```python
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/hourly-energy-consumption/est_hourly.paruqet
/kaggle/input/hourly-energy-consumption/DOM_hourly.csv
/kaggle/input/hourly-energy-consumption/EKPC_hourly.csv
/kaggle/input/hourly-energy-consumption/DUQ_hourly.csv
/kaggle/input/hourly-energy-consumption/DAYTON_hourly.csv
/kaggle/input/hourly-energy-consumption/PJME_hourly.csv
/kaggle/input/hourly-energy-consumption/PJM_Load_hourly.csv
/kaggle/input/hourly-energy-consumption/NI_hourly.csv
/kaggle/input/hourly-energy-consumption/FE_hourly.csv
/kaggle/input/hourly-energy-consumption/COMED_hourly.csv
/kaggle/input/hourly-energy-consumption/AEP_hourly.csv
/kaggle/input/hourly-energy-consumption/pjm_hourly_est.csv
/kaggle/input/hourly-energy-consumption/DEOK_hourly.csv
/kaggle/input/hourly-energy-consumption/PJMW_hourly.csv
```

Energy Consumption Forecastting Using XGBoost

PJM Hourly Energy Consumption Data

PJM Interconnection LLC (PJM) is a regional transmission organization (RTO) in the United States. It is part of the Eastern Interconnection grid operating an electric transmission system serving all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia.

The hourly power consumption data comes from PJM's website and are in megawatts (MW). The regions have changed over the years so data may only appear for certain dates per region.

For the purpose of our project we're going to specifically work on the **AEP_Hourly - American Electric Power** dataset.

Import Libraries

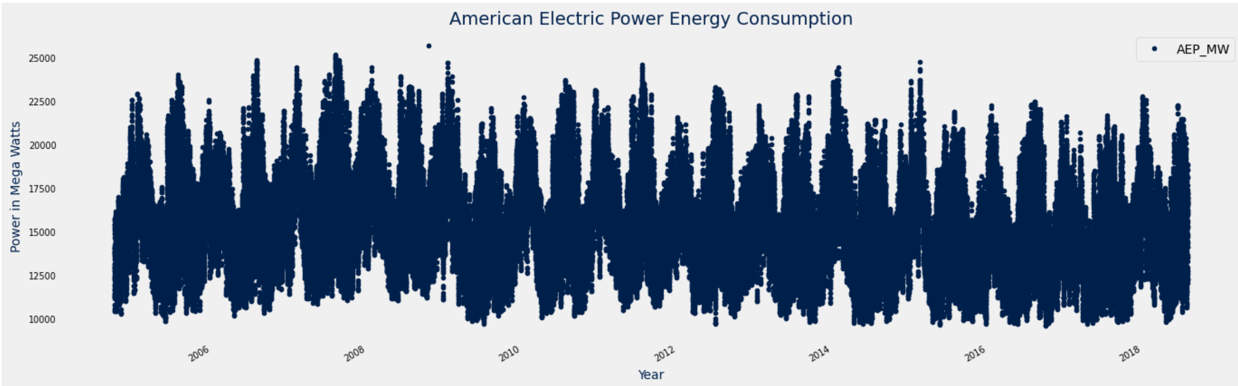
```
# Import all the necessary Libraries
import matplotlib.pyplot as plt # For visualization
import seaborn as sns #for visualization
import xgboost as xgb #for modelling purposes
from xgboost import plot_importance, plot_tree #Feature importance
from sklearn.metrics import mean_squared_error, mean_absolute_error
#to evaluate model performance
from sklearn.preprocessing import LabelEncoder
plt.style.use('fivethirtyeight')
```

Objective

- Split the last year into a test set- can we can build a model to predict energy consumption.
- Find trends in energy consumption around hours of the day, holidays, or long term trends.
- Understand how daily trends change depending of the time of year. Summer trends are very different than winter trends.

Load Data

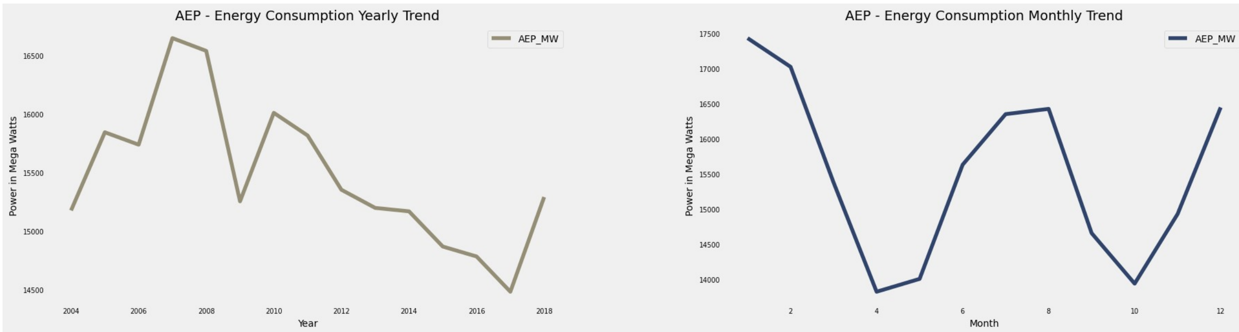
```
aep =
pd.read_csv('/kaggle/input/hourly-energy-consumption/AEP_hourly.csv',i
ndex_col=[0],parse_dates=[0])
col_pal = ['#00204C', '#31446B', '#782170', '#958F78', '#00B050',
'#FFE945']
_ = aep.plot(style='.',figsize=(15,5), color=col_pal[0])
plt.title('American Electric Power Energy Consumption',
fontsize=14,color=col_pal[0])  # Adjust the fontsize for the title
plt.xlabel('Year', fontsize=10,color=col_pal[0])  # Adjust the
fontsize for the x-axis label
plt.ylabel('Power in Mega Watts', fontsize=10,color=col_pal[0])  #
Adjust the fontsize for the y-axis label
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)
```



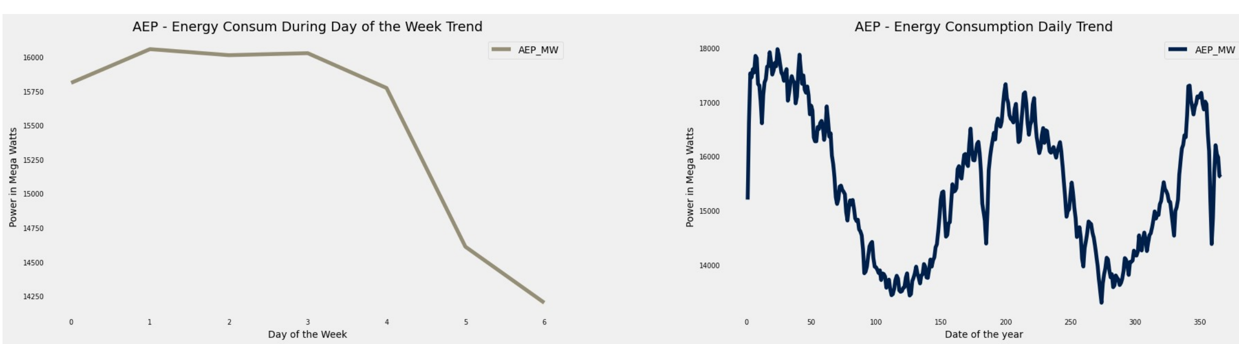
Data Exploration

```
from IPython.display import display_html
import io

#I like seeing the descriptive information about our df
# Capture the outputs
head_output = aep.head().to_html()
describe_output = aep.describe().to_html()

# save the info output
buffer = io.StringIO()
aep.info(buf=buffer)
info_output = buffer.getvalue().replace('\n', '<br>')

# Use display side by side
display_html(f'<div style="display: flex; justify-content: space-
around;">'
             f'<div>{head_output}</div>'
             f'<div>{describe_output}</div>'
             f'<div><pre>{info_output}</pre></div>'
             f'</div>', raw=True)

# Let's copy the df for exploration
df_aep_mw = aep.copy()
df_aep_mw.head()

def analysis_features(df_aep):
    df_aep['date'] = df_aep.index
    df_aep['hour'] = df_aep['date'].dt.hour
    df_aep['dayofweek'] = df_aep['date'].dt.dayofweek
    df_aep['quarter']= df_aep['date'].dt.quarter
    df_aep['month'] = df_aep['date'].dt.month
    df_aep['year'] = df_aep['date'].dt.year
    df_aep['dayofyear'] = df_aep['date'].dt.dayofyear
    df_aep['dayofmonth'] = df_aep['date'].dt.day
    df_aep['weekofyear'] = df_aep['date'].dt.isocalendar().week
    return df_aep
```

```
analysis_features(df_aep_mw)
df_aep_mw.head()

                      AEP_MW                date  hour  dayofweek
quarter  \
Datetime

2004-12-31 01:00:00  13478.0 2004-12-31 01:00:00     1          4
4
2004-12-31 02:00:00  12865.0 2004-12-31 02:00:00     2          4
4
2004-12-31 03:00:00  12577.0 2004-12-31 03:00:00     3          4
4
2004-12-31 04:00:00  12517.0 2004-12-31 04:00:00     4          4
4
2004-12-31 05:00:00  12670.0 2004-12-31 05:00:00     5          4
4

                     month  year  dayofyear  dayofmonth  weekofyear
Datetime
2004-12-31 01:00:00     12  2004        366          31          53
2004-12-31 02:00:00     12  2004        366          31          53
2004-12-31 03:00:00     12  2004        366          31          53
2004-12-31 04:00:00     12  2004        366          31          53
2004-12-31 05:00:00     12  2004        366          31          53

plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
df_aep_mw.groupby(['year']).mean()['AEP_MW'].plot(color=col_pal[3])
plt.title('AEP - Energy Consumption Yearly Trend', fontsize=14)
plt.xlabel('Year', fontsize=10)
plt.ylabel('Power in Mega Watts', fontsize=10)
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)

plt.subplot(1,2,2)
df_aep_mw.groupby(['month']).mean()['AEP_MW'].plot(color=col_pal[1])
plt.title('AEP - Energy Consumption Monthly Trend', fontsize=14)
plt.xlabel('Month', fontsize=10)
plt.ylabel('Power in Mega Watts', fontsize=10)
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)


plt.subplots_adjust(wspace=0.3)
```




```
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
df_aep_mw.groupby(['dayofweek']).mean()
['AEP_MW'].plot(color=col_pal[3])
plt.title('AEP - Energy Consum During Day of the Week Trend',
fontsize=14)
plt.xlabel('Day of the Week', fontsize=10)
plt.ylabel('Power in Mega Watts', fontsize=10)
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)

plt.subplot(1,2,2)
df_aep_mw.groupby(['dayofyear']).mean()
['AEP_MW'].plot(color=col_pal[0])
plt.title('AEP - Energy Consumption Daily Trend', fontsize=14)
plt.xlabel('Date of the year', fontsize=10)
plt.ylabel('Power in Mega Watts', fontsize=10)
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)

plt.subplots_adjust(wspace=0.3)
```



Key Insights

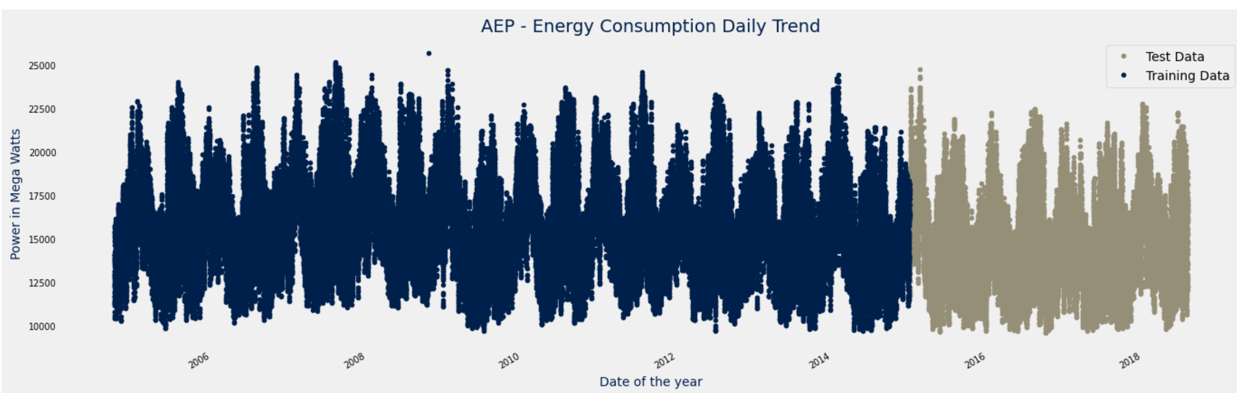
- It's clear from the first chart that energy consumption has dropped **year on yaer**.

- It's also observable that energy consumption is heavly influenced by **sesonality**.
- Furthermore, the **end of the week** where the least electric energy is consumed.

Create New Features

Let's first split the dataset in first since the objective and test of the prediction will be after the dates Jan 1 of 2015. Let's do that:

```
date_of_split = '01-Jan-2015'
aep_train = aep.loc[aep.index <= date_of_split].copy()
aep_test = aep.loc[aep.index > date_of_split].copy()

# A very simple way of displaying what we'll be predicting and what our model will be training on
_ = aep_test.rename(columns={'AEP_MW': 'Test Data'}).join(aep_train.rename(columns={'AEP_MW': 'Training Data'}), how='outer').plot(figsize=(15,5),style = '.',color = [col_pal[3],col_pal[0]])
plt.title('AEP - Energy Consumption Daily Trend', fontsize=14,color=col_pal[0])
plt.xlabel('Date of the year', fontsize=10,color = col_pal[0])
plt.ylabel('Power in Mega Watts', fontsize=10,color = col_pal[0])
plt.xticks(fontsize=7)
plt.yticks(fontsize=7)
plt.legend(fontsize=10)
plt.grid(False)
```




```
import holidays

start_date = '2004-10-01'
end_date = '2018-08-31'

# date range
date_range = pd.date_range(start=start_date, end=end_date)

# holidays for the date range
us_holidays = holidays.US(years=range(2004, 2019))
```

```python
# Convert the holiday dates to a list
holidays = list(us_holidays.keys())


def new_features(df, label=None, lags=[1, 7, 30], rolling_windows=[3,
7, 30]):
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.isocalendar().week

    # Our lag features
    for lag in lags:
        df[f'lag_{lag}'] = df[label].shift(lag)

    # rollling statistics
    for window in rolling_windows:
        df[f'rolling_mean_{window}'] =
df[label].rolling(window=window).mean()
        df[f'rolling_std_{window}'] =
df[label].rolling(window=window).std()

    # Seasonal indicators
    df['is_weekend'] = df['dayofweek'].apply(lambda x: 1 if x >= 5
else 0)
    df['is_holiday'] = df['date'].apply(lambda x: 1 if x in holidays
else 0)  # 'holidays' is a list of holidays that would have occured
with in our df.

    X = df[['hour', 'dayofweek', 'quarter', 'month', 'year',
'dayofyear', 'dayofmonth', 'weekofyear',
           'is_weekend', 'is_holiday'] +
           [f'lag_{lag}' for lag in lags] +
           [f'rolling_mean_{window}' for window in rolling_windows] +
           [f'rolling_std_{window}' for window in rolling_windows]]

    if label:
        y = df[label]
        return X, y
    return X

X_train, y_train = new_features(aep_train, label='AEP_MW')
X_test, y_test = new_features(aep_test, label='AEP_MW')
X_train.head()
```

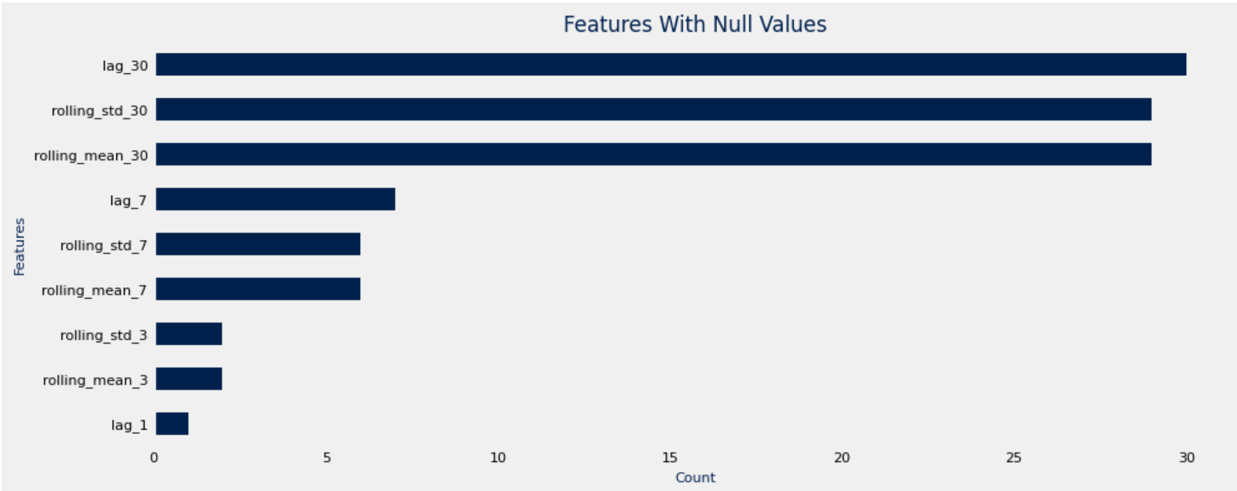
```
                     hour  dayofweek  quarter  month  year  dayofyear  \
Datetime

2004-12-31 01:00:00     1          4        4     12  2004        366

2004-12-31 02:00:00     2          4        4     12  2004        366

2004-12-31 03:00:00     3          4        4     12  2004        366

2004-12-31 04:00:00     4          4        4     12  2004        366

2004-12-31 05:00:00     5          4        4     12  2004        366


                     dayofmonth  weekofyear  is_weekend  is_holiday
lag_1  \
Datetime

2004-12-31 01:00:00          31          53           0           0
NaN
2004-12-31 02:00:00          31          53           0           0
13478.0
2004-12-31 03:00:00          31          53           0           0
12865.0
2004-12-31 04:00:00          31          53           0           0
12577.0
2004-12-31 05:00:00          31          53           0           0
12517.0

                     lag_7  lag_30  rolling_mean_3  rolling_mean_7  \
Datetime
2004-12-31 01:00:00    NaN     NaN             NaN             NaN
2004-12-31 02:00:00    NaN     NaN             NaN             NaN
2004-12-31 03:00:00    NaN     NaN    12973.333333             NaN
2004-12-31 04:00:00    NaN     NaN    12653.000000             NaN
2004-12-31 05:00:00    NaN     NaN    12588.000000             NaN

                     rolling_mean_30  rolling_std_3  rolling_std_7  \
Datetime
2004-12-31 01:00:00              NaN            NaN            NaN
2004-12-31 02:00:00              NaN            NaN            NaN
2004-12-31 03:00:00              NaN     460.165550            NaN
2004-12-31 04:00:00              NaN     186.032255            NaN
2004-12-31 05:00:00              NaN      77.090855            NaN

                     rolling_std_30
Datetime
2004-12-31 01:00:00             NaN
2004-12-31 02:00:00             NaN
2004-12-31 03:00:00             NaN
```

```
2004-12-31 04:00:00                NaN
2004-12-31 05:00:00                NaN
```

```python
print("Length of X_test:", len(X_test))
print("Length of aep_test:", len(aep_test))
print("Length of X_train:", len(X_train))
print("Length of aep_train:", len(aep_train))
```

```
Length of X_test: 31439
Length of aep_test: 31439
Length of X_train: 89834
Length of aep_train: 89834
```

```python
#I like seeing the descriptive information about our
# save the outputs
head_output2 = X_train.head().T.to_html()
describe_output2 = X_train.describe().T.to_html()

# save the info output
buffer = io.StringIO()
X_train.info(buf=buffer)
info_output2 = buffer.getvalue().replace('\n', '<br>')

# Use HTML to display side by side
display_html(f'<div style="display: flex; justify-content: space-
around;">'
             f'<div>{head_output2}</div>'
             f'<div>{describe_output2}</div>'
             f'<div><pre>{info_output2}</pre></div>'
             f'</div>', raw=True)

missing_values = X_train.isnull().sum()
missing_values = missing_values[missing_values > 0]
missing_values.sort_values(ascending=True).plot(kind='barh',
figsize=(10, 4), color= col_pal[0])
plt.title('Features With Null Values', fontsize=12, color =
col_pal[0])
plt.xlabel('Count',fontsize=8,color =  col_pal[0])
plt.ylabel('Features',fontsize=8,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.grid(False)
```



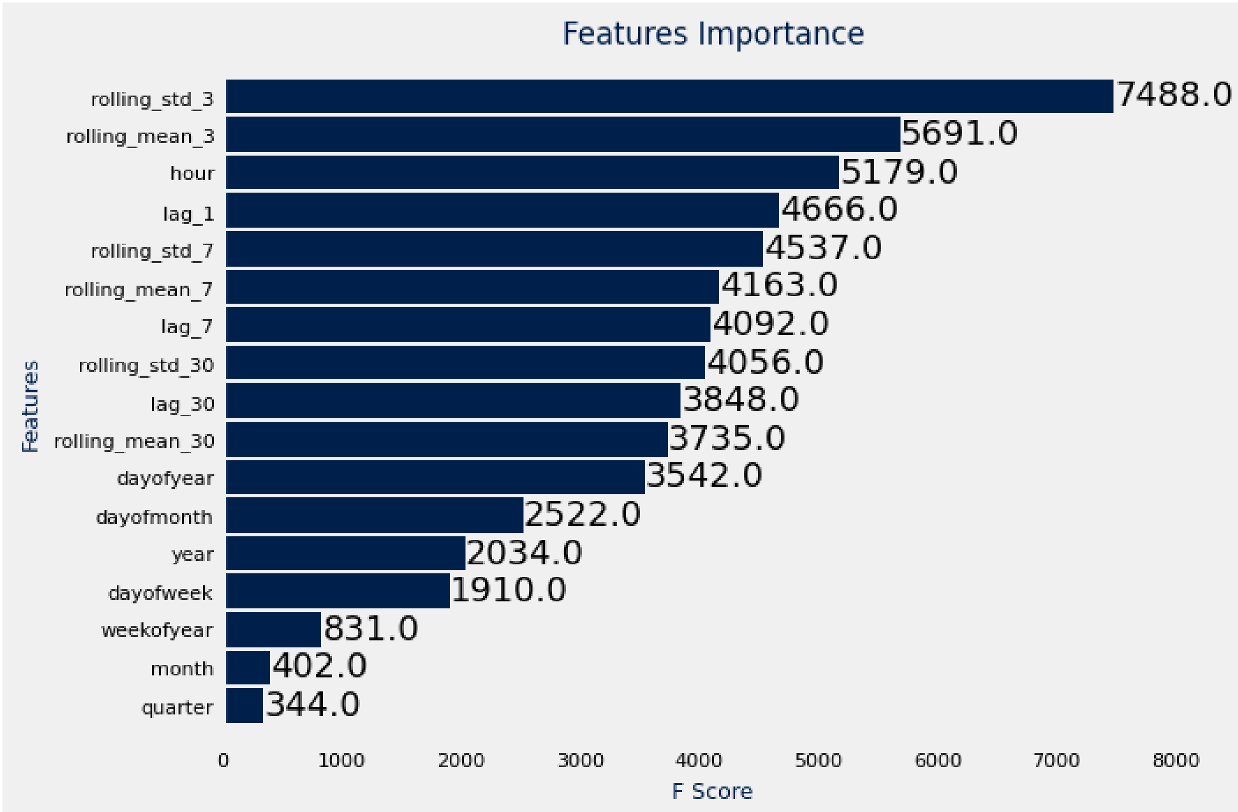

```
%%capture
# List of columns to change data types as well as handle missing
values
cols_to_handle = ['lag_1', 'lag_7', 'lag_30', 'rolling_mean_3',
'rolling_mean_7', 'rolling_mean_30', 'rolling_std_3', 'rolling_std_7',
'rolling_std_30', 'weekofyear', 'is_weekend', 'is_holiday']

# Handle the missing values
X_train[cols_to_handle] =
X_train[cols_to_handle].interpolate(method='linear',
limit_direction='forward').fillna(0);
X_test[cols_to_handle] =
X_test[cols_to_handle].interpolate(method='linear',
limit_direction='forward').fillna(0);

# Convert columns to int32 so that dt is uniform all across the df
for col in cols_to_handle:
    X_train[col] = X_train[col].astype('int32')
    X_test[col] = X_test[col].astype('int32')
```

Create Model

For this project, we're going to use **XGBoost**'s Algorithm, specifically **XGBRegressor**. **XGBRegressor** is a specialized implementation of the XGBoost algorithm designed for regression tasks. **Regression** tasks involve predicting continuous numerical values, such as forecasting sales or estimating prices. **XGBoost** stands for **Extreme Gradient Boosting**, which is a powerful machine learning technique known for its high performance and flexibility. **XGBRegressor** is tailored to handle regression problems effectively by leveraging the core principles of gradient boosting, making it suitable for various predictive modeling tasks where the goal is to predict a continuous output.

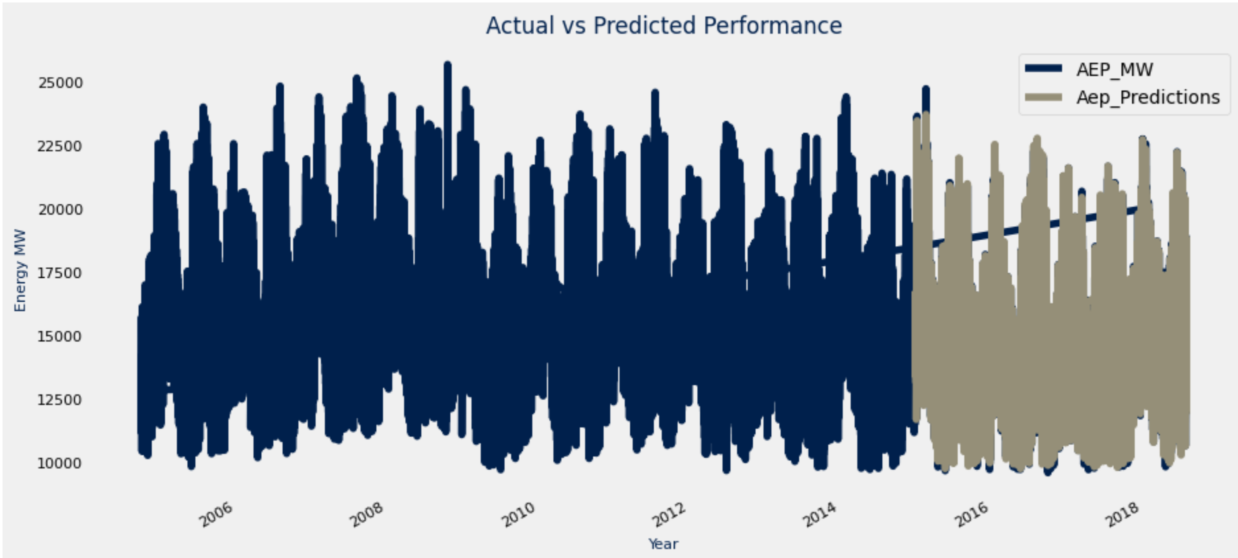
XGBoost builds on the concept of gradient boosting, where multiple simple models, usually decision trees, are combined to create a stronger predictive model. Each decision tree in the ensemble corrects the errors of the previous ones, gradually improving the model's performance. This process results in a robust model capable of capturing complex patterns in the data, which is particularly useful for tasks such as time series forecasting, where understanding intricate temporal dependencies is crucial.

```
%%capture

#Let's create a class for our model from xgb
xgb_model = xgb.XGBRegressor(n_estimators=1000)
#xgb_model.fit(X_train,y_train,eval_set = [(X_train, y_train),
(X_test, y_test)],early_stopping_rounds=50, verbose=False) # The
verbose allows us to not see the model training.
xgb_model.fit(X_train,y_train) # The verbose allows us to not see the
model training.

# Now we plot an F score of how important each of our features are
plt.figure(figsize=(20,10))
ax = plot_importance(xgb_model, height=0.9,color =col_pal[0])
plt.title('Features Importance', fontsize=12, color = col_pal[0])
plt.xlabel('F Score',fontsize=9,color =  col_pal[0])
plt.ylabel('Features',fontsize=9,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.grid(False)


<Figure size 2000x1000 with 0 Axes>
```

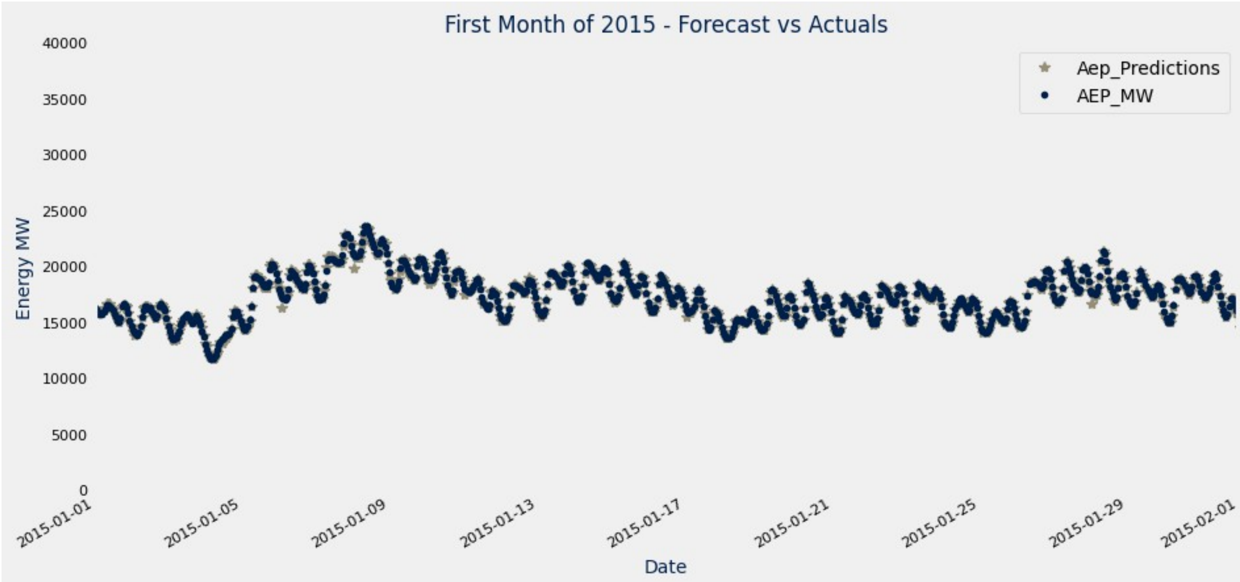


Prediction

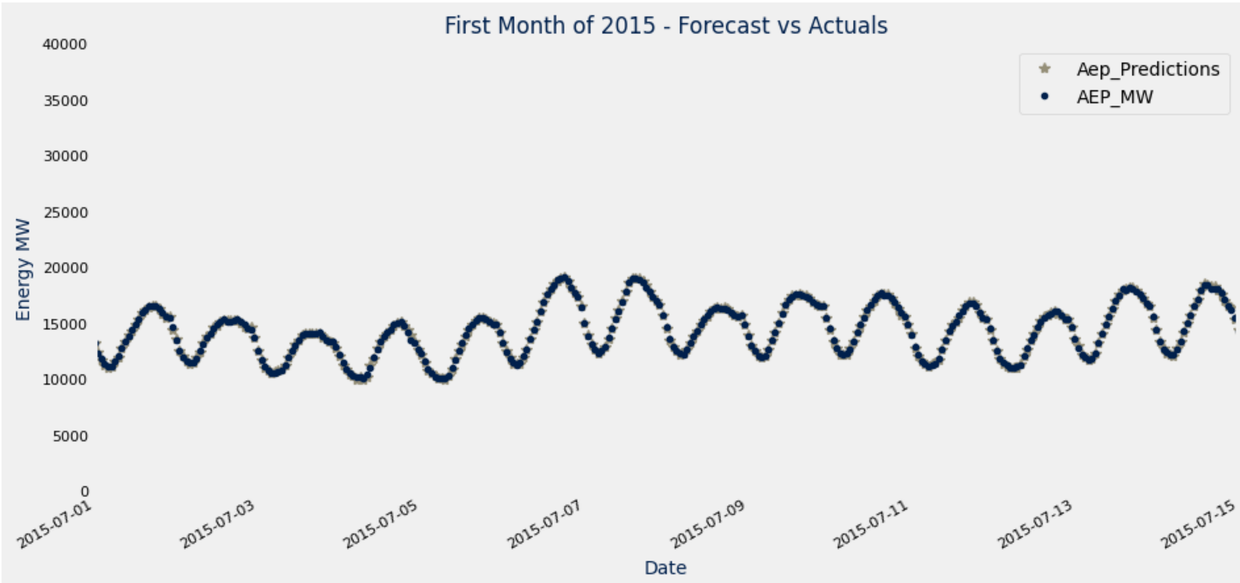
```
aep_test['Aep_Predictions'] = xgb_model.predict(X_test)
aep_comb = pd.concat([aep_test, aep_train],sort=False)

_ = aep_comb[['AEP_MW','Aep_Predictions']].plot(figsize=(10,5),color =
[col_pal[0],col_pal[3]])
plt.title('Actual vs Predicted Performance', fontsize=12, color =
col_pal[0])
plt.xlabel('Year',fontsize=8,color =  col_pal[0])
plt.ylabel('Energy MW',fontsize=8,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.legend(fontsize=10)
plt.grid(False)
```




```
# Let's compare the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ =
aep_comb[['Aep_Predictions','AEP_MW']].plot(ax=ax,style=['*','.'],colo
r = [col_pal[3],col_pal[0]])
ax.set_xbound(lower='01-01-2015',upper='02-01-2015')
ax.set_ylim(0,40000)
plt.title('First Month of 2015 - Forecast vs Actuals', fontsize=12,
color = col_pal[0])
plt.xlabel('Date',fontsize=10,color =  col_pal[0])
plt.ylabel('Energy MW',fontsize=10,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.legend(fontsize=10)
plt.grid(False)
```




```
# Let's compare the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ =
aep_comb[['Aep_Predictions','AEP_MW']].plot(ax=ax,style=['*','.'],colo
r = [col_pal[3],col_pal[0]])
ax.set_xbound(lower='07-01-2015',upper='07-15-2015')
ax.set_ylim(0,40000)
plot = plt.title('First Two Weeks of 2015 Forecast vs Actuals')
plt.title('First Month of 2015 - Forecast vs Actuals', fontsize=12,
color = col_pal[0])
plt.xlabel('Date',fontsize=10,color =  col_pal[0])
plt.ylabel('Energy MW',fontsize=10,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.legend(fontsize=10)
plt.grid(False)
```



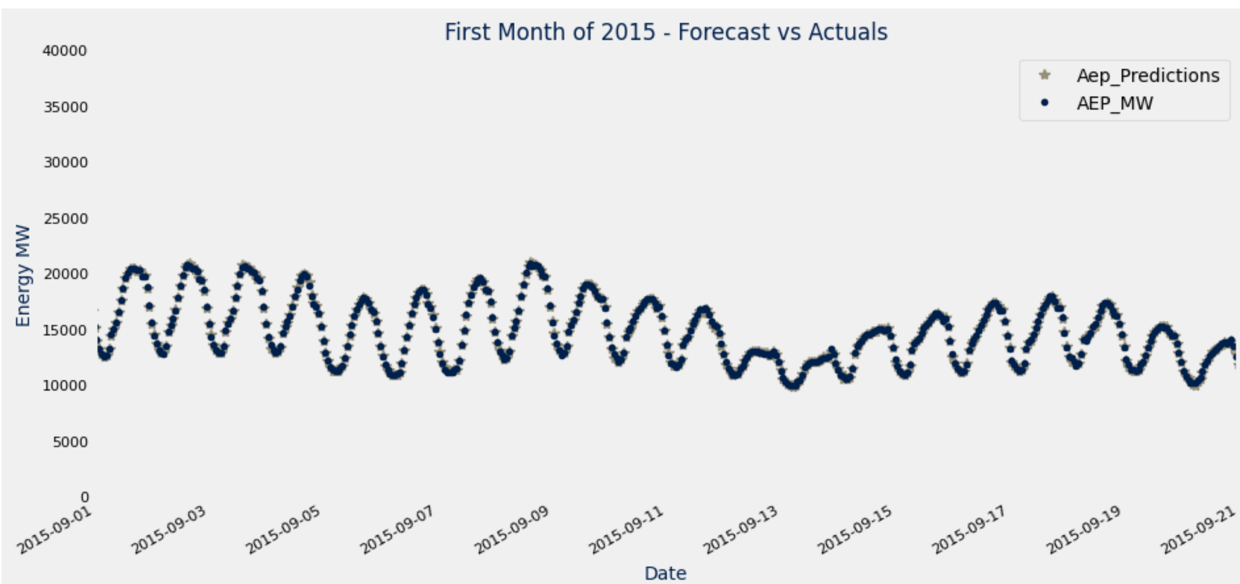
Model Performance & Error Metrics

```
mse =
mean_squared_error(y_true=aep_test['AEP_MW'],y_pred=aep_test['Aep_Pred
ictions'])
mae =
mean_absolute_error(y_true=aep_test['AEP_MW'],y_pred=aep_test['Aep_Pre
dictions'])

print("The Mean Ssquare Error is: ", round(mse,2))
print("The Mean Absolute Error is: ", round(mae,2))

The Mean Ssquare Error is:  11750.01
The Mean Absolute Error is:  68.59

def mean_abs_perc_error(y_true,y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred)/y_true))*100

mape = mean_abs_perc_error(y_true=aep_test['AEP_MW'],
y_pred=aep_test['Aep_Predictions'])
print("The Mean Absolute Percentage Error is: ", round(mape,2),"%")

The Mean Absolute Percentage Error is:  0.48 %

aep_test['error_difference'] = aep_test['AEP_MW'] -
aep_test['Aep_Predictions']
aep_test['error_absolute'] =
aep_test['error_difference'].apply(np.abs)
aep_test['error_percentage'] = ((aep_test['AEP_MW'] -
aep_test['Aep_Predictions']) / aep_test['AEP_MW'])*100
aep_test['error_absolute_perc'] =  (np.abs(aep_test['AEP_MW'] -
aep_test['Aep_Predictions']) / aep_test['AEP_MW'])*100
```

```
errors_ = aep_test.groupby(['year','month','dayofmonth']).mean()
[['AEP_MW','Aep_Predictions','error_difference','error_absolute','erro
r_percentage','error_absolute_perc']]

#The forecasted values
errors_.sort_values('error_difference',ascending=True).head(10)
```

```
                               AEP_MW  Aep_Predictions  error_difference
\
year month dayofmonth

2015 12    25            11078.041667     11361.145508       -283.103963

           24            11466.041667     11636.549805       -170.507975

           27            11998.916667     12167.000000       -168.082682

2016 10    2             11264.000000     11420.069336       -156.068929

           9             11309.083333     11460.838867       -151.755859

2018 4     24            11723.750000     11859.819336       -136.068481

2016 4     23            11366.958333     11483.020508       -116.062826

2015 11    27            11755.083333     11860.136719       -105.053874

2017 4     16            11400.291667     11494.026367        -93.734741

2016 5     8             11171.083333     11258.855469        -87.772298


                         error_absolute  error_percentage
error_absolute_perc
year month dayofmonth

2015 12    25                294.095337         -2.718336
2.813941
           24                178.117350         -1.556654
1.621767
           27                255.303792         -1.359103
2.068011
2016 10    2                 195.253011         -1.551241
1.875590
           9                 171.619629         -1.480253
1.640582
2018 4     24                157.635457         -1.286295
1.464491
2016 4     23                133.451172         -1.094378
1.239339
2015 11    27                114.566243         -0.898100
```

```
0.983253
2017 4      16              121.559448          -0.910499
1.146842
2016 5      8               101.725260          -0.853027
0.970991

#Let's see some of the best predicted days
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ =
aep_comb[['Aep_Predictions','AEP_MW']].plot(ax=ax,style=['*','.'],colo
r = [col_pal[3],col_pal[0]])
ax.set_ylim(0, 40000)
ax.set_xbound(lower='09-01-2015',upper='09-21-2015')
plot = plt.title('Septemeber First Three Weeks - Bad Predictions')
plt.title('First Month of 2015 - Forecast vs Actuals', fontsize=12,
color = col_pal[0])
plt.xlabel('Date',fontsize=10,color =  col_pal[0])
plt.ylabel('Energy MW',fontsize=10,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.legend(fontsize=10)
plt.grid(False)
```




```
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```

```
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plt.title('Septemeber First Three Weeks - Bad Predictions',
fontsize=12, color = col_pal[0])
plt.xlabel('Date',fontsize=10,color =  col_pal[0])
plt.ylabel('Energy MW',fontsize=10,color =  col_pal[0])
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)
plt.legend(fontsize=10)
plt.grid(False)
```