PROJECT TITLE: measure energy consumption

Phase submission documents 3

Introduction to Machine Learning for the Built Environment: Energy consumption has been widely studied in the computer architecture field for decades. While the adoption of energy as a metric in machine learning is emerging, the majority of research is still primarily focused on obtaining high levels of accuracy without any computational constraint. We believe that one of the reasons for this lack of interest is due to their lack of familiarity with approaches to evaluate energy consumption of the different approaches to estimate energy consumption in general and machine learning applications in particular. Our goal is to provide useful guidelines to the machine learning community giving them the fundamental knowledge to use and build specific energy of

Import relevant python packages

Let's use the electrical meter data to create clusters of typical load profiles for analysis. First we can load our conventional packages

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
```

Next let's load all the packages we will need for analysis

In [2]:

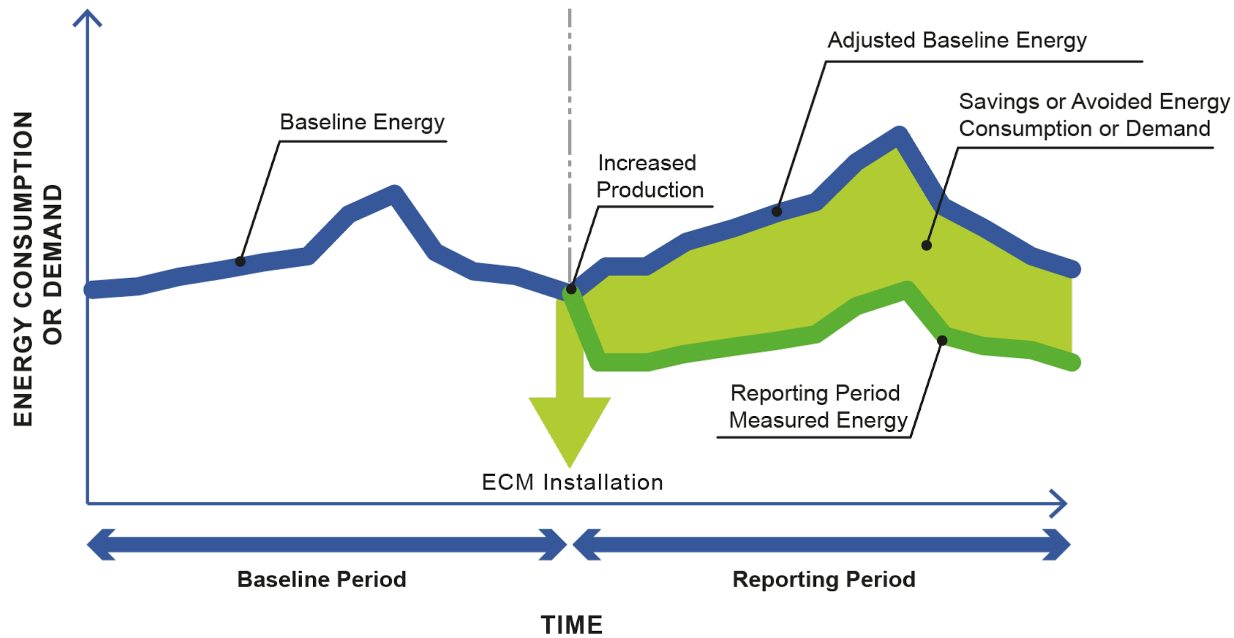
```
import sklearn
from sklearn import metrics
from sklearn.neighbors import KNeighborsRegressor
from scipy.cluster.vq import kmeans, vq, whiten
from scipy.spatial.distance import cdist
import numpy as np
from datetime import datetime
```

Electricity Prediction for Measurement and Verification

Prediction is a common machine learning (ML) technique used on building energy consumption data. This process is valuable for anomaly detection, load profile-based building control and measurement and verification procedures.

The graphic below comes from the IPMVP to show how prediction can be used for M&V to calculate how much energy **would have** been consumed if an energy savings intervention had not been implemented.

Prediction for Measurement and Verification



There is an open publication that gives more information on how prediction in this realm can be approached: https://www.mdpi.com/2504-4990/1/3/56

There is an entire Kaggle Machine Learning competition also focused on this application: https://www.kaggle.com/c/ashrae-energy-prediction

Load electricity data and weather data

First we can load the data from the BDG in the same as our previous weather analysis influence notebook from the Construction Phase videos

In [3]:

```
elec_all_data = 
pd.read_csv("../input/buildingdatagenomeproject2/electricity_cleaned.csv", 
index_col='timestamp', parse_dates=True)
```

In [4]:

```
elec_all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 17544 entries, 2016-01-01 00:00:00 to 2017-12-31 23:00:00
Columns: 1578 entries, Panther_parking_Lorriane to Mouse_science_Micheal
dtypes: float64(1578)
memory usage: 211.3 MB
```

In [5]:

```
buildingname = 'Panther_office_Hannah'
```

In [6]:

```
office_example_prediction_data =
pd.DataFrame(elec_all_data[buildingname].truncate(before='2017-01-01')).fi
llna(method='ffill')
```

In [7]:

```
office_example_prediction_data.info()
```

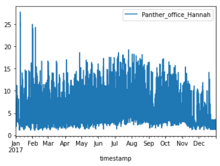
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2017-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 1 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Panther_office_Hannah  8760 non-null   float64
dtypes: float64(1)
memory usage: 136.9 KB
```

In [8]:

```
office_example_prediction_data.plot()
```

Out[8]:

```
<AxesSubplot:xlabel='timestamp'>
```



In [9]:

```
weather_data =
pd.read_csv("../input/buildingdatagenomeproject2/weather.csv",
index_col='timestamp', parse_dates=True)
```

In [10]:

```
weather_data_site = weather_data[weather_data.site_id ==
'Panther'].truncate(before='2017-01-01')
```

In [11]:

```
weather_data_site.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2017-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   site_id          8760 non-null   object
 1   airTemperature   8760 non-null   float64
 2   cloudCoverage    5047 non-null   float64
 3   dewTemperature   8760 non-null   float64
 4   precipDepth1HR   8752 non-null   float64
 5   precipDepth6HR   329 non-null    float64
 6   seaLvlPressure   8522 non-null   float64
 7   windDirection    8511 non-null   float64
 8   windSpeed        8760 non-null   float64
dtypes: float64(8), object(1)
memory usage: 684.4+ KB
```

In [12]:

```
weather_hourly = weather_data_site.resample("H").mean()
weather_hourly_nooutlier = weather_hourly[weather_hourly > -40]
weather_hourly_nooutlier_nogaps =
weather_hourly_nooutlier.fillna(method='ffill')
```

In [13]:

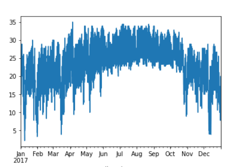
```
temperature = weather_hourly_nooutlier_nogaps["airTemperature"]
```

In [14]:

```
temperature.plot()
```

Out[14]:

```
<AxesSubplot:xlabel='timestamp'>
```



Create Train and Test Datasets

The model is given a set of data that will be used to **train** the model to predict a specific objectice. In this case, we will use a few simple time series features as well as outdoor air temperature to predict how much energy a building uses.

For this demonstration, we will use three months of data from April, May, and June to prediction July.

In [15]:

```
training_months = [4,5,6]
test_months = [7]
```

We can divide the data set by using the `datetime index` of the data frame and a function known as `.isin` to extract the months for the model

In [16]:

```
trainingdata =
office_example_prediction_data[office_example_prediction_data.index.month.
isin(training_months)]
testdata =
office_example_prediction_data[office_example_prediction_data.index.month.
isin(test_months)]
```

In [17]:

```
trainingdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2184 entries, 2017-04-01 00:00:00 to 2017-06-30 23:00:00
Data columns (total 1 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Panther_office_Hannah  2184 non-null   float64
dtypes: float64(1)
memory usage: 34.1 KB
```

In [18]:

```
testdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 744 entries, 2017-07-01 00:00:00 to 2017-07-31 23:00:00
Data columns (total 1 columns):
```

```
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Panther_office_Hannah  744 non-null    float64
dtypes: float64(1)
memory usage: 11.6 KB
```

We can extract the training input data features that will go into the model and the training **label** data which is what are are targeting to predict.

Encoding Categorical Variables

We use the pandas `.get_dummies()` function to change the temporal variables of *time of day* and *day of week* into categories that the model can use more effectively. This process is known as enconding

In [19]:

```
train_features = pd.concat([pd.get_dummies(trainingdata.index.hour),

pd.get_dummies(trainingdata.index.dayofweek),

pd.DataFrame(temperature[temperature.index.month.isin(training_months)].va
lues)], axis=1).dropna()
```

In [20]:

```
train_features.head()
```

Out[20]:

	0	1	2	3	4	5	6	7	8	9	...	22	23	0	1	2	3	4	5	6	0

0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	21.7
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	21.0
2	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	18.9
3	0	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	20.6
4	0	0	0	0	1	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	21.0

5 rows × 32 columns

Train a K-Neighbor Model

This model was chosen after following the process in the cheat sheet until a model that worked and provided good results was found.

In [21]:

```
model = KNeighborsRegressor().fit(np.array(train_features),
np.array(trainingdata.values));
```

In [22]:

```
test_features = np.array(pd.concat([pd.get_dummies(testdata.index.hour),

pd.get_dummies(testdata.index.dayofweek),

pd.DataFrame(temperature[temperature.index.month.isin(test_months)].values
)], axis=1).dropna())
```

Use the Model to predict for the *Test* period

Then the model is given the `test_features` from the period which we want to predict. We can then merge those results and see how the model did

In [23]:

```
predictions = model.predict(test_features)
```

In [24]:

```
predicted_vs_actual = pd.concat([testdata, pd.DataFrame(predictions,
index=testdata.index)], axis=1)
```

In [25]:

```
predicted_vs_actual.columns = ["Actual", "Predicted"]
```

In [26]:

```
predicted_vs_actual.head()
```

Out[26]:

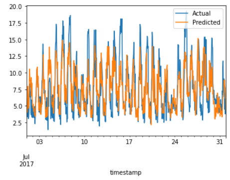
	Actual	Predicted
timestamp		
2017-07-01 00:00:00	5.3370	5.75910
2017-07-01 01:00:00	3.8547	6.02898
2017-07-01 02:00:00	5.5751	4.39686
2017-07-01 03:00:00	4.1248	4.23180
2017-07-01 04:00:00	3.3497	4.03858

In [27]:

```
predicted_vs_actual.plot()
```

Out[27]:

```
<AxesSubplot:xlabel='timestamp'>
```



In [28]:

```
trainingdata.columns = ["Actual"]
```

In [29]:

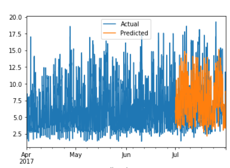
```
predicted_vs_actual_plus_training = pd.concat([trainingdata,
predicted_vs_actual], sort=True)
```

In [30]:

```
predicted_vs_actual_plus_training.plot()
```

Out[30]:

```
<AxesSubplot:xlabel='timestamp'>
```



Evaluation metrics

In order to understand quanitatively how the model performed, we can use various evaluation metrics to understand how well the model compared to reality.

In this situation, let's use the error metric Mean Absolute Percentage Error (MAPE)

In [31]:

```
# Calculate the absolute errors
errors = abs(predicted_vs_actual['Predicted'] -
predicted_vs_actual['Actual'])
# Calculate mean absolute percentage error (MAPE) and add to list
MAPE = 100 * np.mean((errors / predicted_vs_actual['Actual']))
```

In [32]:

```
MAPE
```

Out[32]:

```
34.22379683897996
```