

MATHEMATISCHES FORSCHUNGSINSTITUT OBERWOLFACH

Tagungsbericht 10/1986

Mathematische Stochastik

9.3. bis 15.3.1986

An der diesjährigen Frühjahrstagung "Mathematische Stochastik" nahmen 43 Teilnehmer aus 13 Ländern teil, darunter 6 aus USA, ebensoviele aus den Niederlanden, je drei aus Ungarn und Frankreich, zwei aus der Sowjetunion und je einer aus Indien, Bulgarien, Großbritannien, Israel, Belgien und Österreich. In der Natur der gemeinsamen Frühjahrstagung Mathematische Stochastik = Wahrscheinlichkeitstheorie und Statistik liegt es, daß das Vortragsspektrum relativ breit gestreut ist. Dennoch gab es eine gewisse Schwerpunktsetzung. Diese betraf vor allem die Bereiche: präzise Entwicklungen für die Wahrscheinlichkeiten großer Abweichungen, Anwendungen großer Abweichungen in der Statistik, Selbstüberschneidungen der Brown'schen Bewegung, Statistik stochastischer Prozesse, nichtreguläre Fälle, stochastische Prozesse in der Statistik.

Am Abend des zweiten Tages fand ein Workshop zum Thema "Perkolationstheorie" statt, der von den Herren van den Berg (Delft) und Grimmett (Bristol) geleitet wurde. Diese Veranstaltung fand großes Interesse, auch bei den vornehmlich an Statistik interessierten Teilnehmern.

Tagungsleitung: E. Bolthausen (Berlin), G. Pflug (Gießen)

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## Vortragsauszüge

R. AHLWEDE

### Identification via channels - a second order Coding Theorem.

Identification codes for the discrete memoryless channel (DMC) are studied. The key observation is that  $N = \exp\{\exp\{R \cdot n\}\}$  (double exponentially many!) objects can be identified in blocklength  $n$  with arbitrarily small error probability via a DMC, if randomisation can be used for the encoding procedure.

Moreover, we present a novel (second order) Coding Theorem, which determines the second order identification capacity of the DMC as a function of its transmission matrix. Surprisingly this identification capacity is a well-known quantity: it equals Shannon's transmission capacity for the DMC.

This is joint work with Guenter Dueck, submitted to IEEE Inf. Theory.

L. ARNOLD

### Unique ergodicity for degenerate diffusions

We investigate the invariant probabilities of a possibly degenerate diffusion process on a manifold. Using the support theorems of Stroock, Varadhan and Kunita, the possible candidates for supports of invariant probabilities can be characterized as the invariant control sets of the corresponding control system. There remains the problem of how many invariant probabilities can coexist on one invariant control set  $C$ . Uniqueness of  $C$  is proved under the assumption that the Lie algebra generated by the drift and diffusion vector fields is full at one point in  $C$ . This generalizes the known results obtained by PDE methods. Several versions of the ergodic theorem are given.

L. BIRGÉ

Some properties of the Grenander estimator

Suppose  $f$  is a decreasing density on  $[0, +\infty[$ , with c.d.f.  $F$ ,  $F_n$  is the corresponding empirical distribution (n.i.i.d. variables) and  $\tilde{F}_n$  the Grenander estimator with derivative  $\tilde{f}_n$  ( $\tilde{F}_n$  is the concave envelope of  $F_n$ ). There exists some explicit functional  $L(f, z)$ ,  $z > 0$  which can serve to bound the risk of  $\tilde{F}_n$  in this way

$$\mathbb{E}[\|\tilde{f}_n - f\|_1] \leq 2 L(f, Kn^{-1/2}) \quad K < 1.13$$

and asymptotically

$$\lim_{z \rightarrow 0} z^{-2/3} L(f, z) = 3/2 \int_0^{+\infty} \left| \frac{f(x)f'(x)}{2} \right|^{1/3} dx .$$

Apart from a multiplicative factor of  $K$ , this is in accordance with the asymptotic results of P. Groeneboom. This extends in a straightforward way to unimodal densities with known mode or decreasing densities on  $[a, +\infty[$  with "a" unknown, but also through some minimum distance device to unimodal densities with unknown mode at the price of an extra factor  $5/\sqrt{n}$ . This estimator is also easily proved to be robust: if  $g$  is a decreasing regulation of  $f$ , only an extra  $\|f-g\|_1$  appears in the bound.

A.A. BOROVKOV

Large Deviations for some classes of functionals and their Applications

Let  $a_1(\theta), a_2(\theta) \dots$  be i.i.d. random fields,  $\theta \in \mathbb{R}^k$ ,

$$\zeta_n(\theta) = \sum_{i=1}^n a_i(\theta), \quad \theta \in \Theta \subseteq \mathbb{R}^k$$

Two main types of functionals of  $\zeta_n$ , important in statistics, are considered

$$G_1(\zeta_n) = \sup_{\theta \in \Theta_1} \zeta_n(\theta) - \sup_{\theta \in \Theta_2} \zeta_n(\theta)$$

$$G_2(\zeta_n) = \ln \int_{\Theta_1} \exp(\zeta_n(\theta)) p_1(\theta) d\theta - \ln \int_{\Theta_2} \exp(\zeta_n(\theta)) p_2(\theta) d\theta$$

where  $\theta_i \in \Theta$ ,  $\theta_1 \cap \theta_2 = \emptyset$ ,  $p_i$  are densities on  $\theta_i$ ,  $i=1,2$ . The asymptotic behaviour of the probabilities of large deviations (full spectrum) of  $G_i$ ,  $i=1,2$ , is found.

If  $x_1, \dots, x_n$  is a sample from distribution  $P_\theta$ ,  $\theta \in \Theta$  these results allow (1) to find theorems describing large deviations of the maximum likelihood estimator ( $a_i(\theta) = \ln p_\theta(x_i)$ ,  $p_\theta = \frac{dP_\theta}{d\mu}$ ), (2) to describe the asymptotic of errors of the first and second kind for testing the hypothesis  $H_1 = \{\theta \in \theta_1\}$ ,  $H_2 = \{\theta \in \theta_2\}$  when the distance between  $\theta_1$  and  $\theta_2$  is not small ( $\gg \frac{1}{\sqrt{n}}$ ) and when we use the Bayesian or ratio likelihood tests. The results are obtained in collaboration with A.A. Mogulskii.

## I. CSISZAR

### On the probabilistic background of the maximum entropy principle

Let  $Q$  be a probability measure originally assigned to a given measurable space. The "probability kinematics" problem is the following (philosophical) one: how to "update"  $Q$  if new evidence suggests that the true distribution actually belongs to a set of measures  $\Pi$  not containing  $Q$ . Typically,  $\Pi = \{P: \int f_i dP \geq \alpha_i, i=1, \dots, k\}$  for some functions  $f_i$  and constants  $\alpha_i$ . The maximum entropy principle says that the "proper updating" is the I-projection of  $Q$  on  $\Pi$ , i.e., that  $P^* \in \Pi$  which minimizes the Kullback-Leibler informational divergence  $D(P\|Q)$  subject to  $P \in \Pi$  (if such  $P^*$  exists and is unique). The following conditional limit theorem supports this principle. Theorem (Csiszar 1984): Let  $X_1, X_2, \dots$  be an i.i.d. sequence with common distribution  $Q$ , let  $\hat{P}_n$  be the empirical distribution of  $(X_1, \dots, X_n)$  and let  $P_{\Pi, n}^{(m)}$  be the conditional joint distribution of  $(X_1, \dots, X_m)$  under the condition  $\hat{P}_n \in \Pi$ . Then, if  $\Pi$  is convex and satisfies minor additional regularity hypothesis, we have  $\lim_{n \rightarrow \infty} \frac{1}{n} D(P_{\Pi, n}^{(n)} \| P^{*n}) = 0$ , and consequently  $\lim_{n \rightarrow \infty} D(P_{\Pi, n}^{(m)} \| P^{*m}) = 0$  for every fixed  $m$ .

This theorem is partially extended to the case when  $X_1, X_2, \dots$  is a finite state Markov chain with transition probability matrix  $W$ . Let  $\hat{p}_n^{(2)}$  denote the second order empirical distribution, i.e., the empirical distribution of  $((X_1, X_2), (X_2, X_3), \dots, (X_n, X_{n+1}))$  and let  $\Pi^{(2)}$  be a given set of two-dimensional distributions. Then (under some regularity hypothesis)  $\lim_{n \rightarrow \infty} \Pr\{X_2=x_2, \dots, X_m=x_m | X_1=x_1, \hat{p}_n^{(2)} \in \Pi\} = \prod_{i=1}^{m-1} P^*(x_{i+1} | x_i)$  where  $P^* \in \Pi^{(2)}$  minimizes

$$D(P \| W) = \int P(x, y) \log \frac{P(y|x)}{W(y|x)} \text{ subject to } P \in \Pi^{(2)} \text{ and } \bar{P} = \bar{P} \text{ where } \bar{P} \text{ and } \bar{P} \text{ are the two marginals of } P \text{ and } P(y|x) = P(x, y) / \bar{P}(x).$$

Corollary: .

$$\lim_{n \rightarrow \infty} (\Pr\{X_1=x, \dots, X_m=x_m | \hat{p}_n^{(2)} \in \Pi\} - \Pr\{X_1=x_1 | \hat{p}_n^{(2)} \in \Pi\} \prod_{i=1}^{m-1} P^*(x_{i+1} | x_i)) = 0$$

Thus the limiting conditional distribution corresponds to a Markov chain minimizing Kullback-Leibler divergence rate; however the initial distribution of this limiting Markov chain, i.e. the limit of  $P\{X_1 = \alpha_1 | \hat{p}_n^{(2)} \in \pi\}$  remains to be determined. In general, it differs from the stationary distribution of the Markov chain determined by  $P^*(\cdot, \cdot)$ . This result was jointly obtained with Cover and Choi.

#### D. DACUNHA-CASTELLE

##### Statistics of diffusions

Let  $dx_t = b(x_t, \theta)dt + \sigma^2(x_t)dW_t$  be a D.S.E. To estimate  $\theta$  it is physically impossible to follow the trajectory because it is too irregular. So we have to choose some discretization. For such observation, we study the loss of information. For special problems, only the crossings of the equilibrium levels are observable, specifically if their distance is not too small. We study the estimation of  $\theta$  for this kind of observation, in the ergodic case and for different asymptotics. The keys are a special representation of the transition, Tauberian theorems and some aspects of Sturm-Liouville representation of the Lévy measure of the reciprocal process of local time.

R. DAHLHAUS

Finite sample effects in time series analysis

Many estimates in time series analysis which are asymptotically efficient, can have bad finite sample behaviour. This is true for parametric estimates (e.g. for Yule Walker estimates with roots close to the unit circle) as well as for nonparametric estimates (the nonparametric periodogram is often bad due to the leakage effect).

A mathematical model is presented to describe such effects. As an application the relation between maximum likelihood and approximate maximum likelihood estimation is discussed. It is proved that the use of data tapers can improve a great number of estimates. To illustrate the results simulation examples are presented.

G. DIKTA

Bootstrap approximations of nearest neighbor regression function estimates

Let us assume that  $(X_1, Y_1), \dots, (X_n, Y_n)$  is an i.i.d. sample in the plane with distribution function  $H$ . If the first moment of  $Y$  exists,  $m(X) := \mathbb{E}(Y|X)$  the conditional expectation of  $Y$  given  $X$  is defined. In order to estimate the regression function

$m(x_0) := \mathbb{E}(Y|X=x_0)$  at the point  $x_0$  we use a nearest neighbor estimate

$$m_n(x_0) := \frac{1}{na_n} \sum_{i=1}^n Y_i K\left(\frac{F_n(x_0) - F_n(X_i)}{a_n}\right),$$
 where  $K$  is a kernel

function and  $(a_n)_{n \in \mathbb{N}}$  a sequence of bandwidths.

We show that the bootstrap approximation to the distribution of  $(na_n)^{1/2}(m_n(x_0) - m(x_0))$  is valid and we make a small simulation study to compare confidence intervals for  $m(x_0)$  constructed by normal approximation and by bootstrap approximation.

H. DINGES

Wiener germs

Def. A Wiener germ of order  $m$  with center  $x^*$  is a family of densities on  $U \subseteq \mathbb{R}^d$  of the form

$$f_\varepsilon(x) dx = [2\pi\varepsilon]^{-d/2} \exp(-\frac{1}{\varepsilon}K(x)) \exp(S_0(x) + \varepsilon S_1(x) + \dots + \varepsilon^{m-1} S_{m-1}(x) + O(\varepsilon^m)) dx$$

$$\int f_\varepsilon(x) dx = 1 - O(\varepsilon^m)$$

$S_j$  is  $(m-j)$ -times continuously differentiable

$K(x)$  is  $(m+2)$ -times continuously differentiable

$K^\Pi(x)$  positive definite,  $K(x^*)=0$ ,  $K(x) > 0$  for  $x \neq x^*$

Theorem (Daniels 1954)

$Y_1, Y_2, \dots$ , i.i.d. with integrable charact. function

$$\psi(\theta) := \ln \int \exp(\theta Y) < \infty \quad \text{for } \theta \text{ near } 0$$

$$X_\varepsilon^{(n)} := \frac{1}{n}(Y_1 + \dots + Y_n) =: X_\varepsilon \quad \text{for } \varepsilon = \frac{1}{n}.$$

Another, rather trivial, way to construct Wiener germs is as follows  
 $\{W_\varepsilon : \varepsilon \in \mathbb{R}^+\}$  Wiener process  $W_0 = x^*$  a.s.  $T_0(\omega)$  diffeomorphism,  
 $m$ -times cont. diff.  $T_j(\omega)$   $(m-j)$ -times cont. diff.

$$T(\varepsilon, \omega) = T_0(\omega) + \varepsilon T_1(\omega) + \dots + \varepsilon^m T_m(\omega) + O(\varepsilon^{m+1})$$

$$X_\varepsilon := T(\varepsilon, W_\varepsilon)$$

$\{L(X_\varepsilon) : \varepsilon > 0\}$  is a Wiener germ of order  $m$ .

Theorem (on the tails of onedimensional Wiener germs)

$\{L(X_\varepsilon) : \varepsilon > 0\}$  onedimensional Wiener germ, center  $x^*$ .

Then there exists functions  $A_0(x), A_1(x), \dots, A_m(x)$ ,

$A_j(x)$   $(m-j)$ -times cont. diff. s. that

$$\sqrt{\varepsilon} \Phi^{-1}(\Pr(X_\varepsilon \leq x)) = A_0(x) + \varepsilon A_1(x) + \dots + \varepsilon^m A_m(x) + O^-(\varepsilon, x)$$

$$-\varepsilon \Phi^{-1}(\Pr(X_\varepsilon \geq x)) = A_0(x) + \varepsilon A_1(x) + \dots + \varepsilon^m A_m(x) + O^+(\varepsilon, x)$$

$$O^\pm(\varepsilon, x) = \varepsilon^{(m+1/2)} \left[ q \left( \frac{|A_0(x)|}{\sqrt{\varepsilon}} \right) \right]^{-1} \cdot R^\pm(\varepsilon, x)$$



V. FABIAN

Finite sample behavior of some locally asymptotically minimax estimates

Possibility of numerical investigation of the behavior of the LAM estimate proposed by the author and J. Hannan (ZW, 82) is discussed and results are given of such an investigation for the (i) location parameter case of Cauchy distribution and for (ii) the estimation of  $p, \lambda$  on basis of independent observations of  $X + Y$  with  $X$  binomial  $(n, p)$  and  $Y$  Poisson  $(\lambda)$ , independent of  $X$ .

P.D. FEIGIN

Semimartingale Models and Estimating Equations

The modern setting for both parametric and nonparametric inference for stochastic processes is that of semimartingale models. Although the theory of these models has become quite well-known, many statisticians find it quite formidable. On the other hand, the essence of this theory can be made quite transparent using a heuristic approach.

We illustrate these heuristics for the estimation equation approach due to Godambe and applied by Thavaneswaran and Thompson, and, Hutton and Nelson. The optimum equation is readily recognized and we are able to consider asymptotic theory very much as in M-estimation.

Another example of these heuristics deals with the deviation of the Aalen estimator in the nonparametric multiplicative intensity counting process model.

F. GÖTZE

Distribution of sums over finite range lattice random fields

Consider a strictly stationary  $m$ -dependent random field  $X_j, j \in \mathbb{Z}^d$  which is defined by

$$X_j = h(Y_k : k \in j + \{0, \dots, m\}^d), Y_k, k \in \mathbb{Z}^d \text{ i.i.d.}$$

We investigate the limit distribution of  $S_N = X_1 + \dots + X_N$ . If  $\mathbb{E}|X_1|^4 < \infty$  and  $\frac{1}{N} \text{Var}(S_N) \rightarrow \delta^2 > 0$  we obtain necessary and sufficient conditions such that normal approximations (lattice/nonlattice) hold up to an error of order  $o(n^{-1/2})$ . If  $S_N \in \mathbb{Z}$  we prove that a local limit theorem holds; the limit being a mixture of normal densities over different supporting lattices. The local CLT holds if this distribution is uniform.

The results generalize to general  $m$ -range potential functions  $S_N$  and Gibbsian random fields  $Y_k, k \in \mathbb{Z}^d$  and sharpen a result of Dobrushin and Tirozzi 1976.

G.R. GRIMMETT

Large deviations for rumours, with an application to the design of algorithms

Standard methods for finding all shortest paths between all pairs of vertices of a graph on  $n$  vertices operate in worst-case run-time approximately  $O(n^3)$ . If the edge-lengths are independent random variables whose common distribution function  $F$  satisfies  $F(0) = 0, F'(0) = D$  exists and satisfies  $D > 0$ , then there is an algorithm with expected run-time  $O(n^2 \log n)$ . In analysing this algorithm, we need to understand the following problem. One person in a village of  $n$  people has heard a rumour. He tells it to someone chosen at random. At each stage, each person who knows the rumour tells someone chosen at random (this person may already know the story). Let  $S_n$  be the number of stages until everyone knows the rumour. Then  $S_n / \log_2 n \rightarrow 1 + \log 2$  in probability. Large deviation results and incomplete small deviations results are available for  $S_n$ . This is joint work with Alan Frieze, and the small deviation result is due to B. Pittel.

P. GROENEBOOM

Convex hulls of samples in  $\mathbb{R}^2$

Let  $N_n$  be the number of vertices of the boundary of the convex hull of a sample on  $n$  points, drawn uniformly from the interior of a convex polygon with  $r$  sides. It has been proved by Rényi and Sulanke (Zeitschrift für Wahrscheinlichkeitstheorie 2, 75-84, (1963)) that

$$\mathbb{E} N_n \sim \frac{2}{3} r \log n, n \rightarrow \infty$$

They also proved in this paper, that the expected number of vertices is of order  $n^{1/3}$  for a sample of size  $n$  from the uniform distribution on the interior of an ellipsoid and of order  $\sqrt{\log n}$  for a sample from a 2-dimensional normal distribution. Since the paper by Rényi and Sulanke appeared, many papers have appeared dealing with expectations of functionals of convex hulls, but so far there is no satisfactory distribution theory.

A martingale characterization is given of the (local) limiting process of the vertices of the boundary of the convex hull in the case of a uniform sample from the unit square. From this a central limit theorem for the number of vertices of the boundary of the convex hull is derived. Similar results can be given for the other cases mentioned above.

W. GROSSMANN

Sequences of experiments admitting adaptive estimation

Consider a sequence of experiments with finite dimensional parameter  $\theta$  and a nuisance parameter  $\psi$ . An estimate for  $\theta$  is called adaptive if the ignorance of the nuisance parameter does not cause any loss in efficiency. In order to make this definition applicable for general situation efficiency is measured in terms of minimax bounds of localized experiments. The localization of  $\psi$  has to be done in accordance with the rate of convergence of estimates  $\hat{\psi}_n$  for the nuisance parameter  $\psi$ . Because of the fact that this rate is sometimes too slow to allow usual weak convergence the concept of conditional convergence is introduced. Sufficient conditions for adaptive estimation are stated. The construction method is the Pitman estimate where the nuisance parameter is substituted by an estimate  $\hat{\psi}_n$ .

L. GYÖRFI

Is the histogram a consistent estimator of the density for stationary and ergodic samples?

Estimate a uniform density  $f$  on  $[0,1]$  from stationary and ergodic samples  $X_1, X_2, \dots, X_n$  by a histogram

$$f_n(x) = \frac{u_n(A_{n_i})}{\lambda(A_{n_i})} \quad \text{if } x \in A_{n_i}$$

where  $P_n = \{A_{n_1}, \dots, A_{n_{k_n}}\}$  is a partition of  $[0,1]$  and  $u_n$  and  $\lambda$  stand for the empirical measure of  $X_1, \dots, X_n$  and Lebesgue measure, resp. If the samples are i.i.d. and  $k_n/n \rightarrow 0$  then  $\int |f_n(x) - \mathbb{E}(f_n(x))| dx \rightarrow 0$  a.s. Example is given when the samples are stationary and ergodic and

$$P(\int |f_n(x) - \mathbb{E}(f_n(x))| dx > \frac{1}{2}) > \frac{1}{8} .$$

A. JANSSEN

Asymptotic results for locally most powerful rank tests in non-regular cases

We consider a Weibull type density  $f(x) = x^a r(x) 1_{(0, \infty)}(x)$  for the shape parameter  $a \in (-1/2, 1)$ . Then for the corresponding location family the test problem  $H = \{\theta = 0\}$  against  $K = \{\theta > 0\}$  is treated. Therefore a new theorem for locally most powerful rank tests is proved which applies to the case when  $-1/2 < a < 0$ . Moreover the asymptotic behaviour of these tests is investigated for our non-regular situation. Finally we treat the parametric model. It is shown that under a certain rescaling procedure the corresponding limit experiment  $F$  has the following structure:  $F = (\mathbb{R}^{\mathbb{N}}, \mathbb{B}^{\mathbb{N}}, (Q_\theta)_{\theta \in \mathbb{R}})$

where  $Q_\theta = \mathbb{P}(\sum_{k=1}^n J_k)^{1/1+a} + \theta)_{n \in \mathbb{N}}$  and  $J_k$  is an i.i.d.

sequence which is exponential distributed with mean 1.

W.C.M. KALLENBERG

### Local and non-local measures of efficiency

The performance of a sequence of estimators can be measured by its asymptotic variance  $\sigma^2(\theta)$  and also by its inaccuracy rate. In 'typical cases' the local limit of the standardized inaccuracy rate equals  $\{2\sigma^2(\theta)\}^{-1}$ .

Firstly, the above phenomenon is discussed from several points of view e.g. by relating it to a similar question concerning Bahadur and Pitman efficiency in testing theory. Uniformity of the convergence is a key-point. Secondly, general results on the limiting equivalence of local and non-local measures are obtained. The concepts of Fréchet- and Hadamard differentiability, which imply uniformity, play an important role.

Finally, the theory is applied on linear rank tests, L- and M-estimators.

Ch. A.J. KLAASEN

### Strong Unimodality

It can be shown that a distribution F is strongly unimodal iff any two quantiles of the convolution of F with any other distribution are further apart than the corresponding quantiles of F itself. This characterization of strong unimodality and related ones will be discussed, together with an application to asymptotic estimation.

H. L. KOUL

### Minimum Distance Estimation in Linear Models

In this talk extensions of Cramer-von Mises type minimum distance estimators from the one and two sample location models to the linear models are given. These extensions are based on certain weighted empiricals which are basic to these linear models. The linear models include the autoregressive model with regression components. The class of estimators includes the Hodges-Lehmann type and Darling-Anderson type estimators. A general limit theorem is given which is useful in studying the asymptotic normality and qualitative robustness of these minimum distance estimators.

J. P. KREISS

On adaptive estimation in autoregressive models when there are nuisance functions

We consider stationary solutions  $(X_t)_{t \in \mathbb{Z}}$  of the following difference equation

$$X_t = \theta X_{t-1} + e_t .$$

The errors  $e_t$  are assumed to be i.i.d. random variables with zero mean, finite variance and finite Fisher-Information  $I(f)$ .  $f$  denotes the density of the error-distribution. In a first part we prove asymptotic normality of the above model for the parameter  $(\theta, f)$ , where we use a specific local parametrization (c.f. a preprint of Huang (1984)). The main part of the talk deals with the construction of adaptive estimates of  $\theta$ , if  $f$  is regarded as a nuisance function. Surprisingly it turns out that adaptation is possible, even if the underlying  $f$  is not symmetric. The construction uses ideas of the approach given in Stone (1975). All results hold true for autoregressive processes of order  $p$ , too.

U. KRENGEL

Nonlinear models of diffusion on a finite space

Let  $T$  be an order preserving operator in  $l_1^+$  of a finite space which preserves integrals. It is shown that  $T^n f$  converges for all  $f$  under an aperiodicity condition and that in general there exists  $p \in \mathbb{N}$  such that  $T^{pn} f$  converges. In the case of continuous-time there always is convergence. This extends classical results on Markov chains to the nonlinear case. The exponential speed of convergence need not hold in the nonlinear case. (Joint work with M.A. Akcoglu).

H. KÜNSCH

Jackknife and Bootstrap for general stationary observations

We consider nonparametric variance estimates for M-estimators  $T_n$  defined by  $\sum_{i=1}^{n-r+1} \psi(X_i, X_{i+1}, \dots, X_{i+r-1}; T_n) = 0$ . The  $(X_i)$  are assumed to be a stationary strongly mixing process. Let  $Y_i$  be  $(X_i, X_{i+1}, \dots, X_{i+r-1})$ . For the jackknife define  $T_m(j)$  by



$\sum_{i \in B_j} \psi(Y_i, T_m, (j)) = 0$  where  $B_j = \{j, j+1, \dots, j+m-1\}$ . We then estimate

$\text{Var}(T_n)$  by  $\frac{(n-m)^2}{n^2 m} \sum (T_m, (j) - \bar{T}_m, (\cdot))^2$ . This is shown to be

consistent and asymptotically normal for  $m \rightarrow \infty$ ,  $m/n \rightarrow 0$  if  $\sum k\alpha(k) < \infty$  and  $\psi$  is bounded. It turns out to be equivalent to the Bartlett

estimate of a spectrum. The procedure can be improved by using  $\sum (1-w((i-j)/m))\psi(Y_i, T_m, (j)) = 0$  with a continuous window  $w$ . For

the bootstrap we generate for given  $Y_1, \dots, Y_n$  pseudosamples  $Y_1^* \dots Y_n^*$  where the blocks  $(Y_{km+1}^*, \dots, Y_{(k+1)m}^*)$  ( $k = 0, \dots, \frac{n}{m} - 1$ )

are i.i.d.  $\sim (n-m+1)^{-1} \sum_{i=1}^{n-m+1} \delta(Y_i, \dots, Y_{i+m-1})$ .

L. LE CAM

On the preservation of local asymptotic normality under information loss

Let  $\{\xi_n\}$  be a sequence of experiments,  $\xi_n = \{P_{\theta, n}; \theta \in \Theta_n\}$  given by measures on  $\sigma$ -fields  $A_n$ . Assume that the sequence  $\{\xi_n\}$  satisfies the LAN conditions or the condition of weak Gaussian approximability.

Let  $F_n$  be given by restricting the  $P_{\theta, n}$  to  $\sigma$ -fields  $B_n \subset A_n$ . The LAN property (resp WAG) is inherited by the  $F_n$  in the following cases: a) The  $\xi_n$  are direct products of bounded infinitesimal arrays and the passage to  $B_n$  occurs factorwise. b) There are statistics  $S_n$  and  $T_n$  with  $S_n$  distinguished on  $\xi_n$  and  $T_n$  defined on  $F_n$  and distinguished there such that i)  $\mathcal{L}(S_n | P_{t, n}), t \in \Theta_n$  are asymptotically shift normal ii)  $\mathcal{L}(S_n, T_n | P_{\theta_n, n})$  is asymptotically normal for some sequence  $(\theta_n)$ . If in part (b) one requires instead of (ii) that  $\mathcal{L}(S_n, T_n | P_{\theta_n, n}) \rightarrow \mathcal{L}(X, Y)$  with  $\mathcal{L}(X|Y)$  normal one obtains a related result of R. Davies (Proc. Neyman-Kiefer Conference, Wadsworth, 1985).

P. MAJOR

On the tail behaviour of the distribution function of multiple stochastic integrals

We consider the  $s$  fold product of the measure induced by the standardized empirical process and the integral of a bounded function with respect to it. We are interested in the tail behaviour of the distribution function of this random integral. A large deviation type result is presented for this problem which is in some sense optimal. We prove our result by first proving an analog result about Poisson processes and then applying Poisson approximation of the empirical process.

H. MILBRODT

Asymptotic Theory of Sampling Experiments

The asymptotic behaviour of experiments associated with Poisson sampling, Rejective sampling and Sampford-Durbin sampling is investigated. As superpopulation models so-called  $L^r$ -generated regression parameter families ( $1 \leq r \leq 2$ ) are considered, allowing also the presence of nuisance parameters. Under some assumptions on the first order probabilities of inclusion it can be shown that the sampling experiments converge weakly iff the underlying shift parameter families do. In case of convergence, the limit of the sampling experiments is characterized in terms of Hellinger transforms. Applications include LAM-bounds and criteria for adaptivity, when estimating a continuous linear functional in asymptotically normal (LAN-) situations. They cover especially the case of sampling from an unknown symmetric distribution, which has been subject to detailed investigation in the i.i.d. case.



The rate of convergence in CLT in Hilbert space

Several theorems concerning the bounds of the remainder term in CLT in Hilbert space are exposed. Formulate one of them. Let  $M$  be a real separable Hilbert space with norm  $|\cdot|$ ,  $\{X_k\}_1^n$ , be a sequence of i.i.d.r. v with value in  $M$ ,  $\mathbb{E}X_1 = 0$ ,  $\beta = \mathbb{E}|X_1| < \infty$ ,  $\sigma^2 = \mathbb{E}|X_1|^2$ ,  $\Lambda$  be the covariance operator of r.v.X.

Th. 1 Let  $\{\sigma_k^2\}_1^\infty$ ,  $\sigma_k^2 \geq \sigma_{k+1}^2$  be the eigenvalues of  $\Lambda$  and  $\sigma_j > 0$ ,  $j = 1 - 7$ . Then

$$\sup_{\tau} |P(|n^{-1/2} \sum_1^n X_j - a| < \tau) - P(|Z - a| < \tau)| < c \beta (\sigma^3 + |a|^3) / (\prod_1^7 \sigma_j)^{6/7} \sqrt{n}$$

where  $Z$  is a Gaussian r.v. with the same covariance operator  $\Lambda$  and  $\mathbb{E}Z = 0$ ,  $c$  is an absolute constant.

P. NEY

Large deviations of Markov additive processes

We consider an MA-process  $\{(X_n, S_n); n=0, 1, \dots\}$ , where  $\{X_n\}$  is a M.C. on a general state space  $(\mathbb{E}, \mathcal{E})$  and  $\{S_n\}$  is an  $\mathbb{R}^d$ -valued additive component. Properties of the eigenvalues and eigenfunctions of the transform kernel of the process are proved. These are then used to show that the large deviation principle holds for  $\mathbb{P}_x\{(X_n, S_n) \in A \times \Gamma\}$ ,  $A \in \mathcal{E}$ ,  $\Gamma$  a Borel set in  $\mathbb{R}^d$ . The lower bound (for open  $\Gamma$ ) needs only irreducibility of  $\{X_n\}$  and non-singularity of  $\{S_n\}$  in a standard sense. The upper bound (for closed  $\Gamma$ ) requires a moment hypothesis when  $d \geq 2$ . Regeneration techniques are used extensively in the proofs.

J. OOSTERHOFF

On complete families of distributions

A simple proposition is presented which establishes completeness of (parametric) families of distributions by deriving it from the completeness of other families. Some particular cases are considered, which immediately lead to completeness of non-central distributions, non-null distributions and shift distributions of some well known statistics.

B.L.S.P.. RAO

Least squares and nonlinear Regression

Consider the nonlinear regression model  $X_i = g_i(\theta) + \epsilon_i$ ,  $i \geq 1$ , where  $\mathbb{E}(\epsilon_i) = 0$  and  $\mathbb{E}(\epsilon_i^2) < \infty$ . The problem studied is the estimation of the parameter  $\theta$  by the method of least squares and obtain the asymptotic properties of the least-squares estimator (LSE). The classical method consists of deriving the normal equations and using Taylor expansion around the line parameter of the function  $Q_n(\theta) = \sum_{i=1}^n (X_i - g_i(\theta))^2$ . Clearly this method is not applicable when  $g_i(\theta)$  are not differentiable. Here we present an alternate approach for the study of asymptotic properties of LSE. Weak convergence of suitably normalized version of the least squares random fields  $Q_n(\theta)$  is studied and the asymptotic properties of LSE are obtained via the continuous mapping theorem. Inter alia, the rate of convergence of LSE is discussed. A non-regular case where the classical method is not applicable is presented. Some of the results have appeared in J. Multivariate Analysis and Statistics and Probability Lectures. Others will appear in Statistics and Decisions 4 (1986), Statistics 17 (1986) and Ann. Inst. Statist. Math. (1986).

L. RÜSCHENDORF

Unbiased estimation in generalized moment families

For generalized moment families a characterization of the unbiased estimators of zero is proved, which allows to determine MVUE's in many nonparametric families. As special examples we discuss finite moment families, extension models, nonparametric translation families and distributions with given marginals.

R.J. SERFLING

Maximal probability inequalities for multidimensionally indexed submartingale arrays of random variables and applications

Chow (1960) established a maximal probability inequality for submartingale sequences, thereby extending inequalities of Doob, Hájek and Rényi, and Kolmogorov. Cairoli (1970) extended some of Doob's inequalities to multidimensionally indexed arrays and gave a counter example to possible extension of another of Doob's inequalities. Smythe (1974) gave a similar extension of the Hájek-Rényi inequality. In the present work an analogous extension of Chow's inequality is developed. This yields the results of Cairoli and Smythe as special cases and also a modified version of the other Doob inequality, as well as some other useful corollaries. Important applications include random fields and U-statistics. (This work is joint with T. Christotides.)

J. STEINEBACH

Note on a limit theorem for characteristic functions

Let  $X$  be a (real-valued) random variable on some probability space  $(\Omega, \mathcal{A}, P)$  with distribution function  $F(x) = P(X \leq x)$ ,  $x \in \mathbb{R}$ , and characteristic function  $\varphi(t) = \int e^{itx} dF(x)$ ,  $t \in \mathbb{R}$ . If  $F$  is bounded to the right (or left), a classical limit theorem on  $\varphi$  says that the "extremities" of  $F$ , i.e.  $\text{rex}(F) = x_R = \text{ess sup } X$  (resp.  $\text{lex}(F) = x_L = \text{ess inf } X$ ) are determined by the limit relations

$$x_R = \lim_{s \rightarrow \infty} \frac{1}{s} \log \varphi(-is), \quad x_L = -\lim_{s \rightarrow \infty} \frac{1}{s} \log \varphi(is).$$

Via elementary convexity arguments, some extended versions of the latter relations can be derived which, in particular, provide a well-known characterization of bounded distribution functions. Certain relations to other fields such as "ruin theory" or large deviation problems" are also discussed.

H. STRASSER

Stability of limit experiments for dependent observations.

A family of probability measures on a filtered probability space is called a filtered experiment. It is shown that sequences of filtered experiments, which are obtained by rescaling a fixed experiment, can only have weak limits satisfying an invariance property called stability. In case of independent, identically distributed observations, the result covers previous assertions obtained by Strasser. In general, the result covers the case of dependent observations. It can be explained, how so-called mixed normal situations arise in the limit. As a by-product we show, how an increasing family of experiments can be represented by a filtered experiment.

J. TEUGELS

Tail estimation

In insurance mathematics premiums are often partially determined from the mean and/or the variance of past claim experience. For large claims however one can reasonably assume that the distribution  $F$  of the claims is of the form  $1-F(x) = x^{-\alpha}L(x)$  where  $L$  is slowly varying. One of the main problems then is to estimate  $\alpha$ . One choice will be Hill's estimator. We find the weakest possible conditions for asymptotic normality; they easily lead to quantile and to tail estimation of  $F$  as well.

J. van den BERG

Some results and problems concerning M-dependent sequences.

We discuss some results in a paper by S. Janssen (Ann. Probab. 1984). In particular we present a simpler proof of his main theorem, using standard Markov Chain theory. Some attention is paid to the conjecture that every M-dependent sequence can be "represented" as a finite-window function" of an i.i.d. sequence.

W.R. van ZWET

Kakutani's interval splitting scheme.

Choose a point at random (i.e. according to the uniform distribution) in the interval  $(0,1)$ . Next choose a second point at random in the longest of the two intervals into which  $(0,1)$  is divided by the first point. Continue in the way, at the n-th step choosing a point at random in the longest of the n subintervals into which the first  $(n-1)$  points subdivide  $(0,1)$ . Let  $F_n$  be the empirical distribution function of the first n points chosen. It is known that  $\bar{F}_n$  converges a.s. to the uniform d.f. on  $(0,1)$  (cf. Ann. Prob. 6 (1978), 133). Ronald Pyke and the author have recently shown that the corresponding empirical process converges in distribution to a constant multiple of a Brownian bridge.

W. WEFELMEYER

Regularity of estimator-sequences for real-valued functionals

A family of probability measures dominated by a fixed probability measure P can be identified with a subset of the Hilbert space of P-square integrable functions by considering the square roots of the P-densities. Assume that this subset admits a tangent cone with respect to the Hausdorff distance. Assume, furthermore, that we are given a Hellinger differentiable real-valued functional on

the family of probability measures. Then any estimator-sequence for the functional which is asymptotically linear and asymptotically efficient in  $P$  is locally asymptotically minimax.

M. YOR

Recent progress on multiple points of Brownian motion

The proofs of the existence of double points for 2- and 3-dimensional Brownian motion as well as that of points of multiplicity  $k$  (for any  $k \in \mathbb{N}$ ) and even  $c$  (: power of the continuum) for 2-dimensional Brownian motion were probably the deepest results on Brownian motion obtained in the fifties (Dvoretzky-Erdős-Kakutani - Taylor). Although K. Symanzik's program for Quantum Field theory (1969) involved quantities closely linked with the double points of Brownian motion, and was the origin of Varadhan's renormalization result, the field stayed "comparatively calm" until, at the beginning of the eighties, J. Rosen (with J. Horowitz and D. Geman) showed the existence of local times of intersection and began to develop a related stochastic calculus. As a consequence, Varadhan's renormalization result has been enormously simplified and, more importantly has been adequately extended to all multiplicities in 2 dimensions (J. Rosen and E. Dynkin); a central limit ersatz to Varadhan's result has been obtained in 3 dimensions (the author), and J.F. Le Gall was able to prove a conjecture of S.J. Taylor concerning the Hausdorff measure of  $k$ -multiple points. The last point of the lecture was devoted (too briefly) to results of J.F. Le Gall concerning the Wiener sausage, as well as his limit theorem concerning the asymptotic behaviour of double integrals related to 2-independent 4-dimensional Brownian motions. This theorem is a sort of analogue of the limit theorem for integrable additive functionals of 2-dimensional Brownian motion.

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