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.

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

from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.feature_selection import VarianceThreshold

from sklearn.preprocessing import StandardScaler, MinMaxScaler

import warnings
warnings.filterwarnings('ignore') # to prevent warning msgs
```

IMPORTING DATASET

```
dataset=pd.read_csv('Employee.csv')

df=pd.DataFrame(dataset)
print("Original dataset:")
print(df.head())
```

```
Original dataset:
   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
```

```
df.info()
```

```
<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
```

```
df.describe()
```

	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

Data Cleaning: (Score : 2)

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)

Finding Missing Data and Duplicates

```
df.isnull()
```

	Company	Age	Salary	Place	Country	Gender
0	False	False	True	False	False	False
1	False	False	True	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
..	...	...	...	...	...	...
143	False	False	False	False	False	False
144	False	False	False	False	False	False
145	False	False	False	False	False	False
146	False	False	False	False	False	False

```
147    False  False   False  False    False   False

[148 rows x 6 columns]
```

```
df.isnull().sum()
```

```
Company     8
Age        18
Salary     24
Place      14
Country     0
Gender      0
dtype: int64
```

```
df['Company'].isnull().sum()
```

```
8
```

```
df['Company'].fillna('Unknown', inplace=True)
```

```
df['Company'].isnull().sum()
```

```
0
```

Replace the value 0 in age as NaN

```
print("Number of zeros in 'Age' before replacement:", (df['Age'] ==
0).sum())
df['Age'] = df['Age'].replace(0, np.NaN)
print("Number of NaN values in 'Age' after replacement:",
df['Age'].isna().sum())   #counts the NaN values to confirm the change
```

```
Number of zeros in 'Age' before replacement: 0
Number of NaN values in 'Age' after replacement: 24
```

```
df['Salary'].fillna(df['Salary'].median(), inplace=True)
df['Salary']
```

```
0      5000.0
1      5000.0
2      2300.0
3      3000.0
4      4000.0
        ...
143    9024.0
144    8787.0
145    4034.0
146    5034.0
147    8202.0
Name: Salary, Length: 148, dtype: float64
```

```
df['Place'].fillna('Unknown', inplace=True)
```

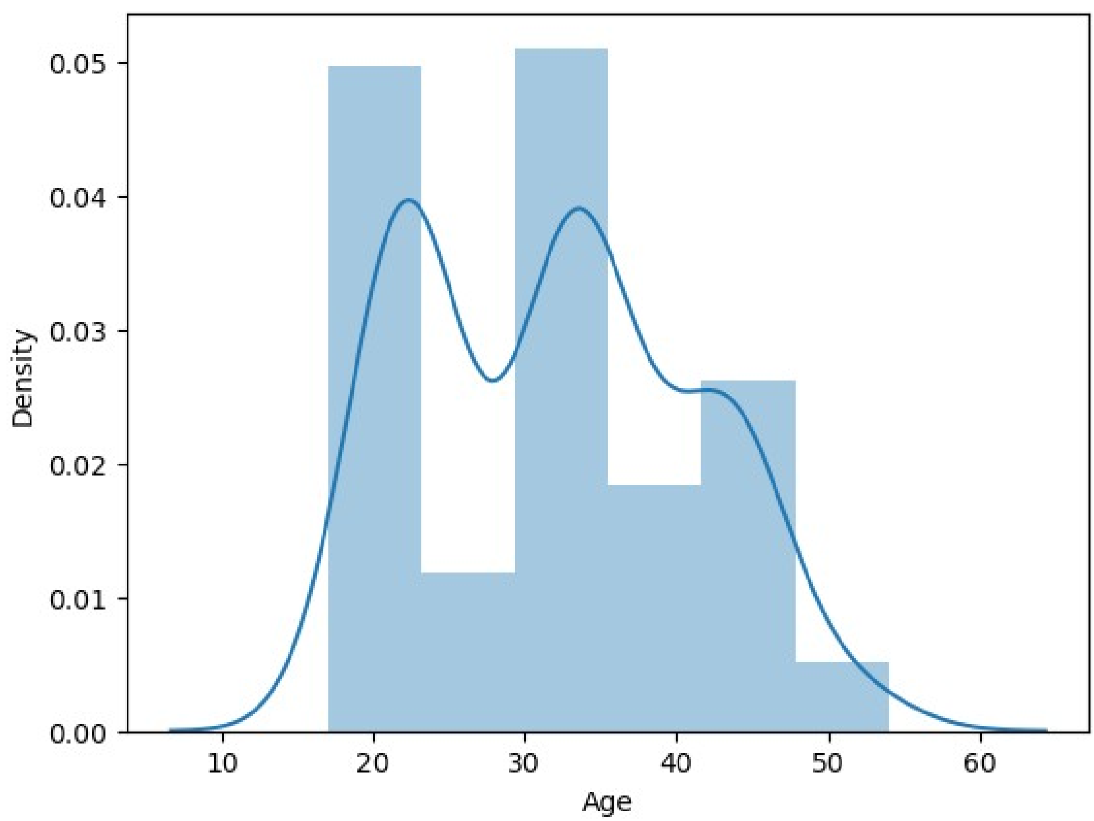
```
df.isnull().sum()
```

```
Company     0
Age        24
Salary      0
Place       0
Country     0
Gender      0
dtype: int64
```

Handle NaN Values

```
sns.distplot(df['Age'])
```

```
<Axes: xlabel='Age', ylabel='Density'>
```



Note : Since the data is slightly skewed median will be better option

```
df['Age'].fillna(df['Age'].median(), inplace=True)

print(df.isnull().sum())
```

```
Company    0
Age        0
Salary     0
Place      0
Country    0
Gender     0
dtype: int64
```

```
df.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
       ...
142    False
143    False
145    False
146    False
147    False
Length: 144, dtype: bool
```

```
df.duplicated().sum()
```

```
0
```

Numerical columns and Categorical columns identified

```
numerical_columns = df.select_dtypes(include=['number']).columns
categorical_columns = df.select_dtypes(include=['object']).columns

print('numerical_columns:',numerical_columns)
```

```
numerical_columns: Index(['Age', 'Salary', 'Gender'], dtype='object')
```

```
print('categorical_columns:',categorical_columns)
```

```
categorical_columns: Index(['Company', 'Place', 'Country'],
dtype='object')
```

```
df
```

```
     Company   Age  Salary     Place 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
..       ...   ...     ...       ...     ...     ...
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 x 6 columns]
```

Data Exploration: (Score : 1)

Explore the data, list down the unique values in each feature and find its length.

```python
for column in df.columns:
    unique_values = df[column].unique()
    print(f"Unique values in {column}: {unique_values}")
    print(f"Number of unique values in {column}: {len(unique_values)}\
n")
```

```
Unique values in Company_Name: [4 2 0 6 5 1 3]
Number of unique values in Company_Name: 7

Unique values in Age: [20.         30.         35.         40.
23.         30.48461538
 34.         45.         18.         22.         32.         37.
 50.         21.         46.         36.         26.         41.
 24.         25.         43.         19.         38.         51.
 31.         44.         33.         17.         54.        ]
Number of unique values in Age: 29

Unique values in Salary: [5000. 2300. 3000. 4000. 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.]
Number of unique values in Salary: 40

Unique values in Place: ['Chennai' 'Mumbai' 'Calcutta' 'Delhi'
'Podicherry' 'Cochin' 'Unknown'
 'Noida' 'Hyderabad' 'Bhopal' 'Nagpur' 'Pune']
Number of unique values in Place: 12

Unique values in Country: [0]
Number of unique values in Country: 1

Unique values in Gender: [0, 1]
Categories (2, int64): [0, 1]
```

```
Number of unique values in Gender: 2
```

Perform the statistical analysis and renaming of the columns.

```
print(df.describe()) # describe() - to get a summary of the statistics for numerical features

       Company_Name         Age       Salary  Country
count    144.000000  144.000000   144.000000    144.0
mean       2.500000   31.855823  5238.194444      0.0
std        1.797434    8.250046  2370.641804      0.0
min        0.000000   17.000000  1089.000000      0.0
25%        1.000000   23.750000  3045.000000      0.0
50%        2.000000   32.000000  5000.000000      0.0
75%        4.000000   36.000000  7084.000000      0.0
max        6.000000   54.000000  9876.000000      0.0

print(df.describe(include = 'object')) # For categorical features, use describe(include='object')

         Place
count      144
unique      12
top     Mumbai
freq        34
```

Renaming Columns

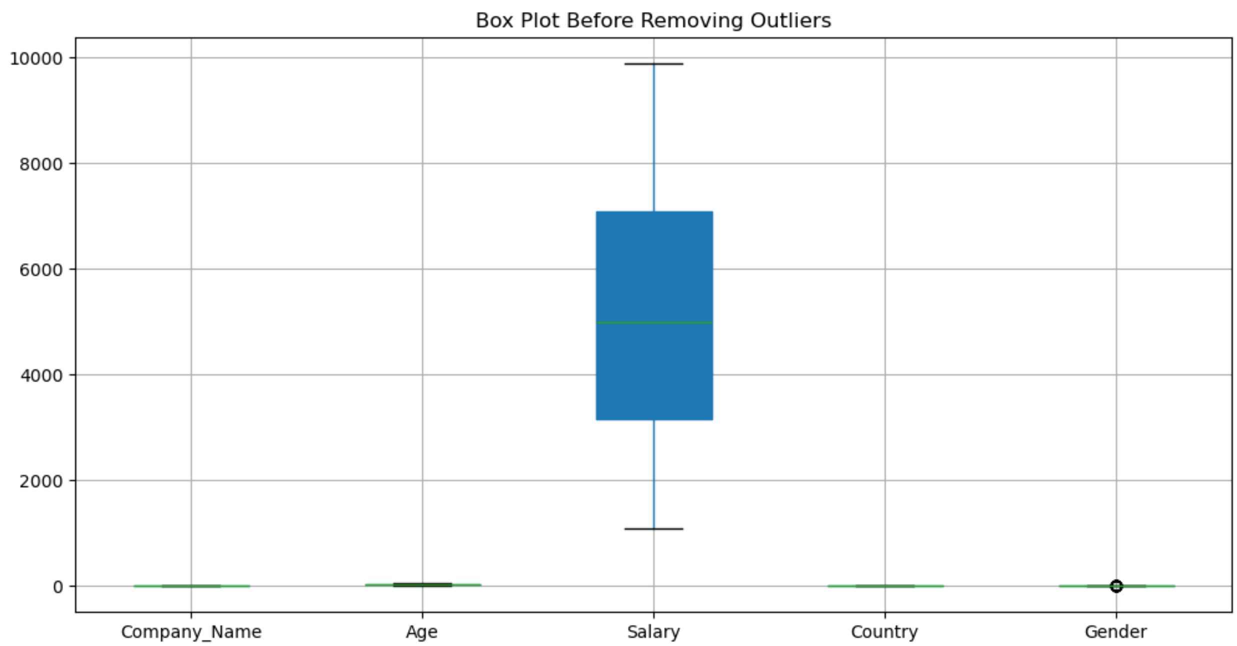
```
df.rename(columns={
    'Company': 'Company_Name'
}, inplace=True)

df['Company_Name']

0          TCS
1      Infosys
2          TCS
3      Infosys
4          TCS
        ...
143        TCS
144    Infosys
145    Infosys
146        TCS
147    Infosys
Name: Company_Name, Length: 148, dtype: object
```

Convert Gender column to a categorical data type

```
df['Gender'] = df['Gender'].astype('category')

print(df['Gender'].dtype)

category
```

Finding and Treating Outliers

```
# Box plot before removing outliers
df.select_dtypes(include='number').boxplot(figsize=(12, 6),
patch_artist=True)
plt.title("Box Plot Before Removing Outliers")
plt.show()
```



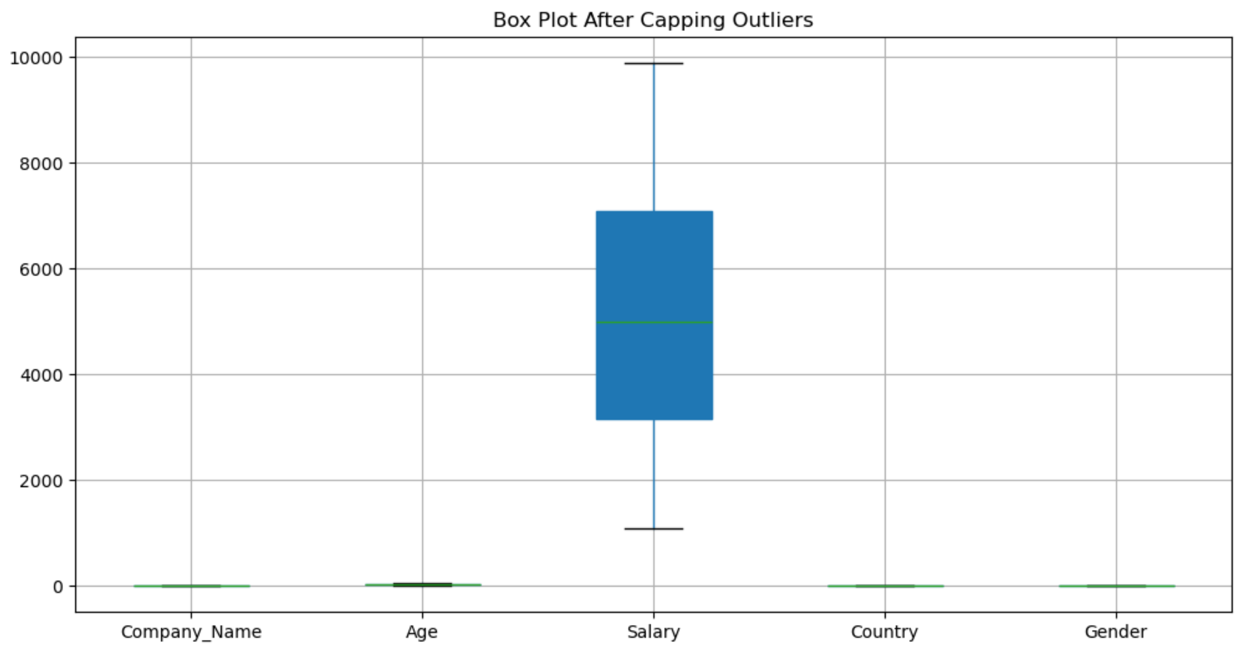
Identify Outliers - IQR METHOD

```
for column in df.select_dtypes(include='number').columns:
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = df[(df[column] < lower_bound) | (df[column] >
upper_bound)]
    print(f"Number of outliers in {column}: {outliers.shape[0]}")
```

```
Number of outliers in Company_Name: 0
Number of outliers in Age: 0
Number of outliers in Salary: 0
Number of outliers in Country: 0
Number of outliers in Gender: 33
```

Removed _ Capping

```
# Capping outliers to the lower and upper bounds
df[column] = df[column].clip(lower=lower_bound, upper=upper_bound)

# Box plot after capping outliers
df.select_dtypes(include='number').boxplot(figsize=(12, 6),
patch_artist=True)
plt.title("Box Plot After Capping Outliers")
plt.show()
```



Data Analysis: (Score : 2)

Filter the data with age >40 and salary<5000

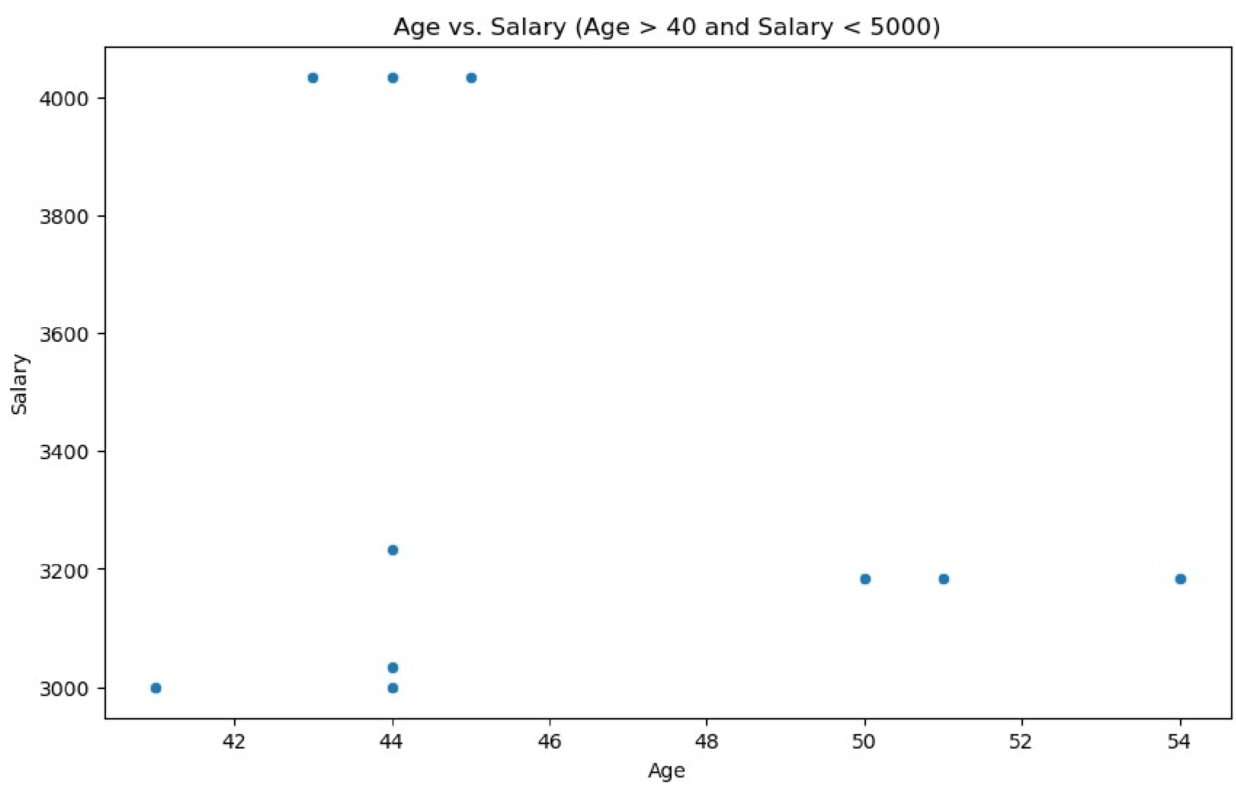
```
filtered_data = df[(df['Age'] > 40) & (df['Salary'] < 5000)]
filtered_data
```

	Company_Name	Age	Salary	Place	Country	Gender
21	2	50.0	3184.0	Delhi	0	0
32	2	45.0	4034.0	Calcutta	0	0
39	2	41.0	3000.0	Mumbai	0	0
50	2	41.0	3000.0	Chennai	0	0

```
57                  2  51.0  3184.0  Hyderabad        0       0
68                  2  43.0  4034.0     Mumbai        0       0
75                  2  44.0  3000.0     Cochin        0       0
86                  2  41.0  3000.0      Delhi        0       0
93                  2  54.0  3184.0     Mumbai        0       0
104                 2  44.0  4034.0      Delhi        0       0
122                 2  44.0  3234.0     Mumbai        0       0
129                 2  50.0  3184.0   Calcutta        0       0
138                 0  44.0  3033.0     Cochin        0       0
140                 2  44.0  4034.0  Hyderabad        0       0
145                 2  44.0  4034.0      Delhi        0       1
```

Plot the chart with age and salary

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.scatterplot(x='Age', y='Salary', data=filtered_data)
plt.title("Age vs. Salary (Age > 40 and Salary < 5000)")
plt.xlabel("Age")
plt.ylabel("Salary")
plt.show()
```

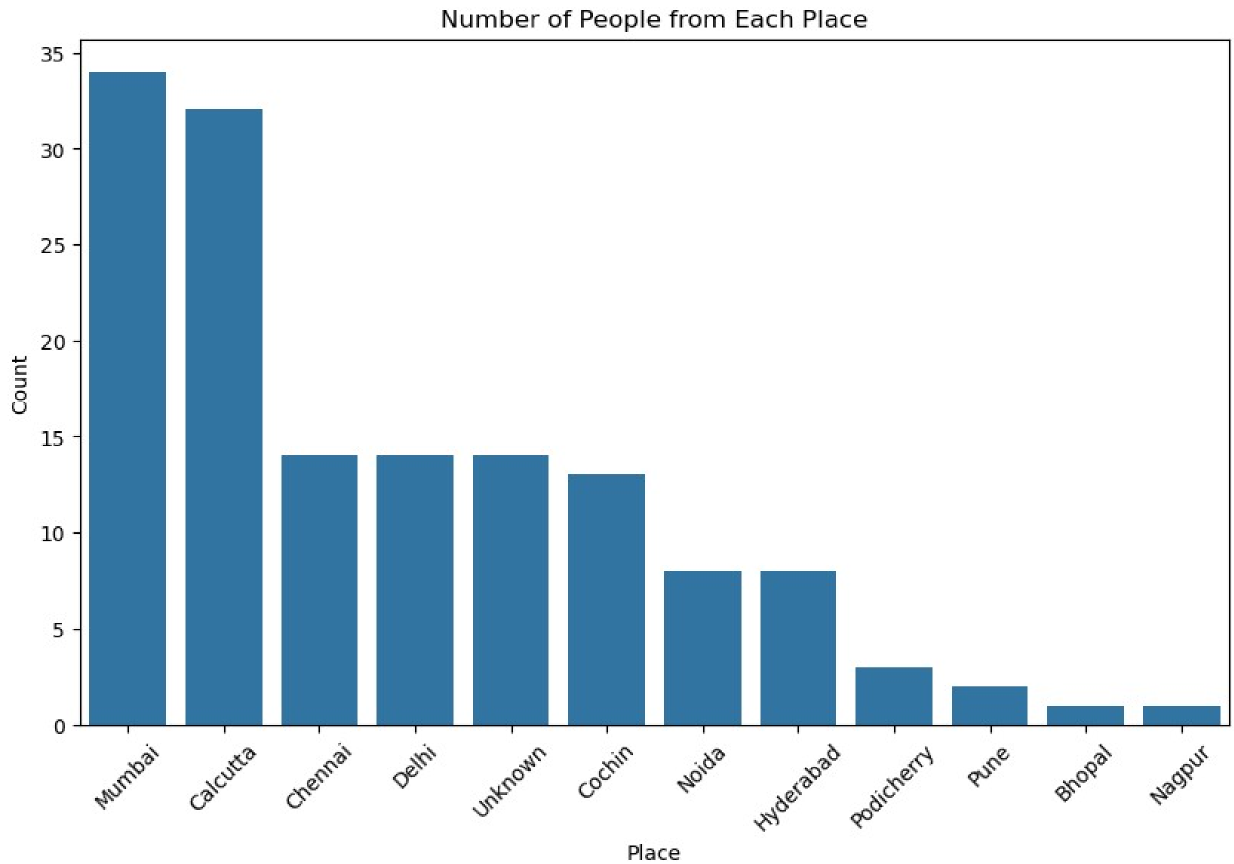


Count the number of people from each place and represent it visually

```
# Count the number of people from each place
place_counts = df['Place'].value_counts()
place_counts
```

```
Place
Mumbai          34
Calcutta        32
Chennai         14
Delhi           14
Unknown         14
Cochin          13
Noida            8
Hyderabad        8
Podicherry       3
Pune             2
Bhopal           1
Nagpur           1
Name: count, dtype: int64
```

```
# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=place_counts.index, y=place_counts.values)
plt.title("Number of People from Each Place")
plt.xlabel("Place")
plt.ylabel("Count")
plt.xticks(rotation=45)
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.

```
numerical_columns = df.select_dtypes(include=['number']).columns
categorical_columns = df.select_dtypes(include=['object']).columns
```

Numerical Columns

```
print('numerical_columns:',numerical_columns)
```

```
numerical_columns: Index(['Age', 'Salary', 'Gender'], dtype='object')
```

Categorical Columns

```
print('categorical_columns:',categorical_columns)
```

```
categorical_columns: Index(['Company_Name', 'Place', 'Country'],
dtype='object')
```

Label Encoding

```
Label_Encoder=LabelEncoder() #label encoding convert categorical to
numerical

df['Company_Name'] = Label_Encoder.fit_transform(df['Company_Name'])
df['Country'] = Label_Encoder.fit_transform(df['Country'])

print(df[['Company_Name']].head())

   Company_Name
0             4
1             2
2             4
3             2
4             4

print(df[['Country']].head())

   Country
0        0
1        0
2        0
3        0
4        0
```

One-Hot Encoding

```
from sklearn.preprocessing import OneHotEncoder

# Assuming 'df' is your original DataFrame and you want to encode the
'Place' column
oneHot = OneHotEncoder(sparse_output=False)  # Use sparse=False to
return a dense array

# Apply OneHotEncoder to the 'Place' column
place_encoded = oneHot.fit_transform(df[['Place']])

# Get the column names for the one-hot encoded columns
place_columns = oneHot.get_feature_names_out(['Place'])

# Drop the original 'Place' column and concatenate the one-hot encoded
columns
df_onehot = pd.concat([
    df.drop('Place', axis=1),  # Drop the original 'Place' column
    pd.DataFrame(place_encoded, columns=place_columns)  # Add the one-
hot encoded columns
```

```
], axis=1)


df_onehot.head()

   Company_Name   Age  Salary  Country  Gender  Place_Bhopal
Place_Calcutta  \
0             4  20.0  5000.0        0       0           0.0
0.0
1             2  30.0  5000.0        0       0           0.0
0.0
2             4  35.0  2300.0        0       0           0.0
1.0
3             2  40.0  3000.0        0       0           0.0
0.0
4             4  23.0  4000.0        0       0           0.0
0.0

   Place_Chennai  Place_Cochin  Place_Delhi  Place_Hyderabad
Place_Mumbai  \
0            1.0           0.0          0.0              0.0
0.0
1            0.0           0.0          0.0              0.0
1.0
2            0.0           0.0          0.0              0.0
0.0
3            0.0           0.0          1.0              0.0
0.0
4            0.0           0.0          0.0              0.0
1.0

   Place_Nagpur  Place_Noida  Place_Podicherry  Place_Pune
Place_Unknown
0           0.0          0.0               0.0         0.0
0.0
1           0.0          0.0               0.0         0.0
0.0
2           0.0          0.0               0.0         0.0
0.0
3           0.0          0.0               0.0         0.0
0.0
4           0.0          0.0               0.0         0.0
0.0
```

y is target variable (dependent variable)

```
y=df_onehot['Salary']

y
```

```
0      5000.0
1      5000.0
2      2300.0
3      3000.0
4      4000.0
        ...
143    9024.0
144    8787.0
145    4034.0
146    5034.0
147    8202.0
Name: Salary, Length: 148, dtype: float64
```

```
# x = df_onehot.drop(['Salary', 'Company_Name', 'Country'], axis=1)

x = df_onehot.drop(['Salary'], axis=1)

x
```

```
     Company_Name   Age  Country  Gender  Place_Bhopal  Place_Calcutta
\
0               4  20.0        0       0           0.0             0.0

1               2  30.0        0       0           0.0             0.0

2               4  35.0        0       0           0.0             1.0

3               2  40.0        0       0           0.0             0.0

4               4  23.0        0       0           0.0             0.0

..            ...   ...      ...     ...           ...             ...

143             4  33.0        0       1           0.0             1.0

144             2  22.0        0       1           0.0             1.0

145             2  44.0        0       1           0.0             0.0

146             4  33.0        0       1           0.0             0.0

147             2  22.0        0       0           0.0             0.0


     Place_Chennai  Place_Cochin  Place_Delhi  Place_Hyderabad
Place_Mumbai  \
0              1.0           0.0          0.0              0.0
0.0
1              0.0           0.0          0.0              0.0
1.0
2              0.0           0.0          0.0              0.0
```

```
0.0
3              0.0          0.0          1.0                0.0
0.0
4              0.0          0.0          0.0                0.0
1.0
..             ...          ...          ...                ...
...
143            0.0          0.0          0.0                0.0
0.0
144            0.0          0.0          0.0                0.0
0.0
145            0.0          0.0          1.0                0.0
0.0
146            0.0          0.0          0.0                0.0
1.0
147            0.0          1.0          0.0                0.0
0.0

     Place_Nagpur  Place_Noida  Place_Podicherry  Place_Pune
Place_Unknown
0             0.0          0.0               0.0         0.0
0.0
1             0.0          0.0               0.0         0.0
0.0
2             0.0          0.0               0.0         0.0
0.0
3             0.0          0.0               0.0         0.0
0.0
4             0.0          0.0               0.0         0.0
0.0
..            ...          ...               ...         ...
...
143           0.0          0.0               0.0         0.0
0.0
144           0.0          0.0               0.0         0.0
0.0
145           0.0          0.0               0.0         0.0
0.0
146           0.0          0.0               0.0         0.0
0.0
147           0.0          0.0               0.0         0.0
0.0

[148 rows x 16 columns]

print(x.isnull().sum())  # Should show 0 if no `NaN` values exist
print(y.isnull().sum())  # Should also show 0 if no `NaN` values exist

Company_Name        0
Age                 0
```

```
Country              0
Gender               0
Place_Bhopal         0
Place_Calcutta       0
Place_Chennai        0
Place_Cochin         0
Place_Delhi          0
Place_Hyderabad      0
Place_Mumbai         0
Place_Nagpur         0
Place_Noida          0
Place_Podicherry     0
Place_Pune           0
Place_Unknown        0
dtype: int64
0
```

Feature Scaling: (Score : 2)

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

Feature Selection Using VarianceThreshold

```
# 1.1 Variance Threshold
var_threshold = VarianceThreshold(threshold=0.1)
X_var = var_threshold.fit_transform(x)
var_selected = x.columns[var_threshold.get_support()].tolist()

print("1. Filter Methods Results:")
print("\na) Variance Threshold")
print(f"Features selected: {len(var_selected)}")
print("Selected features:", var_selected[:5], "...")

1. Filter Methods Results:

a) Variance Threshold
Features selected: 5
Selected features: ['Company_Name', 'Age', 'Gender', 'Place_Calcutta',
'Place_Mumbai'] ...
```

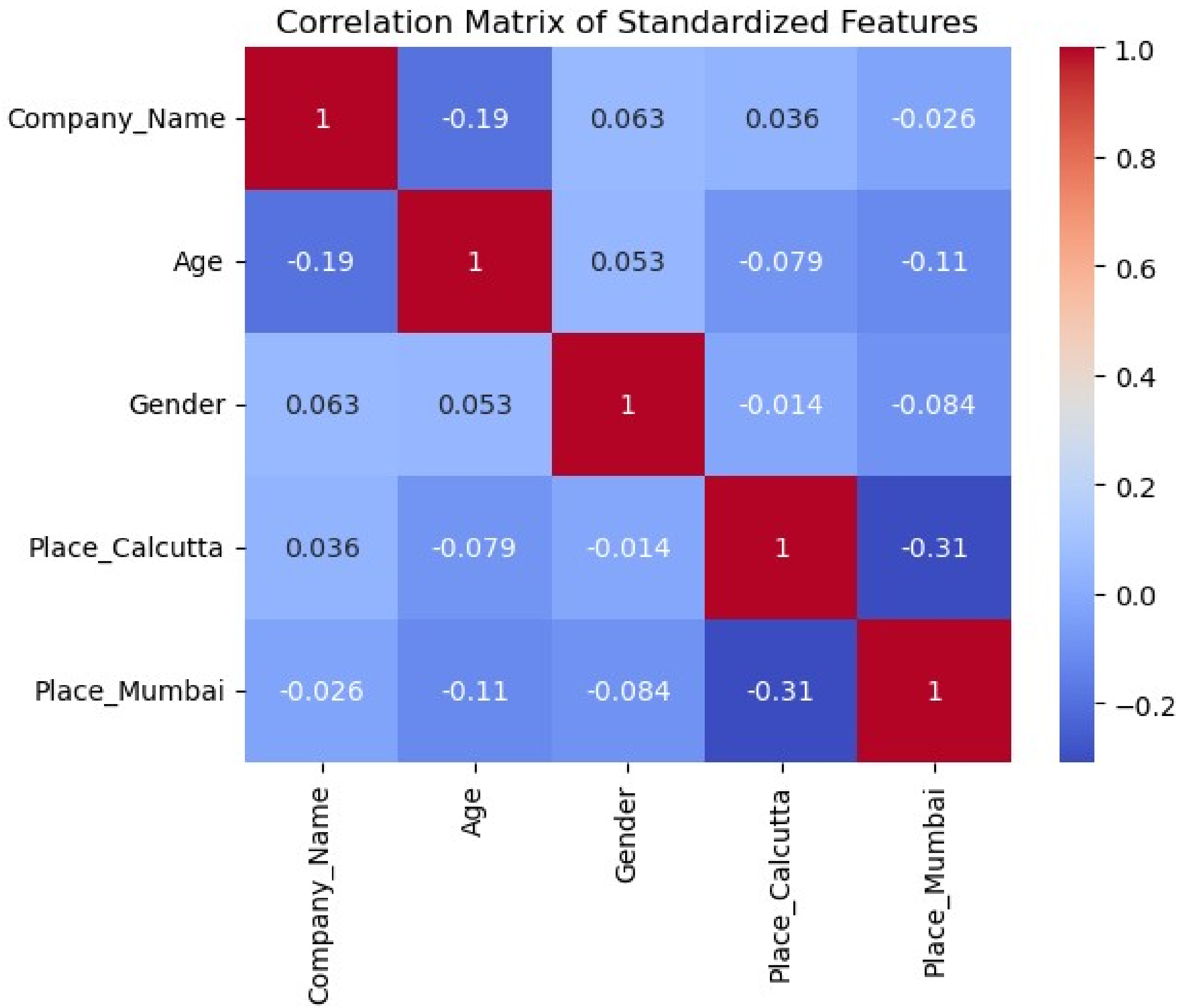
scaling

```
# Create scalers
standard_scaler = StandardScaler()  #standardized : entire data into
standard form
minmax_scaler = MinMaxScaler()      # minmax : entire data into
normalized form
```

```python
# Apply different scaling methods
X_standardized = standard_scaler.fit_transform(X_var)
X_normalized = minmax_scaler.fit_transform(X_var)

# Convert the scaled arrays back into DataFrames with the original column names
X_standardized_df = pd.DataFrame(X_standardized, columns=var_selected)
X_normalized_df = pd.DataFrame(X_normalized, columns=var_selected)

# now we can visualize or use these DataFrames
print(X_standardized_df.head())
print(X_normalized_df.head())
```

```
   Company_Name       Age    Gender  Place_Calcutta  Place_Mumbai
0      0.848436 -1.471033 -0.535683       -0.535683     -0.577350
1     -0.272712 -0.258148 -0.535683       -0.535683      1.732051
2      0.848436  0.348295 -0.535683        1.866775     -0.577350
3     -0.272712  0.954737 -0.535683       -0.535683     -0.577350
4      0.848436 -1.107168 -0.535683       -0.535683      1.732051
   Company_Name       Age  Gender  Place_Calcutta  Place_Mumbai
0      0.666667  0.081081     0.0             0.0           0.0
1      0.333333  0.351351     0.0             0.0           1.0
2      0.666667  0.486486     0.0             1.0           0.0
3      0.333333  0.621622     0.0             0.0           0.0
4      0.666667  0.162162     0.0             0.0           1.0
```

```python
correlation = X_standardized_df.corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix of Standardized Features")
plt.show()
```


Correlation Matrix of Standardized Features
Company_Name
Age
Gender
Place_Calcutta
Place_Mumbai
1 -0.19 0.063 0.036 -0.026
-0.19 1 0.053 -0.079 -0.11
0.063 0.053 1 -0.014 -0.084
0.036 -0.079 -0.014 1 -0.31
-0.026 -0.11 -0.084 -0.31 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2