Task 2. Annual Salary Prediction

July 31, 2020

1 Task 2 - Predictive Analytics

For the Data@ANZ Virtual Experience Program

1. Build a simple regression model to predict the annual salary for each customer using the attributes you identified above

How accurate is your model? Should ANZ use it to segment customers (for whom it does not have this data) into income brackets for reporting purposes?

2. For a challenge: build a decision-tree based model to predict salary. Does it perform better? How would you accurately test the performance of this model?

[1]:
```
import pandas as pd
import numpy as np
```

[2]:
```
df = pd.read_excel('ANZ synthesised transaction dataset.xlsx')
```

[3]:
```
#df.info()
```

1.1 Explore salary feature

1.1.1 First we identify monthly salary for each customer

[4]:
```
df['month'] = pd.DatetimeIndex(df['date']).month
df[['customer_id', 'date', 'month']]
```

[4]:
```
          customer_id       date  month
0      CUS-2487424745 2018-08-01      8
1      CUS-2487424745 2018-08-01      8
2      CUS-2142601169 2018-08-01      8
3      CUS-1614226872 2018-08-01      8
4      CUS-2487424745 2018-08-01      8
...               ...        ...    ...
12038    CUS-55310383 2018-10-31     10
12039  CUS-2688605418 2018-10-31     10
12040  CUS-2663907001 2018-10-31     10
12041  CUS-1388323263 2018-10-31     10
12042  CUS-3129499595 2018-10-31     10
```

```
[12043 rows x 3 columns]
```

[5]:
```python
df['txn_description'].value_counts()
```

[5]:
```
SALES-POS     3934
POS           3783
PAYMENT       2600
PAY/SALARY     883
INTER BANK     742
PHONE BANK     101
Name: txn_description, dtype: int64
```

[6]:
```python
df_salary_payment = df[df['txn_description']== 'PAY/SALARY'].copy()
df_salary_payment.sort_values(by=['customer_id'], inplace=True)
df_salary_payment.head(5)
```

[6]:
```
      status  card_present_flag bpay_biller_code          account currency  \
2530  posted                NaN                0  ACC-2828321672      AUD
4402  posted                NaN                0  ACC-2828321672      AUD
8142  posted                NaN                0  ACC-2828321672      AUD
1744  posted                NaN                0  ACC-2828321672      AUD
6271  posted                NaN                0  ACC-2828321672      AUD

           long_lat txn_description merchant_id  merchant_code first_name  \
2530  153.03 -27.51      PAY/SALARY         NaN            0.0  Stephanie
4402  153.03 -27.51      PAY/SALARY         NaN            0.0  Stephanie
8142  153.03 -27.51      PAY/SALARY         NaN            0.0  Stephanie
1744  153.03 -27.51      PAY/SALARY         NaN            0.0  Stephanie
6271  153.03 -27.51      PAY/SALARY         NaN            0.0  Stephanie

      ...  merchant_suburb merchant_state                    extraction  \
2530  ...              NaN            NaN  2018-08-21T16:00:00.000+0000
4402  ...              NaN            NaN  2018-09-04T16:00:00.000+0000
8142  ...              NaN            NaN  2018-10-02T16:00:00.000+0000
1744  ...              NaN            NaN  2018-08-14T16:00:00.000+0000
6271  ...              NaN            NaN  2018-09-18T16:00:00.000+0000

      amount                    transaction_id    country     customer_id  \
2530  970.47  71cd874fc20741f8b4a589c8286afeb2  Australia  CUS-1005756958
4402  970.47  e588bd113b3645ee82fb386e336c42a1  Australia  CUS-1005756958
8142  970.47  6a0796f6e44c4d49b288a593bdc23503  Australia  CUS-1005756958
1744  970.47  deaff82de78840f08a035e5404ce5e29  Australia  CUS-1005756958
6271  970.47  6b622e0b12324ac2a1b6c946f43bce04  Australia  CUS-1005756958

      merchant_long_lat movement  month
2530                NaN   credit      8
```

```
4402                NaN   credit     9
8142                NaN   credit    10
1744                NaN   credit     8
6271                NaN   credit     9

[5 rows x 24 columns]
```

[7]:
```
df_salary_payment_details = df_salary_payment[['customer_id', 'month', 'amount']]
df_customer_salary = df_salary_payment_details.copy()
```

[8]:
```
# Calculate customer salary payment per month
df_customer_salary = df_salary_payment_details.groupby(by=['customer_id',␣
 ↪'month'], as_index = False).sum()
df_customer_salary.rename(columns={'amount': 'amount_month'}, inplace=True)
df_customer_salary.head(6)
```

[8]:
```
      customer_id  month  amount_month
0  CUS-1005756958      8       3881.88
1  CUS-1005756958      9       3881.88
2  CUS-1005756958     10       4852.35
3  CUS-1117979751      8       7157.30
4  CUS-1117979751      9       7157.30
5  CUS-1117979751     10      10735.95
```

[9]:
```
# Calculate customer number of salary payments per month
df_num_salary = df_salary_payment_details.groupby(by=['customer_id', 'month'] ,␣
 ↪as_index = False).count()
df_customer_salary['num_of_payments'] = df_num_salary['amount']
df_customer_salary.head(6)
```

[9]:
```
      customer_id  month  amount_month  num_of_payments
0  CUS-1005756958      8       3881.88                4
1  CUS-1005756958      9       3881.88                4
2  CUS-1005756958     10       4852.35                5
3  CUS-1117979751      8       7157.30                2
4  CUS-1117979751      9       7157.30                2
5  CUS-1117979751     10      10735.95                3
```

[10]:
```
# Calculate customer base salary payment
df_base_salary = df_salary_payment_details.groupby(by=['customer_id', 'month'],␣
 ↪as_index = False).agg(np.average)
df_customer_salary['base_salary'] = df_base_salary['amount']
df_customer_salary.head(6)
```

[10]:
```
      customer_id  month  amount_month  num_of_payments  base_salary
0  CUS-1005756958      8       3881.88                4       970.47
1  CUS-1005756958      9       3881.88                4       970.47
```

```
2  CUS-1005756958     10       4852.35                5        970.47
3  CUS-1117979751      8       7157.30                2       3578.65
4  CUS-1117979751      9       7157.30                2       3578.65
5  CUS-1117979751     10      10735.95                3       3578.65
```

1.1.2 Calculate Annual Salary Payment per Customer

[11]:
```python
df_annual_salary = df_salary_payment_details.drop(columns=['month'])
df_annual_salary = df_annual_salary.groupby(['customer_id'], as_index = False).
↪sum()
df_annual_salary.rename(columns={'amount': 'annual_salary'}, inplace=True)
df_annual_salary.head(6)
```

[11]:
```
      customer_id  annual_salary
0  CUS-1005756958       12616.11
1  CUS-1117979751       25050.55
2  CUS-1140341822       11499.06
3  CUS-1147642491       22248.07
4  CUS-1196156254       27326.11
5  CUS-1220154422       15976.52
```

[12]:
```python
df_total_payments = df_customer_salary[['customer_id', 'num_of_payments']].
↪groupby(['customer_id'], as_index=False).sum()
df_annual_salary['num_payments'] = df_total_payments['num_of_payments']
df_annual_salary.head(6)
```

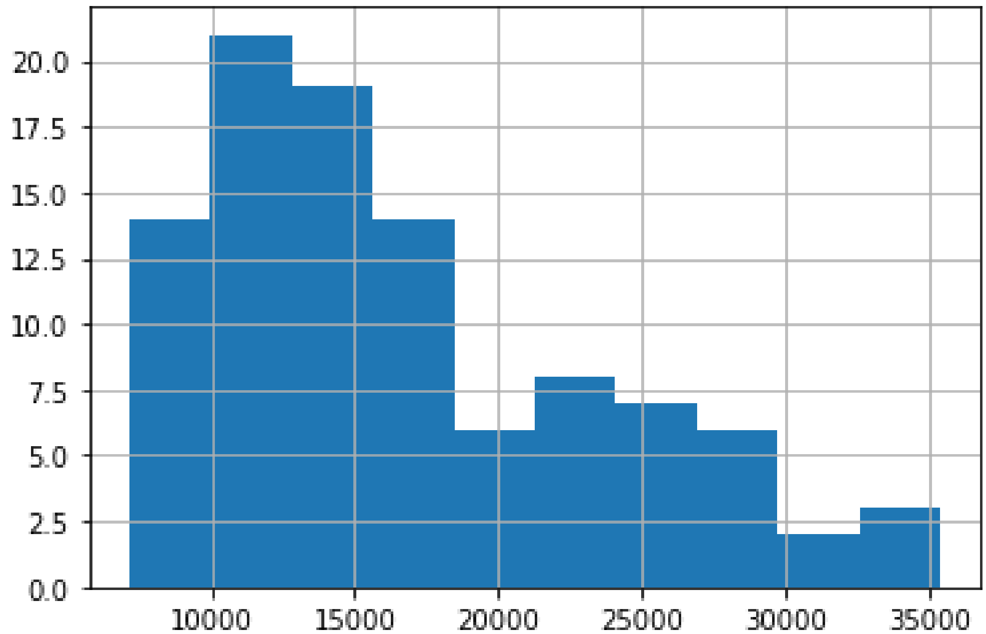
[12]:
```
      customer_id  annual_salary  num_payments
0  CUS-1005756958       12616.11            13
1  CUS-1117979751       25050.55             7
2  CUS-1140341822       11499.06             6
3  CUS-1147642491       22248.07            13
4  CUS-1196156254       27326.11             7
5  CUS-1220154422       15976.52             7
```

[13]:
```python
df_annual_salary['avg_num_payments'] = df_annual_salary['num_payments'].
↪apply(lambda x : round(x/3.))
df_annual_salary.head(6)
```

[13]:
```
      customer_id  annual_salary  num_payments  avg_num_payments
0  CUS-1005756958       12616.11            13                 4
1  CUS-1117979751       25050.55             7                 2
2  CUS-1140341822       11499.06             6                 2
3  CUS-1147642491       22248.07            13                 4
4  CUS-1196156254       27326.11             7                 2
5  CUS-1220154422       15976.52             7                 2
```

[14]:
```
df_annual_salary['annual_salary'].hist(bins=10)
```

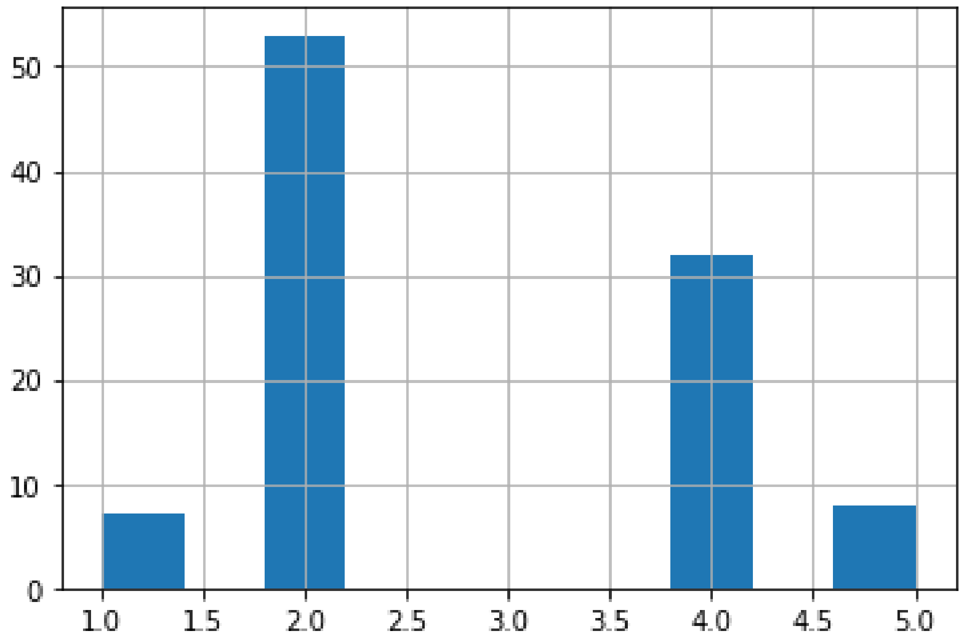
[14]: <matplotlib.axes._subplots.AxesSubplot at 0x1d3f4100470>



Approximately 3 people are the ones with the highest payment salaries.

[15]:
```
df_annual_salary['avg_num_payments'].hist(bins=10)
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1d3f486e470>



A little more than half of 100 customers have 2 payments per month. And one third has 4 payments per month. Could be an important feature to take into consideration.

[16]:
```
df_annual_salary[df_annual_salary['customer_id'] == 'CUS-1005756958']
```

[16]:

	customer_id	annual_salary	num_payments	avg_num_payments
0	CUS-1005756958	12616.11	13	4

[17]:
```
df_customer_salary[df_customer_salary['customer_id'] == 'CUS-1005756958']
```

[17]:

	customer_id	month	amount_month	num_of_payments	base_salary
0	CUS-1005756958	8	3881.88	4	970.47
1	CUS-1005756958	9	3881.88	4	970.47
2	CUS-1005756958	10	4852.35	5	970.47

- The revelant fields in “df_annual_salary” are ‘amount’ and ‘avg_num_payments’
- The revelant field in “df_customer_salary” is ‘salary’

1.2 Explore correlations between annual salary and various customer attributes

There are some original features(readily available in the data) that can be relevant to compare against annual salary, such as: ‘age’, ‘gender’, ‘long_lat’ and ‘balance’

[18]:
```
df_salary_payment[['customer_id','age','gender','long_lat','balance']].nunique()
```

[18]:
```
customer_id    100
age             33
gender           2
long_lat       100
balance        883
dtype: int64
```

It seems the feature BALANCE has different values in each customer. It needs to be average per each customer.

[19]:
```
# Calculating the average of balance for each customer.
df_avg_balance = df_salary_payment[['customer_id','balance']].
 ↪groupby(['customer_id'], as_index=False).mean()
df_avg_balance.head(6)
```

[19]:

	customer_id	balance
0	CUS-1005756958	4718.665385
1	CUS-1117979751	11957.202857
2	CUS-1140341822	5841.720000
3	CUS-1147642491	8813.467692
4	CUS-1196156254	23845.717143
5	CUS-1220154422	9225.907143

1.3 Get unique data per customer

[20]:
```
df_final = df_salary_payment[['customer_id','age','gender','long_lat']].copy()
df_final.drop_duplicates('customer_id', inplace=True)
df_final.reset_index(drop=True,inplace=True)
df_final.head(6)
```

[20]:

	customer_id	age	gender	long_lat
0	CUS-1005756958	53	F	153.03 -27.51
1	CUS-1117979751	21	M	115.81 -31.82
2	CUS-1140341822	28	M	144.97 -37.42
3	CUS-1147642491	34	F	151.04 -33.77
4	CUS-1196156254	34	F	138.52 -35.01
5	CUS-1220154422	25	F	150.50 -23.40

[21]:
```
df_final['balance'] = df_avg_balance['balance']
```

Features like GENDER and LOCATION(long_lat) need to be converted to numbers in order to analyze the correlation between salary.

[22]:
```
# convert gender column to Integer type
df_final['gender'] =  df['gender'].map( {'M':1, 'F':0} )
df_final.head(6)
```

[22]:

```
     customer_id  age  gender      long_lat       balance
0  CUS-1005756958   53       0  153.03 -27.51   4718.665385
1  CUS-1117979751   21       0  115.81 -31.82  11957.202857
2  CUS-1140341822   28       1  144.97 -37.42   5841.720000
3  CUS-1147642491   34       0  151.04 -33.77   8813.467692
4  CUS-1196156254   34       0  138.52 -35.01  23845.717143
5  CUS-1220154422   25       1  150.50 -23.40   9225.907143
```

Calculate distance of customers from Centre of Australia

If we analyze long and lat as single values, that probably won't tell us too much things.

So we are going to use those values to calculated how far a custorm is from the centre of Australia (Lambert Gravitational Centre) [latitude: -25.610111, longitude: 134.354806]

Reference: https://www.wikiwand.com/en/Centre_points_of_Australia

[23]:

```python
long_lat = df_final['long_lat'].str.split(" ", n = 1, expand = True)
df_final['long'] = long_lat[0].astype('float')
df_final['lat'] = long_lat[1].astype('float')
df_final.drop(['long_lat'], axis = 1, inplace=True)
df_final.head(6)
```

[23]:

```
     customer_id  age  gender       balance    long    lat
0  CUS-1005756958   53       0   4718.665385  153.03 -27.51
1  CUS-1117979751   21       0  11957.202857  115.81 -31.82
2  CUS-1140341822   28       1   5841.720000  144.97 -37.42
3  CUS-1147642491   34       0   8813.467692  151.04 -33.77
4  CUS-1196156254   34       0  23845.717143  138.52 -35.01
5  CUS-1220154422   25       1   9225.907143  150.50 -23.40
```

[24]:

```python
centre_latitude = -25.610111
centre_longitude = 134.354806

import math
def calculateDistance(row):
    return math.sqrt((row['long'] - centre_longitude)**2 +  (row['lat'] -␣
 ↪centre_latitude)**2)
```

[25]:

```python
df_final['location_dist'] = df_final.apply(lambda row: calculateDistance(row),␣
 ↪axis=1)
df_final.drop(['long', 'lat'], axis = 1, inplace=True)
df_final.head(6)
```

[25]:

```
     customer_id  age  gender       balance  location_dist
0  CUS-1005756958   53       0   4718.665385      18.771586
1  CUS-1117979751   21       0  11957.202857      19.556905
2  CUS-1140341822   28       1   5841.720000      15.879415
3  CUS-1147642491   34       0   8813.467692      18.573623
```

```
4  CUS-1196156254   34       0  23845.717143      10.281379
5  CUS-1220154422   25       1   9225.907143      16.295763
```

Now, we can concatenate the final information with values we derived/construct ourselves.

- from "df_annual_salary" -> 'amount'(total salary over months) and 'avg_num_payments'
- from "df_customer_salary" -> 'salary' (base salary)

[26]:
```
df_customer_unique = df_customer_salary.drop_duplicates(['customer_id']).
↪reset_index(drop = True)
```

1.3.1 Concatenate original selected features with created ones

[27]:
```
data_annual = pd.concat([df_final, df_annual_salary[['annual_salary',␣
↪'avg_num_payments']]], axis=1)
data  = pd.concat([data_annual, df_customer_unique['base_salary']], axis =1 )
data.head(6)
```

[27]:
```
      customer_id  age  gender       balance  location_dist  annual_salary  \
0  CUS-1005756958   53       0   4718.665385      18.771586       12616.11
1  CUS-1117979751   21       0  11957.202857      19.556905       25050.55
2  CUS-1140341822   28       1   5841.720000      15.879415       11499.06
3  CUS-1147642491   34       0   8813.467692      18.573623       22248.07
4  CUS-1196156254   34       0  23845.717143      10.281379       27326.11
5  CUS-1220154422   25       1   9225.907143      16.295763       15976.52

   avg_num_payments  base_salary
0                 4       970.47
1                 2      3578.65
2                 2      1916.51
3                 4      1711.39
4                 2      3903.73
5                 2      2282.36
```

[28]:
```
# reorder columns
columns = [col for col in data.columns if col != 'annual_salary'] +␣
↪['annual_salary']
data = data[columns]
data.head(6)
```

[28]:
```
      customer_id  age  gender       balance  location_dist  avg_num_payments  \
0  CUS-1005756958   53       0   4718.665385      18.771586                 4
1  CUS-1117979751   21       0  11957.202857      19.556905                 2
2  CUS-1140341822   28       1   5841.720000      15.879415                 2
3  CUS-1147642491   34       0   8813.467692      18.573623                 4
4  CUS-1196156254   34       0  23845.717143      10.281379                 2
5  CUS-1220154422   25       1   9225.907143      16.295763                 2
```

```
   base_salary  annual_salary
0       970.47       12616.11
1      3578.65       25050.55
2      1916.51       11499.06
3      1711.39       22248.07
4      3903.73       27326.11
5      2282.36       15976.52
```

1.3.2 Calculate Pearson Correlation between fields

[29]:
```
df_all_corr = data.corr()
df_all_corr
```

[29]:
```
                      age    gender   balance  location_dist  \
age              1.000000 -0.021263  0.227026      -0.087073
gender          -0.021263  1.000000  0.059663      -0.100321
balance          0.227026  0.059663  1.000000      -0.033805
location_dist   -0.087073 -0.100321 -0.033805       1.000000
avg_num_payments  0.187163 -0.051730 -0.192136      -0.061067
base_salary     -0.135264 -0.072938  0.231019       0.070881
annual_salary   -0.036504 -0.109313  0.198755       0.097938

                  avg_num_payments  base_salary  annual_salary
age                       0.187163    -0.135264      -0.036504
gender                   -0.051730    -0.072938      -0.109313
balance                  -0.192136     0.231019       0.198755
location_dist            -0.061067     0.070881       0.097938
avg_num_payments          1.000000    -0.693218      -0.030318
base_salary              -0.693218     1.000000       0.534883
annual_salary            -0.030318     0.534883       1.000000
```

[30]:
```
df_all_corr= df_all_corr.abs().unstack().sort_values(kind="quicksort",␣
↪ascending=False).reset_index()
df_all_corr.rename(columns={"level_0": "Feature 1", "level_1": "Feature 2", 0:␣
↪'Correlation Coefficient'}, inplace=True)
df_all_corr[df_all_corr['Feature 1'] == 'annual_salary']
```

[30]:
```
        Feature 1         Feature 2  Correlation Coefficient
0   annual_salary     annual_salary                 1.000000
10  annual_salary       base_salary                 0.534883
15  annual_salary           balance                 0.198755
23  annual_salary            gender                 0.109313
28  annual_salary     location_dist                 0.097938
41  annual_salary               age                 0.036504
46  annual_salary  avg_num_payments                 0.030318
```

"base_salary" has a strong correlation with annual_salary.

We can not conclude changes in the variable cause changes in annual_salary based on correlation alone. Only properly controlled experiments enable us to determine whether a relationship is causal.

A low Pearson correlation coefficient does not mean that no relationship exists between the variables.

The variables may have a nonlinear relationship. To check for nonlinear relationships graphically,we will create a scatterplot and use a simple regression model.

[31]:
```
from scipy.stats import pearsonr
def pearsonr_pval(x,y):
    return pearsonr(x,y)[1]

df_all_corr_pValue = data.corr(method=pearsonr_pval)
df_all_corr_pValue= df_all_corr_pValue.unstack().sort_values(kind="quicksort",␣
 ↪ascending=True).reset_index()
df_all_corr_pValue.rename(columns={"level_0": "Feature 1", "level_1": "Feature␣
 ↪2", 0: 'P-Value Correlation'}, inplace=True)
df_all_corr_pValue[df_all_corr_pValue['Feature 1'] == 'annual_salary']
```

[31]:
```
       Feature 1        Feature 2  P-Value Correlation
3   annual_salary      base_salary         9.884301e-09
8   annual_salary          balance         4.743560e-02
17  annual_salary           gender         2.789715e-01
21  annual_salary    location_dist         3.323434e-01
34  annual_salary              age         7.184211e-01
38  annual_salary  avg_num_payments         7.646067e-01
48  annual_salary    annual_salary         1.000000e+00
```

There is inconclusive evidence about the significance of the association between the variables.

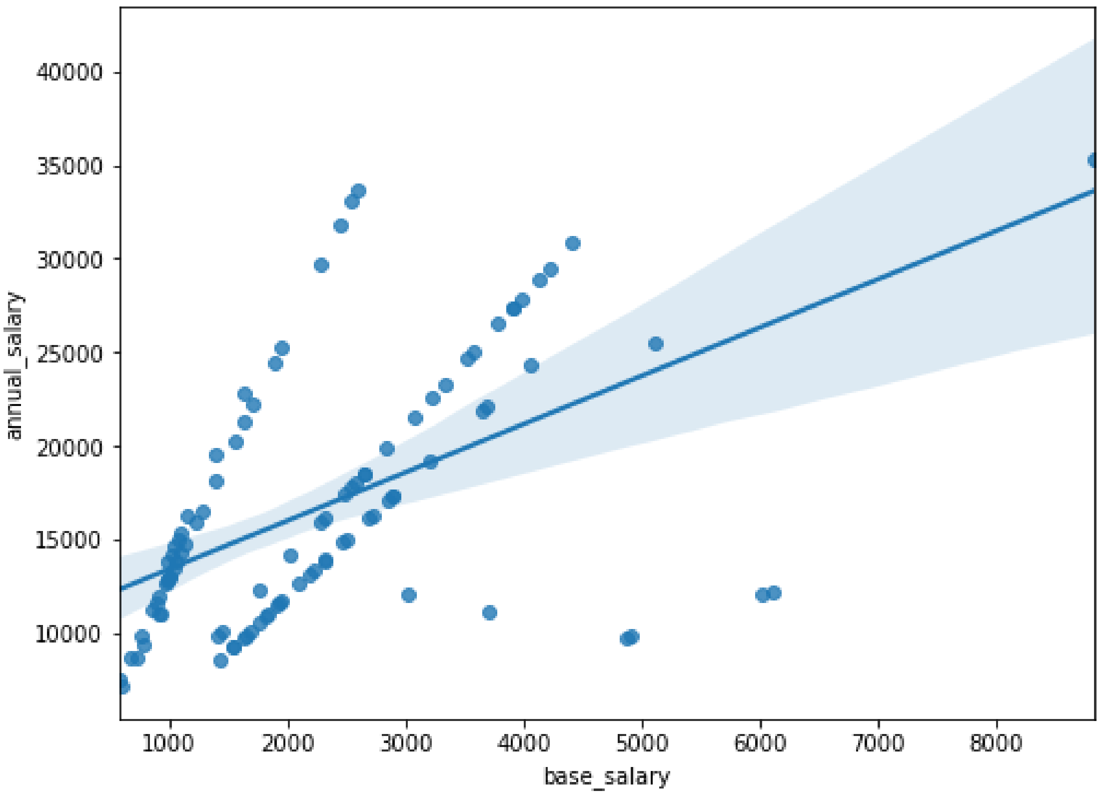
2 Plots to see correlations

[32]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

2.1 Base_salary vs Annual Salary

[33]:
```
plt.figure(figsize=(8, 6))
sns.regplot("base_salary", "annual_salary", data=data)
```

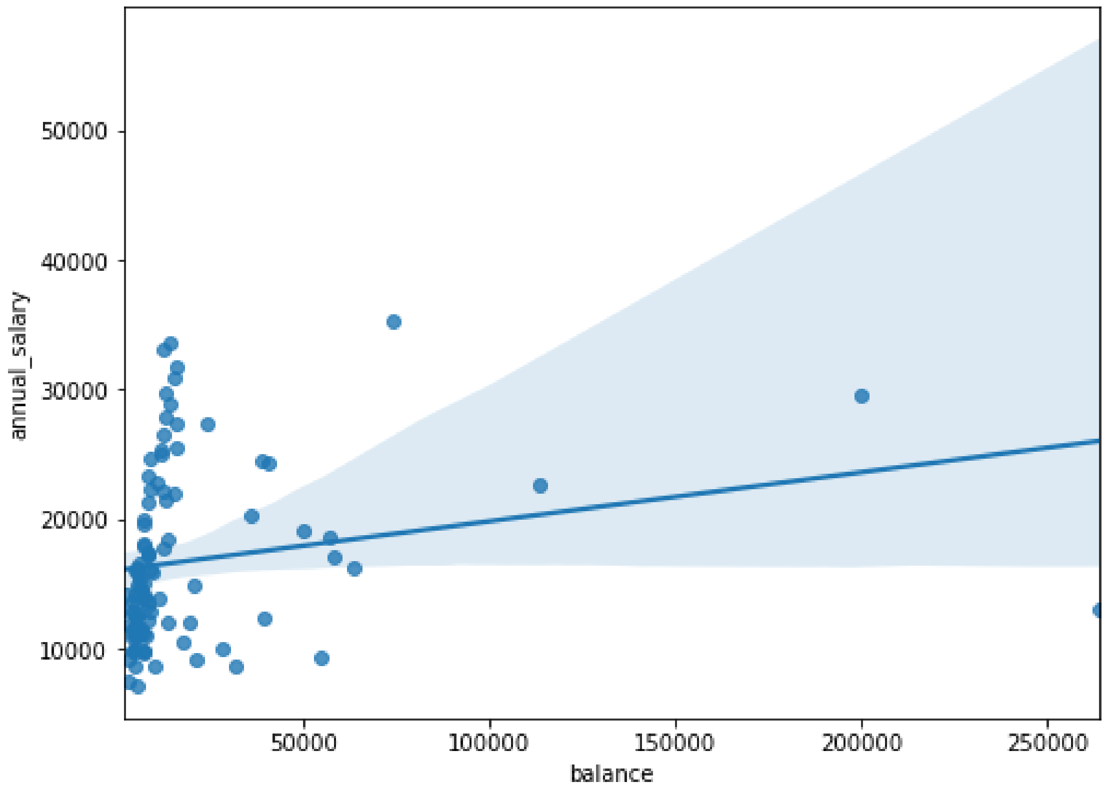
[33]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d3f64ed710>
```



2.2 balance vs Annual Salary

[34]:
```
plt.figure(figsize=(8, 6))
sns.regplot("balance", "annual_salary", data=data)
```

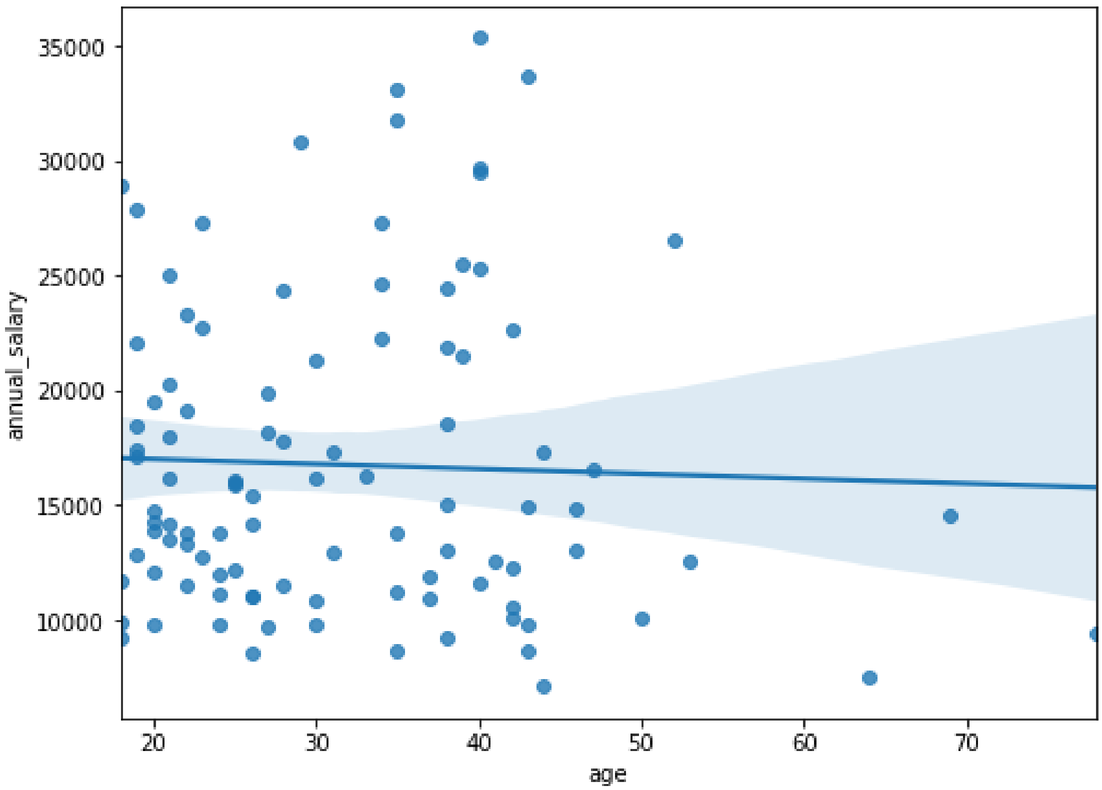
[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1d3f6567be0>



2.3 Age vs Annual Salary

[35]:
```
plt.figure(figsize=(8, 6))
sns.regplot("age", "annual_salary", data=data)
```

[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1d3f65b4f98>



We have an outlier in “Location distance” feature

[36]:
```
data['location_dist'].max()
```

[36]: 560.5273886392439

3 Model Builiding - Regression Model

[37]:
```
X=data[['age' , 'gender', 'balance', 'location_dist', 'avg_num_payments',
 ↪'base_salary']].values
y=data['annual_salary'].values
```

[38]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2,
 ↪random_state=42)
```

[39]:
```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train, y_train)
lr.score(X, y)
```

[39]: 0.5231347070503298

3.1 Regression Model - Results

[40]:
```
from sklearn.metrics import r2_score
y_predict=lr.predict(X_test)
#R-squared is a statistical measure of how close the data are to the fitted␣
↪regression line.
# It is also known as the coefficient of determination, or the coefficient of␣
↪multiple determination for multiple regression
print('Regression Model, R-squared: ', r2_score(y_test, y_predict))
```

```
Regression Model, R-squared:  0.4192405895493032
```

[41]:
```
from sklearn.metrics import mean_squared_error
# RMSE - Root Mean Squared Error
print('Regression Model, RMSE', np.sqrt(mean_squared_error(y_test, y_predict)))
```

```
Regression Model, RMSE 4876.661047214676
```

3.2 Regression Model Analysis

- The model's R-squared shows that it only explains about 40% of variation in customers'annual salary.
- The RMSE of the model over 20% of the data is near 5000, which indicates somehow the inaccuracy of the model.
- Probably, more data is required to develop a more reliable model.

4 Model Builiding - Decision Tree

[42]:
```
from sklearn.tree import DecisionTreeRegressor
dectree = DecisionTreeRegressor(max_depth=5,random_state=0)
dectree.fit(X_train, y_train)
dectree.score(X_train, y_train)
```

[42]: 0.9630003955678947

4.1 Decision Tree Model - Results

[43]:
```
y_predict = dectree.predict(X_test)
print('Decision Tree, R-squared: ', r2_score(y_test, y_predict))
print('Decision Tree, RMSE', np.sqrt(mean_squared_error(y_test, y_predict)))
```

```
Decision Tree, R-squared:  0.1501796279735662
Decision Tree, RMSE 5899.130613268002
```

4.2 Decision Tree Analysis

The Decision Tree model got an R-squared value of 0.96 , which is very close to 1, indicating the model can be able to explain the annual salary variability.

However, the model achieved a RMSE of 5899 which is a litlle bit higher than that of the linear regression model (4876)

5 Final Conclusion

Even though the Decision Tree model is performing better than the Linear Regression model in terms of its R-square value, we can not conclude is will be fine to consider useful as it has a higher RMSE.

This means that the absolute fit of the model is much worse, overall. For that reason, neither of both models should be considered to segment the customers.

Taking in mind that we only have 3 months of data, it would be good to compare the generated models with more data, and also another machine learning technique can be applied in order to see if there is room for improvement.

[ ]:

```
```