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Time Series Prediction Competition: The CATS Benchmark

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***Abstract* – This paper presents the CATS Benchmark and the results of the competition organised during the IJCNN'04 conference in Budapest. Twenty-four papers and predictions have been submitted and seventeen have been selected. The goal of the competition was the prediction of 100 missing values divided into five groups of twenty consecutive values.**

I. INTRODUCTION

Time series forecasting is a challenge in many fields. In finance, one forecasts stock exchange courses or stock market indices; data processing specialists forecast the flow of information on their networks; producers of electricity forecast the load of the following day. The common point to their problems is the following: how can one analyse and use the past to predict the future? Many techniques exist: linear methods such as ARX, ARMA, etc. [1,2], and nonlinear ones such as artificial neural networks [3-7]. In general, these methods try to build a model of the process that is to be predicted. The model is then used on the last values of the series to predict future ones. The common difficulty to all methods is the determination of sufficient and necessary information for a good prediction. If the information is insufficient, the forecasting will be poor. On the contrary, if information is useless or redundant, modelling will be difficult or even skewed.

In parallel with this determination, a prediction model has to be selected. In order to compare different prediction methods several competitions have been organised, for example:

- The SantaFe Competition [7];
- The KULeuven Competition: Avanced Black-Box Techniques for Nonlinear Modeling: Theory and Applications [8];
- The Eunite competition [9].

After the competitions, their results have been published and the time series have become widely used benchmarks.

The goal of these competitions is the prediction of the following values of a given time series (30 to 100 values to predict). Unfortunately, the long-term prediction of time series is a very difficult task, more difficult than the short-term prediction.

Furthermore, after the publication of results, the real values that had to be predicted are also published. Thereafter it becomes more difficult to trust in new results that are published: knowing the results of a challenge may lead, even unconsciously, to bias the selection of model; some speak about "data snooping". It becomes therefore more difficult to assess newly developed methods, and new competitions have to be organized.

In the present CATS competition, the goal was the prediction of 100 missing values of the time series; they are grouped in 5 sets of 20 successive values. The prediction methods have then to be applied several times, allowing a better comparison of the performances. Twenty-four papers and predictions were submitted to the competition. Seventeen papers were accepted according to the quality of the prediction and the quality of the paper itself. Seven papers have been accepted for oral presentation and ten for poster presentation.

In the following, we will present the CATS benchmark in section 2. The different methods that have been selected are listed and compared in section 3.

II. THE CATS BENCHMARK

The proposed time series is the CATS benchmark (for Competition on Artificial Time Series). This series is represented in Fig.1.

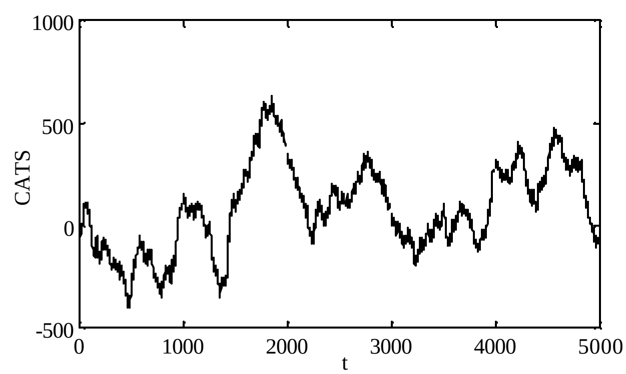

Figure 1: CATS Benchmark.

This artificial time series is given with 5,000 data, among which 100 are missing. The missing values are divided in 5 blocks:

- elements 981 to 1,000;
- elements 1,981 to 2,000;
- elements 2,981 to 3,000;
- elements 3,981 to 4,000;
- elements 4,981 to 5,000.

The Mean Square Error E_1 will be computed on the 100 missing values using:

$$E_1 = \frac{\sum_{t=981}^{1000}(y_t-\hat{y}_t)^2}{100} + \frac{\sum_{t=1981}^{2000}(y_t-\hat{y}_t)^2}{100} + \frac{\sum_{t=2981}^{3000}(y_t-\hat{y}_t)^2}{100} + \frac{\sum_{t=3981}^{4000}(y_t-\hat{y}_t)^2}{100} + \frac{\sum_{t=4981}^{5000}(y_t-\hat{y}_t)^2}{100} \tag{1}$$

The Mean Square Error E_2 will be computed on the 80 first missing values using:

$$E_2 = \frac{\sum_{t=981}^{1000}(y_t-\hat{y}_t)^2}{80} + \frac{\sum_{t=1981}^{2000}(y_t-\hat{y}_t)^2}{80} + \frac{\sum_{t=2981}^{3000}(y_t-\hat{y}_t)^2}{80} + \frac{\sum_{t=3981}^{4000}(y_t-\hat{y}_t)^2}{80} \tag{2}$$

This second error criterion is used because some of the proposed methods are using not only the data before a set of missing values to perform the prediction but also the data after the set. As such procedure is not possible in the case of the fifth set of missing values, error E_2 is used to assess the prediction on the first four blocks only. The Mean Square Error E_1 is the only one that is used for the ranking of the submissions; the Mean Square Error E_2 is used to give some additional information about the performances and the properties of these methods.

The missing parts are given in Fig. 2 to 6 and the numeric values in Tables 1.

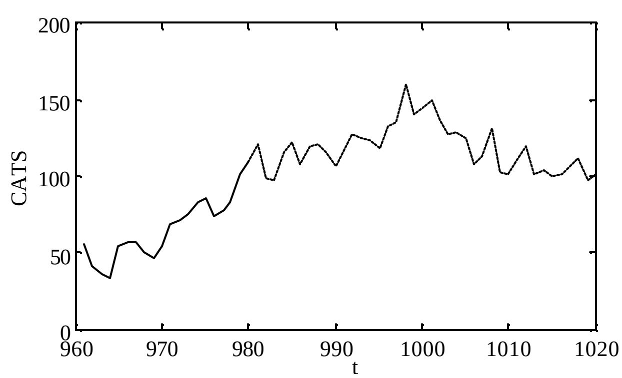

Figure 2: Missing values 981 to 1000 (dotted line).

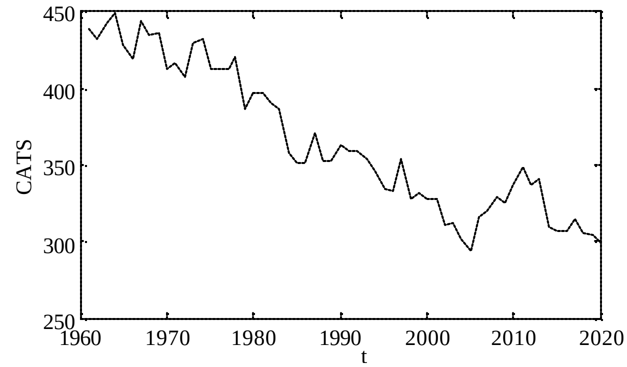

Figure 3: Missing values 1981 to 2000 (dotted line).

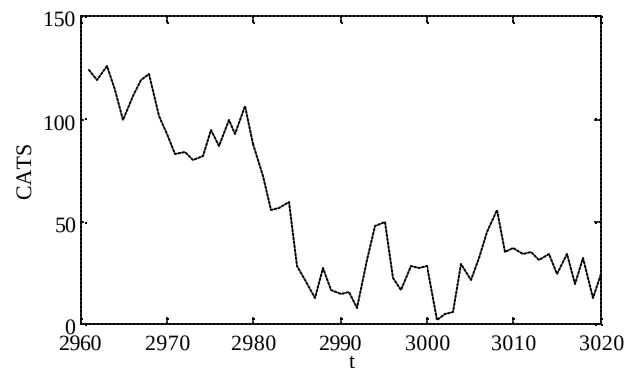

Figure 4: Missing values 2981 to 3000 (dotted line).

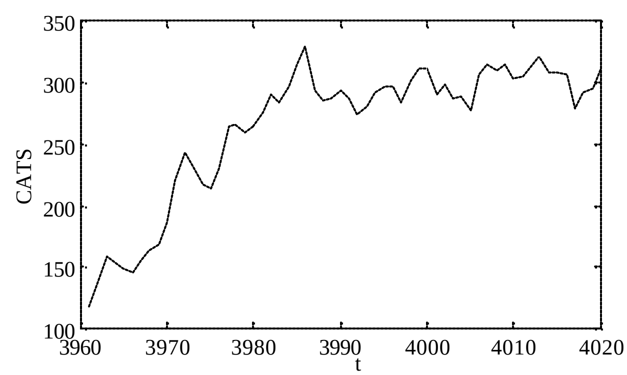

Figure 5: Missing values 3981 to 4000 (dotted line).

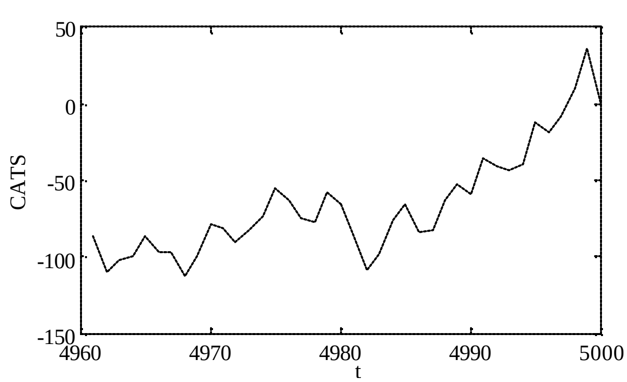

Figure 6: Missing values 4981 to 5000 (dotted line).

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III. RESULTS OF THE COMPETITION

The 24 methods that were submitted to the competition are very different and give very dissimilar results. The results are summarized in Tables 2 and 3 The Error E_1 is in a range between 408 and 1714. It is important to notice that some methods are very good for the prediction of the eighty first values but very bad for the last 20 ones.

The results of the winner [10] are represented in Fig.7 to 11. The results of the winner on the first eighty values only [19] are represented in Fig.12-16.

The method that has been used by the winner of the competition is divided in two parts: the first sub-method provides the short-term prediction and the second sub-method provides the long-term one. Both sub-methods are linear, but according to the author [10] better results could be obtained if the first sub-method was nonlinear. According to this author, the key of a good prediction is this division between two sub-problems.

Due to the lack of space, the many methods used in the papers cannot be reviewed here. More details about the different methods can be found in [10-26] and more details about the competition in [27].

Table 1: Missing Values.

981	**982**	**983**	**984**	**985**	**986**	**987**	**988**	**989**	**990**
102.52	96.56	99.201	106.52	111.91	113.65	114.12	115.55	117.95	120.3
991	**992**	**993**	**994**	**995**	**996**	**997**	**998**	**999**	**1000**
121.99	123.15	124.18	125.4	126.84	127.79	127	124.46	124.39	134.06
1981	**1982**	**1983**	**1984**	**1985**	**1986**	**1987**	**1988**	**1989**	**1990**
393.52	389.05	385.25	381.48	377.66	373.83	370.01	366.21	362.46	358.76
1991	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**
355.14	351.61	348.19	344.9	341.74	338.73	335.89	333.22	330.8	328.23
2981	**2982**	**2983**	**2984**	**2985**	**2986**	**2987**	**2988**	**2989**	**2990**
88.844	82.066	78.695	74.193	70.231	66.215	62.346	58.556	54.864	51.258
2991	**2992**	**2993**	**2994**	**2995**	**2996**	**2997**	**2998**	**2999**	**3000**
47.733	44.273	40.858	37.452	34.001	30.422	26.588	22.31	17.28	11.187
3981	**3982**	**3983**	**3984**	**3985**	**3986**	**3987**	**3988**	**3989**	**3990**
264.84	266.03	268.61	271.98	275.34	278.32	280.87	283.1	285.06	286.81
3991	**3992**	**3993**	**3994**	**3995**	**3996**	**3997**	**3998**	**3999**	**4000**
288.35	289.7	290.88	291.87	292.67	293.27	293.63	293.71	293.43	292.84
4981	**4982**	**4983**	**4984**	**4985**	**4986**	**4987**	**4988**	**4989**	**4990**
-66.378	-61.436	-57.044	-55.044	-53.565	-51.348	-48.714	-46.228	-43.944	-41.666
4991	**4992**	**4993**	**4994**	**4995**	**4996**	**4997**	**4998**	**4999**	**5000**
-39.313	-36.937	-34.58	-32.239	-29.894	-27.544	-25.192	-22.842	-20.494	-18.145

Table 2: Results of the competition, sorted with respect to E_1.

Author	E_1	E_2	Model
[10]	408	346	Kalman Smoother
[11]	441	402	Recurrent Neural Networks
[12]	502	418	Competitive Associative Net
[13]	530	370	Weighted Bidirectional Multi-stream Extended Kalman Filter
[14]	577	395	SVCA Model
[15]	644	542	MultiGrid-Based Fuzzy Systems
[16]	653	351	Double Quantization Forecasting Method
[17]	660	442	Time-reversal Symmetry Method
[18]	676	677	BYY Harmony Learning Based Mixture of Experts Model
[19]	725	222	Ensemble Models
[20]	928	762	Chaotic Neural Networks
[21]	954	994	Evolvable Block-based Neural Networks
[22]	1037	402	Time-line Hidden Markov Experts
[23]	1050	278	Fuzzy Inductive Reasoning
[24]	1156	995	Business Forecasting Approach to Mulitlayer Perceptron Modelling
[25]	1247	1229	A hierarchical Bayesian Learning Scheme for Autoregressive Neural Networks
[26]	1425	894	Hybrid Predictor

Table 3: Results of the competition, sorted with respect to E_2.

Author	E_1	E_2	Model
[19]	725	222	Ensemble Models
[23]	1050	278	Fuzzy Inductive Reasoning
[10]	408	346	Kalman Smoother
[16]	653	351	Double Quantization Forecasting Method
[13]	530	370	Weighted Bidirectional Multi-stream Extended Kalman Filter
[14]	577	395	SVCA Model
[11]	441	402	Recurrent Neural Networks
[22]	1037	402	Time-line Hidden Markov Experts
[12]	502	418	Competitive Associative Net
[17]	660	442	Time-reversal Symmetry Method
[15]	644	542	MultiGrid-Based Fuzzy Systems
[18]	676	677	BYY Harmony Learning Based Mixture of Experts Model
[20]	928	762	Chaotic Neural Networks
[26]	1425	894	Hybrid Predictor
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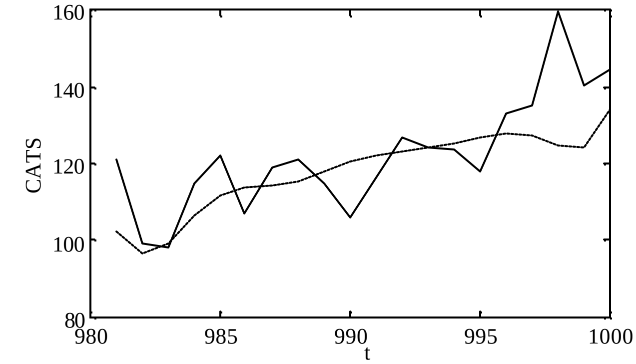

Figure 7: Missing values 981 to 1000 (solid line) and their approximation by [10] (dotted line).

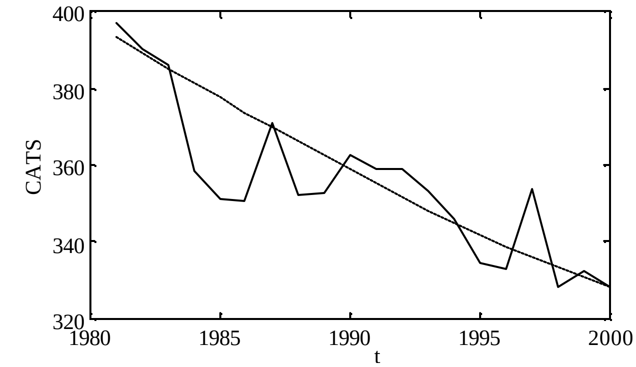

Figure 8: Missing values 1981 to 2000 (solid line) and their approximation by [10] (dotted line).

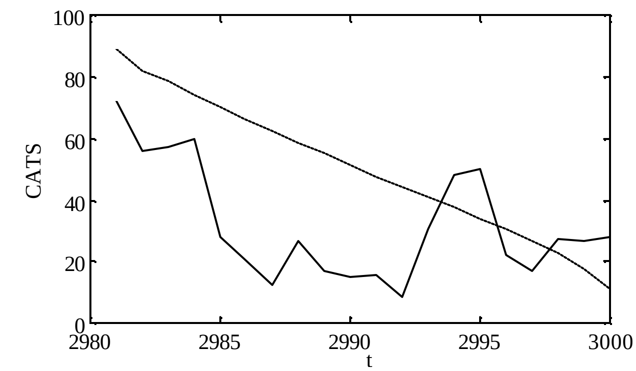

Figure 9: Missing values 2981 to 3000 (solid line) and their approximation by [10] (dotted line).

Figure 10: Missing values 3981 to 4000 (solid line) and their approximation by [10] (dotted line).

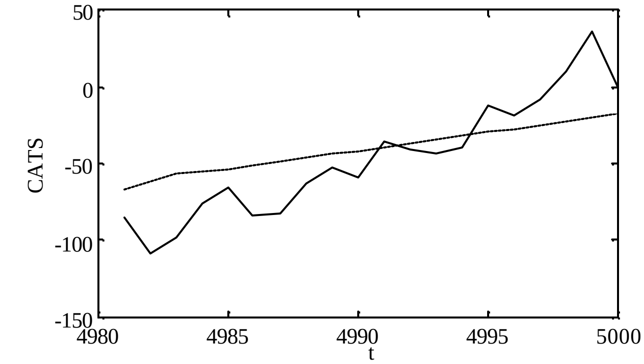

Figure 11: Missing values 4981 to 5000 (solid line) and their approximation by [10] (dotted line).

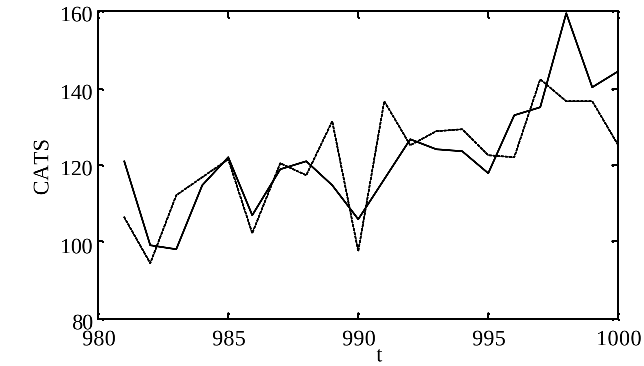

Figure 12: Missing values 981 to 1000 (solid line) and their approximation by [19] (dotted line).

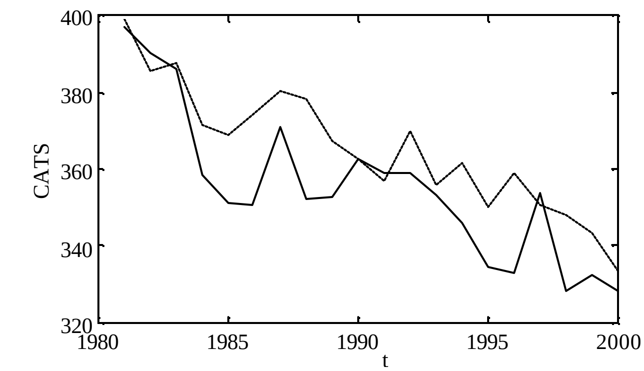

Figure13: Missing values 1981 to 2000 (solid line) and their approximation by [19] (dotted line).

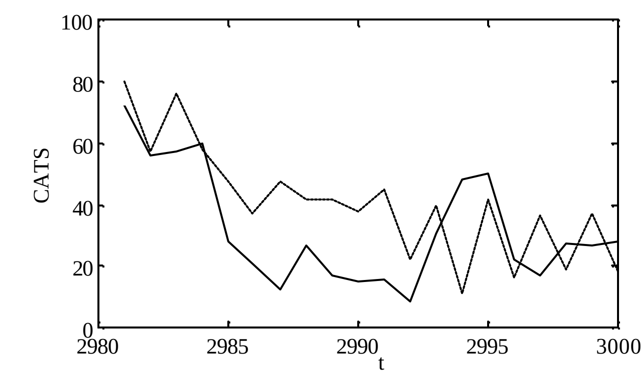

Figure 14: Missing values 2981 to 3000 (solid line) and their approximation by [19] (dotted line).

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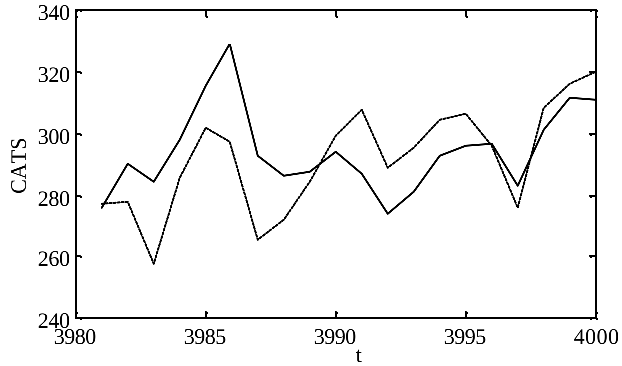

Figure 15: Missing values 3981 to 4000 (solid line) and their approximation by [19] (dotted line).

Figure 16: Missing values 4981 to 5000 (solid line) and their approximation by [19] (dotted line).

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