Final Project Part 2

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Daily Website Traffic Trends: A Time Series Analysis

In [173…

```
# libraries
import pandas as pd
from pandas import DataFrame
import matplotlib.pyplot as plt
from pandas.plotting import autocorrelation_plot
import seaborn as sns
import numpy as np
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
import statsmodels.stats.diagnostic as diag
import statsmodels.api as sm
from pmdarima.arima import auto_arima
import pmdarima
import statsmodels.api as sm
from statsmodels.tsa.ar_model import AutoReg
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.preprocessing.sequence import TimeseriesGenerator
```

In [174…

```
#load the dataset
data_website = pd.read_csv('daily-website-visitors.csv',header=0,parse_dates=True,
                           squeeze=True)
data_website.head(10)
```

```
<ipython-input-174-fca4028a96da>:2: FutureWarning: The squeeze argument has been depreca
ted and will be removed in a future version. Append .squeeze("columns") to the call to s
queeze.


  data_website = pd.read_csv('daily-website-visitors.csv',header=0,parse_dates=True,
```

Out[174…

	Row	Day	Day.Of.Week	Date	Page.Loads	Unique.Visits	First.Time.Visits	Returning.Visits
0	1	Sunday	1	9/14/2014	2,146	1,582	1,430	152
1	2	Monday	2	9/15/2014	3,621	2,528	2,297	231
2	3	Tuesday	3	9/16/2014	3,698	2,630	2,352	278
3	4	Wednesday	4	9/17/2014	3,667	2,614	2,327	287
4	5	Thursday	5	9/18/2014	3,316	2,366	2,130	236

5	6	Friday	6	9/19/2014	2,815	1,863	1,622	241
6	7	Saturday	7	9/20/2014	1,658	1,118	985	133
7	8	Sunday	1	9/21/2014	2,288	1,656	1,481	175
8	9	Monday	2	9/22/2014	3,638	2,586	2,312	274
9	10	Tuesday	3	9/23/2014	4,462	3,257	2,989	268

Dataset Description

Day - Day of week in text format (Sunday, etc.)

Day.Of.Week - Day of week in numeric format (1-7)

Date - Date in mm/dd/yyyy format

Page.Loads - Number of pages loaded on a daily basis

Unique.Visits - Daily number of visitors from whose IP addresses there haven't been hits on any page in over 6 hours

First.Time.Visits - Number of unique visitors who do not have a cookie identifying them as a previous customer

Returning.Visits - Number of unique visitors minus first time visitors

Data preprocessing

In the code chunk below we perform data pre-processing by implementing the following operations:

1. Converting the 'Date' column to datetime format and assigning that column as the index for further time series analysis

1. The quantitative columns in our dataset ['Page.Loads', 'Unique.Visits', 'First.Time.Visits', 'Returning.Visits'] contain commas which we intend to remove.

In [175…

```
#convert date in datetime format and setting the index as Date
data_website.index=pd.to_datetime(data_website['Date'])

# Function to remove commas
def remove_commas(x):
    return float(x.replace(',', ''))

data_website['Page.Loads'] = data_website['Page.Loads'].apply(
    lambda x : remove_commas(x))
data_website['Unique.Visits'] = data_website['Unique.Visits'].apply(
    lambda x : remove_commas(x))
data_website['First.Time.Visits'] = data_website['First.Time.Visits'].apply(
    lambda x : remove_commas(x))
data_website['Returning.Visits'] = data_website['Returning.Visits'].apply(
    lambda x : remove_commas(x))
```

In [176…

```
data_website.describe()
```

Out[176…

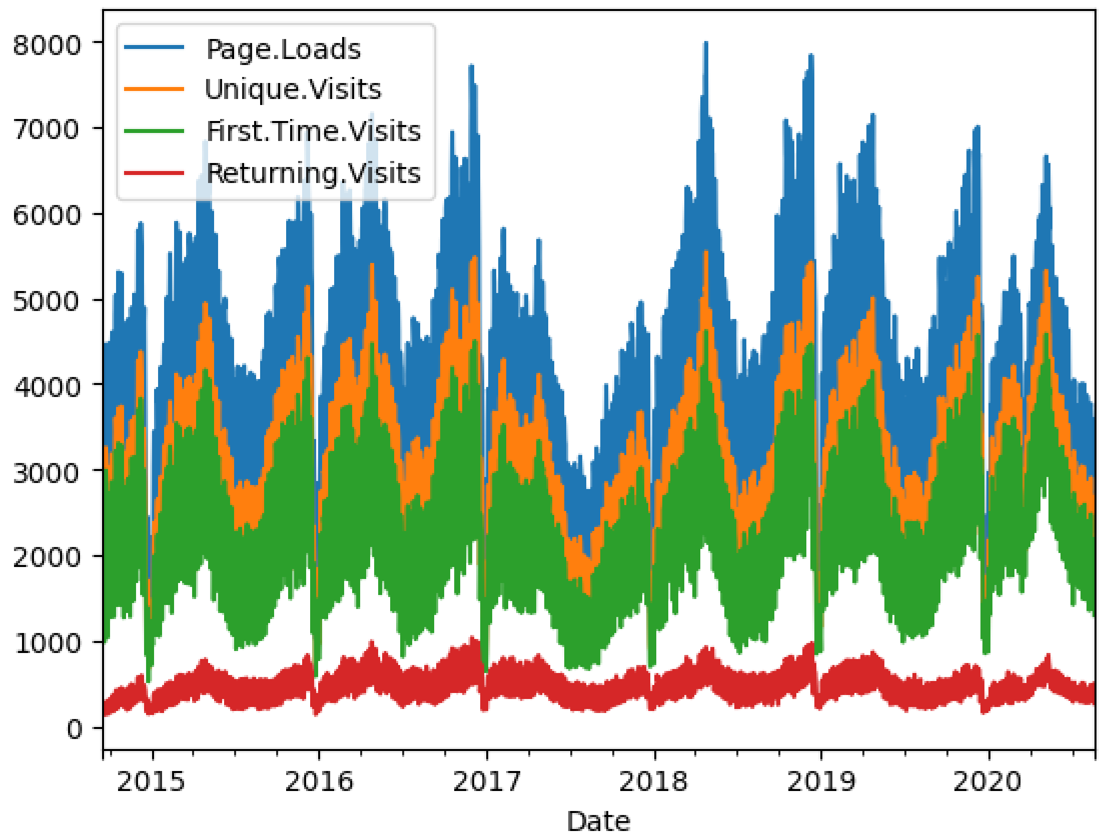
	Row	Day.Of.Week	Page.Loads	Unique.Visits	First.Time.Visits	Returning.Visits
count	2167.000000	2167.000000	2167.000000	2167.000000	2167.000000	2167.000000

mean	1084.000000	3.997231	4116.989386	2943.646516	2431.824181	511.822335
std	625.703338	2.000229	1350.977843	977.886472	828.704688	168.736370
min	1.000000	1.000000	1002.000000	667.000000	522.000000	133.000000
25%	542.500000	2.000000	3114.500000	2226.000000	1830.000000	388.500000
50%	1084.000000	4.000000	4106.000000	2914.000000	2400.000000	509.000000
75%	1625.500000	6.000000	5020.500000	3667.500000	3038.000000	626.500000
max	2167.000000	7.000000	7984.000000	5541.000000	4616.000000	1036.000000

Time Series Visualization

In [177…

```
data_website.iloc[:,3:].plot()
plt.show()
```



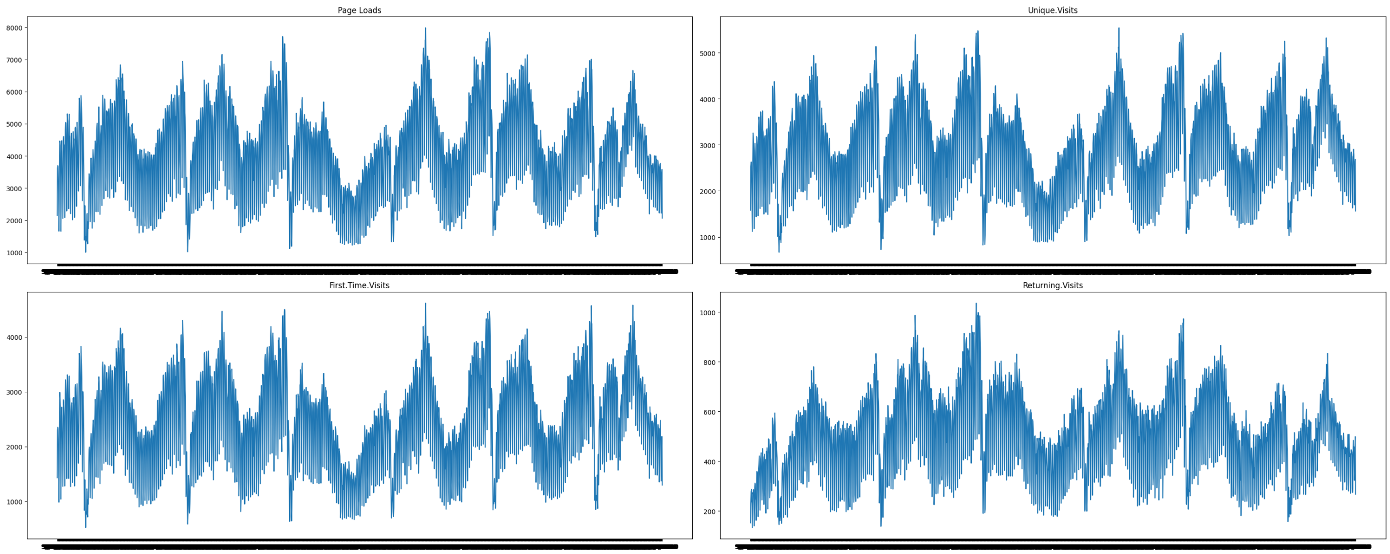
Above plot is a combined plot of variables of interest which are Page.Loads, Unique.Visits, First.Time.Visits, Returning.Visits showing the distribution of data over the years 2014 to 2020.

We can observe that a similar and repeated pattern is followed by all the 4 columns which is a spike in the beginning of the year followed by a dip and again a rise is observed at the end of the year.

In [245…

```
#line plot for all the years for Page Loads, Unique Visits, first time visits and
# Returning Visits for more closer understanding by plotting the graphs individually

fig, axs = plt.subplots(2, 2, figsize=(30, 12))

axs[0, 0].plot(data_website['Date'], data_website['Page.Loads'])
axs[0, 0].set_title('Page Loads')

axs[0, 1].plot(data_website['Date'], data_website['Unique.Visits'])
```

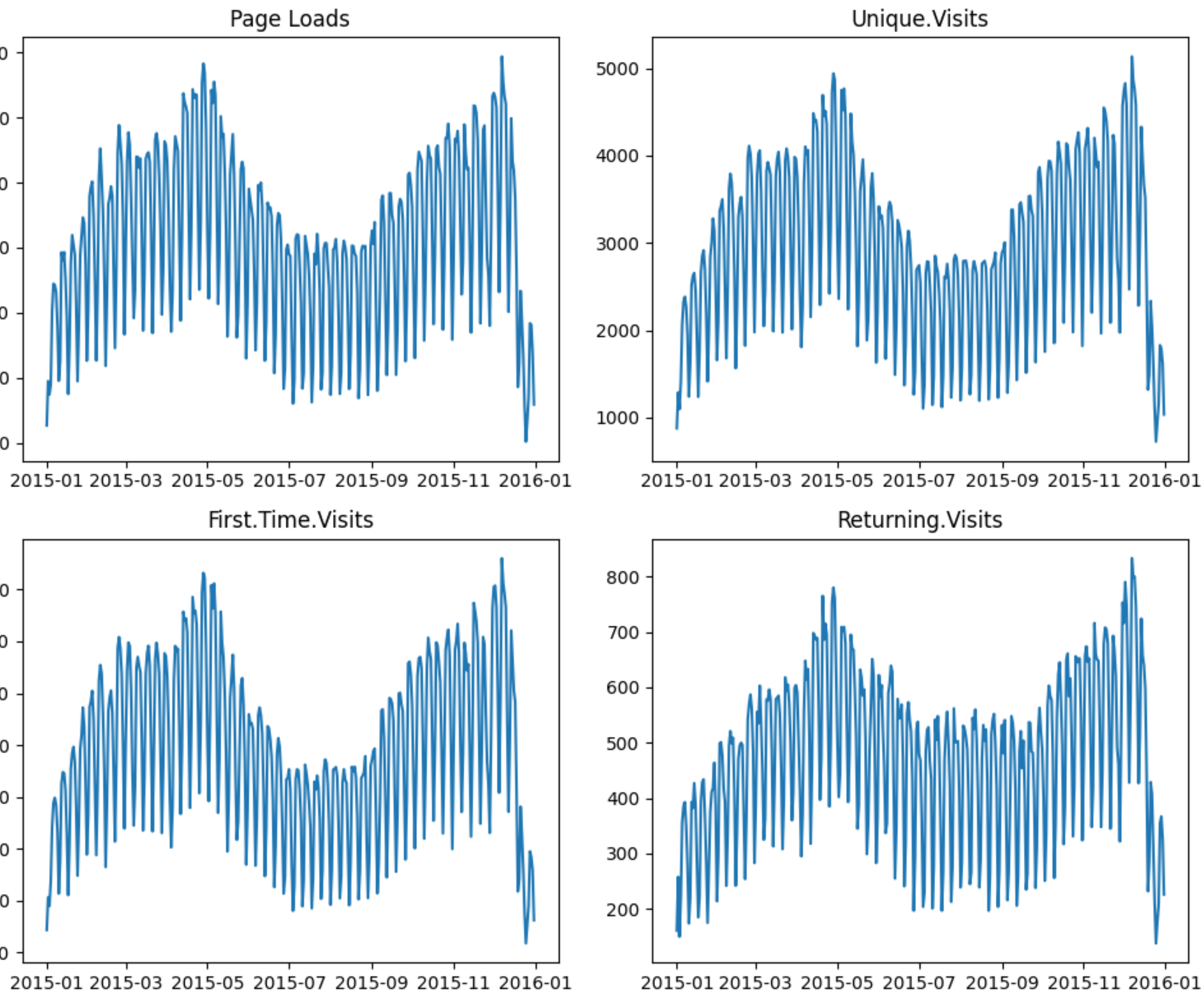
```
axs[0, 1].set_title('Unique.Visits')

axs[1, 0].plot(data_website['Date'], data_website['First.Time.Visits'])
axs[1, 0].set_title('First.Time.Visits')

axs[1, 1].plot(data_website['Date'], data_website['Returning.Visits'])
axs[1, 1].set_title('Returning.Visits')

fig.tight_layout()

plt.show()
```



The line chart shows the progression of a all the 4 attributes- Page loads, unique visits, first time visits and returning visits measured over the course of 2014 to 2020, with dates on the horizontal axis and the count of the occurrances of variables on the vertical axis. The chart suggests that the variable demonstrates a distinct overall pattern, either increasing or decreasing over time. Additionally, there appears to be some level of seasonality present in the data, with regular patterns of fluctuations occurring at fixed intervals. This implies that the variable may be affected by recurring factors such as seasonal changes.

In [179…

```
# understanding trends for one particular year-2015
data = data_website.loc['2015']
fig, axs = plt.subplots(2, 2, figsize=(10, 8))

axs[0, 0].plot(data['Page.Loads'])
axs[0, 0].set_title('Page Loads')

axs[0, 1].plot( data['Unique.Visits'])
axs[0, 1].set_title('Unique.Visits')

# plot the third graph in the bottom left subplot
axs[1, 0].plot(data['First.Time.Visits'])
axs[1, 0].set_title('First.Time.Visits')

# plot the fourth graph in the bottom right subplot
axs[1, 1].plot(data['Returning.Visits'])
axs[1, 1].set_title('Returning.Visits')

# adjust the spacing between the subplots
fig.tight_layout()

# show the plot
plt.show()
```

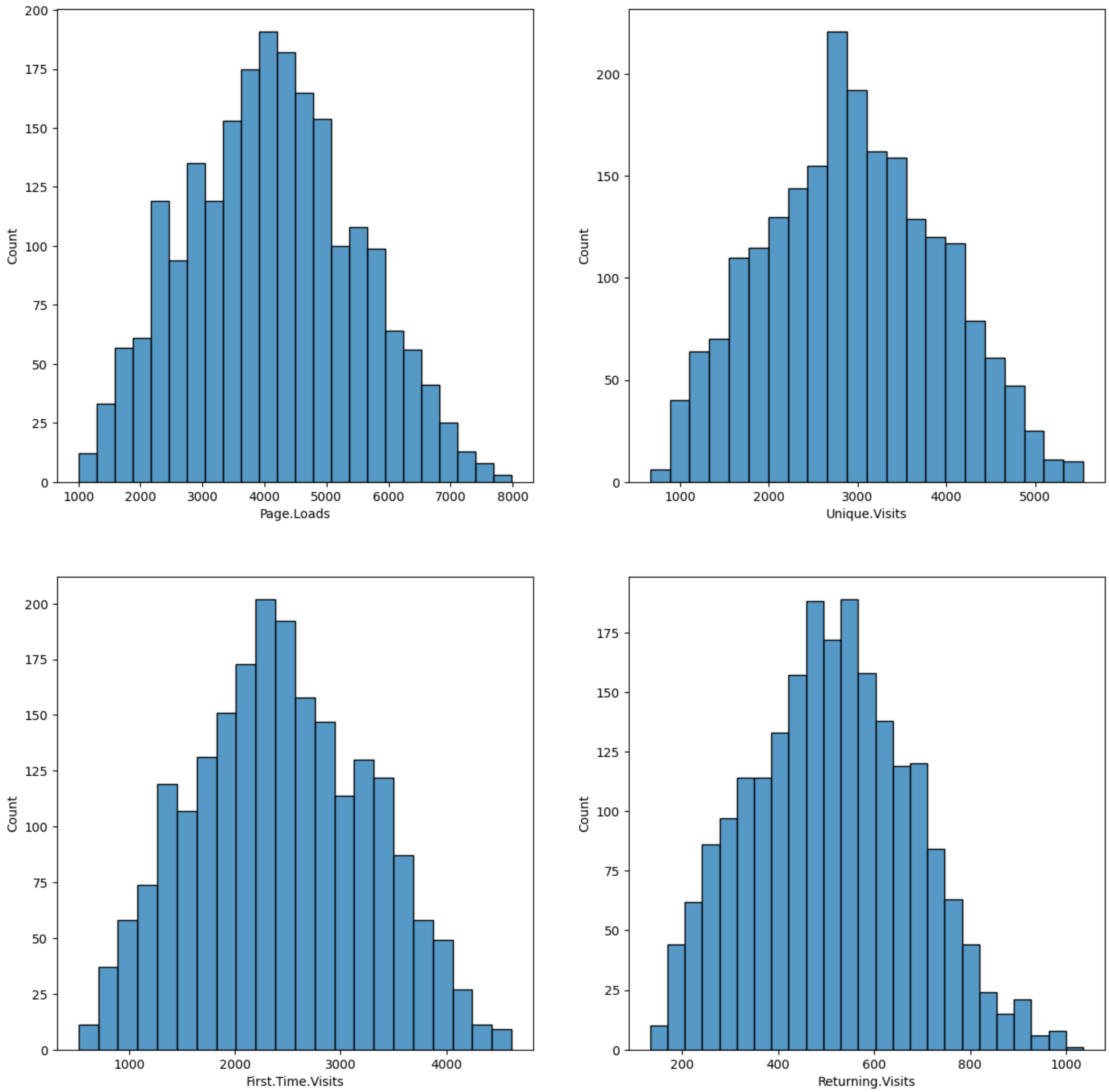


To get a clear understanding of the pattern in the data we take a more closer look by considering only one year's data.

The plot above is taken for a subset of year 2015. Based on the plot, we can infer that the number of visits initially rises until May, then gradually declines which continues till September 2015, and eventually starts to increase again from September onwards.

In [180…

```
#histogram plots
cols_to_plot = ['Page.Loads', 'Unique.Visits', 'First.Time.Visits', 'Returning.Visits']
plt.figure(figsize=(15, 15))
for i, col in enumerate(cols_to_plot):
    plt.subplot(2, 2, i+1)
    sns.histplot(data=data_website, x=col)
```



To understand the distribution of data and check for presence of skewness in the data we plot a Histogram as seen above.

The observation from the above plot is that the data is normally distributed about the mean for all of the 4 attributes.

In [181…

```
#Day wise analysis
day_grouped_data = data_website.iloc[:,1:].groupby('Day')
avg_day_data = day_grouped_data.mean().reset_index()
avg_day_data
```

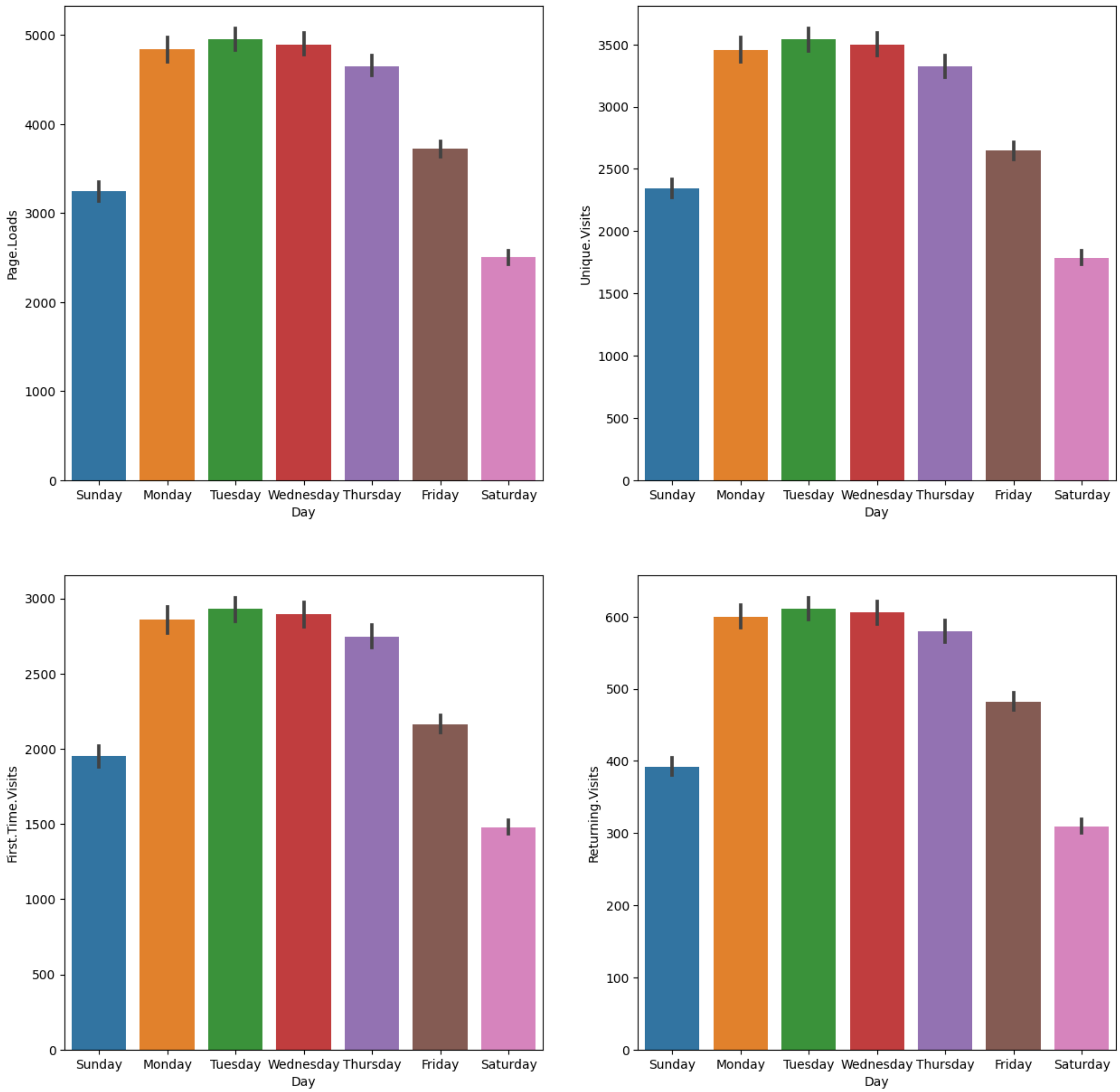
Out[181…

	Day	Day.Of.Week	Page.Loads	Unique.Visits	First.Time.Visits	Returning.Visits
0	Friday	6.0	3719.860841	2646.770227	2164.417476	482.352751
1	Monday	2.0	4845.680645	3458.425806	2858.180645	600.245161
2	Saturday	7.0	2501.025890	1786.747573	1477.181230	309.566343
3	Sunday	1.0	3246.980645	2341.270968	1949.025806	392.245161

4	Thursday	5.0	4651.355987	3327.553398	2747.317152	580.236246
5	Tuesday	3.0	4955.335484	3539.293548	2928.232258	611.061290
6	Wednesday	4.0	4893.916129	3502.012903	2895.490323	606.522581

In [182…

```
# Plot the Bargraph for every continuous variable across day
cols_to_plot = ['Page.Loads', 'Unique.Visits', 'First.Time.Visits', 'Returning.Visits']
plt.figure(figsize=(15, 15))
for i, col in enumerate(cols_to_plot):
    plt.subplot(2, 2, i+1)
    sns.barplot(data=data_website, x='Day', y=col)
```



The objective of the above plot is to understand the daywise analysis for the variables of interest - Page.Loads, Unique.Visits, First.Time.Visits, Returning.Visits.

The observations from the above plots for the 4 attributes are as follows:

1. Page.Loads - Higher number of page loads are observed on Monday, Tuesday and Wednesday whereas lowest number of page loads was observed on Saturday.

1. Unique.Visits - Similar to the trend observed in Page.Loads we can observe that highest number of unique visits are observed on Monday, Tuesday and Wednesday whereas lowest number of unique visits was observed on Saturday.

1. First.Time.Visits - Similar to the trend observed in Page.Loads and Unique.Visits we can observe that highest number of First time visits are observed on Monday, Tuesday and Wednesday whereas lowest number of first time visits was observed on Saturday.

1. Returning.Visits - Again a similar trend is observed in the returning visits data.

Overall, we can conclude that highest trend is observed on Mondays, Tuesdays and Wednesdays whereas lowest trend is observed on Saturdays

Check for white noise

In order to determine whether the time series is White Noise we implement the following techniques:

1. Apply the kpss test -A KPSS test can be used to determine if a time series is trend stationary.This test uses the following null and alternative hypothesis: H0: The time series is trend stationary. HA: The time series is not trend stationary. If the p-value of the test is less than some significance level (e.g. α = .05) then we reject the null hypothesis and conclude that the time series is not trend stationary. Otherwise, we fail to reject the null hypothesis.

2. Apply the Ljung Box Test that gives the Ljung-Box statistic for testing if a time series is white noise, and the corresponding p-value. A p-value of less than 0.05 indicates a significant auto-correlation and proves that the time series is not white noise

1. Apply the Box-Pierce test and it's test statistic is called the Q statistic. For the given time series, we can check if the value of Q deviates from zero in a statistically significant way looking up at the p-value of the test statistic in the Chi-square tables. Usually, a p-value of less than 0.05 indicates a significant auto-correlation and proves that the time series is not white noise

1. Auto-correlation plots: For white noise series, we expect each autocorrelation to be close to zero. Of course, they will not be exactly equal to zero as there is some random variation. For a white noise series, we expect 95% of the spikes in the ACF to lie within ±2/√T where T is the length of the time series. It is common to plot these bounds on a graph of the ACF (the blue shaded region above). If one or more large spikes are outside these bounds, or if substantially more than 5% of spikes are outside these bounds, then the series is probably not white noise.

KPSS Test

In [248…
```
sm.tsa.stattools.kpss(unique_visits, regression='c')
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/stattools.py:2022: InterpolationW
arning: The test statistic is outside of the range of p-values available in the
look-up table. The actual p-value is greater than the p-value returned.

  warnings.warn(
```

Out[248…
```
(0.24528128576326558,
 0.1,
```

```
22,
{'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

The p-value is 0.1. Since this value is not less than .05, we fail to reject the null hypothesis of the KPSS test.

This means we can assume that the time series is stationary.

Testing using Ljung Box and Box Pierce Test

In [183…
```
diag.acorr_ljungbox(data_website['Unique.Visits'], lags=[10], boxpierce=True)
```

Out[183…

	lb_stat	lb_pvalue	bp_stat	bp_pvalue
10	5810.661684	0.0	5790.981658	0.0

Test Statistic for Ljungbox = 5810.661684

p-value for Ljungbox = 0

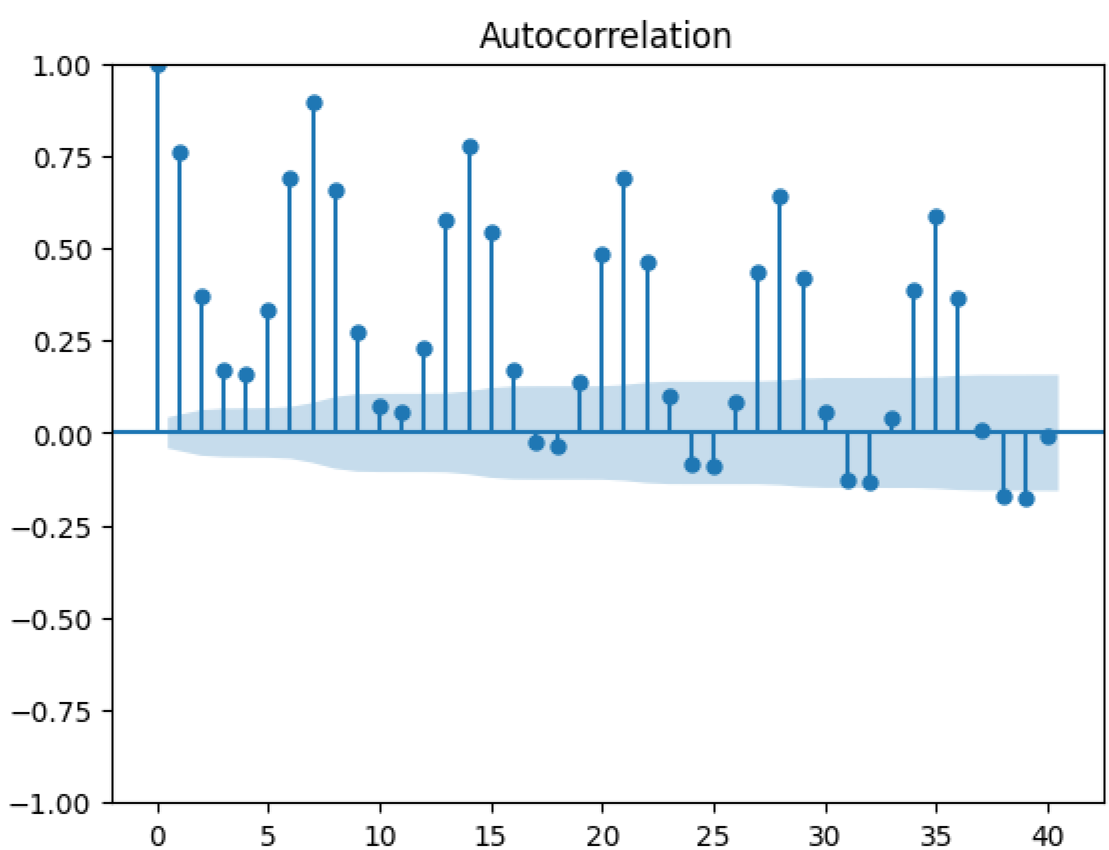
Test Statistic for Box-Pierce Test = 5790.981658

p-value for Box-Pierce = 0

Both the p-values from Chi-Square table are less than 0.01 , So with 99% confidence , we say that the time series is not Pure White noise

Autocorrelation Plot

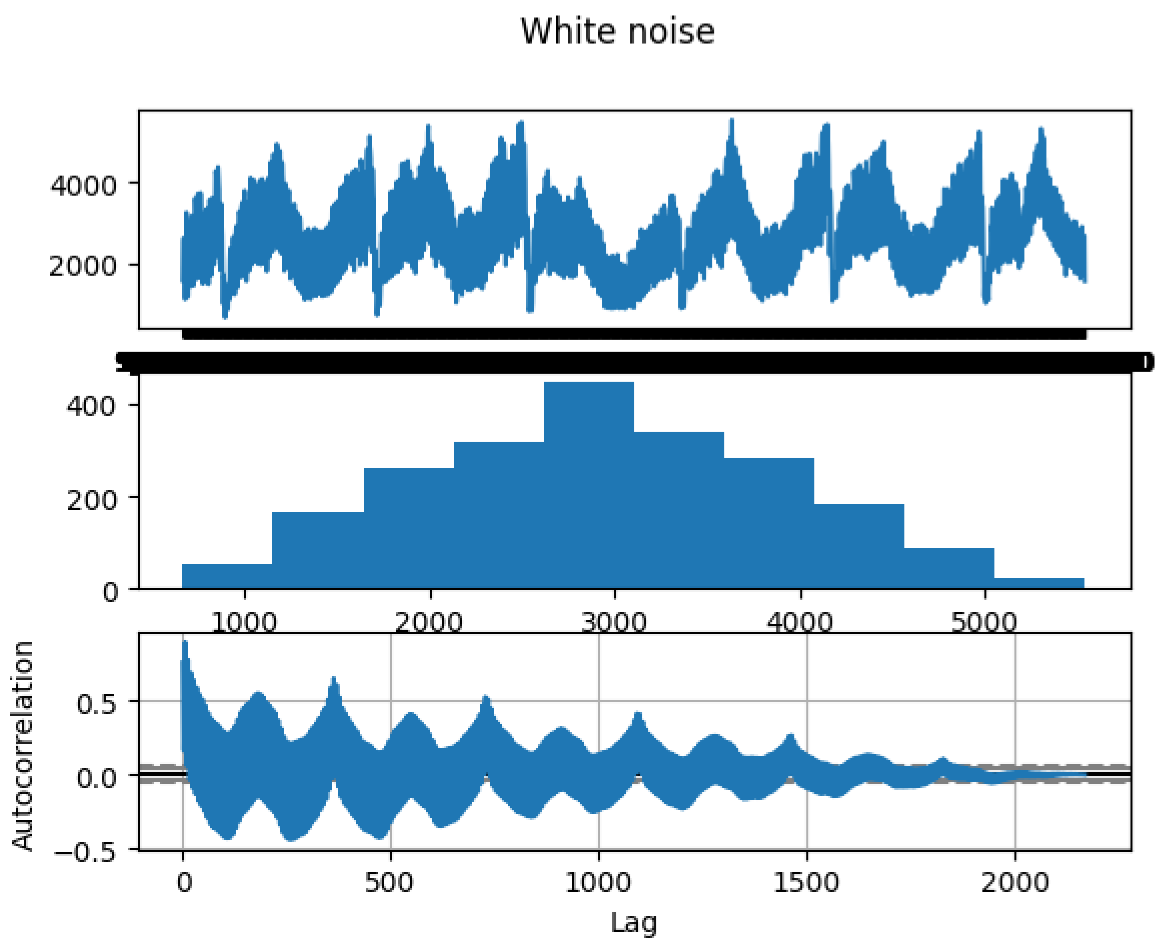
In [184…
```
plot_acf(data_website['Unique.Visits'],lags=40)
plt.show()
```



On looking at the Autocorrelation (ACF) plot above we can say that more than 5% of the spikes are significantly larger than 0 which proves that the time series is not white Noise.

In [185…

```
fig, ax = plt.subplots(3)
fig.suptitle('White noise')
# line plot
ax[0].plot(data_website['Date'], data_website['Unique.Visits']) # should be random
# histogram plot
ax[1].hist(data_website['Unique.Visits'], bins=10) # bell curve (distribution is Gaussia
# autocorrelation
autocorrelation_plot(data_website['Unique.Visits'], ax=ax[2]) # Note a different syntax
plt.show()
```



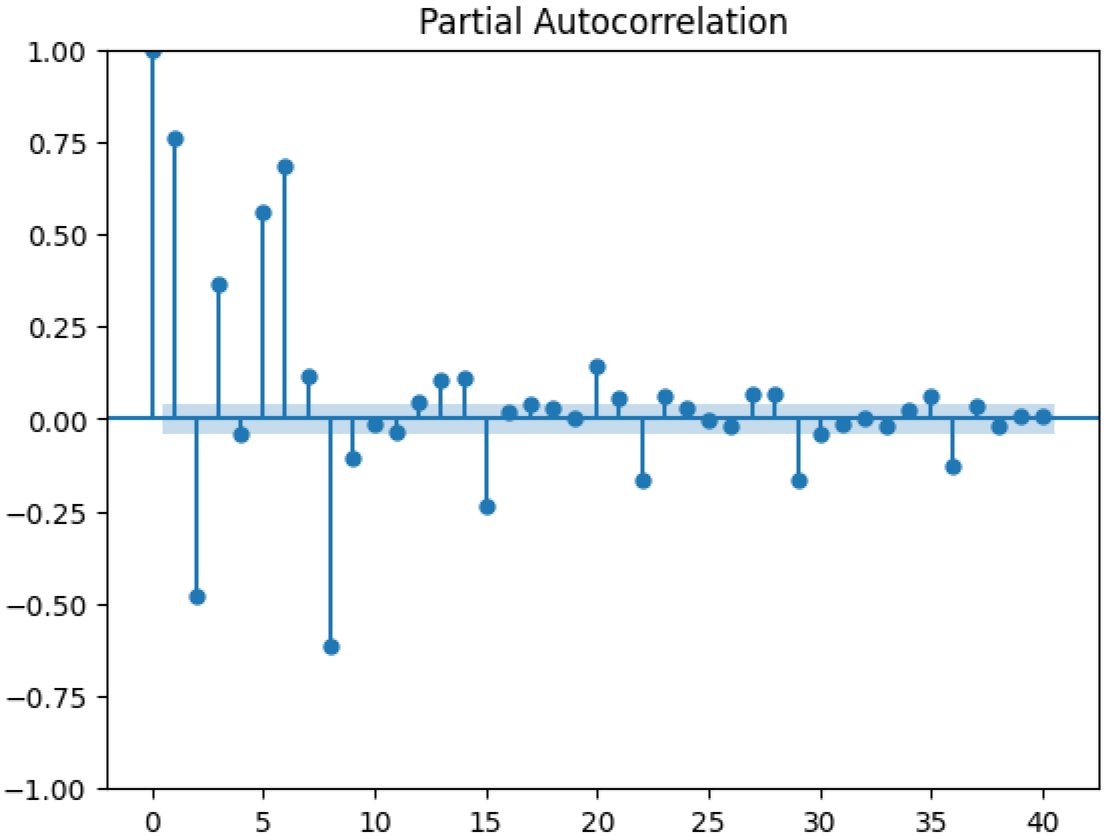
Above we have an additional plot to check for any white noise. We can see the first plot indicates a random trend in the data followed by a histogram plot that has a bell-shaped curved showing a Gaussian distribution and lastly we have plotted an Autocorrelation plot using another method where we can observe dashed lines in grey indicating the bounds and a large amount of data spikes above the bounds indicating that time series is not white Noise

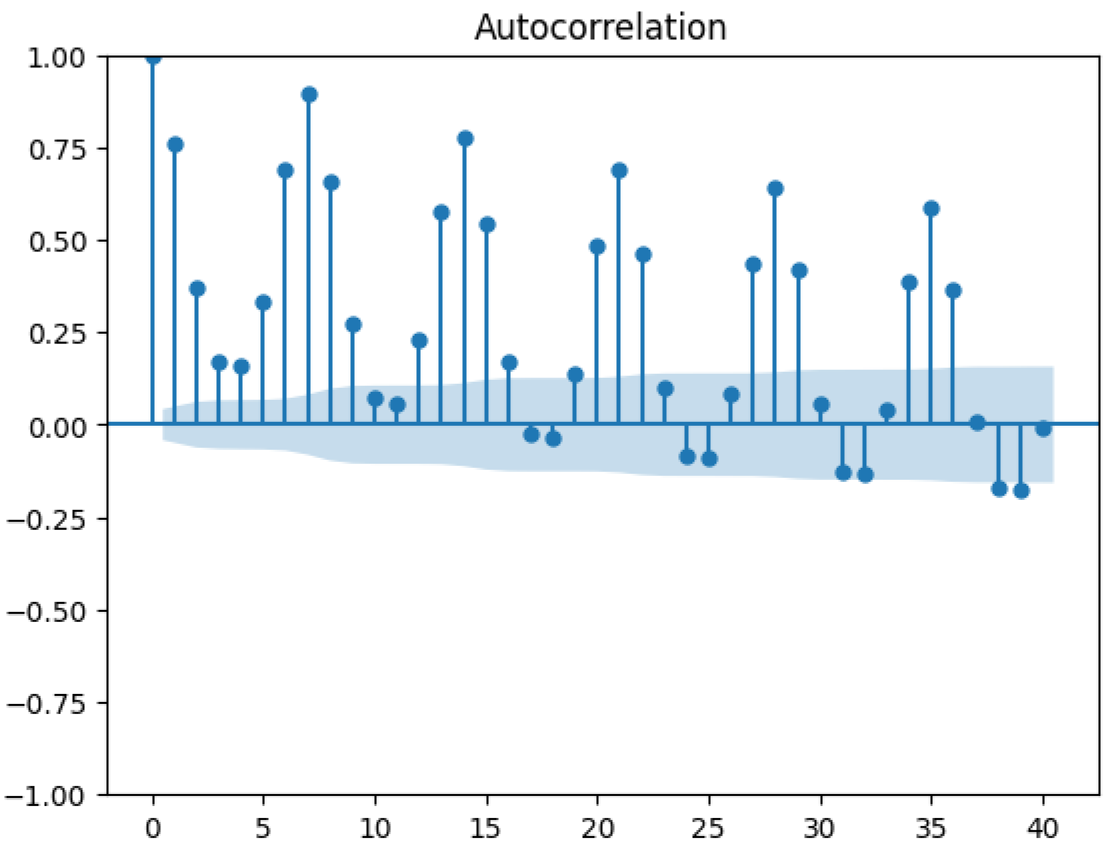
ACF and PACF plots

In [186…

```
plot_pacf(data_website['Unique.Visits'],lags=40)
plot_acf(data_website['Unique.Visits'],lags=40)
plt.show()
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/graphics/tsaplots.py:348: FutureWarni
ng: The default method 'yw' can produce PACF values outside of the [-1,1] interval. Afte
r 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You can use this metho
d now by setting method='ywm'.
  warnings.warn(
```





Above are the two plots -

1. Partial Autocorrelation plot (PACF)
2. Autocorrelation plot (ACF)

The above plots give an indication of how correlated different time period values are. On the x-axis we can observed the lags for example 5 refers to 5 time periods back. In our case we have considered 40 time period lags. On the y-axis we can see the correlation, more specifically the Pearson's correlation that lies between [-1,1]. Higher the value, more the correlation.

On looking at the autocorrelation (ACF) plot which considers the direct and the indirect effect of the values of the previous time lags, We can make the following observations:

1. High degree of autocorrelation between adjacent (lag = 1) and near-adjacent (lag = 7) observations in ACF plot

A partial autocorrelation (PACF) plot mainly focuses on the the direct effect of the values of the previous time lags. We can make the following observations:

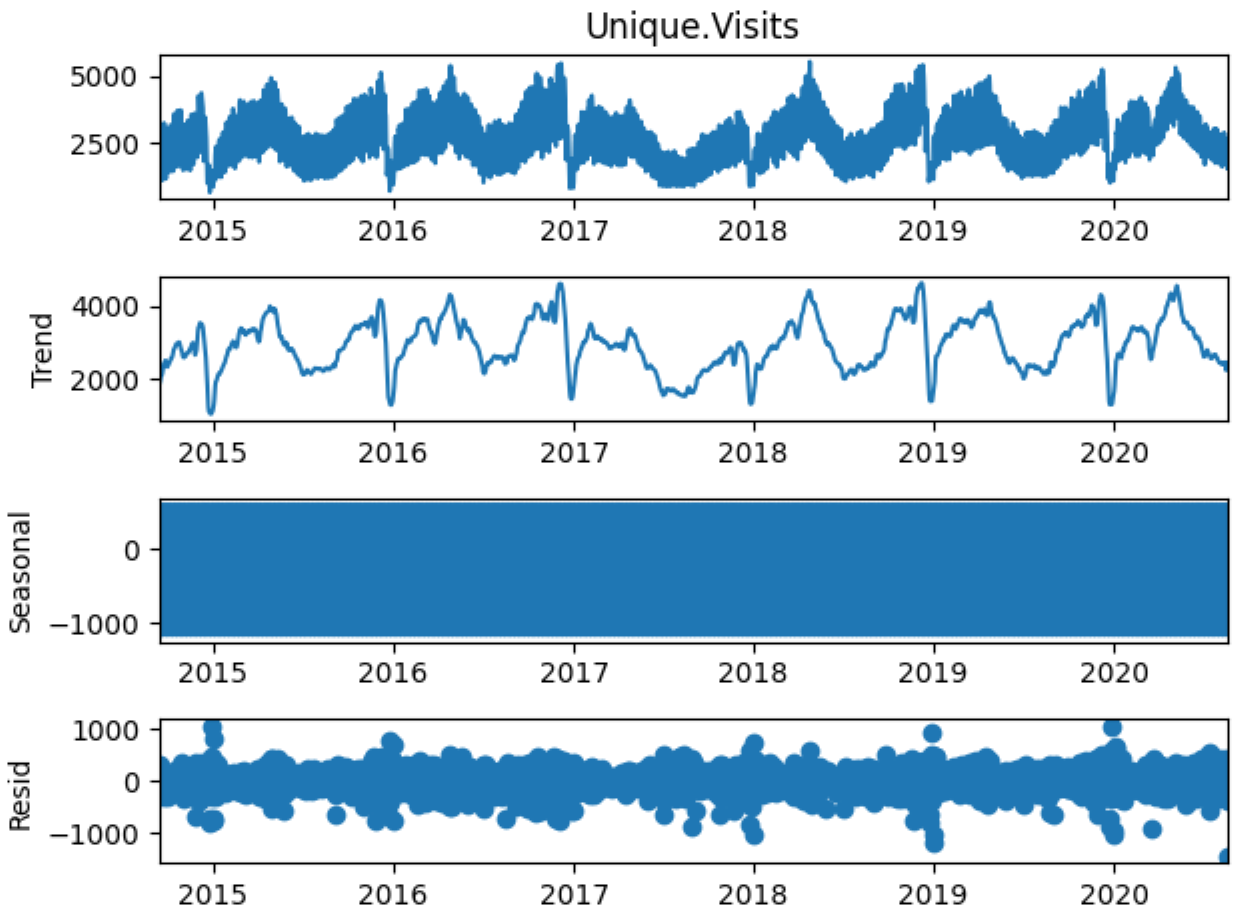
1. There are several autocorrelations that are significantly non-zero. Therefore, the time series is non-random.
2. High degree of autocorrelation between adjacent (lag = 1) and near-adjacent (lag = 6) observations in PACF plot

Time series decomposition

Additive Decomposition

In [187…

```
from statsmodels.tsa.seasonal import seasonal_decompose

unique_visits = data_website['Unique.Visits']

# define a function to perform additive decomposition
def decompose(column, model='additive'):
    decomp = seasonal_decompose(column, model=model, extrapolate_trend='freq')
    return decomp

# perform additive decomposition on 'Unique.Visits'
result_add = decompose(unique_visits, model='additive')

# plot the results
result_add.plot()
plt.show()
```



In [188...

```
new_df_add = pd.concat([result_add.trend, result_add.seasonal, result_add.resid],
                       axis=1)
new_df_add.columns = ['Trend', 'Seasonality', 'Residual']

print(new_df_add.head())
```

```
                 Trend  Seasonality    Residual
Date
2014-09-14  1864.785714  -599.532110  316.746395
2014-09-15  1926.586735   516.560484   84.852781
2014-09-16  1988.387755   597.016277   44.595968
2014-09-17  2100.142857   559.101251  -45.244108
2014-09-18  2110.714286   382.856436 -127.570722
```

In [189...

```
result_add.observed[0]
```

Out[189... 1582.0

In [190...

```
# additive decomposition  formula -> observed = trend+seasonal+residual
result_add.trend[0]+ result_add.seasonal[0]+ result_add.resid[0]
```

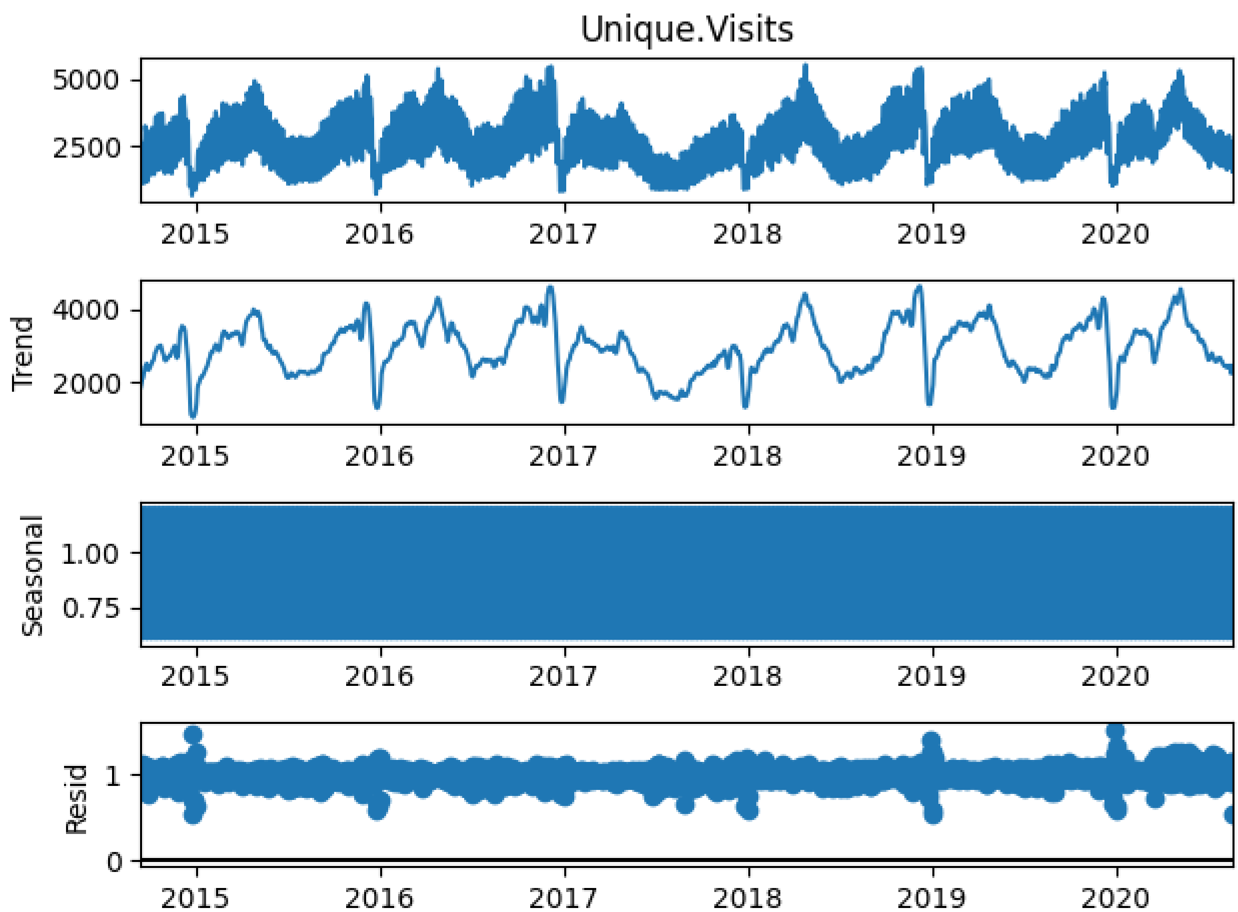
Out[190... 1582.0

The three primary components which are the trend, seasonality, and residual can be seen for above decomposition.We can see from the additive decomposition that there is a clear overall pattern in the data.There is some evidence of seasonality in the data, with regular patterns of fluctuations occurring at fixed intervals . Finally, the residual component shows that there is still some amount of unexplained variation in the data that is not captured by the trend and seasonality components.

Multiplicative Decomposition

In [191…

```python
unique_visits = data_website['Unique.Visits']

# define a function to perform additive decomposition
def decompose(column, model='multiplicative'):
    decomp = seasonal_decompose(column, model=model, extrapolate_trend='freq')
    return decomp

# perform additive decomposition on 'Unique.Visits'
result_mul = decompose(unique_visits, model='multiplicative')

# plot the results
result_mul.plot()
plt.show()
```



In [192…

```python
result_mul.observed[0]
```

Out[192… 1582.0

In [193…

```python
# multiplicative decomposition  formula -> observed = trend*seasonal*residual
result_mul.trend[0]* result_mul.seasonal[0]* result_mul.resid[0]
```

Out[193… 1582.0000000000002

In [194…

```python
new_df_mul = pd.concat([result_mul.trend, result_mul.seasonal, result_mul.resid],
                       axis=1)
new_df_mul.columns = ['Trend', 'Seasonality', 'Residual']

print(new_df_mul.head())
```

```
                 Trend  Seasonality  Residual
```

```
Date
2014-09-14  1864.785714     0.788273  1.076220
2014-09-15  1926.586735     1.173979  1.117707
2014-09-16  1988.387755     1.205204  1.097473
2014-09-17  2100.142857     1.191120  1.044964
2014-09-18  2110.714286     1.132486  0.989811
```

In a multiplicative decomposition, the observed time series is modeled as the product of the three components: trend, seasonality, and residual.We can see that there is a clear overall pattern in the data. There is some evidence of seasonality in the data, with regular patterns of fluctuations occurring at fixed intervals. Finally, the residual component shows that there is still some amount of unexplained variation in the data that is not captured by the trend and seasonality components.

Description of Time series

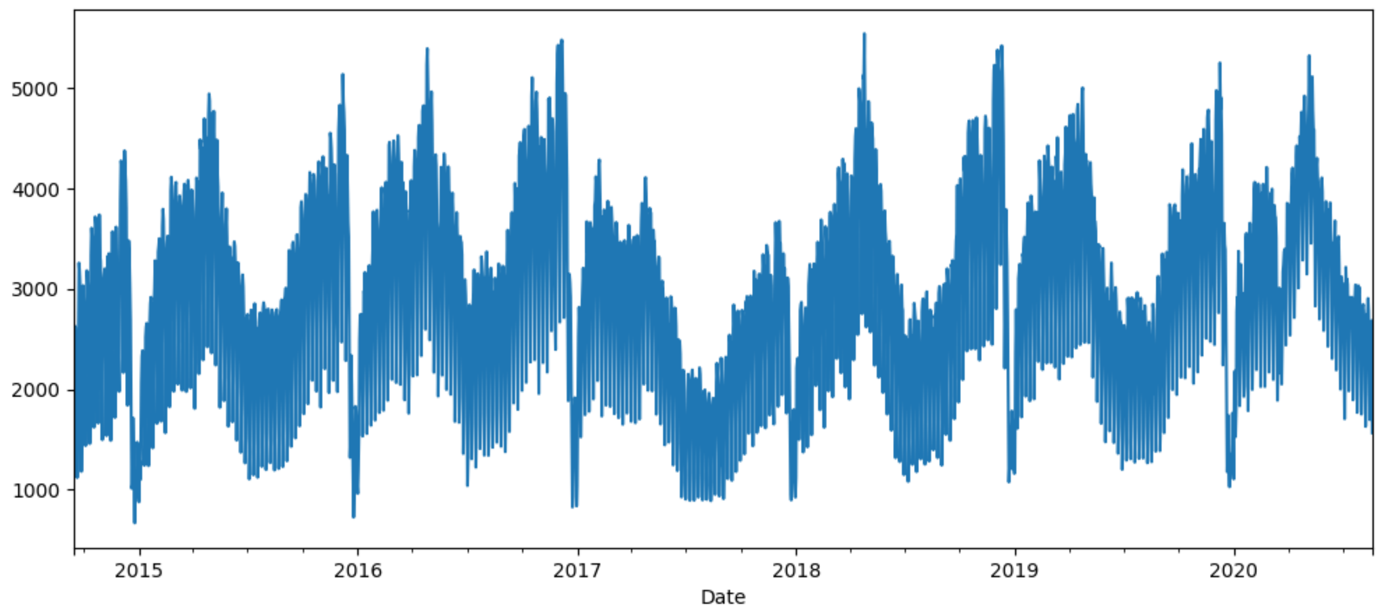
Is it stationary, are there any trends, seasonality ?

In [195…

```
data_website['Unique.Visits'].plot(figsize=(12,5))
```

Out[195…

```
<Axes: xlabel='Date'>
```



On looking at the plot above we can observe that there is **no trend** in the data but we can observe **seasonality** exists in the data. At the beginning of every year there is a spike in the unique number of visits followed by a dip which is again followed by a rise in the unique visits. Since this data belongs to the statistical forecasting teaching notes website the possible reasons for this seasonality can be because at the start of the academic year there a lot of students visiting the website and scrolling different pages to traverse through the notes followed by a decrease in the number of visits in the middle of the year as the pace of the academics get a little slow. However at the end of the year there is a sudden spike possible due to the exam season.

In [196…

```
# ADF Test - null hypothesis - non-stationary - if p-value < 5% reject null hypothesis
adfuller_result = adfuller(data_website['Unique.Visits'].values, autolag='AIC')

print(f'ADF Statistic: {adfuller_result[0]}')

print(f'p-value: {adfuller_result[1]}')

for key, value in adfuller_result[4].items():
```

```
    print('Critial Values:')
    print(f'   {key}, {value}')
```

```
ADF Statistic: -4.475968574445406
p-value: 0.00021726409300080015
Critial Values:
   1%, -3.4334094211542983
Critial Values:
   5%, -2.8628915360971003
Critial Values:
   10%, -2.5674894918770197
```

In order to determine whether our data is stationary or non-stationary we perform the following steps:

1. Visual Inspection - on observing the graph above we can observe that that data shows somewhat a constant mean of approximately 2900 but there is some seasonality present in the data. Hence, visual inspection is not sufficient to check for stationarity in the data.

1. To further verify we perform the ADF (Augmented Dickey-Fuller) test. The ADF test is a statistical test used to determine whether a time series is stationary or non-stationary.

1. In the output you provided, the ADF statistic is -4.283821436187665, and the p-value is 0.0004737578257465072. The p-value is less than the significance level of 0.05, which indicates that the null hypothesis (the time series is non-stationary) can be rejected. The ADF statistic is also less than the critical values at the 1%, 5%, and 10% levels.

1. Therefore, we can conclude that the time series is **Stationary**

TS models

The models planned on being used for training:

1. ARIMA (Autoregressive Integrated Moving Average Model)-ARIMA can capture both short-term and long-term patterns in the data, as well as any seasonal fluctuations that may be present.An ARIMA model could be trained on past website traffic data to predict how much traffic is likely to be seen in the future, and to identify any potential seasonal patterns that might impact the traffic.
2. AutoReg (Autoregression Model)-AR can capture the autoregressive nature of the data, which means that the current value of the time series is dependent on past values. In other words, the traffic levels on a website at any given time are often influenced by the traffic levels that occurred in the past.
3. LSTM (Long Short-Term Memory networks)-Website traffic datasets typically involve time series data, where the number of visitors, pageviews, and other metrics change over time. LSTM models are particularly effective at modeling time series data because they are able to capture long-term dependencies in the data, which is essential for accurately predicting future website traffic.

ARIMA

In [256…

```
#identify the optimal set of parameters for the ARIMA model, based on the
# Akaike information criterion (AIC)
stepwise_fit = auto_arima(unique_visits, trace=True,
suppress_warnings=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=32845.925, Time=2.01 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=34399.149, Time=0.06 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=34191.021, Time=0.09 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=33716.504, Time=0.51 sec
```

```
 ARIMA(0,1,0)(0,0,0)[0]                    : AIC=34397.150, Time=0.04 sec
 ARIMA(1,1,2)(0,0,0)[0] intercept          : AIC=33107.193, Time=1.67 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept          : AIC=32879.741, Time=1.42 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept          : AIC=32768.828, Time=4.66 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept          : AIC=33424.673, Time=1.56 sec
 ARIMA(4,1,2)(0,0,0)[0] intercept          : AIC=30739.253, Time=5.87 sec
 ARIMA(4,1,1)(0,0,0)[0] intercept          : AIC=31813.648, Time=4.69 sec
 ARIMA(5,1,2)(0,0,0)[0] intercept          : AIC=30517.978, Time=9.64 sec
 ARIMA(5,1,1)(0,0,0)[0] intercept          : AIC=31044.387, Time=3.25 sec
 ARIMA(5,1,3)(0,0,0)[0] intercept          : AIC=30498.269, Time=12.34 sec
 ARIMA(4,1,3)(0,0,0)[0] intercept          : AIC=30744.261, Time=5.82 sec
 ARIMA(5,1,4)(0,0,0)[0] intercept          : AIC=30006.504, Time=6.29 sec
 ARIMA(4,1,4)(0,0,0)[0] intercept          : AIC=30287.882, Time=4.52 sec
 ARIMA(5,1,5)(0,0,0)[0] intercept          : AIC=29980.339, Time=7.21 sec
 ARIMA(4,1,5)(0,0,0)[0] intercept          : AIC=30269.626, Time=5.22 sec
 ARIMA(5,1,5)(0,0,0)[0]                    : AIC=29978.342, Time=4.52 sec
 ARIMA(4,1,5)(0,0,0)[0]                    : AIC=30265.950, Time=2.66 sec
 ARIMA(5,1,4)(0,0,0)[0]                    : AIC=30006.539, Time=2.74 sec
 ARIMA(4,1,4)(0,0,0)[0]                    : AIC=30289.769, Time=2.25 sec

Best model:  ARIMA(5,1,5)(0,0,0)[0]
Total fit time: 89.098 seconds
```

We supply our data to the auto_arima function. The function uses the AIC score to judge how good a particular order model is. It tries to minimize the AIC score. We can see the best ARIMA model seems to be of the order (5,1,5) with the minimum AIC score=29978.342. With this information we proceeded to train and fit the model to make prediction

In [258…

```
train=unique_visits.iloc[:-150]
test=unique_visits.iloc[-150:]
print(train.shape,test.shape)
model=sm.tsa.arima.ARIMA(unique_visits,order=(5,1,5))
model=model.fit()
model.summary()
```

```
(2017,) (150,)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/base/model.py:604: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[258…

SARIMAX Results

Dep. Variable:	Unique.Visits	**No. Observations:**	2167
Model:	ARIMA(5, 1, 5)	**Log Likelihood**	-14978.171
Date:	Wed, 05 Apr 2023	**AIC**	29978.342
Time:	01:29:42	**BIC**	30040.829
Sample:	09-14-2014	**HQIC**	30001.193
	- 08-19-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.1316	0.167	-0.787	0.431	-0.459	0.196

ar.L2	-0.6950	0.134	-5.187	0.000	-0.958	-0.432
ar.L3	-0.5452	0.241	-2.261	0.024	-1.018	-0.073
ar.L4	-0.2496	0.134	-1.867	0.062	-0.512	0.012
ar.L5	-0.9285	0.167	-5.575	0.000	-1.255	-0.602
ma.L1	0.1533	0.162	0.945	0.345	-0.165	0.471
ma.L2	0.5432	0.125	4.332	0.000	0.297	0.789
ma.L3	0.4495	0.203	2.210	0.027	0.051	0.848
ma.L4	0.0736	0.120	0.612	0.540	-0.162	0.309
ma.L5	0.7371	0.124	5.953	0.000	0.494	0.980
sigma2	7.064e+04	2046.712	34.512	0.000	6.66e+04	7.46e+04

Ljung-Box (L1) (Q):	45.88	**Jarque-Bera (JB):**	253.77
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.09	**Skew:**	0.00
Prob(H) (two-sided):	0.27	**Kurtosis:**	4.68

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

we reserving the last 150 rows of the data as the testing section. The shapes of the testing and training section can be observed in the above output.

Predictions

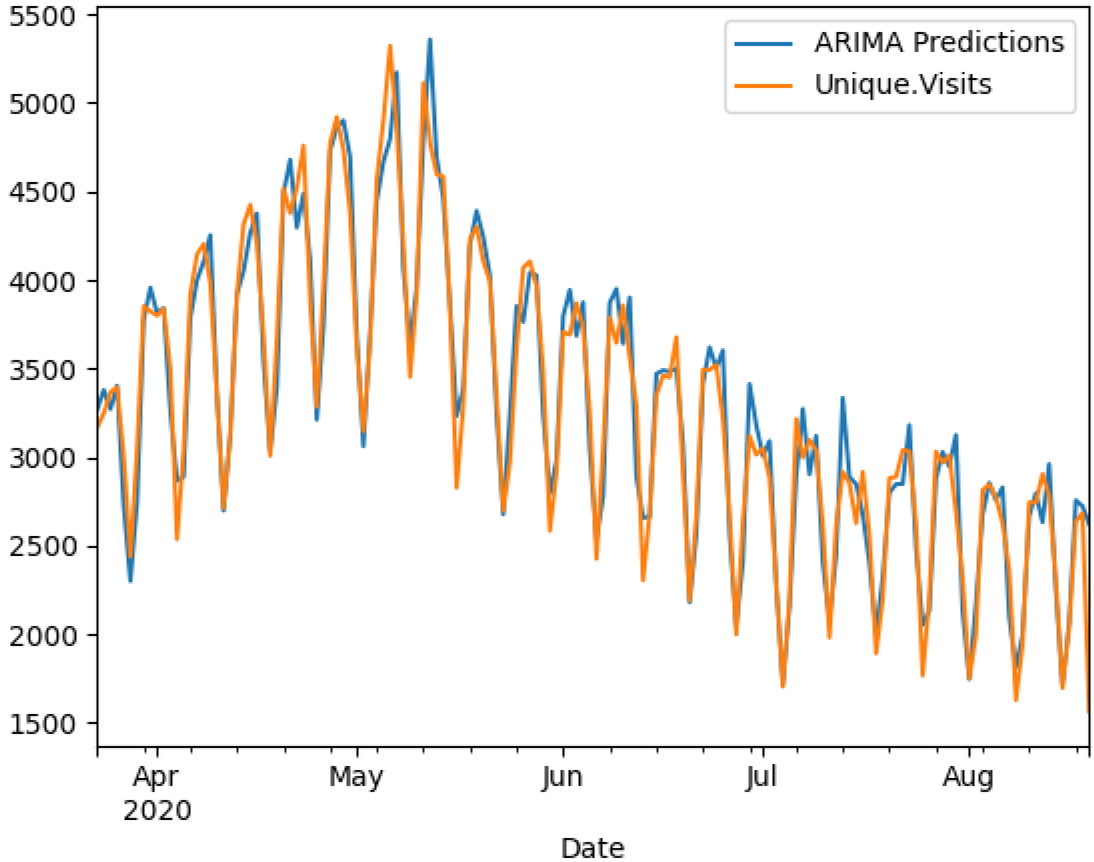
In [259…

```
# plot of the test data showing the actual and the predicted visits by ARIMA model
start=len(train)
end=len(train)+len(test)-1
pred=model.predict(start=start,end=end,typ='levels').rename('ARIMA Predictions')
plt.suptitle("plot of the test data showing the actual and the predicted visits by ARIMA
pred.plot(legend=True)
test.plot(legend=True)
```

Out[259…

```
<Axes: xlabel='Date'>
```

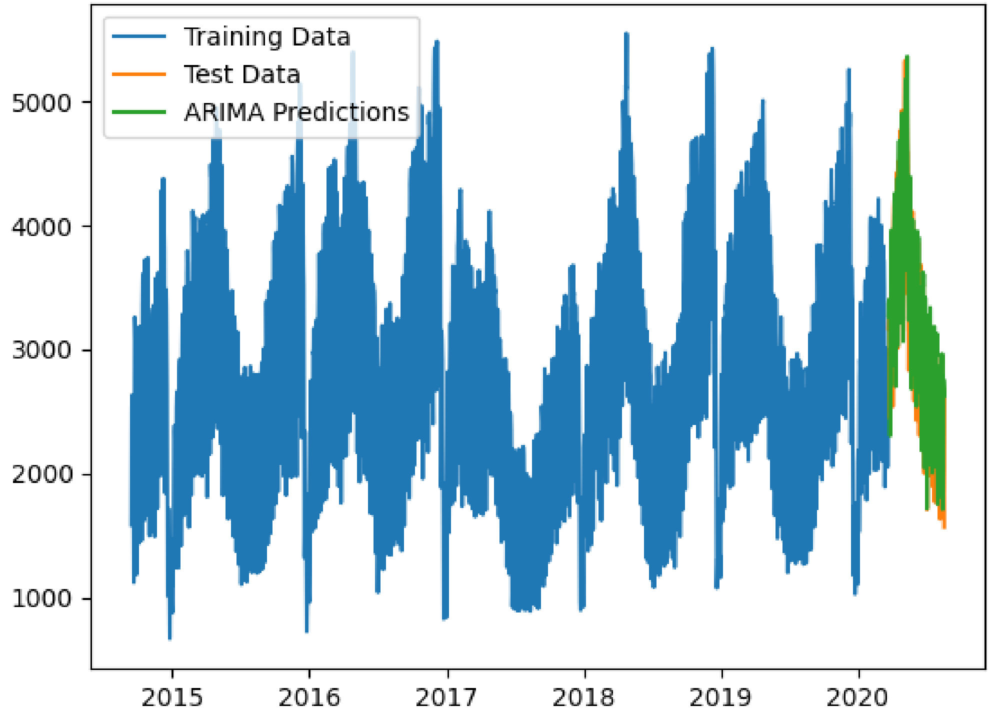
plot of the test data showing the actual and the predicted visits by ARIMA model



In [261…

```
#overall plot
start=len(train)
end=len(train)+len(test)-1
pred=model.predict(start=start,end=end,typ='levels').rename('ARIMA Predictions')
pred_df = pd.concat([train, test, pred], axis=1)
plt.suptitle("Plot of the train and test data showing the actual and the predicted visit
plt.plot(train, label='Training Data')
plt.plot(test, label='Test Data')
plt.plot(pred, label='ARIMA Predictions')
plt.legend(['Training Data', 'Test Data', 'ARIMA Predictions'])
plt.show()
```

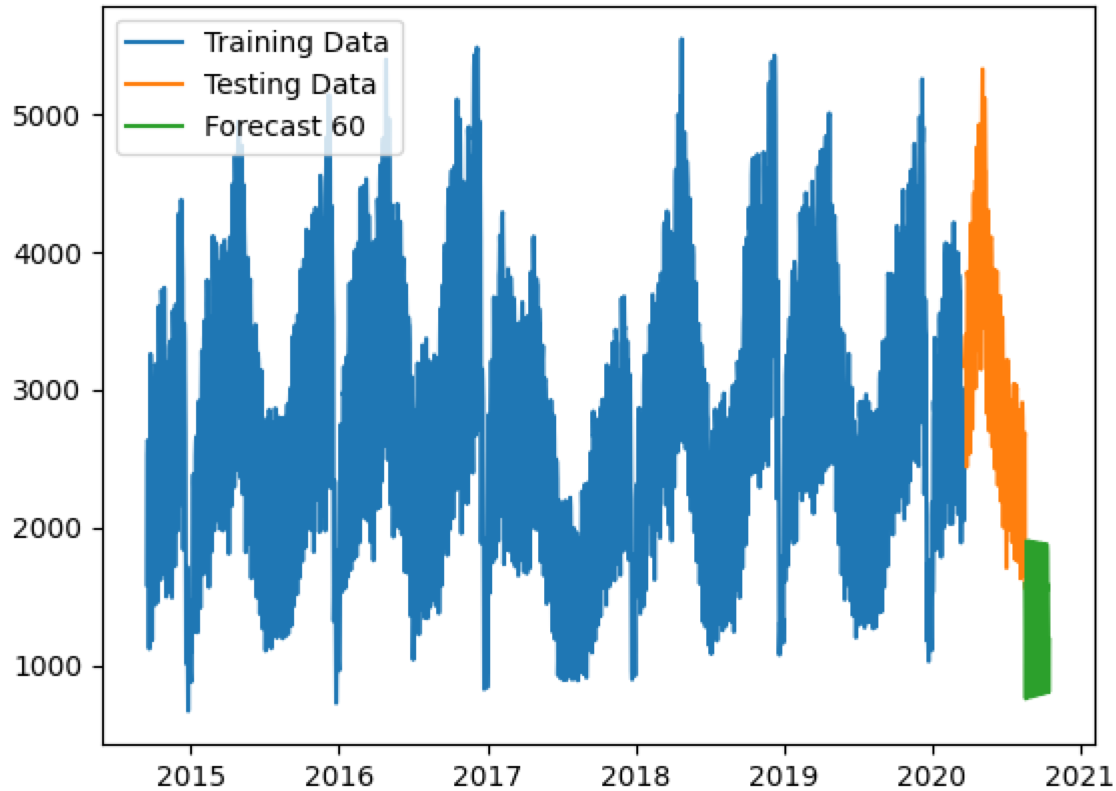
Plot of the train and test data showing the actual and the predicted visits by ARIMA model



In [219…

```
#  forecast for next 60 days
forecast = model.forecast(steps=60)
dates = pd.date_range(start=test.index[-1], periods=60)
forecast_ARIMA = pd.DataFrame({'Date': dates, 'Forecast': forecast})
forecast_ARIMA = forecast_ARIMA.set_index('Date')
plt.suptitle('Forecast for the next 60 days')
plt.plot(train, label='Training Data')
plt.plot(test, label='Testing Data')
plt.plot(forecast_ARIMA, label='Forecast 60')
plt.legend()
plt.show()
```

Forecast for the next 60 days



As we can see the predictions do a pretty good job of matching with the actual trend all though there is a small acceptable lag.

In [222…

```
# evaluate forecasts
rmse = np.sqrt(mean_squared_error(pred, test))
print('RMSE value: %.3f' % rmse)
```

```
RMSE value: 14.494
```

AR Model

In [263…

```
train=unique_visits.iloc[:-150]
test=unique_visits.iloc[-150:]
print(train.shape,test.shape)
lag_values = range(0, 30)
best_lag = 0
lower_rmse = np.inf
for l in lag_values:
    # Fit AR model with current lag value
    model_ar = AutoReg(train, lags=l)
    model_ar_fit = model_ar.fit()
    # Make predictions on test set using fitted model
    predictions = model_ar_fit.predict(start=len(train), end=len(train) + len(test)-1,
                                       dynamic=False)
    rmse = np.sqrt(mean_squared_error(test, predictions))
    print(f"Lags = {l}, RMSE = {rmse}")
    if rmse < lower_rmse:
        lower_rmse = rmse
        best_lag = l

# Print final best lag value
print(f"Best value of lag: {best_lag}")
```

```
(2017,) (150,)
Lags = 0, RMSE = 29.787746234547196
Lags = 1, RMSE = 29.84792009336335
Lags = 2, RMSE = 29.775958479205528
Lags = 3, RMSE = 29.777798403277103
Lags = 4, RMSE = 29.777470656956055
Lags = 5, RMSE = 29.82830010528805
Lags = 6, RMSE = 30.0664768670565
Lags = 7, RMSE = 30.35318636596742
Lags = 8, RMSE = 28.425317833292475
Lags = 9, RMSE = 28.243892220983565
Lags = 10, RMSE = 28.247549055258602
Lags = 11, RMSE = 28.27580704097373
Lags = 12, RMSE = 28.23992676058845
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
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th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```

```
Lags = 13, RMSE = 28.12813456279283
Lags = 14, RMSE = 27.78360414190984
Lags = 15, RMSE = 27.70977102794858
Lags = 16, RMSE = 27.714276942007842
Lags = 17, RMSE = 27.663458523116315
Lags = 18, RMSE = 27.578174252843024
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
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th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
```

```
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
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  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
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ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
Lags = 19, RMSE = 27.55695191618559
Lags = 20, RMSE = 27.265649221126637
Lags = 21, RMSE = 27.215669644452465
Lags = 22, RMSE = 27.19870362640422
Lags = 23, RMSE = 27.181455071949603
Lags = 24, RMSE = 27.131044942199843
Lags = 25, RMSE = 27.14014598407972
Lags = 26, RMSE = 27.185859549912816
Lags = 27, RMSE = 27.00785426929352
Lags = 28, RMSE = 26.88052439248157
Lags = 29, RMSE = 27.03998176491223
Best value of lag: 28
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```

In [264…

```
# Prediction using best AR model with the lag of 28
model_AR = AutoReg(train, lags=best_lag)
model_AR_fit = model_AR.fit()
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/base/tsa_model.py:471: ValueWarni
```

```
ng: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
```

Predictions

In [265…

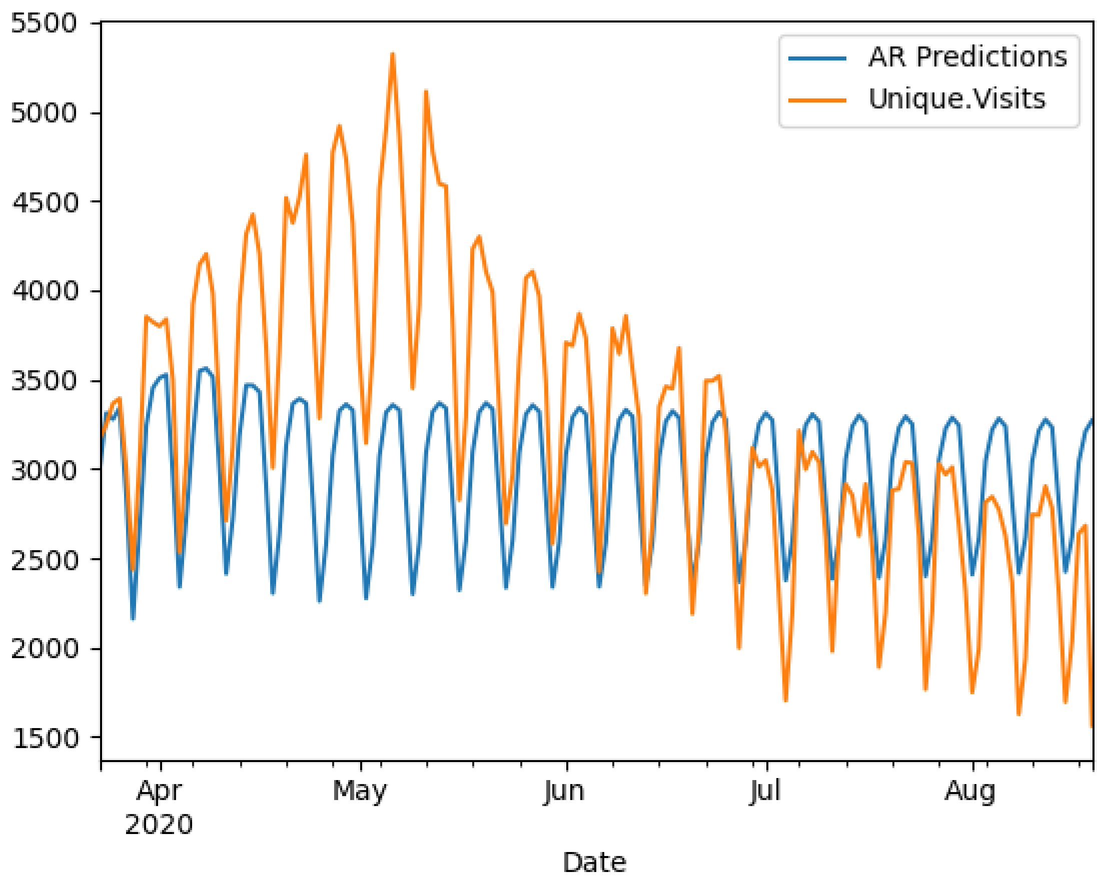
```
start=len(train)
end=len(train)+len(test)-1
pred=model_AR_fit.predict(start=start,end=len(train)+len(test)-1).rename('AR Predictions
plt.suptitle("Plot of the test data showing the actual and the predicted visits by AR mo
pred.plot(legend=True)
test.plot(legend=True)
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```

Out[265…

```
<Axes: xlabel='Date'>
```

Plot of the test data showing the actual and the predicted visits by AR model

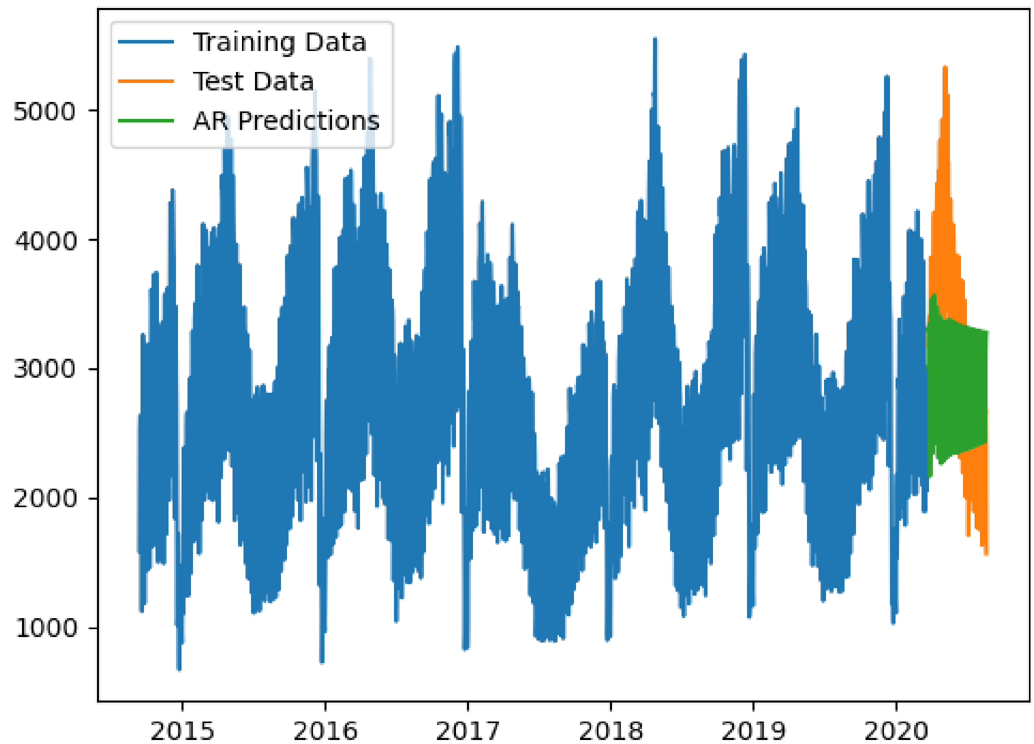


In [266…

```
#overall plot
start=len(train)
end=len(train)+len(test)-1
pred=model_AR_fit.predict(start=start,end=end).rename('AR Predictions')
pred_df = pd.concat([train, test, pred], axis=1)
plt.suptitle("Plot of the train and test data showing the actual and the predicted visit
plt.plot(train, label='Training Data')
plt.plot(test, label='Test Data')
plt.plot(pred, label='AR Predictions')
plt.legend(['Training Data', 'Test Data', 'AR Predictions'])
plt.show()
```

```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```

Plot of the train and test data showing the actual and the predicted visits by AR model

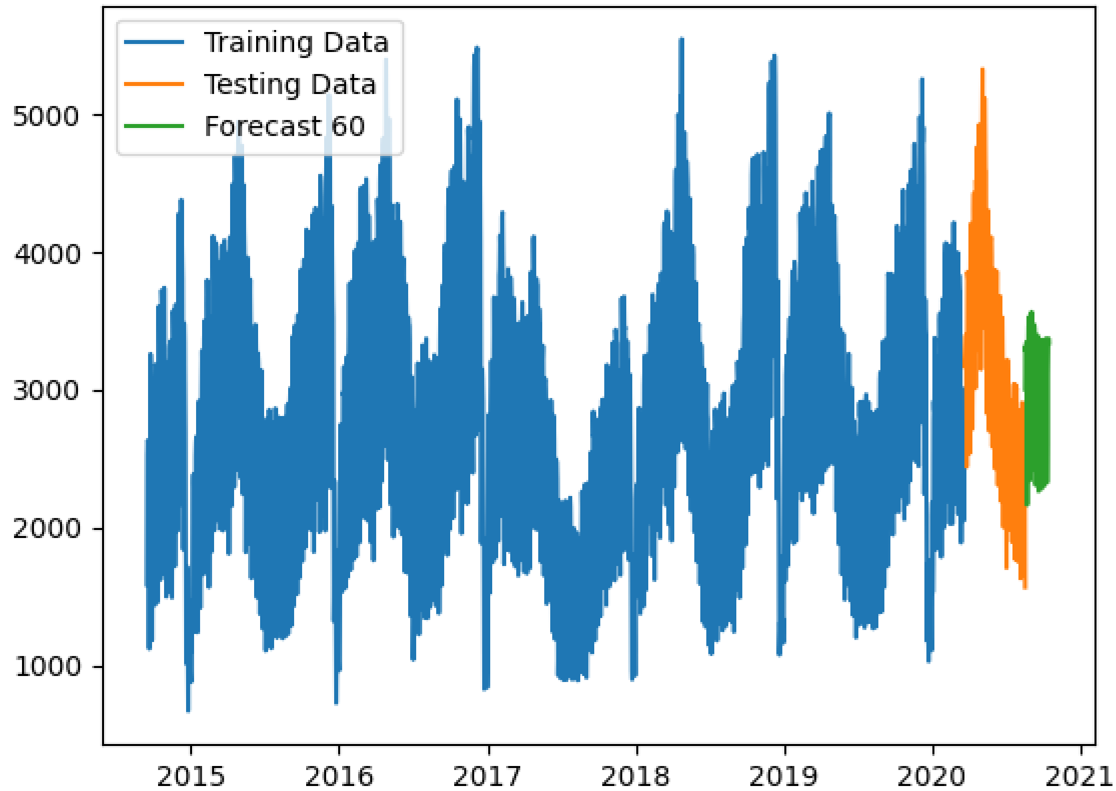


In [229…

```
# forecast for next 60 days
forecast = model_AR_fit.forecast(steps=60)
dates = pd.date_range(start=test.index[-1], periods=60)
forecast_AR = pd.DataFrame({'Date': dates, 'Forecast': forecast})
forecast_AR = forecast_AR.set_index('Date')
plt.suptitle('Forecast for the next 60 days')
plt.plot(train, label='Training Data')
plt.plot(test, label='Testing Data')
plt.plot(forecast_AR, label='Forecast 60')
plt.legend()
plt.show()
```


```
/usr/local/lib/python3.9/dist-packages/statsmodels/tsa/deterministic.py:302: UserWarnin
g: Only PeriodIndexes, DatetimeIndexes with a frequency set, RangesIndexes, and Index wi
th a unit increment support extending. The index is set will contain the position relati
ve to the data length.
  fcast_index = self._extend_index(index, steps, forecast_index)
```

Forecast for the next 60 days



In [231…

```
# evaluate forecasts
rmse = np.sqrt(mean_squared_error(pred, test))
print('RMSE value: %.3f' % rmse)
```

RMSE value: 26.881

LSTM method

In [267…

```
dataset = unique_visits.values
dataset = dataset.astype('float32')
dataset = dataset.reshape(-1,1)
# normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
dataset = scaler.fit_transform(dataset)
train = dataset[:-150]
test = dataset[-150:]
# convert an array of values into a dataset matrix
def create_dataset(dataset, look_back=1):
        dataX, dataY = [], []
        for i in range(len(dataset)-look_back-1):
                a = dataset[i:(i+look_back), 0]
                dataX.append(a)
                dataY.append(dataset[i + look_back, 0])
        return np.array(dataX), np.array(dataY)

# reshape into X=t and Y=t+1
look_back = 1
trainX, trainY = create_dataset(train, look_back)
testX, testY = create_dataset(test, look_back)
trainX = np.reshape(trainX, (trainX.shape[0], 1, trainX.shape[1]))
testX = np.reshape(testX, (testX.shape[0], 1, testX.shape[1]))
model_LSTM = Sequential()
model_LSTM.add(LSTM(4, input_shape=(1, look_back)))
```

```python
model_LSTM.add(Dense(1))
model_LSTM.compile(loss='mean_squared_error', optimizer='adam')
model_LSTM.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)
```

```
Epoch 1/100
2015/2015 - 4s - loss: 0.0575 - 4s/epoch - 2ms/step
Epoch 2/100
2015/2015 - 3s - loss: 0.0235 - 3s/epoch - 1ms/step
Epoch 3/100
2015/2015 - 3s - loss: 0.0182 - 3s/epoch - 1ms/step
Epoch 4/100
2015/2015 - 3s - loss: 0.0178 - 3s/epoch - 2ms/step
Epoch 5/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 6/100
2015/2015 - 5s - loss: 0.0178 - 5s/epoch - 2ms/step
Epoch 7/100
2015/2015 - 7s - loss: 0.0177 - 7s/epoch - 4ms/step
Epoch 8/100
2015/2015 - 4s - loss: 0.0176 - 4s/epoch - 2ms/step
Epoch 9/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
Epoch 10/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 11/100
2015/2015 - 3s - loss: 0.0178 - 3s/epoch - 1ms/step
Epoch 12/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 13/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 14/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 15/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 16/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 17/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 18/100
2015/2015 - 4s - loss: 0.0176 - 4s/epoch - 2ms/step
Epoch 19/100
2015/2015 - 6s - loss: 0.0177 - 6s/epoch - 3ms/step
Epoch 20/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
Epoch 21/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
Epoch 22/100
2015/2015 - 3s - loss: 0.0178 - 3s/epoch - 1ms/step
Epoch 23/100
2015/2015 - 2s - loss: 0.0176 - 2s/epoch - 1ms/step
Epoch 24/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 25/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 26/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 27/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 28/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 29/100
2015/2015 - 3s - loss: 0.0178 - 3s/epoch - 1ms/step
Epoch 30/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 2ms/step
Epoch 31/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 32/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 33/100
```

```
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 34/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 35/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 36/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 37/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 38/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 39/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 2ms/step
Epoch 40/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 41/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 42/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 43/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 44/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 45/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 46/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 47/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 48/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 49/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 50/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 51/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 52/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 2ms/step
Epoch 53/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 54/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 55/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 56/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 57/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 58/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 59/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 60/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 61/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 62/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 63/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 64/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 65/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 66/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 67/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 68/100
```

```
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 69/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 70/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 71/100
2015/2015 - 2s - loss: 0.0176 - 2s/epoch - 1ms/step
Epoch 72/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 73/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 74/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 75/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 2ms/step
Epoch 76/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
Epoch 77/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 2ms/step
Epoch 78/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 79/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 80/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 81/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 82/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 83/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 2ms/step
Epoch 84/100
2015/2015 - 4s - loss: 0.0176 - 4s/epoch - 2ms/step
Epoch 85/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 86/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 2ms/step
Epoch 87/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 88/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
Epoch 89/100
2015/2015 - 4s - loss: 0.0176 - 4s/epoch - 2ms/step
Epoch 90/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 91/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 92/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 93/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 94/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 95/100
2015/2015 - 2s - loss: 0.0177 - 2s/epoch - 1ms/step
Epoch 96/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 97/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 1ms/step
Epoch 98/100
2015/2015 - 3s - loss: 0.0177 - 3s/epoch - 1ms/step
Epoch 99/100
2015/2015 - 3s - loss: 0.0176 - 3s/epoch - 2ms/step
Epoch 100/100
2015/2015 - 4s - loss: 0.0177 - 4s/epoch - 2ms/step
```

Out[267…

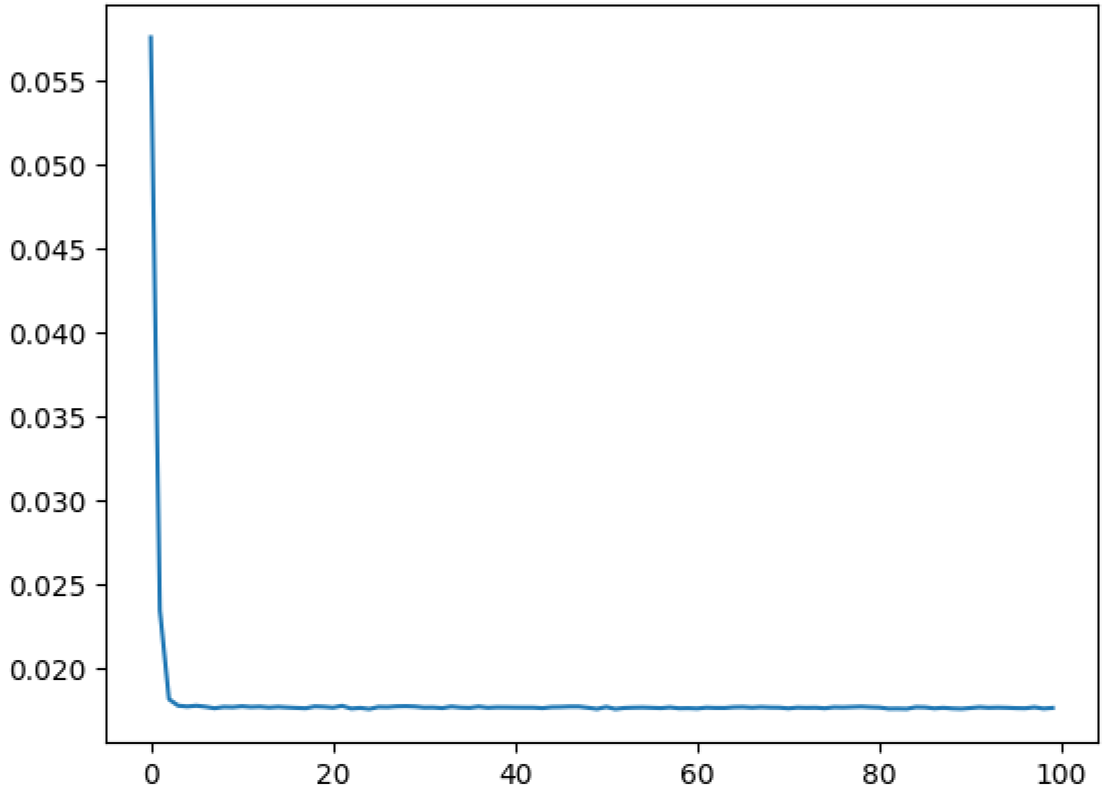
```
<keras.callbacks.History at 0x7f2eff7e17c0>
```

In [269…

```
loss_per_epoch = model_LSTM.history.history['loss']
```

```
plt.plot(range(len(loss_per_epoch)),loss_per_epoch)
```

Out[269… [<matplotlib.lines.Line2D at 0x7f2f07e6afa0>]



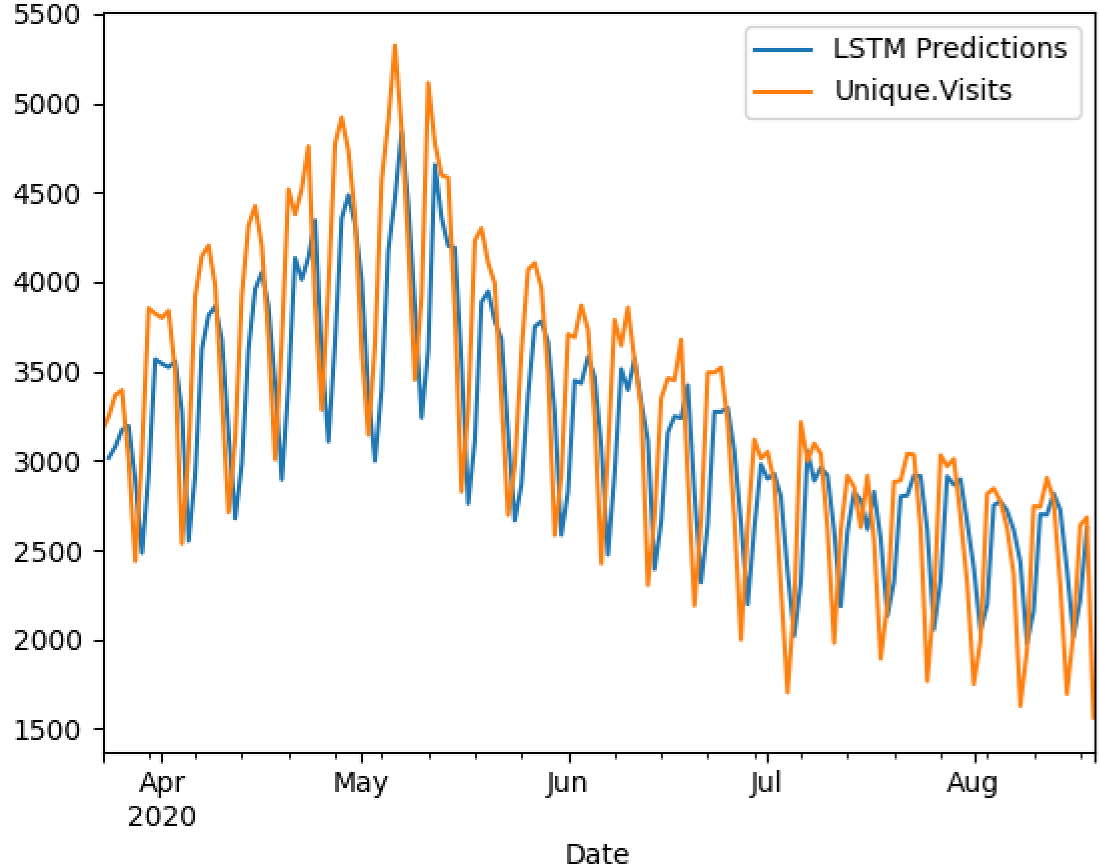
In [271…

```
trainPredict = model_LSTM.predict(trainX)
testPredict = model_LSTM.predict(testX)
trainPredict = scaler.inverse_transform(trainPredict)
testPredict = scaler.inverse_transform(testPredict)
trainPredictPlot = np.empty_like(dataset)
trainPredictPlot[:, :] = np.nan
trainPredictPlot[look_back:len(trainPredict)+look_back, :] = trainPredict
testPredictPlot = np.empty_like(dataset)
testPredictPlot[:, :] = np.nan
testPredictPlot[len(trainPredict)+(look_back*2)+1:len(dataset)-1, :] = testPredict
test1 = unique_visits[-150:]
predict = pd.DataFrame(testPredictPlot, index=unique_visits.index).dropna()
predict.plot(label='LSTM Predictions', legend=True)
test1.plot(label='Unique.Visits', legend=True)
plt.legend(['LSTM Predictions', 'Unique.Visits'])
plt.suptitle("Plot of the test data showing the actual and the predicted visits by LSTM
```

```
63/63 [==============================] - 0s 2ms/step
5/5 [==============================] - 0s 4ms/step
```

Out[271… Text(0.5, 0.98, 'Plot of the test data showing the actual and the predicted visits by LSTM model')

Plot of the test data showing the actual and the predicted visits by LSTM model



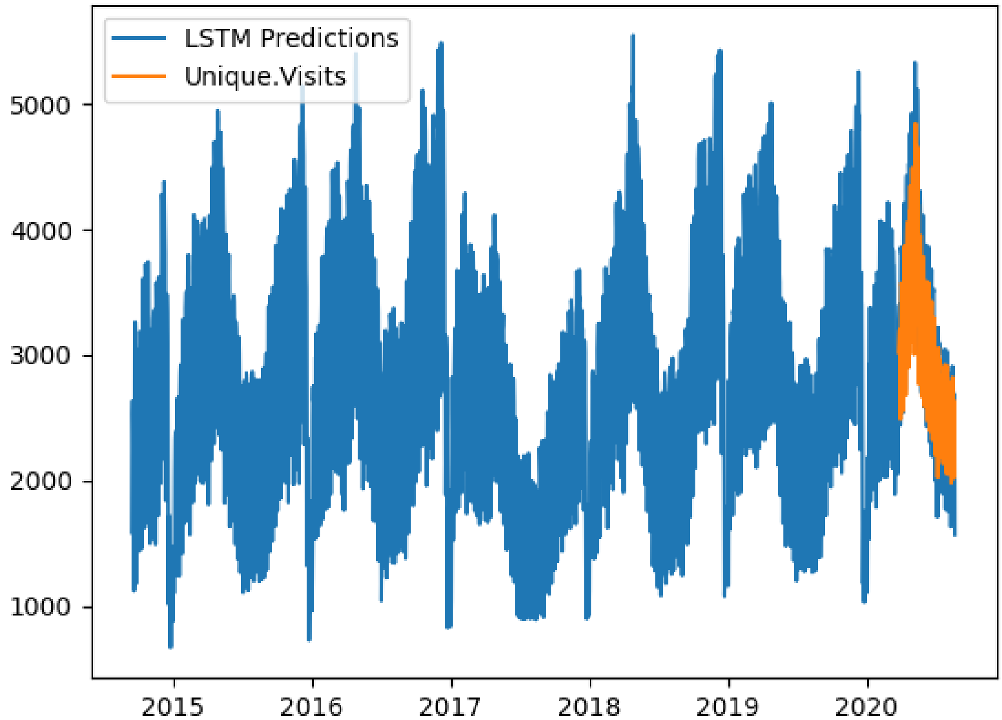
In [272…

```
#overall plot
predict = pd.DataFrame(testPredictPlot, index=unique_visits.index).dropna()
plt.suptitle("Plot of the train and test data showing the actual and the predicted visit
plt.plot(unique_visits)
plt.plot(predict)
plt.legend(['LSTM Predictions', 'Unique.Visits'])
```

Out[272…

```
<matplotlib.legend.Legend at 0x7f2f07888b20>
```

Plot of the train and test data showing the actual and the predicted visits by LSTM model



In [253…

```
# evaluate forecasts
rmse = np.sqrt(mean_squared_error(testPredict, testX))
print(' RMSE value: %.3f' % rmse)
```

```
RMSE value: 20.3
```

Which Model is the best?

After training the data on 3 models i.e. ARIMA , AutoReg and LSTM and comparing their evaluation metrics which is the RMSE score we can observe that the ARIMA Model has the lowest error value of all the 3 models.

Hence,we can conclude that for our Dataset **ARIMA model** is a good fit to forecast the future number of unique visits on the statistical notes teaching website

	Model	RMSE Score
1	ARIMA	14.494
2	AR	26.881
3	LSTM	20.3

Team contributions

Ayesha Tajammul Ahmed Mulla	1. Checked the stationarity and white noise of the dataset, 2. Performed time series modelling using ARIMA 3. Created a write-up detailing the concepts of stationarity, statistics, and approach used for ARIMA 4. Set up meetings on zoom and in-person to collaborate as a team.
Aazin Asif Shaikh	1. Performed data pre-processing , 2. Created time series visualizations, 3. Detailed study of the different types of models, 4. Write-up that explains the concepts of time series modelling and the analysis of plots
Priya Kumari	1. Performed other stationary check methods, Decomposition. 2. Implemented both LSTM and AR models to make predictions, 3. Performed a comparative study of the different models, created a write-up explaining the concepts of the LSTM and AR models

References

https://www.youtube.com/watch?v=S8tpSG6Q2H0&list=PLqYFiz7NM_SMC4ZgXplbreXlRY4Jf4zBP&index=11&ab_channel=NachiketaHebbar

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