

Project Name - Customer Satisfaction Prediction (ML _ FA _ DA projects)(Part 1)

Project Type - Data Analysis

Industry - Unified Mentor

Contribution - Individual

Member Name - Hare Krishana Mishra

Task - 1

Project Summary -

Project Description:

The Customer Support Analysis project involves exploring and analyzing a customer support ticket dataset to identify common issues, track support trends, and segment customers based on ticket characteristics. The dataset includes details such as customer demographics, product purchased, type of support request, resolution status, priority levels, and satisfaction ratings. Through data visualization and segmentation, the project helps uncover key patterns in customer service operations, providing valuable insights for process improvement and decision-making.

Objective:

The objective of this project is to analyze customer support tickets to improve service quality and efficiency. Specifically, the project aims to:

- Identify the most frequent support issues.
- Track ticket trends over time.
- Understand customer demographics and behavior.
- Segment customers based on ticket types and satisfaction ratings.
- Provide insights for optimizing ticket resolution processes.

Key Project Details:

Domain: Data Analytics / Exploratory Data Analysis (EDA)

Difficulty Level: Advanced

Tools & Technologies: Python, Pandas, NumPy, Matplotlib, Seaborn, Scikit-learn, Jupyter Notebook, VS Code, SQL, Excel

Dataset: Customer Support Ticket Dataset containing fields like Ticket ID, Customer Age, Gender, Product Purchased, Ticket Type, Status, Resolution, Priority, Channel, First Response Time, Time to Resolution, and Customer Satisfaction Rating.

Key Steps:

- Data Preprocessing and Cleaning
- Exploratory Data Analysis (EDA)
- Visualizing Ticket Trends and Common Issues
- Segmentation by Ticket Type and Satisfaction Rating
- Analysis of Demographics and Support Channels

Use Cases: Identifying key service pain points, monitoring ticket trends, improving resource allocation, and enhancing the customer experience.

Let's Begin:-

Data Preprocessing

```
In [ ]: # Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
In [ ]: # Load the dataset
data = pd.read_csv('/content/customer_support_tickets.csv')
data
```

Out[]:

	Ticket ID	Customer Name	Customer Email	Customer Age	Customer Gender	Fur
0	1	Marisa O'Brien	carrollallison@example.com	32	Other	Gof
1	2	Jessica Rios	clarkeashley@example.com	42	Female	L
2	3	Christopher Robbins	gonzalestracy@example.com	48	Other	I
3	4	Christina Dillon	bradleyolson@example.org	27	Female	M
4	5	Alexander Carroll	bradleymark@example.com	67	Female	A A
...
8464	8465	David Todd	adam28@example.net	22	Female	L
8465	8466	Lori Davis	russell68@example.com	27	Female	So
8466	8467	Michelle Kelley	ashley83@example.org	57	Female	
8467	8468	Steven Rodriguez	fpowell@example.org	54	Male	Pla
8468	8469	Steven Davis MD	lori20@example.net	53	Other	Phi

8469 rows × 17 columns

```
In [ ]: # Display basic info about the dataset
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8469 entries, 0 to 8468
Data columns (total 17 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Ticket ID                            8469 non-null   int64
1   Customer Name                        8469 non-null   object
2   Customer Email                       8469 non-null   object
3   Customer Age                         8469 non-null   int64
4   Customer Gender                      8469 non-null   object
5   Product Purchased                    8469 non-null   object
6   Date of Purchase                     8469 non-null   object
7   Ticket Type                          8469 non-null   object
8   Ticket Subject                       8469 non-null   object
9   Ticket Description                   8469 non-null   object
10  Ticket Status                        8469 non-null   object
11  Resolution                           2769 non-null   object
12  Ticket Priority                      8469 non-null   object
13  Ticket Channel                       8469 non-null   object
14  First Response Time                  5650 non-null   object
15  Time to Resolution                   2769 non-null   object
16  Customer Satisfaction Rating         2769 non-null   float64
dtypes: float64(1), int64(2), object(14)
memory usage: 1.1+ MB
None
```

```
In [ ]: # Data Preprocessing
        # Handling missing values
        data = data.dropna()
```

```
In [ ]: # Encoding categorical variables
        label_encoders = {}
        for column in data.select_dtypes(include=['object']).columns:
            label_encoders[column] = LabelEncoder()
            data[column] = label_encoders[column].fit_transform(data[column])
```

```
In [ ]: # Define features and target variable
        X = data.drop(['Customer Email', 'Customer Satisfaction Rating'], axis=1)
        y = data['Customer Satisfaction Rating']
```

```
In [ ]: # Splitting the dataset
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
In [ ]: from sklearn.preprocessing import LabelEncoder, StandardScaler

        # Make a copy to avoid altering the original data
        df = data.copy()

        # Drop columns that are not useful for prediction (IDs, names, emails, free-text)
        df = df.drop(['Ticket ID', 'Customer Name', 'Customer Email', 'Ticket Subject', 'Ticket Description', 'Ticket Status', 'Ticket Type', 'Ticket Priority', 'Ticket Channel', 'First Response Time', 'Time to Resolution'], axis=1)

        # Encode categorical columns
        label_encoders = {}
        for col in df.select_dtypes(include=['object']).columns:
            label_encoders[col] = LabelEncoder()
            df[col] = label_encoders[col].fit_transform(df[col])
```

```

df[col] = label_encoders[col].fit_transform(df[col].astype(str))

# Define features and target
X = df.drop('Customer Satisfaction Rating', axis=1)
y = df['Customer Satisfaction Rating']

# Train-test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ran

# Feature scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

```

```

In [ ]: # Remove rows where target is NaN
df = df.dropna(subset=['Customer Satisfaction Rating'])

# Now split again
X = df.drop('Customer Satisfaction Rating', axis=1)
y = df['Customer Satisfaction Rating']

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ran

# Scale features
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Train the model
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(random_state=42)
rfc.fit(X_train, y_train)

```

```

Out[ ]: ▼ RandomForestClassifier ⓘ ⓘ
RandomForestClassifier(random_state=42)

```

```

In [ ]: # Predict on the test set
y_pred = rfc.predict(X_test)

```

```

In [ ]: # Model Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))

```

Accuracy: 0.2069795427196149

Classification Report:

	precision	recall	f1-score	support
1.0	0.21	0.19	0.20	168
2.0	0.20	0.19	0.19	174
3.0	0.23	0.25	0.24	175
4.0	0.18	0.17	0.17	162
5.0	0.21	0.24	0.22	152
accuracy			0.21	831
macro avg	0.21	0.21	0.21	831
weighted avg	0.21	0.21	0.21	831

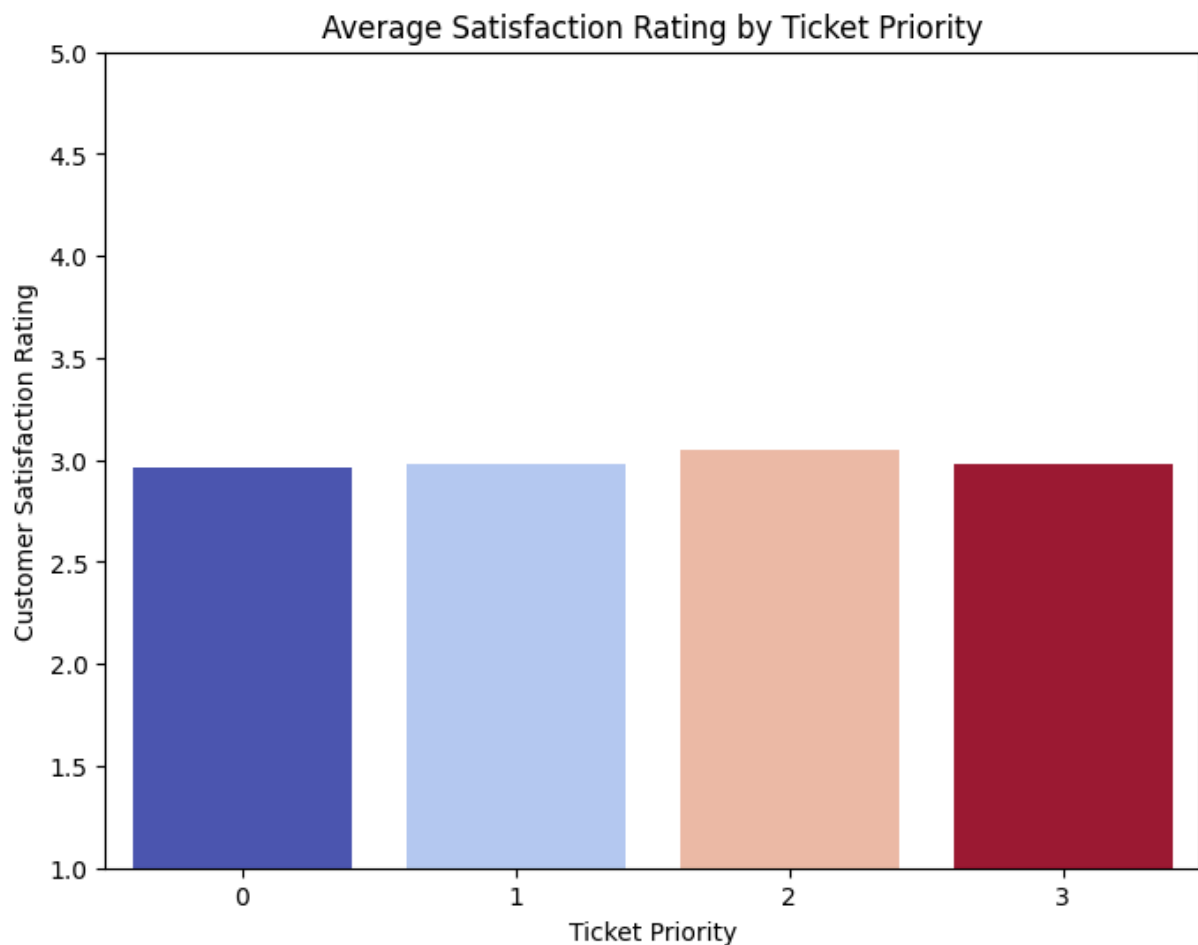
Exploratory Data Analysis (EDA)

Average Customer Satisfaction Score Across Ticket Priority Levels

```
In [ ]: plt.figure(figsize=(8,6))
avg_satisfaction_priority = df.groupby('Ticket Priority')['Customer Satisfaction Rating'].mean()

sns.barplot(
    x='Ticket Priority',
    y='Customer Satisfaction Rating',
    hue='Ticket Priority', # same as x
    data=avg_satisfaction_priority,
    palette='coolwarm',
    legend=False # hides redundant legend
)

plt.title('Average Satisfaction Rating by Ticket Priority')
plt.ylim(1,5)
plt.show()
```

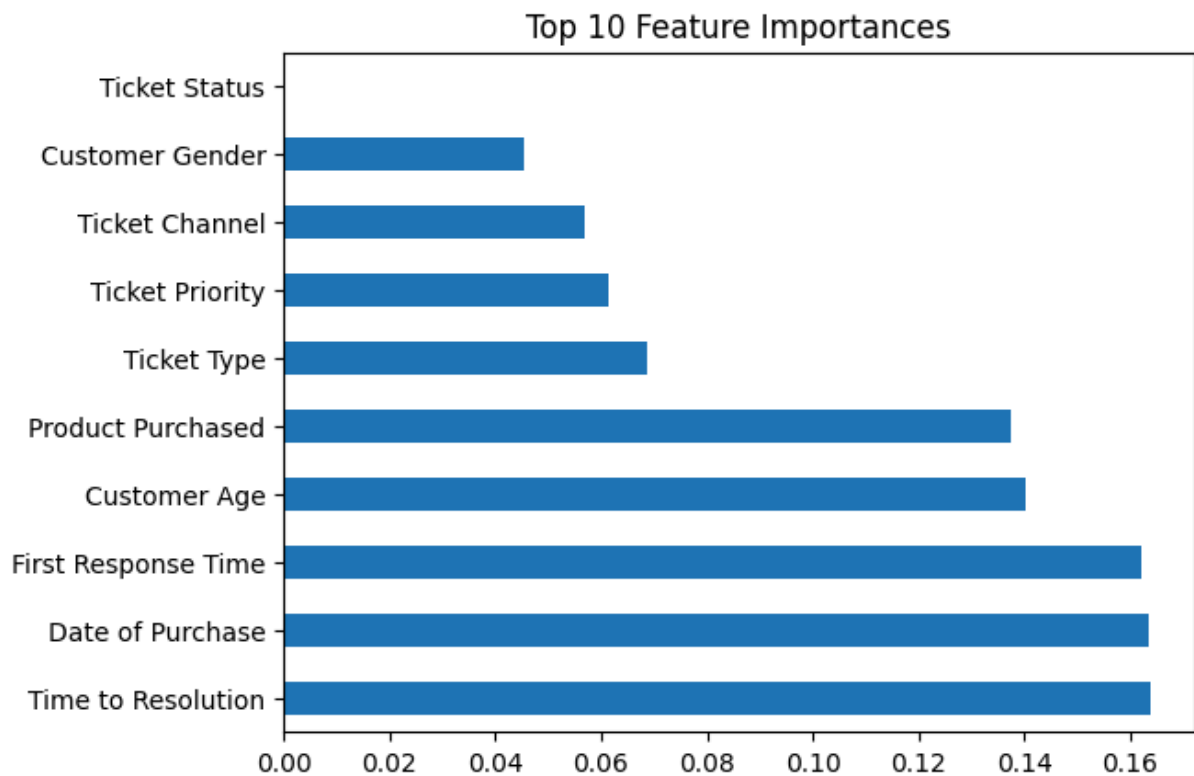


Top 10 Most Influential Features Driving Customer Satisfaction

```
In [ ]: print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
# Visualization of Results
# Feature Importance
feature_importances = pd.Series(rfc.feature_importances_, index=X.columns)
feature_importances.nlargest(10).plot(kind='barh')
plt.title('Top 10 Feature Importances')
plt.show()
```

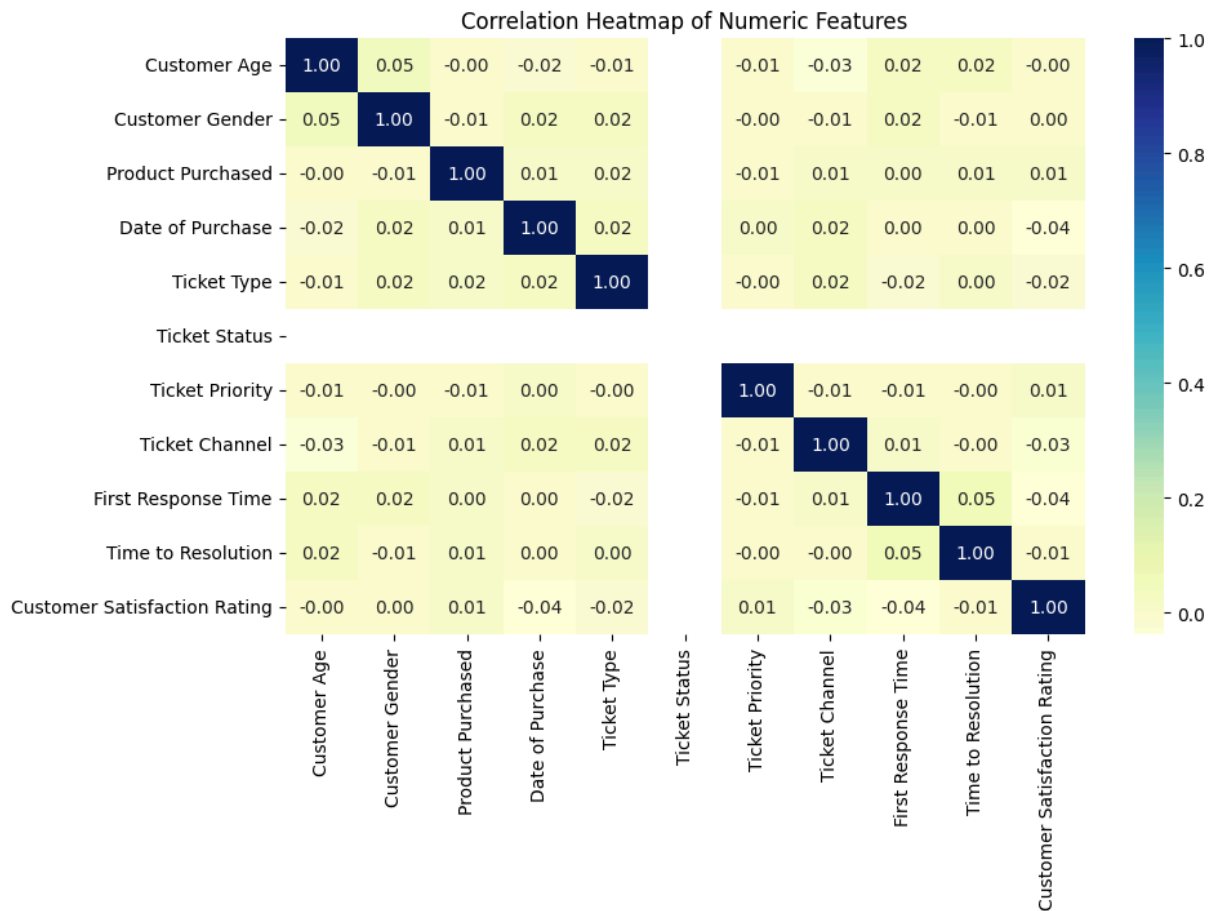
Confusion Matrix:

[32	34	40	33	29]
[36	33	47	28	30]
[36	31	44	30	34]
[29	35	31	27	40]
[21	33	32	30	36]]



Correlation Heatmap: Relationships Between Numeric Features

```
In [ ]: plt.figure(figsize=(10,6))
sns.heatmap(df.corr(), annot=True, cmap='YlGnBu', fmt=".2f")
plt.title('Correlation Heatmap of Numeric Features')
plt.show()
```

Ticket Volume by Channel and Priority Level

```
In [ ]: channel_priority = df.groupby(['Ticket Channel', 'Ticket Priority']).size()

channel_priority.plot(kind='bar', stacked=True, figsize=(10,6), colormap='tab10')
plt.title('Ticket Channel vs Ticket Priority')
plt.ylabel('Number of Tickets')
plt.xticks(rotation=45)
plt.show()
```

