XAI on Time Series Forecasting

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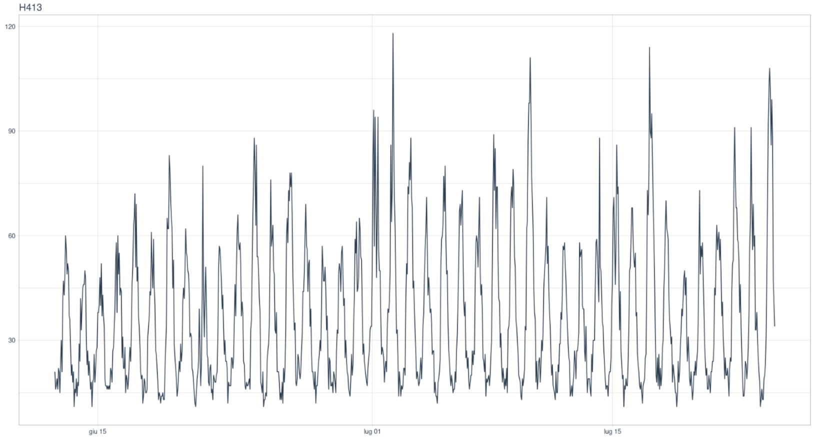
Contents

1. Data

M4 Competition



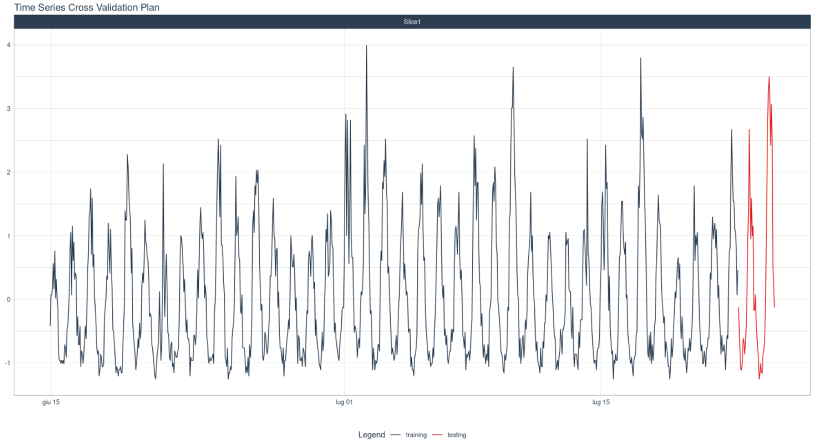
Feature Engineering

In order to be able to use data in a machine learning model, we need to create features that can be used as predictors.

This step is extremely relevant in time series data, since we need to create **features that are able to capture the time dynamics of the data**.

Here, I used lags, rolling features, calendar features and fourier series, obtaining a total of **24 features**.

Train-Test Split



2. Modelling

AutoML with H2O

h2o automatically estimates and tests **6 different ML algorithms**:

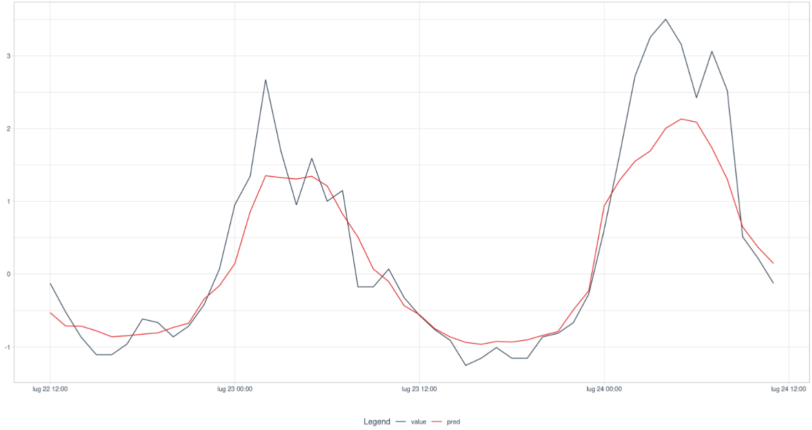
- DRF (This includes both the Distributed Random Forest (DRF) and Extremely Randomized Trees (XRT) models)
- GLM (Generalized Linear Model with regularization)
- XGBoost (XGBoost GBM)
- GBM (H2O GBM)
- DeepLearning (Fully-connected multi-layer artificial neural network)
- StackedEnsemble (Stacked Ensembles, includes an ensemble of all the base models and ensembles using subsets of the base models)

AutoML with H2O

```r
model_h2o_automl <- h2o.automl(
    y = target, x = x_vars,
    training_frame = train_h2o,
    max_runtime_secs = 120,
    max_runtime_secs_per_model = 30,
    max_models = 50,
    nfolds = 5,
    sort_metric = "rmse",
    verbosity = NULL,
    seed = 123
)
```

Best Model

The best model ends up to be a GBM.



3. XAI

XAI in Time Series

In the context of time series forecasting, being able to understand the model's predictions is of paramount importance for 3 main reasons:

1. **Trust**: to be able to trust the model's predictions, especially when it is used to make important future decisions.
2. **Improvement**: to be able to understand the model's weaknesses to improve it.
3. **Combine**: usually model's predictions are combined with human judgement, so understanding what causes such predictions is crucial for business experts to adjust their forecasts.

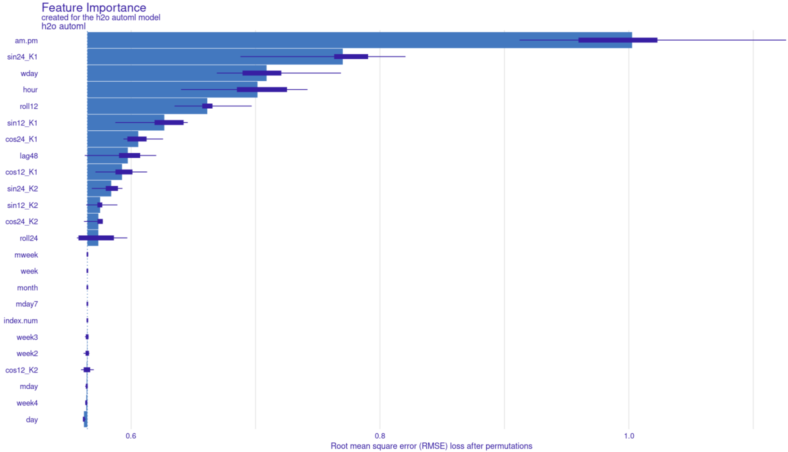
DALEX

To perform a XAI analysis on the automatic black-box model the **DALEX** package, from Dr. Why AI, is used.

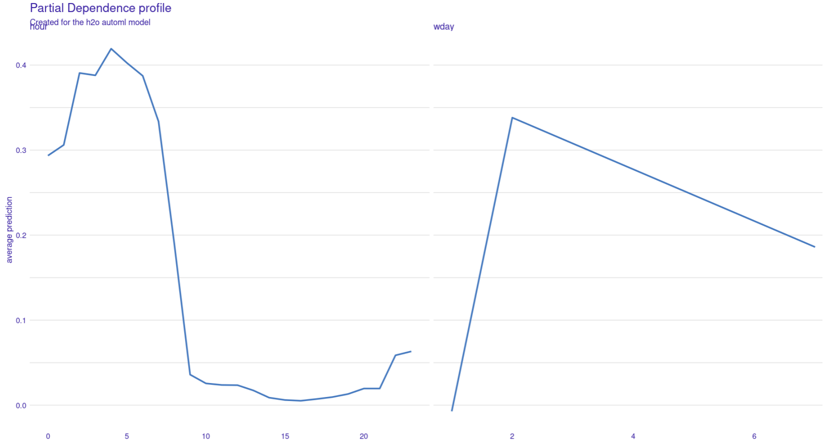
DALEX is a XAI framework which allows to easily adopt several model agnostic explainability techniques, such as:

- Feature Importance
- Partial Dependence
- Break Down
- Shapley Values
- LIME
- Stability Analysis.

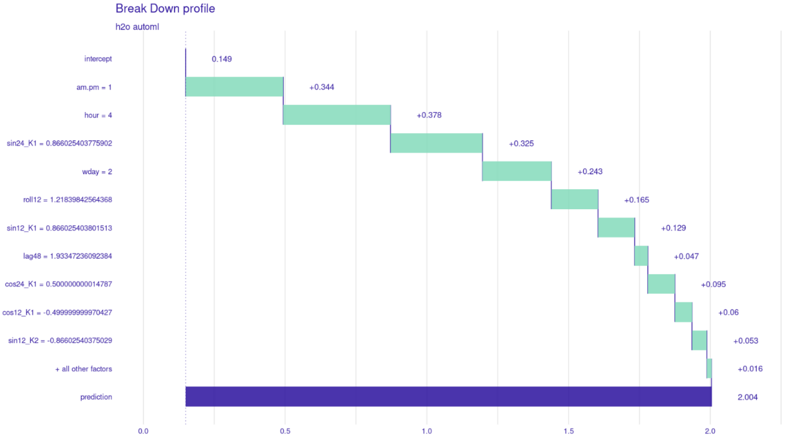
Global - Feature Importance



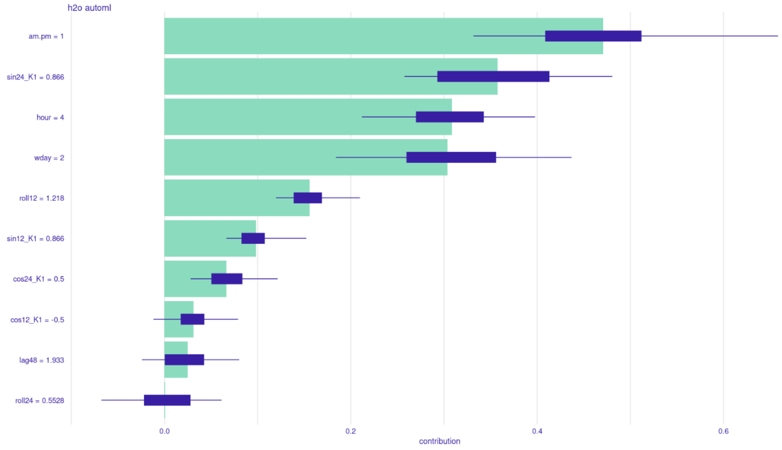
Global - Partial Dependence



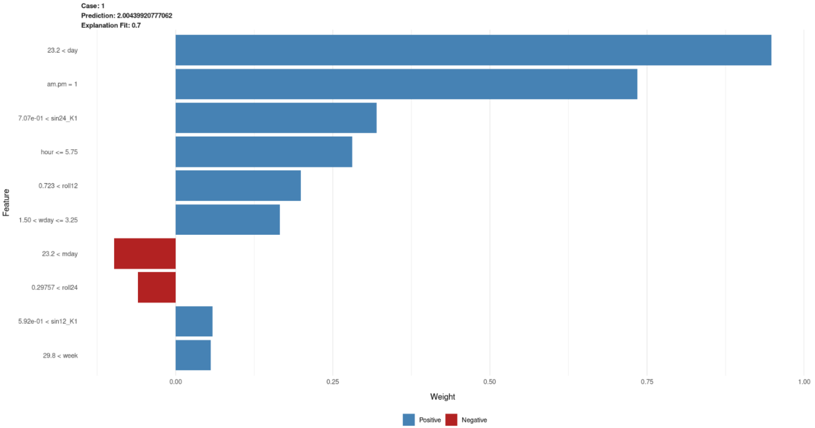
Local - Break Down (observation: 2017-07-24 04:00:00)



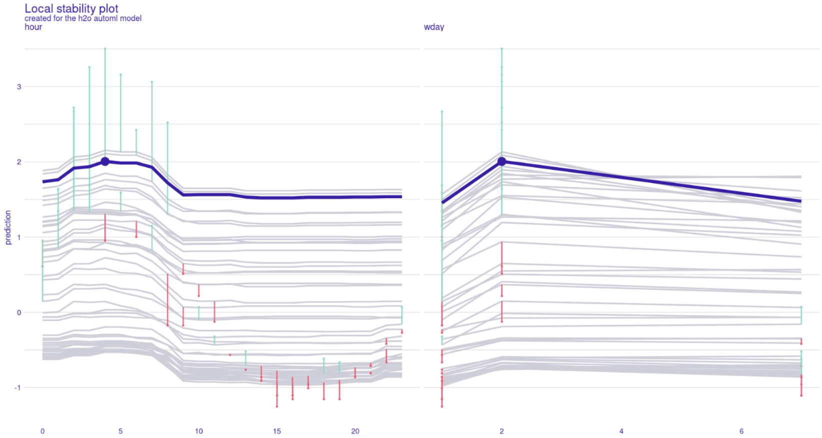
Local - Shapley Values (observation: 2017-07-24 04:00:00)



Local - LIME (observation: 2017-07-24 04:00:00)



Local - Stability Analysis (observation: 2017-07-24 04:00:00)



4. Conclusions

Conclusions

- The most important features are those related to **daily seasonality**, while weekly and monthly seasonality seem to be less relevant.
- There is a clear **intra-day pattern**, with higher predictions during the night, and a downward trending effect within the week.
- The **Break Down** method is the most useful within business contexts since it allows to quantify the contribution of each feature to the final predictions.
- Predictions are relatively **unstable**. The model is underestimating the demand in the morning and overestimating it in the afternoon and evening and judgemental forecasting procedures should take this into account to adjust business predictions.

Thank you!