MATHEMATISCHES FORSCHUNGSINSTITUT OBERWOLFACH

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Mathematische Stochastik

10.3. bis 16.3.1985

Die Tagung wurde geleitet von H.v. Weizsäcker (Kaiserslautern) und P. Huber (Cambridge, MA). Die Themen waren breit gestreut. Sie zeigten klassisch-analytische, modellbildnerische, geometrische und algorithmische Aspekte der Stochastik in wechselseitiger Beziehung zu inner- und außermathematischen Grenzgebieten.

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Vortragsauszüge

E. BOLTHAUSEN

Laplace approximations in the theory of large deviations

Some refinements of the results of Donsker and Varadhan on large deviations for empirical measures of Markov processes are presented. Let X_t be a Markov process either in discrete or continuous time and let L_t be its empirical measure, i.e. $\frac{1}{n}\sum_{j=1}^{n}\delta_{X_j}$ in discrete time or $\frac{1}{t}\int_0^t \delta_{X_s}\,ds$ in continuous time. If f is a Banach space valued function on the state space and Φ is a real valued function on this Banach space then under suitable conditions

$$E_x(\exp(t\Phi(\int f dL_t))) = \rho(x)\exp(t \sup_y (\Phi(y)-h(y)))(1+o(1))$$

where ρ is a positive function on the state space.

K. H. BORGWARDT

The influence of the stochastic model on the expected number of Pivot steps required by the simplex-method

The Simplex-Method, which had been introduced by George B. Dantzig around 1947/48, is still the most efficient algorithm for solving linear programming problems. This holds, although since 1972 several variants of the method were proven to be nonpolynomial, i.e. the number of required pivot steps cannot be bounded from above by a polynomial in the dimensions of the problem, m the number of restrictions, n the number of variables. The search for a polynomial variant is without success until today.

Hence it became clear, that only a theoretical analysis of the average behaviour could explain the efficiency of the method. For that purpose one has to define a stochastic model describing the "distribution of the real-world linear programming problems".

Based on different stochastic models, as
coordinate permutation-invariance model
sign-invariance model
rotation-invariance model
very interesting results on those expectation values could be derived. The result under the different models differ significantly. We want to show how the stochastic assumptions have a direct effect on the results.

H. DINGES

What is Skewness

The contribution dealt with sequences of probability densities of the form

$$\sqrt{\frac{n}{2\pi}}\ \exp(-n\cdot K(x)) \cdot \sqrt{K''(x)} \cdot H(x) \cdot \exp(\frac{1}{n}\ S(n,x))\,dx$$

where $K(x)$, the "entropy function" is convex with $K(\mu) = 0.\ K''(\mu) = \frac{1}{\sigma^2}$
$H(x)$ the "modulating function" is smooth, and
$S(n,x) \longrightarrow S(x)$ uniformly in some neighbourhood of μ .

Such distributions turn up in many situations of asymptotic normality with good large deviation-properties, in particular

- sums of i.i.d. random var. satisfying Cramer's condition (H. Daniels, 1954 "saddle point approximation",...)
- empirical quantiles (Alfers & Dinges, 1983),
- curved bondary absorption of random walks (H. D. Klein forthcoming)

In the present contribution the local behaviour (near $\mu = 0$) was studied

$$K(x) = \frac{1}{2}x^2 + \frac{\delta}{6}x^3 + \left[-\frac{\kappa}{24} + \frac{\delta^2}{18}\right] \cdot x^4 + \ldots$$

$$\ln H(x) = \delta x + \frac{1}{2}(\varepsilon - \gamma\delta)x^2 + \ldots$$

δ = "irritation of mean", ε = "irritation of dispersion"

γ = "coefficient of skewness", κ = "coefficient of kurtosis"

<u>Theorem:</u> Let (X_n) be random variables s. that $\frac{1}{n}\ \frac{1}{\sigma}\,(X-\mu)$ has densities as above then there exists a standard normal Z s. that

$$\sqrt{\frac{n-\varepsilon}{n}}\ \frac{X_n - n\cdot\mu - \delta\sigma}{\sigma\cdot\sqrt{n}} = Z + \frac{1}{\sqrt{n}}\ \frac{\delta}{6}\cdot(Z^2-1) + \frac{1}{n}\cdot\left[\frac{\tilde{\kappa}}{24}\,(Z^3-3Z) - \frac{\gamma^2}{36}\cdot Z\right] + n^{-\frac{3}{2}}\psi_n(Z) \quad (\tilde{\kappa}=\kappa-\frac{4}{3}\cdot\delta^2)$$

J. FRANKE

<u>On recursive autoregressive-moving average estimation</u>

Given a sample $Y_1,\dots,Y_N$ from a weakly stationary process, we want to fit autoregressive-moving average models

$$Y_n + \sum_1^p \alpha_k(p,q)Y_{n-k} = \varepsilon_n + \sum_1^q \theta_k(p,q)\varepsilon_{n-k}$$

to the data for a large range of orders p,q. The ε_k are uncorrelated random variables with common variance σ^2. Under the assumption that Y_n, $-\infty < n < \infty$, is a purely nondeterministic time series, we present an algorithm which allows for a recursive (in p and q) calculation of ARMA(p,q)-coefficient estimates $\hat{\alpha}_k(p,q)$, $1 \le k \le p$, $\hat{\theta}_k(p,q)$, $1 \le k \le q$, from estimates of the autocovariances and of the crosscovariances of the Y_n and the corresponding linear innovations. This algorithm generalizes the well-known Levinson-Durbin algorithm for the pure autoregressive case $(q=0)$, and it is closely related to the Whittle-algorithm for the multivariate autoregressive case. We discuss how our algorithm may be used to make the ARMA-estimation procedure, which includes choosing the model order from the data, of Hannan and Rissane computationally less expensive.

S. GEMAN

<u>Bayesian Image Analysis</u>

We develop a class of probability image models that accomodate smoothness, edges, textures, and other, "higher level", image attributes. These are Markov Random Fields with a three dimensional graph structure. The "bottom" level of the graph is the pixel process, corresponding to the actual digitized image. Successively higher levels correspond to increasingly complex attributes, including locations and orientations of edges, line segments, and polygonal regions. The constructed distribution is employed as a prior distribution on images. Given a degraded picture, we seek the image that maximizes the posterior distribution (the so-called MAP estimator). Maximization is performed by a highly parallel computational technique called stochastic relaxation.

We will present the results of experiments with some simple pictures. These demonstrate: (1) parameter estimation for the prior; and (2) blur and noise removal, segmentation, and boundary-finding at extremely low signal to noise ratios.

F. GÖTZE

<u>Approximations for multivariate U-statistics</u>

Multivariate U-statistics are defined with respect to a vector of kernels $H(x,y) = (H_1(x,y),\dots,H_k(x,y))$ and i.i.d. observations $X_1,\dots,X_N$ in $\mathcal{X}$. They appear for example as leading terms of stochastic expansions of multivariate estimator sequences. Assuming that $H(X_1,X_2)$ has mean zero and a finite absolute third moment, the order of normal approximation for sets with "smooth" boundary is given by $O(N^{-1/2})$, provided the asymptotic covariance is non-degenerate. Furthermore, if $E(H(X_1,X_2) \mid X_1)$ has non lattice distribution an Edgeworth expansion of error $o(N^{-1/2})$ holds for sets with "smooth" boundary.

A. GREVEN

Infinite particle systems on $(\mathbb{N})^S$

We consider a class of Markov processes on $(\mathbb{N})^S$ $(S = \mathbb{Z}^n)$ with transitions of the type: motion of a particle, birth and death of a particle, extinction of all particles at a site and splitting of all particles at a site.
We compare the different processes in our class from the point of view of phase transition.

We show how presence, absence and strength of the interdependence of the fate of different particles influences the longterm behaviour of the process and shapes the appearence of the phase transition. Finally we study the question whether and how the behaviour of the system changes if it evolves in a random environment, i.e. we randomise the birth rates, death rates at each site.

R. GRÜBEL

Asymptotic analysis using Gelfand's theory

We introduce a class of convolution algebras of measures and give a related Wiener-Lévy-Gelfand result. This turned out to be important in the investigation of problems such as the following:
Suppose $(X_k)_{k \in \mathbb{N}}$ is an i.i.d. sequence of random variables with partial sums $(S_n)_{n \in \mathbb{N}_0}$, $S_0 \equiv 0$, $S_n = \sum_{k=1}^{n} X_k$. What can be said about the asymptotic behaviour of

$$\sum_{n=0}^{\infty} a_n \, P(S_n \in x + A) \quad \text{as} \quad x \to \pm\infty ?$$

($(a_n)_{n \in \mathbb{N}} \subset \mathbb{R}$ fixed, A a fixed Borel set).
Questions of this kind arise in renewal theory, in connection with random sums, Wiener-Hopf factors and infinite divisibility. As a concrete example of application of our method we give a new estimate of the renewal function.

P. J. HUBER

Data analysis and projection pursuit

The principal purpose of (exploratory) data analysis is to detect nonanticipated features. In low dimensions (up to 3) this is best done by drawing pictures, histograms, curves, scatter plots (at this point, a short movie illustrating the visual opportunities and problems of 3-d data graphics was shown). For higher dimensions, dimension reducing techniques must be employed. The classical method is principal components analysis, a more recent one is projection pursuit (Kruskal 1969, Tukey and Friedman 1974): find interesting projections by maximizing a certain projection index. Two issues were discussed: (1) the choice of an index, (2) some sampling issues. It can be argued that the least normal projection is the most interesting. This leads to a certain inequality the projection index should satisfy. It holds for the following indices: standardized absolute cumulant, Fisher information, Shannon information. It turns out that with the usual sample sizes the power of tests will be very low, and so the question to be posed is not whether a feature one has discovered is spurious, but how many false leads one is willing to pursue for the sake of a good one.

M. C. JONES

An Introduction to Projection Pursuit

In 1974, Friedman and Tukey introduced "projection pursuit" as a technique for the exploratory analysis of multivariate datasets; the method seeks out "interesting" linear projections of the multivariate data onto a line or plane, thereby yielding an informative collection of "views" of the dataset. In this talk, we concentrate on this exploratory form of the method, considering both the arguments motivating the use of the particular techiques employed and some computational aspects of an efficient implementation of the algorithm. Application to published data illustrates the power of the method. Much further work on this topic (by others) has concentrated on applying these ideas to other multivariate problems such as non-linear multiple regression and multivariate density estimation; the way in which these methods fit into the same basic framework is described.

H. KELLERER

Measure theoretical versions of linear programming

Given Hausdorff spaces X, Y and a kernel P from X to Y consider the following pair of problems:

(1) $\mu \in M_+(X)$, $\mu P \leq \nu$ and μf max!

(2) $g \in B_+(Y)$, $Pg \geq f$ and νg min!

where ν is a finite (Radon) measure and Y and $f(\geq 0)$ is a measurable function on X. Sufficient conditions for the "duality theorem" (D) max(1) = min(2) to hold are derived. They use notions as lower semicontinuity of P, tightness of the pair (P,ν) and discreteness of P. This yields equation (D) respectively for compact support or arbitrary upper semicontinuous functions or all Suslin functions f. Applications concern, among others, marginal problems (as treated in ZW 67) as well as continuous models for network problems (as proposed by K. Jacobs).

W. KLIEMANN

Results on Stochastic Systems

For linear stochastic system $\dot{x}_t = A(\xi_t)x_t$ in $\mathbb{R}^d$, where ξ_t is a diffusion process on a manifold M of dimension m and $A : M \to GL(d,\mathbb{R})$, the Lyapunov exponents $\lambda(x_o,\omega) = \overline{\lim_{t\to\infty}} \frac{1}{t} \log | x(t,x_o,\omega)|$ are studied. The multiplicative ergodic theorem of Oseledec states, that for stationary ξ_t $\lambda(x_o,\omega)$ takes on r values $\lambda_1<\ldots<\lambda_r$, each one realized in a subspace $E_i(\omega)$ of dimension d_i. Nondegeneracy conditions in terms of the Lie algebras generated by the vector fields that determine ξ_t and the pair process (x_t,ξ_t) guarantee that $\lambda(x_o,\omega) = \lambda$ a.s. for all $x_o \in \mathbb{R}^d \sim \{o\}$, hence in these cases only the greatest Lyapunov exponent "can be seen". This is a result in the spirit of Furstenberg's law of large numbers for products of random matrices. Furthermore if one considers without loss of generality the case where trace $A(\xi) = 0$ for all $\xi \in M$, then $\lambda = 0$ iff there exists a $T \in GL(d,\mathbb{R})$ with $T^{-1}A[M]T \subset SO(d,\mathbb{R})$, otherwise $\lambda > 0$. This generalizes known results by Molčanov for the random linear oscillator and theorems on stability of linear, parameter excited systems.

H. KÜNSCH

Robustness in time series

Consider an estimator for the parameters of a stationary ARMA-model of the form

$$\sum_{i=m}^{n} \psi(X_i, X_{i-1},\ldots,X_{i-m+1},T_n) = 0 \text{ or } \sum_{i=1}^{n} \psi_i(X_i,\ldots X_1,T_n) = 0$$

with ψ_i tending to ψ in a suitable sense. We discuss the asymptotic properties of T_n if we have observations $X_i = Y_i + Z_i^\varepsilon$ where Y_i follows the model and Z_i^ε is stationary with $E(|Z_i^\varepsilon|; |Z_i^\varepsilon| < 1) + P(|Z_i^\varepsilon| \geq 1) = \varepsilon$. We study the asymptotic bias as ε tends to zero by differentiating the functional defined by $\lim T_n$ along the arc of the marginals of the contaminated processes. As a consequence we can bound this bias uniformly over certain contaminations by choosing ψ suitably. However, no much robustification is possible for the asymptotic distribution and the asymptotic efficiency. Finally, we discuss robustification in the presence of nonstationary trends.

T. LINDSTRÖM

Nonstandard methods in mathematical stochastics

By means of the ultrapower construction, we give a brief introduction to the basic concepts of nonstandard analysis. In particular, we emphasize hyperfinite sets as natural infinite counterparts of finite sets, carrying much of the same combinatorial structure and information. To illustrate the use of the method in probability theory, we construct Brownian motion as the standard part of a hyperfinite random walk.

P. MAJOR

On the asymptotic behaviour of the product-limit estimator

We consider the so-called Kaplan-Meier product-limit estimate of a distribution function on the basis of censored data. Breslow and Crawley proved that the difference of the estimate and the real distribution function multiplied with $\sqrt{n}$ tends to a Gaussian process. In the talk we gave the exact rate of this convergence. We also discussed some open questions and some technical problems during the proof, which are of independent interest.

P. MATTILA

Unvisible sets

A Borel set E in the plane is unvisible if it is unvisible from almost all directions, that is, its orthogonal projection on almost every line through the origin has length zero. This means that random lines almost surely fail to meet the set. If E has finite one-dimensional Hausdorff measure $H^1(E)$, the unvisibility means irregularity in the sense of Besicovitch, and a lot is known about the geometric structure in this case. In general unvisible sets have Hausdorff dimension at most one, and they may have non-σ-finite H^1 measure. The only C^2 diffeomorphisms preserving unvisibility are the ones mapping line segments onto line segments. Results of K.J. Falconer and M. Talagrand imply that a non-unvisibel set need not be visible from almost all directions.

R. D. MAULDIN

Random Constructions : asymptotic geometric and topological properties

We study some notions of "random constructions" which lead almost surely to a particular type of topological object-Cantor set, Sierpinski curve or Menger curve. We demonstrate that associated with each such construction is a "universal" number, a number α such that almost surely the random object has Hausdorff dimension α.

D. MOLLISON

Epidemic Models: Stucture and Sensitivity

For ecological processes such as epidemics, a wide variety of types of model have been proposed, for instance stochastic branching, percolation and diffusion processes, as well as deterministic differential and difference equation models. While the most interesting theoretical advances of recent years have been on simple spatial stochastic processes, most applied workers still rely on nonspatial models, or on over-complex simulation models.

I shall discuss the relations between various simple epidemic models, with particular reference to the ways in which they include basic epidemiological components and how this affects their qualitative behaviour.

Some aspects of model behaviour (level of prevalence, period of oscillation) appear to be robust, while others, unfortunately including crucial questions of control, are very sensitive to the detailed form of the model components.

References: Mollison, Denis (1984) "Simplifying simple epidemic models", Nature, 310, 224-225. Mollison, Denis&Kuulasmaa, Kari (1985, in press) "Spatial epidemic models: theory and simulations", in "The Population Dynamics of Wildlife Rabies", ed PJ Bacon, Academic Press.

U. MÜLLER-FUNK

Some two-sided LMP tests

The main purpose of the talk is to exhibit the stucture of locally most powerful (LMP) tests for multiparameter families. To that end we present an extension of the Neyman-Pearson lemma that can be applied to certain concave objective functions under linear constraints. This generalizes and complements a result by Isaakson (1951). The whole approach is based on methods from convex programming. The above mentioned result is then used to derive LMP rank tests for one- and multiparameter families and to study their asymptotic behaviour. This offers a different approach to problems studied by Rudnicki (1984) and others. (Joint work with F. Pukelsheim and H. Witting).

M. NAGASAWA

A statistical model for interacting particles and its limit theorem

We consider a system of interacting coloured Brownian motions on $\mathbb{R}^1$ such that n-reds stay always to the left of m-blues. Therefore, if a red and a blue meet, they will be reflected as hard balls, but reds (resp. blues) can cross over. Moreover, the interaction between them is of the mean field type. It is explained that the propagation of chaos for the system holds. 1) The empirical distribution of particles in the system converges weakly to a prob. distribution u(t). 2) Fronts of reds and blues converge to a non-random front. 3) Reds (resp. Blues) become eventually independent of each other and their probability distribution converge to the left part of u(t) (resp. the right part of u(t)), as $n,m \to \infty$ under the constraint $n/(n+m) \to \theta$.

F. OST

<u>Significance of Homologies on DNA - Sequences</u>

According to their biological implication, the analysis of DNA-sequences (ATTGCTACT...) focuses on repeats of strings (words) on a single sequence or the common occurrence of a word on two or more sequences. Suchlike structural patterns are called homologies.

To distiguish between important homologies and merely random effects, the question arises: Are homologies obtained on given sequences significant? What is the probability of getting a certain homology on similar random sequences - e.g., Markov chains? Results on calculating this probability and the asymptotic distributions of some associated random variables are highlighted.

Generalizations and open questions in defining homologies and assessing them within the framework of a stochastic model are commented on.

R. REISCHUK

<u>Probabilistic Algorithms</u>

We give an introduction how computational problems can be solved efficiently by probabilistic methods. Here efficient means that the computation time is bounded by a polynomial in the size of the input. In the distibutional approach one assumes a probability distribution on the input space and defines the time complexity of a deterministic algorithm as the expected number of computational steps with respect to this measure. On the contrary a random algorithm performs internal randomization steps and a computation depends on the input and the specific chosen random sequence. The time complexity in this case is the maximum expected number of steps over all inputs. It is independent of the distribution of the inputs. As an example it is shown how this approach has successfully been applied to storage and retrieval problems using hashing methods.

Further we study probabilistic computations that may yield incorrect results, but with probability less than 1/2, called Monte Carlo algorithms, in contrast to error free Las Vegas algorithms. For some so far difficult computational problems very efficient Monte Carlo algorithms are known, for example for deciding whether a number is prime. Finally the complexity of functions is classified with the help of polynomial time bounded probabilistic algorithms. These classes are called $\mathcal{P}$, $\mathcal{RP}$, $\mathcal{BP}$, $\mathcal{NP}$ and $\mathcal{PP}$.

H. RIEDER

The Role of the LAM Bound in Robust Statistics
or : A "0 - ∞" Law of Bias

Contrary to the parametric Hajek, Le Cam (1972) LAM bound, the LAM bound for functionals, which dates back to Koshem and Levit (1976) and has been employed as a robustness criterion by Beran (1981, 1982) and Millar (1981, 1982) in their studies of minimum Hellinger, respectively $L^2(\mu)$, distinct estimators, may be shown to be a result on bias as every regular estimator but (the optimum) one is assigned bias ∞, hence maximum risk. The robustness content of the functional LAM bound is thus only a qualitative one, namely by the implicit requirement to construct an estimator which is uniformly asymptotically normal over shrinking balls. To call such an estimator robust, however, the centering functional must be so; as for possible robustness theories for functionals we refer to Rieder (1984).

B. D. RIPLEY

Statistical problems in image analysis

One consequence of the increasing use of computers in controlling experiments is that much greater amounts of data are being produced in structured forms. One new type of dataset is a digitized image. The talk will consider statistical models and summaries for digital black/white images as well as giving an overview of the area and future prospects.

M. SCHEUTZOW

Stabilization by additive white noise

We introduce the concepts of stabilization and (weak and strong) destabilization by white noise for n-dimensional diffusion processes. We then determine the minimal dimension n for various classes of diffusion processes where these phenomena occur. By providing an explicit example it is shown that additive white noise can stabilize a two-dimensional unstable deterministic system. We then show by examples that for nonlinear diffusions (solutions of "Mc Kean"- equations) and stochastic delay differential equations stabilization by noise is even possible in dimension one.

A. STOLL

Self-Repellent Random Walks and Polymer Measures in two Dimensions

The statistical description of polymers requires a probability measure ν which takes into account the excluded volume effect.

Thus Edwards proposed the following polymer model: Equip the Wiener measure μ on $C([0,1], \mathbb{R}^d)$ with a density

$$\frac{d\nu}{d\mu}(\omega) = \frac{1}{Z} \exp[-g\, J(\omega)]$$, where the functional

$$J(\omega) = \int_0^1 \int_0^1 \delta(\omega(t) - \omega(s))\,ds\,dt$$ is intended to measure the double points of the path ω, g is a positive coupling constant, and Z is the normalization constant. Varadhan (d=2) and Westwater (d=3) could rigorously establish the polymer measure ν as weak limit of polymer measures ν_n, where the δ- function is replaced by a continuous approximation f_n. By nonstandard analysis, we can give a precise meaning to Edwards' heuristic approach in the two-dimensional case. As a corollary, we obtain that suitably scaled self-repellent random walks weakly converge to the polymer measure ν.

W. STUTE

Nonparametric Estimation of Densities and Hazard Rates in the Presence of Censoring

We first give a brief review of the available method for nonparametric handling of censored data. After that we discuss a representation of local-type characteristics, from which exact a.s. rates of converge and distibutional limit results may be easily derived.

G. WINKLER

From triangles to Gibbs states

The intersection of a decreasing sequence of finite dimensional simplices is a finite dimensional simplex (Borovikov (1952)). More generally: the inverse limit of an inverse system of simplices is again a simplex; the single simplices are neither assumed to be finite dimensional nor compact; the inverse system has to be countably generated. From this general result we derive, that inverse limits exist in the category of standard Borel spaces and substochastic kernels. In this frame concrete models from probability theory and statistical mechanics are considered such as Markov processes and Gibbs states.

M. YOR

An Introduction to Brownian Motion, via Stochastic Calculus

A number of important features of Brownian motion will be presented, using stochastic calculus (the basic facts of which will be briefly recalled at the beginning of the lecture). The features to be presented will be taken among the following:

a) an explicit solution to Skorokhod's problem.
b) the Ray-Knight theorems on Brownian local times.
c) Paul Levy's computations on the stochastic area of planar Brownian motion; a decomposition of Bessel bridges.
d) the arc sine law for one-dimensional Brownian motion.
e) the asymptotic study of winding numbers of the planar Brownian motion.
f) a construction of stable processes from one-dimensional Brownian motion.

Berichterstatter : M. Scheutzow

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