592 Project Report

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2021-05-10

Clustering M4 Daily Data for Forecasting



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Project Goal

verify whether clustering time series can help improve the forecasting accuracy of machine learning methods and whether it can help get a better estimate of the error using cross-validation

Data Set - M4 competition

- M4 data set are 100,000 time series
- split into hourly, daily, weekly, monthly, quarterly, and yearly series
- from diverse range of domains
- competition asks for forecast for each series

Machine Learning in time series forecasting

- regularly outperformed by M4 competition benchmark
- high computational costs
- few data points for time series

Principal Idea: group similar time series

- group time series with similar properties
- each group provides more data points to learn from

Hypothesis

- similar series are simpler to learn by ML algorithms
- improved accuracy of the algorithm

Question: Can this approach help improve forecasting performance?

Time Series Representation

Feature Representation

• shape-, feature-, model-based

Approach in this project: features

- extract features via a software package
- tsfresh extracts around 800 features

Clustering

- unsupervised learning technique
- learn from data without or minimal input

K-Means

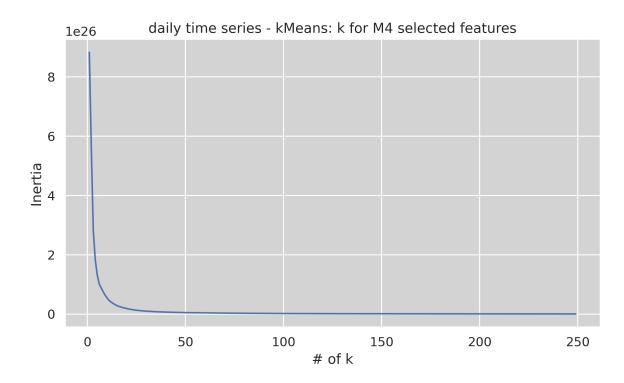
- grouping unlabeled data into predetermined number of groups
- random starting point of points
- iterative adjustment

Deciding k

Inertia

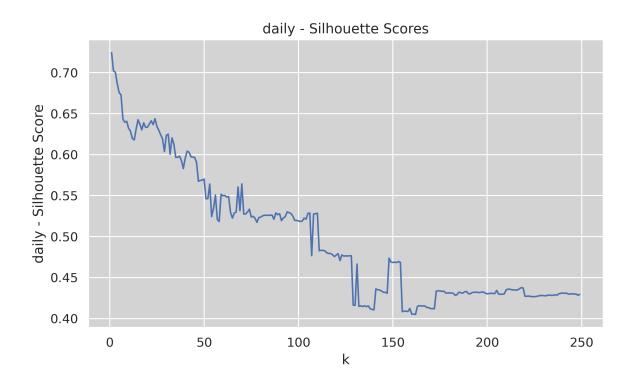
goal: minimize within cluster sum-of-squares

$$\sum_{i=0}^{n} \min_{\mu_j \in C} (||x_i - \mu_j||^2)$$

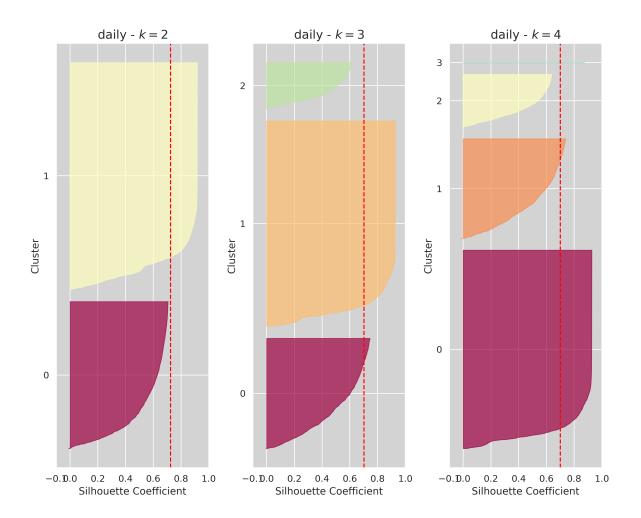


Silhouette score

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$



Silhouette Diagrams



Forecasting

Neural Network

- 3 hidden layers
- $\bullet\,$ features lags 1 7
- \bullet loss: MSE

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

Approach

- full dataset
- clustered datasets
- equivalent random datasets

Cross-Validation

- increase certainty about the error that is encountered in the training
- limit effects of peculiarities in the data on error metrics

Benchmarking

M4 Accuracy Metrics

$$SMAPE = \frac{100}{n} \sum_{t=1}^{n} \frac{F_t - Y_t}{(|F_t| + |Y_t|)/2}$$

$$MASE = mean \left(\frac{|e_j|}{\frac{1}{T-1} \sum_{t=2}^{T} |Y_t - Y_{t-1}|} \right)$$

Challenges

Data Preprocessing

- data format wide vs. long format
- Min-Max feature scaling with cross validation with neural networks
- information leakage

Feature extraction and selection

- tsfresh 800 metrics
- comprehensive vs. efficient

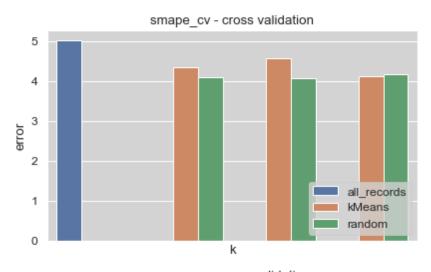
Computational Costs

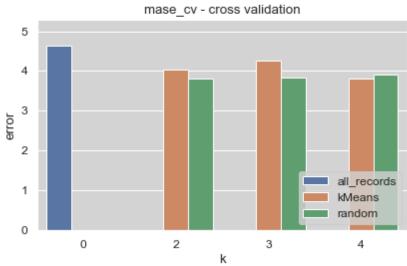
- \bullet 6 vCPU / 32GB RAM
- feature extraction and selection (reason for daily only)
- neural network with cv

Results

Cross validation

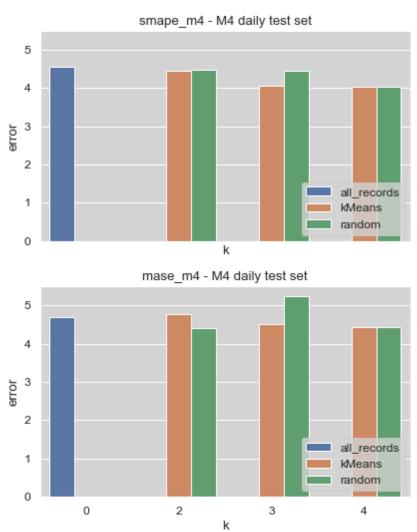
M4 Daily Series - Error Metrics - cross validation





M4 results

M4 Daily Series - Error Metrics - M4 daily test set



Conclusion

 \bullet clustering results not better than random

features vs lags for NN

- possibly better results
- increase of neural network size
- how meaningful are efficient features

Approach to cross validation

- less folds
- MinMax scaler

Uncertainty in the clustering

- reduced uncertainty in the data clustered data
- indication in MASE (higher in test results compared to cv)

Complexity of problem definition

- many moving parts
- M4 Clustering on Github

Outlook

- Algorithm
 - hierarchical and density and grid-based methods
- Feature Choice
 - ranking of features

Thank you for your attention