Seminar zur Emeritierung von Prof. Dr. Josef Steinebach

Programm

Freitag 27. März 2015

im Hörsaal des Mathematischen Instituts (Raum 203)

14:00–14:50	**Prof. Dr. Alexander Aue** (UC Davis):
	Zur Segmentierung von nicht-linearen Zeitreihen
14:55–15:45	**Prof. Dr. Claudia Kirch** (Karlsruhe):
	Change-Points in High Dimensional Settings
15:45–16:15	Kaffeepause
16:20–17:10	**Dr. Stefan Fremdt** (Deutsche Bank, Frankfurt)
	Uniform results on the projection dimension for infinite dimensional functional data
17:15–17:45	**Prof. Dr. Hanspeter Schmidli** (Köln):
	TBA

Abstracts

Prof. Dr. Alexander Aue (UC Davis)

Zur Segmentierung von nicht-linearen Zeitreihen

Zeitreihen, die in der statistischen Praxis auftreten, sind oft nicht-stationär, nicht-linear und asymmetrisch. Traditionelle lineare Zeitreihenmodelle lassen sich auf solche Datensätze nicht direkt anwenden. In diesem Vortrag wird daher eine neue Modellklasse von stückweise stationären autoregressiven Zeitreihen mit zufälligen Koeffizienten eingeführt. Das beste Modell in dieser Klasse wird durch ein Kriterium bestimmt, das seinen Ursprung in der Informations- und Kodierungstheorie hat. Theoretische Resultate besagen, dass die Methodik konsistente Schätzer für die stationären Segmente sowie für die Parameter der autoregressiven Zeitreihe liefert. Begleitende empirische Studien liefern zusätzlich vielversprechende Ergebnisse für endliche Stichproben. Ein Teil dieses Vortrages basiert auf einer langjährigen Kooperation mit Josef Steinebach (Uni Köln), ein anderer Teil auf einer Zusammenarbeit mit Thomas Lee (UC Davis).

Prof. Dr. Claudia Kirch (Karlsruhe)

Change-Points in High Dimensional Settings

While there is considerable work on change-point analysis in univariate time series, more and more data being collected comes from high dimensional multivariate settings. One way to develop an asymptotic framework for such data is to use a Panel data setting where the number of dimensions increases with the sample size. Using contiguous alternatives in such a setup we can compare the asymptotic power of projection procedures (including an oracle projection on the one hand and a random projection on the other hand) with a Panel statistic that uses the full multivariate information. If information is available to constrain the search region of the test, corresponding projections can lead to a considerable gain in power. All procedures depend on the unknown covariance structure between components whose estimation is very problematic in high dimensional situations, and the possible presence of change-points only further increases these difficulties. If the covariance assumptions made are violated, it not only leads to huge size problems for the Panel statistics but also to a massive power loss, where by looking at contiguous alternatives, the asymptotic power effectively becomes equivalent to choosing a random search direction to apply a univariate test. The size of projection procedures on the other hand is robust with respect to the unknown covariance structure between channels. At the same time while the power can also be affected by misspecification, the impact is often considerably smaller. The theoretic results will be accompagnied by small sample simulations.

This is joint work with John Aston (University of Cambridge).

Dr. Stefan Fremdt (Deutsche Bank, Frankfurt)

Uniform results on the projection dimension for infinite dimensional functional data

Functional principal components (FPC's) provide the most important and most extensively used tool for dimension reduction and inference for functional data. The selection of the number, d, of the FPC's to be used in a specific procedure has attracted a fair amount of attention, and a number of reasonably effective approaches exist. Intuitively, they assume that the functional data can be sufficiently well approximated by a projection onto a finite-dimensional subspace, and the error resulting from such an approximation does not impact the conclusions. This has been shown to be a very effective approach, but it is desirable to understand the behavior of many inferential procedures by considering the projections on subspaces spanned by an increasing number of the FPC's. Such an approach reflects more fully the infinite-dimensional nature of functional data, and allows to derive procedures which are fairly insensitive to the selection of d. This is accomplished by considering limits as $d \to \infty$ with the sample size.

We propose a specific framework in which we let $d \to \infty$ by deriving a normal approximation for the partial sum process

$$\sum_{j=1}^{\lfloor du \rfloor} \sum_{i=1}^{\lfloor Nx \rfloor} \xi_{i,j}, \quad 0 \le u \le 1, \quad 0 \le x \le 1,$$

where N is the sample size and $\xi_{i,j}$ is the score of the ith function with respect to the jth FPC.

Our approximation can be used to derive statistics that use segments of observations and segments of the FPC's. We apply our general results to derive two inferential procedures for the mean function: a change-point test and a two-sample test. In addition to the asymptotic theory, the tests are assessed through a small simulation study and a data example.