RESTAURANT VISITORS TIME SERIES ANALYSIS PROJECT

Objective :

```
To forecast the number of vistors in restaurant for a daily data
```

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importing required libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

Loading the data

In [2]:

```
df=pd.read_csv('https://raw.githubusercontent.com/ubaid-shah/Time_Series_Analysis_IT
```

In [3]:

```
df.head(30)
```

Out[3]:

date	weekday	holiday	holiday_name	rest1	rest2	rest3	rest4	total
2016-01-01	Friday	1	New Year's Day	65.0	25.0	67.0	139.0	296.0
2016-01-02	Saturday	0	na	24.0	39.0	43.0	85.0	191.0
2016-01-03	Sunday	0	na	24.0	31.0	66.0	81.0	202.0
2016-01-04	Monday	0	na	23.0	18.0	32.0	32.0	105.0
2016-01-05	Tuesday	0	na	2.0	15.0	38.0	43.0	98.0
2016-01-06	Wednesday	0	na	9.0	11.0	22.0	41.0	83.0
2016-01-07	Thursday	0	na	15.0	6.0	18.0	30.0	69.0
2016-01-08	Friday	0	na	79.0	32.0	22.0	16.0	149.0
2016-01-09	Saturday	0	na	44.0	44.0	47.0	99.0	234.0
2016-01-10	Sunday	0	na	26.0	43.0	49.0	94.0	212.0
2016-01-11	Monday	0	na	9.0	22.0	33.0	37.0	101.0
2016-01-12	Tuesday	0	na	6.0	10.0	21.0	20.0	57.0
2016-01-13	Wednesday	0	na	1.0	29.0	11.0	24.0	65.0
2016-01-14	Thursday	0	na	7.0	22.0	20.0	57.0	106.0
2016-01-15	Friday	0	na	32.0	21.0	21.0	21.0	95.0
2016-01-16	Saturday	0	na	49.0	52.0	50.0	86.0	237.0
2016-01-17	Sunday	0	na	60.0	25.0	62.0	50.0	197.0
2016-01-18	Monday	1	Martin Luther King Day	10.0	19.0	19.0	84.0	132.0
2016-01-19	Tuesday	0	na	12.0	27.0	20.0	41.0	100.0
2016-01-20	Wednesday	0	na	24.0	19.0	17.0	47.0	107.0
2016-01-21	Thursday	0	na	37.0	28.0	13.0	28.0	106.0
2016-01-22	Friday	0	na	39.0	55.0	23.0	44.0	161.0
2016-01-23	Saturday	0	na	42.0	48.0	51.0	47.0	188.0
2016-01-24	Sunday	0	na	59.0	32.0	64.0	50.0	205.0
2016-01-25	Monday	0	na	34.0	33.0	19.0	9.0	95.0
2016-01-26	Tuesday	0	na	9.0	30.0	14.0	23.0	76.0
2016-01-27	Wednesday	0	na	5.0	42.0	20.0	38.0	105.0
2016-01-28	Thursday	0	na	16.0	20.0	22.0	37.0	95.0
2016-01-29	Friday	0	na	57.0	53.0	24.0	16.0	150.0
2016-01-30	Saturday	0	na	46.0	50.0	45.0	84.0	225.0

We want to analyze the total number of visitors

In [4]:

```
data=df["total"]
```

In [5]:

```
data
```

Out[5]:

```
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
Name: total, Length: 517, dtype: float64
```

In [6]:

```
data.info()
```

```
<class 'pandas.core.series.Series'>
DatetimeIndex: 517 entries, 2016-01-01 to 2017-05-31
Series name: total
Non-Null Count  Dtype
--------------  -----
478 non-null    float64
dtypes: float64(1)
memory usage: 8.1 KB
```

In [7]:

```
data[data.isna()]
```

Out[7]:

```
date
2017-04-23   NaN
2017-04-24   NaN
2017-04-25   NaN
2017-04-26   NaN
2017-04-27   NaN
2017-04-28   NaN
2017-04-29   NaN
2017-04-30   NaN
2017-05-01   NaN
2017-05-02   NaN
2017-05-03   NaN
2017-05-04   NaN
2017-05-05   NaN
2017-05-06   NaN
2017-05-07   NaN
2017-05-08   NaN
2017-05-09   NaN
2017-05-10   NaN
2017-05-11   NaN
2017-05-12   NaN
2017-05-13   NaN
2017-05-14   NaN
2017-05-15   NaN
2017-05-16   NaN
2017-05-17   NaN
2017-05-18   NaN
2017-05-19   NaN
2017-05-20   NaN
2017-05-21   NaN
2017-05-22   NaN
2017-05-23   NaN
2017-05-24   NaN
2017-05-25   NaN
2017-05-26   NaN
2017-05-27   NaN
2017-05-28   NaN
2017-05-29   NaN
2017-05-30   NaN
2017-05-31   NaN
Name: total, dtype: float64
```

In [8]:

```
data.tail(45)
```

Out[8]:

```
date
2017-04-17    140.0
2017-04-18     91.0
2017-04-19     79.0
2017-04-20     90.0
2017-04-21    165.0
2017-04-22    226.0
2017-04-23      NaN
2017-04-24      NaN
2017-04-25      NaN
2017-04-26      NaN
2017-04-27      NaN
2017-04-28      NaN
2017-04-29      NaN
2017-04-30      NaN
2017-05-01      NaN
2017-05-02      NaN
2017-05-03      NaN
2017-05-04      NaN
2017-05-05      NaN
2017-05-06      NaN
2017-05-07      NaN
2017-05-08      NaN
2017-05-09      NaN
2017-05-10      NaN
2017-05-11      NaN
2017-05-12      NaN
2017-05-13      NaN
2017-05-14      NaN
2017-05-15      NaN
2017-05-16      NaN
2017-05-17      NaN
2017-05-18      NaN
2017-05-19      NaN
2017-05-20      NaN
2017-05-21      NaN
2017-05-22      NaN
2017-05-23      NaN
2017-05-24      NaN
2017-05-25      NaN
2017-05-26      NaN
2017-05-27      NaN
2017-05-28      NaN
2017-05-29      NaN
2017-05-30      NaN
2017-05-31      NaN
Name: total, dtype: float64
```

we can observe that the observations are recorded only till 24 April so we can remove the null values

In [9]:

```
data.dropna(inplace=True)
```

In [10]:

```
data.info()
```

```
<class 'pandas.core.series.Series'>
DatetimeIndex: 478 entries, 2016-01-01 to 2017-04-22
Series name: total
Non-Null Count  Dtype
--------------  -----
478 non-null    float64
dtypes: float64(1)
memory usage: 7.5 KB
```

In [11]:

```
data.index
```

Out[11]:

```
DatetimeIndex(['2016-01-01', '2016-01-02', '2016-01-03', '2016-01-04',
               '2016-01-05', '2016-01-06', '2016-01-07', '2016-01-08',
               '2016-01-09', '2016-01-10',
               ...
               '2017-04-13', '2017-04-14', '2017-04-15', '2017-04-16',
               '2017-04-17', '2017-04-18', '2017-04-19', '2017-04-20',
               '2017-04-21', '2017-04-22'],
              dtype='datetime64[ns]', name='date', length=478, freq=None)
```

Since the data is on daily basis we will convert index frequency as daily

In [12]:

```
data.index.freq='d'

```

In [13]:

```
data.index
```

Out[13]:

```
DatetimeIndex(['2016-01-01', '2016-01-02', '2016-01-03', '2016-01-04',
               '2016-01-05', '2016-01-06', '2016-01-07', '2016-01-08',
               '2016-01-09', '2016-01-10',
               ...
               '2017-04-13', '2017-04-14', '2017-04-15', '2017-04-16',
               '2017-04-17', '2017-04-18', '2017-04-19', '2017-04-20',
               '2017-04-21', '2017-04-22'],
              dtype='datetime64[ns]', name='date', length=478, freq='D')
```

In [14]:

```
tsa=pd.DataFrame(data)
```

In [15]:

```
tsa
```

Out[15]:

	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
...	...
2017-04-18	91.0
2017-04-19	79.0
2017-04-20	90.0
2017-04-21	165.0
2017-04-22	226.0

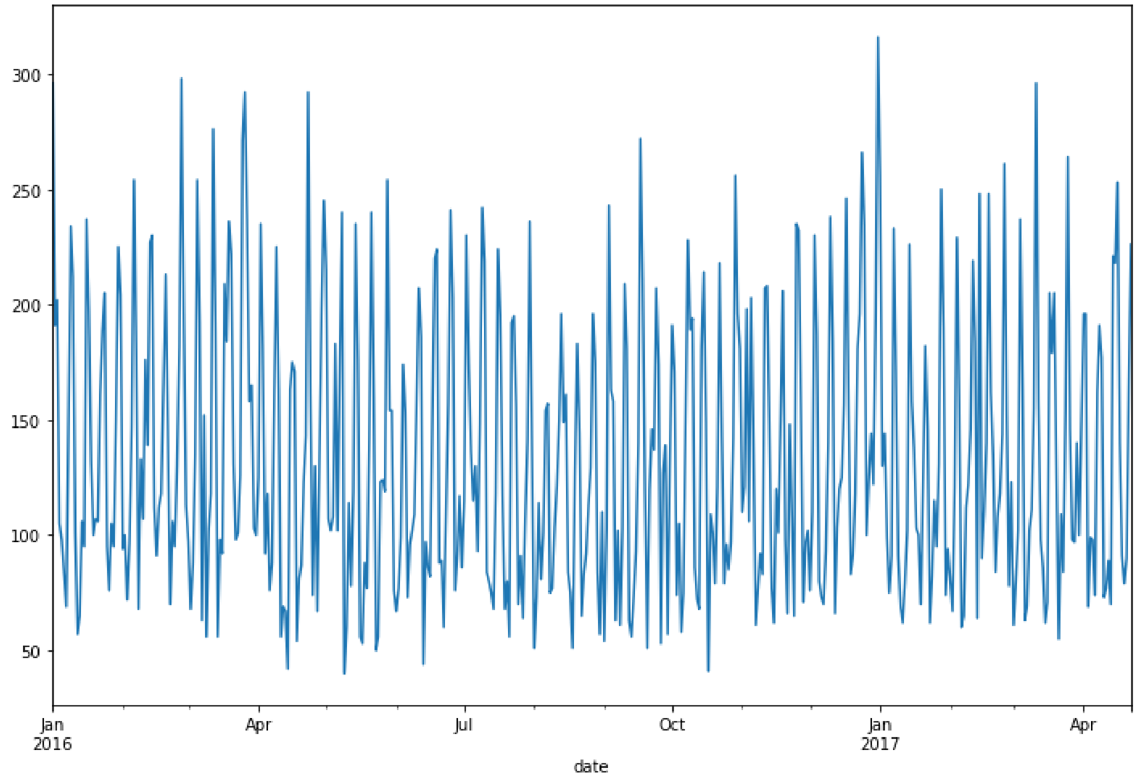
478 rows × 1 columns

In [16]:

```
tsa["total"].plot(figsize=(12,8))
```

Out[16]:

<AxesSubplot:xlabel='date'>



Checking for the STATIONARITY in series

This can be done in 2 ways:

1.PLOTTING GRAPH: ETS decomposition

2.STATISTICAL TEST :Augmented Dickey Fuller Test

In [17]:

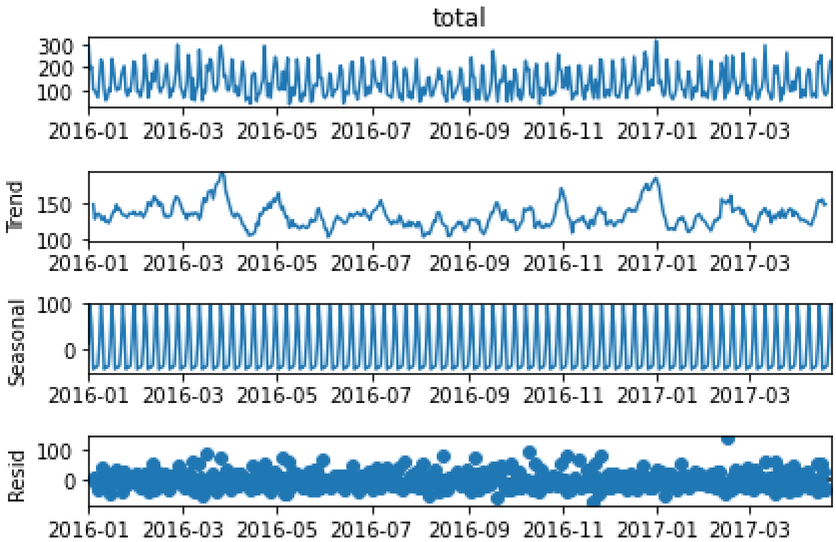
```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [18]:

```
x=seasonal_decompose(tsa["total"])
```

In [19]:

```
1 x.plot();
```

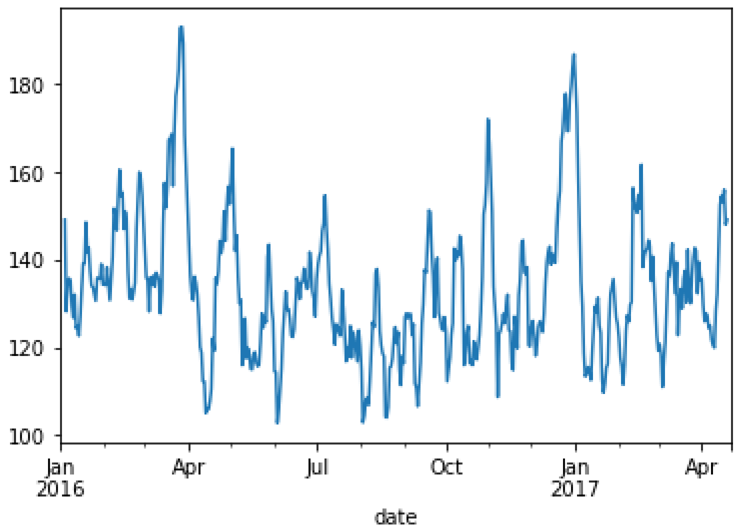


In [20]:

```
1 x.trend.plot()
```

Out[20]:

<AxesSubplot:xlabel='date'>

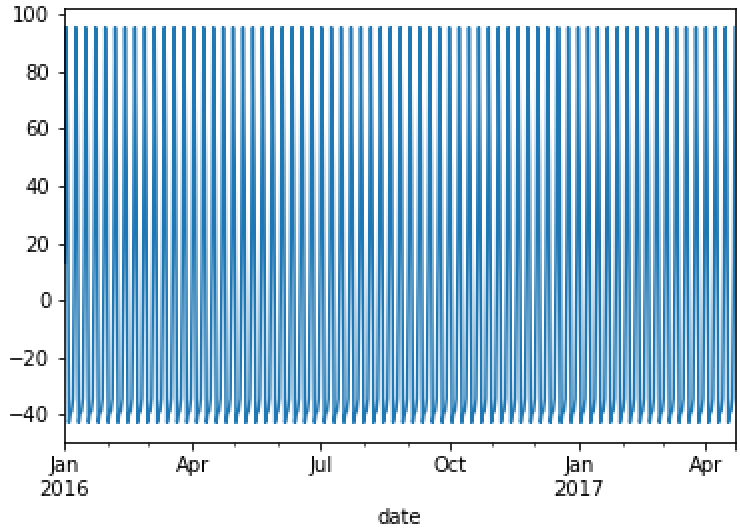


In [21]:

```
1  x.seasonal.plot()
```

Out[21]:

```
<AxesSubplot:xlabel='date'>
```



By the plot above, the data seems to be STATIONARY

Checking stationarity with Statistical test

In [22]:

```
#ADF TEST
from statsmodels.tsa.stattools import adfuller

def adf_test(tsa_data,col):
    print(f"AUGMENTED DICKEY FULLER TEST FOR {col.upper()}")
    print("\nH0: Data has UNIT ROOT and is NON-STATIONARY\nH1: Data has NO UNIT ROOT
    print("Reference p-value:0.05")
    res=adfuller(tsa_data.dropna(),autolag="AIC")
    index=["ADF test statistic","P value","No. of lags used","No of observations"]
    output=pd.Series(res[:4],index=index)
    print()
    print(output)
    print("---"*15)
    print("\nResults of ADF TEST:\n")

    ''' for p value less than 0.05 we reject null hypothesis i.e data is stationary
        else we do not reject H0

    '''
    if res[1]<0.05:
        print("Strong evidence against null hypothesis\nRejet the null hypothesis")
        print("Data has NO UNIT ROOT and is STATIONARY ")
    else:
        print("Weak evidence against null hypothesis")
        print("Do not Reject H0\nData has UNIT ROOT and is NON-STATIONARY ")
```

In [23]:

```
adf_test(tsa.total,"total")
```

```
AUGMENTED DICKEY FULLER TEST FOR TOTAL

H0: Data has UNIT ROOT and is NON-STATIONARY
H1: Data has NO UNIT ROOT and is STATIONARY
Reference p-value:0.05

ADF test statistic     -5.592497
P value                 0.000001
No. of lags used       18.000000
No of observations    459.000000
dtype: float64
---------------------------------------------

Results of ADF TEST:

Strong evidence against null hypothesis
Rejet the null hypothesis
Data has NO UNIT ROOT and is STATIONARY
```

Splitting data into train test dataset

In [24]:

```
train=tsa[:436]
```

In [25]:

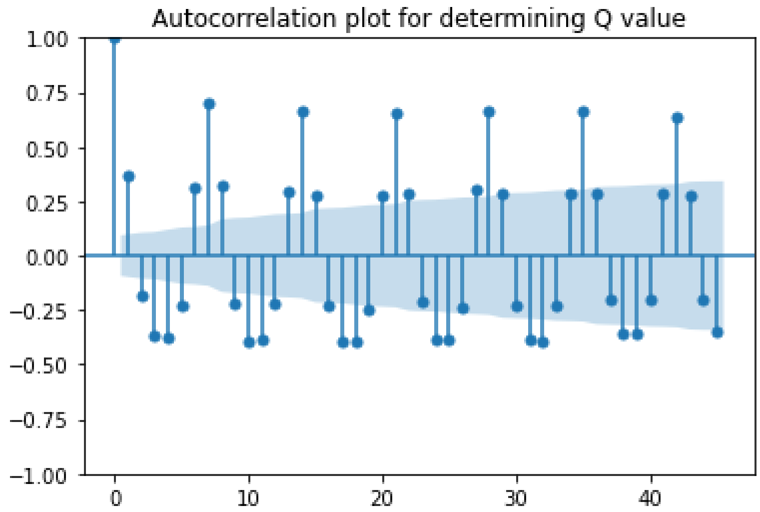
```
test=tsa[436:]
```

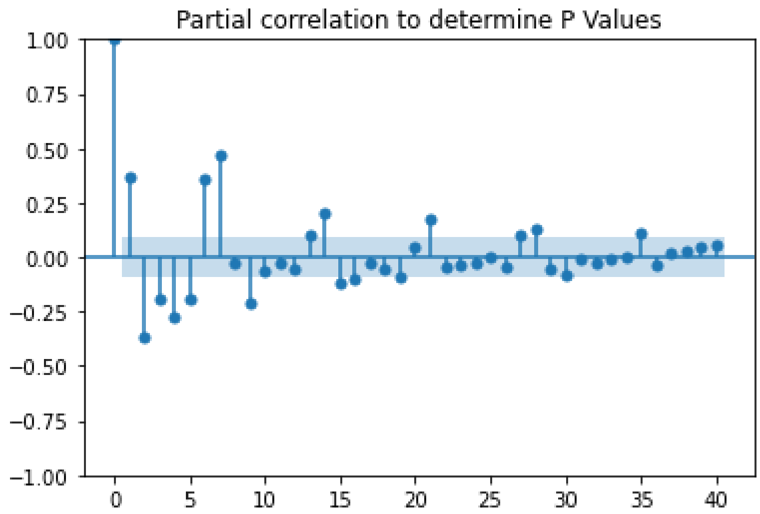
In [26]:

```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

In [27]:

```
title="Autocorrelation plot for determining Q value"
lags=45
plot_acf(train,title=title,lags=lags);
title='Partial correlation to determine P Values'
lags=40
plot_pacf(train,title=title,lags=lags,method='ywm');
```





In [28]:

```
# !pip install pmdarima
```

In [29]:

```
from pmdarima.arima import auto_arima
```

In [30]:

```
arima_model=auto_arima(train,seasonal=True,m=7,stationary=True,stepwise=False,trace=
```

```
 ARIMA(0,0,0)(0,0,0)[7] intercept   : AIC=4809.926, Time=0.42 sec
 ARIMA(0,0,0)(0,0,1)[7] intercept   : AIC=4648.327, Time=0.49 sec
 ARIMA(0,0,0)(0,0,2)[7] intercept   : AIC=4578.361, Time=0.90 sec
 ARIMA(0,0,0)(1,0,0)[7] intercept   : AIC=4499.838, Time=0.94 sec
 ARIMA(0,0,0)(1,0,1)[7] intercept   : AIC=4342.331, Time=1.88 sec
 ARIMA(0,0,0)(1,0,2)[7] intercept   : AIC=4561.333, Time=3.02 sec
 ARIMA(0,0,0)(2,0,0)[7] intercept   : AIC=4442.352, Time=3.17 sec
 ARIMA(0,0,0)(2,0,1)[7] intercept   : AIC=inf, Time=3.21 sec
 ARIMA(0,0,0)(2,0,2)[7] intercept   : AIC=4662.621, Time=4.47 sec
 ARIMA(0,0,1)(0,0,0)[7] intercept   : AIC=4711.793, Time=0.49 sec
 ARIMA(0,0,1)(0,0,1)[7] intercept   : AIC=4606.228, Time=0.79 sec
 ARIMA(0,0,1)(0,0,2)[7] intercept   : AIC=4547.071, Time=1.55 sec
 ARIMA(0,0,1)(1,0,0)[7] intercept   : AIC=4489.132, Time=1.81 sec
 ARIMA(0,0,1)(1,0,1)[7] intercept   : AIC=4403.309, Time=2.82 sec
 ARIMA(0,0,1)(1,0,2)[7] intercept   : AIC=4460.001, Time=3.40 sec
 ARIMA(0,0,1)(2,0,0)[7] intercept   : AIC=4428.498, Time=2.83 sec
 ARIMA(0,0,1)(2,0,1)[7] intercept   : AIC=inf, Time=4.23 sec
 ARIMA(0,0,1)(2,0,2)[7] intercept   : AIC=inf, Time=4.46 sec
 ARIMA(0,0,2)(0,0,0)[7] intercept   : AIC=4713.153, Time=0.75 sec
 ARIMA(0,0,2)(0,0,1)[7] intercept   : AIC=4608.050, Time=1.23 sec
 ARIMA(0,0,2)(0,0,2)[7] intercept   : AIC=4548.843, Time=1.95 sec
 ARIMA(0,0,2)(1,0,0)[7] intercept   : AIC=4489.218, Time=1.92 sec
 ARIMA(0,0,2)(1,0,1)[7] intercept   : AIC=4551.629, Time=3.03 sec
 ARIMA(0,0,2)(1,0,2)[7] intercept   : AIC=4544.175, Time=4.49 sec
 ARIMA(0,0,2)(2,0,0)[7] intercept   : AIC=4427.435, Time=2.89 sec
 ARIMA(0,0,2)(2,0,1)[7] intercept   : AIC=inf, Time=3.60 sec
 ARIMA(0,0,3)(0,0,0)[7] intercept   : AIC=4675.935, Time=0.66 sec
 ARIMA(0,0,3)(0,0,1)[7] intercept   : AIC=4592.070, Time=0.95 sec
 ARIMA(0,0,3)(0,0,2)[7] intercept   : AIC=4544.173, Time=1.65 sec
 ARIMA(0,0,3)(1,0,0)[7] intercept   : AIC=4491.440, Time=2.83 sec
 ARIMA(0,0,3)(1,0,1)[7] intercept   : AIC=inf, Time=3.64 sec
 ARIMA(0,0,3)(2,0,0)[7] intercept   : AIC=4648.146, Time=3.88 sec
 ARIMA(0,0,4)(0,0,0)[7] intercept   : AIC=4674.535, Time=0.92 sec
 ARIMA(0,0,4)(0,0,1)[7] intercept   : AIC=4591.395, Time=1.89 sec
 ARIMA(0,0,4)(1,0,0)[7] intercept   : AIC=4598.356, Time=3.59 sec
 ARIMA(0,0,5)(0,0,0)[7] intercept   : AIC=4665.365, Time=1.54 sec
 ARIMA(1,0,0)(0,0,0)[7] intercept   : AIC=4747.438, Time=0.33 sec
 ARIMA(1,0,0)(0,0,1)[7] intercept   : AIC=4614.530, Time=1.08 sec
 ARIMA(1,0,0)(0,0,2)[7] intercept   : AIC=4550.811, Time=1.87 sec
 ARIMA(1,0,0)(1,0,0)[7] intercept   : AIC=4487.895, Time=1.66 sec
 ARIMA(1,0,0)(1,0,1)[7] intercept   : AIC=4385.420, Time=2.70 sec
 ARIMA(1,0,0)(1,0,2)[7] intercept   : AIC=4504.496, Time=3.41 sec
 ARIMA(1,0,0)(2,0,0)[7] intercept   : AIC=4426.117, Time=3.35 sec
 ARIMA(1,0,0)(2,0,1)[7] intercept   : AIC=4790.769, Time=3.08 sec
 ARIMA(1,0,0)(2,0,2)[7] intercept   : AIC=inf, Time=5.33 sec
 ARIMA(1,0,1)(0,0,0)[7] intercept   : AIC=4713.533, Time=0.89 sec
 ARIMA(1,0,1)(0,0,1)[7] intercept   : AIC=4608.148, Time=1.47 sec
 ARIMA(1,0,1)(0,0,2)[7] intercept   : AIC=4549.394, Time=1.22 sec
 ARIMA(1,0,1)(1,0,0)[7] intercept   : AIC=inf, Time=1.51 sec
 ARIMA(1,0,1)(1,0,1)[7] intercept   : AIC=inf, Time=2.98 sec
 ARIMA(1,0,1)(1,0,2)[7] intercept   : AIC=4508.729, Time=3.64 sec
 ARIMA(1,0,1)(2,0,0)[7] intercept   : AIC=inf, Time=3.18 sec
 ARIMA(1,0,1)(2,0,1)[7] intercept   : AIC=inf, Time=2.00 sec
 ARIMA(1,0,2)(0,0,0)[7] intercept   : AIC=4710.599, Time=1.05 sec
 ARIMA(1,0,2)(0,0,1)[7] intercept   : AIC=4593.505, Time=2.43 sec
 ARIMA(1,0,2)(0,0,2)[7] intercept   : AIC=4549.738, Time=1.80 sec
 ARIMA(1,0,2)(1,0,0)[7] intercept   : AIC=4481.617, Time=2.49 sec
 ARIMA(1,0,2)(1,0,1)[7] intercept   : AIC=4545.472, Time=4.72 sec
 ARIMA(1,0,2)(2,0,0)[7] intercept   : AIC=inf, Time=4.64 sec
 ARIMA(1,0,3)(0,0,0)[7] intercept   : AIC=4674.986, Time=2.19 sec
 ARIMA(1,0,3)(0,0,1)[7] intercept   : AIC=4588.563, Time=3.33 sec
```

```
 ARIMA(1,0,3)(1,0,0)[7] intercept   : AIC=4493.119, Time=2.34 sec
 ARIMA(1,0,4)(0,0,0)[7] intercept   : AIC=4679.071, Time=1.36 sec
 ARIMA(2,0,0)(0,0,0)[7] intercept   : AIC=4681.929, Time=0.26 sec
 ARIMA(2,0,0)(0,0,1)[7] intercept   : AIC=4597.795, Time=0.85 sec
 ARIMA(2,0,0)(0,0,2)[7] intercept   : AIC=4544.937, Time=2.32 sec
 ARIMA(2,0,0)(1,0,0)[7] intercept   : AIC=4489.608, Time=2.50 sec
 ARIMA(2,0,0)(1,0,1)[7] intercept   : AIC=4583.776, Time=3.32 sec
 ARIMA(2,0,0)(1,0,2)[7] intercept   : AIC=4541.858, Time=3.87 sec
 ARIMA(2,0,0)(2,0,0)[7] intercept   : AIC=4427.545, Time=4.14 sec
 ARIMA(2,0,0)(2,0,1)[7] intercept   : AIC=inf, Time=5.76 sec
 ARIMA(2,0,1)(0,0,0)[7] intercept   : AIC=4653.459, Time=1.48 sec
 ARIMA(2,0,1)(0,0,1)[7] intercept   : AIC=4577.374, Time=2.70 sec
 ARIMA(2,0,1)(0,0,2)[7] intercept   : AIC=4535.518, Time=3.74 sec
 ARIMA(2,0,1)(1,0,0)[7] intercept   : AIC=inf, Time=2.89 sec
 ARIMA(2,0,1)(1,0,1)[7] intercept   : AIC=inf, Time=3.32 sec
 ARIMA(2,0,1)(2,0,0)[7] intercept   : AIC=4449.163, Time=5.64 sec
 ARIMA(2,0,2)(0,0,0)[7] intercept   : AIC=4702.467, Time=1.30 sec
 ARIMA(2,0,2)(0,0,1)[7] intercept   : AIC=4608.095, Time=1.82 sec
 ARIMA(2,0,2)(1,0,0)[7] intercept   : AIC=inf, Time=3.29 sec
 ARIMA(2,0,3)(0,0,0)[7] intercept   : AIC=inf, Time=2.36 sec
 ARIMA(3,0,0)(0,0,0)[7] intercept   : AIC=4668.975, Time=0.86 sec
 ARIMA(3,0,0)(0,0,1)[7] intercept   : AIC=4584.808, Time=0.90 sec
 ARIMA(3,0,0)(0,0,2)[7] intercept   : AIC=4538.406, Time=2.51 sec
 ARIMA(3,0,0)(1,0,0)[7] intercept   : AIC=4499.682, Time=3.10 sec
 ARIMA(3,0,0)(1,0,1)[7] intercept   : AIC=4595.054, Time=3.66 sec
 ARIMA(3,0,0)(2,0,0)[7] intercept   : AIC=4588.708, Time=5.72 sec
 ARIMA(3,0,1)(0,0,0)[7] intercept   : AIC=4652.984, Time=1.83 sec
 ARIMA(3,0,1)(0,0,1)[7] intercept   : AIC=4575.298, Time=2.51 sec
 ARIMA(3,0,1)(1,0,0)[7] intercept   : AIC=4520.624, Time=3.17 sec
 ARIMA(3,0,2)(0,0,0)[7] intercept   : AIC=inf, Time=2.05 sec
 ARIMA(4,0,0)(0,0,0)[7] intercept   : AIC=4632.989, Time=1.07 sec
 ARIMA(4,0,0)(0,0,1)[7] intercept   : AIC=4569.184, Time=2.25 sec
 ARIMA(4,0,0)(1,0,0)[7] intercept   : AIC=4499.483, Time=4.53 sec
 ARIMA(4,0,1)(0,0,0)[7] intercept   : AIC=4632.418, Time=0.63 sec
 ARIMA(5,0,0)(0,0,0)[7] intercept   : AIC=4618.102, Time=1.13 sec

Best model:  ARIMA(0,0,0)(1,0,1)[7] intercept
Total fit time: 236.701 seconds
```

In [31]:

```
arima_model.summary()
```

Out[31]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	436
Model:	SARIMAX(1, 0, [1], 7)	**Log Likelihood**	-2167.166
Date:	Tue, 11 Jul 2023	**AIC**	4342.331
Time:	13:52:46	**BIC**	4358.642
Sample:	01-01-2016	**HQIC**	4348.768
	- 03-11-2017		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	1.6404	0.916	1.791	0.073	-0.155	3.436
ar.S.L7	0.9863	0.007	136.449	0.000	0.972	1.000
ma.S.L7	-0.8432	0.041	-20.551	0.000	-0.924	-0.763
sigma2	1183.8244	69.038	17.147	0.000	1048.512	1319.137

Ljung-Box (L1) (Q):	18.47	**Jarque-Bera (JB):**	83.40
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.89	**Skew:**	0.84
Prob(H) (two-sided):	0.50	**Kurtosis:**	4.34

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

ARIMA MODEL

In [32]:

```
from statsmodels.tsa.arima.model import ARIMA,ARIMAResults
```

In [33]:

```
arimamodel=ARIMA(train,order=(0,0,0))
results=arimamodel.fit()
results.summary()
```

Out[33]:

SARIMAX Results

Dep. Variable:	total	**No. Observations:**	436
Model:	ARIMA	**Log Likelihood**	-2402.963
Date:	Tue, 11 Jul 2023	**AIC**	4809.926
Time:	13:52:46	**BIC**	4818.082
Sample:	01-01-2016	**HQIC**	4813.145
	- 03-11-2017		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	133.7477	3.409	39.229	0.000	127.065	140.430
sigma2	3586.4067	321.120	11.168	0.000	2957.022	4215.791

Ljung-Box (L1) (Q):	58.45	**Jarque-Bera (JB):**	37.02
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.87	**Skew:**	0.69
Prob(H) (two-sided):	0.41	**Kurtosis:**	2.62

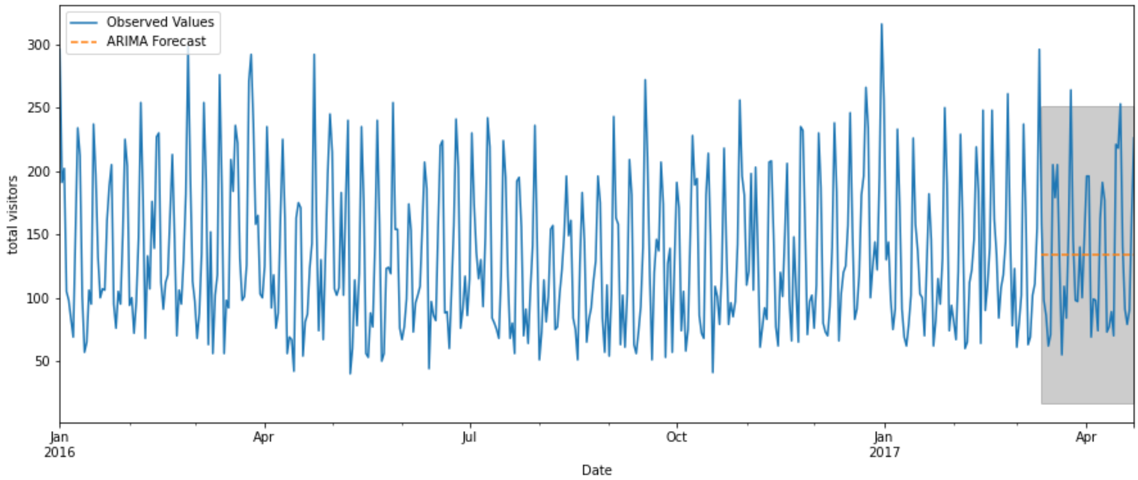
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [34]:

```
prediction=results.get_forecast(steps=len(test))      #steps should be no.of periods
```

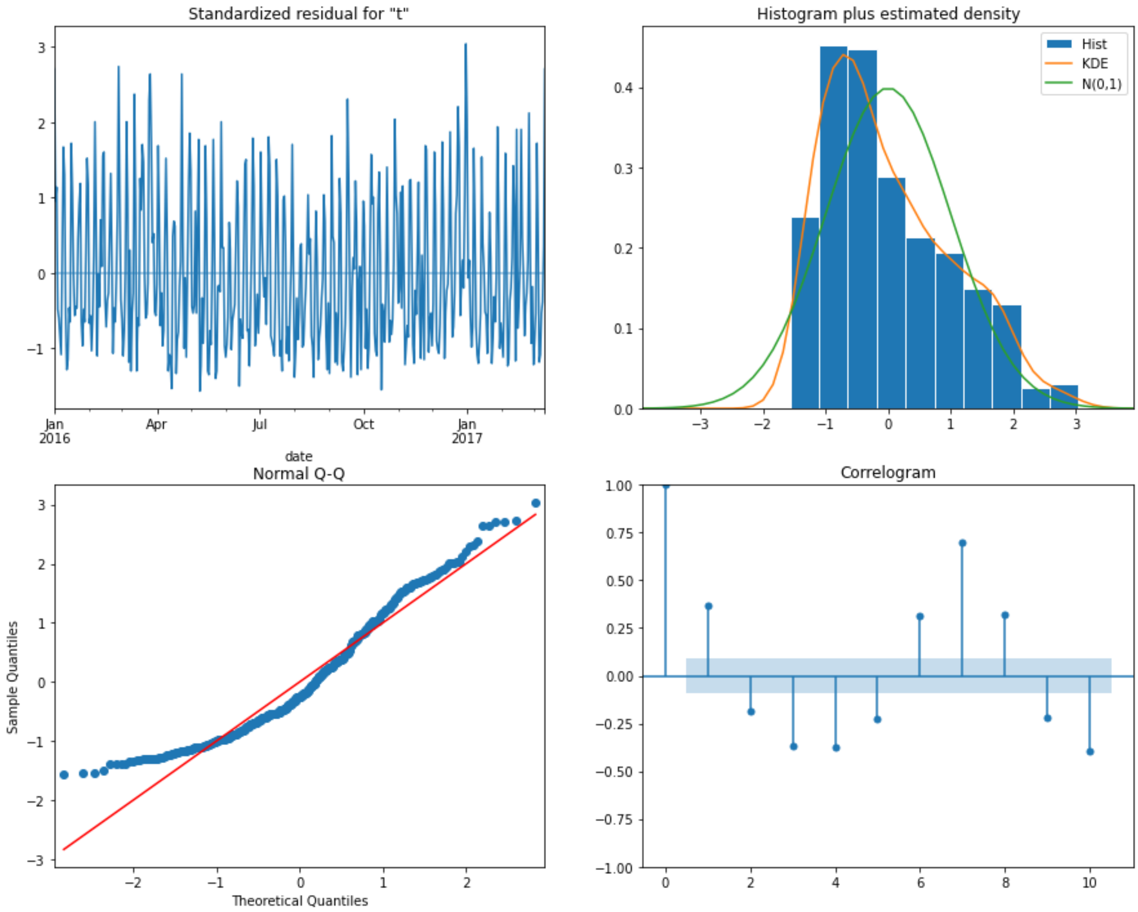
In [35]:

```
ax1=data["2016":].plot(label='Observed Values')
prediction.predicted_mean.plot(ax=ax1,label='ARIMA Forecast',figsize=(15,6),linestyl
pred_ci=prediction.conf_int()
ax1.fill_between(pred_ci.index,pred_ci.iloc[:,0],pred_ci.iloc[:,1],color='k',alpha=0
ax1.set_xlabel('Date')
ax1.set_ylabel('total visitors')
plt.legend(loc='upper left')
plt.show()
```



In [36]:

```
results.plot_diagnostics(figsize = (15, 12))
plt.show()
```



In [37]:

```
# fig1, ax2 = plt.subplots(figsize=(15, 6))
# test.plot(ax=ax2, label='Actual y value')
# prediction.predicted_mean.plot(ax=ax2, label='Predicted Y Values')
# ax2.set(title="Actual vs Predicted value[ARIMA]", xlabel="date", ylabel="Visitors"
# plt.legend()
# plt.show()

```

SARIMAX

In [38]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
```

In [39]:

```
model1=SARIMAX(train,order=(0,0,0),seasonal_order=(1,0,1,7),enforce_stationarity=Fal
fitted_model=model1.fit()
fitted_model.summary()

```

Out[39]:

SARIMAX Results

Dep. Variable:	total	**No. Observations:**	436
Model:	SARIMAX(1, 0, [1], 7)	**Log Likelihood**	-2105.589
Date:	Tue, 11 Jul 2023	**AIC**	4217.178
Time:	13:52:50	**BIC**	4229.355
Sample:	01-01-2016	**HQIC**	4221.987
	- 03-11-2017		
Covariance Type:	opg		

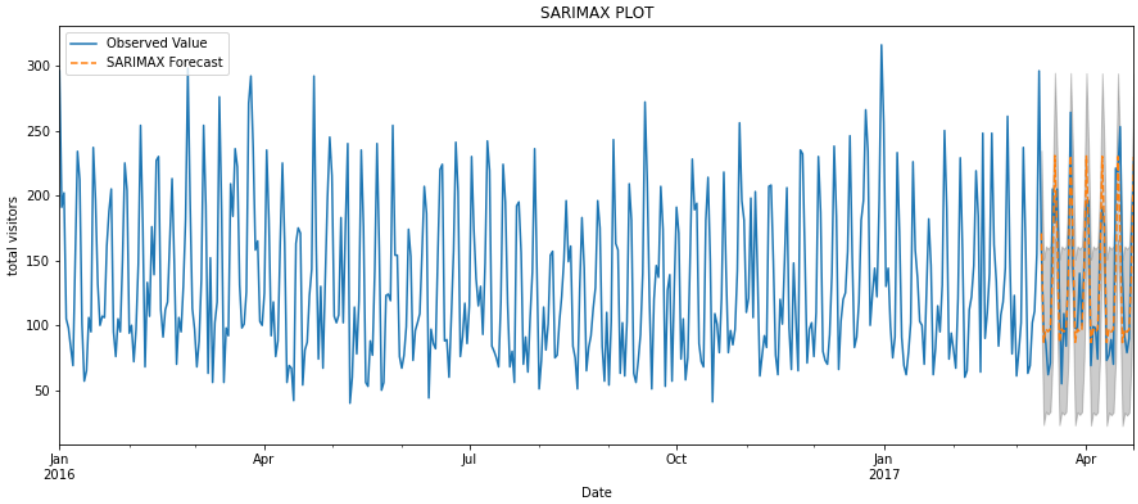
	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L7	0.9992	0.001	1085.998	0.000	0.997	1.001
ma.S.L7	-1.0522	0.026	-39.774	0.000	-1.104	-1.000
sigma2	954.6938	67.169	14.213	0.000	823.046	1086.342

Ljung-Box (L1) (Q):	19.23	**Jarque-Bera (JB):**	112.25
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.09	**Skew:**	0.91
Prob(H) (two-sided):	0.59	**Kurtosis:**	4.74

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

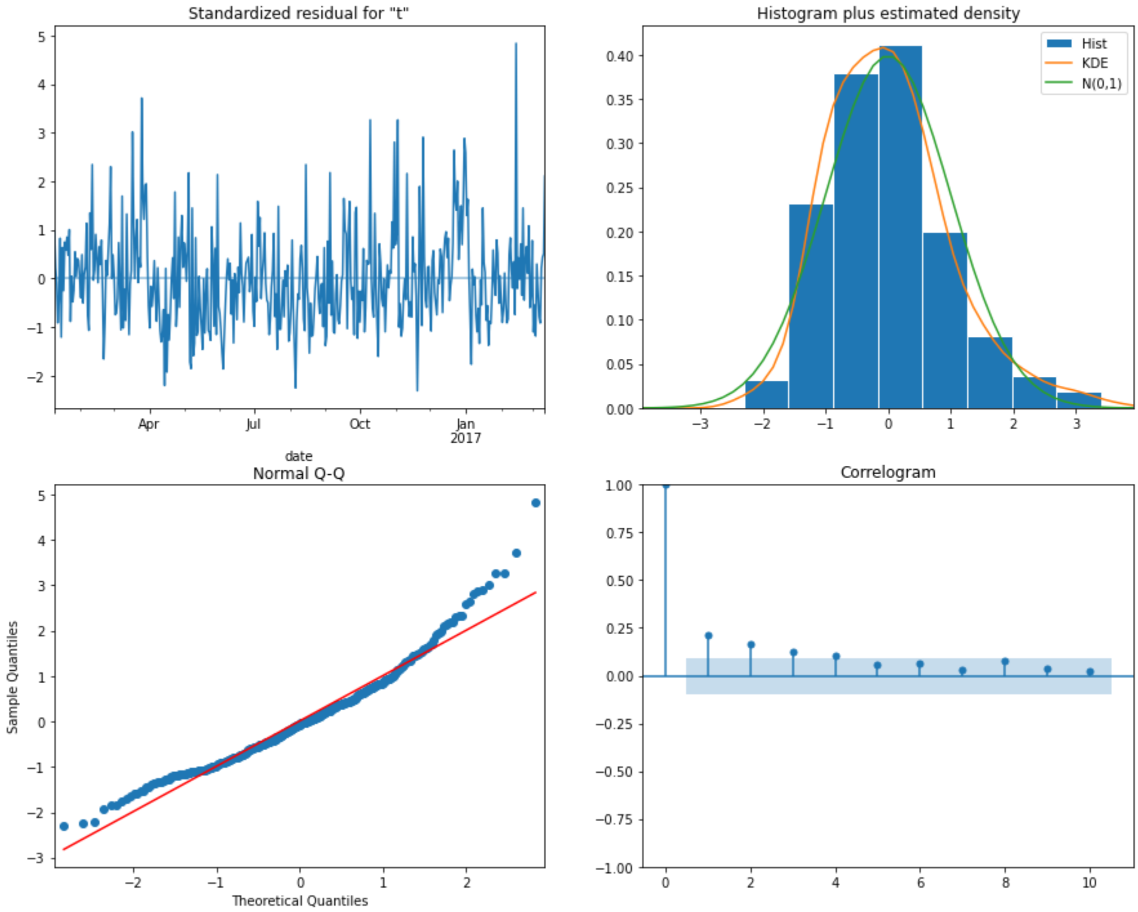
In [40]:

```
pred25=fitted_model.get_forecast(steps=len(test))
ax1=data['2016':].plot(label='Observed Value')
pred25.predicted_mean.plot(ax=ax1,label='SARIMAX Forecast',figsize=(15,6),linestyle=
pred_ci=pred25.conf_int()
ax1.fill_between(pred_ci.index,pred_ci.iloc[:,0],pred_ci.iloc[:,1],color='k',alpha=0
ax1.set_xlabel('Date')
plt.title("SARIMAX PLOT")
ax1.set_ylabel('total visitors')
plt.legend(loc='upper left')
plt.show()
```



In [41]:

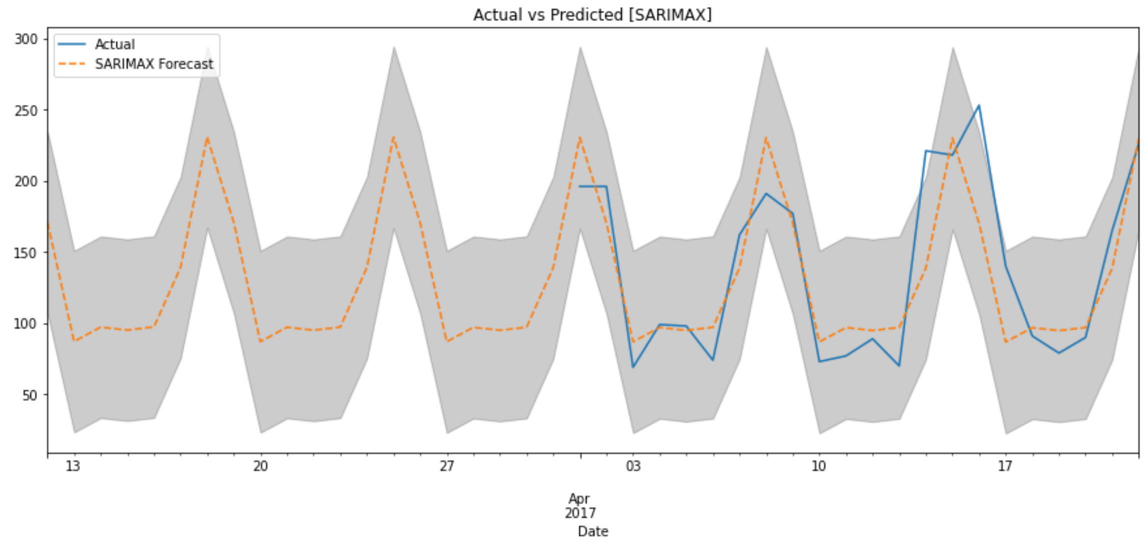
```
fitted_model.plot_diagnostics(figsize = (15, 12))
plt.show()
```



Actual vs Predicted

In [42]:

```
ax3=data["2017-04-01":].plot(label="Actual")
pred25.predicted_mean.plot(ax=ax3,label='SARIMAX Forecast',figsize=(15,6),linestyle=
ax3.fill_between(pred_ci.index,pred_ci.iloc[:,0],pred_ci.iloc[:,1],color="k",alpha=0
ax3.set_xlabel('Date')
plt.title("Actual vs Predicted [SARIMAX]")
ax1.set_ylabel('total visitors')
plt.legend(loc='upper left')
plt.show()
```



Evaluation of Model

In [43]:

```
sarimax_forecast=pred25.predicted_mean
actual_y=test["total"]
mse_sarimax=((sarimax_forecast-actual_y)**2).mean()
print(f"Mean Squared Error of Sarimax model is {round(mse_sarimax,2)}")
print(f"Root Mean Squared Error of Sarimax model is {round(np.sqrt(mse_sarimax),2)}"
```

```
Mean Squared Error of Sarimax model is 1000.45
Root Mean Squared Error of Sarimax model is 31.63
```

LSTM MODEL

In [44]:

```
from sklearn.preprocessing import StandardScaler
```

In [45]:

```
sc=StandardScaler()
scaled_train=sc.fit_transform(np.array(train).reshape(-1,1))
scaled_train
```

Out[45]:

```
array([[ 2.70934655],
       [ 0.95601917],
       [ 1.13970109],
       [-0.48003943],
       [-0.59692792],
       [-0.84740326],
       [-1.08118025],
       [ 0.25468823],
       [ 1.67404848],
       [ 1.30668465],
       [-0.54683286],
       [-1.28156052],
       [-1.14797367],
       [-0.46334108],
       [-0.64702299],
       [ 1.72414355],
       [ 1.05620931],
       [-0.02918382],
```

In [46]:

```
from keras.preprocessing.sequence import TimeseriesGenerator
window_size=50     #no of inputs from trained data
generator=TimeseriesGenerator(scaled_train,scaled_train,length=window_size,batch_siz
```

In [47]:

```
len(generator)
```

Out[47]:

```
386
```

In [48]:

```
x,y=generator[0]
```

In [49]:

```
print(x,y)
```

```
[[[ 2.70934655]
  [ 0.95601917]
  [ 1.13970109]
  [-0.48003943]
  [-0.59692792]
  [-0.84740326]
  [-1.08118025]
  [ 0.25468823]
  [ 1.67404848]
  [ 1.30668465]
  [-0.54683286]
  [-1.28156052]
  [-1.14797367]
  [-0.46334108]
  [-0.64702299]
  [ 1.72414355]
  [ 1.05620931]
  [-0.02918382]
  [-0.56353121]
  [-0.44664272]
  [-0.46334108]
  [ 0.4550685 ]
  [ 0.90592411]
  [ 1.18979616]
  [-0.64702299]
  [-0.96429175]
  [-0.48003943]
  [-0.64702299]
  [ 0.27138658]
  [ 1.52376328]
  [ 1.1730978 ]
  [-0.66372135]
  [-0.56353121]
  [-1.03108518]
  [-0.61362628]
  [ 0.22129151]
  [ 2.0080156 ]
  [ 0.72224219]
  [-1.0978786 ]
  [-0.01248547]
  [-0.44664272]
  [ 0.70554384]
  [ 0.08770467]
  [ 1.55715999]
  [ 1.60725506]
  [-0.36315094]
  [-0.71381642]
  [-0.36315094]
  [-0.26296081]
  [ 0.55525863]]] [[1.323383]]
```

In [50]:

```
import tensorflow as tf
from tensorflow.keras.layers import LSTM,Dense
model=tf.keras.models.Sequential()
model.add(LSTM(256,activation="relu",input_shape=(window_size,1),return_sequences=Tr
model.add(LSTM(124,activation="relu"))
model.add(Dense(1))
```

In [51]:

```
model.compile(loss="mse",optimizer="adam")

```

In [52]:

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lstm (LSTM)                 (None, 50, 256)           264192    
                                                                 
 lstm_1 (LSTM)               (None, 124)               188976    
                                                                 
 dense (Dense)               (None, 1)                 125       
                                                                 
=================================================================
Total params: 453,293
Trainable params: 453,293
Non-trainable params: 0
_________________________________________________________________
```

In [53]:

```
from tensorflow.keras.callbacks import ModelCheckpoint
checkpoint = ModelCheckpoint(r"total.h5",
                             monitor = 'loss', save_best_only = True)
```

In [54]:

```
import random as rd
rd.seed(25)
np.random.seed(13)
tf.random.set_seed(13)
```

In [ ]:

```
history=model.fit(generator,epochs=25,callbacks=[checkpoint])
```

```
Epoch 1/25
386/386 [==============================] - 68s 151ms/step - loss: 1.0102
Epoch 2/25
386/386 [==============================] - 62s 161ms/step - loss: 1.0054
Epoch 3/25
386/386 [==============================] - 51s 131ms/step - loss: 0.9865
Epoch 4/25
386/386 [==============================] - 49s 126ms/step - loss: 138.0985
Epoch 5/25
386/386 [==============================] - 49s 126ms/step - loss: 0.9800
Epoch 6/25
386/386 [==============================] - 49s 127ms/step - loss: 0.9422
Epoch 7/25
386/386 [==============================] - 51s 132ms/step - loss: 2.1069
Epoch 8/25
386/386 [==============================] - 50s 130ms/step - loss: 8923.641
6
Epoch 9/25
386/386 [==============================] - 49s 126ms/step - loss: 1.3110
Epoch 10/25
386/386 [==============================] - 51s 133ms/step - loss: 0.9839
Epoch 11/25
386/386 [==============================] - 55s 142ms/step - loss: 0.8737
Epoch 12/25
 68/386 [====>.........................] - ETA: 40s - loss: 0.9387
```

In [ ]:

```
plt.plot(history.history["loss"])
plt.xlabel("Epochs", fontsize = 10)
plt.ylabel("Loss", fontsize = 10)
plt.legend(["Loss"])
plt.title("Training Loss", fontsize = 15)
plt.show()
```

In [ ]:

```
from tensorflow.keras.models import load_model
model=load_model(r'total.h5')
```

In [ ]:

```
#Creating an empty forecasts list:
lstm_predictions_scaled = []

#Creating a batch of the latest data points based on the window size for forecast:
batch = scaled_train[-window_size:]
#Reshaping the batch as per model requirements:
current_batch = batch.reshape((1, window_size, 1))


for i in range(len(test)):
    lstm_pred = model.predict(current_batch)[0]
    #Appending the next month forecast to the forecasts list:
    lstm_predictions_scaled.append(lstm_pred)
    #removing the earliest data point in its place to preserve the window size:
    current_batch = np.append(current_batch[:, 1:, :], [[lstm_pred]], axis = 1)

#Since the original values were scaled before training the model, we need to
#inverse scale the forecast in order to get the forecast for the original data.
lstm_predictions = sc.inverse_transform(lstm_predictions_scaled)
```

In [ ]:

```
for i in range(0,len(lstm_predictions)):
    pred_value=lstm_predictions[i][0]

pred_value

```

In [ ]:

```
lstm_pred = pd.DataFrame(data = [lstm_predictions[i][0] for i in range(0, len(lstm_p

lstm_pred
```

In [ ]:

```
ax35 = data['2016':].plot(label = 'Observed')

lstm_pred.plot(ax = ax35, label = 'LSTM Forecast', figsize = (15, 6), linewidth = 2,
ax35.set_xlabel('Date')
ax35.set_ylabel('infl')
plt.legend()
plt.show()
```

In [ ]:

```
y_forecasted_LSTM = lstm_pred['LSTM Forecast']
y_truth = test["total"]
mse_LSTM = ((y_forecasted_LSTM - y_truth) ** 2).mean()
print('The Mean Squared Error of LSTM forecast is {}'.format(round(mse_LSTM, 2)))
print('The Root Mean Squared Error of LSTM forecast is {}'.format(round(np.sqrt(mse_
```

In [ ]:

```

```

In [ ]:

```

```