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IBM COLLABARATE

ARTIFICIAL INTELLIGENCE

PROJECT TITLE

MEASURE ENERGY CONSUMPTION

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COLLEGE : PARK COLLEGE OF ENGINEERING AND TECHNOLOGY

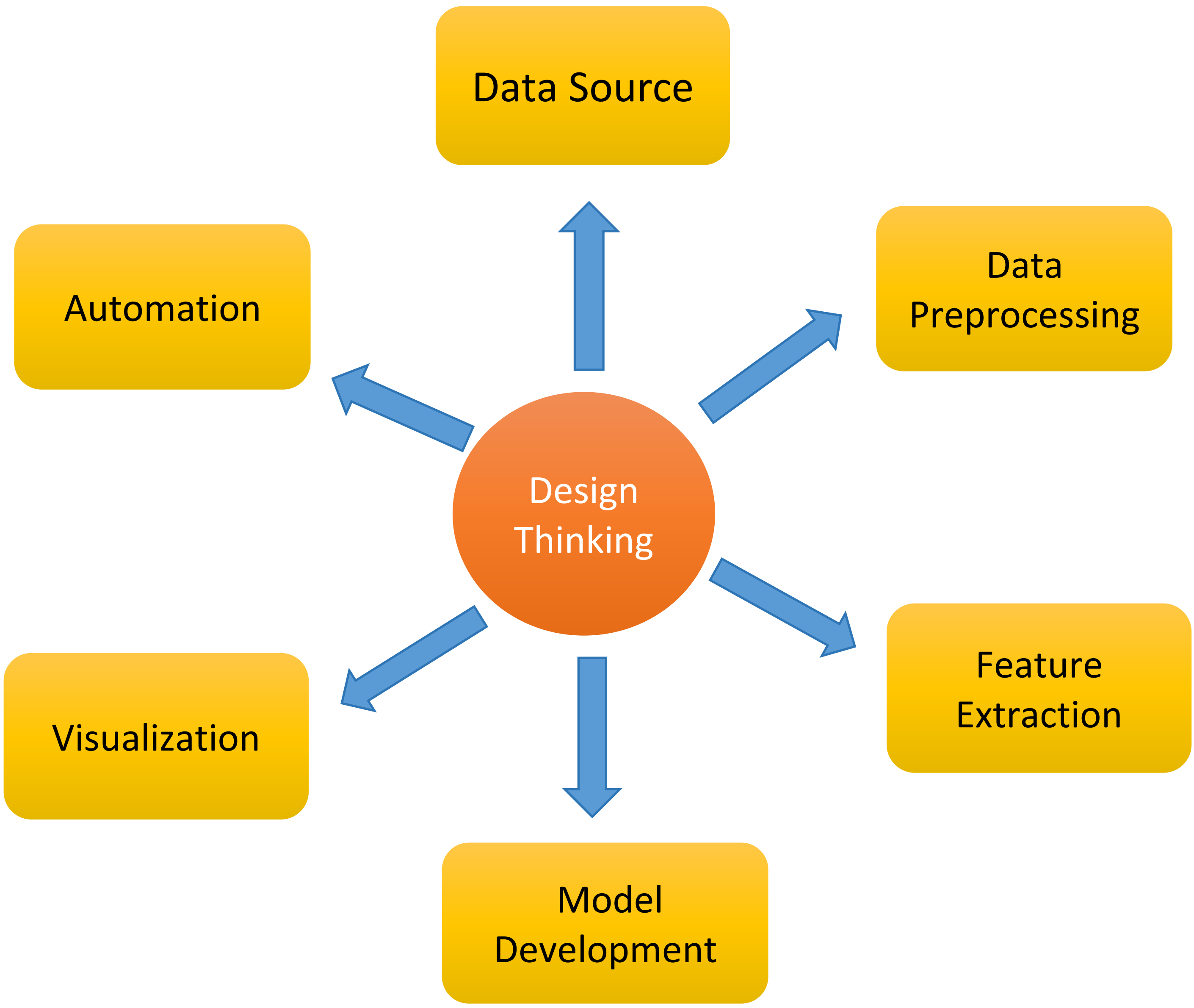
PHASE 1

PROBLEM DEFINITION AND DESIGN THINKING

PROBLEM DEFINITION

The problem at hand is to create an automated system that measures energy consumption,analysis the data,and provides visualizations for informed decision making.This solution aims to enhance efficiency,accuracy,and ease of understanding in managing energy consumption across various sectors.

DESIGN THINKING



PHASE 2

PROJECT INNOVATION IDEA

Steps :

1. Data Collection
2. Data Preprocessing
3. Build Machine Learning Model
4. Create Real Time Monitoring System
5. Build User Engagement
6. Data Analytics And Data Visualization
7. Deployment the Project

PHASE 3

DATA ANALYSIS AND PREPROCESSING

STEP 1:

Import library :

The first step is import the library files.
The library files are numpy for array calculation,pandas for data visualization,matplotlib for plotting,seaborn for statics graphics and also load the dataset using pandas.

STEP 2:

Reformat the Date Time Columns

Hence ,the large amout of dataset are reformated for required analysis and also include date time colums for time series process.

STEP 3:
Cleaning the dataset

The data cleaning process is must for analysis because the dataset have unordered ,anamoly and other soure data . Hence the data cleaning process is used to reduce this problem.

STEP 4 :

Transforming the data

The data are reformatted for best analysis .this reduce the analysis process in less time.

STEP 5:

Show the Energy Consumption Each Year

The main process of analysis are done this section.
The time series analysis is used to analyse energy consumption in each year.
Hence the analysis are shown by statistical plotting perspective.

STEP 6:

Data validation

The final process of data preprocessing is validate the data and show the data using plotting.

PHASE 4

BUILDING MODEL FOR ENERGY PREDICTION

- Hence,we are going to build our prediction model algorithm for measure energy consumption.

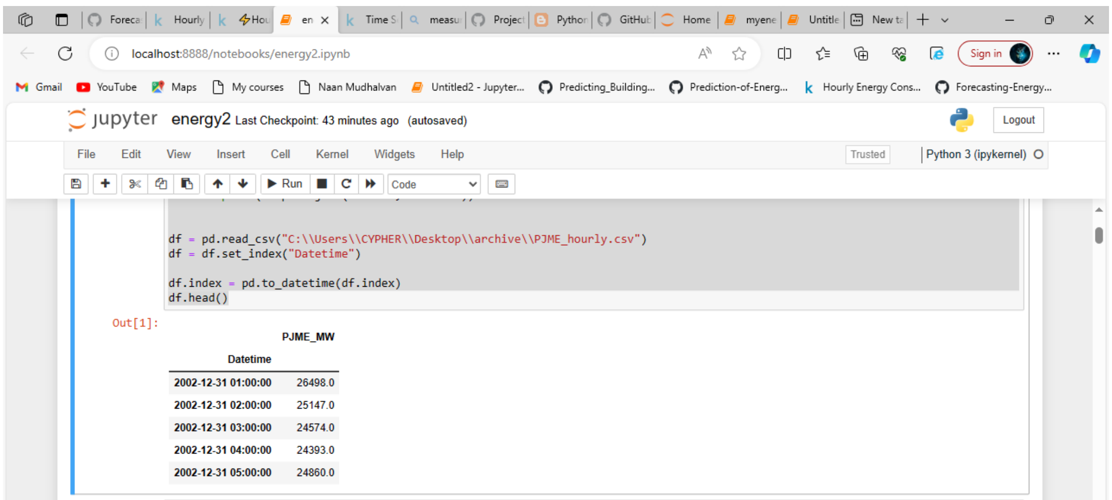
- It consist the process of loading the dataset,data transformation,feature importance,train/test split,Visualize feature to target relationship,modeling,Forecast on Test,Outlier Analysis,Reviewing : Train/Test Split,Feature Horizon,Lag Features,Train Using Cross Validation,Fold Analysis,Retraining on all Data and Predicting Future.

1.IMPORTING LIBRARIES AND DATA SET LOADING

CODE:

```
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 xg


from sklearn.metrics import mean_squared_error

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


df =
pd.read_csv("C:\\Users\\CYPHER\\Desktop\\archive\\PJME_hourly.csv")
df = df.set_index("Datetime")

df.index = pd.to_datetime(df.index)
df.head()
```

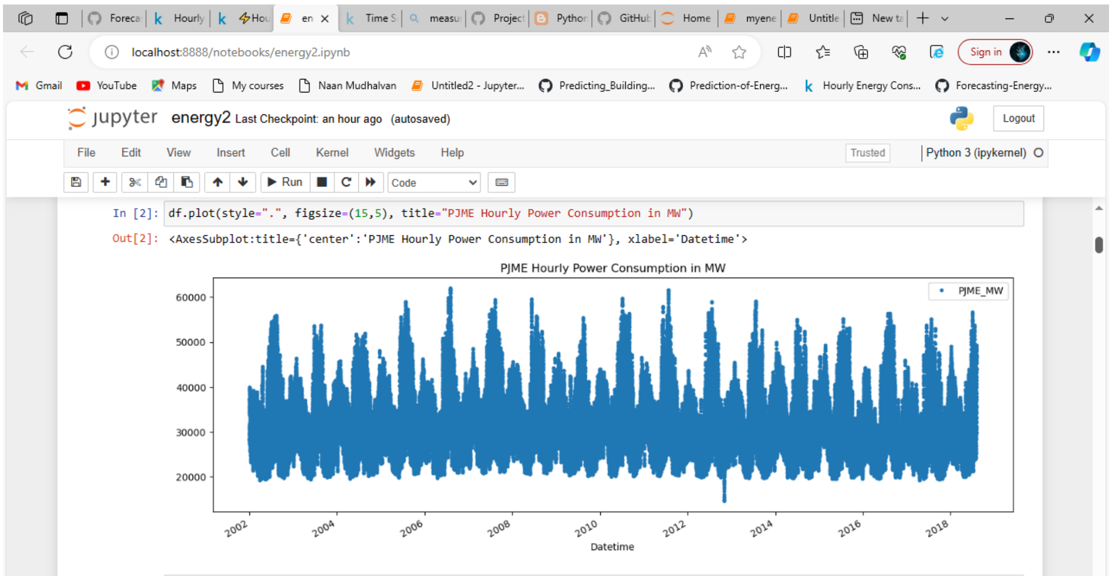
O/P:



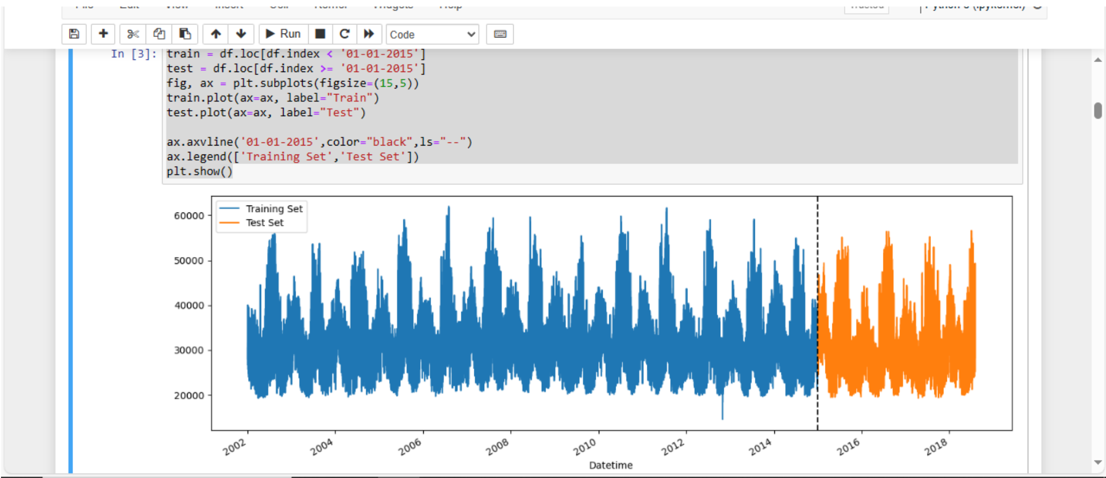
2.TRAIN TEST SPLIT

CODE :

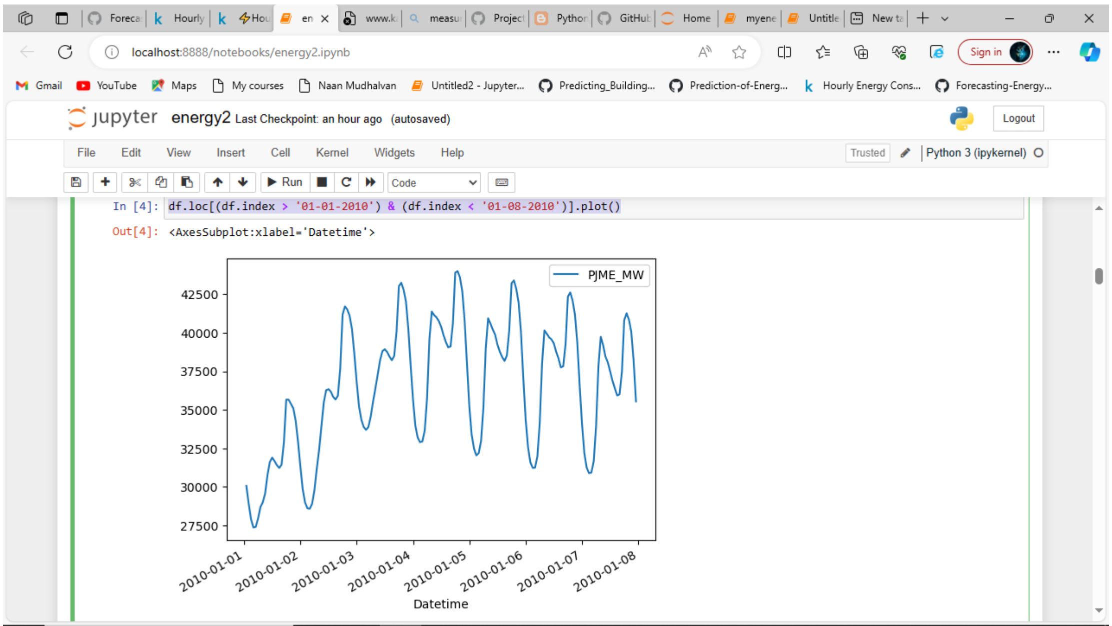
df.plot(style=".", figsize=(15,5), title="PJME Hourly Power Consumption in MW")




```
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="Train")
test.plot(ax=ax, label="Test")

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()
```



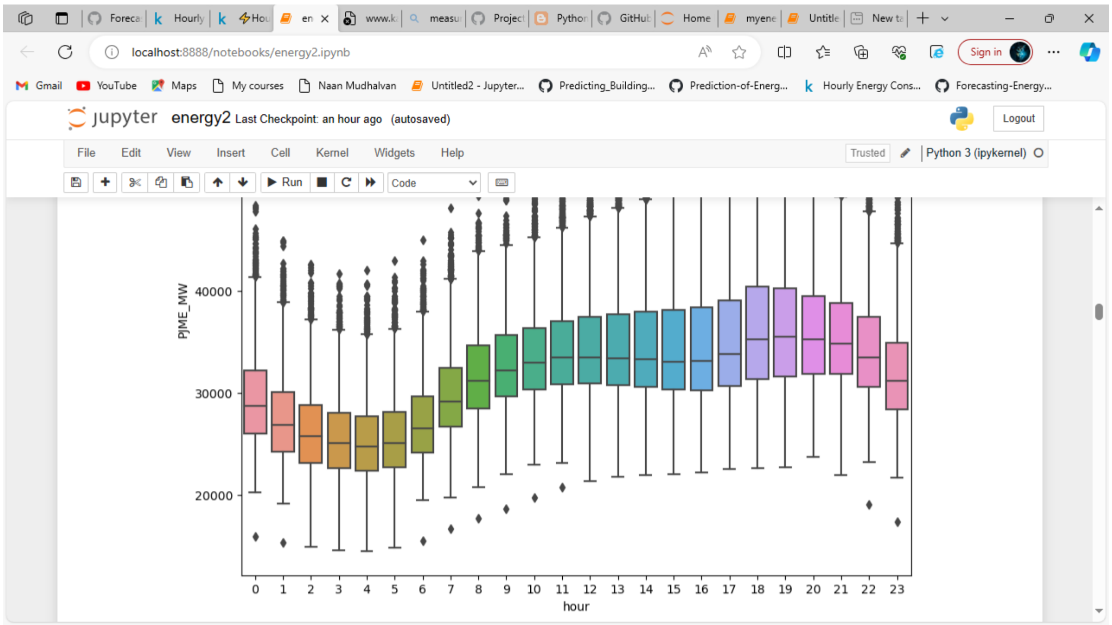
3. FEATURE CREATION

```
def create_time_series_features(dataframe):
    df = dataframe.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

   return df


df = create_time_series_features(df)
```

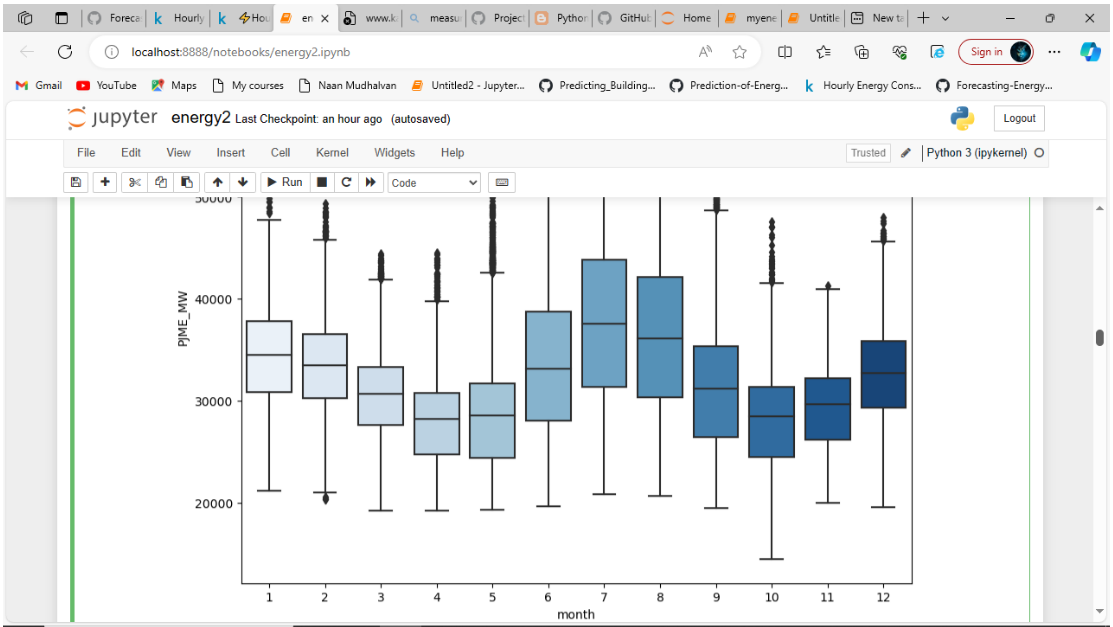
4. VISUALIZE FEATURE TO TARGET RELATIONSHIP

```
fig, ax = plt.subplots(figsize=(10,8))
sns.boxplot(data=df, x="hour",y="PJME_MW")
```

```
ax.set_title("MW By Hour")
plt.show()
```

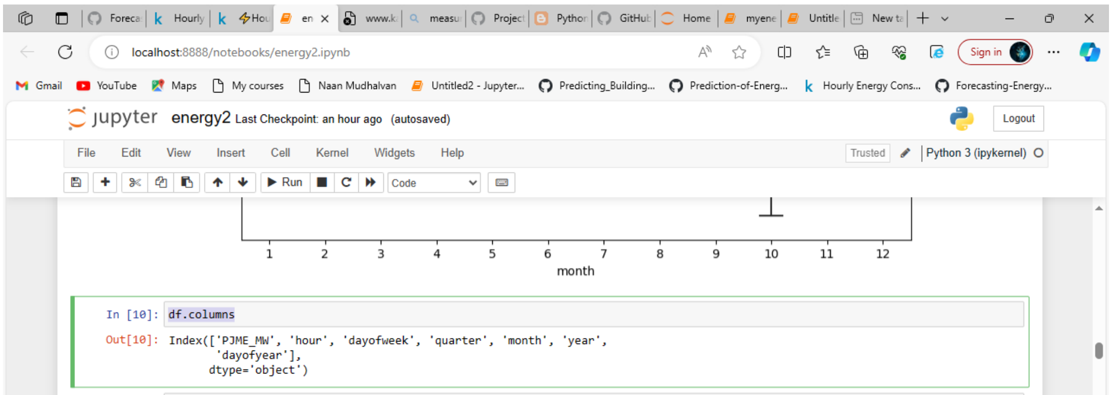



```
fig, ax = plt.subplots(figsize=(10,8))
sns.boxplot(data=df, x="month",y="PJME_MW",palette="Blues")
ax.set_title("MW By Month")
plt.show()
```

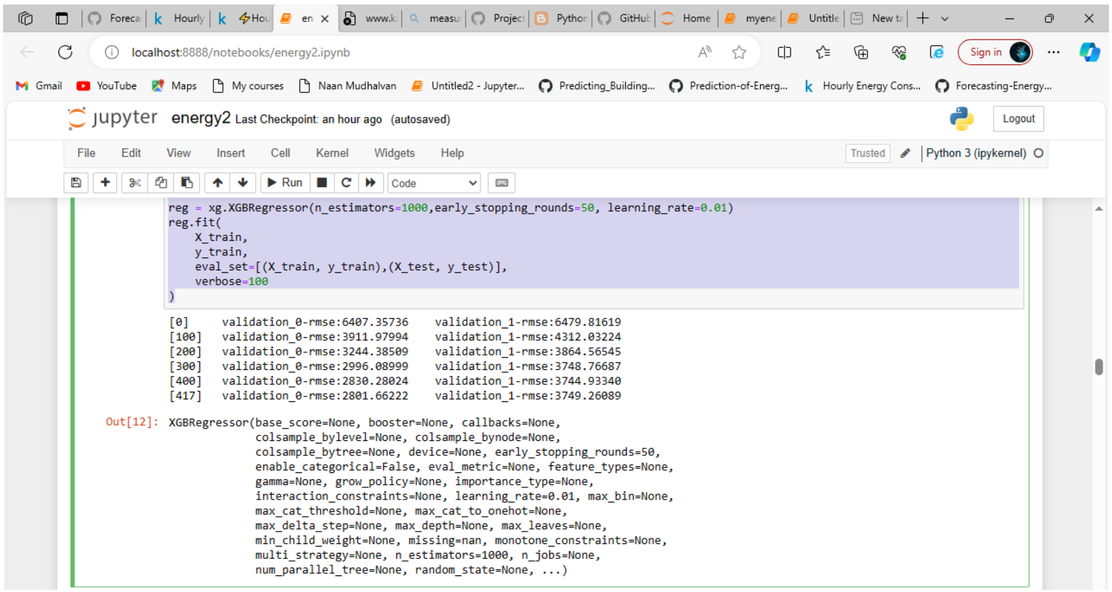


5. MODELING

df.columns

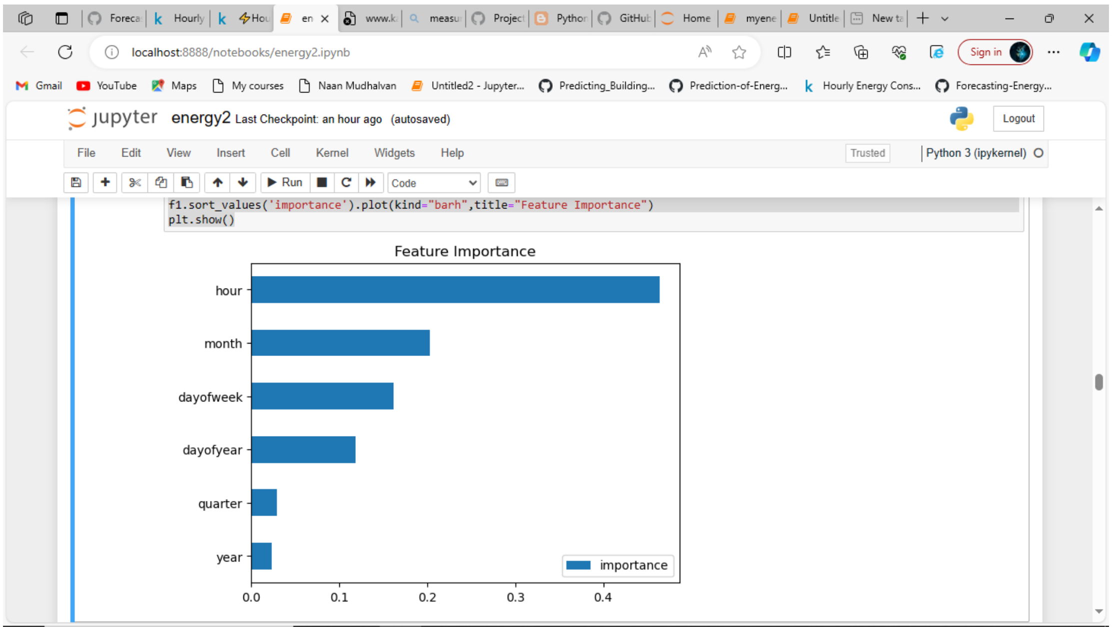



```
FEATURES = ['hour', 'dayofweek', 'quarter', 'month', 'year',
    'dayofyear']

OUTPUT = ['PJME_MW']

train = create_time_series_features(train)
test = create_time_series_features(test)
X_train = train[FEATURES]
y_train = train[OUTPUT]

X_test = test[FEATURES]
y_test = test[OUTPUT]


reg =
xg.XGBRegressor(n_estimators=1000,early_stopping_rounds=50, learning_rate=0.01)
reg.fit(
   X_train,
   y_train,
   eval_set=[(X_train, y_train),(X_test, y_test)],
   verbose=100
)
```



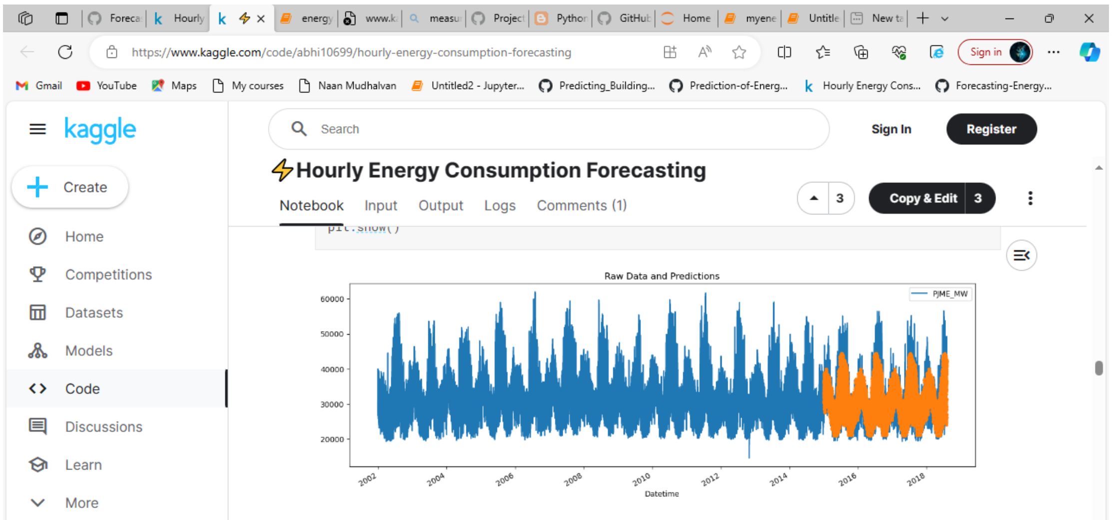
6.FEATURE IMPORTANCE

f1 = pd.DataFrame(data=reg.feature_importances_, index=reg.feature_names_in_, columns=['importance'])
f1.sort_values('importance').plot(kind="barh",title="Feature Importance")
plt.show()

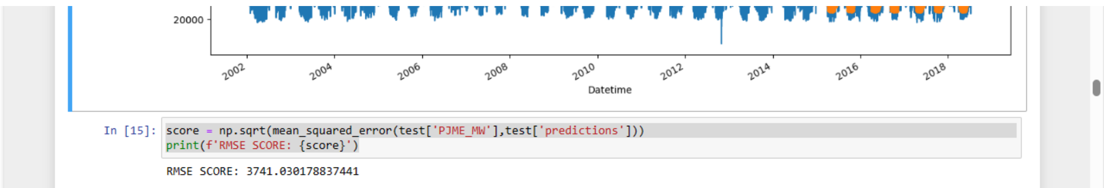


7.FEATURE FORECAST ON TEST

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

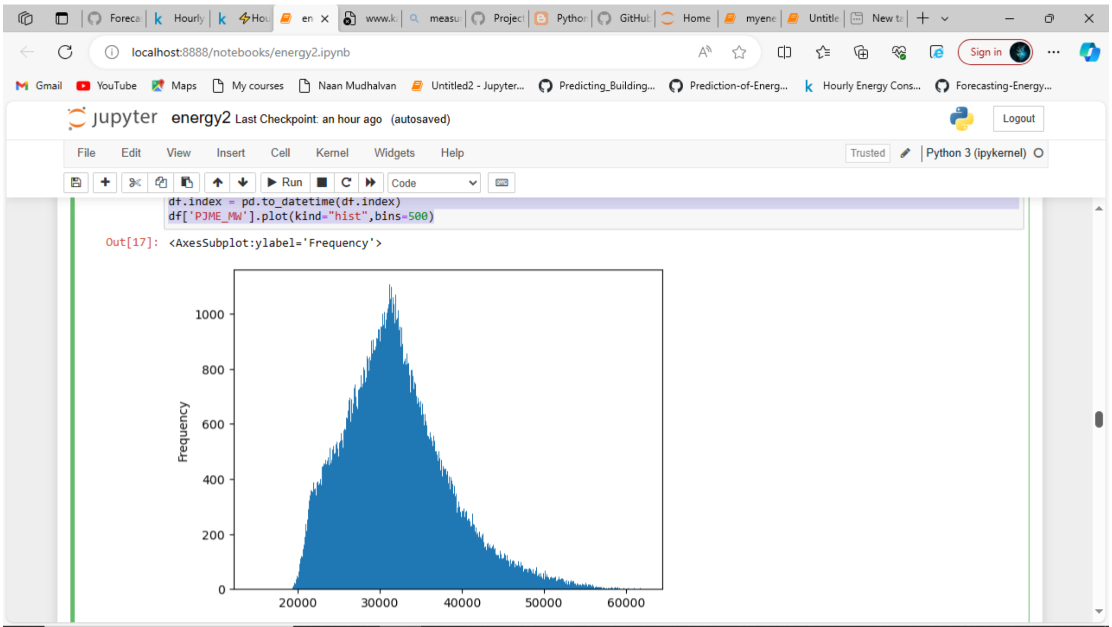


score = np.sqrt(mean_squared_error(test['PJME_MW'],test['predictions']))
print(f'RMSE SCORE: {score}')



8. OUTLIER ANALYSIS

```
df =
pd.read_csv("C:\\Users\\CYPHER\\Desktop\\archive\\PJME_hourly.csv")
df = df.set_index("Datetime")

df.index = pd.to_datetime(df.index)
df['PJME_MW'].plot(kind="hist",bins=500)
```

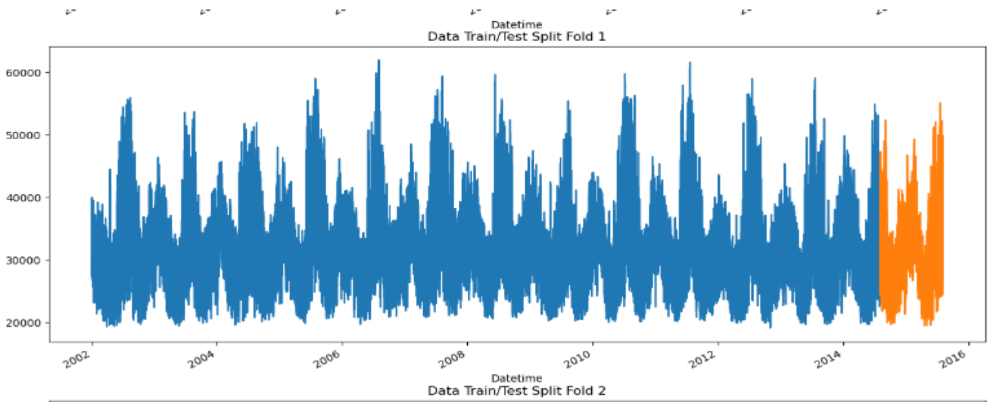


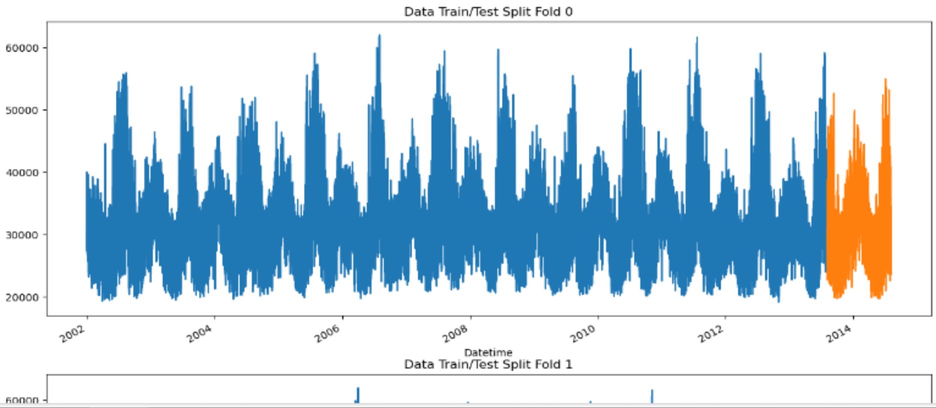

```
df = df.query('PJME_MW > 19_000').copy()
```

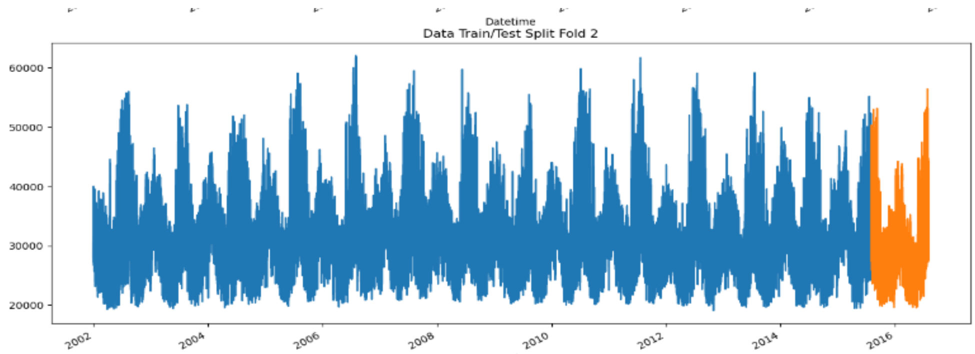
9. REVIEWING TRAIN AND TEST SPLIT

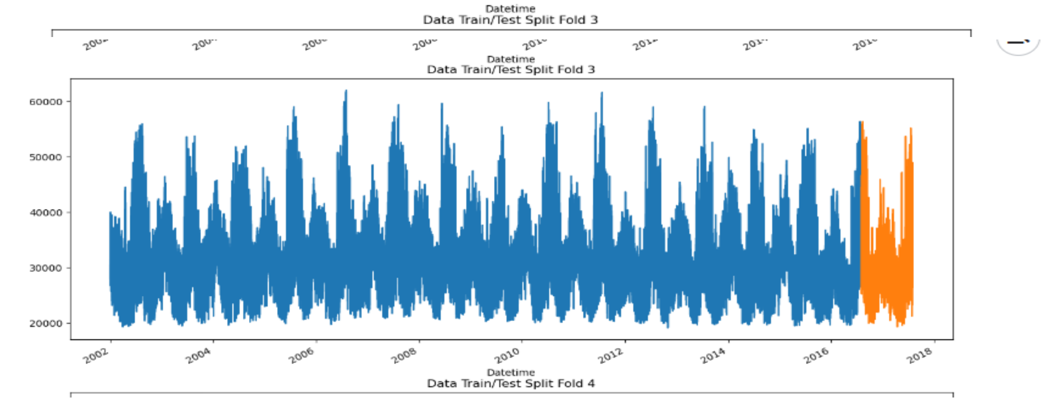
```
from sklearn.model_selection import TimeSeriesSplit
tss = TimeSeriesSplit(n_splits=5, test_size=24*365*1,gap=24)
df = df.sort_index()
fig, axs = plt.subplots(5,1,figsize=(15,35))

fold = 0
for train_idx, val_idx in tss.split(df):
```

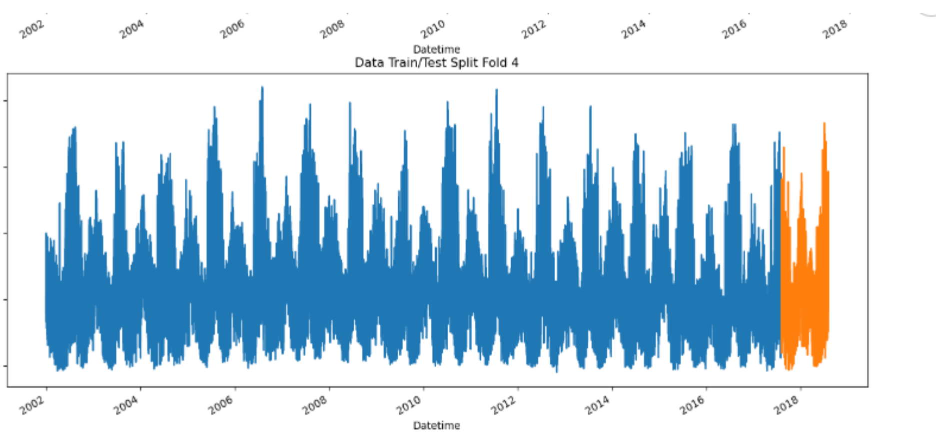
```
train = df.iloc[train_idx]
test = df.iloc[val_idx]

train['PJME_MW'].plot(
    ax=axs[fold],
    label="Training Set",
    title=f"Data Train/Test Split Fold {fold}"
)
test['PJME_MW'].plot(
    ax=axs[fold],
    label="Test Set",
)

fold += 1
```





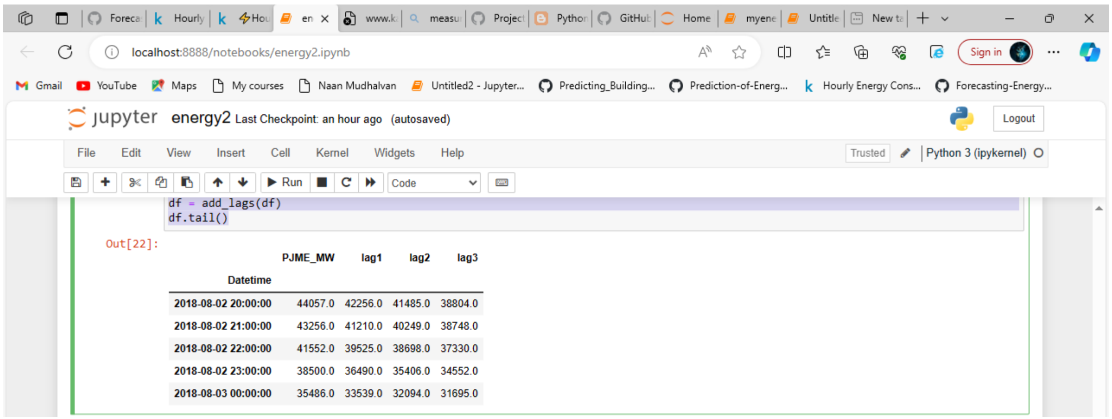

Datetime
Data Train/Test Split Fold 2
Datetime


Data Train/Test Split Fold 3
Datetime
Data Train/Test Split Fold 3
Datetime
Data Train/Test Split Fold 4


Datetime
Data Train/Test Split Fold 4
Datetime

10. FEATURE HORIZON AND LAG FEATURES

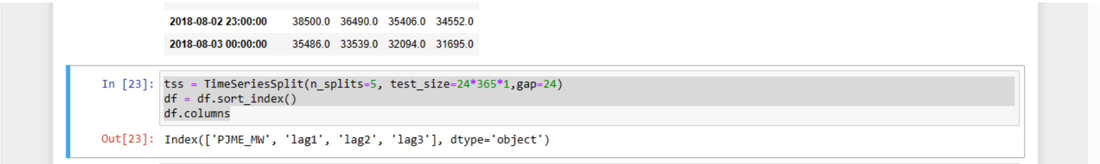
```
df = create_time_series_features(df)


target_map = df['PJME_MW'].to_dict()
def add_lags(dframe):
   df = dframe.copy()
   df['lag1'] = (df.index - pd.Timedelta('364
days')).map(target_map)
   df['lag2'] = (df.index - pd.Timedelta('728
days')).map(target_map)
   df['lag3'] = (df.index - pd.Timedelta('1092
days')).map(target_map)

   return df


df = add_lags(df)
df.tail()
```



Datetime	PJME_MW	lag1	lag2	lag3
2018-08-02 20:00:00	44057.0	42256.0	41485.0	38804.0
2018-08-02 21:00:00	43256.0	41210.0	40249.0	38748.0
2018-08-02 22:00:00	41552.0	39525.0	38698.0	37330.0
2018-08-02 23:00:00	38500.0	36490.0	35406.0	34552.0
2018-08-03 00:00:00	35486.0	33539.0	32094.0	31695.0

11. TRAIN USING CROSS VALIDATION

```
tss = TimeSeriesSplit(n_splits=5, test_size=24*365*1,gap=24)
df = df.sort_index()
df.columns
```

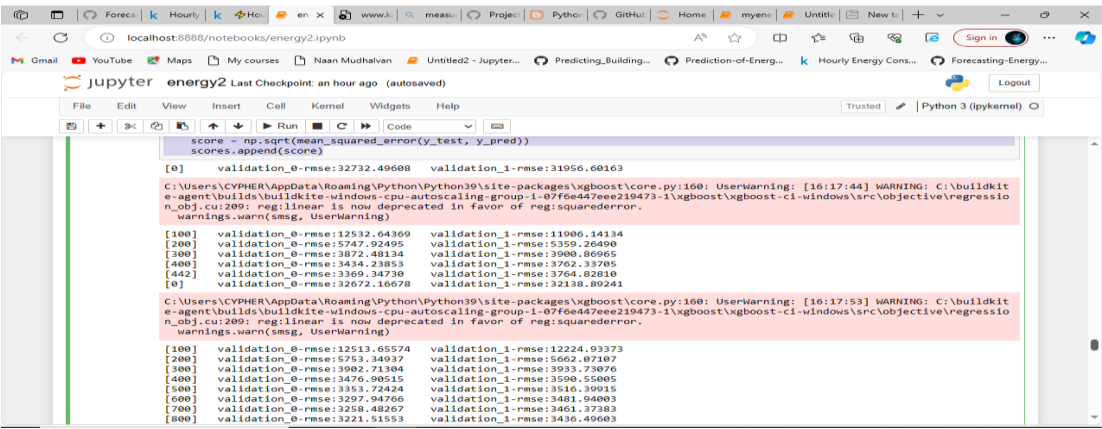


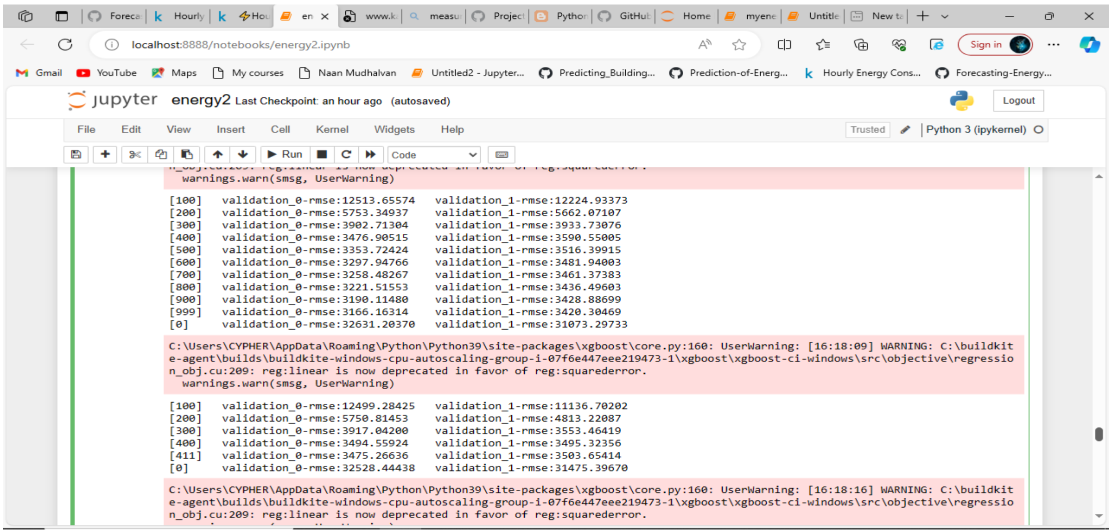
2018-08-02 23:00:00	38500.0	36490.0	35406.0	34552.0
2018-08-03 00:00:00	35486.0	33539.0	32094.0	31695.0

```
In [23]: tss = TimeSeriesSplit(n_splits=5, test_size=24*365*1,gap=24)
         df = df.sort_index()
         df.columns

Out[23]: Index(['PJME_MW', 'lag1', 'lag2', 'lag3'], dtype='object')
```

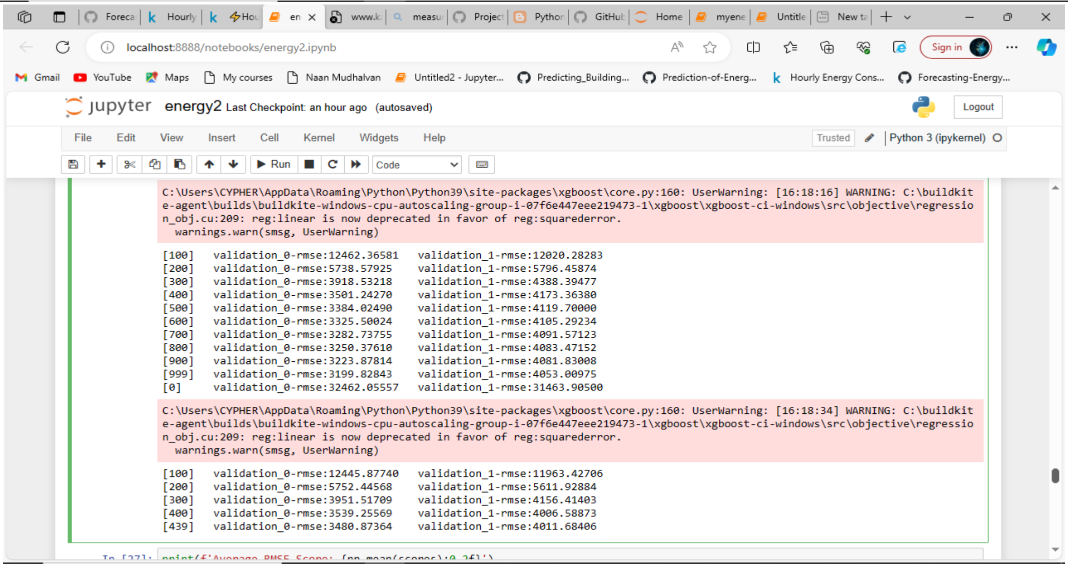
```
fold = 0
preds = []
scores = []

for train_idx, val_idx in tss.split(df):
    train = df.iloc[train_idx]
    test = df.iloc[val_idx]

    train = create_time_series_features(train)
    test = create_time_series_features(test)

    FEATURES = ['hour', 'dayofweek', 'quarter', 'month', 'year', 
'dayofyear',
       'lag1', 'lag2', 'lag3']

    OUTPUT = 'PJME_MW'

    OUTPUT = 'PJME_MW'

    X_train = train[FEATURES]
```

```
y_train = train[OUTPUT]

X_test = test[FEATURES]
y_test = test[OUTPUT]
reg = xg.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
)

y_pred = reg.predict(X_test)
preds.append(y_pred)
score = np.sqrt(mean_squared_error(y_test, y_pred))
scores.append(score)
```





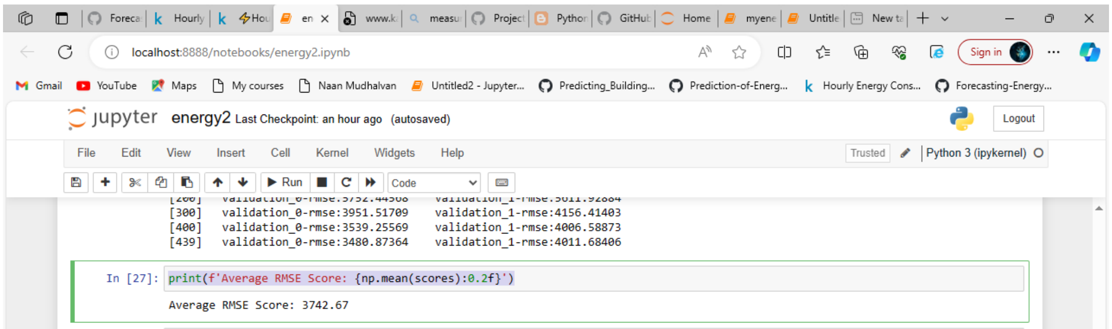
localhost:8888/notebooks/energy2.ipynb
jupyter energy2 Last Checkpoint: an hour ago (autosaved)
warnings.warn(smsg, UserWarning)
[100] validation_0-rmse:12513.65574 validation_1-rmse:12224.93373
[200] validation_0-rmse:5753.34937 validation_1-rmse:5662.07107
[300] validation_0-rmse:3902.71304 validation_1-rmse:3933.73076
[400] validation_0-rmse:3476.90515 validation_1-rmse:3590.55005
[500] validation_0-rmse:3353.72424 validation_1-rmse:3516.39915
[600] validation_0-rmse:3297.94766 validation_1-rmse:3481.94003
[700] validation_0-rmse:3258.48267 validation_1-rmse:3461.37383
[800] validation_0-rmse:3221.51553 validation_1-rmse:3436.49603
[900] validation_0-rmse:3190.11480 validation_1-rmse:3428.88699
[999] validation_0-rmse:3166.16314 validation_1-rmse:3420.30469
[0] validation_0-rmse:32631.20370 validation_1-rmse:31073.29733
C:\Users\CYPHER\AppData\Roaming\Python\Python39\site-packages\xgboost\core.py:160: UserWarning: [16:18:09] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-07f6e447eee219473-1\xgboost\xgboost-ci-windows\src\objective\regression_obj.cu:209: reg:linear is now deprecated in favor of reg:squarederror.
warnings.warn(smsg, UserWarning)
[100] validation_0-rmse:12499.28425 validation_1-rmse:11136.70202
[200] validation_0-rmse:5750.81453 validation_1-rmse:4813.22087
[300] validation_0-rmse:3917.04200 validation_1-rmse:3553.46419
[400] validation_0-rmse:3494.55924 validation_1-rmse:3495.32356
[411] validation_0-rmse:3475.26636 validation_1-rmse:3503.65414
[0] validation_0-rmse:32528.44438 validation_1-rmse:31475.39670
C:\Users\CYPHER\AppData\Roaming\Python\Python39\site-packages\xgboost\core.py:160: UserWarning: [16:18:16] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-07f6e447eee219473-1\xgboost\xgboost-ci-windows\src\objective\regression_obj.cu:209: reg:linear is now deprecated in favor of reg:squarederror.



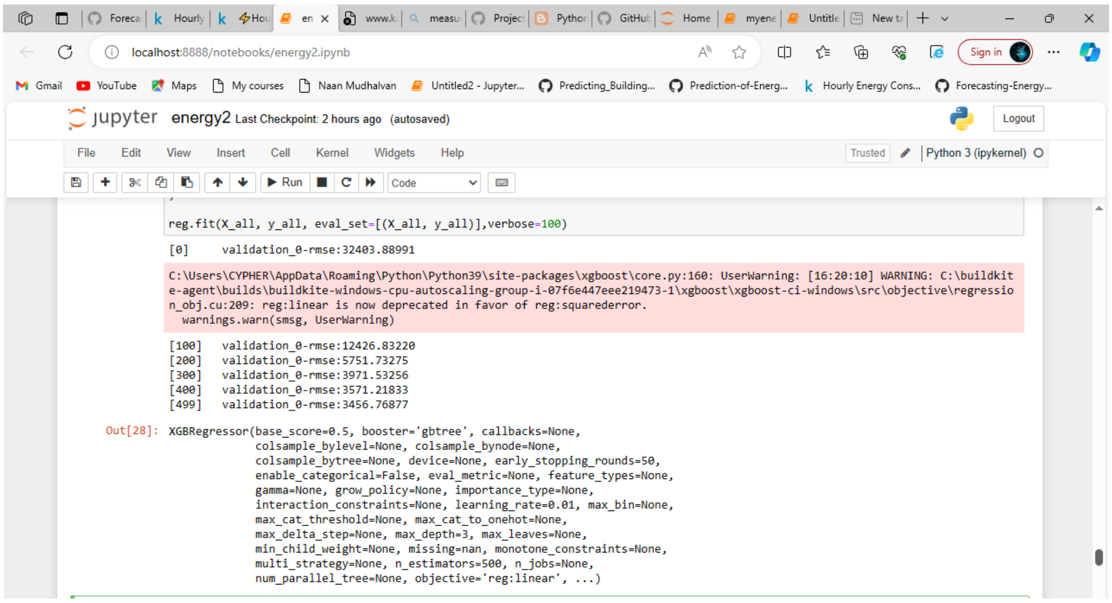
localhost:8888/notebooks/energy2.ipynb
jupyter energy2 Last Checkpoint: an hour ago (autosaved)
C:\Users\CYPHER\AppData\Roaming\Python\Python39\site-packages\xgboost\core.py:160: UserWarning: [16:18:16] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-07f6e447eee219473-1\xgboost\xgboost-ci-windows\src\objective\regression_obj.cu:209: reg:linear is now deprecated in favor of reg:squarederror.
warnings.warn(smsg, UserWarning)
[100] validation_0-rmse:12462.36581 validation_1-rmse:12020.28283
[200] validation_0-rmse:5738.57925 validation_1-rmse:5796.45874
[300] validation_0-rmse:3918.53218 validation_1-rmse:4388.39477
[400] validation_0-rmse:3501.24270 validation_1-rmse:4173.36380
[500] validation_0-rmse:3384.02490 validation_1-rmse:4119.70000
[600] validation_0-rmse:3325.50024 validation_1-rmse:4105.29234
[700] validation_0-rmse:3282.73755 validation_1-rmse:4091.57123
[800] validation_0-rmse:3250.37610 validation_1-rmse:4083.47152
[900] validation_0-rmse:3223.87814 validation_1-rmse:4081.83008
[999] validation_0-rmse:3199.82843 validation_1-rmse:4053.00975
[0] validation_0-rmse:32462.05557 validation_1-rmse:31463.90500
C:\Users\CYPHER\AppData\Roaming\Python\Python39\site-packages\xgboost\core.py:160: UserWarning: [16:18:34] WARNING: C:\buildkite-agent\builds\buildkite-windows-cpu-autoscaling-group-i-07f6e447eee219473-1\xgboost\xgboost-ci-windows\src\objective\regression_obj.cu:209: reg:linear is now deprecated in favor of reg:squarederror.
warnings.warn(smsg, UserWarning)
[100] validation_0-rmse:12445.87740 validation_1-rmse:11963.42706
[200] validation_0-rmse:5752.44568 validation_1-rmse:5611.92884
[300] validation_0-rmse:3951.51709 validation_1-rmse:4156.41403
[400] validation_0-rmse:3539.25569 validation_1-rmse:4006.58873
[439] validation_0-rmse:3480.87364 validation_1-rmse:4011.68406

12.FOLD ANALYSIS & RETRAINING ON ALL DATA

print(f'Average RMSE Score: {np.mean(scores):0.2f}')

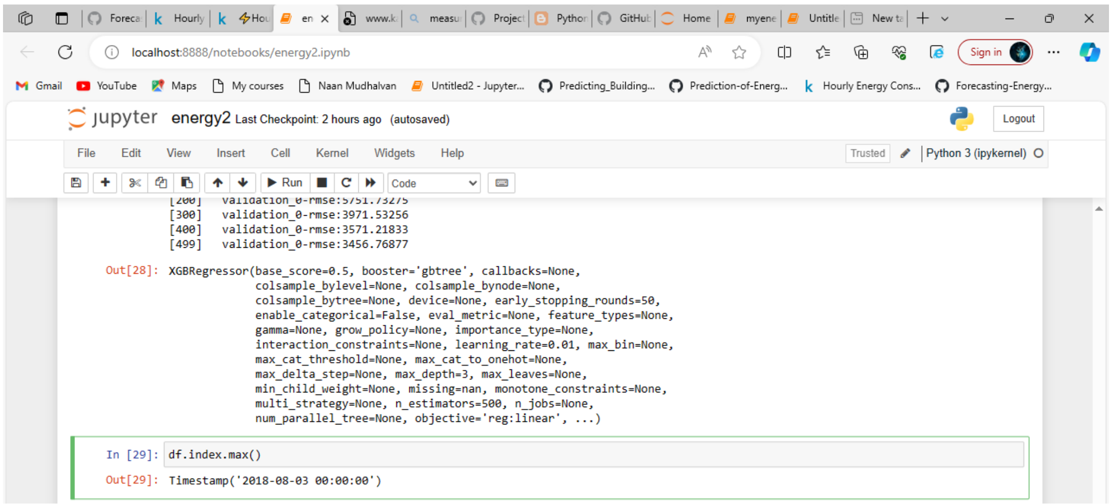



```
df = create_time_series_features(df)

FEATURES = ['hour', 'dayofweek', 'quarter', 'month', 'year', 'dayofyear',
     'lag1', 'lag2', 'lag3']

OUTPUT = 'PJME_MW'

X_all = df[FEATURES]
y_all = df[OUTPUT]

reg = xg.XGBRegressor(
   base_score=0.5,
   booster='gbtree',
   n_estimators=500,
   early_stopping_rounds=50,
   objective='reg:linear',
   max_depth=3,
   learning_rate=0.01
)

reg.fit(X_all, y_all, eval_set=[(X_all, y_all)],verbose=100)
```

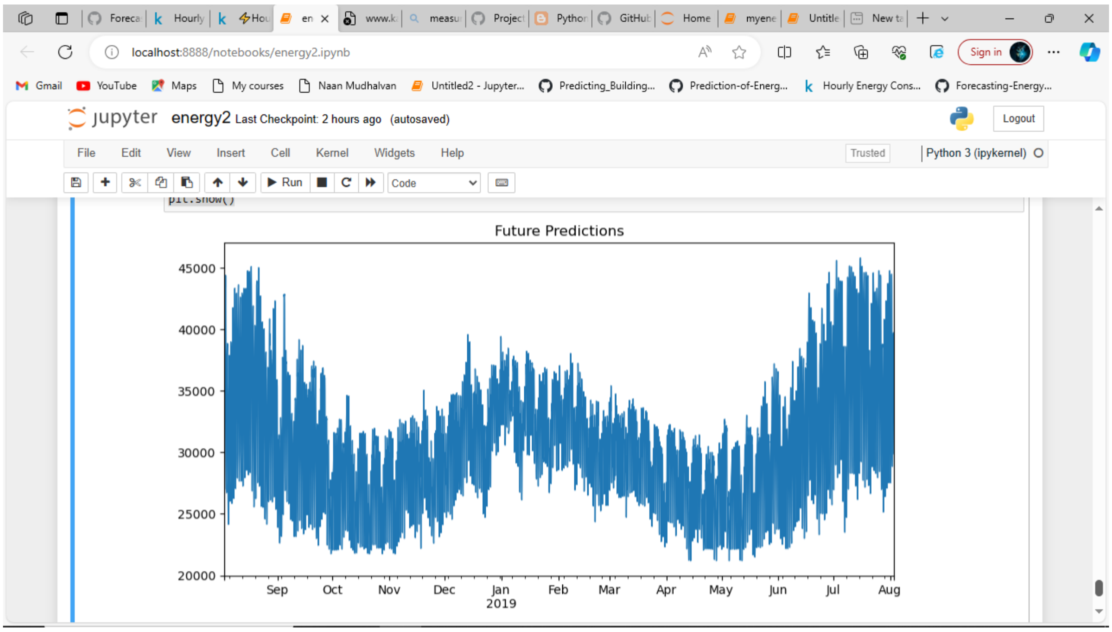


13.PREDICTING FUTURE

df.index.max()



```
future = pd.date_range('2018-08-03','2019-08-03',freq='1h')
future_df = pd.DataFrame(index=future)

future_df['isFuture'] = True

df['isFuture'] = False

df_and_future = pd.concat([df, future_df])

df_and_future = create_time_series_features(df_and_future)
df_and_future = add_lags(df_and_future)
future_w_features = df_and_future.query('isFuture').copy()
future_w_features['pred'] =
reg.predict(future_w_features[FEATURES])
future_w_features['pred'].plot(
    figsize=(10,5),
    ms=1,
    lw=1,
    title="Future Predictions"
)

plt.show()
```



DEPLOYMENT THE PROJECT

- This is the final process of my project MEASURE ENERGY CONSUMPTION .
- Hence ,my project is running in real world environment using watson cloud or python flask.
- This shows my energy consumption prediction approximately related to original result in graphical manner.
- Then it is finally used for future purposed.