```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style = "whitegrid")


!pip install ts2vg
!pip install igraph
!pip install cairocffi
# !pip install pycairo
!pip install pyts
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting ts2vg
  Downloading ts2vg-1.0.0-cp38-cp38-manylinux_2_5_x86_64.manylinux1_x86_64.manyli
     |████████████████████████████████████████| 1.1 MB 4.1 MB/s
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages (
Installing collected packages: ts2vg
Successfully installed ts2vg-1.0.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting igraph
  Downloading igraph-0.10.2-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64
     |████████████████████████████████████████| 3.3 MB 4.4 MB/s
Collecting texttable>=1.6.2
  Downloading texttable-1.6.7-py2.py3-none-any.whl (10 kB)
Installing collected packages: texttable, igraph
Successfully installed igraph-0.10.2 texttable-1.6.7
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting cairocffi
  Downloading cairocffi-1.4.0.tar.gz (69 kB)
     |████████████████████████████████████████| 69 kB 3.1 MB/s
Requirement already satisfied: cffi>=1.1.0 in /usr/local/lib/python3.8/dist-packa
Requirement already satisfied: pycparser in /usr/local/lib/python3.8/dist-packag
Building wheels for collected packages: cairocffi
  Building wheel for cairocffi (setup.py) ... done
  Created wheel for cairocffi: filename=cairocffi-1.4.0-py3-none-any.whl size=88
  Stored in directory: /root/.cache/pip/wheels/01/a9/c0/5c05f9dd73c21f9a77166906
Successfully built cairocffi
Installing collected packages: cairocffi
Successfully installed cairocffi-1.4.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-whe
Collecting pyts
  Downloading pyts-0.12.0-py3-none-any.whl (2.5 MB)
     |████████████████████████████████████████| 2.5 MB 4.3 MB/s
Requirement already satisfied: numba>=0.48.0 in /usr/local/lib/python3.8/dist-pac
Requirement already satisfied: numpy>=1.17.5 in /usr/local/lib/python3.8/dist-pac
Requirement already satisfied: joblib>=0.12 in /usr/local/lib/python3.8/dist-pack
Requirement already satisfied: scipy>=1.3.0 in /usr/local/lib/python3.8/dist-pack
Requirement already satisfied: scikit-learn>=0.22.1 in /usr/local/lib/python3.8/
Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.8/di
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/pyth
Requirement already satisfied: setuptools in /usr/local/lib/python3.8/dist-packa
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.8/
```

```
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.8/dist-packag
Installing collected packages: pyts
Successfully installed pyts-0.12.0
```

Task 1

Generate samples

```
from google.colab import files
uploaded = files.upload()
```

选择文件 未选择任何文件 Upload widget is only available when the cell has been executed

```
Saving sub3_climbingdown.csv to sub3_climbingdown.csv
Saving sub2_walking.csv to sub2_walking.csv
Saving sub2_running.csv to sub2_running.csv
Saving sub2_climbingup.csv to sub2_climbingup.csv
Saving sub2_climbingdown.csv to sub2_climbingdown.csv
Saving sub3_walking.csv to sub3_walking.csv
Saving sub3_running.csv to sub3_running.csv
Saving sub3_climbingup.csv to sub3_climbingup.csv
Saving sub1_walking.csv to sub1_walking.csv
Saving sub1_running.csv to sub1_running.csv
Saving sub1_climbingup.csv to sub1_climbingup.csv
Saving sub1_climbingdown.csv to sub1_climbingdown.csv
```

```
df11 = pd.read_csv('sub1_climbingdown.csv')
df12 = pd.read_csv('sub1_climbingup.csv')
df13 = pd.read_csv('sub1_running.csv')
df14 = pd.read_csv('sub1_walking.csv')
df21 = pd.read_csv('sub2_climbingdown.csv')
df22 = pd.read_csv('sub2_climbingup.csv')
df23 = pd.read_csv('sub2_running.csv')
df24 = pd.read_csv('sub2_walking.csv')
df31 = pd.read_csv('sub3_climbingdown.csv')
df32 = pd.read_csv('sub3_climbingup.csv')
df33 = pd.read_csv('sub3_running.csv')
df34 = pd.read_csv('sub3_walking.csv')
```

```
# generate samples for each of the 3 subject
sub1_up = df11[1000:2023]
sub1_down = df12[1000:2023]
sub1_run = df13[1000:2023]
sub1_walk = df14[1000:2023]
sub2_up = df21[1000:2023]
sub2_down = df22[1000:2023]
sub2_run = df23[1000:2023]
sub2_walk = df24[1000:2023]
```

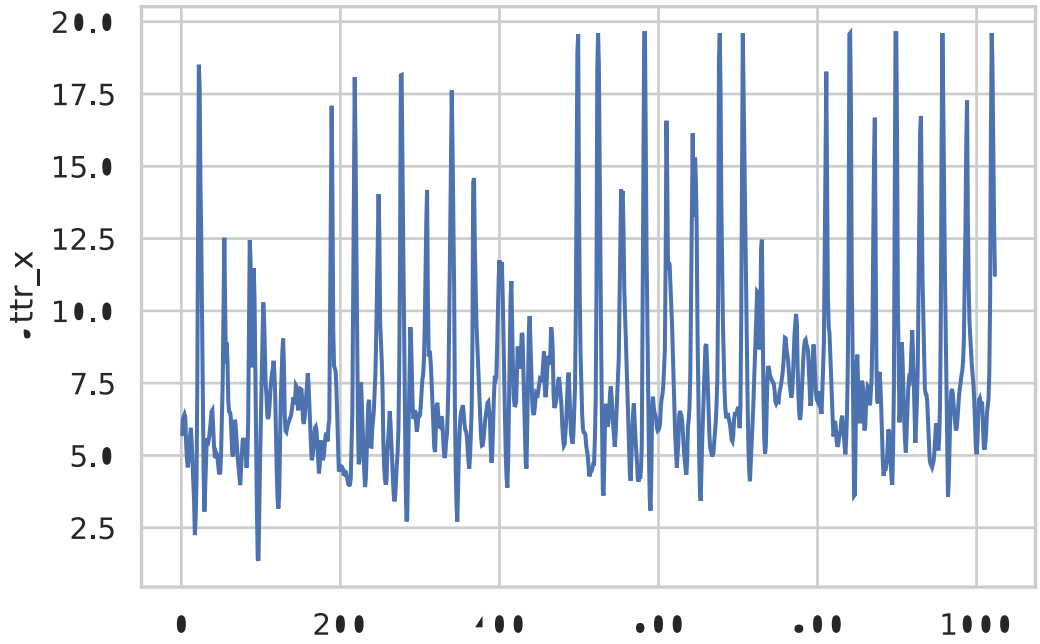
```
sub3_up = df31[1000:2023]
sub3_down = df32[1000:2023]
sub3_run = df33[1000:2023]
sub3_walk = df34[1000:2023]
```

```
sub1_up.head()
```

	id	attr_time	attr_x	attr_y	attr_z
1000	1001	1435996988030	5.722142	4.464588	0.661997
1001	1002	1435996988050	6.258443	6.097433	1.148618
1002	1003	1435996988071	6.345831	7.076063	1.823185
1003	1004	1435996988089	6.412870	7.289746	1.948880
1004	1005	1435996988112	6.301539	6.783970	1.407192

```
# example: when climb up on x accelerometer direction
sns.lineplot(x=range(1, len(sub1_up['attr_x'])+1), y=sub1_up['attr_x'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f927add2d30>
```




```
'''
```

Apply NVG & HVG

Compute the average degree, network diameter, and average path length

```
from networkx.algorithms.shortest_paths.weighted import all_pairs_bellman_ford_path_le
from ts2vg import NaturalVG
from ts2vg import HorizontalVG
import networkx as nx
import igraph as ig

def nvgplot(df, direction):
  ts = df[direction]
  g = NaturalVG()
  g.build(ts)
  ig_g = g.as_igraph()
  ad = np.mean(ig_g.degree())
  nd = ig_g.diameter()
  apl = ig_g.average_path_length()
  return ad, nd, apl

def hvgplot(df, direction):
  ts = df[direction]
  g = HorizontalVG()
  g.build(ts)
  ig_g = g.as_igraph()
  ad = np.mean(ig_g.degree())
  nd = ig_g.diameter()
  apl = ig_g.average_path_length()
  return ad, nd, apl
```

Tabulate all the results

```
def table(dataframe, subject, activity):
  data = {'Method':['NVG', 'NVG', 'NVG', 'HVG', 'HVG', 'HVG'], 'Subject':np.array([sub
        'Activity':np.array([activity]*6)}
  df = pd.DataFrame(data)
  nvg_results = [nvgplot(dataframe, i) for i in ['attr_x', 'attr_y', 'attr_z']]
  hvg_results = [hvgplot(dataframe, i) for i in ['attr_x', 'attr_y', 'attr_z']]
  results = nvg_results + hvg_results
  df[['Average Degree', 'Network Diameter', 'Average Path Length']] = results
  return df


df11 = table(sub1_up, 1, 'Climbing Up')
df12 = table(sub1_down, 1, 'Climbing Down')
df13 = table(sub1_run, 1, 'Running')
df14 = table(sub1_walk, 1, 'Walking')
df21 = table(sub2_up, 2, 'Climbing Up')
df22 = table(sub2_down, 2, 'Climbing Down')
df23 = table(sub2_run, 2, 'Running')
df24 = table(sub2_walk, 2, 'Walking')
df31 = table(sub3_up, 3, 'Climbing Up')
```

```
df32 = table(sub3_down, 3, 'Climbing Down')
df33 = table(sub3_run, 3, 'Running')
df34 = table(sub3_walk, 3, 'Walking')


pd.set_option('display.max_rows', None)
final = pd.concat([df11, df12, df13, df14, df21, df22, df23, df24, df31, df32, df33, d
display(final)
```

	Method	Subject	Accelerometer axis	Activity	Average Degree	Network Di
0	HVG	1	X	Climbing Up	3.953079	
1	HVG	1	Y	Climbing Up	3.947214	
2	HVG	1	Z	Climbing Up	3.968719	
3	HVG	1	X	Climbing Down	3.958944	
4	HVG	1	Y	Climbing Down	3.953079	
5	HVG	1	Z	Climbing Down	3.951124	
6	HVG	1	X	Running	3.955034	
7	HVG	1	Y	Running	3.833822	
8	HVG	1	Z	Running	3.966764	
9	HVG	1	X	Walking	3.960899	
10	HVG	1	Y	Walking	3.951124	
11	HVG	1	Z	Walking	3.958944	
12	HVG	2	X	Climbing Up	3.962854	
13	HVG	2	Y	Climbing Up	3.913978	
14	HVG	2	Z	Climbing Up	3.955034	
15	HVG	2	X	Climbing Down	3.956989	
16	HVG	2	Y	Climbing Down	3.955034	
17	HVG	2	Z	Climbing Down	3.949169	
18	HVG	2	X	Running	3.960899	
19	HVG	2	Y	Running	3.491691	
20	HVG	2	Z	Running	3.972630	
21	HVG	2	X	Walking	3.943304	
22	HVG	2	Y	Walking	3.947214	
23	HVG	2	Z	Walking	3.949169	
24	HVG	3	X	Climbing Up	3.956989	
25	HVG	3	Y	Climbing Up	3.935484	
26	HVG	3	Z	Climbing Up	3.939394	
27	HVG	3	X	Climbing Down	3.945259	
28	HVG	3	Y	Climbing Down	3.945259	
29	HVG	3	Z	Climbing Down	3.929619	

30	HVG	3	X	Running	3.958944
31	HVG	3	Y	Running	3.462366
32	HVG	3	Z	Running	3.976540
33	HVG	3	X	Walking	3.956989
34	HVG	3	Y	Walking	3.964809
35	HVG	3	Z	Walking	3.945259
36	NVG	1	X	Climbing Up	15.616813
37	NVG	1	Y	Climbing Up	14.091887
38	NVG	1	Z	Climbing Up	9.540567
39	NVG	1	X	Climbing Down	15.382209
40	NVG	1	Y	Climbing Down	16.334311
41	NVG	1	Z	Climbing Down	9.955034
42	NVG	1	X	Running	8.375367
43	NVG	1	Y	Running	11.135875
44	NVG	1	Z	Running	8.324536
45	NVG	1	X	Walking	11.460411
46	NVG	1	Y	Walking	11.988270

Generate scatter plots

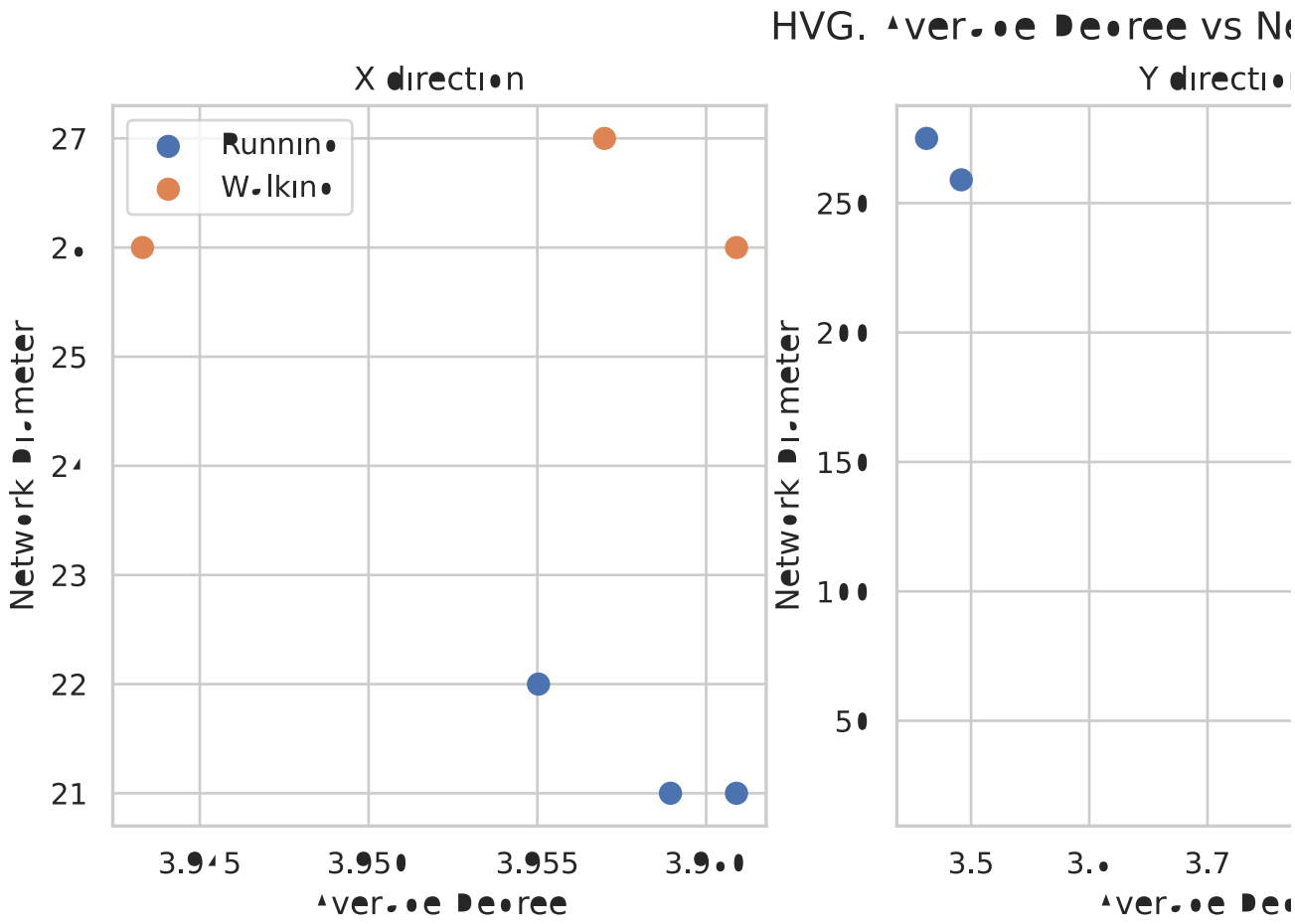
49	NVG	2	Y	Climbing Up	11.650049

Walking & Running

51	NVG	2	X	Climbing Down	11.910068

```
fig = plt.figure(figsize = (15,5))
ax1 = fig.add_subplot(1,3,1)
ax2 = fig.add_subplot(1,3,2)
ax3 = fig.add_subplot(1,3,3)
ax1.set_xlabel('Average Degree')
ax1.set_ylabel('Network Diameter')
ax1.set_title('X direction')
ax2.set_xlabel('Average Degree')
ax2.set_ylabel('Network Diameter')
ax2.set_title('Y direction')
ax3.set_xlabel('Average Degree')
ax3.set_ylabel('Network Diameter')
ax3.set_title('Z direction')
groups = final.groupby(['Method', 'Activity', 'Accelerometer axis'])

for name, group in groups:
```

```
    if (name[0] == 'HVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
      ax1.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
    if (name[0] == 'HVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
      ax2.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
    if (name[0] == 'HVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
      ax3.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na

ax1.legend()
ax2.legend()
ax3.legend()
fig.suptitle('HVG: Average Degree vs Network Diameter')
plt.show()
```

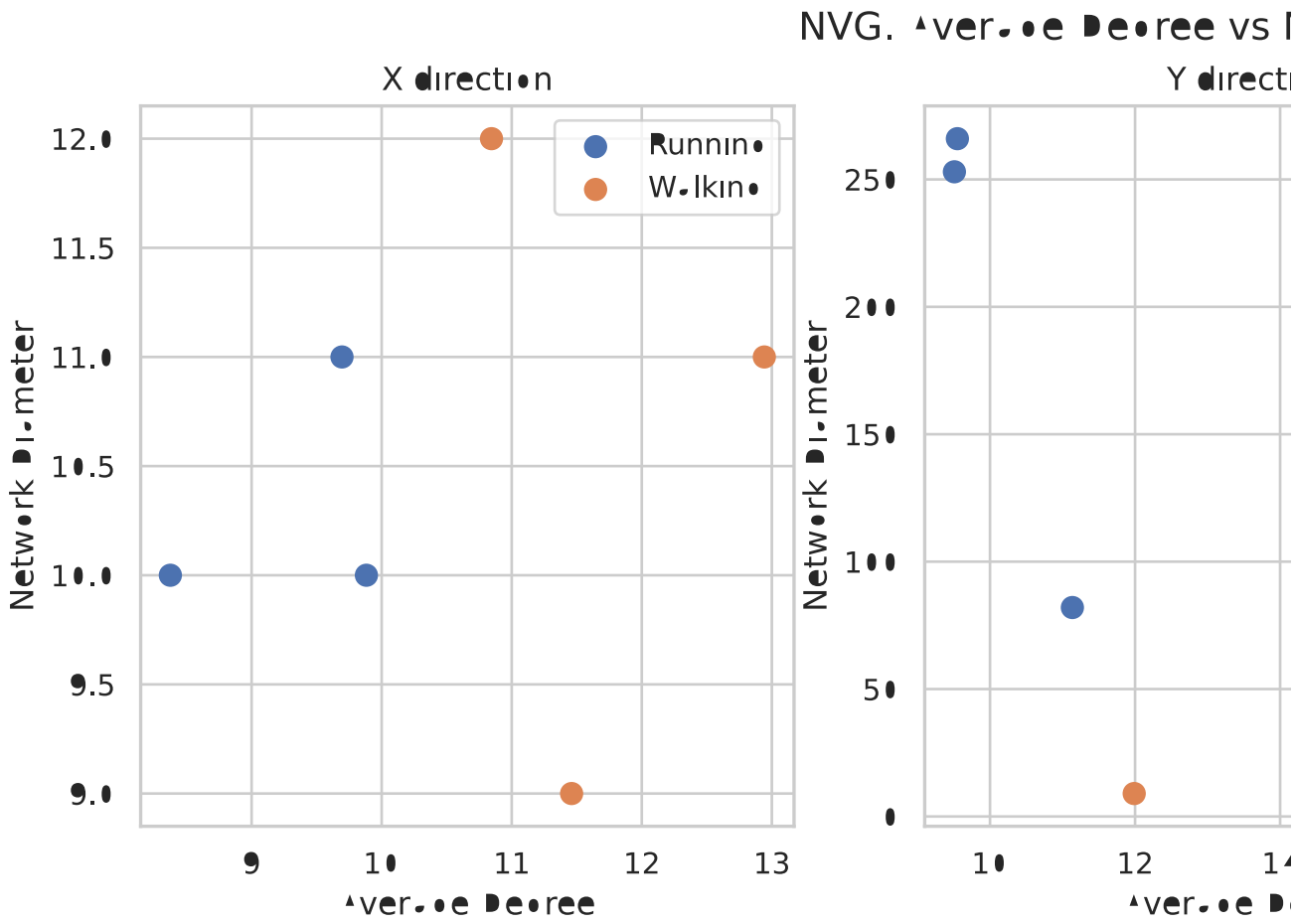



```
'''
```

Climbing Up & Climbing Down

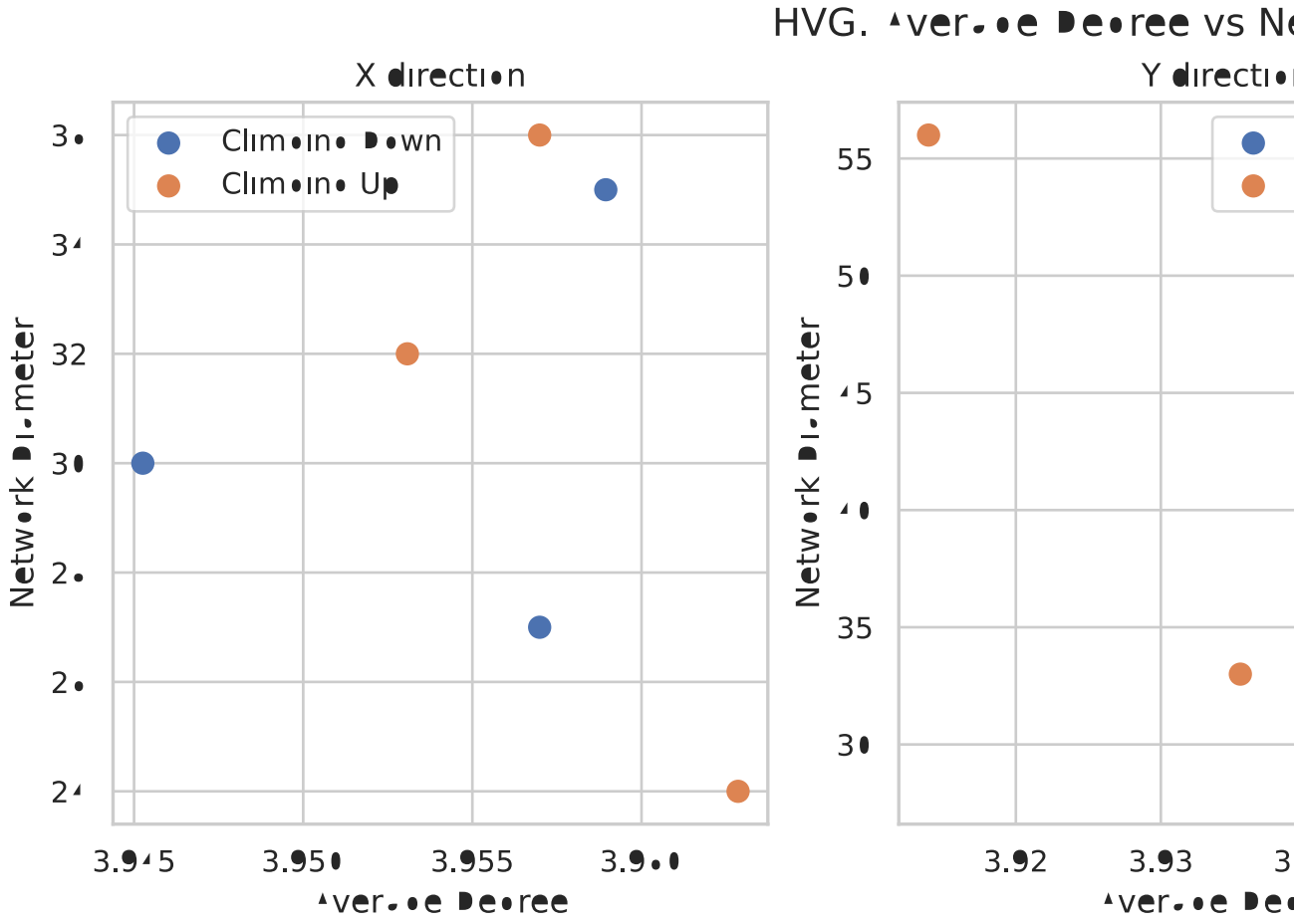
```
fig = plt.figure(figsize = (15,5))
ax1 = fig.add_subplot(1,3,1)
ax2 = fig.add_subplot(1,3,2)
ax3 = fig.add_subplot(1,3,3)
ax1.set_xlabel('Average Degree')
ax1.set_ylabel('Network Diameter')
ax1.set_title('X direction')
```

```
ax2.set_xlabel('Average Degree')
ax2.set_ylabel('Network Diameter')
ax2.set_title('Y direction')
ax3.set_xlabel('Average Degree')
ax3.set_ylabel('Network Diameter')
ax3.set_title('Z direction')

for name, group in groups:
  if (name[0] == 'NVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
    ax1.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
  if (name[0] == 'NVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
    ax2.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
  if (name[0] == 'NVG') and ((name[1] == 'Running') or (name[1] == 'Walking')) and (na
    ax3.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na

ax1.legend()
ax2.legend()
ax3.legend()
fig.suptitle('NVG: Average Degree vs Network Diameter')
plt.show()
```




```
'''

fig = plt.figure(figsize = (15,5))
ax1 = fig.add_subplot(1,3,1)
ax2 = fig.add_subplot(1,3,2)
ax3 = fig.add_subplot(1,3,3)
```

```
  ax1.set_xlabel('Average Degree')
  ax1.set_ylabel('Network Diameter')
  ax1.set_title('X direction')
  ax2.set_xlabel('Average Degree')
  ax2.set_ylabel('Network Diameter')
  ax2.set_title('Y direction')
  ax3.set_xlabel('Average Degree')
  ax3.set_ylabel('Network Diameter')
  ax3.set_title('Z direction')
  for name, group in groups:
    if (name[0] == 'HVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
      ax1.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
    if (name[0] == 'HVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
      ax2.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
    if (name[0] == 'HVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
      ax3.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na

  ax1.legend()
  ax2.legend()
  ax3.legend()
  fig.suptitle('HVG: Average Degree vs Network Diameter')
  plt.show()
```




```
  '''


  fig = plt.figure(figsize = (15,5))
```

```
ax1 = fig.add_subplot(1,3,1)
ax2 = fig.add_subplot(1,3,2)
ax3 = fig.add_subplot(1,3,3)
ax1.set_xlabel('Average Degree')
ax1.set_ylabel('Network Diameter')
ax1.set_title('X direction')
ax2.set_xlabel('Average Degree')
ax2.set_ylabel('Network Diameter')
ax2.set_title('Y direction')
ax3.set_xlabel('Average Degree')
ax3.set_ylabel('Network Diameter')
ax3.set_title('Z direction')
for name, group in groups:
  if (name[0] == 'NVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
    ax1.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
  if (name[0] == 'NVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
    ax2.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na
  if (name[0] == 'NVG') and ((name[1] == 'Climbing Up') or (name[1] == 'Climbing Down'
    ax3.scatter(group['Average Degree'], group['Network Diameter'], s = 60, label = na

ax1.legend()
ax2.legend()
ax3.legend()
fig.suptitle('NVG: Average Degree vs Network Diameter')
plt.show()
```

Task 2

```
from statsmodels.tsa.seasonal import STL
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_absolute_error, mean_squared_error, mean_absolute_per
from statsmodels.tsa.arima.model import ARIMA
from warnings import filterwarnings
from pmdarima.arima import auto_arima

filterwarnings('ignore')
```

1. Get the unionned DataFrame

```
# read the csv files, and change names of three columns mentioned  into shorter names
df_2020 = pd.read_csv('2020_US_Region_Mobility_Report.csv')
df_2021 = pd.read_csv('2021_US_Region_Mobility_Report.csv')
df_2022 = pd.read_csv('2022_US_Region_Mobility_Report.csv')
df_2020 = df_2020.rename(columns={'grocery_and_pharmacy_percent_change_from_baseline':
df_2021 = df_2021.rename(columns={'grocery_and_pharmacy_percent_change_from_baseline':
df_2022 = df_2022.rename(columns={'grocery_and_pharmacy_percent_change_from_baseline':


# acquire 2020-2022 King County info
df_2020_KingCounty = df_2020[df_2020['sub_region_2']=='King County'][['date','Resident

df_2021_KingCounty = df_2021[df_2021['sub_region_2']=='King County'][['date','Resident

df_2022_KingCounty = df_2022[df_2022['sub_region_2']=='King County'][['date','Resident



# use concat func to combine three files into one
df_all = pd.concat([df_2020_KingCounty,df_2021_KingCounty,df_2022_KingCounty])
df_all = df_all.reset_index(drop=True)
df_all
```

	date	Residential	Work	Grocery and Pharmacy
0	2020-02-15	0.0	-3.0	-2.0
1	2020-02-16	-1.0	-2.0	1.0
2	2020-02-17	7.0	-40.0	4.0
3	2020-02-18	1.0	-8.0	2.0
4	2020-02-19	0.0	-7.0	2.0
...	...	...	...	...
969	2022-10-11	9.0	-40.0	-10.0
970	2022-10-12	9.0	-41.0	-10.0

2. Trim DataFrame

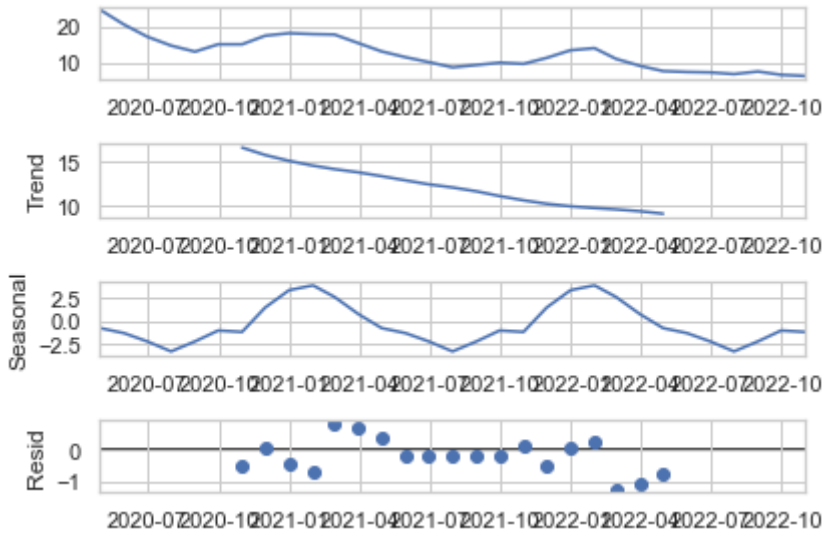
```
# remove the months before April 2020
df_all = df_all[df_all['date']>='2020-04-01']
df_all['date'] = pd.to_datetime(df_all['date'])
df_all
```

	date	Residential	Work	Grocery and Pharmacy
46	2020-04-01	29.0	-70.0	-20.0
47	2020-04-02	30.0	-70.0	-22.0
48	2020-04-03	31.0	-69.0	-21.0
49	2020-04-04	17.0	-48.0	-24.0
50	2020-04-05	15.0	-48.0	-29.0
...	...	...	...	...
969	2022-10-11	9.0	-40.0	-10.0
970	2022-10-12	9.0	-41.0	-10.0
971	2022-10-13	9.0	-41.0	-10.0
972	2022-10-14	9.0	-44.0	-9.0
973	2022-10-15	1.0	-16.0	-15.0

928 rows × 4 columns

3. Decomposition

```
df_Residential = df_all[['date','Residential']].set_index('date')
df_Work = df_all[['date','Work']].set_index('date')
df_GP = df_all[['date','Grocery and Pharmacy']].set_index('date')


# decomposition in an additive model
# put the data at a monthly cadence and fill in missing values
df_Residential = df_Residential.resample('M').mean().ffill()
res1 = seasonal_decompose(df_Residential,model='addtive')
res1.plot()
plt.show()
```

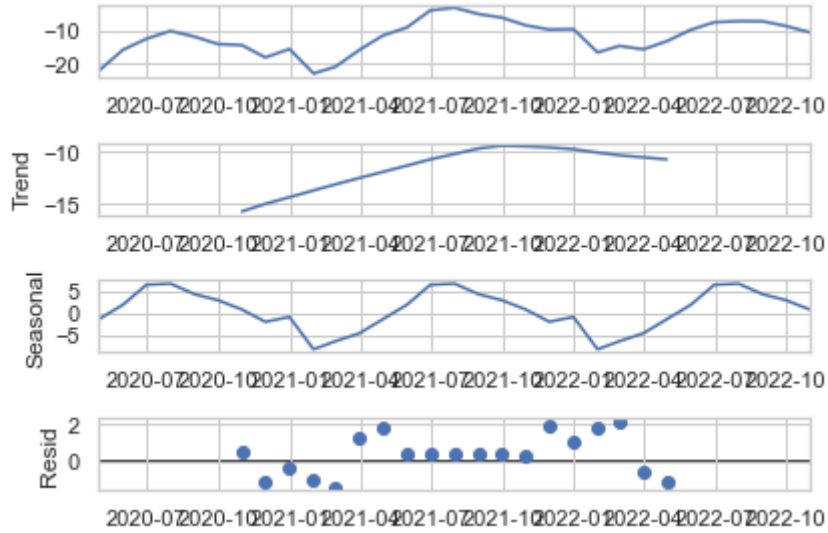


above graph performs that Residential continously decrease and its seasonal periods is about 12 months

```
df_Work = df_Work.resample('M').mean().ffill()
res2 = seasonal_decompose(df_Work,model='addtive')
res2.plot()
plt.show()
```

above graph performs that Work continously increase and its seasonal periods is about 12 months

```
df_GP = df_GP.resample('M').mean().ffill()
res3 = seasonal_decompose(df_GP,model='addtive')
res3.plot()
plt.show()
```



above graph performs that Grocery and Pharmacy continously increase until 10.2022 before having a slight drop and its seasonal periods is about 12 months

4. Exponential Smoothing & ARIMA

```
Residential = df_all[['date','Residential']].reset_index(drop=True)
Work = df_all[['date','Work']].reset_index(drop=True)
GP = df_all[['date','Grocery and Pharmacy']].reset_index(drop=True)

display(Residential.tail())
```

	date	Residential
923	2022-10-11	9.0
924	2022-10-12	9.0
925	2022-10-13	9.0
926	2022-10-14	9.0
927	2022-10-15	1.0

Before we get into the models themselves, split this into a train/test set.

```
# get the train set and test set
Residential_train = Residential.set_index('date')
Residential_test = Residential.set_index('date')

Work_train = Work.set_index('date')
Work_test = Work.set_index('date')

GP_train = GP.set_index('date')
GP_test = GP.set_index('date')


Residential_train = Residential_train.loc[:'2022-04-01']
Residential_test = Residential_test.loc['2022-04-02':]

Work_train = Work_train.loc[:'2022-04-01']
Work_test = Work_test.loc['2022-04-02':]

GP_train = GP_train.loc[:'2022-04-01']
GP_test = GP_test.loc['2022-04-02':]

l = len(Residential_test)
```

Create the plot_train function to build several ES models and plot raw data, Simple ES, Trend ES, Dampened ES, Seasonal ES, Seasonal + Trend ES and Seasonal + Dampened trend ES in one graph, and further to compare.

```
def plot_train(dataframe:pd.DataFrame,ts_column:str):
    df = dataframe.copy()
    # Simple ES: without considering trend or dampening
    simple_es = SimpleExpSmoothing(df[ts_column])
    df['Simple_ES'] = simple_es.fit(smoothing_level=0.2).fittedvalues

    # more complicated Exponential Smoothing
    # trend_only
    trend_es = ExponentialSmoothing(df[ts_column], trend = 'add')
    df['Trend_ES'] = trend_es.fit().fittedvalues

    # Dampened trend
    dampened_es = ExponentialSmoothing(df[ts_column], trend = 'add', damped_trend = Tı
    df['Dampened_ES'] = dampened_es.fit().fittedvalues

    # seasonal_only
    seasonal_es = ExponentialSmoothing(df[ts_column], seasonal = "add")
    df['Seasonal_ES'] = seasonal_es.fit().fittedvalues
```

```
    # seasonal + trend
    seatrd_es = ExponentialSmoothing(df[ts_column], trend = "add", seasonal = "add")
    df['Seasonal+Trend_ES'] = seatrd_es.fit().fittedvalues

    # seasonal + dampend trend
    seadap_es = ExponentialSmoothing(df[ts_column], trend = "add", damped_trend = True
    df['Seasonal+DampendTrend_ES'] = seadap_es.fit().fittedvalues

    column_list_ES = ['Simple_ES','Trend_ES','Dampened_ES','Seasonal_ES','Seasonal+Tre
    df[['Simple_ES','Trend_ES','Dampened_ES','Seasonal_ES','Seasonal+Trend_ES','Seasor

    return simple_es, trend_es, dampened_es, seasonal_es, seatrd_es, seadap_es, colum
```

Define a function to evaluate the models.

```
def score_all_metrics(data: pd.DataFrame, col_names: list,ts_col):
    """Score a set of predictions on all metrics"""

    mae = []
    rmse = []
    mape = []

    for col in col_names:
        mae.append(mean_absolute_error(data[ts_col], data[col]))
        rmse.append(mean_squared_error(data[ts_col], data[col], squared=False))
        mape.append(mean_absolute_percentage_error(data[ts_col], data[col]))

    results_df = pd.DataFrame({
        "ModelName": col_names,
        "MAE": mae,
        "RMSE": rmse,
        "MAPE": mape
    })

    return results_df
```

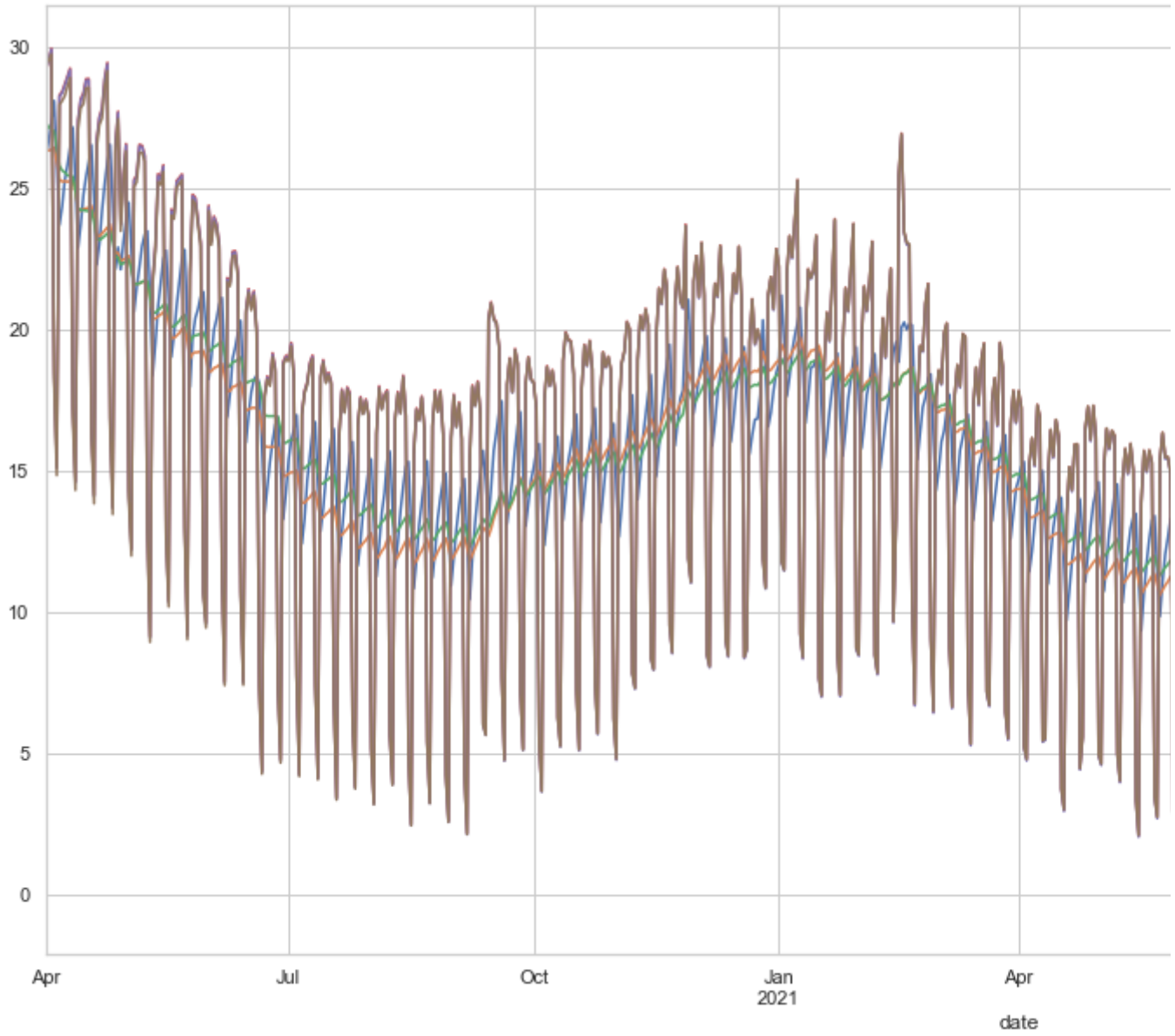
Define a function to build 4 kinds of ARIMA models.

```
def plot_Arima(df:pd.DataFrame,ts_col):
    ar_1 = ARIMA(df[ts_col],order=(1,0,0))
    ma_1 = ARIMA(df[ts_col], order=(0,0,1))
    arima_1 = ARIMA(df[ts_col], order=(1,1,1))
    sarima = ARIMA(df[ts_col], order=(1,1,1), seasonal_order=(1,1,1,12))

    df["AR(1)"] = ar_1.fit().fittedvalues
    df["MA(1)"] = ma_1.fit().fittedvalues
    df["ARIMA(1,1,1)"] = arima_1.fit().fittedvalues
```

```
    df["SARIMA(1,1,1)"] = sarima.fit().fittedvalues

    column_list_ARIMA = ["AR(1)","MA(1)","ARIMA(1,1,1)","SARIMA(1,1,1)"]

    df[[ts_col,"AR(1)","MA(1)","ARIMA(1,1,1)","SARIMA(1,1,1)"]][:'2022-04-01'].plot(fi
    plt.show()

    return ar_1,ma_1,arima_1,sarima,column_list_ARIMA
```

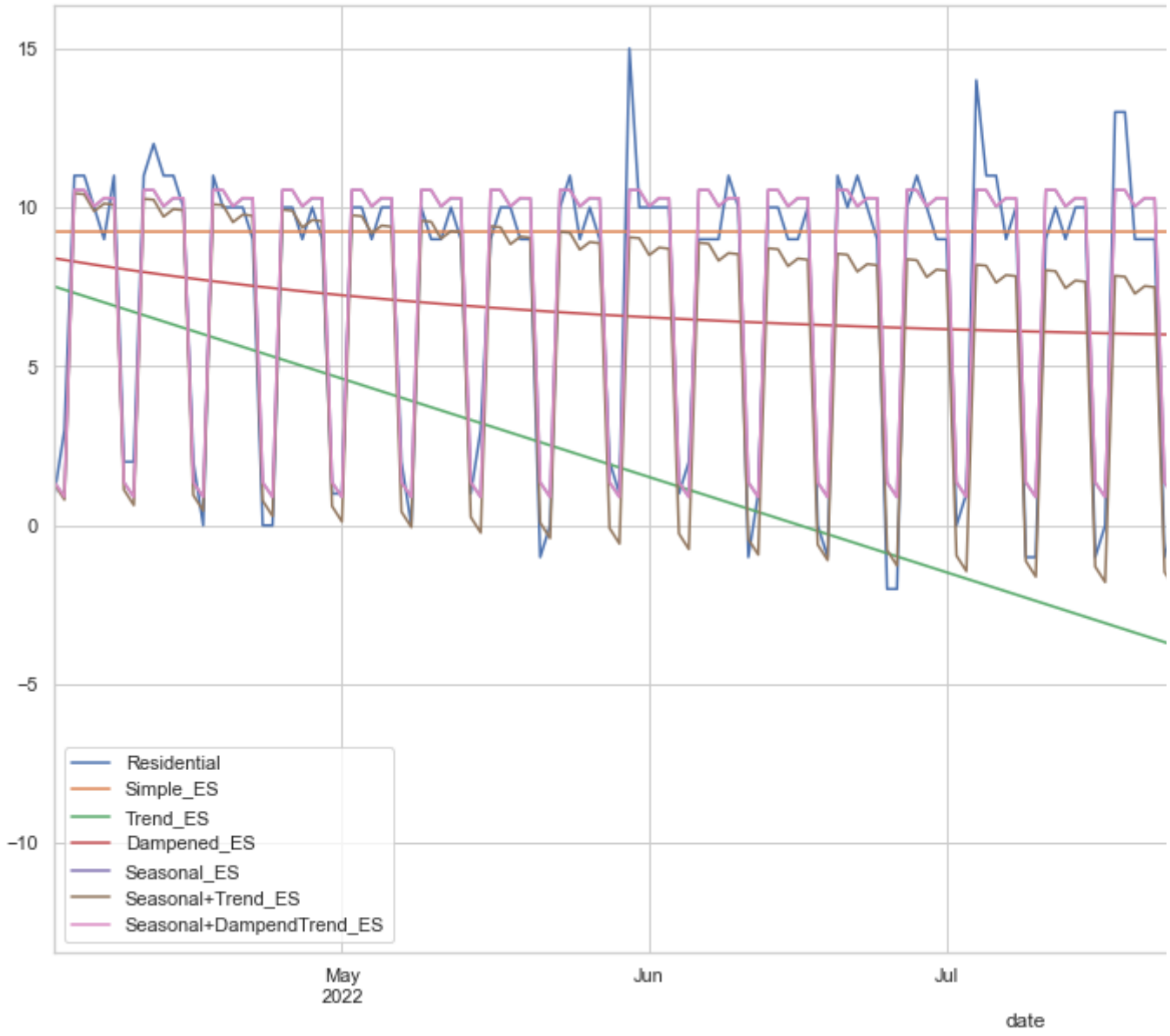
Residential

```
simple_es,trend_es,dampened_es,seasonal_es,seatrd_es,seadap_es,column_list_ES = plot_t
```




```
Residential_test['Simple_ES'] = simple_es.fit(smoothing_level=0.2).forecast(l)
Residential_test['Trend_ES'] = trend_es.fit().forecast(l)
Residential_test['Dampened_ES'] = dampened_es.fit().forecast(l)
```

```
Residential_test['Seasonal_ES']  = seasonal_es.fit().forecast(l)
Residential_test['Seasonal+Trend_ES']  = seatrd_es.fit().forecast(l)
Residential_test['Seasonal+DampendTrend_ES']  = seadap_es.fit().forecast(l)

Residential_test.plot(figsize=(20,10))
plt.show()
```

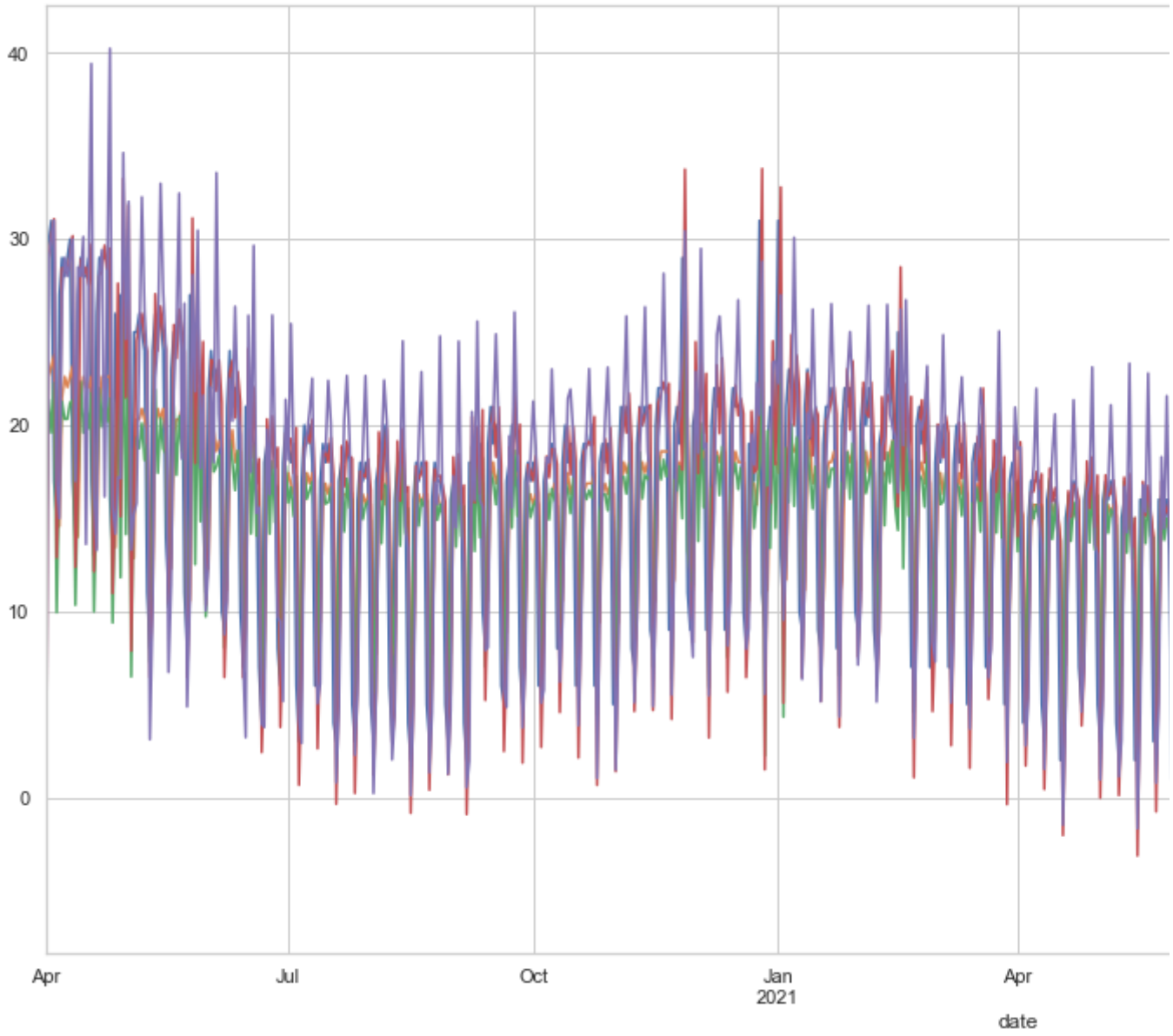



```
exp_smooth_scores = score_all_metrics(Residential_test, column_list_ES, 'Residential')
cm = sns.color_palette("vlag", as_cmap=True)
exp_smooth_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
3	Seasonal_ES	1.107365	1.344165	430209605070989.875000

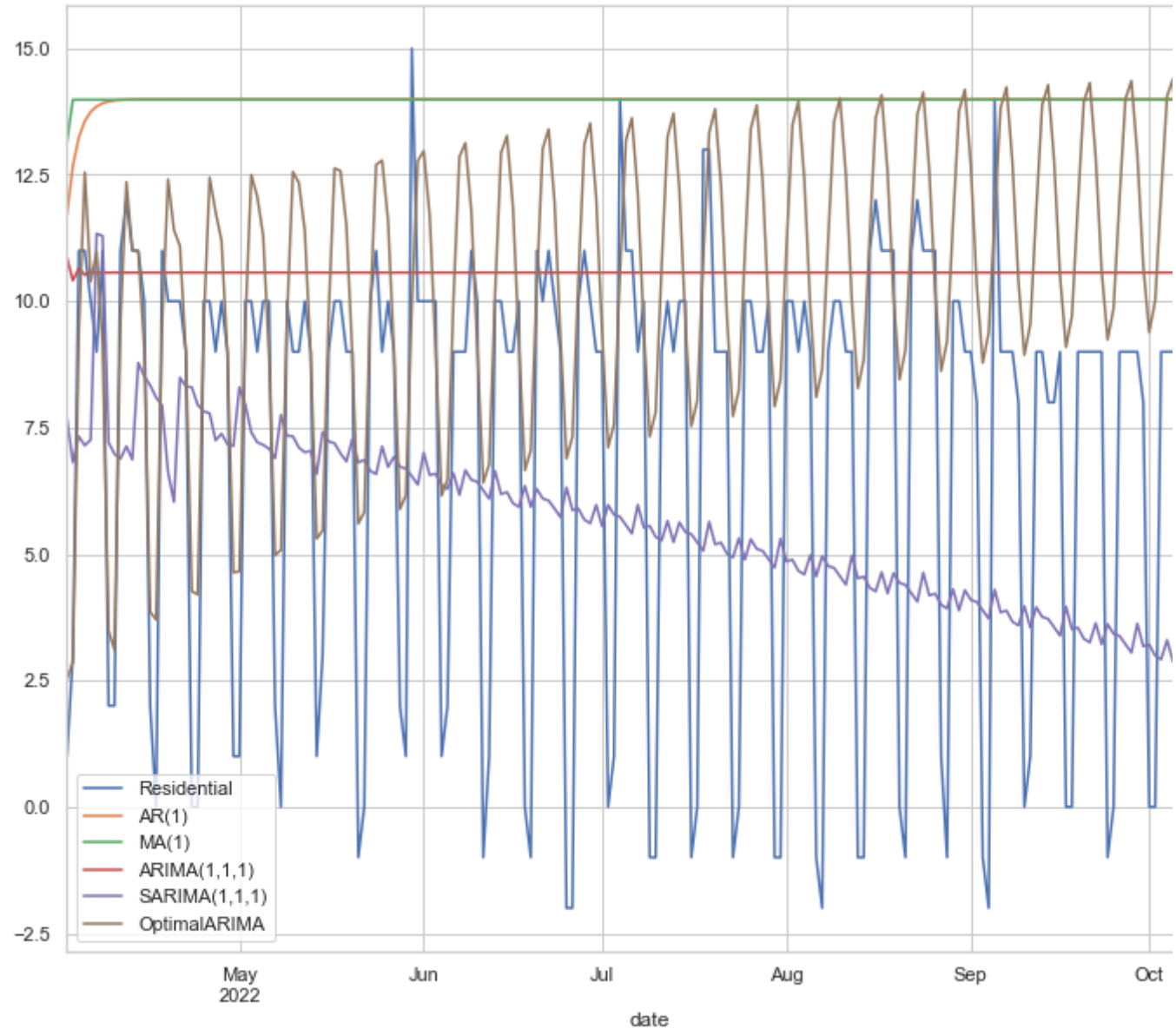
According to the table, we can see MAE, RMSE & MAPE of Seasonal_ES model are lowest, so the Seasonal_ES model is the best model among these ES models for residential dataset.

```
ar_1,ma_1,arima_1,sarima,column_list_ARIMA = plot_Arima(df = Residential_train,ts_col
```




```
Residential_test["AR(1)"] = ar_1.fit().forecast(l)
Residential_test["MA(1)"] = ma_1.fit().forecast(l)
Residential_test["ARIMA(1,1,1)"] = arima_1.fit().forecast(l)
Residential_test["SARIMA(1,1,1)"] = sarima.fit().forecast(l)

model = auto_arima(Residential_train['Residential'], start_p=0,start_q=0,max_p=6,max_
                   max_d=2,seasonal=True,test='adf',error_action='ignore',informat
                  njob=-1,Trace=True,suppress_warnings=True)
model.fit(Residential_train['Residential'])
forecast = model.predict(n_periods=l)
```

```
Residential_test["OptimalARIMA"]=forecast

Residential_test[["Residential","AR(1)","MA(1)","ARIMA(1,1,1)","SARIMA(1,1,1)","Optima
plt.show()
```




```
column_list_ARIMA.append('OptimalARIMA')
arima_scores = score_all_metrics(Residential_test, column_list_ARIMA,'Residential')

cm = sns.color_palette("vlag", as_cmap=True)
arima_scores.style.background_gradient(cmap=cm)
```

ModelName	MAE	RMSE	MAPE

Obviously, Optimal ARIMA model is the best. Then we compare the Seasonal ES and optimal ARIMA model.

2	SARIMA(1,1,1)	4.658524	4.977976	2065468086815825.750000

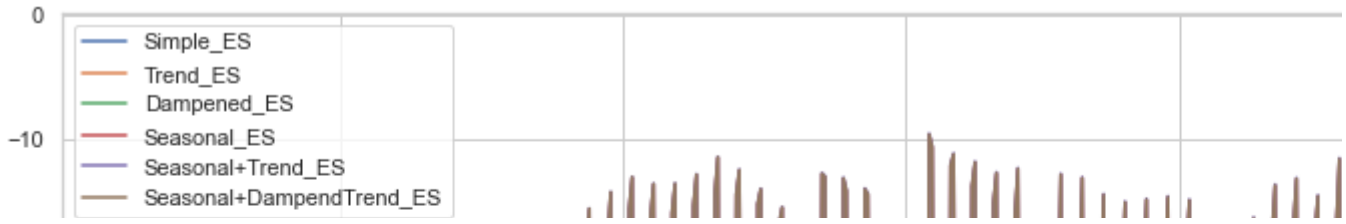
```
comparison_scores = score_all_metrics(Residential_test,['Seasonal_ES','OptimalARIMA'],
cm = sns.color_palette("vlag", as_cmap=True)
comparison_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	Seasonal_ES	1.107365	1.344165	430209605070989.875000
1	OptimalARIMA	3.713663	4.729512	2927937040323818.500000

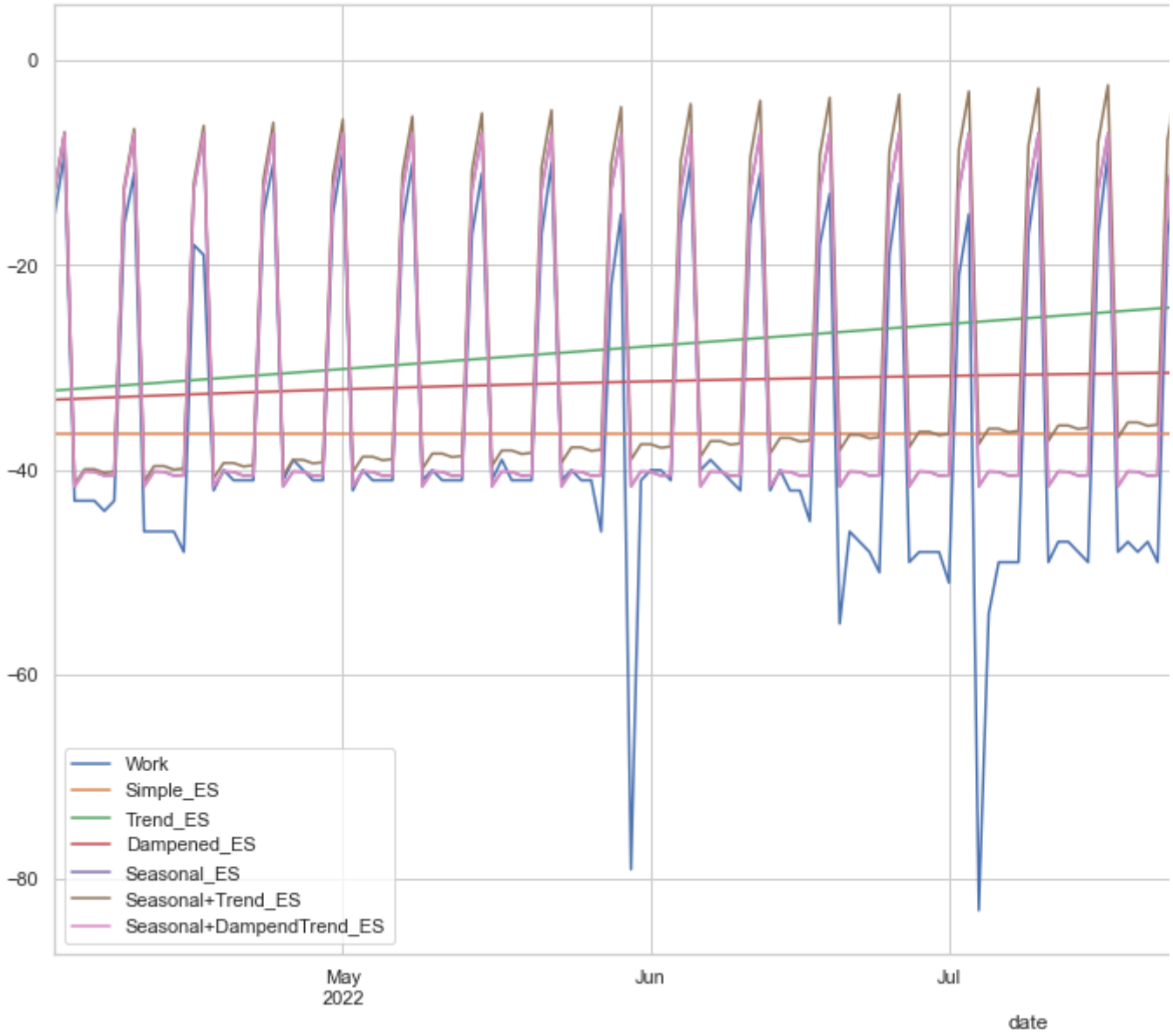
According to the final comparison, for residential dataset, we should choose the Seasonal_ES model to predict the future value.

Work

```
simple_es,trend_es,dampened_es,seasonal_es,seatrd_es,seadap_es,column_list_ES = plot_t
```




```
Work_test['Simple_ES'] = simple_es.fit(smoothing_level = 0.2).forecast(l)
Work_test['Trend_ES'] = trend_es.fit().forecast(l)
Work_test['Dampened_ES'] = dampened_es.fit().forecast(l)
Work_test['Seasonal_ES']  = seasonal_es.fit().forecast(l)
Work_test['Seasonal+Trend_ES']  = seatrd_es.fit().forecast(l)
Work_test['Seasonal+DampendTrend_ES']  = seadap_es.fit().forecast(l)

Work_test.plot(figsize=(20,10))
plt.show()
```



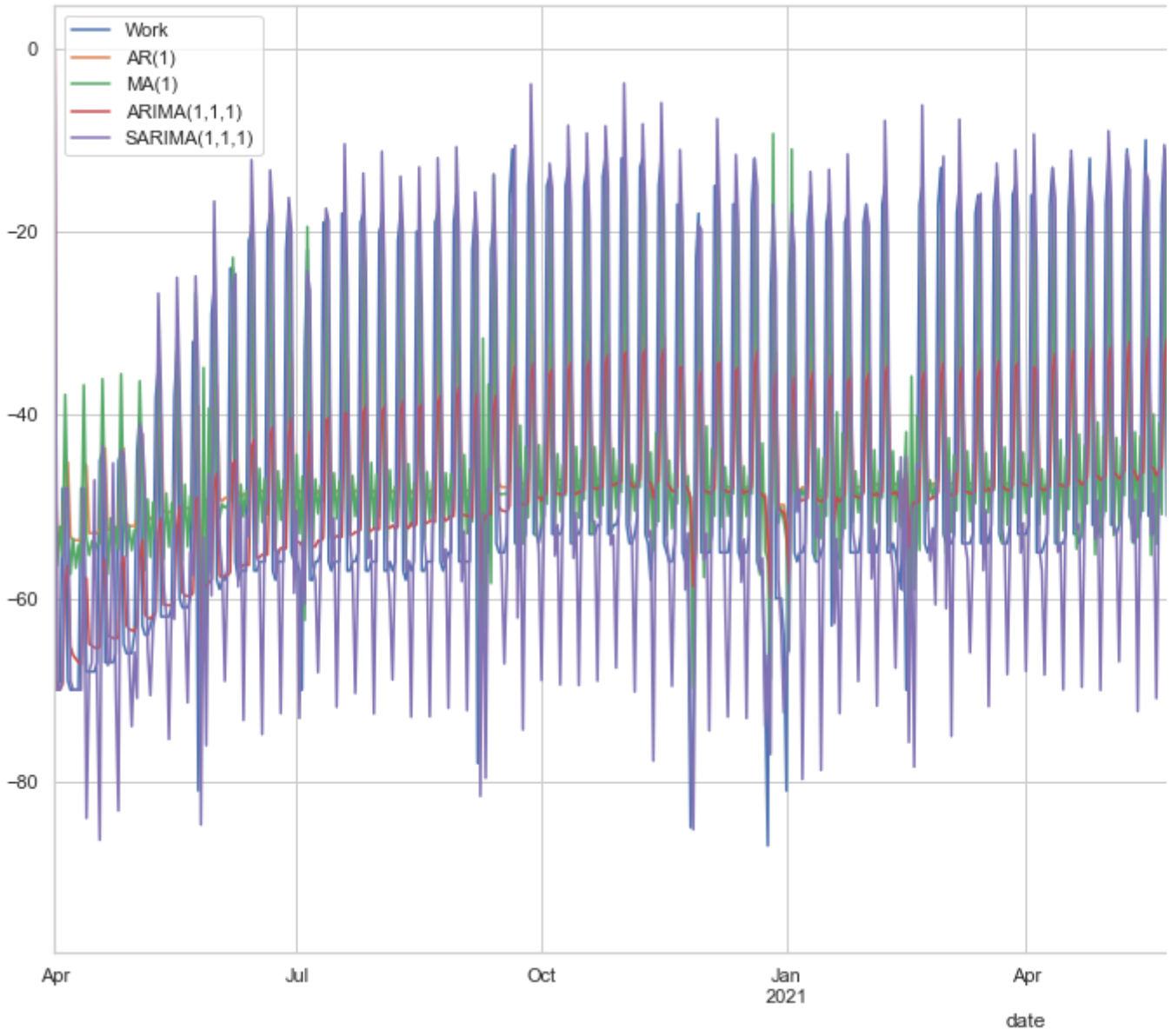

```
exp_smooth_scores = score_all_metrics(Work_test, column_list_ES,'Work')
```

```
cm = sns.color_palette("vlag", as_cmap=True)
exp_smooth_scores.style.background_gradient(cmap=cm)
```

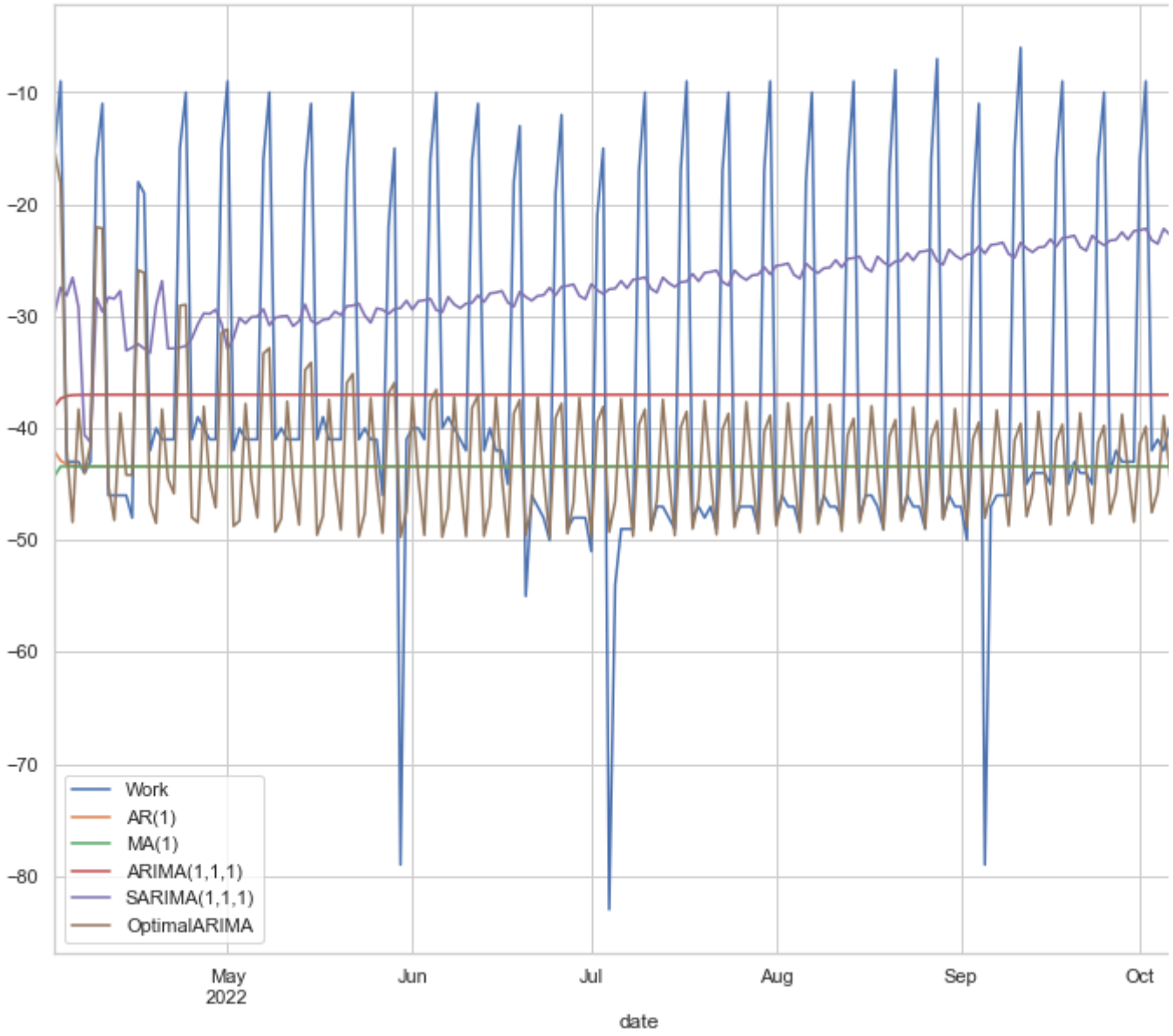
	ModelName	MAE	RMSE	MAPE
0	Simple_ES	12.853442	15.381829	0.683759
1	Trend_ES	17.681843	19.537519	0.598141
2	Dampened_ES	15.207733	16.342316	0.643264
3	Seasonal_ES	4.580390	6.895905	0.147170
4	Seasonal+Trend_ES	8.819598	10.699790	0.313473
5	Seasonal+DampendTrend_ES	4.582780	6.898050	0.147288

MAE, RMSE & MAPE of Seasonal_ES model are lowest, so the Seasonal_ES model is the best model for work dataset.

```
ar_1,ma_1,arima_1,sarima,column_list_ARIMA = plot_Arima(df = Work_train,ts_col = 'Work
```



```
model = auto_arima(Work_train['Work'], start_p=0,start_q=0,max_p=6,max_q=6,
                       max_d=2,seasonal=True,test='adf',error_action='ignore',informat
                      njob=-1,Trace=True,suppress_warnings=True)
model.fit(Work_train['Work'])
forecast=model.predict(n_periods=l)
Work_test["OptimalARIMA"]=forecast

Work_test["AR(1)"] = ar_1.fit().forecast(l)
Work_test["MA(1)"] = ma_1.fit().forecast(l)
Work_test["ARIMA(1,1,1)"] = arima_1.fit().forecast(l)
Work_test["SARIMA(1,1,1)"] = sarima.fit().forecast(l)

Work_test[["Work","AR(1)","MA(1)","ARIMA(1,1,1)","SARIMA(1,1,1)","OptimalARIMA"]].plot
plt.show()
```




```
column_list_ARIMA.append('OptimalARIMA')
```

```
arima_scores = score_all_metrics(Work_test, column_list_ARIMA,'Work')

cm = sns.color_palette("vlag", as_cmap=True)
arima_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	AR(1)	11.281154	16.975968	0.766121
1	MA(1)	11.296514	17.000216	0.767217
2	ARIMA(1,1,1)	12.642837	15.410949	0.687972
3	SARIMA(1,1,1)	16.816196	18.233031	0.611271
4	OptimalARIMA	9.809963	13.930469	0.618932

Optimal ARIMA is the best.

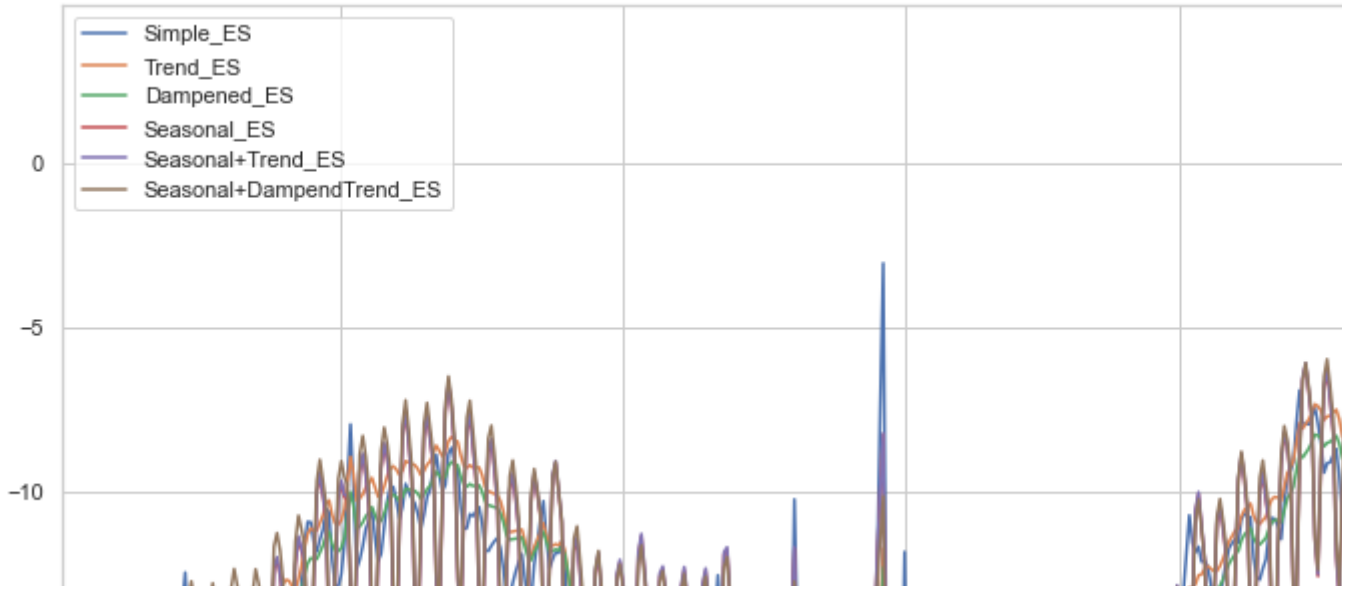
```
comparison_scores = score_all_metrics(Work_test,['Seasonal_ES','OptimalARIMA'],'Work')
cm = sns.color_palette("vlag", as_cmap=True)
comparison_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	Seasonal_ES	4.580390	6.895905	0.147170
1	OptimalARIMA	9.809963	13.930469	0.618932

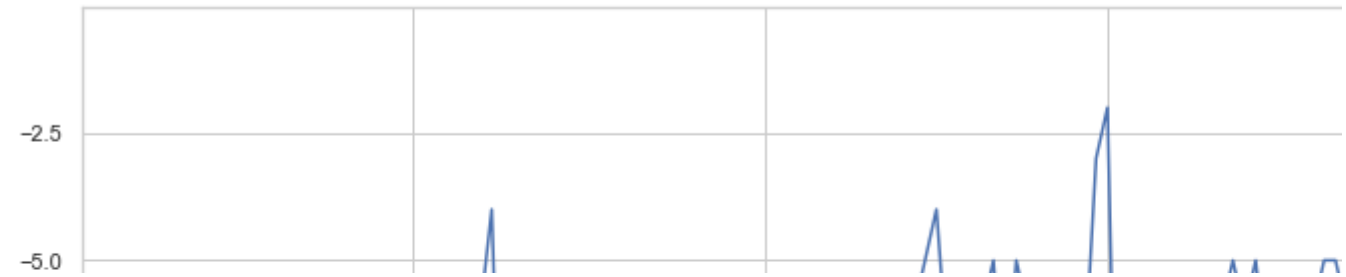
According to the final comparison, for Work dataset, we should choose the Seasonal_ES model to predict the future value.

Grocery and Pharmacy

```
simple_es,trend_es,dampened_es,seasonal_es,seatrd_es,seadap_es,column_list_ES = plot_t
```




```
GP_test['Simple_ES'] = simple_es.fit(smoothing_level=0.2).forecast(l)
GP_test['Trend_ES'] = trend_es.fit().forecast(l)
GP_test['Dampened_ES'] = dampened_es.fit().forecast(l)
GP_test['Seasonal_ES']  = seasonal_es.fit().forecast(l)
GP_test['Seasonal+Trend_ES']  = seatrd_es.fit().forecast(l)
GP_test['Seasonal+DampendTrend_ES']  = seadap_es.fit().forecast(l)

GP_test.plot(figsize=(20,10))
plt.show()
```

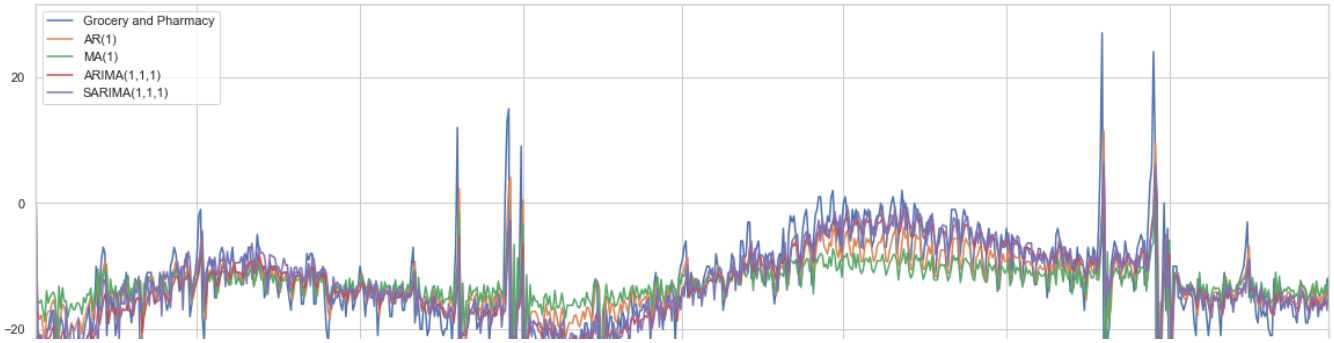



```
exp_smooth_scores = score_all_metrics(GP_test, column_list_ES,'Grocery and Pharmacy')
cm = sns.color_palette("vlag", as_cmap=True)
exp_smooth_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	Simple_ES	5.954748	6.651657	0.984922
1	Trend_ES	8.717949	9.423105	1.375463
2	Dampened_ES	7.015698	7.683899	1.134163
3	Seasonal_ES	6.831581	7.389808	1.047762
4	Seasonal+Trend_ES	5.897030	6.474916	0.915275
5	Seasonal+DampendTrend_ES	7.358644	7.914145	1.121780

MAE, RMSE & MAPE of Seasonal+Trend_ES model are lowest, so the Seasonal+Trend_ES model is the best model for work dataset.

```
ar_1,ma_1,arima_1,sarima,column_list_ARIMA = plot_Arima(df = GP_train,ts_col = 'Grocer
```




```
model = auto_arima(GP_train['Grocery and Pharmacy'], start_p=0,start_q=0,max_p=6,max_q
                      max_d=2,seasonal=True,test='adf',error_action='ignore',informat
                     njob=-1,Trace=True,suppress_warnings=True)
model.fit(GP_train['Grocery and Pharmacy'])
forecast=model.predict(n_periods=l)
GP_test["OptimalARIMA"]=forecast

GP_test["AR(1)"] = ar_1.fit().forecast(l)
GP_test["MA(1)"] = ma_1.fit().forecast(l)
GP_test["ARIMA(1,1,1)"] = arima_1.fit().forecast(l)
GP_test["SARIMA(1,1,1)"] = sarima.fit().forecast(l)

GP_test[["Grocery and Pharmacy","AR(1)","MA(1)","ARIMA(1,1,1)","SARIMA(1,1,1)","Optima
plt.show()
```


```
column_list_ARIMA.append('OptimalARIMA')
arima_scores = score_all_metrics(GP_test, column_list_ARIMA,'Grocery and Pharmacy')

cm = sns.color_palette("vlag", as_cmap=True)
arima_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	AR(1)	4.298193	5.010320	0.740828
1	MA(1)	4.285142	4.998085	0.738999
2	ARIMA(1,1,1)	6.584084	7.256510	1.072965
3	SARIMA(1,1,1)	6.365384	7.084720	1.044060
4	OptimalARIMA	6.042699	6.759310	0.999615

MA(1) is the best.

```
comparison_scores = score_all_metrics(GP_test,['Seasonal+Trend_ES','MA(1)'],'Grocery a
cm = sns.color_palette("vlag", as_cmap=True)
comparison_scores.style.background_gradient(cmap=cm)
```

	ModelName	MAE	RMSE	MAPE
0	Seasonal+Trend_ES	5.897030	6.474916	0.915275
1	MA(1)	4.285142	4.998085	0.738999

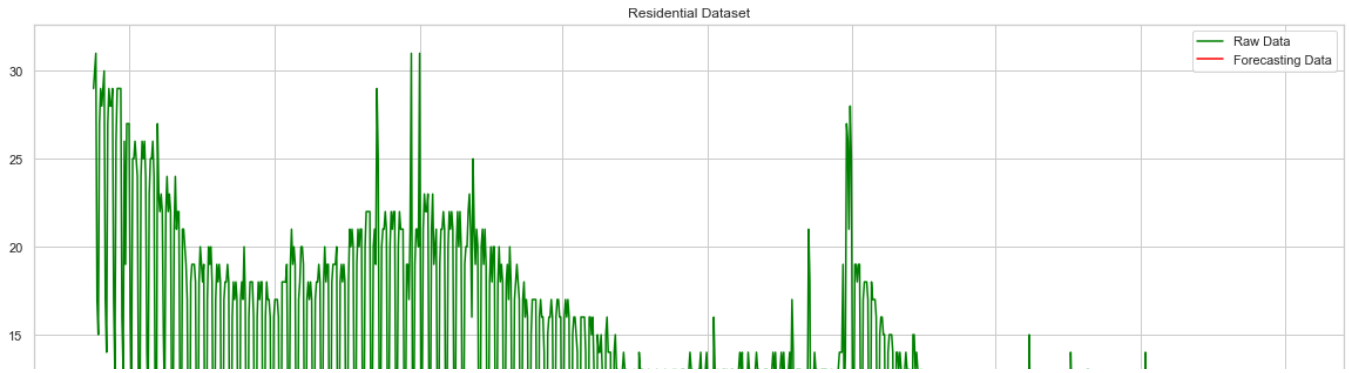
According to the final comparison, for Work dataset, we should choose the MA(1) model to predict the future value.

5. Forecast

```
df_index = pd.date_range('2022-10-16',periods=77)
Residential_Raw = Residential.set_index('date')
Seasonal_es = ExponentialSmoothing(Residential_Raw['Residential'],seasonal='add')
Residential_Forecast = Seasonal_es.fit().forecast(77)
Residential_Forecast = pd.DataFrame(data = Residential_Forecast)
Residential_Forecast.index.name = 'date'
Residential_Forecast
```

date	0
2022-10-16	0.127923
2022-10-17	10.254128
2022-10-18	10.022845
2022-10-19	9.722169
2022-10-20	9.680600
...	...
2022-12-27	10.022845
2022-12-28	9.722169
2022-12-29	9.680600
2022-12-30	9.486935
2022-12-31	0.105399

```
plt.figure(figsize = (20,10))
plt.plot(Residential_Raw, color = 'green', label = 'Raw Data')
plt.plot(Residential_Forecast, color = 'red', label = 'Forecasting Data')
plt.title('Residential Dataset')
plt.legend()
plt.show()
```

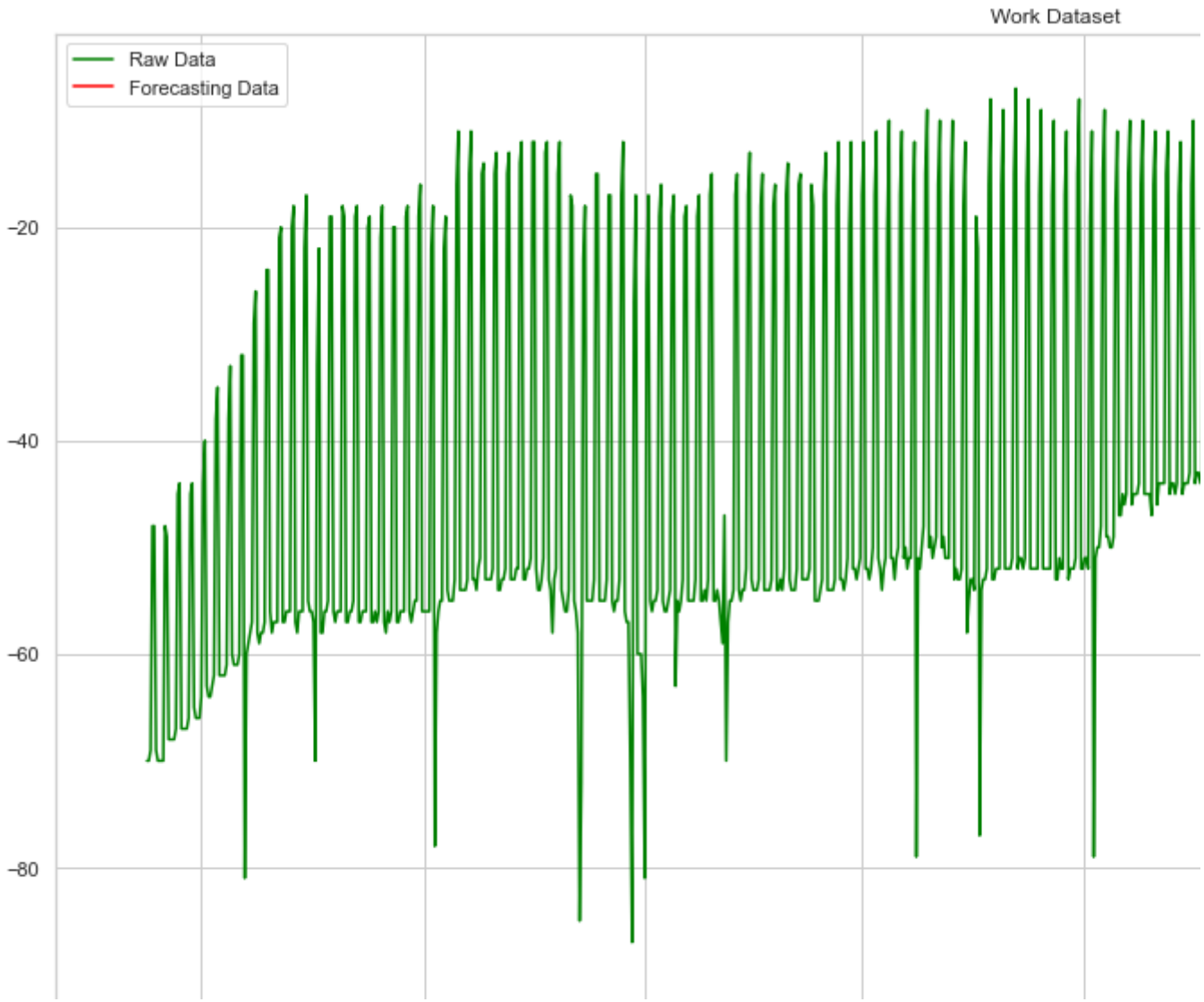



```
Work_Raw = Work.set_index('date')
Seasonal_es = ExponentialSmoothing(Work_Raw['Work'],seasonal='add')
Work_Forecast = Seasonal_es.fit().forecast(77)
Work_Forecast = pd.DataFrame(data = Work_Forecast)
Work_Forecast.index.name = 'date'
Work_Forecast
```

	0
date	
2022-10-16	-7.211537
2022-10-17	-46.141896
2022-10-18	-42.284870
2022-10-19	-42.947056
2022-10-20	-42.626983
...	...
2022-12-27	-42.284870
2022-12-28	-42.947056
2022-12-29	-42.626983
2022-12-30	-44.298728
2022-12-31	-14.695758

77 rows × 1 columns

```
plt.figure(figsize = (20,10))
plt.plot(Work_Raw, color = 'green', label = 'Raw Data')
plt.plot(Work_Forecast, color = 'red', label = 'Forecasting Data')
plt.title('Work Dataset')
plt.legend()
plt.show()
```




```
GP_Raw = GP.set_index('date')
ma_1 = ARIMA(GP_Raw['Grocery and Pharmacy'], order=(0,0,1))
GP_Forecast = ma_1.fit().forecast(77)
GP_Forecast = pd.DataFrame(data = GP_Forecast)
GP_Forecast.index.name = 'date'
GP_Forecast
```

date	predicted_mean
2022-10-16	-14.169816
2022-10-17	-11.974627
2022-10-18	-11.974627
2022-10-19	-11.974627

```
plt.figure(figsize = (20,10))
plt.plot(GP_Raw, color = 'green', label = 'Raw Data')
plt.plot(GP_Forecast, color = 'red', label = 'Forecasting Data')
plt.title('Grocery & Pharmacy Dataset')
plt.legend()
plt.show()
```