Data @ ANZ Internship

Predictive Analytics

Submitted by: Valency Colaco, Masters of Information Technology, University of Sydney

Installing library to access files from Google Drive

In [1]:
```
!pip install PyDrive
```

```
Requirement already satisfied: PyDrive in /usr/local/lib/python3.6/dist-packa
ges (1.3.1)
Requirement already satisfied: google-api-python-client>=1.2 in /usr/local/li
b/python3.6/dist-packages (from PyDrive) (1.7.12)
Requirement already satisfied: oauth2client>=4.0.0 in /usr/local/lib/python3.
6/dist-packages (from PyDrive) (4.1.3)
Requirement already satisfied: PyYAML>=3.0 in /usr/local/lib/python3.6/dist-p
ackages (from PyDrive) (3.13)
Requirement already satisfied: google-auth-httplib2>=0.0.3 in /usr/local/lib/
python3.6/dist-packages (from google-api-python-client>=1.2->PyDrive) (0.0.4)
Requirement already satisfied: httplib2<1dev,>=0.17.0 in /usr/local/lib/pytho
n3.6/dist-packages (from google-api-python-client>=1.2->PyDrive) (0.17.4)
Requirement already satisfied: six<2dev,>=1.6.1 in /usr/local/lib/python3.6/d
ist-packages (from google-api-python-client>=1.2->PyDrive) (1.15.0)
Requirement already satisfied: uritemplate<4dev,>=3.0.0 in /usr/local/lib/pyt
hon3.6/dist-packages (from google-api-python-client>=1.2->PyDrive) (3.0.1)
Requirement already satisfied: google-auth>=1.4.1 in /usr/local/lib/python3.
6/dist-packages (from google-api-python-client>=1.2->PyDrive) (1.17.2)
Requirement already satisfied: pyasn1>=0.1.7 in /usr/local/lib/python3.6/dist
-packages (from oauth2client>=4.0.0->PyDrive) (0.4.8)
Requirement already satisfied: pyasn1-modules>=0.0.5 in /usr/local/lib/python
3.6/dist-packages (from oauth2client>=4.0.0->PyDrive) (0.2.8)
Requirement already satisfied: rsa>=3.1.4 in /usr/local/lib/python3.6/dist-pa
ckages (from oauth2client>=4.0.0->PyDrive) (4.6)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/pytho
n3.6/dist-packages (from google-auth>=1.4.1->google-api-python-client>=1.2->P
yDrive) (4.2.0)
Requirement already satisfied: setuptools>=40.3.0 in /usr/local/lib/python3.
6/dist-packages (from google-auth>=1.4.1->google-api-python-client>=1.2->PyDr
ive) (51.1.1)
```

My Dataset is uploaded to Google Drive, and I want to read it from the drive directly. That's why these steps are required.

In [2]:
```
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
import pandas as pd
import seaborn as sns
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from mpl_toolkits import mplot3d
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import cross_val_predict
from sklearn.ensemble import RandomForestRegressor
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: Futu
reWarning: pandas.util.testing is deprecated. Use the functions in the public
API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [3]:
```
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

In [4]:
```
downloaded = drive.CreateFile({'id':"1yCQs5R05MlbZXni4hylcNKVq_wuawnij"})
downloaded.GetContentFile('ANZ synthesised transaction dataset.xlsx')
```

The File is successfully read and can now be used in the program

In [5]:
```
import pandas as pd
df = pd.read_excel('ANZ synthesised transaction dataset.xlsx')
```

Just checking the file contents

In [6]:
```
df.head()
```

Out[6]:

	status	card_present_flag	bpay_biller_code	account	currency	long_lat	txn_descriptio
0	authorized	1.0	NaN	ACC-1598451071	AUD	153.41 -27.95	PO
1	authorized	0.0	NaN	ACC-1598451071	AUD	153.41 -27.95	SALES-PO
2	authorized	1.0	NaN	ACC-1222300524	AUD	151.23 -33.94	PO
3	authorized	1.0	NaN	ACC-1037050564	AUD	153.10 -27.66	SALES-PO
4	authorized	1.0	NaN	ACC-1598451071	AUD	153.41 -27.95	SALES-PO

In [7]:
```
salary_txns = df[df['txn_description'] == 'PAY/SALARY']
```

Filtered based on Salary Transactions only

In [8]:
```
salary_txns.head()
```

Out[8]:

	status	card_present_flag	bpay_biller_code	account	currency	long_lat	txn_description
50	posted	NaN	0	ACC-588564840	AUD	151.27 -33.76	PAY/SALARY
61	posted	NaN	0	ACC-1650504218	AUD	145.01 -37.93	PAY/SALARY
64	posted	NaN	0	ACC-3326339947	AUD	151.18 -33.80	PAY/SALARY
68	posted	NaN	0	ACC-3541460373	AUD	145.00 -37.83	PAY/SALARY
70	posted	NaN	0	ACC-2776252858	AUD	144.95 -37.76	PAY/SALARY

Cleaning the data by dropping unnecessary fields

In [9]:
```
salary_txns = salary_txns.drop(['status',
                                'card_present_flag',
                                'bpay_biller_code',
                                'currency',
                                'merchant_id',
                                'merchant_code',
                                'merchant_suburb',
                                'merchant_state',
                                'country',
                                'merchant_long_lat',
                                'movement',
                                'txn_description',
                                'extraction',
                                'transaction_id'], axis=1)
salary_txns = salary_txns.reset_index(drop=True)
```

Putting the location data in a usable format

In [10]:
```
long_lat = salary_txns['long_lat'].str.split("-", n = 1, expand = True)
salary_txns['long'] = long_lat[0]
salary_txns['lat'] = long_lat[1]
salary_txns = salary_txns.drop(['long_lat'], axis = 1)
```

In [11]:
```
salary_txns.head()
```

Out[11]:

	account	first_name	balance	date	gender	age	amount	customer_id	long	lat
0	ACC-588564840	Isaiah	8342.11	2018-08-01	M	23	3903.95	CUS-1462656821	151.27	33.76
1	ACC-1650504218	Marissa	2040.58	2018-08-01	F	23	1626.48	CUS-2500783281	145.01	37.93
2	ACC-3326339947	Eric	3158.51	2018-08-01	M	22	983.36	CUS-326006476	151.18	33.80
3	ACC-3541460373	Jeffrey	2517.66	2018-08-01	M	24	1408.08	CUS-1433879684	145.00	37.83
4	ACC-2776252858	Kristin	2271.79	2018-08-01	F	43	1068.04	CUS-4123612273	144.95	37.76

In [12]:
```
salary_txns.nunique()
```

Out[12]:
```
account        100
first_name      80
balance        883
date            65
gender           2
age             33
amount         100
customer_id    100
long            87
lat             85
dtype: int64
```

Now creating a sub-dataset with unique salary data and customers

Salary is paid every fortnight. Calculating average salary paid per fortnight multiplied by 26.071 fortnights a year gives us the annual salary.

In [13]:
```python
customers = list(salary_txns['customer_id'].unique())

customer_data = []

for cust in customers:
    salary_txns_subset = salary_txns[salary_txns['customer_id'] == cust]
    salary_txns_subset = salary_txns_subset.reset_index(drop=True)
    account = salary_txns_subset['account'][0]
    first_name = salary_txns_subset['first_name'][0]
    gender = salary_txns_subset['gender'][0]
    age = salary_txns_subset['age'][0]
    long = salary_txns_subset['long'][0]
    lat = salary_txns_subset['lat'][0]
    avg_balance = round(sum(salary_txns_subset['balance']) / len(salary_txns_s
ubset), 2)
    avg_salary = round(sum(salary_txns_subset['amount']) / len(salary_txns_sub
set), 2)
    row = (cust, account, first_name, gender, age, long, lat, avg_balance, avg
_salary, round(avg_salary*26.071,2))
    customer_data.append(row)

customer_df = pd.DataFrame(customer_data, columns = ('customer_id',
                                                     'account',
                                                     'first_name',
                                                     'gender',
                                                     'age',
                                                     'long',
                                                     'lat',
                                                     'avg_balance',
                                                     'avg_salary',
                                                     'annual_salary')
                          )

# change gender to dummy variable
customer_df = pd.get_dummies(customer_df, columns = ['gender'], drop_first = T
rue)

customer_df.head()
```

Out[13]:

	customer_id	account	first_name	age	long	lat	avg_balance	avg_salary	annual_sa
0	CUS-1462656821	ACC-588564840	Isaiah	23	151.27	33.76	15887.91	3903.95	10177
1	CUS-2500783281	ACC-1650504218	Marissa	23	145.01	37.93	10741.09	1626.48	4240
2	CUS-326006476	ACC-3326339947	Eric	22	151.18	33.80	8317.03	983.36	2563
3	CUS-1433879684	ACC-3541460373	Jeffrey	24	145.00	37.83	3877.38	1408.08	3671
4	CUS-4123612273	ACC-2776252858	Kristin	43	144.95	37.76	5210.70	1068.04	2784

Scatterplot 1 of Annual Salary vs Age

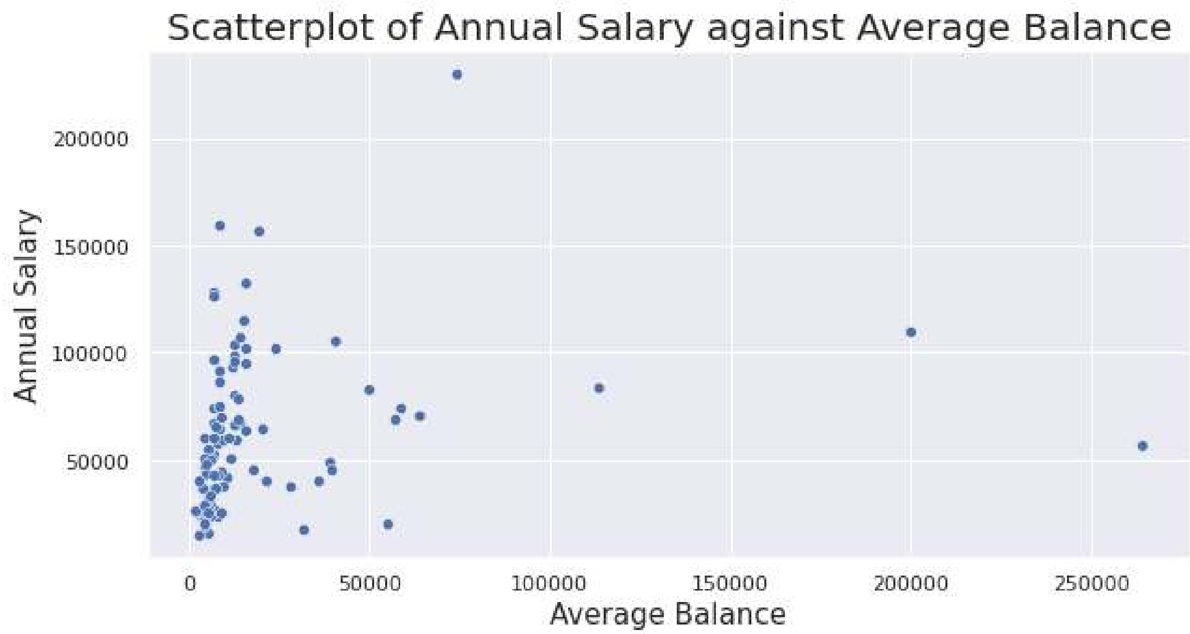
In [14]:
```
sns.set(style="whitegrid")
sns.set(rc={'figure.figsize':(10,5)})
age_salary_graph = sns.scatterplot(x="age", y="annual_salary", hue = 'gender_M', data=customer_df)
age_salary_graph.axes.set_title("Scatterplot of Annual Salary against Age",fontsize=20)
age_salary_graph.set_xlabel("Age", fontsize=15)
age_salary_graph.set_ylabel("Annual Salary", fontsize=15)
```

Out[14]:
```
Text(0, 0.5, 'Annual Salary')
```

Scatterplot 2 of Annual Salary vs Average Balance

In [15]:
```python
sns.set(style="whitegrid")
sns.set(rc={'figure.figsize':(10,5)})
age_salary_graph = sns.scatterplot(x="avg_balance", y="annual_salary", data=customer_df)
age_salary_graph.axes.set_title("Scatterplot of Annual Salary against Average Balance",fontsize=20)
age_salary_graph.set_xlabel("Average Balance", fontsize=15)
age_salary_graph.set_ylabel("Annual Salary", fontsize=15)
```

Out[15]:
```
Text(0, 0.5, 'Annual Salary')
```



Now comes the fun part. We split the refined dataset into 90% training and 10% testing. We also set up the Linear Regression Model here

In [16]:
```python
# Split data
train, test = train_test_split(customer_df, test_size=0.1)
X = train[['age', 'avg_balance', 'long', 'lat', 'gender_M']]
y = train['annual_salary']
X_test = test[['age', 'avg_balance', 'long', 'lat', 'gender_M']]
y_test = test['annual_salary']

# Instantiate model
lm = LinearRegression()

# Fit model
lm.fit(X,y)

# Print the R-squared value for the model
print(lm.score(X, y))
```

```
0.1786352984831029
```

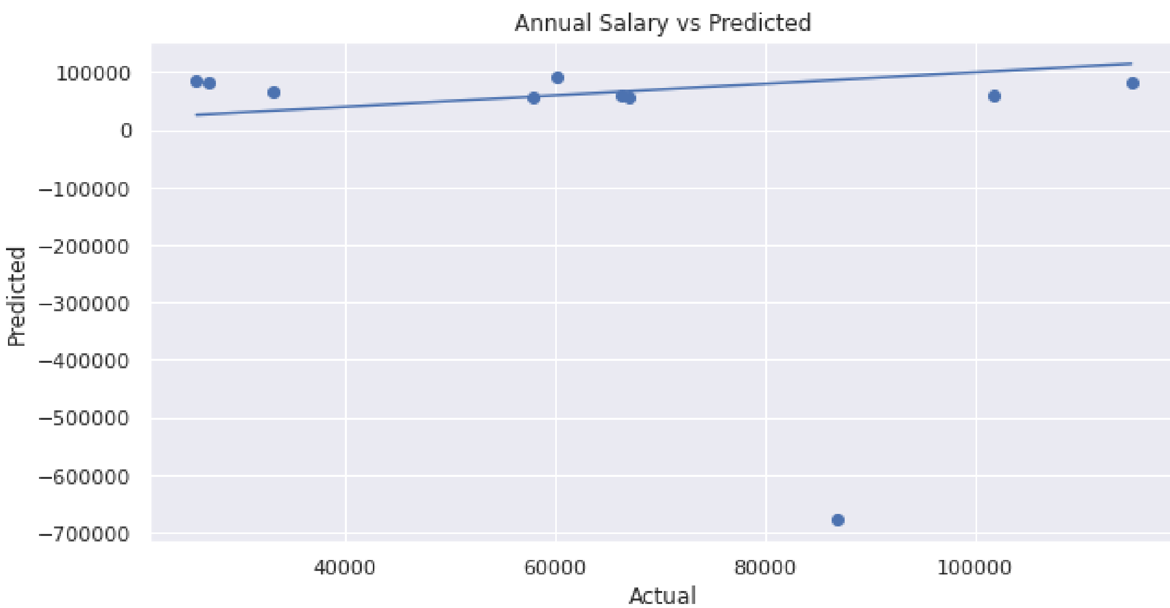
As we can see, the R^2 value is too low due to which the Root Mean Square Error (RMSE) is expected to be high

In [17]:
```
# Predict
y_predict = lm.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_predict)))
```

```
244086.72850206518
```

An abnormal plot because the RMSE is too high

In [18]:
```
# Plot of predicted salary against actual salary
fig, ax = plt.subplots()
ax.scatter(y_test, y_predict)
ax.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()])
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title("Annual Salary vs Predicted")
plt.show()
```



Now setting up the decision tree model

In [19]:
```python
# Instantiate model
model1 =  DecisionTreeRegressor(random_state=0, max_depth=5)

# Fit model
model1.fit(X,y)

# Print the R-squared value for the model
print (model1.score(X, y))
```

```
0.8033930736935384
```

In [20]:
```python
# Predict
y_predict_2 = model1.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_predict_2)))
```

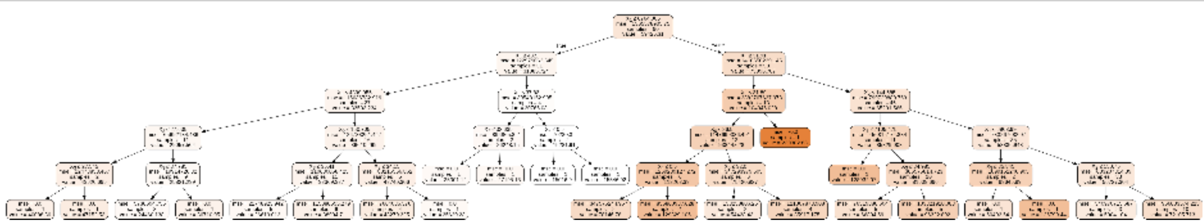
```
28902.27888455127
```

Pretty decent R^2 and low RSME. Plotting the tree now

In [21]:
```python
import io
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
```

In [22]:
```python
anz_dot = io.StringIO()

export_graphviz(model1, out_file=anz_dot,
                filled=True, rounded=True,
                special_characters=True)
graph = pydotplus.graph_from_dot_data(anz_dot.getvalue())
Image(graph.create_png())
```

Out[22]:



In [23]:
```
# Plot of predicted salary against actual salary
fig, ax = plt.subplots()
ax.scatter(y_test, y_predict_2)
ax.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()])
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title("Annual Salary vs Predicted")
plt.show()
```

Setting up the Random Forest Model as a bonus

In [24]:
```
# Instantiate model
model2 =  RandomForestRegressor(n_estimators = 1000, random_state = 0)

# Fit model
model2.fit(X,y)

# Print the R-squared value for the model
model2.score(X, y)
```

Out[24]: 0.8895318644621022

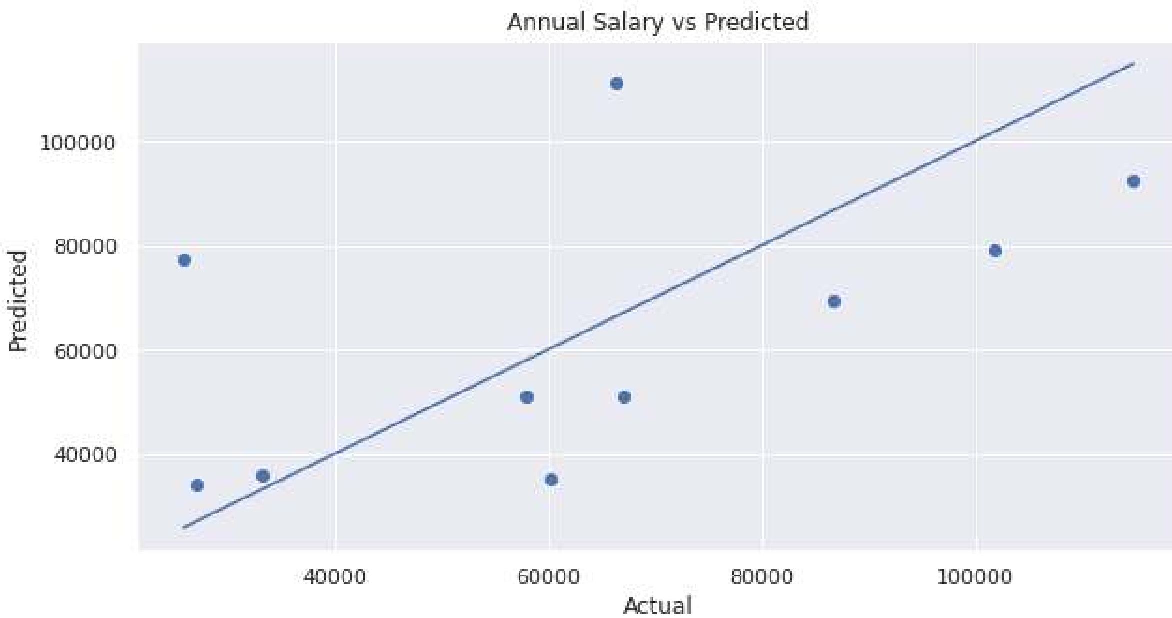
In [25]:
```
# Predict
y_predict_3 = model2.predict(X_test)

# RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_predict_3)))
```

```
26475.59207387387
```

Wow. This was even more accurate

In [26]:

```
# Plot of predicted salary against actual salary
fig, ax = plt.subplots()
ax.scatter(y_test, y_predict_3)
ax.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()])
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title("Annual Salary vs Predicted")
plt.show()
```



Finally, we can see that the Decision Tree model was more accurate than the Linear Regressor. But in my analysis, I discovered that the Random Forest Regressor is even more accurate and this is the one ANZ should use!