Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) helps in understanding the dataset through various techniques like visualization, summary statistics, and feature relationships.

Importing Libraries

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

Loading data

```
Sdf = pd.read_csv(r"D:\Datasets\Csv_excel_txt\Salary_EDA.csv")
Sdf.head()

    Age  Gender Education Level          Job Title  Years of 
Experience  \
0  32.0    Male      Bachelor's  Software Engineer                
5.0   
1  28.0  Female        Master's       Data Analyst                
3.0   
2  45.0    Male             PhD     Senior Manager               
15.0   
3  36.0  Female      Bachelor's    Sales Associate                
7.0   
4  36.0  Female      Bachelor's    Sales Associate                
7.0   

     Salary  
0   90000.0  
1   65000.0  
2  150000.0  
3   60000.0  
4   60000.0  
```

EDA Techniques

1. Checking Basic Information

```
Sdf.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 375 entries, 0 to 374
Data columns (total 6 columns):
```

```
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Age                  373 non-null    float64
 1   Gender               371 non-null    object
 2   Education Level      372 non-null    object
 3   Job Title            370 non-null    object
 4   Years of Experience  373 non-null    float64
 5   Salary               372 non-null    float64
dtypes: float64(3), object(3)
memory usage: 17.7+ KB
```

1. Checking Missing values

```
Sdf.isnull().sum()

Age                    2
Gender                 4
Education Level        3
Job Title              5
Years of Experience    2
Salary                 3
dtype: int64

Sdf.dropna(inplace = True)

Sdf.isnull().sum()

Age                    0
Gender                 0
Education Level        0
Job Title              0
Years of Experience    0
Salary                 0
dtype: int64
```

1. Summary Statistics

Using the IQR Method (Interquartile Range) We use the 1.5 × IQR rule:

- Lower Bound = Q1−1.5×IQR
- Upper Bound = Q3+1.5×IQR
- Any data point below the lower bound or above the upper bound is an outlier.

```
Sdf.describe(include = 'all')

               Age Gender Education Level              Job Title  \
count   366.000000    366             366                    366
unique         NaN      2               3                    169
top            NaN   Male      Bachelor's  Director of Marketing
freq           NaN    189             220                     12
mean     37.459016    NaN             NaN                    NaN
```

```
std       6.962303    NaN              NaN                        NaN
min      23.000000    NaN              NaN                        NaN
25%      32.000000    NaN              NaN                        NaN
50%      36.000000    NaN              NaN                        NaN
75%      44.000000    NaN              NaN                        NaN
max      53.000000    NaN              NaN                        NaN

        Years of Experience         Salary
count            366.000000     366.000000
unique                  NaN            NaN
top                     NaN            NaN
freq                    NaN            NaN
mean              10.045082  100492.759563
std                6.517102   48013.732434
min                0.000000     350.000000
25%                4.000000   56250.000000
50%                9.000000   95000.000000
75%               15.000000  140000.000000
max               25.000000  250000.000000
```

Final Observations:

 Most employees are aged between 32 and 44 years.

 Experience varies widely, but most have 4 to 15 years.

 Salary has a large variation; some extreme low values may be errors or part-time roles.

 More employees have a Bachelor's degree compared to Master's/PhD.

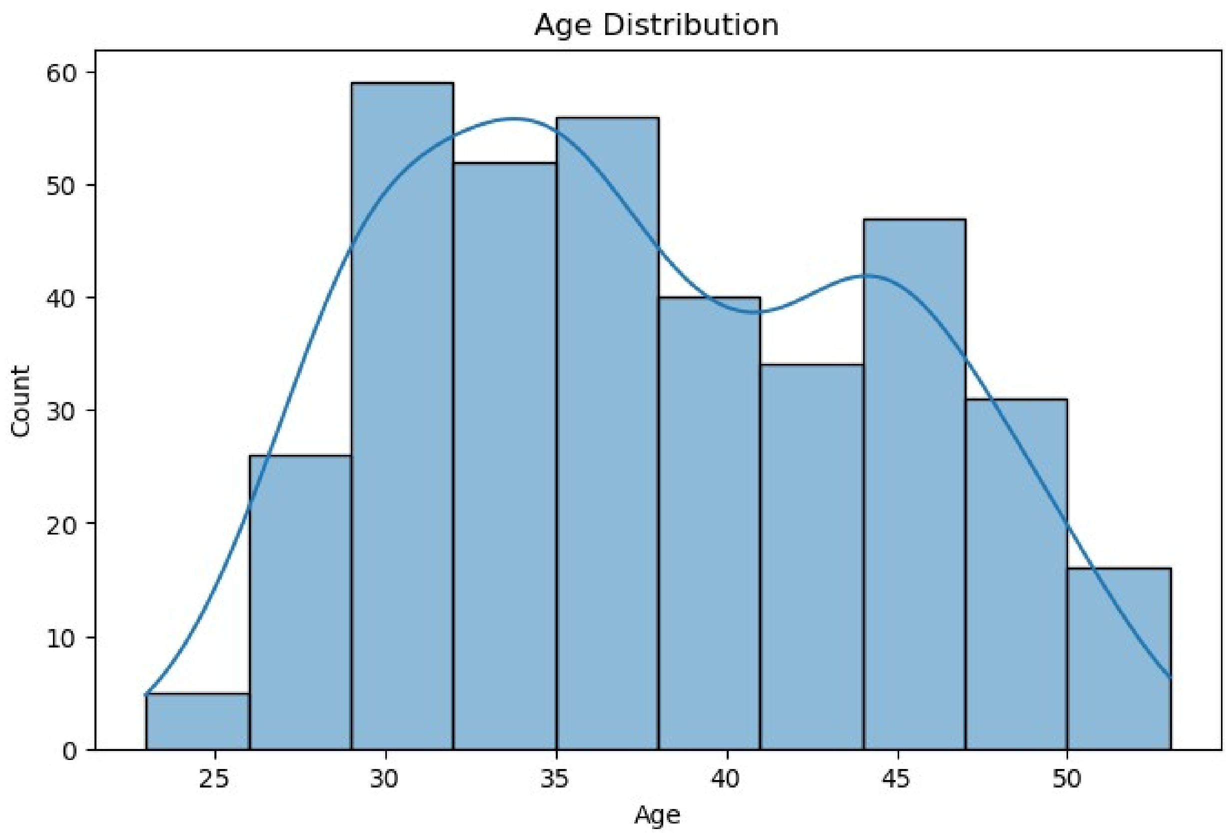
 Gender distribution is fairly balanced, with a slight Male majority.

 Jobs are diverse, with no single job title dominating.

1. Visualization

4.1. Histogram

```
#Visualizing Age Distribution:
plt.figure(figsize=(8,5))
sns.histplot(Sdf['Age'], bins=10, kde=True)
plt.title("Age Distribution")
plt.show()
```



Observations:

- The age values range from 23 to 53 years.
- There is a slight right skew (positively skewed), meaning a few employees are older (50+ years).
- No extreme outliers are visible, as there is no long tail on either side.
- The company primarily employs mid-career professionals (30-45 years old).
- Few young employees (below 25 years) and few older employees (above 50 years).

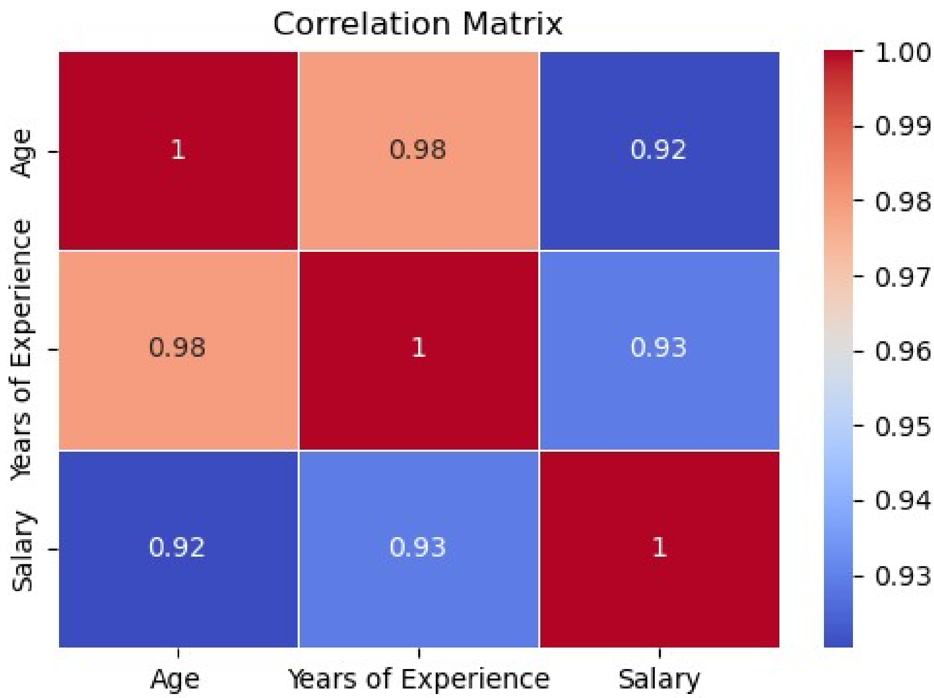
4.2. Heatmap (Numerical data)

```
#Filter numerical data
Sdf_num = Sdf.select_dtypes(include=['number'])
Sdf_num.head()
```

	Age	Years of Experience	Salary
0	32.0	5.0	90000.0
1	28.0	3.0	65000.0
2	45.0	15.0	150000.0
3	36.0	7.0	60000.0
4	36.0	7.0	60000.0

```
plt.figure(figsize=(6,4))
sns.heatmap(Sdf_num.corr(), annot=True, cmap='coolwarm',
```

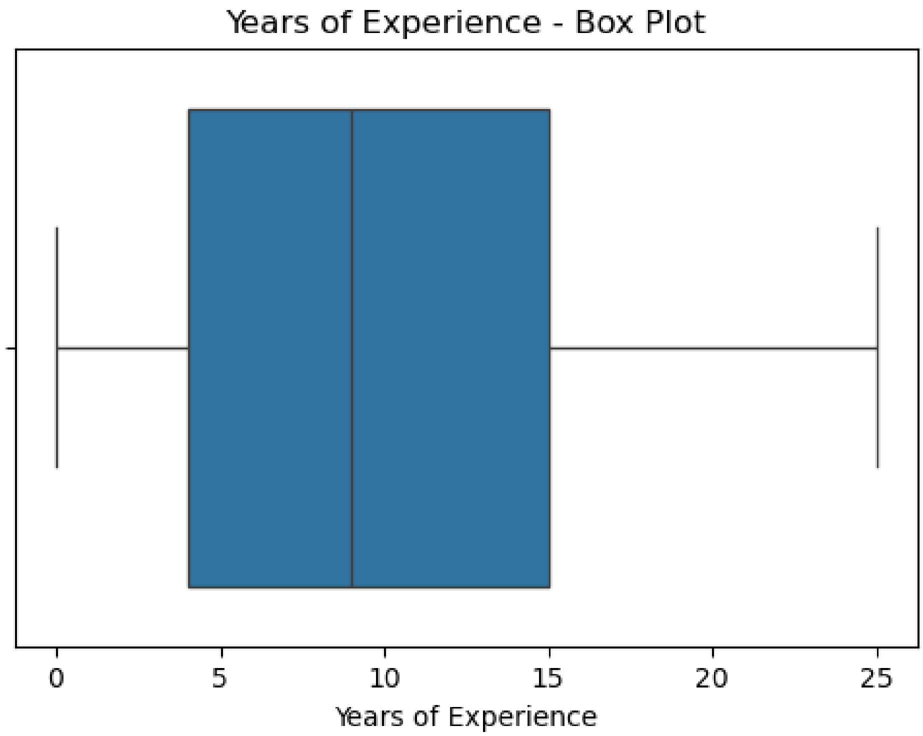
```
linewidths=0.5)
plt.title("Correlation Matrix")
plt.show()
```



Observations: Age and Experience have good correlation

4.3. Boxplot

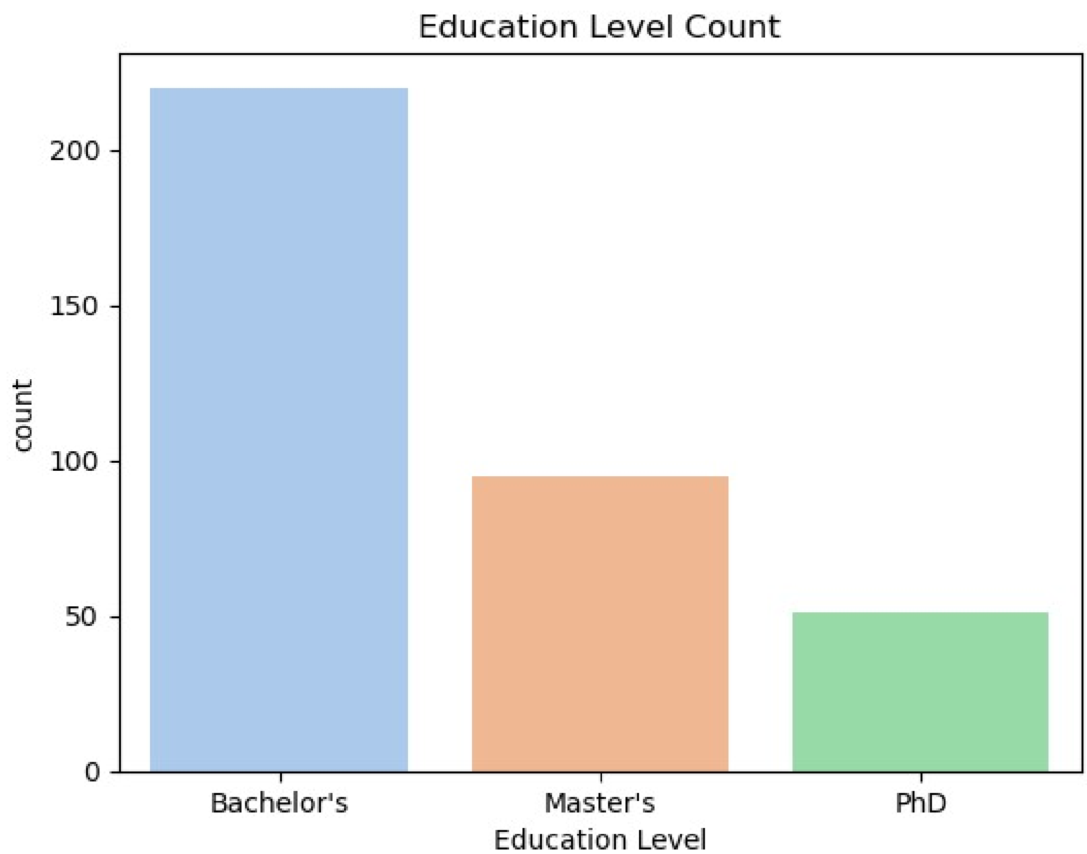
```
plt.figure(figsize=(6,4))
sns.boxplot(x=Sdf['Years of Experience'])
plt.title("Years of Experience - Box Plot")
plt.show()
```



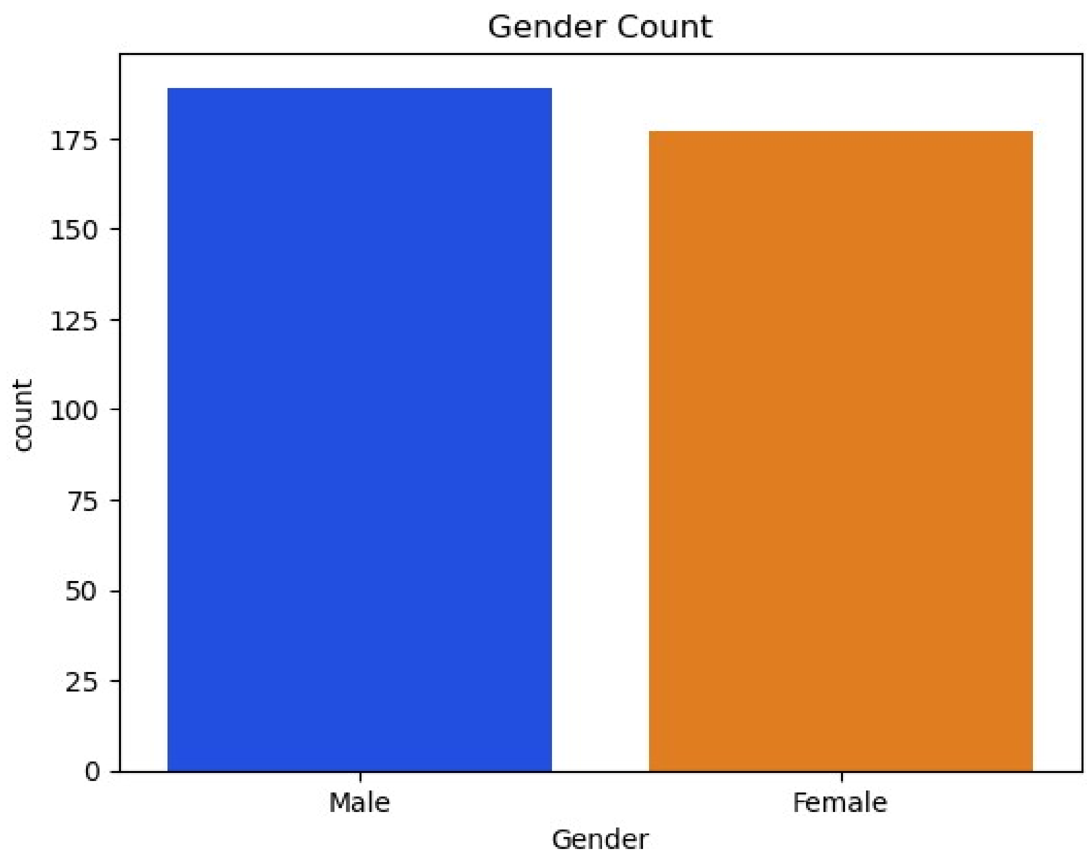

```
plt.figure(figsize=(6,4))
sns.boxplot(x=Sdf["Salary"])
plt.title("Salary - Box Plot")
plt.show()
```

4.4. Countplot

```
sns.countplot(x=Sdf['Education Level'], hue = Sdf['Education Level'],
palette='pastel')
plt.title("Education Level Count")
plt.show()
```

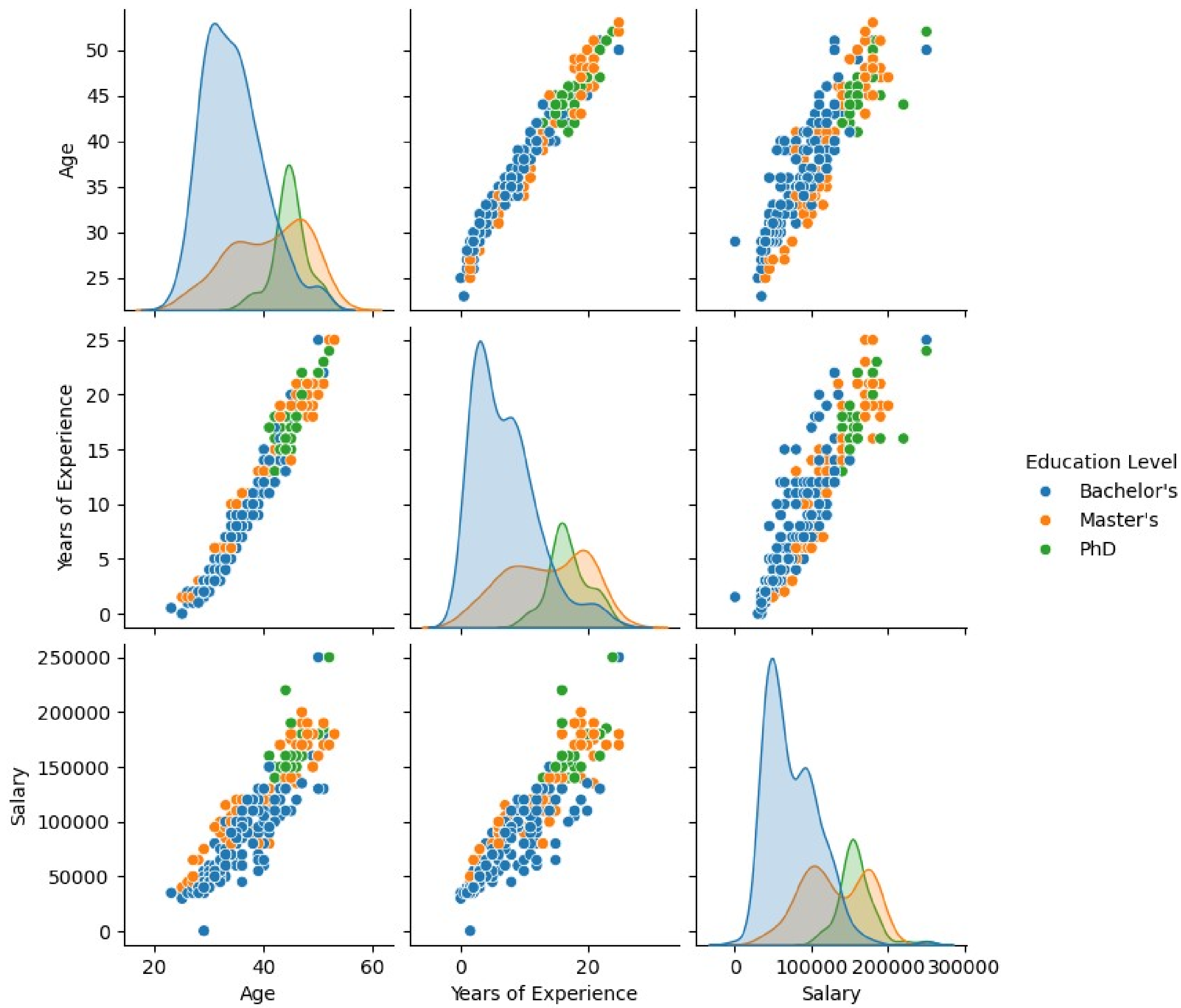



```
sns.countplot(x=Sdf['Gender'], hue=Sdf['Gender'], palette='bright',
legend=False)
plt.title("Gender Count")
plt.show()
```



4.5. Pair plot

```
sns.pairplot(Sdf, hue='Education Level')
plt.show()
```



1. Grouping and Aggregation
   1. Grouping by Education level

```
Sdf.groupby('Education Level')['Salary'].mean()

Education Level
Bachelor's      74683.409091
Master's       129473.684211
PhD            157843.137255
Name: Salary, dtype: float64

Sdf.groupby('Education Level')['Age'].mean()

Education Level
Bachelor's    34.368182
Master's      40.715789
PhD           44.725490
Name: Age, dtype: float64
```

```
Sdf.groupby('Education Level')['Years of Experience'].mean()
```

```
Education Level
Bachelor's      6.970455
Master's       13.421053
PhD            17.019608
Name: Years of Experience, dtype: float64
```

1. Segmentation

```
Fem_Master = Sdf[(Sdf['Gender'] == 'Female') & (Sdf['Education Level']
== "Master's")]

Fem_Master['Salary'].mean()
```

```
121020.40816326531
```

```
Exp20 = Sdf[Sdf['Years of Experience'] > 20]

Exp20['Salary'].mean()
```

```
175892.85714285713
```

1. Aggregation

```
Sdf.groupby('Education Level').agg({'Age': ['count', 'mean']})
```

```
                  Age
                count       mean
Education Level
Bachelor's        220  34.368182
Master's           95  40.715789
PhD                51  44.725490
```

Pivot

```
Sdf.pivot_table(values='Years of Experience', index='Education Level',
columns='Gender', aggfunc='mean')
```

```
Gender              Female      Male
Education Level
Bachelor's        6.990196   6.95339
Master's         12.877551  14.00000
PhD              16.730769  17.32000
```