MATHEMATISCHES FORSCHUNGSINSTITUT OBERWOLFACH

Tagungsbericht 1/1990

Zeitreihenanalyse

1.1. bis 6.1. 1990

An der Tagung über Zeitreihenanalyse, die unter der Leitung von P.L. Davies (Essen), J. Franke (Kaiserslautern) und G. Neuhaus (Hamburg) stattfand, nahmen 38 Statistikerinnen und Statistiker aus neun Ländern teil. Neben einigen allgemeinen aktuellen Themen aus der Zeitreihenanalyse sowie benachbarten Gebieten (z.B. der nichtparametrischen Kurvenschätzung) standen Beiträge im Mittelpunkt, die die neueste Entwicklung in folgenden Problemkreisen widerspiegelten:

- Fragen der datenadaptiven Modellselektion
- Bootstrapping von stationären Prozessen
- Nicht–lineare bzw. nicht–Gaußsche Zeitreihenanalyse
- Robustheitsfragen und andere Aspekte von Abweichungen von klassischen Modell–annahmen

Dabei wurde ein nicht unerhebliches Gewicht auf Fragen der Anwendung (ökonomische Zeitreihen, Hydrologie, Image Processing, etc.) und die sich daraus entwickelnden mathematischen Fragestellungen gelegt.
Die Tagung war für alle Teilnehmer sehr anregend und bot reichlich Gelegenheit zu intensivem Gedankenaustausch und ausgiebiger Diskussion der einzelnen Beiträge.

Die Tagung beschloß der Dank, den Prof. J. Durbin im Namen der Teilnehmer unseren Gastgebern vom Oberwolfacher Forschungsinstitut für die gastfreundliche, ja herzliche Atmosphäre in ihren Räumlichkeiten aussprach, die allen den Aufenthalt während der Tagung äußerst angenehm und fruchtbar gestaltete.

Vortragsauszüge:

J. ANDEL:

Statistical analysis of positive time series

An AR(1)–model for positive random variables X_t can be written as $X_t = b\,X_{t-1} + e_t$, where e_t are iid positive random variables and $b \in [0,1)$. In this case $b^* = \min(X_2/X_1, \ldots, X_n/X_{n-1})$ is a strictly consistent estimator for b under general conditions. The distribution of b^* is known when e_t are exponentially distributed. If we have a stationary AR(p)–model $X_t = b_1 X_{t-1} + \ldots + b_p X_{t-p} + e_t$ with $b_1 \geq 0, \ldots, b_p \geq 0$ and $e_t > 0$, then a good estimator of $(b_1, \ldots, b_p)$ is that which minimizes $b_1 + \ldots b_p$ under the conditions $X_t - b_1 X_{t-1} - \ldots - b_p X_{t-p} \geq 0$ $(t = p+1, \ldots, n)$ and $b_k \geq 0$ $(k = 1, \ldots, p)$. This estimator is also strictly consistent under some conditions concerning the distribution of e_t. The results are generalized to nonlinear models of an autoregressive type.

J. BEHRENS:

Robust order selection for autoregressive processes with outliers

For the purpose of approximating a linear process $\{X_t\}_{t\in Z}$ by an autoregressive process of order p Shibata (1980, AS) called an order selection $\widehat{p_n} \in P_n = \{1, \ldots, p_n\}$ based on the data $X_1, \ldots, X_n$ asymptotically efficient (as. eff.) if

$$\frac{L_n(\widehat{p_n})}{\min\limits_{p\in P_n} L_n(p)} \longrightarrow_{[P]} 1 \quad \text{as } n \to \infty$$

for a given loss function $L_n(p)$ (e.g. MSE of prediction). To generalize this approach in the case of outliers (consider $y_t = x_t\,(1 - z_t) + v_t\, z_t$, $\Pr(z_t = 0)$ large) the least squares estimates are replaced by GM–estimates $\hat{\Phi}_1(p), \ldots, \hat{\Phi}_p(p)$ given by the minimization of

$$\sum_{t=p+1}^{n} \rho(y_{t-1}, \ldots, y_{t-p}, y_t - \sum_{j=1}^{p} \eta_j\, y_{t-j})$$

with respect to $\eta_1, \ldots, \eta_p$ for suitable ρ.

An order selection is called robust as. eff. if it is as. eff. for $L_n(p)$ based on ρ instead of a quadratic function. Under assumptions on $\{y_t\}$, ρ, p_n we can get a robust as. eff. order selection from the data. For special (nonrobust) ρ classical methods as AIC are obtained.

R. Bhansali:

Consistent recursive estimation of the order for ARMA – processes

A new criterion to be used at stage II of the Hannan–Rissanen (1982, Biometrika) procedure is derived, and its consistency established. Simulations suggest that the criterion should provide reasonable results with a finite time series, especially when T, the number of observations, is large.

M. Cameron:

Spectrum estimation with variable bandwidth

The peaks and troughs of spectra often have different curvatures and so, if a kernel estimator is used, a kernel whose bandwidth varies with frequency should be used. As an approach to deciding on the bandwidth at each frequency, we use a step function as a model for the spectrum and determine the positions of discontinuites using partitioning algorithms.
Although discontinuous, these estimates are useful as a diagnostic for highlighting very large or very small periodogram values, as a method of partitioning frequencies for a further band-by-band analysis, and as a method of obtaining a non-parametric estimate of prediction variance.
Simulations show that, as an estimator of prediction variance, the automatic method has substantially less bias than fixed bandwidth estimators for spectra with sharp peaks. The possible cost is a slightly inflated variance of the estimator.

T. Cipra:

Robustification of recursive methods in time series analysis

The contribution is devoted to robustification of some popular recursive methods of smoothing, prediction and estimation in time series. The following topics will be e.g. discussed: 1. robustification of exponential and direct smoothing; 2. recursive version of AM estimates (Approximate Maximum Likelihood Type Estimates) for ARMA models with additive outliers and recursive version of CMM estimates (Conditional–Mean

M–Estimates) for AR-models with additive outliers.

R. Dahlhaus:

Data tapers in time series analysis

The importance of data tapers is discussed for various areas of time series analysis including nonparametric situation, parametric estimation , order selection and prediction. For nonparametric estimation a mathematical model is presented which proves the advantages of data tapers. We consider the integrated relative mean square error over an (with the sample size) increasing class of stationary processes which includes for example ARMA–processes whose roots converge to the unit circle. The model enables us to prove theoretically the leakage effect, a trough effect and a variance effect for spectral estimates. Furthermore, results are presented for the approximation of Toeplitz matrices which lead to better approximation for the Gaussian likelihood function. The results are demonstrated by simulations.

M. Deistler:

Linear dynamic errors–in–variables models

We consider problems of identification of linear dynamic errors–in–variables models (i.e. models where in principle all observations are contaminated by noise). In our framework neither the number of equations nor the classification of the variables into inputs and outputs has to be known a priori. We analyse the relation between the observations and certain system characteristics. In particular we are interested in a description of the set of all systems corresponding to given second moments of the observations and in a characterization of the maximum number of equations compatible with given second moments of the observations. Special emphasis is given to the case of one input (and many outputs in general) and to the case of one output (and many inputs in general).

J. Durbin:

Extensions of Kalman modelling to non–Gaussian data

Some recent work on extensions of the Kalman state space model to deal with non–Gaussian data, including count, binary, categorial and exponential data, will be discussed. The relation to the dynamic generalised linear model is considered. Some further extensions will be suggested. The ideas are exemplified by considering Poisson data.

D. Findley:

Porperties of the log–likelihood ratio supporting the comparison of non–nested, approximating models

We are interested in the behavior of the log–likelihood ratio when incorrect and non–nested models are compared. This situation is very common in practice. We have used AIC in hundreds of such time series modeling situations at the Census Bureau with reasonable success, but it is clear from the problems which occasionally occur that a deeper understanding of this easily calculated statistic is needed. We showed that the situation in which the difference of AIC's (and the likelihood ratio) have a limiting distribution for non–nested comparisons give rise to some interesting theoretical examples but are not too relevant for application. In more relevant situations, the mean square of the log–likelihood ratio has order $N^{1/2}$, so large sample analysis are uninformative. It is important to develop methods to estimate the mean square of the log–likelihood ratio of incorrect models for fixed sample sizes.

Th. Gasser:

Data adaptive curve estimation

In this talk curves may be regression functions, probability and spectral densities and their derivatives. The well–known nonparametric estimators involve the choice of a smoothing parameter, the bandwidth. Based on kernel estimators, we have developped a method for choosing the bandwidth in a rational way from the data while minimizing MSE.
In contrast to popular cross–validation, it relies on the asymptotically optimal bandwidth and needs the integrated squared second derivative of the curve. Both in theory and in simulation the new method is superior to cross-validation, in particular in variability. The method can be generalized to the situation of correlated (mixing) residuals in a regression context.

X. Guyon:

Description of the set of good choice of a model in a parametric identification problem

Suppose that $(X_1,\ldots,X_n) \sim (P_{\theta,n})$, $\theta \in \Theta$ open subset of R^n. Denote $\mathcal{M}=\{1,2,\ldots m\}$ this big model and $P_0 \subseteq \mathcal{M}$ the true one. Let $\widehat{P_n} = \underset{p \subseteq \mathcal{M}}{\arg\min} \{V(\widehat{\theta_p}, T_n) + C(n)/n \cdot p\}$, $p = |P|$

be an estimation of P_0 on the basis of the penalized contrast $V(\theta, T_n)$. We show that

under quite large hypothesis, the set of bad choice $M_n = \{\omega: \widehat{P_n} \neq P_0\}$ can be described by: $M_n \subseteq \{\omega: \| T_n - \gamma_0 \| \geq \eta_0 (C(n)/n)^{1/2}\}$, if $C(n)/n \leq \delta_0$ for some constants η_0, δ_0. This results generalize the work of Bai et. al. (J. Mult. Analysis) done in the specific context of determination of the order of an AR–model.
Applications are given to general time series identification, random fields, linear or non–linear regression, categorial models. Under supplementary hypothesis, control of the probability of M_n are given.

W. Härdle:

Resampling in curve estimation

We consider the problem of resampling from estimated residuals in the context of nonparametric regression smoothing. Let $Y_i = m(x_i) + \varepsilon_i$ and $\widehat{\varepsilon}_i = Y_i - \widehat{m_h}(x_i)$ the estimated residual. We use the so-called

Wild Bootstrap :

Define $\varepsilon_i^* = \eta_i \widehat{\varepsilon}_i$, with η_i iid, having a two–point distribution $G = p\,\delta_a + (1-p)\,\delta_b$ such that $E_G\,\eta_i = 0$, $E_G\,\eta_i^2 = 1$, $E_G\,\eta_i^3 = 1$.

We show that this particular method of resampling works in a variaty of problems, among them construction of simultaneous error bars.

Ch. Hesse:

Some results for processes with infinite variance

Linear processes with infinite variance (such as autoregressive processes with stable innovations) are being used to model certain economic time series such as stock price changes, inflation rates, etc. Interesting statistical problems do arise with respect to the applicability of the classical statistical methods which are almost always designed for situations of finite variance and finite Fisher information. In this talk we study properties of the empirical distribution function, of LS–estimators and of the empirical characteristic function.

J.–P. Kreiss:

Bootstrapping AR(∞)–processes

Many papers about bootstrap techniques in time series analysis discuss the parametric

autoregressive moving average models, which are related to the familiar bootstrap of regression models with fixed design. Related papers to this subject are Freedman (1981), Efron and Tibshirami (1986), Bose (1988), Franke and Kreiss (1989).
All these papers assumed that the model order is known. So we deal with stationary stochastic processes (X_t: $t \in Z$) which possess an AR(∞)–representation, only. That is

$$X_t = \sum_{\nu=1}^{\infty} a_\nu X_{t-\nu} + \varepsilon_t \ , \ t \in Z,$$

(ε_t) iid with zero mean and finite variance. $1 - \sum_{\nu=1}^{\infty} a_\nu z^\nu \neq 0 \ \forall \ |z| \leq 1+\eta$ is also assumed.
To this model we fitted an AR(p(n))–process ($p(n) \to \infty$) on the basis of the given set of data $X_1, ..., X_n$. From this we obtain estimated residuals $\widehat{\varepsilon_{t,n}}$. These values are used to carry through the proposed resampling scheme. We end up with bootstrap values $X^*_{1,n}, ..., X^*_{n,n}$ of the time series itself. Finally we prove that the proposed bootstrap procedure is asymptotically valid as an approximation of the standardized distribution of the empirical autocovariance.

H.R. Künsch:

Variance estimation for dependent observations

We consider a sample of stationary strong mixing process and a statistic T_n obtained by applying a functional to an empirical marginal of fixed dimension. We investigate three procedures to estimate the variance and the centered distribution of T_n respectively: direct estimation of the asymptotic variance, blockwise jackknife and blockwise bootstrap. First we summarize the results of Künsch, Ann. Statist. 17 (1989), and then we present new developments and open problems: techniques for reduce the bias, first order Edgeworth expansions for the studentized statistics, broader classes of statistics (regression estimators, periodogram) and processes with long range dependence.

Pham Dinh Tuan:

Maximum likelihood estimation for multivariate autoregressive models

For short data and when the observed process has sharp spectral peaks, usual methods of autoregressive (AR) model fitting methods may be outperformed by the maximum likelihood (ML) method. Moreover, many of them do not always provide an AR polynomial estimate with roots inside the unit circle and/ or cannot be generalized to the multivariate case. In this work, we develop a simple algorithm to compute the ML estimate for multivariate AR models. We provide an explicit expression for the log-likelihood in terms of the forward and backward AR coefficients and innovation covariances. Further, the gradient of the likelihood with respect to an appropriately choosen set of parameters can be obtained through the resolution of a certain linear system of equations. The estimate can then be constructed by the Fisher's scoring method, or by a conjugated gradient method. Some simulating results will be given illustrating the performance of the method.

B. Pötscher:

Effects of Model selction on inference

The asymptotic properties of parameter estimators in a model which has been selected by a model selection procedure using the same data set are investigated. (The estimation framework considered is essentially Quasi Maximum Likelihood estimation.) In particular, the asymptotic distribution of the parameter estimators is derived for a particular model selection procedure based on a sequence of hypothesis tests. The resulting asymptotic distribution is compared with the distribution delivered by standard asymptotic theory ignoring the model selection process.

P.M. Robinson:

Automatic bandwidth selection in nonparametric and semiparametric frequency domain analysis of time series

Uniform consistency of nonparametric spectral estimation is established in the presence of a general data–dependent bandwidth. A bandwidth is also involved in the estimation of the limiting covariance matrix of ordinary least squares estimates in the presence of disturbance serial correlation of unknown form, and in the efficient estimation of regression coefficients in the presence of disturbance serial correlation of unknown form. In both problems we show that the limiting distribution of the operationally scaled regression estimates is unaffected by use of a general data–dependent bandwidth. We consider a cross–validation method of bandwidth determination. We show that the cross–validated bandwidth converges in probability to the optimal minimum–integrated-mean–squared–error bandwidth. The results we described previously hold for this cross–validated bandwidth.

R. von Sachs:

Peak–insensitive nonparametric spectrum estimation

We study the problem of nonparametric spectrum estimation of a stationary time series that might contain periodic components. In that case the periodogram ordinates at frequencies near the frequencies of the periodic components have significant amplitude, and can be regarded as outliers in an (asymptotically) exponential sample. This motivates us to robustify the usual kernel estimator for the spectral density by applying the theory of M-estimation already being studied in the regression context of deterministic design (see Härdle and Gasser, 1984). Our modified estimator has a certain insensitivity against those regarded outliers in the frequency-domain that, as some advantage, don't need a precise modelling. We show consistency of the resulting spectral estimator in the general case, and asymptotic normality in the special case of a Gaussian time series. The proposed procedure is applied to some simulated series.

W. Schmid:

Tests on the existence of outliers in time series

Suppose that a realization of a process is given, which coincides with an autoregressive process if no outliers occur. In order to check the data on the existence of outliers, a test of discordancy is required.
In my talk I want to present several outlier tests, which base on a comparison of the observations with certain predictors. We distinguish between the case that an upper bound for the number of outliers is known or not. The asymptotic distribution of the test statistic under the null hypothesis (no outlier) is calculated.
A result on the asymptotic behaviour of a likelihood ratio test under the alternative hypothesis is also given. In this case the mean–shift model is used to describe the occurence of outliers. Furthermore these tests have been compared by means of a simulation study.

S. Schnatter:

Aspects of modelling time series with non–linear state space models

Non–linear state space models are a rather interesting, but hardly used technique in time series analysis. Statistical inference for non–linear state space models will be discussed from a Bayesian point of view. An approximate filtering procedure, which is a

modification of the multiprocess filtering approach of Harison/ Stevens, is suggested. Furthermore, Bayesian Forecasting, Model Diagnostics and Model Discrimination for non–linear state space models will be considered.
As an example, non–linear state space models based on a component model with linear trend are presented. These models are applied to a time series of yearly ground water level data from a station in Austria.

U. Stadtmüller:

Laws of iterated – and of single logarithm

We assume that $\{X_n\}$ is a sequence of iid random variables, and we are interested in the asymptotic behaviour of weighted sums $\sum_k a_{nk}X_k$ w.r.to a.s. convergence. We consider weights $\{a_{nk}\}$ which are defined by certain summability methods. The case of the Cesàro method, i.e. $a_{nk} = 1/n$, $1 \le k \le n$, is well known, here we obtain the usual SLLN iff $X_1 \in L_1$ and the LIL iff $X_1 \in L_2$ and $E(X_1) = 0$. A different behaviour occurs in case of e.g. the Euler method, i.e. $a_{nk} = \binom{n}{k} \lambda^k / (1+\lambda)^n$, $1 \le k \le n$, where the LIL is replaced by a law of single logarithm. We consider here a generalization of the Euler method, so called Jakimovski methods, giving laws of iterated – and of single logarithm.

W. Stute:

Prediction intervals for explosive AR(1)–processes

We consider a non–stationary (explosive) AR(1)–process $X_i = \beta X_{i-1} + \varepsilon_i$, $i \ge 1$, $|\beta| > 1$. It is known from Anderson (1959) that the LSE β_n of β converges geometrically fast, the limit distribution depending on the whole of the error distribution F rather than finitely many parameters of F. For prediction of X_{n+s} on the basis of $X_0, X_1, \dots, X_n$ we consider $\hat{X}_{n+s} = \beta_n^s X_n$. In this paper we derive prediction intervals $\hat{I}_{n+s}$ containing $\hat{X}_{n+s}$ such that for given levels ρ_1, ρ_2

$$(*) \qquad P(\; P(X_{n+s} \in \hat{I}_{n+s} \mid X_0, X_1, \dots, X_n) \ge 1 - \rho_1) \to 1 - \rho_2 .$$

The methodology rests on a careful study of the so–called residual empirical process. A bootstrap version of (*) is also valid.

T. Subba Rao:

Nonlinear time series analysis (with special reference to Bilinear models)

We often make two important assumptions when analysing time series. They are (i) stationarity, (ii) linearity (Gaussianity). In real situations, these assumptions may be not realistic. In this talk we concentrate on analysing data which may not be linear. In recent years several nonlinear time series models have been purposed, and one of them is the Bilinear model. In this paper we discuss the properties of this model, especially concentrate on some recent results obtained for identifying (tentative) the order of estimation of the parameters of the model. The methods we develop are canonical correlation analysis similar to the techniques developed by Akaike, Subba Rao, Tsay and Tiao for linear time series models. The methods are illustrated with examples.

M. Taniguchi:

A higher order generalization of LeCam's third lemma

Suppose that $P^{(n)}$ is the probability measure induced by a collection of n observations. It is desired to test a hypothesis H: $P^{(n)} = P_n$ against the alternative A: $P^{(n)} = Q_n$. Let $\mathcal{T}$ be a class of tests specified under H. Then LeCam's third lemma gives an automatic formula of the limiting distribution of $t \in \mathcal{T}$ under H.
Here we generalize this lemma by using a higher order Edgeworth expansion. First, a concept of higher order contiguity is introduced.Then the Edgeworth expansion of $t \in \mathcal{T}$ is given up to second–order under the second–order contiguous alternative. Using this expansion some second–order asymptotic power properties of $t \in \mathcal{T}$ are discussed. The results can be applied to iid case, non–iid case, multivariate analysis and time series analysis. Two concrete examples are given. One is a Gaussian ARMA process (dependent case), and the other is a nonlinear regression model (non–identically distributed case). Finally we give some numerical studies. The results agree with the theory.

A.B. Tsybakov:

Optimal rates of convergence in image processing

We consider the problem of estimation of an unknown image $f: X \to R^1$, $X = [0,1]^N$, from a sequence of observations $y_{in} = f(x_{in}) + \xi_i$, where $x_{in} \in X$ are some points and ξ_i are iid random errors. It is assumed that the image f contains two smooth parts: the informative part where the values of f are large, and the background where the values are small. On the boundary between these two parts there is an abrupt change. It is proved that the minimax risk in the problem of image estimation decreases with a certain rate and the estimator of f is proposed that achieves this optimal rate. This rate depends on the smoothness of f on the informative part and on the background as well as on the smoothness of the boundary.

H. Walk:

On stochastic recursions for linear models with forecast feedback

Convergence problems for learning processes in linear models with forecast feedback motivate investigation of the recursion

$$X_{n+1} = 1/n \cdot \sum_{k=j_n}^{n} B_k X_k + 1/n \cdot S_n$$

(Kottmann, Mohr 1988/89) with $j_n/n \to \alpha \in [0,1)$, random elements B_n and X_n, S_n in $L(\mathfrak{B})$ and $\mathfrak{B}$, resp. ($\mathfrak{B} = R^p$ or more general real separable Banach space). Under the assumptions

$$B_n \xrightarrow{C_1} B \in L(\mathfrak{B}), \; \|B_n\| = O_{C_1}(1), \; S_n/n \to 0,$$

$$\text{spec } B \subset \{\lambda/(1-\alpha^\lambda);\ \text{re } \lambda \geq \gamma\}^C \quad \text{with } \gamma = 1,$$

one obtains $X_n \to 0$ (a.s.). If the spectral condition is sharpened to $\gamma = 1/2$ and the condition on (S_n/n) is replaced by a weak invariance principle with convergence order $n^{-1/2}$ and random limit Y in $C_{\mathfrak{B}}[0,1]$, then under a mild additional assumption a corresponding assertion holds for (X_n) with random limit Z, where $Z(0) = 0$ and Z satisfies the functional stochastic differential equation

$$dZ(t) = B/t \cdot (Z(t) - Z(\alpha t))\, dt + dY(t) \;, t \in (0,1] .$$

M. Weba:

Estimating integrals of continuous time series

In order to estimate integrals of continuous time series, conventional methods use optimal or asymptotically optimal linear estimators. Knowledge of covariances is assumed, or restrictive regularity conditions are required. If classical quadrature formulae are applied pathwise, it is possible to verify convergence (in the p–th mean) towards the desired integral by means of an extension argument; covariances or additional conditions are unnecessary. The extension argument can be generalized in order to estimate multilinear functionals of time series.

Ching-Zong Wei:

Some unsolved problems on nonstationary autoregressive processes

The autoregressive process $X_n = \beta_1 X_{n-1} + \ldots + \beta_p X_{n-p} + \varepsilon_n$ is said to be stationary if all roots of $\varphi(\zeta) = \zeta^p - \beta_1 \zeta^{p-1} - \ldots - \beta_p$ are inside the unit circle. If some roots are on the unit circle, it is said to be unstable, and explosive if some roots are outside the unit circle. In this talk, the consistency and limiting distribution of the least squares estimates are discussed. The unsolved problems that are related to the optimal inference, order selection and control of unstable systems are also presented.

Berichterstatter: Rainer v. Sachs

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