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NATO ADVANCED STUDY INSTITUTE

from identification to learning

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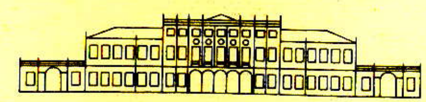

August 22 - September 2, 1994

CENTRO DI CULTURA SCIENTIFICA ALESSANDRO VOLTA, VILLA OLMO, COMO

The NATO Advantced Study Institute will take place from August 22 to September 2, 1994, in the main room of Villa Olmo Como (Italy), with the cooperation of the Centro di Cultura Scientifica Alessandro Volta

FROM IDENTIFICATION TO LEARNING

NATO Advanced Study Institute

The discoveries of the seventeenth century, noticeably the law of motion of celestial mechanics, led to the belief that natural phenomena could be described by means of simple mathematical laws. In our century, however, evidence has emerged that explicit modelling of uncertainty is essential in order to solve the problems posed by the new technologies of communication and control. Fundamental engineering problems as coding, filtering, prediction and control have been solved, leading to new and unexpected horizons for mankind such as the exploration of space, satellite communication, etc. Revolutionary modelling techniques, based on the concept that mathematical models can be directly identified from data, took over the physically motivated model building philosophy.

In this context, much more attention could be paid to the fact that reality may undergo mutations, due to interaction with a changing environment and variations in operating conditions. This is the basic rationale for evolutive modelling (on line tuning of models to data).

This general philosophy of "learning" from experiments is typically associated with the functioning of the brain, a functioning which in many respects remains ununderstood. In spite of the fact that the speed of data processing of a single neuron is slow compared to the speed of computation of present day electronic components, very efficient information treatment and retrieval combined with an extremely sophisticated signal processing architecture must be present in animal brains. In fact, the learning process of a fly is enormously more sophisticated and efficient than present day "neural computation" based algorithms. Much current research activity is motivated by the desire to understand the process of learning in biological brains with the ultimate goal of transforming it to artificial systems. The purpose of this NATO Advanced Study Institute is to present an update picture of the present state in the mathematical theory of evolutive model building. The conceptual links leading to learning algorithms starting from model identification and foundations of adaptive control will be explored. The speakers will present tutorials on the classical statistical approach, the deterministic behaviour based approach and the H-infinity approach to identification. Basic concepts of adaptation and self-tuning will be reviewed. The structure of recursive algorithms and various related computation aspects will be discussed. The concepts of learning from examples will be introduced, and the possibilities offered by neural networks will be critically evaluated.

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PROGRAM

Monday 22, Morning

8.00 - 8.45 - Registration

8.45-9.00 - Welcome from the NATO ASI director

M1. **Picci**
IDENTIFICATION: HISTORY, PROBLEM FORMULATION AND FOUNDATIONS OF THE STATISTICAL APPROACH
A quick history of black-box identification: deconvolution and frequency-domain methods. Ill-posedness and sensitivity to data variations. The statistical approach. The three main ingredients: data, model class and criterion of fit. Discussion of statistical regularity of the data, ergodicity. What can we do about nonstationary data and unstable systems. Finitely parametrized model classes: stationary processes with a rational spectrum. ARMA models. Criteria of fit: prediction error and other criteria. Stochastic model reduction as the basic paradigm of identification. Asymptotic properties of estimators. The meaning of consistency. Model complexity and order estimation. Approximate best fit algorithms, recursiveness. Convergence issues.

M2. **Picci**
STOCHASTIC MODELLING OF TIME SERIES, EXOGENOUS VARIABLES AND INPUTS. STATE SPACE AND INPUT-OUTPUT MODELS
This will cover all the basic stuff state space models, namely spectral factorization, minimal spectral factors and minimality, realization of covariance and spectrum, partial realization of covariance sequences and the

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MORNIGNS lectures ***M1*** *9.00-10.30* ***M2*** *11.00-12.30*
AFTERNOON lectures ***P1*** *14.30-15.30* ***P2*** *15.30-16.30* ***P3*** *17.00-18.00* ***P4*** *18.00-19.00*

positivity issue, positive extensions, the Positive-Real lemma equations, Stochastic realization (from covariance to state-space models). The Riccati equation to compute state space models. The forward and backward innovations realizations. Change of basis. Introduction to stochastic balancing.

Also will discuss the basic features of stochastic systems with exogenous variables, the concept of causality, feedback and feedback free processes, ARMAX models and relations between ARMAX models and EIV models. Identifiability and closed-loop identifiability.

Monday 22, Afternoon

P1. **Deistler**

ERRORS-IN-VARIABLES-APPROACH

Errors-in-variables (EV) models, are models where both inputs and outputs may be corrupted by noise. This is a generalization of the usual framework for system identification, where all noise is added to the outputs or to the equations (and the noise is assumed to be orthogonal to the inputs). The EV approach is justified in particular in the following cases:

(i) If we are interested in the true system underlying the data and if we cannot be sure that the inputs are observed free of noise.

(ii) If we want to approximate a high dimensional data vector by a small number of factors (factor analysis).

(iii) If we use symmetric system models in the sense that we do not distinguish between inputs and outputs a priori.

We consider linear dynamic systems of the form

$$W(z)\hat{X}_t = 0; \qquad W(z) = \sum_{i=\infty}^{\infty} W_j z^j; \qquad W_j \in R^{nxn}$$

where $\hat{x}_t$ are the latent variables. The observed variables are of the form

$$x_j = \hat{x}_t + u_t; \quad Ex_s u_t = 0$$

where u_t is noise. The noise in addition is either assumed to have a diagonal or a bounded spectral density.

The main emphasis of the lecture is on structure theory for system identification for this case; in particular we analyse the set of all observationally equivalent systems for given spectral density, continuity properties of the mapping relating classes of observationally equivalent systems to the spectral density of the observations, and the classes of spectral densities corresponding to a maximum number of outputs.

P2. **Ober**

BALANCED REALIZATIONS AND CANONICAL FORMS

Starting from the material presented in the morning lectures, we explain how balancing can provide canonical forms that are useful for system identification. The state space definitions of balancing are introduced that are necessary to derive the canonical forms and parametrizations of various classes of linear systems. It is shown how a balanced canonical form can be derived for stable systems. The balanced canonical forms for minimal systems, minimum phase and positive real systems are introduced and discussed.

P3,P4 **Campi**

TUTORIAL ON STOCHASTIC PROCESSES

Stationary procasses; ergodicity; conditional expectation; martingales.

Tuesday 23, Morning

M1. **Maciejowski**

MIMO PARAMETER ESTIMATION USING BALANCED REALIZATIONS

Motivation; models with free internal structure. Useful classes of models: stable, minimum-phase, positive-real. Outline of parameter estimation algorithms. Exploiting balanced realizations as canonical forms. Obtaining initial estimates: subspace and other methods. Gradient calculations.

M2. **Picci**

THEORETICAL BACKGROUND OF "SUBSPACE METHODS"

This will present a review of canonical correlation analysis of random processes, Hankel matrices and stochastic balancing with a critical analysis of the heuristic stochastic model reduction method, called balanced *truncation* introduced by Desai and Pal.

Tuesday 23, Afternoon

P1. **Maciejowski**

OBTAINING INITIAL MODELS FROM REAL DATA: APPROXIMATE REALIZATION AND SUBSPACE METHODS

Most of the theoretical material presented so far assumes either that we already have some linear model for the data, or that the data has been generated exactly by some finitely-parametrised linear model. Of course real data never satisfies this condition, and a serious issue, particularly with multivariable data, is how to get started. Another assumption frequently required by the theory is that we start with a stable model, or a minimum-phase model, etc. Again, a problem with real data is that it may give models which don't satisfy these assumptions. In this lecture we shall present some recent methods which overcome these problems. These are based on algorithms used widely in numerical analysis, in particular singular value and QR decompositions.

P2. **Ober**

POSITIVE-REAL BALANCING AND MODEL REDUCTION OF POSITIVE - REAL SYSTEMS.

Maps between various classes of linear systems are discussed. These maps are used to prove the derivation of balanced parametrizations for positive real and minimum phase systems from the result for stable systems. Model reduction for the various classes of systems is discussed. In particular the issue of the preservation of the positive real property in the truncation process is considered. The analytic significance of the system parameters is investigated.

P3. **Maciejowski**

STOCHASTIC MODELLING OF TIME SERIES AND OF CONTROL SYSTEMS: INPUT-OUTPUT AND STATE SPACE MODELS.

Application to input-output modelling and time series analysis. Two practical examples of input-output modelling using balanced realizations (based on real industrial cases). Time-series analysis: Minimum-phase systems and their parametrizations. Modifications required for this case. Approximate covariance realization: Positive-real systems and their parametrizations. Modifications required for this case. An example (probably based on artificial data).

P4. discussion/contributed session

Wednesday 24, Morning

M1. **Willems**

THE LOGIC OF MODELLING.

In this lecture we will explain some essential features of modelling. We will view a model as an exclusion law, and explain behavioral equations in this setting. Next, we will turn to the distinction between manifest and latent variables and introduce the elimination problem in the context of systems described by differential equations. Finally we will illustrate how all this fits modelling by tearing and zooming.

M2. **Khargonekar**

IDENTIFICATION IN H-INFINITY - Part 1.

In this talk, we will present some of the recent research on the problem of identification in H-infinity. This problem is a specific instance of the general problem of robust identification. The problem of identification in H-infinity requires finding identified models given noisy frequency response data for the system. It is desired that the worst case identification error converges to zero as the number of data increases and the noise

level goes to zero. Here worst case error is taken over all bounded noise and all possible unknown systems.
A class of algorithms for the problem of system identification in H-infinity will be presented. These algorithms are characterized by a two-stage structure and involve a class of window functions. Some conditions in terms of properties of the window functions are derived, which guarantee robust convergence of the algorithms. Identification errors are analyzed for several common window functions. A particular window function leads to exponential convergence. This analysis also leads to some insights into the trade-off between the error induced by approximation and that due to noise. Finally, we will present results from two applications studies involving flexible systems.

Wednesday 24, Afternoon

P1. **Willems**
CONTROLLABILITY AND OBSERVABILITY.
Focusing on dynamical systems, we will introduce the concept of controllability in the behavioral setting and contrast it with the classical state space oriented version of controllability. The notion of observability deals with systems with latent variables and has to do with the possibility of deducing the behavior of the latent variables from the behavior of the manifest ones. Test for controllability and observability in terms of the system parameters will be derived.

P2. **Kimura**
STRUCTURE OF THE MODEL SET CONSISTENT WITH THE A PRIORI INFORMATION AND THE NOISY DATA.
First, we deal with the problem of obtaining the smallest model set defined by nominal model, parameter uncertainty bound and unstructured uncertainty bound. We shall show that the problem is reduced to a convex optimization problem. Second, we investigate the structure of transfer function set which includesall the transfer functions (maximal model set) deduced from the plant available information.It is shown that when an upper bound of the norm of the transfer function is given and the noise corrupting the data is not too significant, such a transfer function can be parameterized by a linear fractional transformation of two systems, one of which is completely fixed while the other is an uncertain system whose norm bound is given.

P3,P4. Discussion / contributed session

Thursday 25, Morning

M1. **Willems**
MODELLING FROM DATA.
This lecture will deal with system identification. We will do this entirely in the context of deterministic systems. We will view the central question in system identification as follows: given a cloud of data (for example, a vector time-series), find a model of limited complexity which explains these data within a tolerated complexity. However, before treating this approximation question we will first discuss the notion of the MPUM, the most powerful unfalsified model, and discuss algorithms for constructing it.

M2. **Khargonekar**
IDENTIFICATION IN H-INFINITY - Part 2.

free afternoon

Friday 26, Morning

M1. **Bittanti**
RECURSIVE IDENTIFICATION
Following the general rationale of prediction - error identification methods, recursive identification methods are overviewed, with main emphasis on Recursive Least Squares, in its various forms, and gradient type algorithms.

M2. **Benveniste**
SYSTEM IDENTIFICATION; MONITORING AND DIAGNOSTICS.
Stochastic approximations of the form

$$\theta_k = \theta_{k-1} + \Gamma_k H(\theta_k, X_k)$$

where θ is some parameter for identification and X_k are measurements taken from a system, are used for system identification. We give an

Invariance Principle for random vector field $H(\theta_k, X_k)$ under both

hypothesis of no change $\theta_k^* = \theta_o$ and hypothesis of local change

$\theta^*_k = \theta_o + \tilde{\theta}\ \sqrt{N}$ (θ_k^* true system at instant k, $\tilde{\theta}$ normalized change, N sample length). Based on this invariance principle we develop the asymptotic local approach for slight change detection in dynamical systems. We also discuss diagnostics, i.e., identification of the change; this can be done both in θ parameter space, and in physical φ parameter space - identification is often performed under model reduction so that dim (θ) <<dim (φ). We discuss optimal sensor location in order to maximize test efficiency. And we briefly report on two main applications (vibration mechanics and gas turbine monitoring) with emphasis on robustness issues.

Friday 26, Afternoon

P1. **Willems**
CONTROL AS INTERCONNECTION
This lecture will be dedicated to questions of automatic control. We will view control as interconnection and contrast this point of view with the usual feedback processor structure used in intelligent control. We will subsequently study a number of control problems, notably stabilization, linear-quadratic, and H-infinity control.

P2. **Bittanti**
INTRODUCTION TO SELF TUNING CONTROL
In this lecture, we introduce the basic self-tuning minimum variance control system, which has set the basis for many other adaptive control methods, and is often seen as a classical paradigm in predictive control. By means of the notion of excitation subspace, the behaviour of this nonlinear control system can be clarified, on both sides of identification and control.

P3,P4. discussion/contributed session

Saturday 27, Morning

Discussion / contributed sessions

Monday 29, Morning

M1. Kumar

LEARNING AND PROBABLY APPROXIMATE CORRECT LEARNING

In this talk we develop a model for studying problems of learning. We develop a notion of satisfactory learning called "Probably Approximately Correct Learning".

M2. Mitter

LEARNING, ADAPTIVE CONTROL AND NEURAL NETWORKS Part 1

In this and in the subsequent lecture, I discuss learning and adaptive control from the stochastic control viewpoint as originally proposed by Bellman, Florentin and Feldbaum. A great deal of work was done in this area in the sixties, but the general conclusion was that obtaining optimal solutions was computationally unfeasible. A similar conclusion can be reached for non-linear filtering problems. Indeed, for most problems of interest where the problem is posed in terms of optimality the complexity seems to grow exponentially. Therefore the interesting issue is to pose these problems differently where the complexity can be managed. I approach this question by discussing several examples from filtering and adaptive control where a hierarchical approach provides a way to limit this computational complexity. To make this a successful approach a qualitative understanding of the dynamical behaviour of systems is essential. I suggest that neural networks may well have a role to play here. A guiding principle here is to work with multiple representations corresponding to viewing the system at different levels of abstraction.

Monday 29, Afternoon

P1 Van Schuppen

INTERACTION OF IDENTIFICATION AND CONTROL

A closed-loop system consisting of a control system and an adaptive controller will be called *tuning* for a specific control objective if the real system and the ideal system defined below achieve the same value for the control objective. The *real system* is the system consisting of the unknown control system in closed-loop with the adaptive controller in which the parameters of the adaptive controller have been determined by identification under feedback or in closed-loop. The *ideal system* is the system consisting of the unknown control system in closed-loop with a controller in which the controller has been synthesyzed with knowledge of the unknown control system and such that the closed-loop system satisfies control objective. For which adaptive controller does tuning hold? This question will be considered for both a Gaussain stochastic control system whith full observations and with partial observation. The approach to the problem is based on stochastic realization theory for Gaussian systems. The stated question is answered positively for the control objective of minimum variance and pole placement. Neccessary conditions for tuning are discussed.

P2. Kumar

ON ADAPTIVE CONTROL:
CONVERGENCE OF SELF-TUNING CONTROLLERS

In recent years, systematic methods have been developed for establishing the stability, self-optimality, self-tuning, and convergence properties of adaptive controllers. In this talk we develop the themes of this general theory.

P3. Van Schuppen

RELATION BETWEEN SYSTEM IDENTIFICATION, LEQG OPTIMAL STOCHASTIC CONTROL, AND H-INFINITY OPTIMAL CONTROL WITH AN ENTROPY CRITERION

The purpose of this lecture is to explain the relation between the topics mentioned in the title and to mention implications of this relation for system identification. The optimal stochastic control problem (LEQG) for a linear Gaussian system with an exponential-of-quadratic cost function has been formulated by D.H. Jacobson. The partial observation case was solved by P. Whittle for the discrete - time case and by A. Bensounsan and myself for the continuous time case. The optimal control law consists of a linear filter and a linear feedback map, and is based on two coupled Riccati differential equations. The presentation of the control law does not satisfy one of the definitions of the separation property.

The H-infinity optimal control problem with measurement feedback, and with an entropy criterion was formulated and solved by K. Glover and co-workers. Glover also discovered afterwards that the solutions to the H-infinity optimal control problem and the LEQG optimal stochastic control problem were identical and published a brief analysis of the relation.

In this lecture the relation between he H-infinity entropy criterion and the LEQG optimal stochastic control problem will be discussed. After an introduction to a measure theoretic formulation to information measures, formulas will be presented for the entropy and the mutual information of finite-dimensional Gaussian random variables and for entropy rate and mutual information rate of stationary Gaussian prosesses. The Kullback-Leibler pseudo-distance on the set of probably measures will be calculated for the same objects. Explicit formulas are obtained for the case the stationary Gaussian pocesses are represented by finite-dimensional Gaussian systems.These formulas clarify the relation between the LEQG and the H-infinity problem.

Maximum likelihood estimation is an often used technique in system identification. This method is related to minimization of the Kullback-Leibler distance and hence to the problems mentioned above.

For a parameter estimation problem the same parameter estimator can then be derived by LEQG optimal stochastic control, by H-infinity optimization, by a modified maximum likelihood criterion, and by a Kullback-Leibler distance minimization. The relation between the subjects indicated is likely to be useful for system identification.

P4. E.J.HANNAN MEMORIAL

Tuesday 30, Morning

M1. **Kumar**

PROBABLY APPROXIMATELY LEARNING:
THE VAPNIK-CHERVONENKIS DIMENSION.

Some learning problems are inherently hard, while others are easy. We introduce a combinatorial quantity, called the Vapnik-Chervonenkis Dimension . We show that this quantity, called the V-C dimension for short, measures the difficulty of learning.

M2. **Mitter**

LEARNING, ADAPTIVE CONTROL AND NEURAL NETWORKS - Part 2

Tuesday 30, Afternoon

P1. **Kumar**

PROBABLY APPROXIMATELY LEARNING BASED ON SMOOTH SIMULTANEOUS ESTIMATION.

In this talk we introduce a method of learning based on "smooth simultaneous estimation". We also show how the method can be used to choose the complexity of a model class for fitting the data.

P2. **Albertos**

INTERACTIVE IDENTIFICATION - CONTROL DESIGN.

In order to design a controller suitable to an unprecisely known plant an iterative approach can be followed. Starting from an acceptable controller two steps are implemented: one to adjust the model and the next to refine the controller. This has the effect of distinguishing the requirements for model tuning in response to the controller and controller robustness to measured model errors. Following from this decoupling of the iterative scheme, we are able to focus solely upon the controller tuning in response to measured/achieved performance compared to expected/designed performance. This permits the consideration of iterated controller refinements without the attendant need for model refinement. The advantage of such a scheme is that it obviates the need for external excitation of the tuning experiment — the process noise suffices. Given a stable plant, by starting with a stable initial model and a robust stabilizing controller, the bandwidth of the resulting closed-loop system can be increased progressively through an iterative control-relevant system identification and control design procedure. An example by pole assignment controller design is discussed. A comparison between the different control strategies is performed and some conclusions arise: i) The outlined approach is closely related to human experimental learning. You cautiously control the plant and observe the response. Then try to add some extra features to the basic control already implemented. ii) General statement:" A controlled plant looses some of its possible open-loop wilderness or vivacity, in such a way that its control require strong control actions". Some questions remain open: i) which plants are treatable by this approach? ii) To what extent can the iterative procedure be repeated?

P3,P4. discussion / contributed session

Wednesday 31, Morning

M1. **Cybenko**

MEMORIZATION AND LEARNING: THEORY .

Many learning problems can be abstracted as interpolation with a stochastic component. The interpolation can be done using explicit memorization, meaning the use of lookup tables. Alternately, interpolation can be done with a parametric function model such as neural networks and many regression techniques. In this talk, we present results concerning the respective theories of these approaches, specially about approximation results and convergence rates.

M2. **Pflug**

SEARCHING FOR THE BEST: STOCHASTIC APPROXIMATION; SIMULATED ANNEALING AND RELATED PROCEDURES

The talk gives an overview on stochastic optimization algorithms. The emphasis is on the common structure between stochastic approximation annealing with random observations and bandit processes. In each of the cases, only a stochastic information is available about the objective function and therefore multiple observations have to be taken to get a reliable value. However, the search must be organized in such a way, that not too many observations are taken at uninteresting argument values, i.r. argument values which are far away from the optimum.

The organization of the search and precise must balance the need for getting some information in all areas of the search space and precise information near the optimizers. The principle can be explained and successfully implemented for finite search spaces (bandit processes, discrete stochastic approximation, simulated annealing) and then extended to infinite search spaces. A variant of the simple gradient-type stochastic approximation divides the effort into a part which is based on few observations which tries to get a picture of the landscape of the objective function (basins of attraction, areas of the local and global optima) and a part, based on many observations, where finer search is performed.

The crucial question is how to balance the effort between these two parts. A related and equally important question is how to divide the effort of search between several processors in a distributed setting. Here the question of loosely or tightly coupling several parallel search processes will be discussed.

free afternoon

Thursday 1, Morning

M1. **Ljung**
NEURAL NETWORKS TECHNIQUES FROM AN IDENTIFICATION PERSPECTIVE.
This presentation covers some basic aspects of application of Neural network(NN) model structures in System Identification. We point out the role that general estimation techniques and estimation results have for NN models, both in terms of algorithms and statistical properties. From this perspective, Neural Networks is just another model parametrization. We also point to the specific features of NN structures that explain their usefulness. Among these are (1) good properties to approximate localized non-linearities and (2) good ways of keeping the "efficient number of free parameters" low, using implicit or explicit regularization.

M2. **Vidyasagar**
AN OVERVIEW OF COMPUTATIONAL LEARNING AND ITS APPLICATIONS TO NEURAL NETWORK TRAINING.
Learning theory is a very attractive mathematical formulation of the intuitive notion of `generalizing on the basis of experiment.'' For example, using this theory, one can make *precise* statements as to the ability of neural networks to ``generalize.'' There is a widely-held belief that, if a neural network is trained on a sufficient number of samples, then it will *always* give the correct answer on any future (but previously untrained) input.This is of course impossible. All it can do is to give the correct answer *with high probability* that can approach, but never equal, one. Other possible examples include inferencing in AI expert systems, whereby one is willing to accept a *small* possibility of error in return for greatly reduced CPU time. In this talk, the ``standard'' problem formulation is given, and the main known results are summarized. The applications of these results to the above-mentioned problems are indicated.

Thursday 1, Afternoon

P1,P2. **Benveniste**
WAVELETS IN IDENTIFICATION.
This is a tutorial about nonparametric nonlinear system identification. Advantages and limitations of this approach are discussed from the engineer's point of view. Classical as well as modern techniques are discussed, this includes kernel and project estimates, neural networks and hinging hyperplans, and mainly wavelet estimators. Both practical and mathematical issues are investigated. Advantages and limitations of wavelet based techniques are emphazised. Finally we show how fuzzy models may play a role in this game, as a framework for expressing prior knowledge on the system.

P3,P4. discussion/contributed session

Friday 02, Morning

M1. **Ljung**
IDENTIFIABILITY, PHYSICAL AND SEMI-PHYSICAL MODELS IN SYSTEM IDENTIFICATION
A simple estimation rule says: "Don't estimate what you already know!" This means that one should apply as much physical insight as possible in System Identification. This, however, does not come for free. While all basic estimation techniques cover physicallly parametrized model structures, both linear and non-linear, the practical application of them may be costly: The modeling phase takes time, and may lead to structures with unrealistically many parameters. The minimization of critera of fit may be quite cumbersome, and the information available in observed data may not support all parameters. In this contribution we discuss such techniques, their advantages and problems, and also describe how a less ambitious approach ("semi-physical modeling") often is a good compromise.

For physically parametrized models also Identifiability becomes an important issue: Can the parameters be uniquely estimated from input-output data? The presentation will also contain an overview of the identifiability problem, including some recent results, based on differential algebra.

M2. **Cybenko**
MEMORIZATION AND LEARNING: PRACTICE AND APPLICATIONS IN INFORMATION RETRIEVAL.
The implementation of parametric approaches to learning require the solution of nonlinear optimization problems. At the same time, memory-based lookup tables require the use of efficient data structures and searching schemes. We will present algorithms for these problems, their performance analysis and experiences with actual applications. Recent results on conditioning of training problems and stochastic searching will be presented.
Information retrieval and management is a growing problem with the advent of high speed computer networks. Many retrieval, filtering and management problems in document retrieval can be posed as learning problems. These applications will be described together with state-of-the-art methods for their solution. We will describe new methods for attacking these problems based on learning theory and algorithms.

Friday 02, Afternoon

P1,P2. **Albertos**
FUZZY MODELING AND CONTROL
The purpose of this talk is to present the use of Fuzzy Logic theory to develop tools to model the unprecise knowledge of processes to be controlled and to design a kind of Intelligent Controllers, the so called Fuzzy Controllers. The structure, main components, its use, and the different methodologies to design such a controller will be discussed. Also, the fuzzy logic approach will be shown suitable to represent the approximated knowledge we have about the dynamic behaviour of the plant to be controlled. Dealing with control problems, a model of the process to be controlled and some control specifications must be given. The solution, following a control design methodology, will lead to the controller. It should be considered as a system, a dynamical one, with a set of input/output variables, and a mathematical model expressed by the control algorithms or control laws, with some tunable parameters. The way the controller is considered depends of the involved user. From a control engineer point of view, the controller is just a subprocess which is connected to the plant. Its purpose being the control of the plant, it is conceived in relation with it, as a full dependant system. Sometimes it is combined with other system components, like filters, power amplifiers, and so on. On the other hand, from an instrumentation engineer point of view, the controller is a device processing the measurement signals and providing a control action. This control action is mainly related to the actions the plant operator would take under manual control. In the case of a digital control implementation, it appears as a small part of the global code. This leads to different approaches to design fuzzy controllers. Another option is to enhance classical controllers, like state feedback or PID controllers, adding the approximate knowledge the user has about changes in operating mode, saturations, etc. A practical application on cement kiln control is discussed.

P3,P4 discussion / contributed sessions

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the presentation schedule will be
finalized at the beginning of the school

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Mathematical modelling in learning

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System theoretic properties of recurrent neural networks

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Incremental learning methods

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Robust filtering and prediction of linear systems with uncertain parameters

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Perception of ambiguous figures: a qualitative model based on synergetics and quantum mechanics

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Tutorial on stochastic processes

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Recognition of deformed patterns

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Decentralized fuzzy control of
multivariable process by
direct decomposition

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On chemostat stability

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On some algorithms of
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