ishandutta-18-10-23

October 19, 2023

Fittlyf Internship assessment

In this notebook, the first part and the second part of the internship assessment are solved. The first part deals with the funnel sheet questions and the second part deals with the AB test questions.

Part 1: Funnel Sheet Questions

In this part the missing values will be replaced with suitable methods. Then a function will be created that makes the appropriate graphs. Then appropriate models of machine learning like SARIMA, LSTM and MA would be created for forecasting. Lastly they would be evaluated using Accuracy metrics to see which model worked the best.

[12]:
```
import pandas as pd

# loading the data
df1 = pd.read_excel("/content/sample_data/Funnel.xlsx")
df1.head()
```

[12]:

	Year	Month	Customer Segment	Region	KPI	Value Type	Value
0	2020	12	Clients	India	Lv1_Visitors	Actuals	1354648.0
1	2020	12	Clients	India	Lv2_Visitors	Actuals	2689569.0
2	2020	12	Clients	India	Lv3_Visitors	Actuals	1300571.0
3	2020	12	Clients	India	Lv4_Visitors	Actuals	NaN
4	2020	12	Clients	India	Lv3_Visitors	Actuals	706677.0

[13]:
```
# Calculating the mean of the 'Value' column
mean_value = df1['Value'].mean()

# Replacing blank values with the mean
df1['Value'].fillna(mean_value, inplace=True)
```

[14]:
```
#examining the dataset
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1572 entries, 0 to 1571
Data columns (total 7 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Year              1572 non-null   int64
```

```
 1   Month             1572 non-null   int64
 2   Customer Segment  1572 non-null   object
 3   Region            1572 non-null   object
 4   KPI               1572 non-null   object
 5   Value Type        1572 non-null   object
 6   Value             1572 non-null   float64
dtypes: float64(1), int64(2), object(4)
memory usage: 86.1+ KB
```

[15]:
```
#making collective date column from year and month
df1['date'] = df1['Year'].astype(str) + '-' + df1['Month'].astype(str)
df1['date'] = pd.to_datetime(df1['date'], format='%Y-%m')
df1 = df1.sort_values(by='date')
df1.head()
```

[15]:

	Year	Month	Customer Segment	Region	KPI	Value Type	Value	date
451	2020	1	Clients	India	Lv1_Visitors	Actuals	3322789.0	2020-01-01
1491	2020	1	Customers	Dehradun	Lv1_Visitors	Actuals	28903.0	2020-01-01
1490	2020	1	Customers	India	Lv5_Visitors	Actuals	42569.0	2020-01-01
1489	2020	1	Customers	Uddepy	Lv4_Visitors	Actuals	48209.0	2020-01-01
1488	2020	1	Customers	Uddepy	Lv2_Visitors	Actuals	75152.0	2020-01-01

[16]:
```
#dropping irrelevant columns
df1=df1.drop(['Year','Month'],axis=1)
df1.head()
```

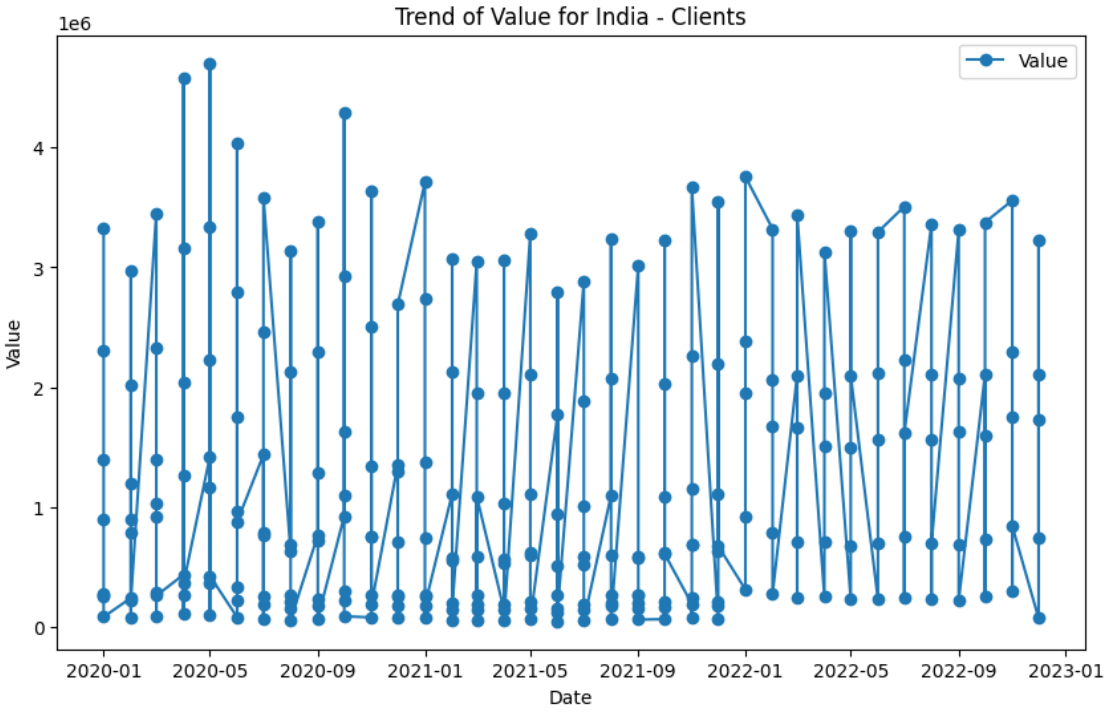
[16]:

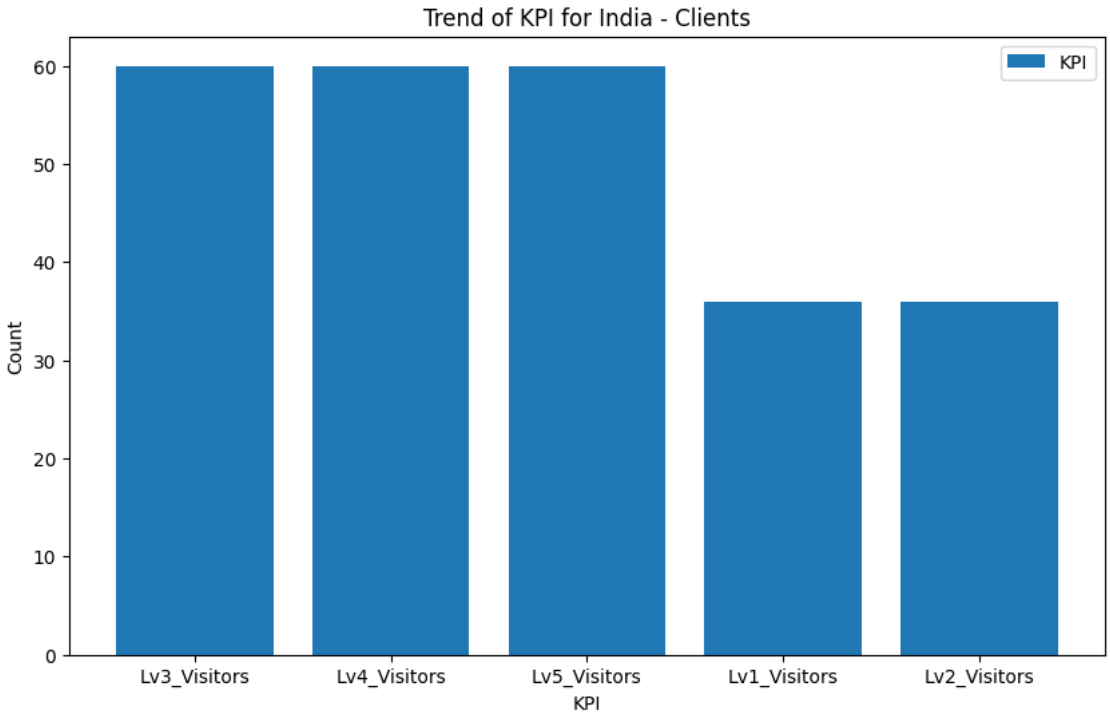
	Customer Segment	Region	KPI	Value Type	Value	date
451	Clients	India	Lv1_Visitors	Actuals	3322789.0	2020-01-01
1491	Customers	Dehradun	Lv1_Visitors	Actuals	28903.0	2020-01-01
1490	Customers	India	Lv5_Visitors	Actuals	42569.0	2020-01-01
1489	Customers	Uddepy	Lv4_Visitors	Actuals	48209.0	2020-01-01
1488	Customers	Uddepy	Lv2_Visitors	Actuals	75152.0	2020-01-01

[17]:
```
import matplotlib.pyplot as plt

#Building a function to generate a graph based on parameters
def generate_graphs(df, region, segment, start_date, end_date):
    # Filter data based on input parameters
    filtered_data = df[(df['Region'] == region) & (df['Customer Segment'] ==␣
 ↪segment) & (df['date'] >= start_date) & (df['date'] <= end_date)]
```

```
    # Making a line graph to show the trend of 'Value' over time
    plt.figure(figsize=(10, 6))
    plt.plot(filtered_data['date'], filtered_data['Value'], marker='o',␣
 ↪linestyle='-', label='Value')

    plt.title(f'Trend of Value for {region} - {segment}')
    plt.xlabel('Date')
    plt.ylabel('Value')
    plt.legend()
    plt.show()

    # Making  a bar graph to show the counts of different KPIs
    plt.figure(figsize=(10, 6))


    kpi_counts = filtered_data['KPI'].value_counts()

    plt.bar(kpi_counts.index, kpi_counts.values, label='KPI')

    plt.title(f'Trend of KPI for {region} - {segment}')
    plt.xlabel('KPI')
    plt.ylabel('Count')


    if len(kpi_counts) > 5:
        plt.xticks(rotation=45)

    plt.legend()

    plt.show()
```

[18]:
```
#mock trial
generate_graphs(df1,'India','Clients', '2020-01-01', '2022-12-01')
```


Trend of Value for India - Clients
1e6
Value
4
3
2
1
0
Value
2020-01
2020-05
2020-09
2021-01
2021-05
2021-09
2022-01
2022-05
2022-09
2023-01
Date


Trend of KPI for India - Clients
KPI
60
50
40
30
20
10
0
Count
Lv3_Visitors
Lv4_Visitors
Lv5_Visitors
Lv1_Visitors
Lv2_Visitors
KPI

[19]:
```
#getting the necessary packages
import numpy as np
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM
```

[20]:
```
#Making the function to train models for SARIMA,MA and LSTM

def train_and_return_models(df, region, segment, start_date, end_date):
    filtered_data = df[(df['Region'] == region) & (df['Customer Segment'] ==␣
 ↪segment) & (df['date'] >= start_date) & (df['date'] <= end_date)].copy()
    filtered_data = filtered_data[['date', 'Value']].copy()
    filtered_data['date'] = pd.to_numeric(filtered_data['date'])

    sarima_model = train_sarima_model(filtered_data)
    ma_model = train_ma_model(filtered_data)
    lstm_model = train_lstm_model(filtered_data)

    return sarima_model, ma_model, lstm_model


def train_sarima_model(data):
    X_train, X_test = train_test_split(data['Value'], test_size=0.2,␣
 ↪shuffle=False)

    order = (1, 0, 0)

    sarima_model = sm.tsa.SARIMAX(X_train,
                                  order=order,
                                  enforce_stationarity=False,
                                  enforce_invertibility=False)

    sarima_results = sarima_model.fit()

    sarima_predictions = sarima_results.get_forecast(steps=len(X_test))

    return pd.DataFrame({'date': X_test.index, 'Value': X_test.values.
 ↪flatten(), 'predicted_values': sarima_predictions.predicted_mean})


def train_ma_model(data):
     X_train, X_test = train_test_split(data, test_size=0.2, shuffle=False)

     ma_model = LinearRegression()
```

```
    ma_model.fit(X_train['date'].values.reshape(-1, 1), X_train['Value'])

    ma_predictions = ma_model.predict(X_test['date'].values.reshape(-1, 1))

    return pd.DataFrame({'date': X_test['date'], 'Value': X_test['Value'],␣
↪'predicted_values': ma_predictions})


def train_lstm_model(data):
   X_train, X_test = train_test_split(data.values.flatten(), test_size=0.2,␣
↪shuffle=False)

   scaler = MinMaxScaler(feature_range=(0, 1))
   scaled_data = scaler.fit_transform(data.values.reshape(-1, 1))

   x_train, y_train = [], []
   for i in range(60, len(scaled_data)):
       x_train.append(scaled_data[i-60:i])
       y_train.append(scaled_data[i])

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

   lstm_model = Sequential()
   lstm_model.add(LSTM(units=50, return_sequences=True, input_shape=(x_train.
↪shape[1], 1)))
   lstm_model.add(LSTM(units=50))
   lstm_model.add(Dense(units=1))

   lstm_model.compile(optimizer='adam', loss='mean_squared_error')
   lstm_model.fit(x_train, y_train, epochs=10, batch_size=32)

   inputs = scaled_data[len(scaled_data)-len(X_test)-60:]
   inputs = inputs.reshape(-1,1)
   inputs  = scaler.transform(inputs)

   x_test = []
   for i in range(60, len(inputs)):
        x_test.append(inputs[i-60:i])

   x_test = np.array(x_test)

   lstm_predictions = lstm_model.predict(x_test)
   lstm_predictions = scaler.inverse_transform(lstm_predictions)

   return pd.DataFrame({'date': data.index[-len(X_test):], 'Value':␣
↪data['Value'].values[-len(X_test):], 'predicted_values': lstm_predictions.
↪flatten()})
```

[21]:
```
#trial run
region = 'India'
segment = 'Customers'
start_date = '2020-01-01'
end_date = '2022-01-01'

sarima_model, ma_model, lstm_model = train_and_return_models(df1, region,␣
 ↪segment, start_date, end_date)
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

```
Epoch 1/10
6/6 [==============================] - 3s 45ms/step - loss: 0.3327
Epoch 2/10
6/6 [==============================] - 0s 42ms/step - loss: 0.2882
Epoch 3/10
6/6 [==============================] - 0s 44ms/step - loss: 0.2471
Epoch 4/10
6/6 [==============================] - 0s 41ms/step - loss: 0.2568
Epoch 5/10
6/6 [==============================] - 0s 43ms/step - loss: 0.2503
Epoch 6/10
6/6 [==============================] - 0s 41ms/step - loss: 0.2482
Epoch 7/10
6/6 [==============================] - 0s 42ms/step - loss: 0.2453
Epoch 8/10
6/6 [==============================] - 0s 43ms/step - loss: 0.2444
Epoch 9/10
6/6 [==============================] - 0s 43ms/step - loss: 0.2451
Epoch 10/10
6/6 [==============================] - 0s 62ms/step - loss: 0.2430
2/2 [==============================] - 1s 13ms/step
```

[22]:
```
# Printing the sarima dataset
print("SARIMA Model Dataset:")
print(sarima_model)
```

```
SARIMA Model Dataset:
     date          Value  predicted_values
100   794  322087.000000     296815.810100
101   793  339528.000000     230950.137431
102   792  465658.000000     179700.555578
103   795  268584.458953     139823.643468
104   805   20305.000000     108795.719690
105   717   17315.000000      84653.126819
106   706   71396.000000      65867.957863
107   704  264643.000000      51251.359945
108   703  303181.000000      39878.295630
109   702  442574.000000      31029.000285
110   622   19882.000000      24143.430492
111   612  420940.000000      18785.820703
112   613  292771.000000      14617.105038
113   614  233125.000000      11373.458901
114   615   79269.000000       8849.602369
115   535   18591.000000       6885.808686
116   522  469431.000000       5357.795671
117   524  232479.000000       4168.860298
118   525   88949.000000       3243.758674
119   523  330165.000000       2523.944096
120  1552   19861.000000       1963.861816
121  1542  447793.000000       1528.066029
122  1543  299158.000000       1188.976623
123  1546   81890.000000        925.133720
124  1544  235941.000000        719.839552
```

[23]:
```
# Printing the MA dataset
print("\nMA Model Dataset:")
print(ma_model)
```

```
MA Model Dataset:
                     date          Value  predicted_values
794   1630454400000000000  322087.000000     371831.215804
793   1630454400000000000  339528.000000     371831.215804
792   1630454400000000000  465658.000000     371831.215804
795   1630454400000000000  268584.458953     371831.215804
805   1630454400000000000   20305.000000     371831.215804
717   1633046400000000000   17315.000000     371253.598807
706   1633046400000000000   71396.000000     371253.598807
704   1633046400000000000  264643.000000     371253.598807
703   1633046400000000000  303181.000000     371253.598807
```

```
702   1633046400000000000  442574.000000     371253.598807
622   1635724800000000000   19882.000000     370656.727910
612   1635724800000000000  420940.000000     370656.727910
613   1635724800000000000  292771.000000     370656.727910
614   1635724800000000000  233125.000000     370656.727910
615   1635724800000000000   79269.000000     370656.727910
535   1638316800000000000   18591.000000     370079.110914
522   1638316800000000000  469431.000000     370079.110914
524   1638316800000000000  232479.000000     370079.110914
525   1638316800000000000   88949.000000     370079.110914
523   1638316800000000000  330165.000000     370079.110914
1552  1640995200000000000   19861.000000     369482.240017
1542  1640995200000000000  447793.000000     369482.240017
1543  1640995200000000000  299158.000000     369482.240017
1546  1640995200000000000   81890.000000     369482.240017
1544  1640995200000000000  235941.000000     369482.240017
```

[24]:
```
# Printing the LSTM dataset
print("\nLSTM Model Dataset:")
print(lstm_model)
```

```
LSTM Model Dataset:
    date          Value  predicted_values
0   1242  642725.000000      2.202322e+17
1   1244  520986.000000      2.202322e+17
2   1245  220736.000000      2.202322e+17
3   1249   57046.000000      2.202322e+17
4   1243  530740.000000      2.202322e+17
5   1159   45563.000000      2.202322e+17
6   1152  608351.000000      2.202322e+17
7   1153  513130.000000      2.202322e+17
8   1154  492346.000000      2.202322e+17
9   1155  200638.000000      2.202322e+17
10  1063  469601.000000      2.202322e+17
11  1064  449360.000000      2.202322e+17
12  1065  187122.000000      2.202322e+17
13  1069   40750.000000      2.202322e+17
14  1062  563598.000000      2.202322e+17
15   979   37264.000000      2.202322e+17
16   972  535634.000000      2.202322e+17
17   973  431464.000000      2.202322e+17
18   974  427893.000000      2.202322e+17
19   975  176228.000000      2.202322e+17
20   882  502679.000000      2.202322e+17
21   889   24110.000000      2.202322e+17
22   885  132905.000000      2.202322e+17
23   884  354660.000000      2.202322e+17
```

```
24   883  381466.000000      2.202322e+17
25   794  322087.000000      2.202322e+17
26   793  339528.000000      2.202322e+17
27   792  465658.000000      2.202322e+17
28   795  268584.458953      2.202322e+17
29   805   20305.000000      2.202322e+17
30   717   17315.000000      2.202322e+17
31   706   71396.000000      2.202322e+17
32   704  264643.000000      2.202322e+17
33   703  303181.000000      2.202322e+17
34   702  442574.000000      2.202322e+17
35   622   19882.000000      2.202322e+17
36   612  420940.000000      2.202322e+17
37   613  292771.000000      2.202322e+17
38   614  233125.000000      2.202322e+17
39   615   79269.000000      2.202322e+17
40   535   18591.000000      2.202322e+17
41   522  469431.000000      2.202322e+17
42   524  232479.000000      2.202322e+17
43   525   88949.000000      2.202322e+17
44   523  330165.000000      2.202322e+17
45  1552   19861.000000      2.202322e+17
46  1542  447793.000000      2.202322e+17
47  1543  299158.000000      2.202322e+17
48  1546   81890.000000      2.202322e+17
49  1544  235941.000000      2.202322e+17
```

[25]:
```python
from sklearn.metrics import mean_absolute_percentage_error, mean_squared_error

#calculating the error metrics
def calculate_error_metrics(dataset):
    actual_values = dataset['Value'].values
    predicted_values = dataset['predicted_values'].values

    mape = mean_absolute_percentage_error(actual_values, predicted_values)
    mse = mean_squared_error(actual_values, predicted_values)

    return mape, mse
```

[26]:
```python
# Getting the error metrics for SARIMA


mape, mse = calculate_error_metrics(sarima_model)

print("Mean Absolute Percentage Error (MAPE):", mape)
print("Mean Squared Error (MSE):", mse)
```

```
Mean Absolute Percentage Error (MAPE): 1.0326339956706214
```

```
Mean Squared Error (MSE): 57324776334.51824
```

[27]:
```
# Getting the error metrics for MA


mape, mse = calculate_error_metrics(ma_model)

print("Mean Absolute Percentage Error (MAPE):", mape)
print("Mean Squared Error (MSE):", mse)
```

```
Mean Absolute Percentage Error (MAPE): 4.438168995752023
Mean Squared Error (MSE): 43404644856.10021
```

[28]:
```
# Getting the error metrics for LSTM


mape, mse = calculate_error_metrics(lstm_model)

print("Mean Absolute Percentage Error (MAPE):", mape)
print("Mean Squared Error (MSE):", mse)
```

```
Mean Absolute Percentage Error (MAPE): 2438313490542.1436
Mean Squared Error (MSE): 4.850223569018413e+34
```

Remark

Due to the lowest error rate in SARIMA the Sarima Model has been chosen.

[29]:
```
# Converting the datasets to csv
file_path_df1 = 'sarima_model.csv'
file_path_df2 = 'ma_model.csv'
file_path_df3 = 'lstm_model.csv'


sarima_model.to_csv(file_path_df1, index=False)
ma_model.to_csv(file_path_df2, index=False)
lstm_model.to_csv(file_path_df3, index=False)
```

[30]:
```
#subsetting the dataset

subset_df = df1[df1['KPI'] == 'Lv5_Visitors']
subset_df
```

[30]:

	Customer Segment	Region	KPI	Value Type	Value	\
1490	Customers	India	Lv5_Visitors	Actuals	42569.0	
456	Clients	India	Lv5_Visitors	Actuals	278010.0	
458	Clients	India	Lv5_Visitors	Actuals	85929.0	
1507	Customers	Dehradun	Lv5_Visitors	Actuals	3875.0	
1511	Customers	Aurangabad	Lv5_Visitors	Actuals	934.0	

```
…              …          …            …          …        …
580         Customers      Ujjain  Lv5_Visitors    Actuals     293.0
571         Customers       India  Lv5_Visitors    Actuals    4625.0
576         Customers      Uddepy  Lv5_Visitors    Actuals    1492.0
578         Customers   Faridabad  Lv5_Visitors    Actuals     399.0
579         Customers    Dehradun  Lv5_Visitors    Actuals     357.0

           date
1490 2020-01-01
456  2020-01-01
458  2020-01-01
1507 2020-01-01
1511 2020-01-01
…          …
580  2022-12-01
571  2022-12-01
576  2022-12-01
578  2022-12-01
579  2022-12-01

[324 rows x 6 columns]
```

[31]:
```
#seeing the combination with the highest customer count

combination_counts = subset_df.groupby(['Region', 'Customer Segment', 'Value␣
 ↪Type', 'date']).size().reset_index(name='Value Count')


sorted_combinations = combination_counts.sort_values(by='Value Count',␣
 ↪ascending=False)


top_5_combinations = sorted_combinations.head(5)
top_5_combinations
```

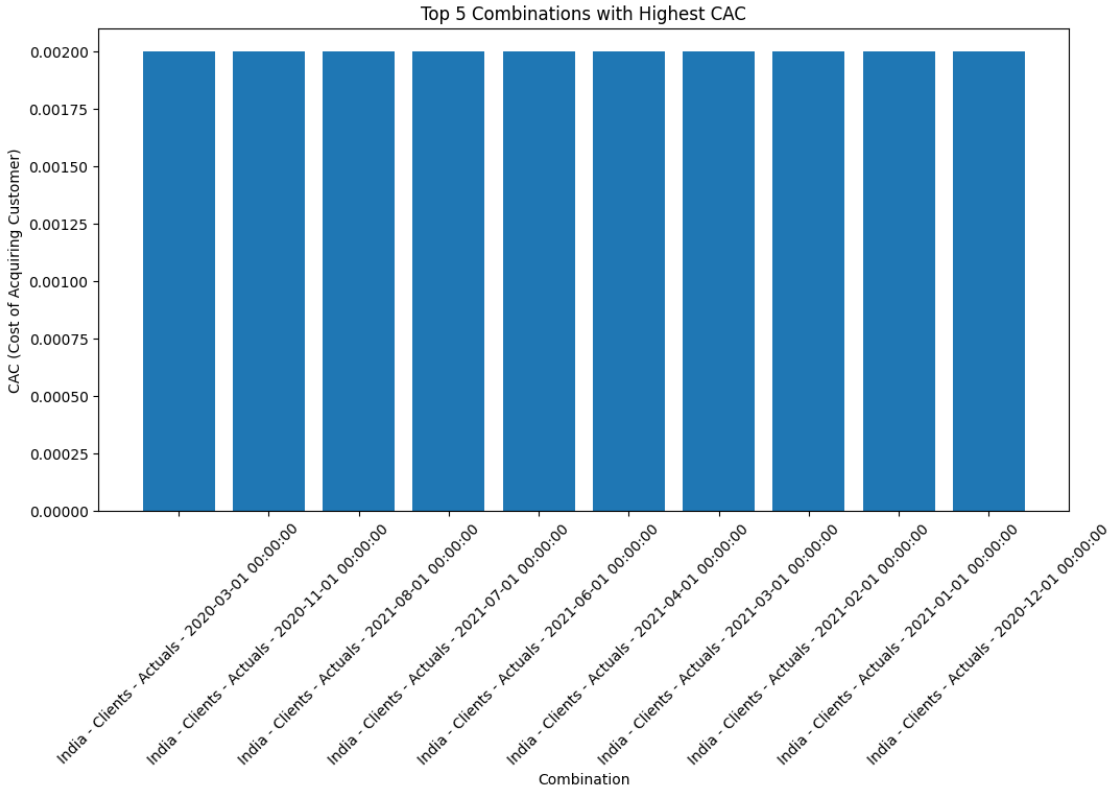
[31]:
```
    Region Customer Segment Value Type       date  Value Count
122  India          Clients    Actuals 2020-03-01            2
130  India          Clients    Actuals 2020-11-01            2
139  India          Clients    Actuals 2021-08-01            2
138  India          Clients    Actuals 2021-07-01            2
137  India          Clients    Actuals 2021-06-01            2
```

[32]:
```
# Finding the combination for highest CAC

customer_count = subset_df.groupby(['Region','Customer Segment','Value Type',␣
 ↪'date']).size()
CAC = (customer_count * 100) / 100000
```

```
top_10_CAC_regions = CAC.sort_values(ascending=False).head(10)
top_10_CAC_regions
```

[32]:
```
Region  Customer Segment  Value Type  date
India   Clients           Actuals     2020-03-01    0.002
                                      2020-11-01    0.002
                                      2021-08-01    0.002
                                      2021-07-01    0.002
                                      2021-06-01    0.002
                                      2021-04-01    0.002
                                      2021-03-01    0.002
                                      2021-02-01    0.002
                                      2021-01-01    0.002
                                      2020-12-01    0.002
dtype: float64
```

[33]:
```
# Creating a bar plot to visualize CAC for the top 10 top_10_CAC_regions
top_10_CAC_regions.index = [f'{index[0]} - {index[1]} - {index[2]} -␣
 ↪{index[3]}' for index in top_10_CAC_regions.index]


plt.figure(figsize=(12, 6))
plt.bar(top_10_CAC_regions.index, top_10_CAC_regions.values)
plt.xlabel('Combination')
plt.ylabel('CAC (Cost of Acquiring Customer)')
plt.title('Top 5 Combinations with Highest CAC')
plt.xticks(rotation=45)

plt.show()
```

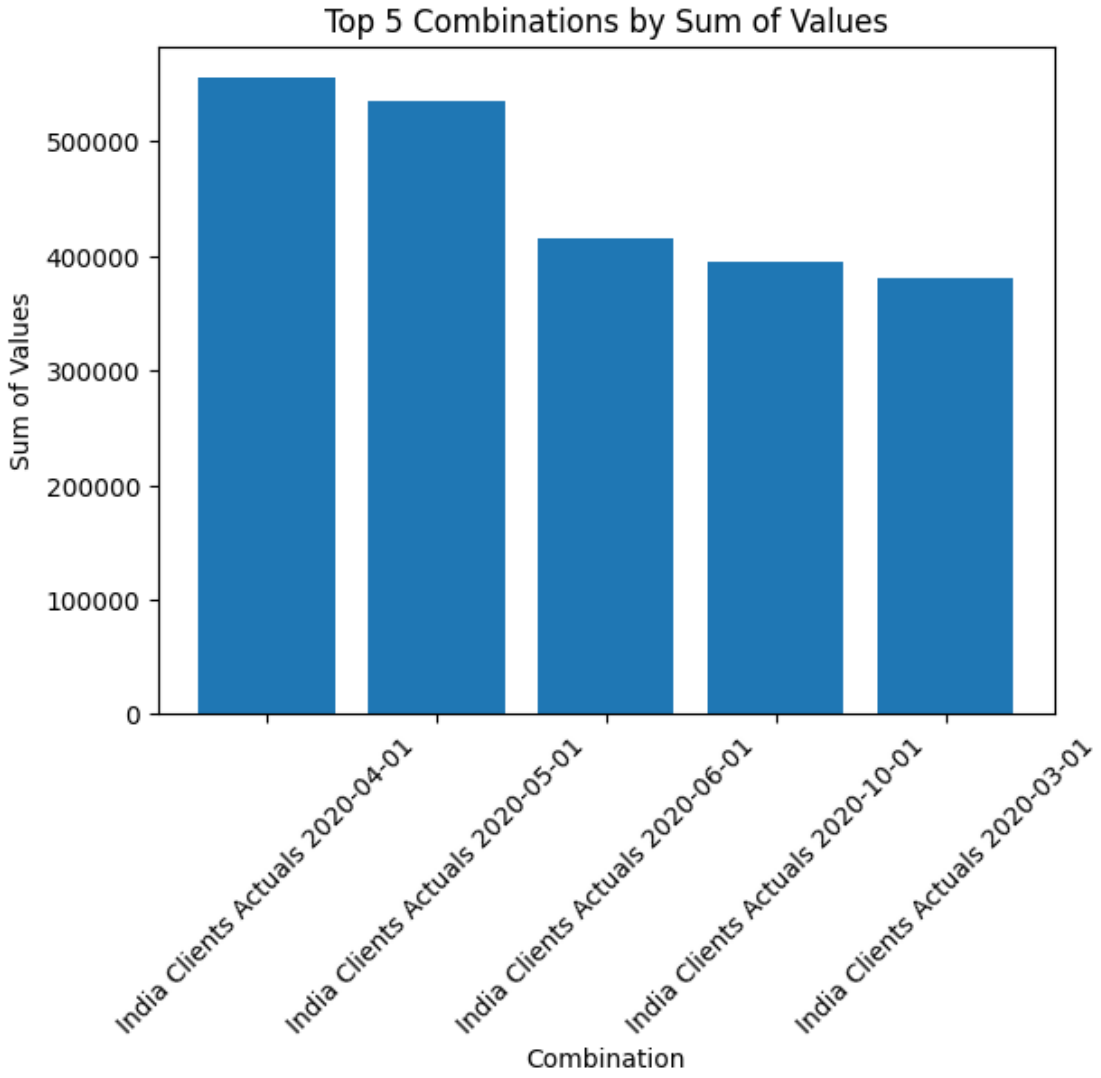


[34]:
```
#seeing which combination generates the highest revenue
value_sum = subset_df.groupby(['Region','Customer Segment','Value Type',␣
 ↪'date'])['Value'].sum()
top_5_values = value_sum.sort_values(ascending=False).head(5)

top_5_values
```

[34]:
```
Region  Customer Segment  Value Type  date
India   Clients           Actuals     2020-04-01    555127.0
                                      2020-05-01    535507.0
                                      2020-06-01    415727.0
                                      2020-10-01    394290.0
                                      2020-03-01    380754.0
Name: Value, dtype: float64
```

[35]:
```
# Visualizing  which combination generates the highest revenue
top_5_values.index = [f"{region} {kpi} {value_type} {date.
 ↪strftime('%Y-%m-%d')}" for region, kpi, value_type, date in top_5_values.
 ↪index]

plt.bar(top_5_values.index.astype(str), top_5_values.values)
plt.xlabel('Combination')
```

```
plt.ylabel('Sum of Values')
plt.title('Top 5 Combinations by Sum of Values')
plt.xticks(rotation=45)
plt.show()
```



[36]:
```
#subsetting for location Dehradun
dh_df = df1[df1['Region'] == 'Dehradun']
dh_df
```

[36]:

	Customer Segment	Region	KPI	Value Type	Value	date
1491	Customers	Dehradun	Lv1_Visitors	Actuals	28903.0	2020-01-01
1495	Customers	Dehradun	Lv2_Visitors	Actuals	21332.0	2020-01-01
1507	Customers	Dehradun	Lv5_Visitors	Actuals	3875.0	2020-01-01

```
1494        Customers  Dehradun  Lv3_Visitors    Actuals   25380.0 2020-01-01
1502        Customers  Dehradun  Lv4_Visitors    Actuals    8578.0 2020-01-01
…               …         …           …         …          …          …
28            Clients  Dehradun  Lv3_Visitors    Actuals  118570.0 2022-12-01
567         Customers  Dehradun  Lv3_Visitors    Actuals    8196.0 2022-12-01
574         Customers  Dehradun  Lv4_Visitors    Actuals    2561.0 2022-12-01
579         Customers  Dehradun  Lv5_Visitors    Actuals     357.0 2022-12-01
564         Customers  Dehradun  Lv2_Visitors    Actuals   16806.0 2022-12-01

[240 rows x 6 columns]
```

[37]:
```
#checking the Lv5 to Lv1 ratio of this region
ratio=len(dh_df[dh_df['KPI'] == 'Lv5_Visitors'])/len(dh_df[dh_df['KPI'] ==␣
 ↪'Lv1_Visitors'])
ratio
```

[37]: 1.0

[38]:
```
#checking the CAC ratio of this region
CAC = len(dh_df[dh_df['KPI'] == 'Lv5_Visitors'])* 100 / 100000
CAC
```

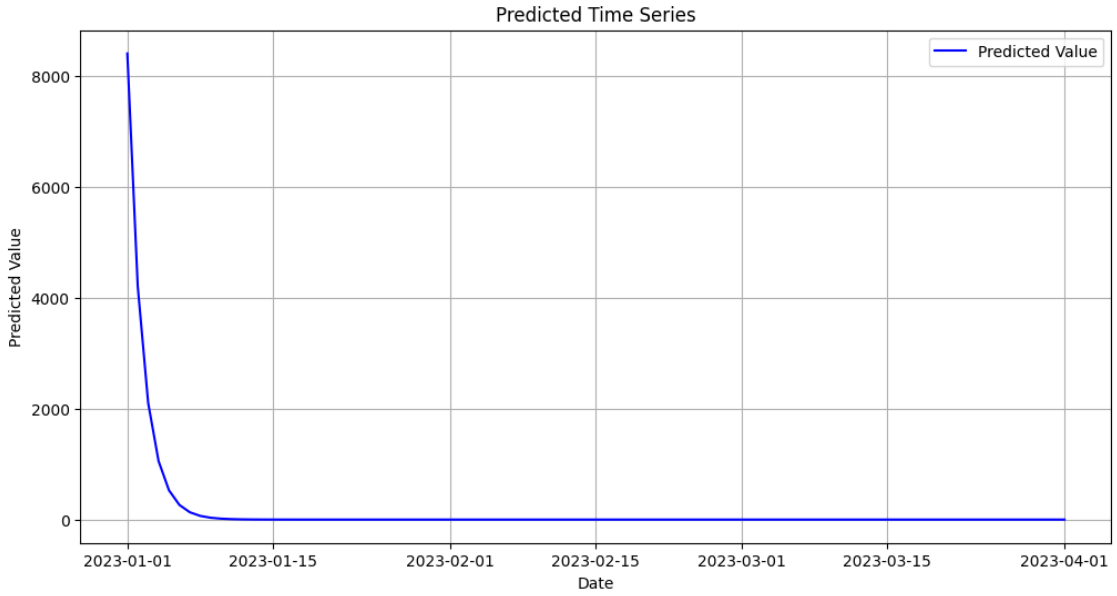
[38]: 0.048

[39]:
```
# Using the sarima model to predict the values for Dehradun region for upcoming␣
 ↪Quarter
order = (1, 0, 0)
sarima_model = sm.tsa.SARIMAX(dh_df['Value'], order=order,␣
 ↪enforce_stationarity=False, enforce_invertibility=False)
sarima_results = sarima_model.fit()


start_date = '2023-01-01'
end_date = '2023-04-01'


forecast = sarima_results.get_forecast(steps=len(pd.date_range(start_date,␣
 ↪end_date, freq='D')))

predicted_values = forecast.predicted_mean
forecast_dates = pd.date_range(start=start_date, end=end_date, freq='D')


predicted_df_dh = pd.DataFrame({'Date': forecast_dates, 'Predicted_Value':␣
 ↪predicted_values})

print(predicted_df_dh)
```

```
          Date  Predicted_Value
240 2023-01-01     8.413609e+03
241 2023-01-02     4.212116e+03
242 2023-01-03     2.108717e+03
243 2023-01-04     1.055690e+03
244 2023-01-05     5.285113e+02
..         …              …
326 2023-03-28     1.212073e-22
327 2023-03-29     6.068017e-23
328 2023-03-30     3.037839e-23
329 2023-03-31     1.520837e-23
330 2023-04-01     7.613787e-24

[91 rows x 2 columns]
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

[40]:
```
# Creating a time series plot for the same
predicted_df_dh.set_index('Date', inplace=True)


plt.figure(figsize=(12, 6))
plt.plot(predicted_df_dh.index, predicted_df_dh['Predicted_Value'],␣
 ↪label='Predicted Value', color='blue')
plt.title('Predicted Time Series')
plt.xlabel('Date')
plt.ylabel('Predicted Value')
plt.legend()
plt.grid(True)
plt.show()
```



[41]:
```
#subsetting for location Uddepy
dh_Ud = df1[df1['Region'] == 'Uddepy']
dh_Ud
```

[41]:

	Customer Segment	Region	KPI	Value Type	Value	date
1489	Customers	Uddepy	Lv4_Visitors	Actuals	48209.0	2020-01-01
1488	Customers	Uddepy	Lv2_Visitors	Actuals	75152.0	2020-01-01
1487	Customers	Uddepy	Lv1_Visitors	Actuals	103882.0	2020-01-01
1486	Customers	Uddepy	Lv3_Visitors	Actuals	108349.0	2020-01-01
1498	Customers	Uddepy	Lv5_Visitors	Actuals	15447.0	2020-01-01
…	…	…	…	…	…	…
27	Clients	Uddepy	Lv4_Visitors	Actuals	118950.0	2022-12-01
22	Clients	Uddepy	Lv3_Visitors	Actuals	371666.0	2022-12-01
37	Clients	Uddepy	Lv5_Visitors	Actuals	14855.0	2022-12-01
565	Customers	Uddepy	Lv4_Visitors	Actuals	16241.0	2022-12-01
576	Customers	Uddepy	Lv5_Visitors	Actuals	1492.0	2022-12-01

[240 rows x 6 columns]

[42]:
```
#checking the Lv5 to Lv1 ratio of this region
ratio=len(dh_Ud[dh_Ud['KPI'] == 'Lv5_Visitors'])/len(dh_Ud[dh_Ud['KPI'] ==␣
 ↪'Lv1_Visitors'])
ratio
```

[42]: 1.0

[43]:
```
#checking the CAC ratio of this region
CAC = len(dh_Ud[dh_Ud['KPI'] == 'Lv5_Visitors'])* 100 / 100000
CAC
```

[43]: 0.048

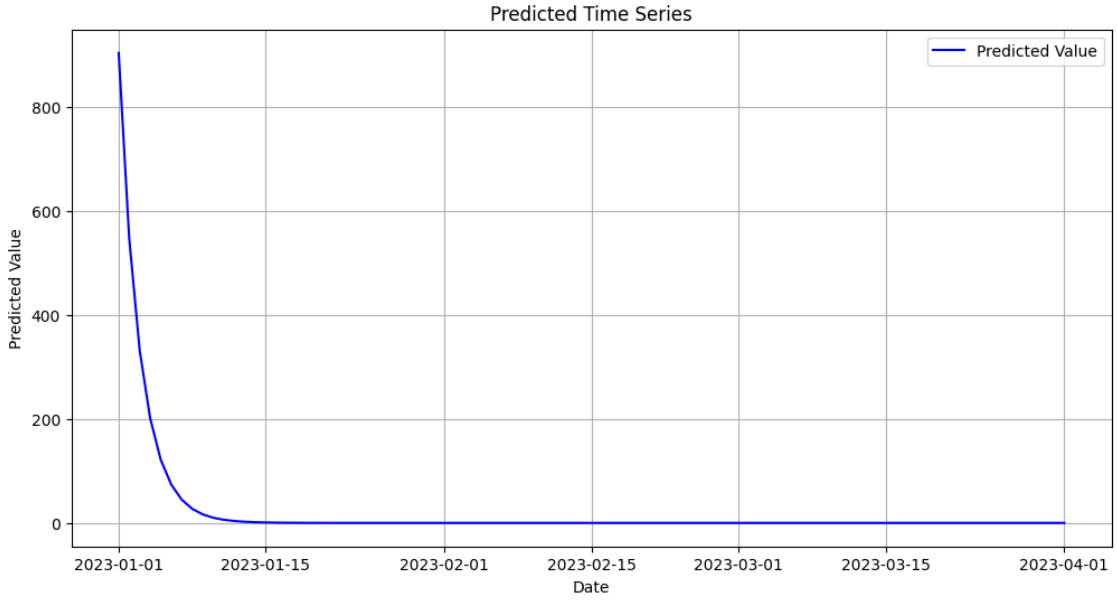
[44]:
```
# Using the sarima model to predict the values for Uddepy region for upcoming␣
 ↪Quarter
order = (1, 0, 0)
sarima_model = sm.tsa.SARIMAX(dh_Ud['Value'], order=order,␣
 ↪enforce_stationarity=False, enforce_invertibility=False)
sarima_results = sarima_model.fit()


start_date = '2023-01-01'
end_date = '2023-04-01'


forecast = sarima_results.get_forecast(steps=len(pd.date_range(start_date,␣
 ↪end_date, freq='D')))

predicted_values = forecast.predicted_mean
forecast_dates = pd.date_range(start=start_date, end=end_date, freq='D')


predicted_df_ud= pd.DataFrame({'Date': forecast_dates, 'Predicted_Value':␣
 ↪predicted_values})

print(predicted_df_ud)
```

```
          Date  Predicted_Value
240 2023-01-01     9.037655e+02
241 2023-01-02     5.474477e+02
242 2023-01-03     3.316115e+02
243 2023-01-04     2.008707e+02
244 2023-01-05     1.216756e+02
..         …              …
326 2023-03-28     1.708958e-16
327 2023-03-29     1.035186e-16
328 2023-03-30     6.270543e-17
329 2023-03-31     3.798325e-17
330 2023-04-01     2.300801e-17

[91 rows x 2 columns]
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
```

```
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

[45]:
```
# Creating a time series plot for the same
predicted_df_ud.set_index('Date', inplace=True)


plt.figure(figsize=(12, 6))
plt.plot(predicted_df_ud.index, predicted_df_ud['Predicted_Value'],␣
 ↪label='Predicted Value', color='blue')
plt.title('Predicted Time Series')
plt.xlabel('Date')
plt.ylabel('Predicted Value')
plt.legend()
plt.grid(True)
plt.show()
```



[46]:
```
#subsetting for location Indore
dh_in = df1[df1['Region'] == 'Indore']
dh_in
```

[46]:

	Customer Segment	Region	KPI	Value Type	Value	date
490	Clients	Indore	Lv5_Visitors	Actuals	19556.0	2022-01-01
487	Clients	Indore	Lv4_Visitors	Actuals	40124.0	2022-01-01
479	Clients	Indore	Lv1_Visitors	Actuals	147244.0	2022-01-01
482	Clients	Indore	Lv2_Visitors	Actuals	85963.0	2022-01-01
484	Clients	Indore	Lv3_Visitors	Actuals	74326.0	2022-01-01
442	Clients	Indore	Lv2_Visitors	Actuals	73121.0	2022-02-01
444	Clients	Indore	Lv3_Visitors	Actuals	62801.0	2022-02-01
447	Clients	Indore	Lv4_Visitors	Actuals	33654.0	2022-02-01
450	Clients	Indore	Lv5_Visitors	Actuals	16621.0	2022-02-01
438	Clients	Indore	Lv1_Visitors	Actuals	127288.0	2022-02-01
409	Clients	Indore	Lv5_Visitors	Actuals	14214.0	2022-03-01
406	Clients	Indore	Lv4_Visitors	Actuals	28492.0	2022-03-01
403	Clients	Indore	Lv3_Visitors	Actuals	55520.0	2022-03-01
401	Clients	Indore	Lv2_Visitors	Actuals	64633.0	2022-03-01
397	Clients	Indore	Lv1_Visitors	Actuals	115360.0	2022-03-01
356	Clients	Indore	Lv1_Visitors	Actuals	111786.0	2022-04-01
360	Clients	Indore	Lv2_Visitors	Actuals	63090.0	2022-04-01
362	Clients	Indore	Lv3_Visitors	Actuals	54853.0	2022-04-01
365	Clients	Indore	Lv4_Visitors	Actuals	27677.0	2022-04-01
368	Clients	Indore	Lv5_Visitors	Actuals	13498.0	2022-04-01
324	Clients	Indore	Lv4_Visitors	Actuals	26418.0	2022-05-01
314	Clients	Indore	Lv1_Visitors	Actuals	120072.0	2022-05-01
319	Clients	Indore	Lv2_Visitors	Actuals	69917.0	2022-05-01
320	Clients	Indore	Lv3_Visitors	Actuals	59968.0	2022-05-01
327	Clients	Indore	Lv5_Visitors	Actuals	12773.0	2022-05-01
278	Clients	Indore	Lv2_Visitors	Actuals	73607.0	2022-06-01
279	Clients	Indore	Lv3_Visitors	Actuals	56466.0	2022-06-01
283	Clients	Indore	Lv4_Visitors	Actuals	28059.0	2022-06-01
286	Clients	Indore	Lv5_Visitors	Actuals	13384.0	2022-06-01
273	Clients	Indore	Lv1_Visitors	Actuals	122356.0	2022-06-01
235	Clients	Indore	Lv1_Visitors	Actuals	115834.0	2022-07-01
237	Clients	Indore	Lv2_Visitors	Actuals	69890.0	2022-07-01
240	Clients	Indore	Lv3_Visitors	Actuals	51267.0	2022-07-01
242	Clients	Indore	Lv4_Visitors	Actuals	27102.0	2022-07-01
245	Clients	Indore	Lv5_Visitors	Actuals	12854.0	2022-07-01
204	Clients	Indore	Lv5_Visitors	Actuals	12512.0	2022-08-01
201	Clients	Indore	Lv4_Visitors	Actuals	26648.0	2022-08-01
198	Clients	Indore	Lv3_Visitors	Actuals	51169.0	2022-08-01
196	Clients	Indore	Lv2_Visitors	Actuals	69795.0	2022-08-01
192	Clients	Indore	Lv1_Visitors	Actuals	115776.0	2022-08-01
163	Clients	Indore	Lv5_Visitors	Actuals	13384.0	2022-09-01
156	Clients	Indore	Lv3_Visitors	Actuals	54655.0	2022-09-01

```
155          Clients  Indore  Lv2_Visitors    Actuals   72145.0 2022-09-01
150          Clients  Indore  Lv1_Visitors    Actuals  122401.0 2022-09-01
160          Clients  Indore  Lv4_Visitors    Actuals   27453.0 2022-09-01
116          Clients  Indore  Lv3_Visitors    Actuals   60089.0 2022-10-01
114          Clients  Indore  Lv2_Visitors    Actuals   77078.0 2022-10-01
110          Clients  Indore  Lv1_Visitors    Actuals  129633.0 2022-10-01
122          Clients  Indore  Lv5_Visitors    Actuals   15486.0 2022-10-01
119          Clients  Indore  Lv4_Visitors    Actuals   31457.0 2022-10-01
81           Clients  Indore  Lv5_Visitors    Actuals   16528.0 2022-11-01
68           Clients  Indore  Lv1_Visitors    Actuals  135254.0 2022-11-01
74           Clients  Indore  Lv3_Visitors    Actuals   67546.0 2022-11-01
73           Clients  Indore  Lv2_Visitors    Actuals   80884.0 2022-11-01
78           Clients  Indore  Lv4_Visitors    Actuals   33489.0 2022-11-01
36           Clients  Indore  Lv4_Visitors    Actuals   30773.0 2022-12-01
32           Clients  Indore  Lv2_Visitors    Actuals   72804.0 2022-12-01
33           Clients  Indore  Lv3_Visitors    Actuals   64064.0 2022-12-01
40           Clients  Indore  Lv5_Visitors    Actuals    4335.0 2022-12-01
26           Clients  Indore  Lv1_Visitors    Actuals  119475.0 2022-12-01
```

[47]:
```
#checking the Lv5 to Lv1 ratio of this region
ratio=len(dh_in[dh_in['KPI'] == 'Lv5_Visitors'])/len(dh_in[dh_in['KPI'] ==␣
 ↪'Lv1_Visitors'])
ratio
```

[47]: 1.0

[48]:
```
#checking the CAC ratio of this region
CAC = len(dh_in[dh_in['KPI'] == 'Lv5_Visitors'])* 100 / 100000
CAC
```

[48]: 0.012

[49]:
```
# Using the sarima model to predict the values for indore region for upcoming␣
 ↪Quarter
order = (1, 0, 0)
sarima_model = sm.tsa.SARIMAX(dh_in['Value'], order=order,␣
 ↪enforce_stationarity=False, enforce_invertibility=False)
sarima_results = sarima_model.fit()


start_date = '2023-01-01'
end_date = '2023-04-01'


forecast = sarima_results.get_forecast(steps=len(pd.date_range(start_date,␣
 ↪end_date, freq='D')))
```

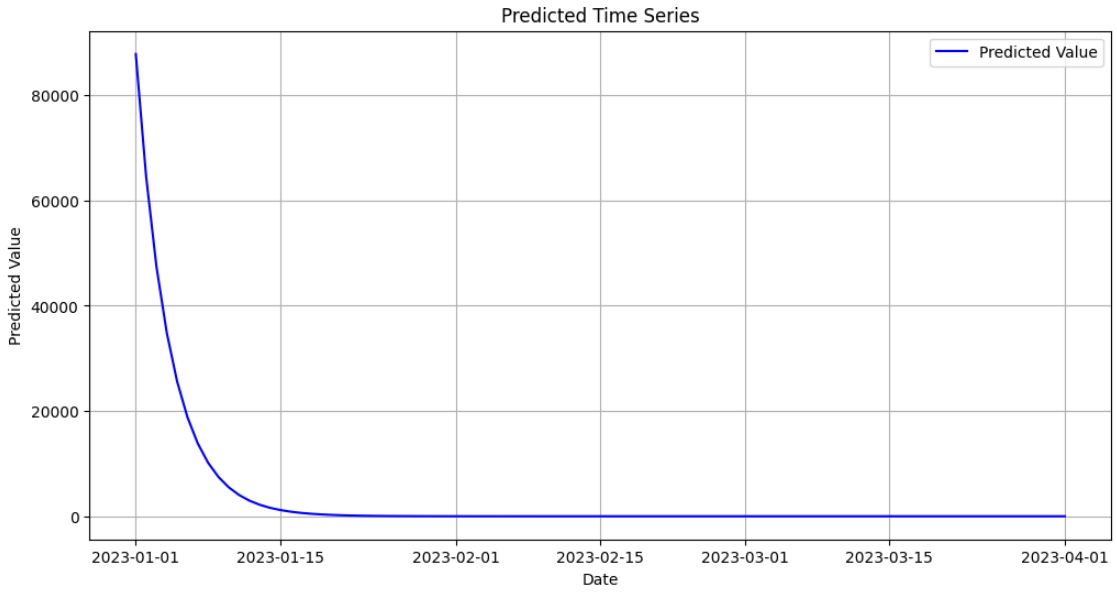
```
predicted_values = forecast.predicted_mean
forecast_dates = pd.date_range(start=start_date, end=end_date, freq='D')


predicted_df_in= pd.DataFrame({'Date': forecast_dates, 'Predicted_Value':␣
 ↪predicted_values})

print(predicted_df_in)
```

```
          Date  Predicted_Value
60  2023-01-01     8.781801e+04
61  2023-01-02     6.454910e+04
62  2023-01-03     4.744569e+04
63  2023-01-04     3.487412e+04
64  2023-01-05     2.563362e+04
..         …              …
146 2023-03-28     2.792212e-07
147 2023-03-29     2.052367e-07
148 2023-03-30     1.508556e-07
149 2023-03-31     1.108838e-07
150 2023-04-01     8.150319e-08

[91 rows x 2 columns]
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

[50]:
```
# Creating a time series plot for the same
predicted_df_in.set_index('Date', inplace=True)


plt.figure(figsize=(12, 6))
plt.plot(predicted_df_in.index, predicted_df_in['Predicted_Value'],␣
 ↪label='Predicted Value', color='blue')
```

```
plt.title('Predicted Time Series')
plt.xlabel('Date')
plt.ylabel('Predicted Value')
plt.legend()
plt.grid(True)
plt.show()
```



[51]:
```
#subsetting for location Ujjain
dh_uj = df1[df1['Region'] == 'Ujjain']
dh_uj
```

[51]:

	Customer Segment	Region	KPI	Value Type	Value	date
1492	Customers	Ujjain	Lv3_Visitors	Actuals	25661.0	2020-01-01
1493	Customers	Ujjain	Lv1_Visitors	Actuals	25434.0	2020-01-01
1508	Customers	Ujjain	Lv5_Visitors	Actuals	3393.0	2020-01-01
1501	Customers	Ujjain	Lv4_Visitors	Actuals	9881.0	2020-01-01
1496	Customers	Ujjain	Lv2_Visitors	Actuals	19891.0	2020-01-01
…	…	…	…	…	…	…
580	Customers	Ujjain	Lv5_Visitors	Actuals	293.0	2022-12-01
563	Customers	Ujjain	Lv1_Visitors	Actuals	18327.0	2022-12-01
566	Customers	Ujjain	Lv2_Visitors	Actuals	11600.0	2022-12-01
568	Customers	Ujjain	Lv3_Visitors	Actuals	6821.0	2022-12-01
575	Customers	Ujjain	Lv4_Visitors	Actuals	2556.0	2022-12-01

[240 rows x 6 columns]

[52]:
```
#checking the Lv5 to Lv1 ratio of this region
ratio=len(dh_uj[dh_uj['KPI'] == 'Lv5_Visitors'])/len(dh_uj[dh_uj['KPI'] ==␣
 ↪'Lv1_Visitors'])
ratio
```

[52]: 1.0

[53]:
```
#checking the CAC ratio of this region
CAC = len(dh_uj[dh_uj['KPI'] == 'Lv5_Visitors'])* 100 / 100000
CAC
```

[53]: 0.048

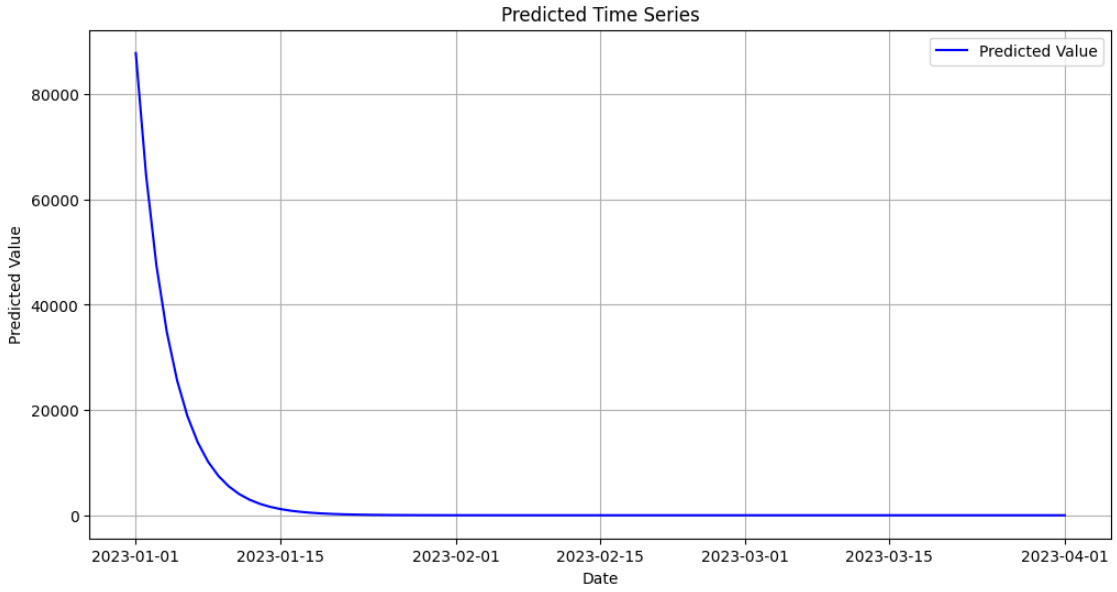
[54]:
```
# Using the sarima model to predict the values for Ujjain region for upcoming␣
 ↪Quarter
order = (1, 0, 0)
sarima_model = sm.tsa.SARIMAX(dh_in['Value'], order=order,␣
 ↪enforce_stationarity=False, enforce_invertibility=False)
sarima_results = sarima_model.fit()


start_date = '2023-01-01'
end_date = '2023-04-01'


forecast = sarima_results.get_forecast(steps=len(pd.date_range(start_date,␣
 ↪end_date, freq='D')))

predicted_values = forecast.predicted_mean
forecast_dates = pd.date_range(start=start_date, end=end_date, freq='D')


predicted_df_uj= pd.DataFrame({'Date': forecast_dates, 'Predicted_Value':␣
 ↪predicted_values})

print(predicted_df_uj)
```

```
          Date  Predicted_Value
60  2023-01-01     8.781801e+04
61  2023-01-02     6.454910e+04
62  2023-01-03     4.744569e+04
63  2023-01-04     3.487412e+04
64  2023-01-05     2.563362e+04
..         …              …
146 2023-03-28     2.792212e-07
147 2023-03-29     2.052367e-07
148 2023-03-30     1.508556e-07
```

```
149 2023-03-31     1.108838e-07
150 2023-04-01     8.150319e-08

[91 rows x 2 columns]
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:473:
ValueWarning: An unsupported index was provided and will be ignored when e.g.
forecasting.
  self._init_dates(dates, freq)
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
ValueWarning: No supported index is available. Prediction results will be given
with an integer index beginning at `start`.
  return get_prediction_index(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/base/tsa_model.py:836:
FutureWarning: No supported index is available. In the next version, calling
this method in a model without a supported index will result in an exception.
  return get_prediction_index(
```

[55]:
```
# Creating a time series plot for the same
predicted_df_uj.set_index('Date', inplace=True)


plt.figure(figsize=(12, 6))
plt.plot(predicted_df_uj.index, predicted_df_uj['Predicted_Value'],␣
 ↪label='Predicted Value', color='blue')
plt.title('Predicted Time Series')
plt.xlabel('Date')
plt.ylabel('Predicted Value')
plt.legend()
plt.grid(True)
plt.show()
```



Part 2:AB Test Questions

In this segment we are going to be creating functions that automate the hypothesis Testing.

[69]:
```
#getting the dataset
df2=pd.read_excel('/content/sample_data/ABtest.xlsx')
df2.head()
```

[69]:

	Months (Date)	Date	Variants	DeviceType	Sum of Clicks	Sum of Visitors
0	Mar	2023-03-29	Control	Desktop	31312	298032
1	Mar	2023-03-29	Control	Mobile	18399	192144
2	Mar	2023-03-29	Control	Others	34	375
3	Mar	2023-03-29	Control	Tablet	660	7646
4	Mar	2023-03-29	Treatment	Desktop	10067	32737

[70]:
```
#dropping timestamp
df2=df2.drop(['Date'],axis=1)
df2.head()
```

[70]:

	Months (Date)	Variants	DeviceType	Sum of Clicks	Sum of Visitors
0	Mar	Control	Desktop	31312	298032

```
1           Mar    Control     Mobile          18399          192144
2           Mar    Control     Others             34             375
3           Mar    Control     Tablet            660            7646
4           Mar  Treatment    Desktop          10067           32737
```

[71]:
```
#making a new feature
df2['CTR'] = (df2['Sum of Clicks'] / df2['Sum of Visitors']) * 100
df2['CTR']
```

[71]:
```
0      10.506254
1       9.575631
2       9.066667
3       8.631964
4      30.751138
         …
139    10.183790
140    24.704114
141    15.351082
142     8.108108
143    17.945007
Name: CTR, Length: 144, dtype: float64
```

[75]:
```
#subsetting according to needs
Control_data=df2[df2['Variants'] == 'Control']
Treatment_data=df2[df2['Variants'] == 'Treatment']
Desktop_data=df2[df2['Variants'] == 'Desktop']
Mobile_data=df2[df2['Variants'] == 'Mobile']
```

[86]:
```
import statsmodels.stats.api as sms

# Checking if we have reached the minimum sample size
MDE = 0.03  # Minimum Detectable Effect (3%)
alpha = 0.05  # Significance level (95%)
power = 0.80  # Statistical power (80%)


effect_size = sms.proportion_effectsize(0.5, 0.5 + MDE)
required_sample_size = sms.NormalIndPower().solve_power(effect_size, power,␣
 ↪alpha, ratio=1)


actual_sample_size = len(df2)
if actual_sample_size >= required_sample_size:
    print("The required sample size has been reached.")
else:
    print("More data is needed to reach the required sample size.")
```

The required sample size has been reached.

[87]:
```
from scipy import stats

# Checking  for statistical significance at 95% confidence
control_group = Control_data['CTR']
treatment_group = Treatment_data['CTR']
alpha = 0.05

t_stat, p_value = stats.ttest_ind(control_group, treatment_group)

if p_value < alpha:
    print("The test has reached statistical significance at 95% confidence.")
else:
    print("The test has not reached statistical significance at 95% confidence.
 ↪")
```

The test has reached statistical significance at 95% confidence.

[88]:
```
from scipy import stats
# Defining significance level (alpha)
alpha = 0.05

# Function to check for statistical significance
def check_statistical_significance(group1, group2, alpha):
    t_stat, p_value = stats.ttest_ind(group1, group2)
    return p_value < alpha
```

[89]:
```
# Performing the test for overall data vs. desktop data
overall_group = df2['CTR']
desktop_group = Desktop_data['CTR']
overall_vs_desktop_significance = check_statistical_significance(overall_group,␣
 ↪desktop_group, alpha)

# Checking if each comparison reaches statistical significance
if overall_vs_desktop_significance:
    print("The test for overall data vs. desktop data has reached statistical␣
 ↪significance.")
else:
    print("The test for overall data vs. desktop data has not reached␣
 ↪statistical significance.")
```

The test for overall data vs. desktop data has not reached statistical significance.

[91]:
```
# Perform the test for overall data vs. mobile data
mobile_group = Mobile_data['CTR']
```

```
overall_vs_mobile_significance = check_statistical_significance(overall_group,␣
 ↪mobile_group, alpha)

# Checking if each comparison reaches statistical significance
if overall_vs_mobile_significance:
    print("The test for overall data vs. mobile data has reached statistical␣
 ↪significance.")
else:
    print("The test for overall data vs. mobile data has not reached␣
 ↪statistical significance.")
```

```
The test for overall data vs. mobile data has not reached statistical
significance.
```

Conclusion

We can conclude the following:

1.The required sample size for the test has been reached. which means we collected enough data to perform a reliable statistical analysis.

2.The test has reached statistical significance at a 95% confidence level. This indicates the change in the sign-up button color has had a measurable impact on the Click-Through Rate (CTR) for the entire audience.

3.Desktop and Mobile Significance: The test for the desktop and mobile segment data has not reached statistical significance which means that there is no statistically significant difference in CTR between the control and treatment groups for users on these devices.