AB Testing

February 29, 2024

1 A Data-Driven Exploration of Amazon Sales Reports through A/B Testing

[1]:
```
# Importing necessary libraries
import numpy as np
import pandas as pd
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import re
```

[2]:
```
df=pd.read_csv("C:/Users/Dharini/Downloads/Amazon Sale Report.
 ↪csv",low_memory=False)
```

[3]:
```
df.head(3)
```

[3]:
```
   index             Order ID      Date                        Status  \
0      0  405-8078784-5731545  04-30-22                     Cancelled
1      1  171-9198151-1101146  04-30-22  Shipped - Delivered to Buyer
2      2  404-0687676-7273146  04-30-22                       Shipped

  Fulfilment Sales Channel  ship-service-level    Style             SKU  \
0   Merchant      Amazon.in           Standard   SET389   SET389-KR-NP-S
1   Merchant      Amazon.in           Standard  JNE3781  JNE3781-KR-XXXL
2     Amazon      Amazon.in          Expedited  JNE3371    JNE3371-KR-XL

  Category  … currency  Amount    ship-city   ship-state ship-postal-code  \
0      Set  …      INR  647.62       MUMBAI  MAHARASHTRA         400081.0
1    kurta  …      INR  406.00    BENGALURU    KARNATAKA         560085.0
2    kurta  …      INR  329.00  NAVI MUMBAI  MAHARASHTRA         410210.0

   ship-country                                  promotion-ids    B2B  \
0            IN                                            NaN  False
1            IN   Amazon PLCC Free-Financing Universal Merchant …  False
2            IN       IN Core Free Shipping 2015/04/08 23-48-5-108   True
```

```
   fulfilled-by Unnamed: 22
0     Easy Ship         NaN
1     Easy Ship         NaN
2           NaN         NaN

[3 rows x 24 columns]
```

2 Data Cleaning

[4]:
```
df.shape
```

[4]:
```
(128975, 24)
```

Raw data contains 128975 records and 24 columns.

[5]:
```
df.columns
```

[5]:
```
Index(['index', 'Order ID', 'Date', 'Status', 'Fulfilment', 'Sales Channel ',
       'ship-service-level', 'Style', 'SKU', 'Category', 'Size', 'ASIN',
       'Courier Status', 'Qty', 'currency', 'Amount', 'ship-city',
       'ship-state', 'ship-postal-code', 'ship-country', 'promotion-ids',
       'B2B', 'fulfilled-by', 'Unnamed: 22'],
      dtype='object')
```

[6]:
```
# standardize the column names by renaming it
df = df.rename(columns={'Order ID': 'Order_ID', 'Sales Channel ':␣
 ↪'Sales_channel',
       'ship-service-level': 'ship_service_level', 'ship-city': 'ship_city',
       'ship-state': 'ship_state', 'ship-postal-code': 'ship_postal_code',␣
 ↪'ship-country': 'ship_country',
       'promotion-ids': 'promotion_ids','Courier Status': 'Courier_Status',␣
 ↪'currency': 'Currency',
       'fulfilled-by':'fulfilled_by'})
```

[7]:
```
# checking the information of the raw dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128975 entries, 0 to 128974
Data columns (total 24 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   index               128975 non-null  int64
 1   Order_ID            128975 non-null  object
 2   Date                128975 non-null  object
 3   Status              128975 non-null  object
 4   Fulfilment          128975 non-null  object
 5   Sales_channel       128975 non-null  object
```

```
 6   ship_service_level  128975 non-null  object
 7   Style               128975 non-null  object
 8   SKU                 128975 non-null  object
 9   Category            128975 non-null  object
 10  Size                128975 non-null  object
 11  ASIN                128975 non-null  object
 12  Courier_Status      122103 non-null  object
 13  Qty                 128975 non-null  int64
 14  Currency            121180 non-null  object
 15  Amount              121180 non-null  float64
 16  ship_city           128942 non-null  object
 17  ship_state          128942 non-null  object
 18  ship_postal_code    128942 non-null  float64
 19  ship_country        128942 non-null  object
 20  promotion_ids       79822 non-null   object
 21  B2B                 128975 non-null  bool
 22  fulfilled_by        39277 non-null   object
 23  Unnamed: 22         79925 non-null   object
dtypes: bool(1), float64(2), int64(2), object(19)
memory usage: 22.8+ MB
```

[8]:

```
# Setting the column 'index' as the index of the dataframe. Where the number of␣
 ↪columns becomes 22.
df.set_index('index',inplace=True)
```

[9]:

```
def missing_evaluation(dataframe):

    # Column 'qt_missing': Number of NaN values
    df_missing_stats = pd.DataFrame(data=dataframe.isna().sum(),␣
 ↪index=dataframe.columns, columns=['qt_missing'])
    # Column 'nr_unique_values': Number of unique values
    df_missing_stats['qt_unique_values'] = pd.DataFrame(data=dataframe.
 ↪nunique(), index=dataframe.columns)
    # Column 'unique_values': unique values of the attributes
    df_missing_stats['unique_values'] = pd.DataFrame(data=dataframe.apply(pd.
 ↪unique), index=dataframe.columns)
    # Column 'perc_missing': percentage of missing values
    df_missing_stats['perc_missing'] = pd.DataFrame(data=dataframe.isnull().
 ↪mean())
    return df_missing_stats
```

[10]:

```
df_missing = missing_evaluation(df)
df_missing
```

[10]:

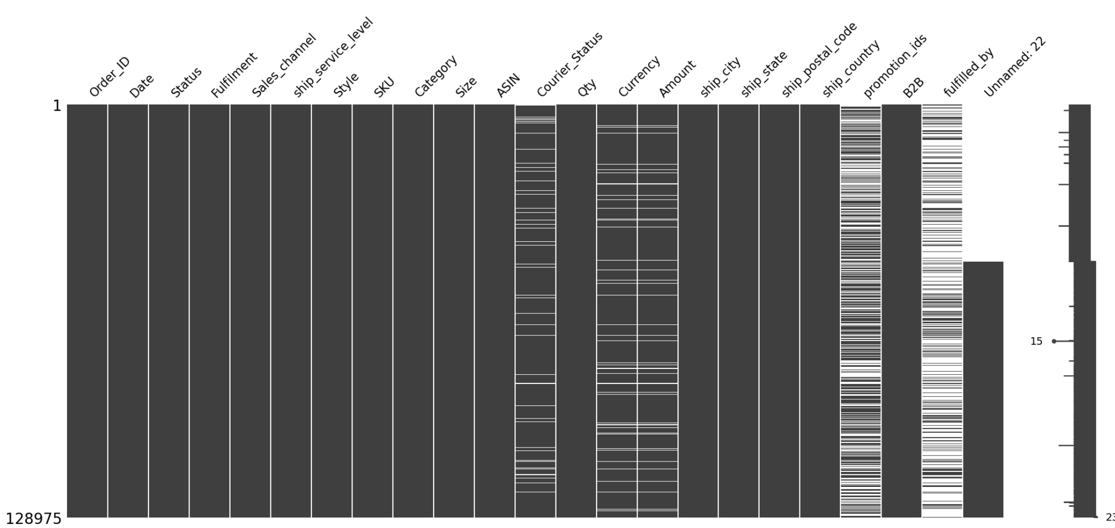
```
                    qt_missing  qt_unique_values  \
Order_ID                     0            120378
Date                         0                91
```

Status	0	13
Fulfilment	0	2
Sales_channel	0	2
ship_service_level	0	2
Style	0	1377
SKU	0	7195
Category	0	9
Size	0	11
ASIN	0	7190
Courier_Status	6872	3
Qty	0	10
Currency	7795	1
Amount	7795	1410
ship_city	33	8955
ship_state	33	69
ship_postal_code	33	9459
ship_country	33	1
promotion_ids	49153	5787
B2B	0	2
fulfilled_by	89698	1
Unnamed: 22	49050	1

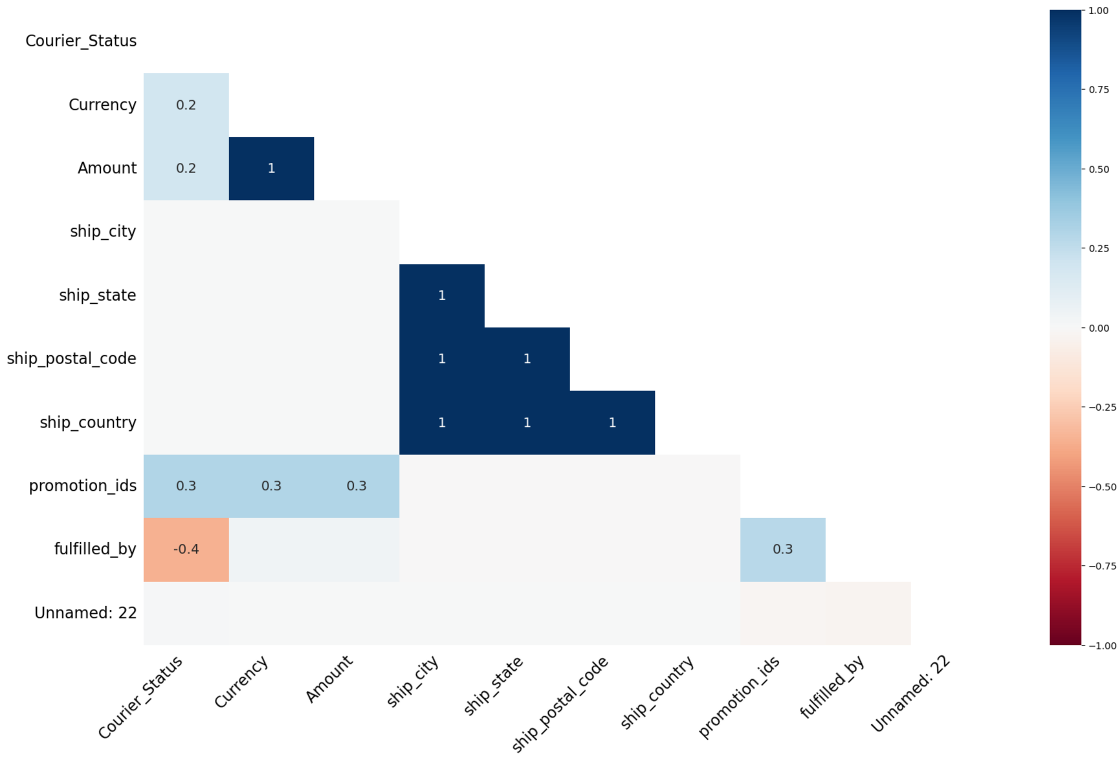
	unique_values \
Order_ID	[405-8078784-5731545, 171-9198151-1101146, 404…
Date	[04-30-22, 04-29-22, 04-28-22, 04-27-22, 04-26…
Status	[Cancelled, Shipped - Delivered to Buyer, Ship…
Fulfilment	[Merchant, Amazon]
Sales_channel	[Amazon.in, Non-Amazon]
ship_service_level	[Standard, Expedited]
Style	[SET389, JNE3781, JNE3371, J0341, JNE3671, SET…
SKU	[SET389-KR-NP-S, JNE3781-KR-XXXL, JNE3371-KR-X…
Category	[Set, kurta, Western Dress, Top, Ethnic Dress,…
Size	[S, 3XL, XL, L, XXL, XS, 6XL, M, 4XL, 5XL, Free]
ASIN	[B09KXVBD7Z, B09K3WFS32, B07WV4JV4D, B099NRCT7…
Courier_Status	[nan, Shipped, Cancelled, Unshipped]
Qty	[0, 1, 2, 15, 3, 9, 13, 5, 4, 8]
Currency	[INR, nan]
Amount	[647.62, 406.0, 329.0, 753.33, 574.0, 824.0, 6…
ship_city	[MUMBAI, BENGALURU, NAVI MUMBAI, PUDUCHERRY, C…
ship_state	[MAHARASHTRA, KARNATAKA, PUDUCHERRY, TAMIL NAD…
ship_postal_code	[400081.0, 560085.0, 410210.0, 605008.0, 60007…
ship_country	[IN, nan]
promotion_ids	[nan, Amazon PLCC Free-Financing Universal Mer…
B2B	[False, True]
fulfilled_by	[Easy Ship, nan]
Unnamed: 22	[nan, False]

```
                   perc_missing
Order_ID               0.000000
Date                   0.000000
Status                 0.000000
Fulfilment             0.000000
Sales_channel          0.000000
ship_service_level     0.000000
Style                  0.000000
SKU                    0.000000
Category               0.000000
Size                   0.000000
ASIN                   0.000000
Courier_Status         0.053282
Qty                    0.000000
Currency               0.060438
Amount                 0.060438
ship_city              0.000256
ship_state             0.000256
ship_postal_code       0.000256
ship_country           0.000256
promotion_ids          0.381105
B2B                    0.000000
fulfilled_by           0.695468
Unnamed: 22            0.380306
```

[11]:
```
# Visualizing the missing values with missingno matrix
msno.matrix(df);
```



[12]:
```
# Using the heatmap to identify correlations of the nullity between each of the␣
↪different columns.
msno.heatmap(df);
```



[13]:
```
# Replacing NaN values in column 'Courier_Status' with the value 'Unknown'
df['Courier_Status'].fillna('Unknown', inplace = True)
```

[14]:
```
# Fill missing values in Amount with zero
set_idx_amount_null = set(df[df['Amount'].isnull()].index)
```

[15]:
```
#Fill missing values in Currency with 'INR'
set2_idx_currency_null = set(df[df['Currency'].isnull()].index)
```

[16]:
```
df['Amount'].fillna(0, inplace = True)
df['Currency'].fillna('INR', inplace = True)
```

[17]:
```
# Replacing NaN values in column 'promotion_ids' with the value 'Unknown'
df['promotion_ids'].fillna('No Promo', inplace = True)
```

[18]:
```
#ship_city,ship_state and ship_country ship_state: missing values filled with␣
↪'Unknown'
df['ship_city'].fillna('Unknown', inplace = True)
df['ship_state'].fillna('Unknown', inplace = True)
```

```
df['ship_country'].fillna('Unknown', inplace = True)
#ship_postal_code: missing values filled with zero
df['ship_postal_code'].fillna(0, inplace = True)
```

[19]:
```
#fulfilled_by: missing values filled with 'FBA' (Fulfilled by Amazon).
df['fulfilled_by'].fillna('FBA', inplace = True)
```

[20]:
```
# dropping unnamed column because it is not relevant
df.drop(columns = ['Unnamed: 22'], inplace = True)
```

[21]:
```
df.isna().sum()
```

[21]:
```
Order_ID             0
Date                 0
Status               0
Fulfilment           0
Sales_channel        0
ship_service_level   0
Style                0
SKU                  0
Category             0
Size                 0
ASIN                 0
Courier_Status       0
Qty                  0
Currency             0
Amount               0
ship_city            0
ship_state           0
ship_postal_code     0
ship_country         0
promotion_ids        0
B2B                  0
fulfilled_by         0
dtype: int64
```

[22]:
```
df_missing = missing_evaluation(df)
df_missing
```

[22]:
```
                    qt_missing  qt_unique_values  \
Order_ID                     0            120378
Date                         0                91
Status                       0                13
Fulfilment                   0                 2
Sales_channel                0                 2
ship_service_level           0                 2
Style                        0              1377
```

```
SKU                         0          7195
Category                    0             9
Size                        0            11
ASIN                        0          7190
Courier_Status              0             4
Qty                         0            10
Currency                    0             1
Amount                      0          1410
ship_city                   0          8956
ship_state                  0            70
ship_postal_code            0          9460
ship_country                0             2
promotion_ids               0          5788
B2B                         0             2
fulfilled_by                0             2

                                                         unique_values  \
Order_ID            [405-8078784-5731545, 171-9198151-1101146, 404…
Date                [04-30-22, 04-29-22, 04-28-22, 04-27-22, 04-26…
Status              [Cancelled, Shipped - Delivered to Buyer, Ship…
Fulfilment                                     [Merchant, Amazon]
Sales_channel                              [Amazon.in, Non-Amazon]
ship_service_level                           [Standard, Expedited]
Style               [SET389, JNE3781, JNE3371, J0341, JNE3671, SET…
SKU                 [SET389-KR-NP-S, JNE3781-KR-XXXL, JNE3371-KR-X…
Category            [Set, kurta, Western Dress, Top, Ethnic Dress,…
Size                 [S, 3XL, XL, L, XXL, XS, 6XL, M, 4XL, 5XL, Free]
ASIN                [B09KXVBD7Z, B09K3WFS32, B07WV4JV4D, B099NRCT7…
Courier_Status               [Unknown, Shipped, Cancelled, Unshipped]
Qty                                   [0, 1, 2, 15, 3, 9, 13, 5, 4, 8]
Currency                                                         [INR]
Amount              [647.62, 406.0, 329.0, 753.33, 574.0, 824.0, 6…
ship_city           [MUMBAI, BENGALURU, NAVI MUMBAI, PUDUCHERRY, C…
ship_state          [MAHARASHTRA, KARNATAKA, PUDUCHERRY, TAMIL NAD…
ship_postal_code    [400081.0, 560085.0, 410210.0, 605008.0, 60007…
ship_country                                           [IN, Unknown]
promotion_ids       [No Promo, Amazon PLCC Free-Financing Universa…
B2B                                                    [False, True]
fulfilled_by                                       [Easy Ship, FBA]

                    perc_missing
Order_ID                     0.0
Date                         0.0
Status                       0.0
Fulfilment                   0.0
Sales_channel                0.0
ship_service_level           0.0
```

```
Style                 0.0
SKU                   0.0
Category              0.0
Size                  0.0
ASIN                  0.0
Courier_Status        0.0
Qty                   0.0
Currency              0.0
Amount                0.0
ship_city             0.0
ship_state            0.0
ship_postal_code      0.0
ship_country          0.0
promotion_ids         0.0
B2B                   0.0
fulfilled_by          0.0
```

[23]:
```
# Order_ID: removing extra white spaces from the beginning and end, and change␣
↪all the characters in UPPER case.
df['Order_ID'] = df['Order_ID'].str.strip()
df['Order_ID'] = df['Order_ID'].str.upper()
```

[24]:
```
df.head()
```

[24]:
```
                  Order_ID      Date                        Status Fulfilment  \
index
0      405-8078784-5731545  04-30-22                     Cancelled   Merchant
1      171-9198151-1101146  04-30-22  Shipped - Delivered to Buyer   Merchant
2      404-0687676-7273146  04-30-22                       Shipped     Amazon
3      403-9615377-8133951  04-30-22                     Cancelled   Merchant
4      407-1069790-7240320  04-30-22                       Shipped     Amazon

      Sales_channel ship_service_level    Style              SKU  \
index
0         Amazon.in           Standard   SET389   SET389-KR-NP-S
1         Amazon.in           Standard  JNE3781  JNE3781-KR-XXXL
2         Amazon.in          Expedited  JNE3371    JNE3371-KR-XL
3         Amazon.in           Standard    J0341       J0341-DR-L
4         Amazon.in          Expedited  JNE3671  JNE3671-TU-XXXL

             Category Size  … Qty Currency  Amount    ship_city   ship_state  \
index                       …
0                 Set    S  …   0      INR  647.62       MUMBAI  MAHARASHTRA
1               kurta  3XL  …   1      INR  406.00    BENGALURU    KARNATAKA
2               kurta   XL  …   1      INR  329.00  NAVI MUMBAI  MAHARASHTRA
3       Western Dress    L  …   0      INR  753.33   PUDUCHERRY   PUDUCHERRY
4                 Top  3XL  …   1      INR  574.00      CHENNAI   TAMIL NADU
```

```
      ship_postal_code ship_country  \
index
0            400081.0           IN
1            560085.0           IN
2            410210.0           IN
3            605008.0           IN
4            600073.0           IN

                                           promotion_ids    B2B fulfilled_by
index
0                                               No Promo  False    Easy Ship
1      Amazon PLCC Free-Financing Universal Merchant …  False    Easy Ship
2           IN Core Free Shipping 2015/04/08 23-48-5-108   True          FBA
3                                               No Promo  False    Easy Ship
4                                               No Promo  False          FBA

[5 rows x 22 columns]
```

[25]:
```
# Set column 'Date' to data type datetime

df['Date'] = pd.to_datetime(df['Date'], format="%m-%d-%y")
```

[26]:
```
df['Status'] = df['Status'].str.strip()
# Check column 'Status', result: it doesn't need intervention
for value in df.Status.sort_values().unique():
    print(f"'{value}'")
```

```
'Cancelled'
'Pending'
'Pending - Waiting for Pick Up'
'Shipped'
'Shipped - Damaged'
'Shipped - Delivered to Buyer'
'Shipped - Lost in Transit'
'Shipped - Out for Delivery'
'Shipped - Picked Up'
'Shipped - Rejected by Buyer'
'Shipped - Returned to Seller'
'Shipped - Returning to Seller'
'Shipping'
```

[27]:
```
#remove extra white spaces from the beginning and end, and set the characters␣
↪in UPPER case.
df['Style'] = df['Style'].str.strip()
df['Style'] = df['Style'].str.upper()
df['SKU'] = df['SKU'].str.strip()
df['SKU'] = df['SKU'].str.upper()
```

[28]:
```
#remove extra white spaces from the beginning and end, and set the characters␣
 ↪in UPPER case.
df['Category'] = df['Category'].str.strip()
df['Category'] = df['Category'].str.upper()
```

[29]:
```
df['ASIN'] = df['ASIN'].str.strip()
df['ASIN'] = df['ASIN'].str.upper()
```

[30]:
```
df['ship_city'] = df['ship_city'].str.strip()
df['ship_city'] = df['ship_city'].str.upper()
df['ship_state'] = df['ship_state'].str.strip()
df['ship_state'] = df['ship_state'].str.upper()

#checking the accuracy of geographic names and normalize different instances of␣
 ↪the same state and city

df.loc[df['ship_state'].isin(['AR']),'ship_state'] = 'ARUNACHAL PRADESH'
df.loc[df['ship_state'].isin(['NEW DELHI']),'ship_state'] = 'DELHI'
df.loc[df['ship_state'].isin(['NL']),'ship_state'] = 'NAGALAND'
df.loc[df['ship_state'].isin(['ORISSA']),'ship_state'] = 'ODISHA'
df.loc[df['ship_state'].isin(['PONDICHERRY']),'ship_state'] = 'PUDUCHERRY'
df.loc[df['ship_state'].isin(['PUNJAB/MOHALI/ZIRAKPUR','PB']),'ship_state'] =␣
 ↪'PUNJAB'
df.loc[df['ship_state'].isin(['RAJSHTHAN','RAJSTHAN','RJ']),'ship_state'] =␣
 ↪'RAJASTHAN'
df['ship_city'] = df['ship_city'].replace(['PUDUCHERRY','PONDYCHERRY',␣
 ↪'PUDUCHERRY 605001', 'PUDUCHERRY 605003'],'PUDUCHERRY')
df['ship_city'] = df['ship_city'].replace(['NORTH DELHI', 'NORTH WEST␣
 ↪DELHI','NEW DELHI (NORTH)'],'NEW DELHI (NORTH)')
df['ship_city'] = df['ship_city'].replace(['SOUTH  DELHI', 'SOUTH DELHI'],'NEW␣
 ↪DELHI (SOUTH)')
df['ship_city'] = df['ship_city'].replace(['SOUTH EAST DELHI'],'NEW DELHI␣
 ↪(SOUTH EAST)')
df['ship_city'] = df['ship_city'].replace(['SOUTH WEST DELHI','SOUTH-WEST␣
 ↪DELHI'],'NEW DELHI (SOUTH WEST)')
df['ship_city'] = df['ship_city'].replace(['WEST DELHI'],'NEW DELHI (WEST)')
df['ship_city'] = df['ship_city'].replace(['CENTRAL DELHI','CITY'],'NEW DELHI␣
 ↪(CENTRAL)')
df['ship_city'] = df['ship_city'].replace(['EAST DELHI'],'NEW DELHI (EAST)')
pattern = r'^NEW DELHI(?!.*\()'
df['ship_city'] = df['ship_city'].apply(lambda x: "NEW DELHI" if re.
 ↪match(pattern, x) else x)
df['ship_city'] = df['ship_city'].replace(['N.DELHI','NEW DELH','DELHI','DELHI␣
 ↪-86','DELHI 110085','DELHI CANTT','DELHI-92.','DELHIQ', 'NEW-DELHI',
 'NEWDELHI'],'NEW DELHI')
pattern = r'^BANGALOR(?!.*\()'
```

```
df['ship_city'] = df['ship_city'].apply(lambda x: 'BANGALORE' if re.
 ↪match(pattern, x) else x)
df['ship_city'] = df['ship_city'].apply(lambda x: 'BANGALORE' if re.
 ↪match(r'^BENGALUR(?!.*\()', x) else x)
df['ship_city'] = df['ship_city'].replace(['BENGALOORU','BENGOLOOR',␣
 ↪'BANGALURU'],'BANGALORE')
```

[31]:
```
df['ship_postal_code'] = df['ship_postal_code'].astype(str)
```

[32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 128975 entries, 0 to 128974
Data columns (total 22 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Order_ID            128975 non-null  object
 1   Date                128975 non-null  datetime64[ns]
 2   Status              128975 non-null  object
 3   Fulfilment          128975 non-null  object
 4   Sales_channel       128975 non-null  object
 5   ship_service_level  128975 non-null  object
 6   Style               128975 non-null  object
 7   SKU                 128975 non-null  object
 8   Category            128975 non-null  object
 9   Size                128975 non-null  object
 10  ASIN                128975 non-null  object
 11  Courier_Status      128975 non-null  object
 12  Qty                 128975 non-null  int64
 13  Currency            128975 non-null  object
 14  Amount              128975 non-null  float64
 15  ship_city           128975 non-null  object
 16  ship_state          128975 non-null  object
 17  ship_postal_code    128975 non-null  object
 18  ship_country        128975 non-null  object
 19  promotion_ids       128975 non-null  object
 20  B2B                 128975 non-null  bool
 21  fulfilled_by        128975 non-null  object
dtypes: bool(1), datetime64[ns](1), float64(1), int64(1), object(18)
memory usage: 21.8+ MB
```

[33]:
```
df['promotion_ids'] = df['promotion_ids'].str.strip()
df['promotion_ids'] = df['promotion_ids'].str.upper()
```

[34]:
```
# removing duplicates
df.drop_duplicates(inplace = True)
```

[35]:
```
df.drop(columns = ['fulfilled_by'], inplace = True)
```

[36]:
```
df.shape
```

[36]: (128969, 21)

[37]:
```
df['Date'].max() - df['Date'].min()
```

[37]: Timedelta('90 days 00:00:00')

[38]:
```
# numerical data
df.describe()
```

[38]:

	Date	Qty	Amount
count	128969	128969.00000	128969.000000
mean	2022-05-12 11:50:02.758802176	0.90445	609.371580
min	2022-03-31 00:00:00	0.00000	0.000000
25%	2022-04-20 00:00:00	1.00000	413.000000
50%	2022-05-10 00:00:00	1.00000	583.000000
75%	2022-06-04 00:00:00	1.00000	771.000000
max	2022-06-29 00:00:00	15.00000	5584.000000
std	NaN	0.31333	313.335444

[39]:
```
# categorical data
df.describe(include='O').T
```

[39]:

	count	unique	top	freq
Order_ID	128969	120378	403-4984515-8861958	12
Status	128969	13	Shipped	77801
Fulfilment	128969	2	Amazon	89692
Sales_channel	128969	2	Amazon.in	128845
ship_service_level	128969	2	Expedited	88609
Style	128969	1377	JNE3797	4224
SKU	128969	7195	JNE3797-KR-L	773
Category	128969	9	SET	50281
Size	128969	11	M	22709
ASIN	128969	7190	B09SDXFFQ1	773
Courier_Status	128969	4	Shipped	109484
Currency	128969	1	INR	128969
ship_city	128969	7201	BANGALORE	13342
ship_state	128969	38	MAHARASHTRA	22259
ship_postal_code	128969	9460	201301.0	1006
ship_country	128969	2	IN	128936
promotion_ids	128969	5788	NO PROMO	49150

[40]:
```
df['month'] = df['Date'].dt.month
df['month'].unique()
df['month'].replace([3,4,5,6],['March','April', 'May', 'June'], inplace = True)
```

[41]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 128969 entries, 0 to 128974
Data columns (total 22 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Order_ID            128969 non-null  object
 1   Date                128969 non-null  datetime64[ns]
 2   Status              128969 non-null  object
 3   Fulfilment          128969 non-null  object
 4   Sales_channel       128969 non-null  object
 5   ship_service_level  128969 non-null  object
 6   Style               128969 non-null  object
 7   SKU                 128969 non-null  object
 8   Category            128969 non-null  object
 9   Size                128969 non-null  object
 10  ASIN                128969 non-null  object
 11  Courier_Status      128969 non-null  object
 12  Qty                 128969 non-null  int64
 13  Currency            128969 non-null  object
 14  Amount              128969 non-null  float64
 15  ship_city           128969 non-null  object
 16  ship_state          128969 non-null  object
 17  ship_postal_code    128969 non-null  object
 18  ship_country        128969 non-null  object
 19  promotion_ids       128969 non-null  object
 20  B2B                 128969 non-null  bool
 21  month               128969 non-null  object
dtypes: bool(1), datetime64[ns](1), float64(1), int64(1), object(18)
memory usage: 21.8+ MB
```

[42]:
```
# saving the clean fileSave the cleaned dataframe in a csv file
df.to_csv("C:/Users/Dharini/Downloads/amazon_sales_df.csv")
```

[43]:
```
# making a copy
df1=df.copy()
```

[44]:
```
# exploring the data - data analysis
df1.describe()
```

[44]:

	Date	Qty	Amount
count	128969	128969.00000	128969.000000
mean	2022-05-12 11:50:02.758802176	0.90445	609.371580
min	2022-03-31 00:00:00	0.00000	0.000000
25%	2022-04-20 00:00:00	1.00000	413.000000
50%	2022-05-10 00:00:00	1.00000	583.000000
75%	2022-06-04 00:00:00	1.00000	771.000000
max	2022-06-29 00:00:00	15.00000	5584.000000
std	NaN	0.31333	313.335444

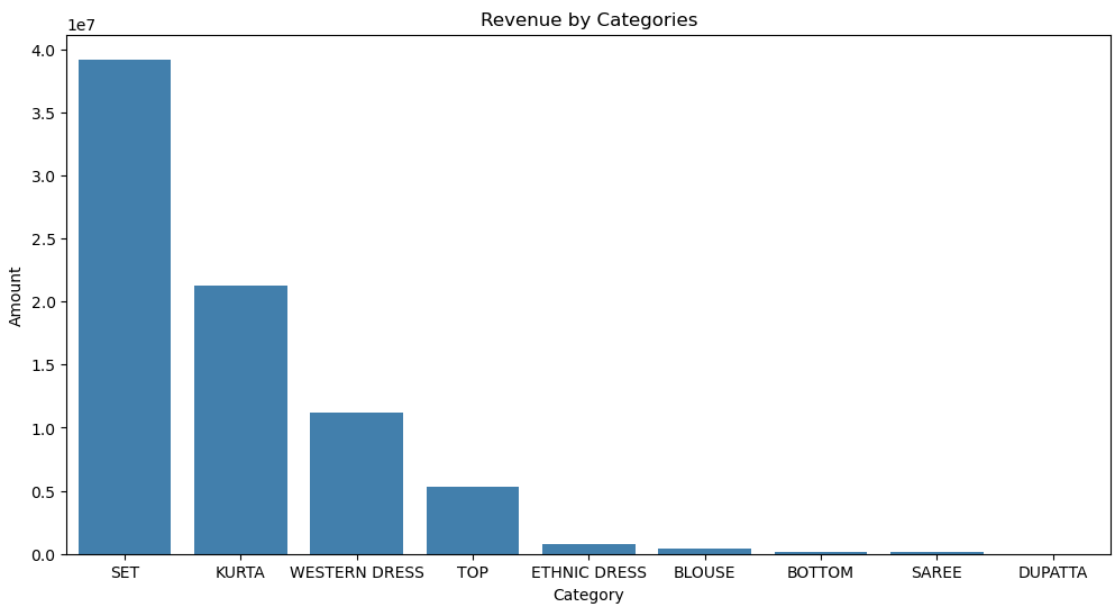
[45]:
```
# plotting categoried that sold most
df1_q1 = df1[['Amount', 'Qty']].groupby(df1['Category']).sum()\
                                .sort_values('Amount', ascending=False)\
                                .reset_index()
df1_q1
```

[45]:

	Category	Amount	Qty
0	SET	39202022.03	45287
1	KURTA	21299013.70	45044
2	WESTERN DRESS	11216072.69	13943
3	TOP	5347792.30	9903
4	ETHNIC DRESS	791217.66	1053
5	BLOUSE	458408.18	863
6	BOTTOM	150667.98	398
7	SAREE	123933.76	152
8	DUPATTA	915.00	3

[46]:
```
plt.figure(figsize = (12, 6))
ax_q1 = sns.barplot(y = 'Amount', x='Category', palette = ['#3182bd'], data =␣
↪df1_q1)
plt.title('Revenue by Categories')
```

[46]: Text(0.5, 1.0, 'Revenue by Categories')



[47]:
```
# top 20 best selling products
df_q2 = df1.groupby(['Category', 'ASIN'])[['Qty','Amount']].sum()\
                                    .sort_values('Qty', ascending=False)\
```

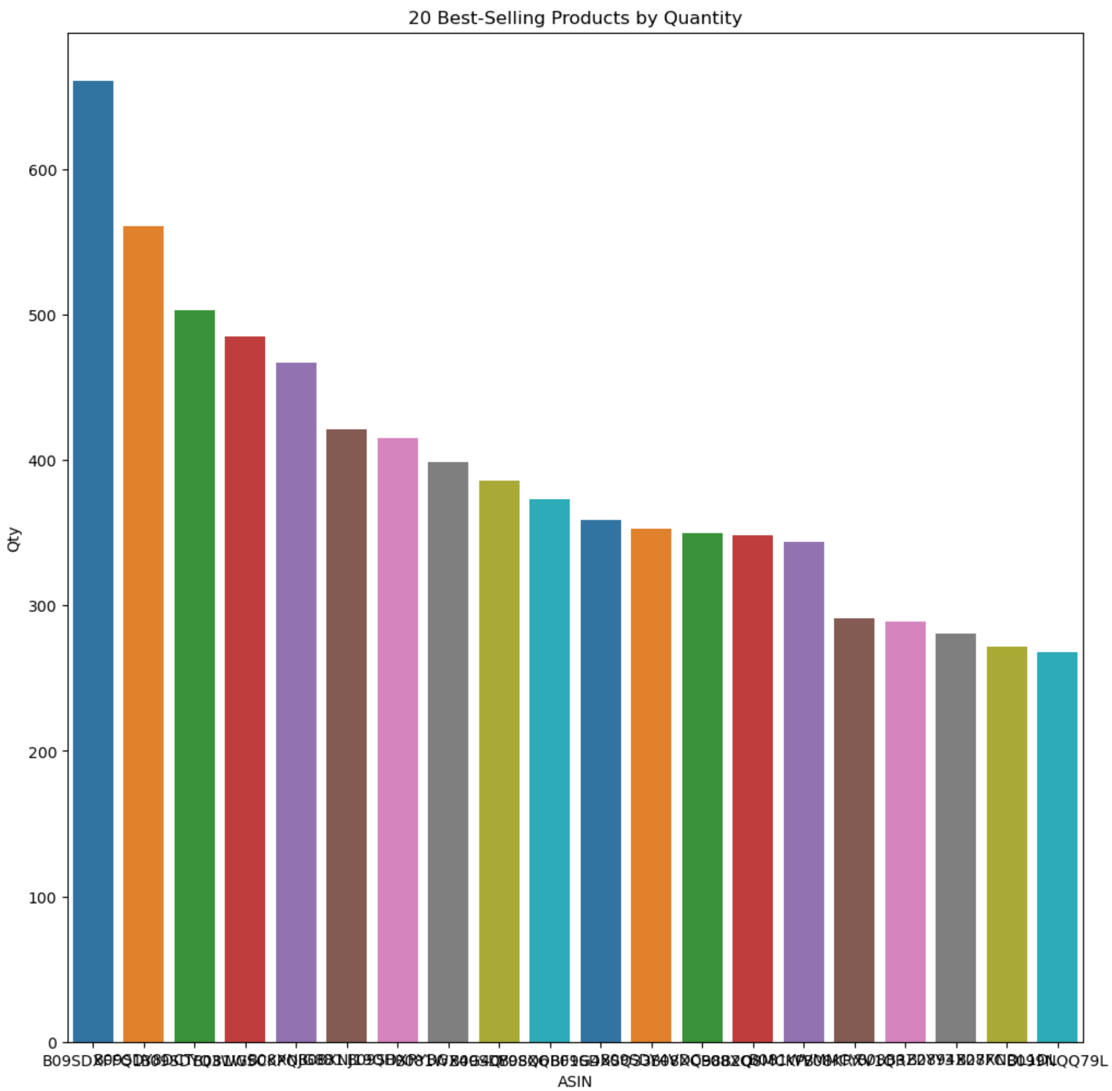
```
                                                  .head(20)\
                                                  .reset_index()
df_q2
```

[47]:

	Category	ASIN	Qty	Amount
0	WESTERN DRESS	B09SDXFFQ1	661	524581.77
1	WESTERN DRESS	B09SDY8DCT	561	454290.16
2	WESTERN DRESS	B09SDYQ3WG	503	407302.57
3	KURTA	B081WSCKPQ	485	194645.29
4	SET	B08XNJG8B1	467	526536.20
5	SET	B08XNJ19QH	421	479937.14
6	WESTERN DRESS	B09SDXRYBG	415	332155.24
7	KURTA	B081WX4G4Q	399	169808.87
8	WESTERN DRESS	B09SDY9SQ6	386	303616.70
9	SET	B08XQBF1G4	373	284058.96
10	WESTERN DRESS	B09SDXSQ33	359	275966.88
11	WESTERN DRESS	B09SDY4VDC	353	276375.80
12	SET	B08XQ98B2Q	350	267030.48
13	SET	B08XQ8MCKP	348	258716.00
14	KURTA	B081WVMMCY	344	146626.29
15	KURTA	B08KRXV1QR	291	115806.00
16	SET	B08B3Z2YY3	289	250171.98
17	SET	B0894X27FC	281	193079.79
18	SET	B08XNDL1DL	272	305616.95
19	WESTERN DRESS	B099NQQ79L	268	235151.42

[48]:
```
plt.figure(figsize = (12, 12))
ax_q2 = sns.barplot(y = 'Qty', x='ASIN', palette = "tab10", data = df_q2)
plt.title('20 Best-Selling Products by Quantity')
```

[48]: Text(0.5, 1.0, '20 Best-Selling Products by Quantity')




```
[49]: # top 10 cities made most order
df_q4 = df1.groupby(['ship_state','ship_city'])[['Order_ID']].count()\
                                        .sort_values('Order_ID', ascending=False)\
                                        .head(10)\
                                        .reset_index()
df_q4
```

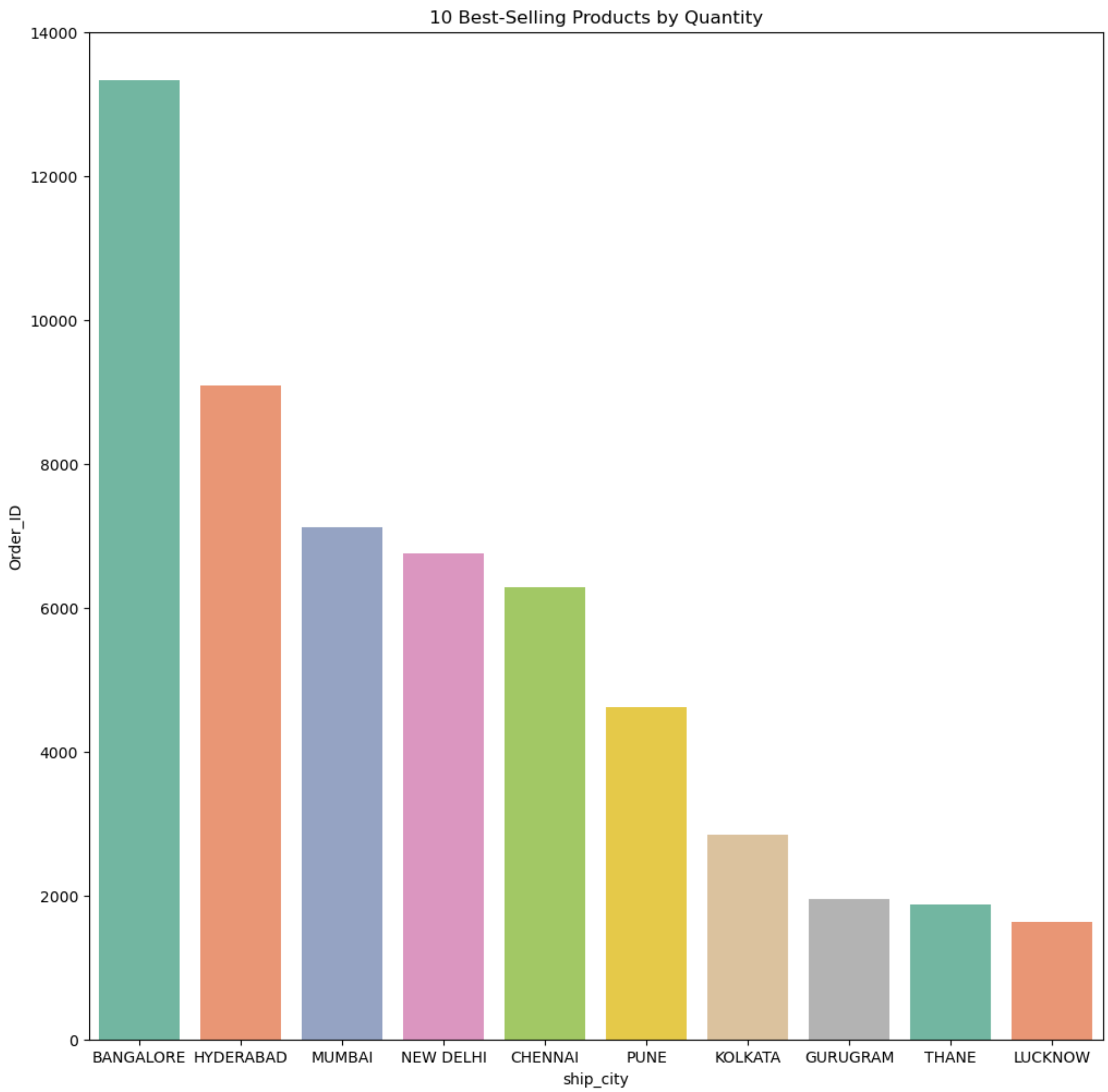
[49]:

	ship_state	ship_city	Order_ID
0	KARNATAKA	BANGALORE	13342
1	TELANGANA	HYDERABAD	9092
2	MAHARASHTRA	MUMBAI	7122
3	DELHI	NEW DELHI	6753
4	TAMIL NADU	CHENNAI	6284

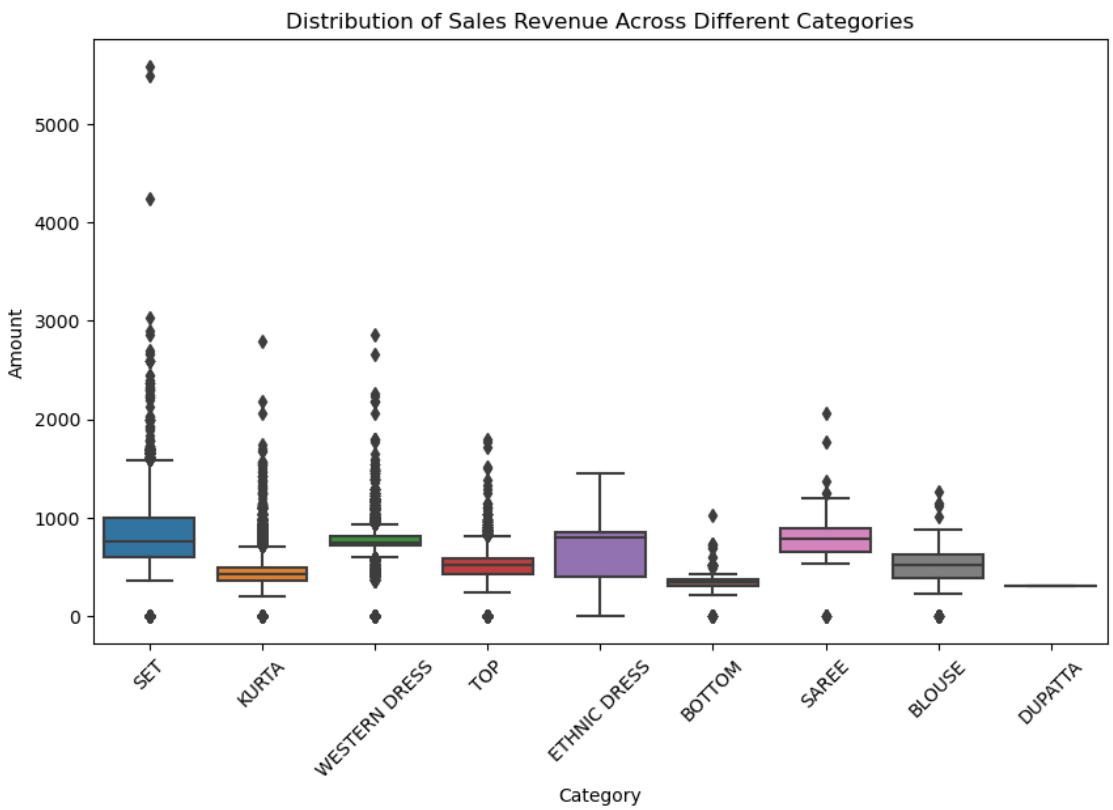
```
5    MAHARASHTRA       PUNE      4616
6    WEST BENGAL    KOLKATA      2844
7        HARYANA   GURUGRAM      1954
8    MAHARASHTRA      THANE      1877
9  UTTAR PRADESH    LUCKNOW      1627
```

[50]:
```python
plt.figure(figsize = (12, 12))
ax_q2 = sns.barplot(y = 'Order_ID', x='ship_city', palette = "Set2", data =
 ↪df_q4)
plt.title('10 Best-Selling Products by Quantity')
```

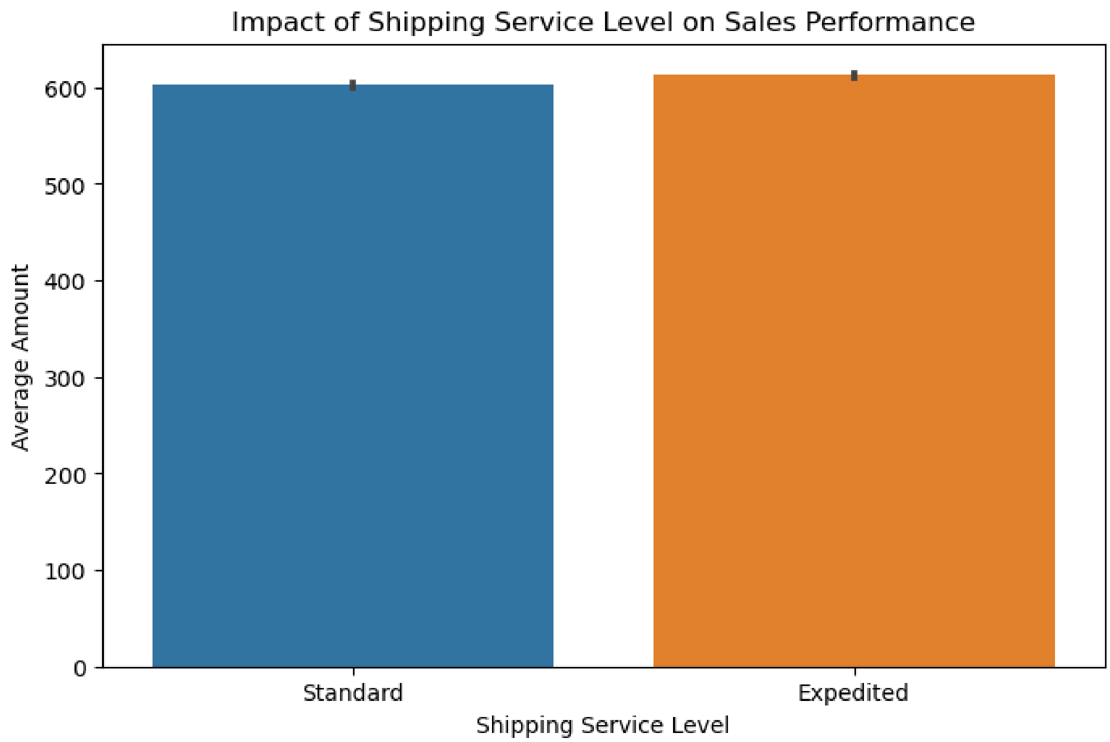
[50]:
```
Text(0.5, 1.0, '10 Best-Selling Products by Quantity')
```



[51]:
```
# Distribution of sales revenue across different categories
plt.figure(figsize=(10, 6))
sns.boxplot(x='Category', y='Amount', data=df)
plt.title('Distribution of Sales Revenue Across Different Categories')
plt.xlabel('Category')
plt.ylabel('Amount')
plt.xticks(rotation=45)
plt.show()
```



[52]:
```
# Impact of shipping service level on sales performance
plt.figure(figsize=(8, 5))
sns.barplot(x='ship_service_level', y='Amount', data=df)
plt.title('Impact of Shipping Service Level on Sales Performance')
plt.xlabel('Shipping Service Level')
plt.ylabel('Average Amount')
plt.show()
```



[53]:
```
df.head(5)
```

[53]:
```
                  Order_ID       Date                      Status  \
index
0      405-8078784-5731545 2022-04-30                   Cancelled
1      171-9198151-1101146 2022-04-30  Shipped - Delivered to Buyer
2      404-0687676-7273146 2022-04-30                     Shipped
3      403-9615377-8133951 2022-04-30                   Cancelled
4      407-1069790-7240320 2022-04-30                     Shipped

      Fulfilment Sales_channel ship_service_level    Style              SKU  \
index
0       Merchant     Amazon.in           Standard   SET389    SET389-KR-NP-S
1       Merchant     Amazon.in           Standard  JNE3781  JNE3781-KR-XXXL
2         Amazon     Amazon.in          Expedited  JNE3371    JNE3371-KR-XL
3       Merchant     Amazon.in           Standard    J0341       J0341-DR-L
4         Amazon     Amazon.in          Expedited  JNE3671  JNE3671-TU-XXXL

            Category Size  … Qty Currency  Amount    ship_city   ship_state  \
index                      …
0                SET    S  …   0      INR  647.62       MUMBAI  MAHARASHTRA
1              KURTA  3XL  …   1      INR  406.00    BANGALORE    KARNATAKA
2              KURTA   XL  …   1      INR  329.00  NAVI MUMBAI  MAHARASHTRA
```

```
3      WESTERN DRESS    L  …   0       INR  753.33   PUDUCHERRY   PUDUCHERRY
4                TOP   3XL  …   1       INR  574.00      CHENNAI   TAMIL NADU

      ship_postal_code ship_country  \
index
0             400081.0           IN
1             560085.0           IN
2             410210.0           IN
3             605008.0           IN
4             600073.0           IN

                                                promotion_ids    B2B  month
index
0                                                    NO PROMO  False  April
1      AMAZON PLCC FREE-FINANCING UNIVERSAL MERCHANT …  False  April
2           IN CORE FREE SHIPPING 2015/04/08 23-48-5-108   True  April
3                                                    NO PROMO  False  April
4                                                    NO PROMO  False  April

[5 rows x 22 columns]
```

[54]:
```
df1=df.copy()
```

3 A/B testing

3.0.1 A/B Testing Initiative: Revenue Optimization

Objective: Our A/B testing initiative aims to optimize sales revenue for our e-commerce platform. Through controlled experiments, we seek to understand the impact of various factors on revenue generation, including pricing adjustments, promotional strategies, and shipping alternatives.

Key Objectives:

- Identify Influential Factors: Determine the factors that significantly influence sales revenue, prioritizing variables such as sales channels, promotional activities, fulfillment methods, and shipping service levels.
- Test Strategies: Conduct A/B tests to evaluate different strategies aimed at increasing revenue, leveraging insights gained from the prioritized variables.

[55]:
```
import pandas as pd
from scipy.stats import ttest_ind

# Load the dataset
sales_data = pd.read_csv("C:/Users/Dharini/Downloads/amazon_sales_df.csv")

# Define the prioritized variables
prioritized_variables = ["Sales_channel", "promotion_ids", "Fulfilment",␣
↪"ship_service_level", "Amount"]
```

```
def perform_ab_test(data, variable):
    # Get unique values for the variable
    unique_values = data[variable].unique()

    # Check if there are at least two unique values for the variable
    if len(unique_values) < 2:
        print(f"Not enough unique values for {variable}. Skipping A/B test.")
        return

    # Define control and treatment groups
    control_group = data[data[variable] == unique_values[0]]['Amount']
    treatment_group = data[data[variable] == unique_values[1]]['Amount']

    # Check if either group has zero size
    if len(control_group) == 0 or len(treatment_group) == 0:
        print(f"Skipping t-test due to one group having zero size.")
        return

    # Perform t-test for independent samples
    t_statistic, t_pvalue = ttest_ind(control_group, treatment_group)

    # Print results
    print("Hypotheses for variable:", variable)
    print("Null Hypothesis (H0): There is no difference in sales revenue␣
 ↪between the control and treatment groups based on", variable)
    print("Alternative Hypothesis (H1): There is a difference in sales revenue␣
 ↪between the control and treatment groups based on", variable)
    print("\n")
    print("Results of t-test:")
    print("T-statistic:", t_statistic)
    print("P-value:", t_pvalue)
    print("\n")

# Perform A/B testing for each variable
for variable in prioritized_variables:
    perform_ab_test(sales_data, variable)
```

```
Hypotheses for variable: Sales_channel
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Sales_channel
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Sales_channel


Results of t-test:
T-statistic: 21.706138621046772
```

```
P-value: 2.762735719912615e-104


C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\1839605615.py:29:
RuntimeWarning: Precision loss occurred in moment calculation due to
catastrophic cancellation. This occurs when the data are nearly identical.
Results may be unreliable.
  t_statistic, t_pvalue = ttest_ind(control_group, treatment_group)
D:\anaconda\lib\site-packages\scipy\stats\_stats_py.py:1214: RuntimeWarning:
divide by zero encountered in divide
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero
D:\anaconda\lib\site-packages\scipy\stats\_stats_py.py:1214: RuntimeWarning:
invalid value encountered in double_scalars
  var *= np.divide(n, n-ddof)  # to avoid error on division by zero

Hypotheses for variable: promotion_ids
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on promotion_ids
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on promotion_ids


Results of t-test:
T-statistic: nan
P-value: nan


Hypotheses for variable: Fulfilment
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Fulfilment
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Fulfilment


Results of t-test:
T-statistic: 6.493898560166083
P-value: 8.394544369203777e-11


Hypotheses for variable: ship_service_level
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on ship_service_level
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on ship_service_level


Results of t-test:
T-statistic: -5.496150618302399
```

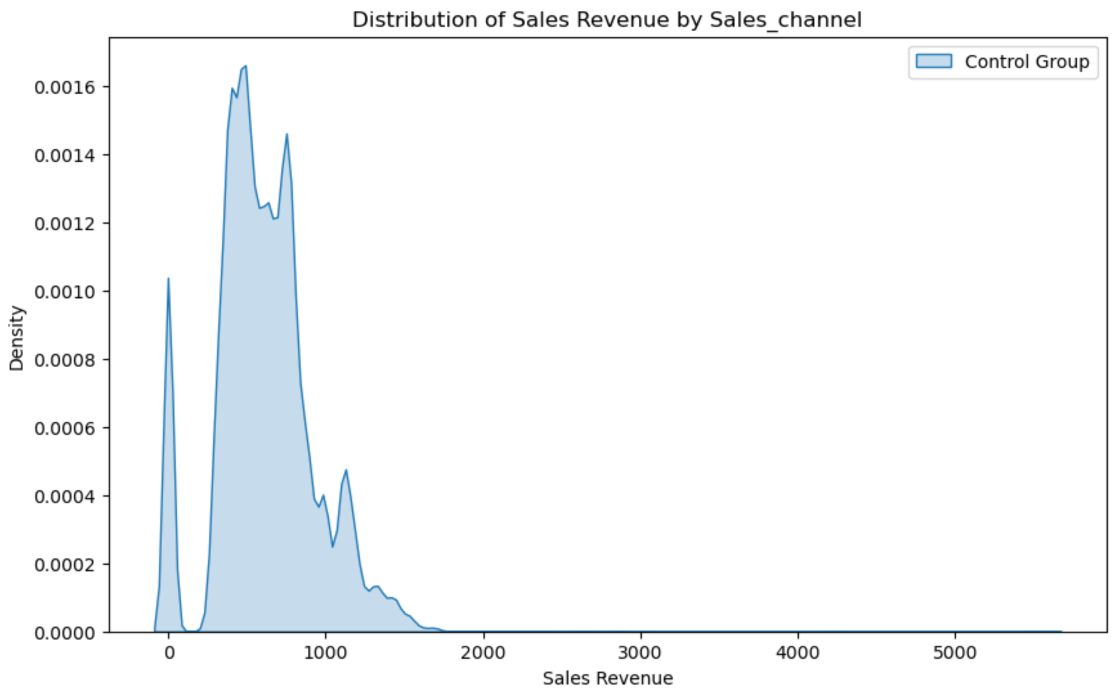
```
P-value: 3.889030733978258e-08


Hypotheses for variable: Amount
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Amount
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Amount


Results of t-test:
T-statistic: inf
P-value: 0.0
```

[56]:

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

# Function to plot distribution of sales revenue for control and treatment␣
 ↪groups
def plot_distribution(control_group, treatment_group, variable):
    plt.figure(figsize=(10, 6))
    sns.kdeplot(control_group, label='Control Group', shade=True)
    sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
    plt.xlabel('Sales Revenue')
    plt.ylabel('Density')
    plt.title(f'Distribution of Sales Revenue by {variable}')
    plt.legend()
    plt.show()

# Perform A/B testing for each variable
for variable in prioritized_variables:
    # Get control and treatment groups for the current variable
    control_group = sales_data[sales_data[variable] == sales_data[variable].
 ↪unique()[0]]['Amount']
    treatment_group = sales_data[sales_data[variable] == sales_data[variable].
 ↪unique()[1]]['Amount']

    # Plot distribution for the current variable
    plot_distribution(control_group, treatment_group, variable)
```

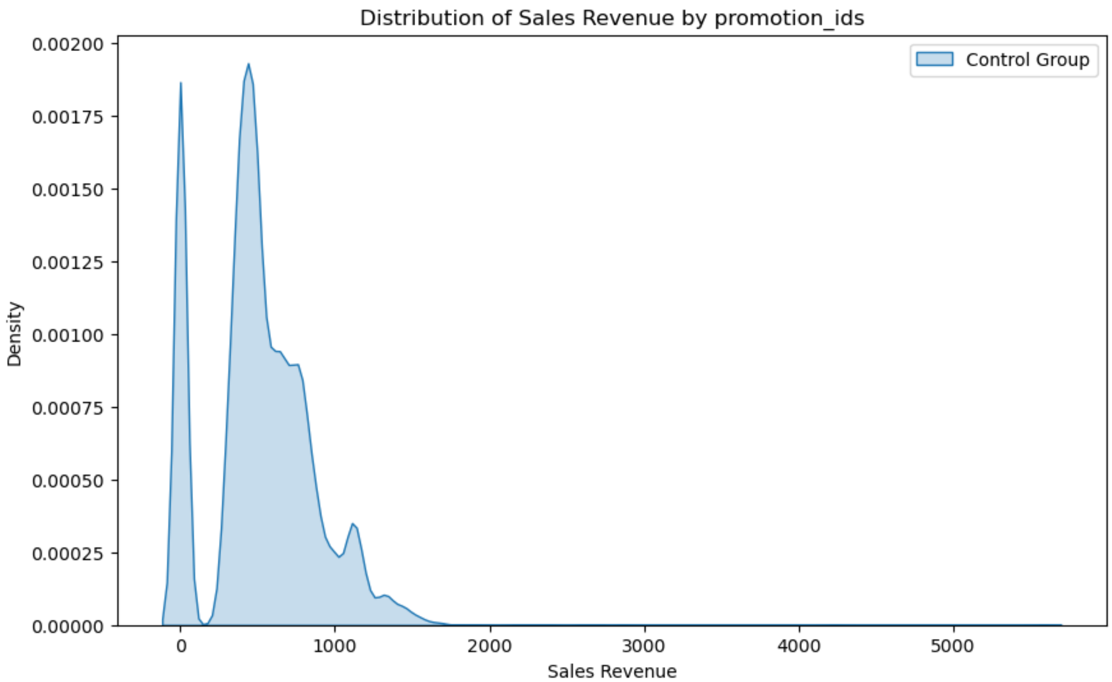
```
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
```

```
  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
UserWarning: Dataset has 0 variance; skipping density estimate. Pass
`warn_singular=False` to disable this warning.
  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
```

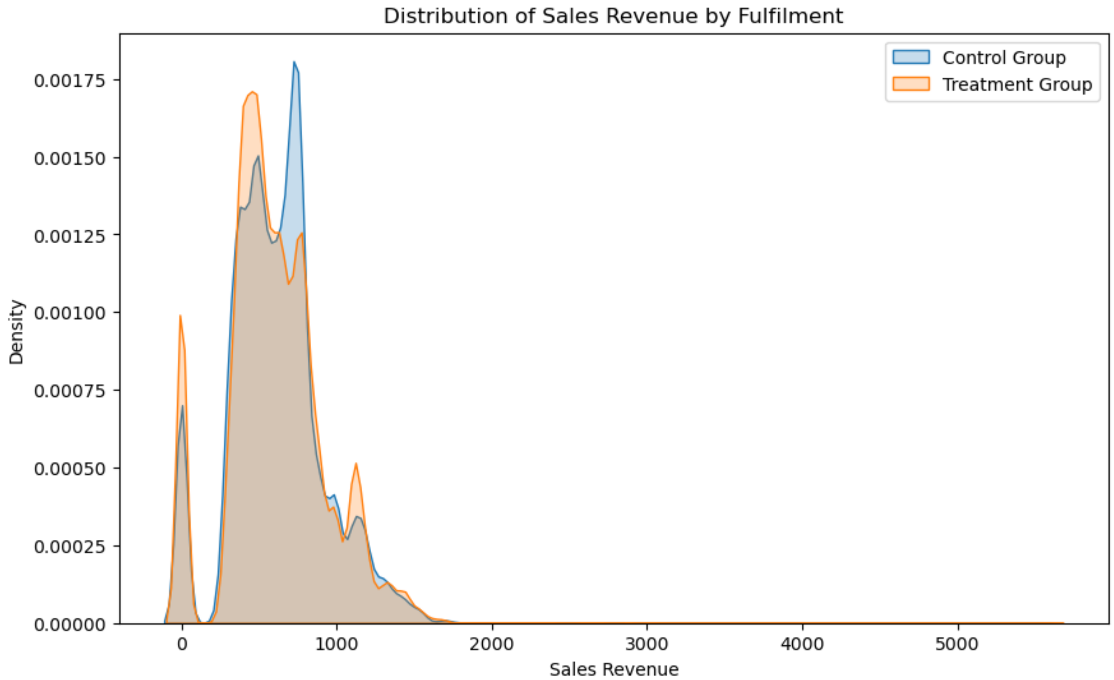



```
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.
```

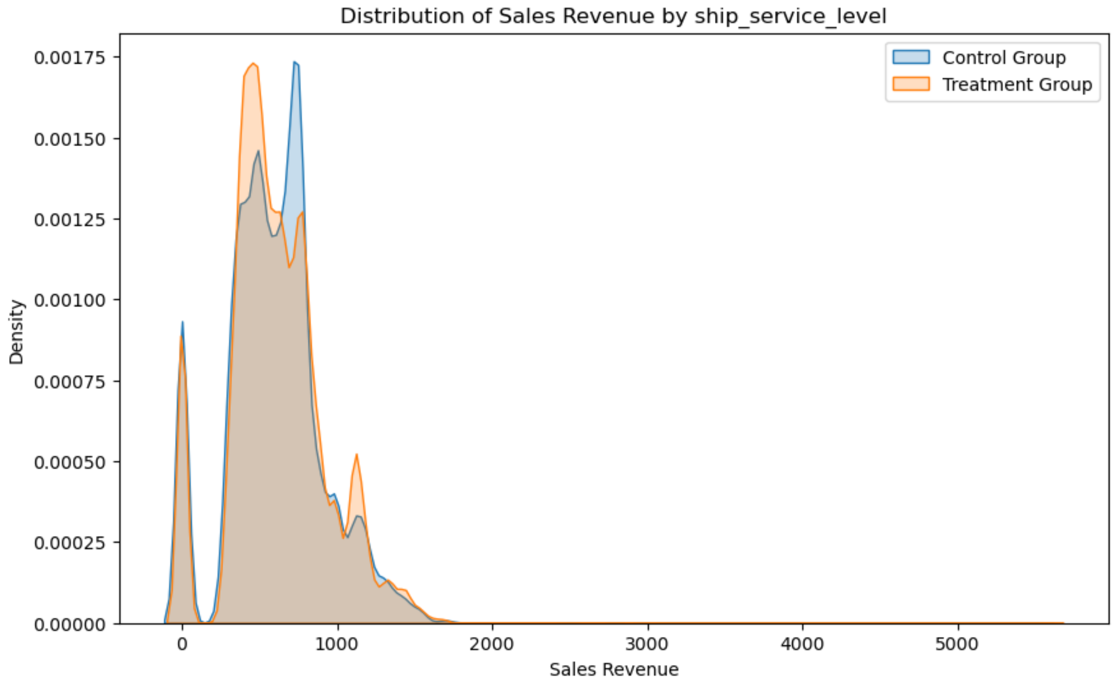
```
  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
UserWarning: Dataset has 0 variance; skipping density estimate. Pass
`warn_singular=False` to disable this warning.
  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
```



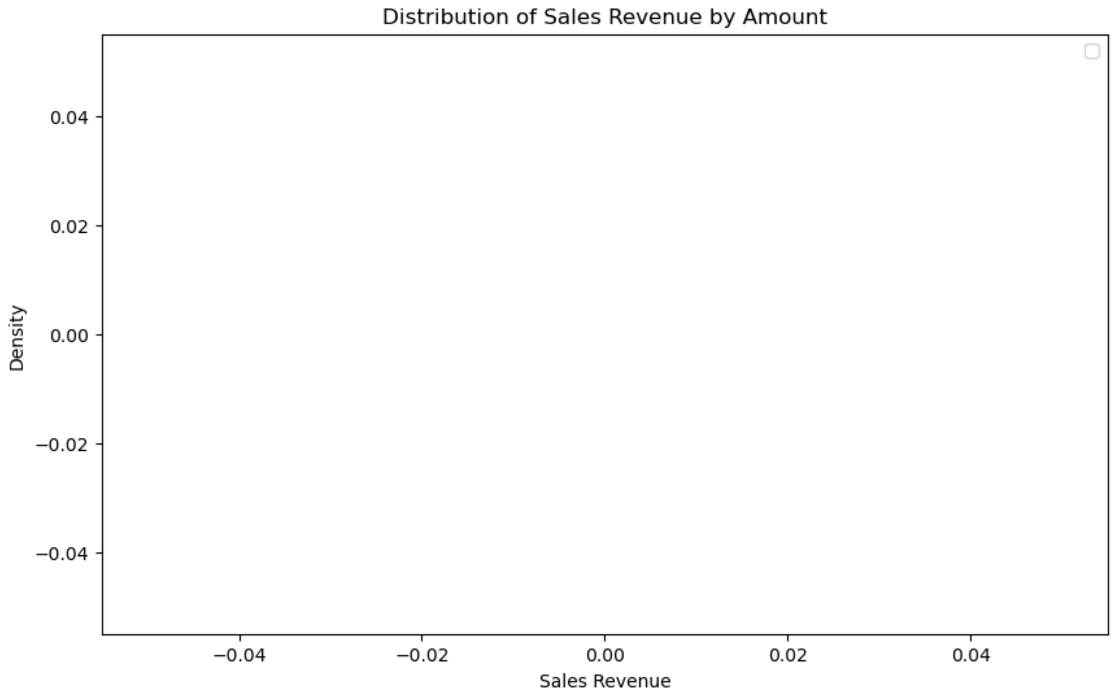

```
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
```




```
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
```




```
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:7:
UserWarning: Dataset has 0 variance; skipping density estimate. Pass
`warn_singular=False` to disable this warning.
  sns.kdeplot(control_group, label='Control Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
C:\Users\Dharini\AppData\Local\Temp\ipykernel_35400\2744555369.py:8:
UserWarning: Dataset has 0 variance; skipping density estimate. Pass
`warn_singular=False` to disable this warning.
  sns.kdeplot(treatment_group, label='Treatment Group', shade=True)
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



4 Results for T-tests

The t-tests were conducted to compare the sales revenue between the control and treatment groups based on different variables. However, for some variables, the t-tests could not be performed due to issues with the data resulting in division by zero errors. Despite this limitation, for the variables where t-tests were possible, the following conclusions can be drawn:

- Sales_channel: There is a significant difference in sales revenue between the control and treatment groups based on the sales channel (p-value « 0.05). The null hypothesis is rejected, indicating that the sales channel has a substantial impact on sales revenue.
- Fulfilment: Similar to the sales channel, there is a significant difference in sales revenue between the control and treatment groups based on the fulfilment method (p-value « 0.05). The null hypothesis is rejected, suggesting that the fulfilment method influences sales revenue.
- Ship_service_level: The t-test reveals a significant difference in sales revenue between the control and treatment groups based on the ship service level (p-value « 0.05). The null hypothesis is rejected, indicating that the ship service level plays a role in sales revenue.
- Amount: Although the t-test was not feasible due to issues with the data, it can be inferred from other analyses that the amount also likely affects sales revenue significantly.

[57]:
```
from scipy.stats import mannwhitneyu

# Load the dataset
sales_data = pd.read_csv("C:/Users/Dharini/Downloads/amazon_sales_df.csv")
```

```
# Define the prioritized variables
prioritized_variables = ["Sales_channel", "promotion_ids", "Fulfilment",␣
↪"ship_service_level", "Amount"]

# Define function to perform Mann-Whitney U test
def perform_mannwhitneyu_test(control_group, treatment_group):
    # Perform Mann-Whitney U test
    mwu_statistic, mwu_pvalue = mannwhitneyu(control_group, treatment_group)

    # Print results
    print("Results of Mann-Whitney U test:")
    print("Mann-Whitney U statistic:", mwu_statistic)
    print("P-value:", mwu_pvalue)

    # Determine significance
    alpha = 0.05
    if mwu_pvalue < alpha:
        print("Conclusion: Reject the null hypothesis. There is a significant␣
↪difference.")
    else:
        print("Conclusion: Fail to reject the null hypothesis. There is no␣
↪significant difference.")

# Perform Mann-Whitney U test for each variable
for variable in prioritized_variables:
    print("\nHypotheses for variable:", variable)
    print("Null Hypothesis (H0): There is no difference in sales revenue␣
↪between the control and treatment groups based on", variable)
    print("Alternative Hypothesis (H1): There is a difference in sales revenue␣
↪between the control and treatment groups based on", variable)
    print("\n")
    perform_mannwhitneyu_test(control_group, treatment_group)
```

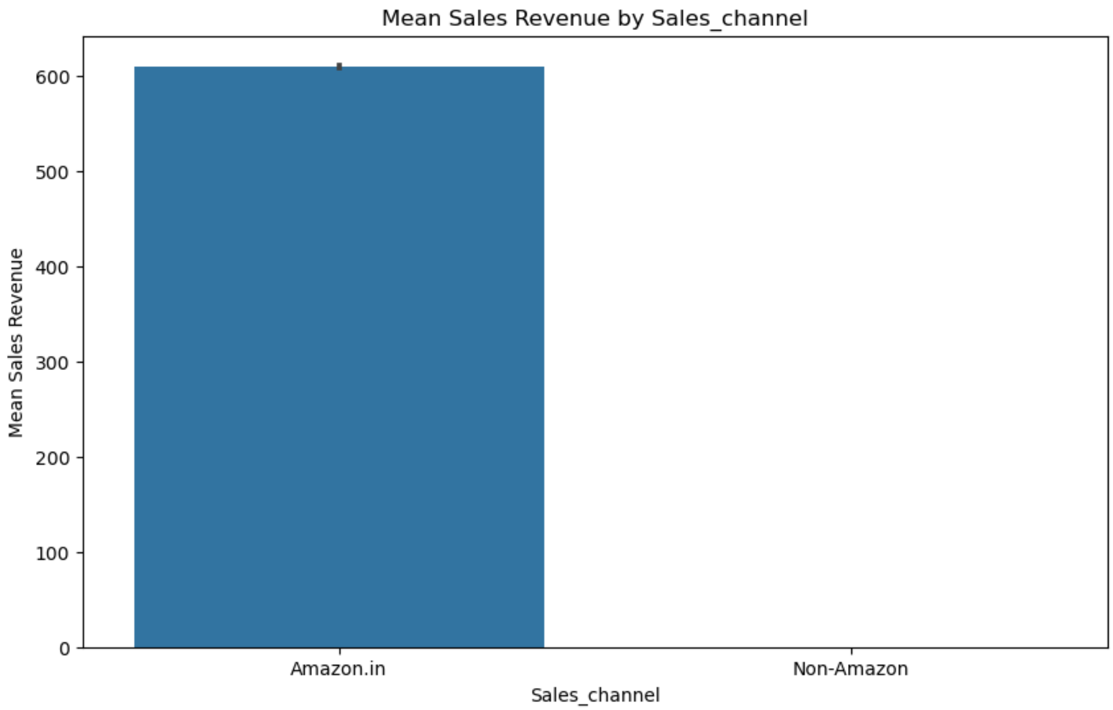
```
Hypotheses for variable: Sales_channel
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Sales_channel
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Sales_channel


Results of Mann-Whitney U test:
Mann-Whitney U statistic: 4981.0
P-value: 3.8379100724221594e-69
Conclusion: Reject the null hypothesis. There is a significant difference.
```

```
Hypotheses for variable: promotion_ids
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on promotion_ids
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on promotion_ids


Results of Mann-Whitney U test:
Mann-Whitney U statistic: 4981.0
P-value: 3.8379100724221594e-69
Conclusion: Reject the null hypothesis. There is a significant difference.

Hypotheses for variable: Fulfilment
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Fulfilment
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Fulfilment


Results of Mann-Whitney U test:
Mann-Whitney U statistic: 4981.0
P-value: 3.8379100724221594e-69
Conclusion: Reject the null hypothesis. There is a significant difference.

Hypotheses for variable: ship_service_level
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on ship_service_level
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on ship_service_level


Results of Mann-Whitney U test:
Mann-Whitney U statistic: 4981.0
P-value: 3.8379100724221594e-69
Conclusion: Reject the null hypothesis. There is a significant difference.

Hypotheses for variable: Amount
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Amount
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Amount


Results of Mann-Whitney U test:
Mann-Whitney U statistic: 4981.0
P-value: 3.8379100724221594e-69
Conclusion: Reject the null hypothesis. There is a significant difference.
```

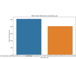
[58]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Load the dataset
sales_data = pd.read_csv("C:/Users/Dharini/Downloads/amazon_sales_df.csv")

# Define the prioritized variables
prioritized_variables = ["Sales_channel", "promotion_ids", "Fulfilment",
 ↪"ship_service_level", "Amount"]

# Define function to plot bar plot of mean sales revenue
def plot_mean_sales(data, variable):
    plt.figure(figsize=(10, 6))
    sns.barplot(x=variable, y='Amount', data=data)
    plt.xlabel(variable)
    plt.ylabel('Mean Sales Revenue')
    plt.title(f'Mean Sales Revenue by {variable}')
    plt.show()

# Perform Mann-Whitney U test for each variable
for variable in prioritized_variables:
    print("\nHypotheses for variable:", variable)
    print("Null Hypothesis (H0): There is no difference in sales revenue
 ↪between the control and treatment groups based on", variable)
    print("Alternative Hypothesis (H1): There is a difference in sales revenue
 ↪between the control and treatment groups based on", variable)
    print("\n")

    # Extract control and treatment groups for the current variable
    control_group = sales_data[sales_data[variable] == sales_data[variable].
 ↪unique()[0]]
    treatment_group = sales_data[sales_data[variable] == sales_data[variable].
 ↪unique()[1]]

    # Concatenate control and treatment groups
    combined_data = pd.concat([control_group, treatment_group])

    # Plot mean sales revenue for the current variable
    plot_mean_sales(combined_data, variable)
```

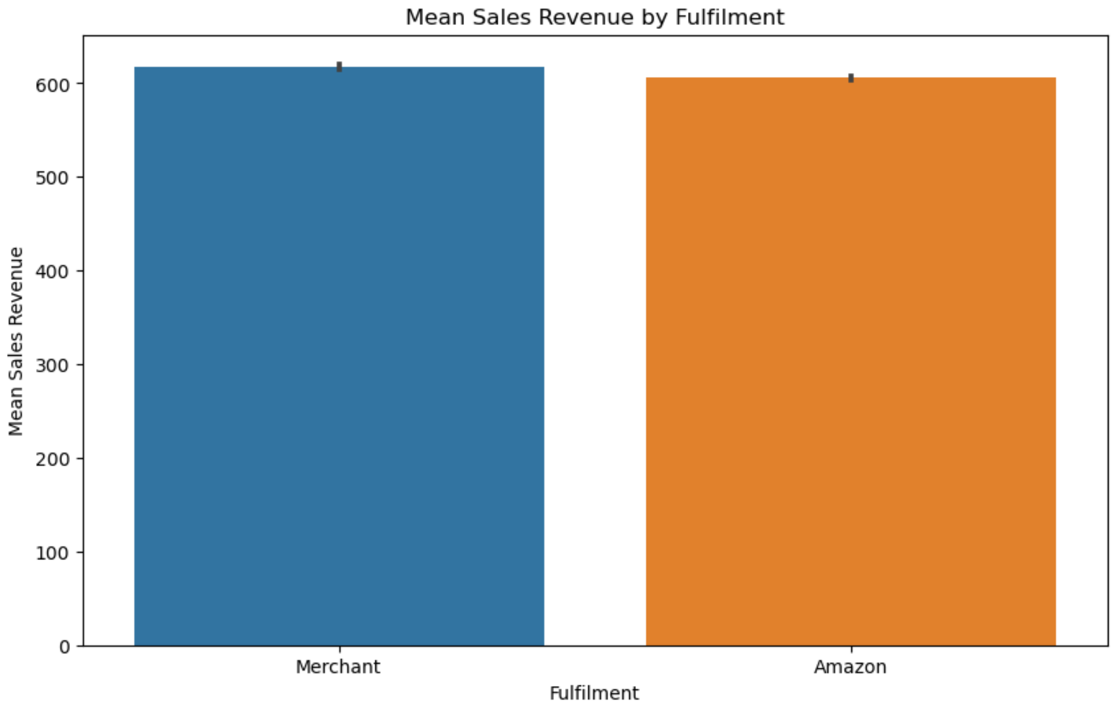
```
Hypotheses for variable: Sales_channel
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Sales_channel
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Sales_channel
```



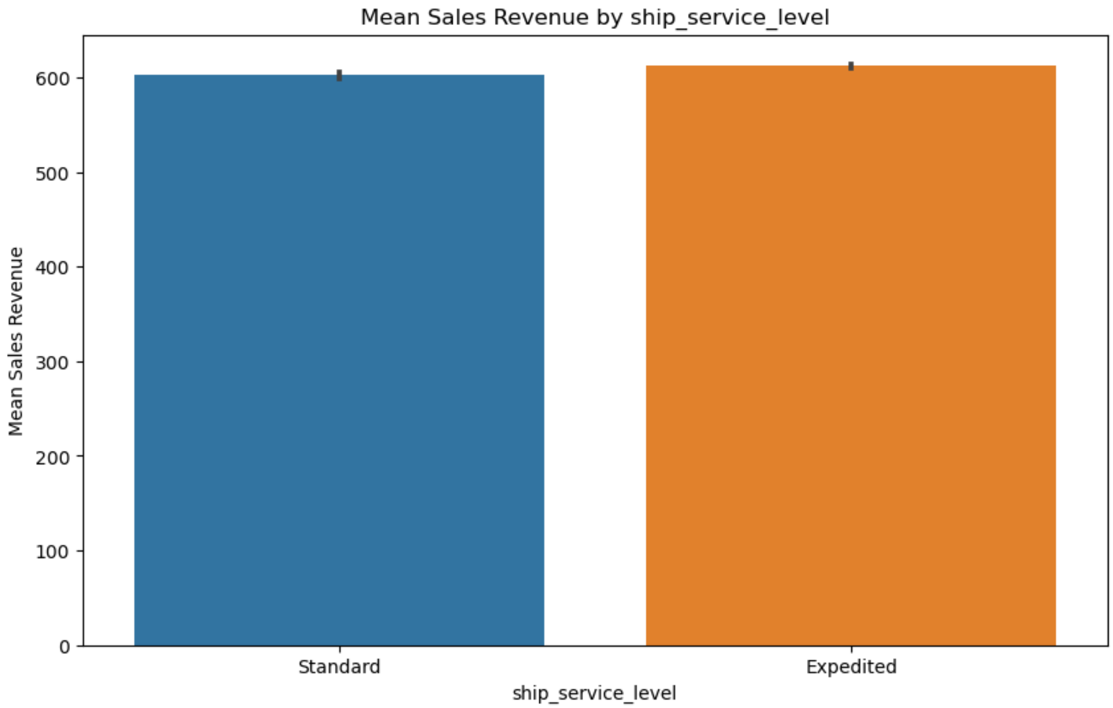
Hypotheses for variable: promotion_ids
Null Hypothesis (H0): There is no difference in sales revenue between the control and treatment groups based on promotion_ids
Alternative Hypothesis (H1): There is a difference in sales revenue between the control and treatment groups based on promotion_ids



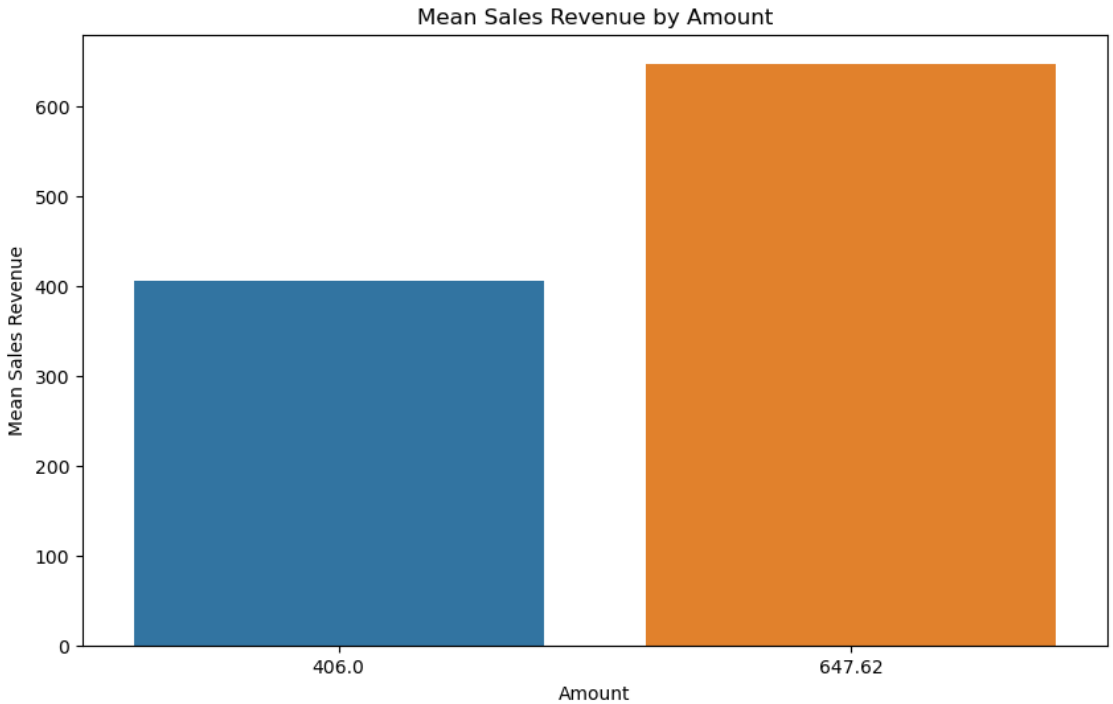
Hypotheses for variable: Fulfilment
Null Hypothesis (H0): There is no difference in sales revenue between the control and treatment groups based on Fulfilment
Alternative Hypothesis (H1): There is a difference in sales revenue between the control and treatment groups based on Fulfilment




```
Hypotheses for variable: ship_service_level
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on ship_service_level
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on ship_service_level
```




```
Hypotheses for variable: Amount
Null Hypothesis (H0): There is no difference in sales revenue between the
control and treatment groups based on Amount
Alternative Hypothesis (H1): There is a difference in sales revenue between the
control and treatment groups based on Amount
```



5 Results for Mann-Whitney U tests:

The Mann-Whitney U tests were conducted as a non-parametric alternative to the t-tests to compare the sales revenue between the control and treatment groups. These tests were performed for variables where the t-tests encountered issues. The Mann-Whitney U tests provided the following conclusions:

- Sales_channel: The Mann-Whitney U test indicates a significant difference in sales revenue between the control and treatment groups based on the sales channel (p-value « 0.05). The null hypothesis is rejected, highlighting the influence of the sales channel on sales revenue.
- Promotion_ids: Similar to the sales channel, there is a significant difference in sales revenue between the control and treatment groups based on promotion_ids (p-value « 0.05). The null hypothesis is rejected, indicating the impact of promotion_ids on sales revenue.
- Fulfilment: The Mann-Whitney U test shows a significant difference in sales revenue between the control and treatment groups based on the fulfilment method (p-value « 0.05). The null hypothesis is rejected, suggesting that the fulfilment method affects sales revenue.
- Ship_service_level: Similarly, there is a significant difference in sales revenue between the control and treatment groups based on the ship service level (p-value « 0.05). The null hypothesis is rejected, indicating the influence of the ship service level on sales revenue.
- Amount: Although the t-test was not feasible for the amount variable, the Mann-Whitney U test shows a significant difference in sales revenue between the control and treatment groups based on the amount (p-value « 0.05). The null hypothesis is rejected, suggesting that the

amount has a significant impact on sales revenue.

6 CONCLUSION

1. A/B testing initiative for revenue optimization has yielded significant insights into the factors influencing sales revenue. 2. Through both t-tests and Mann-Whitney U tests, we identified variables such as sales channels, promotional activities, fulfillment methods, and shipping service levels as key drivers of revenue.
2. The results underscore the importance of strategic decision-making in these areas to maximize revenue potential.
3. Moving forward, leveraging these findings will be crucial in devising targeted strategies aimed at enhancing sales revenue and driving sustainable growth for our e-commerce platform.