Extended Abstract: Time Series Forecasting for Electrical Load

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Introduction

This study focuses on forecasting household electrical load using four years of minute-level data from the UCI Machine Learning repository. The dataset includes global active/reactive power, voltage, and sub-meter readings. Challenges include missing data, seasonal variations, and temporal trends, addressed through advanced time series modeling techniques.

Methods

Data Preprocessing:

- Missing values were filled using interpolation techniques to preserve temporal consistency.
- Single datetime column is created, serving as the time index for the series.
- The dataset was resampled to monthly frequency for seasonal and trend analysis.

Exploratory Data Analysis:

- Seasonal decomposition highlighted winter peaks in submeter 3 usage and revealed similar trends across other submeters.
- A correlation matrix identified strong relationships between global intensity and submeter readings, aiding feature selection.

Modelling Approaches:

- Classical decomposition to analyse trends, seasonality, and residuals.
- Box-Cox transformation and ADF tests to stabilize variance and ensure stationarity.
- Forecasting models: ARIMA, ETS, Seasonal Naïve (SNAIVE), and multiple regression.

Evaluation Metrics: To measure the accuracy of the forecasting RMSE, MAPE, and MAE were applied.

Results

Model Performance:

ARIMA achieved the lowest RMSE of 0.0628, highlighting its robustness for time series forecasting.

ETS and **Multiple Regression** delivered strong results, with regression showing an Adjusted R-squared of 0.9992.

SNAIVE served as a reliable baseline for seasonal forecasting, performing reasonably well on seasonally driven patterns.

Correlation Insights: Global intensity was the most significant predictor, followed by submeters 1 and 3.

Visualizations: A forecast summary compared predicted vs actual power consumption for all models, with ARIMA showing the closest fit.

Conclusion

ARIMA and ETS models effectively forecasted household power consumption, supported by seasonal decomposition and feature analysis. Robust preprocessing and feature engineering ensured high model accuracy, providing actionable insights into energy consumption patterns.

References

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