Importing Libraries

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout
from datetime import datetime
import matplotlib.dates as mdates
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.model_selection import train_test_split
```

```
df = pd.read_csv('/content/drive/MyDrive/CENTAIC/energydata_complete.csv')
```

```
df.head()
```

	date	Appliances	lights	T1	RH_1	T2	RH_2	T3	RH_3	
0	2016-01-11 17:00:00	60	30	19.89	47.596667	19.2	44.790000	19.79	44.730000	19.(
1	2016-01-11 17:10:00	60	30	19.89	46.693333	19.2	44.722500	19.79	44.790000	19.(
2	2016-01-11 17:20:00	50	30	19.89	46.300000	19.2	44.626667	19.79	44.933333	18.9
3	2016-01-11 17:30:00	50	40	19.89	46.066667	19.2	44.590000	19.79	45.000000	18.8
4	2016-01-11 17:40:00	60	40	19.89	46.333333	19.2	44.530000	19.79	45.000000	18.8

5 rows × 29 columns

Exploratory Data Analysis

```
obs, cols = df.shape
print("Totla Number of Observations : ", obs)
print("TOtal Number of Columns : ", cols)
```

```
Totla Number of Observations :  19735
TOtal Number of Columns :  29
```

```
list_cols = df.columns
print("List of Columns in a dataset : ", list_cols)
```

```
List of Columns in a dataset :  Index(['date', 'Appliances', 'lights', 'T1', 'RH_1', 'T2', 'RH_2', 'T3',
       'RH_3', 'T4', 'RH_4', 'T5', 'RH_5', 'T6', 'RH_6', 'T7', 'RH_7', 'T8',
       'RH_8', 'T9', 'RH_9', 'T_out', 'Press_mm_hg', 'RH_out', 'Windspeed',
       'Visibility', 'Tdewpoint', 'rv1', 'rv2'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19735 entries, 0 to 19734
Data columns (total 29 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   date         19735 non-null  object
 1   Appliances   19735 non-null  int64
 2   lights       19735 non-null  int64
 3   T1           19735 non-null  float64
 4   RH_1         19735 non-null  float64
 5   T2           19735 non-null  float64
 6   RH_2         19735 non-null  float64
 7   T3           19735 non-null  float64
 8   RH_3         19735 non-null  float64
```

```
 9   T4           19735 non-null  float64
 10  RH_4         19735 non-null  float64
 11  T5           19735 non-null  float64
 12  RH_5         19735 non-null  float64
 13  T6           19735 non-null  float64
 14  RH_6         19735 non-null  float64
 15  T7           19735 non-null  float64
 16  RH_7         19735 non-null  float64
 17  T8           19735 non-null  float64
 18  RH_8         19735 non-null  float64
 19  T9           19735 non-null  float64
 20  RH_9         19735 non-null  float64
 21  T_out        19735 non-null  float64
 22  Press_mm_hg  19735 non-null  float64
 23  RH_out       19735 non-null  float64
 24  Windspeed    19735 non-null  float64
 25  Visibility   19735 non-null  float64
 26  Tdewpoint    19735 non-null  float64
 27  rv1          19735 non-null  float64
 28  rv2          19735 non-null  float64
dtypes: float64(26), int64(2), object(1)
memory usage: 4.4+ MB
```

```
df['date'] = pd.to_datetime(df['date'])
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19735 entries, 0 to 19734
Data columns (total 29 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   date         19735 non-null  datetime64[ns]
 1   Appliances   19735 non-null  int64
 2   lights       19735 non-null  int64
 3   T1           19735 non-null  float64
 4   RH_1         19735 non-null  float64
 5   T2           19735 non-null  float64
 6   RH_2         19735 non-null  float64
 7   T3           19735 non-null  float64
 8   RH_3         19735 non-null  float64
 9   T4           19735 non-null  float64
 10  RH_4         19735 non-null  float64
 11  T5           19735 non-null  float64
 12  RH_5         19735 non-null  float64
 13  T6           19735 non-null  float64
 14  RH_6         19735 non-null  float64
 15  T7           19735 non-null  float64
 16  RH_7         19735 non-null  float64
 17  T8           19735 non-null  float64
 18  RH_8         19735 non-null  float64
 19  T9           19735 non-null  float64
 20  RH_9         19735 non-null  float64
 21  T_out        19735 non-null  float64
 22  Press_mm_hg  19735 non-null  float64
 23  RH_out       19735 non-null  float64
 24  Windspeed    19735 non-null  float64
 25  Visibility   19735 non-null  float64
 26  Tdewpoint    19735 non-null  float64
 27  rv1          19735 non-null  float64
 28  rv2          19735 non-null  float64
dtypes: datetime64[ns](1), float64(26), int64(2)
memory usage: 4.4 MB
```

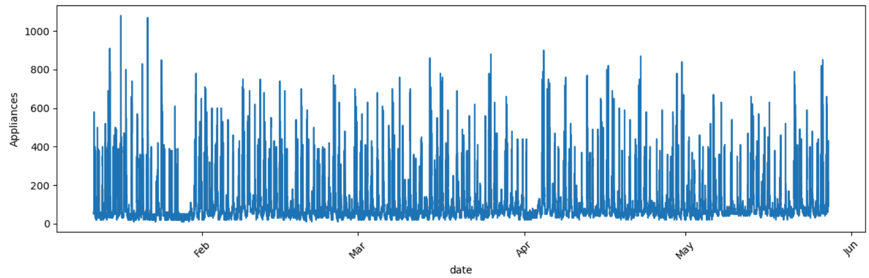
```
df.isnull().sum()
```

```
Appliances_energy     0
lights_energy         0
T_kitchen             0
RH_kitchen            0
T_livingroom          0
RH_livingroom         0
T_laundryroom         0
RH_laundryroom        0
T_officeroom          0
RH_officeroom         0
T_bathroom            0
RH_bathroom           0
T_OutsideBuliding     0
RH_OutsideBuilding    0
T_ironingroom         0
RH_ironingroom        0
T_teenagerroom2       0
RH_teenagerroom2      0
T_parentsroom         0
RH_parentsroom        0
T_out                 0
```

```
Press_mm_hg          0
RH_out               0
Windspeed            0
Visibility           0
Tdewpoint            0
rv1                  0
rv2                  0
dtype: int64
```

```
df.set_index('date', inplace=True)
```

```
plt.figure(figsize=(12, 4))
sns.lineplot(data=df, x=df.index, y='Appliances')
ax = plt.gca()
# Set major ticks format
ax.xaxis.set_major_locator(mdates.MonthLocator())
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b'))
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



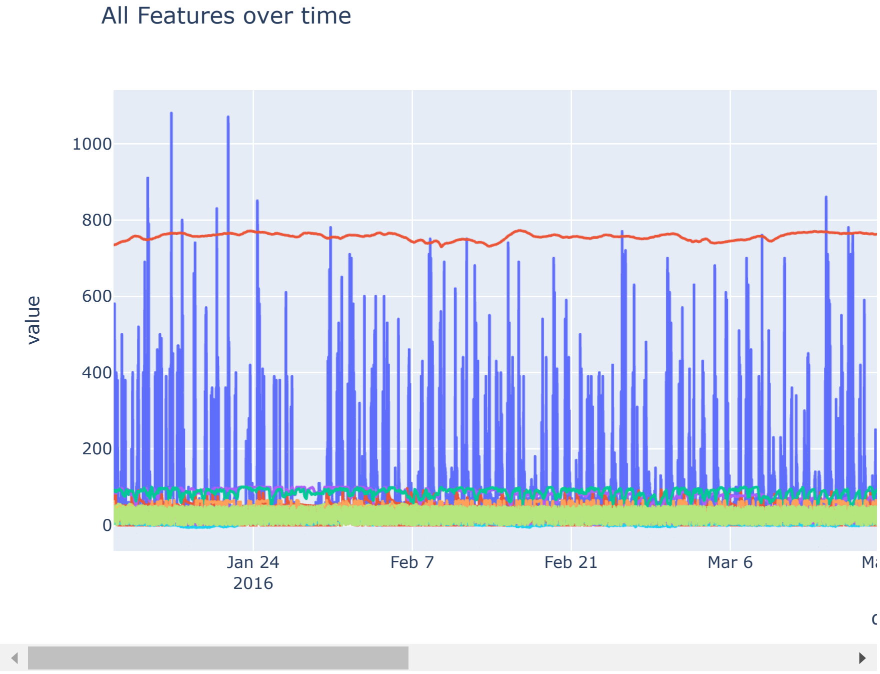

```
unique_years = df.index.to_period('Y').nunique()
print(f'The dataset spans {unique_years} unique Years.')
```

```
The dataset spans 1 unique Years.
```

```
unique_months = df.index.to_period('M').nunique()
print(f'The dataset spans {unique_months} unique Months.')
```

```
The dataset spans 5 unique Months.
```

```
df_reset = df.reset_index()
fig = px.line(df_reset, x='date', y=df_reset.columns[1:], title='All Features over time')
fig.show()
```



We observe distinct peaks representing periods of both high and low appliance usage, likely indicative of nighttime and daytime, respectively.

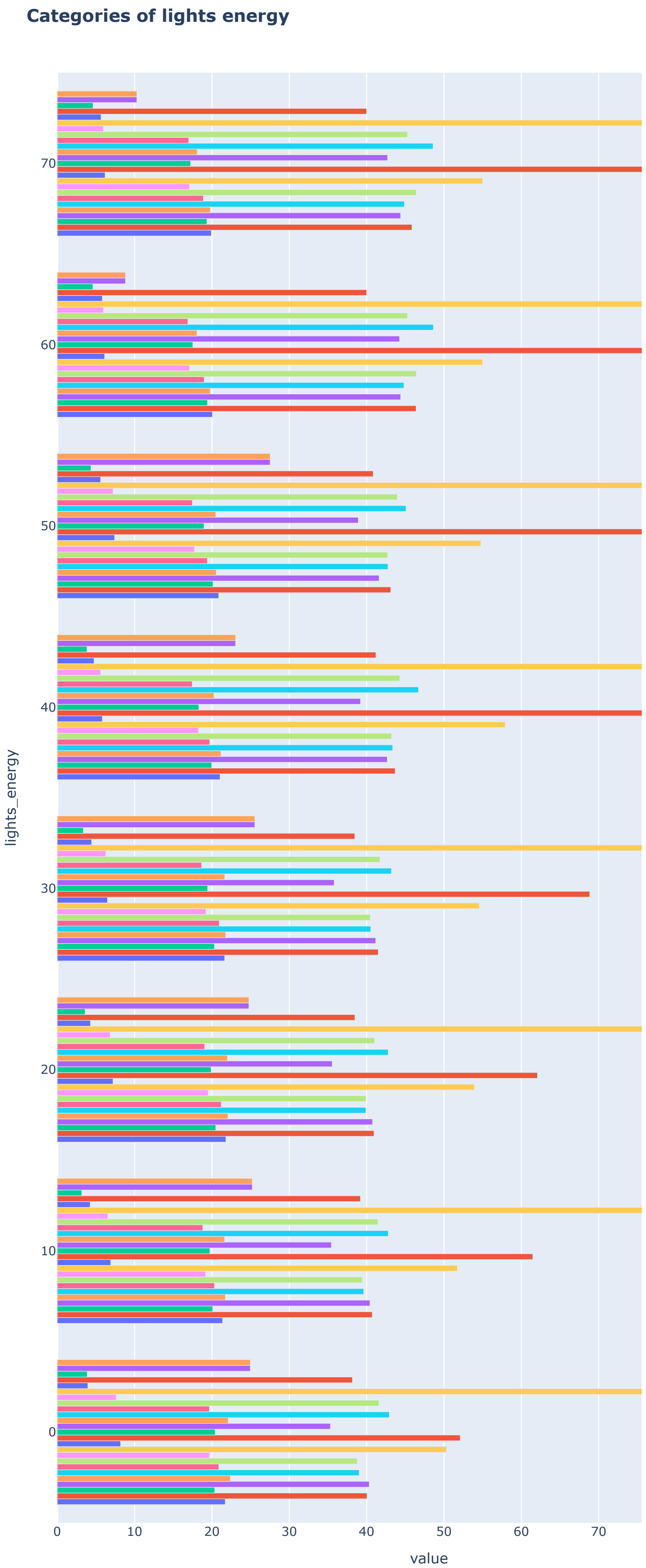
```
df.rename(columns = {'Appliances':'Appliances_energy'}, inplace = True)
df.rename(columns={'lights':'lights_energy'} ,inplace=True)
df.rename(columns={'T1':'T_kitchen'} ,inplace=True)
df.rename(columns={'RH_1':'RH_kitchen'} ,inplace=True)
df.rename(columns={'T2':'T_livingroom'} ,inplace=True)
df.rename(columns={'RH_2':'RH_livingroom'} ,inplace=True)
df.rename(columns={'T3':'T_laundryroom'} ,inplace=True)
df.rename(columns={'RH_3':'RH_laundryroom'} ,inplace=True)
df.rename(columns={'T4':'T_officeroom'} ,inplace=True)
df.rename(columns={'RH_4':'RH_officeroom'} ,inplace=True)
df.rename(columns={'T5':'T_bathroom'} ,inplace=True)
df.rename(columns={'RH_5':'RH_bathroom'} ,inplace=True)
df.rename(columns={'T6':'T_OutsideBuliding'} ,inplace=True)
df.rename(columns={'RH_6':'RH_OutsideBuilding'} ,inplace=True)
df.rename(columns={'T7':'T_ironingroom'} ,inplace=True)
df.rename(columns={'RH_7':'RH_ironingroom'} ,inplace=True)
df.rename(columns={'T8':'T_teenagerroom2'} ,inplace=True)
df.rename(columns={'RH_8':'RH_teenagerroom2'} ,inplace=True)
df.rename(columns={'T9':'T_parentsroom'} ,inplace=True)
df.rename(columns={'RH_9':'RH_parentsroom'} ,inplace=True)
```

```
df_lights_energy = df.groupby('lights_energy').agg({'Appliances_energy' : 'mean', 'T_kitchen':'mean', 'RH_kitchen':'mean',
                                                    'T_livingroom':'mean', 'RH_livingroom':'mean', 'T_laundryroom':'mean',
                                                     'RH_laundryroom':'mean','T_officeroom':'mean', 'RH_officeroom':'mean',
                                                     'T_bathroom':'mean', 'RH_bathroom':'mean','T_OutsideBuliding':'mean',
                                                     'RH_OutsideBuilding':'mean', 'T_ironingroom':'mean','RH_ironingroom':'mean',
                                                     'T_teenagerroom2':'mean', 'RH_teenagerroom2':'mean','T_parentsroom':'mean',
                                                     'RH_parentsroom':'mean', 'T_out':'mean', 'Press_mm_hg':'mean',
                                                     'RH_out':'mean','Windspeed':'mean', 'Visibility':'mean',
                                                    'Tdewpoint':'mean', 'rv1':'mean', 'rv2':'mean'})
df_lights_energy
```

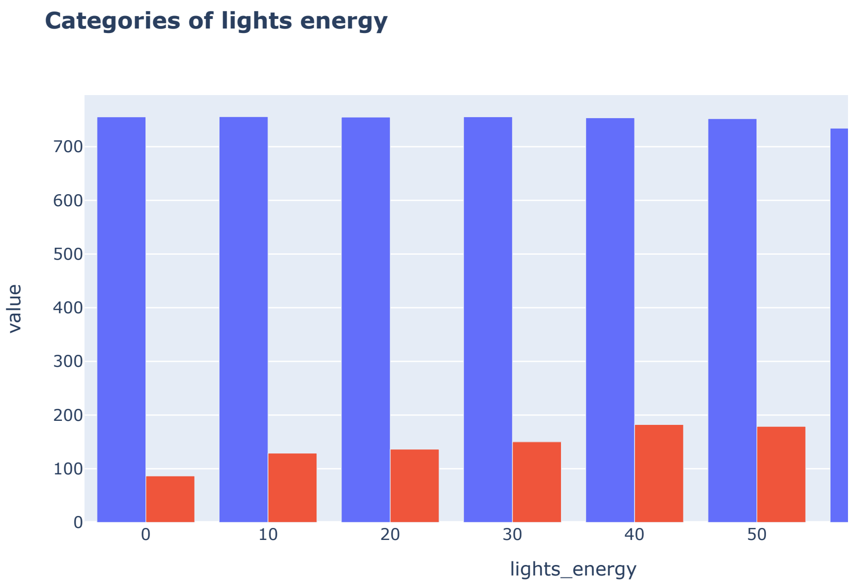
	Appliances_energy	T_kitchen	RH_kitchen	T_livingroom	RH_livingroom
lights_energy					
0	86.584710	21.723160	40.050783	20.363159	40.340166
10	129.037071	21.379647	40.739160	20.091564	40.436926
20	136.428571	21.809905	40.955904	20.498642	40.772480
30	150.214669	21.650877	41.501385	20.329447	41.179115
40	182.337662	21.051775	43.693539	19.980135	42.667587
50	178.888889	20.885556	43.118889	20.145556	41.607778
60	580.000000	20.066667	46.396667	19.426667	44.400000
70	230.000000	19.926667	45.863333	19.356667	44.400000

8 rows × 27 columns

```
px.bar(data_frame=df_lights_energy.drop(['Press_mm_hg','Appliances_energy'],axis = 1), barmode='group',orientation = 'h',
       width=1000, height=1600,title = "<b>Categories of lights energy</b>")
```


Categories of lights energy
lights_energy
value
0
10
20
30
40
50
60
70

```
px.bar(data_frame=df_lights_energy[['Press_mm_hg','Appliances_energy']], barmode='group',
       width=1000, height=500,title = "<b>Categories of lights energy</b>")
```




```
descriptive_stats = df.describe(include='all')
descriptive_stats
```

	Appliances_energy	lights_energy	T_kitchen	RH_kitchen	T_livingroom	RH_
count	19735.000000	19735.000000	19735.000000	19735.000000	19735.000000	1!
mean	97.694958	3.801875	21.686571	40.259739	20.341219	
std	102.524891	7.935988	1.606066	3.979299	2.192974	
min	10.000000	0.000000	16.790000	27.023333	16.100000	
25%	50.000000	0.000000	20.760000	37.333333	18.790000	
50%	60.000000	0.000000	21.600000	39.656667	20.000000	
75%	100.000000	0.000000	22.600000	43.066667	21.500000	
max	1080.000000	70.000000	26.260000	63.360000	29.856667	

8 rows × 28 columns

```
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df)
def create_sequences(data, seq_length):
    xs = []
    ys = []
    for i in range(len(data)-seq_length-1):
        x = data[i:(i+seq_length)]
        y = data[i+seq_length]
        xs.append(x)
        ys.append(y)
    return np.array(xs), np.array(ys)
seq_length = 10
X, y = create_sequences(scaled_data, seq_length)
```

```
X.shape
```

```
(19724, 10, 28)
```

```
y.shape
```

```
(19724, 28)
```

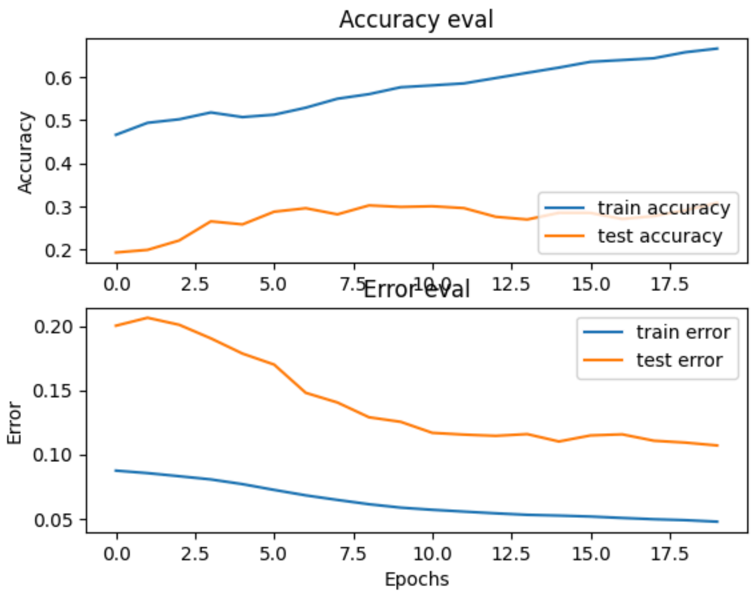
LSTM

```
model = Sequential()
model.add(LSTM(128, input_shape=(X.shape[1], X.shape[2]), return_sequences=True))
# model.add(Dropout(0.2))
model.add(LSTM(64, return_sequences=False))
# model.add(Dropout(0.2))
# model.add(LSTM(32, return_sequences=False))
# model.add(Dropout(0.2))
model.add(Dense(X.shape[2]))

model.compile(optimizer='adam', loss='mae', metrics=['accuracy'])
```

```
history = model.fit(X, y, epochs=20, batch_size=16, validation_split=0.2, shuffle=False)
```

```
Epoch 1/20
987/987 [==============================] - 17s 9ms/step - loss: 0.0874 - accuracy: 0.4661 - val_loss: 0.2004 - val_accuracy: 0.1932
Epoch 2/20
987/987 [==============================] - 6s 6ms/step - loss: 0.0855 - accuracy: 0.4939 - val_loss: 0.2066 - val_accuracy: 0.1992
Epoch 3/20
987/987 [==============================] - 8s 9ms/step - loss: 0.0830 - accuracy: 0.5021 - val_loss: 0.2011 - val_accuracy: 0.2210
Epoch 4/20
987/987 [==============================] - 6s 6ms/step - loss: 0.0805 - accuracy: 0.5179 - val_loss: 0.1905 - val_accuracy: 0.2654
Epoch 5/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0769 - accuracy: 0.5072 - val_loss: 0.1787 - val_accuracy: 0.2583
Epoch 6/20
987/987 [==============================] - 9s 9ms/step - loss: 0.0724 - accuracy: 0.5128 - val_loss: 0.1701 - val_accuracy: 0.2877
Epoch 7/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0681 - accuracy: 0.5290 - val_loss: 0.1481 - val_accuracy: 0.2958
Epoch 8/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0646 - accuracy: 0.5498 - val_loss: 0.1405 - val_accuracy: 0.2816
Epoch 9/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0612 - accuracy: 0.5604 - val_loss: 0.1290 - val_accuracy: 0.3024
Epoch 10/20
987/987 [==============================] - 8s 8ms/step - loss: 0.0586 - accuracy: 0.5764 - val_loss: 0.1254 - val_accuracy: 0.2989
Epoch 11/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0569 - accuracy: 0.5808 - val_loss: 0.1169 - val_accuracy: 0.3004
Epoch 12/20
987/987 [==============================] - 9s 9ms/step - loss: 0.0555 - accuracy: 0.5853 - val_loss: 0.1155 - val_accuracy: 0.2961
Epoch 13/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0541 - accuracy: 0.5977 - val_loss: 0.1145 - val_accuracy: 0.2760
Epoch 14/20
987/987 [==============================] - 8s 8ms/step - loss: 0.0529 - accuracy: 0.6099 - val_loss: 0.1159 - val_accuracy: 0.2697
Epoch 15/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0524 - accuracy: 0.6220 - val_loss: 0.1101 - val_accuracy: 0.2852
Epoch 16/20
987/987 [==============================] - 8s 8ms/step - loss: 0.0516 - accuracy: 0.6354 - val_loss: 0.1148 - val_accuracy: 0.2849
Epoch 17/20
987/987 [==============================] - 6s 6ms/step - loss: 0.0505 - accuracy: 0.6395 - val_loss: 0.1157 - val_accuracy: 0.2710
Epoch 18/20
987/987 [==============================] - 7s 7ms/step - loss: 0.0495 - accuracy: 0.6437 - val_loss: 0.1107 - val_accuracy: 0.2776
Epoch 19/20
987/987 [==============================] - 9s 10ms/step - loss: 0.0488 - accuracy: 0.6576 - val_loss: 0.1092 - val_accuracy: 0.2910
Epoch 20/20
987/987 [==============================] - 8s 8ms/step - loss: 0.0476 - accuracy: 0.6661 - val_loss: 0.1070 - val_accuracy: 0.3082
```

```
def plot_history(history):
  fig, axs = plt.subplots(2)

  #create accuracy subplot
  axs[0].plot(history.history["accuracy"], label = 'train accuracy')
  axs[0].plot(history.history["val_accuracy"], label= 'test accuracy')
  axs[0].set_ylabel("Accuracy")
  axs[0].legend(loc='lower right')
  axs[0].set_title("Accuracy eval")


  #create loss subplot
  axs[1].plot(history.history["loss"], label = 'train error')
  axs[1].plot(history.history["val_loss"], label = 'test error')
  axs[1].set_ylabel("Error")
  axs[1].set_xlabel("Epochs")
  axs[1].legend(loc='upper right')
  axs[1].set_title("Error eval")

  plt.show()

plot_history(history)
```



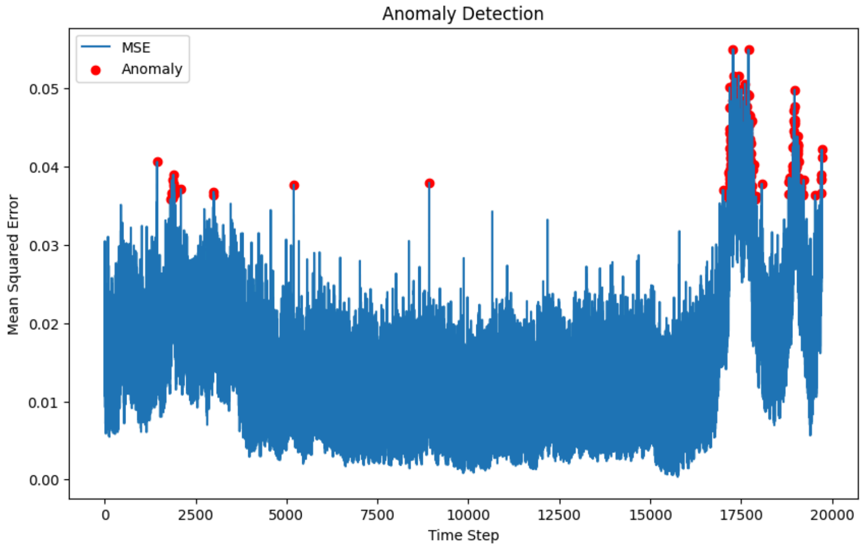

```
predictions = model.predict(X)

# Calculate MSE
mse = np.mean(np.power(y - predictions, 2), axis=1)

threshold = np.quantile(mse, 0.98)
anomalies = mse > threshold
```

```
617/617 [==============================] - 2s 3ms/step
```

```
anomalies
```

```
array([False, False, False, ...,  True, False, False])
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
plt.plot(mse, label='MSE')
plt.ylabel('Mean Squared Error')
plt.xlabel('Time Step')
anomalies_indices = np.where(anomalies)[0]
plt.scatter(anomalies_indices, mse[anomalies_indices], color='r', label='Anomaly')
plt.title('Anomaly Detection')
plt.legend()
plt.show()
```




```
# anomalies_indices = np.where(anomalies)[0]
# anomalies_indices
```

Autoencoders and Decoders

```
scaler = MinMaxScaler()
df_scaled = scaler.fit_transform(df)

# Split data into training and test sets
X_train, X_test = train_test_split(df_scaled, test_size=0.2, random_state=42)
```

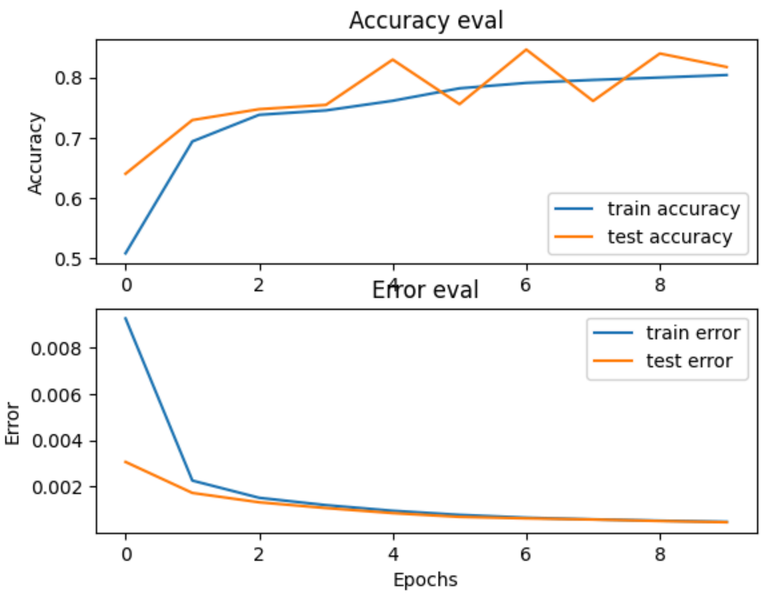
```
input_dim = X_train.shape[1]

model = Sequential()
# Encoder
model.add(Dense(64, activation='relu', input_shape=(input_dim,)))
# model.add(Dropout(0.2))
model.add(Dense(32, activation='relu'))
# model.add(Dropout(0.2))

# Decoder
model.add(Dense(64, activation='relu'))
model.add(Dense(input_dim, activation='sigmoid'))  # Output layer

model.compile(optimizer='adam', loss='mse',  metrics=['accuracy'])
```

```
history_aut = model.fit(X_train, X_train,  # input and output are the same for autoencoders
          epochs=10,
          batch_size=16,
          validation_data=(X_test, X_test),
          shuffle=True)
```

```
Epoch 1/10
987/987 [==============================] - 8s 5ms/step - loss: 0.0092 - accuracy: 0.5087 - val_loss: 0.0031 - val_accuracy: 0.6405
Epoch 2/10
987/987 [==============================] - 4s 4ms/step - loss: 0.0023 - accuracy: 0.6940 - val_loss: 0.0017 - val_accuracy: 0.7294
Epoch 3/10
987/987 [==============================] - 4s 4ms/step - loss: 0.0015 - accuracy: 0.7381 - val_loss: 0.0013 - val_accuracy: 0.7474
Epoch 4/10
987/987 [==============================] - 5s 5ms/step - loss: 0.0012 - accuracy: 0.7454 - val_loss: 0.0011 - val_accuracy: 0.7545
Epoch 5/10
987/987 [==============================] - 4s 4ms/step - loss: 9.6534e-04 - accuracy: 0.7613 - val_loss: 8.6536e-04 - val_accuracy:
Epoch 6/10
987/987 [==============================] - 4s 4ms/step - loss: 7.8910e-04 - accuracy: 0.7820 - val_loss: 7.0222e-04 - val_accuracy:
Epoch 7/10
987/987 [==============================] - 5s 5ms/step - loss: 6.6771e-04 - accuracy: 0.7910 - val_loss: 6.3833e-04 - val_accuracy:
```

```
Epoch 8/10
987/987 [==============================] - 8s 8ms/step - loss: 5.9544e-04 - accuracy: 0.7959 - val_loss: 5.9034e-04 - val_accuracy:
Epoch 9/10
987/987 [==============================] - 4s 4ms/step - loss: 5.3867e-04 - accuracy: 0.7998 - val_loss: 5.2531e-04 - val_accuracy:
Epoch 10/10
987/987 [==============================] - 4s 4ms/step - loss: 4.9203e-04 - accuracy: 0.8040 - val_loss: 4.7261e-04 - val_accuracy:
```

```
plot_history(history_aut)
```




```
reconstructions = model.predict(X_test)

mse = np.mean(np.power(X_test - reconstructions, 2), axis=1)
```

```
124/124 [==============================] - 0s 2ms/step
```

```
print(X_test.shape)
```

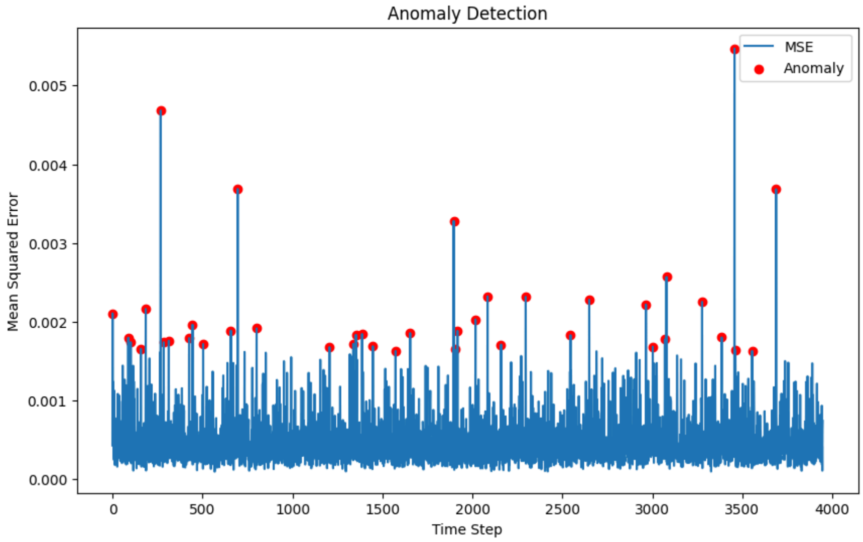
```
(3947, 28)
```

```
print(len(mse))
```

```
3947
```

```
anomaly_threshold = np.percentile(mse, 99)  # Example: 95th percentile
anomalies = mse > anomaly_threshold
```

```
import matplotlib.pyplot as plt

# Plot MSE
plt.figure(figsize=(10,6))
plt.plot(mse, label='MSE')
plt.ylabel('Mean Squared Error')
plt.xlabel('Time Step')

# Highlight anomalies
anomalies_indices = np.where(anomalies)[0]
plt.scatter(anomalies_indices, mse[anomalies_indices], color='r', label='Anomaly')

plt.title('Anomaly Detection')
plt.legend()
plt.show()
```



Continual Learning(RL)

```
df_ad = df.copy()
```

```
train_data, test_data = train_test_split(df_ad, test_size=0.2)

# Initialize parameters
num_features = train_data.shape[1] - 1  # Assuming last column is the target
num_actions = 2  # High (1) or low (0) energy usage

# Function to initialize Q-model
def initialize_q_model(num_features, num_actions):
    model = Sequential()
    model.add(Dense(64, input_dim=num_features, activation='relu'))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(num_actions, activation='linear'))
    model.compile(loss='mse', optimizer='adam')
    return model

q_model = initialize_q_model(num_features, num_actions)

learning_rate = 0.1
discount_factor = 0.9
epsilon = 0.2
num_episodes = 1000

# Function to get initial state from dataset
def get_initial_state_from_dataset(data, index):
    return data.iloc[index, :-1].values  # Assuming last column is the target

# Function to predict energy usage
def predict_energy_usage(state, action):
    # Define the threshold to split energy usage into high and low
    energy_values = [0, 10, 20, 30, 40, 50, 60, 70]
    median_value = np.median(energy_values)

    # Predict high or low usage based on the action
    if action == 1:  # High energy usage
        # Return a value greater than the median
        high_usage_value = max(energy_values, key=lambda x: x > median_value)
    else:  # Low energy usage
        # Return a value less than or equal to the median
        low_usage_value = min(energy_values, key=lambda x: x <= median_value)

    return high_usage_value if action == 1 else low_usage_value
```

```
def calculate_reward(predicted_usage, actual_usage):
    # Simple reward calculation
    return -abs(predicted_usage - actual_usage)


# # def get_next_state_from_dataset(data, current_state):
# #     # Find the index of the current state in the dataset
# #     current_index = data.index[data.iloc[:, :-1].values == current_state].tolist()[0]
# #     # Get the state of the next time step
# #     if current_index + 1 < len(data):
# #         return data.iloc[current_index + 1, :-1].values
# #     else:
# #         return None  # Indicates end of data
# def get_next_state_from_dataset(data, current_state):
#     # Convert the current state to a DataFrame row for comparison
#     state_df = pd.DataFrame([current_state], columns=data.columns[:-1])  # Exclude the target column

#     # Find the row in data that matches the current state
#     matching_rows = data[(data.iloc[:, :-1] == state_df.iloc[0]).all(axis=1)]

#     # Get the index of the matching row
#     if not matching_rows.empty:
#         current_index = matching_rows.index[0]
#         # Check if there is a next state
#         if current_index + 1 < len(data):
#             # Return the state of the next time step
#             return data.iloc[current_index + 1, :-1].values
#         else:
#             # If there is no next state, handle it (e.g., return None)
#             return None
#     else:
#         # Handle the case where no matching row is found
#         # This will depend on your specific requirements
#         return default_next_state  # You need to define this
def get_next_state_from_dataset(data, current_state):
    # Convert the current state to a DataFrame row for comparison
    state_df = pd.DataFrame([current_state], columns=data.columns[:-1])  # Exclude the target column

    # Find the row in data that matches the current state
    matching_rows = data[(data.iloc[:, :-1] == state_df.iloc[0]).all(axis=1)]

    # Get the index of the matching row
    if not matching_rows.empty:
        # Get the current index as a datetime object
        current_index = matching_rows.index[0]

        # Find the next index in the DataFrame
        # Here, we handle datetime index correctly
        next_index = data.index[data.index > current_index].min()

        # Check if there is a next state
        if not pd.isna(next_index) and next_index in data.index:
            # Return the state of the next time step
            return data.loc[next_index, data.columns[:-1]].values
        else:
            # If there is no next state, handle it (e.g., return None)
            return None
    else:
        # Handle the case where no matching row is found
        return None  # Or however you want to handle this case




def update_q_model(model, state, action, reward, next_state, learning_rate, discount_factor):
    # Predict Q-values for current state
    current_q = model.predict(state.reshape(1, -1))[0]

    # Predict Q-values for next state
    next_max_q = np.max(model.predict(next_state.reshape(1, -1))) if next_state is not None else 0

    # Update Q-value for the action taken
    current_q[action] = current_q[action] + learning_rate * (reward + discount_factor * next_max_q - current_q[action])

    # Fit model
    model.fit(state.reshape(1, -1), current_q.reshape(1, -1), epochs=1, verbose=0)
```

```
# def get_actual_usage(data, state):
#     # Find the index of the current state in the dataset
#     current_index = data.index[data.iloc[:, :-1].values == state].tolist()[0]
#     # Get the actual energy usage value from the dataset
#     actual_usage = data.iloc[current_index, -1]  # Assuming last column is energy usage
#     return actual_usage
def get_actual_usage(data, state):
    # Convert state array to a DataFrame row for comparison
    state_df = pd.DataFrame([state], columns=data.columns[:-1])  # Exclude the target column

    # Find the row in data that matches the state
    matching_rows = data[(data.iloc[:, :-1] == state_df.iloc[0]).all(axis=1)]

    # If a matching row is found, return its energy usage value
    if not matching_rows.empty:
        return matching_rows.iloc[0, -1]  # Assuming the energy usage is in the last column
    else:
        # Handle the case where no matching row is found
```

```
import matplotlib.pyplot as plt
import numpy as np

# Function to calculate reward
# ... (existing function) ...
```