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Spatiotemporal forecasting with convolutionals and tensor decomposition

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The work reviews two most popular method used for time-series processing: SSA (Singular Spectrum Analysis) and it's tensor generalization TSSA (Tensor Singular Spectrum Analysis) in constraints of comparable computation time.

Singular spectrum analysis (SSA) is a method widely used in the past decades in different areas, from economics to biology and social science. One of main advantages is its ability to extract underlying frequencies from complex and multidimensional data, resulting in variable number of components. SSA consists of two main stages: decomposition and reconstruction, both adjustable in terms of methods and hyperparameters used.

Its modification, tensor singular spectrum analysis (TSSA), offers a more robust and accurate results by converting a series into a tensor and using parallel factor analysis (PARAFAC) decomposition instead of the usual SVD. It optimizes usage of information initially available to a model in cost of working with more multidimensional data SSA does. The problem of reconstruction is left untouched however.

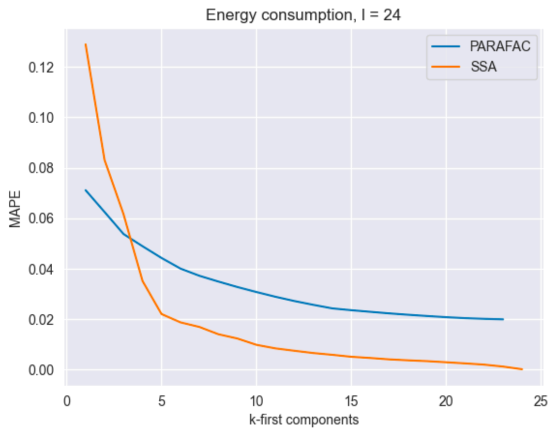
Empirical mode decomposition (EMD) can then be used to supervise TSSA, giving us TSSA-EMD. It provides a better way to identify the number of frequency components within each subspace. With such enhancement algorithms achieves a distinguishable growth in accuracy of signal reconstruction with denoising, leaving other methods far behind in particular tasks.

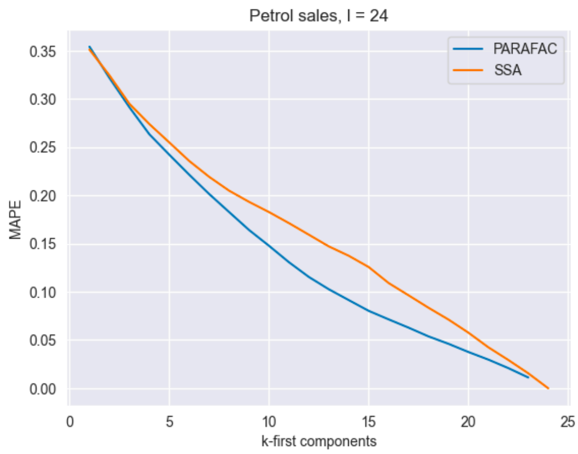
Basic SSA shows adequate results when working with series of constant-limited variation function. However it becomes highly unstable in two basic cases. With several outliers already false frequencies are extracted at decomposition stage, what does not lead to reconstruction defects but enforces unacceptable error even at earlier points of prediction. A variation growth affects SSA the same way, usually creating frequencies of much higher amplitude than are expected. That makes the early predictions seem accurate, yet giving unrealistic forecast long-wise.

To conclude, SSA is a powerful but a limited method.

At the same time SSA does not utilize spatial information. Given a set of parallel time series it is meant to decompose each separately. TSSA instead can show better performance by working with them as with a whole dataset. Knowing this we experiment to determine the difference between SSA and TSSA forecasting and try to create a robust model of signal decomposition, reconstruction and prediction.

We experiment on well-explored real-life datasets: oil sails, 365 points; energy consumption, 8760 points. Result of the reconstruction stage of both methods yield MAPE score, that is compared for both methods:





Brief conclusion of the experiments are as follows:

- SSA requires no hyperparameter tuning
- TSSA is more accurate, but requires much greater hyperparameter tuning to achieve the same accuracy
- In most cases TSSA is slower
- Algorithms do not replace each other but complement