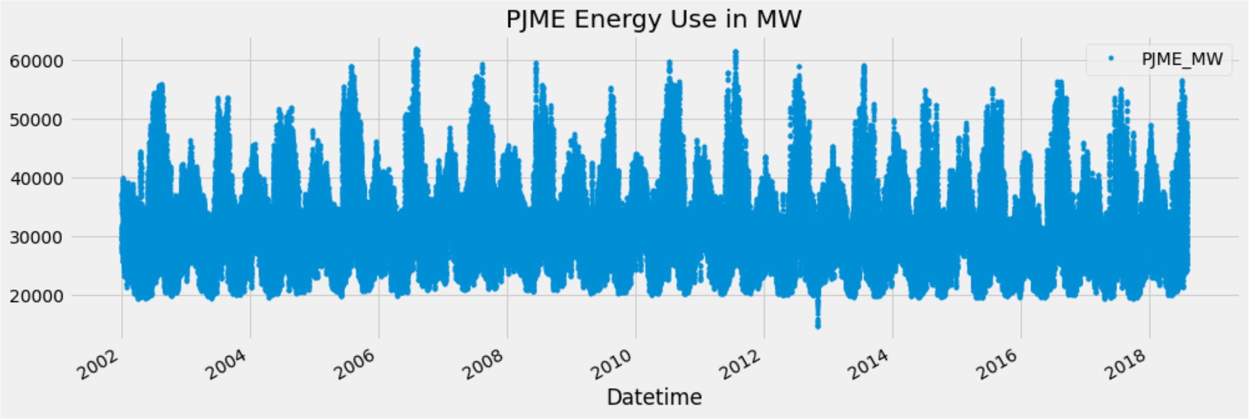
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import xgboost as xgb
from sklearn.metrics import mean_squared_error
color_pal = sns.color_palette()
plt.style.use('fivethirtyeight')
```

Types of Time Series Data

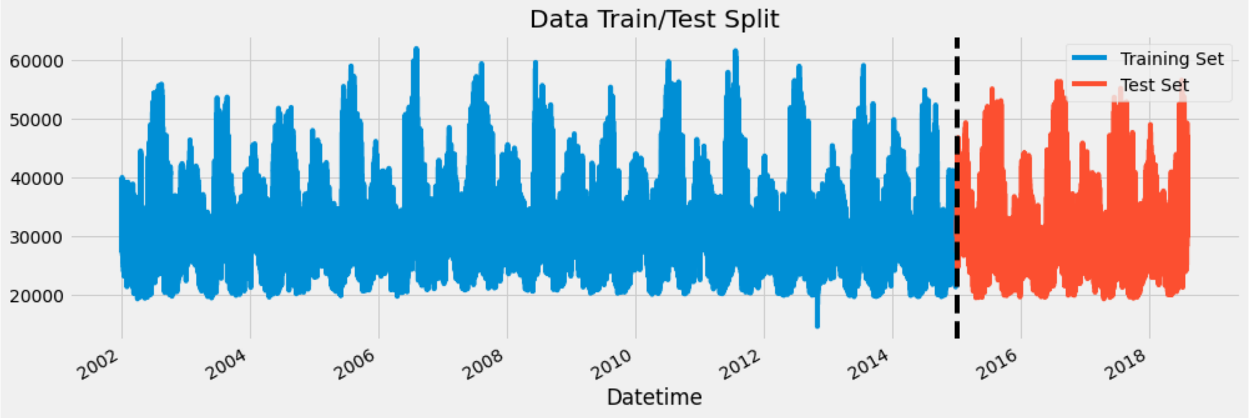
reference: https://engineering.99x.io/time-series-forecasting-in-machine-learning-3972f7a7a467

```python
df = pd.read_csv('../input/hourly-energy-consumption/PJME_hourly.csv')
df = df.set_index('Datetime')
df.index = pd.to_datetime(df.index)

df.plot(style='.',
        figsize=(15, 5),
        color=color_pal[0],
        title='PJME Energy Use in MW')
plt.show()
```

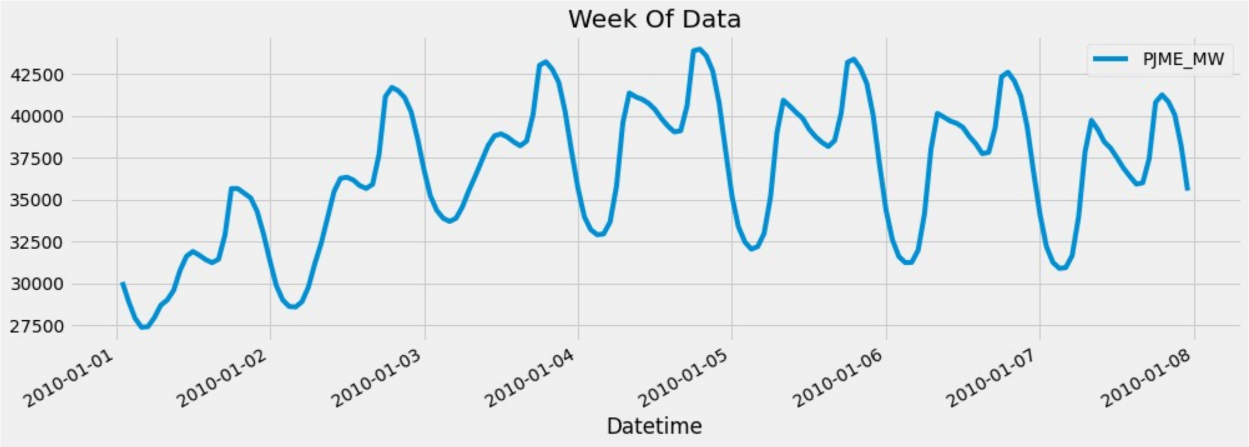


Train / Test Split

```
train = df.loc[df.index < '01-01-2015']
test = df.loc[df.index >= '01-01-2015']

fig, ax = plt.subplots(figsize=(15, 5))
train.plot(ax=ax, label='Training Set', title='Data Train/Test Split')
test.plot(ax=ax, label='Test Set')
ax.axvline('01-01-2015', color='black', ls='--')
ax.legend(['Training Set', 'Test Set'])
plt.show()
```



```
df.loc[(df.index > '01-01-2010') & (df.index < '01-08-2010')] \
    .plot(figsize=(15, 5), title='Week Of Data')
plt.show()
```

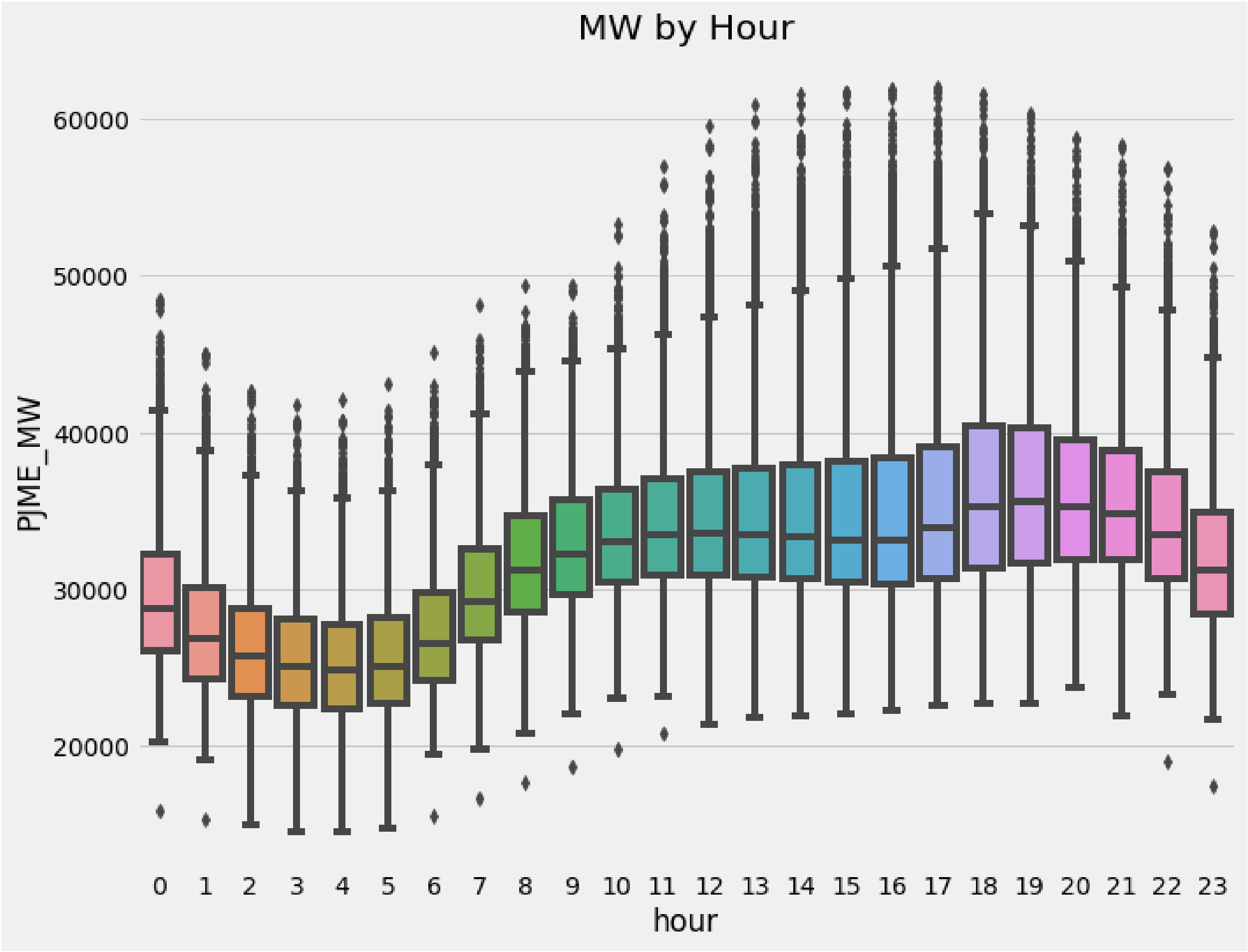


Feature Creation

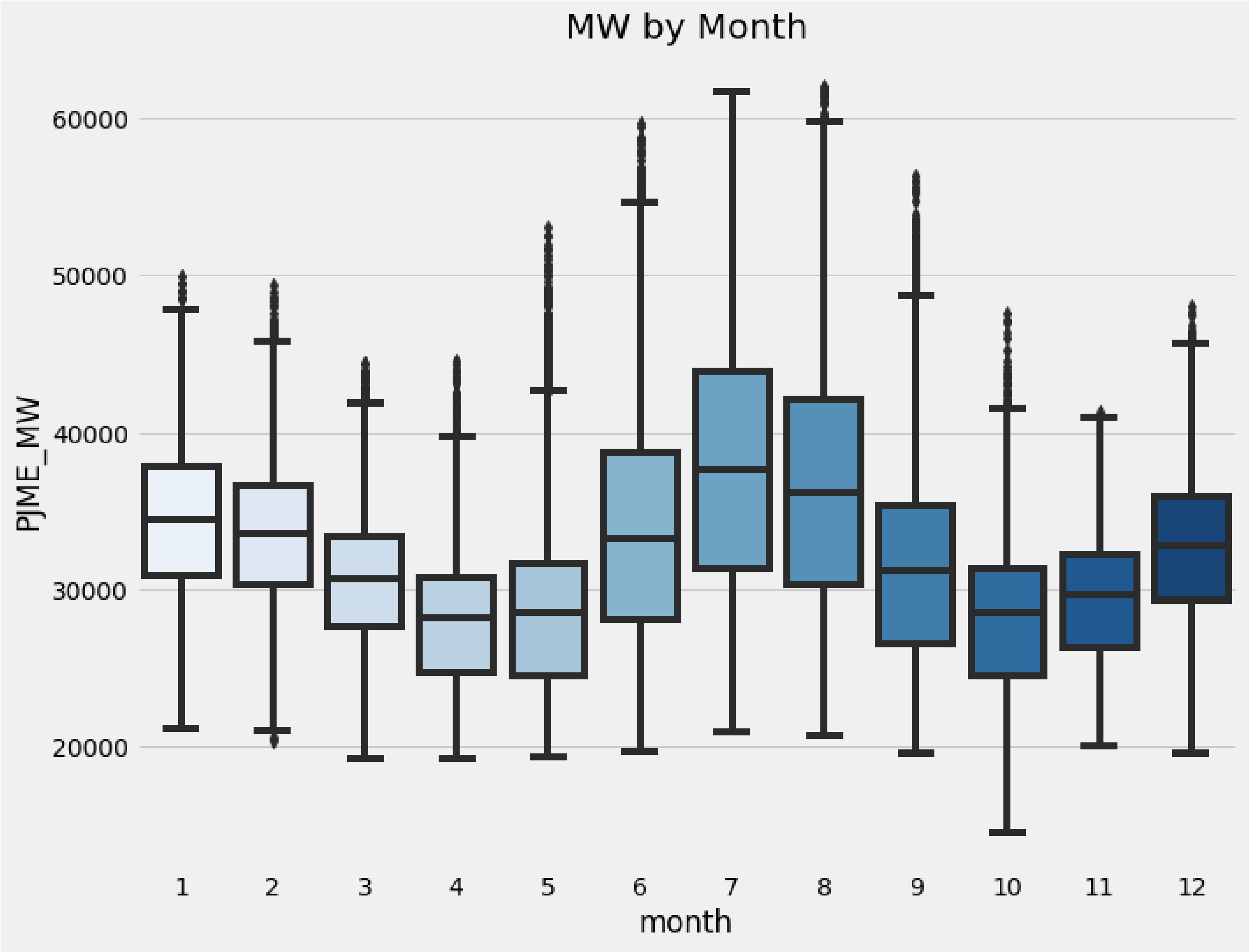
```
def create_features(df):
    """
    Create time series features based on time series index.
    """
    df = df.copy()
    df['hour'] = df.index.hour
    df['dayofweek'] = df.index.dayofweek
    df['quarter'] = df.index.quarter
    df['month'] = df.index.month
    df['year'] = df.index.year
    df['dayofyear'] = df.index.dayofyear
    df['dayofmonth'] = df.index.day
    df['weekofyear'] = df.index.isocalendar().week
    return df

df = create_features(df)
```

Visualize our Feature / Target Relationship

```
fig, ax = plt.subplots(figsize=(10, 8))
sns.boxplot(data=df, x='hour', y='PJME_MW')
ax.set_title('MW by Hour')
plt.show()
```



```
fig, ax = plt.subplots(figsize=(10, 8))
sns.boxplot(data=df, x='month', y='PJME_MW', palette='Blues')
ax.set_title('MW by Month')
plt.show()
```



Create our Model

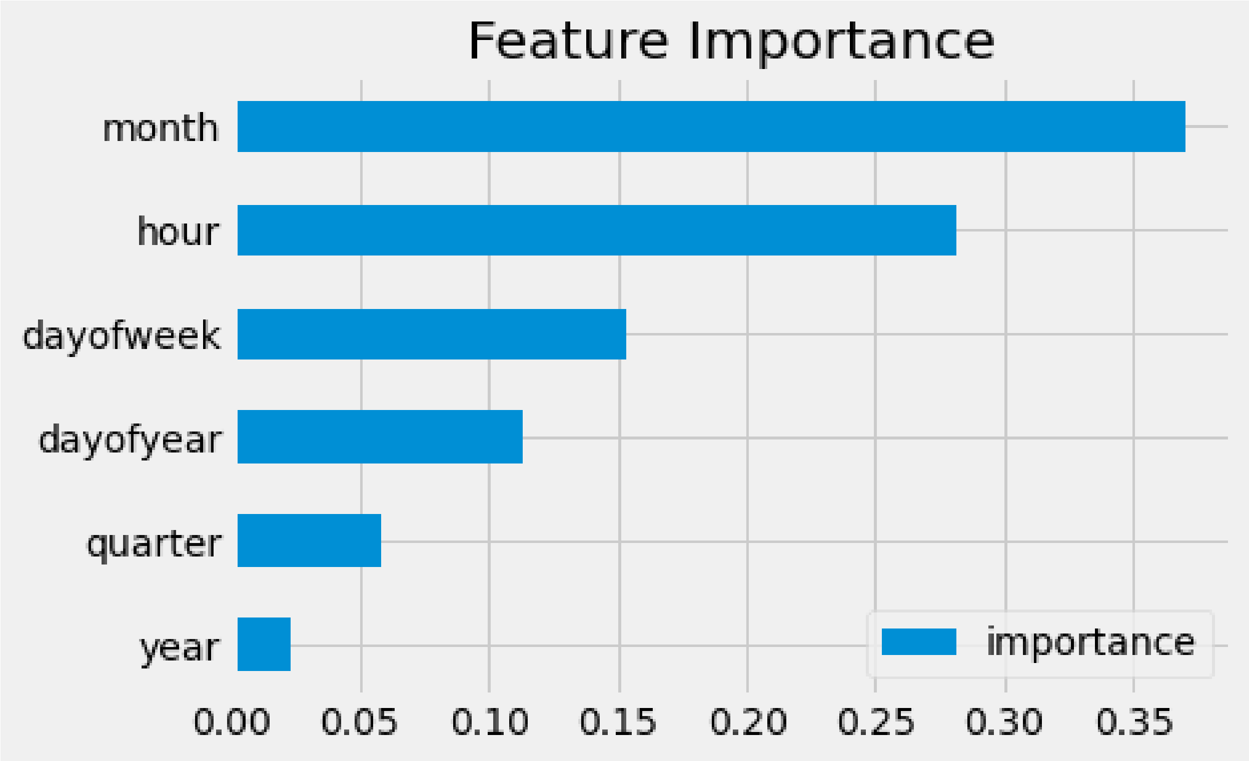
```
train = create_features(train)
test = create_features(test)

FEATURES = ['dayofyear', 'hour', 'dayofweek', 'quarter', 'month',
'year']
TARGET = 'PJME_MW'

X_train = train[FEATURES]
y_train = train[TARGET]

X_test = test[FEATURES]
y_test = test[TARGET]

reg = xgb.XGBRegressor(base_score=0.5, booster='gbtree',
                       n_estimators=1000,
                       early_stopping_rounds=50,
                       objective='reg:linear',
                       max_depth=3,
                       learning_rate=0.01)
reg.fit(X_train, y_train,
        eval_set=[(X_train, y_train), (X_test, y_test)],
        verbose=100)
```

```
[17:12:26] WARNING: ../src/objective/regression_obj.cu:203: reg:linear
is now deprecated in favor of reg:squarederror.
[0]	validation_0-rmse:32605.13860	validation_1-rmse:31657.15907
[100]	validation_0-rmse:12581.21576	validation_1-rmse:11743.75117
[200]	validation_0-rmse:5835.12473	validation_1-rmse:5365.67712
[300]	validation_0-rmse:3915.75572	validation_1-rmse:4020.67027
[400]	validation_0-rmse:3443.16487	validation_1-rmse:3853.40425
[500]	validation_0-rmse:3285.33827	validation_1-rmse:3805.30193
[600]	validation_0-rmse:3201.92939	validation_1-rmse:3772.44905
[700]	validation_0-rmse:3148.14225	validation_1-rmse:3750.91088
[800]	validation_0-rmse:3109.24250	validation_1-rmse:3733.89694
[900]	validation_0-rmse:3079.40078	validation_1-rmse:3725.61208
[999]	validation_0-rmse:3052.73502	validation_1-rmse:3722.92243
```

```
XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1,
colsample_bytree=1,
             early_stopping_rounds=50, enable_categorical=False,
             eval_metric=None, gamma=0, gpu_id=-1,
grow_policy='depthwise',
             importance_type=None, interaction_constraints='',
             learning_rate=0.01, max_bin=256, max_cat_to_onehot=4,
             max_delta_step=0, max_depth=3, max_leaves=0,
min_child_weight=1,
             missing=nan, monotone_constraints='()',
n_estimators=1000,
             n_jobs=0, num_parallel_tree=1, objective='reg:linear',
             predictor='auto', random_state=0, reg_alpha=0, ...)
```

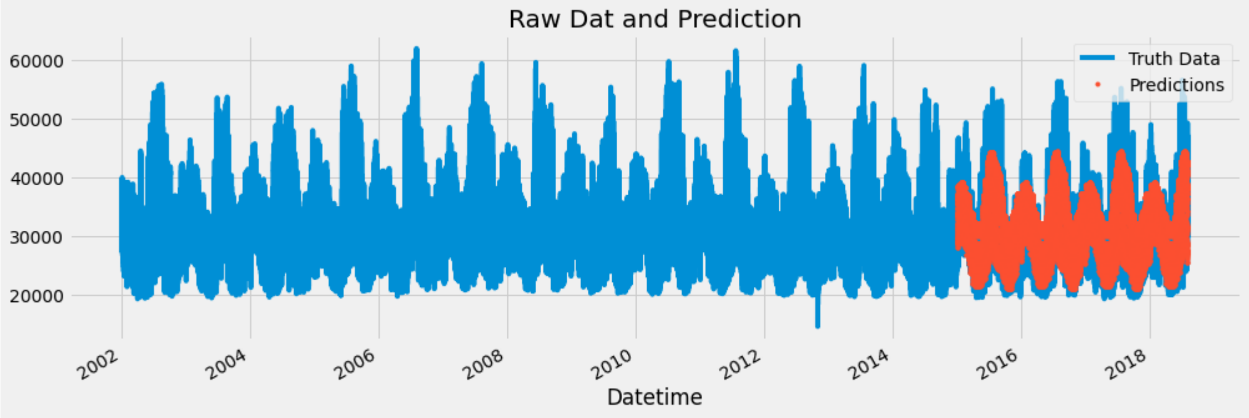
Feature Importance

```
fi = pd.DataFrame(data=reg.feature_importances_,
             index=reg.feature_names_in_,
             columns=['importance'])
fi.sort_values('importance').plot(kind='barh', title='Feature
Importance')
plt.show()
```

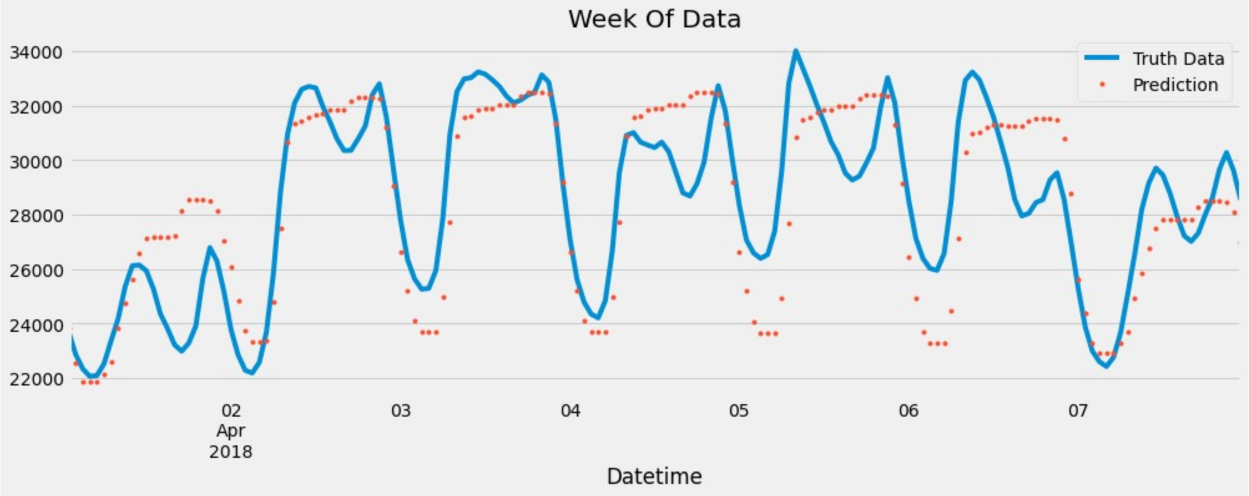


Forecast on Test

```
test['prediction'] = reg.predict(X_test)
df = df.merge(test[['prediction']], how='left', left_index=True,
right_index=True)
ax = df[['PJME_MW']].plot(figsize=(15, 5))
df['prediction'].plot(ax=ax, style='.')
plt.legend(['Truth Data', 'Predictions'])
ax.set_title('Raw Dat and Prediction')
plt.show()
```



```
ax = df.loc[(df.index > '04-01-2018') & (df.index < '04-08-2018')]
['PJME_MW'] \
    .plot(figsize=(15, 5), title='Week Of Data')
df.loc[(df.index > '04-01-2018') & (df.index < '04-08-2018')]
['prediction'] \
    .plot(style='.')
plt.legend(['Truth Data','Prediction'])
plt.show()
```



Score (RMSE)

```
score = np.sqrt(mean_squared_error(test['PJME_MW'],
test['prediction']))
print(f'RMSE Score on Test set: {score:0.2f}')

RMSE Score on Test set: 3721.75
```

Calculate Error

- Look at the worst and best predicted days

```
test['error'] = np.abs(test[TARGET] - test['prediction'])
test['date'] = test.index.date
test.groupby(['date'])
['error'].mean().sort_values(ascending=False).head(10)

date
2016-08-13    12839.595459
2016-08-14    12780.209554
2016-09-10    11356.302002
2015-02-20    10965.976237
2016-09-09    10864.953451
```

```
2018-01-06    10506.844889
2016-08-12    10124.050618
2015-02-21     9881.798503
2015-02-16     9781.549805
2018-01-07     9739.143555
Name: error, dtype: float64
```