MACHINE LEARNING ASSIGNMENT 2 EDA AND DATA PREPROCESSING

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 [1]:
```
import warnings
import sys
if not sys.warnoptions:
    warnings.simplefilter("ignore")
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
```

In [3]:
```
data = pd.read_csv("Employee.csv")
data
```

Out[3]:

	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
...	...	...	...	...	...	...
143	TCS	33.0	9024.0	Calcutta	India	1
144	Infosys	22.0	8787.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

148 rows × 6 columns

Data Exploration: 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 [4]:
```
data3 = data.copy()
data3
```

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
...	...	...	...	...	...	...
143	TCS	33.0	9024.0	Calcutta	India	1
144	Infosys	22.0	8787.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

148 rows × 6 columns

In [5]:
```
print("Displaying first 10 rows")
print("\t")
data3.head(10)
```

```
Displaying first 10 rows
```

Out[5]:

	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
5	Infosys	NaN	5000.0	Calcutta	India	0
6	TCS	NaN	6000.0	Chennai	India	1
7	Infosys	23.0	7000.0	Mumbai	India	1
8	TCS	34.0	8000.0	Calcutta	India	1
9	CTS	45.0	9000.0	Delhi	India	0

In [6]:
```
print("Displaying last 15 rows")
print("\t")
data3.tail(15)
```

```
Displaying last 15 rows
```

Out[6]:

	Company	Age	Salary	Place	Country	Gender
133	NaN	22.0	8943.0	Chennai	India	0
134	Tata Consultancy Services	31.0	8345.0	Mumbai	India	0
135	CTS	40.0	9284.0	Calcutta	India	1
136	NaN	NaN	NaN	Delhi	India	0
137	CTS	31.0	2034.0	Mumbai	India	0
138	CTS	44.0	3033.0	Cochin	India	0
139	Congnizant	22.0	2934.0	Noida	India	0
140	Infosys	44.0	4034.0	Hyderabad	India	0
141	TCS	33.0	5034.0	Calcutta	India	0
142	Infosys Pvt Lmt	22.0	8202.0	Mumbai	India	0
143	TCS	33.0	9024.0	Calcutta	India	1
144	Infosys	22.0	8787.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

In [7]:
```
print("The shape of the dataset is:")
data3.shape
```

```
The shape of the dataset is:
```

Out[7]:
```
(148, 6)
```

In [8]:
```
print("Feature properties of the dataset is:")
print("\t")
data3.info()
```

```
Feature properties of the dataset is:

<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 [9]:
```
print("Feature names of the dataset is:")
data3.columns
```

```
Feature names of the dataset is:
```

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

In [10]:
```
print("Statistical Analysis of the dataset")
print("\t")
data3.describe()
```

```
Statistical Analysis of the dataset
```

Out[10]:

	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 [11]:
```
print("Unique Value Analysis of the Dataset")
print("\t")
for column in data3.columns:
    unique_values = data3[column].unique() # Displays unique values in a column
    count_unique_values = len(unique_values) # Displays number of unique values in
    print(f"Column Name: {column}")
    print(f"Unique Values: {unique_values}")
    print(f"Number of Unique Values: {count_unique_values}")
    print("\n")
```

```
Unique Value Analysis of the Dataset

Column Name: Company
Unique Values: ['TCS' 'Infosys' 'CTS' nan 'Tata Consultancy Services' 'Congnizant'
 'Infosys Pvt Lmt']
Number of Unique Values: 7


Column Name: Age
Unique Values: [20. 30. 35. 40. 23. nan 34. 45. 18. 22. 32. 37. 50. 21. 46. 36. 26.
41.
 24. 25. 43. 19. 38. 51. 31. 44. 33. 17.  0. 54.]
Number of Unique Values: 30


Column Name: Salary
Unique Values: [  nan 2300. 3000. 4000. 5000. 6000. 7000. 8000. 9000. 1089. 1234. 30
30.
 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.]
Number of Unique Values: 41


Column Name: Place
Unique Values: ['Chennai' 'Mumbai' 'Calcutta' 'Delhi' 'Podicherry' 'Cochin' nan 'Noi
da'
 'Hyderabad' 'Bhopal' 'Nagpur' 'Pune']
Number of Unique Values: 12


Column Name: Country
Unique Values: ['India']
Number of Unique Values: 1


Column Name: Gender
Unique Values: [0 1]
Number of Unique Values: 2
```

In [12]:
```
print("Renamed Features of the Dataset")
print("\t")
data3.columns = data3.columns.str.upper()
data3
```

```
Renamed Features of the Dataset
```

Out[12]:

	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
...	...	...	...	...	...	...
143	TCS	33.0	9024.0	Calcutta	India	1
144	Infosys	22.0	8787.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

148 rows × 6 columns

In [13]:
```
print("Rename Place to City")
print("\t")
data3 = data3.rename(columns={'PLACE': 'CITY'})
data3
```

```
Rename Place to City
```

Out[13]:

	COMPANY	AGE	SALARY	CITY	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
...	...	...	...	...	...	...
143	TCS	33.0	9024.0	Calcutta	India	1
144	Infosys	22.0	8787.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

148 rows × 6 columns

Data Cleaning: Find the missing and inappropriate values, treat them appropriately. Remove all duplicate rows. Find the outliers. Replace the value 0 in age as NaN. Treat the null values in all columns using any measures (removing/ replace the values with mean/median/mode).

In [14]:
```
print("Missing/Null values in each column:")
print('\t')
missing_values = data3.isnull().sum()
missing_values
```

```
Missing/Null values in each column:
```

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

In [15]:
```
print("Duplicate values in the dataset:")
print('\t')
data3.duplicated().sum()
```

```
Duplicate values in the dataset:
```

Out[15]:
```
np.int64(4)
```

In [16]:
```
data3.shape
```

Out[16]:
```
(148, 6)
```

In [17]:
```
data3.drop_duplicates(inplace=True)
```

In [18]:
```
data3.shape
```

Out[18]:
```
(144, 6)
```

In [19]:
```
print("Replacing 0 with NaN values in the age column")
print('\t')
data3['AGE'] = data3['AGE'].replace(0,np.nan)
data3
```

```
Replacing 0 with NaN values in the age column
```

Out[19]:

	COMPANY	AGE	SALARY	CITY	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
...	...	...	...	...	...	...
142	Infosys Pvt Lmt	22.0	8202.0	Mumbai	India	0
143	TCS	33.0	9024.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

144 rows × 6 columns

In [20]:
```
print("Replacing missing values in the numerical columns with median and mode")
print('\t')
data3['AGE'] = data3['AGE'].fillna(data3['AGE'].median())
data3['SALARY'] = data3['SALARY'].fillna(data3['SALARY'].median())
data3
```

```
Replacing missing values in the numerical columns with median and mode
```

Out[20]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	20.0	5000.0	Chennai	India	0
1	Infosys	30.0	5000.0	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
...	...	...	...	...	...	...
142	Infosys Pvt Lmt	22.0	8202.0	Mumbai	India	0
143	TCS	33.0	9024.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

144 rows × 6 columns

In [21]:
```
print("Replacing missing values in the categorical columns with mode")
print('\t')
data3['COMPANY'] = data3['COMPANY'].fillna(data3['COMPANY'].mode()[0])
data3['CITY'] = data3['CITY'].fillna(data3['CITY'].mode()[0])
data3['GENDER'] = data3['GENDER'].fillna(data3['GENDER'].mode()[0])
data3
```

```
Replacing missing values in the categorical columns with mode
```

Out[21]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	20.0	5000.0	Chennai	India	0
1	Infosys	30.0	5000.0	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
...	...	...	...	...	...	...
142	Infosys Pvt Lmt	22.0	8202.0	Mumbai	India	0
143	TCS	33.0	9024.0	Calcutta	India	1
145	Infosys	44.0	4034.0	Delhi	India	1
146	TCS	33.0	5034.0	Mumbai	India	1
147	Infosys	22.0	8202.0	Cochin	India	0

144 rows × 6 columns

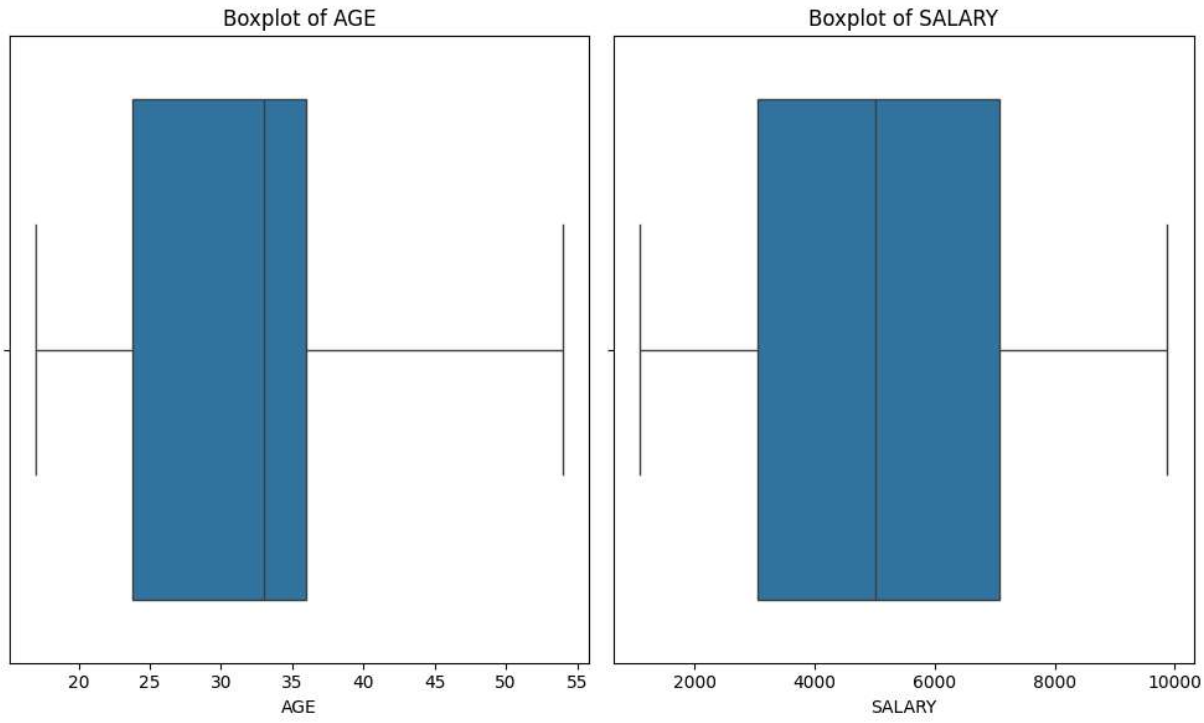
In [22]:
```
print("Boxplot Graph to visualize outliers in AGE and SALARY columns")
print('\t')
plt.figure(figsize=(10, 6))

# Plot for Age
plt.subplot(1, 2, 1)
sns.boxplot(x=data3['AGE'])
plt.title('Boxplot of AGE')
plt.xlabel('AGE')

# Plot for Salary
plt.subplot(1, 2, 2)
sns.boxplot(x=data3['SALARY'])
plt.title('Boxplot of SALARY')
plt.xlabel('SALARY')

# Show the plots
plt.tight_layout()
plt.show()
```

```
Boxplot Graph to visualize outliers in AGE and SALARY columns
```



In [23]:
```
print("Using IQR Method to determine outliers in the AGE column")
print('\t')
Q1_age = data3['AGE'].quantile(0.25)
Q3_age = data3['AGE'].quantile(0.75)

IQR_age = Q3_age - Q1_age

# Calculate the lower and upper bounds for outliers in 'age'
lower_bound_age = Q1_age - 1.5 * IQR_age
upper_bound_age = Q3_age + 1.5 * IQR_age

# Identify outliers in the 'age' column
age_outliers = data3[(data3['AGE'] < lower_bound_age) | (data3['AGE'] > upper_bound

print("Using IQR Method to determine outliers in the SALARY column")
print('\t')
Q1_salary = data3['SALARY'].quantile(0.25)
Q3_salary = data3['SALARY'].quantile(0.75)
IQR_salary = Q3_salary - Q1_salary

# Calculate the lower and upper bounds for outliers in 'salary'
lower_bound_salary = Q1_salary - 1.5 * IQR_salary
upper_bound_salary = Q3_salary + 1.5 * IQR_salary

# Identify outliers in the 'salary' column
salary_outliers = data3[(data3['SALARY'] < lower_bound_salary) | (data3['SALARY'] >

# 3. Display the outliers in Age and Salary columns
print("Outliers in Age:")
print(age_outliers)
print("\n")
print("Outliers in Salary:")
print(salary_outliers)
```

```
Using IQR Method to determine outliers in the AGE column

Using IQR Method to determine outliers in the SALARY column

Outliers in Age:
Empty DataFrame
Columns: [COMPANY, AGE, SALARY, CITY, COUNTRY, GENDER]
Index: []


Outliers in Salary:
Empty DataFrame
Columns: [COMPANY, AGE, SALARY, CITY, COUNTRY, GENDER]
Index: []
```

The above findings indicate that there are no outliers in AGE and SALARY column.

Data Analysis:

Filter the data with age >40 and salary<5000. Plot the chart with age and salary. Count the number of people from each place and represent it visually.

In [24]:
```
print("Filtered data of employees with age > 40 and Salary < 5000")
print('\t')
filtered_data = data3[(data3['AGE'] > 40) & (data3['SALARY'] < 5000)]
filtered_data
```

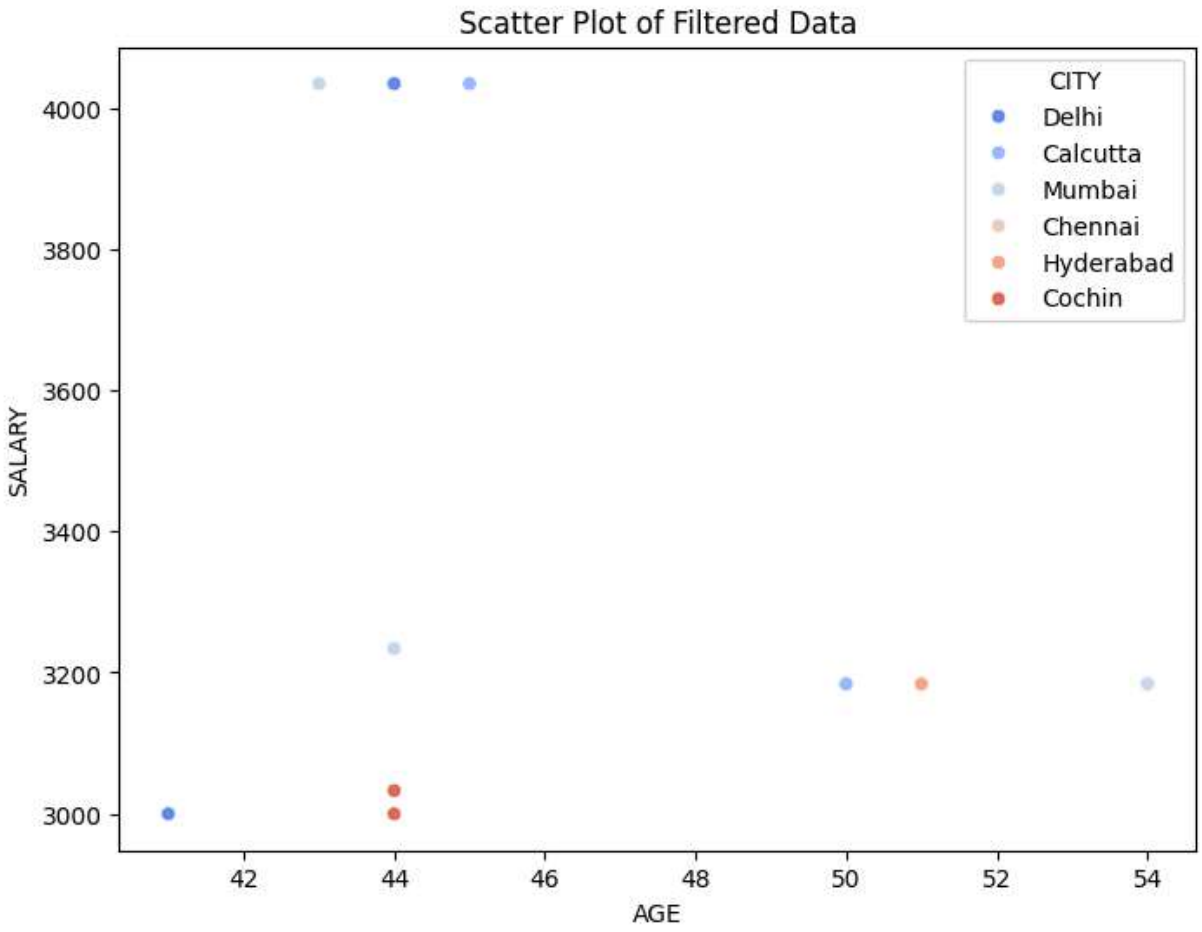
```
Filtered data of employees with age > 40 and Salary < 5000
```

Out[24]:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
21	Infosys	50.0	3184.0	Delhi	India	0
32	Infosys	45.0	4034.0	Calcutta	India	0
39	Infosys	41.0	3000.0	Mumbai	India	0
50	Infosys	41.0	3000.0	Chennai	India	0
57	Infosys	51.0	3184.0	Hyderabad	India	0
68	Infosys	43.0	4034.0	Mumbai	India	0
75	Infosys	44.0	3000.0	Cochin	India	0
86	Infosys	41.0	3000.0	Delhi	India	0
93	Infosys	54.0	3184.0	Mumbai	India	0
104	Infosys	44.0	4034.0	Delhi	India	0
122	Infosys	44.0	3234.0	Mumbai	India	0
129	Infosys	50.0	3184.0	Calcutta	India	0
138	CTS	44.0	3033.0	Cochin	India	0
140	Infosys	44.0	4034.0	Hyderabad	India	0
145	Infosys	44.0	4034.0	Delhi	India	1

In [ ]:

In [25]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(data=filtered_data, x='AGE', y='SALARY', hue='CITY', palette='coolw
plt.title('Scatter Plot of Filtered Data')
plt.xlabel('AGE')
plt.ylabel('SALARY')
plt.legend(title='CITY')
plt.show()
```



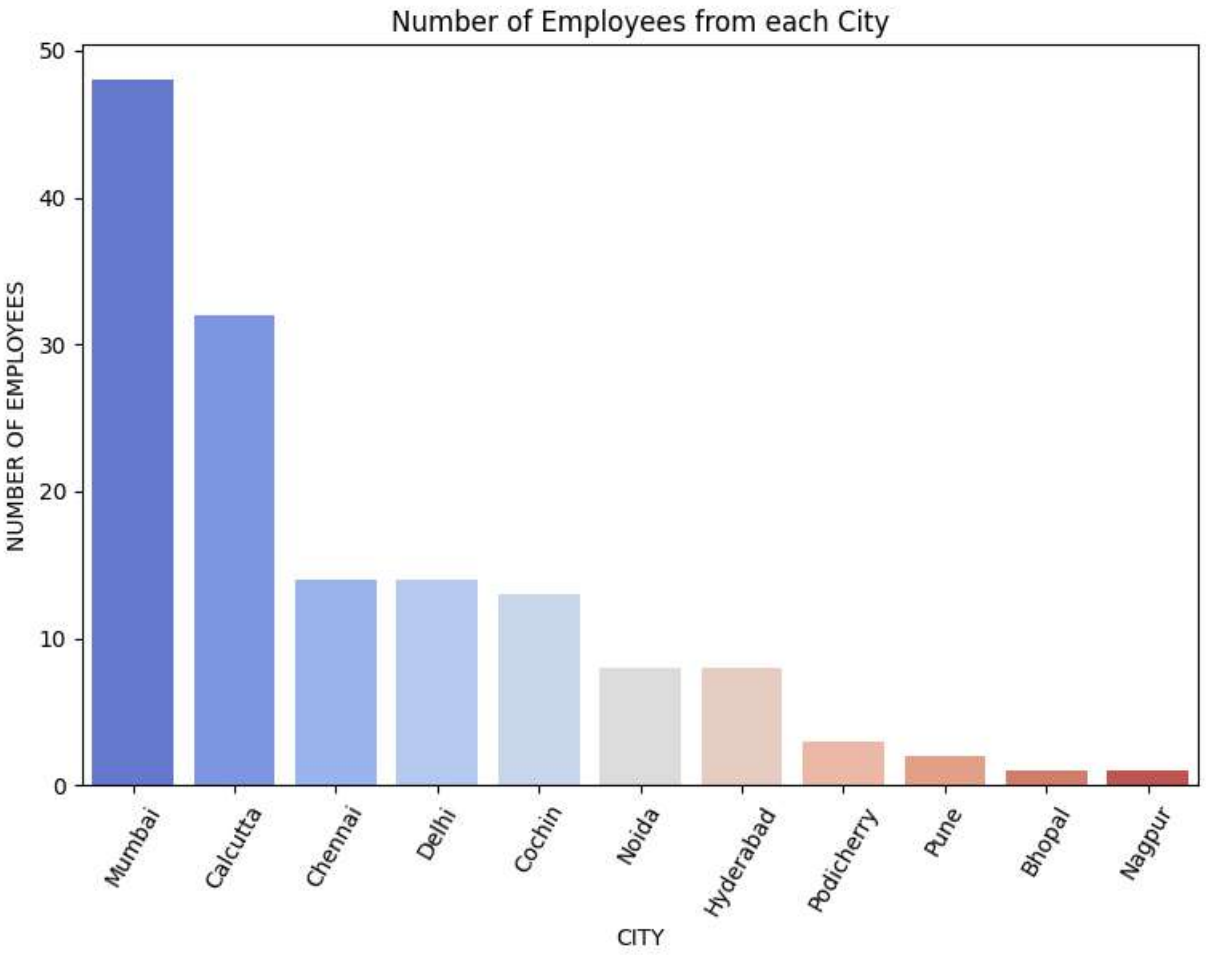
In [26]:
```
print("Count of employees from each City")
print('\t')
city_counts = data3['CITY'].value_counts()
city_counts
```

```
Count of employees from each City
```

Out[26]:
```
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 [27]:
```
plt.figure(figsize = (9, 6))
sns.barplot(x = city_counts.index, y = city_counts.values, palette='coolwarm')
plt.title('Number of Employees from each City')
plt.xlabel('CITY')
plt.ylabel('NUMBER OF EMPLOYEES')
```

```
plt.xticks(rotation = 60)
plt.show()
```



Data Encoding:

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 [30]:
```
print("Output after OneHot Encoding")
print('\t')
from sklearn.preprocessing import OneHotEncoder

# Identify categorical variables
categorical_columns = ['COMPANY', 'CITY', 'COUNTRY', 'GENDER']

# Apply One-Hot Encoding using pd.get_dummies for 'company', 'place', 'country_name
data_encoded = pd.get_dummies(data3, columns=['COMPANY', 'CITY', 'COUNTRY', 'GENDER

# Display the first few rows of the encoded dataframe
print(data_encoded.head())
```

```
Output after OneHot Encoding

    AGE  SALARY  COMPANY_Congnizant  COMPANY_Infosys  COMPANY_Infosys Pvt Lmt  \
0  20.0  5000.0               False            False                    False
1  30.0  5000.0               False             True                    False
2  35.0  2300.0               False            False                    False
3  40.0  3000.0               False             True                    False
4  23.0  4000.0               False            False                    False

   COMPANY_TCS  COMPANY_Tata Consultancy Services  CITY_Calcutta  \
0         True                              False          False
1        False                              False          False
2         True                              False           True
3        False                              False          False
4         True                              False          False

   CITY_Chennai  CITY_Cochin  CITY_Delhi  CITY_Hyderabad  CITY_Mumbai  \
0          True        False       False           False        False
1         False        False       False           False         True
2         False        False       False           False        False
3         False        False        True           False        False
4         False        False       False           False         True

   CITY_Nagpur  CITY_Noida  CITY_Podicherry  CITY_Pune  GENDER_1
0        False       False            False      False     False
1        False       False            False      False     False
2        False       False            False      False     False
3        False       False            False      False     False
4        False       False            False      False     False
```

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

In [31]:

```
print("Output after executing StandardScaler and MinMaxScaler")
print('\t')
from sklearn.preprocessing import StandardScaler, MinMaxScaler

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

# Select only the numerical columns i.e., 'AGE', 'SALARY'
numerical_columns = ['AGE', 'SALARY']

# Apply StandardScaler to numerical columns
data_standard_scaled = data3.copy()
data_standard_scaled[numerical_columns] = standard_scaler.fit_transform(data_standa

# Apply MinMaxScaler to numerical columns
data_minmax_scaled = data3.copy()
data_minmax_scaled[numerical_columns] = minmax_scaler.fit_transform(data_minmax_sca

# Display the first few rows of the scaled data
print("Data after Standard Scaling:")
print(data_standard_scaled.head(20))
```

```
print("\nData after Min-Max Scaling:")
print(data_minmax_scaled.head(20))
```

Output after executing StandardScaler and MinMaxScaler

Data after Standard Scaling:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	-1.484676	-0.100827	Chennai	India	0
1	Infosys	-0.267174	-0.100827	Mumbai	India	0
2	TCS	0.341577	-1.243735	Calcutta	India	0
3	Infosys	0.950328	-0.947426	Delhi	India	0
4	TCS	-1.119426	-0.524127	Mumbai	India	0
5	Infosys	0.098077	-0.100827	Calcutta	India	0
6	TCS	0.098077	0.322472	Chennai	India	1
7	Infosys	-1.119426	0.745771	Mumbai	India	1
8	TCS	0.219827	1.169070	Calcutta	India	1
9	CTS	1.559079	1.592369	Delhi	India	0
10	CTS	-1.119426	-0.100827	Mumbai	India	0
11	CTS	0.219827	-1.756350	Calcutta	India	0
12	CTS	1.559079	-0.100827	Chennai	India	0
13	CTS	-1.728177	-1.694972	Mumbai	India	0
14	Infosys	0.950328	-0.947426	Calcutta	India	0
15	TCS	-1.119426	-0.947426	Delhi	India	0
16	Infosys	-1.119426	-0.934727	Podicherry	India	0
17	TCS	0.219827	-0.100827	Cochin	India	0
18	TCS	-1.241176	-0.100827	Chennai	India	0
19	Infosys	-0.023674	-0.100827	Mumbai	India	0

Data after Min-Max Scaling:

	COMPANY	AGE	SALARY	CITY	COUNTRY	GENDER
0	TCS	0.081081	0.445089	Chennai	India	0
1	Infosys	0.351351	0.445089	Mumbai	India	0
2	TCS	0.486486	0.137817	Calcutta	India	0
3	Infosys	0.621622	0.217480	Delhi	India	0
4	TCS	0.162162	0.331285	Mumbai	India	0
5	Infosys	0.432432	0.445089	Calcutta	India	0
6	TCS	0.432432	0.558894	Chennai	India	1
7	Infosys	0.162162	0.672698	Mumbai	India	1
8	TCS	0.459459	0.786503	Calcutta	India	1
9	CTS	0.756757	0.900307	Delhi	India	0
10	CTS	0.162162	0.445089	Mumbai	India	0
11	CTS	0.459459	0.000000	Calcutta	India	0
12	CTS	0.756757	0.445089	Chennai	India	0
13	CTS	0.027027	0.016502	Mumbai	India	0
14	Infosys	0.621622	0.217480	Calcutta	India	0
15	TCS	0.162162	0.217480	Delhi	India	0
16	Infosys	0.162162	0.220895	Podicherry	India	0
17	TCS	0.459459	0.445089	Cochin	India	0
18	TCS	0.135135	0.445089	Chennai	India	0
19	Infosys	0.405405	0.445089	Mumbai	India	0

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