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subcomponents and by the synthesis of the forecast. Multiple runs have demonstrated the stability and consistence of predictions for quasi-periodical signals with Signal-to-Noise Ratio 0.5 and more. The algorithm should be used with a great precaution for signals with supposed chaotic behaviour, SSA decomposition should be excluded in this case. The climate system on the last millenniums scales is probably dominated by the 900 years periodical component. The prediction suggests that the present short-time global warming trend will continue for at least 200 years and be followed by a reverse in the temperature trend [7].

References

1. Sundqvist H. et al.: Arctic Holocene proxy climate database – new approaches to assessing geochronological accuracy and encoding climate variables. Clim. Past, 10, 1605–1631, (2014), doi:10.5194/cp-10-1605-2014
2. Ghil, M., R. M. Allen, M. D. Dettinger, K. Ide, D. Kondrashov, et al.: Advanced spectral methods for climatic time series. Rev. Geophys. 40(1), 3.1–3.41, (2002)
3. Farmer, J. D., and Sidorowich, J. J.: Predicting chaotic time series. Phys. Rev. Lett., v. 59, no. 8, p. 845–848 (1987)
4. Lorenz, E.: Deterministic non-periodic flow. J. Atmos. Sci., v. 20, p. 130–141 (1963)
5. NSIDC User Services, The Greenland summit ice cores CD-ROM, GISP-2/GRIP: World Data Center A for Glaciology, CIRES, Univ. Colorado, Boulder, CR-ROM (1997)
6. Johnsen, S., Dansgaard, W., and White, J.: The origin of arctic precipitation under present and glacial conditions: Tellus, v. B41, p. 452–468 (1992)
7. Kotov S., Harff J.: A Comparison of Greenland Ice and Baltic Sea Sediment Record: a Contribution to Climate Change Analysis. Mathematical Geology, v. 38, N. 6 (2006)

Combining simple exponential smoothing models for time series forecasting

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Abstract. Simple exponential smoothing is a well-known technique for forecasting univariate time series without trend and seasonality. Forecast combinations such as medians or means are known to improve the accuracy of point forecasts. In this paper we have experimented with combining the forecasts of several simple exponential smoothing models with different smoothing factors. Experimental results, using the M3-competition time series, show that the combined forecasts outperform the forecasts of the model that best fits the series.

Keywords: Combined forecast, Time series forecasting, Simple exponential smoothing

1 Introduction

Time series forecasting is a key tool in many areas, such as Hydrology, Business or Biology, wherein well-known statistical models such as ARIMA or exponential smoothing are used to make predictions about the future values of a time series [1]. Very often a large number of series need to be forecast, in this situation an automatic forecasting algorithm is an essential tool [2].

Ensemble learning [3] is a useful technique used by data mining practitioners to improve classification and numeric prediction accuracy. In this technique instead of learning one model from a training data set several models are learned. That is, multiple models that "fit well" the training data are selected from a candidate model space containing models that "explain" the training data. In order to make predictions an ensemble learner combines the predictions of its learned models using a combination function such as the average or the median. The predictive performance of an ensemble learner often outperforms the performance of the individual models comprising the ensemble. Why? A single model can be either too simple and not capture the essential patterns in the data, or too complex and overfit the data. In fact, there is hardly ever a true underlying model, and even if there was, selecting that model will not necessarily give the best predictions, because the parameter estimation may not be accurate. On the other hand, an ensemble of models can capture different patterns of the data and reduce the danger of overfitting or the uncertainty of choosing the wrong model.

The idea underlying ensemble learning has also been applied in time series forecasting to produce combined forecasts [4–6]. One of the four conclusions of