Date	Time	Format	Speaker
30 May	9-9.05	Welcome	Jon Forster
	9.05-9.55	Talk	George Michailidis
	9.55-10.10	Coffee break	
	10.10-11	Talk	Carey Priebe
	11-11.50	Talk	Yao Xie
	11.50-13.30	Lunch	
	13.30-15.30	Panel discussions (session 1)	
	15.30-15.45	Coffee break	
	15.45-16.35	Talk	Feiyu Jiang
	16.35-17.25	Talk	Guillem Rigaill
	17.25-17.45	Day 1 conclusions	
	17.45-19	Wine reception	
31 May	9-9.50	Talk	Paul Fearnhead
	9.50-10.10	Coffee break	
	10.10-11	Talk	Chun Yip Yau
	11-11.50	Talk	Olga Klopp
	11.50-14	Lunch	
	14-15.30	ECR short talks	
	15.30-15.45	Coffee break	
	15.45-16.35	Talk	Aaditya Ramdas
	16.35-17.25	Talk	Weining Wang
	17.25-17.45	Day 2 conclusions	
	19-21	Dinner @Radcliffe (invitation only)	
1 June	9-9.50	Talk	Paromita Dubey
	9.50-10.40	Talk	Lorenzo Cappello
	10.40-11	Coffee break	
	11-12.30	Panel discussions (session 2)	

ECR short talks: Fan Wang; Hyeyoung Maeng; Mengyi Gong; Wanshan Li; Haotian Xu; Zilong Xie; Mengchu Li; Yudong Chen; Federica Spoto.

30 May: Panel discussions (session 1)

- Deep learning related

  Discussants: Paromita Dubey, Pierpaolo Brutti, Aaditya Ramdas, Yao Xie, Weining Wang

- Model selection related

  Discussants: Benjamin Yakir, Guillem Rigaill, Sabyasachi Chatterjee, Feiyu Jiang

- Limiting distributions

  Discussants: Lajos Horvath, Chun Yip Yau, Weining Wang, Haotian Xu

1 June: Panel discussions (session 2)

- Sequential analysis

  Discussants: Aaditya Ramdas, Guillem Rigaill, Yao Xie, George Michailidis

- Dynamic networks

  Discussants: Carey Priebe, Qiwei Yao, Olga Klopp

- Other topics

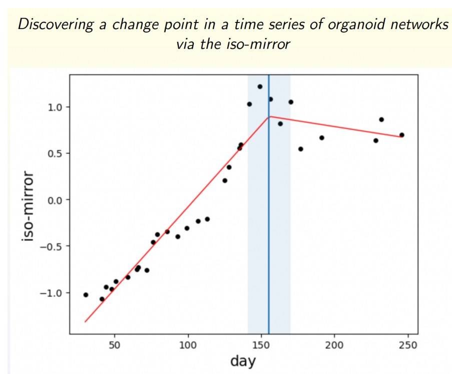
  - Transfer learning
    Discussants: Haeran Cho, Fan Wang
  - Robustness
    Discussant: Mengchu Li
  - Improvement of metrics of interest upon change point detection
    Discussant: Wanshan Li

30 May

<u>George Michailidis</u>
Title: Computational and Inference Issues in Offline Change Point Detection
Abstract: The talk discusses the following two topics: (i) computational considerations in change point detection for complex statistical models and (ii) construction of confidence intervals in high-dimensional mean shift models. For the first topic, we consider specific examples of computationally less demanding surrogate models and the settings wherein they can provide accurate estimates of the underlying change points. For the second topic, a locally refitted least squares estimator is proposed that enables construction of component-wise and simultaneous limiting distributions (and thus confidence intervals) for the change points in both vanishing and non-vanishing signal size regimes. Further, we study the relationship between the distributions of these regimes, that enables construction of regime adaptive confidence intervals.

<u>Carey Priebe</u>
Title: Discovering a change point and piecewise linear structure in a time series of networks via the iso-mirror

Abstract: We present a novel statistical method called spectral mirror estimation to analyze a time series of networks. This method produces a one-dimensional iso-mirror representation of the dynamics of the time series of networks which can extract piecewise linear structure. Classical change point analysis can then be applied to this representation.



<u>Yao Xie</u>
Title: Window-limited adaptive CUSUM for online change-point detection
Abstract: We study the online changepoint detection problem and propose a joint detection/estimation scheme, Window-Limited CUSUM, combining the cumulative sum (CUSUM) test with a sliding window-based consistent estimate of the post-change parameters. We characterize the optimal choice of the window size and show that the Window-Limited CUSUM enjoys first-order asymptotic optimality as the average run length approaches infinity under the optimal choice of window length. Compared to existing schemes with similar asymptotic optimality properties, our test can be much faster computed because it can recursively update the CUSUM statistic by employing the estimate of the post-change parameters. We demonstrate the use of the general framework on subspace change, network change, and neural network-based change-point detections.

<u>Feiyu Jiang</u>
Title: High-Dimensional Dynamic Pricing under Non-Stationarity: Learning and Earning with Change-Point Detection
Abstract: We consider a high-dimensional dynamic pricing problem under non-stationarity, where a firm sells products to T sequentially arriving consumers that behave according to an unknown demand model with potential changes at unknown times. The demand model is

assumed to be a high-dimensional generalized linear model (GLM), allowing for a feature vector in $\mathbb{R}^d$ that encodes products and consumer information. To achieve optimal revenue (i.e., least regret), the firm needs to learn and exploit the unknown GLMs while monitoring for potential change-points. To tackle such a problem, we first design a novel penalized likelihood-based online change-point detection algorithm for high-dimensional GLMs, which is the first algorithm in the change-point literature that achieves optimal minimax localization error rate for high-dimensional GLMs. A change-point detection assisted dynamic pricing (CPDP) policy is further proposed and achieves a near-optimal regret of order $O(s\sqrt{\Upsilon_T T}\log(Td))$, where s is the sparsity level, and Υ_T is the number of change-points. This regret is accompanied with a minimax lower bound, demonstrating the optimality of CPDP (up to logarithmic factors). In particular, the optimality with respect to Υ_T is seen for the first time in the dynamic pricing literature and is achieved via a novel accelerated exploration mechanism. Extensive simulation experiments and a real data application on online lending illustrate the efficiency of the proposed policy and the importance and practical value of handling non-stationarity in dynamic pricing.
This is joint work with Zifeng Zhao (Norte Dame), Yi Yu (Warwick) and Xi Chen (NYU). https://arxiv.org/abs/2303.07570.

Guillem Rigaill
Title: Fast Online Changepoint Detection via Functional Pruning CUSUM statistics
Abstract: Many modern applications of online changepoint detection require the ability to process high-frequency observations, sometimes with limited available computational resources. Online algorithms for detecting a change in mean often involve using a moving window, or specifying the expected size of change. Such choices affect which changes the algorithms have most power to detect. We introduce an algorithm, Functional Online CuSUM (FOCuS), which is equivalent to running these earlier methods simultaneously for all sizes of window, or all possible values for the size of change. Our theoretical results give tight bounds on the expected computational cost per iteration of FOCuS, with this being logarithmic in the number of observations.
This is joint work with Gaetano Romano, Idris Eckley and Paul Fearnhead from Lancaster University. https://arxiv.org/abs/2110.08205, https://www.jmlr.org/papers/v24/21-1230.html

31 May

Paul Fearnhead

Title: Testing for a change in mean after changepoint detection

Abstract: While many methods are available to detect structural changes in a time series, few procedures are available to quantify the uncertainty of these estimates post-detection. In this work, we fill this gap by proposing a new framework to test the null hypothesis that there is no change in mean around an estimated changepoint. We further show that it is possible to efficiently carry out this framework in the case of changepoints estimated by binary segmentation and its variants, segmentation, or the fused lasso. Our setup allows us to condition on much less information than existing approaches, which yields higher powered tests.
This is joint work with Sean Jewell, Daniela Witten and Rachel Carrington.

Chun Yip Yau

Title: A Composite Likelihood-based Approach for Change-point Detection in Spatio-temporal Processes

Abstract: This paper develops a unified and computationally efficient method for change-point inference in non-stationary spatio-temporal processes. By modeling a non-stationary spatio-temporal process as a piecewise stationary spatio-temporal process, we consider simultaneous estimation of the number and locations of change-points, and model parameters in each segment. A composite likelihood-based criterion is developed for change-point and parameter estimation. Under the framework of increasing domain asymptotics, theoretical results including consistency and distribution of the estimators are derived under mild conditions. In contrast to classical results in fixed dimensional time series that the localization error of change-point estimator is $O_p(1)$, exact recovery of true change-points can be achieved in the spatio-temporal setting. More surprisingly, the consistency of change-point estimation can be achieved without any penalty term in the criterion function. In addition, we further establish consistency of the change-point estimator under the infill asymptotics framework where the time domain is increasing while the spatial sampling domain is fixed. A computationally efficient pruned dynamic programming algorithm is developed for the challenging criterion optimization problem. Extensive simulation studies and an application to the U.S. precipitation data are provided to demonstrate the effectiveness and practicality of the proposed method.

Olga Klopp

Title: Change-Point Detection in Dynamic Networks

Abstract: Structural changes occur in dynamic networks quite frequently and its detection is an important question in many applications. Real-life networks are often incompletely observed due to individual non-response or network size. In this work we consider the problem of change-point detection at a temporal sequence of partially observed networks. The goal is to test whether there is a change in the network parameters. Our approach is based on the Matrix CUSUM test statistic and allows growing size of networks. We show that the proposed test is minimax optimal and robust to missing links. We also demonstrate the good behavior of our approach in practice.

Haotian Xu

Title: Online network change point detection with missing values and temporal dependence

Abstract: In this talk, we focus on online change point detection in dynamic networks with dependence and heterogeneous missing pattern across the networks and the time course. The

missingness probabilities, the entrywise sparsity of networks, the rank of networks and the jump size in terms of the Frobenius norm, are all allowed to vary as functions of the pre-change sample size. To the best of our knowledge, such general framework has not been rigorously studied before in the literature. We propose a polynomial-time change point detection algorithm, with a version of soft-impute algorithm (e.g., Mazumder et al., 2010; Klopp, 2015) as the imputation sub-routine. We investigate the fundamental limits of this problem and show that the detection delay of our algorithm is nearly optimal, saving for logarithmic factors, in some low-rank regimes, with a pre-specified tolerance on the probability of false alarms. Extensive numerical experiments are conducted demonstrating the outstanding performances of our proposed method in practice. The proposed methods are implemented in the R package changepoints.
This is joint work with Paromita Dubey (USC) and Yi Yu (Warwikc).
https://arxiv.org/abs/2110.06450.

Federica Spoto
Title: Spherical autoregressive multiple change-point detection
Abstract: Spatio-temporal processes arise very naturally in a number of different applied fields, like Cosmology, Astrophysics, Geophysics, Climate and Atmospheric Science. In most of these areas, the detection of structural breaks or regime shifts in the data stream is key. To this end, we aim at generalizing the recently introduced SPHAR(p) process by allowing for temporal changes in its functional parameters and variability structure. Our approach, which intrinsically integrates the spatial and temporal dimensions, could give multiscale insights into both the global and local behavior of changes, and its performance will be tested on a real dataset of global surface temperature anomalies.

Mengyi Gong
Title: A changepoint-based approach to modelling soil moisture dynamics
Abstract: Soil moisture is an important measure of soil health that scientists model via soil drydown curves. The typical modelling process requires manually identifying the segments corresponding to the drying process and fitting exponential decay models to these segments to extract key infiltration parameters. This can be repetitive and time consuming. The result is often a static overview of the infiltration property.
With the advancement of sensor technology, scientists can now obtain higher frequency measurements over longer periods in a larger number of locations. To enable automatic data processing, a changepoint-based approach is developed to identify structural changes in the time series and to investigate the dynamics of the infiltration properties. Specifically, timings of the sudden rises in soil moisture over a long time series are captured and the parameters characterising the drydown processes following the sudden rises are estimated simultaneously. An algorithm based on the penalised exact linear time (PELT) method was developed to identify the changepoints. Applying the algorithm to simulated and real data show good performance of the method.
This method can be considered as a complement to the conventional soil drydown modelling. It requires little data pre-processing and can be applied to a soil moisture time series directly. The segment specific parameters also allow the method to capture any temporal variations in the drydown process, thus providing a more comprehensive summary of the data.
To improve the flexibility of the approach, so that the segments corresponding to low temperature or saturated period when no drydown occurs can also be identified, a method based on the on-line inference of multiple changepoints is currently being investigated. It allows the selection of

different types of models while detecting the changepoints to describe the segments with distinctively different patterns. Extension to estimate the parameters unique to each segment is under development.
This is joint work with Prof. Rebecca Killick and Prof. Christopher Nemeth.

Yudong Chen & Mengchu Li (10 min each)
Title: Robust high-dimensional change point detection under heavy tails
Abstract: We study the mean change point detection problem for heavy-tailed high-dimensional data. Firstly, we show that when each component of the error vector follows an independent sub-Weibull distribution, a CUSUM-type statistic achieves the minimax testing rate in almost all sparsity regimes. Secondly, when the error distributions have polynomially decaying tails – admitting bounded αth moment for some $\alpha \geq 4$, we introduce a median-of-means-type statistic that achieves a near-optimal testing rate in both the dense and the sparse regime. A 'black-box' robust sparse mean estimator is then combined with the median-of-means-type statistic to achieve optimality in the sparse regime. Although such an estimator is usually computationally inefficient for its original purpose of mean estimation, our combined approach for change point detection is polynomial-time. Lastly, we investigate the even more challenging case when $2 \leq \alpha < 4$ and unveil a new phenomenon that the (minimax) testing rate has no sparse regime, i.e. testing sparse changes is information-theoretically as hard as testing dense changes. We show that the dependence of the testing rate on the data dimension exhibits a phase transition at $\alpha = 4$. This is joint work with Tengyao Wang (LSE) and Yi Yu (Warwick).

Hyeyoung Maeng
Title: Robust bottom-up approach for high-dimensional changepoint detection
Abstract: The impact of sparsity of change has been actively studied under the high-dimensional settings. While many methods have been developed for detecting sparse changes, few methods are available for a more general alternative where both sparse and dense changes exist. It is known that the L_2 aggregation performs well in detecting dense and gentle changes, while the L_∞ aggregation is more effective for detecting sparse and strong changes. To achieve robustness against sparsity in detecting changepoints, we use both L_2 and L_∞ aggregations by combining their ranks. We perform these aggregations in a bottom-up way by consecutively merging neighbouring segments of the data starting from the finest level. Compared to many existing variants of binary segmentation which operate a top-down (i.e. divisive) algorithm, bottom-up approach performs well for a set of signals with long segments or frequent change-points with short segments or a mix of those. This is joint work with Tengyao Wang and Piotr Fryzlewicz at London School of Economics.

Fan Wang
Title: Online Change Point Detection in Multilayer Random Dot Product Graphs.
Abstract: We begin by introducing the multilayer random dot product graph (MRDPG) model, which extends the random dot product graph model to multilayer networks. The MRDPG model is useful for incorporating nodes' latent positions when understanding connectivity.
Moving from a single MRDPG to a sequence of MRDPGs, we are concerned with an online change point detection problem in dynamic multilayer random dot product graphs (D-MRDPGs), especially with random latent positions. At every time point, we observe a realisation from an L-layered MRDPG. Across layers, we assume that common node sets and random latent positions are shared but allow for different connectivity matrices. Formulating the realisation as an

adjacency tensor, the connectivity is characterised by an L-dimensional distribution. Across time, we assume that the distribution sequence possesses an abrupt change. Our goal is to detect this distributional change in an online fashion. With control of false alarms, we aim to detect the change with minimal delay. We devise a novel nonparametric change point detection algorithm, with a kernel estimator in its core, allowing for the case when the density does not exist. An upper bound on the detection delay is derived, allowing for the node labels to vary across time and the model parameters, including the number of nodes, the dimension of latent position and the magnitude of the change, to vary as functions of the change point location.
This is joint work with Wanshan Li (CMU), Oscar Madrid (UCLA), Yi Yu (Warwick) and Alessandro Rinaldo (CMU).

Zilong Xie
Title: A Simultaneous Change Detection Method for Large-Scale Market Basket Data
Abstract: Large-scale market basket data provides valuable insight into customer behaviour and can be used to develop more effective recommendation systems. This study aims to detect changes in customer product preferences using longitudinal market basket data. Existing change point detection methods are not suitable for this task due to the high-dimensional and complex data structures. To address this, we propose a new model that combines factor analysis, a multinomial choice model, and change points. A likelihood-based procedure is proposed that simultaneously decides whether a change point exists for each customer, infers the location of each change point, and estimates the unknown model parameters. To efficiently solve the optimisation of the likelihood-based procedure, a stochastic optimisation algorithm is proposed. Simulation and real data analysis results are presented to demonstrate the efficacy of the proposed procedure.
This is joint work with Yunxiao Chen (LSE), Shiqi Liu (Fudan & Warwick), Wen Yu (Fudan) and Yi Yu (Warwick).

Wanshan Li
Title: Detecting Abrupt Changes in Sequential Pairwise Comparison Data
Abstract: The Bradley-Terry-Luce (BTL) model is a classic and very popular statistical approach for eliciting a global ranking among a collection of items using pairwise comparison data. In applications in which the comparison outcomes are observed as a time series, it is often the case that data are non-stationary, in the sense that the true underlying ranking changes over time. In this paper we are concerned with localizing the change points in a high-dimensional BTL model with piece-wise constant parameters. We propose novel and practicable algorithms based on dynamic programming that can consistently estimate the unknown locations of the change points. We provide consistency rates for our methodology that depend explicitly on the model parameters, the temporal spacing between two consecutive change points and the magnitude of the change. We corroborate our findings with extensive numerical experiments and a real-life example.

Aaditya Ramdas
Title: E-detectors and backward confidence sequences
Abstract: This talk will present two general reduction schemes for nonparametric sequential change detection based on e-processes and confidence sequences. E-processes are nonparametric composite generalizations of likelihood ratios, and confidence sequences are time-uniform sequential generalizations of confidence intervals. The reduction schemes are designed for complementary settings: e-detectors work when the pre- and post-change (composite) classes of

distributions are non-intersecting (eg: "the entropy changed from < 0.25 to > 0.25"), while backward confidence sequences work when they are identical (eg: "the entropy changed"). Both schemes nonasymptotically control the average run length. In parametric settings, both achieve the optimal detection delays up to constants. They provide the first change detection schemes for many nonparametric problems, and we can sometimes prove that they adapt to unknown parameters (eg: unknown variance for mean changes). Most importantly, the schemes are very simple to implement, making them easily portable to new application settings as "baseline" methods.
This is joint work with Jaehyeok Shin (ex-PhD student), Shubhanshu Shekhar (current postdoc) and Alessandro Rinaldo. Preprints are at https://arxiv.org/abs/2203.03532 and https://arxiv.org/abs/2302.02544.

Weining Wang
Title: ℓ_2 Inference for Change Points in High-Dimensional Time Series via a Two-Way MOSUM
Abstract: We propose a new inference method for multiple change-point detection in high-dimensional time series, targeting dense or spatially clustered signals. Specifically, we aggregate MOSUM (moving sum) statistics cross-sectionally by an ℓ_2-norm and maximize them over time. To account for breaks only occurring in a few clusters, we also introduce a novel Two-Way MOSUM statistic, aggregated within each cluster and maximized over clusters and time. Such aggregation scheme substantially improves the performance of change-point inference. This study contributes to both theory and methodology. Theoretically, we develop an asymptotic theory concerning the limit distribution of an ℓ_2-aggregated statistic to test the existence of breaks. The core of our theory is to extend a high-dimensional Gaussian approximation theorem fitting to non-stationary, spatial-temporally dependent data generating processes. We provide consistency results of estimated break numbers, time stamps and sizes of breaks. Furthermore, our theory facilitates novel change-point detection algorithms involving a newly proposed Two-Way MOSUM statistics. We show that our test enjoys power enhancement in the presence of spatially clustered breaks. A simulation study presents favorable performance of our testing method for non-sparse signals. Two applications concerning equity returns and COVID-19 cases in the United States demonstrate the applicability of our proposed algorithm.

1 June

Paromita Dubey

Title: Depth-Based Change Point Detection for Random Objects

Abstract: In this talk, I will present a new change point detection test for sequences of random objects taking values in an arbitrary metric space. The new test currently focuses on the offline setting with a single change point alternative. Starting from the distribution of distances around the individual data points, the new scan statistic leads to a test that is powerful against all alternatives under only mild conditions on the ambient data space. I will discuss the asymptotic distribution of the test statistic under the null hypothesis of no change points and the power of the new test under contiguous alternatives. Next, I will establish that the proposed change point estimator is consistent. I will illustrate the success of this new approach on multiple simulations in a variety of settings and in real data applications. Finally, I will discuss future extensions to the online setting and multiple change point alternatives.

Lorenzo Cappello

Title: Variance change point detection with credible sets

Abstract: We introduce a novel Bayesian approach to detect changes in the variance of a Gaussian sequence model, focusing on quantifying the uncertainty in the change point locations and providing a scalable algorithm for inference. We do that by framing the problem as a product of multiple single changes in the scale parameter. We fit the model through an iterative procedure similar to what is done for additive models. The novelty is that each iteration returns a probability distribution on time instances, which captures the uncertainty in the change point location. Leveraging a recent result in the literature, we will show that our proposal is a variational approximation of the exact model posterior distribution. We study the convergence of the algorithm and the change point localization rate. Numerical experiments, applications to biological data, and future extensions will be discussed.