# E-Commerce Analytics: Swiggy, Zomato, Blinkit



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

import warnings
warnings.filterwarnings('ignore')
```

```
In [2]: ## Load the Dataset
df = pd.read_csv(r"C:\Users\chitt\Downloads\Ecommerce_Delivery_Analytics_New.csv
df
```

Out[2]:

		Order ID	Customer ID	Platform	Order Date & Time	Delivery Time (Minutes)	Product Category	Order Value (INR)	Customa Feedbac
	0	ORD000001	CUST2824	JioMart	19:29.5	30	Fruits & Vegetables	382	Fa deliver grea servica
	1	ORD000002	CUST1409	Blinkit	54:29.5	16	Dairy	279	Quick an reliable
	2	ORD000003	CUST5506	JioMart	21:29.5	25	Beverages	599	Iten missin froi orde
	3	ORD000004	CUST5012	JioMart	19:29.5	42	Beverages	946	Iten missin froi orde
	4	ORD000005	CUST4657	Blinkit	49:29.5	30	Beverages	334	Fa deliver greaservica
	•••			•••	•••				
99	995	ORD099996	CUST5324	JioMart	49:29.5	24	Dairy	289	Packagin could b bette
99	996	ORD099997	CUST1677	JioMart	18:29.5	19	Snacks	322	Goc quali <sup>.</sup> product
99	9997	ORD099998	CUST8198	JioMart	27:29.5	41	Dairy	135	Fa deliver grea service
99	998	ORD099999	CUST9975	JioMart	14:29.5	31	Grocery	973	Quick an reliable
99	999	ORD100000	CUST3748	JioMart	41:29.5	34	Fruits & Vegetables	453	Packagin could t bette
100	0000	rows × 11 co	lumns						
4									•
	: Disp	play basis i	info						

In [3]: ## Display basis info
df.head()

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	Order ID	Customer ID	Platform	Order Date & Time	Delivery Time (Minutes)	Product Category	Order Value (INR)	Customer Feedback	S
0	ORD000001	CUST2824	JioMart	19:29.5	30	Fruits & Vegetables	382	Fast delivery, great service!	
1	ORD000002	CUST1409	Blinkit	54:29.5	16	Dairy	279	Quick and reliable!	
2	ORD000003	CUST5506	JioMart	21:29.5	25	Beverages	599	Items missing from order.	
3	ORD000004	CUST5012	JioMart	19:29.5	42	Beverages	946	Items missing from order.	
4	ORD000005	CUST4657	Blinkit	49:29.5	30	Beverages	334	Fast delivery, great service!	

In [4]: df.tail()

Out[4]:

	Order ID	Customer ID	Platform	Order Date & Time	Delivery Time (Minutes)	Product Category	Order Value (INR)	Customa Feedbac
99995	ORD099996	CUST5324	JioMart	49:29.5	24	Dairy	289	Packagin could t bette
99996	ORD099997	CUST1677	JioMart	18:29.5	19	Snacks	322	Goc quali <sup>.</sup> product
99997	ORD099998	CUST8198	JioMart	27:29.5	41	Dairy	135	Fa deliver grea service
99998	ORD099999	CUST9975	JioMart	14:29.5	31	Grocery	973	Quick an reliable
99999	ORD100000	CUST3748	JioMart	41:29.5	34	Fruits & Vegetables	453	Packagin could t bette
4								Þ

In [5]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype
0	Order ID	100000 non-null	object
1	Customer ID	100000 non-null	object
2	Platform	100000 non-null	object
3	Order Date & Time	100000 non-null	object
4	Delivery Time (Minutes)	100000 non-null	int64
5	Product Category	100000 non-null	object
6	Order Value (INR)	100000 non-null	int64
7	Customer Feedback	100000 non-null	object
8	Service Rating	100000 non-null	int64
9	Delivery Delay	100000 non-null	object
10	Refund Requested	100000 non-null	object

dtypes: int64(3), object(8)
memory usage: 8.4+ MB

In [6]: df.describe()

Out[6]: Delive	ry Time (Minutes)	Order Value (INR)	<b>Service Rating</b>
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	•		_
count	100000.000000	100000.000000	100000.000000
mean	29.536140	590.994400	3.240790
std	9.958933	417.409058	1.575962
min	5.000000	50.000000	1.000000
25%	23.000000	283.000000	2.000000
50%	30.000000	481.000000	3.000000
75%	36.000000	770.000000	5.000000
max	76.000000	2000.000000	5.000000

```
In [7]: ## Check for missing values
    df.isnull().sum()
```

```
Out[7]: Order ID 0
Customer ID 0
Platform 0
Order Date & Time 0
Delivery Time (Minutes) 0
Product Category 0
```

Order Value (INR)

Customer Feedback

Service Rating

Delivery Delay

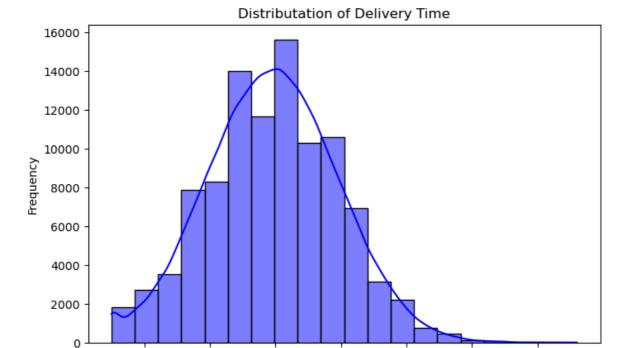
Refund Requested

dtype: int64

In [8]: ## Check for duplicate rows
df.duplicated().sum()

Out[8]: 0

```
In [9]: ## Handle missing vallues
         df.dropna(inplace=True)
In [10]: df.dtypes
Out[10]: Order ID
                                     object
         Customer ID
                                     object
         Platform
                                     object
         Order Date & Time
                                     object
         Delivery Time (Minutes)
                                     int64
         Product Category
                                    object
         Order Value (INR)
                                     int64
         Customer Feedback
                                    object
         Service Rating
                                    int64
         Delivery Delay
                                    object
         Refund Requested
                                    object
         dtype: object
In [11]: df.columns
Out[11]: Index(['Order ID', 'Customer ID', 'Platform', 'Order Date & Time',
                 'Delivery Time (Minutes)', 'Product Category', 'Order Value (INR)',
                 'Customer Feedback', 'Service Rating', 'Delivery Delay',
                 'Refund Requested'],
                dtype='object')
In [12]: df.shape
Out[12]: (100000, 11)
In [13]: ## EDA
         ## Histplot
         plt.figure(figsize=(8,5))
         sns.histplot(df['Delivery Time (Minutes)'], bins=20, kde=True, color='blue')
         plt.title('Distributation of Delivery Time')
         plt.xlabel('Delivery Time (Minutes)')
         plt.ylabel('Frequency')
         plt.show()
```



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Delivery Time (Minutes)

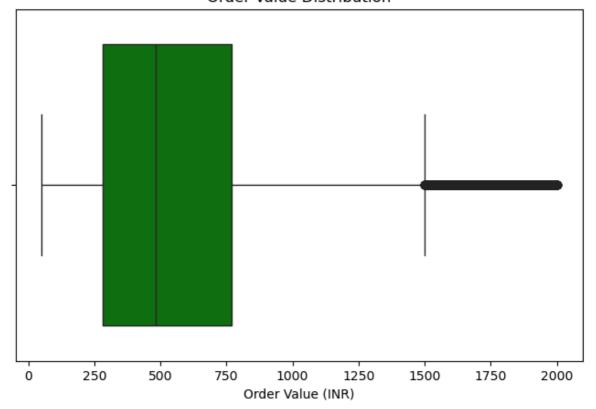
```
In [14]: ## Boxplot
    plt.figure(figsize=(8,5))
    sns.boxplot(x=df['Order Value (INR)'], color='green')
    plt.title('Order Value Distribution')
    plt.xlabel('Order Value (INR)')
    plt.show()
```

30

10

20

#### Order Value Distribution



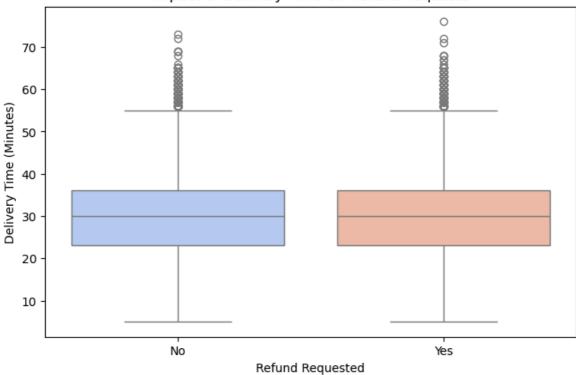
```
In [15]: plt.figure(figsize=(8, 5))
    sns.boxplot(x=df['Refund Requested'], y=df['Delivery Time (Minutes)'], palette='
    plt.title('Impact of Delivery Time on Refund Requests')
```

70

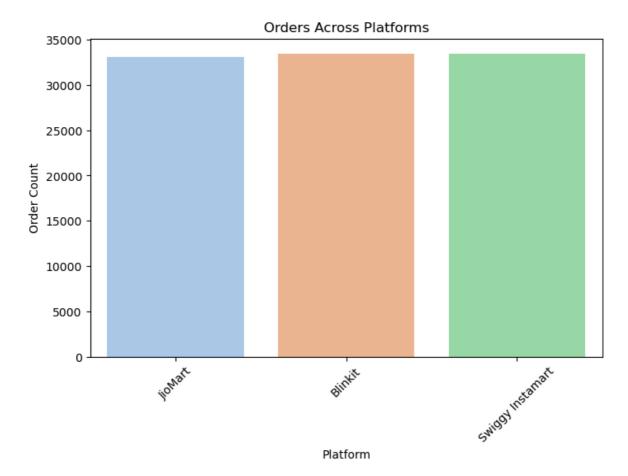
60

```
plt.xlabel('Refund Requested')
plt.ylabel('Delivery Time (Minutes)')
plt.show()
```

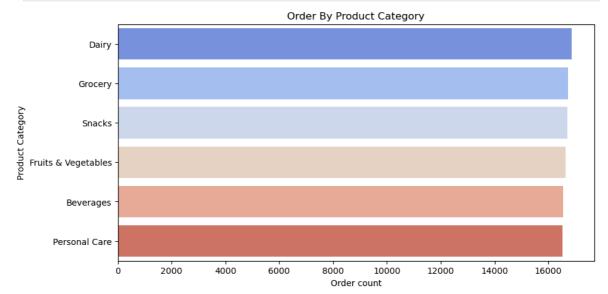
### Impact of Delivery Time on Refund Requests



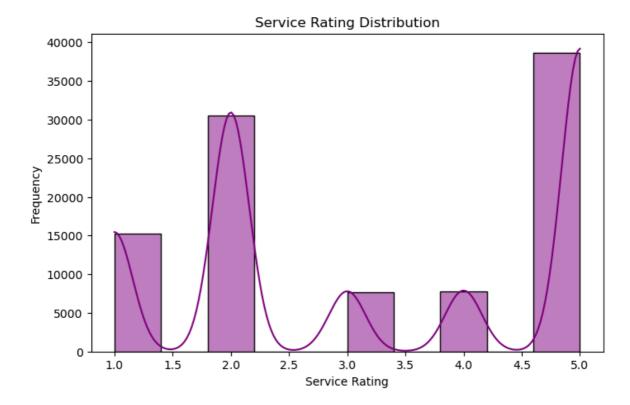
```
In [16]: ## Countplot
    plt.figure(figsize=(8, 5))
    sns.countplot(data=df, x='Platform', palette='pastel')
    plt.title('Orders Across Platforms')
    plt.xlabel('Platform')
    plt.ylabel('Order Count')
    plt.xticks(rotation=45)
    plt.show()
```



```
In [17]: plt.figure(figsize=(10,5))
    sns.countplot(data=df, y='Product Category', order=df['Product Category'].value_
    plt.title('Order By Product Category')
    plt.xlabel('Order count')
    plt.ylabel('Product Category')
    plt.show()
```

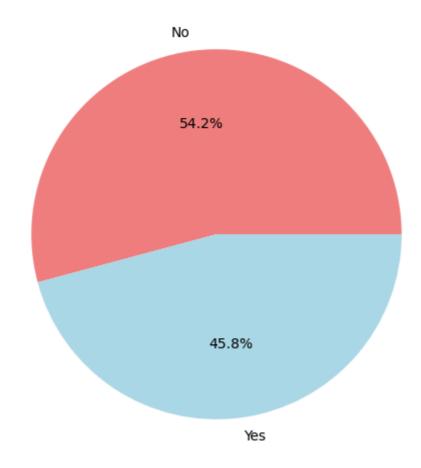


```
In [18]: plt.figure(figsize=(8,5))
    sns.histplot(df['Service Rating'], bins=10, kde=True, color='purple')
    plt.title('Service Rating Distribution')
    plt.xlabel('Service Rating')
    plt.ylabel('Frequency')
    plt.show()
```



```
In [19]: ## Pie Plot
    plt.figure(figsize=(6, 6))
    df['Refund Requested'].value_counts().plot(kind='pie', autopct='%1.1f%%', colors
    plt.title('Refund Request Distribution')
    plt.ylabel('')
    plt.show()
```

### Refund Request Distribution



In [20]: plt.figure(figsize=(10, 6))
 sns.heatmap(df.select\_dtypes(include=['number']).corr(), annot=True, cmap='coolw
 plt.title('Feature Correlation Heatmap')
 plt.show()



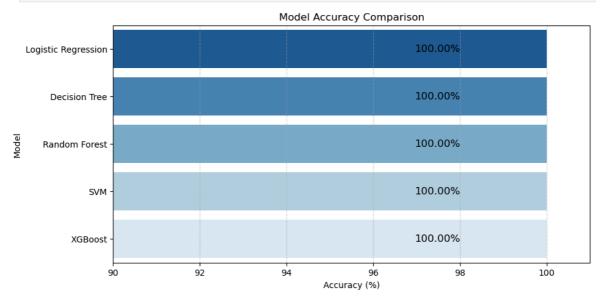
```
In [21]: ## Predictive Modeling
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler, LabelEncoder
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.linear_model import LogisticRegression
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.svm import SVC
         from xgboost import XGBClassifier
         from sklearn.metrics import accuracy_score, classification_report, confusion_mat
In [22]: df['Refund Requested']=df['Refund Requested'].map({'No':0,'Yes':1})
         df['Delivery Delay']=df['Delivery Delay'].map({'No':0,'Yes':1})
In [23]: df.drop(['Order ID', 'Customer ID', 'Order Date & Time'], axis=1, inplace=True)
In [24]: # Encoding categorical features
         categorical_cols = ['Platform', 'Product Category', 'Customer Feedback']
         df = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
In [25]: # Splitting Features and Target
         X = df.drop(columns=['Refund Requested'])
         y = df['Refund Requested']
In [26]: # Train-Test Split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
In [53]: # Standardization
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
In [55]: # Dictionary to store models and results
         models = {
             "Logistic Regression": LogisticRegression(),
             "Decision Tree": DecisionTreeClassifier(),
             "Random Forest": RandomForestClassifier(),
             "SVM": SVC(),
             "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss')
         }
In [57]: # Training and Evaluating Models
         for name, model in models.items():
             model.fit(X_train, y_train)
             y_pred = model.predict(X_test)
             acc = accuracy_score(y_test, y_pred)
             print(f" * {name}: Accuracy = {acc:.4f}")
             print(confusion_matrix(y_test, y_pred))
             print(classification_report(y_test, y_pred))
             print("-" * 50)
```

```
◆ Logistic Regression: Accuracy = 1.0000
[[10836
[ 0 9164]]
         precision recall f1-score support
             1.00 1.00
                                 10836
                             1.00
                            1.00
                                   9164
        1
             1.00
                    1.00
                            1.00
                                   20000
  accuracy
           1.00 1.00
1.00 1.00
  macro avg
                            1.00
                                    20000
                            1.00 20000
weighted avg
◆ Decision Tree: Accuracy = 1.0000
[[10836 0]
[ 0 9164]]
          precision recall f1-score support
             1.00
        0
                    1.00
                           1.00
                                  10836
             1.00 1.00
        1
                           1.00
                                   9164
  accuracy
                            1.00 20000
            1.00 1.00
  macro avg
                           1.00
                                  20000
                            1.00
                                  20000
weighted avg
             1.00
                    1.00
_____
◆ Random Forest: Accuracy = 1.0000
[[10836 0]
[ 0 9164]]
         precision recall f1-score support
           1.00 1.00 1.00
                                  10836
             1.00
                    1.00
        1
                            1.00
                                   9164
                            1.00
                                    20000
  accuracy
  macro avg
             1.00 1.00
                            1.00
                                   20000
weighted avg
             1.00
                    1.00
                           1.00
                                   20000
-----
• SVM: Accuracy = 1.0000
[[10836 0]
[ 0 9164]]
          precision recall f1-score support
             1.00
                    1.00
                            1.00
                                  10836
        1
             1.00
                    1.00
                             1.00
                                    9164
                            1.00
                                    20000
  accuracy
           1.00
                    1.00
                           1.00
                                   20000
  macro avg
             1.00 1.00
weighted avg
                             1.00
                                   20000
◆ XGBoost: Accuracy = 1.0000
[[10836
       01
[ 0 9164]]
          precision recall f1-score support
            1.00 1.00
1.00 1.00
                                 10836
        0
                           1.00
        1
                           1.00
                                   9164
```

```
accuracy 1.00 20000 macro avg 1.00 1.00 1.00 20000 weighted avg 1.00 1.00 1.00 20000
```

-----

```
In [59]: results = {
             "Logistic Regression": 1.0,
             "Decision Tree": 1.0,
             "Random Forest": 1.0,
             "SVM": 1.0,
             "XGBoost": 1.0
         }
         # Convert to percentage
         model_names = list(results.keys())
         accuracies = [acc * 100 for acc in results.values()]
         # Plot
         plt.figure(figsize=(10, 5))
         sns.barplot(x=accuracies, y=model_names, palette="Blues_r")
         # Add value labels
         for index, value in enumerate(accuracies):
             plt.text(value - 2, index, f"{value:.2f}%", va='center', ha='right', fontsiz
         # Titles and labels
         plt.xlabel("Accuracy (%)")
         plt.ylabel("Model")
         plt.title("Model Accuracy Comparison")
         plt.xlim(90, 101) # Focus on high accuracy range
         plt.grid(axis='x', linestyle="--", alpha=0.5)
         plt.show()
```



# **Completed**