Data Professional Salary Prediction

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Contents

1 Introduction

This project explores predicting salaries of data professionals using advanced machine learning techniques. It aims to understand the most influential factors affecting salaries in this field using regression models.

[49]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.linear_model import Lasso,Ridge
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
from sklearn.metrics import r2_score
from sklearn.preprocessing import  StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import  mean_absolute_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier,plot_tree
from sklearn.ensemble import  RandomForestClassifier
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.cluster import KMeans,AgglomerativeClustering
from sklearn.metrics import silhouette_score
import scipy.cluster.hierarchy as sch
from sklearn.preprocessing import  LabelEncoder
from sklearn.decomposition import  PCA
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import VarianceThreshold
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import  parse
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.statespace.sarimax import SARIMAX
import statsmodels.api as sm
from imblearn.over_sampling import  SMOTE
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

2 Load the Dataset

Initially, we must load the dataset and examine its structure

[3]:
```
df=pd.read_csv('Salary Prediction of Data Professions.csv')
df
```

[3]:

	FIRST NAME	LAST NAME	SEX	DOJ	CURRENT DATE	DESIGNATION
0	TOMASA	ARMEN	F	5-18-2014	01-07-2016	Analyst
1	ANNIE	NaN	F	NaN	01-07-2016	Associate
2	OLIVE	ANCY	F	7-28-2014	01-07-2016	Analyst
3	CHERRY	AQUILAR	F	04-03-2013	01-07-2016	Analyst
4	LEON	ABOULAHOUD	M	11-20-2014	01-07-2016	Analyst
...	...	...	..	...	...	...
2634	KATHERINE	ALSDON	F	6-28-2011	01-07-2016	Senior Manager
2635	LOUISE	ALTARAS	F	1-14-2014	01-07-2016	Analyst
2636	RENEE	ALVINO	F	1-23-2014	01-07-2016	Analyst
2637	TERI	ANASTASIO	F	3-17-2014	01-07-2016	Analyst
2638	GREGORY	ABARCA	M	9-18-2014	01-07-2016	Analyst

	AGE	SALARY	UNIT	LEAVES USED	LEAVES REMAINING	RATINGS
0	21.0	44570	Finance	24.0	6.0	2.0
1	NaN	89207	Web	NaN	13.0	NaN
2	21.0	40955	Finance	23.0	7.0	3.0
3	22.0	45550	IT	22.0	8.0	3.0
4	NaN	43161	Operations	27.0	3.0	NaN
...	...	...	...	...	...	...
2634	36.0	185977	Management	15.0	15.0	5.0
2635	23.0	45758	IT	17.0	13.0	2.0
2636	21.0	47315	Web	29.0	1.0	5.0
2637	24.0	45172	Web	23.0	7.0	3.0
2638	24.0	49176	Marketing	17.0	13.0	2.0

	PAST EXP
0	0
1	7
2	0
3	0
4	3
...	...
2634	10
2635	0
2636	0
2637	1
2638	2

[2639 rows x 13 columns]

[4]:
```
df.head(5)
```

[4]:

	FIRST NAME	LAST NAME	SEX	DOJ	CURRENT DATE	DESIGNATION	AGE
0	TOMASA	ARMEN	F	5-18-2014	01-07-2016	Analyst	21.0
1	ANNIE	NaN	F	NaN	01-07-2016	Associate	NaN
2	OLIVE	ANCY	F	7-28-2014	01-07-2016	Analyst	21.0
3	CHERRY	AQUILAR	F	04-03-2013	01-07-2016	Analyst	22.0
4	LEON	ABOULAHOUD	M	11-20-2014	01-07-2016	Analyst	NaN

	SALARY	UNIT	LEAVES USED	LEAVES REMAINING	RATINGS	PAST EXP
0	44570	Finance	24.0	6.0	2.0	0
1	89207	Web	NaN	13.0	NaN	7
2	40955	Finance	23.0	7.0	3.0	0
3	45550	IT	22.0	8.0	3.0	0
4	43161	Operations	27.0	3.0	NaN	3

[5]:
```
df.tail(5)
```

[5]:

	FIRST NAME	LAST NAME	SEX	DOJ	CURRENT DATE	DESIGNATION	AGE
2634	KATHERINE	ALSDON	F	6-28-2011	01-07-2016	Senior Manager	36.0
2635	LOUISE	ALTARAS	F	1-14-2014	01-07-2016	Analyst	23.0
2636	RENEE	ALVINO	F	1-23-2014	01-07-2016	Analyst	21.0
2637	TERI	ANASTASIO	F	3-17-2014	01-07-2016	Analyst	24.0
2638	GREGORY	ABARCA	M	9-18-2014	01-07-2016	Analyst	24.0

	SALARY	UNIT	LEAVES USED	LEAVES REMAINING	RATINGS	PAST EXP
2634	185977	Management	15.0	15.0	5.0	10
2635	45758	IT	17.0	13.0	2.0	0
2636	47315	Web	29.0	1.0	5.0	0
2637	45172	Web	23.0	7.0	3.0	1
2638	49176	Marketing	17.0	13.0	2.0	2

[6]:
```
df.sample(5)
```

[6]:

	FIRST NAME	LAST NAME	SEX	DOJ	CURRENT DATE	DESIGNATION	AGE
1232	LONNIE	ACERRA	M	12-18-2014	01-07-2016	Analyst	21.0
478	REBECCA	ALPAUGH	F	02-02-2014	01-07-2016	Analyst	22.0
2530	VILMA	APRIGLIANO	F	1-18-2014	01-07-2016	Analyst	23.0
197	CARIDAD	ARMWOOD	F	06-11-2014	01-07-2016	Analyst	23.0
2555	JEWELL	ANGELI	F	3-27-2012	01-07-2016	Manager	32.0

	SALARY	UNIT	LEAVES USED	LEAVES REMAINING	RATINGS	PAST EXP
1232	48626	Marketing	27.0	3.0	2.0	0
478	49744	Web	28.0	2.0	2.0	0
2530	46984	Web	24.0	6.0	4.0	0
197	45022	Finance	23.0	7.0	3.0	0
2555	112363	Finance	18.0	12.0	3.0	7

[7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2639 entries, 0 to 2638
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   FIRST NAME        2639 non-null   object
 1   LAST NAME         2637 non-null   object
 2   SEX               2639 non-null   object
 3   DOJ               2638 non-null   object
 4   CURRENT DATE      2639 non-null   object
 5   DESIGNATION       2639 non-null   object
 6   AGE               2636 non-null   float64
 7   SALARY            2639 non-null   int64
 8   UNIT              2639 non-null   object
 9   LEAVES USED       2636 non-null   float64
 10  LEAVES REMAINING  2637 non-null   float64
 11  RATINGS           2637 non-null   float64
 12  PAST EXP          2639 non-null   int64
dtypes: float64(4), int64(2), object(7)
memory usage: 268.2+ KB
```

[8]:
```
df.columns=df.columns.str.lower()
df
```

[8]:

	first name	last name	sex	doj	current date	designation
0	TOMASA	ARMEN	F	5-18-2014	01-07-2016	Analyst
1	ANNIE	NaN	F	NaN	01-07-2016	Associate
2	OLIVE	ANCY	F	7-28-2014	01-07-2016	Analyst
3	CHERRY	AQUILAR	F	04-03-2013	01-07-2016	Analyst
4	LEON	ABOULAHOUD	M	11-20-2014	01-07-2016	Analyst
...	...	...	..	...	...	...
2634	KATHERINE	ALSDON	F	6-28-2011	01-07-2016	Senior Manager
2635	LOUISE	ALTARAS	F	1-14-2014	01-07-2016	Analyst
2636	RENEE	ALVINO	F	1-23-2014	01-07-2016	Analyst
2637	TERI	ANASTASIO	F	3-17-2014	01-07-2016	Analyst
2638	GREGORY	ABARCA	M	9-18-2014	01-07-2016	Analyst

	age	salary	unit	leaves used	leaves remaining	ratings
0	21.0	44570	Finance	24.0	6.0	2.0
1	NaN	89207	Web	NaN	13.0	NaN
2	21.0	40955	Finance	23.0	7.0	3.0
3	22.0	45550	IT	22.0	8.0	3.0
4	NaN	43161	Operations	27.0	3.0	NaN
...	...	...	...	...	...	...
2634	36.0	185977	Management	15.0	15.0	5.0
2635	23.0	45758	IT	17.0	13.0	2.0
2636	21.0	47315	Web	29.0	1.0	5.0

```
2637  24.0   45172         Web          23.0               7.0      3.0
2638  24.0   49176   Marketing          17.0              13.0      2.0

      past exp
0            0
1            7
2            0
3            0
4            3
...        ...
2634        10
2635         0
2636         0
2637         1
2638         2

[2639 rows x 13 columns]
```

3 Summary Statistics

We utilize summary statistics to gain an overview of the numerical features

[9]:
```
df.describe()
```

[9]:
```
                age         salary  leaves used  leaves remaining      ratings  \
count  2636.000000    2639.000000  2636.000000       2637.000000  2637.000000
mean     24.756449   58136.678287    22.501517          7.503223     3.486159
std       3.908228   36876.956944     4.604469          4.603193     1.114933
min      21.000000   40001.000000    15.000000          0.000000     2.000000
25%      22.000000   43418.000000    19.000000          4.000000     2.000000
50%      24.000000   46781.000000    22.000000          8.000000     3.000000
75%      25.000000   51401.500000    26.000000         11.000000     4.000000
max      45.000000  388112.000000    30.000000         15.000000     5.000000

          past exp
count  2639.000000
mean      1.566881
std       2.728416
min       0.000000
25%       0.000000
50%       1.000000
75%       2.000000
max      23.000000
```

[10]:
```
columns_to_select = ['age', 'salary', 'leaves used', 'leaves remaining',␣
 ↪'ratings', 'past exp']
df1=df[columns_to_select]
```

```
df1.corr()
```

[10]:

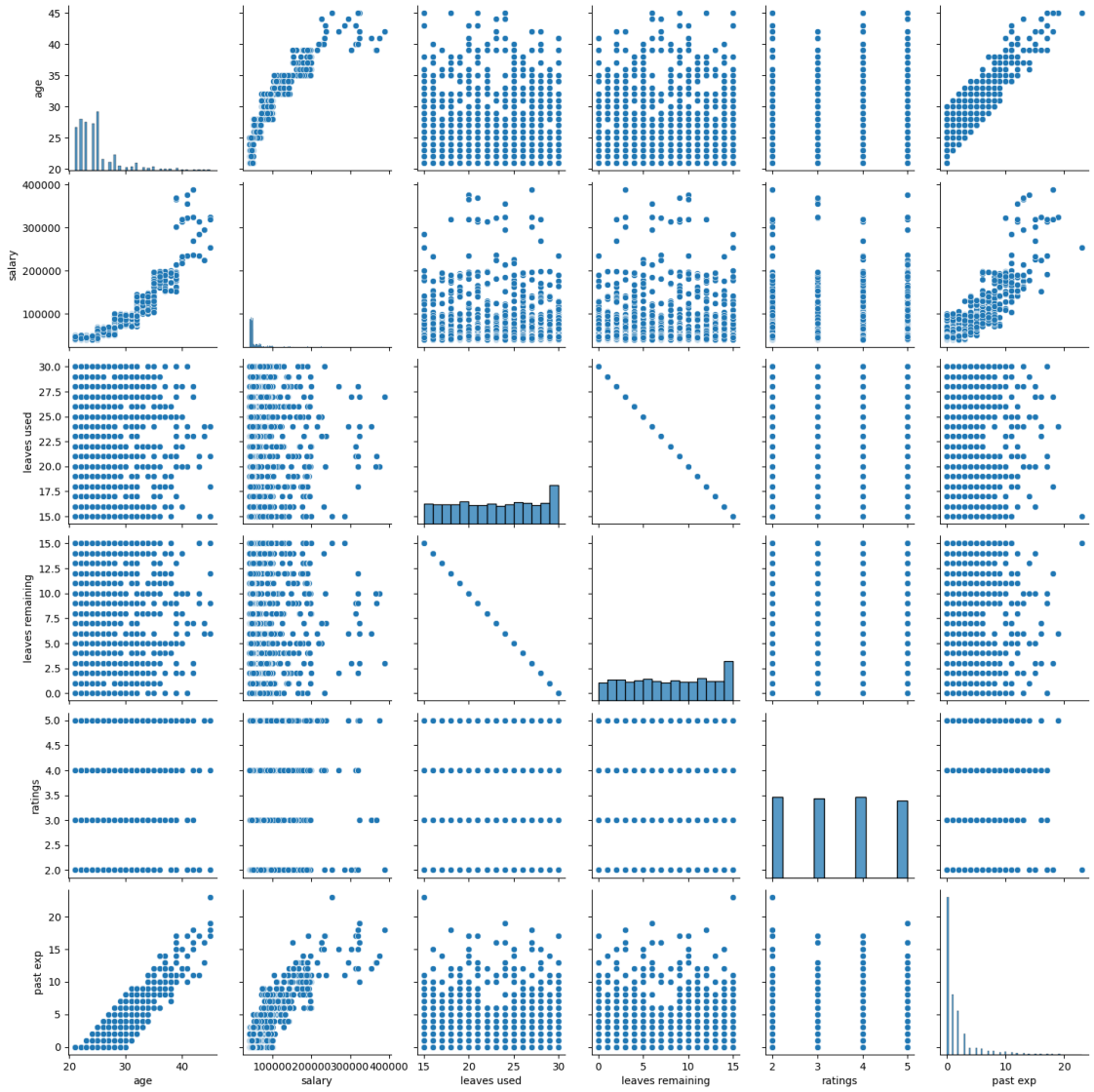
	age	salary	leaves used	leaves remaining	ratings	past exp
age	1.000000	0.872213	0.007825	-0.006515	0.036801	0.903926
salary	0.872213	1.000000	0.006498	-0.005422	0.020248	0.854046
leaves used	0.007825	0.006498	1.000000	-1.000000	0.002200	0.008601
leaves remaining	-0.006515	-0.005422	-1.000000	1.000000	-0.003415	-0.006728
ratings	0.036801	0.020248	0.002200	-0.003415	1.000000	0.040123
past exp	0.903926	0.854046	0.008601	-0.006728	0.040123	1.000000

4 Data Visualization

We will employ various plots to visualize the distribution of salaries and investigate relationships between SALARY and other features.

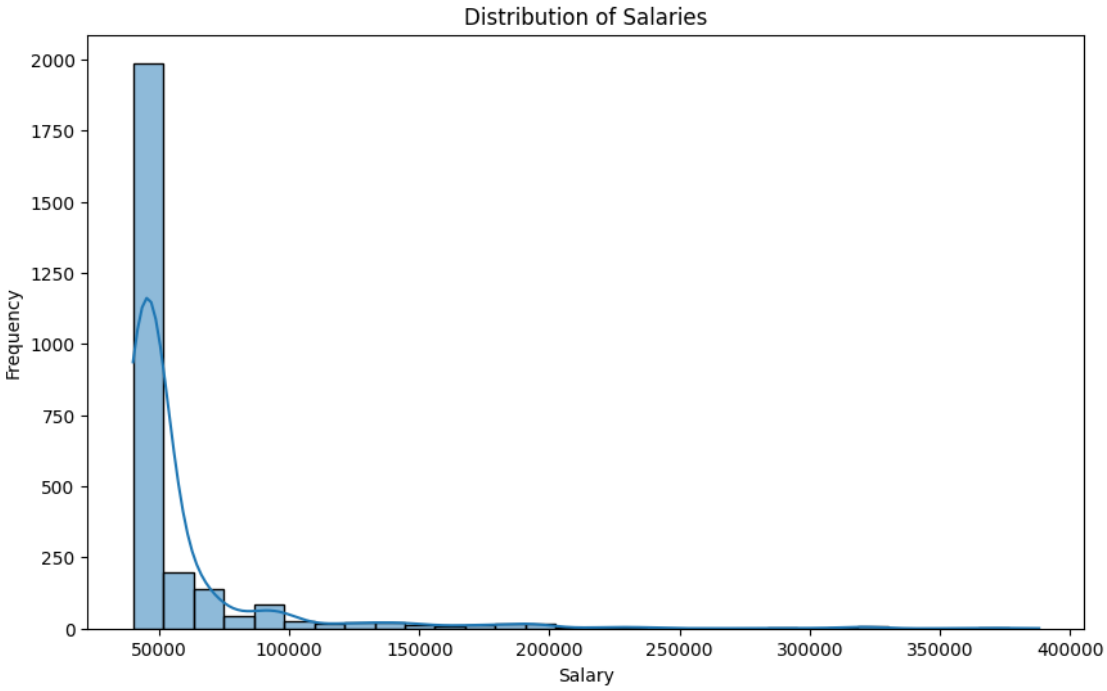
[11]:
```
sns.pairplot(df)
```

[11]:
```
<seaborn.axisgrid.PairGrid at 0x1a0c1a3a290>
```



4.1 Distribution of Salaries

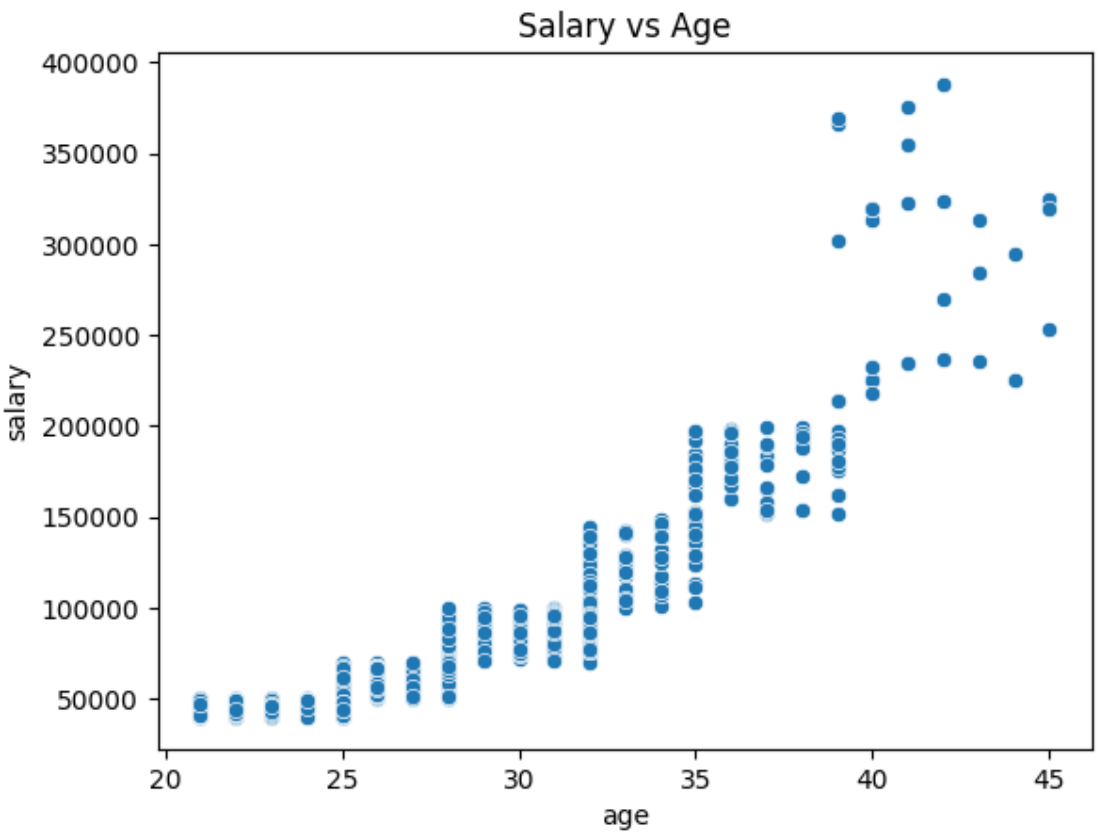
[12]:
```
plt.figure(figsize=(10,6))
sns.histplot(df['salary'],bins=30,kde=True)
plt.title('Distribution of Salaries')
plt.xlabel('Salary')
plt.ylabel('Frequency')
plt.show()
```



4.2 Relationshep between salary and age

[13]:
```
sns.scatterplot(x='age',y='salary',data=df)
plt.title('Salary vs Age')
```

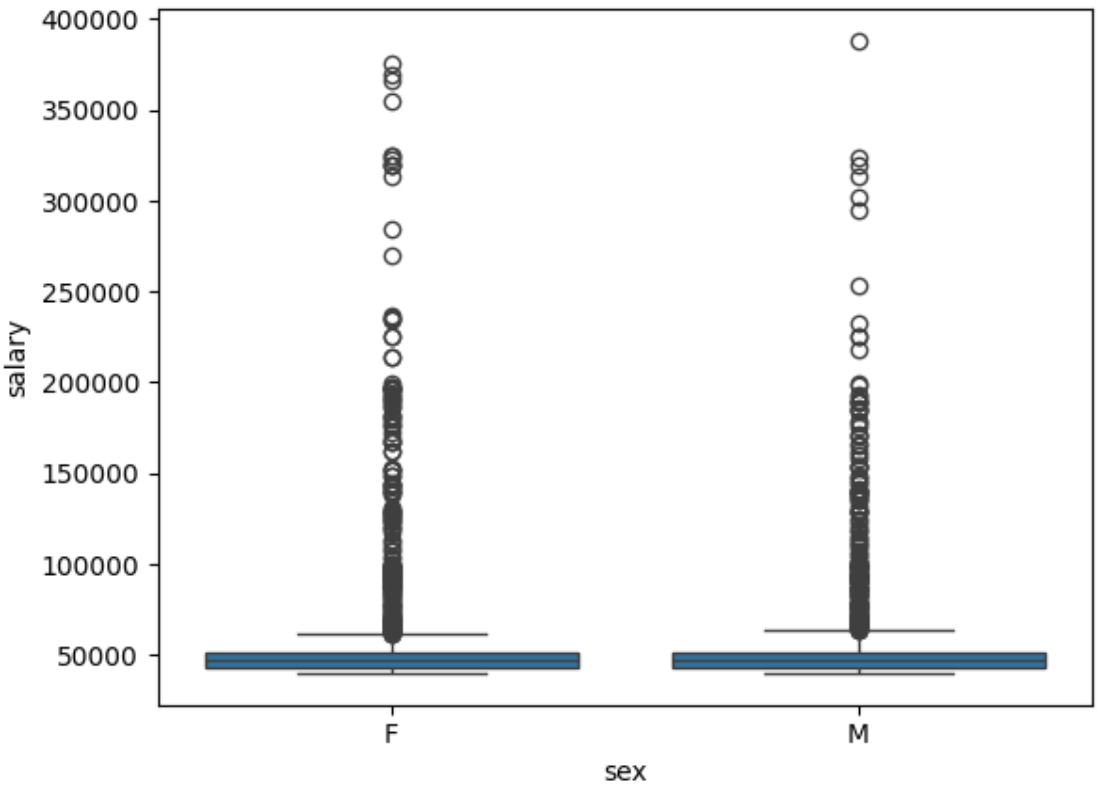
[13]:
```
Text(0.5, 1.0, 'Salary vs Age')
```



4.3 The salary by gender

[14]:
```
sns.boxplot(x="sex",y='salary',data=df)
```

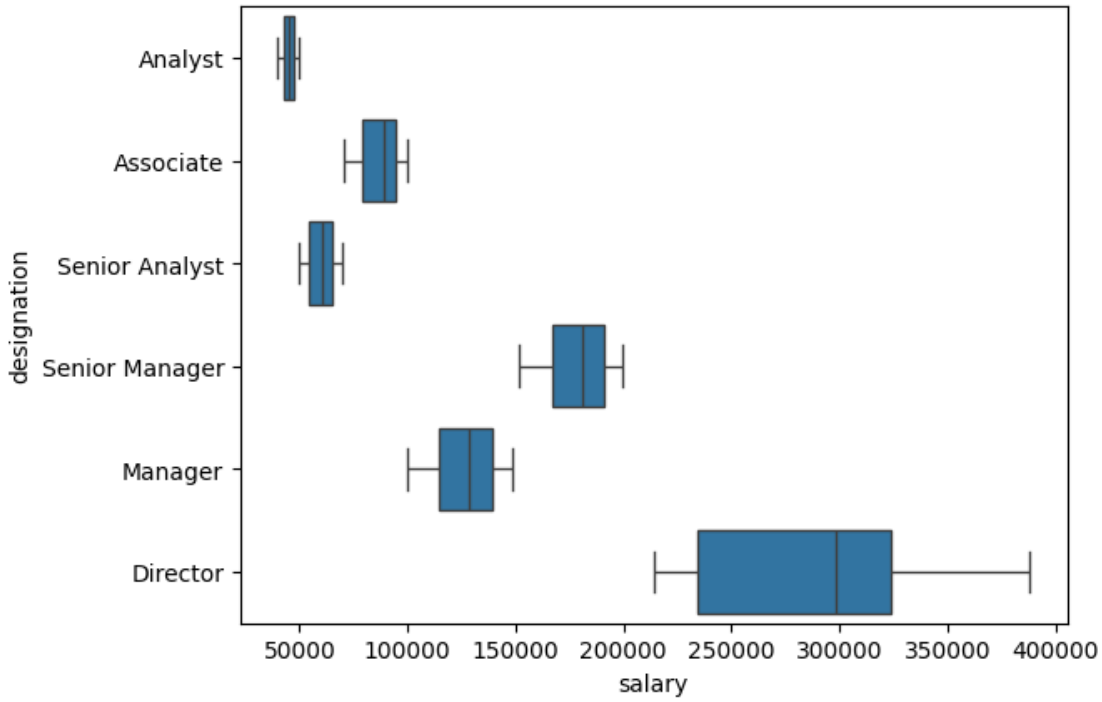
[14]:
```
<Axes: xlabel='sex', ylabel='salary'>
```



4.4 The salary by designation

[16]:
```
sns.boxplot(x='salary',y='designation',data=df)
```

[16]:
```
<Axes: xlabel='salary', ylabel='designation'>
```



5 Correlation Matrix

[17]:
```
df1
```

[17]:

	age	salary	leaves used	leaves remaining	ratings	past exp
0	21.0	44570	24.0	6.0	2.0	0
1	NaN	89207	NaN	13.0	NaN	7
2	21.0	40955	23.0	7.0	3.0	0
3	22.0	45550	22.0	8.0	3.0	0
4	NaN	43161	27.0	3.0	NaN	3
...	...	...	...	...	...	...
2634	36.0	185977	15.0	15.0	5.0	10
2635	23.0	45758	17.0	13.0	2.0	0
2636	21.0	47315	29.0	1.0	5.0	0
2637	24.0	45172	23.0	7.0	3.0	1
2638	24.0	49176	17.0	13.0	2.0	2

[2639 rows x 6 columns]

[18]:
```
df1.corr()
```

[18]:

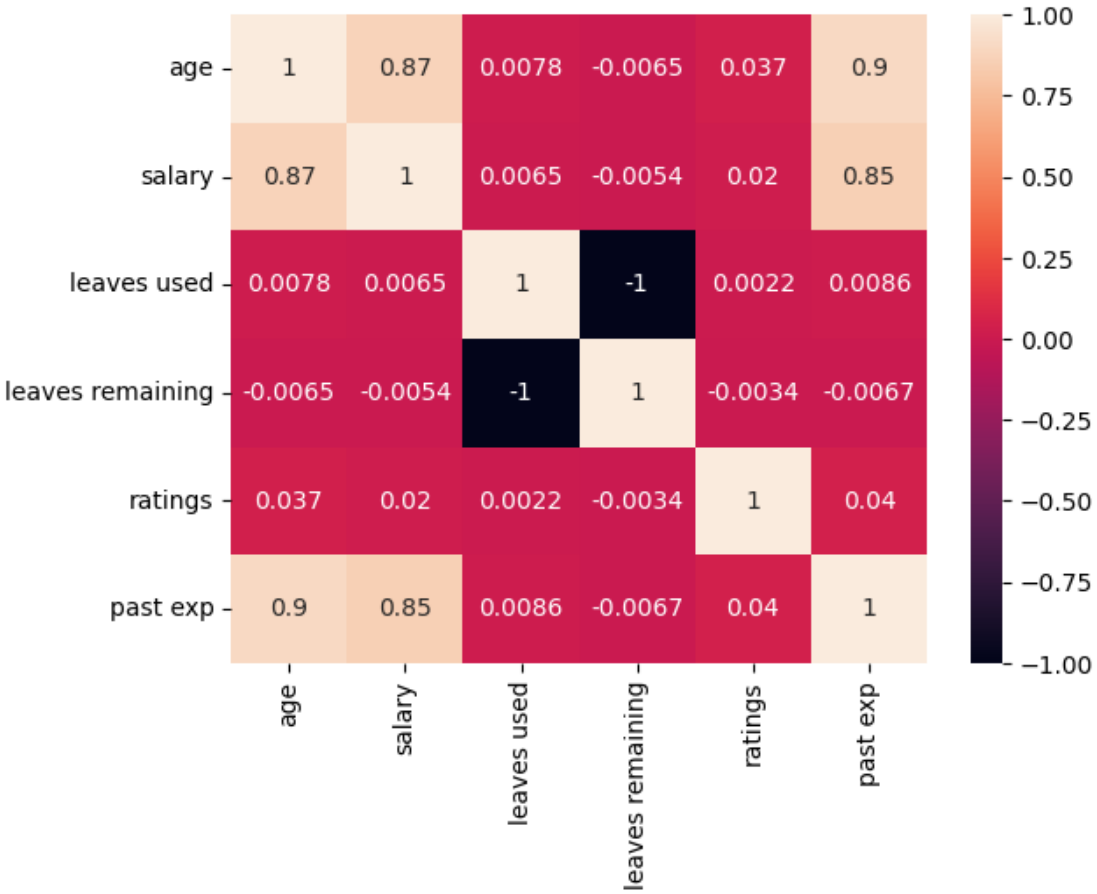
	age	salary	leaves used	leaves remaining	ratings	\
age	1.000000	0.872213	0.007825	-0.006515	0.036801	

```
salary            0.872213  1.000000     0.006498         -0.005422  0.020248
leaves used       0.007825  0.006498     1.000000         -1.000000  0.002200
leaves remaining -0.006515 -0.005422    -1.000000          1.000000 -0.003415
ratings           0.036801  0.020248     0.002200         -0.003415  1.000000
past exp          0.903926  0.854046     0.008601         -0.006728  0.040123

                  past exp
age               0.903926
salary            0.854046
leaves used       0.008601
leaves remaining -0.006728
ratings           0.040123
past exp          1.000000
```

[19]:
```
sns.heatmap(df1.corr(),annot=True)
```

[19]: <Axes: >



6 Data preprocessing

Prepare the data for model training. This involves handling missing values, encoding categorical variables, and scaling or normalizing features as necessary.

[20]:
```
df.isnull().sum()
```

[20]:
```
first name          0
last name           2
sex                 0
doj                 1
current date        0
designation         0
age                 3
salary              0
unit                0
leaves used         3
leaves remaining    2
ratings             2
past exp            0
dtype: int64
```

[21]:
```
df.head()
```

[21]:

	first name	last name	sex	doj	current date	designation	age	\
0	TOMASA	ARMEN	F	5-18-2014	01-07-2016	Analyst	21.0	
1	ANNIE	NaN	F	NaN	01-07-2016	Associate	NaN	
2	OLIVE	ANCY	F	7-28-2014	01-07-2016	Analyst	21.0	
3	CHERRY	AQUILAR	F	04-03-2013	01-07-2016	Analyst	22.0	
4	LEON	ABOULAHOUD	M	11-20-2014	01-07-2016	Analyst	NaN	

	salary	unit	leaves used	leaves remaining	ratings	past exp
0	44570	Finance	24.0	6.0	2.0	0
1	89207	Web	NaN	13.0	NaN	7
2	40955	Finance	23.0	7.0	3.0	0
3	45550	IT	22.0	8.0	3.0	0
4	43161	Operations	27.0	3.0	NaN	3

[22]:
```
le=LabelEncoder()
for col in df.select_dtypes(include='object'):
    df[col]=le.fit_transform(df[col])
df.head()
```

[22]:

	first name	last name	sex	doj	current date	designation	age	salary	\
0	2208	2436	0	751	0	0	21.0	44570	
1	127	2475	0	967	0	1	NaN	89207	
2	1770	1671	0	865	0	0	21.0	40955	
3	392	2137	0	109	0	0	22.0	45550	

```
4        1377        161    1  494             0            0   NaN   43161

   unit  leaves used  leaves remaining  ratings  past exp
0     0         24.0               6.0      2.0         0
1     5          NaN              13.0      NaN         7
2     0         23.0               7.0      3.0         0
3     1         22.0               8.0      3.0         0
4     4         27.0               3.0      NaN         3
```

7 Machine Learning Model Development

7.1 Linear Regression

[23]:
```
df.fillna(df.mean(),inplace=True)
```

[24]:
```
x=df.drop('salary',axis=1)
y=df['salary']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=42)
x_train,x_test,y_train,y_test
```

[24]:
```
(      first name  last name  sex  doj  current date  designation   age  unit  \
 2395         627       1637    0  304             0            0  22.0     2
 440         2130       1821    0  101             0            0  24.0     2
 508         1867        615    1  399             0            4  27.0     1
 76          1254       1553    0  214             0            0  24.0     5
 522          968       2172    0  711             0            0  24.0     4
 ...          ...        ...  ...  ...           ...          ...   ...   ...
 1638          56        910    1  495             0            0  25.0     3
 1095         285       1762    0  380             0            5  36.0     0
 1130        1233       1585    0  668             0            0  23.0     5
 1294        1871        131    1  880             0            0  23.0     5
 860          787       1996    0  886             0            0  23.0     3

       leaves used  leaves remaining  ratings  past exp
 2395         18.0              12.0      2.0         0
 440          26.0               4.0      4.0         0
 508          26.0               4.0      5.0         4
 76           29.0               1.0      3.0         1
 522          15.0              15.0      4.0         1
 ...           ...               ...      ...       ...
 1638         25.0               5.0      4.0         2
 1095         18.0              12.0      2.0         8
 1130         20.0              10.0      4.0         0
 1294         18.0              12.0      5.0         1
 860          25.0               5.0      4.0         1

 [2111 rows x 12 columns],
```

```
      first name  last name  sex  doj  current date  designation   age  unit  \
1322        1533       2466    0  566             0            5  36.0     1
1185        1595       2139    0  705             0            0  24.0     1
2572         673       2036    0  244             0            0  24.0     5
1709         323       1417    0  406             0            0  24.0     5
809         1141       2053    0  240             0            1  28.0     5
...          ...        ...  ...  ...           ...          ...   ...   ...
812         1670       1507    0  522             0            4  28.0     5
544         2184       2314    0  189             0            4  28.0     2
1278         971       1108    1  488             0            0  25.0     0
1199         716        868    1   60             0            0  25.0     2
2257        2275       1592    0  400             0            0  22.0     2

      leaves used  leaves remaining  ratings  past exp
1322         27.0               3.0      3.0         6
1185         23.0               7.0      3.0         1
2572         21.0               9.0      4.0         1
1709         27.0               3.0      5.0         1
809          29.0               1.0      2.0         0
...           ...               ...      ...       ...
812          15.0              15.0      4.0         2
544          15.0              15.0      2.0         2
1278         15.0              15.0      4.0         2
1199         29.0               1.0      3.0         2
2257         19.0              11.0      5.0         0

[528 rows x 12 columns],
2395     40031
440      45482
508      51930
76       43638
522      48476
         ...
1638     46071
1095    181470
1130     49449
1294     49873
860      45636
Name: salary, Length: 2111, dtype: int64,
1322    179845
1185     48441
2572     40707
1709     43144
809      84967
         ...
812      54166
544      55693
```

```
1278     42014
1199     45188
2257     43064
Name: salary, Length: 528, dtype: int64)
```

[25]:
```
model=LinearRegression()
model.fit(x_train,y_train)
```

[25]:
```
LinearRegression()
```

[28]:
```
y_pred=model.predict(x_test)
print(y_pred)
mse=mean_squared_error(y_test,y_pred)
print("Mean squared error:", mse)
```

```
[136022.72737355  51571.65550578  51733.51461151  52386.51639039
  68473.71543761  42162.60521125  80754.65322171  41536.08258218
 186117.71944406  31470.7402991   79338.84399651  67259.82283521
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  76622.75954561  60294.74003575  60814.76147739  36837.82485957]
Mean squared error: 399539912.04154205
```

[29]:
```
mae=mean_absolute_error(y_test,y_pred)
print("Mean absolute error:", mae)
```

```
Mean absolute error: 12531.69107970105
```

[31]:
```
r2=r2_score(y_test,y_pred)
print('R-squared score :',r2)
```

```
R-squared score : 0.7593911334181406
```

[32]:
```
model.score(x_test,y_test)
```

[32]:
```
0.7593911334181406
```

[33]:
```
model.score(x_train,y_train)
```

[33]:
```
0.7930278833905532
```

7.2 Decision Trees

[34]:
```
dt=DecisionTreeRegressor()
dt.fit(x_train,y_train)
```

[34]:
```
DecisionTreeRegressor()
```

[35]:
```
y_pred1=dt.predict(x_test)
y_pred1
```

[35]:
```
array([186356.,  44649.,  49190.,  40329.,  73397.,  46966.,  62169.,
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       49499.,  40113.,  44005.])
```

[36]:
```
mse1=mean_absolute_error(y_test,y_pred1)
mse1
```

[36]:
```
5150.545454545455
```

[37]:
```
r2_1=r2_score(y_test,y_pred1)
r2_1
```

[37]:
```
0.9301813151795492
```

7.3 Random Forest

[39]:
```
rf=RandomForestRegressor()
rf.fit(x_train,y_train)
```

[39]:
```
RandomForestRegressor()
```

[40]:
```
y_pred2=rf.predict(x_test)
y_pred2
```

[40]:
```
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```

[41]:
```
mse2=mean_absolute_error(y_test,y_pred2)
mse2
```

[41]: 4317.633579545454

[42]:
```
r2_2=r2_score(y_test,y_pred2)
r2_2
```

[42]: 0.7593911334181406

7.4 Gradient Boosting

[57]:
```
from sklearn.ensemble import GradientBoostingRegressor
gb=GradientBoostingRegressor()
gb
```

[57]: GradientBoostingRegressor()

[58]:
```
gb.fit(x_train,y_train)
y_pred3=gb.predict(x_test)
y_pred3
```

[58]:
```
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```

[59]:
```
mse3=mean_absolute_error(y_test,y_pred3)
print('Mean Absolute Error:',mse3)
```

```
Mean Absolute Error: 4661.074643221528
```

[60]:
```
r2_3=r2_score(y_test,y_pred3)
print('R-squared:',r2_3)
```

```
R-squared: 0.9313643404629065
```

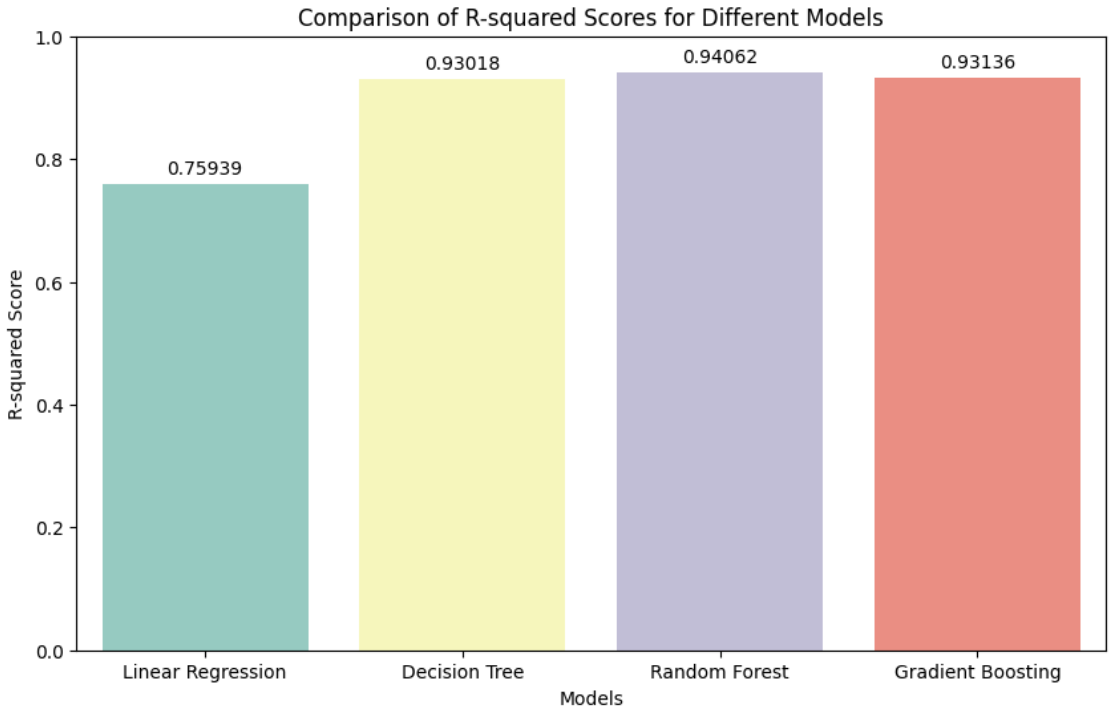
7.5 Comparison of R-squared Scores for different Models

[68]:
```
r2=0.75939113
r2_1=0.93018131
r2_2=0.94062267
r2_3=0.93136434
models=['Linear Regression','Decision Tree','Random Forest','Gradient Boosting']
r2_scores=[r2,r2_1,r2_2,r2_3]
plt.figure(figsize=(10,6))
ax=sns.barplot(x=models,y=r2_scores,palette='Set3')
for m,score in enumerate(r2_scores):
    ax.text(m , score +0.01 ,f'{score:.5f}', ha='center' , va='bottom')
plt.xlabel('Models')
plt.ylabel('R-squared Score')
plt.title('Comparison of R-squared Scores for Different Models')
plt.ylim(0,1)
plt.show()
```

```
C:\Users\KHALID\AppData\Local\Temp\ipykernel_21836\1556638125.py:8:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax=sns.barplot(x=models,y=r2_scores,palette='Set3')
```


Comparison of R-squared Scores for Different Models
R-squared Score
1.0
0.8
0.6
0.4
0.2
0.0
0.75939
0.93018
0.94062
0.93136
Linear Regression
Decision Tree
Random Forest
Gradient Boosting
Models

[ ]:

[ ]:

8 Conclusion

This project focused on predicting salaries of data professionals has provided valuable insights into the realm of data science and machine learning. Through an in-depth analysis of a comprehensive dataset including attributes such as experience, education, job title, and geographic location, we developed and evaluated multiple regression models.

The results highlight the effectiveness of various models:

- Random Forest (RF) achieved an impressive R^2 of 0.9406, showcasing its robust predictive power in capturing the complexities of salary prediction.
- Gradient Boosting (GB) closely followed with an R^2 of 0.9314, demonstrating strong performance in refining predictions through iterative learning.
- Linear Regression (RL), while showing moderate performance with an R^2 of 0.7594, provided a baseline understanding of salary prediction based on linear relationships.

These findings underscore the importance of model selection and optimization in accurately predicting salaries within the data profession. Furthermore, the project's insights into influential factors such as experience, education, and job role provide actionable information for individuals and organizations aiming to make informed decisions regarding compensation strategies.

Project Outcome

The project successfully:

- Developed and evaluated predictive models for salary prediction using machine learning techniques.
- Identified Random Forest as the most effective model for predicting data professional salaries, achieving an R^2 of 0.9406.
- Demonstrated the applicability of Gradient Boosting for refining predictions with an R^2 of 0.9314.

In conclusion, this project not only enhanced our proficiency in data analysis and predictive modeling but also illustrated the significant impact of data-driven approaches in guiding strategic decisions within the dynamic landscape of data professions.

9 References

Dataset : Kaggle - Salary Prediction of Data Professions