EDA and Preprocessing Machine Learning Assignment II

Objective:

The main objective of this project is to design and implement a robust data preprocessing system that addresses common challenges such as missing values, outliers, inconsistent formatting, and noise. By performing effective data preprocessing, the project aims to enhance the quality, reliability, and usefulness of the data for machine learning.

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [4]:
```
df=pd.read_csv('Employee.csv')
df.head()
```

Out[4]:

	Company	Age	Salary	Place	Country	Gender
0	TCS	20.0	NaN	Chennai	India	0
1	Infosys	30.0	NaN	Mumbai	India	0
2	TCS	35.0	2300.0	Calcutta	India	0
3	Infosys	40.0	3000.0	Delhi	India	0
4	TCS	23.0	4000.0	Mumbai	India	0

In [5]:
```
print(f"\nFeature properties of the dataset:\n")
df.info()
```

```
Feature properties of the dataset:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148 entries, 0 to 147
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   Company  140 non-null    object 
 1   Age      130 non-null    float64
 2   Salary   124 non-null    float64
 3   Place    134 non-null    object 
 4   Country  148 non-null    object 
 5   Gender   148 non-null    int64  
dtypes: float64(2), int64(1), object(3)
memory usage: 7.1+ KB
```

In [6]:
```
df.shape
```

Out[6]:
```
(148, 6)
```

In [7]:
```
dfc=df.copy()
```

In [8]:
```
# Encode Gender: Male = 1, Female = 0
dfc['Gender'] = dfc['Gender'].apply(lambda x: 'Male' if x == 1 else 'Female')
```

In [9]:
```
dfc.columns
```

Out[9]:
```
Index(['Company', 'Age', 'Salary', 'Place', 'Country', 'Gender'], dtype='object')
```

In [10]:
```
dfc.head()
```

Out[10]:

	Company	Age	Salary	Place	Country	Gender
0	TCS	20.0	NaN	Chennai	India	Female
1	Infosys	30.0	NaN	Mumbai	India	Female
2	TCS	35.0	2300.0	Calcutta	India	Female
3	Infosys	40.0	3000.0	Delhi	India	Female
4	TCS	23.0	4000.0	Mumbai	India	Female

In [11]:
```
dfc.describe()
```

Out[11]:

	Age	Salary
count	130.000000	124.000000
mean	30.484615	5312.467742
std	11.096640	2573.764683
min	0.000000	1089.000000
25%	22.000000	3030.000000
50%	32.500000	5000.000000
75%	37.750000	8000.000000
max	54.000000	9876.000000

Data Exploration: (Score : 2)

Explore the data, list down the unique values in each feature and find its length. Perform the statistical analysis and renaming of the columns.

In [13]:
```
# 1. Unique values and their counts
unique_values = {
    col: {"unique": df[col].unique().tolist(), "count": len(df[col].unique())} for
}
```

In [14]:
```
print("Unique Values and Counts:\n", unique_values)
```

```
Unique Values and Counts:
 {'Company': {'unique': ['TCS', 'Infosys', 'CTS', nan, 'Tata Consultancy Service
s', 'Congnizant', 'Infosys Pvt Lmt'], 'count': 7}, 'Age': {'unique': [20.0, 30.0,
35.0, 40.0, 23.0, nan, 34.0, 45.0, 18.0, 22.0, 32.0, 37.0, 50.0, 21.0, 46.0, 36.0,
26.0, 41.0, 24.0, 25.0, 43.0, 19.0, 38.0, 51.0, 31.0, 44.0, 33.0, 17.0, 0.0, 54.
0], 'count': 30}, 'Salary': {'unique': [nan, 2300.0, 3000.0, 4000.0, 5000.0, 6000.
0, 7000.0, 8000.0, 9000.0, 1089.0, 1234.0, 3030.0, 3045.0, 3184.0, 4824.0, 5835.0,
7084.0, 8943.0, 8345.0, 9284.0, 9876.0, 2034.0, 7654.0, 2934.0, 4034.0, 5034.0, 82
02.0, 9024.0, 4345.0, 6544.0, 6543.0, 3234.0, 4324.0, 5435.0, 5555.0, 8787.0, 345
4.0, 5654.0, 5009.0, 5098.0, 3033.0], 'count': 41}, 'Place': {'unique': ['Chenna
i', 'Mumbai', 'Calcutta', 'Delhi', 'Podicherry', 'Cochin', nan, 'Noida', 'Hyderaba
d', 'Bhopal', 'Nagpur', 'Pune'], 'count': 12}, 'Country': {'unique': ['India'], 'c
ount': 1}, 'Gender': {'unique': [0, 1], 'count': 2}}
```

In [15]:
```
# Display unique values and their lengths for each feature
for col in df.columns:
    unique_vals = df[col].unique()
    print(f"Feature: {col}\nUnique Values: {unique_vals}\nCount: {len(unique_vals)}
```

```
Feature: Company
Unique Values: ['TCS' 'Infosys' 'CTS' nan 'Tata Consultancy Services' 'Congnizant'
 'Infosys Pvt Lmt']
Count: 7

Feature: Age
Unique Values: [20. 30. 35. 40. 23. nan 34. 45. 18. 22. 32. 37. 50. 21. 46. 36. 2
6. 41.
 24. 25. 43. 19. 38. 51. 31. 44. 33. 17.  0. 54.]
Count: 30

Feature: Salary
Unique Values: [  nan 2300. 3000. 4000. 5000. 6000. 7000. 8000. 9000. 1089. 1234.
3030.
 3045. 3184. 4824. 5835. 7084. 8943. 8345. 9284. 9876. 2034. 7654. 2934.
 4034. 5034. 8202. 9024. 4345. 6544. 6543. 3234. 4324. 5435. 5555. 8787.
 3454. 5654. 5009. 5098. 3033.]
Count: 41

Feature: Place
Unique Values: ['Chennai' 'Mumbai' 'Calcutta' 'Delhi' 'Podicherry' 'Cochin' nan 'N
oida'
 'Hyderabad' 'Bhopal' 'Nagpur' 'Pune']
Count: 12

Feature: Country
Unique Values: ['India']
Count: 1

Feature: Gender
Unique Values: [0 1]
Count: 2
```

statistical analysis

In [17]:
```
print("\nStatistical Analysis (Numeric Columns):\n", df.describe())
```

```
Statistical Analysis (Numeric Columns):
               Age       Salary      Gender
count  130.000000   124.000000  148.000000
mean    30.484615  5312.467742    0.222973
std     11.096640  2573.764683    0.417654
min      0.000000  1089.000000    0.000000
25%     22.000000  3030.000000    0.000000
50%     32.500000  5000.000000    0.000000
75%     37.750000  8000.000000    0.000000
max     54.000000  9876.000000    1.000000
```

In [18]:
```
dfc.head(2)
```

Out[18]:

	Company	Age	Salary	Place	Country	Gender
0	TCS	20.0	NaN	Chennai	India	Female
1	Infosys	30.0	NaN	Mumbai	India	Female

Rename the columns : Here all the names are capitalising and changing 'Place' to 'City'

In [20]:
```
dfc.columns = dfc.columns.str.upper()
```

In [21]:
```
dfc.head()
```

Out[21]:

	COMPANY	AGE	SALARY	PLACE	COUNTRY	GENDER
0	TCS	20.0	NaN	Chennai	India	Female
1	Infosys	30.0	NaN	Mumbai	India	Female
2	TCS	35.0	2300.0	Calcutta	India	Female
3	Infosys	40.0	3000.0	Delhi	India	Female
4	TCS	23.0	4000.0	Mumbai	India	Female

In [22]:
```
#Changing the "Place" to "City"
dfc.rename(columns={'PLACE':'CITY'},inplace=True)
dfc.head()
```

Out[22]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	20.0	NaN	Chennai	India	Female
1	Infosys	30.0	NaN	Mumbai	India	Female
2	TCS	35.0	2300.0	Calcutta	India	Female
3	Infosys	40.0	3000.0	Delhi	India	Female
4	TCS	23.0	4000.0	Mumbai	India	Female

Data Cleaning: (Score : 2)

Find the missing and inappropriate values, treat them appropriately

In [25]:
```
dfc.isnull().sum()
```

Out[25]:
```
COMPANY     8
AGE        18
SALARY     24
CITY       14
COUNTRY     0
GENDER      0
dtype: int64
```

Treating the missing values in Company with mode value

In [27]:
```
#Imputation method
dfc['COMPANY'].fillna(dfc['COMPANY'].mode()[0],inplace=True)
dfc['COMPANY'].isnull().sum()
```

Out[27]:
```
0
```

Treating the missing values in City with mode value

In [29]:
```
#Imputation method
dfc['CITY'].fillna(dfc['CITY'].mode()[0],inplace=True)
dfc['CITY'].isnull().sum()
```

Out[29]:
```
0
```

Treating the missing values in AGE with mode value

In [31]:
```
#Imputation method
dfc['AGE'].fillna(dfc['AGE'].mode()[0],inplace=True)
dfc['AGE'].isnull().sum()
```

Out[31]:
```
0
```

Treating the missing values in SALARY with median value .

In [33]:
```
#Imputation method
dfc['SALARY'].fillna(dfc['SALARY'].mean(),inplace=True)
dfc['SALARY'].isnull().sum()
```

Out[33]:
```
0
```

Remove all duplicate rows.

In [35]:
```
dfc.duplicated().sum()
```

Out[35]:
```
4
```

In [36]:
```
dfc.drop_duplicates(inplace=True)
```

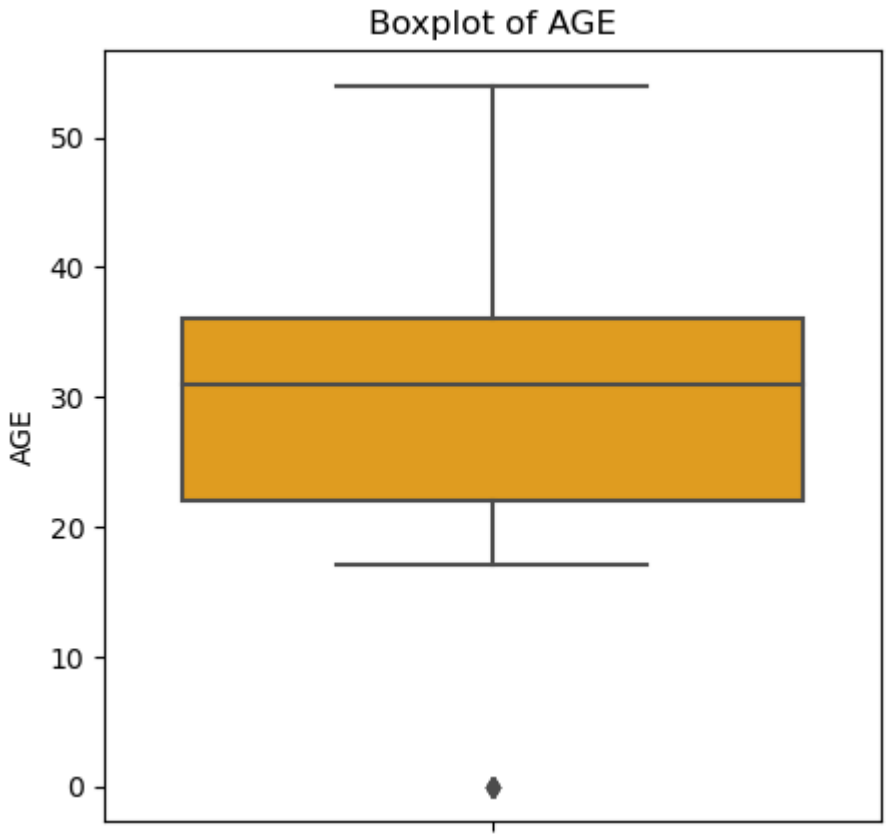
In [37]:
```
dfc.duplicated().sum()
```

Out[37]:
```
0
```

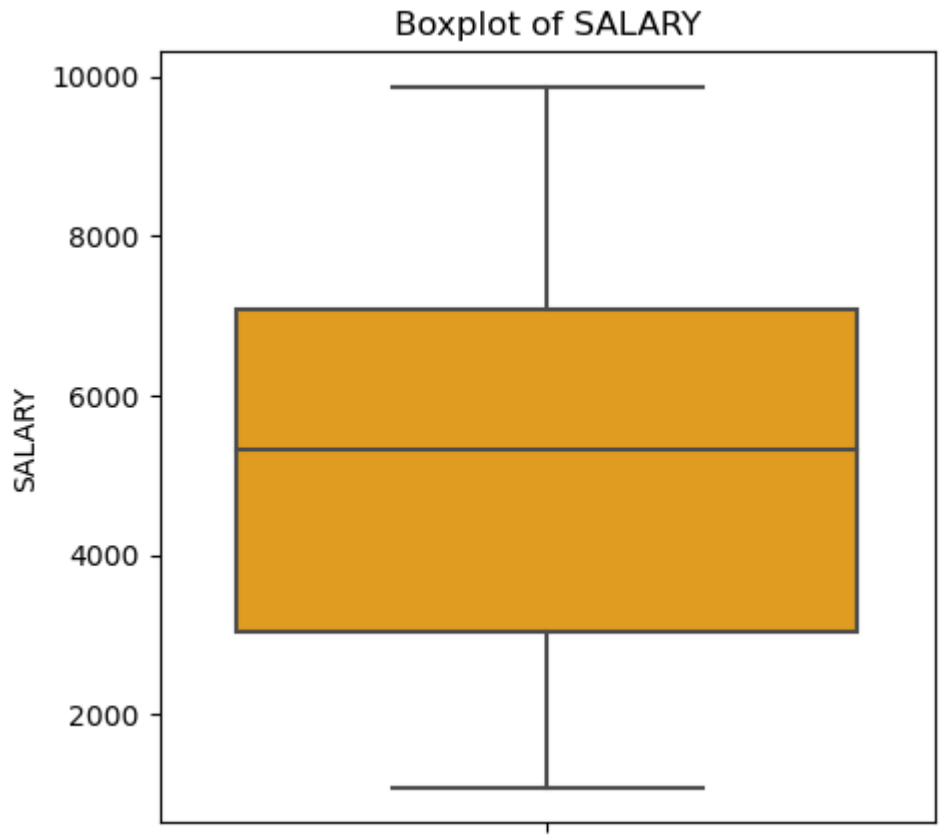
Find the outliers.

Finding outliers using plotting a box plot

In [40]:
```
plt.figure(figsize=(5,5))
sns.boxplot(y=dfc['AGE'],color='orange')
plt.title('Boxplot of AGE')
plt.ylabel('AGE')
plt.show()
```



In [41]:
```
plt.figure(figsize=(5,5))
sns.boxplot(y=dfc['SALARY'],color='orange')
plt.title('Boxplot of SALARY')
plt.ylabel('SALARY')
plt.show()
```



Using IQR method, finding the outlier

In [43]:
```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
q1=dfc['AGE'].quantile(0.25)
q3=dfc['AGE'].quantile(0.75)
iqr=q3-q1
lower_lim=q1-iqr*1.5
upper_lim=q3+iqr*1.5

print(f"Lower Limit: {lower_lim}, Upper Limit: {upper_lim}")
```

```
Lower Limit: 1.0, Upper Limit: 57.0
```

In [44]:
```
#Detecting outliers
outliers = dfc[(dfc['AGE'] < lower_lim) | (dfc['AGE'] > upper_lim)]
print(f"Number of outliers detected: {len(outliers)}")
```

```
Number of outliers detected: 6
```

In [45]:
```
#Trimming method for removing outliers
dfc_cleaned=dfc[(dfc['AGE']>lower_lim) & (dfc['AGE']<upper_lim)]
print(f"Dataset after trimming: {dfc_cleaned.shape}")
```

```
Dataset after trimming: (138, 6)
```

In [46]:
```
#Detecting outliers
outliers = dfc_cleaned[(dfc_cleaned['AGE'] < lower_lim) | (dfc_cleaned['AGE'] > upp
print(f"Number of outliers detected: {len(outliers)}")
```

```
Number of outliers detected: 0
```

Outliers in AGE is cleaned and saved as dfc_cleaned

In [48]:
```
# Calculate Q1 (25th percentile) and Q3 (75th percentile)
q1=dfc['SALARY'].quantile(0.25)
```

```
q3=dfc['SALARY'].quantile(0.75)
iqr=q3-q1
low_lim=q1-iqr*1.5
up_lim=q3+iqr*1.5

print(f"Lower Limit: {low_lim}, Upper Limit: {up_lim}")
```

```
Lower Limit: -3013.5, Upper Limit: 13142.5
```

In [49]:
```
#Detecting outliers
outliers = dfc[(dfc['SALARY'] < low_lim) | (dfc['SALARY'] > up_lim)]
print(f"Number of outliers detected: {len(outliers)}")
```

```
Number of outliers detected: 0
```

There is no outlier for SALARY Column

Replace the value 0 in age as NaN

In [52]:
```
# Replace 0 with NaN in the 'Age' column
dfc['AGE'] = dfc['AGE'].replace(0, np.nan)
```

Data Analysis: (Score : 2)

Filter the data with age >40 and salary<5000

In [55]:
```
print('Filtered data : \n')
filtered=dfc[(dfc['AGE']> 40) & (dfc['SALARY']<5000)]
filtered
```

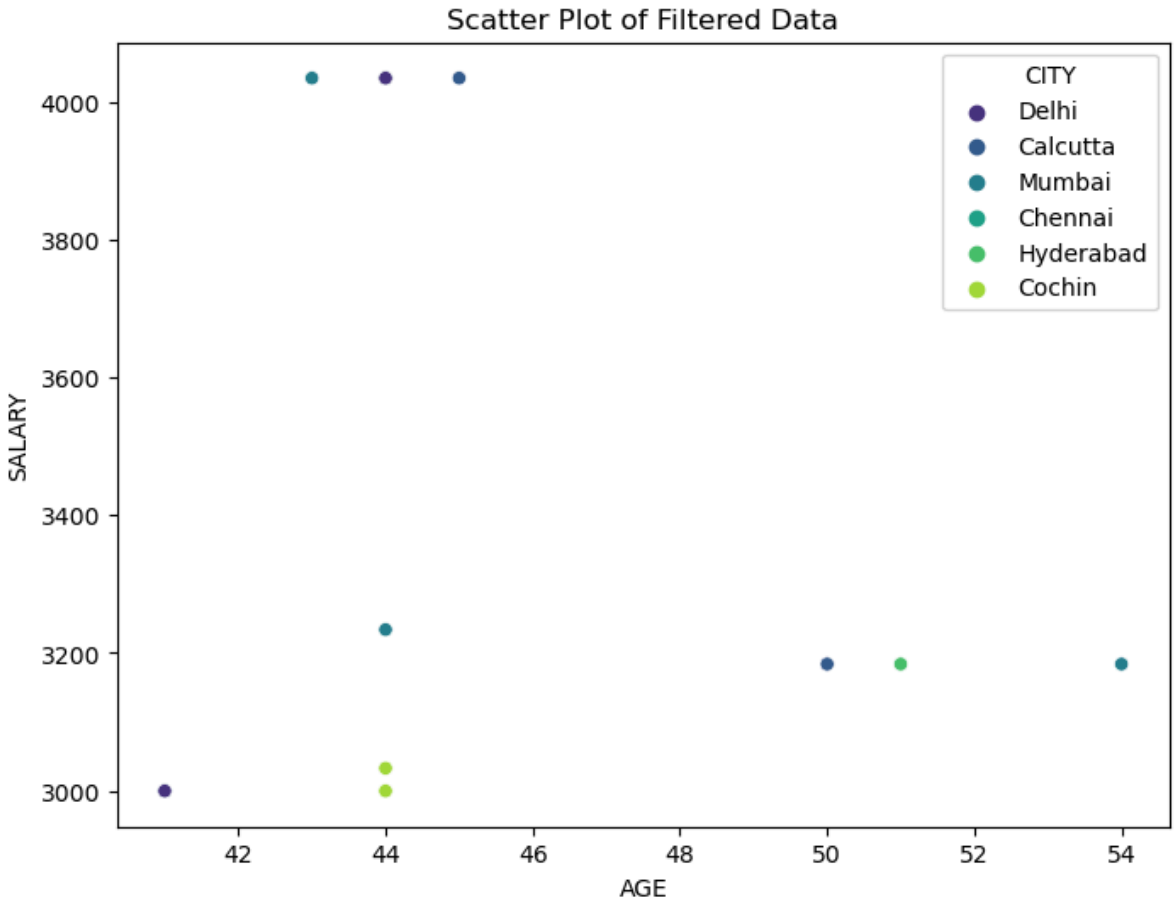
```
Filtered data :
```

Out[55]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
21	Infosys	50.0	3184.0	Delhi	India	Female
32	Infosys	45.0	4034.0	Calcutta	India	Female
39	Infosys	41.0	3000.0	Mumbai	India	Female
50	Infosys	41.0	3000.0	Chennai	India	Female
57	Infosys	51.0	3184.0	Hyderabad	India	Female
68	Infosys	43.0	4034.0	Mumbai	India	Female
75	Infosys	44.0	3000.0	Cochin	India	Female
86	Infosys	41.0	3000.0	Delhi	India	Female
93	Infosys	54.0	3184.0	Mumbai	India	Female
104	Infosys	44.0	4034.0	Delhi	India	Female
122	Infosys	44.0	3234.0	Mumbai	India	Female
129	Infosys	50.0	3184.0	Calcutta	India	Female
138	CTS	44.0	3033.0	Cochin	India	Female
140	Infosys	44.0	4034.0	Hyderabad	India	Female
145	Infosys	44.0	4034.0	Delhi	India	Male

Plot the chart with age and salary

In [57]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(data=filtered, x='AGE', y='SALARY', hue='CITY', palette='viridis')
plt.title('Scatter Plot of Filtered Data')
plt.xlabel('AGE')
plt.ylabel('SALARY')
plt.legend(title='CITY')
plt.show()
```



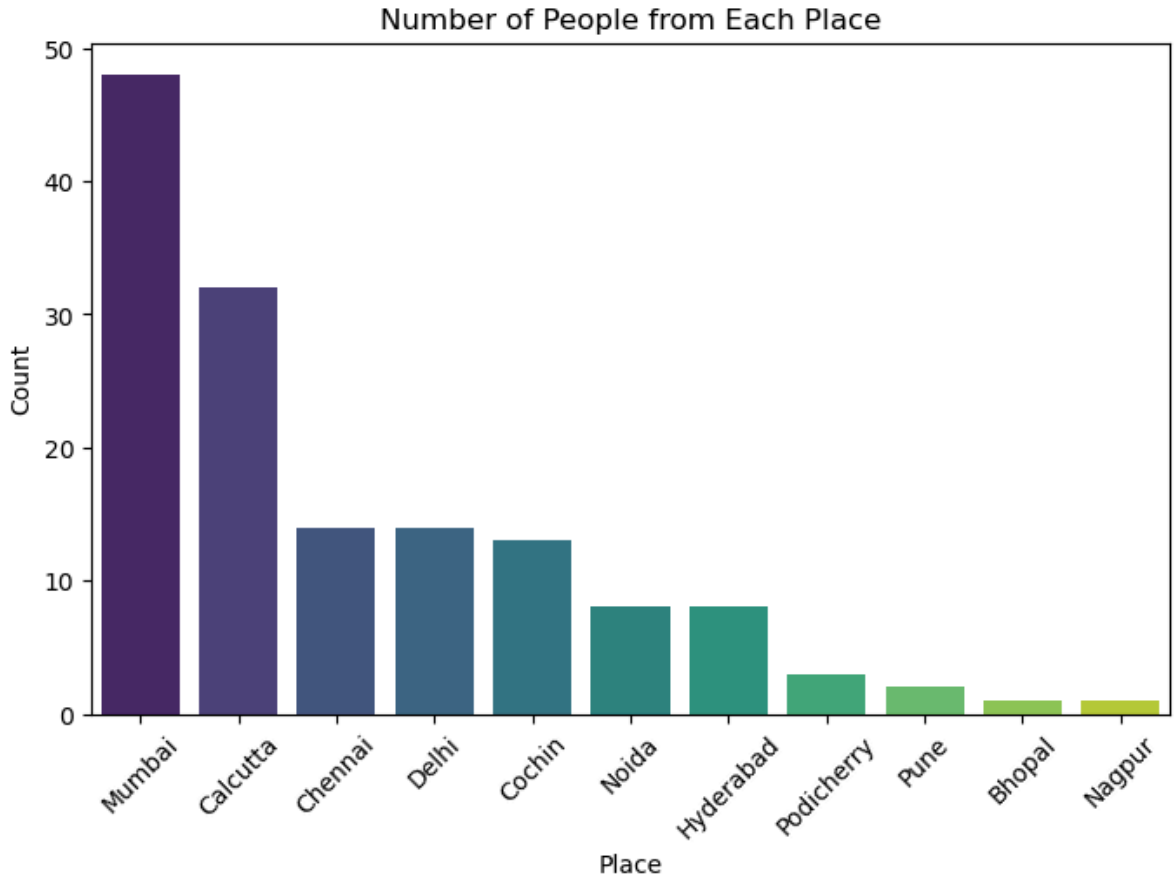
Count the number of people from each place and represent it visually

In [59]:
```
# Count the number of people from each place
place_count = dfc['CITY'].value_counts()
place_count
```

Out[59]:
```
CITY
Mumbai        48
Calcutta      32
Chennai       14
Delhi         14
Cochin        13
Noida          8
Hyderabad      8
Podicherry     3
Pune           2
Bhopal         1
Nagpur         1
Name: count, dtype: int64
```

In [60]:
```
# Plot the counts
plt.figure(figsize=(8, 5))
sns.barplot(x=place_count.index, y=place_count.values, palette='viridis')
```

```
plt.title('Number of People from Each Place')
plt.xlabel('Place')
plt.xticks(rotation=45)
plt.ylabel('Count')
plt.show()
```



Data Encoding: (Score : 2)

Convert categorical variables into numerical representations using techniques such as one-hot encoding, label encoding, making them suitable for analysis by machine learning algorithms.

In [63]:
```
from sklearn.preprocessing import LabelEncoder
```

In [64]:
```
dfc.head(2)
```

Out[64]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	20.0	5312.467742	Chennai	India	Female
1	Infosys	30.0	5312.467742	Mumbai	India	Female

In [114…
```
# Apply Label Encoding
label_encoder = LabelEncoder()
dfc['AGE']=label_encoder.fit_transform(dfc['AGE'])
dfc['SALARY']=label_encoder.fit_transform(dfc['SALARY'])
```

In [116…
```
print('Dataset after Label encoding for Nominal columns :\n')
dfc.head(3)
```

Dataset after Label encoding for Nominal columns :

Out[116]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	4	3	21	2	0	0
1	2	10	21	6	0	0
2	4	15	3	1	0	0

In [ ]:

In [118…

```
# Apply One-Hot Encoding
one_hot_encoded = pd.get_dummies(dfc, columns=['CITY', 'COMPANY', 'COUNTRY','GENDER
print("One-Hot Encoded Data:")
print(one_hot_encoded)
```

```
One-Hot Encoded Data:
     AGE  SALARY  CITY_0  CITY_1  CITY_2  CITY_3  CITY_4  CITY_5  CITY_6  \
0      3      21   False   False    True   False   False   False   False
1     10      21   False   False   False   False   False   False    True
2     15       3   False    True   False   False   False   False   False
3     19       5   False   False   False   False    True   False   False
4      6      12   False   False   False   False   False   False    True
..   ...     ...     ...     ...     ...     ...     ...     ...     ...
142    5      33   False   False   False   False   False   False    True
143   13      38   False    True   False   False   False   False   False
145   22      13   False   False   False   False    True   False   False
146   13      19   False   False   False   False   False   False    True
147    5      33   False   False   False    True   False   False   False

     CITY_7  ...  CITY_10  COMPANY_0  COMPANY_1  COMPANY_2  COMPANY_3  \
0     False  ...    False      False      False      False      False
1     False  ...    False      False      False       True      False
2     False  ...    False      False      False      False      False
3     False  ...    False      False      False       True      False
4     False  ...    False      False      False      False      False
..      ...  ...      ...        ...        ...        ...        ...
142   False  ...    False      False      False      False       True
143   False  ...    False      False      False      False      False
145   False  ...    False      False      False       True      False
146   False  ...    False      False      False      False      False
147   False  ...    False      False      False       True      False

     COMPANY_4  COMPANY_5  COUNTRY_0  GENDER_0  GENDER_1
0         True      False       True      True     False
1        False      False       True      True     False
2         True      False       True      True     False
3        False      False       True      True     False
4         True      False       True      True     False
..         ...        ...        ...       ...       ...
142      False      False       True      True     False
143       True      False       True     False      True
145      False      False       True     False      True
146       True      False       True     False      True
147      False      False       True      True     False

[144 rows x 22 columns]
```

Feature Scaling: (Score : 2)

After the process of encoding, perform the scaling of the features using standardscaler and minmaxscaler.

In [120…
```
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Initialize StandardScaler and MinMaxScaler
standard_scaler = StandardScaler()
minmax_scaler = MinMaxScaler()
```

In [124…
```
# Select only the numerical columns i.e., 'AGE', 'SALARY'
numerical_columns = ['AGE', 'SALARY']
# Apply StandardScaler to numerical columns
dfc_standard_scaled = dfc.copy()
dfc_standard_scaled[numerical_columns] = standard_scaler.fit_transform(dfc_standard

# Applying MinMaxScaler to numerical columns
dfc_minmax_scaled = dfc.copy()
dfc_minmax_scaled[numerical_columns] = minmax_scaler.fit_transform(dfc_minmax_scale

# Display the first few rows of the scaled data
print("Data after Standard Scaling:")
print(dfc_standard_scaled.head(10))

print("\nData after Min-Max Scaling:")
print(dfc_minmax_scaled.head(10))
```

```
Data after Standard Scaling:
   COMPANY       AGE    SALARY  CITY  COUNTRY  GENDER
0        4 -1.246731  0.139604     2        0       0
1        2 -0.312378  0.139604     6        0       0
2        4  0.355017 -1.368123     1        0       0
3        2  0.888933 -1.200598     4        0       0
4        4 -0.846294 -0.614259     6        0       0
5        2 -0.979773 -0.195446     1        0       0
6        4 -0.979773  0.558417     2        0       1
7        2 -0.846294  0.809705     6        0       1
8        4  0.221538  1.060993     1        0       1
9        0  1.422849  1.479806     4        0       0

Data after Min-Max Scaling:
   COMPANY       AGE  SALARY  CITY  COUNTRY  GENDER
0        4  0.107143   0.525     2        0       0
1        2  0.357143   0.525     6        0       0
2        4  0.535714   0.075     1        0       0
3        2  0.678571   0.125     4        0       0
4        4  0.214286   0.300     6        0       0
5        2  0.178571   0.425     1        0       0
6        4  0.178571   0.650     2        0       1
7        2  0.214286   0.725     6        0       1
8        4  0.500000   0.800     1        0       1
9        0  0.821429   0.925     4        0       0
```

Feature Scaling using MIN-MAX Scaling method and STANDARD Scaling method is done

In [ ]:
```
```