to develop practical solutions. But the academic community itself also needs to embrace these collaborations.
For example, consider the collaboration between Fisher Black, Myron Scholes and Robert Merton. Black was at Goldman and Scholes and Merton were at MIT. The Black-Scholes-Merton model gave an answer to the question of how to price options. The notion of pricing by hedging was fundamental to the creation of the quantitative finance industry as well as the academic area of mathematical finance. On the other hand, publication of the paper was difficult – it was rejected by a number of journals before finally being printed by the Journal of Political Economy.
Similarly, consider the Heath-Jarrow-Morton interest rate model. Heath and Jarrow are academics, but they had many ties to industry and solved an important problem. Prior to HJM, interest rate modeling was very ad-hock and there were outstanding questions about whether or not various models were arbitrage free. The HJM model, by rephrasing interest rate models in terms of the evolution of each individual instantaneous forward rate, gave a universal framework for interest rate modeling and answered many of these questions.
But these are extreme cases of solutions that were breakthroughs on both the academic and industrial fronts. More often, I'd expect the collaboration to start with trying to apply the appropriate theory to a problem. This will expose the shortcomings of the theory and lead to the development of a more powerful theory that is more applicable to real world problems. In other words, being willing to get down and dirty.

What interesting research problems do you see that are not being addressed by academics?
The literature is so vast that it's hard to say what's not being addressed by academics. I can tell you about a couple of things that I haven't seen addressed.
One is a better theory of risk. Financial risk models try to quantify the losses that one might experience at a specific horizon time in the future and the odds of suffering such losses. But they only analyze current holdings. They ignore the fact that people are constantly trading, so holdings are changing over time. Assuming fixed positions is ok if the horizon is short relative to the holding period of the positions. But the assumption breaks down as trading frequency increases. For example, it's useless for high frequency trading. It also breaks for long horizon analysis. A better theory would be able to take into account the trading that can be done before the horizon.
Secondly, the theory only addresses quantifying risk. It's not prescriptive, in the sense that it doesn't say what to do about it. Risk is reduced by either holding more capital (so that large future losses can be survived), or by reducing positions (so that the size of future losses are reduced). There's no real theory of how best to manage these risks that are being quantified. Another issue that's a big problem in industry is quantifying over-fitting. Everyone knows how to do in sample and out of sample tests and knows when a regression has too many variables.

But the practice both in industry and in academia is to try something and if it doesn't work, try something else. The problem is that "doesn't work" means it lacks predictive power on the out of sample data. This amounts to fitting models to both the in sample and out of sample data by hand, which undermines the out of sample check. The end result is that a lot of models that are claimed to have predictive power really don't, and many supposedly great trading strategies lose money. We're starting to see some research here, but there's a lot of work to be done.

There are dozens of MS programs in Financial Math and Engineering graduating thousands of MS students every year. What do you think about the industry's demand for these graduates? What do you see in the future of these MS programs?

That's a very good question. Just like you asked about collaboration between industry and academics, there needs to be more collaboration between industry and the MS programs. The programs have to make an effort to update themselves and make sure they're giving students the foundation that industry needs.

To be more specific, most of these programs started with a focus on option pricing. This made sense because that's where the quant jobs used to be, and there was a large support group that needed to know about option pricing. If the PhDs were getting the core quant jobs, the MS student were still needed in structuring deals, selling deals, auditing, etc. But this all changed with the financial crisis. Post crisis, option trading isn't the money making proposition that it used to be.

Understanding option pricing is still an important part of a solid foundation. And in fact, it's more complicated post-crisis, with everyone trying to account for basis spreads, credit risk, funding costs, etc, in all over the counter derivatives positions. But it shouldn't be the only track in a financial engineering program. Other areas are in greater demand now.

On the sell side, many quants have moved into risk analysis and model validation. This is both in the banks as well as in the big 4 on both the auditing as well as the consulting side.

The buy side is getting more sophisticated. Quant funds are on the rise. So statistics, data handling, and time series analysis is more important now. There's also a lot of interest these days in machine learning and blockchain, but students will be best prepared for such things by having a strong foundation in the fundamentals.

There's also a greater need for following good software engineering practices. Financial engineering programs have often been weak in software engineering. For option pricing and hedging work in the front office, this didn't matter so much. But with algorithmic trading, high speed trading, and quantitative investment, infrastructure becomes more important, requiring stronger software engineering skills. Ignore this and you can end up like Knight Capital, where in 2012 they lost over $400 million in a day due to a "computer glitch", putting them at risk of bankruptcy.

– interviewed by Tim Leung, University of Washington, USA

4 Events

4.1 Upcoming Events

- ▹ *XIXTH WORKSHOP ON QUANTITATIVE FINANCE*,
  Rome, Italy, January 24-26, 2018.
- ▹ *17TH WINTER SCHOOL ON MATHEMATICAL FINANCE*,
  Lunteren, The Netherlands, January 22-24, 2018.
- ▹ *SECOND EASTERN CONFERENCE ON FINANCIAL MATHEMATICS*,
  Columbia University, NYU Courant Institute of Mathematical Sciences, and NYU Tandon School of Engineering, November 3-5, 2017.

4.2 Past Events

- *WORKSHOP ON "MEASUREMENT AND CONTROL OF SYSTEMIC RISK"*,
  Centre de recherches mathématiques, Montréal, Canada, September 25-28, 2017.
- *WORKSHOP ON "RISK MEASUREMENT AND REGULATORY ISSUES IN BUSINESS"*,
  Centre de recherches mathématiques, Montréal, Canada, September 11-14, 2017.
- *CONFERENCE ON MATHEMATICAL MODELING IN FINANCE (MMF 2017)*,
  Imperial College London, UK, August 31-September 2, 2017.
- *2017 SIAM WORKSHOP ON NETWORK SCIENCE (NS17)*,
  Pittsburgh, PA, USA, July 13-14, 2017.
- *8TH GENERAL AMAMEF CONFERENCE ON MATHEMATICAL FINANCE*,
  Amsterdam, June 19-23, 2017.
- *COMMODITY AND ENERGY MARKETS CONFERNECE 2017**,
  University of Oxford and the Energy and Commodity Financeat ESSEC Business School,
  June 14-15, 2017.
- *SUMMER SCHOOL AND SUBSEQUENT WORKSHOP ON EQUILIBRIUM THEORY*,
  Carnegie Mellon University, June 12-15, 2017.
- *RESEARCH CONFERENCE ON THE OCCASION OF THE 10TH ANNIVERSARY OF THE CENTER FINANCIAL MATHEMATICS AND ACTUARIAL RESEARCH AT UC SANTA BARBARA*,
  UCSB campus, May 19-21, 2017.
- *CONFERENCE MATHEMATICAL FINANCE, PROBABILITY, AND PARTIAL DIFFERENTIAL EQUATIONS CONFERENCE**,
  Rutgers University, New Brunswick, NJ, May 17-19, 2017.
- *SECOND NATIONAL CONFERENCE OF WOMEN AND FINANCIAL MATHEMATICS (WFM2017)*,
  Institute for Pure and Applied Mathematics (IPAM) on the UCLA campus, April 27-28, 2017.
- *MINISYMPOSIUM ON HIGH FREQUENCY TRADING*,
  University of Pittsburgh, March 25-26, 2017.
- *8TH WESTERN CONFERENCE ON MATHEMATICAL FINANCE (WCMF8)*,
  University of Washington's Seattle campus, March 24-25, 2017.