IT-641 Deep Learning

Lab 5

INSTRUCTIONS:

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DATASET01 - Monthly ocean dataset

1. Importing Required Libraries

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2. Data Understanding

[ ] ↳ *4 cells hidden*

Seprating Data Frames

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TASK 1-3

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Lag Feature

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FOR GCAG DATASET

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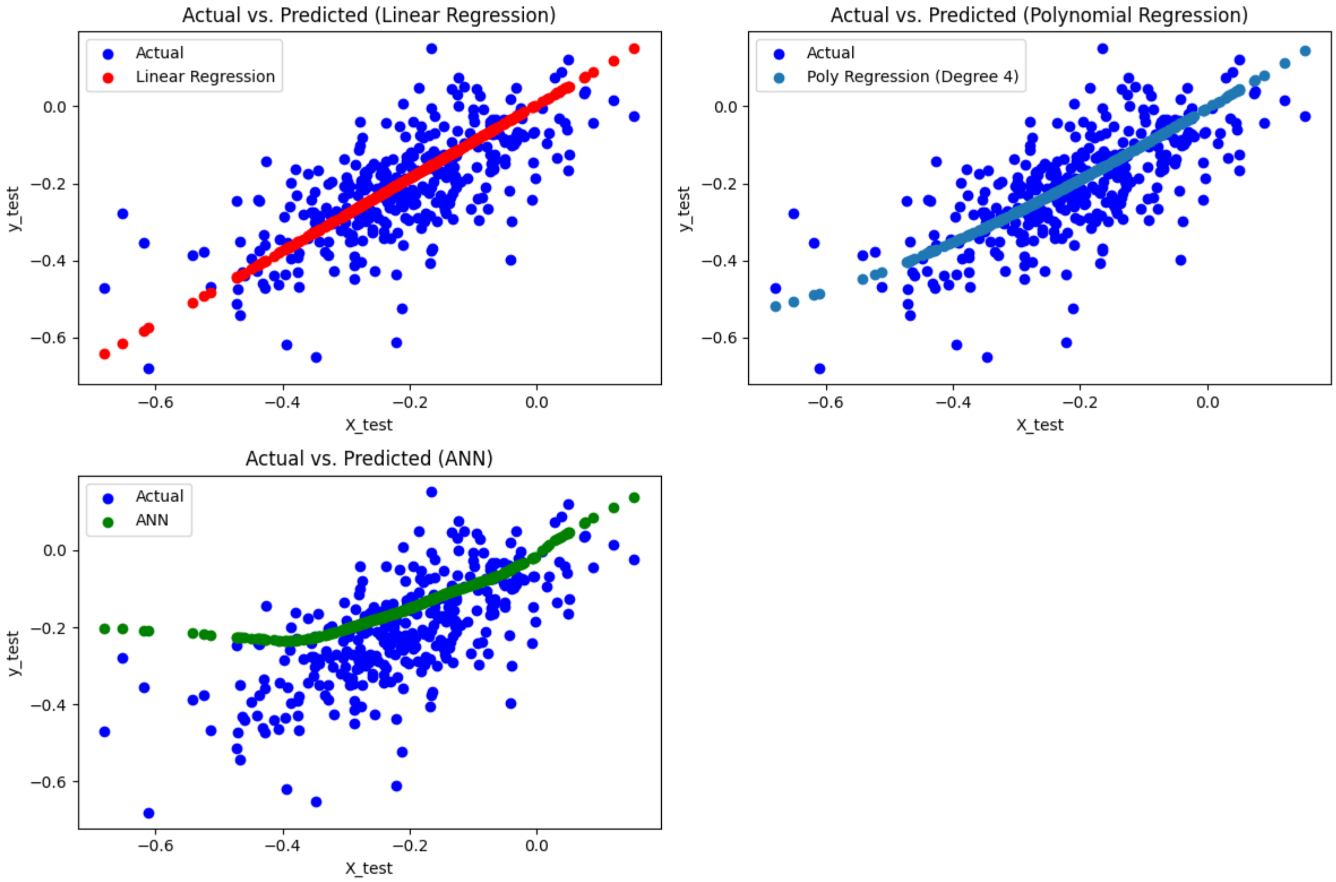
Task5. Plot graphs showing the result for all the models.

```
# Predictions for all models
linear_reg_preds = linear_reg_model.predict(X_test)
poly_reg_preds = [poly_reg_model.predict(poly_features.transform(X_test)) for _, poly_reg_model in pol
ann_preds = ann_model.predict(X_test)

# Plotting the results
plt.figure(figsize=(12, 8))

# Actual vs. Predicted for Linear Regression
plt.subplot(2, 2, 1)
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test, linear_reg_preds, color='red', label='Linear Regression')
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (Linear Regression)')
plt.legend()

```

```
# Actual vs. Predicted for Polynomial Regression
plt.subplot(2, 2, 2)
plt.scatter(X_test, y_test, color='blue', label='Actual')
for degree, poly_reg_model in poly_reg_models:
    plt.scatter(X_test, poly_reg_model.predict(poly_features.transform(X_test)), label=f'Poly Regressi
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (Polynomial Regression)')
plt.legend()

# Actual vs. Predicted for ANN
plt.subplot(2, 2, 3)
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test, ann_preds, color='green', label='ANN')
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (ANN)')
plt.legend()

plt.tight_layout()
plt.show()

```

```
11/11 [==============================] - 0s 2ms/step
```



6. Compare RMSE, MAE, MSE for the created models.

```
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Function to calculate RMSE, MAE, and MSE
def calculate_metrics(y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
```

```
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    return rmse, mae, mse

# Calculate metrics for Linear Regression
linear_reg_rmse, linear_reg_mae, linear_reg_mse = calculate_metrics(y_test, linear_reg_preds)

# Calculate metrics for Polynomial Regression models
poly_reg_metrics = []
for degree, poly_reg_model in poly_reg_models:
    poly_reg_preds = poly_reg_model.predict(poly_features.transform(X_test))
    rmse, mae, mse = calculate_metrics(y_test, poly_reg_preds)
    poly_reg_metrics.append((degree, rmse, mae, mse))

# Calculate metrics for ANN
ann_rmse, ann_mae, ann_mse = calculate_metrics(y_test, ann_preds)

# Print and compare metrics
print(f"Linear Regression - RMSE: {linear_reg_rmse}, MAE: {linear_reg_mae}, MSE: {linear_reg_mse}")

for degree, rmse, mae, mse in poly_reg_metrics:
    print(f"Polynomial Regression (Degree {degree}) - RMSE: {rmse}, MAE: {mae}, MSE: {mse}")

print(f"ANN - RMSE: {ann_rmse}, MAE: {ann_mae}, MSE: {ann_mse}")

```

```
Linear Regression - RMSE: 0.10685999521568819, MAE: 0.08251771071017241, MSE: 0.011419058577496902
Polynomial Regression (Degree 4) - RMSE: 0.10337531742011694, MAE: 0.08009041191718375, MSE: 0.010686456251709931
ANN - RMSE: 0.12506471580165127, MAE: 0.0958508650961165, MSE: 0.0156411831385478
```

7 Compare the results and justify which one is better.

Polynomial regression with degree= 4 will works better in this as it gives us less error in other cases. Data is non linear in this case.

FOR GISTEMP DATASET

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_gistemp, y_gistemp,
                                                    test_size=0.2, shuffle=False)
X_train = np.array(X_train).reshape(-1, 1)
y_train = list(y_train)
X_test = np.array(X_test).reshape(-1, 1)
y_test = list(y_test)
```

TASK 4 Model train

4. Create and train LinearRegression, PolynomialRegression (with three different number of polynomial features) and ANN model for both datasets.

```
# Reshape data to match model input requirements
X_train = np.array(X_train).reshape(-1, 1)
y_train = np.array(y_train)  # Convert y_train to a NumPy array
X_test = np.array(X_test).reshape(-1, 1)
y_test = np.array(y_test)  # Convert y_test to a NumPy array
```

```
#Checking which degree is working best
poly = PolynomialFeatures(2)
new_x = poly.fit_transform(X_train)

model = LinearRegression()
```

```
model.fit(new_x, y_train)

new_x = poly.fit_transform(X_test)

y_pred = pd.Series(model.predict(new_x))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
rmse
```

```
0.12426652001566257
```

```
#Checking which degree is working best
poly = PolynomialFeatures(3)
new_x = poly.fit_transform(X_train)

model = LinearRegression()
model.fit(new_x, y_train)

new_x = poly.fit_transform(X_test)

y_pred = pd.Series(model.predict(new_x))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
rmse
```

```
0.12149788572830693
```

```
#Checking which degree is working best
poly = PolynomialFeatures(4)
new_x = poly.fit_transform(X_train)

model = LinearRegression()
model.fit(new_x, y_train)

new_x = poly.fit_transform(X_test)

y_pred = pd.Series(model.predict(new_x))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
rmse
```

```
0.1209652282880449
```

```
#Checking which degree is working best
poly = PolynomialFeatures(5)
new_x = poly.fit_transform(X_train)

model = LinearRegression()
model.fit(new_x, y_train)

new_x = poly.fit_transform(X_test)

y_pred = pd.Series(model.predict(new_x))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
rmse
```

```
0.12095827506545165
```

```
#Checking which degree is working best
poly = PolynomialFeatures(6)
new_x = poly.fit_transform(X_train)

model = LinearRegression()
model.fit(new_x, y_train)

new_x = poly.fit_transform(X_test)

y_pred = pd.Series(model.predict(new_x))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
rmse
```

```
0.12162328362286128
```

In this dataset degree 5 works well we will do further for degree 5

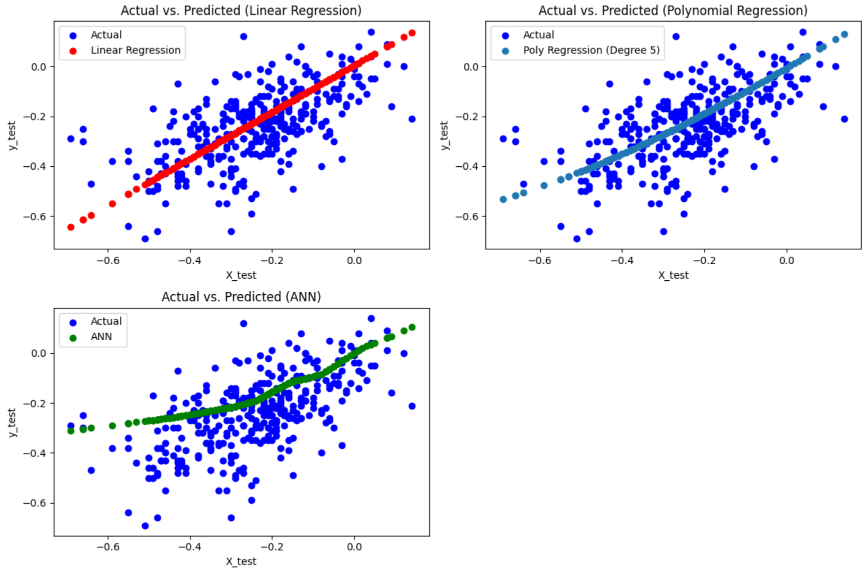
```
# Create and train Linear Regression model
linear_reg_model = LinearRegression()
linear_reg_model.fit(X_train, y_train)

# Create and train Polynomial Regression models with different degrees
poly_degrees = [5]
poly_reg_models = []


for degree in poly_degrees:
    poly_features = PolynomialFeatures(degree=degree)
    X_train_poly = poly_features.fit_transform(X_train)
    X_test_poly = poly_features.transform(X_test)

    poly_reg_model = LinearRegression()
    poly_reg_model.fit(X_train_poly, y_train)

    poly_reg_models.append((degree, poly_reg_model))

# Create and train an Artificial Neural Network (ANN) model
ann_model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(1,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1)  # Output layer
])

# Compile the ANN model
ann_model.compile(optimizer='adam', loss='mean_squared_error')

# Train the ANN model
ann_model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2)
```

```
Epoch 94/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0140 - val_loss: 0.0228
Epoch 95/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0140 - val_loss: 0.0290
Epoch 96/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0141 - val_loss: 0.0223
Epoch 97/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0139 - val_loss: 0.0274
Epoch 98/100
33/33 [==============================] - 0s 4ms/step - loss: 0.0140 - val_loss: 0.0238
Epoch 99/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0140 - val_loss: 0.0285
Epoch 100/100
33/33 [==============================] - 0s 3ms/step - loss: 0.0141 - val_loss: 0.0237
<keras.src.callbacks.History at 0x7a3579a81f30>
```

Task5. Plot graphs showing the result for all the models.

```
import matplotlib.pyplot as plt

# Predictions for all models
linear_reg_preds = linear_reg_model.predict(X_test)
poly_reg_preds = [poly_reg_model.predict(poly_features.transform(X_test)) for _, poly_reg_model in pol
ann_preds = ann_model.predict(X_test)

# Plotting the results
plt.figure(figsize=(12, 8))

# Actual vs. Predicted for Linear Regression
plt.subplot(2, 2, 1)
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test, linear_reg_preds, color='red', label='Linear Regression')
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (Linear Regression)')
plt.legend()

# Actual vs. Predicted for Polynomial Regression
plt.subplot(2, 2, 2)
plt.scatter(X_test, y_test, color='blue', label='Actual')
for degree, poly_reg_model in poly_reg_models:
    plt.scatter(X_test, poly_reg_model.predict(poly_features.transform(X_test)), label=f'Poly Regressi
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (Polynomial Regression)')
plt.legend()

# Actual vs. Predicted for ANN
plt.subplot(2, 2, 3)
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test, ann_preds, color='green', label='ANN')
plt.xlabel('X_test')
plt.ylabel('y_test')
plt.title('Actual vs. Predicted (ANN)')
plt.legend()

plt.tight_layout()
plt.show()

```

```
11/11 [==============================] - 0s 2ms/step
```



TASK6. Compare RMSE, MAE, MSE for the created models.

```
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Function to calculate RMSE, MAE, and MSE
def calculate_metrics(y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    return rmse, mae, mse

# Calculate metrics for Linear Regression
linear_reg_rmse, linear_reg_mae, linear_reg_mse = calculate_metrics(y_test, linear_reg_preds)

# Calculate metrics for Polynomial Regression models
poly_reg_metrics = []
for degree, poly_reg_model in poly_reg_models:
    poly_reg_preds = poly_reg_model.predict(poly_features.transform(X_test))
    rmse, mae, mse = calculate_metrics(y_test, poly_reg_preds)
    poly_reg_metrics.append((degree, rmse, mae, mse))

# Calculate metrics for ANN
ann_rmse, ann_mae, ann_mse = calculate_metrics(y_test, ann_preds)

# Print and compare metrics
print(f"Linear Regression - RMSE: {linear_reg_rmse}, MAE: {linear_reg_mae}, MSE: {linear_reg_mse}")

for degree, rmse, mae, mse in poly_reg_metrics:
    print(f"Polynomial Regression (Degree {degree}) - RMSE: {rmse}, MAE: {mae}, MSE: {mse}")

print(f"ANN - RMSE: {ann_rmse}, MAE: {ann_mae}, MSE: {ann_mse}")
```

```
Linear Regression - RMSE: 0.12634578473993902, MAE: 0.09770004663970339, MSE: 0.015963257321551006
Polynomial Regression (Degree 5) - RMSE: 0.12095827506545165, MAE: 0.09411205597383832, MSE: 0.014630904306809463
ANN - RMSE: 0.13814090837163306, MAE: 0.10843921525228352, MSE: 0.01908291056573992
```

TASK 7 RESULT

The Polynomial Regression (Degree 5) model has the lowest RMSE and MSE which means it has the smallest average prediction error and the smallest squared prediction errors, respectively.

The Linear Regression model also performs well but has slightly higher RMSE and MSE compared to the Polynomial Regression (Degree 5).

The ANN model has the highest RMSE and MSE , indicating that its predictions have a larger error compared to the other two models.

Therefore, based on the provided metrics, the Polynomial Regression (Degree 5) model appears to be the best-performing model for this dataset. It has the lowest RMSE and MSE, which suggests that it provides the most accurate predictions among the three models. However, it's essential to consider other factors such as model complexity, training time, and interpretability when choosing the best model for a specific application.

```

```

DATASET-02 - Electricity load forecasting

Time Series Forecasting Loading of Panama with reference to Weather Parameters & Special Days. There are a total 15 features in this data set.

● 12 features are Numerical continuous values : Weather Parameters

● 03 nos. of parameters contains the details of the Special days (Holidays, Holidays_ID, School days

● No null values in data sets

Output- To be predicted

Loading of the Panama in 'nat_demand' column

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from warnings import simplefilter
from sklearn.linear_model import LinearRegression
from tensorflow.keras.models import Sequential,Model
from tensorflow.keras.layers import Dense,Input,Dropout
from tensorflow.keras.utils import to_categorical,plot_model
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.neural_network import MLPRegressor
from math import sqrt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

```

```
df = pd.read_csv("https://raw.githubusercontent.com/Jatansahu/DEEP_LEARNING_ASSIGNMENTS/main/LAB_05/El
```

Data Understanding

```
df
```

	nat_demand	T2M_toc	QV2M_toc	TQL_toc	W2M_toc	T2M_san	QV2M_san	TQL_san	W2M_san	T2M_dav	QV2M_dav	TQL_dav
datetime												
2015-03-01 01:00:00	970.3450	25.865259	0.018576	0.016174	21.850546	23.482446	0.017272	0.001855	10.328949	22.662134	0.016562	0.096100
2015-03-01 02:00:00	912.1755	25.899255	0.018653	0.016418	22.166944	23.399255	0.017265	0.001327	10.681517	22.578943	0.016509	0.087646
2015-03-01 03:00:00	900.2688	25.937280	0.018768	0.015480	22.454911	23.343530	0.017211	0.001428	10.874924	22.531030	0.016479	0.078735
2015-03-01 04:00:00	889.9538	25.957544	0.018890	0.016273	22.110481	23.238794	0.017128	0.002599	10.518620	22.512231	0.016487	0.068390
2015-03-01 05:00:00	893.6865	25.973840	0.018981	0.017281	21.186089	23.075403	0.017059	0.001729	9.733589	22.481653	0.016456	0.064362
...	...	...	...	...	...	...	...	...	...	...	...	...
2019-12-31 19:00:00	1301.6065	26.635645	0.018421	0.013165	13.184052	25.135645	0.018048	0.064240	3.086798	23.620020	0.016697	0.073425
2019-12-												

This is the hourly data of electricity load from 01 March 2015 to 31 December 2019

Dataset Description (With some google search),

nat_demand: National electricity load

T2M: Temperature at 2 meters

QV2M: Relative humidity at 2 meters

TQL: Liquid precipitation

W2M: Wind speed at 2 meters

And after the underscore is the city

toc: Tocumen, Panama city

san: Santiago city

dav: David city The rest of variables:

Holiday_ID: Unique identification number integer

holiday: Holiday binary indicator (1=holiday, 0=regular day)

school: School period binary indicator (1=school, 0=vacations)

Data sources provide hourly records. The data composition is the following:

Historical electricity load, available on daily post-dispatch reports, from the grid operator (CND).

Historical weekly forecasts available on weekly pre-dispatch reports, both from CND.

Calendar information related to school periods, from Panama's Ministery of Education.

Calendar information related to holidays, from "When on Earth?" website. Weather variables, such as temperature, relative humidity, precipitation, and wind speed, for three main cities in Panama, from Earthdata.

Information Source --> https://www.kaggle.com/datasets/saurabhshahane/electricity-load-forecasting

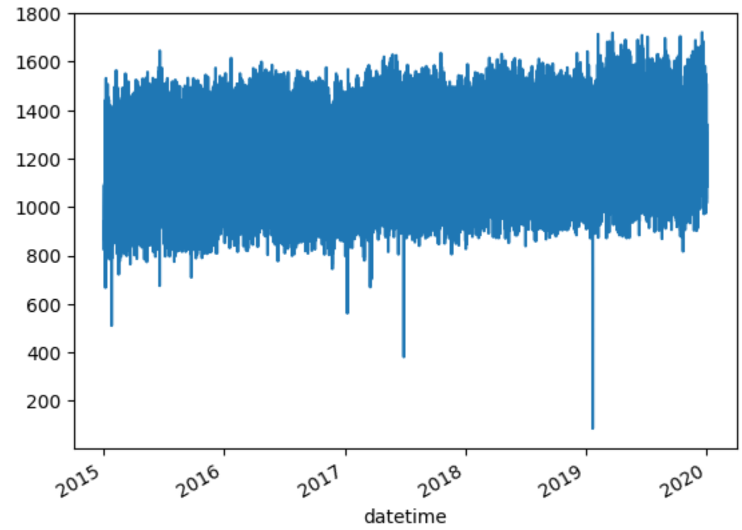
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 43775 entries, 2015-03-01 01:00:00 to 2019-12-31 23:00:00
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   nat_demand  43775 non-null  float64
 1   T2M_toc     43775 non-null  float64
 2   QV2M_toc    43775 non-null  float64
 3   TQL_toc     43775 non-null  float64
 4   W2M_toc     43775 non-null  float64
 5   T2M_san     43775 non-null  float64
 6   QV2M_san    43775 non-null  float64
 7   TQL_san     43775 non-null  float64
```

```
 8   W2M_san     43775 non-null  float64
 9   T2M_dav     43775 non-null  float64
 10  QV2M_dav    43775 non-null  float64
 11  TQL_dav     43775 non-null  float64
 12  W2M_dav     43775 non-null  float64
 13  Holiday_ID  43775 non-null  int64
 14  holiday     43775 non-null  int64
 15  school      43775 non-null  int64
dtypes: float64(13), int64(3)
memory usage: 5.7 MB
```

```
df['nat_demand'].plot()
```

```
<Axes: xlabel='datetime'>
```




```
def make_lags(df, lags):
    ret_df = pd.concat({f'lag_{i}_':df.shift(i) for i in range(1,lags+1)},axis=1)
    columns = [''.join(col).strip() for col in ret_df.columns.values]
    ret_df.columns = columns
    return ret_df
```

```
df.columns
```

```
Index(['nat_demand', 'T2M_toc', 'QV2M_toc', 'TQL_toc', 'W2M_toc', 'T2M_san',
       'QV2M_san', 'TQL_san', 'W2M_san', 'T2M_dav', 'QV2M_dav', 'TQL_dav',
       'W2M_dav', 'Holiday_ID', 'holiday', 'school'],
      dtype='object')
```

Feature Selection

```
import pandas as pd

# Assuming you have a DataFrame 'df' with your data
threshold = 0.5  # Set your desired correlation threshold

# Calculate the correlation of features with 'nat_demand'
correlation_with_target = df.corr()['nat_demand'].abs()

# Create a mask for features to keep (True) or remove (False)
mask = (correlation_with_target >= threshold) | (correlation_with_target.isna())

# Apply the mask to your DataFrame
df_filtered = df.loc[:, mask]
```

In this, we keep only the features with a correlation coefficient(Absolutive so it counts negative correlatiob also) greater than or equal to the specified threshold.

```
df
```

datetime	nat_demand	T2M_toc	QV2M_toc	TQL_toc	W2M_toc	T2M_san	QV2M_san	TQL_san	W2M_san	T2M_dav	QV2M_dav	TQL_dav
2015-03-01 01:00:00	970.3450	25.865259	0.018576	0.016174	21.850546	23.482446	0.017272	0.001855	10.328949	22.662134	0.016562	0.096100
2015-03-01 02:00:00	912.1755	25.899255	0.018653	0.016418	22.166944	23.399255	0.017265	0.001327	10.681517	22.578943	0.016509	0.087646
2015-03-01 03:00:00	900.2688	25.937280	0.018768	0.015480	22.454911	23.343530	0.017211	0.001428	10.874924	22.531030	0.016479	0.078735
2015-03-01 04:00:00	889.9538	25.957544	0.018890	0.016273	22.110481	23.238794	0.017128	0.002599	10.518620	22.512231	0.016487	0.068390
2015-03-01 05:00:00	893.6865	25.973840	0.018981	0.017281	21.186089	23.075403	0.017059	0.001729	9.733589	22.481653	0.016456	0.064362
...	...	...	...	...	...	...	...	...	...	...	...	...
2019-12-31 19:00:00	1301.6065	26.635645	0.018421	0.013165	13.184052	25.135645	0.018048	0.064240	3.086798	23.620020	0.016697	0.073425
2019-12-31 20:00:00	1250.9634	26.495935	0.018162	0.014713	13.443892	24.769373	0.017781	0.058838	3.659980	23.284998	0.016606	0.064362
2019-12-31 21:00:00	1193.6802	26.354456	0.017980	0.013836	13.442195	24.479456	0.017606	0.038086	3.769294	23.041956	0.016492	0.054260
2019-12-31 22:00:00	1130.4575	26.166895	0.017965	0.018486	13.420656	24.112207	0.017393	0.020386	3.872397	22.862207	0.016401	0.055557
2019-12-31 23:00:00	1084.4737	25.976373	0.018072	0.023315	13.749788	23.663873	0.017156	0.019531	4.165276	22.726373	0.016302	0.061371

43775 rows × 16 columns

```
df_filtered
```

datetime	nat_demand	T2M_toc	T2M_san	T2M_dav
2015-03-01 01:00:00	970.3450	25.865259	23.482446	22.662134
2015-03-01 02:00:00	912.1755	25.899255	23.399255	22.578943
2015-03-01 03:00:00	900.2688	25.937280	23.343530	22.531030
2015-03-01 04:00:00	889.9538	25.957544	23.238794	22.512231
2015-03-01 05:00:00	893.6865	25.973840	23.075403	22.481653
...	...	...	...	...
2019-12-31 19:00:00	1301.6065	26.635645	25.135645	23.620020
2019-12-31 20:00:00	1250.9634	26.495935	24.769373	23.284998
2019-12-31 21:00:00	1193.6802	26.354456	24.479456	23.041956
2019-12-31 22:00:00	1130.4575	26.166895	24.112207	22.862207
2019-12-31 23:00:00	1084.4737	25.976373	23.663873	22.726373

43775 rows × 4 columns

```
X = df_filtered.loc[:, df_filtered.columns != 'nat_demand']
y = df_filtered['nat_demand']
```

```
# X_train = np.array(X_train).reshape(-1, 1)
# y_train = np.array(y_train)  # Convert y_train to a NumPy array
# X_test = np.array(X_test).reshape(-1, 1)
# y_test = np.array(y_test)  # Convert y_test to a NumPy array
```

```
X
```

	T2M_toc	T2M_san	T2M_dav
datetime			
2015-03-01 01:00:00	25.865259	23.482446	22.662134
2015-03-01 02:00:00	25.899255	23.399255	22.578943
2015-03-01 03:00:00	25.937280	23.343530	22.531030
2015-03-01 04:00:00	25.957544	23.238794	22.512231
2015-03-01 05:00:00	25.973840	23.075403	22.481653
...	...	...	...
2019-12-31 19:00:00	26.635645	25.135645	23.620020
2019-12-31 20:00:00	26.495935	24.769373	23.284998
2019-12-31 21:00:00	26.354456	24.479456	23.041956
2019-12-31 22:00:00	26.166895	24.112207	22.862207
2019-12-31 23:00:00	25.976373	23.663873	22.726373

43775 rows × 3 columns

```
1 X0 = make_lags(X.iloc[:,:], lags=2)
```

```
1 X0
```

	lag_1_T2M_toc	lag_1_T2M_san	lag_1_T2M_dav	lag_2_T2M_toc	lag_2_T2M_san	lag_2_T2M_dav
datetime						
2015-03-01 01:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2015-03-01 02:00:00	25.865259	23.482446	22.662134	NaN	NaN	NaN
2015-03-01 03:00:00	25.899255	23.399255	22.578943	25.865259	23.482446	22.662134
2015-03-01 04:00:00	25.937280	23.343530	22.531030	25.899255	23.399255	22.578943
2015-03-01 05:00:00	25.957544	23.238794	22.512231	25.937280	23.343530	22.531030
...	...	...	...	...	...	...
2019-12-31 19:00:00	26.999292	25.733667	24.132104	28.112024	26.893274	24.916711
2019-12-31 20:00:00	26.635645	25.135645	23.620020	26.999292	25.733667	24.132104
2019-12-31 21:00:00	26.495935	24.769373	23.284998	26.635645	25.135645	23.620020
2019-12-31 22:00:00	26.354456	24.479456	23.041956	26.495935	24.769373	23.284998
2019-12-31 23:00:00	26.166895	24.112207	22.862207	26.354456	24.479456	23.041956

43775 rows × 6 columns

```
1 X = pd.concat([X.iloc[:,0:], X0], axis=1)
```

```
1 Xx = X.copy()
```

```
1 X
```

	T2M_toc	T2M_san	T2M_dav	lag_1_T2M_toc	lag_1_T2M_san	lag_1_T2M_dav	lag_2_T2M_toc	lag_2_T2M_san	lag_2_T2M_dav
datetime									

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 43775 entries, 2015-03-01 01:00:00 to 2019-12-31 23:00:00
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   T2M_toc        43775 non-null  float64
 1   T2M_san        43775 non-null  float64
 2   T2M_dav        43775 non-null  float64
 3   lag_1_T2M_toc  43774 non-null  float64
 4   lag_1_T2M_san  43774 non-null  float64
 5   lag_1_T2M_dav  43774 non-null  float64
 6   lag_2_T2M_toc  43773 non-null  float64
 7   lag_2_T2M_san  43773 non-null  float64
 8   lag_2_T2M_dav  43773 non-null  float64
dtypes: float64(9)
memory usage: 4.3 MB
```

```
y
```

```
datetime
2015-03-01 01:00:00     970.3450
2015-03-01 02:00:00     912.1755
2015-03-01 03:00:00     900.2688
2015-03-01 04:00:00     889.9538
2015-03-01 05:00:00     893.6865
                         ...    
2019-12-31 19:00:00    1301.6065
2019-12-31 20:00:00    1250.9634
2019-12-31 21:00:00    1193.6802
2019-12-31 22:00:00    1130.4575
2019-12-31 23:00:00    1084.4737
Name: nat_demand, Length: 43775, dtype: float64
```

```
X.dropna(inplace=True)
y, X = y.align(X, join='inner')
X = np.asarray(X).astype('float32')
```

```
 X.shape, y.shape
```

```
((43773, 9), (43773,))
```

Splitting dataset

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,shuffle=False)
```

Standardization

```
 from sklearn.preprocessing import StandardScaler
 scaler = StandardScaler()
 X_train = scaler.fit_transform(X_train)
 X_test= scaler.transform(X_test)
```

```
X_train.shape, y_train.shape
```

```
((35018, 9), (35018,))
```

```
# # Reshape data to match model input requirements
# X_train = np.array(X_train).reshape(-1, 1)
# y_train = np.array(y_train)  # Convert y_train to a NumPy array
# X_test = np.array(X_test).reshape(-1, 1)
# y_test = np.array(y_test)  # Convert y_test to a NumPy array
```

Model Selection

```
   #Checking which degree is working best
degree = [2,3,4,5]
for i in degree:
  poly = PolynomialFeatures(i)
  new_x = poly.fit_transform(X_train)

  model = LinearRegression()
  model.fit(new_x, y_train)

  new_x = poly.fit_transform(X_test)

  y_pred = pd.Series(model.predict(new_x))
  rmse = np.sqrt(mean_squared_error(y_test, y_pred))
  print(f"RMSE for degree {i} is", rmse)
```

```
RMSE for degree 2 is 141.24272565501363
RMSE for degree 3 is 148.32982052076815
RMSE for degree 4 is 138.30065491038113
RMSE for degree 5 is 148.74826423043328
```

```
# Create and train Linear Regression model
linear_reg_model = LinearRegression()
linear_reg_model.fit(X_train, y_train)

# Create and train Polynomial Regression models with different degrees
poly_degrees = [4]   # Change degree which works best
poly_reg_models = []


for degree in poly_degrees:
    poly_features = PolynomialFeatures(degree=degree)
    X_train_poly = poly_features.fit_transform(X_train)
    X_test_poly = poly_features.transform(X_test)
    poly_reg_model = LinearRegression()
    poly_reg_model.fit(X_train_poly, y_train)

    poly_reg_models.append((degree, poly_reg_model))

# Create and train an Artificial Neural Network (ANN) model
ann_model = keras.Sequential([
    layers.Dense(16, activation='relu', input_shape=(9,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(64, activation='relu'),
    layers.Dense(32, activation='relu'),
    layers.Dense(16, activation='relu'),
    layers.Dense(1)  # Output layer
])

# Compile the ANN model
ann_model.compile(optimizer='adam', loss='mean_squared_error')

# Train the ANN model
ann_model.fit(X_train, y_train, epochs=40, batch_size=32, validation_split=0.2)

```

```
Epoch 1/40
876/876 [==============================] - 3s 3ms/step - loss: 209721.8594 - val_loss: 21218.4922
Epoch 2/40
876/876 [==============================] - 2s 3ms/step - loss: 16871.1797 - val_loss: 18001.6797
Epoch 3/40
876/876 [==============================] - 3s 3ms/step - loss: 16251.5732 - val_loss: 18242.0645
Epoch 4/40
876/876 [==============================] - 2s 2ms/step - loss: 15881.6230 - val_loss: 15874.8711
Epoch 5/40
876/876 [==============================] - 2s 2ms/step - loss: 15592.6826 - val_loss: 14744.7490
Epoch 6/40
876/876 [==============================] - 2s 2ms/step - loss: 15588.8125 - val_loss: 19204.2480
Epoch 7/40
876/876 [==============================] - 2s 2ms/step - loss: 15451.8330 - val_loss: 14890.7461
Epoch 8/40
876/876 [==============================] - 2s 2ms/step - loss: 15377.7949 - val_loss: 14241.8467
Epoch 9/40
```

```
876/876 [==============================] - 3s 3ms/step - loss: 15273.3652 - val_loss: 19738.2891
Epoch 10/40
876/876 [==============================] - 2s 2ms/step - loss: 15272.5342 - val_loss: 17489.2148
Epoch 11/40
876/876 [==============================] - 2s 2ms/step - loss: 15247.3887 - val_loss: 19448.5039
Epoch 12/40
876/876 [==============================] - 2s 2ms/step - loss: 15049.1895 - val_loss: 18737.1543
Epoch 13/40
876/876 [==============================] - 2s 2ms/step - loss: 15047.5605 - val_loss: 13587.7236
Epoch 14/40
876/876 [==============================] - 2s 2ms/step - loss: 14793.4521 - val_loss: 16121.6875
Epoch 15/40
876/876 [==============================] - 3s 4ms/step - loss: 14532.1934 - val_loss: 14170.2285
Epoch 16/40
876/876 [==============================] - 2s 2ms/step - loss: 14417.3594 - val_loss: 19749.9629
Epoch 17/40
876/876 [==============================] - 2s 2ms/step - loss: 14256.9385 - val_loss: 18700.4160
Epoch 18/40
876/876 [==============================] - 2s 2ms/step - loss: 14211.5947 - val_loss: 11815.4961
Epoch 19/40
876/876 [==============================] - 2s 2ms/step - loss: 13969.0381 - val_loss: 17206.2520
Epoch 20/40
876/876 [==============================] - 2s 2ms/step - loss: 13885.5430 - val_loss: 14041.0488
Epoch 21/40
876/876 [==============================] - 3s 3ms/step - loss: 13817.2852 - val_loss: 12591.3008
Epoch 22/40
876/876 [==============================] - 2s 2ms/step - loss: 13798.7529 - val_loss: 19565.0254
Epoch 23/40
876/876 [==============================] - 2s 2ms/step - loss: 13761.7139 - val_loss: 18036.4316
Epoch 24/40
876/876 [==============================] - 2s 2ms/step - loss: 13700.1582 - val_loss: 18365.7129
Epoch 25/40
876/876 [==============================] - 2s 2ms/step - loss: 13659.7314 - val_loss: 17233.2051
Epoch 26/40
876/876 [==============================] - 2s 2ms/step - loss: 13646.6357 - val_loss: 16227.2656
Epoch 27/40
876/876 [==============================] - 3s 3ms/step - loss: 13547.4580 - val_loss: 15636.2568
Epoch 28/40
876/876 [==============================] - 2s 2ms/step - loss: 13700.1777 - val_loss: 14385.8896
Epoch 29/40
876/876 [==============================] - 2s 2ms/step - loss: 13543.9697 - val_loss: 13434.6475
```

```
# Predictions for all models
linear_reg_preds = linear_reg_model.predict(X_test)
poly_reg_preds = [poly_reg_model.predict(poly_features.transform(X_test)) for _, poly_reg_model in pol
ann_preds = ann_model.predict(X_test)
```

```
274/274 [==============================] - 0s 1ms/step
```

```
from sklearn.metrics import mean_squared_error, mean_absolute_error

# Function to calculate RMSE, MAE, and MSE
def calculate_metrics(y_true, y_pred):
```

After adding two more layer and increasing nodes in ANN I found that ANN is performing better than Polynomial regression. Initially I found that Polynomial with degree 4 works best.

Challenge - I am facing challenge while plotting time series graphs. I tried by different methods but not getting better visualization.

```
# Calculate metrics for Linear Regression
```

```
# fig, ax = plt.subplots(figsize=(15, 5))
# fig.autofmt_xdate()
# plt.plot(X_test, y_test,
#          color='darkgray', alpha=0.8, label='Original')
# # plt.plot(linear_reg_preds, label='Training prediction')
# plt.plot(X_test, linear_reg_preds, label='Testing prediction')
# plt.legend()
# # ax.set_xticks([i for i in list(elec_df['datetime'])[::1000]])
# # plt.xticks(rotation=60)
# plt.show()
```

```
ann_rmse, ann_mae, ann_mse = calculate_metrics(y_test, ann_preds)
```

```

print(f"Linear Regression - RMSE: {linear_reg_rmse}, MAE: {linear_reg_mae}, MSE: {linear_reg_mse}")

for degree, rmse, mae, mse in poly_reg_metrics:
    print(f"Polynomial Regression (Degree {degree}) - RMSE: {rmse}, MAE: {mae}, MSE: {mse}")

print(f"ANN - RMSE: {ann_rmse}, MAE: {ann_mae}, MSE: {ann_mse}")
```

```
Linear Regression - RMSE: 146.6986571506399, MAE: 118.55872228666209, MSE: 21520.496009800987
Polynomial Regression (Degree 4) - RMSE: 138.30065491038113, MAE: 110.17540567291904, MSE: 19127.071148640323
ANN - RMSE: 132.0439735506955, MAE: 107.29326549309992, MSE: 17435.610951056773
```