IAMP News Bulletin
October 2019

International Association of Mathematical Physics

International Association of Mathematical Physics News Bulletin, October 2019

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Cover picture: Rahul Pandit and Herbert Spohn at the Boltzmann prize ceremony during the conference StatPhys27 (picture courtesy of Claudio Esses)

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ISSN 2304-7348
News Bulletin (International Association of Mathematical Physics)

The 2019 Boltzmann Award and Medal

As we announced in the April issue of the IAMP News Bulletin, Herbert Spohn has won this year's Boltzmann Medal. The official description of the Boltzmann Prize is reprinted below from the the Statphys website at https://statphys27.df.uba.ar/boltzmann.html, with permission.

The 2019 Boltzmann Award and Medal

The Boltzmann Award was instituted by the Commission on Statistical Physics (C3) of the IUPAP to honor outstanding achievements in Statistical Physics. It is presented by the Commission at the STATPHYS meeting. The award consists of a glided medal (the Boltzmann Medal) with the inscription of Ludwig Boltzmann.

Short Biography

After post-doc years at Yeshiva, Princeton, Rutgers, and Leuven, Herbert Spohn joined the statistical physics group at the Ludwig-Maximilians-University and later moved to a chair in mathematical physics at the Technical University, both in Munich. Spohn's contributions cover the full spectrum from foundational rigorous work to experimentally testable predictions. In collaboration with S. Katz and J.L. Lebowitz, he introduced the field-driven 'KLS' lattice gas model with Ising interactions that is nowadays referred to in textbooks as the 'standard model' of non-equilibrium stationary states. In an earlier paper he proved the ubiquitous occurrence of long-ranged correlations, a result that rose to prominence many years later in the context of generic scale invariance and macroscopic fluctuation theory. His 1991 review article with J. Krug on stochastic growth processes set the stage for much of the subsequent work on the subject. In 2000 Spohn initiated the 'second wave' of research on the one-dimensional version of the KPZ problem that continues to gain momentum to this day. The beautiful and far-reaching insight on the universality properties of this problem culminated in the publication with T. Sasamoto of the first exact solution of the one-dimensional KPZ equation. Through a multi-component version of the KPZ equation, Spohn also unified the understanding of anomalous transport in one-dimensional fluids. In 1993 Spohn settled a long-standing controversy about the dynamics of crystal surfaces below the roughening transition showing that the dynamics can be properly formulated and solved as a moving boundary problem, an observation that has been tremendously influential in theoretical and computational materials science. Jointly with J.L. Lebowitz, Spohn showed that fluctuation theorems similar to those previously established for chaotic systems arise naturally in a large class of stochastic models, a contribution that marked the beginning of the current wave of interest in generic properties of non-equilibrium stationary states. Spohn has made important contributions to kinetic theory of both particles and waves (classical and quantum), open quantum systems, Schrödinger operators and other topics too numerous to list here.

His 1980 review article on Markovian limits related to kinetic theory and the 1991 monograph *Large scale dynamics of interacting particles* are key reference works in the field.

Herbert Spohn is professor emeritus at the Technical University Munich. Amongst other distinctions, Spohn was awarded the 2014 Georg Cantor Medal of the Association of German Mathematicians, the 2015 Poincaré Prize of the International Association of Mathematical Physics, and the 2017 Max Planck Medal of the German Physical Society. He received honorary doctorates from Université Paris-Dauphine and Université Paris-Diderot.

Svetlana Jitomirskaya wins the 2020 Heineman Prize

Congratulations to *Svetlana Jitomirskaya* of the University of California, Irvine, who has recently been awarded the 2020 Dannie Heineman Prize for Mathematical Physics!

The Prize acknowledges her "work on the spectral theory of almost-periodic Schrödinger operators and related questions in dynamical systems. In particular, for her role in the solution of the Ten Martini problem, concerning the Cantor set nature of the spectrum of all almost Mathieu operators, and in the development of the fundamental mathematical aspects of the localization and metal-insulator transition phenomena."

The News Bulletin anticipates a full announcement in an upcoming issue.

Life outside the bubble

by MANWAH LILIAN WONG (Vancouver, Canada)

Finding a life outside the bubble is not easy. In mathematical terms, first we have to prove the existence of a world outside for this problem to be well posed.

When I was a graduate student, I didn't realize the options beyond what's offered by academia, where I often felt some level of disdain among academics for the industry. "Your freedom will be taken away," "What happens to your research?" and "You'll live like a slave!" I was told. These words stuck with me throughout my school years, and I still hear them from aspiring scientists who are interested in yet hesitant about switching to industry.

First, I must admit that establishing a life outside the bubble is not easy. There are lots of things to learn: coding, statistics, probability, machine learning, the list seemed endless. But those are hard skills most scientists don't have problems acquiring. Soft skills could be more intriguing for some scientists because, apparently, there are behaviors that are acceptable in academia but not quite in industry, like picking a problem that offers no obvious benefit for your employer, or not striving to play well with one's colleagues. Just as in academia, corporate affairs can be very political. However, unlike in academia, most players in industry aren't protected by tenure, though ousted players could find their second lives in other companies. This significantly changes the dynamics of the game, because hardly can anyone claim the turf forever.

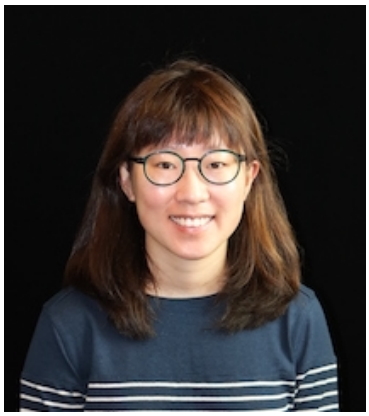
In fact, I'm still learning to play my cards in industry. At the same time, I'm learning new applied mathematics and computing science, subjects that I didn't have much exposure to in school, which I now immensely enjoy. I don't at all regret branching out into these areas, which are of very different flavors than mathematical physics but are still very challenging and intellectually stimulating. My newly acquired knowledge even sheds light on topics I learned as a graduate student. For almost all the topics I want to learn in industry, there are lots of online resources I could refer to, questions are actively discussed by a community of scientists. There are different "eureka!" moments for scientists in industry, but the joy of problem solving never eludes me.

If anything, I miss the blissful summer holidays, I miss the opportunity to travel with fellow researchers and the free time to read. Times in academia was a beautiful chapter of my life shared with wonderful friends and collaborators. However, now with a permanent job that pays a real salary, I no longer have to be busy with grant applications once every few months, to worry about my papers being rejected after a one-year wait, or to spend a big chunk of my small savings on moving cross-country due to job changes. Now my work has a much wider audience and a more visible impact, and I enjoy a different level of fulfilment. What I find particularly liberating is that my career is no longer in the hands of a few bigwigs in my area of research who are protected by their tenure. This is not to say that industry is a paradise, but it is big enough that there is room for everyone to advance and contribute in their own ways. Just like any organization, companies can have their dark sides, but it is much easier for an employee to leave the company than a researcher to leave his area of research.

To stay or not to stay in the bubble, that is a personal decision. However, if you are at the stage of your career when you have to decide soon, making an informed decision backed by

research may be better than one based on hearsay. Take the initiative to reach out to scientists in industry, try applying for internships (coding is usually a prerequisite), and and learn how the job application process works so you prepare accordingly. Many graduate students have overlooked the fact that one's career does not only dictate what one does during the day, it also affects the outlook of one's personal life such as where one lives (city versus a university town) or even when to start a family.

Take your career in your hands, for no one else has greater interests in developing your career than you!



Author's note: Lilian Wong was a research mathematician before becoming a scientist in the data industry. She will return in a future issue of the News Bulletin *with some practical advice for academics making the transition to a career in industry.*

Can you hear what a drum is? A personal tale of mathematics, business, and AI

by HELMUT LINDE (Nussloch, Germany)

Introduction

'Can one hear the shape of a drum?' [6] seems to be one of the phrases most often alluded to in mathematical physics. At its core, the question is what we can learn about a real-world system based on observations and assumptions. In the case of the drum, the observation is a sound frequency spectrum and the assumptions are (1) that the sound was actually emitted by a drum as opposed to some other source and (2) a physical model of how a drum works. Inspired by artificial intelligence (AI) research, it seems quite natural to wonder: Can we take this process of inference from observation to the extreme? After all, a human brain seems to start into life with only very limited 'hardwired' assumptions about its environment and knowledge about percussion instruments has certainly not been hammered into our DNA by evolutionary pressure. What if we drop the assumptions that we are hearing a drum and that we know how a drum works – can we still learn something from pure observations? What type and quantity of such observations would we need? Or, conversely, what are the minimum assumptions that an intelligent observer needs to make in order to 'understand' his or her environment purely from observation?

Before I elaborate more on these questions, let me take a step back and comment on the purpose and scope of this article. I am writing this text for the IAMP Bulletin to share some experiences from my professional career – which has evolved from academic research to management of commercial data science organizations – with the mathematical physics community. I am gladly embracing this opportunity for two reasons: On the one hand, I hope that this account might be helpful to some young researchers who are still in doubt about their future career options. On the other hand, it gives me the opportunity to share with this community some thoughts on why we need more contributions from mathematical physics to advance the field of AI.

From Mathematics to Management

So how did I get involved with AI in the first place? As is often the case with career paths, chance had a hand in this.

Back in high school I knew that I wanted to study physics and mathematics because I believed (and I still do) that these two fields offer a unique perspective to understand the world we are living in. But I never was quite sure whether to target a career in academia or not, so after finishing my diploma at the University of Stuttgart in Germany I did an internship in management consulting at McKinsey & Company, supporting a restructuring project at a chemical production plant in Switzerland. Getting some practical industry experience through an internship is something that I would recommend strongly to every student – whether you plan

to stay in academia or not. After the internship I was still eager to learn more about science and do some research myself and so I became a Ph.D. student in mathematical physics at the Catholic University in Santiago de Chile. After finishing my studies there and through a chain of coincidences I landed my first industry job at the software company SAP as the executive assistant to the global head of the consulting organization – a sizeable field force of more than 10,000 employees. It had nothing to do with mathematics or physics, but it was a fantastic development opportunity: I firmly believe that the best way to learn business management is by example. And there is hardly a job that gives you more exposure to top managers and their different leadership styles than that of an executive assistant. After two or three years, which is the typical time horizon for such a position, a new opportunity arose: Someone had come up with the idea that SAP could offer professional services around forecasting and optimization (which today you would call 'data science', but in 2009 the term was not yet widespread). Since this was somewhat related to my educational background, I applied for the job to establish the mathematics and engineering team of this new business. So over the next seven or so years I worked on building up a data science consulting business for SAP. Slowly but surely my team and I found customers all over the world and in many different industries and we worked on projects as diverse as sales promotion analytics in retail, inventory optimization for railway spare parts, or efficiently planning the staffing of an airline's call centers.

In 2017 a new opportunity emerged and I became the Global Head of Data Science at the German science and technology company Merck KGaA (which for historical reasons operates under the name EMD in the USA and Canada). In this new role it was my task to build up a data-science team which would support the three business sectors of the company – healthcare, life sciences and performance materials – with advanced analytics projects. Similar to my time at SAP, my team acts as internal consultants, working on many different use cases: Be it the estimation of price elasticities from sales data, the optimization of production equipment based on machine sensor information, or the automated visual analysis of microscopy samples from cancer patients. We also see a huge opportunity to apply more computational modeling of chemical properties and reactions to different areas of our company, especially in R&D and manufacturing. I therefore included a computational chemistry team in the data science organization.

In a company as large as ours (over 52,000 employees globally), it is not surprising that many colleagues across the business work on topics related to analytics – for example on planning and analyzing clinical studies, optimizing our e-commerce platform or making supply chain decisions. Traditionally, we did not have any strong link between these different groups of analysts or data scientists. So we established the role of a Global Data Science Community Lead who is tasked with forming and maintaining a professional network among the more than 300 analytics professionals in the company. The aim of the community is to further develop our internal data science practice by providing education and exchanging experience (e.g. during our annual company-internal data science conference), creating synergies between different groups and projects, and making our company an even more attractive employer for data scientists.

What makes a strong data scientist?

Based on my personal observations from our recruiting activities, becoming a data scientist is increasingly seen as an attractive career option by students of mathematics or natural sciences. Those who have intentions to enter the field, or who have recently done so, might wonder what it takes to be successful in data science. I will therefore share a few thoughts on this point:

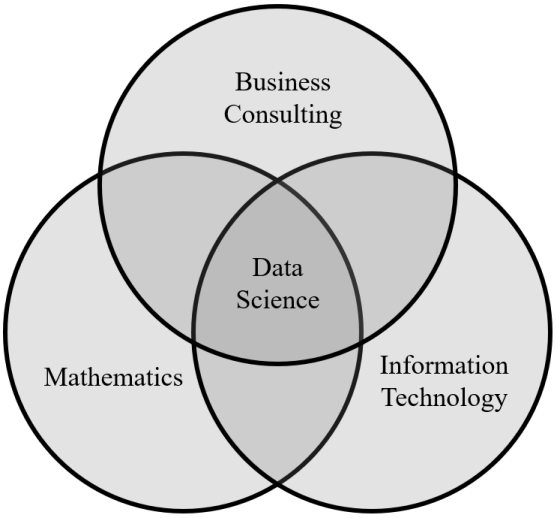


Figure 1: The 'canonical' definition of Data Science emphasizes the interdisciplinary overlap of understanding and modeling business processes, finding conceptual solutions based on algorithms or statistics, and implementing these solutions in software programs or enterprise solutions.

When it comes to data science skills, obviously there is the mathematical or algorithmic component. You have to know and understand a wide range of machine learning algorithms from simple regressions or decision trees to deep learning. It is also important to know the basics of statistics and in particular to develop a very solid understanding of which conclusions you may or may not draw from the results of a data analysis. Not all of these topics may be included in the typical curriculum of a mathematical physicist, but a training in mathematics or natural sciences gives you an excellent basis to learn the missing pieces quickly.

Then there is the technical side: Data scientists need to write code or implement solutions with IT technology such as visualization frameworks, data management tools, databases, or statistical software packages. Digitalization is an imperative for almost every business today – so if you want to become a data scientist or not, for a mathematician it is generally advisable to develop a good understanding of computational methods and IT technology.

Finally and most importantly, there is the 'business consulting side' of being a data scientist: Ultimately, almost all analytics projects in the industry aim at solving some real-world problem – and the real world is usually a bit messy. Business processes can be complex with many special cases and exceptions. The data available may be incomplete, ambiguous or sometimes simply wrong. Processes or IT systems may have changed in the past and they may change

again in the future. The job of the data scientist is to create simplified quantitative models for business processes under such VUCA[1] conditions – simple and robust enough to perform actual calculations, but not simple to the point of becoming useless. The spirit of such model-building is indeed very close to how physicists describe natural phenomena and this is what makes them, in my opinion, highly qualified for data science roles.

Up to this point I have focused on how mathematical physicists can have a successful and rewarding career as data scientists, who typically make a living by applying methods from machine learning and AI to business problems. But I believe that the mathematical sciences have a much larger role to play in taking AI to the next level. To understand the why and the how, we need to take a closer look at the current limitations of AI and its fantastic promises for the future.

Checklist for prospective data scientists: If you are currently working in mathematical physics and you consider developing your career towards data science, here are some ideas for you:

- Train your modeling skills! Rather than focusing on purely abstract mathematical questions, try to make a connection between the beautiful precise theory and some messy real-world problem.
- Learn how to code! Pure mathematics is interesting, fun, and it sharpens your mind - but by itself it's of limited use in the business world. There are abundant resources available online where you can learn relevant technical skills like Python or SQL development for free (e.g. at Codecademy or at edX).
- Participate in a challenge! For example, many companies post real-life data science problems on the Kaggle platform. It gives you a chance to train your algorithmic skills, compare your performance to other participants, and maybe even win a prize.
- Learn about enterprise software! A lot of people know how to build a machine learning prototype in Python, but only few of them know what it means to convert it into a production-ready solution for many users which can be run and maintained by a company's IT department. Sadly - based on my impressions from many job interviews - not even the computer science departments of universities seem to be a particularly good place to learn these skills. Therefore...
- Complete one or two internships! It can be a great learning opportunity, it will help with your decision of what is the right career path to pursue, and it will significantly increase your credibility when you interview for a permanent position in the industry.

[1] Volatile, uncertain, complex, and ambiguous

Quo vadis, AI?

The field of artificial intelligence has seen a rapid development and a lot of public attention over the last couple of years. Much of it was driven by different varieties of deep learning which had its break-through with image recognition in 2012 [7]. Artificial neural networks have since then enabled significant progress in several areas of AI research like computer vision, voice synthesis, or computer game playing and they have made their way into many applications like voice assistants, cell phone cameras or autonomous vehicles.

But despite these impressive success stories, deep learning still suffers from severe limitations: For one thing, enormous amounts of labeled data are required to train the networks. Where a human child might learn to recognize an animal species or a class of objects by seeing only a few examples, a deep neural network typically needs thousands or tens of thousands of images to achieve similar accuracy. For another thing, today's algorithms clearly are far away from grasping the essence of an *entity* or a class in the way humans do. Many examples show how even the most modern neural networks fail spectacularly in cases that seem trivial to humans [13].

While neural networks are quite fashionable nowadays, their conceptual foundations are actually rather old: They have already been studied intensely in the 1950s and 1960s. And while they are inspired by the brain's anatomy, they represent a very rudimentary model of its functioning at best. Today's deep neural networks are still quite similar to those classical networks, with the most notable difference being their higher number of layers. They owe their success in recent years largely to an increase in computing power and the availability of huge amounts of training data.

A long-term vision in the field of AI is to overcome those limitations and build systems which are as versatile and effective at solving cognitive tasks as the human brain. In particular, such a system – typically referred to as a 'strong AI', 'general AI' or 'artifical general intelligence' (AGI) – would pass the famous Turing test [15] by tricking a human conversation partner in an online chat (and taking into account recent advances in voice synthesis certainly also on the phone) into believing that it is actually another human rather than a machine.

It is heavily debated if and when the realization of strong AI will be possible, but the focus of the discussion seems to have shifted from the 'if' to the 'when' over the last years, and a majority of AI researchers place their bets on a time horizon within this century[1]. The advent of Strong AI is likely to trigger the most dramatic changes to society and economy in human history. The precise nature of these changes cannot be foreseen as of today, but there is a growing body of literature that provides several different perspectives on this fascinating and important question [1, 2, 8, 14].

Independent of if and when strong AI will be achieved, it seems likely that any step in that direction will yield by-products of significant intellectual and economic value – for example:

- Computer vision with minimal training data: While deep neural networks achieve human-level accuracy in certain image-recognition tasks, the requirement of large training data sets still renders many use cases technically or economically unfeasible. In particular, this is the case when the system needs to learn a large number of edge cases or when the availability of training data is limited.

- Accurate action recognition: It is still quite challenging to automatically recognize actions performed in a video sequence. Advances in action recognition might unlock economically relevant use cases, e.g. in security surveillance or in human-machine interaction.

- Motion control: Despite impressive advances in robotics and motion control, even simple animals are in command of a motion control system which is more flexible, adaptive, robust and versatile than modern robots. For example, picking up a large variety of different objects (with different size, weight, shape and stability) is still a very difficult task for a robot today. Finding algorithms which mimic biological motion control could dramatically expand the range of use cases for robotics (e.g. in industrial, logistics or household applications) while reducing their cost of development.

Given such great opportunities it is not surprising that large companies want to bring themselves into a position where they can profit from the expected technological advances in AI - and Merck KGaA is no exception.

Artificial Intelligence Research at Merck KGaA

At Merck KGaA we are involved in artificial intelligence from several different perspectives: Firstly, we apply the technology internally in different areas to improve efficiency and expand revenues. Secondly, we happen to be a supplier of materials to the semiconductor industry. Therefore any increase in the world-wide demand for AI technology affects our business directly via the market growth in computer hardware. And finally, we see AI as the corner stone for many new business models that are between and beyond the current business sectors of our company.

It is therefore imperative for a company like ours to be well connected to the academic research community in the field of AI. For one thing, this will allow us to become aware of new trends and understand their impact much quicker, which translates into an earlier adaption of new technologies in the business. For another, with a growing number of already several hundred data scientists and analysts in house we want and need to be perceived as a top employer for talents in the data science space. And finally, throughout Merck's 350 years of history, scientific research has always been the engine of value creation. We believe that the same will hold true in the digital age and that our research activities must expand beyond the realm of medicine and chemistry.

For these reasons, we have started to build up a small research group [11] focusing on the next generation of AI algorithms beyond the deep learning paradigm. As explained before, the current wave of progress in AI was driven by increased computing power and availability of massive amounts of training data. Our core belief is that the next wave of progress in AI will come from a true conceptional break-through that will move us beyond the 70-year-old model of neural networks. The source for such a break-through can, in our opinion, come from a highly interdisciplinary approach which takes input from informatics, neuroscience and mathematics. We have explained the reasons for these beliefs in a white paper on our research strategy [10], where we have also explored the connection to neurosciences in more detail. In

the following I will concentrate on some contributions to the field of AI which I hope for from mathematics.

A Mathematical Theory of Intelligence?

According to a definition by Legg and Hutter [9], "intelligence measures an agent's ability to achieve goals in a wide range of environments." In contrast, today's computer algorithms are successful only in certain narrow domains like playing Go or recognizing dog breeds in an image. Since we do not know how to build truly flexible learning systems, we put strong assumptions and prior knowledge about the respective domain into the algorithms. This can happen either explicitly, e.g., by hard-coding the rules of Go or by training with many labeled images of dogs, or implicitly, e.g. via the carefully chosen topology of an artificial neural network. And here we come back to the famous mathematical physics problem about percussion instruments: 'Can one hear the shape of a drum?'

This question shows interesting parallels to how AI is approached today: One makes strong assumptions about the system in question (the physics of a drum) and one obtains data which is generated by the system according to some prescribed mechanism (the sound frequency spectrum of a drumbeat). One then tries to infer something about the system (the geometrical shape of the drum) based on the observed data.

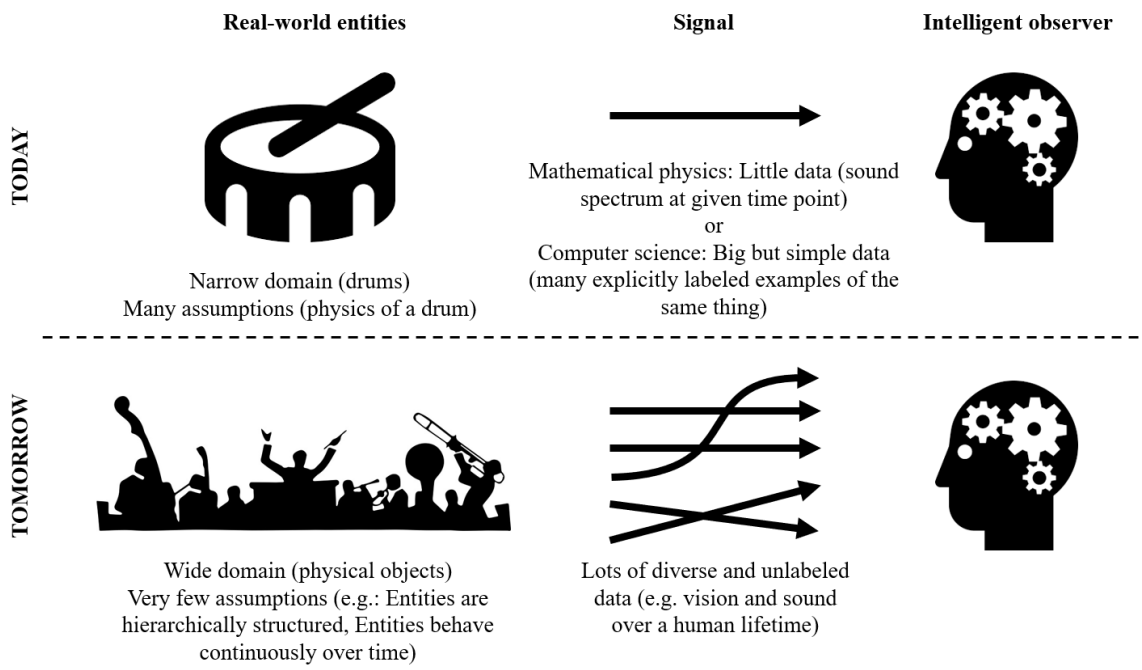


Figure 2: Both in AI and in mathematics research, there is an opportunity to study more general models of how reality is perceived by an intelligent observer – relying less on assumptions and more on statistics of the observed signal.

Our human brain though works fundamentally differently: We are not born with a hardwired knowledge of what a drum is. We learn it over time by processing sensory perception. In other

words: While most of us would probably not be able to hear the shape of a drum, taken the combined experiences of our lifetime, we do hear (and see and feel) what a drum is and how it works.

As of today, there is no known algorithm which could learn 'what a drum is' in a way similar to a human child. I suspect that one reason is the lack of a theoretical framework for how an environment as rich and diverse as our real world can be perceived and analyzed by an intelligent observer. Could we generalize the question 'Can one hear the shape of a drum?' by dropping assumptions about drums and their physics? To what extent is this feasible? ('You hear something - figure out what it is!')

Roughly speaking, and again being guided by our conception of the human brain, we should not make any assumptions which could not have been hard-coded into our cognitive system via the process of natural selection (which clearly excludes the physics of a drum or the rules of Go). But we can take this even further: Based on the anatomical homogeneity of the neocortex and its plasticity (i.e. the ability of cortical tissue to specialize on very different tasks), it is conjectured by neuroscientists [12, 4] that a considerable part of human intelligence is based on essentially one 'cortical algorithm'. It performs tasks as different as recognizing objects in an image, the text in a book, or a song on the radio. Taking this hypothesis seriously, in our attempt to build a system which learns to 'understand' its environment from sensory perception we should not even make assumptions which are specific to any given type of sensory input. For example, we should not assume translational invariance in image recognition, because it is not clear how such an assumption would apply to audio signals. Such an invariance should rather be inferred by the system from observations only[2]. Consequently, our assumptions must be limited to very basic facts about the world, which are true for entities as different as images, songs or written words, and which have been true for the millions of years that were required for evolution to hard-wire them into our cortical algorithm. Such assumptions might be, for example, that real-world entities

- are built up hierarchically,
- are rather stable over time, even if their appearance changes constantly,
- and/or present themselves as sequences of events during a time interval.

These very basic assumptions are true for experiences as diverse as seeing a cat jump onto a table, reading a novel, or hearing a piece of music. Yet there are indications that they might be helpful to make sense out of an initially unintelligible stream of incoming data, be it acoustic, visual, or other types of signals.

To make these ideas more concise, let's explore how they might be translated to mathematical problems. The task is to build and analyze abstract models of the process by which

[2]Of course, matters in biology are usually not perfectly black or white. Our cognitive system has evolved certain pre-processing steps which are specific to their respective type of sensory input, possibly to make the incoming signals easier to process by the hypothetical cortical algorithm. For example, the eye's retina performs sophisticated computations before sending the signal to the downstream brain areas [3]. For the task of finding the cortical algorithm, though, it is probably a reasonable starting point to ignore such pre-processing and rather focus on the abstract and generic concepts.

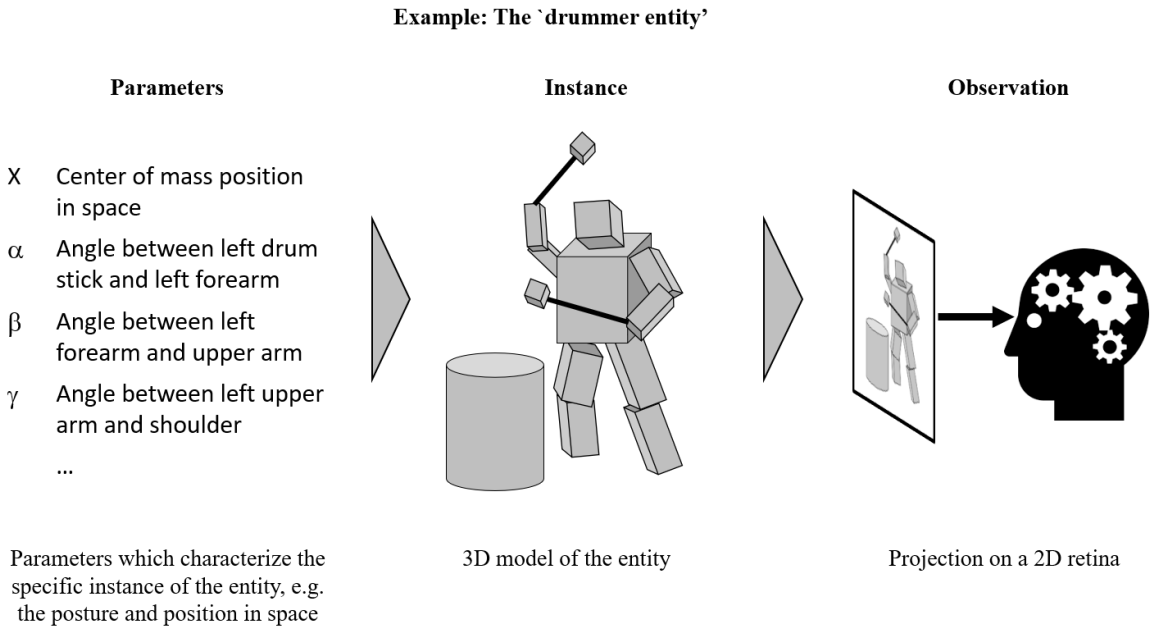


Figure 3: In our model the *world* is inhabited by *entities*, which for each choice of parameters give rise to an *instance*, respectively. A *history* is a random process by which the parameters vary over time, possibly subject to certain constraints. Given an *observation* of this process, for example the color values perceived by projecting the 3D instance onto a 2D retina, can you characterize the entities which have generated the observations? (Hint: Your brain can! At least approximately.)

an intelligent observer (be it human, animal, or machine) perceives its environment and forms an internal representation of the entities in this environment – starting with only minimal assumptions. The starting point for this modeling process is to define a *world* which consists of *entities*. An entity represents a 'thing' which can be perceived by an intelligent observer. In our real world it could be, for example, a physical object or a word or a song, but mathematically it is rather a mapping from some set of parameters to a set of possible observations. For example, in our model the entity 'drummer' (see Figure 3) would be described by a set of parameters which describe the position and posture of the musician in three-dimensional space and these parameters would be mapped to a picture on the observer's retina. A *history* in this model world is now a random process in which the parameters of all the entities change over time. The fundamental question is: Given only the observations during a history and some rudimentary assumptions about the mechanics of the random process - can you characterize the entities?

The modeling approach described above is generic enough to give rise to a large class of mathematical problems. Their difficulty varies greatly, depending, for example, on number, type, and complexity of the entities, on whether the temporal length of the history is finite or not, or on potential losses of information during the observation process (e.g. projection from three to two dimensions in the case of vision).

Of course, many mathematical methods aim at inferring from observations the hidden parameters which control some random process. Actually, a large share of data science work can be interpreted in this way. For example, the framework of 'independent component analysis' [5] treats models in which a linear mixture of mutually independent random variables is observed with the objective to infer the individual distribution of each of those variables. But so far, no model gets even close to the flexibility and effectiveness of the hypothesized cortical algorithm. One reason may be that none of those models is based on the same assumptions that are hard-wired in our brains. It seems to me a very worthwhile endeavor for mathematical physicists to define and analyze new models, trying to get closer to the cortical algorithm. The three assumptions stated above (hierarchical structure, stability of time, and expression as time sequences) could serve as a starting point.

When it comes to understanding intelligence - both natural and artificial - we are still in very early stages of what promises to become a fascinating and rewarding scientific journey. It will take joint efforts from computer scientists, neuroscientists, and mathematicians to make progress. Our AI research group at Merck KGaA is being set up with a mix of experts from these three areas to foster interdisciplinary collaboration. We are also collaborating with academic partners through a variety of formats, and if you are interested to do research along the lines describes above, please feel free to reach out to me.

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The author is a mathematical physicist by training who worked on spectral analysis of differential operators for his Ph.D. thesis. He is now the Global Head of Data Science at the large German science and technology company Merck KGaA.

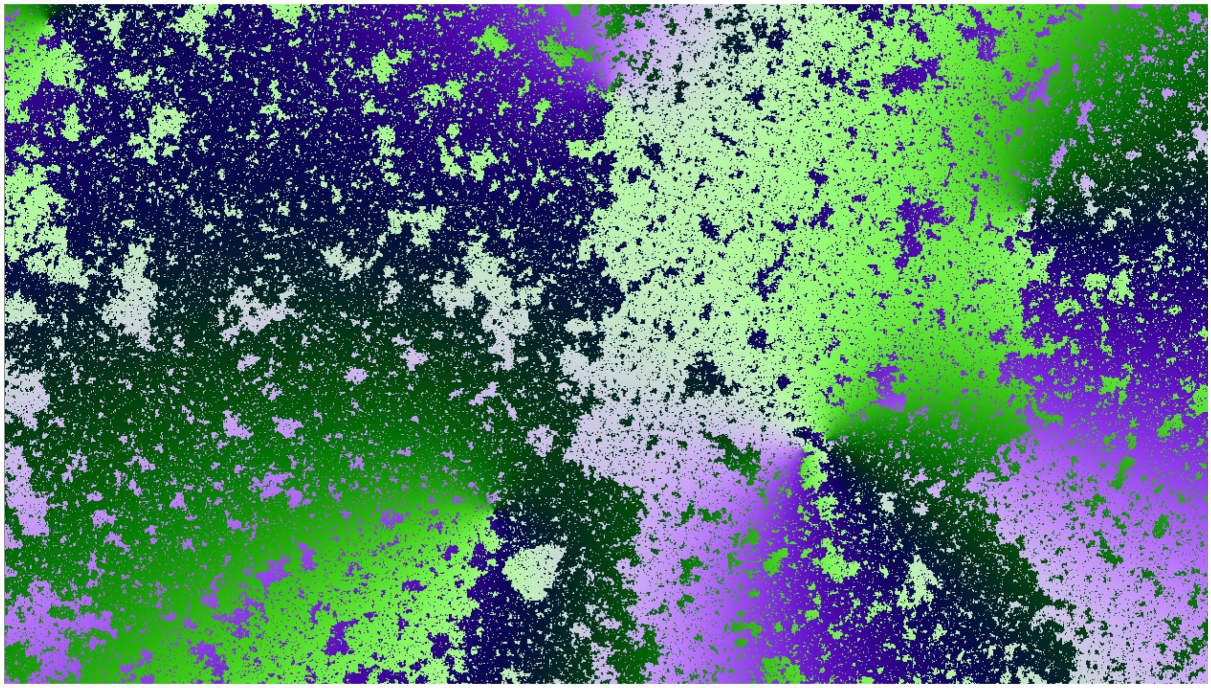
New journal: Probability and Mathematical Physics

IAMP is proud to welcome as an associate member the new journal, *Probability and Mathematical Physics* (https://msp.org).

We invite submissions to the new MSP journal *Probability and Mathematical Physics*, founded to meet the needs of the community and led by Alexei Borodin (MIT), Hugo Duminil-Copin (IHES & Geneva), Robert Seiringer (IST Austria), and Sylvia Serfaty (Courant), with the help of the Editorial Board, currently 18 strong.

PMP publishes research of the highest quality, originality, and importance. It welcomes submissions of research articles in mathematical physics (broadly interpreted) and in the topics of probability connected to physics. High-quality and timely survey or expository articles will also be published.

PMP is published by Mathematical Sciences Publishers (MSP, https://msp.org), the non-profit that also started *Geometry & Topology* and *Analysis & PDE*. MSP believes that fair-priced scholar-led subscription journals remain the best stewards of quality and fairness, and strives to offer the highest quality at the lowest sustainable prices. MSP also developed EditFlow, the popular peer-review web application.



News from the IAMP Executive Committee

New individual members

IAMP welcomes the following new members

1. PROF. SEMYON DYATLOV, Massachusetts Institute of Technology, USA.
2. DR. MAXIMILIAN PECHMANN, University of Tennessee, USA.
3. DR. ROBERTO GARRA, University of Roma 1, Italy.

Recent conference announcements

Supergeometry, supersymmetry and quantization

Dec. 16-19, 2019. University of Luxembourg.

http://math.uni.lu/SuperWork/SuperConference.html

Operator Theory Analysis and Mathematical Physics

Jan. 8-14, 2020. Mexico City.

https://silva.iimas.unam.mx/otamp2020/

Open positions

Assistant Professor of Mathematical Physics, ETH Zurich

The Department of Mathematics at ETH Zurich (http://www.math.ethz.ch) invites applications for the above-mentioned position (non tenure track).

Candidates should hold a PhD or equivalent in mathematics or physics, and should have demonstrated the ability to carry out independent research work. At the assistant professor level, commitment to teaching students of mathematics, physics, and other natural sciences and engineering, and the ability to lead a research group are expected. The new professor will be part of the National Centre of Competence in Research NCCR SwissMAP (http://www.nccr-swissmap.ch).

Assistant professorships have been established to promote the careers of younger scientists. The initial appointment is for four years with the possibility of renewal for a three-year period.

Please apply online at http://www.facultyaffairs.ethz.ch.

Applications should include a curriculum vitae, a list of publications, a statement of future research and teaching interests, and a description of the three most important achievements. The letter of application should be addressed to the President of ETH Zurich, Prof. Dr. Joël Mesot. The closing date for applications is 31 December 2019. ETH Zurich is an equal opportunity and family friendly employer, strives to increase the number of women professors, and is responsive to the needs of dual career couples.

For more information on these positions and for an updated list of academic job announcements in mathematical physics and related fields visit

http://www.iamp.org/page.php?page=page_positions

Benjamin Schlein (IAMP Secretary)

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