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Local trends for time series pre-preparation in forecasting problems

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Abstract. The paper focuses on the studying local trends that describe intermediate movements in non-stationary time series.

The first part of the article considers the possibilities of methods of identifying patterns in historical trends using piecewise linear approximation, piecewise logarithmic approximation and the method of local principal components. Local trends have been created using the segmentation method of the bottom-up time series, which allowed identifying the main directions of time series movement. The paper determines the quality criteria and the algorithm for identifying local trends using the proposed methods. There have been some experiments for each time series preprocessing method. It is assumed that the sequence of historical local trends describes the long-term relationship in a time series and might be successfully used for forecasting, for example, based on hybrid neural network methods.

The second part of the paper considers the classical application of the Hough transformation for random points approximation on a plane by line segments. There is a disadvantage of this method comparing with the dynamic Hough transformation that takes into account the sample dynamics and can be used in online learning. The authors consider the forecasting algorithm with simultaneous calculation of a local trend using the dynamic Hough transformation. The algorithm is easily extended to other methods of data approximation, which have been considered in the first part of the paper.

Computational experiments included real data and used the proposed method. They provided forecasts. The experiments showed that the proposed method helps determining time series trends. The complex periodicity electrocardiogram data and closing prices of Gazprom shares were used for all experiments.

Keywords: local trend, approximation, principal components, Hough transformation, time series, forecasting.

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