

AlexNguyen_ElectricityForecasting

April 27, 2025

0.1 Time Series Forecasting - Electricity

0.1.1 Alex Nguyen

0.1.2 1. Read the dataset

```
[ ]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.dates as mdates
import matplotlib.pyplot as plt
import statsmodels.api as sm

from datetime import datetime
from pmdarima import preprocessing as AutoARIMA
from pmdarima.preprocessing import FourierFeaturizer
from sklearn.metrics import mean_absolute_error, root_mean_squared_error
from sklearn.model_selection import train_test_split
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.seasonal import seasonal_decompose
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from statsmodels.tsa.stattools import adfuller
from pmdarima import pipeline
```

```
[ ]: data = pd.read_csv('energydata_complete.csv')
data
```

```
[ ]:          date  Appliances  lights      T1    RH_1  \
0  2016-01-11 17:00:00        60      30  19.890000  47.596667
1  2016-01-11 17:10:00        60      30  19.890000  46.693333
2  2016-01-11 17:20:00        50      30  19.890000  46.300000
3  2016-01-11 17:30:00        50      40  19.890000  46.066667
4  2016-01-11 17:40:00        60      40  19.890000  46.333333
...
19730  2016-05-27 17:20:00       ...     ...      ...
19731  2016-05-27 17:30:00       ...     ...      ...
19732  2016-05-27 17:40:00       ...     ...      ...
19733  2016-05-27 17:50:00       ...     ...      ...
```

19734	2016-05-27	18:00:00	430	10	25.500000	46.600000	\
0	19.200000	44.790000	19.790000	44.730000	19.000000	...	17.033333
1	19.200000	44.722500	19.790000	44.790000	19.000000	...	17.066667
2	19.200000	44.626667	19.790000	44.933333	18.926667	...	17.000000
3	19.200000	44.590000	19.790000	45.000000	18.890000	...	17.000000
4	19.200000	44.530000	19.790000	45.000000	18.890000	...	17.000000
...
19730	25.890000	42.025714	27.200000	41.163333	24.700000	...	23.200000
19731	25.754000	42.080000	27.133333	41.223333	24.700000	...	23.200000
19732	25.628571	42.768571	27.050000	41.690000	24.700000	...	23.200000
19733	25.414000	43.036000	26.890000	41.290000	24.700000	...	23.200000
19734	25.264286	42.971429	26.823333	41.156667	24.700000	...	23.200000
0	45.5300	6.600000	733.5	92.000000	7.000000	63.000000	\
1	45.5600	6.483333	733.6	92.000000	6.666667	59.166667	
2	45.5000	6.366667	733.7	92.000000	6.333333	55.333333	
3	45.4000	6.250000	733.8	92.000000	6.000000	51.500000	
4	45.4000	6.133333	733.9	92.000000	5.666667	47.666667	
...
19730	46.7900	22.733333	755.2	55.666667	3.333333	23.666667	
19731	46.7900	22.600000	755.2	56.000000	3.500000	24.500000	
19732	46.7900	22.466667	755.2	56.333333	3.666667	25.333333	
19733	46.8175	22.333333	755.2	56.666667	3.833333	26.166667	
19734	46.8450	22.200000	755.2	57.000000	4.000000	27.000000	
0	Tdewpoint	rv1	rv2				
0	5.300000	13.275433	13.275433				
1	5.200000	18.606195	18.606195				
2	5.100000	28.642668	28.642668				
3	5.000000	45.410389	45.410389				
4	4.900000	10.084097	10.084097				
...				
19730	13.333333	43.096812	43.096812				
19731	13.300000	49.282940	49.282940				
19732	13.266667	29.199117	29.199117				
19733	13.233333	6.322784	6.322784				
19734	13.200000	34.118851	34.118851				

[19735 rows x 29 columns]

0.1.3 2. Analyse and visualise the data

2.1 Skimming data

```
[ ]: # check data type and NA  
data.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
```

```
[ ]: data.columns
```

```
[ ]: 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')
```

```
[ ]: # Rv1 and rv2 are introduced to dataset to reduce features from initial dataset
    ↪to test Boruta algorithm [1]. We don't need them anymore, so drop.
data = data.drop(['rv1', 'rv2'], axis = 1)
data.columns
```

```
[ ]: 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'],
      dtype='object')
```

```
[ ]: # rename variables
rename_dict = {
    'Appliances': 'appliance',
    'lights': 'light',
    'T1': 'temp_kitchen',
    'RH_1': 'humid_kitchen',
    'T2': 'temp_living',
    'RH_2': 'humid_living',
    'T3': 'temp_laundry',
    'RH_3': 'humid_laundry',
    'T4': 'temp_office',
    'RH_4': 'humid_office',
    'T5': 'temp_bath',
    'RH_5': 'humid_bath',
    'T6': 'temp_outbuilding',
    'RH_6': 'humid_outbuilding',
    'T7': 'temp_iron',
    'RH_7': 'humid_iron',
    'T8': 'temp_kid',
    'RH_8': 'humid_kid',
    'T9': 'temp_parent',
    'RH_9': 'humid_parent',
    'T_out': 'tempt_weather',
    'Press_mm hg': 'pressure_weather',
    'RH_out': 'humid_weather',
    'Windspeed': 'wind_weather',
    'Visibility': 'vis_weather',
    'Tdewpoint': 'tdew_weather',
    'rv1': 'random_1',
    'rv2': 'random_2'
}
data.rename(columns=rename_dict, inplace=True)
data.columns
```

```
[ ]: Index(['date', 'appliance', 'light', 'temp_kitchen', 'humid_kitchen',
       'temp_living', 'humid_living', 'temp_laundry', 'humid_laundry',
       'temp_office', 'humid_office', 'temp_bath', 'humid_bath',
       'temp_outbuilding', 'humid_outbuilding', 'temp_iron', 'humid_iron',
       'temp_kid', 'humid_kid', 'temp_parent', 'humid_parent', 'tempt_weather',
       'pressure_weather', 'humid_weather', 'wind_weather', 'vis_weather',
       'tdew_weather'],
      dtype='object')
```

```
[ ]: # as [1, p. 93], time information is the most important feature to appliance's energy consumption, we create this variable as well
      data['date'] = pd.to_datetime(data['date'], format='%Y-%m-%d %H:%M:%S', utc=True)

def convert_to_seconds(x):
    return x.hour * 3600 + x.minute * 60 + x.second

data['sec_midnight'] = data['date'].apply(convert_to_seconds)
data['sec_midnight'].describe()
```

```
[ ]: count      19735.000000
mean       42907.129465
std        24940.020831
min         0.000000
25%     21600.000000
50%     43200.000000
75%     64200.000000
max     85800.000000
Name: sec_midnight, dtype: float64
```

```
[ ]: #convert date to index
data.index = pd.to_datetime(data.date)
data.drop('date', axis=1, inplace=True)
data.sort_index(inplace=True)
data.head()
```

```
[ ]:          appliance  light  temp_kitchen  humid_kitchen \
date
2016-01-11 17:00:00+00:00      60      30      19.89      47.596667
2016-01-11 17:10:00+00:00      60      30      19.89      46.693333
2016-01-11 17:20:00+00:00      50      30      19.89      46.300000
2016-01-11 17:30:00+00:00      50      40      19.89      46.066667
2016-01-11 17:40:00+00:00      60      40      19.89      46.333333

                           temp_living  humid_living  temp_laundry \
date
2016-01-11 17:00:00+00:00      19.2      44.790000      19.79
```

2016-01-11 17:10:00+00:00	19.2	44.722500	19.79
2016-01-11 17:20:00+00:00	19.2	44.626667	19.79
2016-01-11 17:30:00+00:00	19.2	44.590000	19.79
2016-01-11 17:40:00+00:00	19.2	44.530000	19.79
date			
2016-01-11 17:00:00+00:00	44.730000	19.000000	45.566667
2016-01-11 17:10:00+00:00	44.790000	19.000000	45.992500
2016-01-11 17:20:00+00:00	44.933333	18.926667	45.890000
2016-01-11 17:30:00+00:00	45.000000	18.890000	45.723333
2016-01-11 17:40:00+00:00	45.000000	18.890000	45.530000
date			
2016-01-11 17:00:00+00:00	48.900000	17.033333	45.53
2016-01-11 17:10:00+00:00	48.863333	17.066667	45.56
2016-01-11 17:20:00+00:00	48.730000	17.000000	45.50
2016-01-11 17:30:00+00:00	48.590000	17.000000	45.40
2016-01-11 17:40:00+00:00	48.590000	17.000000	45.40
date			
2016-01-11 17:00:00+00:00	6.600000	733.5	92.0
2016-01-11 17:10:00+00:00	6.483333	733.6	92.0
2016-01-11 17:20:00+00:00	6.366667	733.7	92.0
2016-01-11 17:30:00+00:00	6.250000	733.8	92.0
2016-01-11 17:40:00+00:00	6.133333	733.9	92.0
date			
2016-01-11 17:00:00+00:00	7.000000	63.000000	5.3
2016-01-11 17:10:00+00:00	6.666667	59.166667	5.2
2016-01-11 17:20:00+00:00	6.333333	55.333333	5.1
2016-01-11 17:30:00+00:00	6.000000	51.500000	5.0
2016-01-11 17:40:00+00:00	5.666667	47.666667	4.9
date			
2016-01-11 17:00:00+00:00	61200		
2016-01-11 17:10:00+00:00	61800		
2016-01-11 17:20:00+00:00	62400		
2016-01-11 17:30:00+00:00	63000		
2016-01-11 17:40:00+00:00	63600		

[5 rows x 27 columns]

2.2 Analyse and visualise data

```
[ ]: # summary numeric  
data.describe()
```

```
[ ]:          appliance      light  temp_kitchen  humid_kitchen  temp_living  \  
count  19735.000000  19735.000000  19735.000000  19735.000000  19735.000000  
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  
  
          humid_living  temp_laundry  humid_laundry  temp_office  humid_office  \  
count  19735.000000  19735.000000  19735.000000  19735.000000  19735.000000  
mean   40.420420    22.267611    39.242500    20.855335    39.026904  
std    4.069813    2.006111    3.254576    2.042884    4.341321  
min    20.463333    17.200000    28.766667    15.100000    27.660000  
25%   37.900000    20.790000    36.900000    19.530000    35.530000  
50%   40.500000    22.100000    38.530000    20.666667    38.400000  
75%   43.260000    23.290000    41.760000    22.100000    42.156667  
max   56.026667    29.236000    50.163333    26.200000    51.090000  
  
          ...       humid_kid  temp_parent  humid_parent  tempt_weather  \  
count  ...  19735.000000  19735.000000  19735.000000  19735.000000  
mean   ...  42.936165    19.485828    41.552401    7.411665  
std    ...  5.224361    2.014712    4.151497    5.317409  
min    ...  29.600000    14.890000    29.166667    -5.000000  
25%   ...  39.066667    18.000000    38.500000    3.666667  
50%   ...  42.375000    19.390000    40.900000    6.916667  
75%   ...  46.536000    20.600000    44.338095    10.408333  
max   ...  58.780000    24.500000    53.326667    26.100000  
  
          pressure_weather  humid_weather  wind_weather  vis_weather  \  
count  19735.000000  19735.000000  19735.000000  19735.000000  
mean   755.522602    79.750418    4.039752    38.330834  
std    7.399441     14.901088    2.451221    11.794719  
min    729.300000    24.000000    0.000000    1.000000  
25%   750.933333    70.333333    2.000000    29.000000  
50%   756.100000    83.666667    3.666667    40.000000  
75%   760.933333    91.666667    5.500000    40.000000  
max   772.300000    100.000000   14.000000    66.000000  
  
          tdew_weather  sec_midnight  
count  19735.000000  19735.000000  
mean   3.760707    42907.129465
```

```

std          4.194648  24940.020831
min         -6.600000   0.000000
25%        0.900000  21600.000000
50%        3.433333  43200.000000
75%        6.566667  64200.000000
max        15.500000  85800.000000

```

[8 rows x 27 columns]

```

[ ]: # define sensor and weather feature variables
sensor = ['light', 'sec_midnight', 'temp_kitchen', 'humid_kitchen', ↴
    ↵'temp_living', 'humid_living', 'temp_laundry',
    ↵'humid_laundry', 'temp_office', 'humid_office', 'temp_bath', ↴
    ↵'humid_bath', 'temp_outbuilding', 'humid_outbuilding',
    ↵'temp_iron', 'humid_iron', 'temp_kid', 'humid_kid', 'temp_parent', ↴
    ↵'humid_parent']

weather = ['tempt_weather', 'pressure_weather', 'humid_weather', 'wind_weather', ↴
    ↵'vis_weather', 'tdew_weather']

```

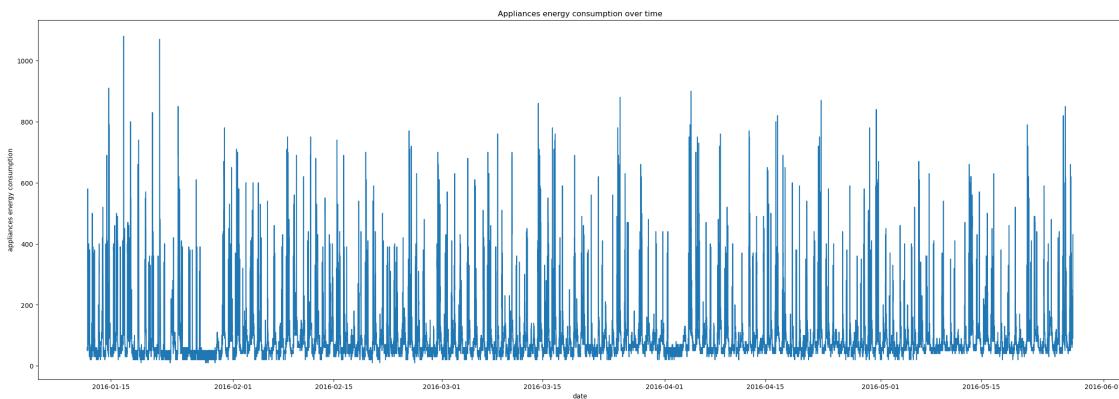
2.2.1 Target visualisation

```

[ ]: # visualise target
import warnings
warnings.filterwarnings("ignore")

plt.figure(figsize=(30, 10))
sns.lineplot(data['appliance'])
plt.title('Appliances energy consumption over time')
plt.xlabel('date')
plt.ylabel('appliances energy consumption')
plt.show()

```

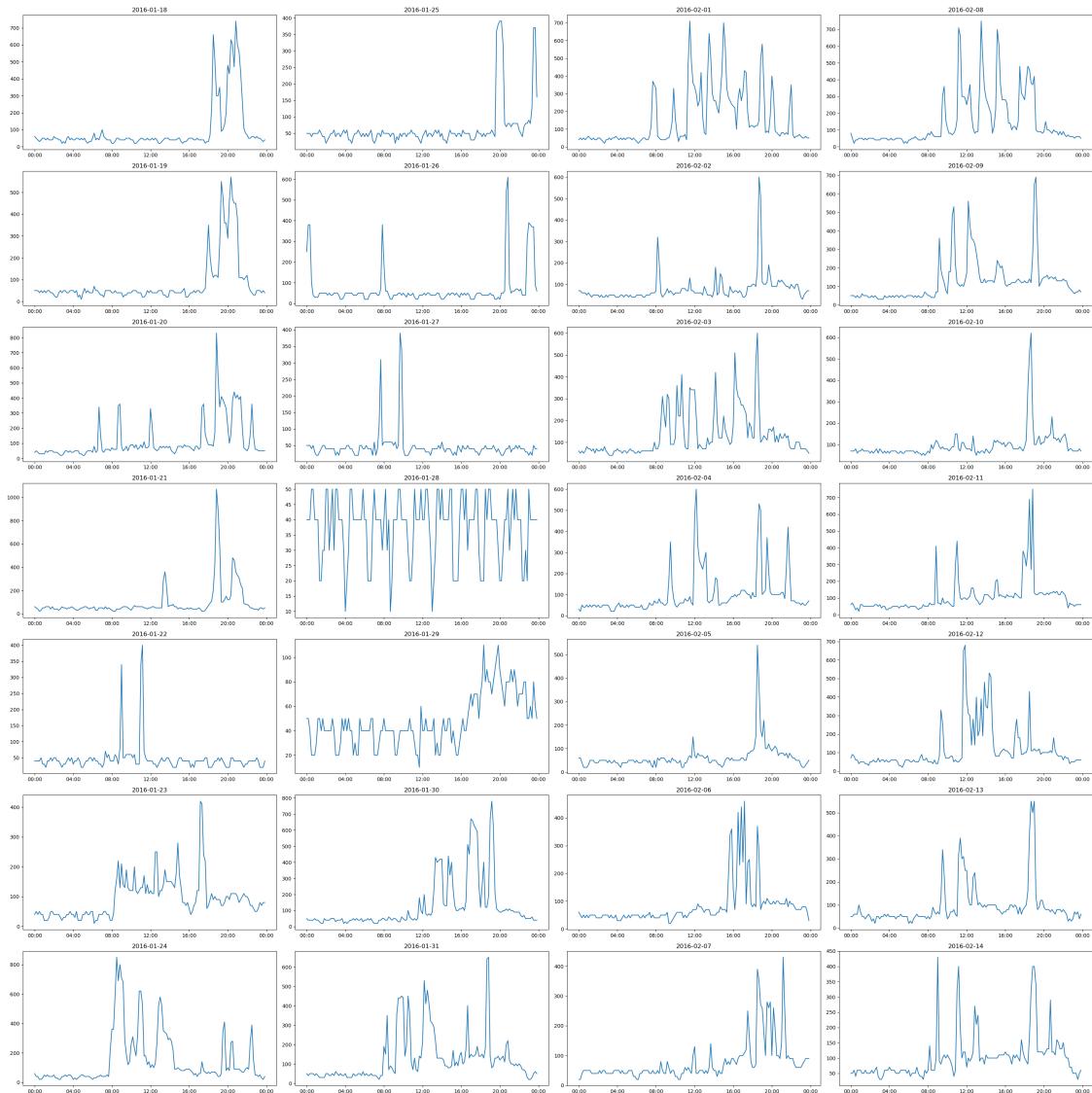


```
[ ]: # have a closer look for 4 weeks data
start_date = '2016-01-18'
end_date = pd.to_datetime(start_date) + pd.DateOffset(days=27)

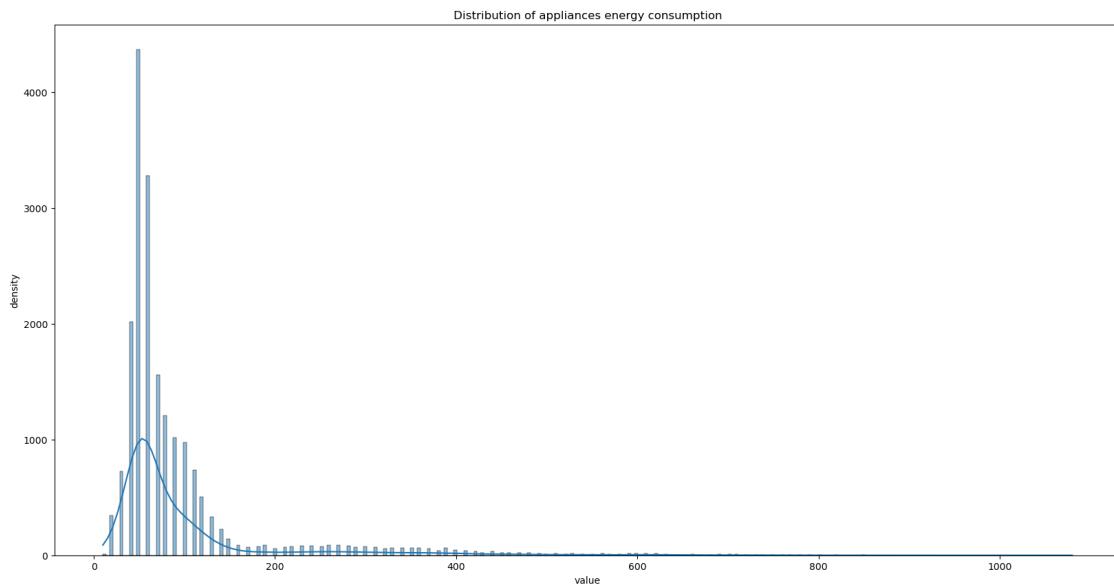
fig, axes = plt.subplots(nrows=7, ncols=4, figsize=(30, 30))

for i, day in enumerate(pd.date_range(start=start_date, end=end_date)):
    daily_data = data.loc[day.strftime('%Y-%m-%d')]
    ax = axes[i % 7, i // 7]
    ax.plot(daily_data.index, daily_data['appliance'])
    ax.xaxis.set_major_locator(mdates.HourLocator(interval=4))
    ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))
    ax.set_title(day.strftime('%Y-%m-%d'))

plt.tight_layout()
plt.show()
```

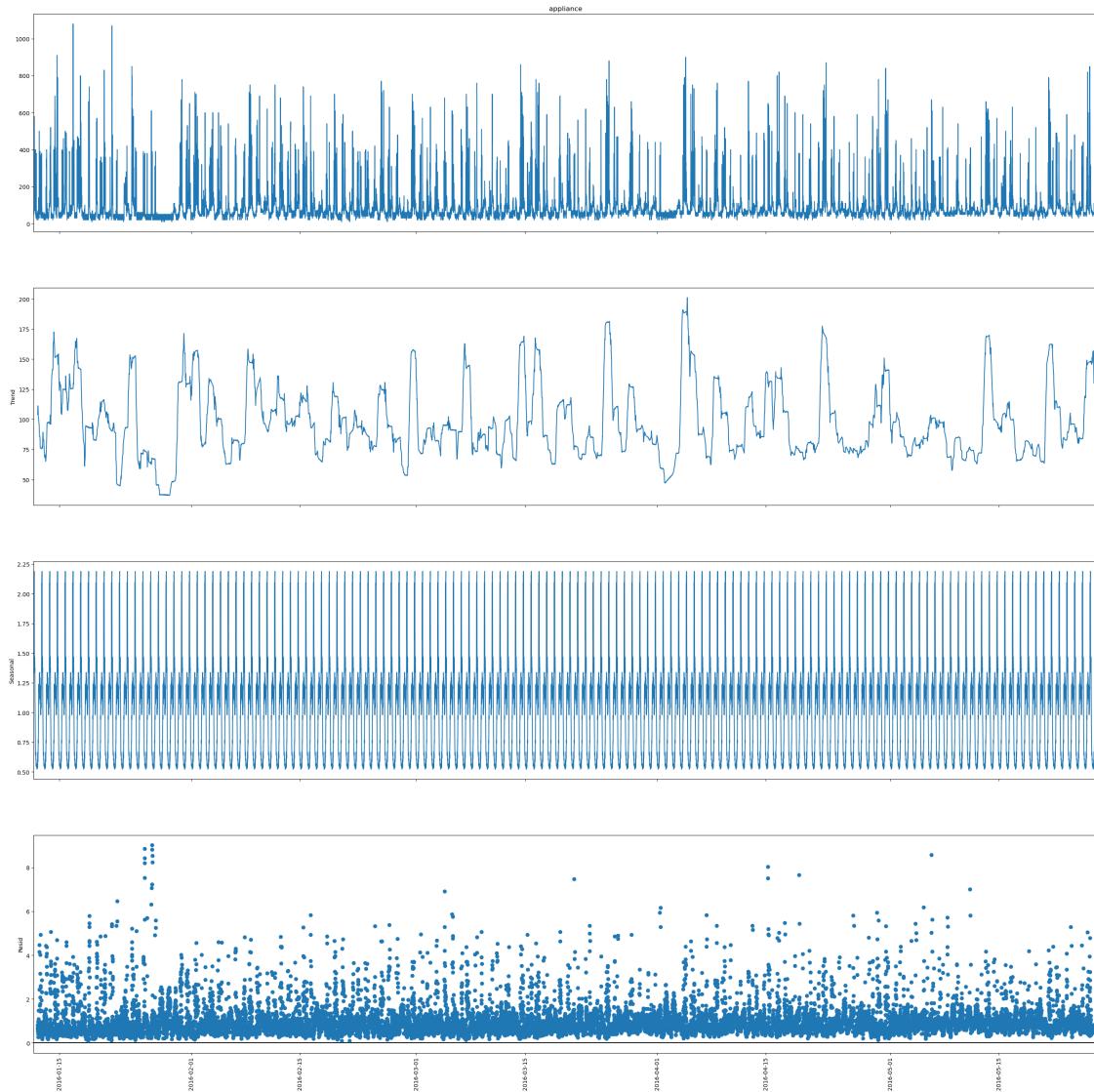


```
[ ]: # distribution of target
plt.figure(figsize=(20, 10))
sns.histplot(data['appliance'], kde=True)
plt.title('Distribution of appliances energy consumption')
plt.xlabel('value')
plt.ylabel('density')
plt.show()
```



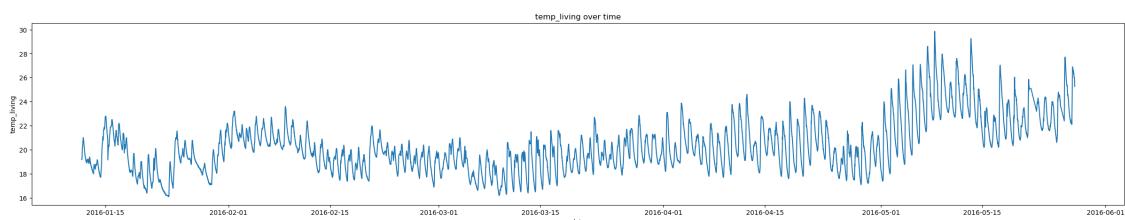
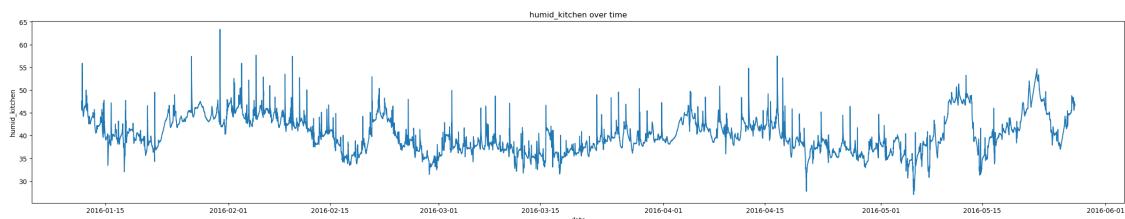
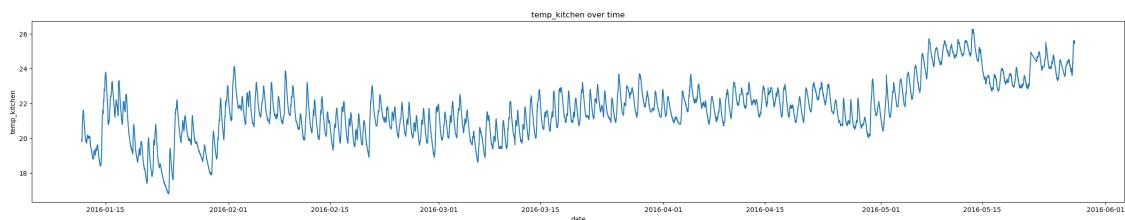
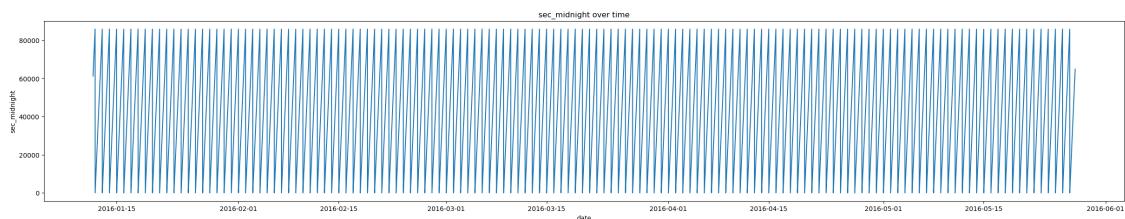
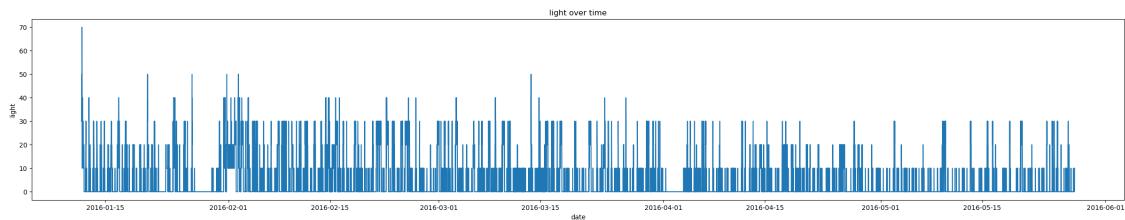
```
[ ]: # too much noise in data appliance, decompose to separate trend, seasonality, and noise [4, p. 401-402]
plt.figure(figsize=(30, 30))
dcp_appliance = sm.tsa.seasonal_decompose(data['appliance'], model='multiplicative', period=144)
dcp_appliance.plot()
plt.gcf().set_size_inches(30, 30)
plt.xticks(rotation=90)
plt.show()
```

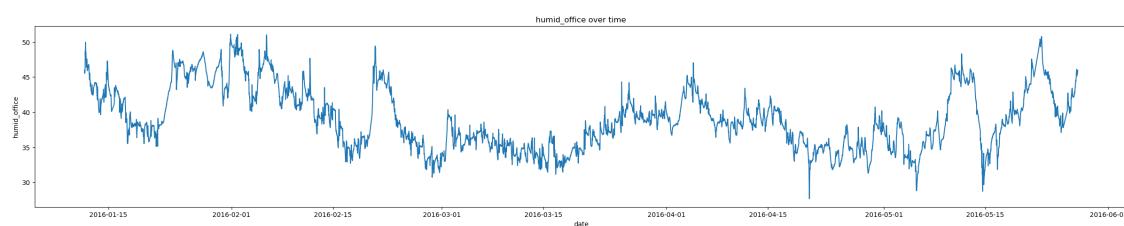
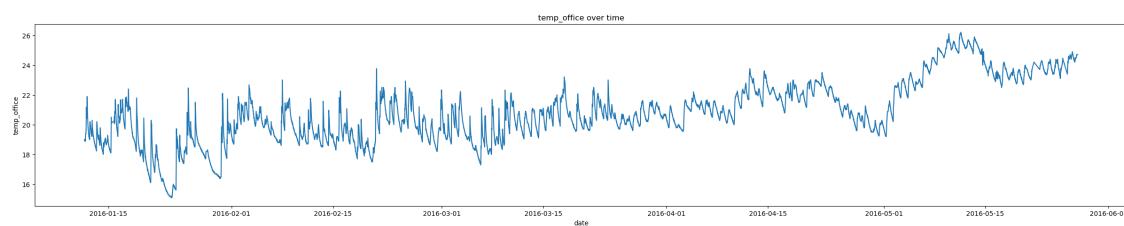
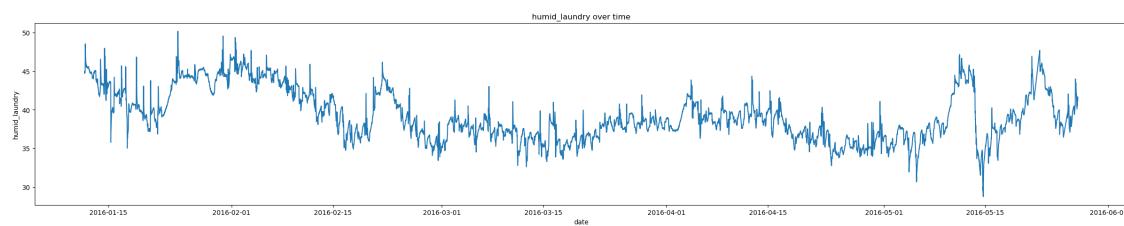
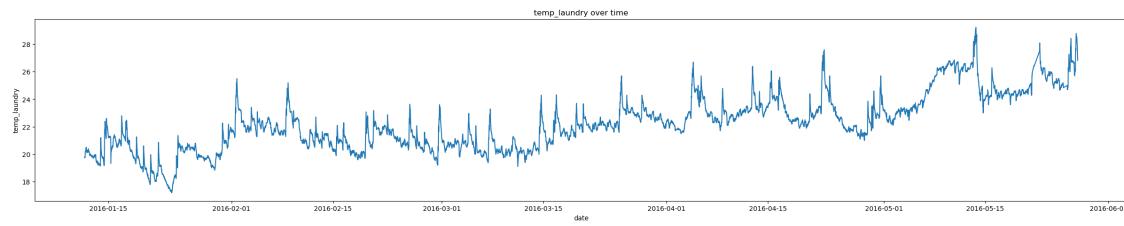
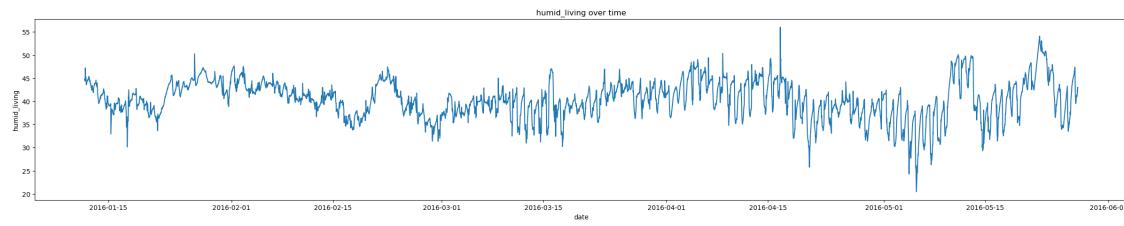
<Figure size 3000x3000 with 0 Axes>

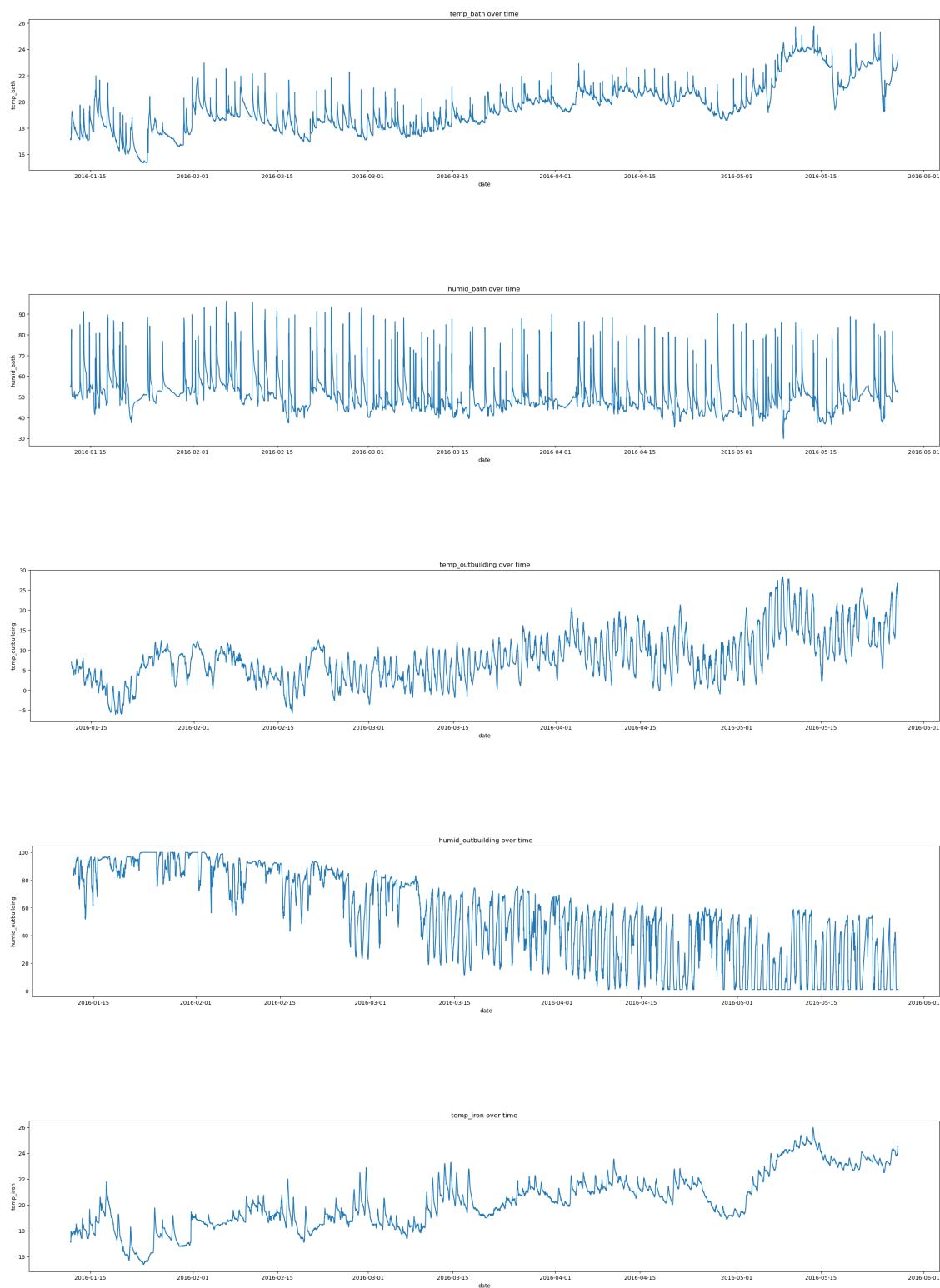


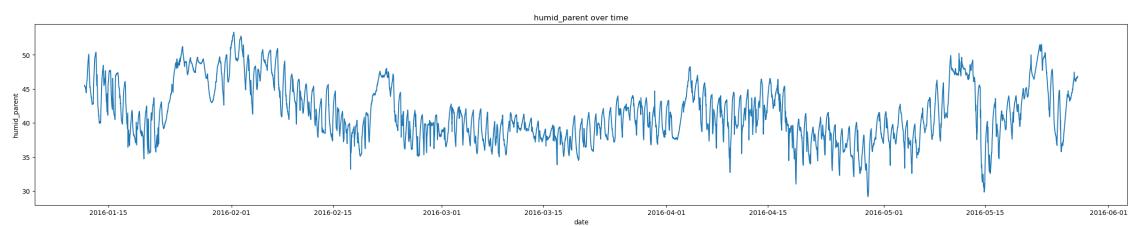
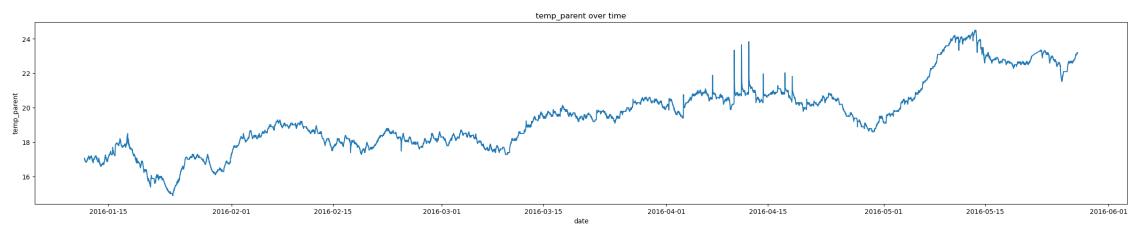
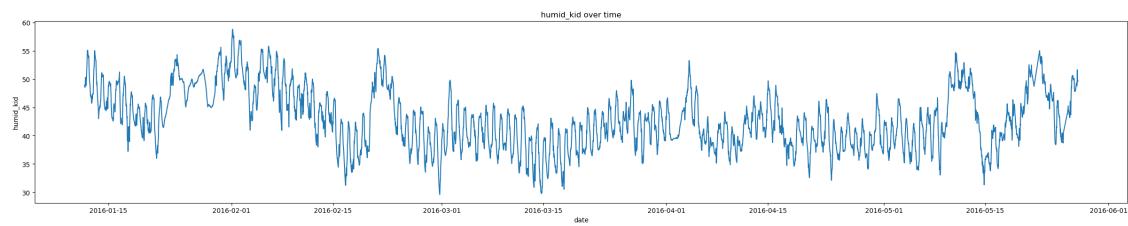
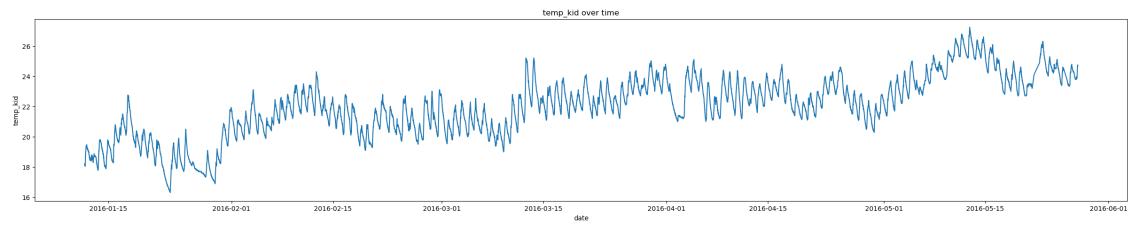
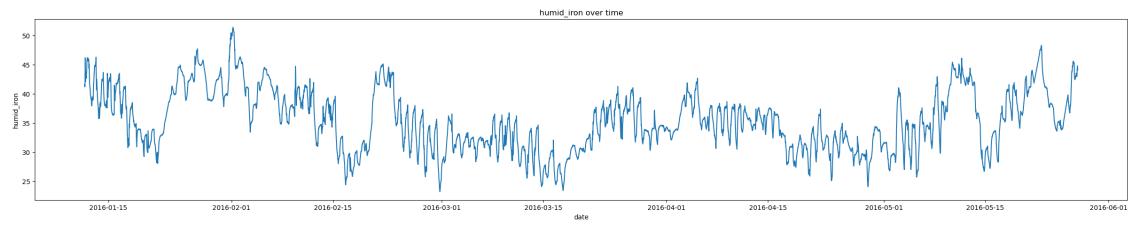
2.2.2 Sensor features visualisation

```
[ ]: # visualise sensor features
for feature in sensor:
    plt.figure(figsize=(30, 5))
    sns.lineplot(data[feature])
    plt.title(f'{feature} over time')
    plt.xlabel('date')
    plt.ylabel(f'{feature}')
    plt.show()
```





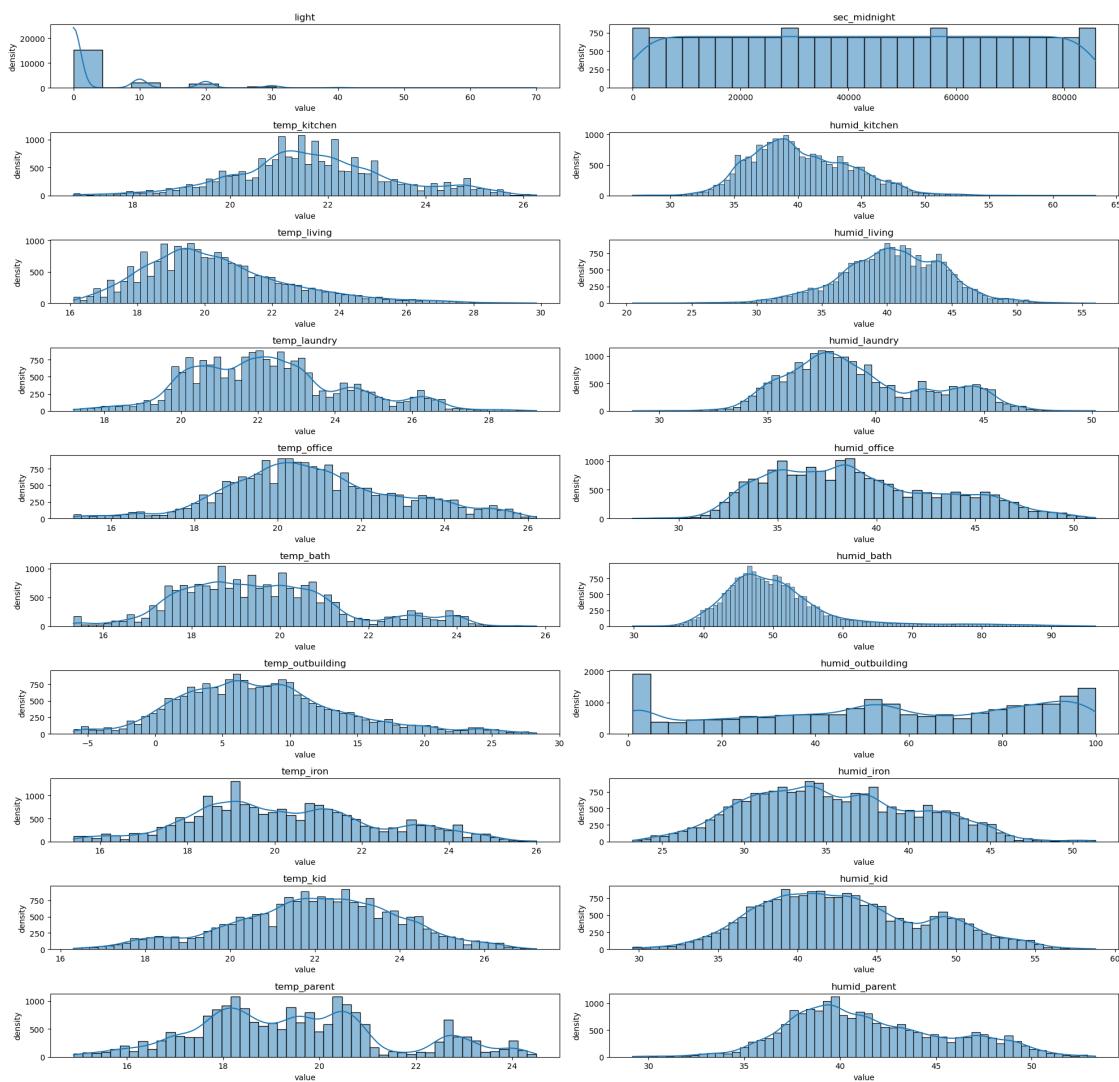




```
[ ]: # distribution of sensor features
fig, axs = plt.subplots(10, 2, figsize=(20,20))
axs = axs.flatten()

for ax, feature in zip(axs, sensor):
    sns.histplot(data[feature], kde=True, ax=ax)
    ax.set_title(feature)
    ax.set_xlabel('value')
    ax.set_ylabel('density')

plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

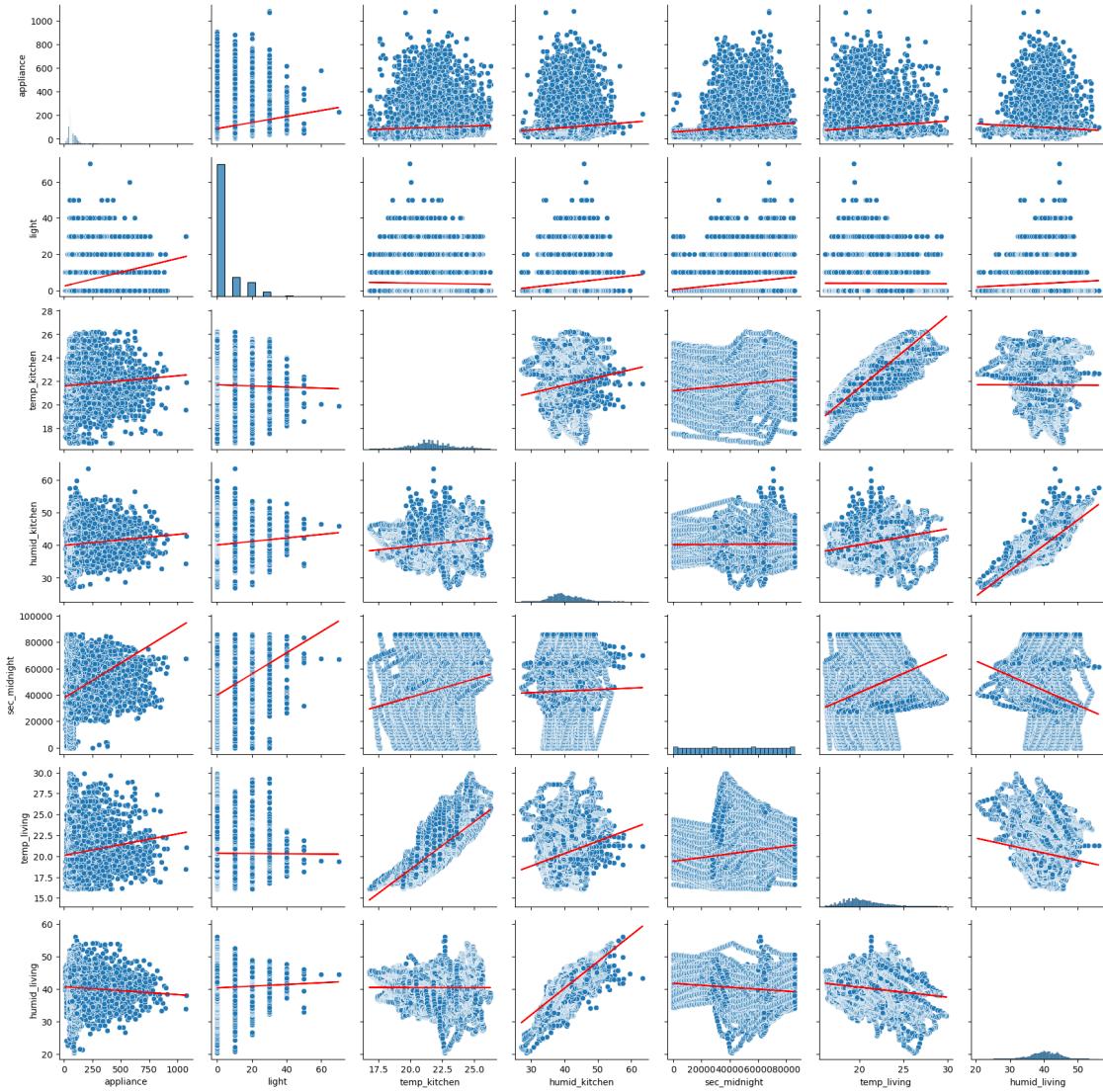


- Check relationship between target and sensor features:

```
[ ]: # define trend line
def plot_trend(x, y, **kwargs):
    coeffs = np.polyfit(x, y, 1)
    plt.plot(x, coeffs[0] * x + coeffs[1], color='red')

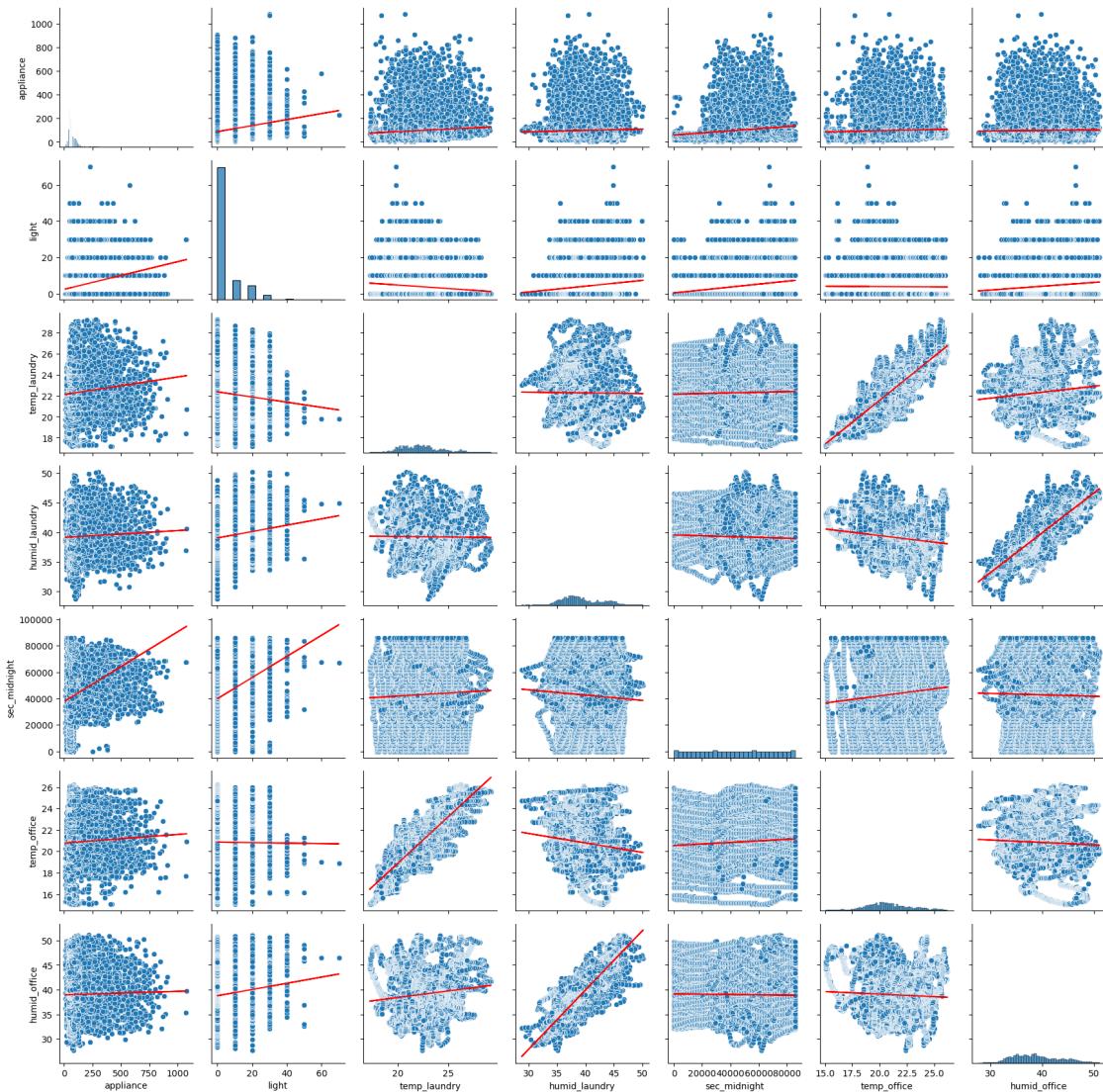
[ ]: # sensor features too large, we divided into different plots
sensor_appliance1 = data[['appliance', 'light', 'temp_kitchen', 'humid_kitchen', 'sec_midnight', 'temp_living', 'humid_living']].copy()

g = sns.PairGrid(sensor_appliance1)
g.map_offdiag(sns.scatterplot)
g.map_offdiag(plot_trend)
g.map_diag(sns.histplot)
plt.show()
```



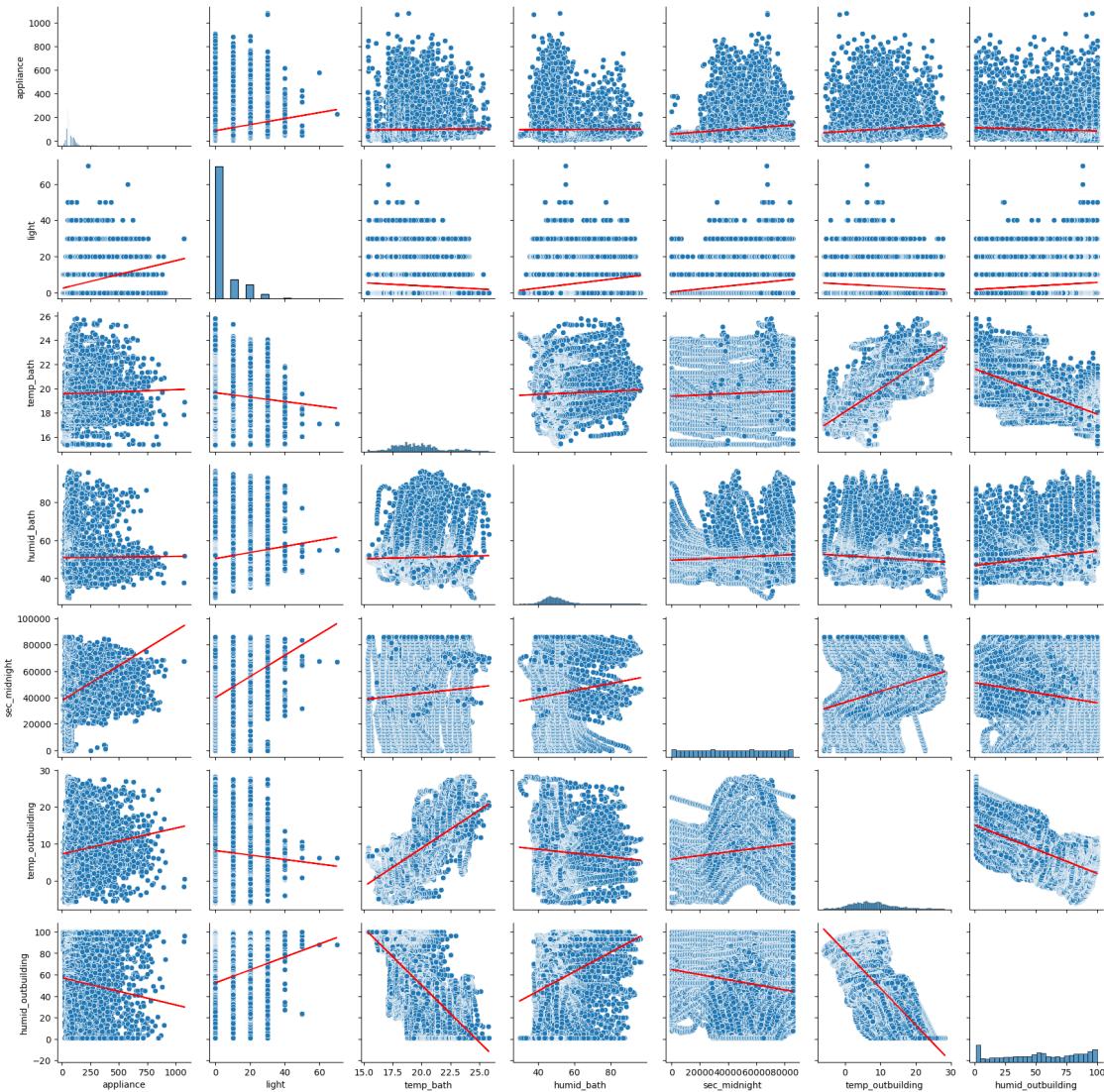
```
[ ]: # sensor features too large, we divided into different plots
sensor_appliance2 = data[['appliance', 'light', 'temp_laundry', 'humid_laundry',
                           'sec_midnight', 'temp_office', 'humid_office']].copy()

g = sns.PairGrid(sensor_appliance2)
g.map_offdiag(sns.scatterplot)
g.map_offdiag(plot_trend)
g.map_diag(sns.histplot)
plt.show()
```



```
[ ]: # sensor features too large, we divided into different plots
sensor_appliance3 = data[['appliance', 'light', 'temp_bath', 'humid_bath',
                           'sec_midnight', 'temp_outbuilding', □
                           ↵'humid_outbuilding']].copy()

g = sns.PairGrid(sensor_appliance3)
g.map_offdiag(sns.scatterplot)
g.map_offdiag(plot_trend)
g.map_diag(sns.histplot)
plt.show()
```



```
[ ]: # sensor features too large, we divided into different plots
```

```

sensor_appliance4 = data[['appliance', 'light', 'temp_iron', 'humid_iron', 'sec_midnight',
                           'temp_kid', 'humid_kid', 'temp_parent', 'humid_parent']] .copy()

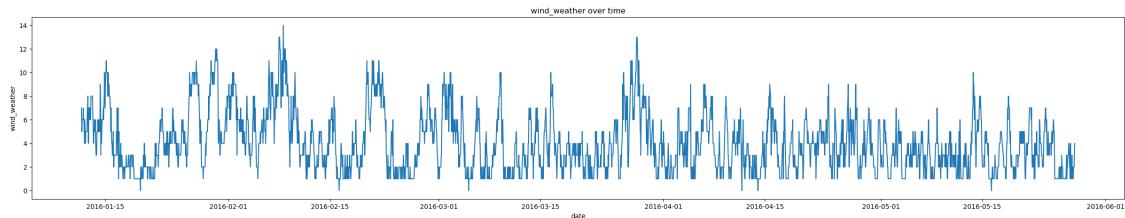
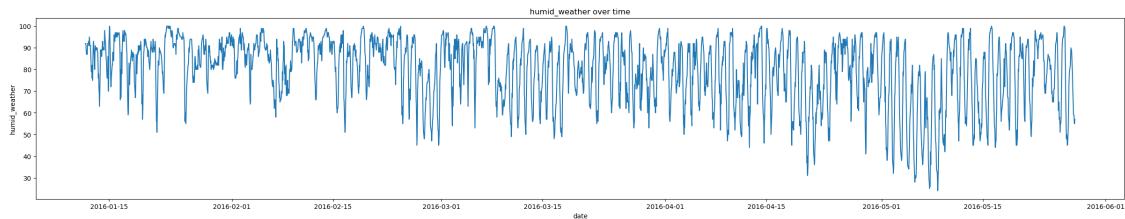
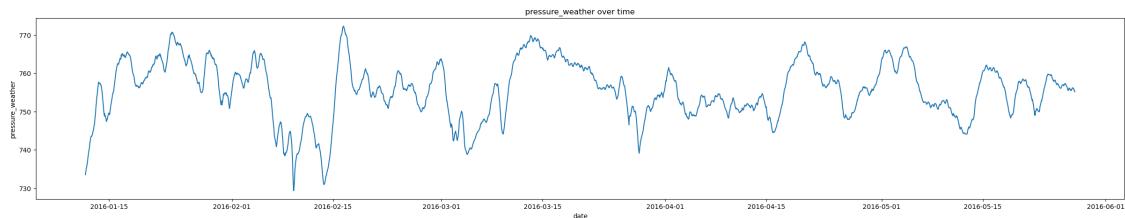
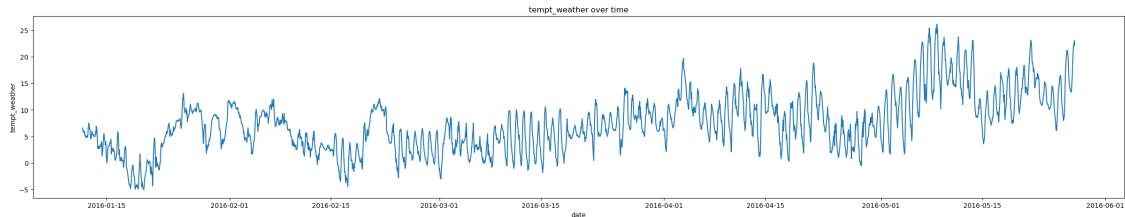
g = sns.PairGrid(sensor_appliance4)
g.map_offdiag(sns.scatterplot)
g.map_offdiag(plot_trend)
g.map_diag(sns.histplot)
plt.show()

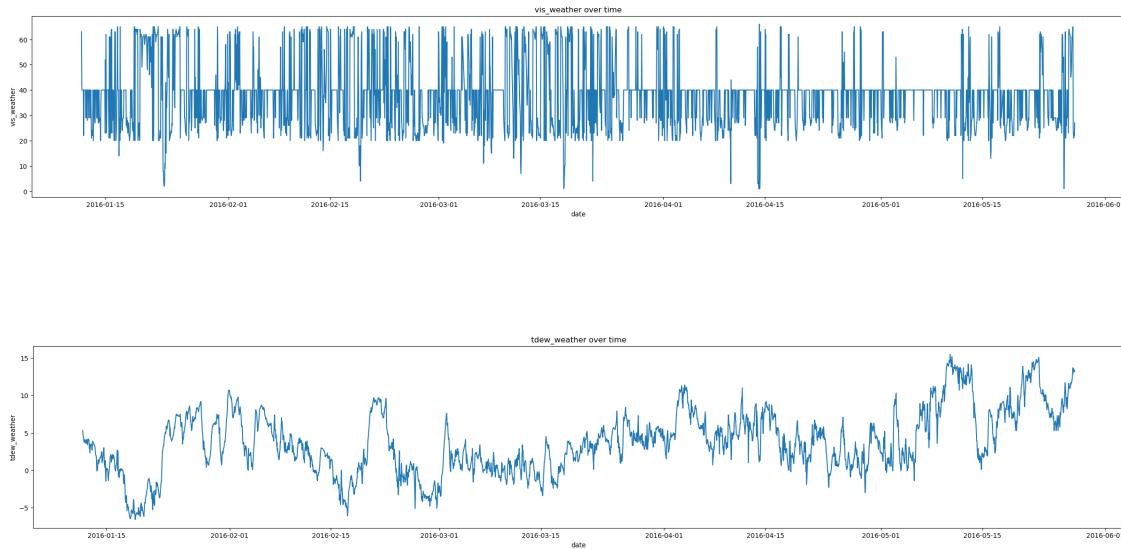
```



2.2.3 Weather features visualisation

```
[ ]: # visualise weather features
for feature in weather:
    plt.figure(figsize=(30, 5))
    sns.lineplot(data[feature])
    plt.title(f'{feature} over time')
    plt.xlabel('date')
    plt.ylabel(f'{feature}')
    plt.show()
```

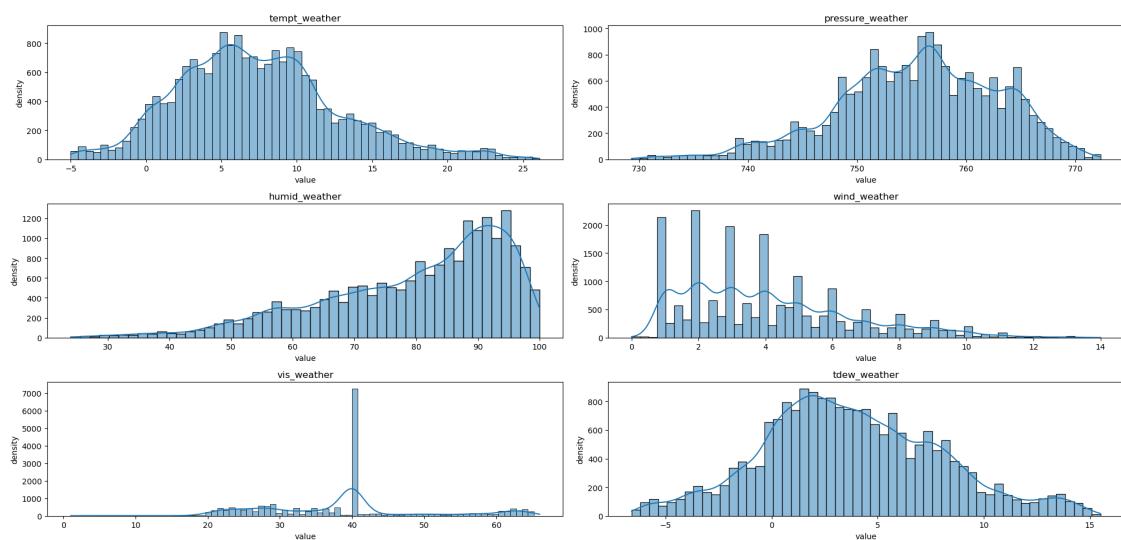




```
[ ]: # distribution of weather features
fig, axs = plt.subplots(3, 2, figsize=(20,10))
axs = axs.flatten()

for ax, feature in zip(axs, weather):
    sns.histplot(data[feature], kde=True, ax=ax)
    ax.set_title(feature)
    ax.set_xlabel('value')
    ax.set_ylabel('density')

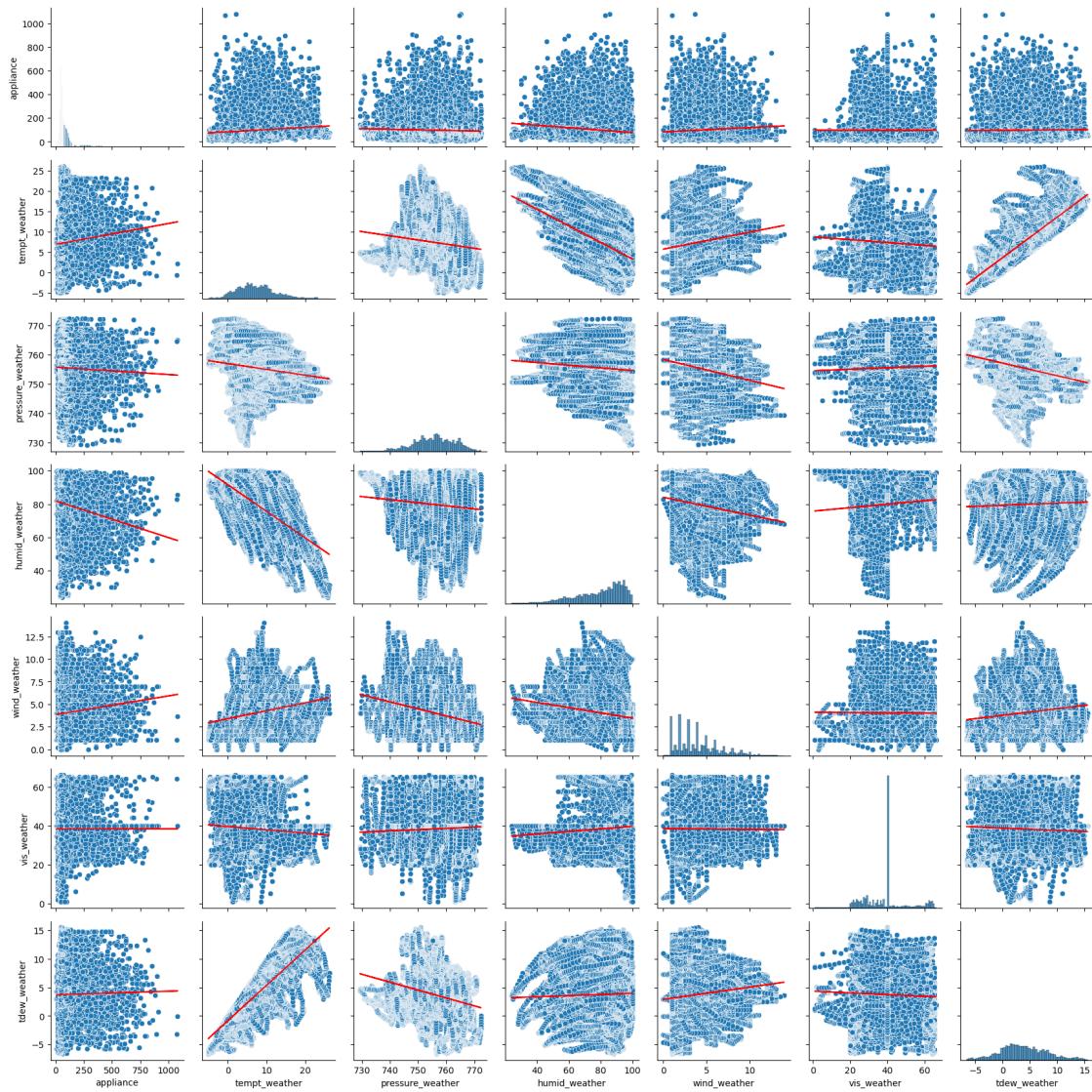
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



- Check relationship between target and weather features:

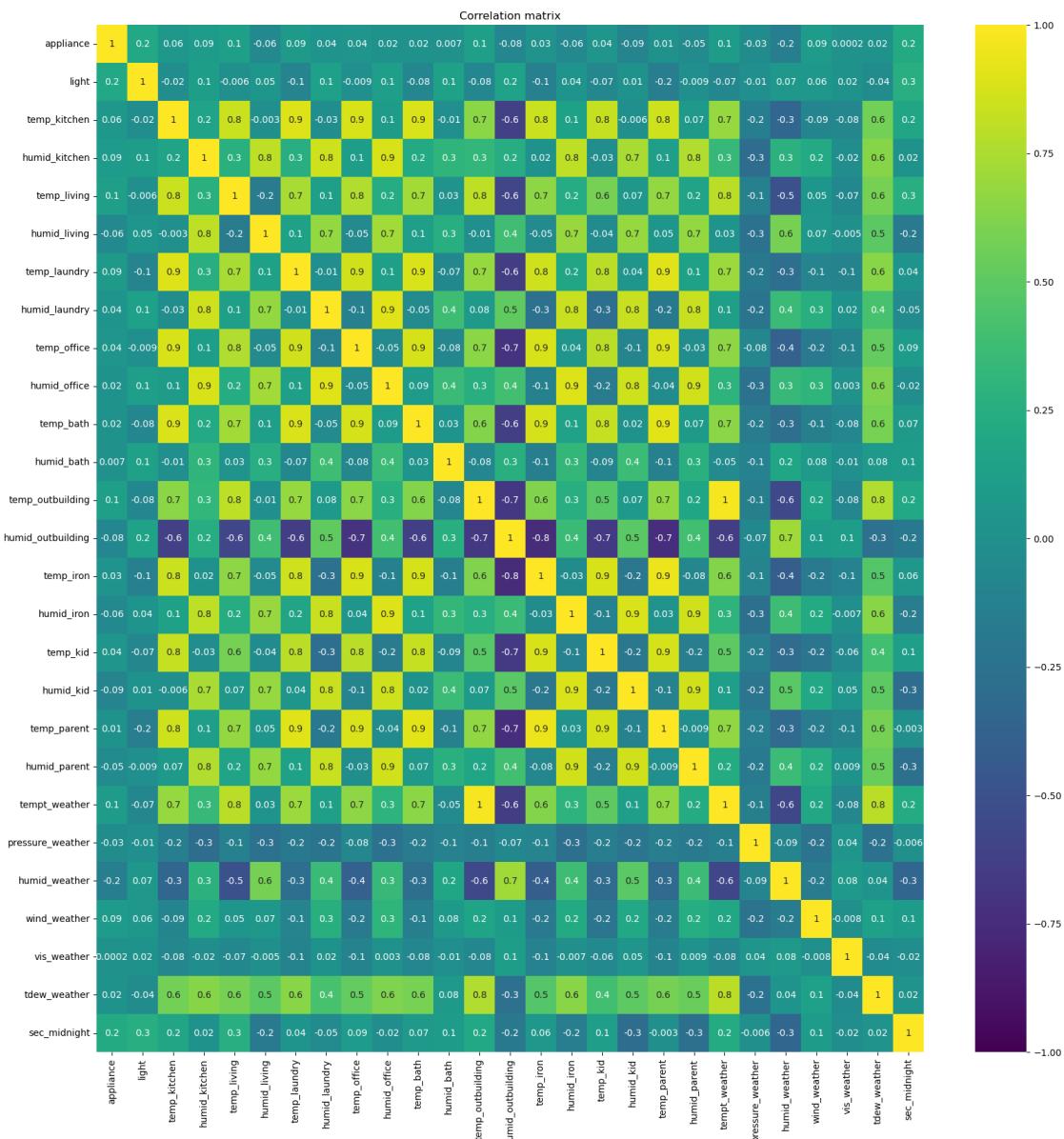
```
[ ]: # weather features
weather_appliance = data[['appliance', 'tempt_weather', 'pressure_weather', □
    ↵'humid_weather',
    'wind_weather', 'vis_weather', 'tdew_weather']].copy()

g = sns.PairGrid(weather_appliance)
g.map_offdiag(sns.scatterplot)
g.map_offdiag(plot_trend)
g.map_diag(sns.histplot)
plt.show()
```



2.3 Check correlation

```
[ ]: plt.figure(figsize=(20, 20))
corr = data.corr(numeric_only=True)
matrix = np.triu(corr)
sns.heatmap(corr, vmax=1.0, vmin=-1.0, fmt='.1g', annot=True, cmap='viridis')
plt.title('Correlation matrix')
plt.show()
```



2.4 Analyse discussion

2.4.1 Relationship between variables From 2.3, there are some observations:

- Appliances energy consumption has a high variability. When looking at loser data within 1 month, it seems that it is not seasonal by the day of the week but by hourly and daily. It appears to be affected by the previous day's consumption. When decomposing with multiplicative method, no trend obviously, but have uniform seasonal change. Non-uniform noise that represents outliers and missing values.
- Light energy consumption is also quite similar to appliance energy consumption but has less variability. All the sensor features appears to have seasonal data by daily.
- All features, including sensor and weather appears non-uniform distribution -> need scaled
- It seems like the appliance energy consumption increases if light energy consumption, and temperature in all rooms increase. Energy consumptions increase from midnight the previous day to the next midnight. There is no strong evidence to show any relationship between humidity, weather features and energy consumption.

2.4.2 Model selection We'll use 3 different methods for time series forecasting as [4, p. 4] to compare the results:

- Smoothing based method: Seasonal Naive as a baseline
- Regression based method: AutoARIMA [5]
- Machine learning based method: LSTM [5]

2.4.3 Feature selections and Pre-processing steps With [1, pp. 92-93], we've known that all features have large correlation with each features and helps to reduce RMSE of appliances energy consumption prediction. However, many features have small correlation with appliances energy consumption, we'll use PCA to reduce the dimension for better forecasting models. [7]

0.1.4 3. Implement prediction models

3.1 Pre-processing

```
[ ]: # create data for modelling
model_data = data.copy()
model_data.head()
```

	appliance	light	temp_kitchen	humid_kitchen	\
date					
2016-01-11 17:00:00+00:00	60	30	19.89	47.596667	
2016-01-11 17:10:00+00:00	60	30	19.89	46.693333	
2016-01-11 17:20:00+00:00	50	30	19.89	46.300000	
2016-01-11 17:30:00+00:00	50	40	19.89	46.066667	
2016-01-11 17:40:00+00:00	60	40	19.89	46.333333	

	temp_living	humid_living	temp_laundry	\
date				
2016-01-11 17:00:00+00:00	19.2	44.790000	19.79	
2016-01-11 17:10:00+00:00	19.2	44.722500	19.79	
2016-01-11 17:20:00+00:00	19.2	44.626667	19.79	
2016-01-11 17:30:00+00:00	19.2	44.590000	19.79	
2016-01-11 17:40:00+00:00	19.2	44.530000	19.79	

	humid_laundry	temp_office	humid_office	...	\
date					
2016-01-11 17:00:00+00:00	44.730000	19.000000	45.566667	...	

```

2016-01-11 17:10:00+00:00      44.790000    19.000000    45.992500 ...
2016-01-11 17:20:00+00:00      44.933333    18.926667    45.890000 ...
2016-01-11 17:30:00+00:00      45.000000    18.890000    45.723333 ...
2016-01-11 17:40:00+00:00      45.000000    18.890000    45.530000 ...

                           humid_kid  temp_parent  humid_parent \
date
2016-01-11 17:00:00+00:00    48.900000    17.033333    45.53
2016-01-11 17:10:00+00:00    48.863333    17.066667    45.56
2016-01-11 17:20:00+00:00    48.730000    17.000000    45.50
2016-01-11 17:30:00+00:00    48.590000    17.000000    45.40
2016-01-11 17:40:00+00:00    48.590000    17.000000    45.40

                           tempt_weather  pressure_weather  humid_weather \
date
2016-01-11 17:00:00+00:00     6.600000      733.5        92.0
2016-01-11 17:10:00+00:00     6.483333      733.6        92.0
2016-01-11 17:20:00+00:00     6.366667      733.7        92.0
2016-01-11 17:30:00+00:00     6.250000      733.8        92.0
2016-01-11 17:40:00+00:00     6.133333      733.9        92.0

                           wind_weather  vis_weather  tdew_weather \
date
2016-01-11 17:00:00+00:00     7.000000     63.000000     5.3
2016-01-11 17:10:00+00:00     6.666667     59.166667     5.2
2016-01-11 17:20:00+00:00     6.333333     55.333333     5.1
2016-01-11 17:30:00+00:00     6.000000     51.500000     5.0
2016-01-11 17:40:00+00:00     5.666667     47.666667     4.9

                           sec_midnight
date
2016-01-11 17:00:00+00:00      61200
2016-01-11 17:10:00+00:00      61800
2016-01-11 17:20:00+00:00      62400
2016-01-11 17:30:00+00:00      63000
2016-01-11 17:40:00+00:00      63600

```

[5 rows x 27 columns]

[]: model_data.columns

[]: Index(['appliance', 'light', 'temp_kitchen', 'humid_kitchen', 'temp_living',
 'humid_living', 'temp_laundry', 'humid_laundry', 'temp_office',
 'humid_office', 'temp_bath', 'humid_bath', 'temp_outbuilding',
 'humid_outbuilding', 'temp_iron', 'humid_iron', 'temp_kid', 'humid_kid',
 'temp_parent', 'humid_parent', 'tempt_weather', 'pressure_weather',
 'humid_weather', 'wind_weather', 'vis_weather', 'tdew_weather',

```

'sec_midnight'],
dtype='object')

[ ]: # scale data for pca
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

features = ['light', 'temp_kitchen', 'humid_kitchen', 'temp_living',
            'humid_living', 'temp_laundry', 'humid_laundry', 'temp_office',
            'humid_office', 'temp_bath', 'humid_bath', 'temp_outbuilding',
            'humid_outbuilding', 'temp_iron', 'humid_iron', 'temp_kid', 'humid_kid',
            'temp_parent', 'humid_parent', 'tempt_weather', 'pressure_weather',
            'humid_weather', 'wind_weather', 'vis_weather', 'tdew_weather',
            'sec_midnight']

feature = model_data[features]
target = model_data['appliance']

scaler = StandardScaler()
feature_scaled = scaler.fit_transform(feature)
feature_scaled.shape

```

[]: (19735, 26)

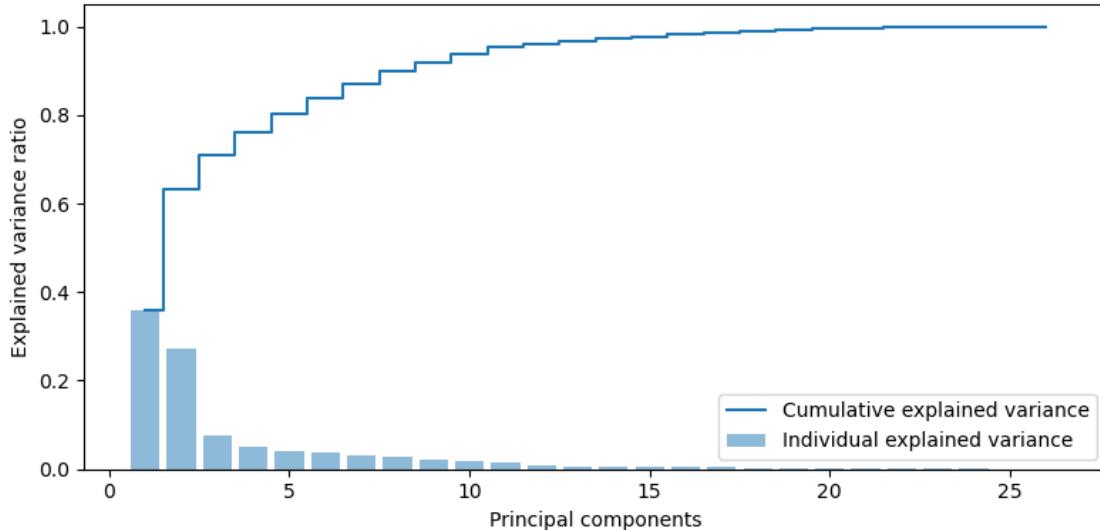
```

[ ]: # check how many components should use for pca
pca = PCA()
feature_pca = pca.fit_transform(feature_scaled)

explained_variance = pca.explained_variance_ratio_

plt.figure(figsize=(8, 4))
plt.bar(range(1, len(explained_variance)+1), explained_variance, alpha=0.5, □
    align='center',
    label='Individual explained variance')
plt.step(range(1, len(explained_variance)+1), np.cumsum(explained_variance), □
    where='mid',
    label='Cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
plt.legend(loc='best')
plt.tight_layout()
plt.show()

```



```
[ ]: # we can see there's none explanation from the components 12, suggest have 11
      ↵components ~ 11 features
pca = PCA(n_components=11)
feature_reduced = pca.fit_transform(feature_scaled)
feature_reduced.shape
```

```
[ ]: (19735, 11)
```

```
[ ]: # merge data together to train model
pca_col = ['PCA1', 'PCA2', 'PCA3', 'PCA4', 'PCA5', 'PCA6', 'PCA7', 'PCA8', 'PCA9',
           ↵'PCA10', 'PCA11']
df_pca = pd.DataFrame(feature_reduced, columns=pca_col, index=model_data.index)

df_pca['appliance'] = target

final_data = df_pca

final_data.describe()
```

```
[ ]:          PCA1        PCA2        PCA3        PCA4        PCA5  \
count  19735.000000  1.973500e+04  1.973500e+04  1.973500e+04  1.973500e+04
mean    0.000000  1.152134e-17  2.304268e-17 -2.304268e-17 -1.152134e-17
std     3.056950  2.662081e+00  1.412408e+00  1.163478e+00  1.023178e+00
min    -6.828388 -6.970744e+00 -3.491848e+00 -2.589856e+00 -3.484948e+00
25%   -2.185861 -2.000712e+00 -1.123086e+00 -7.623705e-01 -6.924520e-01
50%   -0.465450  3.869719e-01  1.437731e-01 -2.864891e-01  1.400935e-02
75%    1.785984  1.940998e+00  1.056798e+00  5.427464e-01  6.841799e-01
max    9.048071  7.196335e+00  3.880941e+00  5.785400e+00  3.698356e+00
```

	PCA6	PCA7	PCA8	PCA9	PCA10	\
count	1.973500e+04	1.973500e+04	1.973500e+04	1.973500e+04	1.973500e+04	
mean	2.304268e-17	-5.760671e-18	-2.880335e-18	6.336738e-17	-4.824562e-17	
std	9.889328e-01	9.178525e-01	8.345308e-01	7.466408e-01	6.997467e-01	
min	-3.490086e+00	-4.222105e+00	-2.614079e+00	-2.300641e+00	-2.637617e+00	
25%	-6.789331e-01	-4.792773e-01	-5.768780e-01	-5.034695e-01	-4.482365e-01	
50%	-1.626084e-02	-9.237270e-02	2.999405e-03	4.391792e-02	-3.392166e-02	
75%	6.300275e-01	4.008055e-01	5.656004e-01	5.101629e-01	4.262045e-01	
max	3.645304e+00	4.425286e+00	3.714766e+00	2.625079e+00	2.764790e+00	
	PCA11	appliance				
count	1.973500e+04	19735.000000				
mean	-2.304268e-17	97.694958				
std	6.105242e-01	102.524891				
min	-2.415395e+00	10.000000				
25%	-3.999050e-01	50.000000				
50%	-9.833825e-03	60.000000				
75%	3.890267e-01	100.000000				
max	2.598727e+00	1080.000000				

3.2 Define and train seasonal Naive model

```
[ ]: # our data is 10min interval, to predict 1 week data, we split data points of
    ↵24 x 6 * 7 = 1008 to predict the next week
split_point = 1008
train_snaive = final_data.iloc[:split_point]
test_snaive = final_data.iloc[-split_point:]

# define seasonal naive model
snaive_forecast = final_data['appliance'].shift(1008).tail(split_point)
snaive_forecast
```

```
[ ]: date
2016-05-20 18:10:00+00:00    490.0
2016-05-20 18:20:00+00:00    280.0
2016-05-20 18:30:00+00:00    280.0
2016-05-20 18:40:00+00:00    310.0
2016-05-20 18:50:00+00:00    280.0
...
2016-05-27 17:20:00+00:00    80.0
2016-05-27 17:30:00+00:00    70.0
2016-05-27 17:40:00+00:00    80.0
2016-05-27 17:50:00+00:00    70.0
2016-05-27 18:00:00+00:00    90.0
Name: appliance, Length: 1008, dtype: float64
```

3.3 Define and train autoARIMA model

```
[ ]: # split data into train and validation sets
import pmdarima
from pmdarima import auto_arima

train_arima, test_arima = final_data.iloc[:int(0.8 * len(final_data))], final_data.iloc[int(0.8 * len(final_data)):]
```

```
[ ]: #decompose seasonal by using Fourier
_, ff_X = FourierFeaturizer(144, k=6).fit_transform(train_arima['appliance'])

new_feature = ['PCA1', 'PCA2', 'PCA3', 'PCA4', 'PCA5', 'PCA6',
               'PCA7', 'PCA8', 'PCA9', 'PCA10', 'PCA11']

exog = pd.concat([ff_X, train_arima[new_feature].reset_index(drop=True)], axis=1)
exog
```

```
[ ]: FOURIER_S144-0  FOURIER_C144-0  FOURIER_S144-1  FOURIER_C144-1 \
0          0.043619      0.999048      0.087156      0.996195
1          0.087156      0.996195      0.173648      0.984808
2          0.130526      0.991445      0.258819      0.965926
3          0.173648      0.984808      0.342020      0.939693
4          0.216440      0.976296      0.422618      0.906308
...
15783     -0.642772     -0.766057      0.984801      0.173688
15784     -0.675575     -0.737291      0.996191      0.087196
15785     -0.707093     -0.707121      1.000000      0.000040
15786     -0.737264     -0.675605      0.996198      -0.087116
15787     -0.766032     -0.642803      0.984815      -0.173609

FOURIER_S144-2  FOURIER_C144-2  FOURIER_S144-3  FOURIER_C144-3 \
0          0.130526      0.991445      0.173648      0.984808
1          0.258819      0.965926      0.342020      0.939693
2          0.382683      0.923880      0.500000      0.866025
3          0.500000      0.866025      0.642788      0.766044
4          0.608761      0.793353      0.766044      0.642788
...
15783     -0.865997     0.500050      0.342095      -0.939665
15784     -0.793318     0.608807      0.173727      -0.984794
15785     -0.707066     0.707147      0.000080      -1.000000
15786     -0.608716     0.793388      -0.173569      -0.984822
15787     -0.499950     0.866054      -0.341945      -0.939720

FOURIER_S144-4  FOURIER_C144-4  ...      PCA2      PCA3      PCA4 \
0          0.216440      0.976296  ... -4.584734   2.267430   2.028781
1          0.422618      0.906308  ... -4.512067   2.211060   2.060636
2          0.608761      0.793353  ... -4.424334   2.164937   2.097534
```

3	0.766044	0.642788	...	-4.395544	2.333612	2.891894	
4	0.887011	0.461749	...	-4.373549	2.269404	2.945647	
...	
15783	0.342037	0.939687	...	0.549532	-1.523905	-0.820407	
15784	0.537314	0.843382	...	0.527817	-1.479021	-0.819717	
15785	0.707119	0.707094	...	0.495588	-1.400451	-0.832804	
15786	0.843401	0.537285	...	0.524051	-1.340333	-0.847591	
15787	0.939699	0.342004	...	0.543966	-1.279992	-0.854967	
	PCA5	PCA6	PCA7	PCA8	PCA9	PCA10	PCA11
0	-0.495716	2.864711	-1.638600	0.690243	-0.781087	-1.454360	0.610827
1	-0.613119	2.560064	-1.647138	0.690984	-0.887842	-1.450524	0.539807
2	-0.736862	2.257623	-1.675274	0.662663	-0.989287	-1.450704	0.526745
3	-0.721332	1.958864	-2.313756	1.302523	-1.056990	-1.773713	0.565939
4	-0.844331	1.654080	-2.352275	1.255474	-1.144801	-1.774929	0.592575
...
15783	0.510085	-0.076017	-0.546337	-0.400061	-0.432233	-0.494858	-0.794005
15784	0.524414	-0.081250	-0.577666	-0.451219	-0.417823	-0.511003	-0.786366
15785	0.558164	-0.098041	-0.600981	-0.487431	-0.422496	-0.549756	-0.821596
15786	0.580022	-0.102203	-0.631907	-0.507281	-0.457407	-0.542587	-0.824544
15787	0.590126	-0.108208	-0.666996	-0.551745	-0.444510	-0.551457	-0.749895

[15788 rows x 23 columns]

```
[ ]: arima_model = auto_arima(train_arima['appliance'], exogenous=exog,
                           start_p=1, start_q=1, max_p=3, max_q=3,
                           m=144, start_P=0, seasonal=False, d=1, D=1,
                           trace=True, error_action='ignore', □
                           ↵suppress_warnings=True)

print(arima_model.summary())
```

Performing stepwise search to minimize aic

ARIMA(1,1,1)(0,0,0)[0]	intercept	:	AIC=178368.848, Time=3.71 sec
ARIMA(0,1,0)(0,0,0)[0]	intercept	:	AIC=180426.307, Time=0.22 sec
ARIMA(1,1,0)(0,0,0)[0]	intercept	:	AIC=180382.539, Time=0.16 sec
ARIMA(0,1,1)(0,0,0)[0]	intercept	:	AIC=180335.432, Time=1.65 sec
ARIMA(0,1,0)(0,0,0)[0]		:	AIC=180424.308, Time=0.13 sec
ARIMA(2,1,1)(0,0,0)[0]	intercept	:	AIC=178013.288, Time=3.13 sec
ARIMA(2,1,0)(0,0,0)[0]	intercept	:	AIC=179432.157, Time=0.56 sec
ARIMA(3,1,1)(0,0,0)[0]	intercept	:	AIC=177975.486, Time=9.34 sec
ARIMA(3,1,0)(0,0,0)[0]	intercept	:	AIC=179115.377, Time=0.77 sec
ARIMA(3,1,2)(0,0,0)[0]	intercept	:	AIC=177977.362, Time=14.81 sec
ARIMA(2,1,2)(0,0,0)[0]	intercept	:	AIC=177977.844, Time=8.00 sec
ARIMA(3,1,1)(0,0,0)[0]		:	AIC=177973.486, Time=1.48 sec
ARIMA(2,1,1)(0,0,0)[0]		:	AIC=178011.289, Time=0.76 sec
ARIMA(3,1,0)(0,0,0)[0]		:	AIC=179113.378, Time=0.32 sec
ARIMA(3,1,2)(0,0,0)[0]		:	AIC=177975.363, Time=2.34 sec

```

ARIMA(2,1,0)(0,0,0)[0] : AIC=179430.158, Time=0.27 sec
ARIMA(2,1,2)(0,0,0)[0] : AIC=177975.844, Time=1.38 sec

Best model: ARIMA(3,1,1)(0,0,0)[0]
Total fit time: 49.071 seconds
                    SARIMAX Results
=====
Dep. Variable:                  y      No. Observations:          15788
Model: SARIMAX(3, 1, 1)      Log Likelihood:             -88981.743
Date: Tue, 07 May 2024        AIC:                         177973.486
Time: 23:03:16                BIC:                         178011.820
Sample: 01-11-2016 - 04-30-2016 HQIC:                         177986.173
Covariance Type: opg
=====

            coef    std err      z   P>|z|    [0.025    0.975]
-----
ar.L1      0.7346    0.005  133.787      0.000     0.724     0.745
ar.L2     -0.1957    0.005  -39.667      0.000    -0.205    -0.186
ar.L3      0.0589    0.005   11.012      0.000     0.048     0.069
ma.L1     -0.9174    0.004  -237.851      0.000    -0.925    -0.910
sigma2    4604.7886   15.914  289.346      0.000   4573.597   4635.980
=====

====

Ljung-Box (L1) (Q):      0.00  Jarque-Bera (JB):
314697.72
Prob(Q):                 0.99  Prob(JB):
0.00
Heteroskedasticity (H):  0.81  Skew:
2.87
Prob(H) (two-sided):    0.00  Kurtosis:
24.11
=====

====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

```

3.4 Define and train LSTM model Follow code instruction of [6]:

```
[ ]: # split data into train and validation sets
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

train_lstm, test_lstm = final_data.iloc[:int(0.8 * len(final_data))], final_data.iloc[int(0.8 * len(final_data)):]
```

```
[ ]: # convert to x_train, y_train
x_train, y_train = [], []
for i in range(144, len(train_lstm)):
    x_train.append(train_lstm.iloc[i-144:i, 0].values)
    y_train.append(train_lstm.iloc[i, 0])

x_train, y_train = np.array(x_train), np.array(y_train)
```

```
[ ]: # define model
lstm_model = Sequential()
lstm_model.add(LSTM(units=64, return_sequences=True, dropout=0.15,
                     recurrent_dropout=0.25,
                     input_shape=(x_train.shape[1],1)))
lstm_model.add(LSTM(units=64))
lstm_model.add(Dense(1))
lstm_model.compile(loss='mean_squared_error', optimizer='adam')
lstm_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 144, 64)	16,896
lstm_1 (LSTM)	(None, 64)	33,024
dense (Dense)	(None, 1)	65

Total params: 49,985 (195.25 KB)

Trainable params: 49,985 (195.25 KB)

Non-trainable params: 0 (0.00 B)

```
[ ]: # Train data
lstm_model.fit(x_train, y_train, epochs=20, batch_size=32, verbose=2)
```

Epoch 1/20

489/489 - 27s - 55ms/step - loss: 0.6691

Epoch 2/20

489/489 - 27s - 56ms/step - loss: 0.6282

Epoch 3/20

489/489 - 28s - 57ms/step - loss: 0.6861

```
Epoch 4/20
489/489 - 28s - 57ms/step - loss: 0.6535
Epoch 5/20
489/489 - 29s - 59ms/step - loss: 0.6882
Epoch 6/20
489/489 - 28s - 56ms/step - loss: 0.6542
Epoch 7/20
489/489 - 27s - 54ms/step - loss: 0.6610
Epoch 8/20
489/489 - 28s - 57ms/step - loss: 0.6587
Epoch 9/20
489/489 - 27s - 56ms/step - loss: 0.6899
Epoch 10/20
489/489 - 27s - 55ms/step - loss: 0.6465
Epoch 11/20
489/489 - 27s - 56ms/step - loss: 0.6838
Epoch 12/20
489/489 - 28s - 57ms/step - loss: 0.6578
Epoch 13/20
489/489 - 27s - 56ms/step - loss: 0.6807
Epoch 14/20
489/489 - 27s - 56ms/step - loss: 0.6504
Epoch 15/20
489/489 - 27s - 55ms/step - loss: 0.6762
Epoch 16/20
489/489 - 27s - 56ms/step - loss: 0.6975
Epoch 17/20
489/489 - 27s - 55ms/step - loss: 0.6582
Epoch 18/20
489/489 - 27s - 56ms/step - loss: 0.6828
Epoch 19/20
489/489 - 28s - 56ms/step - loss: 0.6692
Epoch 20/20
489/489 - 28s - 56ms/step - loss: 0.6605
```

```
[ ]: <keras.src.callbacks.history.History at 0x3570b9f70>
```

0.1.5 4. Test prediction models

4.1 Test seasonal Naive model

```
[ ]: test_snaive['snaive_forecast'] = snaive_forecast[:len(test_snaive)]  
  
snaive_mae = mean_absolute_error(test_snaive['appliance'],  
    ↪test_snaive['snaive_forecast'])  
snaive_rmse = root_mean_squared_error(test_snaive['appliance'],  
    ↪test_snaive['snaive_forecast'])  
  
print(f"Mean Absolute Error of Seasonal Naive: {snaive_mae}")
```

```
print(f"Root Mean Squared Error of Season Naive: {snaive_rmse}")
```

Mean Absolute Error of Seasonal Naive: 61.68650793650794
Root Mean Squared Error of Season Naive: 124.08554396956248

4.2 Test autoARIMA model

```
[ ]: _, ff_test = FourierFeaturizer(6 * 24, k=6).  
      ↪fit_transform(test_arima['appliance'])  
ff_test
```

```
[ ]:    FOURIER_S144-0  FOURIER_C144-0  FOURIER_S144-1  FOURIER_C144-1  \  
0       0.043619      0.999048      0.087156      0.996195  
1       0.087156      0.996195      0.173648      0.984808  
2       0.130526      0.991445      0.258819      0.965926  
3       0.173648      0.984808      0.342020      0.939693  
4       0.216440      0.976296      0.422618      0.906308  
...     ...          ...          ...          ...  
3942    0.675594      -0.737274     -0.996196      0.087146  
3943    0.642791      -0.766041     -0.984809      0.173638  
3944    0.608765      -0.793350     -0.965928      0.258809  
3945    0.573581      -0.819149     -0.939696      0.342011  
3946    0.537304      -0.843389     -0.906312      0.422609  
  
    FOURIER_S144-2  FOURIER_C144-2  FOURIER_S144-3  FOURIER_C144-3  \  
0       0.130526      0.991445      0.173648      0.984808  
1       0.258819      0.965926      0.342020      0.939693  
2       0.382683      0.923880      0.500000      0.866025  
3       0.500000      0.866025      0.642788      0.766044  
4       0.608761      0.793353      0.766044      0.642788  
...     ...          ...          ...          ...  
3942    0.793362      0.608750     -0.173628     -0.984811  
3943    0.866033      0.499988     -0.342001     -0.939699  
3944    0.923885      0.382670     -0.499983     -0.866035  
3945    0.965930      0.258805     -0.642772     -0.766057  
3946    0.991447      0.130512     -0.766032     -0.642803  
  
    FOURIER_S144-4  FOURIER_C144-4  FOURIER_S144-5  FOURIER_C144-5  
0       0.216440      0.976296      0.258819      0.965926  
1       0.422618      0.906308      0.500000      0.866025  
2       0.608761      0.793353      0.707107      0.707107  
3       0.766044      0.642788      0.866025      0.500000  
4       0.887011      0.461749      0.965926      0.258819  
...     ...          ...          ...          ...  
3942    -0.537296     0.843394     0.965918     -0.258847  
3943    -0.342016     0.939694     0.866011     -0.500025  
3944    -0.130522     0.991445     0.707086     -0.707127  
3945    0.087160      0.996194     0.499975     -0.866040
```

```
3946      0.300710      0.953716      0.258791     -0.965933
```

```
[3947 rows x 12 columns]
```

```
[ ]: exog_test = pd.concat([ff_test, test_arima[new_feature].  
    ↪reset_index(drop=True)], axis=1)  
exog_test
```

```
[ ]:      FOURIER_S144-0  FOURIER_C144-0  FOURIER_S144-1  FOURIER_C144-1  \  
0      0.043619      0.999048      0.087156      0.996195  
1      0.087156      0.996195      0.173648      0.984808  
2      0.130526      0.991445      0.258819      0.965926  
3      0.173648      0.984808      0.342020      0.939693  
4      0.216440      0.976296      0.422618      0.906308  
...      ...      ...      ...      ...  
3942     0.675594     -0.737274     -0.996196      0.087146  
3943     0.642791     -0.766041     -0.984809      0.173638  
3944     0.608765     -0.793350     -0.965928      0.258809  
3945     0.573581     -0.819149     -0.939696      0.342011  
3946     0.537304     -0.843389     -0.906312      0.422609  
  
      FOURIER_S144-2  FOURIER_C144-2  FOURIER_S144-3  FOURIER_C144-3  \  
0      0.130526      0.991445      0.173648      0.984808  
1      0.258819      0.965926      0.342020      0.939693  
2      0.382683      0.923880      0.500000      0.866025  
3      0.500000      0.866025      0.642788      0.766044  
4      0.608761      0.793353      0.766044      0.642788  
...      ...      ...      ...      ...  
3942     0.793362     0.608750     -0.173628     -0.984811  
3943     0.866033     0.499988     -0.342001     -0.939699  
3944     0.923885     0.382670     -0.499983     -0.866035  
3945     0.965930     0.258805     -0.642772     -0.766057  
3946     0.991447     0.130512     -0.766032     -0.642803  
  
      FOURIER_S144-4  FOURIER_C144-4  ...      PCA2      PCA3      PCA4  \  
0      0.216440      0.976296  ...  0.608137  -1.204359  -0.858059  
1      0.422618      0.906308  ...  0.650529  -1.104861  -0.858436  
2      0.608761      0.793353  ...  0.689496  -1.001275  -0.871682  
3      0.766044      0.642788  ...  0.715758  -0.684631  -0.131879  
4      0.887011      0.461749  ...  0.810913  -0.763136  -0.945739  
...      ...      ...  ...      ...      ...  
3942     -0.537296     0.843394  ...  -2.607310   1.098305  -0.542532  
3943     -0.342016     0.939694  ...  -2.585757   1.083144  -0.521041  
3944     -0.130522     0.991445  ...  -2.741860   1.264196   0.276275  
3945      0.087160     0.996194  ...  -2.739476   1.216238   0.312973  
3946      0.300710     0.953716  ...  -2.693941   1.156784   0.354489
```

```

PCA5      PCA6      PCA7      PCA8      PCA9      PCA10     PCA11
0    0.600859 -0.116013 -0.661672 -0.569872 -0.453323 -0.570276 -0.724249
1    0.622264 -0.135333 -0.622998 -0.575063 -0.463900 -0.611276 -0.701582
2    0.647750 -0.156291 -0.597857 -0.581361 -0.481467 -0.643841 -0.666822
3    0.818357 -0.169749 -1.159206  0.114460 -0.489575 -0.972849 -0.582185
4    0.724204 -0.197998 -0.520005 -0.531384 -0.593469 -0.713800 -0.639889
...
3942  0.422911 -1.433150  0.181687 -0.398155 -0.526756 -0.117342  0.004837
3943  0.415284 -1.351469  0.171883 -0.407689 -0.447852 -0.063877  0.023987
3944  0.548698 -1.268516 -0.474391  0.218250 -0.312469 -0.287833  0.169180
3945  0.528738 -1.182534 -0.509758  0.177834 -0.187134 -0.238784  0.198198
3946  0.513887 -1.091140 -0.480793  0.212202 -0.120547 -0.136056  0.152778

```

[3947 rows x 23 columns]

```

[ ]: # test data
arima_forecast = arima_model.predict(n_periods=test_arima.shape[0], 
                                     exogenous=exog_test)
arima_forecast

```

```

[ ]: 2016-04-30 08:20:00+00:00    251.811605
2016-04-30 08:30:00+00:00    172.577446
2016-04-30 08:40:00+00:00    137.342933
2016-04-30 08:50:00+00:00    124.128802
2016-04-30 09:00:00+00:00    116.652338
...
2016-05-27 17:20:00+00:00    104.878877
2016-05-27 17:30:00+00:00    104.878877
2016-05-27 17:40:00+00:00    104.878877
2016-05-27 17:50:00+00:00    104.878877
2016-05-27 18:00:00+00:00    104.878877
Freq: 10T, Length: 3947, dtype: float64

```

```

[ ]: test_arima['arima_forecast'] = arima_forecast[:len(test_arima)]
test_arima

```

```

[ ]:          PCA1      PCA2      PCA3      PCA4      PCA5 \
date
2016-04-30 08:20:00+00:00 -0.963322  0.608137 -1.204359 -0.858059  0.600859
2016-04-30 08:30:00+00:00 -0.898395  0.650529 -1.104861 -0.858436  0.622264
2016-04-30 08:40:00+00:00 -0.834813  0.689496 -1.001275 -0.871682  0.647750
2016-04-30 08:50:00+00:00 -0.729720  0.715758 -0.684631 -0.131879  0.818357
2016-04-30 09:00:00+00:00 -0.589682  0.810913 -0.763136 -0.945739  0.724204
...
2016-05-27 17:20:00+00:00  8.015026 -2.607310  1.098305 -0.542532  0.422911
2016-05-27 17:30:00+00:00  7.944387 -2.585757  1.083144 -0.521041  0.415284
2016-05-27 17:40:00+00:00  7.838545 -2.741860  1.264196  0.276275  0.548698

```

```

2016-05-27 17:50:00+00:00 7.712669 -2.739476 1.216238 0.312973 0.528738
2016-05-27 18:00:00+00:00 7.607120 -2.693941 1.156784 0.354489 0.513887

PCA6      PCA7      PCA8      PCA9      PCA10  \
date
2016-04-30 08:20:00+00:00 -0.116013 -0.661672 -0.569872 -0.453323 -0.570276
2016-04-30 08:30:00+00:00 -0.135333 -0.622998 -0.575063 -0.463900 -0.611276
2016-04-30 08:40:00+00:00 -0.156291 -0.597857 -0.581361 -0.481467 -0.643841
2016-04-30 08:50:00+00:00 -0.169749 -1.159206 0.114460 -0.489575 -0.972849
2016-04-30 09:00:00+00:00 -0.197998 -0.520005 -0.531384 -0.593469 -0.713800
...
...      ...      ...      ...      ...
2016-05-27 17:20:00+00:00 -1.433150 0.181687 -0.398155 -0.526756 -0.117342
2016-05-27 17:30:00+00:00 -1.351469 0.171883 -0.407689 -0.447852 -0.063877
2016-05-27 17:40:00+00:00 -1.268516 -0.474391 0.218250 -0.312469 -0.287833
2016-05-27 17:50:00+00:00 -1.182534 -0.509758 0.177834 -0.187134 -0.238784
2016-05-27 18:00:00+00:00 -1.091140 -0.480793 0.212202 -0.120547 -0.136056

PCA11    appliance   arima_forecast
date
2016-04-30 08:20:00+00:00 -0.724249      370     251.811605
2016-04-30 08:30:00+00:00 -0.701582      590     172.577446
2016-04-30 08:40:00+00:00 -0.666822      320     137.342933
2016-04-30 08:50:00+00:00 -0.582185      310     124.128802
2016-04-30 09:00:00+00:00 -0.639889      260     116.652338
...
...      ...      ...
2016-05-27 17:20:00+00:00 0.004837      100     104.878877
2016-05-27 17:30:00+00:00 0.023987       90     104.878877
2016-05-27 17:40:00+00:00 0.169180      270     104.878877
2016-05-27 17:50:00+00:00 0.198198      420     104.878877
2016-05-27 18:00:00+00:00 0.152778      430     104.878877

[3947 rows x 13 columns]

```

```

[ ]: arima_mae = mean_absolute_error(test_arima['appliance'], test_arima['arima_forecast'])
arima_rmse = root_mean_squared_error(test_arima['appliance'], test_arima['arima_forecast'])

print(f"Mean Absolute Error of AutoARIMA: {arima_mae}")
print(f"Root Mean Squared Error of AutoARIMA: {arima_rmse}")

```

Mean Absolute Error of AutoARIMA: 56.37533780661013
Root Mean Squared Error of AutoARIMA: 91.23359123841618

4.3 Test LSTM model

```

[ ]: # predict values using past 144 from the test data
inputs = model_data.iloc[-len(test_lstm) - 144:, 0].values

```

```

y_pred = []
for i in range(144, inputs.shape[0]):
    X_test = inputs[i-144:i].reshape(1,-1)
    lstm_forecast = lstm_model.predict(X_test)
    y_pred.append(lstm_forecast[0, 0])

```

```

1/1      0s 30ms/step
1/1      0s 18ms/step
1/1      0s 17ms/step
1/1      0s 17ms/step
1/1      0s 15ms/step
1/1      0s 15ms/step
1/1      0s 15ms/step
1/1      0s 15ms/step
1/1      0s 14ms/step
1/1      0s 15ms/step
1/1      0s 21ms/step
1/1      0s 23ms/step
1/1      0s 15ms/step
1/1      0s 15ms/step
1/1      0s 16ms/step
1/1      0s 15ms/step
1/1      0s 17ms/step
1/1      0s 16ms/step
1/1      0s 15ms/step
1/1      0s 15ms/step
1/1      0s 17ms/step
1/1      0s 15ms/step
1/1      0s 16ms/step
1/1      0s 18ms/step
1/1      0s 23ms/step
1/1      0s 24ms/step
1/1      0s 18ms/step
1/1      0s 54ms/step
1/1      0s 18ms/step
1/1      0s 20ms/step
1/1      0s 16ms/step
1/1      0s 15ms/step

```


1/1 0s 15ms/step
1/1 0s 18ms/step
1/1 0s 15ms/step
1/1 0s 15ms/step
1/1 0s 16ms/step
1/1 0s 16ms/step
1/1 0s 15ms/step
1/1 0s 16ms/step
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3.5710223,
4.2377806,
4.1269965,
4.1426845,
3.9999719,
4.10507,
4.0952373,
4.085566,
4.08102,
4.0787535,
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4.157076,

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4.506499,  
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4.4915013,  
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4.1663833,  
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4.2960525,  
4.2948575,  
4.493994,  
4.3025103,  
4.2893457,  
4.1541066,  
4.1627293,  
...]
```

```
[ ]: # calculate MAE and RSME  
lstm_mae = mean_absolute_error(test_lstm['appliance'], y_pred)  
lstm_rmse = root_mean_squared_error(test_lstm['appliance'], y_pred)  
  
print(f"Mean Absolute Error of LSTM: {lstm_mae}")  
print(f"Root Mean Squared Error of LSTM: {lstm_rmse}")
```

```
Mean Absolute Error of LSTM: 92.37607531092092  
Root Mean Squared Error of LSTM: 129.91874565550856
```

0.1.6 5. Forecasting results

5.1 Forecasting from seasonal Naive model

```
[ ]: import plotly.graph_objects as go
from plotly.subplots import make_subplots

fig = make_subplots(rows=1, cols=1, shared_xaxes=True, vertical_spacing=0.03)

fig.add_trace(go.Scatter(x=train_snaive.index, y=train_snaive['appliance'],  
    ↪name='training data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_snaive.index, y=test_snaive['appliance'],  
    ↪name='validation data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_snaive.index, y=test_snaive['snaive_forecast'],  
    ↪name='forecasting'), row=1, col=1)

fig.update_layout(title='Seasonal Naive Forecasting of Appliances Energy  
↳Consumption')
fig.show()
```

5.2 Forecasting from AutoARIMA

```
[ ]: fig = make_subplots(rows=1, cols=1, shared_xaxes=True, vertical_spacing=0.03)

fig.add_trace(go.Scatter(x=train_arima.index, y=train_arima['appliance'],  
    ↪name='training data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_arima.index, y=test_arima['appliance'],  
    ↪name='validation data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_arima.index, y=test_arima['arima_forecast'],  
    ↪name='forecasting'), row=1, col=1)

fig.update_layout(title='AutoARIMA Forecasting of Appliances Energy  
↳Consumption')
fig.show()
```

5.3 Forecasting from LSTM

```
[ ]: lstm_forecast = lstm_forecast.flatten()

lstm_forecast = lstm_forecast[:len(test_lstm['appliance'])]

fig = make_subplots(rows=1, cols=1, shared_xaxes=True, vertical_spacing=0.03)

fig.add_trace(go.Scatter(x=train_lstm.index, y=train_lstm['appliance'],  
    ↪name='Training Data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_lstm.index, y=test_lstm['appliance'],  
    ↪name='Validation Data'), row=1, col=1)
fig.add_trace(go.Scatter(x=test_lstm.index, y=lstm_forecast,  
    ↪name='Forecasting'), row=1, col=1)
```

```
fig.update_layout(title='LSTM Forecasting of Appliances Energy Consumption')
fig.show()
```

0.1.7 6. Compare the results from all candidate models, choose the best model, justify your choice and discuss the results

Compare the results from all candidate models, the best model in this is AutoARIMA with lowest MAE 56.375 and RSME 91.234. However, the RSME and MAE still high, it should be further investigate. Some reasons could be affect the results are:

- * Appliance energy consumption has both seasonality in hourly and daily with wide variance.
- * Many features to fit to the models and they also have wide variance and seasonality as well.

```
[ ]: test_result = {'MAE': [snaive_mae, arima_mae, lstm_mae],
                  'RSME': [snaive_rmse, arima_rmse, lstm_rmse]}

test_result = pd.DataFrame(test_result, index=['Seasonal Naive', 'AutoARIMA',
                                               'LSTM'])

print('The test result of all models\n', test_result)
```

The test result of all models

	MAE	RSME
Seasonal Naive	61.686508	124.085544
AutoARIMA	56.375338	91.233591
LSTM	92.376075	129.918746

0.1.8 7. Reflection

After this analysis, I have learned that:

- * Time series with seasonality are quite hard to process and predict model because many influences and need further way to process the data before fitting to the model.
- * Deep learning methods do not always give the optimised results and take a lot of time to run and proceed.
- * With many features, we should use PCA to reduce the dimensions.

0.1.9 8. References

- [1] Candanedo, LM, Feldheim, V & Deramaix, D 2017, ‘Data driven prediction models of energy use of appliances in a low-energy house’, *ELSEVIER Energy and Buildings*, vol. 140, pp. 81-97.
- [2] University of Adelaide 2024-1, COMP_SCI_7306 Mining Big Data - Module 6 Lecture: Time Series, pdf, The University of Adelaide, viewed 5 May 2024, https://myuni.adelaide.edu.au/courses/91968/files/14968123?module_item_id=3274629.
- [3] Chandra, MG 2022, ‘Appliances Energy - Time Series Analysis’, Kaggle, Python notebook, viewed 5 May 2024, <https://www.kaggle.com/code/gaganmaahi224/appliances-energy-time-series-analysis#notebook-container>.
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- [5] University of Adelaide 2024-1, COMP_SCI_7306 Mining Big Data - Module 7 Workshop: Time Series, The University of Adelaide, Python notebook, viewed 5 May 2024, https://myuni.adelaide.edu.au/courses/91968/pages/module-7-workshop-time-series?module_item_id=3274638.
- [6] https://github.com/ranasingh-gkp/Time_series_forcasting/blob/main/Time_series_forcasting.ipynb
- [7] University of Adelaide 2024-1, COMP_SCI_7306 Mining Big Data - Module 6 - Live Sessions, The University of Adelaide, Python notebook, viewed 5 May 2024, <https://myuni.adelaide.edu.au/courses/91968/files/14319131?wrap=1>.