Notebook

May 12, 2024

Necessary imports

[5]:
```
import warnings
import itertools
#from pandas import datetime
#from pandas import read_csv
import numpy as np
import pandas as pd
from pandas.plotting import autocorrelation_plot
from sklearn.metrics import mean_squared_error
from math import sqrt
import statsmodels.api as smf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima_model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
import seaborn as sns
sns.set(style="whitegrid")
```

[6]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[7]:
```
import pandas as pd


df_train =df=pd.read_excel("/content/drive/MyDrive/AP moller/DS_ML Coding␣
↪Challenge Dataset (1).xlsx",sheet_name='Training Dataset')
```

[8]:
```
df_train
```

[8]:
```
        ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0              NTM3           X1       A28        WHOLESALE        Large
1              NTM2           X1        A9           DIRECT        Large
2              NTM3           X2       A20           DIRECT        Large
3              NTM3           X1       A18        WHOLESALE        Small
4              NTM2           X1       A28           DIRECT        Large
…                …            …         …               …          …
550171         NTM2           X1        A5           DIRECT        Large
550172         NTM3           X1       A14           DIRECT        Large
550173         NTM2           X1        A5           DIRECT        Small
550174         NTM2           X1        A7           DIRECT        Small
550175         NTM1           X1        A3           DIRECT        Small

        Product Type Month of Sourcing  Sourcing Cost
0             Powder        2021-05-01         10.158
1             Powder        2020-10-01        134.281
2             Powder        2020-12-01         12.456
3             Powder        2021-02-01        107.220
4             Liquid        2020-11-01        197.763
…              …                 …             …
550171        Powder        2020-07-01        136.469
550172        Liquid        2020-10-01         72.559
550173        Powder        2021-03-01        147.639
550174        Powder        2021-02-01        150.044
550175        Powder        2020-11-01        139.421

[550176 rows x 8 columns]
```

[9]:
```python
df_train= df_train.sort_values(by='Month of Sourcing', ascending=False)
```

[10]:
```python
df_train
```

[10]:
```
        ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0              NTM3           X1       A28        WHOLESALE        Large
410215         NTM3           X1       A24           DIRECT        Small
227368         NTM2           X1       A11           DIRECT        Large
136731         NTM1           X1        A9           DIRECT        Large
227357         NTM3           X1       A24           DIRECT        Small
…                …            …         …               …          …
420994         NTM1           X2       A43           DIRECT        Small
67975          NTM1           X2       A44           DIRECT        Large
420992         NTM1           X1        A3           DIRECT        Small
210469         NTM1           X2       A21           DIRECT        Small
338840         NTM2           X1        A5           DIRECT        Large

        Product Type Month of Sourcing  Sourcing Cost
0             Powder        2021-05-01         10.158
```

```
410215       Powder       2021-05-01        64.463
227368       Liquid       2021-05-01       151.696
136731       Powder       2021-05-01       146.982
227357       Powder       2021-05-01        73.149
…             …             …            …
420994       Powder       2020-07-01       157.094
67975        Liquid       2020-07-01         0.001
420992       Powder       2020-07-01       136.924
210469       Powder       2020-07-01        71.853
338840       Powder       2020-07-01       136.469

[550176 rows x 8 columns]
```

[11]:
```python
df_train.shape
```

[11]:
```
(550176, 8)
```

[12]:
```python
df_test=pd.read_excel('/content/drive/MyDrive/AP moller/DS_ML Coding Challenge␣
 ↪Dataset (1).xlsx',sheet_name='Test Dataset')
df_test
```

[12]:
```
   ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0         NTM1           X1        A1           DIRECT        Small
1         NTM1           X1       A10           DIRECT        Large
2         NTM1           X1       A10             ECOM        Large
3         NTM1           X1       A11           DIRECT        Large
4         NTM1           X1        A2           DIRECT        Large
..         …           …         …              …           …
91        NTM3           X1       A44           DIRECT        Small
92        NTM3           X1        A8           DIRECT        Large
93        NTM3           X1        A8           DIRECT        Small
94        NTM3           X2       A20           DIRECT        Large
95        NTM3           X3       A22           RETAIL        Large

   Product Type Month of Sourcing  Sourcing Cost
0        Powder        2021-06-21         103.68
1        Powder        2021-06-21         155.75
2        Powder        2021-06-21         143.02
3        Powder        2021-06-21         139.39
4        Powder        2021-06-21         169.42
..          …               …            …
91       Liquid        2021-06-21          89.57
92       Powder        2021-06-21         114.57
93       Powder        2021-06-21         111.26
94       Powder        2021-06-21          32.32
95       Powder        2021-06-21          40.73
```

```
[96 rows x 8 columns]
```

[13]:
```python
df_test = df_test.dropna(how='all')
df_test
```

[13]:
```
   ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0         NTM1           X1        A1           DIRECT        Small
1         NTM1           X1       A10           DIRECT        Large
2         NTM1           X1       A10             ECOM        Large
3         NTM1           X1       A11           DIRECT        Large
4         NTM1           X1        A2           DIRECT        Large
..         …          …       …              …          …
91        NTM3           X1       A44           DIRECT        Small
92        NTM3           X1        A8           DIRECT        Large
93        NTM3           X1        A8           DIRECT        Small
94        NTM3           X2       A20           DIRECT        Large
95        NTM3           X3       A22           RETAIL        Large

   Product Type Month of Sourcing  Sourcing Cost
0        Powder        2021-06-21         103.68
1        Powder        2021-06-21         155.75
2        Powder        2021-06-21         143.02
3        Powder        2021-06-21         139.39
4        Powder        2021-06-21         169.42
..          …               …            …
91       Liquid        2021-06-21          89.57
92       Powder        2021-06-21         114.57
93       Powder        2021-06-21         111.26
94       Powder        2021-06-21          32.32
95       Powder        2021-06-21          40.73

[96 rows x 8 columns]
```

[14]:
```python
TrainTestCombined = pd.concat([df_train, df_test], ignore_index=True)
TrainTestCombined
```

[14]:
```
       ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0             NTM3           X1       A28        WHOLESALE        Large
1             NTM3           X1       A24           DIRECT        Small
2             NTM2           X1       A11           DIRECT        Large
3             NTM1           X1        A9           DIRECT        Large
4             NTM3           X1       A24           DIRECT        Small
…             …          …       …              …          …
550267        NTM3           X1       A44           DIRECT        Small
550268        NTM3           X1        A8           DIRECT        Large
550269        NTM3           X1        A8           DIRECT        Small
550270        NTM3           X2       A20           DIRECT        Large
```

```
550271        NTM3          X3       A22          RETAIL        Large

       Product Type Month of Sourcing  Sourcing Cost
0            Powder        2021-05-01         10.158
1            Powder        2021-05-01         64.463
2            Liquid        2021-05-01        151.696
3            Powder        2021-05-01        146.982
4            Powder        2021-05-01         73.149
…              …              …             …
550267       Liquid        2021-06-21         89.570
550268       Powder        2021-06-21        114.570
550269       Powder        2021-06-21        111.260
550270       Powder        2021-06-21         32.320
550271       Powder        2021-06-21         40.730

[550272 rows x 8 columns]
```

##number of duplicate rows

[15]:
```
duplicate_rows_train = df_train[df_train.duplicated()]

# Get the number of duplicate rows
num_duplicate_rows_train = len(duplicate_rows_train)

print("Number of duplicate rows in training set:", num_duplicate_rows_train)
```

```
Number of duplicate rows in training set: 541165
```

[16]:
```
duplicate_rows_test = df_test[df_test.duplicated()]

# Get the number of duplicate rows
num_duplicate_rows_test = len(duplicate_rows_test)

print("Number of duplicate rows in testing set:", num_duplicate_rows_test)
```

```
Number of duplicate rows in testing set: 0
```

[17]:
```
duplicate_rows = TrainTestCombined[TrainTestCombined.duplicated()]

# Get the number of duplicate rows
num_duplicate_rows = len(duplicate_rows)

print("Number of duplicate rows in combined dataset:", num_duplicate_rows)
```

```
Number of duplicate rows in combined dataset: 541165
```

[18]:
```
duplicate_rows
```

[18]:
```
        ProductType Manufacturer Area Code Sourcing Channel Product Size  \
20             NTM1           X1        A1           DIRECT        Small
31             NTM1           X1       A33           DIRECT        Large
46             NTM2           X1        A6           DIRECT        Large
52             NTM1           X2       A40           DIRECT        Large
55             NTM2           X2       A31           DIRECT        Large
…               …          …        …             …          …
550171         NTM1           X2       A43           DIRECT        Small
550172         NTM1           X2       A44           DIRECT        Large
550173         NTM1           X1        A3           DIRECT        Small
550174         NTM1           X2       A21           DIRECT        Small
550175         NTM2           X1        A5           DIRECT        Large

       Product Type Month of Sourcing  Sourcing Cost
20           Powder        2021-05-01        114.899
31           Powder        2021-05-01        133.300
46           Powder        2021-05-01        144.391
52           Liquid        2021-05-01         24.479
55           Powder        2021-05-01          4.428
…             …               …             …
550171       Powder        2020-07-01        157.094
550172       Liquid        2020-07-01          0.001
550173       Powder        2020-07-01        136.924
550174       Powder        2020-07-01         71.853
550175       Powder        2020-07-01        136.469

[541165 rows x 8 columns]
```

[19]:
```
(550176-541165)
```

[19]: 9011

[20]:
```
(550272-542796)
```

[20]: 7476

[23]:
```
df=df_train.copy()
```

##Number of null values

[24]:
```
null_summary = df.isnull().sum()
null_summary
```

[24]:
```
ProductType         0
Manufacturer        0
Area Code           0
Sourcing Channel    0
Product Size        0
```

```
Product Type         0
Month of Sourcing    0
Sourcing Cost        0
dtype: int64
```

[25]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 550176 entries, 0 to 338840
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   ProductType        550176 non-null  object
 1   Manufacturer       550176 non-null  object
 2   Area Code          550176 non-null  object
 3   Sourcing Channel   550176 non-null  object
 4   Product Size       550176 non-null  object
 5   Product Type       550176 non-null  object
 6   Month of Sourcing  550176 non-null  datetime64[ns]
 7   Sourcing Cost      550176 non-null  float64
dtypes: datetime64[ns](1), float64(1), object(6)
memory usage: 37.8+ MB
```

##describing the dataset

[26]:
```python
df.describe()
```

[26]:

	Month of Sourcing	Sourcing Cost
count	550176	550176.000000
mean	2020-12-08 10:27:28.769848576	108.816793
min	2020-07-01 00:00:00	-196.070000
25%	2020-10-01 00:00:00	57.000000
50%	2020-12-01 00:00:00	132.000000
75%	2021-03-01 00:00:00	146.147000
max	2021-05-01 00:00:00	32632.500000
std	NaN	104.390097

##number of rows where the soourcing cost is zero

[27]:
```python
df[df["Sourcing Cost"]==0].count()
```

[27]:
```
ProductType          10084
Manufacturer         10084
Area Code            10084
Sourcing Channel     10084
Product Size         10084
Product Type         10084
Month of Sourcing    10084
Sourcing Cost        10084
```

```
dtype: int64
```

##number of rows where the sourcing cost is negative

[28]:
```
negative_entries = df[df['Sourcing Cost'] < 0]

print("Number of rows with negative sourcing cost:", len(negative_entries))
```

```
Number of rows with negative sourcing cost: 2231
```

##categorical columns

[29]:
```
categorical_columns = df.select_dtypes(include=['object']).columns.tolist()

print("Categorical Columns:")
for col in categorical_columns:
    print(col)
```

```
Categorical Columns:
ProductType
Manufacturer
Area Code
Sourcing Channel
Product Size
Product Type
```

##unique entries in each categorical column

[30]:
```
for col in categorical_columns:
    unique_entries = df[col].nunique()
    print(f"Number of unique entries in {col}: {unique_entries}")
```

```
Number of unique entries in ProductType: 3
Number of unique entries in Manufacturer: 3
Number of unique entries in Area Code: 45
Number of unique entries in Sourcing Channel: 4
Number of unique entries in Product Size: 3
Number of unique entries in Product Type: 2
```

##outlier detection

[31]:
```
numeric_columns = df.select_dtypes(include=['number']).columns
numeric_columns
```

[31]:
```
Index(['Sourcing Cost'], dtype='object')
```

##inter-quartile range

[32]:
```
import pandas as pd
```

```python
def detect_outliers_iqr(column):

    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)

    IQR = Q3 - Q1


    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    return (column < lower_bound) | (column > upper_bound)


numeric_columns = df.select_dtypes(include=['number']).columns
outliers_mask = df[numeric_columns].apply(detect_outliers_iqr)


outliers = df[outliers_mask.any(axis=1)]
print("Rows containing outliers:")
print(outliers)
```

```
Rows containing outliers:
       ProductType Manufacturer Area Code Sourcing Channel Product Size  \
227129        NTM2           X1       A16           DIRECT        Small
228770        NTM2           X1       A16           DIRECT        Small
468492        NTM2           X1       A16           DIRECT        Small
525026        NTM2           X1       A16           DIRECT        Small
505209        NTM2           X1       A16           DIRECT        Small
…              …            …         …               …             …
214770        NTM2           X1       A23           RETAIL        Large
62189         NTM2           X1       A37           DIRECT        Large
63828         NTM2           X1       A37           DIRECT        Large
422548        NTM1           X2       A42           DIRECT        Small
70294         NTM2           X1       A37           DIRECT        Small

       Product Type Month of Sourcing  Sourcing Cost
227129       Powder        2021-05-01       1005.303
228770       Powder        2021-05-01        536.562
468492       Powder        2021-05-01        473.106
525026       Powder        2021-05-01        536.562
505209       Powder        2021-05-01       1005.303
…               …               …            …
214770       Powder        2020-07-01       2412.380
62189        Powder        2020-07-01        336.522
63828        Powder        2020-07-01        336.522
422548       Powder        2020-07-01        288.119
70294        Powder        2020-07-01        720.000
```

```
[2666 rows x 8 columns]
```

[33]:
```python
# Drop the rows containing outliers
cleaned_df = df[~outliers_mask.any(axis=1)]

# Display information about the removed outliers
print("Number of outliers removed:", outliers.shape[0])

# Display the cleaned DataFrame
print("DataFrame after removing outliers:")
print(cleaned_df)
```

```
Number of outliers removed: 2666
DataFrame after removing outliers:
       ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0             NTM3           X1       A28        WHOLESALE        Large
410215        NTM3           X1       A24           DIRECT        Small
227368        NTM2           X1       A11           DIRECT        Large
136731        NTM1           X1        A9           DIRECT        Large
227357        NTM3           X1       A24           DIRECT        Small
…             …             …       …             …          …
420994        NTM1           X2       A43           DIRECT        Small
67975         NTM1           X2       A44           DIRECT        Large
420992        NTM1           X1        A3           DIRECT        Small
210469        NTM1           X2       A21           DIRECT        Small
338840        NTM2           X1        A5           DIRECT        Large

       Product Type Month of Sourcing  Sourcing Cost
0            Powder        2021-05-01         10.158
410215       Powder        2021-05-01         64.463
227368       Liquid        2021-05-01        151.696
136731       Powder        2021-05-01        146.982
227357       Powder        2021-05-01         73.149
…             …              …             …
420994       Powder        2020-07-01        157.094
67975        Liquid        2020-07-01          0.001
420992       Powder        2020-07-01        136.924
210469       Powder        2020-07-01         71.853
338840       Powder        2020-07-01        136.469

[547510 rows x 8 columns]
```

[34]:
```python
df=cleaned_df
len(df)
```

[34]: 547510

##Z-score method

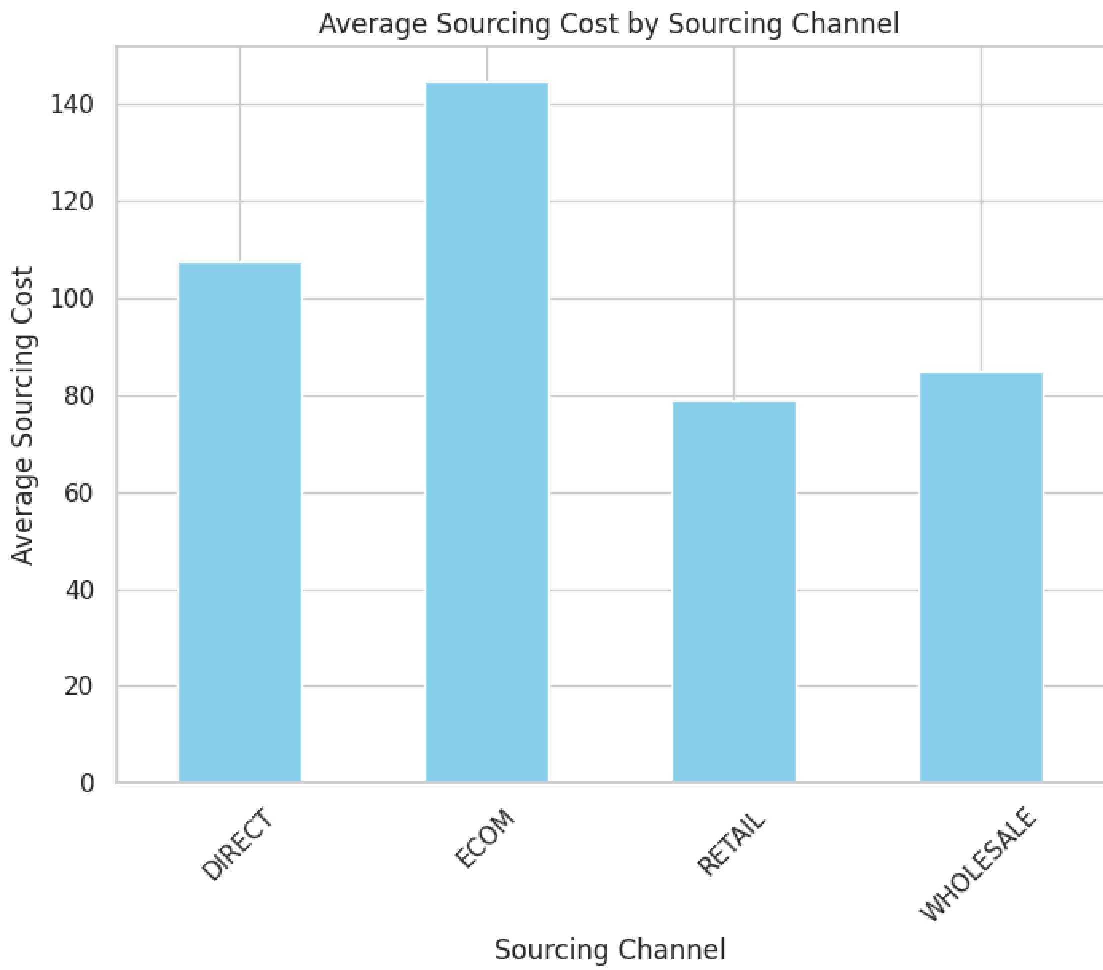
[35]:
```python
from scipy import stats

# Function to detect outliers using Z-score
def detect_outliers_zscore(column, threshold=3):
    z_scores = stats.zscore(column)
    return abs(z_scores) > threshold

# Apply outlier detection to numeric columns in the DataFrame
outliers_mask = df[numeric_columns].apply(detect_outliers_zscore)
outliers = df[outliers_mask.any(axis=1)]
print("Rows containing outliers:")
print(len(outliers))
```

```
Rows containing outliers:
24
```

#Exploratory Data Analysis

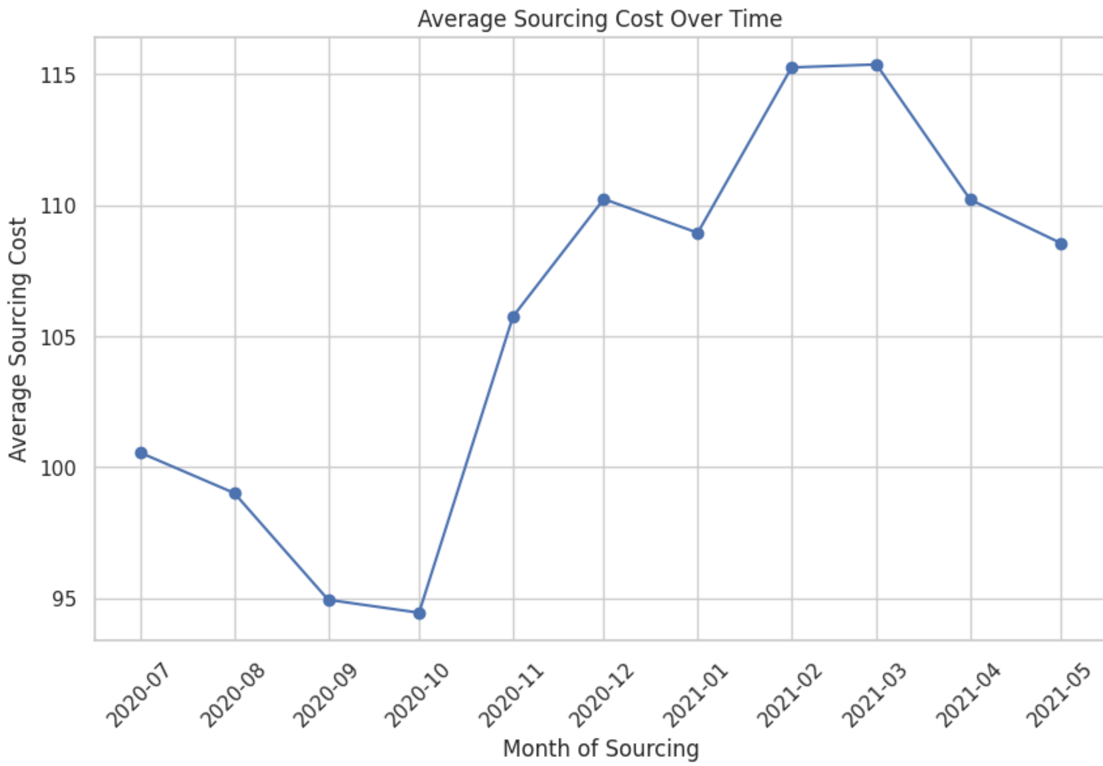
[100]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
```

[107]:
```python
# Bar plot of average 'Sourcing Cost' by 'Sourcing Channel'
plt.figure(figsize=(8, 6))
df.groupby('Sourcing Channel')['Sourcing Cost'].mean().plot(kind='bar',␣
 ↪color='skyblue')
plt.xlabel('Sourcing Channel')
plt.ylabel('Average Sourcing Cost')
plt.title('Average Sourcing Cost by Sourcing Channel')
plt.xticks(rotation=45)
plt.show()
```



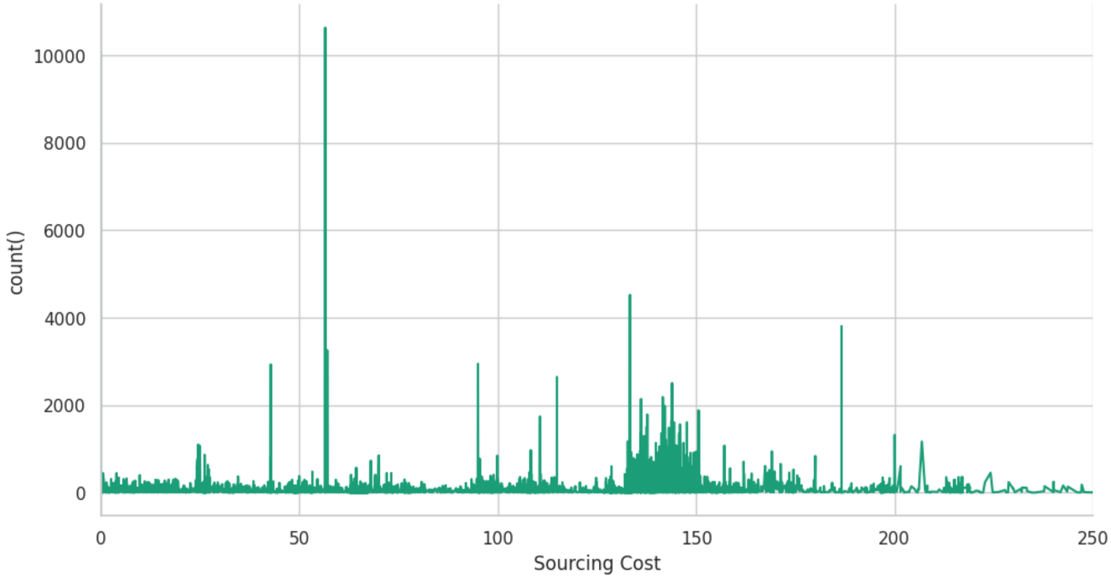
The Sourcing Channel 'ECOM' tends to have the highest average Sourcing Cost compared to other channels in the dataset.

[108]:
```
#Time series plot of 'Sourcing Cost' over time(month)
#Note- here i had to downsample the cost value due to the number of values␣
↪being too large to plot
monthly_sourcing_cost = df.groupby('Month of Sourcing')['Sourcing Cost'].mean()
plt.figure(figsize=(10, 6))
plt.plot(monthly_sourcing_cost.index, monthly_sourcing_cost.values, marker='o',␣
↪linestyle='-')
plt.xlabel('Month of Sourcing')
plt.ylabel('Average Sourcing Cost')
plt.title('Average Sourcing Cost Over Time')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



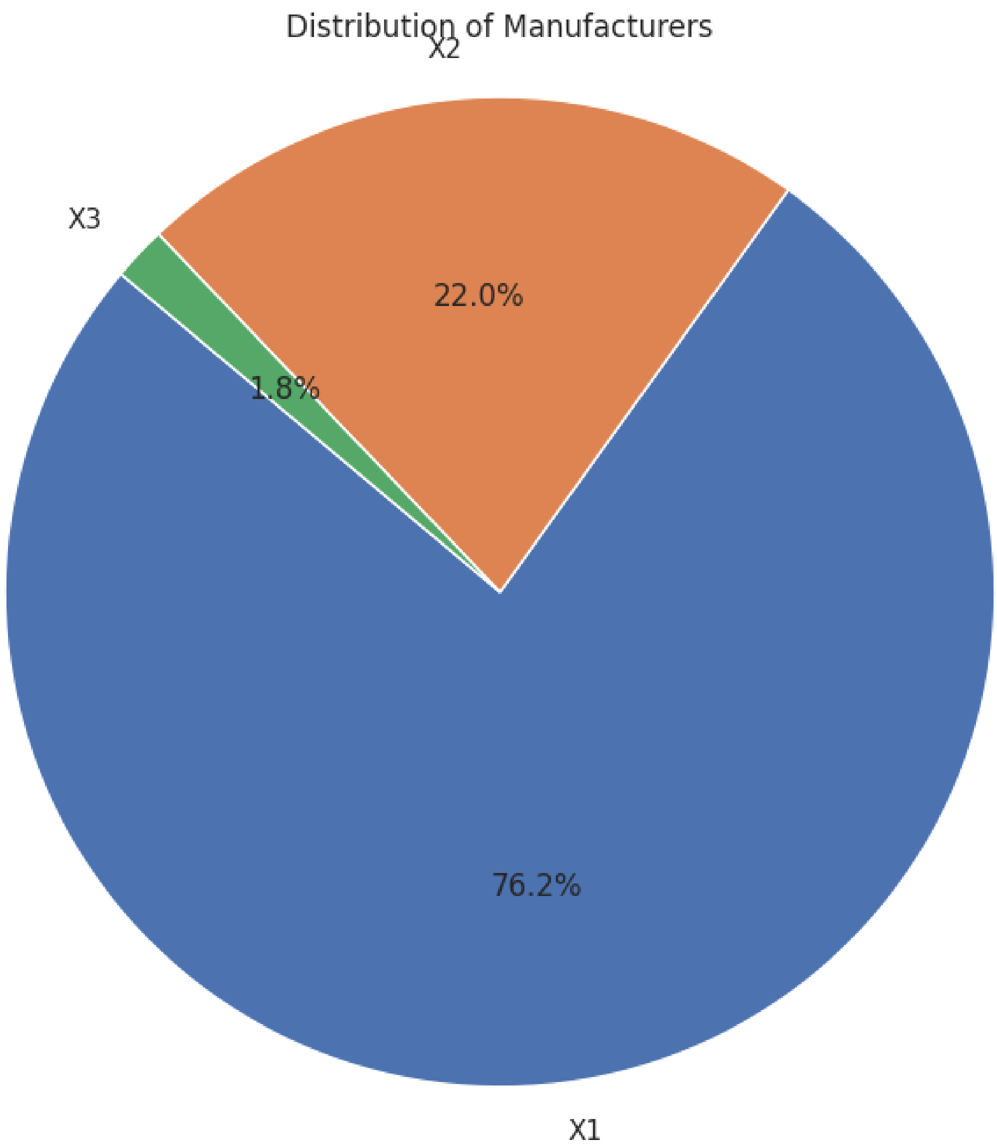
[109]:
```
from matplotlib import pyplot as plt
import seaborn as sns
def _plot_series(series, series_name, series_index=0):
  palette = list(sns.palettes.mpl_palette('Dark2'))
  counted = (series['Sourcing Cost']
              .value_counts()
            .reset_index(name='counts')
            .rename({'index': 'Sourcing Cost'}, axis=1)
            .sort_values('Sourcing Cost', ascending=True))
  xs = counted['Sourcing Cost']
  ys = counted['counts']
  plt.plot(xs, ys, label=series_name, color=palette[series_index %␣
 ↪len(palette)])

fig, ax = plt.subplots(figsize=(10, 5.2), layout='constrained')
df_sorted = df.sort_values('Sourcing Cost', ascending=True)
_plot_series(df_sorted, '')
sns.despine(fig=fig, ax=ax)
plt.xlabel('Sourcing Cost')
_ = plt.ylabel('count()')
plt.xlim(0,250)
```

[109]: (0.0, 250.0)

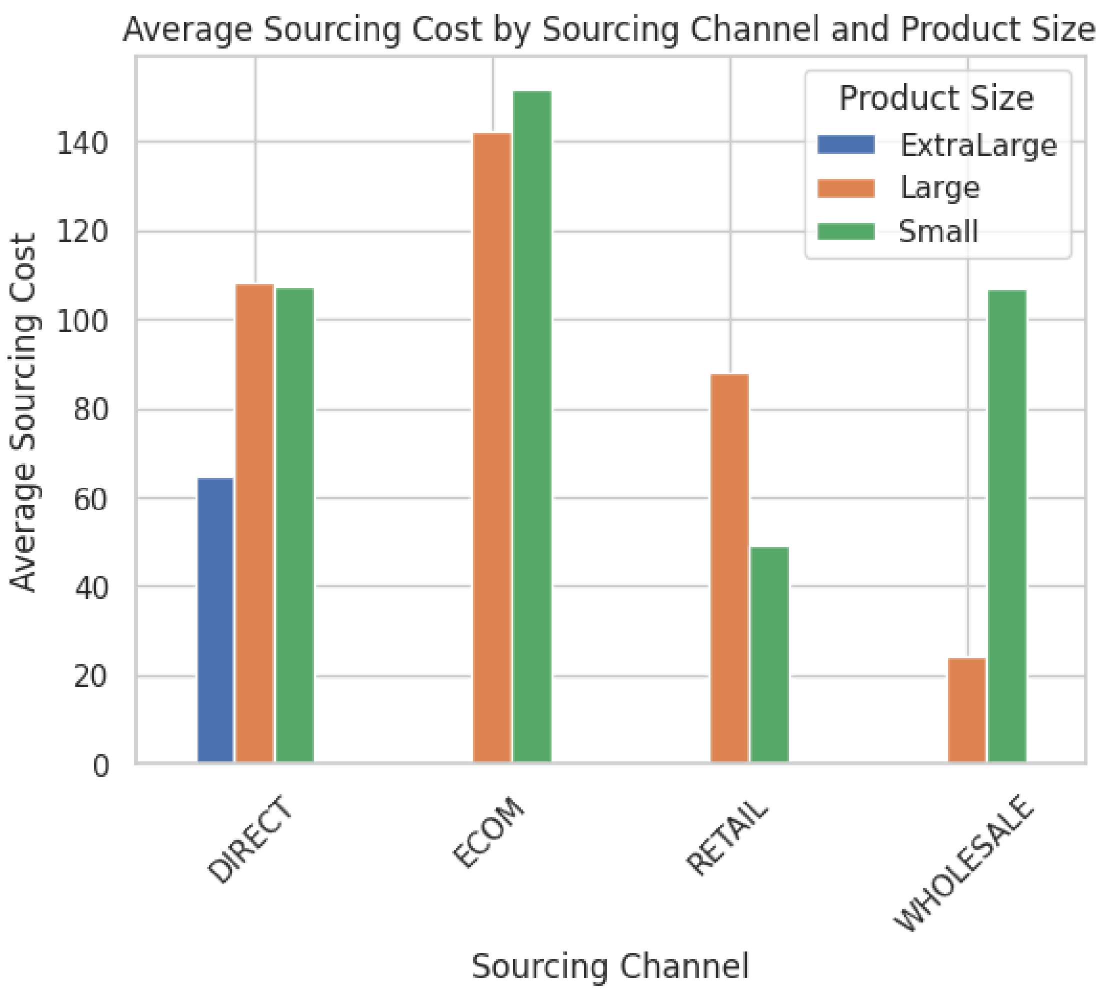


[110]:

```
# Pie chart of manufacturers
plt.figure(figsize=(8, 8))
manufacturer_counts = df['Manufacturer'].value_counts()
plt.pie(manufacturer_counts, labels=manufacturer_counts.index, autopct='%1.
↪1f%%', startangle=140)
plt.title('Distribution of Manufacturers')
plt.axis('equal')
plt.show()
```



[114]:
```
custom_labels = {1: 'Large', 2: 'Small', 0:'Extra Large'}
df.groupby(['Sourcing Channel', 'Product Size'])['Sourcing Cost'].mean().
 ↪unstack().plot(kind='bar')



plt.xlabel('Sourcing Channel')
plt.ylabel('Average Sourcing Cost')
plt.title('Average Sourcing Cost by Sourcing Channel and Product Size')
plt.xticks(rotation=45)
plt.show()
```



##Preprocessing

- encoding
- feature engineering
- handle duplicate values
- scaling of numerical features (when passing to model)
- missing values(no missing values)
- handling outliers
- negative entries in sourcing cost

[44]:
```
df.head()
```

[44]:
```
  ProductType Manufacturer Area Code Sourcing Channel Product Size  \
0        NTM3           X1       A28        WHOLESALE        Large
```

```
410215          NTM3            X1        A24           DIRECT         Small
227368          NTM2            X1        A11           DIRECT         Large
136731          NTM1            X1         A9           DIRECT         Large
227357          NTM3            X1        A24           DIRECT         Small

       Product Type Month of Sourcing  Sourcing Cost
0            Powder        2021-05-01         10.158
410215       Powder        2021-05-01         64.463
227368       Liquid        2021-05-01        151.696
136731       Powder        2021-05-01        146.982
227357       Powder        2021-05-01         73.149
```

[45]:
```
df_training =df.copy()
```

[46]:
```
df_testing=df_test.copy()
```

[47]:
```
from sklearn.preprocessing import LabelEncoder
def label_encode_categorical_columns(df, categorical_columns):
    # Make a copy of the DataFrame to avoid modifying the original
    df_encoded = df.copy()

    # Initialize LabelEncoder
    label_encoder = LabelEncoder()

    # Iterate over each categorical column and perform label encoding
    for col in categorical_columns:
        # Fit label encoder and transform the column
        df_encoded[col] = label_encoder.fit_transform(df_encoded[col])

    return df_encoded
```

[48]:
```
from sklearn.preprocessing import MinMaxScaler
def Normalize_column(df, numeric_columns):
    scaler = MinMaxScaler()
    # Fit and transform the scaler on the numerical columns
    df[numeric_columns] = scaler.fit_transform(df[numeric_columns])
    return df
```

[63]:
```
label_encoder = LabelEncoder()
df_training=label_encode_categorical_columns(df_training,categorical_columns)

df_training['Month of Sourcing'] = label_encoder.
 ↪fit_transform(df_training['Month of Sourcing'])
df_testing=label_encode_categorical_columns(df_testing,categorical_columns)
df_testing['Month of Sourcing'] = label_encoder.fit_transform(df_testing['Month␣
 ↪of Sourcing'])
```

[64]:
```
df_training.head()
```

[64]:
```
        ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0                 2             0         19                 3             1
410215            2             0         16                 0             2
227368            1             0          2                 0             1
136731            0             0         44                 0             1
227357            2             0         16                 0             2

        Product Type  Month of Sourcing  Sourcing Cost
0                  1                 10       0.200889
410215             1                 10       0.361896
227368             0                 10       0.620529
136731             1                 10       0.606552
227357             1                 10       0.387648
```

[65]:
```
df_testing.head()
```

[65]:
```
   ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0            0             0          0                 0             2
1            0             0          1                 0             1
2            0             0          1                 1             1
3            0             0          2                 0             1
4            0             0         11                 0             1

   Product Type  Month of Sourcing  Sourcing Cost
0             1                  0       0.431713
1             1                  0       0.657544
2             1                  0       0.602333
3             1                  0       0.586590
4             1                  0       0.716832
```

[66]:
```
df_training= Normalize_column(df_training, numeric_columns)
df_testing= Normalize_column(df_testing, numeric_columns)
```

[67]:
```
df_training.head()
```

[67]:
```
        ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0                 2             0         19                 3             1
410215            2             0         16                 0             2
227368            1             0          2                 0             1
136731            0             0         44                 0             1
227357            2             0         16                 0             2

        Product Type  Month of Sourcing  Sourcing Cost
0                  1                 10       0.200889
410215             1                 10       0.361896
```

```
227368           0              10      0.620529
136731           1              10      0.606552
227357           1              10      0.387648
```

[68]:
```
df_testing.head()
```

[68]:
```
   ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0            0             0          0                 0             2
1            0             0          1                 0             1
2            0             0          1                 1             1
3            0             0          2                 0             1
4            0             0         11                 0             1

   Product Type  Month of Sourcing  Sourcing Cost
0             1                  0       0.431713
1             1                  0       0.657544
2             1                  0       0.602333
3             1                  0       0.586590
4             1                  0       0.716832
```

##traditional machine learning

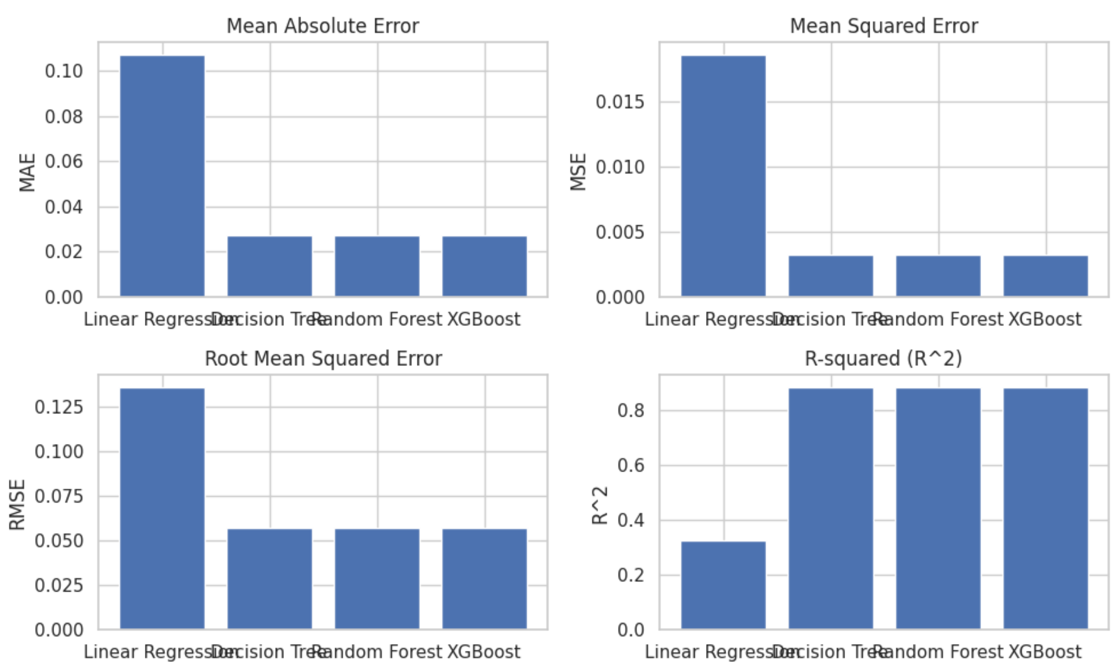
[69]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
import matplotlib.pyplot as plt

# Assuming your preprocessed dataset is stored in a pandas DataFrame named 'df'

# Split the dataset into training and testing sets
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df_training.drop(["Sourcing Cost"], axis=1), df_training["Sourcing Cost"], test_size=0.2, random_state=42)
```

[70]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
import matplotlib.pyplot as plt
```

```python
# Assuming your preprocessed dataset is stored in a pandas DataFrame named 'df'

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df_training.drop(["Sourcing␣
↪Cost"],axis=1), df_training["Sourcing Cost"], test_size=0.2, random_state=42)
```

[71]:
```python
# Initialize models
linear_reg = LinearRegression()
decision_tree = DecisionTreeRegressor()
random_forest = RandomForestRegressor()
xgboost = XGBRegressor()

# Fit models
linear_reg.fit(X_train, y_train)
decision_tree.fit(X_train, y_train)
random_forest.fit(X_train, y_train)
xgboost.fit(X_train, y_train)

# Make predictions
y_pred_linear_reg = linear_reg.predict(X_test)
y_pred_decision_tree = decision_tree.predict(X_test)
y_pred_random_forest = random_forest.predict(X_test)
y_pred_xgboost = xgboost.predict(X_test)

# Calculate error metrics
def calculate_error_metrics(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    rmse = mean_squared_error(y_true, y_pred, squared=False)
    r2 = r2_score(y_true, y_pred)
    return mae, mse, rmse, r2

mae_linear_reg, mse_linear_reg, rmse_linear_reg, r2_linear_reg =␣
↪calculate_error_metrics(y_test, y_pred_linear_reg)
mae_decision_tree, mse_decision_tree, rmse_decision_tree, r2_decision_tree =␣
↪calculate_error_metrics(y_test, y_pred_decision_tree)
mae_random_forest, mse_random_forest, rmse_random_forest, r2_random_forest =␣
↪calculate_error_metrics(y_test, y_pred_random_forest)
mae_xgboost, mse_xgboost, rmse_xgboost, r2_xgboost =␣
↪calculate_error_metrics(y_test, y_pred_xgboost)

# Plot evaluation metrics
models = ['Linear Regression', 'Decision Tree', 'Random Forest', 'XGBoost']
mae_values = [mae_linear_reg, mae_decision_tree, mae_random_forest, mae_xgboost]
mse_values = [mse_linear_reg, mse_decision_tree, mse_random_forest, mse_xgboost]
rmse_values = [rmse_linear_reg, rmse_decision_tree, rmse_random_forest,␣
↪rmse_xgboost]
```

```python
r2_values = [r2_linear_reg, r2_decision_tree, r2_random_forest, r2_xgboost]

plt.figure(figsize=(10, 6))

plt.subplot(2, 2, 1)
plt.bar(models, mae_values)
plt.title('Mean Absolute Error')
plt.ylabel('MAE')

plt.subplot(2, 2, 2)
plt.bar(models, mse_values)
plt.title('Mean Squared Error')
plt.ylabel('MSE')

plt.subplot(2, 2, 3)
plt.bar(models, rmse_values)
plt.title('Root Mean Squared Error')
plt.ylabel('RMSE')

plt.subplot(2, 2, 4)
plt.bar(models, r2_values)
plt.title('R-squared (R^2)')
plt.ylabel('R^2')

plt.tight_layout()
plt.show()
```



[72]:
```
r2_values
```

[72]:
```
[0.3231536406689248,
 0.8821268067235862,
 0.8821184862783993,
 0.8815434326345656]
```

##Testing

[73]:
```
df_testing_1=df_testing.drop(["Sourcing Cost"],axis=1)
df_testing_1["Month of Sourcing"]=11
df_testing_1.head()
```

[73]:
```
   ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0            0             0          0                 0             2
1            0             0          1                 0             1
2            0             0          1                 1             1
3            0             0          2                 0             1
4            0             0         11                 0             1

   Product Type  Month of Sourcing
0             1                 11
1             1                 11
2             1                 11
3             1                 11
4             1                 11
```

[74]:
```
y_test_pred_random_forest = random_forest.predict(df_testing_1)
```

[75]:
```
y_true=df_testing["Sourcing Cost"]
y_true
```

[75]:
```
0     0.431713
1     0.657544
2     0.602333
3     0.586590
4     0.716832
        …
91    0.370517
92    0.478943
93    0.464588
94    0.122219
95    0.158694
Name: Sourcing Cost, Length: 96, dtype: float64
```

[76]:
```
r2 = r2_score(y_true, y_test_pred_random_forest)
r2
```

[76]: 0.6088622798782557

##Deep learning approaches for time series

[77]:
```
df_training.drop(columns=['Sourcing Cost'])
```

[77]:
```
        ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0                 2             0         19                 3             1
410215            2             0         16                 0             2
227368            1             0          2                 0             1
136731            0             0         44                 0             1
227357            2             0         16                 0             2
…               …             …          …                …             …
420994            0             1         36                 0             2
67975             0             1         37                 0             1
420992            0             0         21                 0             2
210469            0             1         13                 0             2
338840            1             0         40                 0             1

        Product Type  Month of Sourcing
0                  1                 10
410215             1                 10
227368             0                 10
136731             1                 10
227357             1                 10
…                …                 …
420994             1                  0
67975              0                  0
420992             1                  0
210469             1                  0
338840             1                  0

[547510 rows x 7 columns]
```

#LSTM(Best model)

[78]:
```
# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
```

```
# Step 3: Prepare data
X = df_training.drop(columns=['Sourcing Cost']).values  # Input features (all␣
↪columns except 'Sourcing Cost')
y = df_training['Sourcing Cost'].values  # Target variable

# Reshape input features for LSTM (assuming a single time step)
# The reshape is necessary for LSTM input (samples, time steps, features)
X = X.reshape(X.shape[0], 1, X.shape[1])

# Step 4: Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)



# Step 8: Make forecasts
# You can make forecasts using model.predict() on new data
# Example: y_pred = model.predict(X_new_data)
```

[79]:
```
X_train.shape
```

[79]: (438008, 1, 7)

[80]:
```
lstm_model = Sequential([
    LSTM(units=50, input_shape=(X_train.shape[1], X_train.shape[2])),
    Dense(1)
])

lstm_model.compile(optimizer='adam', loss='mse')
lstm_model.fit(X_train, y_train, epochs=25, batch_size=32, verbose=1)

loss = lstm_model.evaluate(X_test, y_test, verbose=0)
print(f'Test Loss: {loss}')
```

```
Epoch 1/25
13688/13688 [==============================] - 52s 3ms/step - loss: 0.0104
Epoch 2/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0083
Epoch 3/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0079
Epoch 4/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0075
Epoch 5/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0073
Epoch 6/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0070
Epoch 7/25
13688/13688 [==============================] - 46s 3ms/step - loss: 0.0067
```

```
Epoch 8/25
13688/13688 [==============================] - 47s 3ms/step - loss: 0.0063
Epoch 9/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0060
Epoch 10/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0056
Epoch 11/25
13688/13688 [==============================] - 46s 3ms/step - loss: 0.0053
Epoch 12/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0051
Epoch 13/25
13688/13688 [==============================] - 47s 3ms/step - loss: 0.0050
Epoch 14/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0049
Epoch 15/25
13688/13688 [==============================] - 45s 3ms/step - loss: 0.0048
Epoch 16/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0048
Epoch 17/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0047
Epoch 18/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0046
Epoch 19/25
13688/13688 [==============================] - 46s 3ms/step - loss: 0.0045
Epoch 20/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0045
Epoch 21/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0044
Epoch 22/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0044
Epoch 23/25
13688/13688 [==============================] - 44s 3ms/step - loss: 0.0043
Epoch 24/25
13688/13688 [==============================] - 43s 3ms/step - loss: 0.0043
Epoch 25/25
13688/13688 [==============================] - 46s 3ms/step - loss: 0.0043
Test Loss: 0.004411341156810522
```

[ ]:

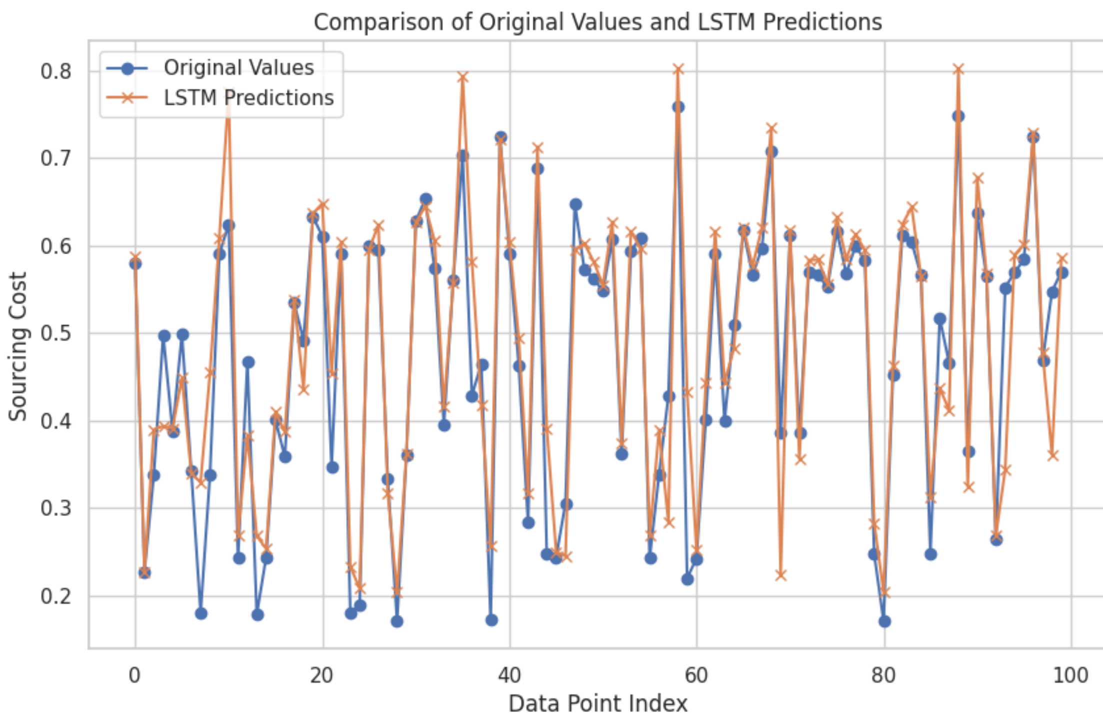
```python
model_file_path = 'lstm_model.h5'

# Save the model
lstm_model.save(model_file_path)

print("LSTM model saved successfully at:", model_file_path)
```

[81]:

```python
import matplotlib.pyplot as plt
```

```
# Step 1: Make predictions using the trained LSTM model
y_pred = lstm_model.predict(X_test)

# Step 2: Extract the first 100 data points from the original dataset and LSTM
 ↪predictions
original_values = y_test[:100]  # Original values
predicted_values = y_pred[:100]  # LSTM predictions

# Step 3: Plot the original values and LSTM predictions
plt.figure(figsize=(10, 6))
plt.plot(original_values, label='Original Values', marker='o')
plt.plot(predicted_values, label='LSTM Predictions', marker='x')
plt.title('Comparison of Original Values and LSTM Predictions')
plt.xlabel('Data Point Index')
plt.ylabel('Sourcing Cost')
plt.legend()
plt.grid(True)
plt.show()
```

```
3422/3422 [==============================] - 8s 2ms/step
```



[82]:
```
r2 = r2_score(original_values, predicted_values)
r2
```

[82]: 0.8421635064329565

##TESTING DATASET

[88]:
```
from sklearn.preprocessing import LabelEncoder

# Assuming your training set DataFrame is named 'train_df'
# Assuming 'categorical_columns' is a list containing the names of categorical␣
↪columns

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Iterate over each categorical column and perform label encoding
for col in categorical_columns:
    # Fit label encoder and transform the column
    df_test[col] = label_encoder.fit_transform(df_test[col])
```

[89]:
```
df_test.head()
```

[89]:
```
   ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0            0             0          0                 0             2
1            0             0          1                 0             1
2            0             0          1                 1             1
3            0             0          2                 0             1
4            0             0         11                 0             1

   Product Type Month of Sourcing  Sourcing Cost
0             1        2021-06-21         103.68
1             1        2021-06-21         155.75
2             1        2021-06-21         143.02
3             1        2021-06-21         139.39
4             1        2021-06-21         169.42
```

[90]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the scaler on the numerical columns
df_test[numeric_columns] = scaler.fit_transform(df_test[numeric_columns])
```

[91]:
```
df_test
```

[91]:
```
     ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0              0             0          0                 0             2
1              0             0          1                 0             1
2              0             0          1                 1             1
3              0             0          2                 0             1
4              0             0         11                 0             1
```

```
..           …           …       …               …           …
91            2             0       37              0             2
92            2             0       43              0             1
93            2             0       43              0             1
94            2             1       12              0             1
95            2             2       14              2             1

    Product Type Month of Sourcing  Sourcing Cost
0              1        2021-06-21       0.431713
1              1        2021-06-21       0.657544
2              1        2021-06-21       0.602333
3              1        2021-06-21       0.586590
4              1        2021-06-21       0.716832
..           …               …             …
91             0        2021-06-21       0.370517
92             1        2021-06-21       0.478943
93             1        2021-06-21       0.464588
94             1        2021-06-21       0.122219
95             1        2021-06-21       0.158694

[96 rows x 8 columns]
```

[92]:
```
df_test["Month of Sourcing"] = label_encoder.fit_transform(df_test["Month of␣
↪Sourcing"])
```

[93]:
```
df_test.head()
```

[93]:
```
   ProductType  Manufacturer  Area Code  Sourcing Channel  Product Size  \
0            0             0          0                 0             2
1            0             0          1                 0             1
2            0             0          1                 1             1
3            0             0          2                 0             1
4            0             0         11                 0             1

   Product Type  Month of Sourcing  Sourcing Cost
0             1                  0       0.431713
1             1                  0       0.657544
2             1                  0       0.602333
3             1                  0       0.586590
4             1                  0       0.716832
```

[94]:
```
X = df_test.drop(columns=['Sourcing Cost']).values  # Input features (all␣
↪columns except 'Sourcing Cost')
y = df_test['Sourcing Cost'].values  # Target variable

# Reshape input features for LSTM (assuming a single time step)
# The reshape is necessary for LSTM input (samples, time steps, features)
```

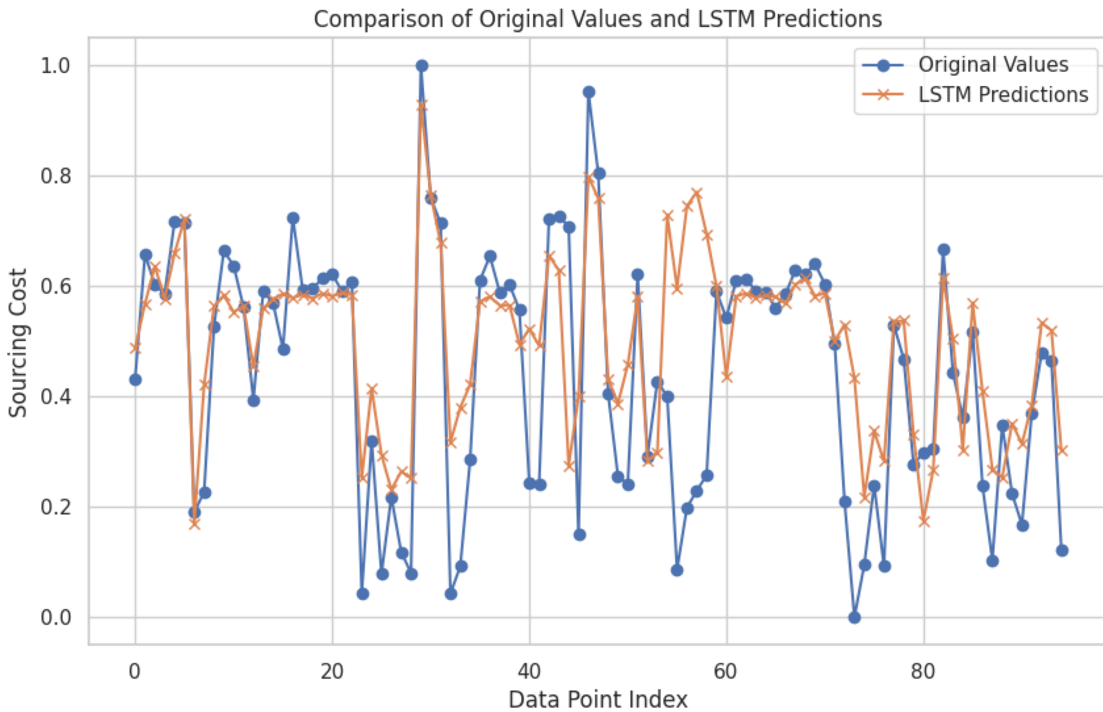
```
X = X.reshape(X.shape[0], 1, X.shape[1])
```

[95]:
```
X.shape
```

[95]: (96, 1, 7)

[96]:
```
import matplotlib.pyplot as plt

# Step 1: Make predictions using the trained LSTM model
y_pred = lstm_model.predict(X)

# Step 2: Extract the first 100 data points from the original dataset and LSTM␣
↪predictions
original_values = y[:-1]  # Original values
predicted_values = y_pred[:-1]  # LSTM predictions

# Step 3: Plot the original values and LSTM predictions
plt.figure(figsize=(10, 6))
plt.plot(original_values, label='Original Values', marker='o')
plt.plot(predicted_values, label='LSTM Predictions', marker='x')
plt.title('Comparison of Original Values and LSTM Predictions')
plt.xlabel('Data Point Index')
plt.ylabel('Sourcing Cost')
plt.legend()
plt.grid(True)
plt.show()
```

```
3/3 [==============================] - 0s 4ms/step
```



as we can see, LSTM is able to classify and forcast the points quite accurately

```
[ ]:
```