

Predictive_Analytics

February 26, 2021

```
[2]: import os
import sys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from datetime import datetime, timedelta
import missingno as msno
from geopy.geocoders import Nominatim
import seaborn as sns
```

```
[63]: from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn import metrics
```

```
[75]: import statsmodels.api as sm
from sklearn import tree
import pydotplus
```

```
[4]: df_clean = pd.read_csv('data/df_clean.csv')
df_clean.head()
```

```
[4]:
```

	status	card_present_flag	bpay_biller_code	account	currency	\
0	authorized	1.0	NaN	ACC-1598451071	AUD	
1	authorized	0.0	NaN	ACC-1598451071	AUD	
2	authorized	1.0	NaN	ACC-1222300524	AUD	
3	authorized	1.0	NaN	ACC-1037050564	AUD	
4	authorized	1.0	NaN	ACC-1598451071	AUD	

	txn_description	merchant_id	first_name	balance	\
0	POS	81c48296-73be-44a7-befa-d053f48ce7cd	Diana	35.39	
1	SALES-POS	830a451c-316e-4a6a-bf25-e37caedca49e	Diana	21.20	
2	POS	835c231d-8cdf-4e96-859d-e9d571760cf0	Michael_1	5.71	
3	SALES-POS	48514682-c78a-4a88-b0da-2d6302e64673	Rhonda	2117.22	
4	SALES-POS	b4e02c10-0852-4273-b8fd-7b3395e32eb0	Diana	17.95	

	date	...	transaction_id	country	\
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```

0  2018-08-01 00:00:00 ... a623070bfead4541a6b0fff8a09e706c Australia
1  2018-08-01 00:00:00 ... 13270a2a902145da9db4c951e04b51b9 Australia
2  2018-08-01 00:00:00 ... feb79e7ecd7048a5a36ec889d1a94270 Australia
3  2018-08-01 00:00:00 ... 2698170da3704fd981b15e64a006079e Australia
4  2018-08-01 00:00:00 ... 329adf79878c4cf0aeb4188b4691c266 Australia

```

```

      customer_id movement customer_long customer_lat merchant_long \
0  CUS-2487424745    debit      153.41      -27.95      153.38
1  CUS-2487424745    debit      153.41      -27.95      151.21
2  CUS-2142601169    debit      151.23      -33.94      151.21
3  CUS-1614226872    debit      153.10      -27.66      153.05
4  CUS-2487424745    debit      153.41      -27.95      153.44

```

```

      merchant_lat customer_state age_group
0      -27.99      Queensland      21-30
1      -33.87      Queensland      21-30
2      -33.87 New South Wales      31-40
3      -26.68      Queensland      31-40
4      -28.06      Queensland      21-30

```

[5 rows x 26 columns]

0.1 Predictive Analytics

Explore correlations between customer attributes, build a regression and a decision-tree prediction model based on your findings.

Using the same transaction dataset, identify the annual salary for each customer

Explore correlations between annual salary and various customer attributes (e.g. age). These attributes could be those that are readily available in the data (e.g. age) or those that you construct or derive yourself (e.g. those relating to purchasing behaviour). Visualise any interesting correlations using a scatter plot.

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?

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?

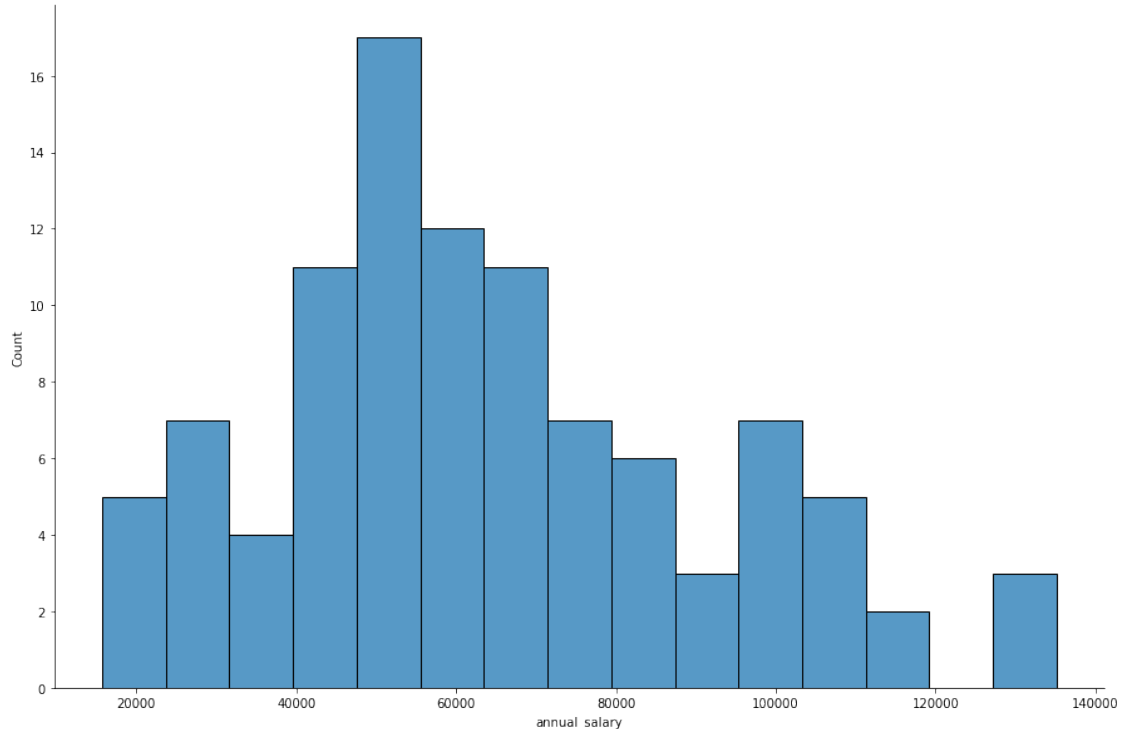
- Data Wrangling
- Linear Regression
- Tree Regression

0.1.1 Identify the annual salary for each customer

```
[22]: customer = df_clean.customer_id.unique()
salary_interval = []
date_interval = []
for i in customer:
    temp = df_clean[(df_clean.customer_id == i) & (df_clean.txn_description == 'PAY/SALARY')][['amount', 'date']]
    temp['date'] = pd.to_datetime(temp['date'])
    count = len(temp)
    s = []
    lvl = []
    for j in range(count - 1):
        s.append(temp['date'].iloc[j+1] - temp['date'].iloc[j])
        lvl.append(temp['amount'].iloc[j])
    salary_interval.append(max(lvl))
    date_interval.append(max(s).days)

annual_salary = pd.DataFrame({'customer_id': customer, 'annual_salary': np.rint(np.array(salary_interval)/np.array(date_interval))*365.25})
```

```
[23]: plt.figure(figsize = (15, 10))
sns.histplot(x = 'annual_salary', data = annual_salary, bins = 15)
sns.despine();
```



```
[24]: # create a dataframe to store relevant features for customers

customer_table = df_clean[['customer_id', 'gender', 'age', 'customer_state']]\
.drop_duplicates()\
.reset_index(drop=True)

#customer = pd.merge(customer, annual_salary, how = 'left', on = 'customer_id')

customer_table.head()
```

```
[24]:
```

	customer_id	gender	age	customer_state
0	CUS-2487424745	F	26	Queensland
1	CUS-2142601169	M	38	New South Wales
2	CUS-1614226872	F	40	Queensland
3	CUS-2688605418	M	20	New South Wales
4	CUS-4123612273	F	43	Victoria

```
[31]: temp_1 = df_clean.groupby('customer_id').agg({'date': 'nunique',
        'transaction_id': 'count',
        'amount': 'mean',
        'balance': 'mean',
        })

#temp_1.columns = ['-'.join(col) for col in temp_1.columns.values]
```

```
temp_1 = temp_1.reset_index()

temp_1.head()
```

```
[31]:
```

	customer_id	date	transaction_id	amount	balance
0	CUS-1005756958	40	73	222.862603	2275.852055
1	CUS-1117979751	60	100	339.843700	9829.929000
2	CUS-1140341822	42	80	212.632500	5699.212250
3	CUS-1147642491	54	118	245.600169	9032.841186
4	CUS-1196156254	79	245	147.145796	22272.433755

```
[32]: temp_3 = df_clean.groupby(['customer_id', 'txn_description']).size().
↳ unstack(fill_value = 0).reset_index()

temp_3.head()
```

```
[32]:
```

txn_description	customer_id	INTER	BANK	PAY/SALARY	PAYMENT	PHONE	BANK	\
0	CUS-1005756958		0	13	9		3	
1	CUS-1117979751		1	7	40		0	
2	CUS-1140341822		3	6	6		0	
3	CUS-1147642491		2	13	27		0	
4	CUS-1196156254		5	7	70		0	

txn_description	POS	SALES-POS
0	26	22
1	26	26
2	39	26
3	38	38
4	74	89

```
[33]: features = customer_table.merge(temp_1, how = 'left', on = 'customer_id')\
.merge(temp_3, how = 'left', on='customer_id')\
.merge(annual_salary, how = 'left', on='customer_id')

features.drop(['customer_id'], axis = 1)

# age and state
dummy_gender_and_state = pd.get_dummies(features[['gender', 'customer_state']],
↳ drop_first = True)

features = features.merge(dummy_gender_and_state,
                           how = 'left',
                           left_index = True,
                           right_index = True)
```

```
features_before_scaled = features\  
.drop(['gender', 'customer_state', 'transaction_id', 'customer_id'],  
      axis = 1)
```

```
[34]: unscaled_features = features_before_scaled.drop(['annual_salary'], axis = 1)  
      unscaled_targets = features_before_scaled['annual_salary']
```

```
[59]: np.log(unscaled_features[['age', 'amount', 'balance', 'PAYMENT',  
                              'POS', 'SALES-POS']] + 1 ).hist()
```

/Users/murongcui/opt/anaconda3/lib/python3.7/site-
packages/pandas/plotting/_tools.py:307: MatplotlibDeprecationWarning:

The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().rowspan.start instead.

/Users/murongcui/opt/anaconda3/lib/python3.7/site-
packages/pandas/plotting/_tools.py:307: MatplotlibDeprecationWarning:

The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().colspan.start instead.

/Users/murongcui/opt/anaconda3/lib/python3.7/site-
packages/pandas/plotting/_tools.py:313: MatplotlibDeprecationWarning:

The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().rowspan.start instead.

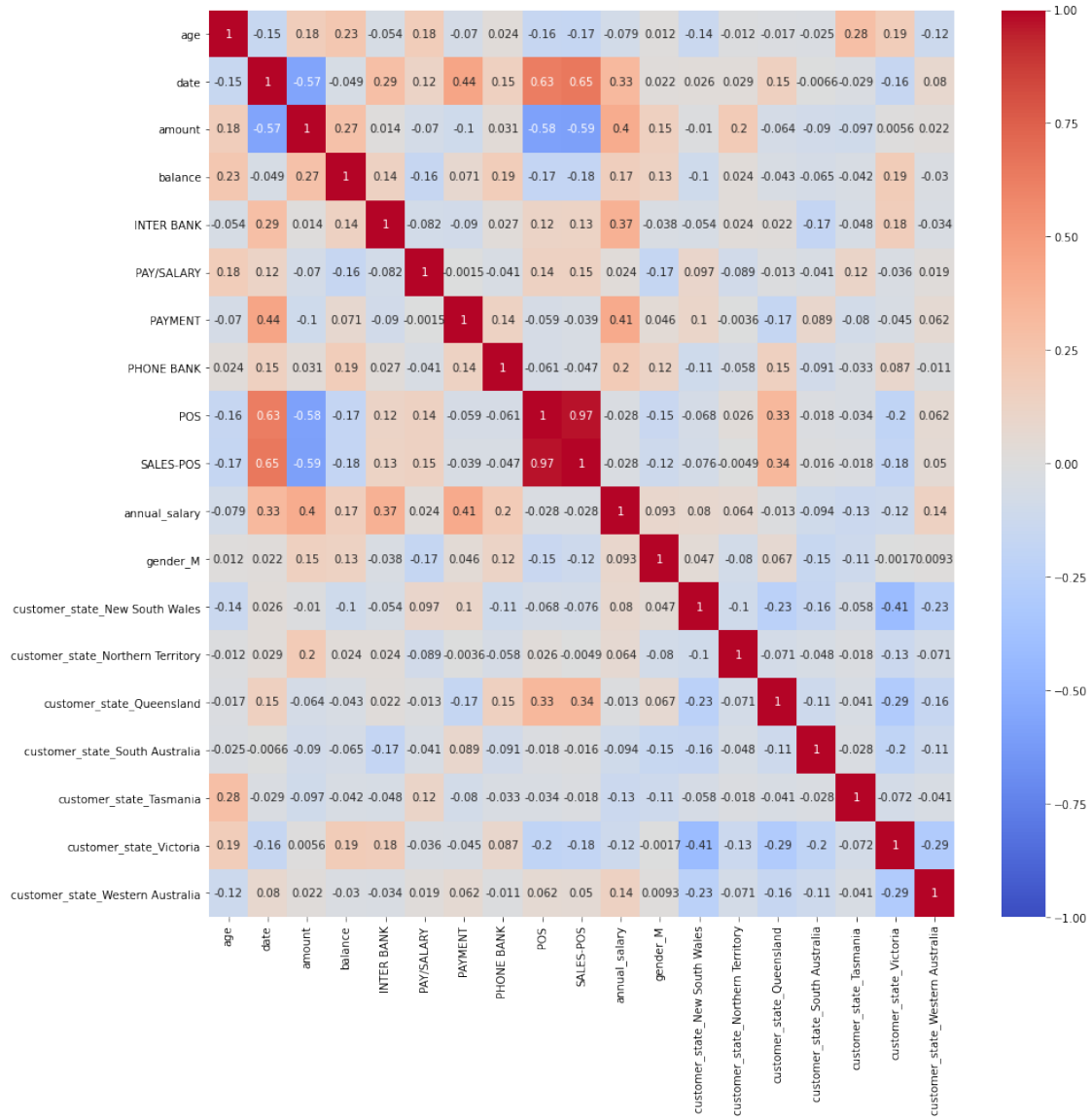
/Users/murongcui/opt/anaconda3/lib/python3.7/site-
packages/pandas/plotting/_tools.py:313: MatplotlibDeprecationWarning:

The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().colspan.start instead.

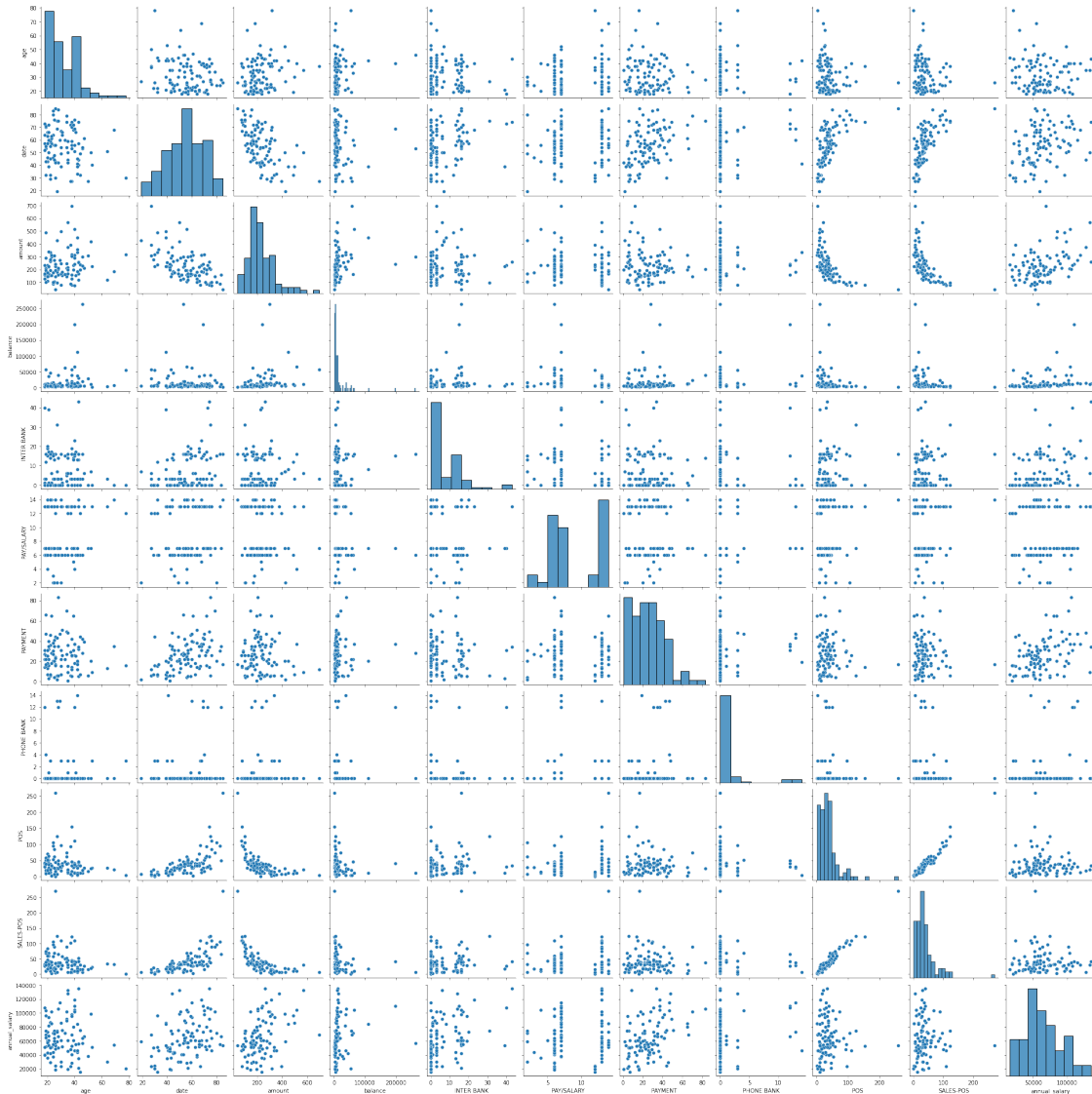
```
[59]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f904cf20390>,  
            <matplotlib.axes._subplots.AxesSubplot object at 0x7f904d1dc810>],  
          [<matplotlib.axes._subplots.AxesSubplot object at 0x7f904d0e7250>,  
            <matplotlib.axes._subplots.AxesSubplot object at 0x7f904d2a3790>],  
          [<matplotlib.axes._subplots.AxesSubplot object at 0x7f904d2d9ad0>,  
            <matplotlib.axes._subplots.AxesSubplot object at 0x7f904d30ef50>]],  
          dtype=object)
```



```
[35]: # heatmap correlation
plt.figure(figsize = (15, 15))
sns.heatmap(features_before_scaled.corr(),
            annot = True,
            vmin=-1,
            vmax=1,
            center= 0,
            cmap= 'coolwarm');
```



```
[38]: sns.pairplot(features_before_scaled[['age', 'date', 'amount', 'balance',
      'INTER BANK', 'PAY/SALARY', 'PAYMENT', 'PHONE BANK',
      'POS', 'SALES-POS', 'annual_salary']]);
```

```
[39]: x_train, x_test, y_train, y_test = train_test_split(unscaled_features,
                                                         unscaled_targets,
                                                         train_size = 0.75,
                                                         random_state = 42)
```

```
[40]: print(x_train.shape, y_train.shape)
      print(x_test.shape, y_test.shape)
```

```
(75, 18) (75,)
(25, 18) (25,)
```

```
[81]: # Linear Regression
      reg = LinearRegression()
```

```

reg.fit(x_train, y_train)

print('Coefficients: \n', reg.coef_)
print('Variance scoore: {}'.format(reg.score(x_test, y_test)))

y_predict = reg.predict(x_test)

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

```

Coefficients:

```

[-3.02559388e+02  9.74889410e+02  2.38865182e+02 -5.03831247e-02
 8.40748344e+02 -1.20070118e+02  5.82145079e+02  6.81689061e+02
 3.68798245e+02 -1.73015216e+02  9.21004934e+02  1.29969189e+03
-1.82530572e+04 -2.37524994e+03  9.10756908e+03  0.00000000e+00
 8.79873458e+02  2.38898674e+03]

```

Variance scoore: 0.19377141872307824

21682.55408012313

```

[51]: ## plotting residual errors in training data
plt.scatter(reg.predict(x_train), reg.predict(x_train) - y_train,
            color = "green", s = 10, label = 'Train data')

## plotting residual errors in test data
plt.scatter(reg.predict(x_test), reg.predict(x_test) - y_test,
            color = "blue", s = 10, label = 'Test data')

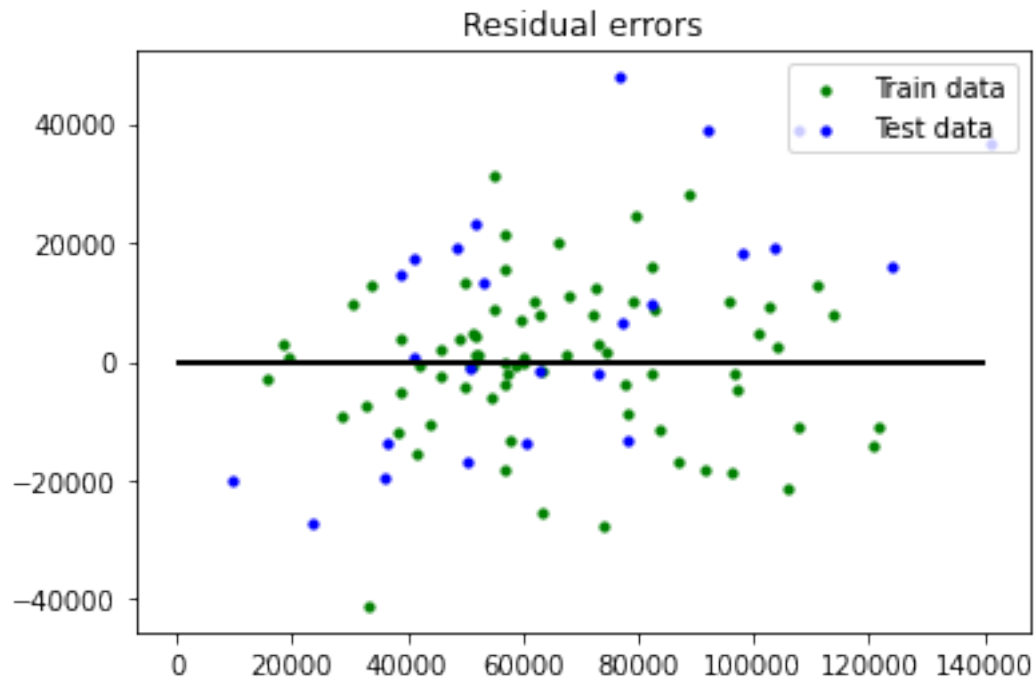
## plotting line for zero residual error
plt.hlines(y = 0, xmin = 0, xmax = 140000, linewidth = 2)

## plotting legend
plt.legend(loc = 'upper right')

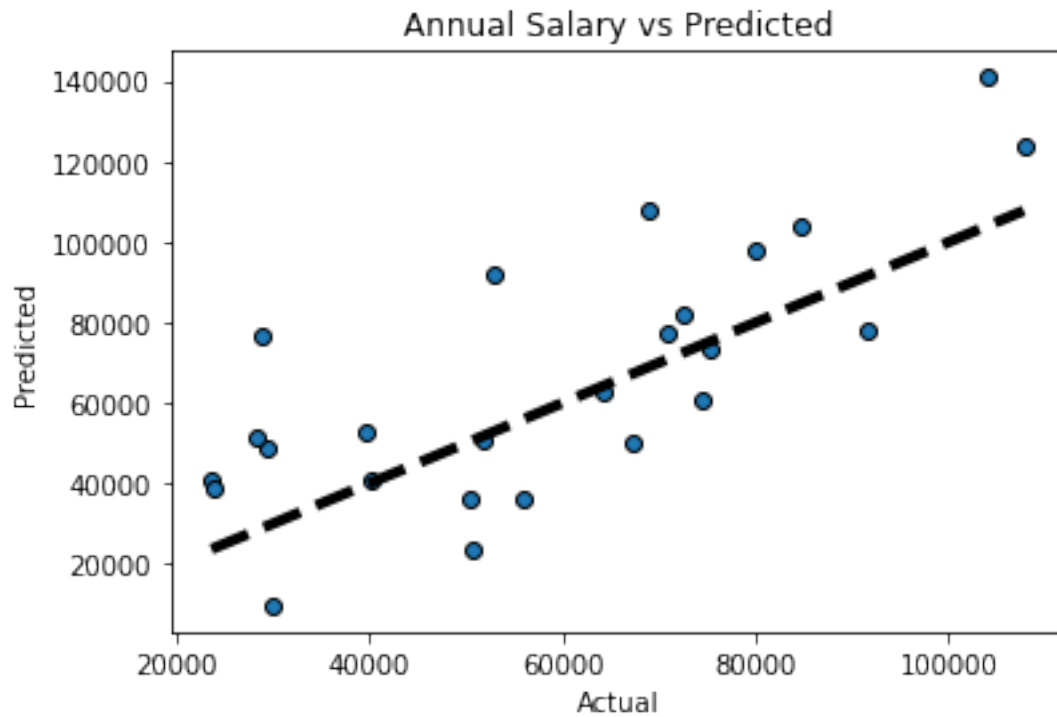
## plot title
plt.title("Residual errors")

## function to show plot
plt.show()

```



```
[64]: # Plot of predicted salary against actual salary
fig, ax = plt.subplots()
ax.scatter(y_test, y_predict, edgecolors=(0, 0, 0))
ax.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=4)
ax.set_xlabel('Actual')
ax.set_ylabel('Predicted')
ax.set_title("Annual Salary vs Predicted")
plt.show()
```



0.1.2 Desicion Tree

```
[79]: # Instantiate model
      clf = DecisionTreeRegressor(max_depth=5,random_state=0)

      # Fit model
      clf = clf.fit(x_train,y_train)

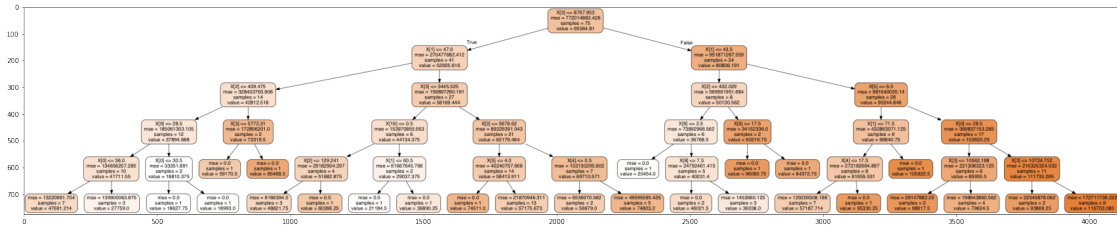
      # Print the R-squared value for the model
      clf.score(x_train, y_train)

      y_predict_2 = clf.predict(x_test)

      y_predict_2
```

```
[79]: array([ 56979.      ,  96060.75    ,  57187.71428571,  57175.67307692,
        74803.2     ,  98617.5     , 105922.5     ,  48821.75     ,
        57175.67307692,  48821.75    ,  56979.      ,  74803.2     ,
        74511.      ,  56979.      ,  47691.21428571,  18993.      ,
        36038.      ,  27759.      ,  47691.21428571,  74803.2     ,
        115703.08333333,  57187.71428571,  60266.25    ,  56979.      ,
        79624.5      ])
```

```
[85]: plt.figure(figsize = (30, 15))
dot_data=tree.export_graphviz(clf,filled=True,rounded=True)
graph=pydotplus.graph_from_dot_data(dot_data)
graph.write_png('tree.png')
plt.imshow(plt.imread('tree.png'));
```



```
[80]: # RMSE
print(np.sqrt(metrics.mean_squared_error(y_test, y_predict_2)))
```

27051.730726294394

[]: