timeserieslab11-rohramehak-251524

May 15, 2024

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
!pip install pmdarima
```

```
Collecting pmdarima
  Downloading pmdarima-2.0.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86
_64.manylinux_2_28_x86_64.whl (2.1 MB)
                           2.1/2.1 MB
39.0 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.4.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.10)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.25.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.3)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (1.11.4)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-
packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (24.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=0.19->pmdarima) (2024.1)
```

```
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->pmdarima)
(3.5.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels>=0.13.2->pmdarima) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels>=0.13.2->pmdarima) (1.16.0)
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.4
```

Importing libraries

```
[ ]: import pandas as pd
     from matplotlib import pyplot as plt
     import numpy as np
     from pmdarima import auto_arima
     from statsmodels.tsa.statespace.sarimax import SARIMAX
     from sklearn.metrics import mean_absolute_percentage_error
     from statsmodels.tsa.holtwinters import ExponentialSmoothing
     import warnings
     from statsmodels.tools.sm_exceptions import ConvergenceWarning
     warnings.simplefilter('ignore', ConvergenceWarning)
     from statsmodels.tsa.seasonal import seasonal_decompose
```

Restaurants data

```
[ ]: df = pd.read_csv('/content/drive/MyDrive/TSA_BDA_2024/Lab11/RestaurantVisitors.
      ↪csv', index_col='date',parse_dates=True)
```

```
[ ]: df
```

```
[ ]:               weekday  holiday    holiday_name  rest1  rest2  rest3  rest4  \
     date
     2016-01-01     Friday        1  New Year's Day   65.0   25.0   67.0  139.0
     2016-01-02   Saturday        0              na   24.0   39.0   43.0   85.0
     2016-01-03     Sunday        0              na   24.0   31.0   66.0   81.0
     2016-01-04     Monday        0              na   23.0   18.0   32.0   32.0
     2016-01-05    Tuesday        0              na    2.0   15.0   38.0   43.0
     …                 …       …               …      …      …      …      …
     2017-05-27   Saturday        0              na    NaN    NaN    NaN    NaN
     2017-05-28     Sunday        0              na    NaN    NaN    NaN    NaN
     2017-05-29     Monday        1    Memorial Day    NaN    NaN    NaN    NaN
     2017-05-30    Tuesday        0              na    NaN    NaN    NaN    NaN
     2017-05-31  Wednesday        0              na    NaN    NaN    NaN    NaN

               total
     date
     2016-01-01  296.0
```

```
2016-01-02  191.0
2016-01-03  202.0
2016-01-04  105.0
2016-01-05   98.0
…           …
2017-05-27    NaN
2017-05-28    NaN
2017-05-29    NaN
2017-05-30    NaN
2017-05-31    NaN

[517 rows x 8 columns]
```

[ ]:
```
df.index.freq = 'D'
df1 = df.dropna()
df1.tail()
```

[ ]:

date	weekday	holiday	holiday_name	rest1	rest2	rest3	rest4	total
2017-04-18	Tuesday	0	na	30.0	30.0	13.0	18.0	91.0
2017-04-19	Wednesday	0	na	20.0	11.0	30.0	18.0	79.0
2017-04-20	Thursday	0	na	22.0	3.0	19.0	46.0	90.0
2017-04-21	Friday	0	na	38.0	53.0	36.0	38.0	165.0
2017-04-22	Saturday	0	na	97.0	20.0	50.0	59.0	226.0

[ ]:
```
cols=['rest1','rest2','rest3','rest4','total']
for col in cols:
 df1[col]=df1[col].astype(int)
```

```
<ipython-input-7-015192da4e31>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col]=df1[col].astype(int)
<ipython-input-7-015192da4e31>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col]=df1[col].astype(int)
<ipython-input-7-015192da4e31>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

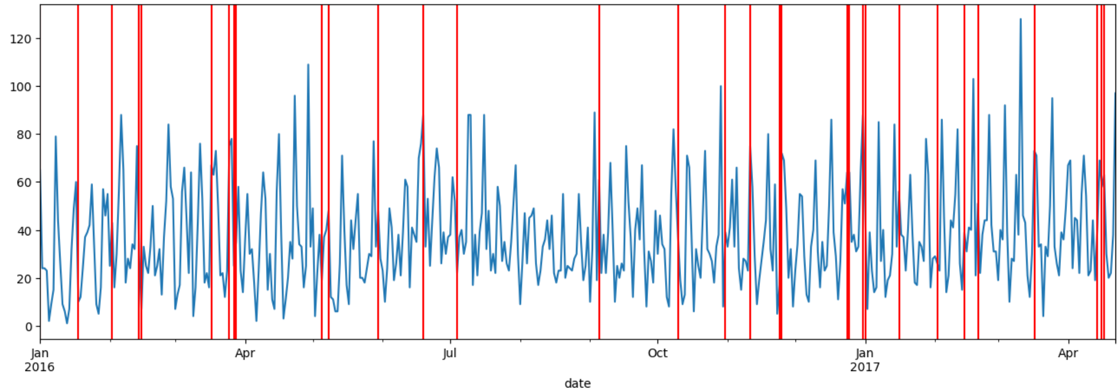
```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col]=df1[col].astype(int)
<ipython-input-7-015192da4e31>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col]=df1[col].astype(int)
<ipython-input-7-015192da4e31>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1[col]=df1[col].astype(int)
```

[ ]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 478 entries, 2016-01-01 to 2017-04-22
Freq: D
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   weekday       478 non-null    object
 1   holiday       478 non-null    int64
 2   holiday_name  478 non-null    object
 3   rest1         478 non-null    int64
 4   rest2         478 non-null    int64
 5   rest3         478 non-null    int64
 6   rest4         478 non-null    int64
 7   total         478 non-null    int64
dtypes: int64(6), object(2)
memory usage: 33.6+ KB
```

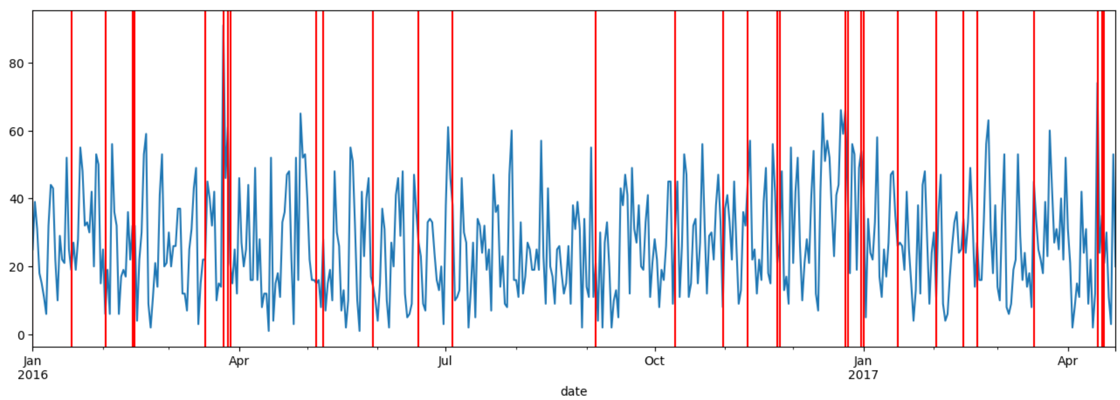
Time series restaurant 1

[ ]:
```
ax=df1['rest1'].plot(figsize=(16,5))
for x in df1.query('holiday==1').index:
 ax.axvline(x=x,color='r')
```



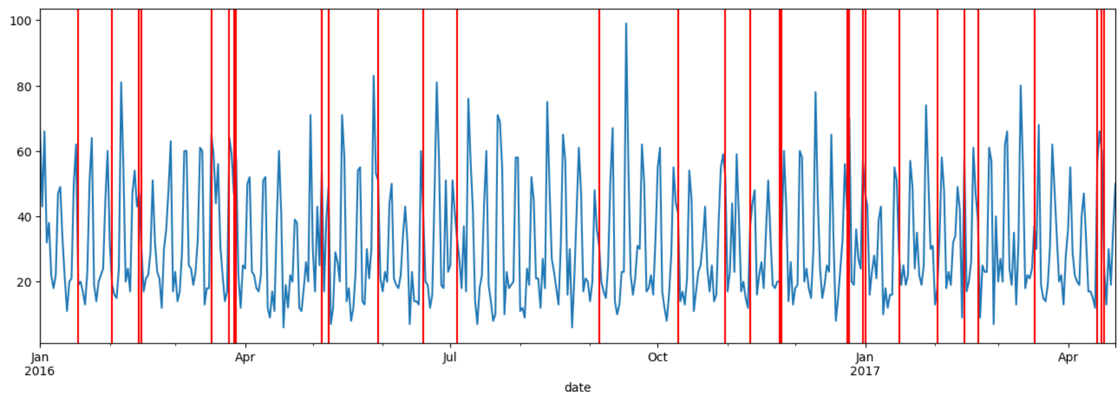
Time series restaurant 2

[ ]:
```
ax=df1['rest2'].plot(figsize=(16,5))
for x in df1.query('holiday==1').index:
 ax.axvline(x=x,color='r')
```



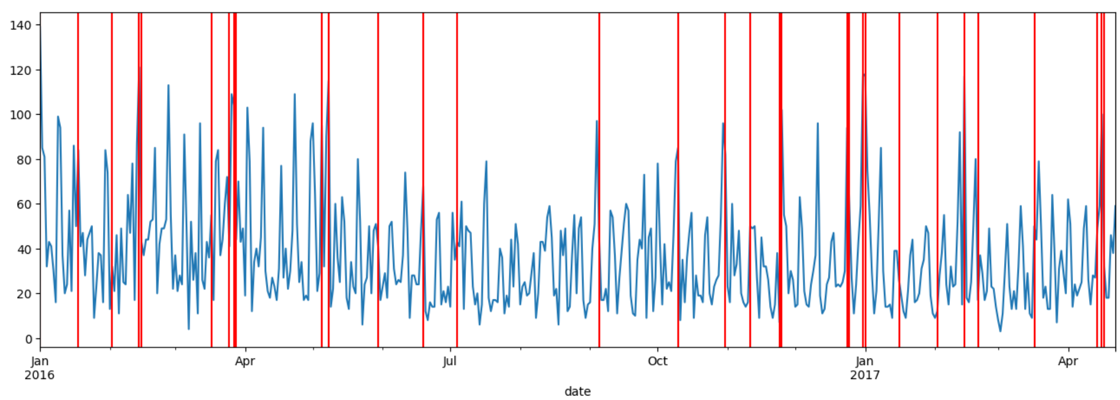
Time series restaurant 3

[ ]:
```
ax=df1['rest3'].plot(figsize=(16,5))
for x in df1.query('holiday==1').index:
 ax.axvline(x=x,color='r')
```



Time series restaurant 4

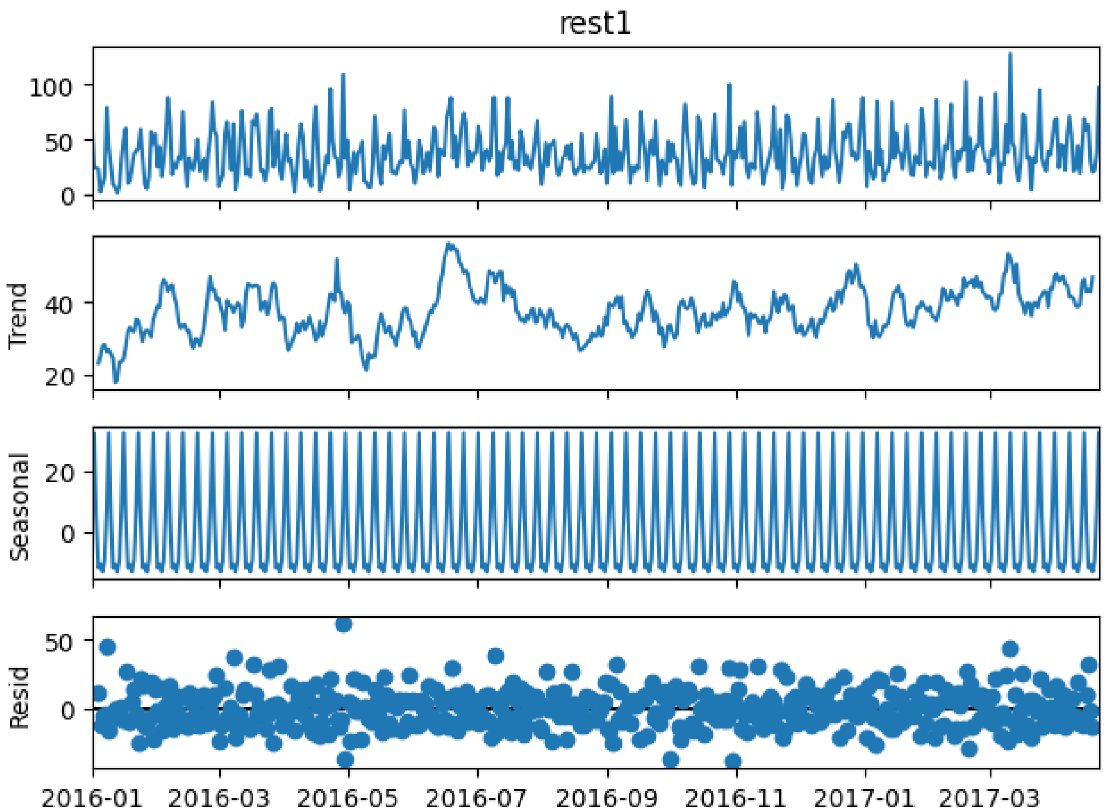
[ ]:
```
ax=df1['rest4'].plot(figsize=(16,5))
for x in df1.query('holiday==1').index:
 ax.axvline(x=x,color='r')
```

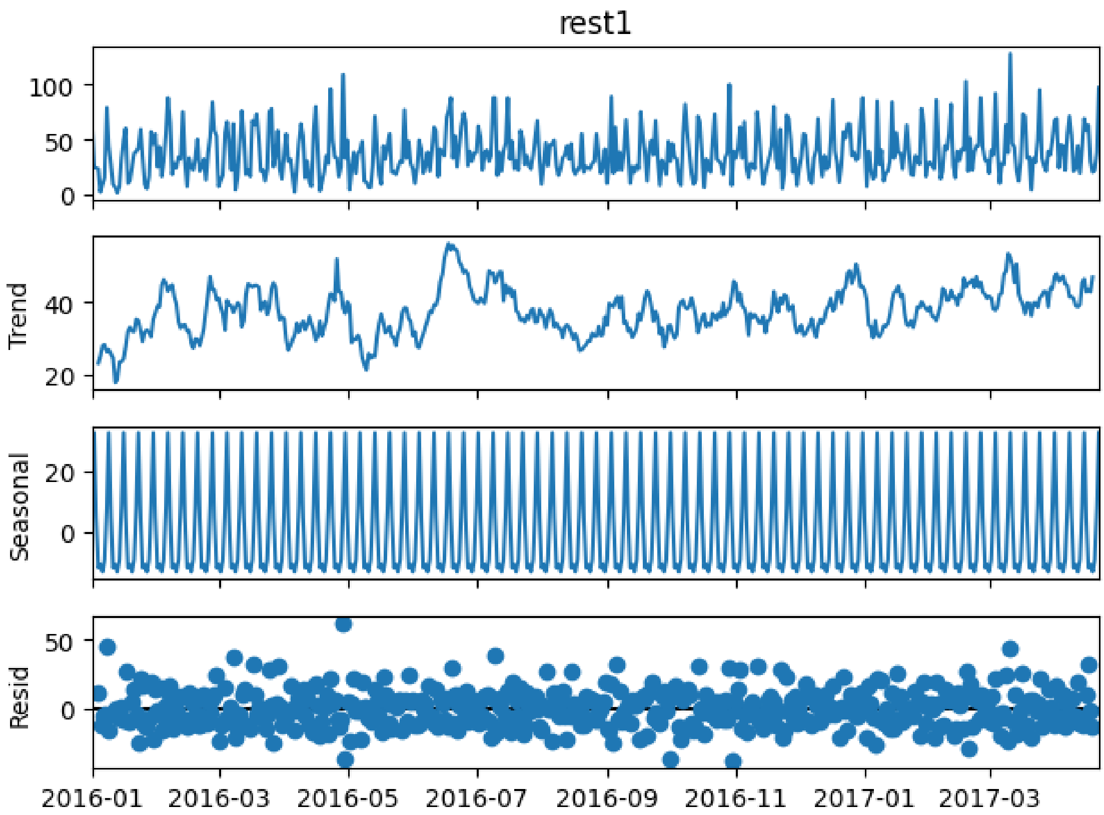


Plots for restaurant 1

[ ]:
```
result_rest1=seasonal_decompose(df1['rest1'])
result_rest1.plot()
```

[ ]:

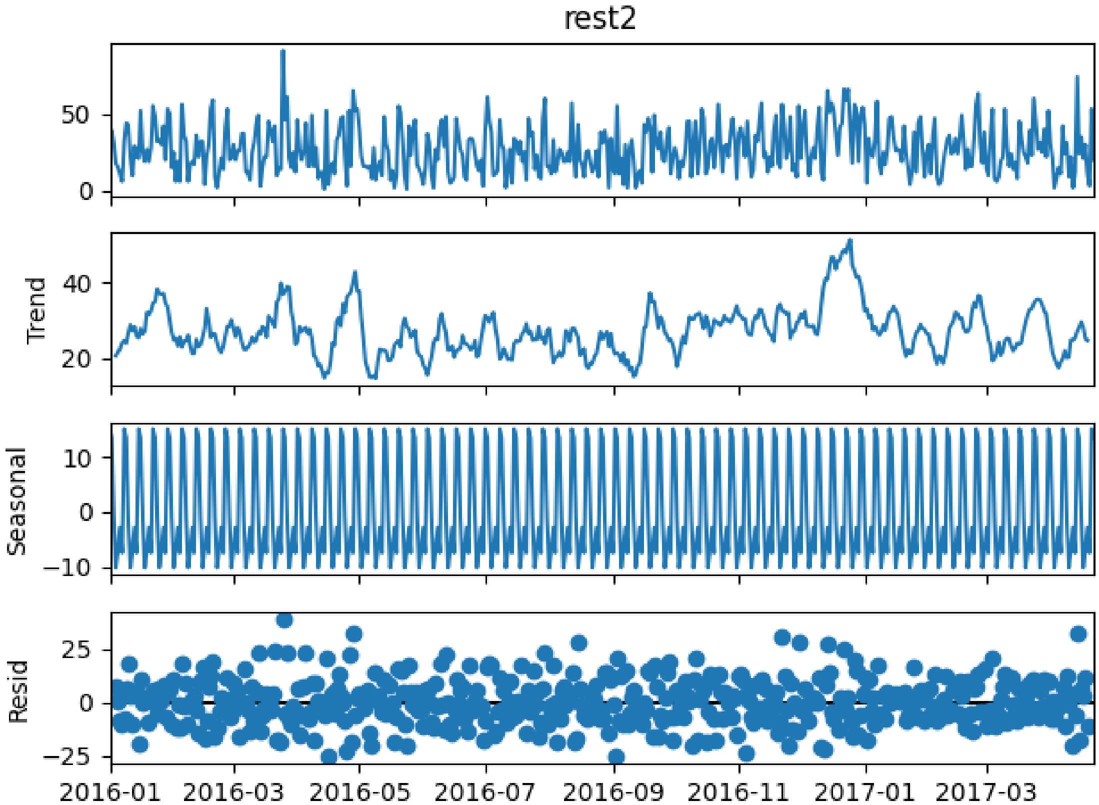

rest1
100
50
0
Trend
40
20
Seasonal
20
0
Resid
50
0
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01
2017-03

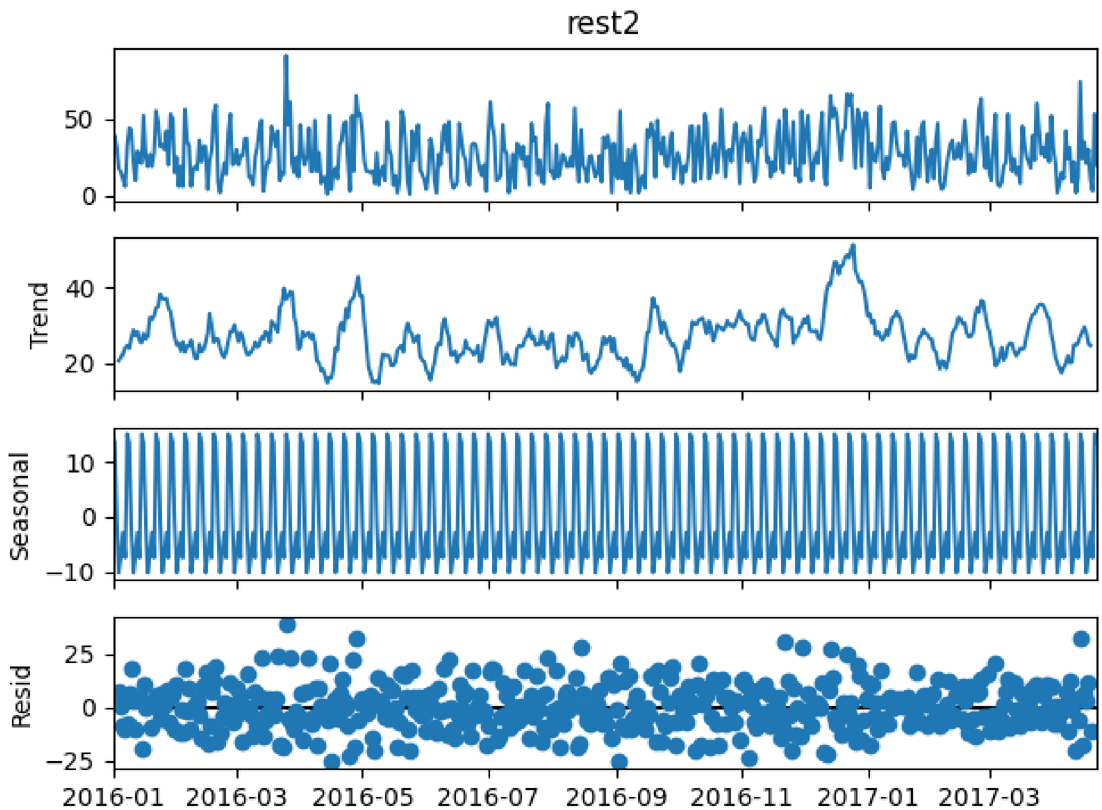


Plots for restaurant 2 time series

[ ]:
```
result_rest2=seasonal_decompose(df1['rest2'])
result_rest2.plot()
```

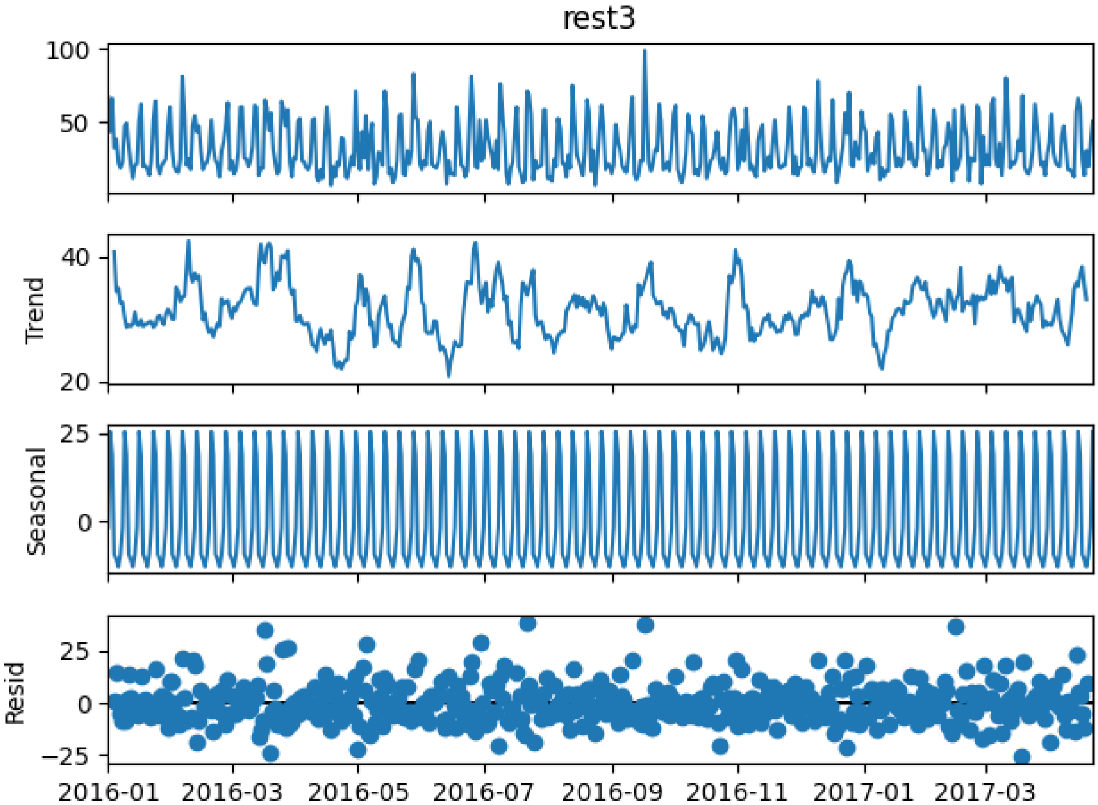
[ ]:

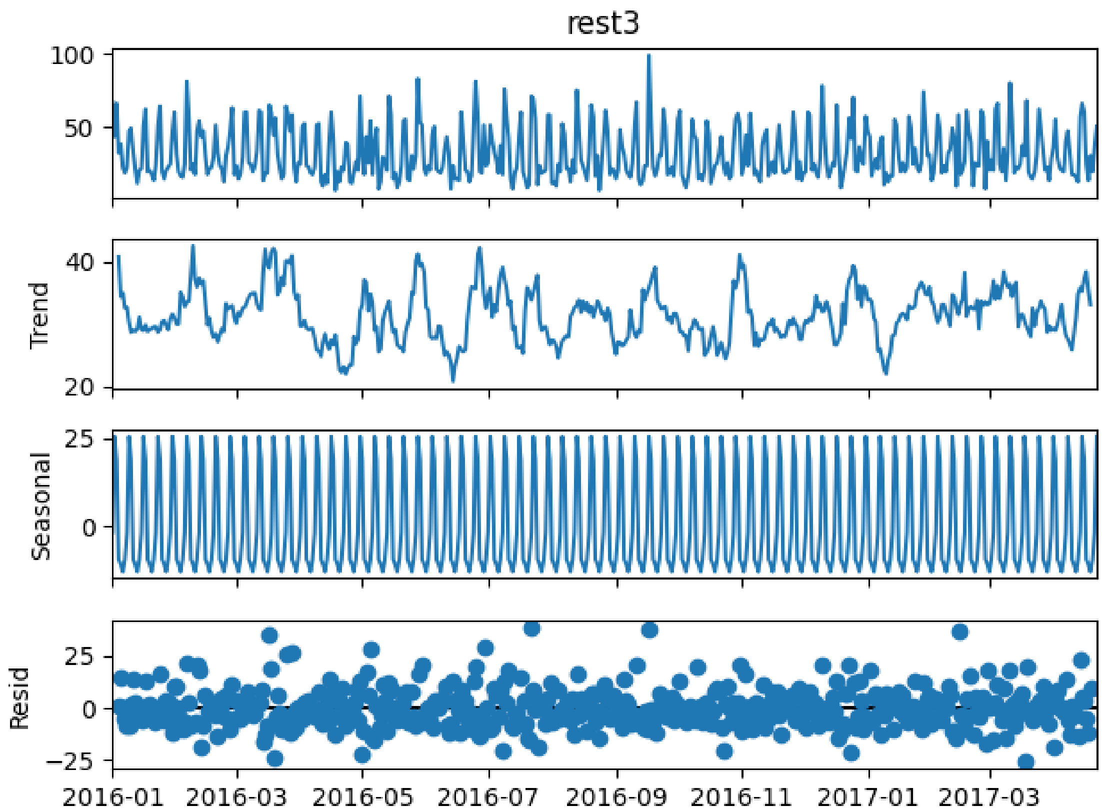

rest2
50
0
Trend
40
20
Seasonal
10
0
−10
Resid
25
0
−25
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01
2017-03




```
[ ]: result_rest3=seasonal_decompose(df1['rest3'])
     result_rest3.plot()
```

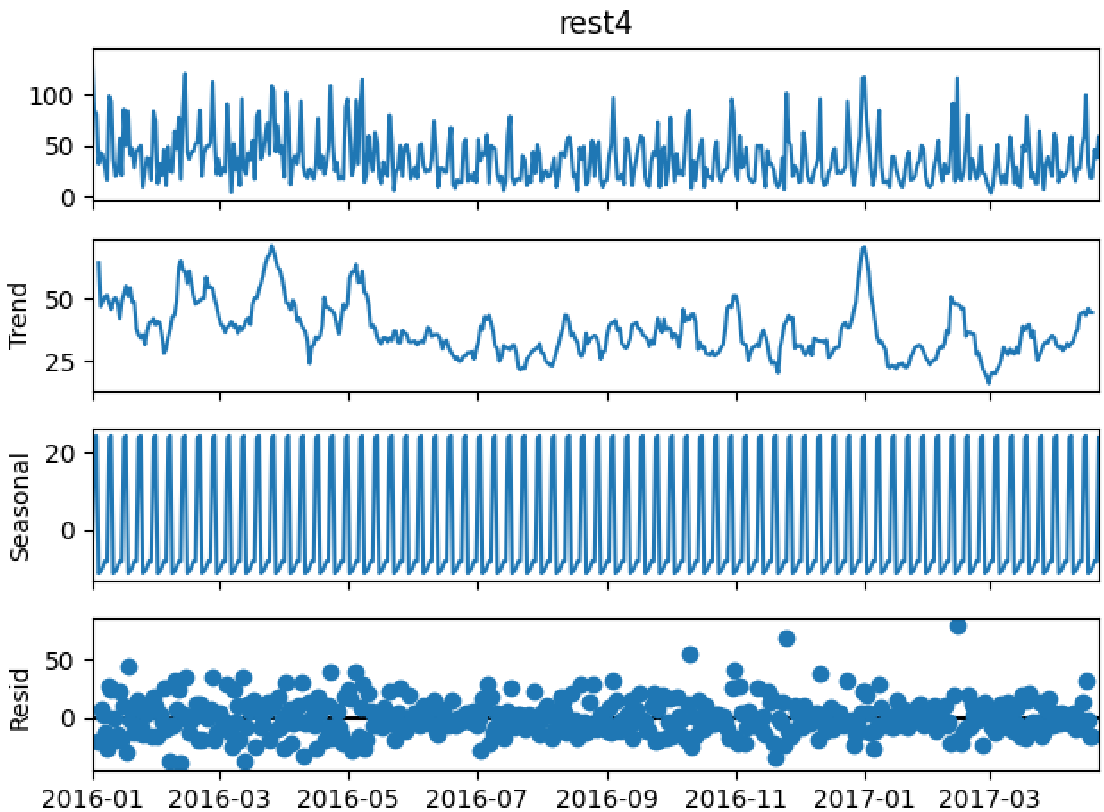
```
[ ]:
```

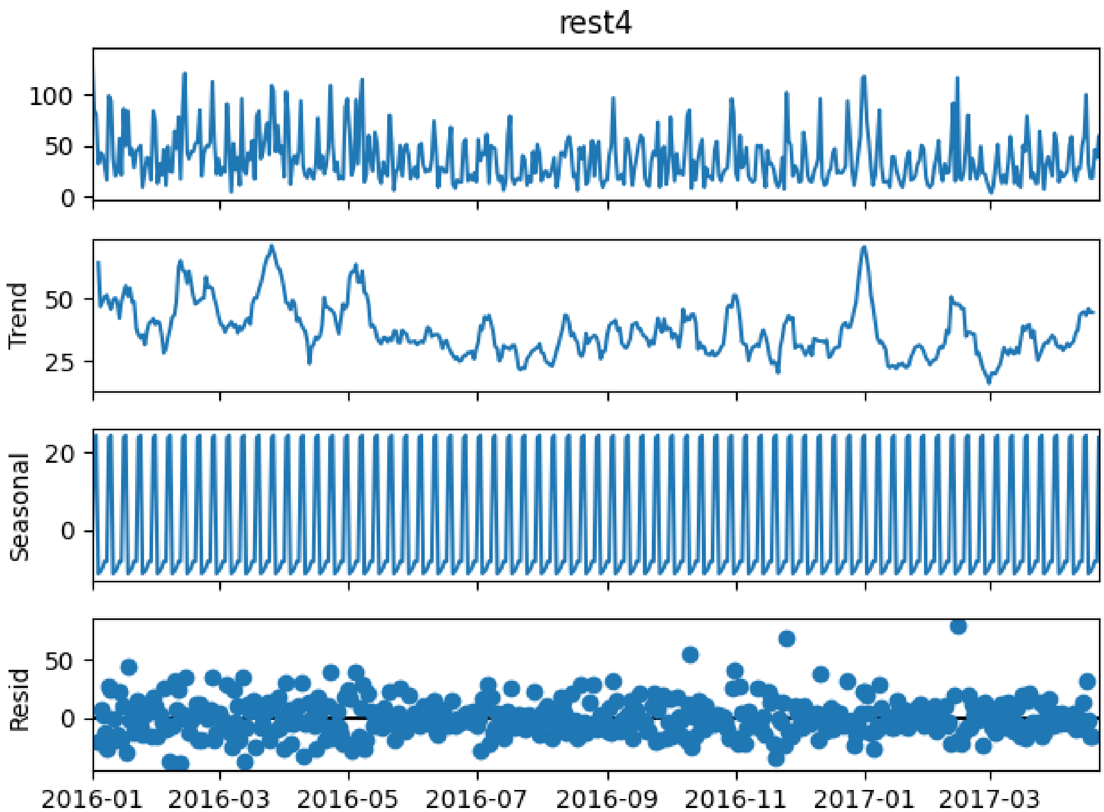

rest3
100
50
Trend
40
20
Seasonal
25
0
Resid
25
0
−25
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01
2017-03



[ ]:
```
result_rest4=seasonal_decompose(df1['rest4'])
result_rest4.plot()
```

[ ]:


rest4
100
50
0
Trend
50
25
Seasonal
20
0
Resid
50
0
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01
2017-03



using auto_arima for automatically selecting the optimal ARIMA model parameters for all 4 time series separately

[ ]:
```
auto_arima(df1['rest1'], exogenous = df1['holiday'], start_p =0 , start_q= 0,␣
 ↪max_p =5, max_q = 5 , stepwise=True, seasonal=True,m=7,trace=True).summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(1,0,1)[7] intercept   : AIC=4288.103, Time=1.59 sec
 ARIMA(0,1,0)(0,0,0)[7] intercept   : AIC=4498.869, Time=0.06 sec
 ARIMA(1,1,0)(1,0,0)[7] intercept   : AIC=4282.164, Time=0.78 sec
 ARIMA(0,1,1)(0,0,1)[7] intercept   : AIC=inf, Time=1.99 sec
 ARIMA(0,1,0)(0,0,0)[7]             : AIC=4496.872, Time=0.03 sec
 ARIMA(1,1,0)(0,0,0)[7] intercept   : AIC=4459.994, Time=0.14 sec
 ARIMA(1,1,0)(2,0,0)[7] intercept   : AIC=4233.491, Time=0.94 sec
 ARIMA(1,1,0)(2,0,1)[7] intercept   : AIC=inf, Time=1.84 sec
 ARIMA(1,1,0)(1,0,1)[7] intercept   : AIC=4124.750, Time=2.03 sec
 ARIMA(1,1,0)(0,0,1)[7] intercept   : AIC=4354.529, Time=0.42 sec
 ARIMA(1,1,0)(1,0,2)[7] intercept   : AIC=inf, Time=2.23 sec
 ARIMA(1,1,0)(0,0,2)[7] intercept   : AIC=4324.385, Time=1.28 sec
 ARIMA(1,1,0)(2,0,2)[7] intercept   : AIC=inf, Time=9.52 sec
 ARIMA(2,1,0)(1,0,1)[7] intercept   : AIC=inf, Time=4.30 sec
```

```
 ARIMA(1,1,1)(1,0,1)[7] intercept   : AIC=3961.998, Time=3.06 sec
 ARIMA(1,1,1)(0,0,1)[7] intercept   : AIC=inf, Time=2.49 sec
 ARIMA(1,1,1)(1,0,0)[7] intercept   : AIC=inf, Time=3.36 sec
 ARIMA(1,1,1)(2,0,1)[7] intercept   : AIC=3963.752, Time=9.23 sec
 ARIMA(1,1,1)(1,0,2)[7] intercept   : AIC=inf, Time=14.45 sec
 ARIMA(1,1,1)(0,0,0)[7] intercept   : AIC=inf, Time=1.48 sec
 ARIMA(1,1,1)(0,0,2)[7] intercept   : AIC=inf, Time=3.15 sec
 ARIMA(1,1,1)(2,0,0)[7] intercept   : AIC=inf, Time=2.53 sec
 ARIMA(1,1,1)(2,0,2)[7] intercept   : AIC=inf, Time=3.21 sec
 ARIMA(0,1,1)(1,0,1)[7] intercept   : AIC=inf, Time=3.13 sec
 ARIMA(2,1,1)(1,0,1)[7] intercept   : AIC=inf, Time=2.61 sec
 ARIMA(1,1,2)(1,0,1)[7] intercept   : AIC=inf, Time=2.31 sec
 ARIMA(0,1,2)(1,0,1)[7] intercept   : AIC=inf, Time=1.78 sec
 ARIMA(2,1,2)(1,0,1)[7] intercept   : AIC=inf, Time=1.62 sec
 ARIMA(1,1,1)(1,0,1)[7]             : AIC=inf, Time=1.53 sec

Best model:  ARIMA(1,1,1)(1,0,1)[7] intercept
Total fit time: 83.327 seconds
```

[ ]:

Dep. Variable:	y	**No. Observations:**	478
Model:	SARIMAX(1, 1, 1)x(1, 0, 1, 7)	**Log Likelihood**	-1974.999
Date:	Wed, 15 May 2024	**AIC**	3961.998
Time:	11:43:42	**BIC**	3987.003
Sample:	01-01-2016 - 04-22-2017	**HQIC**	3971.829
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
intercept	5.752e-05	0.000	0.203	0.839	-0.000	0.001
ar.L1	-0.0243	0.046	-0.523	0.601	-0.115	0.067
ma.L1	-0.9839	0.009	-107.063	0.000	-1.002	-0.966
ar.S.L7	0.9981	0.002	596.498	0.000	0.995	1.001
ma.S.L7	-0.9303	0.023	-39.780	0.000	-0.976	-0.884
sigma2	222.6720	14.239	15.638	0.000	194.764	250.580

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	21.29
Prob(Q):	0.93	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.74	**Skew:**	0.50
Prob(H) (two-sided):	0.06	**Kurtosis:**	3.30

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

[ ]:
```
auto_arima(df1['rest2'], exogenous = df1['holiday'], start_p =0 , start_q= 0,
 max_p =5, max_q = 5 , stepwise=True, seasonal=True,m=7,trace=True).summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,0,0)(1,0,1)[7] intercept   : AIC=3796.678, Time=2.25 sec
 ARIMA(0,0,0)(0,0,0)[7] intercept   : AIC=3993.941, Time=0.07 sec
 ARIMA(1,0,0)(1,0,0)[7] intercept   : AIC=3879.592, Time=1.42 sec
```

```
ARIMA(0,0,1)(0,0,1)[7] intercept   : AIC=3913.211, Time=1.08 sec
ARIMA(0,0,0)(0,0,0)[7]             : AIC=4653.097, Time=0.05 sec
ARIMA(0,0,0)(0,0,1)[7] intercept   : AIC=3927.769, Time=0.68 sec
ARIMA(0,0,0)(1,0,0)[7] intercept   : AIC=3891.413, Time=0.89 sec
ARIMA(0,0,0)(2,0,1)[7] intercept   : AIC=3816.916, Time=2.68 sec
ARIMA(0,0,0)(1,0,2)[7] intercept   : AIC=3806.983, Time=2.48 sec
ARIMA(0,0,0)(0,0,2)[7] intercept   : AIC=3904.015, Time=0.49 sec
ARIMA(0,0,0)(2,0,0)[7] intercept   : AIC=3858.705, Time=1.03 sec
ARIMA(0,0,0)(2,0,2)[7] intercept   : AIC=inf, Time=1.49 sec
ARIMA(1,0,0)(1,0,1)[7] intercept   : AIC=3789.098, Time=1.59 sec
ARIMA(1,0,0)(0,0,1)[7] intercept   : AIC=3913.497, Time=0.44 sec
ARIMA(1,0,0)(2,0,1)[7] intercept   : AIC=3836.022, Time=5.19 sec
ARIMA(1,0,0)(1,0,2)[7] intercept   : AIC=3798.604, Time=3.48 sec
ARIMA(1,0,0)(0,0,0)[7] intercept   : AIC=3974.721, Time=0.07 sec
ARIMA(1,0,0)(0,0,2)[7] intercept   : AIC=3889.658, Time=1.13 sec
ARIMA(1,0,0)(2,0,0)[7] intercept   : AIC=3846.742, Time=1.61 sec
ARIMA(1,0,0)(2,0,2)[7] intercept   : AIC=3906.871, Time=3.46 sec
ARIMA(2,0,0)(1,0,1)[7] intercept   : AIC=3786.202, Time=2.31 sec
ARIMA(2,0,0)(0,0,1)[7] intercept   : AIC=3915.045, Time=1.18 sec
ARIMA(2,0,0)(1,0,0)[7] intercept   : AIC=3881.496, Time=2.02 sec
ARIMA(2,0,0)(2,0,1)[7] intercept   : AIC=3850.233, Time=4.89 sec
ARIMA(2,0,0)(1,0,2)[7] intercept   : AIC=3807.869, Time=3.16 sec
ARIMA(2,0,0)(0,0,0)[7] intercept   : AIC=3973.489, Time=0.22 sec
ARIMA(2,0,0)(0,0,2)[7] intercept   : AIC=3891.652, Time=1.71 sec
ARIMA(2,0,0)(2,0,0)[7] intercept   : AIC=3847.373, Time=2.00 sec
ARIMA(2,0,0)(2,0,2)[7] intercept   : AIC=3915.546, Time=7.25 sec
ARIMA(3,0,0)(1,0,1)[7] intercept   : AIC=3810.621, Time=3.99 sec
ARIMA(2,0,1)(1,0,1)[7] intercept   : AIC=inf, Time=3.14 sec
ARIMA(1,0,1)(1,0,1)[7] intercept   : AIC=3799.630, Time=2.00 sec
ARIMA(3,0,1)(1,0,1)[7] intercept   : AIC=inf, Time=4.98 sec
ARIMA(2,0,0)(1,0,1)[7]             : AIC=3793.470, Time=1.22 sec

Best model:  ARIMA(2,0,0)(1,0,1)[7] intercept
Total fit time: 71.782 seconds
```

[ ]:

Dep. Variable:	y	**No. Observations:**	478
Model:	SARIMAX(2, 0, 0)x(1, 0, [1], 7)	**Log Likelihood**	-1887.101
Date:	Wed, 15 May 2024	**AIC**	3786.202
Time:	11:44:54	**BIC**	3811.220
Sample:	01-01-2016 - 04-22-2017	**HQIC**	3796.038
Covariance Type:	opg		

	coef	std err	z	P> |z|	[0.025	0.975]
intercept	0.6968	0.343	2.031	0.042	0.025	1.369
ar.L1	0.1320	0.047	2.825	0.005	0.040	0.224
ar.L2	0.1037	0.040	2.562	0.010	0.024	0.183
ar.S.L7	0.9626	0.015	62.290	0.000	0.932	0.993
ma.S.L7	-0.7804	0.042	-18.365	0.000	-0.864	-0.697
sigma2	151.0947	8.986	16.814	0.000	133.482	168.707

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	31.33
Prob(Q):	0.91	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.78	**Skew:**	0.56
Prob(H) (two-sided):	0.11	**Kurtosis:**	3.55

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

[ ]:
```
auto_arima(df1['rest3'], exogenous = df1['holiday'], start_p =0 , start_q= 0,
  max_p =5, max_q = 5 , stepwise=True, seasonal=True,m=7,trace=True).summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,0,0)(1,0,1)[7] intercept   : AIC=3654.398, Time=1.38 sec
 ARIMA(0,0,0)(0,0,0)[7] intercept   : AIC=4113.097, Time=0.03 sec
 ARIMA(1,0,0)(1,0,0)[7] intercept   : AIC=3865.463, Time=1.84 sec
 ARIMA(0,0,1)(0,0,1)[7] intercept   : AIC=3963.602, Time=0.51 sec
 ARIMA(0,0,0)(0,0,0)[7]             : AIC=4790.278, Time=0.02 sec
 ARIMA(0,0,0)(0,0,1)[7] intercept   : AIC=3984.802, Time=0.29 sec
 ARIMA(0,0,0)(1,0,0)[7] intercept   : AIC=3864.802, Time=0.48 sec
 ARIMA(0,0,0)(2,0,1)[7] intercept   : AIC=3822.189, Time=3.01 sec
 ARIMA(0,0,0)(1,0,2)[7] intercept   : AIC=3703.219, Time=3.38 sec
 ARIMA(0,0,0)(0,0,2)[7] intercept   : AIC=3906.933, Time=3.22 sec
 ARIMA(0,0,0)(2,0,0)[7] intercept   : AIC=3781.022, Time=5.11 sec
 ARIMA(0,0,0)(2,0,2)[7] intercept   : AIC=3909.204, Time=12.28 sec
 ARIMA(1,0,0)(1,0,1)[7] intercept   : AIC=3674.265, Time=3.37 sec
 ARIMA(0,0,1)(1,0,1)[7] intercept   : AIC=3676.310, Time=3.75 sec
 ARIMA(1,0,1)(1,0,1)[7] intercept   : AIC=inf, Time=2.33 sec
 ARIMA(0,0,0)(1,0,1)[7]             : AIC=inf, Time=0.79 sec

Best model:  ARIMA(0,0,0)(1,0,1)[7] intercept
Total fit time: 41.870 seconds
```

[ ]:

Dep. Variable:	y	**No. Observations:**	478
Model:	SARIMAX(1, 0, [1], 7)	**Log Likelihood**	-1823.199
Date:	Wed, 15 May 2024	**AIC**	3654.398
Time:	11:45:36	**BIC**	3671.076
Sample:	01-01-2016 - 04-22-2017	**HQIC**	3660.955
Covariance Type:	opg		

	coef	std err	z	P> |z|	[0.025	0.975]
intercept	0.1148	0.103	1.118	0.264	-0.087	0.316
ar.S.L7	0.9963	0.003	316.533	0.000	0.990	1.002
ma.S.L7	-0.9240	0.029	-31.713	0.000	-0.981	-0.867
sigma2	117.9847	6.087	19.385	0.000	106.055	129.914

Ljung-Box (L1) (Q):	1.12	**Jarque-Bera (JB):**	156.85
Prob(Q):	0.29	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.67	**Skew:**	1.05
Prob(H) (two-sided):	0.01	**Kurtosis:**	4.86

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

[ ]:
```
auto_arima(df1['rest4'], exogenous = df1['holiday'], start_p =0 , start_q= 0,␣
↪max_p =5, max_q = 5 , stepwise=True, seasonal=True,m=7,trace=True).summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(1,0,1)[7] intercept   : AIC=4386.707, Time=1.25 sec
 ARIMA(0,1,0)(0,0,0)[7] intercept   : AIC=4585.754, Time=0.10 sec
 ARIMA(1,1,0)(1,0,0)[7] intercept   : AIC=4430.846, Time=0.72 sec
 ARIMA(0,1,1)(0,0,1)[7] intercept   : AIC=4340.249, Time=1.23 sec
 ARIMA(0,1,0)(0,0,0)[7]             : AIC=4583.769, Time=0.05 sec
 ARIMA(0,1,1)(0,0,0)[7] intercept   : AIC=4399.114, Time=0.53 sec
 ARIMA(0,1,1)(1,0,1)[7] intercept   : AIC=inf, Time=3.35 sec
 ARIMA(0,1,1)(0,0,2)[7] intercept   : AIC=inf, Time=1.11 sec
 ARIMA(0,1,1)(1,0,0)[7] intercept   : AIC=inf, Time=0.37 sec
 ARIMA(0,1,1)(1,0,2)[7] intercept   : AIC=4178.177, Time=2.47 sec
 ARIMA(0,1,1)(2,0,2)[7] intercept   : AIC=inf, Time=4.79 sec
 ARIMA(0,1,1)(2,0,1)[7] intercept   : AIC=inf, Time=6.38 sec
 ARIMA(0,1,0)(1,0,2)[7] intercept   : AIC=4384.934, Time=1.45 sec
 ARIMA(1,1,1)(1,0,2)[7] intercept   : AIC=inf, Time=3.44 sec
 ARIMA(0,1,2)(1,0,2)[7] intercept   : AIC=4174.637, Time=3.30 sec
 ARIMA(0,1,2)(0,0,2)[7] intercept   : AIC=inf, Time=5.04 sec
 ARIMA(0,1,2)(1,0,1)[7] intercept   : AIC=inf, Time=5.43 sec
 ARIMA(0,1,2)(2,0,2)[7] intercept   : AIC=inf, Time=7.65 sec
 ARIMA(0,1,2)(0,0,1)[7] intercept   : AIC=inf, Time=0.91 sec
 ARIMA(0,1,2)(2,0,1)[7] intercept   : AIC=inf, Time=10.72 sec
 ARIMA(1,1,2)(1,0,2)[7] intercept   : AIC=inf, Time=12.22 sec
 ARIMA(0,1,3)(1,0,2)[7] intercept   : AIC=4169.615, Time=5.18 sec
 ARIMA(0,1,3)(0,0,2)[7] intercept   : AIC=inf, Time=4.56 sec
 ARIMA(0,1,3)(1,0,1)[7] intercept   : AIC=inf, Time=8.63 sec
 ARIMA(0,1,3)(2,0,2)[7] intercept   : AIC=inf, Time=16.16 sec
 ARIMA(0,1,3)(0,0,1)[7] intercept   : AIC=inf, Time=1.77 sec
 ARIMA(0,1,3)(2,0,1)[7] intercept   : AIC=inf, Time=9.77 sec
 ARIMA(1,1,3)(1,0,2)[7] intercept   : AIC=inf, Time=6.54 sec
 ARIMA(0,1,4)(1,0,2)[7] intercept   : AIC=inf, Time=5.91 sec
 ARIMA(1,1,4)(1,0,2)[7] intercept   : AIC=inf, Time=8.78 sec
 ARIMA(0,1,3)(1,0,2)[7]             : AIC=4167.449, Time=3.58 sec
```

```
ARIMA(0,1,3)(0,0,2)[7]             : AIC=4300.055, Time=1.77 sec
ARIMA(0,1,3)(1,0,1)[7]             : AIC=4165.771, Time=1.49 sec
ARIMA(0,1,3)(0,0,1)[7]             : AIC=4322.990, Time=0.74 sec
ARIMA(0,1,3)(1,0,0)[7]             : AIC=4292.929, Time=0.84 sec
ARIMA(0,1,3)(2,0,1)[7]             : AIC=4167.495, Time=5.35 sec
ARIMA(0,1,3)(0,0,0)[7]             : AIC=4373.078, Time=0.55 sec
ARIMA(0,1,3)(2,0,0)[7]             : AIC=inf, Time=1.50 sec
ARIMA(0,1,3)(2,0,2)[7]             : AIC=inf, Time=4.81 sec
ARIMA(0,1,2)(1,0,1)[7]             : AIC=inf, Time=1.18 sec
ARIMA(1,1,3)(1,0,1)[7]             : AIC=inf, Time=2.92 sec
ARIMA(0,1,4)(1,0,1)[7]             : AIC=4164.564, Time=4.70 sec
ARIMA(0,1,4)(0,0,1)[7]             : AIC=4324.310, Time=1.27 sec
ARIMA(0,1,4)(1,0,0)[7]             : AIC=4294.836, Time=0.65 sec
ARIMA(0,1,4)(2,0,1)[7]             : AIC=4166.176, Time=3.33 sec
ARIMA(0,1,4)(1,0,2)[7]             : AIC=4166.110, Time=3.66 sec
ARIMA(0,1,4)(0,0,0)[7]             : AIC=4369.737, Time=0.41 sec
ARIMA(0,1,4)(0,0,2)[7]             : AIC=4302.011, Time=2.80 sec
ARIMA(0,1,4)(2,0,0)[7]             : AIC=inf, Time=2.63 sec
ARIMA(0,1,4)(2,0,2)[7]             : AIC=4166.137, Time=5.79 sec
ARIMA(1,1,4)(1,0,1)[7]             : AIC=4169.765, Time=2.83 sec
ARIMA(0,1,5)(1,0,1)[7]             : AIC=inf, Time=1.93 sec
ARIMA(1,1,5)(1,0,1)[7]             : AIC=inf, Time=6.75 sec
ARIMA(0,1,4)(1,0,1)[7] intercept   : AIC=inf, Time=5.54 sec

Best model:  ARIMA(0,1,4)(1,0,1)[7]
Total fit time: 207.020 seconds
```

[ ]:

Dep. Variable:	y	**No. Observations:**	478
Model:	SARIMAX(0, 1, 4)x(1, 0, [1], 7)	**Log Likelihood**	-2075.282
Date:	Wed, 15 May 2024	**AIC**	4164.564
Time:	11:49:03	**BIC**	4193.736
Sample:	01-01-2016	**HQIC**	4176.034
	- 04-22-2017		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	-0.8280	0.040	-20.793	0.000	-0.906	-0.750
ma.L2	-0.0316	0.055	-0.571	0.568	-0.140	0.077
ma.L3	-0.0402	0.058	-0.693	0.488	-0.154	0.073
ma.L4	-0.0841	0.045	-1.875	0.061	-0.172	0.004
ar.S.L7	0.9968	0.002	407.237	0.000	0.992	1.002
ma.S.L7	-0.9281	0.024	-38.457	0.000	-0.975	-0.881
sigma2	341.1262	15.838	21.538	0.000	310.084	372.168

Ljung-Box (L1) (Q):	0.24	**Jarque-Bera (JB):**	204.96
Prob(Q):	0.62	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.72	**Skew:**	0.93
Prob(H) (two-sided):	0.04	**Kurtosis:**	5.61

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

1. for rest1 we have SARIMAX (1,1,1 x 1 ,0,1,7)
2. for rest2 we have SARIMAX (2,0,0 x 1 ,0,1,7)
3. for rest3 we have SARIMAX (0,0,0 x 1 ,0,1,7)
4. for rest3 we have SARIMAX (0,1,4 x 1 ,0,1,7)

[ ]:
```
train=df1.iloc[:-12]
test=df1.iloc[-12:]
```

Fitting data to all models for respective time series

[ ]:
```
model_rest1=SARIMAX(train['rest1'],order=(1,1,1),seasonal_order=(1,0,1,7), exog␣
↪= train['holiday']).fit()
model_rest1.summary()
```

[ ]:

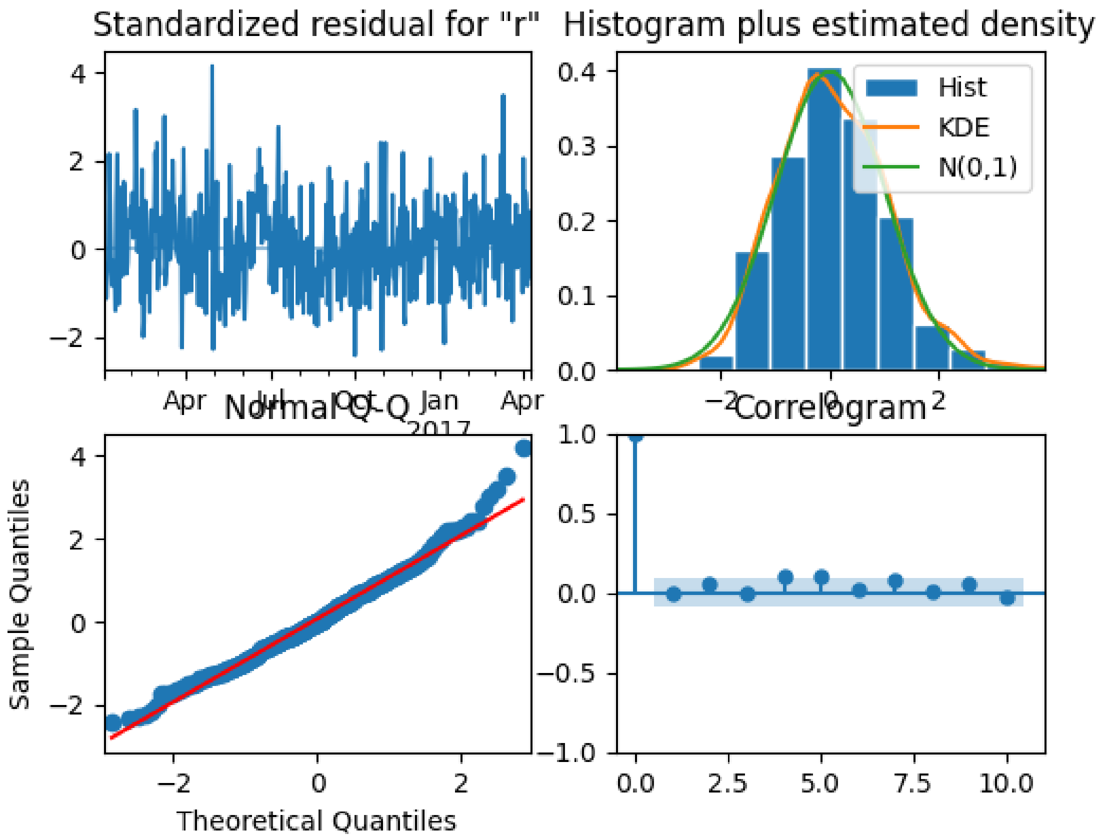
Dep. Variable:	rest1	**No. Observations:**	466
Model:	SARIMAX(1, 1, 1)x(1, 0, 1, 7)	**Log Likelihood**	-1913.993
Date:	Wed, 15 May 2024	**AIC**	3839.986
Time:	12:07:45	**BIC**	3864.839
Sample:	01-01-2016 - 04-10-2017	**HQIC**	3849.768
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
holiday	13.1820	2.251	5.856	0.000	8.770	17.594
ar.L1	-0.0018	0.044	-0.041	0.967	-0.088	0.084
ma.L1	-0.9970	0.003	-349.897	0.000	-1.003	-0.991
ar.S.L7	0.9980	0.002	571.676	0.000	0.995	1.001
ma.S.L7	-0.9232	0.024	-38.108	0.000	-0.971	-0.876
sigma2	211.5058	12.884	16.416	0.000	186.254	236.758

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	19.54
Prob(Q):	0.94	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.67	**Skew:**	0.43
Prob(H) (two-sided):	0.01	**Kurtosis:**	3.51

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

[ ]:
```
model_rest1.plot_diagnostics();
```



[ ]:
```
start=len(train)
end=start+len(test)-1
predictions_rest1=model_rest1.predict(start=start,end=end,dynamic=False,␣
  ↪exog=test['holiday']).rename('SARImax(1,1,1)x (1, 0, 1, 7)')
```

[ ]:
```
model_rest2=SARIMAX(train['rest2'],order=(2,0,0),seasonal_order=(1,0,1,7),␣
  ↪exog=train['holiday']).fit()
model_rest2.summary()
```

[ ]:

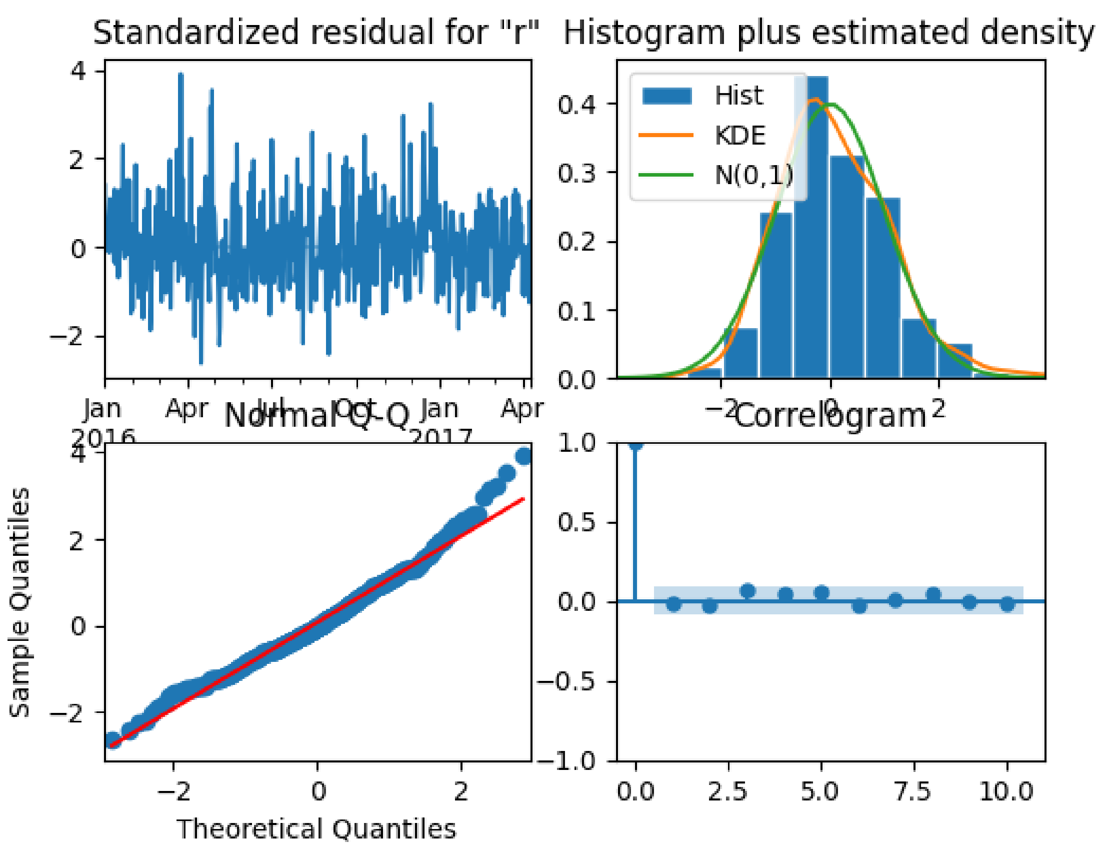
Dep. Variable:	rest2	**No. Observations:**	466
Model:	SARIMAX(2, 0, 0)x(1, 0, [1], 7)	**Log Likelihood**	-1837.479
Date:	Wed, 15 May 2024	**AIC**	3686.958
Time:	12:10:41	**BIC**	3711.823
Sample:	01-01-2016	**HQIC**	3696.744
	- 04-10-2017		
Covariance Type:	opg		

	coef	std err	z	P> |z|	[0.025	0.975]
holiday	6.1697	2.170	2.843	0.004	1.916	10.423
ar.L1	0.1591	0.048	3.330	0.001	0.065	0.253
ar.L2	0.1306	0.043	3.010	0.003	0.046	0.216
ar.S.L7	0.9977	0.002	517.649	0.000	0.994	1.001
ma.S.L7	-0.8794	0.026	-33.436	0.000	-0.931	-0.828
sigma2	149.6457	8.956	16.709	0.000	132.093	167.199

Ljung-Box (L1) (Q):	0.13	**Jarque-Bera (JB):**	24.88
Prob(Q):	0.72	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.76	**Skew:**	0.49
Prob(H) (two-sided):	0.09	**Kurtosis:**	3.56

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

[ ]:
```
model_rest2.plot_diagnostics();
```



[ ]:
```
start=len(train)
end=start+len(test)-1
```

```
predictions_rest2=model_rest2.predict(start=start,end=end,dynamic=False,
    exog=test['holiday']).rename('SARImax(2,0,0)x (1, 0, 1, 7)')
```

[ ]:
```
model_rest3=SARIMAX(train['rest3'],order=(0,0,0),seasonal_order=(1,0,1,7),
    exog=train['holiday']).fit()
model_rest3.summary()
```

[ ]:

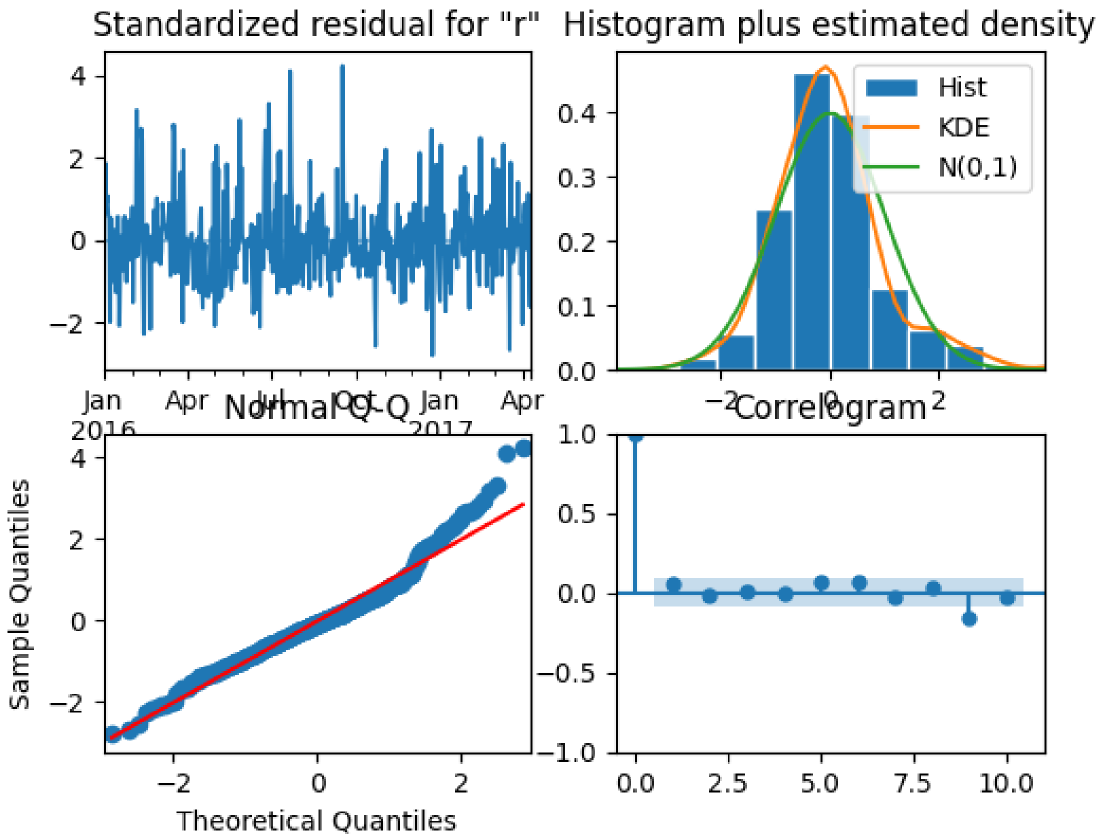
Dep. Variable:	rest3	**No. Observations:**	466
Model:	SARIMAX(1, 0, [1], 7)	**Log Likelihood**	-1758.135
Date:	Wed, 15 May 2024	**AIC**	3524.270
Time:	12:11:03	**BIC**	3540.846
Sample:	01-01-2016	**HQIC**	3530.794
	- 04-10-2017		
Covariance Type:	opg		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
holiday	13.0672	1.252	10.438	0.000	10.614	15.521
ar.S.L7	1.0000	5.78e-05	1.73e+04	0.000	1.000	1.000
ma.S.L7	-0.9950	0.130	-7.642	0.000	-1.250	-0.740
sigma2	101.0527	13.127	7.698	0.000	75.325	126.781

Ljung-Box (L1) (Q):	1.54	**Jarque-Bera (JB):**	97.42
Prob(Q):	0.21	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.78	**Skew:**	0.73
Prob(H) (two-sided):	0.12	**Kurtosis:**	4.70

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

[ ]:
```
model_rest3.plot_diagnostics();
```



[ ]:
```
start=len(train)
end=start+len(test)-1
predictions_rest3=model_rest3.predict(start=start,end=end,dynamic=False,␣
    ↪exog=test['holiday']).rename('SARImax(0,0,0)x (1, 0, 1, 7)')
```

[ ]:
```
model_rest4=SARIMAX(train['rest4'],order=(0,1,4),seasonal_order=(1,0,1,7),␣
    ↪exog=train['holiday']).fit()
model_rest4.summary()
```

[ ]:

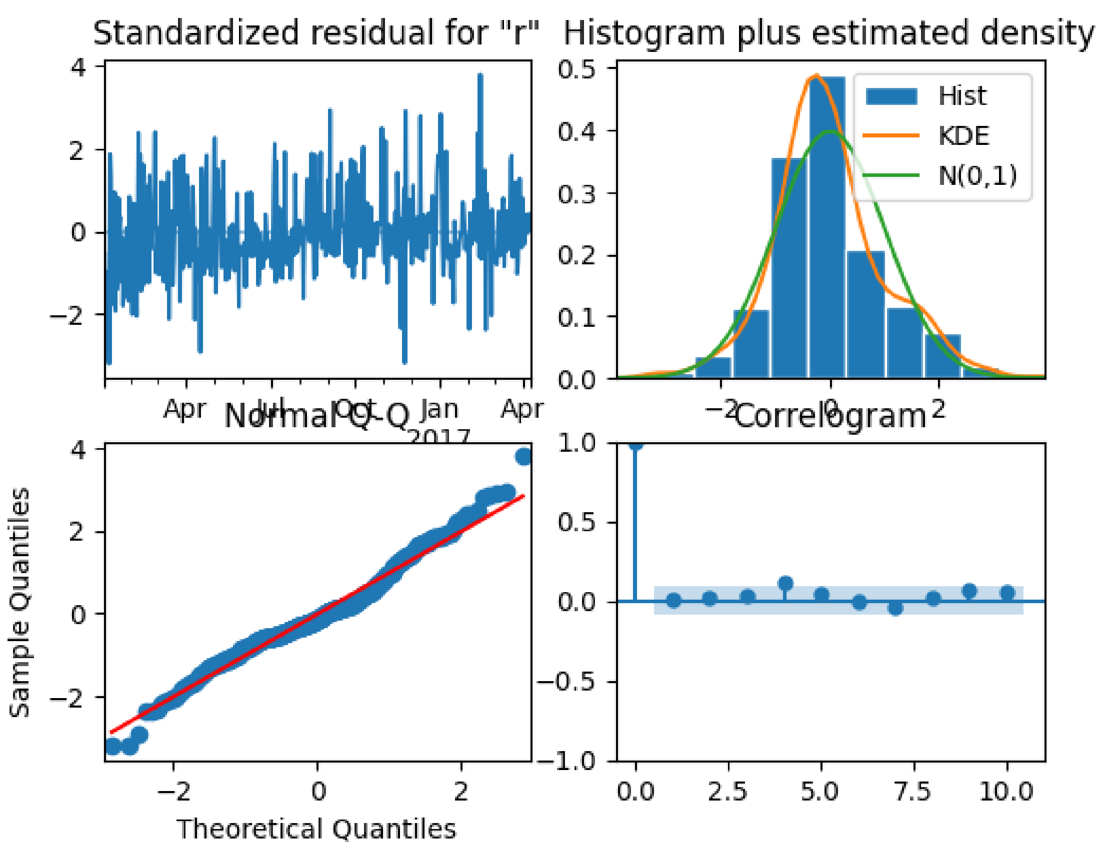
Dep. Variable:	rest4	**No. Observations:**	466
Model:	SARIMAX(0, 1, 4)x(1, 0, [1], 7)	**Log Likelihood**	-1975.672
Date:	Wed, 15 May 2024	**AIC**	3967.345
Time:	12:11:49	**BIC**	4000.481
Sample:	01-01-2016 - 04-10-2017	**HQIC**	3980.387
Covariance Type:	opg		

	coef	std err	z	P> |z|	[0.025	0.975]
holiday	33.2224	1.976	16.812	0.000	29.349	37.095
ma.L1	-0.8844	0.041	-21.668	0.000	-0.964	-0.804
ma.L2	-0.0140	0.062	-0.224	0.823	-0.136	0.108
ma.L3	-0.0309	0.072	-0.427	0.670	-0.173	0.111
ma.L4	-0.0608	0.050	-1.208	0.227	-0.159	0.038
ar.S.L7	0.9965	0.003	382.985	0.000	0.991	1.002
ma.S.L7	-0.9126	0.027	-34.360	0.000	-0.965	-0.861
sigma2	277.6064	16.217	17.118	0.000	245.821	309.392

Ljung-Box (L1) (Q):	0.06	**Jarque-Bera (JB):**	26.47
Prob(Q):	0.80	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.73	**Skew:**	0.38
Prob(H) (two-sided):	0.05	**Kurtosis:**	3.89

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

[ ]:
```
model_rest4.plot_diagnostics();
```



```
[ ]: start=len(train)
     end=start+len(test)-1
     predictions_rest4=model_rest4.predict(start=start,end=end,dynamic=False,␣
      ↪exog=test['holiday']).rename('SARImax(0,1,4)x (1, 0, 1, 7)')
```

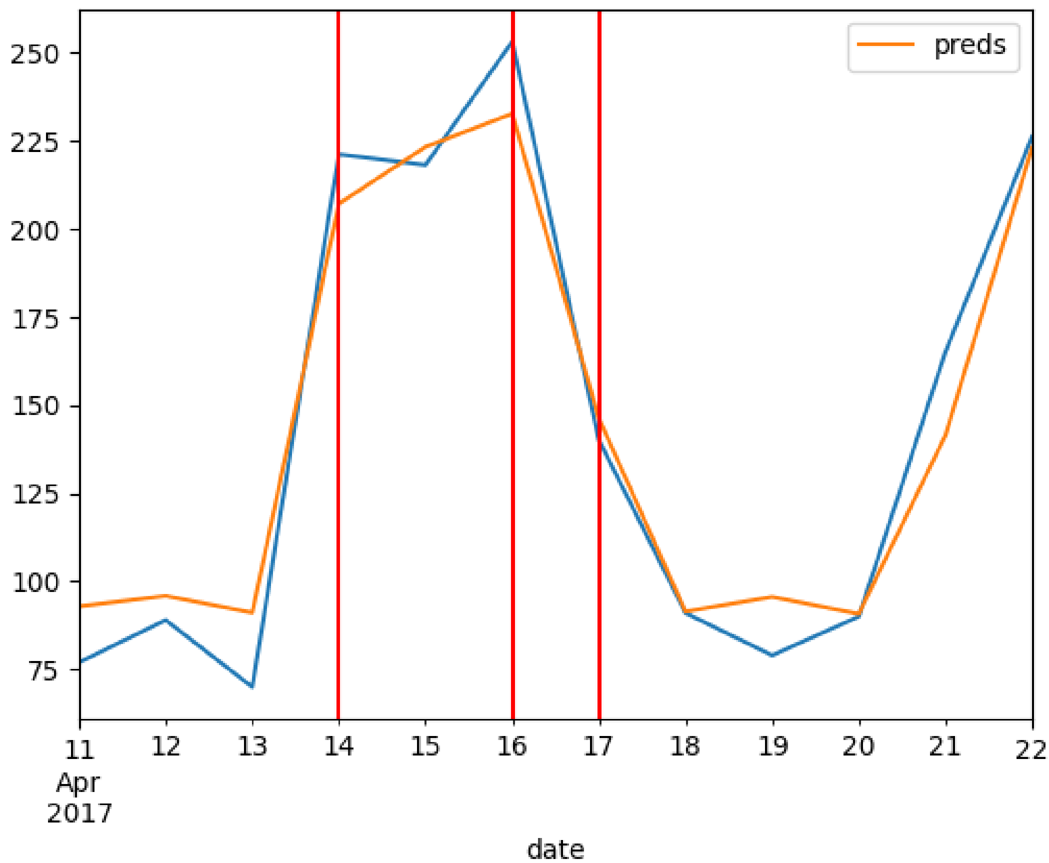
Aggregating predictions from all models to see total customers from all 4 restaurants

```
[ ]: predictions_total = predictions_rest1 + predictions_rest2 + predictions_rest3␣
      ↪+predictions_rest4
     predictions_total
```

```
[ ]: 2017-04-11     92.898621
     2017-04-12     95.859431
     2017-04-13     91.086233
     2017-04-14    207.037557
     2017-04-15    223.126629
     2017-04-16    232.531090
     2017-04-17    146.131602
     2017-04-18     91.431586
     2017-04-19     95.575462
     2017-04-20     90.745328
     2017-04-21    141.361139
     2017-04-22    222.868314
     Freq: D, dtype: float64
```

Compariosn of "total" actual customers vs separately predcted

```
[ ]: ax=test['total'].plot()
     predictions_total.plot(legend=True, label="preds")
     for x in test.query('holiday==1').index:
      ax.axvline(x=x,color='r')
```




```
[ ]: mean_absolute_percentage_error(test['total'],predictions_total)*100
```

```
[ ]: 9.801164725409066
```

The mean abs pecent error is significantly lower than the model predictions made directly on the "total" customers time series in the lecture (18.7)

0.0.1 Regression

on the "total" cusotmers time series using 7 days + holidays + weekdays as features

```
[ ]: df1
```

```
[ ]:              weekday  holiday    holiday_name  rest1  rest2  rest3  rest4  \
     date
     2016-01-01     Friday        1  New Year's Day     65     25     67    139
     2016-01-02   Saturday        0              na     24     39     43     85
     2016-01-03     Sunday        0              na     24     31     66     81
     2016-01-04     Monday        0              na     23     18     32     32
     2016-01-05    Tuesday        0              na      2     15     38     43
```

```
…               …       …                …    …    …    …    …
2017-04-18    Tuesday        0                na     30     30     13     18
2017-04-19  Wednesday        0                na     20     11     30     18
2017-04-20   Thursday        0                na     22      3     19     46
2017-04-21     Friday        0                na     38     53     36     38
2017-04-22   Saturday        0                na     97     20     50     59

            total
date
2016-01-01    296
2016-01-02    191
2016-01-03    202
2016-01-04    105
2016-01-05     98
…             …
2017-04-18     91
2017-04-19     79
2017-04-20     90
2017-04-21    165
2017-04-22    226

[478 rows x 8 columns]
```

[ ]:
```
data_reg = df1.copy()
```

[ ]:
```
data_reg
```

[ ]:
```
              weekday  holiday    holiday_name  rest1  rest2  rest3  rest4  \
date
2016-01-01     Friday        1  New Year's Day     65     25     67    139
2016-01-02   Saturday        0                na     24     39     43     85
2016-01-03     Sunday        0                na     24     31     66     81
2016-01-04     Monday        0                na     23     18     32     32
2016-01-05    Tuesday        0                na      2     15     38     43
…               …       …                …    …    …    …    …
2017-04-18    Tuesday        0                na     30     30     13     18
2017-04-19  Wednesday        0                na     20     11     30     18
2017-04-20   Thursday        0                na     22      3     19     46
2017-04-21     Friday        0                na     38     53     36     38
2017-04-22   Saturday        0                na     97     20     50     59

            total
date
2016-01-01    296
2016-01-02    191
2016-01-03    202
2016-01-04    105
```

```
2016-01-05      98
…              …
2017-04-18      91
2017-04-19      79
2017-04-20      90
2017-04-21     165
2017-04-22     226

[478 rows x 8 columns]
```

[ ]:
```
data_reg['total'].shift(0)
```

[ ]:
```
date
2016-01-01     296
2016-01-02     191
2016-01-03     202
2016-01-04     105
2016-01-05      98
              …
2017-04-18      91
2017-04-19      79
2017-04-20      90
2017-04-21     165
2017-04-22     226
Freq: D, Name: total, Length: 478, dtype: int64
```

[ ]:
```
for i in range(7,0,-1):
    print(i)
    data_reg['t= ' + str(i)] =df1['total'].shift(i)
```

```
7
6
5
4
3
2
1
```

[ ]:
```
data_reg
```

[ ]:
```
              weekday  holiday    holiday_name  rest1  rest2  rest3  rest4  \
date
2016-01-01     Friday        1  New Year's Day     65     25     67    139
2016-01-02   Saturday        0              na     24     39     43     85
2016-01-03     Sunday        0              na     24     31     66     81
2016-01-04     Monday        0              na     23     18     32     32
2016-01-05    Tuesday        0              na      2     15     38     43
```

```
…              …       …              …     …     …     …      …
2017-04-18    Tuesday        0               na    30     30     13     18
2017-04-19  Wednesday        0               na    20     11     30     18
2017-04-20   Thursday        0               na    22      3     19     46
2017-04-21     Friday        0               na    38     53     36     38
2017-04-22   Saturday        0               na    97     20     50     59

            total   t= 7   t= 6   t= 5   t= 4   t= 3   t= 2   t= 1
date
2016-01-01    296    NaN    NaN    NaN    NaN    NaN    NaN    NaN
2016-01-02    191    NaN    NaN    NaN    NaN    NaN    NaN  296.0
2016-01-03    202    NaN    NaN    NaN    NaN    NaN  296.0  191.0
2016-01-04    105    NaN    NaN    NaN    NaN  296.0  191.0  202.0
2016-01-05     98    NaN    NaN    NaN  296.0  191.0  202.0  105.0
…            …    …    …    …    …    …    …    …
2017-04-18     91   77.0   89.0   70.0  221.0  218.0  253.0  140.0
2017-04-19     79   89.0   70.0  221.0  218.0  253.0  140.0   91.0
2017-04-20     90   70.0  221.0  218.0  253.0  140.0   91.0   79.0
2017-04-21    165  221.0  218.0  253.0  140.0   91.0   79.0   90.0
2017-04-22    226  218.0  253.0  140.0   91.0   79.0   90.0  165.0

[478 rows x 15 columns]
```

[ ]:
```python
data_reg.dropna(inplace=True)
```

[ ]:
```python
data_reg
```

[ ]:
```
              weekday  holiday holiday_name  rest1  rest2  rest3  rest4  \
date
2016-01-08     Friday        0           na     79     32     22     16
2016-01-09   Saturday        0           na     44     44     47     99
2016-01-10     Sunday        0           na     26     43     49     94
2016-01-11     Monday        0           na      9     22     33     37
2016-01-12    Tuesday        0           na      6     10     21     20
…              …       …           …     …     …     …      …
2017-04-18    Tuesday        0           na     30     30     13     18
2017-04-19  Wednesday        0           na     20     11     30     18
2017-04-20   Thursday        0           na     22      3     19     46
2017-04-21     Friday        0           na     38     53     36     38
2017-04-22   Saturday        0           na     97     20     50     59

            total   t= 7   t= 6   t= 5   t= 4   t= 3   t= 2   t= 1
date
2016-01-08    149  296.0  191.0  202.0  105.0   98.0   83.0   69.0
2016-01-09    234  191.0  202.0  105.0   98.0   83.0   69.0  149.0
2016-01-10    212  202.0  105.0   98.0   83.0   69.0  149.0  234.0
2016-01-11    101  105.0   98.0   83.0   69.0  149.0  234.0  212.0
```

```
2016-01-12     57   98.0   83.0   69.0  149.0  234.0  212.0  101.0
…             …     …     …     …     …     …     …     …
2017-04-18     91   77.0   89.0   70.0  221.0  218.0  253.0  140.0
2017-04-19     79   89.0   70.0  221.0  218.0  253.0  140.0   91.0
2017-04-20     90   70.0  221.0  218.0  253.0  140.0   91.0   79.0
2017-04-21    165  221.0  218.0  253.0  140.0   91.0   79.0   90.0
2017-04-22    226  218.0  253.0  140.0   91.0   79.0   90.0  165.0

[471 rows x 15 columns]
```

[ ]:
```python
data_reg.drop(columns=['holiday_name', 'rest1', 'rest3', 'rest4', 'rest2'],
 ↪inplace=True)
```

[ ]:
```python
data_reg
```

[ ]:
```
              weekday  holiday  total   t= 7   t= 6   t= 5   t= 4   t= 3  \
date
2016-01-08     Friday        0    149  296.0  191.0  202.0  105.0   98.0
2016-01-09   Saturday        0    234  191.0  202.0  105.0   98.0   83.0
2016-01-10     Sunday        0    212  202.0  105.0   98.0   83.0   69.0
2016-01-11     Monday        0    101  105.0   98.0   83.0   69.0  149.0
2016-01-12    Tuesday        0     57   98.0   83.0   69.0  149.0  234.0
…                   …        …      …      …      …      …      …      …
2017-04-18    Tuesday        0     91   77.0   89.0   70.0  221.0  218.0
2017-04-19  Wednesday        0     79   89.0   70.0  221.0  218.0  253.0
2017-04-20   Thursday        0     90   70.0  221.0  218.0  253.0  140.0
2017-04-21     Friday        0    165  221.0  218.0  253.0  140.0   91.0
2017-04-22   Saturday        0    226  218.0  253.0  140.0   91.0   79.0

             t= 2   t= 1
date
2016-01-08   83.0   69.0
2016-01-09   69.0  149.0
2016-01-10  149.0  234.0
2016-01-11  234.0  212.0
2016-01-12  212.0  101.0
…             …      …
2017-04-18  253.0  140.0
2017-04-19  140.0   91.0
2017-04-20   91.0   79.0
2017-04-21   79.0   90.0
2017-04-22   90.0  165.0

[471 rows x 10 columns]
```

[ ]:
```python
weekday_mapping = {
    'Monday': 0,
```

```
    'Tuesday': 1,
    'Wednesday': 2,
    'Thursday': 3,
    'Friday': 4,
    'Saturday': 5,
    'Sunday': 6
}

data_reg['weekday'] = data_reg['weekday'].apply(lambda x: weekday_mapping.
 ↪get(x))
```

[ ]:
```
data_reg
```

[ ]:
```
            total weekday  holiday   t= 7   t= 6   t= 5   t= 4   t= 3   t= 2  \
date
2016-01-08    149    None        0  296.0  191.0  202.0  105.0   98.0   83.0
2016-01-09    234    None        0  191.0  202.0  105.0   98.0   83.0   69.0
2016-01-10    212    None        0  202.0  105.0   98.0   83.0   69.0  149.0
2016-01-11    101    None        0  105.0   98.0   83.0   69.0  149.0  234.0
2016-01-12     57    None        0   98.0   83.0   69.0  149.0  234.0  212.0
…             …      …        …     …      …      …      …      …      …
2017-04-18     91    None        0   77.0   89.0   70.0  221.0  218.0  253.0
2017-04-19     79    None        0   89.0   70.0  221.0  218.0  253.0  140.0
2017-04-20     90    None        0   70.0  221.0  218.0  253.0  140.0   91.0
2017-04-21    165    None        0  221.0  218.0  253.0  140.0   91.0   79.0
2017-04-22    226    None        0  218.0  253.0  140.0   91.0   79.0   90.0

             t= 1
date
2016-01-08   69.0
2016-01-09  149.0
2016-01-10  234.0
2016-01-11  212.0
2016-01-12  101.0
…             …
2017-04-18  140.0
2017-04-19   91.0
2017-04-20   79.0
2017-04-21   90.0
2017-04-22  165.0

[471 rows x 10 columns]
```

[ ]:
```
cols = list(data_reg.columns)
cols.remove('total')
cols.insert(0, 'total')
data_reg = data_reg[cols]
```

```
[ ]: data_reg
```

```
[ ]:            total weekday  holiday   t= 7   t= 6   t= 5   t= 4   t= 3   t= 2  \
     date
     2016-01-08   149    None        0  296.0  191.0  202.0  105.0   98.0   83.0
     2016-01-09   234    None        0  191.0  202.0  105.0   98.0   83.0   69.0
     2016-01-10   212    None        0  202.0  105.0   98.0   83.0   69.0  149.0
     2016-01-11   101    None        0  105.0   98.0   83.0   69.0  149.0  234.0
     2016-01-12    57    None        0   98.0   83.0   69.0  149.0  234.0  212.0
     …            …     …        …     …     …     …     …     …     …
     2017-04-18    91    None        0   77.0   89.0   70.0  221.0  218.0  253.0
     2017-04-19    79    None        0   89.0   70.0  221.0  218.0  253.0  140.0
     2017-04-20    90    None        0   70.0  221.0  218.0  253.0  140.0   91.0
     2017-04-21   165    None        0  221.0  218.0  253.0  140.0   91.0   79.0
     2017-04-22   226    None        0  218.0  253.0  140.0   91.0   79.0   90.0

                 t= 1
     date
     2016-01-08   69.0
     2016-01-09  149.0
     2016-01-10  234.0
     2016-01-11  212.0
     2016-01-12  101.0
     …            …
     2017-04-18  140.0
     2017-04-19   91.0
     2017-04-20   79.0
     2017-04-21   90.0
     2017-04-22  165.0

     [471 rows x 10 columns]
```

```
[ ]: X = data_reg.iloc[:,1:].values
```

```
[ ]: y = data_reg.iloc[:, 0].values
```

```
[ ]: from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
     from sklearn.metrics import mean_absolute_percentage_error
     from sklearn.model_selection import train_test_split
```

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.
      ↪025,random_state=42)
```

```
[ ]: y_test_total =y_test
     len(y_test)
```

```
[ ]: 12
```

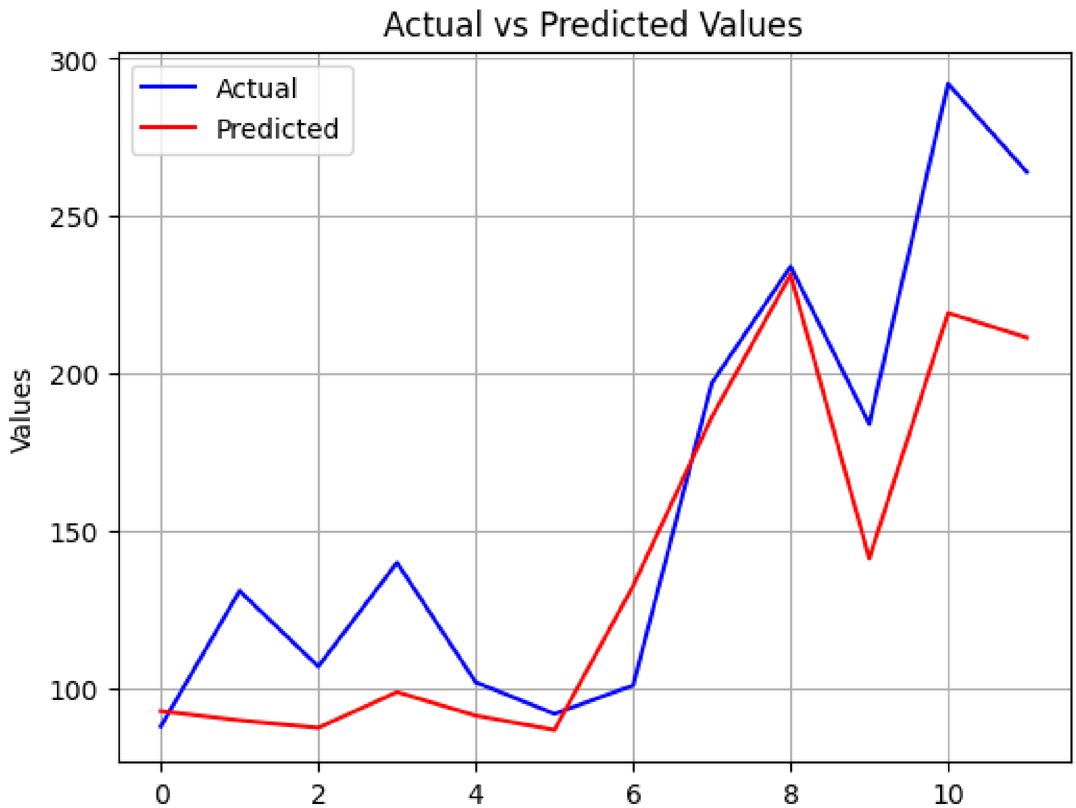
[ ]:
```
from sklearn.model_selection import GridSearchCV

parameters = {
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [3, 4, 5, 6, 7,8, 9, 10],
    'n_estimators': [100, 200, 500],
    'max_features' : [3,4,5, 6, 7, 8, 9]

}
clf_gbm = GridSearchCV(GradientBoostingRegressor(), parameters, cv=8)
clf_gbm.fit(X_train, y_train)

print("Best parameters:", clf_gbm.best_params_)
print("Best score:", clf_gbm.best_score_)
```

```
Best parameters: {'learning_rate': 0.01, 'max_depth': 3, 'max_features': 9,
'n_estimators': 500}
Best score: 0.7474838783464414
```

[ ]:
```
gb_regressor = GradientBoostingRegressor(n_estimators=500, max_depth=3,␣
 ↪learning_rate=0.01, max_features=9, random_state=42)
gb_regressor.fit(X_train, y_train)
gb_y_pred = gb_regressor.predict(X_test)
gb_mse = mean_absolute_percentage_error(y_test, gb_y_pred)*100
print("Gradient Boosting Mean abs percent Error:", gb_mse)
```

```
Gradient Boosting Mean abs percent Error: 17.187200168600658
```

[ ]:
```
plt.plot(y_test, color='blue', label='Actual')
plt.plot(gb_y_pred, color='red', label='Predicted')
plt.ylabel('Values')
plt.title('Actual vs Predicted Values')
plt.legend()
plt.grid(True)
plt.show()
```




```
[ ]: rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)
     rf_regressor.fit(X_train, y_train)
     rf_y_pred = rf_regressor.predict(X_test)
     rf_mse = mean_absolute_percentage_error(y_test, rf_y_pred)*100
     print("Random Forest Mean abs percent Error:", rf_mse)
```

```
Random Forest Mean abs percent Error: 18.95050111051191
```

```
[ ]: import xgboost as xgb
```

```
[ ]: xgb_regressor = xgb.XGBRegressor(objective ='reg:squarederror', random_state=42)
     xgb_regressor.fit(X_train, y_train)
     xgb_y_pred = xgb_regressor.predict(X_test)
     xgb_mse = mean_absolute_percentage_error(y_test, xgb_y_pred)*100
     print("XGBoost Mean abs percent Error:", xgb_mse)
```

```
XGBoost Mean abs percent Error: 21.296742771445174
```

For the direct , total customers time series fitting ,the gradient Boosting regression error metric (17.1) does better than SARIMAX (18.75) from the lectures