Amazon Sales Report Data Analysis Project

Introduction

In this data analysis project, I explore and analyze an Amazon sales report using Python and popular data science libraries such as Pandas, Matplotlib, and Seaborn. The goal is to derive meaningful insights and showcase data visualization skills.

Import Python Libraries

In [3]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Load the Data

In [51]:
```
df = pd.read_csv('Amazon Sale Report.csv')
```

Explore the Data

In [52]:
```
df.head()
```

Out[52]:

	index	Order ID	Date	Status	Fulfilment	Sales Channel	ship-service-level	Category	Size	Courier Status
0	0	405-8078784-5731545	04-30-22	Cancelled	Merchant	Amazon.in	Standard	T-shirt	S	On the Way
1	1	171-9198151-1101146	04-30-22	Shipped - Delivered to Buyer	Merchant	Amazon.in	Standard	Shirt	3XL	Shipped
2	2	404-0687676-7273146	04-30-22	Shipped	Amazon	Amazon.in	Expedited	Shirt	XL	Shipped
3	3	403-9615377-8133951	04-30-22	Cancelled	Merchant	Amazon.in	Standard	Blazzer	L	On the Way
4	4	407-1069790-7240320	04-30-22	Shipped	Amazon	Amazon.in	Expedited	Trousers	3XL	Shipped

5 rows × 21 columns

In [53]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128976 entries, 0 to 128975
Data columns (total 21 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   index               128976 non-null  int64  
 1   Order ID            128976 non-null  object 
 2   Date                128976 non-null  object 
 3   Status              128976 non-null  object 
 4   Fulfilment          128976 non-null  object 
 5   Sales Channel       128976 non-null  object 
 6   ship-service-level  128976 non-null  object 
 7   Category            128976 non-null  object 
 8   Size                128976 non-null  object 
 9   Courier Status      128976 non-null  object 
 10  Qty                 128976 non-null  int64  
 11  currency            121176 non-null  object 
 12  Amount              121176 non-null  float64
 13  ship-city           128941 non-null  object 
 14  ship-state          128941 non-null  object 
 15  ship-postal-code    128941 non-null  float64
 16  ship-country        128941 non-null  object 
 17  B2B                 128976 non-null  bool   
 18  fulfilled-by        39263 non-null   object 
 19  New                 0 non-null       float64
 20  PendingS            0 non-null       float64
dtypes: bool(1), float64(4), int64(2), object(14)
memory usage: 19.8+ MB
```

In [54]:
```
df.describe()
```

Out[54]:

	index	Qty	Amount	ship-postal-code	New	PendingS
count	128976.000000	128976.000000	121176.000000	128941.000000	0.0	0.0
mean	64486.130427	0.904401	648.562176	463945.677744	NaN	NaN
std	37232.897832	0.313368	281.185041	191458.488954	NaN	NaN
min	0.000000	0.000000	0.000000	110001.000000	NaN	NaN
25%	32242.750000	1.000000	449.000000	382421.000000	NaN	NaN
50%	64486.500000	1.000000	605.000000	500033.000000	NaN	NaN
75%	96730.250000	1.000000	788.000000	600024.000000	NaN	NaN
max	128974.000000	15.000000	5584.000000	989898.000000	NaN	NaN

In [55]:
```
df.describe(include = 'object')
```

Out[55]:

	Order ID	Date	Status	Fulfilment	Sales Channel	ship-service-level	Category	Size	Couri Stat
count	128976	128976	128976	128976	128976	128976	128976	128976	1289
unique	120229	91	13	2	2	2	9	11	
top	403-4984515-8861958	05-03-2022	Shipped	Amazon	Amazon.in	Expedited	T-shirt	M	Shipp
freq	12	2085	77815	89713	128852	88630	50292	22373	1094

In [56]:
```
df.shape
```

Out[56]:
```
(128976, 21)
```

In [57]:
```
df.columns
```

Out[57]:
```
Index(['index', 'Order ID', 'Date', 'Status', 'Fulfilment', 'Sales Channe
l',
       'ship-service-level', 'Category', 'Size', 'Courier Status', 'Qty',
       'currency', 'Amount', 'ship-city', 'ship-state', 'ship-postal-cod
e',
       'ship-country', 'B2B', 'fulfilled-by', 'New', 'PendingS'],
      dtype='object')
```

Data Cleaning

In [58]:
```
df.isnull().sum()
```

Out[58]:
```
index                      0
Order ID                   0
Date                       0
Status                     0
Fulfilment                 0
Sales Channel              0
ship-service-level         0
Category                   0
Size                       0
Courier Status             0
Qty                        0
currency                7800
Amount                  7800
ship-city                 35
ship-state                35
ship-postal-code          35
ship-country              35
B2B                        0
fulfilled-by           89713
New                   128976
PendingS              128976
dtype: int64
```

In [59]:
```
# Drop Column 'New' and 'PendingS'

df.drop(columns = ['New', 'PendingS'], axis = 1, inplace = True)
```

In [60]:
```
# Drop Null Values :

df.dropna(inplace = True)
```

In [61]:
```
# Change datatype of 'Date' from object to datetime:

df['Date'] = pd.to_datetime(df['Date'])
```

In [62]:
```
# Change datatype of 'ship-postal-code' from float to int:

df['ship-postal-code'] = df['ship-postal-code'].astype(int)
```

In [63]:
```
df.info()
```

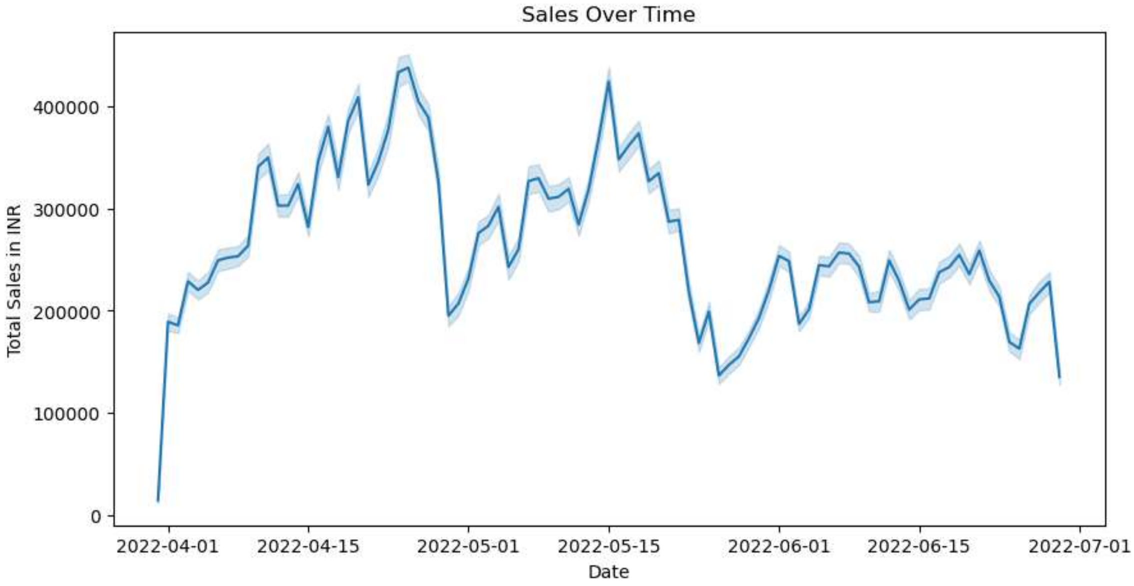
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 37514 entries, 0 to 128892
Data columns (total 19 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   index               37514 non-null  int64
 1   Order ID            37514 non-null  object
 2   Date                37514 non-null  datetime64[ns]
 3   Status              37514 non-null  object
 4   Fulfilment          37514 non-null  object
 5   Sales Channel       37514 non-null  object
 6   ship-service-level  37514 non-null  object
 7   Category            37514 non-null  object
 8   Size                37514 non-null  object
 9   Courier Status      37514 non-null  object
 10  Qty                 37514 non-null  int64
 11  currency            37514 non-null  object
 12  Amount              37514 non-null  float64
 13  ship-city           37514 non-null  object
 14  ship-state          37514 non-null  object
 15  ship-postal-code    37514 non-null  int32
 16  ship-country        37514 non-null  object
 17  B2B                 37514 non-null  bool
 18  fulfilled-by        37514 non-null  object
dtypes: bool(1), datetime64[ns](1), float64(1), int32(1), int64(2), object
(13)
memory usage: 5.3+ MB
```

Data Analysis and Visualization

Sales Over Time

In [87]:
```
plt.figure(figsize = (10,5))
sns.lineplot(x = 'Date', y = 'Amount', data = df, palette = 'YlGnBu', estim
plt.title('Sales Over Time')
plt.xlabel('Date')
plt.ylabel('Total Sales in INR')
plt.show()
```

```
C:\Users\ratne\AppData\Local\Temp\ipykernel_15876\1164441813.py:2: UserWar
ning: Ignoring `palette` because no `hue` variable has been assigned.
  sns.lineplot(x = 'Date', y = 'Amount', data = df, palette = 'YlGnBu', es
timator = sum)
```



Product Size

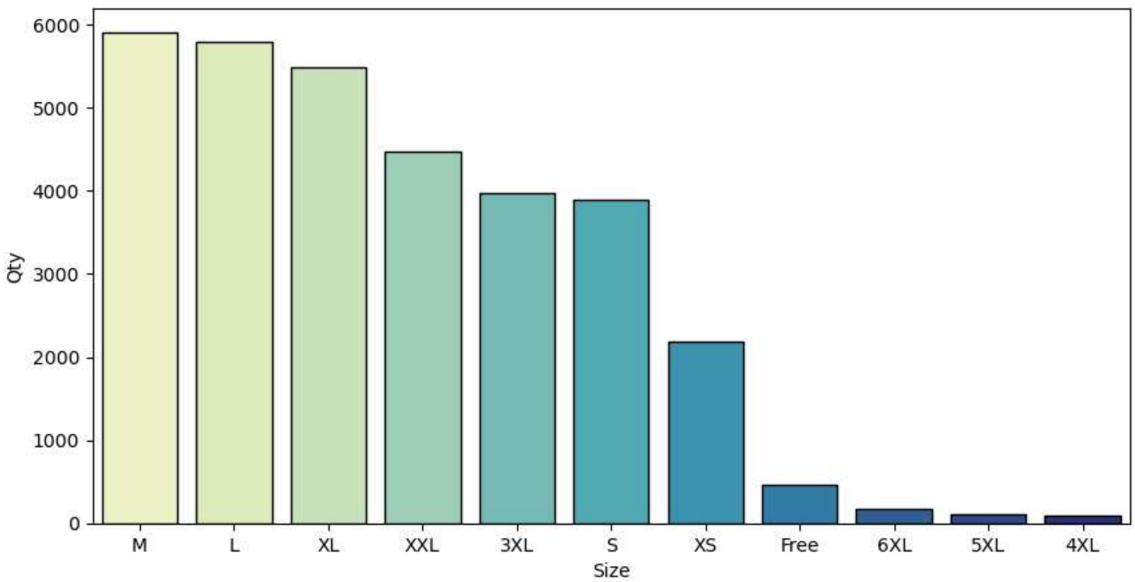
In [373]:
```
Total_Qty = df.groupby(['Size'], as_index = False)['Qty'].sum().sort_values
```

In [374]:
```
Total_Qty
```

Out[374]:

	Size	Qty
6	M	5905
5	L	5795
8	XL	5481
10	XXL	4465
0	3XL	3972
7	S	3896
9	XS	2191
4	Free	467
3	6XL	170
2	5XL	104
1	4XL	93

In [123]:
```
plt.figure(figsize = (10,5))
sns.barplot(x = 'Size', y = 'Qty', data =Total_Qty, edgecolor = 'Black', pa
plt.xticks()
plt.show()
```



Size Analysis Summary

After analyzing the size distribution in the dataset, it is evident that the majority of customers prefer purchasing items in medium (M) size. This is followed by large (L) size, and extra-large (XL) size comes third in popularity.

The distribution is as follows:

- Medium (M) size accounts for the highest number of purchases.
- Large (L) size is the second most preferred choice among customers.
- Extra-large (XL) size has a lower frequency compared to M and L sizes.

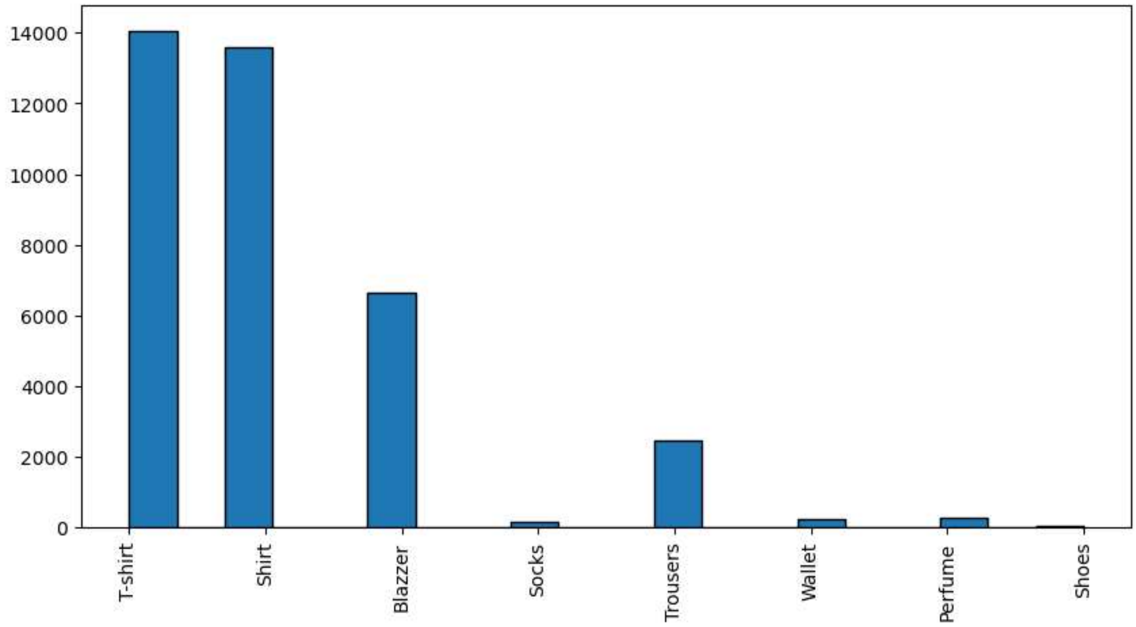
This information provides valuable insights into customer preferences, which can be crucial

Category

In [375]:
```
df['Category'].value_counts()
```

Out[375]:
```
T-shirt     14062
Shirt       13595
Blazzer      6661
Trousers     2459
Perfume       295
Wallet        228
Socks         183
Shoes          31
Name: Category, dtype: int64
```

In [316]:
```
df['Category']  = df['Category'].astype(str)
column_data = df['Category']
plt.figure(figsize = (10,5))
plt.hist(column_data, bins = 20, edgecolor = 'Black')
plt.xticks(rotation = 90)
plt.show()
```



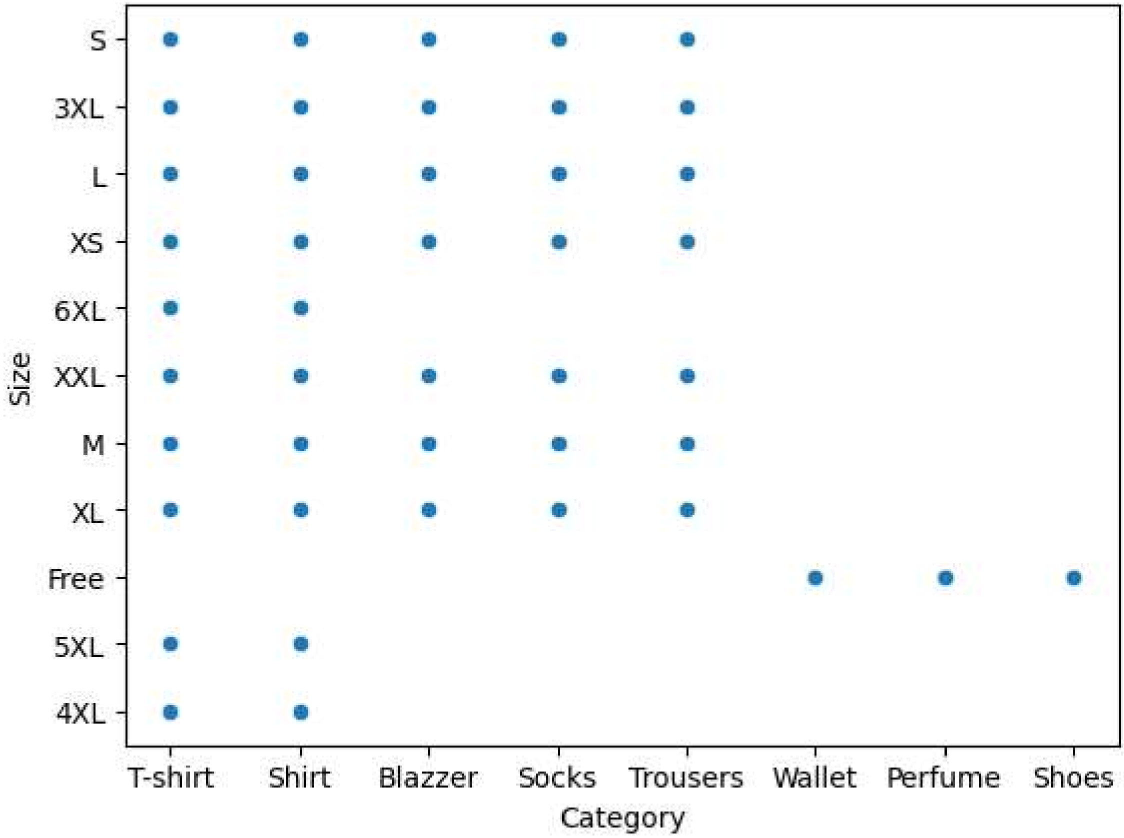
Category Analysis Summary

In exploring product categories, an unexpected trend emerges. T-shirts lead, yet the surprising demand for blazers hints at a potential rising trend or distinct customer preference. Notably, wallets outperform shoes, suggesting opportunities for targeted marketing. These insights offer a nuanced view for strategic product positioning and customer engagement.

Size Distribution Across Product Categories

In [149]:
```
sns.scatterplot(x = df['Category'], y = df['Size'], palette = 'YlGnBu')
plt.show()
```

```
C:\Users\ratne\AppData\Local\Temp\ipykernel_15876\1288521506.py:1: UserWar
ning: Ignoring `palette` because no `hue` variable has been assigned.
  sns.scatterplot(x = df['Category'], y = df['Size'], palette = 'YlGnBu')
```



Product Size Availability Analysis

Analyzing the size availability within each product category unveils interesting patterns. T-shirts and shirts stand out by offering a comprehensive range of sizes. Intriguingly, free size is exclusively available for wallets, perfumes, and shoes, perhaps catering to the versatile nature of these accessories. Blazzer, socks, and trousers showcase inclusivity with sizes ranging from S to 3XL, emphasizing a broad customer base. This nuanced size distribution not only aligns with fashion industry trends but also underscores the targeted sizing strategies employed across diverse product categories.

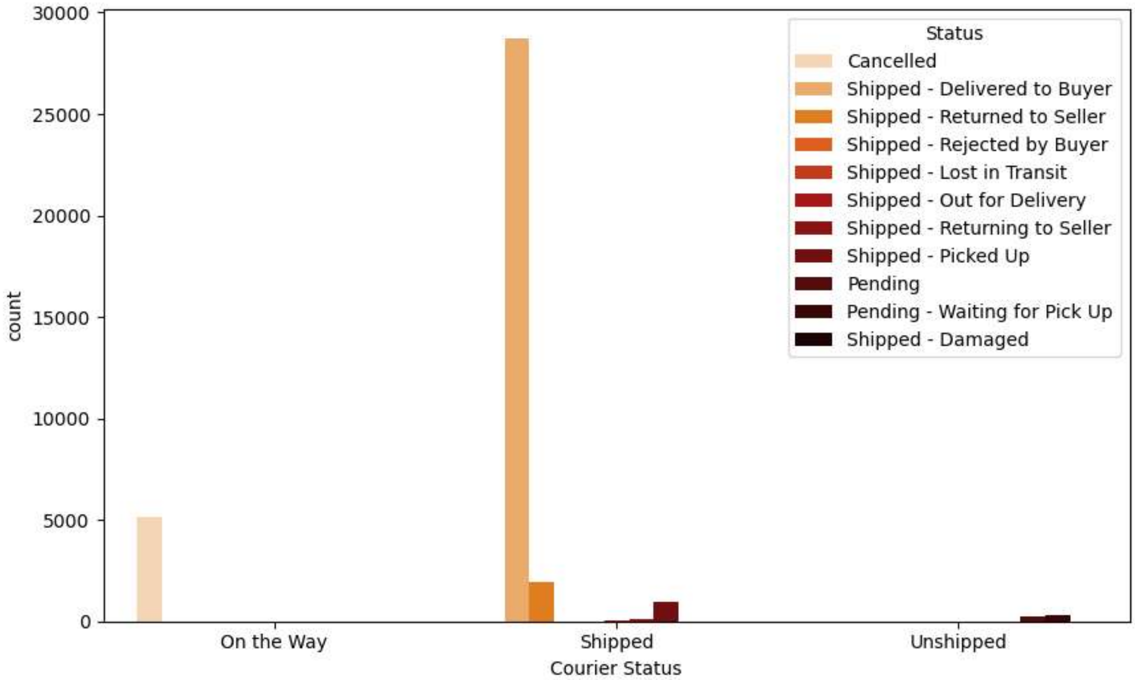
Courier Sevice Status

In [376]:

Out[376]:
```
Shipped - Delivered to Buyer     0.766141
Cancelled                        0.136776
Shipped - Returned to Seller     0.051927
Shipped - Picked Up              0.025937
Pending - Waiting for Pick Up    0.007491
Pending                          0.006478
Shipped - Returning to Seller    0.003865
Shipped - Out for Delivery       0.000933
Shipped - Rejected by Buyer      0.000293
Shipped - Lost in Transit        0.000133
Shipped - Damaged                0.000027
Name: Status, dtype: float64
```

In [372]:
```
plt.figure(figsize = (10,6))
sns.countplot(x = 'Courier Status', data = df, hue = 'Status', palette = 'g

plt.show()
```



Status Analysis

The analysis of courier status reveals that the majority of products have been successfully delivered, highlighting the efficiency and reliability of the delivery process.

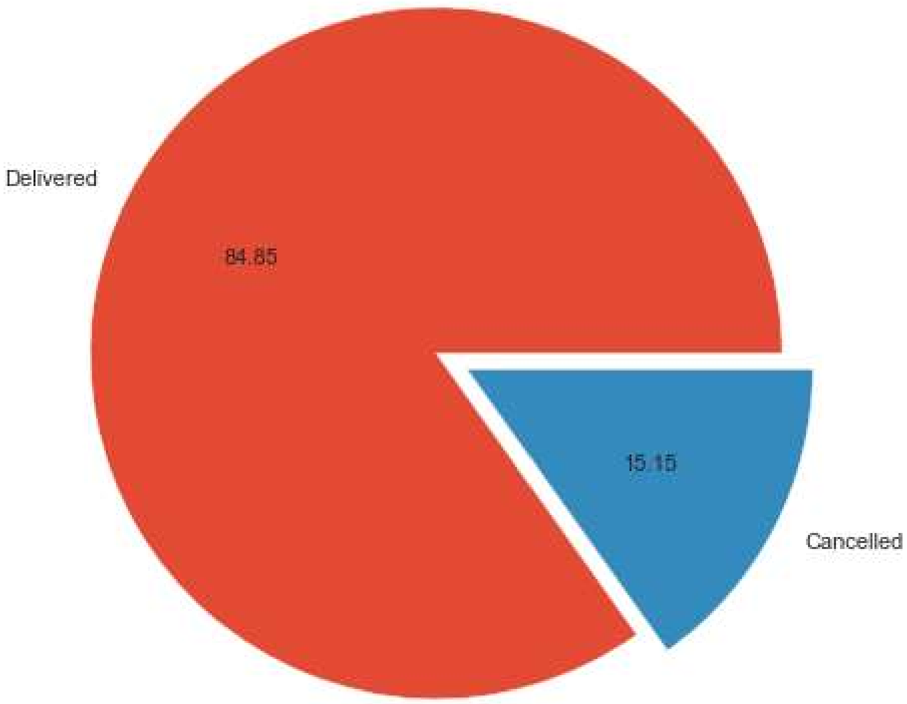
Delivered vs Cancelled Orders

In [236]:
```
Delivered = df.loc[df['Status'] == 'Shipped - Delivered to Buyer'].count()[(

Cancelled = df.loc[df['Status'] == 'Cancelled'].count()[0]
```

Out[236]: 5131

In [246]:
```
labels = ('Delivered', 'Cancelled')
plt.pie([Delivered, Cancelled], labels = labels, autopct = '%.2f', explode :
plt.style.use('ggplot')
plt.show()
```



Order Status Analysis

Examining order statuses reveals a robust delivery success rate of 84.85%, signaling efficient fulfillment processes. However, a 15.15% cancellation rate suggests potential areas for improvement, emphasizing the need for enhanced order management to optimize the overall customer experience.

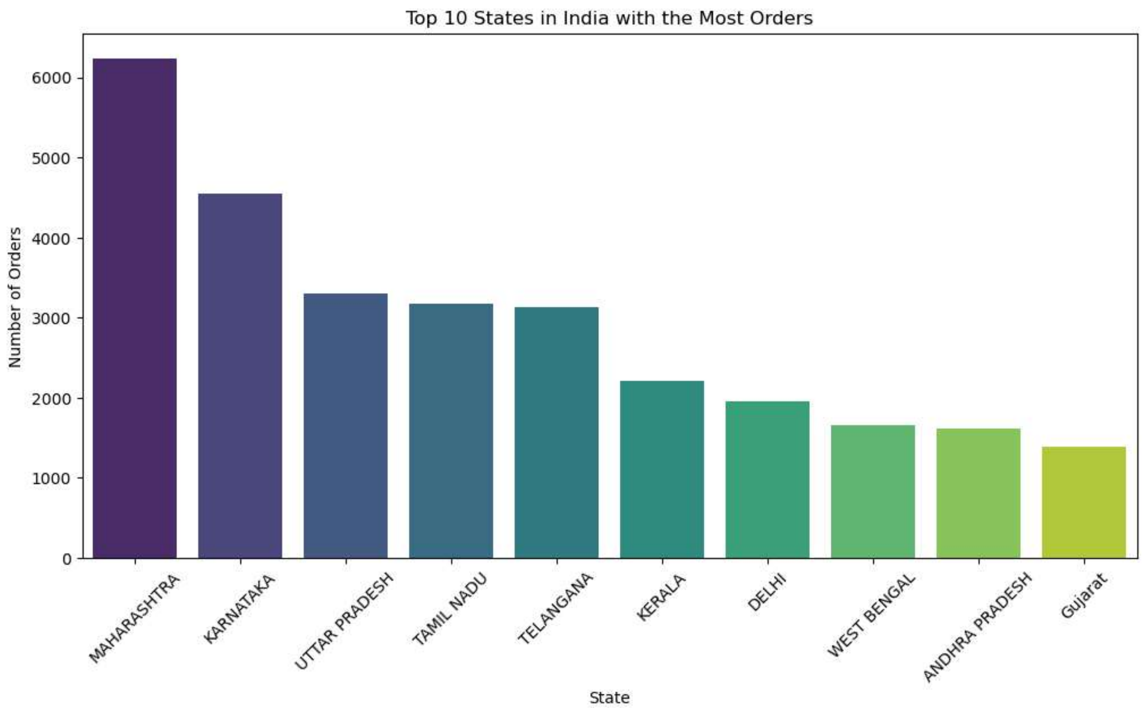
Geographical Distribution

In [304]:
```
Top_10_State = df['ship-state'].value_counts().head(10)
```

In [305]:
```
Top_10_State
```

Out[305]:
```
MAHARASHTRA       6236
KARNATAKA         4550
UTTAR PRADESH     3298
TAMIL NADU        3167
TELANGANA         3136
KERALA            2213
DELHI             1955
WEST BENGAL       1653
ANDHRA PRADESH    1621
Gujarat           1382
Name: ship-state, dtype: int64
```

In [312]:
```
plt.figure(figsize=(12, 6))
sns.barplot(x=Top_10_State.index, y=Top_10_State.values, palette='viridis')
plt.xlabel('State')
plt.ylabel('Number of Orders')
plt.title('Top 10 States in India with the Most Orders')
plt.xticks(rotation=45)
plt.show()
```



Top 10 State Dynamics

Maharashtra's leading order count suggests a robust market influenced by factors like population density and economic activity. Karnataka follows, driven by Bengaluru's e-commerce influence. The substantial orders in populous states like Uttar Pradesh and Tamil Nadu indicate widespread customer engagement. Telangana's tech hub and Kerala's tech-savvy population likely contribute to their higher order numbers. Diverse economic activities in Delhi, West Bengal, Andhra Pradesh, and Gujarat impact their order volumes. Understanding these regional dynamics is crucial for tailored marketing and logistical strategies.

B2B vs B2C

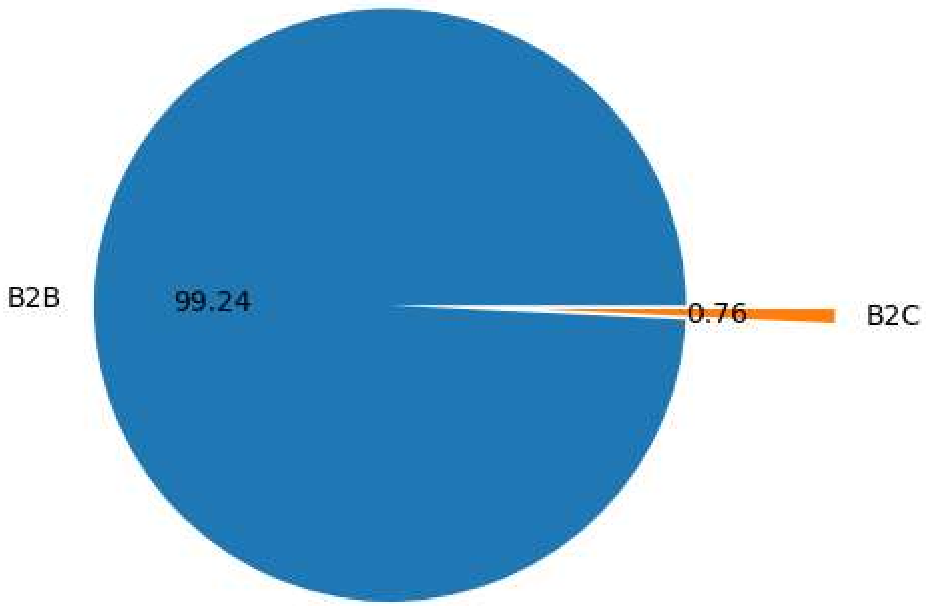
In [359]:
```
B2B_Check = df.loc[df['B2B'] == False].count()[0]
B2C_Check = df.loc[df['B2B'] == True].count()[0]
```

In [358]:
```
df['B2B'].value_counts()
```

Out[358]:
```
False    37228
True       286
Name: B2B, dtype: int64
```

In [364]:
```
B2B_ = [B2B_Check, B2C_Check]
labels = ('B2B', 'B2C')
explode = (0,.5)
```

In [365]:
```
plt.pie(B2B_, labels = labels, autopct = '%.2f', explode = explode)
plt.show()
```



Sales Trade Insight

The prevalence of 37228 non-B2B transactions, overshadowing 286 B2B transactions, underscores a consumer-driven trend in the sales report. This highlights the imperative for Amazon to prioritize strategies tailored to individual customers, ensuring optimized user experience and sustained revenue growth.

Comprehensive Sales Landscape Analysis:

The data analysis unveils a strategic landscape where Maharashtra plays a pivotal role, potentially fueled by urban centers. The prominence of B2B transactions signifies a wholesale focus, requiring strong retailer partnerships. The reliance on Amazon's fulfillment highlights a commitment to efficiency. T-shirts, especially in M-Size, dominate, showcasing a keen understanding of market preferences. To harness these insights, targeted marketing in

In [ ]:

```

```