DE GRUYTER Depend. Model. 2019; 7:169–180

Interview Article Open Access

Christian Genest* and Matthias Scherer

The world of vines

An interview with Claudia Czado

https://doi.org/10.1515/demo-2019-0008
Received May 21, 2019; accepted May 28, 2019

Claudia Czado is an Associate Professor of Applied Mathematical Statistics at Technische Universität München (TUM), Germany. She received a Diplom in Mathematics from Georg-August-Universität in Göttingen in 1984, and an MSc in Operations Research and Industrial Engineering from Cornell University, Ithaca, NY, in 1987. Her PhD, completed in 1989, is also from Cornell. Her first regular academic appointment was at York University, Toronto, Canada, as an Assistant Professor. She was promoted to the rank of Associate Professor with tenure in 1994. In 1998, she returned to Germany and took up her present position in the Department of Mathematics at TUM. She is the author or co-author of over 125 research articles and two books published by Springer: a 2011 German-language textbook with Thorsten Schmidt titled "Mathematische Statistik", and a 2019 solo monograph on "Analyzing Dependent Data with Vine Copulas: A Practical Guide with R".

This ninth contribution to the *Dependence Modeling* series of interviews features Claudia Czado, who is widely regarded as the main promoter and developer of statistical inference techniques for vine copula models. Renowned for her vast experience, energy, and broad view of the field, she kindly revisits with us the key moments which shaped her professional career and shares some of her recipes for success. The interview was conducted in part and finalized during her visit to Montréal, May 4–25, 2019. In the following, our questions to Claudia are typeset in bold-face.

1 Background

Could you please say a few words about your family background and early education?

I grew up in Borken, a small town in northern Hesse, Germany, about 140 km north of Frankfurt, in a family with four children. During my high school years, I discovered that I liked mathematical structures and not so much the experimental side of physics, chemistry, and biology. My older brother studied mathematics in Göttingen. After I finished high school, I visited him there and attended a few math lectures to find out if this field of study would be something for me. He thought this would scare me off, but this was not the case. I then bought an introductory analysis textbook written by an influential professor at Göttingen, Hans Grauert (1930–2011), and after I went through the material, I thought I was well prepared for studies in mathematics and enrolled.

***Corresponding Author: Christian Genest:** Department of Mathematics and Statistics, McGill University, Montréal (Québec) Canada. Email: christian.genest@mcgill.ca
Matthias Scherer: Lehrstuhl für Finanzmathematik, Technische Universität München, Garching, Germany.

Göttingen has a long tradition in mathematics. Did you feel it as a student?

In my region, Marburg and Göttingen were the closest universities and Göttingen was known for the sciences, so I enrolled there. Since I did not know any other universities, Göttingen was nothing special to me. The mathematics buildings were old and the entrance hall, where I often met with other students, was called "Hilbertraum" (Hilbert space). I only later realized the significance of this name. At first the course choices were mostly limited to calculus and linear algebra, but then I chose the probability and statistics curriculum. After an introductory probability course, you had to take a course in measure theory, then a second probability course, and finally mathematical statistics. These four courses were based on lecture notes written by Professors Krengel, Denker, and Hering of the Institut für Mathematische Stochastik. The content was very mathematical and we often spent hours searching for hints in books to solve problems.

What led you to pursue graduate studies in the USA?

This was a decision completely detached from any professional considerations. During my high school years, I became interested in Native Americans. We all read the novel "Winnetou" from the German writer Karl May (1842–1912), who wrote about First Nations even though he had never visited North America. Besides their history and customs, I was interested in their current living conditions. After I found out that there was an exchange scholarship at Cornell University for students from Göttingen, I applied for it. To support my application, I asked Prof. Manfred Denker if he knew someone at Cornell. He said he had read interesting work by Prof. Murad Taqqu on functional limit theorems. So, in my application I claimed that I wanted to write my Master's thesis on this topic.

Tell us a bit about your experience at Cornell.

In Göttingen, I decided to specialize in probability and statistics, where I saw more potential for employment than in algebra or number theory. Once my one-year fellowship was confirmed, I took my first flight ever and arrived with the overnight bus at the station in Ithaca, NY. My first impression of this small town was not very positive, but I thought I would survive the year. In the Department of Operations Research and Industrial Engineering, I took a reading course with Prof. Taqqu. Once, I had to give a seminar on a paper of his and because my English was not so good, he took over during my talk and said he could finish faster. This was a humbling experience for me. Of course, there were great moments, too. The following summer, I traveled across Canada by train and then down the West Coast of the USA. At last, I saw some Natives when I visited the Navajo and Hopi reservations in Arizona.

After one year, I returned to Göttingen and wrote my Diploma thesis on functional laws of the iterated logarithm for self-similar processes. At this time, I noticed that no asymptotic normality result had yet been proved and I asked Prof. Denker to map out the necessary steps to prove it. He described the general approach to me and I was able to fill in all the necessary steps by myself.

After my graduation in Göttingen, I returned to Cornell and Prof. Taqqu asked me to write a survey paper with him [49]. Subsequently, I asked him if I could pursue a PhD at Cornell and he was able to provide me with a teaching assistantship to cover my tuition fees and living expenses. In my first year as a PhD student, I audited a course on basic probability from Prof. Eugene Dynkin (1924–2014). Despite my prior knowledge of probability, I found it very hard. I was glad that as an auditor, I did not need to write the final exam or pass the oral in which he would ask questions on the problems you had missed in the written part.

After some time, it became apparent that Prof. Taqqu was moving to Boston University, where he still is today. Since I did not want to move, I needed to find a new supervisor. My initial research project was to loosen some regularity conditions for the functional laws of the iterated logarithm. I made numerous attempts but after pages and pages of calculations, they all failed. So I was happy to look for a different area. I chose statistics, since statistical methods and data analysis seemed more useful to me. I wrote my thesis with Prof. Thomas Santner, who introduced me to binary regression. Here, I investigated the effects of link specifications both asymptotically and in small samples. It was neat to conduct simulations in Fortran on the (then) brand new Cornell supercomputer.

In the Operations Research and Industrial Engineering Department, there was only a small group of 10–15 students per year. Many of them came from abroad such as Martin Kulldorff (now at Harvard Medical School) and Nelson Tanaka (affiliated to the Universidade de São Paulo). Another student I have fond memories of is Lisa Meier McShane, who works for the Division of Cancer Treatment and Diagnosis at the US National Can-

Figure 1: Claudia and her father Rudolf at her PhD graduation party in Ithaca, NY, in the summer of 1989.

cer Institute. At Cornell, the curriculum was broad and included known researchers in optimization such as Michael Todd (ellipsoid method) and Leslie Trotter (discrete and combinatorial optimization). Besides Tom Santner, my professors were Bruce Turnbull (survival analysis), Lionel Weiss (experimental design), and Robert Bechhofer (order statistics), among others.

After graduation, you moved to Canada. What was your experience there?

After graduation from Cornell, I decided to apply for a university position in North America. I knew that such a position in Germany would not be possible for me without the additional qualification of a "Habilitation". After a six-month teaching position at McGill University, Montréal, I took a tenure-track position in the Department of Mathematics and Statistics at York University in Toronto.

At York, I was exposed to S, the precursor statistical software to R. I was one of the first few S users there along with Georges Monette and John Fox. I was also introduced to the emerging area of Bayesian inference using Markov Chain Monte Carlo (MCMC) methods when Michael Newton came for a job interview. Although he ultimately chose to go to Madison-Wisconsin, we stayed in contact after having discussed the problem of choosing a prior for the link function in a binary regression problem [39]. This was a natural extension of my PhD thesis at Cornell. Much later on, the Bayesian MCMC approach would turn out to be very useful for vine modeling [16, 30]. Other samplers based on, e.g., Hamiltonian Monte Carlo can be used as well, especially for dynamic dependence models [24].

But we're getting ahead of ourselves! What else did you work on while in Toronto?

After publishing the results of my PhD thesis [12], I studied the benefits of an orthogonal parametrization for the link function in the case of a single parameter [9, 13] and developed a more flexible family of link functions, which could modify each tail of the link separately [10]. I also helped with the statistical consulting service at York University, which was run by John Fox, Georges Monette, and Peggy Ng. In addition, Peggy was heavily involved in teaching service courses and we remained close friends until her recent death.

Later on, I started cooperating with Axel Munk, who was then based in Bochum (Germany). Manfred Denker introduced me to him once, when I gave a talk in Göttingen. Axel had developed asymptotic nonparametric tests for assessing the similarity of distributions. This is needed for bio-equivalence testing in medical research. Here, I learned that the asymptotic variance of such test statistics might be difficult to compute and one needs carefully designed simulation studies to evaluate the finite-sample performance of bio-equivalence tests based on asymptotic variance estimators [11, 34].

You finally went back to Germany in 1998. How did this come about?

I enjoyed my working experience in Canada, but I had a preference for the German way of living and interacting. I knew I could only apply successfully for a tenured position at a German University after my promotion to Associate Professor. After this happened in 1994, I spent a sabbatical year in Munich and Berlin to connect with German statisticians — during my time in Göttingen, I had only known of German probabilists. It took me two more years to get a tenured position, since openings in the field of applied statistics were hardly advertised in Germany. In 1998, I moved to TUM as an Associate Professor in Applied Mathematical Statistics, where I work to this day.

2 Statistics in general

What differences do you see between the German and North American academic worlds?

In Germany, statistics is more fragmented than in the North American or British system. In German mathematics departments, you find competition for resources between theoretical statisticians and researchers in probability. Some economics departments and medical schools have statistics positions, too, but the work is then centered on these specific applications. A statistician who wants to develop statistical modeling and estimation approaches for applications in different areas has few places to go. Only at the Ludwig Maximilians Universität in Munich and the Technische Universität Dortmund do you find statistics departments. As I like to see if my models can fit complex data structures, I prefer to work among statisticians. Also in mathematics departments, you are often the sole statistician and, therefore, not very exposed to statistical thinking and new trends such as machine learning.

You often say that you are a "statistical modeler". What do you mean by that?

A statistical modeler is a researcher who likes to build data-driven statistical models for complex structures, and who develops and implements inference in statistical software. The proposed models and tools have to be validated through simulation and real data analysis. Additionally, a statistical modeler is interested in exploratory data analysis to select an appropriate model and to quantify its improvement over other approaches for the data at hand.

What is the importance of visualization tools in statistical modeling?

Visualization tools are great for exploring a data set before choosing a model. In the case of statistical dependence modeling, the famous representation theorem by Sklar [46] states that the joint distribution can be built from marginal distributions and a copula. Therefore, ordinary scatter plots of pairs of variables mix the marginal behavior and the dependence pattern. While it is valid to consider scatter plots of data transformed to the $[0, 1]$ copula scale to assess dependence patterns, signature shapes are not available on that scale.

When we transform to $\mathcal{N}(0, 1)$ margins, we can easily check if the Gaussian copula is appropriate. This is the case when elliptical contours around the origin are visible. Deviations from the elliptical shape require us to look for non-Gaussian copulas. Additionally, diamond contour shapes indicate a Student t copula, while pear shapes can be often modeled by Archimedean copulas such as the Clayton or Gumbel families. Contour shapes which are not symmetric around the main diagonal might indicate Tawn copula dependence or might require nonparametric fitting. Visualization tools are not limited to the bivariate case; even contour volumes in three dimensions give useful information about the dependence structure present in the data [21].

How about computational methods?

I am a big fan of computational statistics since I like to see statistical methods applied to real data sets. In the area of "Big Data", I also think that it is important to look for interdisciplinary knowledge, especially in computer science. For a starting researcher in statistics, excellent computing skills are vital. I think the importance of statistical limit theory will decrease with time, which is natural, since in the pre-computing days this was the only way to investigate the behavior of statistical procedures. Nowadays, some models are so complex that sample sizes need to be unrealistically large — even in the era of "Big Data" — for model calibration assessed by simulation to be effective. In such cases, I prefer simulation studies based on real data situations.

Let me add that I still see room for carefully designed statistical modeling in the era of "black box" data science ruled by learning algorithms, because in many subject areas data will continue to be scarce or limited to a thousand observations, say. Here, training and learning from data alone will not be possible. Further, statistical models can give interpretable insights into the underlying driving factors, which might be more helpful than machine learning output in process design and control.

3 Landscaping the "vine yard"

Your research career took a dramatic upward swing when you encountered copulas and vines. How did that story begin?

This is a funny story. In 2005, I had a sabbatical and asked Arnoldo Frigessi from the Department of Biostatistics at the University of Oslo if he was interested in hosting me for some time. He agreed and upon my arrival he asked me to read papers by Roger Cooke, Tim Bedford, and Dorota Kurowicka from the Technische Universiteit Delft [5, 6, 26]. A group around Kjersti Aas, Daniel Berg, and Henrik Bakken at the Norwegian Computing Centre had become interested in the construction of multivariate distributions suggested in these papers. This vine construction only uses building blocks comprised of bivariate copulas evaluated at conditional functions. They wanted me to help them understand the construction in more detail. I did this with a set of handwritten multi-colored slides which I still have.

This was a completely new area for me. I had never worked with copulas and graphical structures such as trees. Initially, the construction of trees, where edges in a given tree become nodes in the next tree, looked very weird to me. Since they were paying me, I thought I would do this for four weeks and then return to my own research interests, but I never stopped.

The group in Delft was interested in risk analysis and used expert knowledge to determine partial correlations. These are the parameters in a vine with only Gaussian bivariate copulas. They focused on this case for estimation. I thought that we could use other bivariate copula families and estimate the parameters using a joint maximum likelihood approach in small dimensions. For the likelihood we were able to develop a way to express the conditional distribution functions recursively. The idea of a sequential estimation approach was born out of discussions to cut the high-dimensional estimation into smaller pieces. Arnoldo Frigessi coined the words "pair copula construction" and we started to call the bivariate building blocks "pair copulas". We realized that the sequential estimate can be used as a starting point to perform joint maximum likelihood estimation. I also found that the representation of the complete vine structure in a single display was not easily interpretable in high dimensions and I opted for drawing the linked vine trees separately. This is implemented in the R package `VineCopula` [45].

How did things develop from there?

After our paper [1] came out, Roger Cooke and Dorota Kurowicka organized small workshops in Delft in 2007 and 2008, where I first met Harry Joe. In these early days, we were interested in parameter estimation for a given vine tree structure with pre-specified pair copula families. We first concentrated on some easy structures such as the canonical (C) and drawable (D) vine. A big problem was that the number of regular vine structures grows super exponentially, so we could not afford to try them all in dimensions of 5 or more. At the Oslo workshop in 2009, Arnoldo Frigessi set a challenge for the next workshop: we should be able to select and estimate vine copulas in a dimension of 100. This was quite intimidating since there are more different vine structures than atoms in the universe in dimensions larger than 23, as my former PhD student Eike Brechmann calculated using the formula given in [31].

A considerable part of the vine literature is due to your research group in Munich. How about giving us a rundown of the main achievements and contributors?

After realizing the potential of vine-based modeling, I was fortunate to gather research funds from diverse sponsors. It has been very exciting for me to build up a small group and maintain it for the past ten years. My broad statistical training and experience has been very fruitful in picking PhD topics where vines could make an impact, so I am afraid this will be a long list.

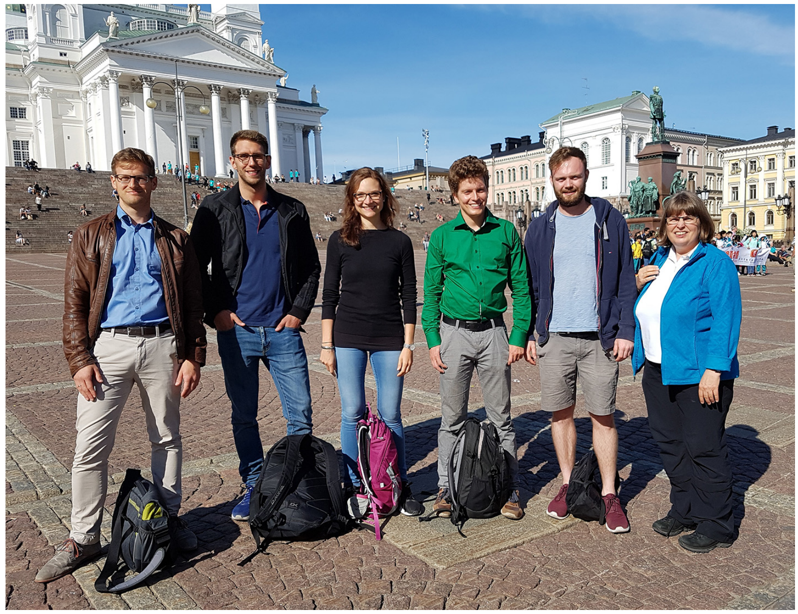

Figure 2: From left to right: Dominik Müller, Matthias Killiches, Nicole Barthel, Daniel Kraus, Alexander Kreuzer, and Claudia Czado. Photo taken in Helsinki, Finland, during the European Meeting of Statisticians held in July, 2017.

I started with a postdoctoral fellow, Aleksey Min, who, with me, developed the first Bayesian estimation methods for vine-based models [30]. Aleksey is now a colleague in Financial Mathematics at TUM. These Bayesian techniques were extended much later by my recent PhD graduate Lutz Gruber [16]. Then I had the good fortune to get Eike Brechmann interested in vines. As an MSc student, and later as a PhD student, he was instrumental in many early papers, especially in the area of truncated vines [8] and the first high-dimensional application to financial stock data [7].

A really big step forward was the development of a simple selection algorithm for the vine tree structure. This was largely due to my Master's student Jeffrey Dißmann. Our joint paper [14] made arbitrary regular vine modeling operational for the first time. My Humboldt funded postdoc, Anastasios Panagiotelis (now an Associate Professor at Monash University, in Melbourne), and Harry Joe contributed to the development of a pair copula construction for discrete variables [40]. Later, Jakob Stöber extended this to mixed components [48]. Regime switching is an oft studied scenario for financial data and Stöber and Czado [47] introduced vines to this area.

Back in 2006, Hanea et al. [17] considered Bayesian belief nets or directed acyclic graphs (DAGs) in the context of vines. With Alex Bauer and Thomas Klein, I developed in [4] a test using specific regular vines for determining the edges in a DAG. My recent PhD graduate Dominik Müller was able to build truncated regular vine tree structures which satisfy the conditional independence constraints induced by a Gaussian DAG [32]. This extended the Gaussian model through the flexibility of vine copulas. He also made great initial contributions to extend vine models to several thousand nodes [33].

Another area I found interesting is the inclusion of spatial effects, resulting in paper [15]. I was on the lookout for new pair copula families and when I was approached by Thomas Nagler for a Master's thesis. I asked him to investigate nonparametric pair copulas [36], given that he had studied nonparametric methods during a semester at KU Leuven. His computational contributions helped to bring the software `VineCopula` to the next level.

What challenges did you face in developing your R package for vine copulas?

Since the vine construction allows for so many different vine structures, it is not easy to program the likelihood. This might explain why vine constructions lay dormant for almost eight years after the first publications from the Delft group. If you want a complex model to be applied, you must provide easy-to-use software for estimation, prediction, and visualization. Immediately after my first stay in Oslo, I started writing small prototype programs for estimation in dimension 3. This was picked up by Daniel Berg from the Norwegian Computing Center, who provided the first workable R package for C- and D-vines, including the calculation of conditional distribution functions.

Since we wanted to include visualization tools such as vine tree structure plots and normalized contour plots to help to choose the pair copula family, I decided to build our own package in Munich. Because software constantly needs to be kept up to date, I was — and continue to be — keen to hire PhD students with an interest in maintaining and developing the package. I think Aleksey Min was the first to work on this for C- and D-vines; we named the package `CDVine`. Jeffrey Dißmann provided the first implementation of regular vine models, while Eike Brechmann introduced vine tree structure plots and tests for the truncation level of vines. The package was then renamed `VineCopula`. Ulf Schepsmeier and Jakob Stöber added further parametric pair copula families and provided numerical Hessian matrix estimates for the joint vine distribution. In addition, there were very helpful contributions from Harry Joe and Benedikt Gräler. Since 2014, Thomas Nagler has maintained the `VineCopula` package [45].

There are more specialized R packages related to vines. Packages `kdevine` [35], `penRvine` [43], and `pencopulaCond` [42] implement nonparametric vine copula models. D-vine quantile regression, introduced by Kraus and Czado [22] and extended to discrete components by Schallhorn et al. [41], is implemented in `vinereg` [37]. In the package `gamCopula` developed by Vatter and Nagler [50], the parameters of the pair copulas can vary flexibly with covariates. This also allows one to fit non-simplified vines. The package `pacotest` [28] based on Kurz and Spanhel [29] implements a test for the simplifying assumption.

A recent alternative to `VineCopula` is the `vinecopulib project` (vinecopulib.org). Its core is an efficient C++ implementation of the most important features of `VineCopula` needed for high-dimensional applications. In addition, it makes it possible to mix parametric with nonparametric pair copulas and provides an interface with both R and Python.

You have a long history of collaborating with Harry Joe. How did it start and why is this collaboration so successful?

I first met Harry in 2008, at the PhD defense of Anca Hanea in Delft, and I was very intimidated by his knowledge of copulas. At the time, I was just beginning to get a good grasp of this area. I was very happy to visit him in Vancouver in 2010. We started thinking about spatial dependence, but we could only make significant progress later, using the local composite approach of Erhardt et al. [15]. Harry came to Munich as a John von Neumann Gastprofessor and participated in the 2011 vine workshop. I was glad that he liked our environment. At the time, we also met with my postdoc Anastasios Panagiotelis to discuss pair copula constructions for discrete random variables. We continued to meet at vine copula workshops and he came to Munich on several other occasions. I guess since we are both interested in vines but from quite different angles (he more theoretical and I more applied), we always have things to discuss. Recently, I was even able to secure a Mercator Fellowship from the German Science Foundation (Deutsche Forschungsgemeinschaft or DFG) to get Harry to come to Munich to work with us on statistical learning with vines.

You mentioned various conferences that fuelled the work on vines. What were they?

As I already said, the Delft group first organized workshops in 2007 and 2008; a third followed in 2009 in Oslo. This led to the book by Kurowicka and Joe [27] summarizing the results of the three workshops. I should also mention the 2010 workshop organized by Piotr Jaworski [18]. In 2011 and 2016, I organized vine workshops in Munich, the second time with you, Matthias. Some vine copula researchers also met at the Banff Research Station (in Alberta, Canada) in 2013 and again in Oberwolfach (Germany) in 2015. In 2014, we had a large workshop involving copulas and vines in Beijing organized by Haijun Li, and a CRM-CANSSI Workshop in Montréal, which you organized, Christian. With Benedikt Gräler, I also hosted a Spatial Copula Workshop in Münster. The next vine workshop will be in Munich in July.

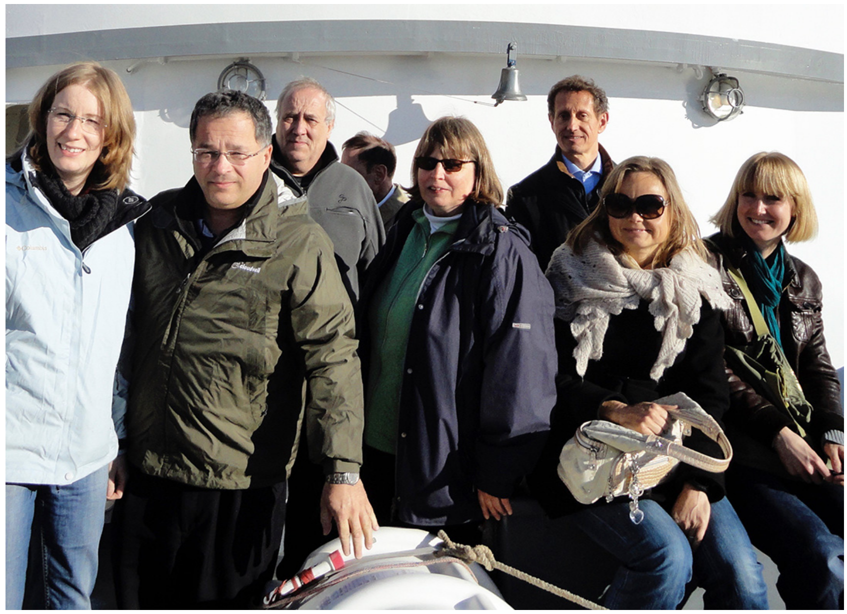

Figure 3: Boat trip on May 5, 2010, as part of the Third Annual Conference on Extreme Events and Related Issues held in Stavanger, Norway. From left to right: Johanna Nešlehová, Christian Genest, Christian Gouriéroux, Claudia Czado, Tom Arild Fearnley, Kjersti Aas, and Ingrid Hobæk Haff.

What have you been working on recently?

Generalized linear models were central to my early research in statistics, so I think it would be nice to develop copula-based extensions. This also brings me back to research problems from the health sciences that I used to work on earlier in my career. Here, I would like to mention the recent work by Daniel Kraus on D-vine quantile regression [22] and Matthias Killiches on recurrent unbalanced measurements and their relationship to linear mixed models [20]. In 2014, Paul Jannsen from Universiteit Hasselt, in Belgium, asked me if vine copulas could be used to model multivariate survival times. For this, I needed to refresh my knowledge, which I did by teaching a survival analysis course. After that I recruited Nicole Barthel for a Master's thesis and then as a PhD student. She just graduated. In her thesis, she developed, among other things, an inference framework using vine copulas for recurrent events, e.g., in repeated asthma attacks [3].

A few weeks ago, you also finished a book on vines. What motivated you to write it?

In addition to the books by Kurowicka and Cooke [25] and Joe [19], I felt that there was a need for a beginner's book on vines. While I see many interesting applications from fields so diverse as finance, health, and engineering, no comprehensive introduction for users was available. I hope that my book titled "Analyzing Dependent Data with Vine Copulas: A Practical Guide With R" will be able to fill this gap. It will appear in June 2019. Earlier versions served as a textbook for a course on vine copulas I taught several times at TUM.

At times, it sounds as though vines are your hammer and everything looks like a nail. In your experience, what are the limitations of vines?

Yes, it may sometimes sound that way. However, think of the normal distribution, which is central to so many areas of statistics. Using the vine copula approach, we can investigate if the dependence structure induced by the multivariate Gaussian distribution is appropriate for the data at hand or whether the model can be extended by a vine-based model. The only limitation is the availability of large enough samples, as it is a data-driven modeling approach. In the era of "Big Data", this is not a major limitation. I also think that vines can play a role in statistical learning and data mining, where I plan to concentrate my research efforts in the future.

What about the simplifying assumption at the root of vine copula modeling?

As I already mentioned, the number of vine structures is enormous. Also, we now have the option of estimating pair copulas nonparametrically [36, 38]. For these reasons, I do not think the simplifying assump-

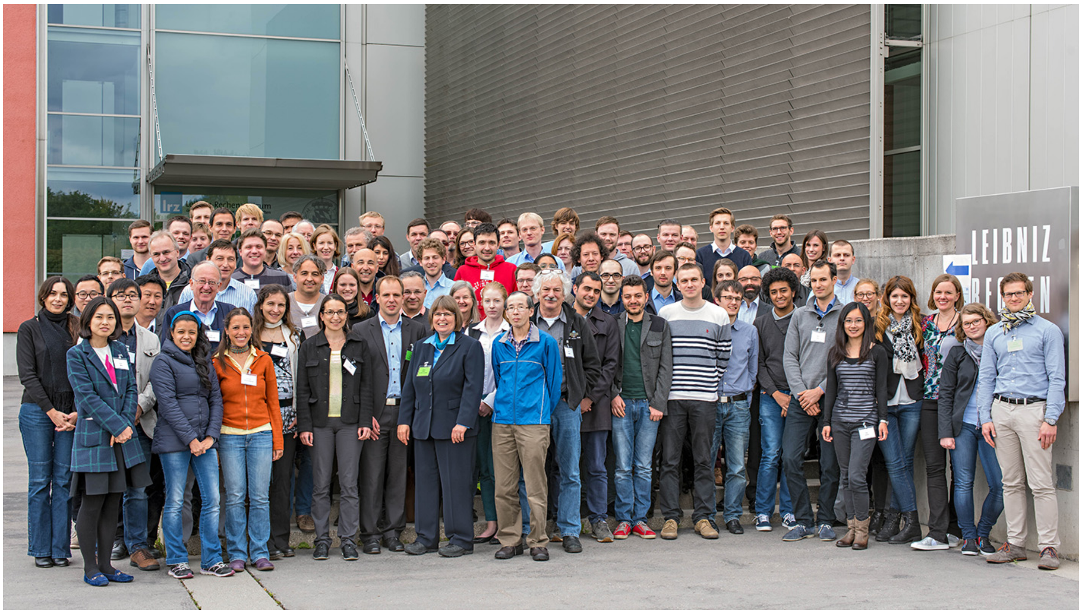

Figure 4: Group photo taken at the workshop "Dependence Modeling in Finance, Insurance and Environmental Science" held in Munich, May 17–19, 2016. Claudia is in the first row. Beyond her, four researchers previously interviewed by *Dependence Modeling* appear in the photograph; can you find them? The answer is given in the Acknowledgments.

tion is a huge problem. Even in moderate dimensions, the sample sizes required to estimate non-simplified vines has to be very large. I would also like to mention that there exist methods to estimate non-simplified vines starting with [2] and computationally more feasible in higher dimensions in [44, 50]. Additionally, as proposed by Kraus and Czado [23], it is feasible to select simplified vines using tests for the simplifying assumption implemented in `pacotest` [28]. I think a more fruitful area for research is time-dynamic vine copula models, especially for financial data.

4 Miscellaneous

At TUM, you were involved in the "Women-for-Math-Science" program for a long time. How has the role of women in mathematics changed during your career?

With the help of two female students, I actually designed and initiated this program to get female students interested in pursuing a university career in mathematics. When I was studying at university, both in Göttingen and at Cornell, I never had a female professor. There have now been changes in this situation at TUM but this is the result of the hard work of the departmental women's representatives and changing attitudes in the Department and society at large.

In an area where resources such as professorships are rare, competition will always be fierce, so women will have to continue to stand their ground for a long time to come. To attract more talented female mathematicians to a university career, I think a major hurdle is not talent, but lack of self-esteem and confidence in one's own abilities. To overcome these obstacles, it is helpful to introduce special prizes for best performing female students, to encourage them to present their work in conferences, and to cooperate with other researchers, as our experience with the program "Women-for-Math-Science" showed. Additionally, I think the ability to work in research teams, and improvements in working conditions to balance family and work life for both female and male parents, would be helpful.

You are a fervent advocate of collaborative work. Do you think that the days of the "lone mathematician" are over?

I had the good fortune to find a topic that allowed me to pursue research in many directions. When I had the opportunity to build up a small group, I made sure that we met and talked regularly to exchange ideas and results. Additionally, I find open communication very helpful and value everyone's input. Everyone's research output benefits this way. I also believe that this is a successful strategy for tackling complex problems. I enjoy interdisciplinary research, which comes with the challenge to find a common language to understand each other and the benefit of looking at the same problem from different angles. This helped me show that vines can be useful to investigate a variety of research problems.

What is your secret to running a successful research group of young scientists?

First, you should know that before I could organize a research group, I needed to find funding for it. For that, one first has to develop a vision. Then comes the hard work of writing grant applications to fund the research. It was always helpful for recruitment (once I had funding) to attract good students at the Master's level and give them small projects in my research area. For Master's supervision, I always involve a current PhD student as a co-advisor. We meet regularly to discuss the student's progress and help in the organization and write-up of their thesis. The same is true for PhD students, but with more freedom to choose the direction of their research. Initially, I have a precise doctoral project in mind and I consider myself responsible for overcoming obstacles as they occur. I am interested in finding solutions to problems rather than leaving someone alone. I also make sure that PhD students go to conferences to present their work and that they spend some time abroad with researchers in their field to learn new methods and approaches I am not familiar with.

You are known to work very hard and to be highly accessible to your students throughout the week. In contrast, you manage not to work on weekends. How do you do that?

I strongly believe in a work-life balance. My experience is that if I overwork, my motivation and creativity suffer, in addition to my health and well-being. On weekdays, I concentrate and work hard but on weekends, I need to do something different. Of course, this requires keeping a good overview of my workload, setting realistic goals, and learning to say no to some tasks and opportunities.

What are your hobbies?

I have many interests. In contrast to my intellectual activities, I enjoy doing something with my hands, such as pottery, drawing, photography, and gardening. I also like reading and traveling.

Acknowledgments and credits. Thank you for granting us this interview, Claudia. The answer to the question stated in Figure 4 is (from left to right): Paul Embrechts, Christian Genest, Harry Joe, Roger Cooke. Claudia's headshot next to the abstract was taken by Astrid Eckert. Figures 1, 2, 3, and 4 are courtesy of Lisa McShane, Claudia Czado, Johanna Nešlehová, and Andreas Heddergott, respectively.

References

[1] Aas, K., C. Czado, A. Frigessi, and H. Bakken (2009). Pair-copula constructions of multiple dependence. *Insurance Math. Econom. 44*(2), 182–198.

[2] Acar, E.F., C. Genest, and J. Nešlehová (2012). Beyond simplified pair-copula constructions. *J. Multivariate Anal. 110*, 74–90.

[3] Barthel, N., C. Geerdens, C. Czado, and P. Janssen (2019). Dependence modeling for recurrent event times subject to right-censoring with D-vine copulas. *Biometrics*, to appear. Available at https://onlinelibrary.wiley.com/doi/full/10.1111/biom.13014.

[4] Bauer, A., C. Czado, and T. Klein (2012). Pair-copula constructions for non-Gaussian DAG models. *Canad. J. Statist. 40*(1), 86–109.

[5] Bedford, T. and R.M. Cooke (2001). Probability density decomposition for conditionally dependent random variables modeled by vines. *Ann. Math. Artif. Intell. 32*(1-4), 245–268.

[6] Bedford, T. and R.M. Cooke (2002). Vines – a new graphical model for dependent random variables. *Ann. Statist. 30*(4), 1031–1068.

[7] Brechmann, E.C. and C. Czado (2013). Risk management with high-dimensional vine copulas: An analysis of the Euro Stoxx 50. *Stat. Risk Model. 30*(4), 307–342.

[8] Brechmann, E.C., C. Czado, and K. Aas (2012). Truncated regular vines in high dimensions with application to financial data. *Canad. J. Statist. 40*(1), 68–85.
[9] Czado, C. (1993). Norm restricted maximum likelihood estimators for binary regression models with parametric link. *Comm. Statist. Theory Methods 22*(8), 2259–2274.
[10] Czado, C. (1994). Parametric link modification of both tails in binary regression. *Statist. Papers 35*(1), 189–201.
[11] Czado, C. and A. Munk (1998). Assessing the similarity of distributions – finite sample performance of the empirical Mallows distance. *J. Statist. Comput. Simulation 60*(4), 319–346.
[12] Czado, C. and T.J. Santner (1992). The effect of link misspecification on binary regression inference. *J. Statist. Plann. Inference 33*(2), 213–231.
[13] Czado, C. and T.J. Santner (1992). Orthogonalizing parametric link transformation families in binary regression analysis. *Canad. J. Statist. 20*(1), 51–61.
[14] Dißmann, J., E.C. Brechmann, C. Czado, and D. Kurowicka (2013). Selecting and estimating regular vine copulae and application to financial returns. *Comput. Statist. Data Anal. 59*, 52–69.
[15] Erhardt, T.M., C. Czado, and U. Schepsmeier (2015). Spatial composite likelihood inference using local C-vines. *J. Multivariate Anal. 138*, 74–88.
[16] Gruber, L.F. and C. Czado (2018). Bayesian model selection of regular vine copulas. *Bayesian Anal. 13*(4), 1111–1135.
[17] Hanea, A.M., D. Kurowicka, and R.M. Cooke (2006). Hybrid method for quantifying and analyzing Bayesian belief nets. *Qual. Reliab. Eng. Int. 22*(6), 709–729.
[18] Jaworski, P., F. Durante, and W.K. Härdle (2013). *Copulae in Mathematical and Quantitative Finance.* Springer, Heidelberg.
[19] Joe, H. (2014). *Dependence Modeling with Copulas*. CRC Press, Boca Raton FL.
[20] Killiches, M. and C. Czado (2018). A D-vine copula based model for repeated measurements extending linear mixed models with homogeneous correlation structure. *Biometrics 74*(3), 997–1005.
[21] Killiches, M., D. Kraus, and C. Czado (2017). Examination and visualisation of the simplifying assumption for vine copulas in three dimensions. *Aust. N. Z. J. Stat. 59*(1), 95–117.
[22] Kraus, D. and C. Czado (2017). D-vine copula based quantile regression. *Comput. Statist. Data Anal. 110*, 1–18.
[23] Kraus, D. and C. Czado (2017). Growing simplified vine copula trees: improving Dißmann's algorithm. Available at https://arxiv.org/abs/1703.05203.
[24] Kreuzer, A. and C. Czado (2019). Efficient Bayesian inference for univariate and multivariate non linear state space models with univariate autoregressive state equation. Available at https://arxiv.org/abs/1902.10412.
[25] Kurowicka, D. and R.M. Cooke (2006). *Uncertainty Analysis with High Dimensional Dependence Modelling*. John Wiley & Sons, Chichester.
[26] Kurowicka, D. and R.M. Cooke (2007). Sampling algorithms for generating joint uniform distributions using the vine-copula method. *Comput. Statist. Data Anal. 51*(6), 2889–2906.
[27] Kurowicka, D. and H. Joe (2010). *Dependence Modeling: Vine Copula Handbook*. World Scientific Publishing, Singapore.
[28] Kurz, M.S. (2017). `pacotest`: *Testing for Partial Copulas and the Simplifying Assumption in Vine Copulas*. R package version 0.3.1. Available on CRAN.
[29] Kurz, M.S. and F. Spanhel (2017). Testing the simplifying assumption in high-dimensional vine copulas. Available at https://arxiv.org/abs/1706.02338.
[30] Min, A. and C. Czado (2010). Bayesian inference for multivariate copulas using pair-copula constructions. *J. Financial Econom. 8*(4), 511–546.
[31] Morales-Nápoles, O. (2010). Counting vines. In D. Kurowicka and H. Joe (Eds.), *Dependence Modeling: Vine Copula Handbook*, pp. 189–218. World Scientific Publishing, Singapore.
[32] Müller, D. and C. Czado (2018). Representing sparse Gaussian DAGs as sparse R-vines allowing for non-Gaussian dependence. *J. Comput. Graph. Statist. 27*(2), 334–344.
[33] Müller, D. and C. Czado (2019). Dependence modelling in ultra high dimensions with vine copulas and the Graphical Lasso. *Comput. Statist. Data Anal. 137*, 211–232.
[34] Munk, A. and C. Czado (1998). Nonparametric validation of similar distributions and assessment of goodness of fit. *J. R. Stat. Soc. Ser. B Stat. Methodol. 60*(1), 223–241.
[35] Nagler, T. (2017). `kdevine`: *Multivariate Kernel Density Estimation with Vine Copulas*. R package version 0.4.2. Available on CRAN.
[36] Nagler, T. and C. Czado (2016). Evading the curse of dimensionality in nonparametric density estimation with simplified vine copulas. *J. Multivariate Anal. 151*, 69–89.
[37] Nagler, T. and D. Kraus (2017). `vinereg`: *D-Vine Quantile Regression*. R package version 0.2.0.
[38] Nagler, T., C. Schellhase, and C. Czado (2017). Nonparametric estimation of simplified vine copula models: comparison of methods. *Depend. Model. 5*, 99–120.
[39] Newton, M.A., C. Czado, and R. Chappell (1996). Bayesian inference for semiparametric binary regression. *J. Amer. Statist. Assoc. 91*(433), 142–153.
[40] Panagiotelis, A., C. Czado, and H. Joe (2012). Pair copula constructions for multivariate discrete data. *J. Amer. Statist. Assoc. 107*(499), 1063–1072.

[41] Schallhorn, N., D. Kraus, T. Nagler, and C. Czado (2017). D-vine quantile regression with discrete variables. Available at https://arxiv.org/abs/1705.08310.

[42] Schellhase, C. (2017). `pencopulaCond`: *Estimating Non-Simplified Vine Copulas Using Penalized Splines*. R package version 0.2. Available on CRAN.

[43] Schellhase, C. (2017). `penRvine`: *Flexible R-Vines Estimation Using Bivariate Penalized Splines*. R package version 0.2. Available on CRAN.

[44] Schellhase, C. and F. Spanhel (2018). Estimating non-simplified vine copulas using penalized splines. *Stat. Comput. 28*(2), 387–409.

[45] Schepsmeier, U., J. Stöber, E.C. Brechmann, B. Gräler, T. Nagler, and T. Erhardt et al. (2018). `VineCopula`: *Statistical Inference of Vine Copulas*. R package version 2.1.8. Available on CRAN.

[46] Sklar, A. (1959). Fonctions de répartition à n dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris 8*, 229–231.

[47] Stöber, J. and C. Czado (2014). Regime switches in the dependence structure of multidimensional financial data. *Comput. Statist. Data Anal. 76*, 672–686.

[48] Stöber, J., H.G. Hong, C. Czado, and P. Ghosh (2015). Comorbidity of chronic diseases in the elderly: Patterns identified by a copula design for mixed responses. *Comput. Statist. Data Anal. 88*, 28–39.

[49] Taqqu, M.S. and C. Czado (1985). A survey of functional laws of the iterated logarithm for self-similar processes. *Comm. Statist. Stochastic Models 1*(1), 77–115.

[50] Vatter, T. and T. Nagler (2018). Generalized additive models for pair-copula constructions. *J. Comput. Graph. Statist. 27*(4), 715–727.