Salary Prediction of Data Science Jobs

Introduction

The objective of this analysis is to fit and compare 4 different models to predict the salaries offered by various data science job positions using the data collected from job ads posted on glassdoor by several US compaines.

This report is organized as follows:

- Section 1 Overview
- Section 2 Data Preprocessing
- Section 3 Data Exploration & Visualisation
- Section 4 Data Modelling
- Section 5 Summary

Overview

Data Source

The dataset contains 2.4k observations. The descriptive features include 3 numeric and 9 nominal categorical features. The target feature is a continuous variable containing the average salaries of each job posting. The dataset was sourced from Kaggle at https://www.kaggle.com/atharvap329/glassdoor-data-science-job-data (https://www.kaggle.com/atharvap329/glassdoor-data-science-job-data).

Data Preprocessing

Importing the required packages and loading dataset

All the packages required for this analysis are imported into the notebook. Following this, the csv files containing the data for each state is imported using the read.csv in pandas. Since, the data is in multiple csv files, they are combined to form a single dataframe job_df.

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns

import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib
plt.style.use('ggplot')
from matplotlib.pyplot import figure

%matplotlib inline


pd.options.mode.chained_assignment = None
```

In [2]:

```
df_sf = pd.read_csv('Data_Job_SF.csv', na_values=['-1'])
df_tx = pd.read_csv('Data_Job_TX.csv', na_values=['-1'])
df_wa = pd.read_csv('Data_Job_WA.csv', na_values=['-1'])

#Merging the data from three files
job_df = pd.concat([df_sf , df_tx,df_wa] , axis = 0 , ignore_index = True)
pd.set_option('display.max_columns', None)

print(job_df.shape)
print("----------------------------")
print(job_df.info())
```

```
(2424, 12)
----------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2424 entries, 0 to 2423
Data columns (total 12 columns):
Job_title      2424 non-null object
Company        2424 non-null object
State          2422 non-null object
City           2418 non-null object
Min_Salary     1777 non-null float64
Max_Salary     1777 non-null float64
Job_Desc       2424 non-null object
Industry       2100 non-null object
Rating         2189 non-null float64
Date_Posted    2424 non-null object
Valid_until    2424 non-null object
Job_Type       2424 non-null object
dtypes: float64(3), object(9)
memory usage: 227.4+ KB
None
```

The datset has a total of 2424 observations consisting of 12 descriptive features. The target feature, Average Salary is a combination of the features Min_Salary and Max_Salary.

In [3]:

```
#Checking ID like columns
print(job_df.loc[: ,job_df.nunique() == 1].columns)
```

```
Index([], dtype='object')
```

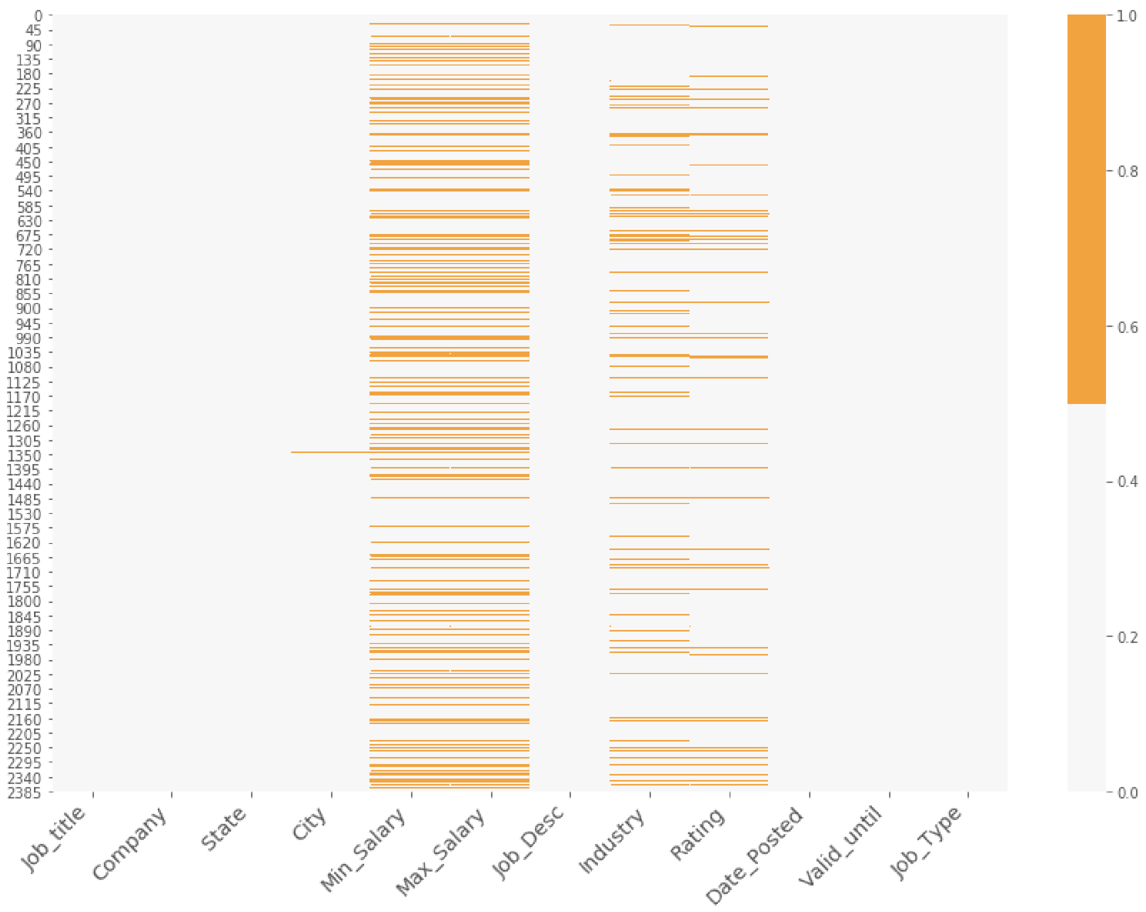
Next, we check for missing values in the dataset. A heatmap is plotted to visualize the amount of missing values.

In [4]:

```
#Checking for missing values
matplotlib.rcParams['figure.figsize'] = (15,10)

colours = ['#f7f7f7', '#f1a340'] # specify the colours - yellow is missing. blue is not missing.
chart = sns.heatmap(job_df.isnull(), cmap=sns.color_palette(colours))

chart.set_xticklabels(
    chart.get_xticklabels(),
    rotation=45,
    horizontalalignment='right',
    fontweight='light',
    fontsize='x-large'

)
```

Out[4]:

```
[Text(0.5, 0, 'Job_title'),
 Text(1.5, 0, 'Company'),
 Text(2.5, 0, 'State'),
 Text(3.5, 0, 'City'),
 Text(4.5, 0, 'Min_Salary'),
 Text(5.5, 0, 'Max_Salary'),
 Text(6.5, 0, 'Job_Desc'),
 Text(7.5, 0, 'Industry'),
 Text(8.5, 0, 'Rating'),
 Text(9.5, 0, 'Date_Posted'),
 Text(10.5, 0, 'Valid_until'),
 Text(11.5, 0, 'Job_Type')]
```



From the above heatmap, we can see that there is a significant number of missing values in the features in_Salary, Max_Salary, Industry and Rating represented by the orange lines. There are a few missing values in the City feature and two missing values in the State feature. Next, we check the actual count of these missing value using the isna() function.

In [5]:

```
#fetching the counts for missing values
null_col_list = [col for col in job_df.columns if job_df[col].isna().any()]
job_df[null_col_list].isna().sum()
```

Out[5]:

```
State           2
City            6
Min_Salary    647
Max_Salary    647
Industry      324
Rating        235
dtype: int64
```

In [6]:

```
pct_missing = np.mean(job_df['Industry'].isnull())
print('{}%'.format(round(pct_missing*100)))
```

```
13.0%
```

In [7]:

```
#Imputing for State and city

#State
state_index = job_df[job_df['State'].isnull() == True].index
job_df.loc[state_index,:]
```

Out[7]:

	Job_title	Company	State	City	Min_Salary	Max_Salary	Job_Desc	Industry
1585	Data Scientist	HRUCKUS	NaN	Crystal City, state=Virginia, Virginia	NaN	NaN	This company is in a hiring surge in response ...	Business Services
1791	Machine Learning Scientist	HRUCKUS	NaN	Crystal City, state=Virginia, Virginia	NaN	NaN	This company is in a hiring surge in response ...	Business Services

Examining the missing values in the state feature, we can that the state name is included along with the city name.The nan values are imputed with the respective state names and the state name is removed from the city feature.

In [8]:

```
#Imputing the correct value after inspecting
job_df.loc[state_index,'State'] = 'VA'
job_df.loc[state_index,'City'] = 'Crystal City'
job_df.loc[state_index,:]
```

Out[8]:

	Job_title	Company	State	City	Min_Salary	Max_Salary	Job_Desc	Industry	Rati
1585	Data Scientist	HRUCKUS	VA	Crystal City	NaN	NaN	This company is in a hiring surge in response ...	Business Services	ɛ
1791	Machine Learning Scientist	HRUCKUS	VA	Crystal City	NaN	NaN	This company is in a hiring surge in response ...	Business Services	ɛ

Following this, we take a look at the observations with missing city feature.

In [9]:

```
#City
city_index = job_df[job_df['City'].isnull() == True].index
job_df.loc[city_index,:]
```

Out[9]:

	Job_title	Company	State	City	Min_Salary	Max_Salary	Job_D
925	Data Scientist	Next Level Business Services, Inc.	Texas	NaN	NaN	NaN	Greetings,\n\nI hope are doing well.\n\n
961	Data scientist	LiveMindz	Texas	NaN	NaN	NaN	Need I Engineer,Data Scie
1128	Research Scientist	The University of Texas at Dallas	Texas	NaN	NaN	NaN	Posting Num S02931P\n\nDepartm Compu
1344	Software Engineer - System and DevOps, AMP Dat...	Apple	Texas	NaN	NaN	NaN	This company is hiring surge in respo
1345	Software Engineer – Full Stack, AMP Data Scien...	Apple	Texas	NaN	NaN	NaN	This company is hiring surge in respo
1474	Sr. Data Analyst/Systems Analyst	DatamanUSA	Texas	NaN	NaN	NaN	Â\n\nTitle:ÂSenior I Analyst\n\nDuration:/

In [10]:

```
# Removing the nan values from Min_Salary
job_df = job_df[job_df['Min_Salary'].notna()]
```

In [11]:

```
job_df.shape
```

Out[11]:

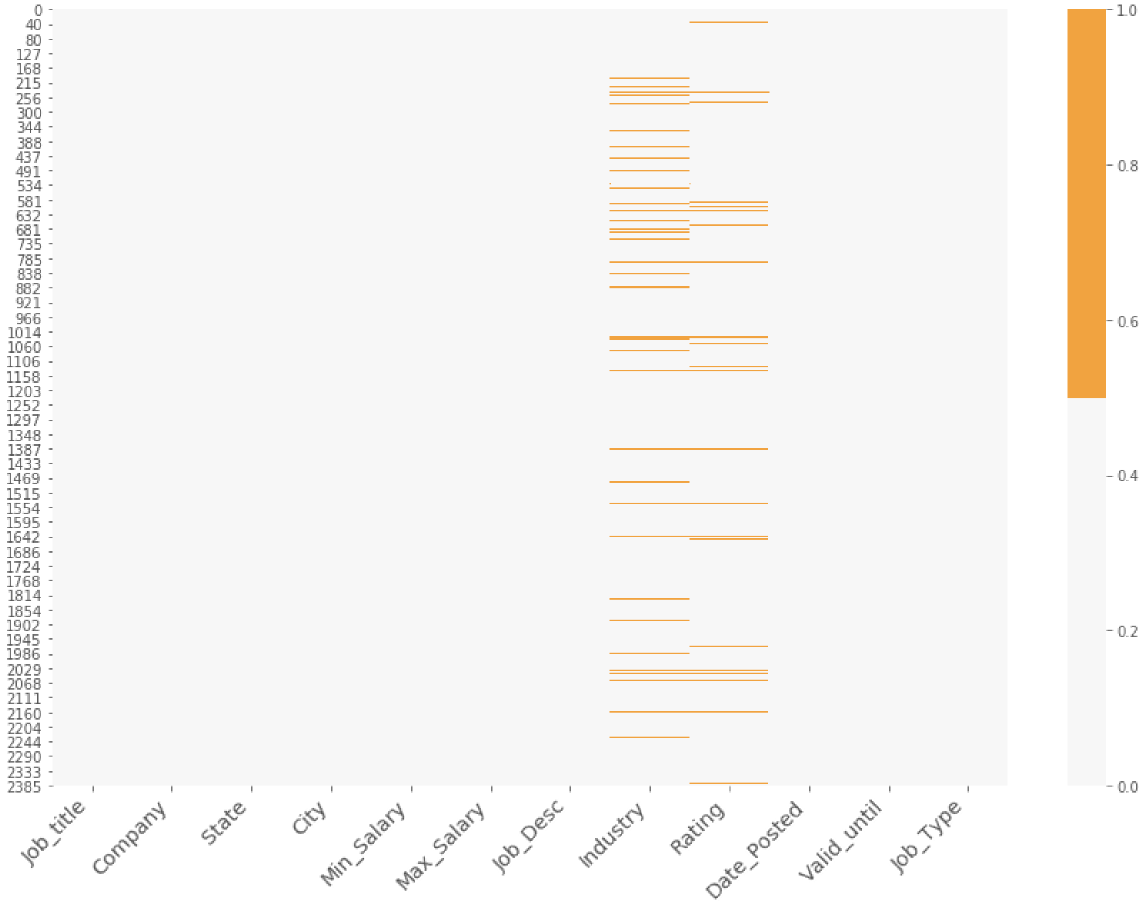
```
(1777, 12)
```

In [12]:

```
#Checking for missing values
matplotlib.rcParams['figure.figsize'] = (15,10)

colours = ['#f7f7f7', '#f1a340'] # specify the colours - yellow is missing. blue is not missing.
chart = sns.heatmap(job_df.isnull(), cmap=sns.color_palette(colours))

chart.set_xticklabels(
    chart.get_xticklabels(),
    rotation=45,
    horizontalalignment='right',
    fontweight='light',
    fontsize='x-large'

)
```

Out[12]:

```
[Text(0.5, 0, 'Job_title'),
 Text(1.5, 0, 'Company'),
 Text(2.5, 0, 'State'),
 Text(3.5, 0, 'City'),
 Text(4.5, 0, 'Min_Salary'),
 Text(5.5, 0, 'Max_Salary'),
 Text(6.5, 0, 'Job_Desc'),
 Text(7.5, 0, 'Industry'),
 Text(8.5, 0, 'Rating'),
 Text(9.5, 0, 'Date_Posted'),
 Text(10.5, 0, 'Valid_until'),
 Text(11.5, 0, 'Job_Type')]
```



Removing the nan values from the Industry and Rating Feature.

In [13]:

```
job_df = job_df[job_df['Industry'].notna() & job_df['Rating'].notna()]
```

Finally, we check if there are anymore missing values left in the dataset.

In [14]:

```
job_df.isna().sum()
```

Out[14]:

```
Job_title      0
Company        0
State          0
City           0
Min_Salary     0
Max_Salary     0
Job_Desc       0
Industry       0
Rating         0
Date_Posted    0
Valid_until    0
Job_Type       0
dtype: int64
```

Since there are no more missing in the dataset. We move onto some feature transformation. In order to make good use of the Job_Desc feature, we introduce a few additonal features using some frequently occuring keywords in the IT job decriptions. These features are of binary nature and shows if a job description contains this specific keyword or not. The keywords considered here are python, aws and visualization.

In [15]:

```
df = pd.DataFrame()
keyskills = ['python','aws','visualization']

for keyword in keyskills:
    job_df[keyword] = job_df['Job_Desc'].apply(lambda x: 1 if keyword in x.lower() else 
0)
    print(job_df[keyword].value_counts())
```

```
0    911
1    734
Name: python, dtype: int64
0    1286
1     359
Name: aws, dtype: int64
0    1332
1     313
Name: visualization, dtype: int64
```

In [16]:

```
job_df.head(10)
```

Out[16]:

	Job_title	Company	State	City	Min_Salary	Max_Salary	Job_Desc	In
0	Senior Data Scientist - Underwriting Algorithms	Faire	CA	San Francisco	151875.0	170407.0	Faire is using machine learning to change whol...	Bu S
1	Data Scientist	GovTech	CA	San Francisco	78594.0	147225.0	We are looking for Data Scientists who are int...	Gove
2	Data Scientist	Triplebyte	CA	San Francisco	145000.0	225000.0	This company is in a hiring surge in response ...	Infor Tech
3	Data Scientist	Notion Labs	CA	San Francisco	105765.0	142959.0	So, what will you do as a Data Scientist at No...	Infor Tech
5	Staff Machine Learning Engineer	Tapjoy	CA	San Francisco	137705.0	224163.0	Join the Mobile Future with Tapjoy\n\nData Sci...	Infor Tech
6	Senior Data Scientist	Autodesk	CA	San Francisco	163578.0	182543.0	This company is in a hiring surge in response ...	Infor Tech
7	Data Scientist	Formation	CA	San Francisco	119642.0	135250.0	Formation provides personalization for the lar...	Infor Tech
8	Director of Data	Strava	CA	San Francisco	84400.0	167186.0	About StravaStrava is Swedish for "strive," wh...	Infor Tech
9	Data Scientist	Duetto	CA	San Francisco	108809.0	173353.0	We are an ambitious, well-funded, high-growth ...	Infor Tech
10	Data Scientist	Demandbase	CA	San Francisco	148171.0	160387.0	The world's largest and fastest-growing compan...	Infor Tech

A new feature called Ad Validity is introduced. It is calculated by finding the difference between the features Valid_until and Date_Posted for each observation. This new feature shows the number of days an ad is up and running.

In [17]:

```
# Making Ad Validity Feature
job_df['Valid_until'] = pd.to_datetime(job_df['Valid_until'])
job_df['Date_Posted'] = pd.to_datetime(job_df['Date_Posted'])
job_df["Ad Validity"] = job_df["Valid_until"] - job_df["Date_Posted"]
job_df["Ad Validity"] = job_df["Ad Validity"].dt.days
```

The target feature (Avg_Salary) is formed by finding the average of features Max_Salary and Min_Salary for each observation.

In [18]:

```
# Creating Avg_Salary Feature
job_df["Avg_Salary"] = round((job_df["Max_Salary"] + job_df["Min_Salary"])/2, 2)
```

Next, we define two functions namely title_simplifier and seniority. The title simplifier function helps in generalizing the job title feature as same jobs can have different titles in different companies. The second function seniority helps in identifying the seniority or experience level of the job from the job title.

In [19]:

```
def title_simplifier(title):
    if 'data scientist' in title.lower():
        return 'data scientist'
    elif 'data engineer' in title.lower():
        return 'data engineer'
    elif 'analyst' in title.lower():
        return 'analyst'
    elif 'machine learning' in title.lower():
        return 'mle'
    elif 'manager' in title.lower():
        return 'manager'
    elif 'director' in title.lower():
        return 'director'
    else:
        return 'other'

def seniority(title):
    if 'sr' in title.lower() or 'senior' in title.lower() or 'sr' in title.lower() or
'lead' in title.lower() or 'principal' in title.lower():
            return 'senior'
    elif 'jr' in title.lower() or 'jr.' in title.lower():
        return 'jr'
    else:
        return 'Experienced'
```

The function title simplifier is applied on the job title feature and the resulting output is stored as a new feature called job_simp.

In [20]:

```
job_df['job_simp'] = job_df['Job_title'].apply(title_simplifier)
job_df['job_simp'].value_counts()
```

Out[20]:

```
other             627
data scientist    424
data engineer     293
analyst           185
mle                60
manager            36
director           20
Name: job_simp, dtype: int64
```

The function seniority is applied on the job title feature and the resulting output is stored as a new feature called seniority.

In [21]:

```
job_df['seniority'] = job_df['Job_title'].apply(seniority)
job_df['seniority'].value_counts()
```

Out[21]:

```
Experienced    1186
senior          458
jr                1
Name: seniority, dtype: int64
```

Next, all the columns not required for this analysis are dropped from the dataset.

In [22]:

```
# Dropping the unnecessary columns
job_df.drop(columns = ["Min_Salary","Max_Salary","Date_Posted","Valid_until","Company",
"Job_title", "City", "Job_Desc"],inplace = True)
job_df.head(10)
```

Out[22]:

	State	Industry	Rating	Job_Type	python	aws	visualization	Ad Validity	Avg_Salary
0	CA	Business Services	4.3	FULL_TIME	0	0	0	30	161141.0
1	CA	Government	3.6	FULL_TIME	1	0	0	35	112909.5
2	CA	Information Technology	3.6	FULL_TIME	0	0	0	38	185000.0
3	CA	Information Technology	5.0	FULL_TIME	0	0	0	32	124362.0
5	CA	Information Technology	3.5	FULL_TIME	1	0	0	42	180934.0
6	CA	Information Technology	4.0	FULL_TIME	0	0	0	35	173060.5
7	CA	Information Technology	3.1	FULL_TIME	0	0	0	37	127446.0
8	CA	Information Technology	4.4	FULL_TIME	0	0	0	31	125793.0
9	CA	Information Technology	4.4	FULL_TIME	0	1	1	42	141081.0
10	CA	Information Technology	4.5	FULL_TIME	0	1	1	37	154279.0

Data Exploration & Visualisation

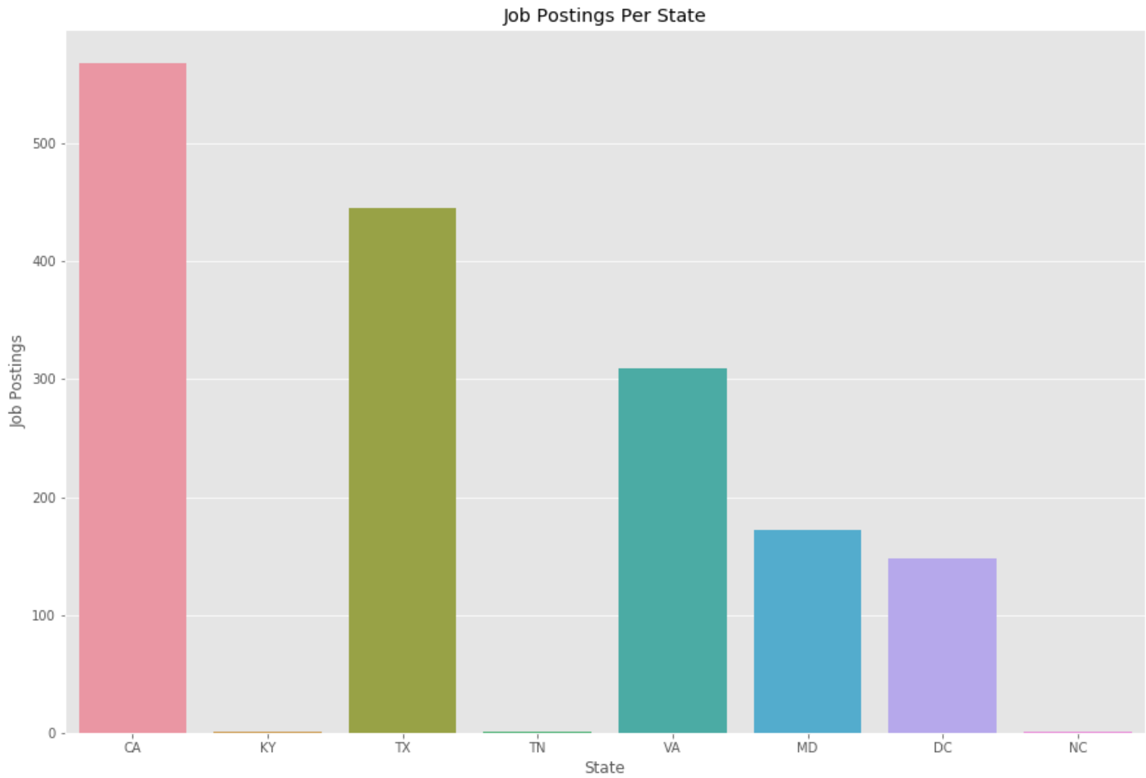
In this section, we conduct an exploratory data analysis of the dataset. This is done to uncover initial patterns, characteristics and also gain a better understanding of the data. Visualizations are plotted to examine single variables, two-variable relationships and three-variable relationships.

In [23]:

```
# Single Varible Plot 1
sns.countplot(x = job_df["State"])
plt.title('Job Postings Per State')
# Set x-axis label
plt.xlabel('State')
# Set y-axis label
plt.ylabel('Job Postings')
```

Out[23]:

```
Text(0, 0.5, 'Job Postings')
```

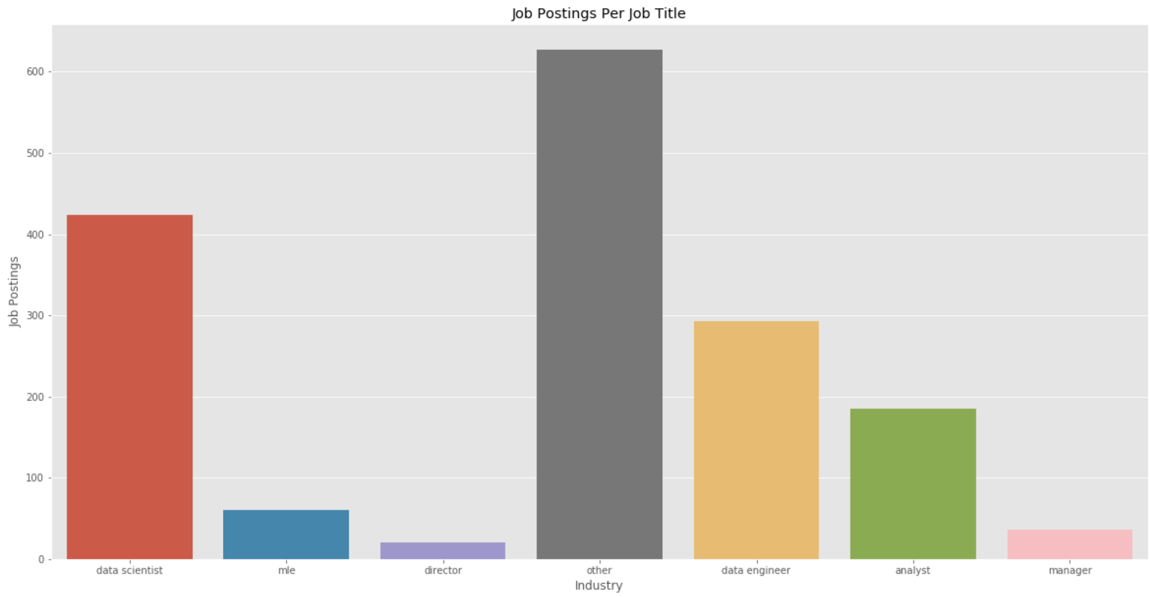


In [24]:

```
#Single Varible Plot 2
plt.figure(figsize=(20,10))
sns.countplot(x=job_df["job_simp"])
plt.title('Job Postings Per Job Title')
# Set x-axis label
plt.xlabel('Industry')
# Set y-axis label
plt.ylabel('Job Postings')
```

Out[24]:

```
Text(0, 0.5, 'Job Postings')
```

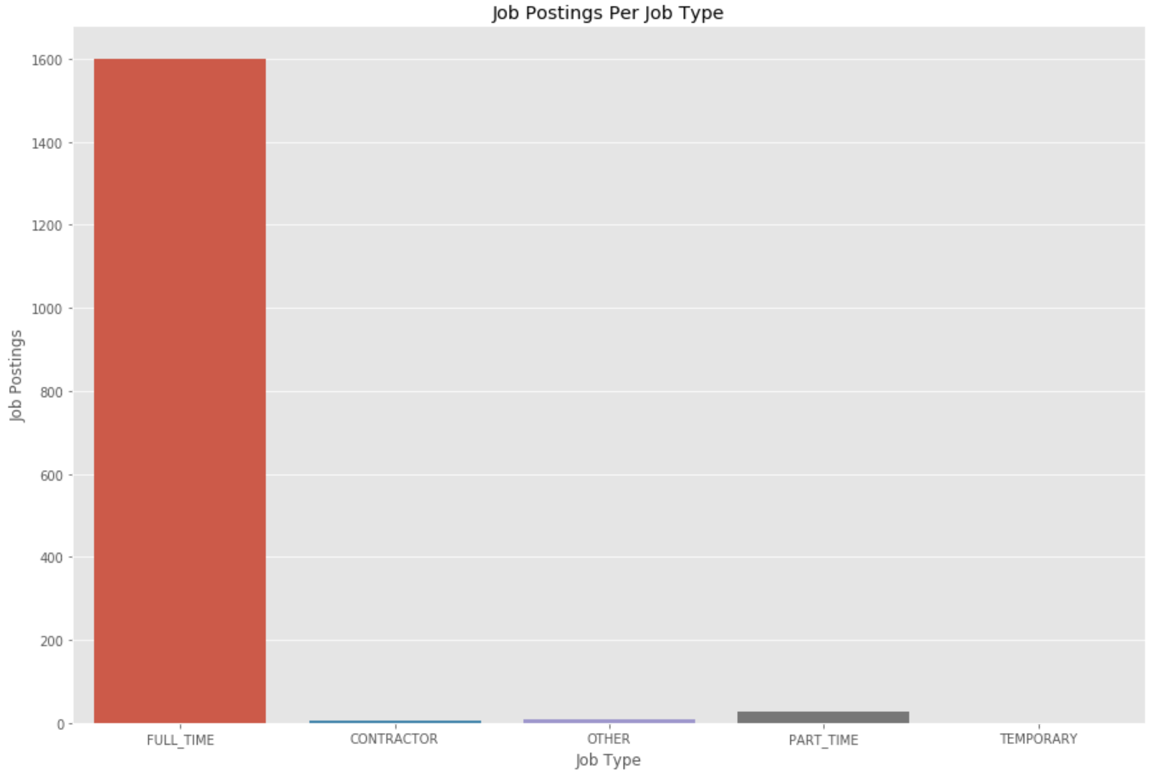


In [25]:

```
#Single Varible Plot 3
sns.countplot(x=job_df["Job_Type"])
plt.title('Job Postings Per Job Type')
# Set x-axis label
plt.xlabel('Job Type')
# Set y-axis label
plt.ylabel('Job Postings')
```

Out[25]:

```
Text(0, 0.5, 'Job Postings')
```

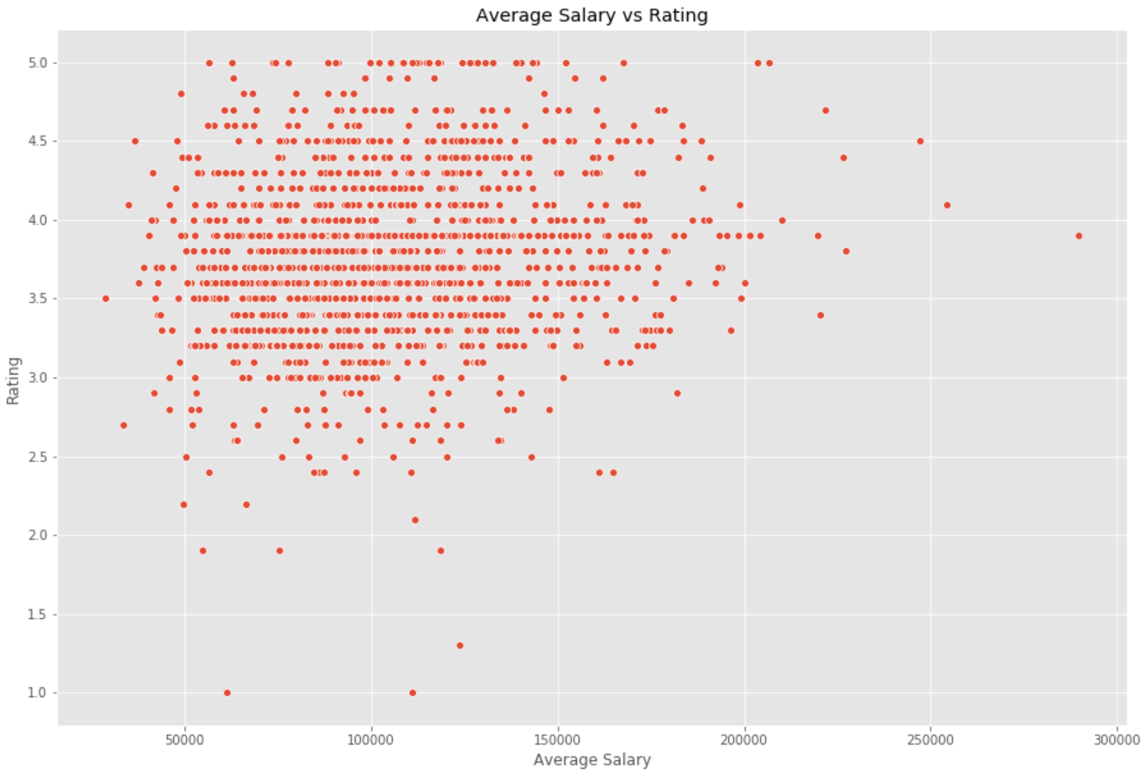


In [26]:

```
#Double Variable Plot 1
sns.scatterplot(job_df["Avg_Salary"], job_df["Rating"])
plt.title('Average Salary vs Rating')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Rating')
```

Out[26]:

```
Text(0, 0.5, 'Rating')
```

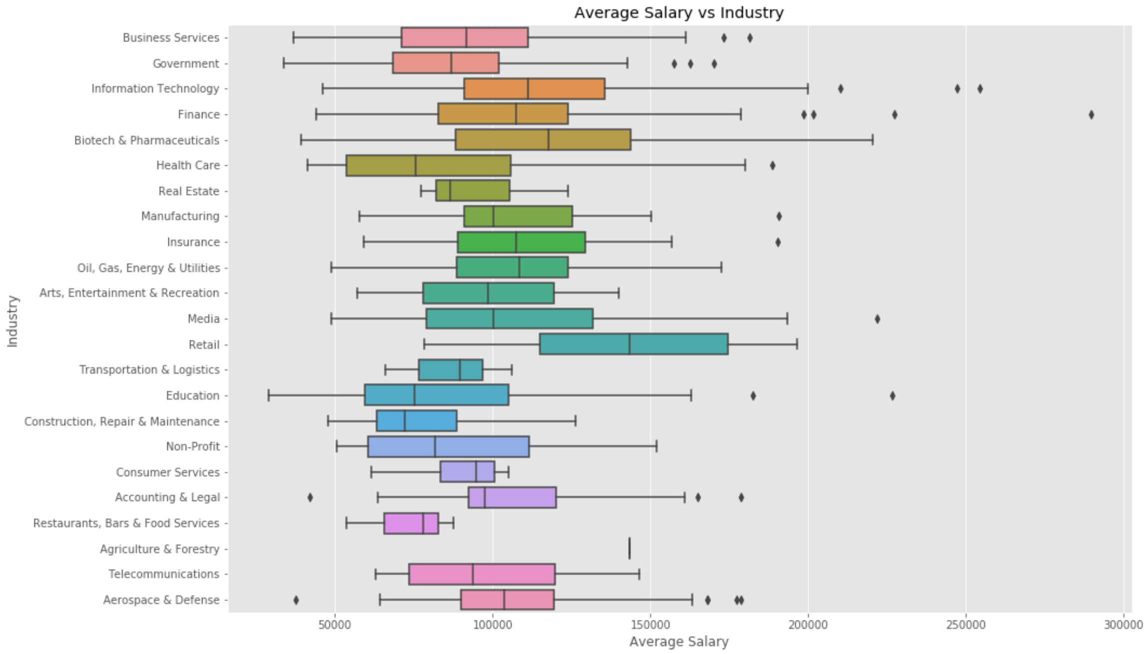


In [27]:

```
#Double Variable Plot 2
sns.boxplot(job_df["Avg_Salary"], job_df["Industry"])
plt.title('Average Salary vs Industry')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Industry')
```

Out[27]:

```
Text(0, 0.5, 'Industry')
```

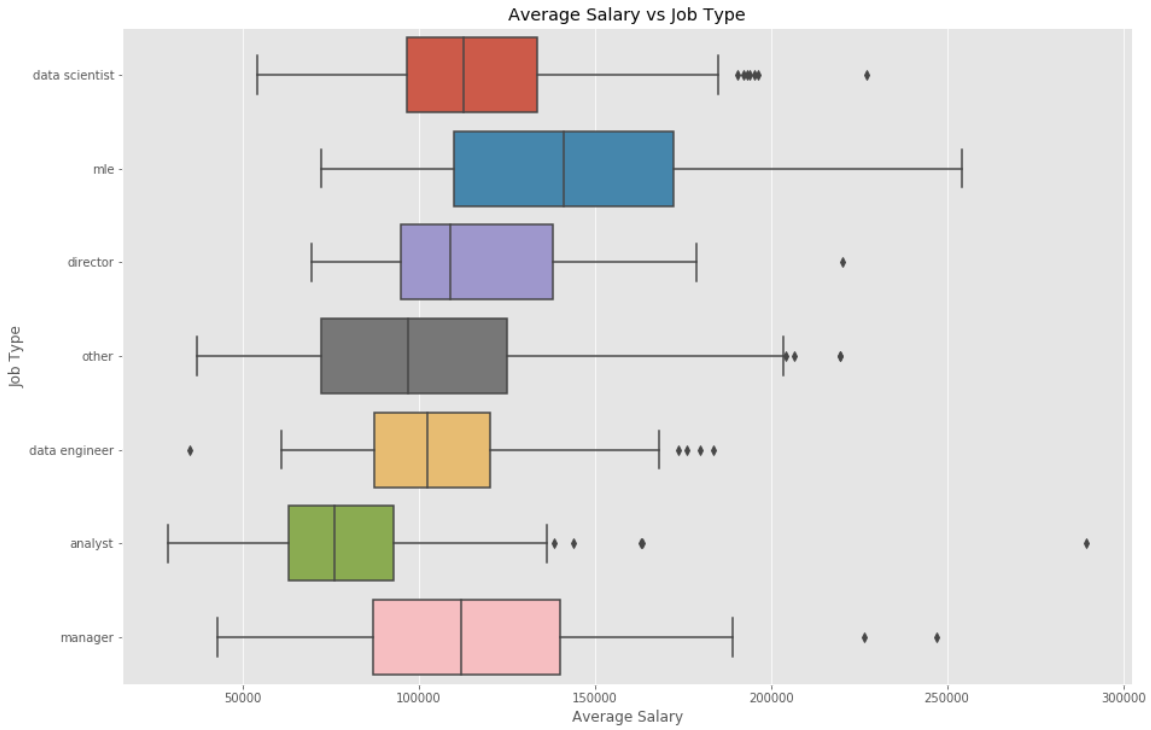


In [28]:

```
#Double Variable Plot 3
sns.boxplot(job_df["Avg_Salary"], job_df["job_simp"])
plt.title('Average Salary vs Job Type')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Job Type')
```

Out[28]:

```
Text(0, 0.5, 'Job Type')
```

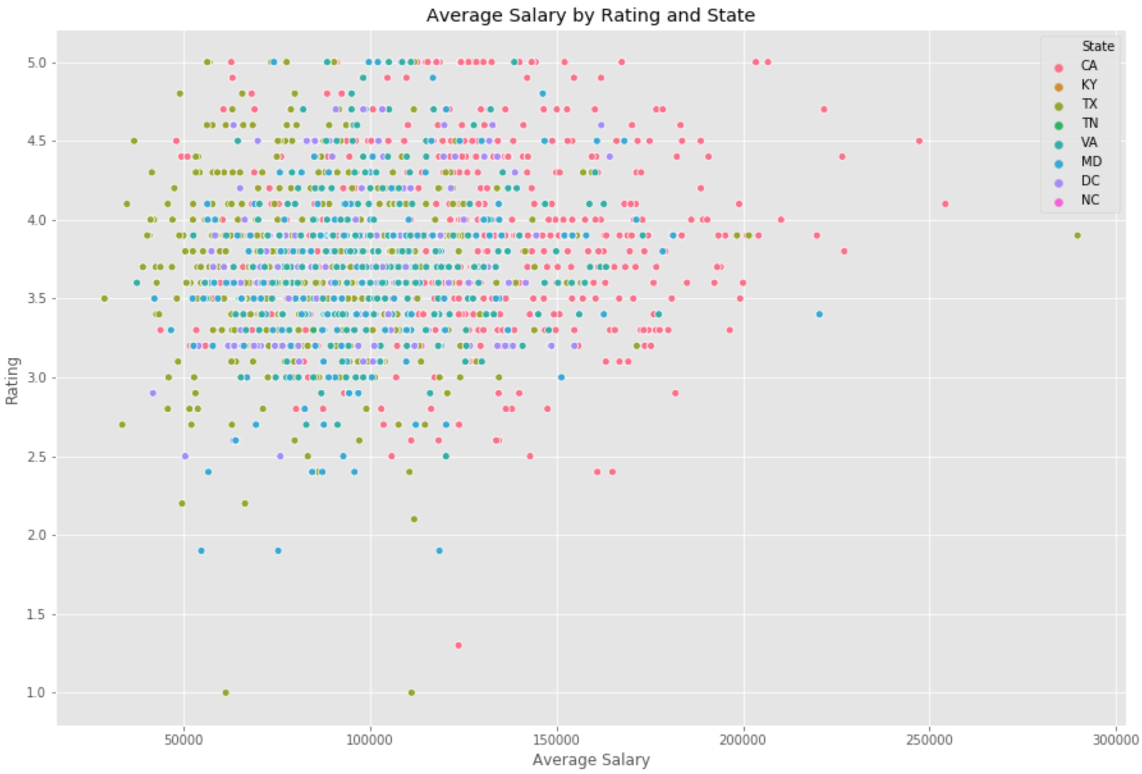


In [29]:

```
#Triple Variable Plot 1
sns.scatterplot(job_df["Avg_Salary"], job_df["Rating"], hue=job_df["State"])
plt.title('Average Salary by Rating and State')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Rating')
```

Out[29]:

```
Text(0, 0.5, 'Rating')
```

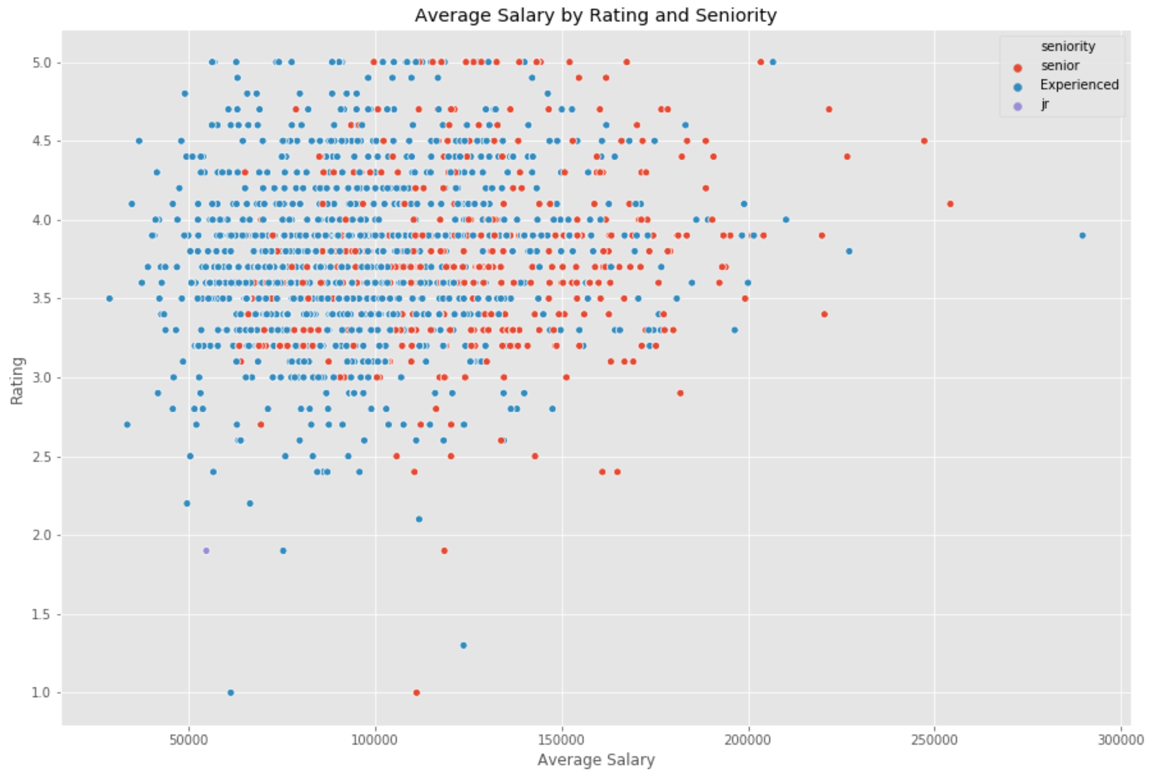


In [30]:

```
# Triple Variable Plot 2
sns.scatterplot(job_df["Avg_Salary"], job_df["Rating"], hue=job_df["seniority"])
plt.title('Average Salary by Rating and Seniority')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Rating')
```

Out[30]:

```
Text(0, 0.5, 'Rating')
```

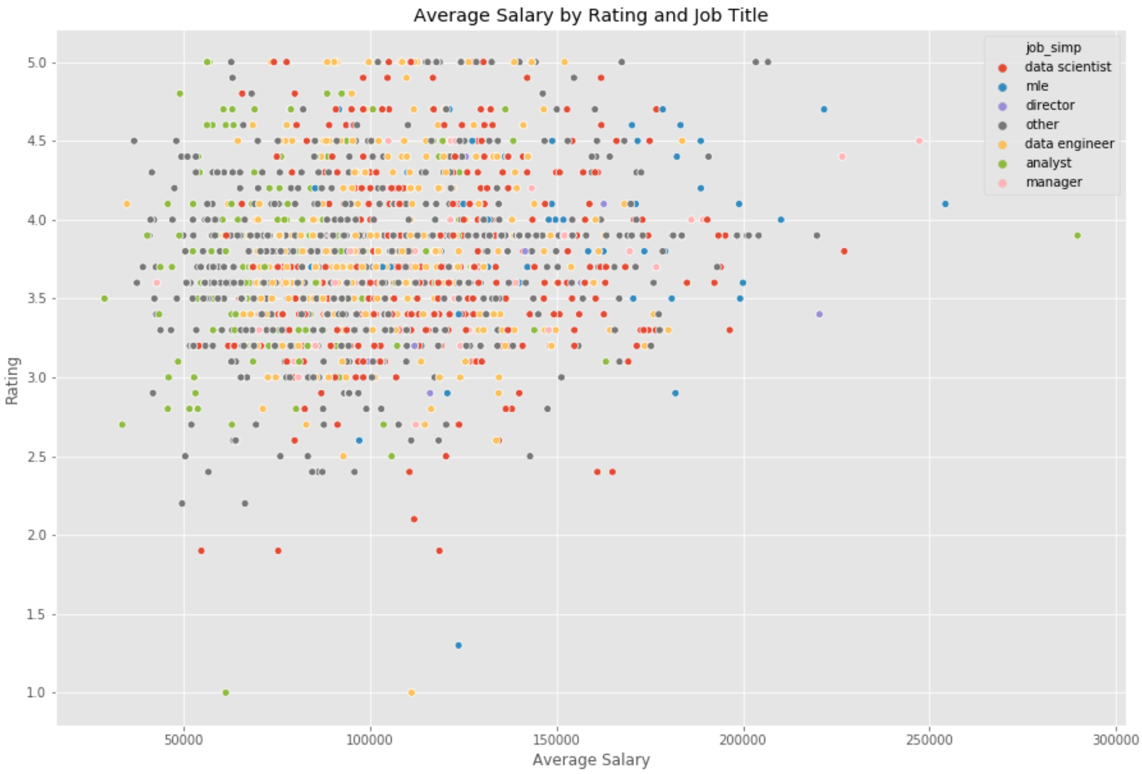


In [31]:

```
# Triple Varible Plot 3
sns.scatterplot(job_df["Avg_Salary"], job_df["Rating"], hue=job_df["job_simp"])
plt.title('Average Salary by Rating and Job Title')
# Set x-axis label
plt.xlabel('Average Salary')
# Set y-axis label
plt.ylabel('Rating')
```

Out[31]:

```
Text(0, 0.5, 'Rating')
```



In [32]:

```
# Average Salary based on Job Title & Seniority
pd.pivot_table(job_df, index = ['job_simp','seniority'], values = 'Avg_Salary')
```

Out[32]:

job_simp	seniority	Avg_Salary
analyst	Experienced	74579.253623
	senior	97858.425532
data engineer	Experienced	98937.742105
	senior	118272.849515
data scientist	Experienced	109865.898387
	jr	54925.500000
	senior	135827.345133
director	Experienced	114475.447368
	senior	220490.000000
manager	Experienced	114852.038462
	senior	130814.000000
mle	Experienced	133352.525641
	senior	162722.309524
other	Experienced	92529.577586
	senior	129515.947853

Data Modelling

- The data is first split into 2 dataframes - Data and target. Data contains the descriptive features while target contains the target feature Avg_Salary.
- Categorical features are converted to numerical form with the help of encoding using the get dummies function.
- Split the dataset into two parts with training set being 80% and test set being 20%.
- Perform feature selection using RandomForestRegressor.
- Train the model with training set data with selected features.
- Evaluate the performance of the model using Mean Absolute Error(MAE) as evaluation metric.
- pick the model which has the lowest MAE and tune the model parameters.
- predict the values on test set with best model and fine-tuned parameters.

In [33]:

```
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import cross_val_score

# Data Transformation

# Data
Data = job_df.drop(["Avg_Salary"], axis = 1)
Data = pd.get_dummies(Data)


# Target
target = (job_df[["Avg_Salary"]]).values
```

Feature selection

- RandomForestRegressor is used to highlight the top features which is relevant to the modelling.
- Feature importance is known by the property "feature*importances*" based on Gini impurity.

In [34]:

```
from sklearn.ensemble import RandomForestRegressor
num_features =20
model_rfi = RandomForestRegressor(n_estimators=100)
model_rfi.fit(Data, target)
fs_indices_rfi = np.argsort(model_rfi.feature_importances_)[::-1][0:num_features]
```

In [35]:

```
best_features_rfi = Data.columns[fs_indices_rfi].values
Data = Data[best_features_rfi]
```

In [36]:

```
# Spliting the data into train and test split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(Data, target, test_size=0.2, random
_state=42)
```

In [37]:

```
'''
Function to plot the graph of predicted versus actual salaries.
'''

def plot_graph(actual,predicted):
    fig, ax = plt.subplots()
    ax.scatter(actual, predicted)
    ax.plot([actual.min(), actual.max()], [actual.min(), actual.max()], 'k--', lw=4)
    ax.set_title("Plot of actual versus predicted salaries")
    ax.set_xlabel('Actual Salary')
    ax.set_ylabel('Predicted Salary')
    plt.show()
```

In [38]:

```
# Multiple linear regression

import statsmodels.api as sm

X_sm = X = sm.add_constant(X_train)
model = sm.OLS(y_train,X_sm)
model.fit().summary()
```

Out[38]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.497
Model:	OLS	**Adj. R-squared:**	0.489
Method:	Least Squares	**F-statistic:**	64.01
Date:	Mon, 01 Jun 2020	**Prob (F-statistic):**	5.58e-177
Time:	23:40:47	**Log-Likelihood:**	-15181.
No. Observations:	1316	**AIC:**	3.040e+04
Df Residuals:	1295	**BIC:**	3.051e+04
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	7.066e+04	2.67e+04	2.647	0.008	1.83e+04	1.23e+05
State_CA	2.659e+04	1863.894	14.266	0.000	2.29e+04	3.02e+04
Rating	4395.5961	1333.035	3.297	0.001	1780.451	7010.742
Ad Validity	61.7920	168.948	0.366	0.715	-269.649	393.233
seniority_senior	5.646e+04	2.52e+04	2.240	0.025	7003.533	1.06e+05
job_simp_analyst	-5.395e+04	6418.087	-8.405	0.000	-6.65e+04	-4.14e+04
seniority_Experienced	2.88e+04	2.52e+04	1.143	0.253	-2.06e+04	7.82e+04
job_simp_other	-3.193e+04	6182.107	-5.165	0.000	-4.41e+04	-1.98e+04
python	-4112.7504	1624.207	-2.532	0.011	-7299.116	-926.385
Industry_Information Technology	7775.4747	1876.995	4.143	0.000	4093.190	1.15e+04
State_TX	-7856.1927	1879.816	-4.179	0.000	-1.15e+04	-4168.374
job_simp_data scientist	-1.727e+04	6289.344	-2.746	0.006	-2.96e+04	-4934.648
Industry_Finance	1.422e+04	3418.686	4.159	0.000	7510.801	2.09e+04
aws	-546.7746	1818.152	-0.301	0.764	-4113.620	3020.071
Industry_Aerospace & Defense	1.474e+04	2952.771	4.992	0.000	8948.140	2.05e+04
job_simp_mle	-6587.5798	7266.813	-0.907	0.365	-2.08e+04	7668.436
Industry_Business Services	-4265.5521	2134.745	-1.998	0.046	-8453.490	-77.614
visualization	-844.5020	1938.883	-0.436	0.663	-4648.199	2959.195
job_simp_manager	-2.509e+04	7711.164	-3.254	0.001	-4.02e+04	-9965.686
Industry_Retail	2.41e+04	6117.803	3.940	0.000	1.21e+04	3.61e+04
job_simp_data engineer	-2.853e+04	6372.372	-4.477	0.000	-4.1e+04	-1.6e+04

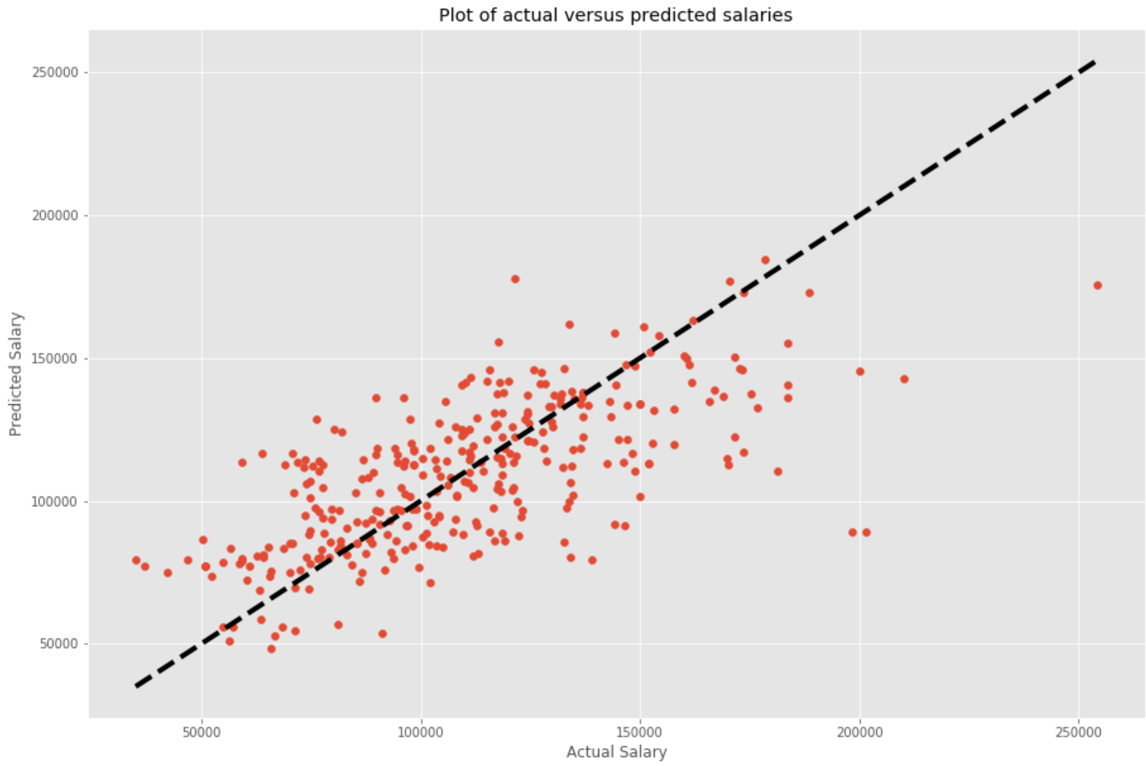
Omnibus:	271.135	**Durbin-Watson:**	1.919
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1464.201
Skew:	0.845	**Prob(JB):**	0.00
Kurtosis:	7.883	**Cond. No.**	2.29e+03

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.29e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Most of the selected parameters are significant at 5% significance level.

In [39]:

```
# Make predictions on test data
from sklearn.linear_model import LinearRegression
reg = LinearRegression().fit(X_train, y_train)
predictions = reg.predict(X_test)
plot_graph(y_test, predictions)
```



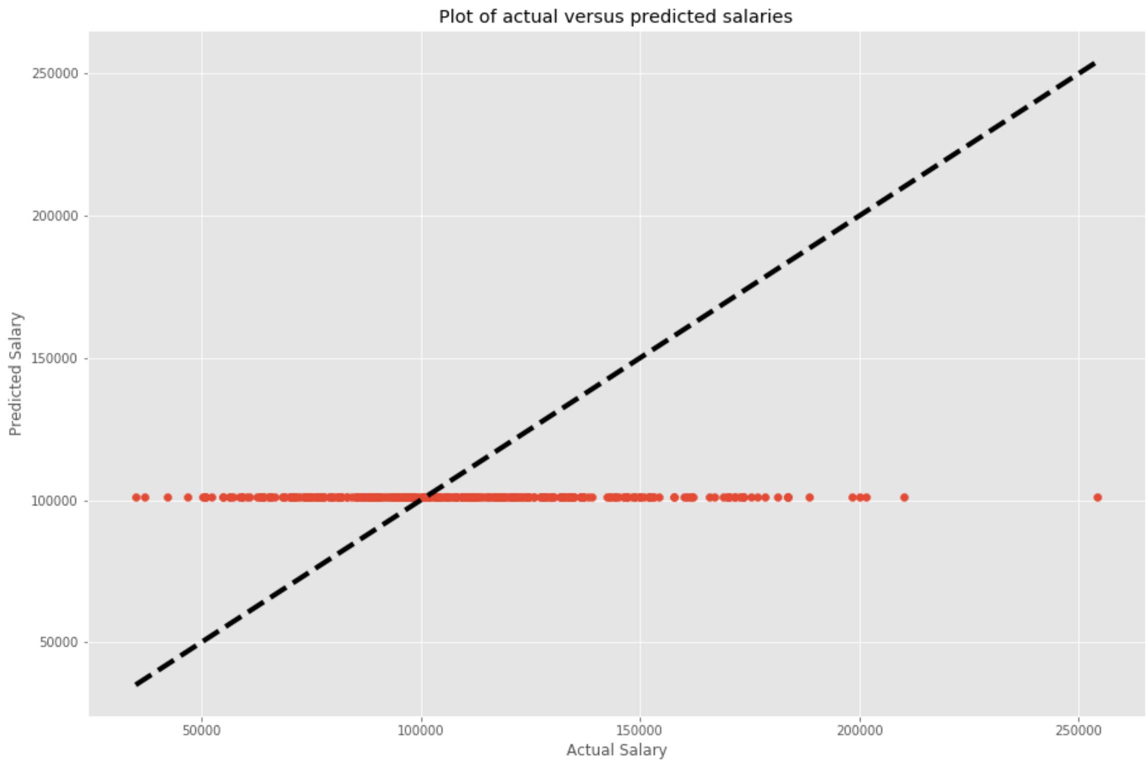
In [40]:

```
#Support Vector Model
from sklearn.svm import SVR
regressor = SVR(kernel = 'rbf', gamma='auto')


mae_svr = round(np.mean(-cross_val_score(regressor,X_train,y_train, scoring = 'neg_mean
_absolute_error', cv= 10)),3)
print("MAE for support vector regressor model is ",mae_svr)
```

```
MAE for support vector regressor model is  27504.6
```

In [41]:

```
# Make predictions on test data
regressor.fit(X_train,y_train)
predictions = regressor.predict(X_test)
plot_graph(y_test, predictions)
```



In [42]:

```
# Random forest Regression

rf = RandomForestRegressor()

mae_rf = round(np.mean(-cross_val_score(rf,X_train,y_train, scoring = 'neg_mean_absolut
e_error', cv= 10)),3)
print("MAE for Random Forest regressor model is ",mae_rf)
```

```
MAE for Random Forest regressor model is  19202.802
```

In [43]:

```
# Make predictions on test data
rf.fit(X_train,y_train)
predictions = rf.predict(X_test)
plot_graph(y_test, predictions)
```

In [44]:

```
# Ridge regression model
from sklearn.linear_model import Ridge
ridge = Ridge(alpha = 0.001)

mae_ridge = round(np.mean(-cross_val_score(ridge,X_train,y_train, scoring = 'neg_mean_a
bsolute_error', cv= 10)),3)
print("MAE for Ridge regressor model is",mae_ridge)
```

```
MAE for Ridge regressor model is 19174.119
```

In [45]:

```
# Make predictions on test data
ridge.fit(X_train,y_train)
predictions = ridge.predict(X_test)
plot_graph(y_test, predictions)
```

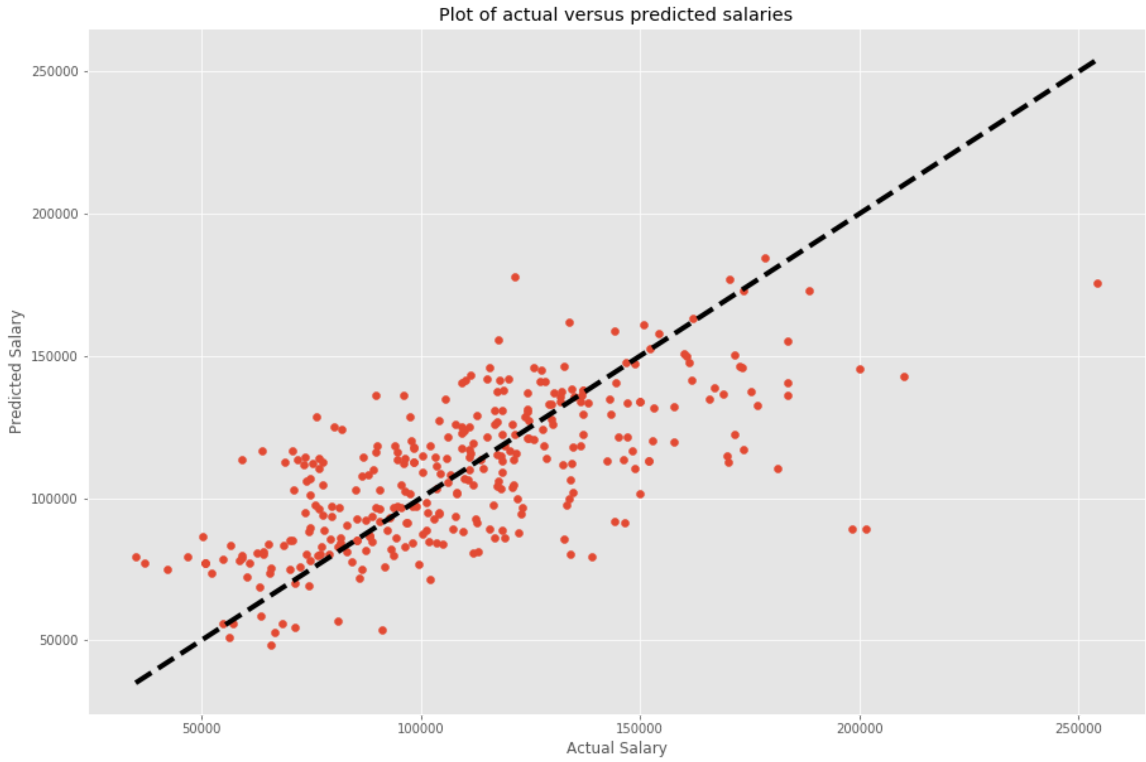
In [46]:

```
# Lasso regression model
from sklearn.linear_model import Lasso
lasso = Lasso(alpha = 0.001)

mae_lasso = round(np.mean(-cross_val_score(lasso,X_train,y_train, scoring = 'neg_mean_a
bsolute_error', cv= 10)),3)
print("MAE for Lasso regressor model is",mae_lasso)
```

```
MAE for Lasso regressor model is 19163.081
```

In [47]:

```
# Make predictions on test data
lasso.fit(X_train,y_train)
predictions = lasso.predict(X_test)
plot_graph(y_test, predictions)
```



In [48]:

```
# tune models GridsearchCV
from sklearn.model_selection import GridSearchCV
parameters = {'n_estimators':range(10,300,10), 'criterion':('mse','mae'), 'max_feature
s':('auto','sqrt','log2')}

gs = GridSearchCV(rf,parameters,scoring='neg_mean_absolute_error',cv=3)
gs.fit(X_train,y_train)

print("Best score is ",round(-gs.best_score_,3))
print("Optimized parameters for random forest regressor",gs.best_estimator_)
```

```
Best score is  17798.711
Optimized parameters for random forest regressor RandomForestRegressor(boo
tstrap=True, criterion='mae', max_depth=None,
                      max_features='log2', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=60,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

In [49]:

```
rf = RandomForestRegressor(bootstrap=True, criterion='mae', max_depth=None,
                      max_features='log2', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=60,
                      n_jobs=None, oob_score=False, random_state=None,
                      verbose=0, warm_start=False)
```

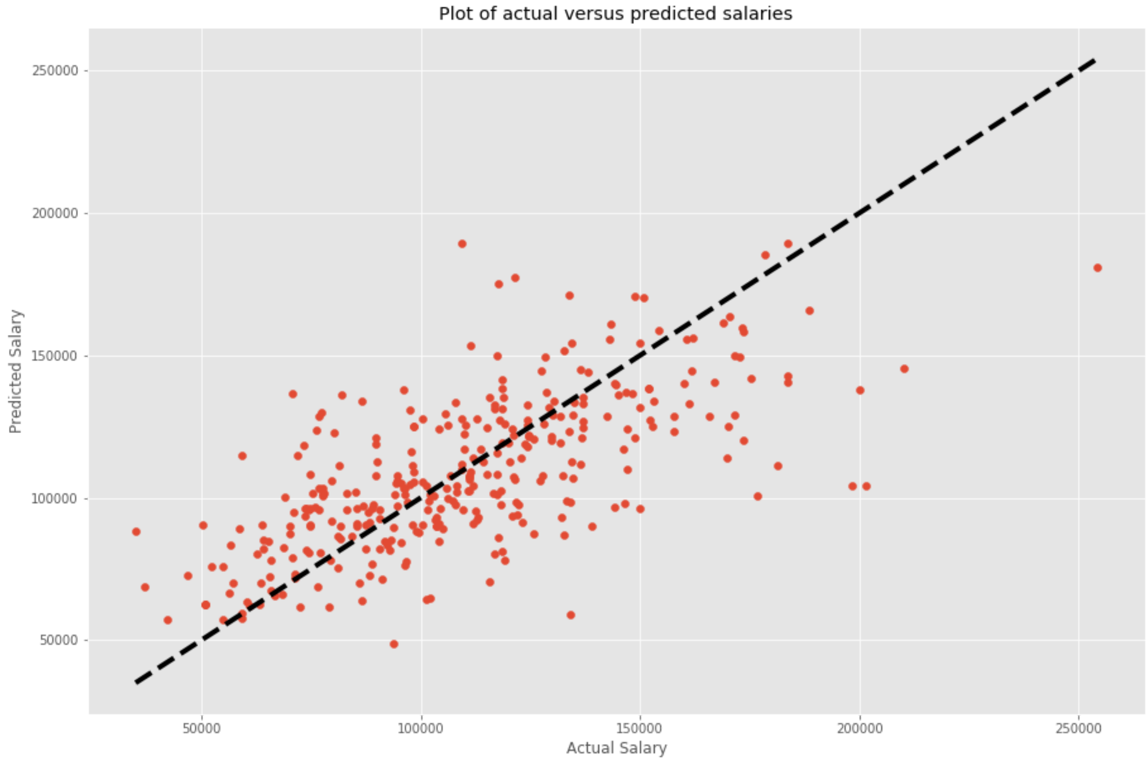
In [50]:

```
# Make predictions on test data
rf.fit(X_train,y_train)
predictions = rf.predict(X_test)
# Performance metrics
errors = abs(predictions - y_test)
# Calculate mean absolute percentage error (MAPE)
mape = np.mean(100 * (errors / y_test))

# Calculate and display accuracy
accuracy = 100 - mape
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 64.81 %.
```

In [51]:

```
plot_graph(y_test,predictions)
```



Summary

- Data Preprocessing - Checked for missing values, modified some features
- Data Exploration - Visualizations are plotted to examine single variables, two-variable relationships and three-variable relationships.
- Various regression models like multi-linear model, Ridge model, Lasso model, Support vector regressor model and Random Forest models were considered for training
- Random Forest regressor turned out to be best with lowest MAE among the other models while support vector regression was the worst performing model for this dataset.
- Random forest regressor was further fine-tuned by using GridSearchCV method to find the optimal parameters.
- This model predicts with an accuracy of 65% on the un-seen data.
- However, the prediction accuracy can be improved further by incorporating neural networks, increasing the data size by scraping more glassdoor data from the web.