Innovationlab Big Data Science

Energeeks - ASHRAE Great Energy Predictor III

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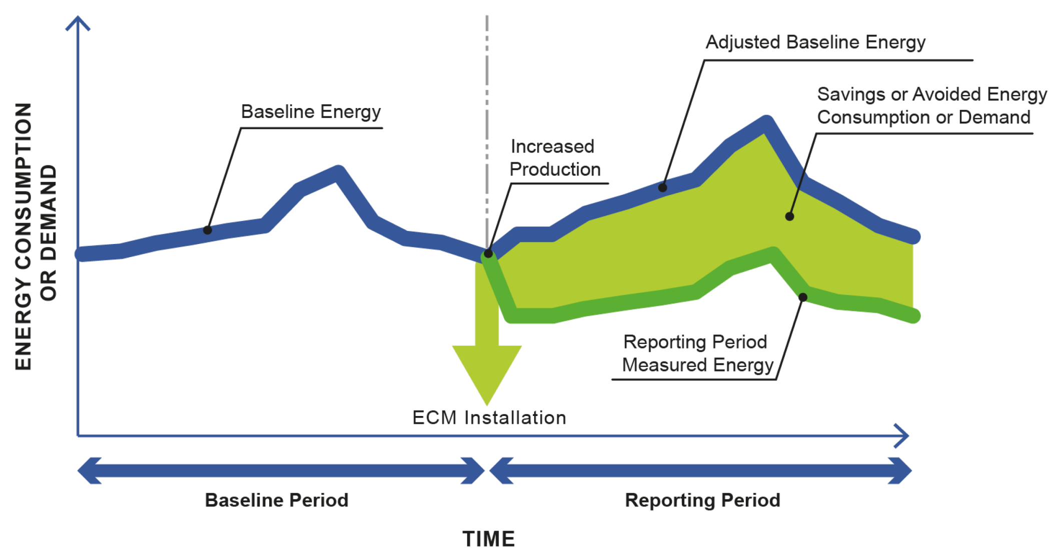
Institut for Statistics

Agenda

1. ASHRAE Great Energy Predictor III
2. Our Project
3. Retrospective
4. Next steps

ASHRAE Great Energy Predictor III

The Challenge



The Dataset

- Training Data
  - Contains $\approx$ 20 mio. rows
  - Timespan: 1 year, from 2016 to 2017
- Test Data
  - Contains $\approx$ 40 mio. rows
  - Timespan: 2 years, from 2016 to 2018
- Target
  - Hourly readings from four different meters (kWh)
    $\rightarrow$ electricity, chilledwater, steam, hotwater
- Features:
  - train.csv: building_id, timestamp, meter, meter_reading
  - building_metadata.csv: site_id, building_id, primary_use, square_feet, year_built, floor_count
  - weather_train.csv: site_id, timestamp, air_temperature, wind_direction, ...

Dataframe.head()

```
In [5]: train.head()
```

Out[5]:

	building_id	meter	timestamp	meter_reading
0	0	0	2016-01-01 00:00:00	0.0
1	1	0	2016-01-01 00:00:00	0.0
2	2	0	2016-01-01 00:00:00	0.0
3	3	0	2016-01-01 00:00:00	0.0
4	4	0	2016-01-01 00:00:00	0.0

```
In [4]: metadata.head()
```

Out[4]:

	site_id	building_id	primary_use	square_feet	year_built	floor_count
0	0	0	Education	7432	2008.0	NaN
1	0	1	Education	2720	2004.0	NaN
2	0	2	Education	5376	1991.0	NaN
3	0	3	Education	23685	2002.0	NaN
4	0	4	Education	116607	1975.0	NaN

```
In [7]: weather.head()
```

Out[7]:

	site_id	timestamp	air_temperature	cloud_coverage	dew_temperature	precip_depth_1_hr	sea_level_pressure	wind_direction	wind_speed
0	0	2016-01-01 00:00:00	25.0	6.0	20.0	NaN	1019.7	0.0	0.0
1	0	2016-01-01 01:00:00	24.4	NaN	21.1	-1.0	1020.2	70.0	1.5
2	0	2016-01-01 02:00:00	22.8	2.0	21.1	0.0	1020.2	0.0	0.0
3	0	2016-01-01 03:00:00	21.1	2.0	20.6	0.0	1020.1	0.0	0.0
4	0	2016-01-01 04:00:00	20.0	2.0	20.0	-1.0	1020.0	250.0	2.6

Our Project

Pipeline Overview

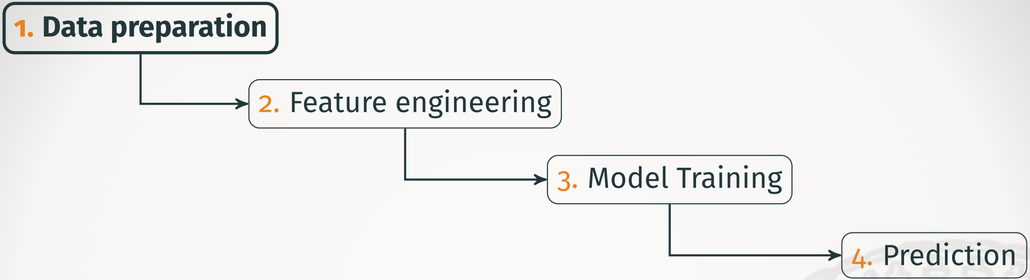
1. Data preparation
2. Feature engineering
3. Model Training
4. Prediction

Project Structure

Using Cookiecutter: `https://drivendata.github.io/cookiecutter-data-science/`

```
+-- data
|   +-- external            <- Data from third party sources.
|   +-- interim             <- Intermediate data that has been transformed.
|   +-- processed           <- The final, canonical data sets.
|   +-- raw                 <- The original, immutable data dump.
|
+-- src
    +-- data
    |   +-- make_dataset.py     <- Data preparation.
    |
    +-- features
    |   +-- build_features.py   <- Feature engineering.
    |
    +-- models
        +-- predict_model.py    <- Prediction.
        +-- train_model.py      <- Model Training.
```

Pipeline Overview



- Exclude faulty readings.
- Impute missing data.
- Align timestamps.
- Merge data frames.

Pipeline Overview

1. Data preparation

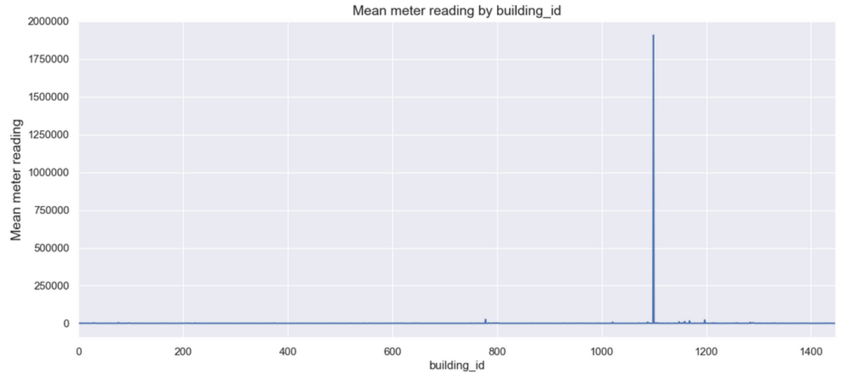
2. Feature engineering

3. Model Training

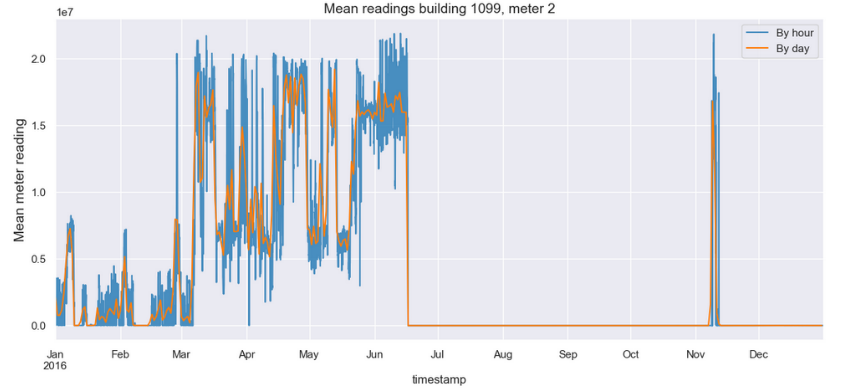
4. Prediction

- **Exclude faulty readings.**
- Impute missing data.
- Align timestamps.
- Merge data frames.

Exclude faulty readings



Exclude faulty readings



Pipeline Overview

1. Data preparation

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- Exclude faulty readings.
- **Impute missing data.**
- Align timestamps.
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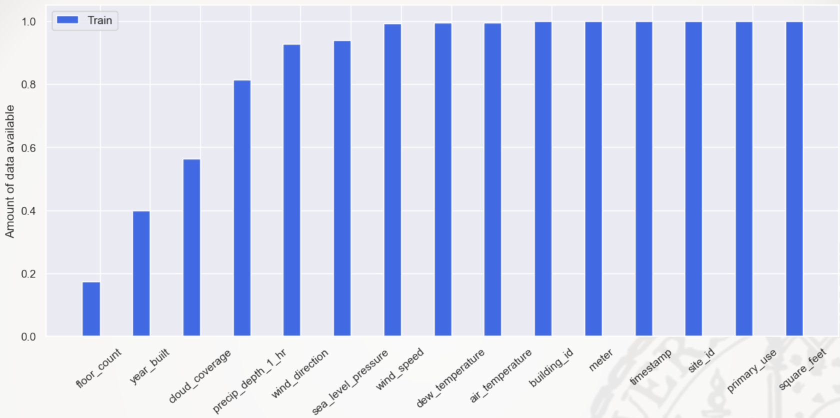
Impute missing data




```
from sklearn.impute import Imputer
from sklearn.model_selection import cross_val_score
imp = Imputer_name(missing_values=np.nan, strategy='mean, median, most_frequent, zero, knn')
```

Pipeline Overview

1. Data preparation

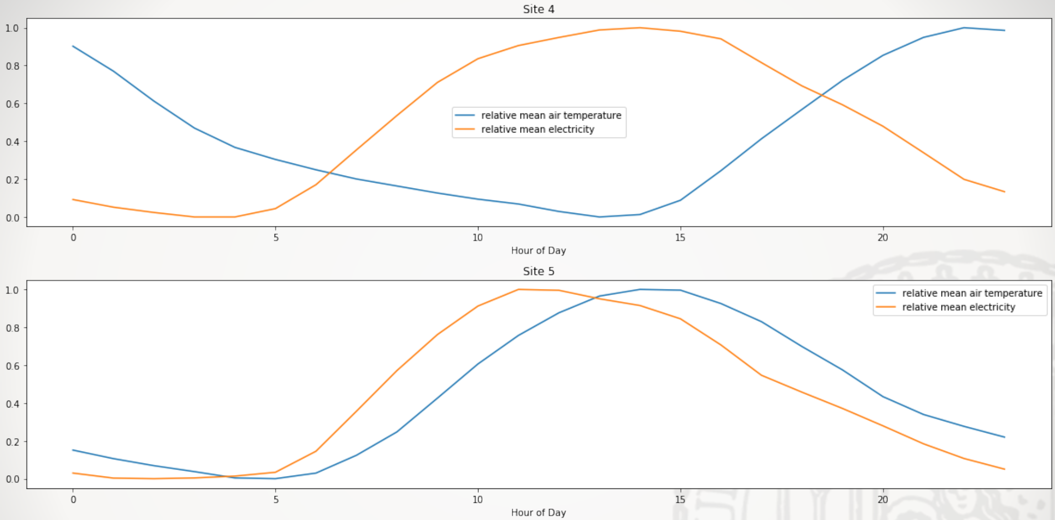
2. Feature engineering

3. Model Training

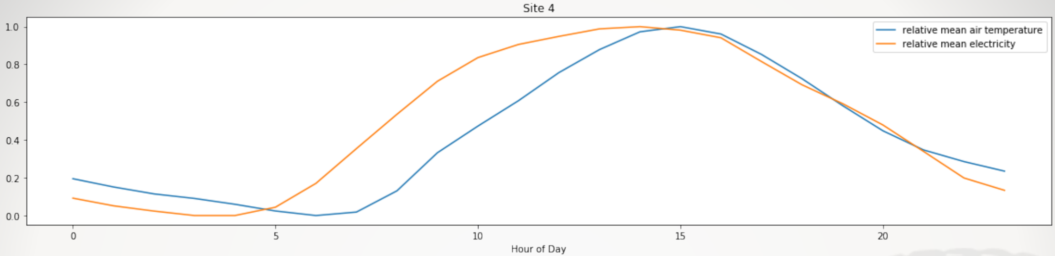
4. Prediction

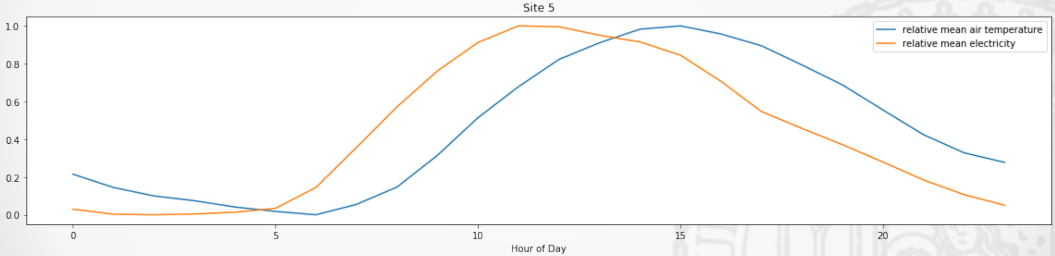
- Exclude faulty readings.
- Impute missing data.
- **Align timestamps.**
- Merge data frames.

Without Timestamp-Alignment



With Timestamp-Alignment





Pipeline Overview

1. **Data preparation**
2. Feature engineering
3. Model Training
4. Prediction

- Exclude faulty readings.
- Impute missing data.
- Align timestamps.
- **Merge data frames.**

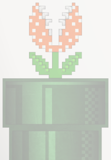
Pipeline Overview

1. Data preparation
2. **Feature engineering**
3. Model Training
4. Prediction

- Encode categorical data.
- Transform year_built into age.
- Logarithmic scaling of square_feet.
- Add lag features.
- Encode cyclic data.

Pipeline Overview

1. Data preparation
2. Feature engineering
3. **Model Training**
4. Prediction



Which frameworks were used?

dmlc XGBoost

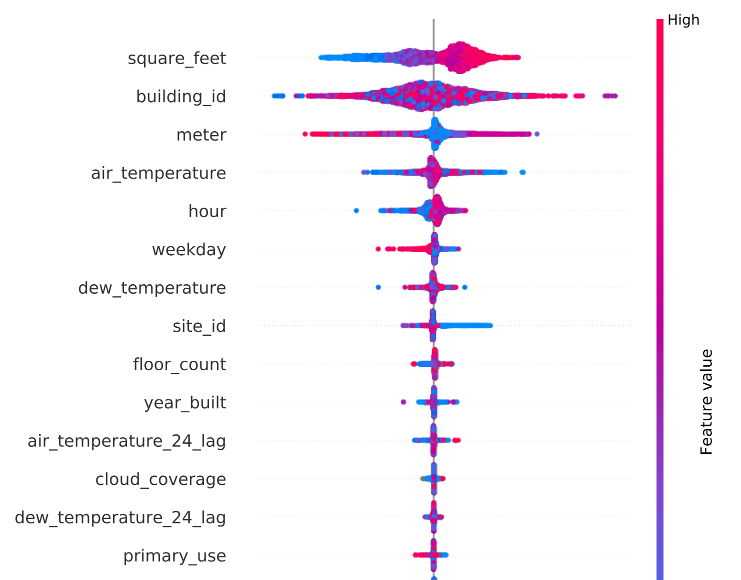
Microsoft LightGBM

Yandex CatBoost

What's the best model? I

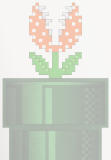
- Favorite framework so far: LightGBM
  - → Extreme fast
  - → Low RAM Usage
- Cross Validation (4-Fold w/o shuffle)
- Mean-stacking strategy
- Bayesian Hyperparameter Optimization with hyperopt
- RMSLE: 1.06

SHAP Values

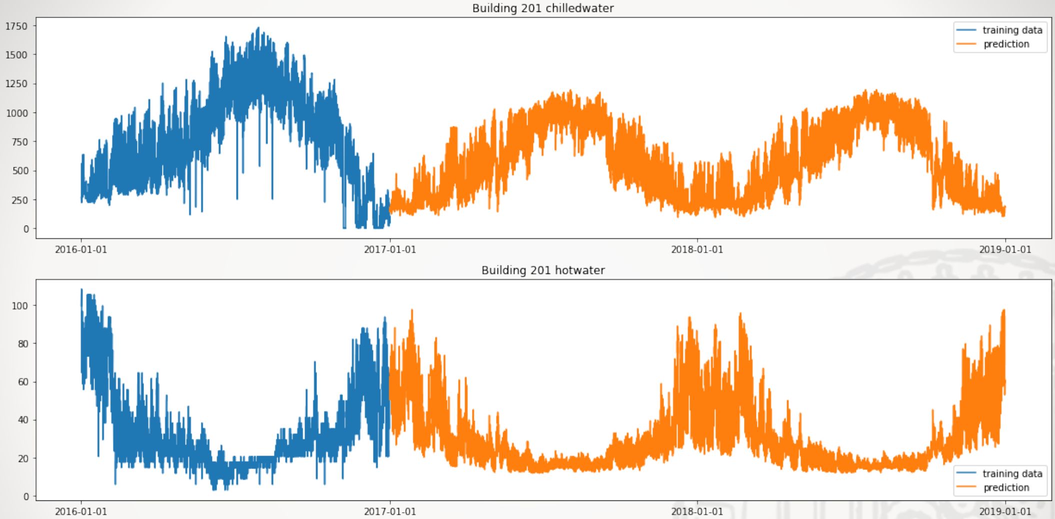

square_feet
building_id
meter
air_temperature
hour
weekday
dew_temperature
site_id
floor_count
year_built
air_temperature_24_lag
cloud_coverage
dew_temperature_24_lag
primary_use
High
Feature value

Pipeline Overview

1. Data preparation
2. Feature engineering
3. Model Training
4. **Prediction**



Prediction


Building 201 chilledwater
1750
1500
1250
1000
750
500
250
0
2016-01-01
2017-01-01
2018-01-01
2019-01-01
training data
prediction
Building 201 hotwater
100
80
60
40
20
0
2016-01-01
2017-01-01
2018-01-01
2019-01-01
training data
prediction

Leaks & a broken Leaderboard

- Identification of sites and buildings via timestamp
- Public availability of energy consumption

→ Scraping of 1 mio. test labels

→ Data Science competition → Web Scraping competition

- Allegedly no leaked data in private Leaderboard

Retrospective

Collaboration

https://github.com/energeeks/ashrae-energy-prediction

GitHub

DISCORD

Problems & Success stories

Problems:

- Underestimation of tickets
- Sprints were a bit difficult to plan (constantly had new ideas)

Success stories:

- Ticket system (Kanban Board)
- Team members have different backgrounds and strengths
- Python notebooks

Next steps

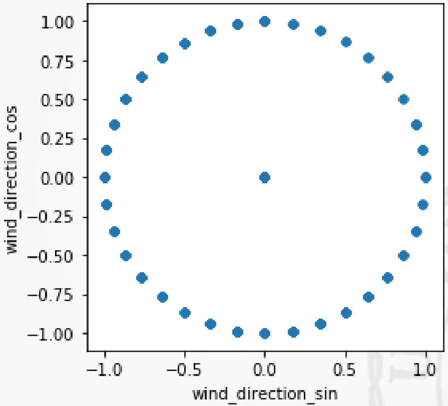
Next steps

- Phase I: Kaggle Challenge
  - Include more features
  - Model stacking/ blending
  - December 19, 2019 - Final submission deadline.
- Phase II: Create web-application
  - User gives building metadata
  - Use model from Phase I to predict future energy consumption
  - Include weather APIs for weather forecasting

Thank you for your attention! :)

Cyclic-Encoding

```
df["wind_direction_sin"] = np.sin(2 * np.pi * df["wind_direction"] / 360)
df["wind_direction_cos"] = np.cos(2 * np.pi * df["wind_direction"] / 360)
df.loc[df["wind_direction"].isna(), ["wind_direction_sin", "wind_direction_cos"]] = 0
df.loc[df["wind_speed"] == 0, ["wind_direction_sin", "wind_direction_cos"]] = 0
```



What's the best model? II

Parameters	**Score: 1.07**	**Score: 1.06**
Boosting Type	GBDT	DART
Early Stopping	YES	NO
Number of Leaves	3480	3630
Learning Rate	0.05	0.05
Training Time	Low	High