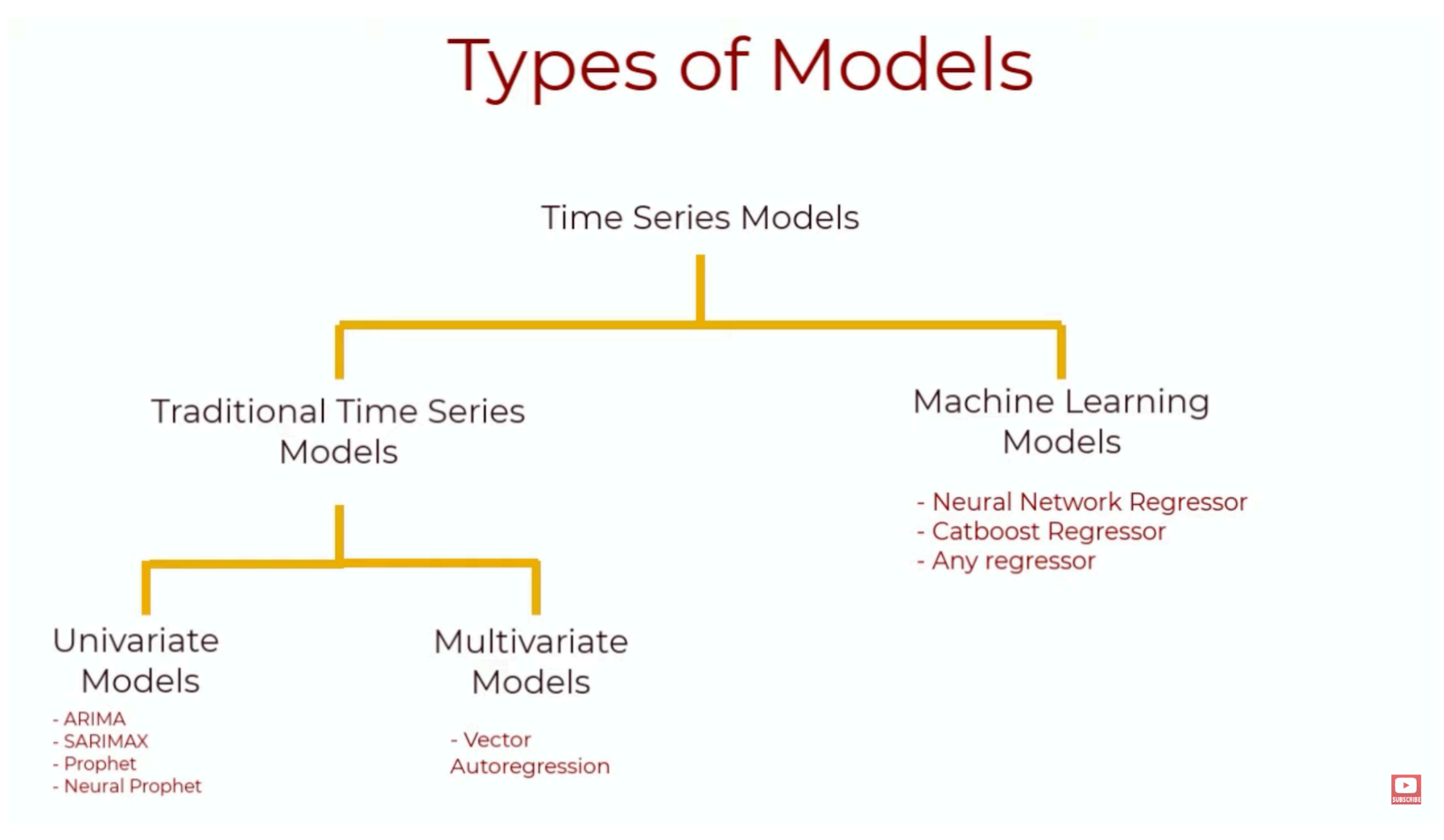
Hourly Time Series Forecasting using XGBoost

In this notebook we will walk through time series forecasting using XGBoost. The data we will be using is hourly energy consumption.




```
In [ ]:
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
import xgboost as xgb
from xgboost import plot_importance, plot_tree
from sklearn.metrics import mean_squared_error, mean_absolute_error
plt.style.use('fivethirtyeight')
```

Data

The data we will be using is hourly power consumption data from PJM. Energy consumtion has some unique charachteristics. It will be interesting to see how prophet picks them up.

PJM Dataset Description

Pulling the `PJM East` which has data from 2004-2018 for the entire east region.

```
In [67]:
pjme = pd.read_csv('AEP_hourly.csv', index_col=[0], parse_dates=[0])
```

```
In [ ]:
pjme.head()
```

Out[ ]:

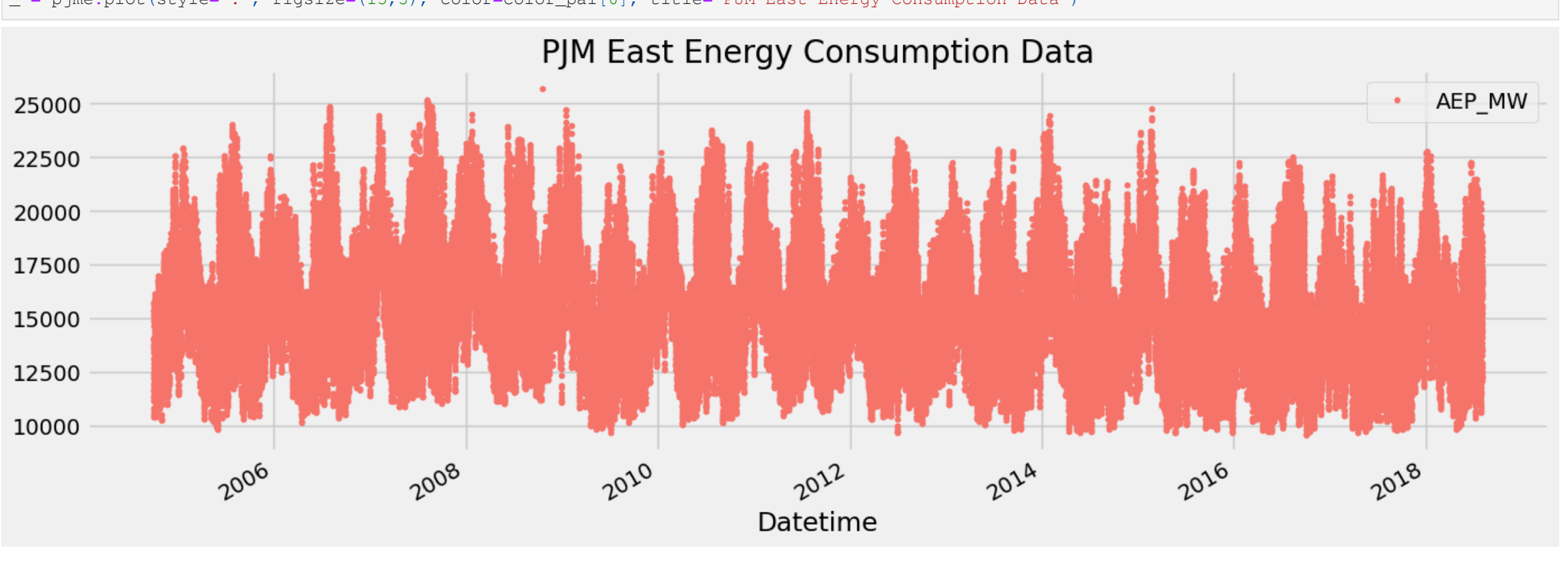
Datetime	AEP_MW
2004-12-31 01:00:00	13478.0
2004-12-31 02:00:00	12865.0
2004-12-31 03:00:00	12577.0
2004-12-31 04:00:00	12517.0
2004-12-31 05:00:00	12670.0

```
In [ ]:
pjme.tail()
```

Out[ ]:

Datetime	AEP_MW
2018-01-01 20:00:00	21089.0
2018-01-01 21:00:00	20999.0
2018-01-01 22:00:00	20820.0
2018-01-01 23:00:00	20415.0
2018-01-02 00:00:00	19993.0

```
In [64]:
color_pal = ["#F8766D", "#D39200", "#93AA00", "#00BA38", "#00C19F", "#00B9E3", "#619CFF", "#DB72FB"]
_ = pjme.plot(style='.', figsize=(15,5), color=color_pal[0], title='PJM East Energy Consumption Data')
```



Train/Test Split

Cut off the data after 2015 to use as our validation set.

```
In [68]:
split_date = '01-Jan-2015'
pjme_train = pjme.loc[pjme.index < split_date].copy()
pjme_test = pjme.loc[pjme.index >= split_date].copy()
```

```
In [ ]:
pjme_train.tail()
```

Out[ ]:

Datetime	AEP_MW
2014-01-01 20:00:00	16433.0
2014-01-01 21:00:00	16376.0
2014-01-01 22:00:00	16151.0
2014-01-01 23:00:00	15687.0
2014-01-02 00:00:00	15201.0

```
In [ ]:
pjme_test.head()
```

Out[ ]:

Datetime	AEP_MW
2015-01-01 00:00:00	16375.0
2015-12-31 01:00:00	12415.0
2015-12-31 02:00:00	12087.0
2015-12-31 03:00:00	12010.0
2015-12-31 04:00:00	11972.0

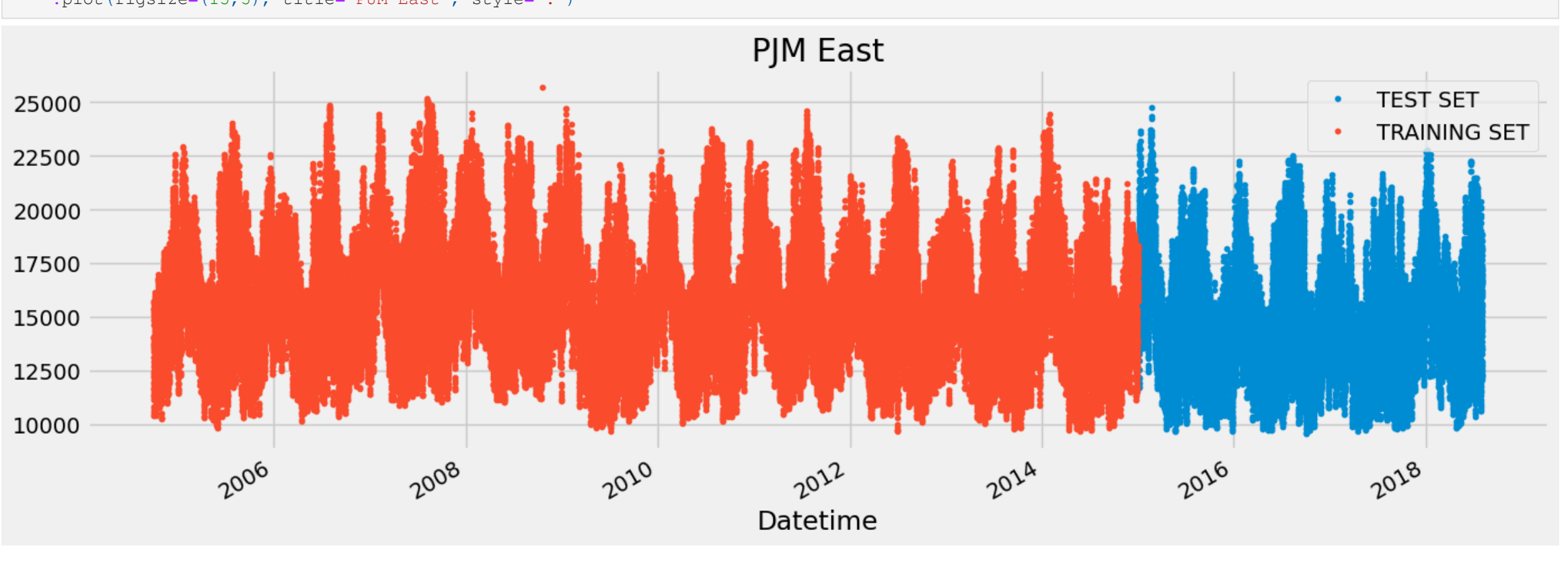
```
In [69]:
pjme_test \
    .rename(columns={'AEP_MW': 'TEST SET'}) \
    .join(pjme_train.rename(columns={'AEP_MW': 'TRAINING SET'}), how='outer')
```

Out[69]:

Datetime	TEST SET	TRAINING SET
2004-10-01 01:00:00	NaN	12379.0
2004-10-01 02:00:00	NaN	11935.0
2004-10-01 03:00:00	NaN	11692.0
2004-10-01 04:00:00	NaN	11597.0
2004-10-01 05:00:00	NaN	11681.0
...	...	...
2018-08-02 20:00:00	17673.0	NaN
2018-08-02 21:00:00	17303.0	NaN
2018-08-02 22:00:00	17001.0	NaN
2018-08-02 23:00:00	15964.0	NaN
2018-08-03 00:00:00	14809.0	NaN

121273 rows × 2 columns

```
In [ ]:
_ = pjme_test \
    .rename(columns={'AEP_MW': 'TEST SET'}) \
    .join(pjme_train.rename(columns={'AEP_MW': 'TRAINING SET'}), how='outer') \
    .plot(figsize=(15,5), title='PJM East', style='.')
```



Create Time Series Features

```
In [70]:
def create_features(df, label=None):
    """
    Creates time series features from datetime index
    """
    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.weekofyear

    X = df[['hour','dayofweek','quarter','month','year',
           'dayofyear','dayofmonth','weekofyear']]
    if label:
        y = df[label]
        return X, y
    return X
```

```
In [71]:
X_train, y_train = create_features(pjme_train, label='AEP_MW')
X_test, y_test = create_features(pjme_test, label='AEP_MW')
```

```
<ipython-input-70-ef221b55ea67>:13: FutureWarning: Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar
().week instead.
  df['weekofyear'] = df['date'].dt.weekofyear
<ipython-input-70-ef221b55ea67>:13: FutureWarning: Series.dt.weekofyear and Series.dt.week have been deprecated. Please use Series.dt.isocalendar
().week instead.
  df['weekofyear'] = df['date'].dt.weekofyear
```

```
In [72]:
X_train.head()
```

Out[72]:

Datetime	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear
2004-12-31 01:00:00	1	4	4	12	2004	366	31	53
2004-12-31 02:00:00	2	4	4	12	2004	366	31	53
2004-12-31 03:00:00	3	4	4	12	2004	366	31	53
2004-12-31 04:00:00	4	4	4	12	2004	366	31	53
2004-12-31 05:00:00	5	4	4	12	2004	366	31	53

```
In [73]:
y_train.head()
```

```
Out[73]:
Datetime
2004-12-31 01:00:00    13478.0
2004-12-31 02:00:00    12865.0
2004-12-31 03:00:00    12577.0
2004-12-31 04:00:00    12517.0
2004-12-31 05:00:00    12670.0
Name: AEP_MW, dtype: float64
```

```
In [ ]:
X_test.head()
```

Out[ ]:

Datetime	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear
2015-01-01 00:00:00	0	3	1	1	2015	1	1	1
2015-12-31 01:00:00	1	3	4	12	2015	365	31	53
2015-12-31 02:00:00	2	3	4	12	2015	365	31	53
2015-12-31 03:00:00	3	3	4	12	2015	365	31	53
2015-12-31 04:00:00	4	3	4	12	2015	365	31	53

Create XGBoost Model

```
In [74]:
reg = xgb.XGBRegressor(n_estimators=1000)
reg.fit(X_train, y_train,
        eval_set=[(X_train, y_train), (X_test, y_test)],
        early_stopping_rounds=50,
        #eval_metric ='mae',
       verbose=False) # Change verbose to True if you want to see it train
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/sklearn.py:835: UserWarning: `early_stopping_rounds` in `fit` method is deprecated for better compa
tibility with scikit-learn, use `early_stopping_rounds` in constructor or`set_params` instead.
  warnings.warn(
```

```
Out[74]:
XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             n_estimators=1000, n_jobs=None, num_parallel_tree=None,
             predictor=None, random_state=None, ...)
```

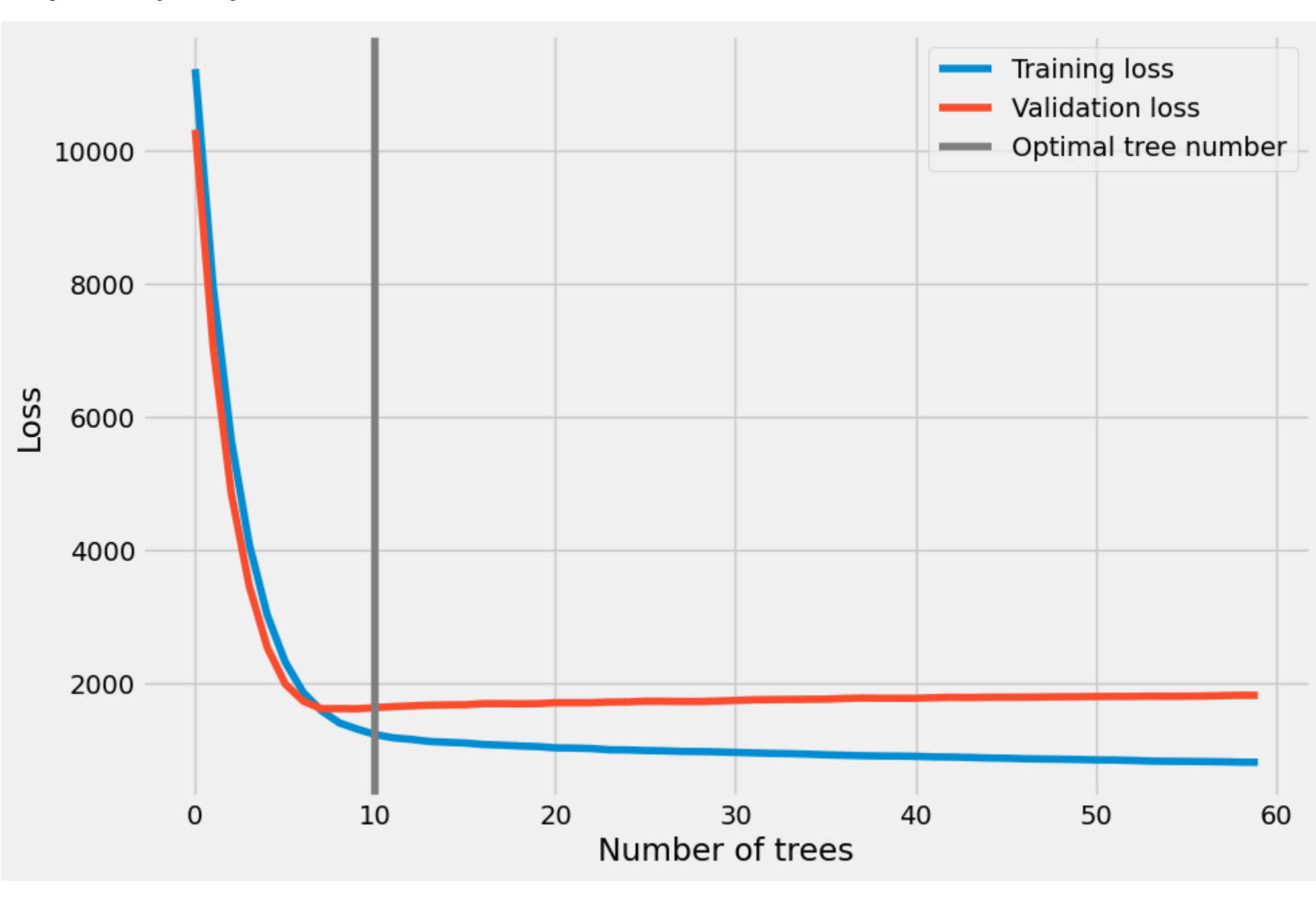
```
In [75]:
reg.best_ntree_limit
```

```
Out[75]:
10
```

```
In [ ]:
results = reg.evals_result()

plt.figure(figsize=(10,7))
plt.plot(results["validation_0"]["rmse"], label="Training loss")
plt.plot(results["validation_1"]["rmse"], label="Validation loss")
plt.axvline(10, color="gray", label="Optimal tree number")
plt.xlabel("Number of trees")
plt.ylabel("Loss")
plt.legend()
```

```
Out[ ]:
<matplotlib.legend.Legend at 0x7cf712248940>
```

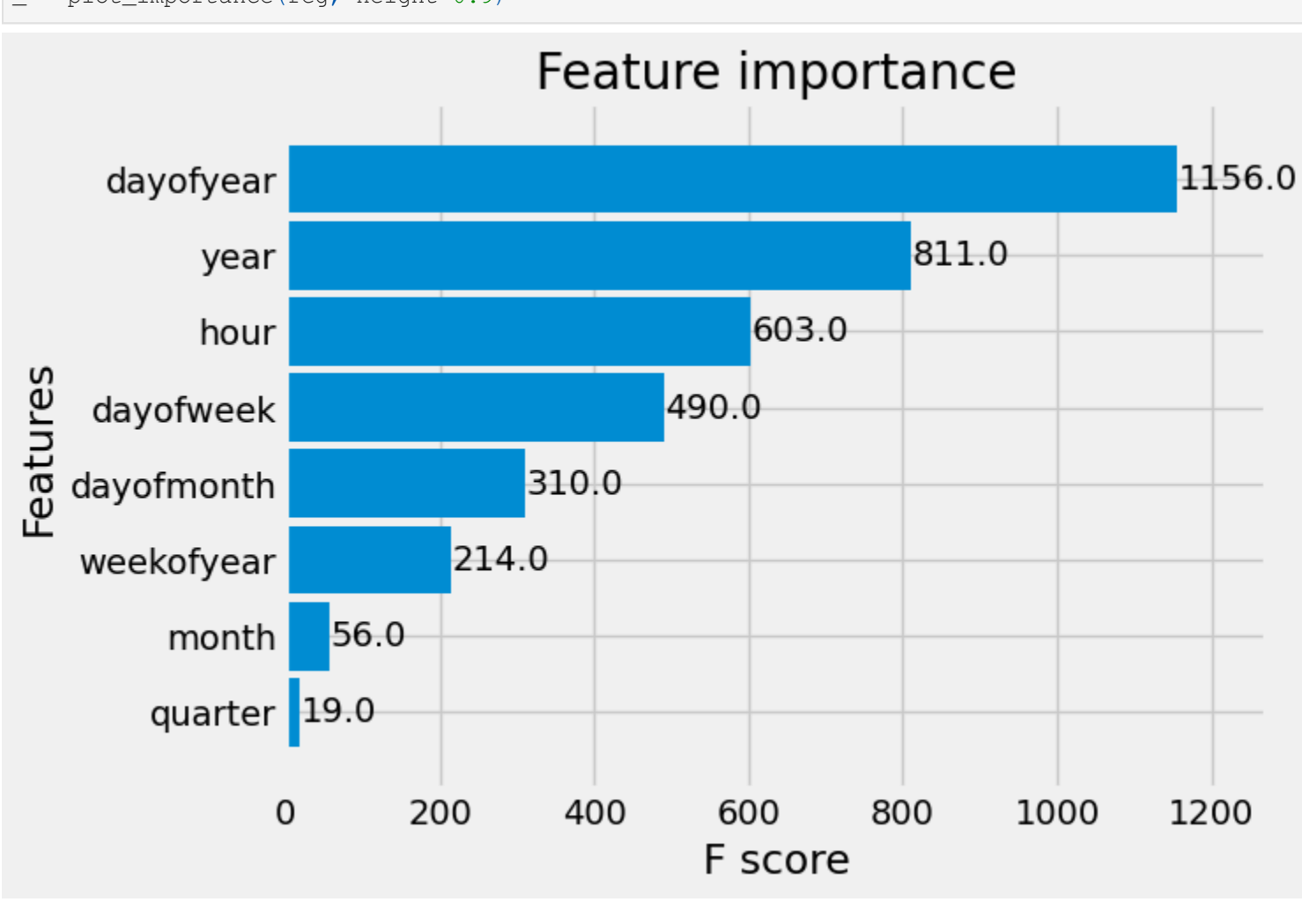


Feature Importances

Feature importance is a great way to get a general idea about which features the model is relying on most to make the prediction. This is a metric that simply sums up how many times each feature is split on.

We can see that the day of year was most commonly used to split trees, while hour and year came in next. Quarter has low importance due to the fact that it could be created by different dayofyear splits.

```
In [ ]:
_ = plot_importance(reg, height=0.9)
```

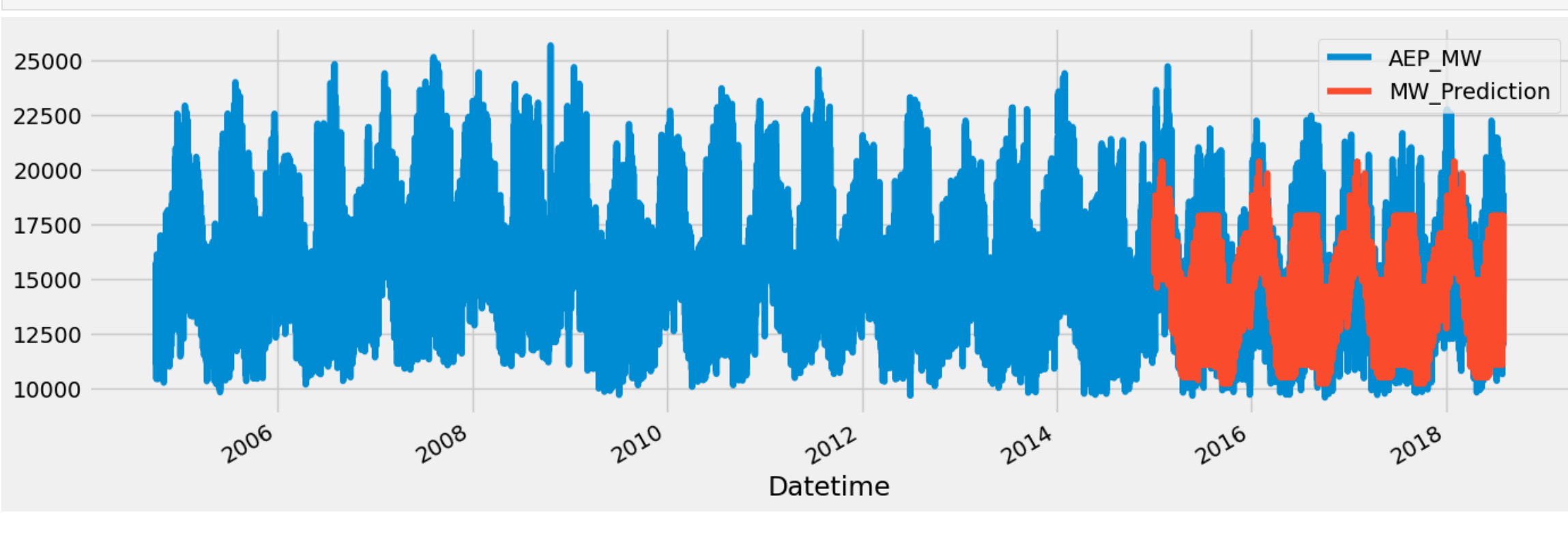


Forecast on Test Set

```
In [ ]:
pjme_test['MW_Prediction'] = reg.predict(X_test, ntree_limit=reg.best_ntree_limit)
pjme_all = pd.concat([pjme_test, pjme_train], sort=False)
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:122: UserWarning: ntree_limit is deprecated, use `iteration_range` or model slicing instea
d.
  warnings.warn(
```

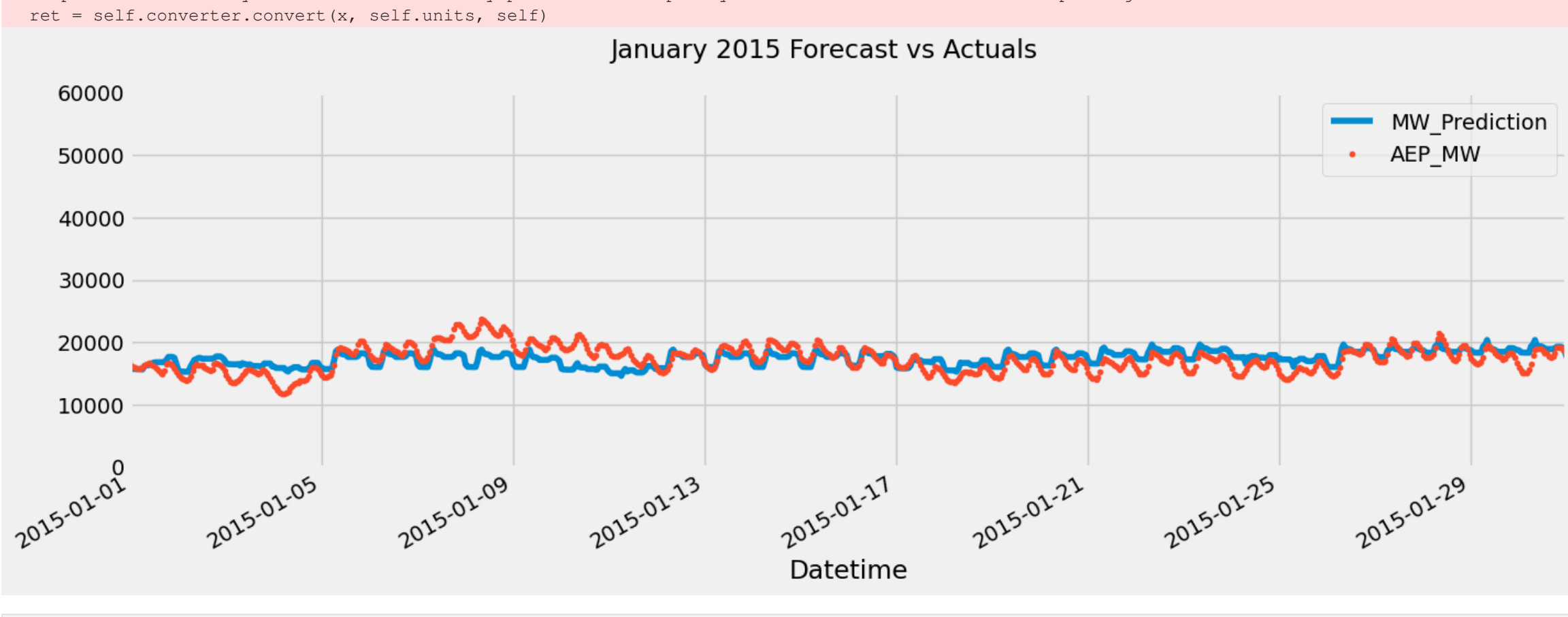
```
In [ ]:
_ = pjme_all[['AEP_MW','MW_Prediction']].plot(figsize=(15, 5))
```



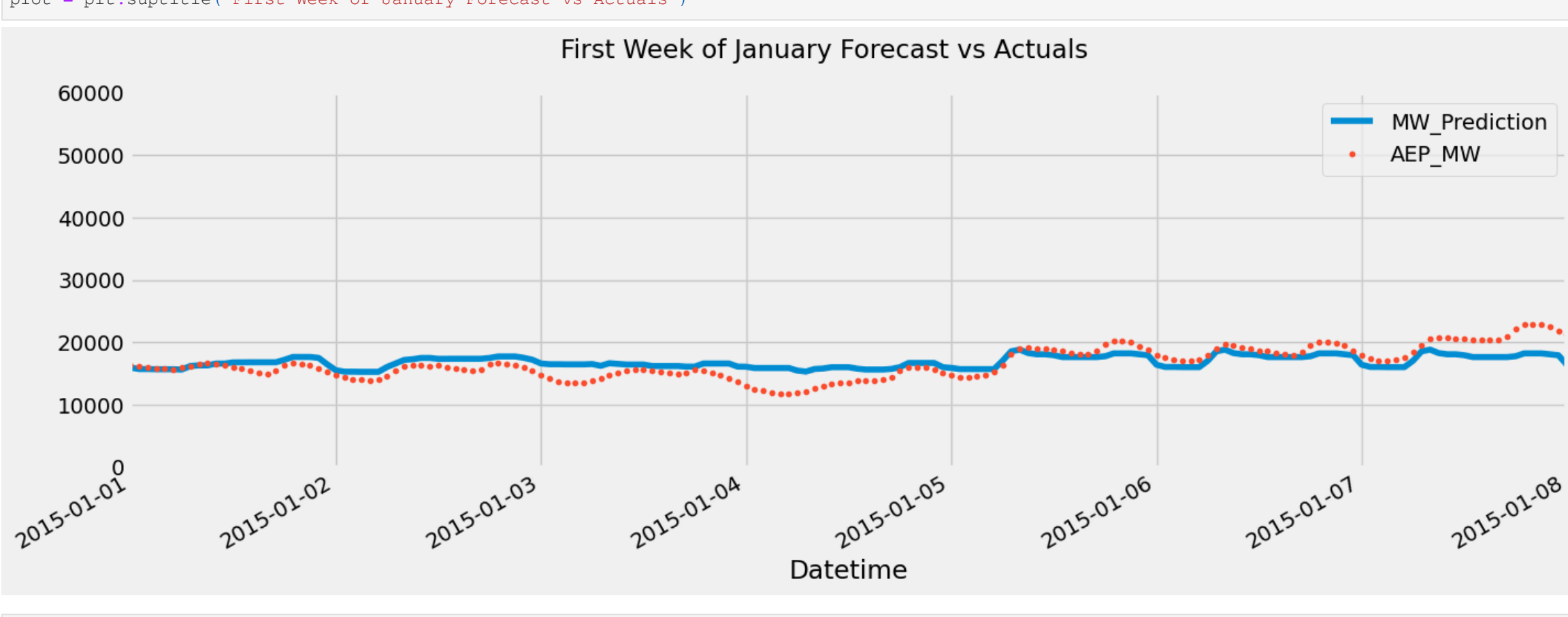
Look at first month of predictions

```
In [76]:
# Plot the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_xbound(lower='01-01-2015', upper='31-01-2015')
ax.set_ylim(0, 60000)
plot = plt.suptitle('January 2015 Forecast vs Actuals')
```

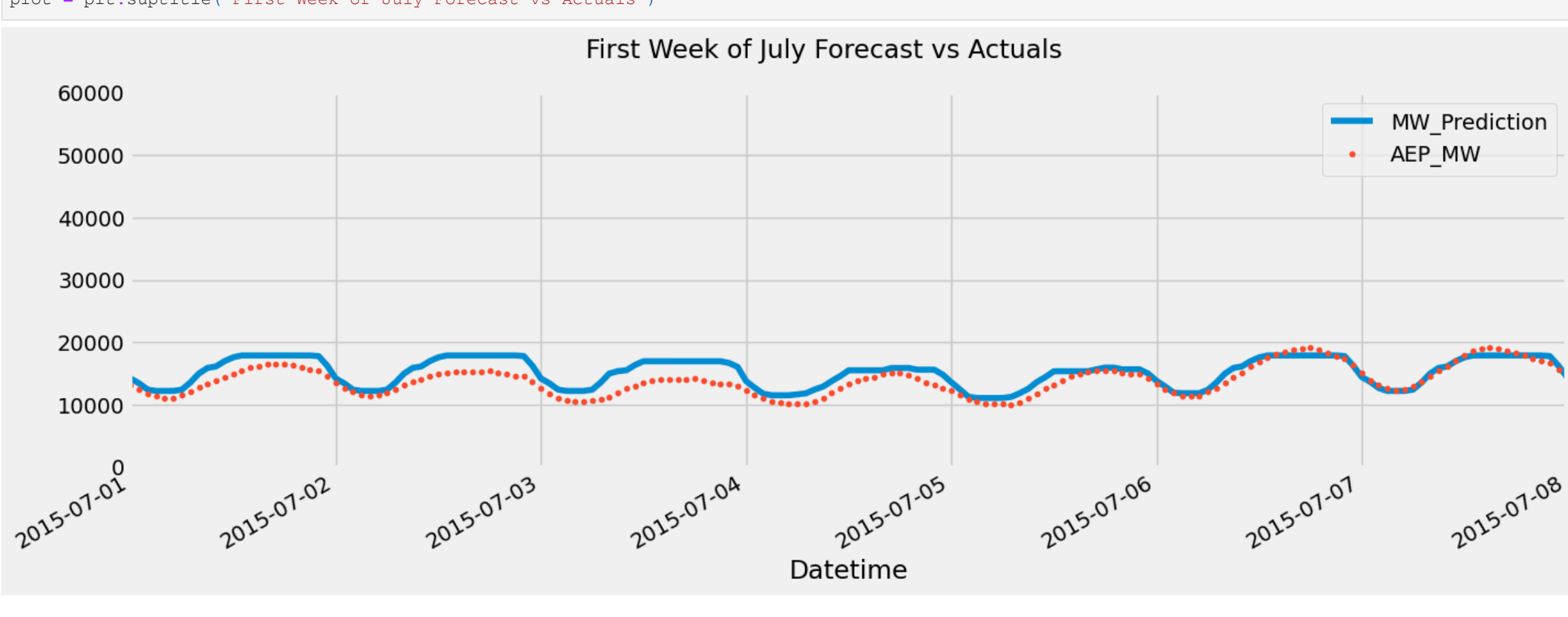
```
/usr/local/lib/python3.10/dist-packages/matplotlib/axis.py:1732: UserWarning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the default)
was specified. This may lead to inconsistently parsed dates! Specify a format to ensure consistent parsing.
  ret = self.converter.convert(x, self.units, self)
```




```
In [77]:
# Plot the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_xbound(lower='01-01-2015', upper='01-08-2015')
ax.set_ylim(0, 60000)
plot = plt.suptitle('First Week of January Forecast vs Actuals')
```




```
In [ ]:
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_ylim(0, 60000)
ax.set_xbound(lower='07-01-2015', upper='07-08-2015')
plot = plt.suptitle('First Week of July Forecast vs Actuals')
```



Error Metrics On Test Set

Our RMSE error is 2603992.46

Our MAE error is 1237.15

Our MAPE error is 8.26%

```
In [ ]:
mean_squared_error(y_true=pjme_test['AEP_MW'],
                   y_pred=pjme_test['MW_Prediction'])
```

```
Out[ ]:
2603992.4608340324
```

```
In [ ]:
mean_absolute_error(y_true=pjme_test['AEP_MW'],
                   y_pred=pjme_test['MW_Prediction'])
```

```
Out[ ]:
1237.1565526908894
```

I like using Mean Absolute Percent Error (MAPE) because it gives an easy to interperate percentage showing how off the predictions are. MAPE isn't included in sklearn so we need to use a custom function.

```
In [ ]:
def mean_absolute_percentage_error(y_true, y_pred):
    """Calculates MAPE given y_true and 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
```

```
In [ ]:
mean_absolute_percentage_error(y_true=pjme_test['AEP_MW'],
                   y_pred=pjme_test['MW_Prediction'])
```

```
Out[ ]:
8.269100832237395
```

Look at Worst and Best Predicted Days

```
In [ ]:
pjme_test['error'] = pjme_test['AEP_MW'] - pjme_test['MW_Prediction']
pjme_test['abs_error'] = pjme_test['error'].apply(np.abs)
error_by_day = pjme_test.groupby(['year','month','dayofmonth']) \
    .mean()[['AEP_MW','MW_Prediction','error','abs_error']]
```

```
<ipython-input-48-f4426ad61062>:4: FutureWarning: The default value of numeric_only in DataFrameGroupBy.mean is deprecated. In a future version, nu
meric_only will default to False. Either specify numeric_only or select only columns which should be valid for the function.
  .mean()[['AEP_MW','MW_Prediction','error','abs_error']]
```

```
In [ ]:
# Over forecasted days
error_by_day.sort_values('error', ascending=True).head(10)
```

Out[ ]:

year	month	dayofmonth	AEP_MW	MW_Prediction	error	abs_error
2017	1	22	12295.541667	16617.755859	-4322.213257	4322.213257
		21	12891.375000	16998.253906	-4106.878784	4106.878784
	2	23	13437.333333	17466.605469	-4029.272257	4029.272257
	1	23	14428.125000	18355.708984	-3927.583822	3927.583822
	2	24	13111.625000	17028.085938	-3916.460327	3916.460327
		22	13582.750000	17466.605469	-3883.855591	3883.855591
2018	1	22	14509.750000	18355.708984	-3845.958822	3845.958822
2015	12	25	11078.041667	14744.450195	-3666.408691	3666.408691
2017	1	25	14862.458333	18526.291016	-3663.832194	3663.832194
2016	7	4	12048.000000	15698.813477	-3650.813599	3650.813599

Notice anything about the over forecasted days?

- #1 worst day - July 4th, 2016 - is a holiday.
- #3 worst day - December 25, 2015 - Christmas
- #5 worst day - July 4th, 2016 - is a holiday.
  Looks like our model may benefit from adding a holiday indicator.

```
In [ ]:
# Worst absolute predicted days
error_by_day.sort_values('abs_error', ascending=False).head(10)
```

Out[ ]:

year	month	dayofmonth	AEP_MW	MW_Prediction	error	abs_error
2015	2	20	22047.041667	16497.130859	5549.910360	5549.910360
		19	22249.500000	16980.845703	5268.654704	5268.654704
2018	1	6	20847.833333	15838.145508	5009.687012	5009.687012
		7	19803.375000	15392.000977	4411.373657	4411.373657
2015	1	8	21873.333333	17498.212891	4375.120117	4375.120117
2017	1	22	12295.541667	16617.755859	-4322.213257	4322.213257
	12	28	19396.291667	15211.729492	4184.562541	4184.562541
2015	2	16	21129.791667	16985.570312	4144.221720	4144.221720
2017	1	21	12891.375000	16998.253906	-4106.878784	4106.878784
2018	1	2	20938.500000	16851.175781	4087.323649	4087.323649

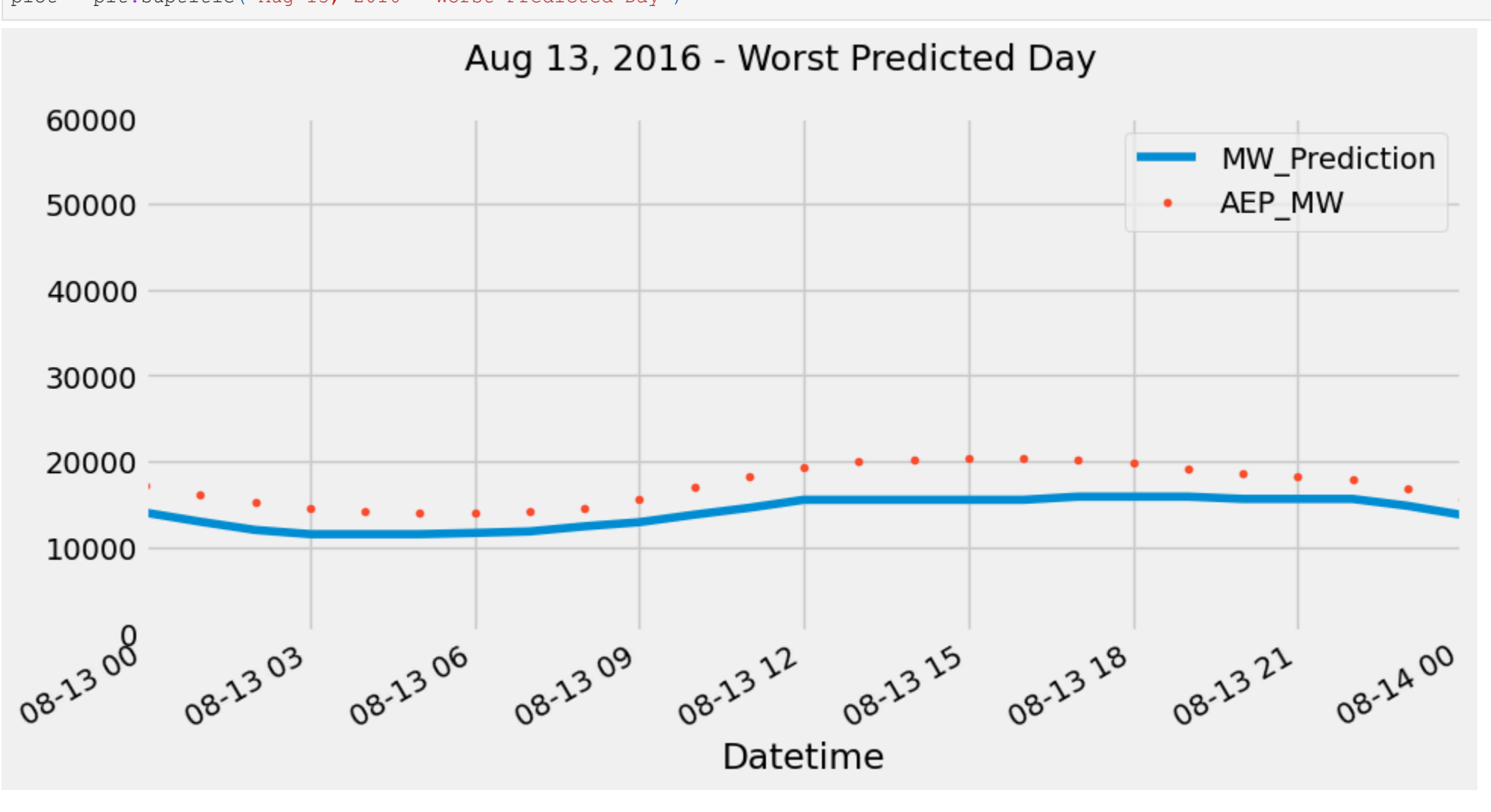
```
In [ ]:
# Best predicted days
error_by_day.sort_values('abs_error', ascending=True).head(10)
```

Out[ ]:

year	month	dayofmonth	AEP_MW	MW_Prediction	error	abs_error
2017	11	8	14602.750000	14602.944336	-0.194499	203.348145
	10	28	12723.833333	12744.442383	-20.609945	214.556559
2018	6	23	14103.291667	14031.847656	71.444499	257.030436
	4	28	12237.583333	12252.049805	-14.466715	259.215576
2015	9	30	13556.583333	13707.753906	-151.170573	264.743652
2017	4	1	12569.208333	12430.795898	138.413249	267.858317
	11	16	14938.958333	14918.472656	20.485596	279.215413
2016	12	12	15836.333333	15871.379883	-35.046468	283.550537
	3	5	14801.166667	14795.766602	5.399740	290.247559
	12	2	15458.250000	15604.367188	-146.117350	291.865316

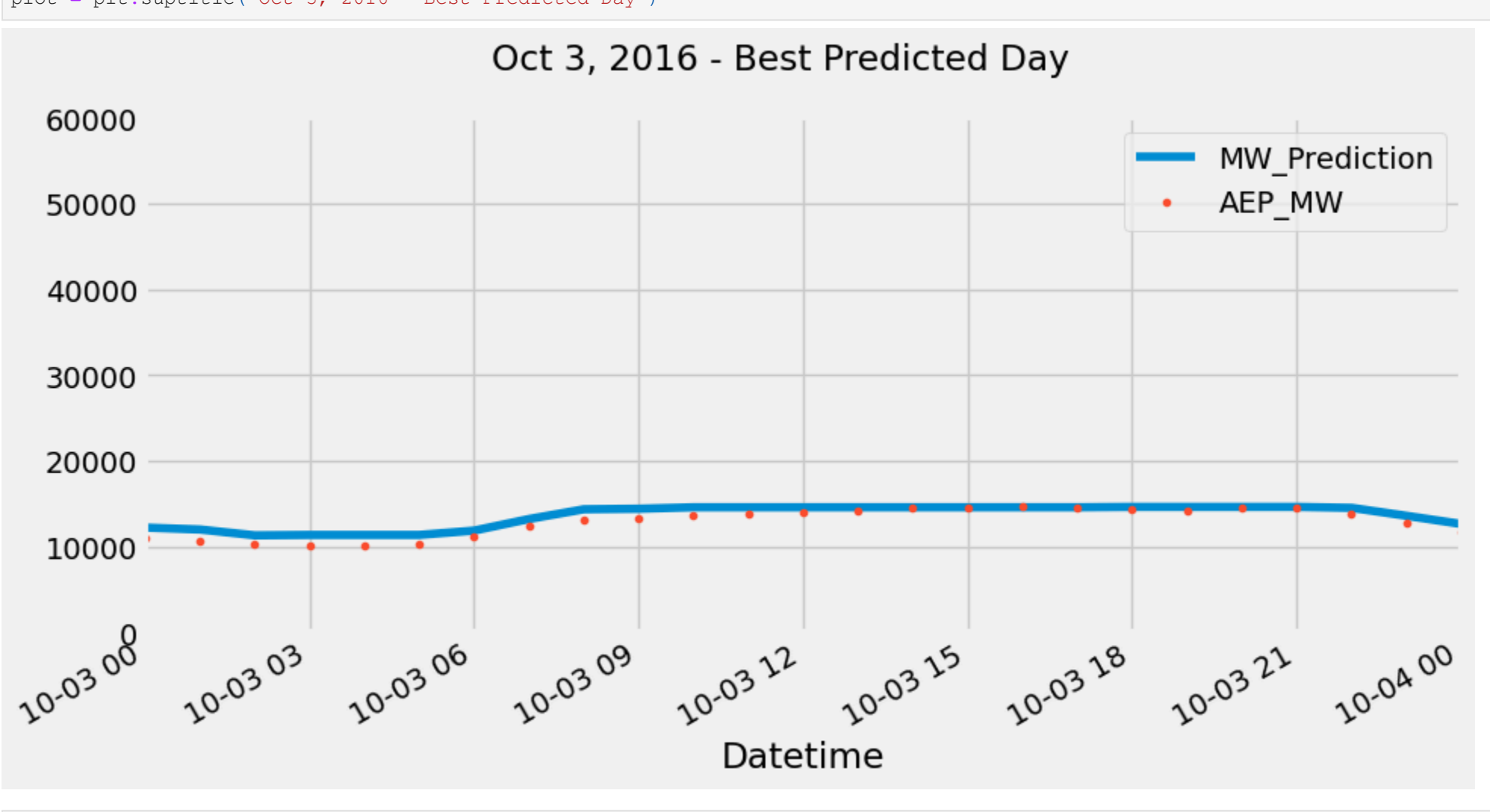
Plotting some best/worst predicted days

```
In [ ]:
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_ylim(0, 60000)
ax.set_xbound(lower='08-13-2016', upper='08-14-2016')
plot = plt.suptitle('Aug 13, 2016 - Worst Predicted Day')
```

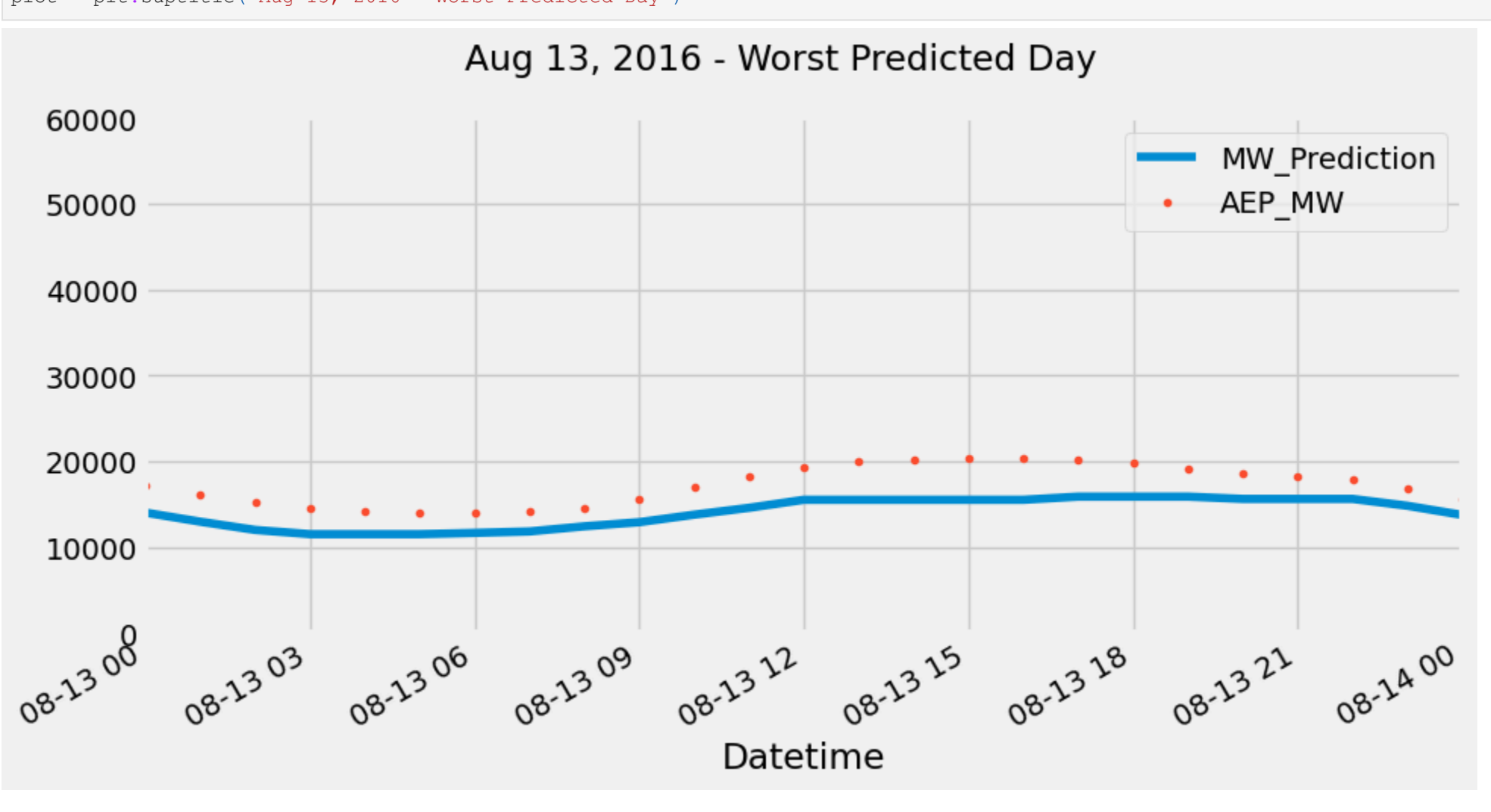


This one is pretty impressive. SPOT ON!

```
In [ ]:
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_ylim(0, 60000)
ax.set_xbound(lower='10-03-2016', upper='10-04-2016')
plot = plt.suptitle('Oct 3, 2016 - Best Predicted Day')
```




```
In [ ]:
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ = pjme_all[['MW_Prediction','AEP_MW']].plot(ax=ax,
                                              style=['-','.'])
ax.set_ylim(0, 60000)
ax.set_xbound(lower='08-13-2016', upper='08-14-2016')
plot = plt.suptitle('Aug 13, 2016 - Worst Predicted Day')
```



Up next?

- Add Lag variables
- Add holiday indicators.
- Add weather data source.

To Understand the difference between Traditional vs ML Approach for Time Series Forecasing

Another Case Study