Salary Prediction

About Dataset

This dataset has total of 6704 rows and 6 columns

1) Age - Age of the employee

2) Gender - Gender of the employee

3) Education Level - Education level of employee

4) Job Title - Job title of the employee

5) Years of Experience - experience of the employee

6) Salary - Salary of the employee

In [1]:
```
# import needed libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

In [2]:
```
# read a csv file
salary_df = pd.read_csv('Salary_Data.csv')
salary_df.head()
```

Out[2]:

	Age	Gender	Education Level	Job Title	Years of Experience	Salary
0	32.0	Male	Bachelor's	Software Engineer	5.0	90000.0
1	28.0	Female	Master's	Data Analyst	3.0	65000.0
2	45.0	Male	PhD	Senior Manager	15.0	150000.0
3	36.0	Female	Bachelor's	Sales Associate	7.0	60000.0
4	52.0	Male	Master's	Director	20.0	200000.0

In [3]:
```
# get a quick info about dataset
salary_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6704 entries, 0 to 6703
Data columns (total 6 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Age                  6702 non-null   float64
 1   Gender               6702 non-null   object 
 2   Education Level      6701 non-null   object 
 3   Job Title            6702 non-null   object 
 4   Years of Experience  6701 non-null   float64
 5   Salary               6699 non-null   float64
dtypes: float64(3), object(3)
memory usage: 314.4+ KB
```

Data preprocessing Part 1

In [4]:
```
# detecting the null values
salary_df.isnull().sum()
```

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

In [5]:
```
# drop the null values
salary_df.dropna(inplace = True)
```

In [6]:
```
# description of data
salary_df.describe()
```

Out[6]:

	Age	Years of Experience	Salary
count	6698.000000	6698.000000	6698.000000
mean	33.623022	8.095178	115329.253061
std	7.615784	6.060291	52789.792507
min	21.000000	0.000000	350.000000
25%	28.000000	3.000000	70000.000000
50%	32.000000	7.000000	115000.000000
75%	38.000000	12.000000	160000.000000
max	62.000000	34.000000	250000.000000

In [7]:
```
# checking the unique values of job title
salary_df['Job Title'].unique()
```

Out[7]:
```
array(['Software Engineer', 'Data Analyst', 'Senior Manager',
       'Sales Associate', 'Director', 'Marketing Analyst',
       'Product Manager', 'Sales Manager', 'Marketing Coordinator',
       'Senior Scientist', 'Software Developer', 'HR Manager',
       'Financial Analyst', 'Project Manager', 'Customer Service Rep',
       'Operations Manager', 'Marketing Manager', 'Senior Engineer',
       'Data Entry Clerk', 'Sales Director', 'Business Analyst',
       'VP of Operations', 'IT Support', 'Recruiter', 'Financial Manager',
       'Social Media Specialist', 'Software Manager', 'Junior Developer',
       'Senior Consultant', 'Product Designer', 'CEO', 'Accountant',
       'Data Scientist', 'Marketing Specialist', 'Technical Writer',
       'HR Generalist', 'Project Engineer', 'Customer Success Rep',
       'Sales Executive', 'UX Designer', 'Operations Director',
       'Network Engineer', 'Administrative Assistant',
       'Strategy Consultant', 'Copywriter', 'Account Manager',
       'Director of Marketing', 'Help Desk Analyst',
       'Customer Service Manager', 'Business Intelligence Analyst',
       'Event Coordinator', 'VP of Finance', 'Graphic Designer',
       'UX Researcher', 'Social Media Manager', 'Director of Operations',
       'Senior Data Scientist', 'Junior Accountant',
       'Digital Marketing Manager', 'IT Manager',
       'Customer Service Representative', 'Business Development Manager',
       'Senior Financial Analyst', 'Web Developer', 'Research Director',
       'Technical Support Specialist', 'Creative Director',
       'Senior Software Engineer', 'Human Resources Director',
       'Content Marketing Manager', 'Technical Recruiter',
       'Sales Representative', 'Chief Technology Officer',
       'Junior Designer', 'Financial Advisor', 'Junior Account Manager',
       'Senior Project Manager', 'Principal Scientist',
       'Supply Chain Manager', 'Senior Marketing Manager',
       'Training Specialist', 'Research Scientist',
       'Junior Software Developer', 'Public Relations Manager',
       'Operations Analyst', 'Product Marketing Manager',
       'Senior HR Manager', 'Junior Web Developer',
       'Senior Project Coordinator', 'Chief Data Officer',
       'Digital Content Producer', 'IT Support Specialist',
       'Senior Marketing Analyst', 'Customer Success Manager',
       'Senior Graphic Designer', 'Software Project Manager',
       'Supply Chain Analyst', 'Senior Business Analyst',
       'Junior Marketing Analyst', 'Office Manager', 'Principal Engineer',
       'Junior HR Generalist', 'Senior Product Manager',
       'Junior Operations Analyst', 'Senior HR Generalist',
       'Sales Operations Manager', 'Senior Software Developer',
       'Junior Web Designer', 'Senior Training Specialist',
       'Senior Research Scientist', 'Junior Sales Representative',
       'Junior Marketing Manager', 'Junior Data Analyst',
       'Senior Product Marketing Manager', 'Junior Business Analyst',
       'Senior Sales Manager', 'Junior Marketing Specialist',
       'Junior Project Manager', 'Senior Accountant', 'Director of Sales',
       'Junior Recruiter', 'Senior Business Development Manager',
       'Senior Product Designer', 'Junior Customer Support Specialist',
       'Senior IT Support Specialist', 'Junior Financial Analyst',
       'Senior Operations Manager', 'Director of Human Resources',
       'Junior Software Engineer', 'Senior Sales Representative',
       'Director of Product Management', 'Junior Copywriter',
       'Senior Marketing Coordinator', 'Senior Human Resources Manager',
       'Junior Business Development Associate', 'Senior Account Manager',
       'Senior Researcher', 'Junior HR Coordinator',
       'Director of Finance', 'Junior Marketing Coordinator',
       'Junior Data Scientist', 'Senior Operations Analyst',
       'Senior Human Resources Coordinator', 'Senior UX Designer',
       'Junior Product Manager', 'Senior Marketing Specialist',
       'Senior IT Project Manager', 'Senior Quality Assurance Analyst',
       'Director of Sales and Marketing', 'Senior Account Executive',
```

```
'Director of Business Development', 'Junior Social Media Manager',
'Senior Human Resources Specialist', 'Senior Data Analyst',
'Director of Human Capital', 'Junior Advertising Coordinator',
'Junior UX Designer', 'Senior Marketing Director',
'Senior IT Consultant', 'Senior Financial Advisor',
'Junior Business Operations Analyst',
'Junior Social Media Specialist',
'Senior Product Development Manager', 'Junior Operations Manager',
'Senior Software Architect', 'Junior Research Scientist',
'Senior Financial Manager', 'Senior HR Specialist',
'Senior Data Engineer', 'Junior Operations Coordinator',
'Director of HR', 'Senior Operations Coordinator',
'Junior Financial Advisor', 'Director of Engineering',
'Software Engineer Manager', 'Back end Developer',
'Senior Project Engineer', 'Full Stack Engineer',
'Front end Developer', 'Front End Developer',
'Director of Data Science', 'Human Resources Coordinator',
'Junior Sales Associate', 'Human Resources Manager',
'Juniour HR Generalist', 'Juniour HR Coordinator',
'Digital Marketing Specialist', 'Receptionist',
'Marketing Director', 'Social Media Man', 'Delivery Driver'],
dtype=object)
```

In [8]:
```
# checking the value counts
salary_df['Job Title'].value_counts()
```

Out[8]:
```
Software Engineer              518
Data Scientist                 453
Software Engineer Manager      376
Data Analyst                   363
Senior Project Engineer        318
                              ...
Account Manager                  1
Help Desk Analyst                1
Senior Training Specialist       1
Junior Web Designer              1
Software Project Manager         1
Name: Job Title, Length: 191, dtype: int64
```

In [9]:
```
# creating the variable for reducing the number of job titles
job_title_stats = salary_df['Job Title'].value_counts()
job_title_stats_less_than_50 = job_title_stats[job_title_stats<=50]
job_title_stats_less_than_50.count()
```

Out[9]:
```
153
```

In [10]:
```
# reducing the number of job titles
salary_df['Job Title'] = salary_df['Job Title'].apply(lambda x: 'Others' if x in jo
salary_df['Job Title'].nunique()
```

Out[10]:
```
39
```

In [11]:
```
# checking unique values in education level
salary_df['Education Level'].unique()
```

Out[11]:
```
array(["Bachelor's", "Master's", 'PhD', "Bachelor's Degree",
       "Master's Degree", 'High School', 'phD'], dtype=object)
```

In [12]:
```
salary_df['Education Level'].replace(["Bachelor's Degree","Master's Degree","phD"]
```

In [13]:
```
salary_df.Gender.value_counts()
# three genders present in this dataset
```

Out[13]:
```
Male      3671
Female    3013
Other       14
Name: Gender, dtype: int64
```

Exploratory data analysis

In [14]:
```
salary_df.head()
```

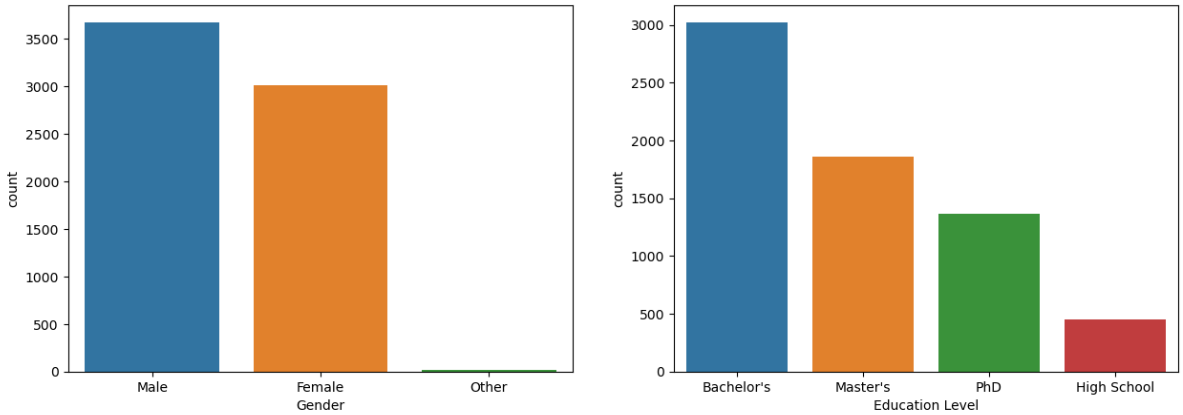
Out[14]:

	Age	Gender	Education Level	Job Title	Years of Experience	Salary
0	32.0	Male	Bachelor's	Software Engineer	5.0	90000.0
1	28.0	Female	Master's	Data Analyst	3.0	65000.0
2	45.0	Male	PhD	Others	15.0	150000.0
3	36.0	Female	Bachelor's	Sales Associate	7.0	60000.0
4	52.0	Male	Master's	Others	20.0	200000.0

Distribution of catogorical variables

In [15]:
```
fig, ax = plt.subplots(1,2,figsize=(15,5))
sns.countplot(x='Gender',data=salary_df,ax = ax[0])
sns.countplot(x='Education Level',data = salary_df,ax=ax[1])
```

Out[15]: <Axes: xlabel='Education Level', ylabel='count'>



The first chart reveals that a significant portion of the employees are males, while the second chart indicates that the majority of employees have completed a bachelor's degree.

Distribution of Continuous variables

In [16]:
```
fig, ax = plt.subplots(1,3,figsize=(20,5))
sns.histplot(salary_df['Age'],ax=ax[0])
sns.histplot(salary_df['Years of Experience'],ax=ax[1])
sns.histplot(salary_df['Salary'],ax=ax[2])
```

Out[16]: <Axes: xlabel='Salary', ylabel='Count'>

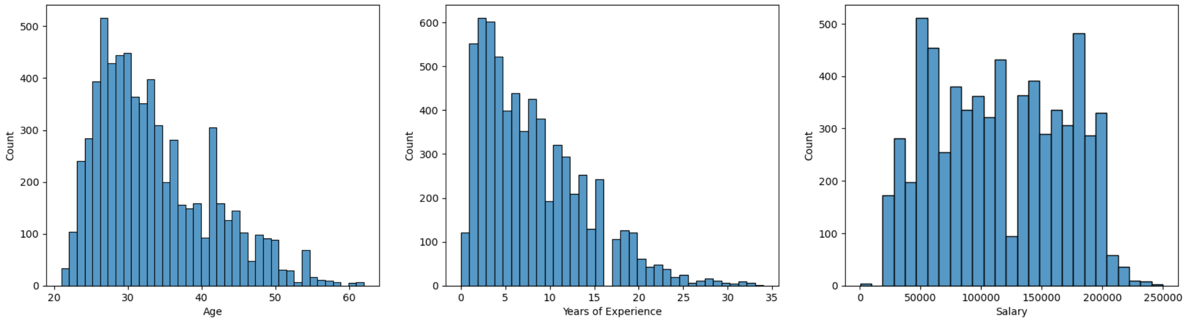


Chart 1 highlights that the majority of employees fall within the 23 to 37 years age range, emphasizing a youthful workforce.

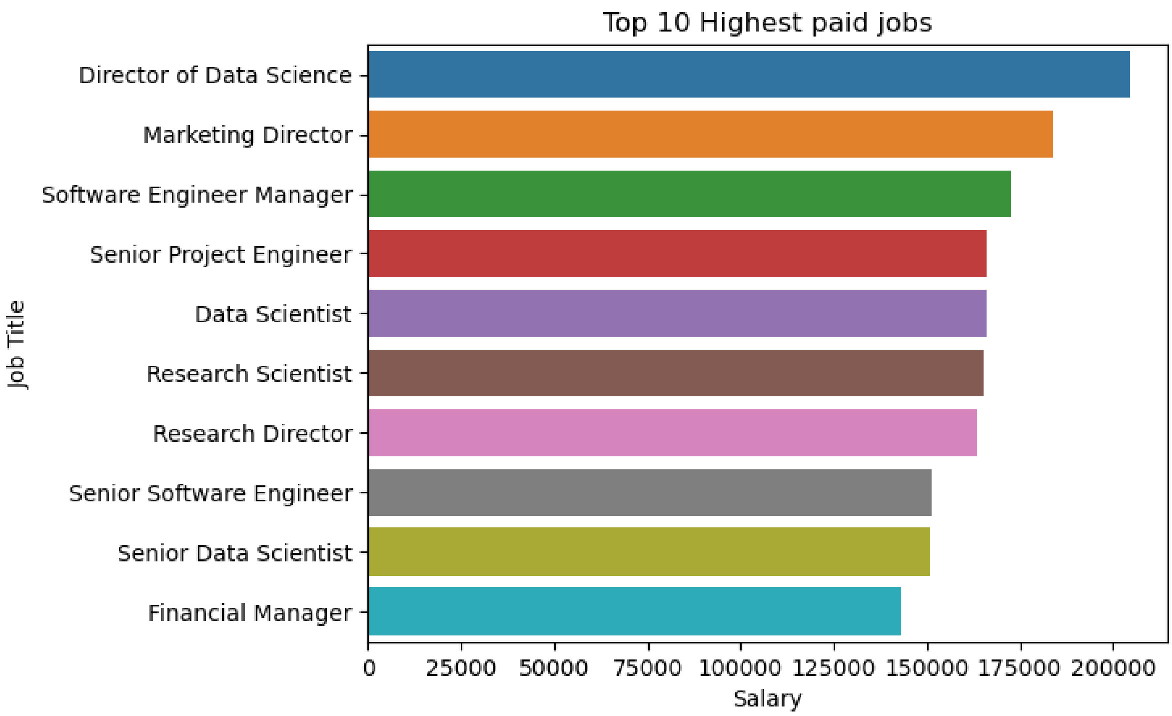
The second chart illustrates employees experience levels with the majority having 1 to 10 years of experience.

The third chart demontrates the salary distribution with most employees earning salaries between 50,000 to 2,00,000.

Top 10 Highest paid jobs

In [17]:
```
mean_salary_by_job = salary_df.groupby('Job Title')['Salary'].mean().reset_index()
sorted_data = mean_salary_by_job.sort_values(by='Salary',ascending=False)
sns.barplot(x='Salary',y='Job Title',data=sorted_data.head(10)).set(title='Top 10 H
```

Out[17]:
```
[Text(0.5, 1.0, 'Top 10 Highest paid jobs')]
```



Based on this chart we can know Director of data science gets a highest mean salary

Relationship with Target variable

In [18]:
```
fig, ax = plt.subplots(1,2,figsize=(15,5))
sns.barplot(x='Gender',y='Salary',data=salary_df,ax=ax[0]).set(title='Relationship
sns.boxplot(x='Education Level',y='Salary',data=salary_df,ax=ax[1]).set(title='Rel
```

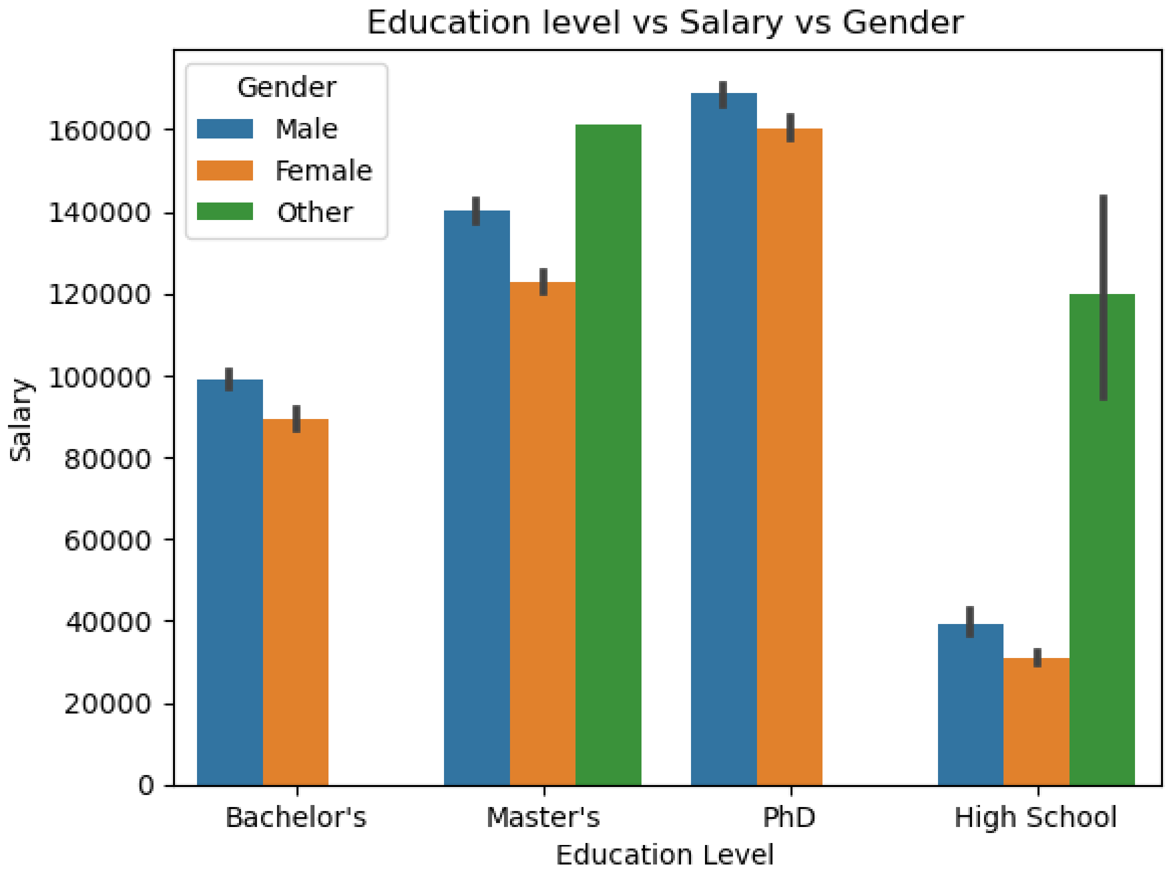
Out[18]:
```
[Text(0.5, 1.0, 'Relationship between Education Level and Salary')]
```

In chart 1 demonstrates the salary distribution among the genders. Employees from the other genders get a high salary as compared to the other two genders, but they are very less in count.

Through chart second we can ascertain PhD holders have a high median salary

In [19]:
```
sns.barplot(x='Education Level',y='Salary',data=salary_df,hue='Gender').set(title=
```

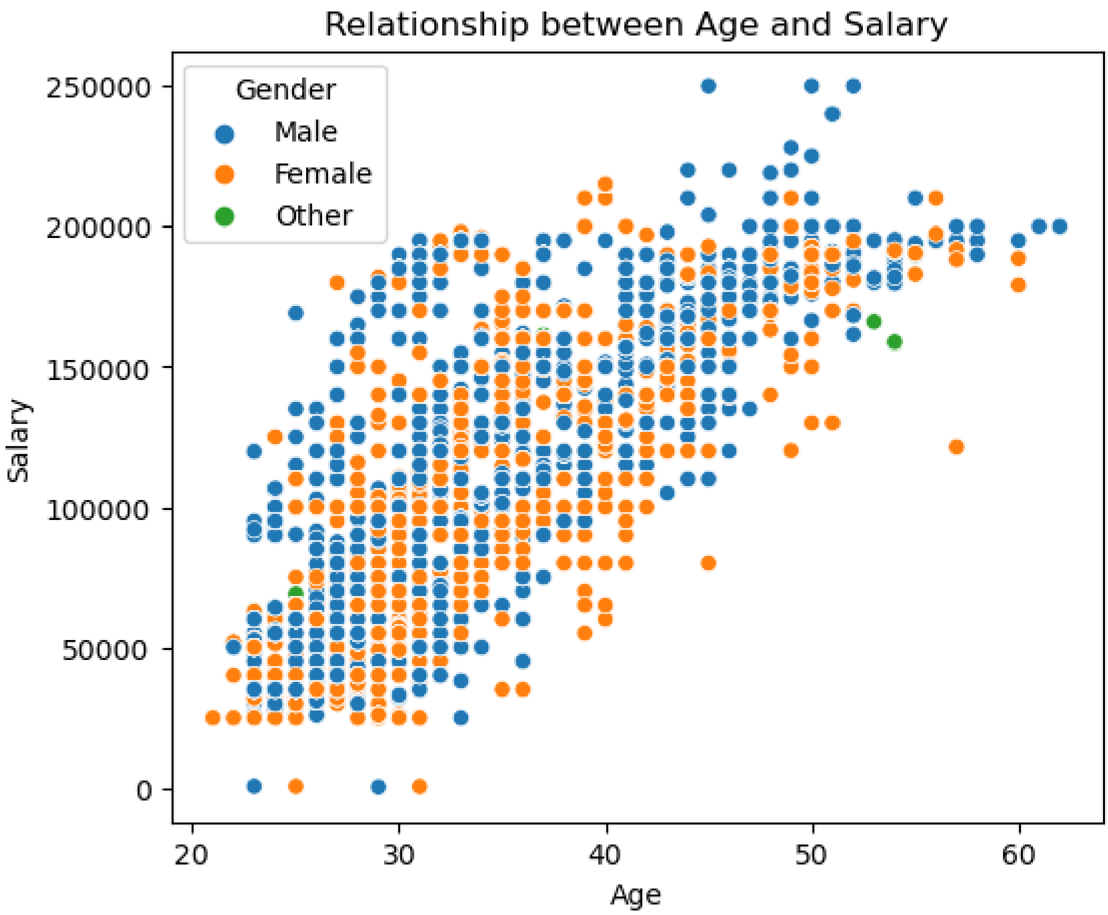
Out[19]:
```
[Text(0.5, 1.0, 'Education level vs Salary vs Gender')]
```



This chart shows education level and salary among the genders. In all education level catogory male gets high salary than female. In Master's and High School catogory other gender gets a high salary than males and females.

In [20]:
```
plt.figure(figsize=(6,5))
sns.scatterplot(x='Age',y='Salary',data=salary_df,hue='Gender').set(title='Relatio
```

Out[20]:
```
[Text(0.5, 1.0, 'Relationship between Age and Salary')]
```



This chart shows relationship between age and salary of employees. It illustrates that as age increases salary also increses. Gender distribution are also equal.

In [21]:
```
plt.figure(figsize=(6,5))
sns.scatterplot(x='Years of Experience',y='Salary',data=salary_df,hue='Gender').se
```

Out[21]:
```
[Text(0.5, 1.0, 'Relationship between Experience and Salary')]
```

This chart shows relationship between experience and salary of employees. It illustrates that as experience increases salary also increses. Gender distribution are also same.

Data Preprocessing Part 2

Detecting the Outliers

In [22]:
```
# detecting the outliers in salary column using IQR method
Q1 = salary_df.Salary.quantile(0.25)
Q3 = salary_df.Salary.quantile(0.75)
IQR = Q3-Q1
lower = Q1-1.5*IQR
upper = Q3+1.5*IQR
```

In [23]:
```
salary_df[salary_df.Salary>upper]
```

Out[23]:

Age	Gender	Education Level	Job Title	Years of Experience	Salary

In [24]:
```
salary_df[salary_df.Salary<lower]
```

Out[24]:

Age	Gender	Education Level	Job Title	Years of Experience	Salary

No outliers found in Salary column

In [25]:
```
# Mapping Education Level column
education_mapping = {"High School":0,"Bachelor's":1,"Master's":2,"PhD":3}
```

```
salary_df['Education Level'] = salary_df['Education Level'].map(education_mapping)
```

In [26]:
```
# Label encoding the catogorical variable
le = LabelEncoder()
salary_df['Gender'] = le.fit_transform(salary_df['Gender'])
```

In [27]:
```
# Correlation plot
sns.heatmap(salary_df.corr(),annot = True)
```

Out[27]: <Axes: >

Through this heatmap we can know age, education level, expereince are highly correlated to the salary.

In [28]:
```
# Creating dummies for Job titles
dummies = pd.get_dummies(salary_df['Job Title'],drop_first=True)
salary_df = pd.concat([salary_df,dummies],axis=1)
```

In [29]:
```
# Drop Job Title column
salary_df.drop('Job Title',inplace=True,axis=1)
salary_df.head()
```

Out[29]:

	Age	Gender	Education Level	Years of Experience	Salary	Content Marketing Manager	Data Analyst	Data Scientist	Digital Marketing Manager	Direc of D Scie
0	32.0	1	1	5.0	90000.0	0	0	0	0	
1	28.0	0	2	3.0	65000.0	0	1	0	0	
2	45.0	1	3	15.0	150000.0	0	0	0	0	
3	36.0	0	1	7.0	60000.0	0	0	0	0	
4	52.0	1	2	20.0	200000.0	0	0	0	0	

5 rows × 43 columns

In [30]:

```
# Separate the dataset into features and target
features = salary_df.drop('Salary',axis=1)
target = salary_df['Salary']
```

Train Test Split

In [31]:

```
x_train,x_test,y_train,y_test = train_test_split(features,target,test_size=0.25,ra
x_train.shape
```

Out[31]: (5023, 42)

Salary Prediction

In [32]:

```
# Create a dictionary for hyperparameter tuning
model_params = {
    'Linear_Regression':{
        'model':LinearRegression(),
        'params':{

        }
    },
    'Decision_Tree':{
        'model':DecisionTreeRegressor(),
        'params':{
            'max_depth':[2,4,6,8,10],
            'random_state':[0,42],
            'min_samples_split':[1,5,10,20]
        }
    },
    'Random_Forest':{
        'model':RandomForestRegressor(),
        'params':{
            'n_estimators':[10,30,20,50,80]
        }
    }
}
```

In [33]:

```
# Hyper parameter tuning through grid search cv
score=[]

for model_name,m in model_params.items():
```

```
    clf = GridSearchCV(m['model'],m['params'],cv=5,scoring='neg_mean_squared_error
    clf.fit(x_train,y_train)

    score.append({
        'Model':model_name,
        'Params':clf.best_params_,
        'MSE(-ve)':clf.best_score_
    })
pd.DataFrame(score)
```

Out[33]:

	Model	Params	MSE(-ve)
0	Linear_Regression	{}	-4.732258e+08
1	Decision_Tree	{'max_depth': 10, 'min_samples_split': 1, 'ran...	-1.481118e+08
2	Random_Forest	{'n_estimators': 30}	-6.822087e+07

Random Forest model has a lowest neagtive mean squared error which corresponds to the highest positive value of MSE.

In [34]:
```
# Order of the best models
s = pd.DataFrame(score)
sort = s.sort_values(by = 'MSE(-ve)',ascending=False)
sort
```

Out[34]:

	Model	Params	MSE(-ve)
2	Random_Forest	{'n_estimators': 30}	-6.822087e+07
1	Decision_Tree	{'max_depth': 10, 'min_samples_split': 1, 'ran...	-1.481118e+08
0	Linear_Regression	{}	-4.732258e+08

Model Evaluation

Random Forest

In [35]:
```
# Random Forest model
rfr = RandomForestRegressor(n_estimators=20)
rfr.fit(x_train,y_train)
```

Out[35]:
```
▾ RandomForestRegressor
RandomForestRegressor(n_estimators=20)
```

In [36]:
```
rfr.score(x_test,y_test)
```

Out[36]:
```
0.9714296129632989
```

In [37]:
```
y_pred_rfr = rfr.predict(x_test)
```

In [38]:
```
print("Mean Squared Error :",mean_squared_error(y_test,y_pred_rfr))
print("Mean Absolute Error :",mean_absolute_error(y_test,y_pred_rfr))
print("Root Mean Squared Error :",mean_squared_error(y_test,y_pred_rfr,squared=Fal
```

```
Mean Squared Error : 81462114.97429907
Mean Absolute Error : 3556.565248531793
Root Mean Squared Error : 9025.63654122517
```

Decision Tree

In [39]:
```
# Decision Tree model
dtr = DecisionTreeRegressor(max_depth=10,min_samples_split=1,random_state=0)
dtr.fit(x_train,y_train)
```

Out[39]:
```
DecisionTreeRegressor
DecisionTreeRegressor(max_depth=10, min_samples_split=1, random_state=0)
```

In [40]:
```
dtr.score(x_test,y_test)
```

Out[40]:
```
0.9434787076679223
```

In [41]:
```
y_pred_dtr = dtr.predict(x_test)
```

In [42]:
```
print("Mean Squared Error :",mean_squared_error(y_test,y_pred_dtr))
print("Mean Absolute Error :",mean_absolute_error(y_test,y_pred_dtr))
print("Root Mean Squared Error :",mean_squared_error(y_test,y_pred_dtr,squared=Fal
```

```
Mean Squared Error : 161157915.3105976
Mean Absolute Error : 7325.361557312708
Root Mean Squared Error : 12694.798750299178
```

Linear Regression

In [43]:
```
# Linear regression model
lr = LinearRegression()
lr.fit(x_train,y_train)
```

Out[43]:
```
LinearRegression
LinearRegression()
```

In [44]:
```
lr.score(x_test,y_test)
```

Out[44]:
```
0.8288218169608395
```

In [45]:
```
y_pred_lr = lr.predict(x_test)
```

In [46]:
```
print("Mean Squared Error :",mean_squared_error(y_test,y_pred_lr))
print("Mean Absolute Error :",mean_absolute_error(y_test,y_pred_lr))
print("Root Mean Squared Error :",mean_squared_error(y_test,y_pred_lr,squared=False
```

```
Mean Squared Error : 488076581.17878264
Mean Absolute Error : 16310.3481305285
Root Mean Squared Error : 22092.45529991591
```

Conclusion

Among three models it appears that the Random forest model is performing the best in terms of the R2 score and other evaluation metrics used.

==> The Random Forest model is the most accurate among these models, with a accuracy of 97.14%

==> The Decision Tree model also performs well with a accuracy of 94.34%

==> The Linear Regression model has the lowest score, suggesting it may not capture the underlying patterns in the data as effectively as the other models