SPEAKERS

| | | | | | |
|---|---|---|---|---|---|
| P.-A. | ABSIL | Nicolas | COURTY | Antonio | ORTEGA |
| Sophie | ACHARD | Yohann | DE CASTRO | David | SHUMAN |
| Sergio | BARBAROSSA | Xiaowen | DONG | Dorina | THANOU |
| Simon | BARTHELMÉ | Mireille | EL GHECHE | Dimitri | VAN DE VILLE |
| Robert | BEINERT | Kimon | FOUNTOULAKIS | Titouan | VAYER |
| Pierre | BORGNAT | Elvin | ISUFI | Nicolas | VERZELEN |
| Fabienne | CASTELL | Haggai | MARRON | Ulrike | VON LUXBURG |

## Machine Learning & Signal Processing

# LearnGraph'22

## on Graphs

November 7-11

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Andreas LOUKAS
Nelly PUSTELNIK
Nicolas TREMBLAY
Samuel VAITER

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# Monday, November 7th, 2022

## 09:00am – 09:45am: Welcome to the CIRM!

## 09:45am – 10:30am: Sophie Achard (CNRS, Université Grenoble Alpes)

**Title**: Statistical comparisons of spatio-temporal networks (abstract)

## 10:30am – 11:00am: Coffee break

## 11:00am – 11:45am: Nicolas Verzelen (INRAE Montpellier)

**Title**: Localization in 1D non-parametric latent space models from pairwise affinities (abstract)

## 12:30pm – 02:00pm: Lunch

## 02:00pm – 04:00pm: Free discussion

The library (with several private rooms inside) is available to discuss, along with the Chapelle room and billiard room.

## 04:00pm – 04:45pm: Robert Beinert (TU Berlin)

**Title**: Learning from sparse data via normalizing flows (abstract)

## 04:45pm – 05:15pm: Coffee break

## 05:15pm – 06:00pm: David Shuman (Olin College)

**Title**: Signal Processing on the Permutahedron: Tight Spectral Frames for Ranked Data Analysis (abstract)

## 06:00pm – 07:30pm: Poster session I with welcome cocktail

## 07:30pm: Dinner

# Tuesday, November 8th, 2022

## 09:00am – 09:45am: Haggai Maron (NVIDIA Research)

**Title**: Subgraph-based networks for expressive, efficient, and domain-independent graph learning (abstract)

## 09:45am – 10:30am: Dorina Thanou (EPFL)

**Title**: The inductive bias of message passing neural networks (abstract)

## 10:30am – 11:00am: Coffee break

## 11:00am – 11:45am: Simon Barthelmé (CNRS, Université Grenobles-Alpes)

**Title**: Graph Sampling using Determinantal Point Processes (abstract)

## 12:30pm – 02:00pm: Lunch

## 02:00pm – 04:00pm: Free discussion

## 04:00pm – 04:45am: Kimon Fountoulakis (University of Waterloo)

**Title**: Graph Attention Retrospective (abstract)

## 04:45pm – 05:15pm: Coffee break

## 05:15pm – 06:00pm: Titouan Vayer (Inria Lyon)

**Title**: Towards Compressive Recovery of Sparse Precision Matrices (abstract)

## 06:00pm – 06:45pm: Dimitri Van De Ville (EPFL)

**Title**: Graph Signal Processing to Quantify Brain Structure-Function Coupling (abstract)

## 07:30pm: Dinner

# Wednesday, November 9th, 2022

## 09:00am – 09:45am: Pierre-Antoine Absil (UC Louvain)

**Title**: Graph-regularized matrix completion (abstract)

## 09:45am – 10:30am: Fabienne Castell (Aix-Marseille Université)

**Title**: Spectral estimation through Kirchoff's random forests (abstract)

## 10:30am – 11:00am: Coffee break

## 11:00am – 11:45am: Xiaowen Dong (University of Oxford)

**Title**: On the stability of spectral graph filters and beyond (abstract)

## 12:30pm – 02:00pm: Lunch

## 02:00pm – 07:30pm: Free afternoon

Trip to the calanques (bring an adequate pair of shoes!)

## 07:30pm: Dinner

# Thursday, November 10th, 2022

### 09:00am – 09:45am: Antonio Ortega (University of Southern California)

**Title**: Graph Constructions for Machine Learning Applications: New Insights and Algorithms (abstract)

### 09:45am – 10:30am: Ulrike Von Luxburg (University of Tübingen)

**Title**: Clustering with Tangles (abstract)

### 10:30am – 11:00am: Coffee break

### 11:00am – 11:45am: Nicolas Courty (Université Bretagne Sud)

**Title**: Optimal transport for graph-signal processing (abstract)

### 12:30pm – 02:00pm: Lunch

### 02:00pm – 04:00pm: Free discussion

### 04:00pm – 04:45pm: Yohann de Castro (Université Claude Bernard)

**Title**: Markov Random Geometric Graph (MRGG): A Growth Model for Temporal Dynamic Networks (abstract)

### 04:45pm – 05:15pm: Coffee break

### 05:15pm – 06:00pm: Sergio Barbarossa (Sapienza Università di Roma)

**Title**: Topological Signal Processing and Learning (abstract)

### 06:00pm – 07:30pm: Poster session II with cocktails

### 07:30pm: Dinner "Bouillaibaisse"

# Friday, November 11th, 2022

## 09:00am – 09:45am: Mireille El Gheche (Sony AI Zurich)

**Title**: Optimization Problems on Graphs (abstract)

## 09:45am – 10:30am: Pierre Borgnat (CNRS, ENS Lyon)

**Title**: Metric Learning for attributed graphs (abstract)

## 10:30am – 11:00am: Coffee break

## 11:00am – 11:45am: Elvin Isufi (TU Delft)

**Title**: Graph Neural Networks over Random Graphs (abstract)

## 12:30pm – 02:00pm: Lunch

## 02:00pm: Goodbye!

# Abstracts

## Pierre-Antoine Absil (UC Louvain)

**Title**: Graph-regularized matrix completion
**Abstract**: There is a broad interest in developing recommender systems that guide the choice of users between several available items. For example, as popularized by the Netflix prize, the items can be movies and the users can be customers. Each customer has rated some movies, and the recommendation task is to predict how much the customers would like the movies they did not rate, so as to make a personalized recommendation. A popular model posits that the movies-by-users matrix of ratings is approximately low-rank. This leads to the mathematical problem of finding a matrix of low rank that is optimal, in the sense that it agrees as well as possible (according to some criterion, e.g., mean square error) with the measured entries. Oftentimes, complementary information about the items or users is available that can be encoded as a graph. This yields a computational task termed graph-regularized low-rank matrix completion. Upstream, this topic will lead us in the realm of low-rank optimization, involving concepts of optimization on manifolds. Downstream, we will look at some applications of current interest that depart from classical recommendation tasks.

## Sophie Achard (CNRS, Université Grenoble Alpes)

**Title**: Statistical comparisons of spatio-temporal networks
**Abstract**: In the scenario where multiple instances of networks with same nodes are available and nodes are attached to spatial features, it is worth combining both information in order to explain the role of the nodes. The explainability of node role in complex networks is very difficult, however crucial in different application scenarios such as social science, neuroscience, computer science... Many efforts have been made on the quantification of hubs revealing particular nodes in a network using a given structural property. Yet, for spatio-temporal networks, the identification of node role remains largely unexplored. In this talk, I will show limitations of classical methods on a real datasets coming from brain connectivity comparing healthy subjects to coma patients. Then, I will present recent work using equivalence relation of the nodal structural properties. Comparisons of graphs with same nodes set is evaluated with a new similarity score based on graph structural patterns. This score provides a nodal index to determine node role distinctiveness in a graph family. Finally, illustrations on different datasets concerning human brain functional connectivity will be described.

## Sergio Barbarossa (Sapienza Università di Roma)

**Title**: Topological Signal Processing and Learning
**Abstract**: The goal of this lecture is to introduce the basic tools for processing signals defined over a topological space. In the last years, processing signals defined over graphs is a research field that attracted a lot of works because of its widespread applications. Graphs are just a simple example of a topological space, incorporating only pairwise relations. In the first part of this lecture, I will start introducing simplicial and cell complexes as examples of spaces incorporating higher order relations and still possessing a rich algebraic structure that facilitates the extraction of useful information from signals defined over

these spaces. I will motivate the introduction of a simplicial (or cell) Fourier Transform and show how to design filters and derive effective sampling strategies over a cell complex. Then I will present methods to infer the structure of the space from data. In the second part, I will move to the design of topological neural networks, operating on data living on a topological space. A number of applications will be presented to highlight the potentials of the proposed methods.

## Simon Barthelmé (CNRS, Université Grenobles-Alpes)

**Title**: Graph Sampling using Determinantal Point Processes
**Abstract**: A "graph signal" is a signal that is indexed by the nodes of a graph. For instance, in a social network, every node represents a user, every edge represents friendship, and an example of a graph signal may be the political leaning of each user. Since people tend to be friends with others with similar beliefs, we know that the signal is likely to be "smooth on the graph", meaning that it does not vary too much locally. For such smooth signals, we may be able to reconstruct the entire signal by measuring only at a small set of locations. We can think of this task as performing a survey on the graph, or as subsampling the nodes. Determinantal Point Processes (DPPs) offer a very generic way of dealing with such subsampling problems. In this talk I'll describe DPPs and show how they can be used to sample nodes in large graphs.

## Robert Beinert (TU Berlin)

**Title**: Learning from sparse data via normalizing flows
**Abstract**: Learning neural networks using only a small amount of data is an important ongoing research topic with tremendous potential for applications. We introduce a regularizer for the variational modeling of inverse problems in imaging based on normalizing flows, called patchNR. It involves a normalizing flow learned on patches of very few images. The subsequent reconstruction method is completely unsupervised and the same regularizer can be used for different forward operators acting on the same class of images. By investigating the distribution of patches versus those of the whole image class, we prove that our variational model is indeed a MAP approach. Numerical examples for low-dose CT, limited-angle CT and superresolution of material images demonstrate that our method provides high quality results among unsupervised methods, but requires only very few data. In the second part of the talk I will generalize normalizing flows to stochastic normalizing flows to improve their expressivity. Normalizing flows, diffusion normalizing flows and variational autoencoders are powerful generative models. A unified framework to handle these approaches appear to be Markov chains. We consider stochastic normalizing flows as a pair of Markov chains fulfilling some properties and show how many state-of-the-art models for data generation fit into this framework. Indeed including stochastic layers improves the expressivity of the network and allows for generating multimodal distributions from unimodal ones. The Markov chains point of view enables us to couple both deterministic layers as invertible neural networks and stochastic layers as Metropolis-Hasting layers, Langevin layers, variational autoencoders and diffusion normalizing flows in a mathematically sound way. Our framework establishes a useful mathematical tool to combine the various approaches.

## Pierre Borgnat (CNRS, ENS Lyon)

**Title**: Metric Learning for attributed graphs
**Abstract**: The choice of good distances and similarity measures between objects is important for many machine learning methods. Therefore, many metric learning algorithms have been developed in recent years, mainly for Euclidean data in order to improve performance of classification or clustering methods.However, due to difficulties in establishing computable, efficient and differentiable distances between attributed graphs, few metric learning algorithms adapted to graphs have been developed, despite the strong interest of the community. In this work, we address this question by proposing a new Simple Graph Metric Learning (SGML) model with few trainable parameters that we base on Simple Convolutional Neural Networks and elements of optimal transport theory. This model allows us to build an appropriate distance from a database of labeled (attributed) graphs to improve the performance of simple classification algorithms such as k-NN. Some properties of the distance will be discussed. Especially, this distance can be trained efficiently (with a good scaling) while maintaining good performance as illustrated by the experimental study that we conducted. Joint work with Yacouba Kaloga and Amaury Habrard

## Fabienne Castell (Aix-Marseille Université)

**Title**: Spectral estimation through Kirchoff's random forests
**Abstract**: Let $L$ be the Laplacian of a non oriented edge-weighted graph $G$, with spectral measure $\sigma$. Associated to $L$ and an extra parameter $q$, we can construct a random rooted spanning forest on $G$, the so-called Kirchoff's forest. We show that this forest can be used to get good estimations of the Stieltjes transform of $\sigma$, with a cost which is almost linear in the number of nodes of $G$. These estimations can then be used to obtain estimations of the cdf of $\sigma$. This a joint work with P.O. Amblard, S. Barthelmé, A. Gaudillière, C. Mélot, M. Quattropani, N. Tremblay.

## Nicolas Courty (Université Bretagne Sud)

**Title**: Optimal transport for graph-signal processing
**Abstract**: In this talk I will discuss how a variant of the classical optimal transport problem, known as the Gromov-Wasserstein distance, can help in designing learning tasks over graphs, and allow to transpose classical signal processing or data analysis tools such as dictionary learning or online change detection, for learning over those types of structured objects. Both theoretical and practical aspects will be discussed.

## Yohann de Castro (Université Claude Bernard)

**Title**: Markov Random Geometric Graph (MRGG): A Growth Model for Temporal Dynamic Networks
**Abstract**: In this talk, we introduce a growth model for relatively dense networks based on Markovian latent variables. We show that one can infer the latent Markovian dynamic and the latent pairwise distances between nodes, and predict the probabilities of connection of a new node entering the network. This talk is based on the article: "Markov Random Geometric Graph (MRGG): A Growth Model for Temporal Dynamic Networks", with Q. Duchemin, Electronic Journal of Statistics, Volume 16, Pages 671-699, 2022.

## Xiaowen Dong (University of Oxford)

**Title**: On the stability of spectral graph filters and beyond

**Abstract**: Data collected in network domains, hence supported by an (irregular) graph rather than a (regular) grid-like structure, are becoming pervasive. Typical examples include gene expression data associated with a protein-protein interaction graph, or behaviours of a group of individuals in a social network. Graph-based signal processing and machine learning are recent techniques that have been developed to handle such graph-structured data and have seen applications in such diverse fields as drug discovery, fake news detection, and traffic prediction. However, a theoretical understanding of the robustness of these models against perturbation to the input graph domain has been lacking. In this talk, I will present our results on the stability bounds of spectral graph filters as well as other recent work on the robustness of graph machine learning models, which together will contribute to the deployment of these models in real-world scenarios.

## Mireille El Gheche (Sony AI Zurich)

**Title**: Optimization Problems on Graphs

**Abstract**: In many network-based applications, high-dimensional data naturally reside on the vertices of weighted graphs. Graph signal processing merges algebraic and spectral graph theoretic concepts with computational harmonic analysis to process such signals on graphs. In this presentation, we outline the main challenges of the area and highlight the importance of incorporating the irregular structures of graph data domains when processing signals on graphs. We then detail two novel approaches to solve two important problems. First, we will present a recent framework based on optimal transport for the graph alignment problem, which derive a simple, yet novel and powerful, distance between graphs based on the Wasserstein distance between the distribution of random Gaussian models following the two graphs being compared. Second, we will show a graph-based depth refinement framework introducing a novel regularizer which promotes the reconstruction of piece-wise planar scenes explicitly, but, thanks to the graph underneath, it is flexible enough to handle non fully piece-wise planar scenes as well.

## Kimon Fountoulakis (University of Waterloo)

**Title**: Graph Attention Retrospective

**Abstract**: Graph-based learning is a rapidly growing sub-field of machine learning with applications in social networks, citation networks, and bioinformatics. One of the most popular type of models is graph attention networks. These models were introduced to allow a node to aggregate information from the features of neighbor nodes in a non-uniform way in contrast to simple graph convolution which does not distinguish the neighbors of a node. In this paper, we study theoretically this expected behaviour of graph attention networks. We prove multiple results on the performance of the graph attention mechanism for the problem of node classification for a contextual stochastic block model. Here the features of the nodes are obtained from a mixture of Gaussians and the edges from a stochastic block model where the features and the edges are coupled in a natural way. First, we show that in an "easy" regime, where the distance between the means of the Gaussians is large enough, graph attention maintains the weights of intra-class edges and significantly reduces the weights of the inter-class edges. As a corollary, we show that this implies perfect node classification independent of the weights of inter-class edges. However, a classical argument shows that in the "easy" regime, the graph is not needed at all to classify the data with high probability. In the "hard" regime, we show that every attention mechanism fails to distinguish intra-class from inter-class edges. We evaluate our theoretical results on synthetic and real-world data.

## Elvin Isufi (TU Delft)

**Title**: Graph Neural Networks over Random Graphs

**Abstract**: Graph neural networks (GNNs) model nonlinear representations in graph data with applications in distributed agent coordination, control, and planning among others. Current GNNs assume scenarios with deterministic graphs but ignore random topological changes that occur due to environment, human factors, or external attacks. Motivated by the latter, we developed a stochastic framework for GNNs intersecting it with random graph theory and stochastic optimisation. This framework has the following three thrusts. First, we investigated the stability of GNNs to stochastic graph perturbations. The stability result indicates GNNs can maintain performance under mild random perturbations and identifies the role played by the graph stochasticity, filter property and NN architecture.Second, we put forth stochastic graph neural networks (SGNNs) that account for the graph stochasticity during training. SGNNs make each node rely on its neighbors with some uncertainty and thus, become robust to random topological changes. Statistical analysis on the variance of the SGNN output is conduct to identify how random SGNN realizations deviate from the optimized expectation. While providing theoretical implications, there is no guarantee about these random deviations and undesirable performance may appear in individual realizations even when the expected performance is satisfactory. Hence, third, we proposed a learning strategy for SGNNs with constrained variance that searches for a balance between the expected performance and the stochastic deviation. It adheres to solving a variance-constrained stochastic optimization problem, where we introduce a primal-dual learning algorithm for a saddle point solution. We show stochastic deviations can be explicitly controlled and thus, individual SGNN performance can be guaranteed. The talk will be based on the following three papers:

- Gao, Zhan, Elvin Isufi, and Alejandro Ribeiro. "Stability of graph convolutional neural networks to stochastic perturbations." Signal Processing 188 (2021): 108216.
- Gao, Zhan, Elvin Isufi, and Alejandro Ribeiro. "Stochastic graph neural networks." IEEE Transactions on Signal Processing 69 (2021): 4428-4443.
- Gao, Zhan, and Elvin Isufi. "Learning Stochastic Graph Neural Networks with Constrained Variance." arXiv preprint arXiv:2201.12611 (2022).

## Haggai Maron (NVIDIA Research)

**Title**: Subgraph-based networks for expressive, efficient, and domain-independent graph learning

**Abstract**: While message-passing neural networks (MPNNs) are the most popular architectures for graph learning, their expressive power is inherently limited. In order to gain increased expressive power while retaining efficiency, several recent works apply MPNNs to subgraphs of the original graph. As a starting point, the talk will introduce the Equivariant

Subgraph Aggregation Networks (ESAN) architecture, which is a representative framework for this class of methods. In ESAN, each graph is represented as a set of subgraphs, selected according to a predefined policy. The sets of subgraphs are then processed using an equivariant architecture designed specifically for this purpose. I will then present a recent follow-up work that revisits the symmetry group suggested in ESAN and suggests that a more precise choice can be made if we restrict our attention to a specific popular family of subgraph selection policies. We will see that using this observation, one can make a direct connection between subgraph GNNs and Invariant Graph Networks (IGNs), thus providing new insights into subgraph GNNs' expressive power and design space.

## Antonio Ortega (University of Southern California)

**Title**: Graph Constructions for Machine Learning Applications: New Insights and Algorithms

**Abstract**: Graphs have long been used in a wide variety of problems, such as in analysis of social networks, machine learning, network protocol optimization or image processing. In the last few years, a growing body of work has been developed to extend and complement well known concepts in spectral graph theory, leading to the emergence of Graph Signal Processing (GSP) as a broad research field. In this talk we focus on summarizing recent results that lead to a GSP perspective of machine learning problems. The key observation is that representations of sample data points (e.g., images in a training set) can be used to construct graphs, with nodes representing samples, label information resulting in graph signals, and edge weights capturing the relative positions of samples in feature space. We will first review how this perspective has been used in well known techniques for label propagation and semi-supervised learning. Then, we will introduce the non-negative kernel regression (NNK) graph construction, describe its properties, and introduce example applications in machine learning areas such as i) model explainability, ii) local interpolative classification and iii) self-supervised learning.

## David Shuman (Olin College)

**Title**: Signal Processing on the Permutahedron: Tight Spectral Frames for Ranked Data Analysis

**Abstract**: Ranked data sets, where m judges/voters specify a preference ranking of n objects/candidates, are increasingly prevalent in contexts such as political elections, computer vision, recommender systems, and bioinformatics. The vote counts for each ranking can be viewed as an n! data vector lying on the permutahedron, which is a Cayley graph of the symmetric group with vertices labeled by permutations and an edge when two permutations differ by an adjacent transposition. Leveraging combinatorial representation theory and recent progress in signal processing on graphs, we investigate a novel, scalable transform method to interpret and exploit structure in ranked data. We represent data on the permutahedron using an overcomplete dictionary of atoms, each of which captures both smoothness information about the data (typically the focus of spectral graph decomposition methods in graph signal processing) and structural information about the data (typically the focus of symmetry decomposition methods from representation theory). These atoms have a more naturally interpretable structure than any known basis for signals on the permutahedron, and they form a Parseval frame, ensuring beneficial numerical properties such as energy preservation. We develop specialized algorithms and open software that take advantage of the symmetry and structure of the permutahedron to improve the scalability of the proposed method, making it more applicable to the high-dimensional ranked data found in applications.

## Dorina Thanou (EPFL)

**Title**: The inductive bias of message passing neural networks

**Abstract**: Recent literature extensively analyzed the representation power of graph neural networks and ways to build more expressive architectures than the standard message-passing neural networks (MPNNs). Yet, MPNNs remain the most widely used class of networks thanks to their favorable computational complexity and good empirical performance. This talk will focus on the inductive bias of MPNNs, and will shed some light on the question: Inside that class of functions that MPNNs can learn, what are the functions that they tend to learn? We will show that MPNNs tend to learn representations of rooted subtrees that are smooth with respect to Weisfeiler-Lehman similarity measure. This bias contributes to the good empirical performance achieved on real word datasets. Overall, our analysis provides insight on the generalization abilities of graph networks, and, in particular, on the conditions under which they can generalize to larger graphs than they have been trained on.

## Dimitri Van De Ville (EPFL)

**Title**: Graph Signal Processing to Quantify Brain Structure-Function Coupling

**Abstract**: State-of-the-art magnetic resonance imaging (MRI) provides unprecedented opportunities to study brain structure (anatomy) and function (physiology). Based on such data, graph representations can be built where nodes are associated to brain regions and edge weights to strengths of structural or functional connections. In particular, structural graphs capture major neural pathways in white matter, while functional graphs map out statistical interdependencies between pairs of regional activity traces. Network analysis of these graphs has revealed emergent system-level properties of brain structure or function, such as efficiency of communication and modular organization. In this talk, graph signal processing (GSP) will be presented as a novel framework to integrate brain structure, contained in the structural graph, with brain function, characterized by activity traces that can be considered as time-dependent graph signals. Such a perspective allows to define novel meaningful graph-filtering operations of brain activity that take into account smoothness of signals on the anatomical backbone. This allows to define a new measure of "coupling" between structure and function, termed the structural decoupling index (SDI), based on how activity is expressed on structural graph harmonics of different graph frequencies. To provide statistical inference, we extend the well-known Fourier phase randomization method to generate surrogate data to the graph setting. The SDI reveals a behaviorally relevant spatial gradient, where sensory regions tend to be more coupled with structure, and high-level cognitive ones less so. In addition, SDI maps are informative both for task decoding and individual fingerprinting pointing again toward the different involvement of unimodal and transmodal regions, respectively. Finally, recent work will highlight how the spatial resolution of GSP brain graphs can be increased to the voxel level, representing a few hundredth thousands of nodes.

## Titouan Vayer (Inria Lyon)

**Title**: Towards Compressive Recovery of Sparse Precision Matrices

**Abstract**: We consider the problem of learning a graph modeling the statistical relations of the $d$ variables of a dataset with $n$ samples. Standard approaches amount to searching for a precision matrix $\mathbf{\Theta}$ representative of a Gaussian graphical model that adequately explains the data. However, most maximum likelihood based estimators usually require to store the $d^2$ values of the empirical covariance matrix, which is often too costly in a high-dimensional setting. In this work we adopt a "compressive" viewpoint and look for estimating a sparse $\mathbf{\Theta}$ from a *sketch* of the data, *i.e.* a low-dimensional vector of size $m << d^2$ carefully designed from the data using nonlinear random features. Under certain assumptions on the spectrum of $\mathbf{\Theta}$, we show that it is theoretically possible to estimate it robustly from a sketch of size $m = \mathcal{O}\left((d+2k)\ln(d)\right)$ where $k$ is the maximal number of edges of the underlying graph and with an error that decreases in $\mathcal{O}(n^{-1/2})$. These guarantees are inspired from the compressed sensing theory and involve restricted isometric properties and instance optimal decoders. Our estimator requires solving a non-convex inverse problem and we investigate the possibility of achieving practical recovery by a variant of the Davis-Yin three operator splitting algorithm. We compare our approach with "Graphical LASSO" type estimators on synthetic datasets. Finally, we discuss in a last part the limitations and perspectives of this work, which partially answers some questions but also opens many others.

## Nicolas Verzelen (INRAE Montpellier)

**Title**: Localization in 1D non-parametric latent space models from pairwise affinities

**Abstract**: We consider the problem of estimating latent positions in a one-dimensional torus from a graph pairwise affinities. The observed affinity between a pair of items is modeled as a noisy observation of a function $f(x_i^*, x_j^*)$ of the latent positions $x_i^*, x_j^*$ of the two items on the torus. The affinity function $f$ is unknown, and it is only assumed to fulfill some shape constraints ensuring that $f(x, y)$ is large when the distance between $x$ and $y$ is small, and vice-versa. This non-parametric modeling includes in particular random geometric graphs and seriation problems. We introduce an estimation procedure that provably localizes all the latent positions with a maximum error of the order with high-probability. This rate is proven to be minimax optimal. A computationally efficient variant of the procedure is also analyzed under some more restrictive assumptions.

## Ulrike Von Luxburg (University of Tübingen)

**Title**: Clustering with Tangles

**Abstract**: Originally, tangles were invented as an abstract tool in mathematical graph theory to prove the famous graph minor theorem. In the talk, I will showcase the potential of tangles in machine learning applications. Given a collection of cuts of any dataset, tangles aggregate these cuts to point in the direction of a dense structure. As a result, a cluster is softly characterized by a set of consistent pointers. This highly flexible approach can solve clustering problems in various setups, ranging from questionnaires over community detection in graphs to clustering points in metric spaces.