

Importing Libraries

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

Loading and Viewing Data

```
ld=pd.read_csv(r"C:\Mypythonfiles\Salary_EDA.csv")
```

```
ld
```

	Age	Gender	Education Level	Job Title \
0	32.0	Male	Bachelor's	Software Engineer
1	28.0	Female	Master's	Data Analyst
2	45.0	Male	PhD	Senior Manager
3	36.0	Female	Bachelor's	Sales Associate
4	36.0	Female	Bachelor's	Sales Associate
...
370	35.0	Female	Bachelor's	Senior Marketing Analyst
371	43.0	Male	Master's	Director of Operations
372	29.0	Female	Bachelor's	Junior Project Manager
373	34.0	Male	Bachelor's	Senior Operations Coordinator
374	44.0	Female	PhD	Senior Business Analyst

	Years of Experience	Salary
0	5.0	90000.0
1	3.0	65000.0
2	15.0	150000.0
3	7.0	60000.0
4	7.0	60000.0
...
370	8.0	85000.0
371	19.0	170000.0
372	2.0	40000.0
373	7.0	90000.0
374	15.0	150000.0

```
[375 rows x 6 columns]
```

```
ld.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

ld.isnull().sum()

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

ld.dropna(inplace=True)
ld.isnull().sum()

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

```

Conclusion: All null values are dropped. now the features have non-null values.

```

ld.dropna(inplace=True)
ld.info()

<class 'pandas.core.frame.DataFrame'>
Index: 366 entries, 0 to 374
Data columns (total 6 columns):
#   Column                Non-Null Count  Dtype
---  ---
0   Age                   366 non-null   float64
1   Gender                366 non-null   object
2   Education Level       366 non-null   object
3   Job Title              366 non-null   object
4   Years of Experience    366 non-null   float64
5   Salary                 366 non-null   float64
dtypes: float64(3), object(3)
memory usage: 20.0+ KB

```

```
ld.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

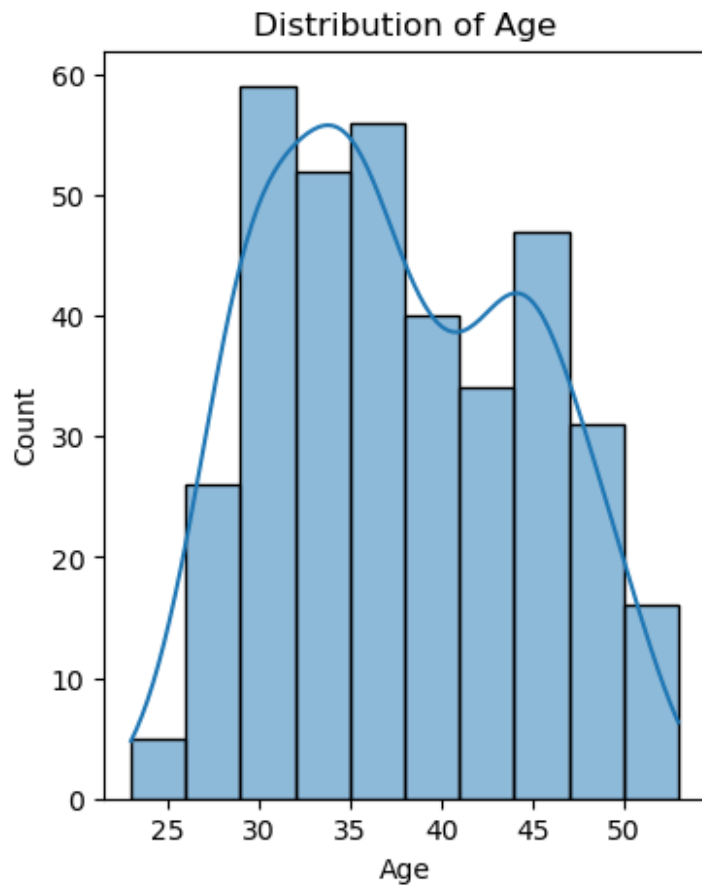
Conclusions:

1. Age, Years of Experience and salary are of datatype float.
2. The average age is approximately 37 years min is 23 and max is 53, Majority range is between 32 and 44.
3. The most frequent gender is Male.
4. The average salary is 100492.
5. The average years of Experience is 10 year.
6. NaN-> not applicable for non-numeric values.
7. We have 6 features and 375 rows.
8. salary: there might be outlier.

Visualization

1. Analyse age distribution [Histogram]

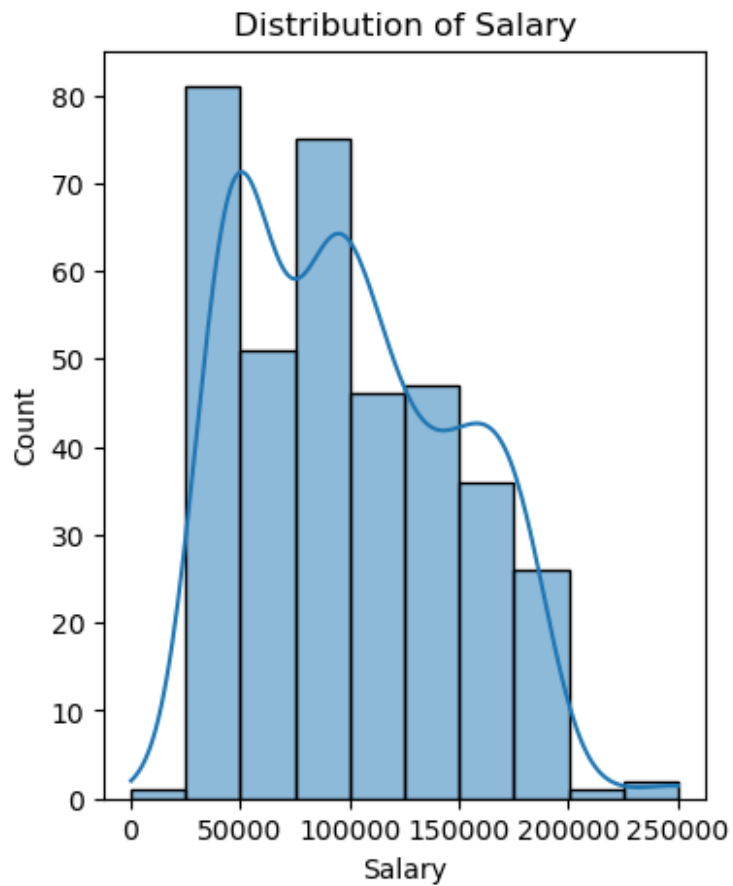
```
plt.figure(figsize=(4,5))
sns.histplot(ld["Age"], kde=True, bins=10)
plt.title("Distribution of Age")
plt.show()
```



Conclusion: majority range is 30. no outlier exist. minority of people have age of 25. there is a slite positive skew.

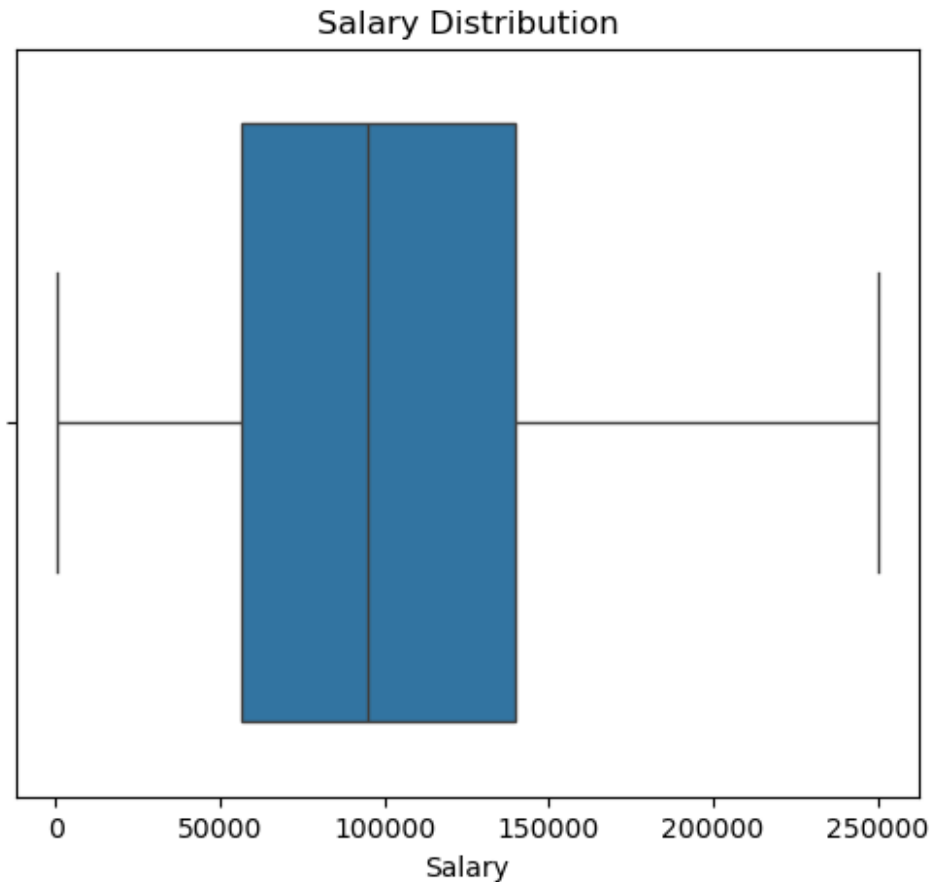
Analyse the distribution of salary usins hist

```
plt.figure(figsize=(4,5))
sns.histplot(ld["Salary"],kde=True,bins=10)
plt.title("Distribution of Salary")
plt.show()
```



1.positive skew. 2.majority of salary range is 50000. 3.minority of salary range is 250000. 4.no outlier is exist.

```
plt.figure(figsize=(6,5))
sns.boxplot(x=ld["Salary"])
plt.title("Salary Distribution")
plt.show()
```



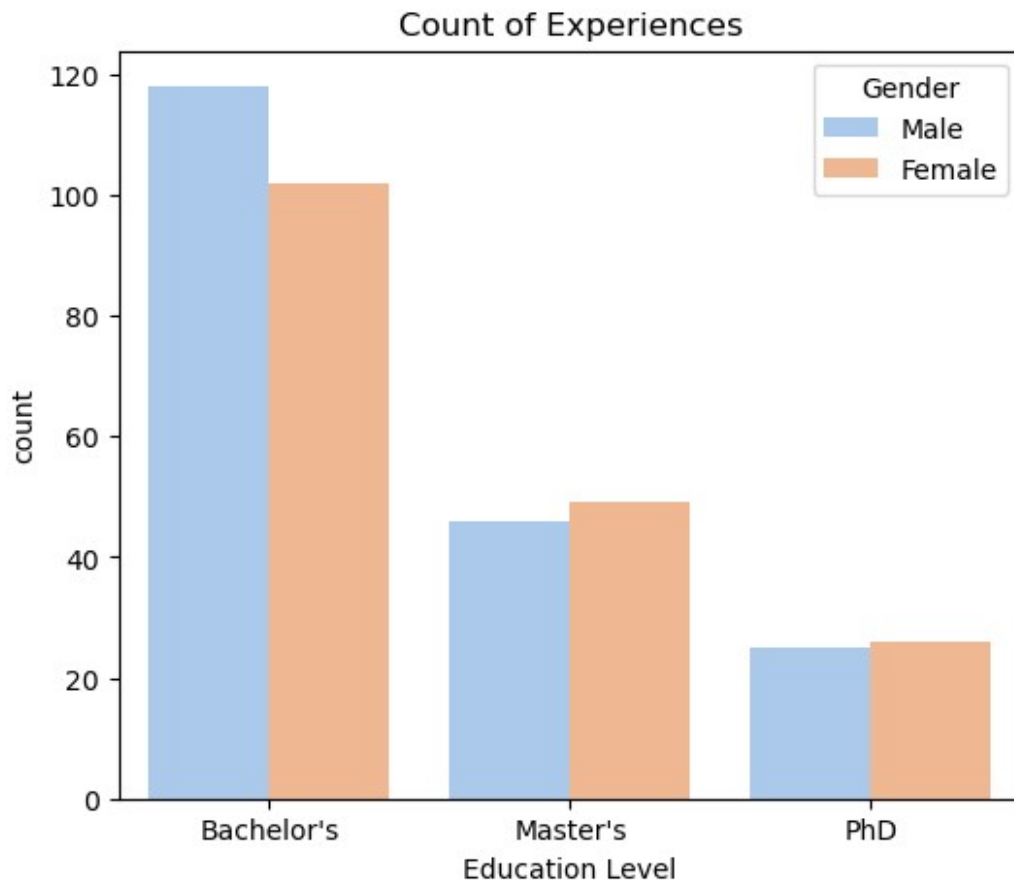
Conclusiopn: 1.No abnormal outlier is exist. 2.average salary is 100000. 3.upper limit is 150000 and lower limit is 50000.

```
ndf=ld.select_dtypes(include=["number"])
ndf.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

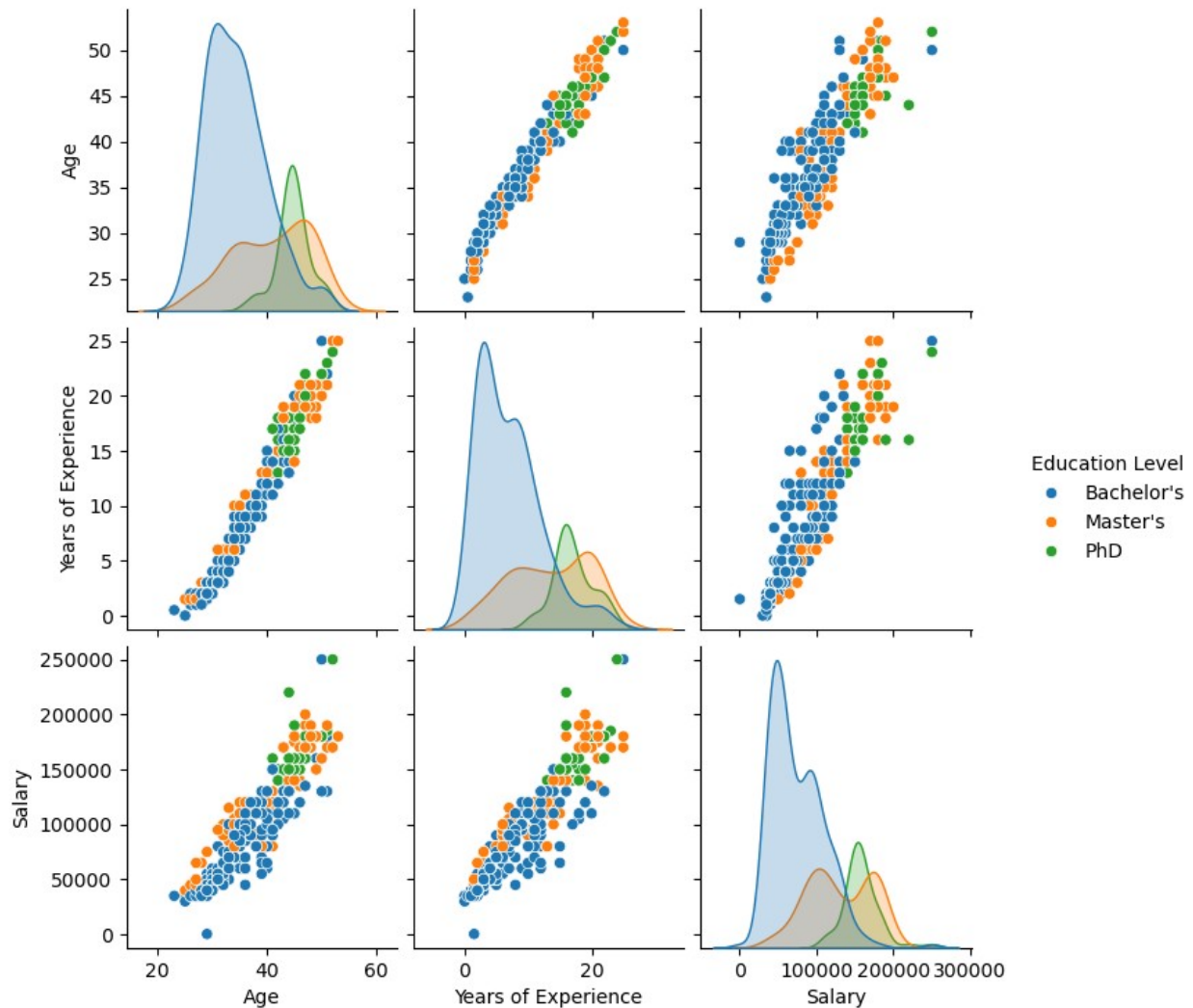
4)

```
plt.figure(figsize=(6,5))
sns.countplot(x=ld["Education
Level"],palette="pastel",hue=ld["Gender"])
plt.title("Count of Experiences")
plt.show()
```



1. It shows the counts of gender and education level 2. male gender is dominating the Bachelor's. 3. Ph.D is the highest education level, males are dominating.

```
sns.pairplot(ld, hue="Education Level")  
<seaborn.axisgrid.PairGrid at 0x21b40663110>
```



1. It shows the pairplot of the education level of the employee.
2. Age affects the Experience.
3. Experience affects the Salary.
4. Bachelor's level is dominating in all the fields of education level.
5. We observed that age increases.
6. The peak salary is given to Bachelor degree people.
7. Employee with bachelor in degree is consistent.

group education level and find average salary for every category

```
ld.groupby("Education Level")["Salary"].mean()
```

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

```
ld.groupby("Gender")["Salary"].mean()
```



```
Gender
Female    97033.898305
Male     103732.010582
Name: Salary, dtype: float64
```

```
ld.groupby("Age")["Salary"].mean()
```

```
Age
23.0    35000.000000
25.0    35000.000000
26.0    38333.333333
27.0    45000.000000
28.0    41250.000000
29.0    42841.304348
30.0    46666.666667
31.0    54285.714286
32.0    66666.666667
33.0    70625.000000
34.0    90625.000000
35.0    89772.727273
36.0    84545.454545
37.0   103750.000000
38.0   104000.000000
39.0    92916.666667
40.0   103076.923077
41.0   116363.636364
42.0   124090.909091
43.0   141250.000000
44.0   147750.000000
45.0   153529.411765
46.0   151500.000000
47.0   171666.666667
48.0   178125.000000
49.0   170000.000000
50.0   177500.000000
51.0   171000.000000
52.0   210000.000000
53.0   180000.000000
Name: Salary, dtype: float64
```

```
ld.groupby("Years of Experience")["Salary"].mean()
```

```
Years of Experience
0.0    33333.333333
0.5    35000.000000
1.0    36000.000000
1.5    36279.166667
2.0    41833.333333
3.0    51379.310345
4.0    58500.000000
```

5.0	63125.000000
6.0	83750.000000
7.0	82000.000000
8.0	88800.000000
9.0	101818.181818
10.0	100555.555556
11.0	100500.000000
12.0	105000.000000
13.0	118000.000000
14.0	125769.230769
15.0	134375.000000
16.0	159411.764706
17.0	143000.000000
18.0	150416.666667
19.0	166333.333333
20.0	166250.000000
21.0	173846.153846
22.0	162222.222222
23.0	177500.000000
24.0	250000.000000
25.0	200000.000000

Name: Salary, dtype: float64

```
ld4=ld.select_dtypes(include=["number"])
ld4
```

	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
...
370	35.0	8.0	85000.0
371	43.0	19.0	170000.0
372	29.0	2.0	40000.0
373	34.0	7.0	90000.0
374	44.0	15.0	150000.0

[366 rows x 3 columns]

```
ld2=ld[(ld["Gender"]=="Female")&(ld["Education Level"]=="Master's")]
ld2["Salary"].mean()
```

121020.40816326531