ANZ

Data@ANZ

Virtual Experience Program

PREDICTIVE ANALYTICS

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Predictive Analytics

In [1]:
```
#importing packages for data analysis
import pandas as pd
import numpy as np

#importing packages for data visualization
import seaborn as sns
sns.set()
import matplotlib.pyplot as plt
import matplotlib.dates
import datetime

#allows charts to appear in the notebook
%matplotlib inline

#setting plot stuyle
plt.style.use('ggplot')

#ignoring warnings
import warnings
warnings.filterwarnings("ignore")

#setting column display
pd.options.display.max_columns = None
```

In [2]:
```
#importing dataset
df_original = pd.read_excel('ANZ synthesised transaction dataset.xlsx')
```

In [3]:
```
df_original.head()
```

Out[3]:

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

In [4]:
```
column_list = df_original.columns.tolist()
for column in column_list:
    print( column, ':', df_original[column].nunique())
```

```
status : 2
card_present_flag : 2
```

```
bpay_biller_code : 3
account : 100
currency : 1
long_lat : 100
txn_description : 6
merchant_id : 5725
merchant_code : 1
first_name : 80
balance : 12006
date : 91
gender : 2
age : 33
merchant_suburb : 1609
merchant_state : 8
extraction : 9442
amount : 4457
transaction_id : 12043
country : 1
customer_id : 100
merchant_long_lat : 2703
movement : 2
```

In [5]:
```
df_original['movement'].value_counts()
```

Out[5]:
```
debit     11160
credit      883
Name: movement, dtype: int64
```

The above piece of code shows the number of unique values in each of the columns. Here we are particularly interested in the 'movement' column and we have found out that there are only two types of transaction took place. Hence we create two columns in the dataframe showing the debit and credit amounts.

Adding Debit & Credit Amount Columns in Dataframe

In [6]:
```
df = df_original.copy()
df['Debit_amount'] = np.where(df_original['movement'] == 'debit', df_orig
inal['amount'], np.nan)
df['Credit_amount'] = np.where(df_original['movement'] == 'credit', df_or
iginal['amount'], np.nan)
df
```

Out[6]:

	status	card_present_flag	bpay_biller_code	account	currency	long_lat	txn_descripti
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

...	...	...	...	...	...	...	
12038	authorized	0.0	NaN	ACC-3021093232	AUD	149.83 -29.47	PO
12039	authorized	1.0	NaN	ACC-1608363396	AUD	151.22 -33.87	SALES-PO
12040	authorized	1.0	NaN	ACC-3827517394	AUD	151.12 -33.89	PO
12041	authorized	1.0	NaN	ACC-2920611728	AUD	144.96 -37.76	SALES-PO
12042	authorized	1.0	NaN	ACC-1443681913	AUD	150.92 -33.77	SALES-PO

12043 rows × 25 columns

Executing the following piece of code, we get a glimpse of some summery statistics. We can see debit amount on an average in 52.57 AUD, whereas mean credit amount is much higher, which is 1898.73 AUD.

In [7]:
```
df.describe()
```

Out[7]:

	card_present_flag	merchant_code	balance	age	amount	Debit_amount
count	7717.000000	883.0	12043.000000	12043.000000	12043.000000	11160.000000
mean	0.802644	0.0	14704.195553	30.582330	187.933588	52.572343
std	0.398029	0.0	31503.722652	10.046343	592.599934	156.354143
min	0.000000	0.0	0.240000	18.000000	0.100000	0.100000
25%	1.000000	0.0	3158.585000	22.000000	16.000000	15.190000
50%	1.000000	0.0	6432.010000	28.000000	29.000000	26.930000
75%	1.000000	0.0	12465.945000	38.000000	53.655000	45.000000
max	1.000000	0.0	267128.520000	78.000000	8835.980000	7081.090000

Calculating Percentage of Missing Values in Each Column

In [8]:
```
df.isna().sum()/len(df) * 100
```

Out[8]:
```
status                0.000000
card_present_flag    35.921282
bpay_biller_code     92.651333
account               0.000000
currency              0.000000
long_lat              0.000000
txn_description       0.000000
merchant_id          35.921282
merchant_code        92.667940
first_name            0.000000
balance               0.000000
date                  0.000000
```

```
gender                0.000000

age                   0.000000
merchant_suburb      35.921282
merchant_state       35.921282
extraction            0.000000
amount                0.000000
transaction_id        0.000000
country               0.000000
customer_id           0.000000
merchant_long_lat    35.921282
movement              0.000000
Debit_amount          7.332060
Credit_amount        92.667940
dtype: float64
```

From the above piece of code, we get some information about missing values, which should be dealt carefully in order to do further analysis. Here we gather an idea about dropping columns with highest number of missing values.

Extracting Customer Details

We want to extract details of each customer through running the following code.

In [9]:
```
customer_details = df.groupby(['customer_id'])
customer_details
```

Out[9]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x000000000C778A0
8>
```

We proceed towards our target of creating a new dataframe which is suitable for data analysis.

In [10]:
```
df1 = customer_details.apply(lambda x: x['transaction_id'].count())
df2 = customer_details.apply(lambda x: x['Debit_amount'].count())
df3 = customer_details.apply(lambda x: x['Debit_amount'].sum())
df4 = customer_details.apply(lambda x: x['Credit_amount'].count())
df5 = customer_details.apply(lambda x: x['Credit_amount'].sum())
```

In [11]:
```
frames = [df1,df2,df3,df4,df5]
col_names = ['total_tr_count','Debit_tr_count','total_Debit_amount','cred
it_transaction_count',
             'total_Credit_amount']
customer_df = pd.concat(frames, axis = 1, join = 'outer', keys = col_name
s)
customer_df
```

Out[11]:

	total_tr_count	Debit_tr_count	total_Debit_amount	credit_transaction_count	total_Credi
customer_id					
CUS-1005756958	73	60	3652.86	13	
CUS-1117979751	100	93	8933.82	7	
CUS-1140341822	80	74	5511.54	6	
CUS-1147642491	118	105	6732.75	13	
CUS-1196156254	245	238	8724.61	7	

...	...	...	...	...
CUS-72755508	58	46	2734.53	12
CUS-809013380	124	111	5328.18	13
CUS-860700529	233	227	7248.16	6
CUS-880898248	78	72	2858.57	6
CUS-883482547	178	171	8797.19	7

100 rows × 5 columns

We have till now built some part of our required dataframe. Now, we are using first() and last() for creating columns containing the information of opening (beginning of August) and closing balance (end of October) of the customers.

In [12]:
```
df6 = customer_details.first()
df7 = customer_details.last()
#There are some meaningless columns in df6 and df7 which will be dropped
 later.
```

In [13]:
```
df6['Opening_bal'] = np.where(df6['movement']=='debit', df6['balance']+df
6['amount'],
                              df6['balance']-df6['amount'])
```

In [14]:
```
df6['Closing_bal']= df7['balance']
```

In [15]:
```
final_customer_df = pd.DataFrame()
cluster_df = pd.DataFrame() #Required later for cluster analysis

cluster_df = pd.merge(df6,customer_df, on = 'customer_id')
drop_features = ['status','bpay_biller_code','currency','long_lat',
                 'card_present_flag','amount', 'merchant_id',
                 'merchant_code', 'balance','date','merchant_suburb','mer
chant_state',
                 'extraction','transaction_id', 'country','merchant_long_
lat','movement',
                 'Debit_amount', 'Credit_amount']
cluster_df.drop(drop_features, axis = 1, inplace = True )
final_customer_df = cluster_df.copy( deep = True )
final_customer_df.drop(['txn_description'], axis= 1 , inplace = True)
```

In [16]:
```
final_customer_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 100 entries, CUS-1005756958 to CUS-883482547
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   account             100 non-null    object
 1   first_name          100 non-null    object
 2   gender              100 non-null    object
 3   age                 100 non-null    int64
 4   Opening_bal         100 non-null    float64
 5   Closing_bal         100 non-null    float64
 6   total_tr_count      100 non-null    int64
 7   Debit_tr_count      100 non-null    int64
 8   total_Debit_amount  100 non-null    float64
```

```
 9   credit_transaction_count  100 non-null    int64

 10  total_Credit_amount       100 non-null    float64
dtypes: float64(4), int64(4), object(3)
memory usage: 9.4+ KB
```

Identification of Annual Salary

Here our task is to determine the annual salary of each of the customers.

In [17]:
```
ctn_count = final_customer_df['credit_transaction_count'].value_counts()
ctn_count
```

Out[17]:
```
6     28
13    27
7     24
14     8
12     5
2      4
4      2
5      1
3      1
Name: credit_transaction_count, dtype: int64
```

From the above output, we can see that there are 28 number of customers who have 6 credit transactions and so on. As all the credit transactions in the given dataset are of 'PAY/SALARY' type, hence we can use this data to calculate the annual salary of the customers. Here 6 and 7 credit transactions in 3 months imply the case of getting salary bi-weekly. Similarly, 12, 13 and 14 number of transactions indicate weekly arrival of salary and 3 number of credit transactions implies the event of monthly salary. All of the above conclusions can be drawn looking at the transaction dates and their intervals.But if we look closely on the remaining cases, suspicion arises and we want to extract more details related to the remaining credit transactions.

In [18]:
```
def credit_details(df,customer_id,customer_detail):
    list_of_customers = customer_detail.index.tolist()
    list_of_indices = [0,1,2]
    for x in list_of_indices:
        try:
            each_customer_details = df[df[customer_id] == list_of_custome
rs[x]]
            customer_credit_details = each_customer_details[each_customer
_details['Credit_amount'].notnull()]
            credit_related_details = customer_credit_details[['account',
'txn_description','customer_id','date',
                                                        'Credit_amount','trans
action_id']]
            print(credit_related_details.set_index('customer_id'))
        except Exception:
            continue
```

In [19]:
```
suspected = ctn_count.index.tolist()[5:]
suspected
```

Out[19]:
```
[2, 4, 5, 3]
```

In [20]:
```
for count in suspected:
    suspected_customer_details = final_customer_df[final_customer_df['cre
dit_transaction_count']
                                                        == count]
    print('Number of Credit Transactions : ', count)
```

```
    with pd.option_context('expand_frame_repr', False):
            credit_details(df,'customer_id', suspected_customer_details
)
```

```
Number of Credit Transactions :  2
                       account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-1739931018  ACC-1217063613      PAY/SALARY 2018-09-26        4863.62

8659baa692924427aefbf4077c5a9d67
CUS-1739931018  ACC-1217063613      PAY/SALARY 2018-10-26        4863.62
e6d8f31d269d4e8388e115719a59dd98
                       account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-2178051368  ACC-3100725361      PAY/SALARY 2018-09-26        6107.23
7eb1fdb7aefb40d1a8ada1d27f556542
CUS-2178051368  ACC-3100725361      PAY/SALARY 2018-10-26        6107.23
56e1a0f55f354624a3c713c37415d216
                     account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-497688347  ACC-211792489      PAY/SALARY 2018-08-23        4910.9  2
b4ecc820d834f6ea016b40abbfbfde5
CUS-497688347  ACC-211792489      PAY/SALARY 2018-10-23        4910.9  1
c410d75288f4fbb832f88d7f612693b
Number of Credit Transactions :  4
                       account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-1816693151  ACC-1523339231      PAY/SALARY 2018-08-20        8835.98
b608ce5142664a79af4fa071a886c8f7
CUS-1816693151  ACC-1523339231      PAY/SALARY 2018-09-20        8835.98
854ded55d0034ac8b9e91e16334768ca
CUS-1816693151  ACC-1523339231      PAY/SALARY 2018-10-19        8835.98
873a3f11d03d41a99c55a5b1a3850e1a
CUS-1816693151  ACC-1523339231      PAY/SALARY 2018-10-19        8835.98
d996300131a641c8bf25f86e1aef9bc6
                       account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-2110742437  ACC-2270192619      PAY/SALARY 2018-08-06        3026.95
c1d51fe6ac554d37b93d57dba64d6674
CUS-2110742437  ACC-2270192619      PAY/SALARY 2018-09-06        3026.95
11372fe1819f48a8b0260bf3c046e4e0
CUS-2110742437  ACC-2270192619      PAY/SALARY 2018-10-05        3026.95
812d58434d704041aa033b5ae904efe9
CUS-2110742437  ACC-2270192619      PAY/SALARY 2018-10-05        3026.95
efbc0cb742af4879a122c99ae728354b
Number of Credit Transactions :  5
                      account txn_description       date  Credit_amount
transaction_id
customer_id
CUS-2376382098  ACC-354106658      PAY/SALARY 2018-08-15        5103.51
41ce67e6c8a4474385fd1646963b6758
CUS-2376382098  ACC-354106658      PAY/SALARY 2018-09-14        5103.51
188e04b6e00f44f3a43afbf232a6f5c3
CUS-2376382098  ACC-354106658      PAY/SALARY 2018-09-14        5103.51
7faf986ac5a341e3adfdb7030ec03f48
CUS-2376382098  ACC-354106658      PAY/SALARY 2018-10-15        5103.51
dfff2531d8434969b7f385d364772534
CUS-2376382098  ACC-354106658      PAY/SALARY 2018-10-15        5103.51
e4e7f0dd7c504c45990277dad7a8a86c
Number of Credit Transactions :  3
                      account txn_description       date  Credit_amount
```

```
transaction_id
customer_id
CUS-423725039  ACC-2153562714      PAY/SALARY 2018-08-24        3712.56
13d1b673d560462aa9b879f6b3730e39
CUS-423725039  ACC-2153562714      PAY/SALARY 2018-09-24        3712.56
8d7ddef22c7c4404b63137f3ebd1a6ff
CUS-423725039  ACC-2153562714      PAY/SALARY 2018-10-24        3712.56
fe1b1a6bdd9b43f7985acc4af7b0a101
```

Here, we have taken only 3 customers having suspicious number of credit transaction counts. Observing the above output, we can see the customer we have 2 credit transactions (on September and October) dated exactly with a difference of 1 month. Hence, we can assume that these customers may have engaged in a job since September, and hence their salary are considered to be arrived monthly.

Now, for the customers with 4 and 5 number of credit transactions, we observe that there are 2 credit transanctions of same amount on same date, which is unusual. The reason of this is assumed to be the Synthesisation of the dataset. Looking at the transaction dates, we can categorize them in the monthly salary class.

Calculating Annual Salary of Each customer

In [21]:
```python
#calculating wages
final_customer_df['wage'] = final_customer_df['total_Credit_amount'] / final_customer_df['credit_transaction_count']

final_customer_df['Annual_Salary'] = pd.Series()
#calculating annual salary
weekly = [12,13,14]
bi_weekly = [6,7]
monthly = [2,3,4,5]
for i in range(len(final_customer_df['credit_transaction_count'])):
    final_customer_df['Annual_Salary'][i] = np.where(final_customer_df['credit_transaction_count'][i]
                                             in weekly,final_customer_df['wage'][i] * 52,
                                             np.where(final_customer_df['credit_transaction_count'][i]
                                             in bi_weekly, final_customer_df['wage'][i] * 26,
                                                       final_customer_df['wage'][i]*12))
```

In [22]:
```python
pd.options.display.max_rows = None
final_customer_df[['Annual_Salary']]
```

Out[22]:

	Annual_Salary
customer_id	
CUS-1005756958	50464.44
CUS-1117979751	93044.90
CUS-1140341822	49829.26
CUS-1147642491	88992.28
CUS-1196156254	101496.98
CUS-1220154422	59341.36
CUS-1233833708	31009.16
CUS-1271030853	60223.80

CUS-127297539	59217.08
CUS-134193016	52615.68
CUS-134833760	98430.28
CUS-1388323263	54242.24
CUS-1433879684	36610.08
CUS-1462656821	101502.70
CUS-1478398256	94887.26
CUS-1499065773	64231.70
CUS-1604596597	65000.00
CUS-1609060617	74223.24
CUS-1614226872	46388.68
CUS-1617121891	86548.02
CUS-164374203	72565.48
CUS-1646183815	40685.84
CUS-1646621553	57143.32
CUS-1654129794	29952.00
CUS-1669695324	63717.16
CUS-1739931018	58363.44
CUS-1790886359	79849.64
CUS-1816693151	106031.76
CUS-1842679196	39589.16
CUS-1892177589	75070.84
CUS-1896554896	60025.42
CUS-1928710999	64619.62
CUS-2031327464	118578.72
CUS-2059096722	81130.40
CUS-2083971310	75049.52
CUS-2110742437	36323.40
CUS-2142601169	52110.76
CUS-2155701614	127048.48
CUS-2178051368	73286.76
CUS-2206365095	40069.12
CUS-2283904812	57686.98
CUS-2317998716	68633.76
CUS-2348881191	54639.26
CUS-2370108457	56678.96
CUS-2376382098	61242.12
CUS-2484453271	42661.58
CUS-2487424745	52710.84
CUS-2500783281	84576.96
CUS-2505971401	101221.64
CUS-2599279756	42389.36
CUS-261674136	114537.80

CUS-2630892467	47876.92
CUS-2650223890	44873.40
CUS-2663907001	105424.02
CUS-2688605418	60327.80
CUS-2695611575	47707.40
CUS-2738291516	132327.52
CUS-2819545904	84012.76
CUS-2977593493	37361.48
CUS-3026014945	73843.90
CUS-3117610635	70681.26
CUS-3129499595	51804.48
CUS-3142625864	134576.52
CUS-3151318058	45703.32
CUS-3174332735	95600.44
CUS-3180318393	72603.96
CUS-3201519139	47671.00
CUS-3249305314	97809.40
CUS-325142416	59972.38
CUS-3255104878	34550.36
CUS-326006476	51134.72
CUS-331942311	47921.64
CUS-3325710106	57184.40
CUS-3336454548	107437.98
CUS-3378712515	55111.68
CUS-3395687666	45703.06
CUS-3431016847	50153.22
CUS-3462882033	83070.26
CUS-3702001629	39979.68
CUS-3716701010	66168.44
CUS-3904958894	43721.08
CUS-3989008654	69884.10
CUS-4023861240	66005.68
CUS-4123612273	55538.08
CUS-4142663097	91457.86
CUS-423725039	44550.72
CUS-443776336	51508.60
CUS-495599312	68831.88
CUS-497688347	58930.80
CUS-511326734	51100.92
CUS-51506836	72293.88
CUS-527400765	109617.04
CUS-537508723	66895.66
CUS-55310383	85109.44
[illegible]	[illegible]

CUS-586638664	50759.54
CUS-72755508	37716.64
CUS-809013380	53927.64
CUS-860700529	47024.12
CUS-880898248	37283.48
CUS-883482547	103413.96

In [23]:
```
final_customer_df['Quarterly_savings_amount'] = final_customer_df['total_
Credit_amount'] - final_customer_df['total_Debit_amount']
```

In [24]:
```
pd.options.display.max_rows = 10
final_customer_df
```

Out[24]:

	account	first_name	gender	age	Opening_bal	Closing_bal	total_tr_count	Debit_t
customer_id								
CUS-1005756958	ACC-2828321672	Stephanie	F	53	470.44	9310.03	73	
CUS-1117979751	ACC-4065652575	Lucas	M	21	2390.35	18387.41	100	
CUS-1140341822	ACC-80388494	Dustin	M	28	832.74	6820.26	80	
CUS-1147642491	ACC-3233697971	Robin	F	34	14.89	15387.21	118	
CUS-1196156254	ACC-3485804958	Jessica	F	34	12563.48	30899.53	245	
...	...	...	...	...	...	...	...	
CUS-72755508	ACC-53508546	Kimberly	F	35	341.93	7036.56	58	
CUS-809013380	ACC-1990648130	Kaitlyn	F	21	1718.38	9872.11	124	
CUS-860700529	ACC-1903037542	Jeffrey	M	30	13.64	5243.81	233	
CUS-880898248	ACC-2970114956	Robert	M	26	5288.87	12346.59	78	
CUS-883482547	ACC-1710017148	Michelle	F	19	1654.87	20699.90	178	

100 rows × 14 columns

Finally we have created our final Desired dataframe.

1. Multiple Linear Regression Model

Selecting Important Columns for MLR

In [25]:
```
cluster_df1 = final_customer_df.copy() #Later required for clustering usi
ng 2 variables
regression_drop = ['account','first_name','wage','Quarterly_savings_amoun
t']
regression_df = final_customer_df.drop(regression_drop, axis = 1)
```

In [26]:
```
regression_df.head()
```

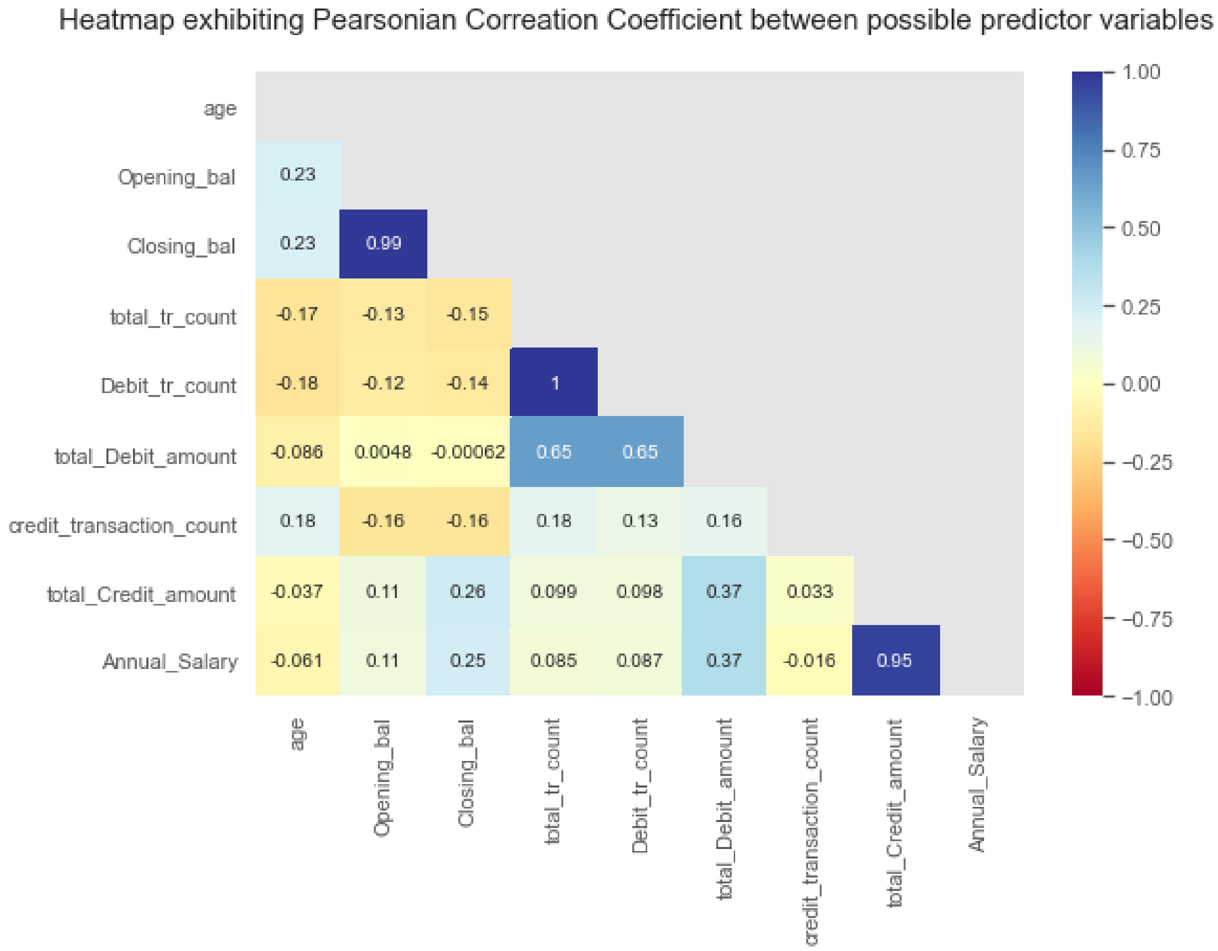
Out[26]:

customer_id	gender	age	Opening_bal	Closing_bal	total_tr_count	Debit_tr_count	total_Debit_amo
CUS-1005756958	F	53	470.44	9310.03	73	60	3652
CUS-1117979751	M	21	2390.35	18387.41	100	93	8933
CUS-1140341822	M	28	832.74	6820.26	80	74	5511
CUS-1147642491	F	34	14.89	15387.21	118	105	6732
CUS-1196156254	F	34	12563.48	30899.53	245	238	8724

Checking correlation between possible regressor variables

In [27]:

```
corr_matrix = np.triu(regression_df.corr())
plt.figure(figsize = (9,6))
plt.title('Heatmap exhibiting Pearsonian Correation Coefficient between p
ossible predictor variables \n'
          , fontsize = 15)
sns.heatmap(regression_df.corr(), cmap = 'RdYlBu', annot = True,  vmin =
-1, vmax = 1
            , mask = corr_matrix);
```



Dropping columns implying presence of multicolinearity

In [28]:

```
features_to_drop = ['Opening_bal','total_tr_count']
regression_df = regression_df.drop(features_to_drop, axis = 1)
```

Creating Dummy Variables for Gender (Categorical) column

In [29]:
```
regression_df = pd.get_dummies(regression_df, prefix = 'gender')
regression_df.rename( columns = {'gender_F' : 'Female', 'gender_M' : 'Mal
e'}, inplace = True )
```

In [30]:
```
regression_df
```

Out[30]:

	age	Closing_bal	Debit_tr_count	total_Debit_amount	credit_transaction_count	total_Cr
customer_id						
CUS-1005756958	53	9310.03	60	3652.86	13	
CUS-1117979751	21	18387.41	93	8933.82	7	
CUS-1140341822	28	6820.26	74	5511.54	6	
CUS-1147642491	34	15387.21	105	6732.75	13	
CUS-1196156254	34	30899.53	238	8724.61	7	
...	...	...	...	...	...	
CUS-72755508	35	7036.56	46	2734.53	12	
CUS-809013380	21	9872.11	111	5328.18	13	
CUS-860700529	30	5243.81	227	7248.16	6	
CUS-880898248	26	12346.59	72	2858.57	6	
CUS-883482547	19	20699.90	171	8797.19	7	

100 rows × 9 columns

Here feature scaling is not done as it will not effect the model significantly.

Fitting Multiple Linear Regression Model

In [31]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

target = regression_df['Annual_Salary']
predictors = regression_df.drop(['Annual_Salary'], axis = 1)

X_train, X_test, y_train, y_test = train_test_split(predictors, target, t
est_size=0.2, random_state=0)
```

In [32]:
```
regressor = LinearRegression()
clf = regressor.fit(X_train, y_train)
```

Getting Regression coefficients and intercept

In [33]:
```
#To retrieve the intercept:
print(regressor.intercept_)
```

```
#For retrieving the slope:
print(regressor.coef_)
```

```
12890.359181656793
[-4.50633110e+01 -1.09021035e-02 -1.55295874e+01  6.49463246e-01
 -2.49647810e+02  3.31800819e+00 -9.85562022e+02  9.85562022e+02]
```

In [34]:
```
y_pred = regressor.predict(X_test)
result_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred })
result_df
```

Out[34]:

	Actual	Predicted
customer_id		
CUS-1790886359	79849.64	83916.971102
CUS-443776336	51508.60	52554.953525
CUS-1140341822	49829.26	51626.234954
CUS-2695611575	47707.40	51204.367504
CUS-3395687666	45703.06	47115.260246
...	...	...
CUS-1896554896	60025.42	59313.725816
CUS-1646621553	57143.32	62973.755290
CUS-1669695324	63717.16	61556.096422
CUS-2059096722	81130.40	78755.289662
CUS-127297539	59217.08	58474.098412

20 rows × 2 columns

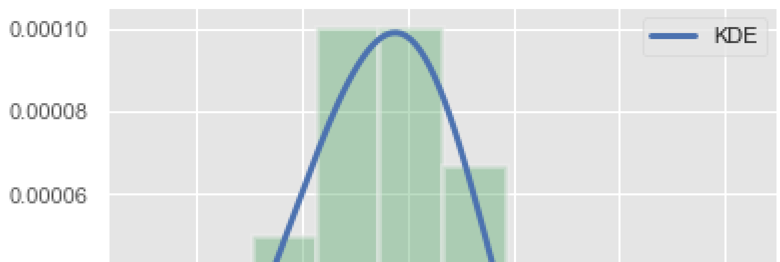
We have perfectly fitted our linear regression model. Now we want to check some basic assumptions of the linear regression. One of the most important assumption is normality of the errors. There are multiple methods of checking normality. Graphical method involves histogram and Q-Q plot whereas hypothesis testing method involves Shapiro-Wilk Test, Anderson-Darling test, Kolmogorov-Smirnov. We have used both graphical and hypothesis testing method to check the model assumption of normality.

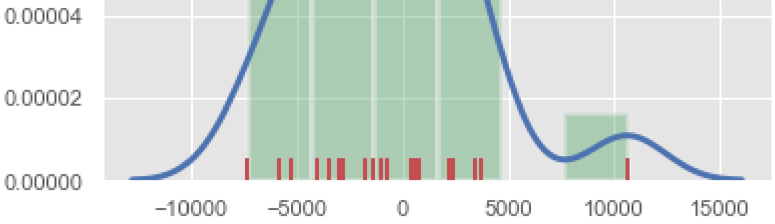
Normality Test :

1. Graphical Method (Histogram)

In [35]:
```
#finding errors = y_hat - y
error = result_df['Actual'] - result_df['Predicted']
```

In [36]:
```
plt.style.use('ggplot')
plt.figure()
sns.distplot(error, kde = True, rug = True,  rug_kws = {'linewidth': 2,
'color' : 'r'},
             hist_kws = {'linewidth': 3, 'color': 'g'},
            kde_kws = {'color' : 'b', 'lw': 3, 'label': 'KDE'});
```





From the above Histogram with kernel density estimate, we can visually conclude that the error distribution has not deviated very much from the normal distribution. Now we check using hypothesis testing.

2. Using Test Statistics (Shapiro-Wilk and Anderson-Darling Test)

In [37]:

```
print('Test Results of Shapiro-Wilk Test : ') # Good test for less than 5000 samples
from scipy import stats
shapiro_test = stats.shapiro(error)
print('Statistic : %.3f' % shapiro_test.statistic)
p_value = 0.05
if shapiro_test.pvalue > p_value:
    print('Fails to reject the null hypothesis of normality at 5% level of significance')
else:
    print( 'Rejects the null hypothesis of normality at 5% level of significance')


print( '\n')

print('Test Results of Anderson-Darling Test :')
anderson = stats.anderson(error)
print('Statistic: %.3f' % anderson.statistic)
for i in range(len(anderson.critical_values)):
    sl = anderson.significance_level[i]
    if anderson.statistic < anderson.critical_values[i]:
        print('Fails to reject the null hypothesis of normality at %d%% level of significance' % sl)
    else:
        print( 'Rejects the null hypothesis of normality at %d%% level of significance' % sl)
```

```
Test Results of Shapiro-Wilk Test :
Statistic : 0.951
Fails to reject the null hypothesis of normality at 5% level of significance


Test Results of Anderson-Darling Test :
Statistic: 0.273
Fails to reject the null hypothesis of normality at 15% level of significance
Fails to reject the null hypothesis of normality at 10% level of significance
Fails to reject the null hypothesis of normality at 5% level of significance
Fails to reject the null hypothesis of normality at 2% level of significance
Fails to reject the null hypothesis of normality at 1% level of significance
```

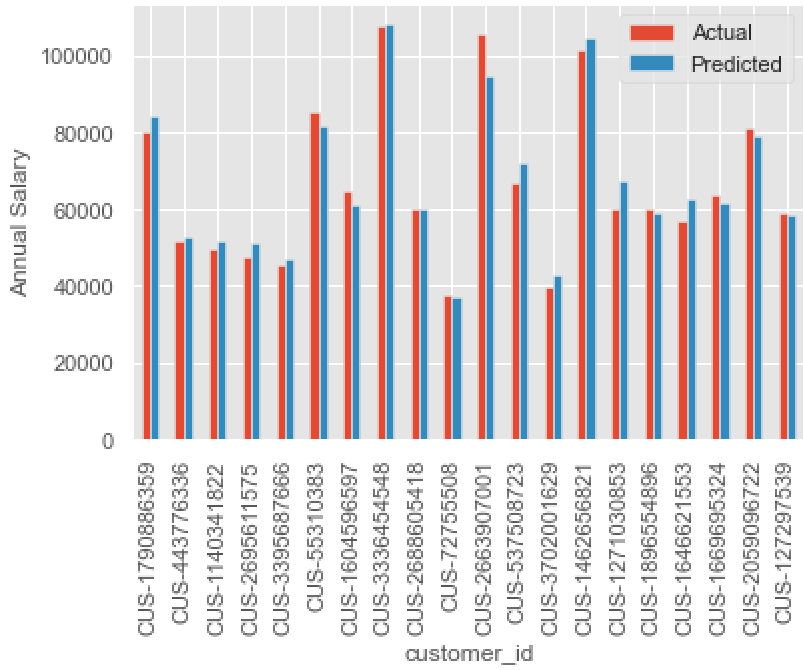
From the above hypothesis tests, we can conclude that there is no significant violation of model assumptions.Also, we have already tried to eliminate the possibility of existence of multicollinearity.

Hence, it is perfect to apply Linear Regression model in the current dataset.

Graphical Comparison of Actual and Predicted Salary

In [64]:
```
result_df.plot(kind='bar')

#plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
#plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.ylabel('Annual Salary')
plt.show()
```



Checking Model Accuracy

In [39]:
```
def mape(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred
))
print('Mean Absolute Percentage Error: ', mape(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_te
st, y_pred )))
```

```
Mean Absolute Error: 3073.7885564645176
Mean Absolute Percentage Error:  4.636103050955255
Mean Squared Error: 15917509.691530734
Root Mean Squared Error: 3989.6753867364614
```

Here we have computed different measures of model accuracy. RMSE is about 3989 which is quite large, hence the linear regresson model performance is not ideal for this data.

On the other hand, We get a MAPE value of 4.64%. Hence, we can conclude that the multiple linear regression model has performed moderately well as a predictive model for the given dataset. Now we look forward to another popular supervised machine learning algorithm.

2. Decision Tree Regression

Fitting the Model using RandomizedSearchCV

In this cross validation method, we have to create a list of possible values for different arguments in the function. Then using param_gridargument we have to provide our created set of possible parameter values and as the regressor argument we have to provide the regressor function (here DTR) This RandomizedSearchCV function then checks taking combination of arguments randomly and provides us the best accuracy score and that combination of arguments.

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(predictors, target, t
est_size = 0.2, random_state=0)
from sklearn.model_selection import RandomizedSearchCV
model_params = { 'criterion' : [ "mse", "friedman_mse", "mae"] ,'splitte
r' : ["best", "random"],
                'max_depth' : [2,3,4,5], 'min_samples_split' : [10,12,13,
14,15,16,18,20] ,
               'max_features' : ["auto", "sqrt", "log2"] }

from sklearn.tree import DecisionTreeRegressor # Import Decision Tree Reg
ressor
model = DecisionTreeRegressor()

# Creating Decision Tree regressor object
clf1 = RandomizedSearchCV(model, model_params, n_iter = 10000, cv = 10)

# Train Decision Tree regressor
clf1 = clf1.fit(X_train,y_train)
#Predict the response for test dataset
y_pred = clf1.predict(X_test)

#clf.score(X_test, y_test)
result_df1 = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred })
print(result_df1)
```

```
                  Actual      Predicted
customer_id
CUS-1790886359  79849.64   90769.986667
CUS-443776336   51508.60   53672.357143
CUS-1140341822  49829.26   46295.087273
CUS-2695611575  47707.40   46295.087273
CUS-3395687666  45703.06   46295.087273
...                  ...            ...
CUS-1896554896  60025.42   53672.357143
CUS-1646621553  57143.32   61793.524000
CUS-1669695324  63717.16   61793.524000
CUS-2059096722  81130.40   69159.090000
CUS-127297539   59217.08   61793.524000

[20 rows x 2 columns]
```

In [41]:
```
from pprint import pprint
pprint(clf1.best_estimator_.get_params())
```

```
{'criterion': 'mse',
 'max_depth': 5,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 13,
 'min_weight_fraction_leaf': 0.0,
 'presort': False,
 'random_state': None
```

```
 'random_state': None,
 'splitter': 'best'}
```

We have also used another cross validation technique namely GridSearchCV which produces similar results but it takes all possible combination of arguments. But, this technique does not improved the result significantly.

Checking Model Accuracy

In [42]:
```
from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred
))
print('Mean Absolute Percentage Error: ', mape(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_te
st, y_pred )))
```

```
Mean Absolute Error: 4784.111705411255
Mean Absolute Percentage Error:  6.534526554431901
Mean Squared Error: 41761375.064742595
Root Mean Squared Error: 6462.304160649094
```

In [43]:
```
clf1.score(X_test, y_test)
```

Out[43]:
```
0.898686732967573
```

As we can see, DTR has RMSE of about 6462, amlost double than multiple linear regression model and its MAPE score is 6.53% which is again larger than MLR model. Hence, we can conclude, multiple linear regression model has performed better in this predictive data analysis.

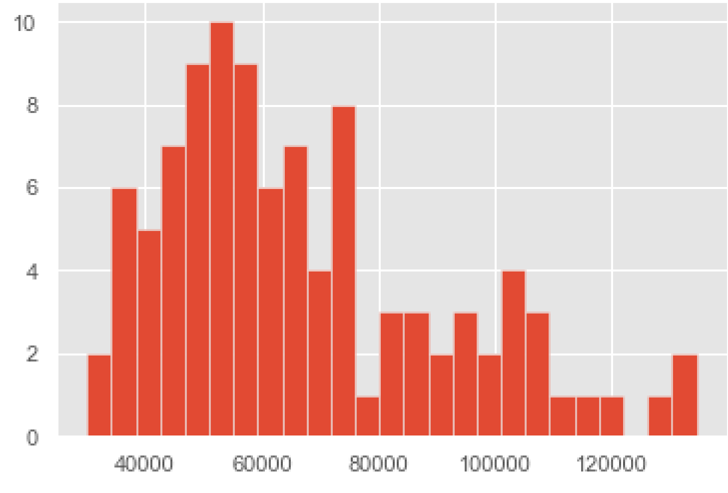
But if we look individually, the DTR model has accuracy score of 89.9% which is quite good. Hence we can say that our model has performed well.

Now we will discuss One way of improving the model accuracy by using decision tree classifier.

Using Decision Tree Classifier

We know in case of DTC, the target variable should be categorical. Hence, in order to implement this model, we have to modify the target variable accordingly. One way is creating class intervals of annual salary and label encode them.

In [44]:
```
plt.figure()
plt.hist(regression_df['Annual_Salary'], bins = 25);
```



As seen from the above graph, even if we categorize and label encode the customers annual salary into 25 classes, there will be salary intervals of length around 4500 AUS, hence it will yield crude outputs, exact estimate can not be predicted. But this is one way to use the decision tree classifier algorithm and if we take more than 25 classes, it may yield good result.

Data Segmentation Using Cluster Analysis Technique

In [45]:
```
cluster_df = pd.get_dummies(cluster_df, columns = ['gender', 'txn_descrip
tion'] )
```

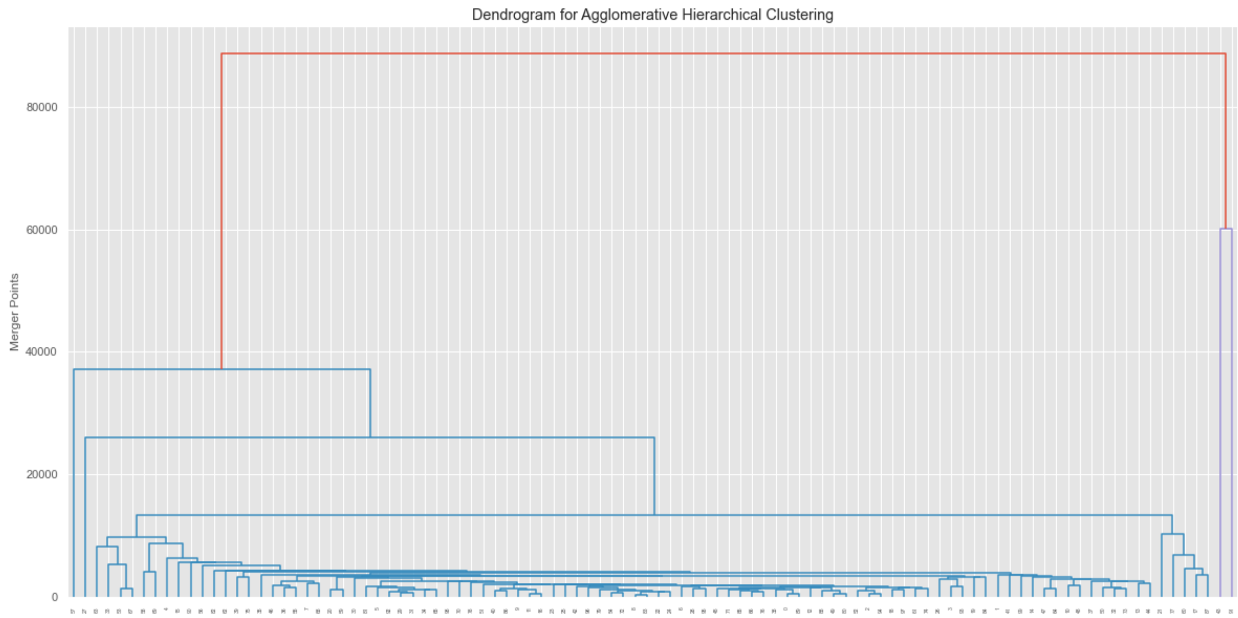
In [46]:
```
cluster_df.drop(['account','first_name','total_tr_count','Opening_bal'],
axis = 1, inplace = True )
```

Hierarchical Clustering Algorithm

Here we create the distance matrix using Euclidean distance metric and then single linkage Agglomerative Hierarchical Clustering method is used to create a dendrogram which serves the purpose of finding optimal number of clusters visually as well as creates a nested set of partitions of the given dataset.

In [47]:
```
plt.figure(figsize = (20,10))
import scipy.cluster.hierarchy as hc
dendrogram = hc.dendrogram(hc.linkage(cluster_df, method = 'single'))

plt.title('Dendrogram for Agglomerative Hierarchical Clustering')
plt.ylabel('Merger Points', fontsize = 12)
plt.show()
```



In [48]:
```
from sklearn.cluster import AgglomerativeClustering
ahc = AgglomerativeClustering(n_clusters = 3  , affinity = 'euclidean', l
inkage = 'single')
y_ahc = ahc.fit_predict(cluster_df)
print(y_ahc)
```

```
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
```

In [49]:
```
np.unique(y_ahc, return_counts = True ) # Counting class frequency
```
Out[49]:
```
(array([0, 1, 2], dtype=int64), array([98,  1,  1], dtype=int64))
```

Based on the above output we can say that the clustering algorithm based on the whole data performed very poorly. Hence we look for other data segmentation ideas.

Clustering based on two variables

Age vs Closing Balance

In [50]:
```
cluster_df1
```
Out[50]:

customer_id	account	first_name	gender	age	Opening_bal	Closing_bal	total_tr_count	Debit_t
CUS-1005756958	ACC-2828321672	Stephanie	F	53	470.44	9310.03	73	
CUS-1117979751	ACC-4065652575	Lucas	M	21	2390.35	18387.41	100	
CUS-1140341822	ACC-80388494	Dustin	M	28	832.74	6820.26	80	
CUS-1147642491	ACC-3233697971	Robin	F	34	14.89	15387.21	118	
CUS-1196156254	ACC-3485804958	Jessica	F	34	12563.48	30899.53	245	
...	...	...	...	...	...	...	...	
CUS-72755508	ACC-53508546	Kimberly	F	35	341.93	7036.56	58	
CUS-809013380	ACC-1990648130	Kaitlyn	F	21	1718.38	9872.11	124	
CUS-860700529	ACC-1903037542	Jeffrey	M	30	13.64	5243.81	233	
CUS-880898248	ACC-2970114956	Robert	M	26	5288.87	12346.59	78	
CUS-883482547	ACC-1710017148	Michelle	F	19	1654.87	20699.90	178	

100 rows × 14 columns

Feature Scaling

In [51]:
```
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler()

c_age_sal = pd.DataFrame()
c_age_sal  = cluster_df1[[ 'age','Closing_bal' ]]
c_age_sal[['Closing_bal' ]] = minmax.fit_transform(c_age_sal[[ 'Closing_b
al' ]])
```

In [52]:
```
c_age_sal #scaled dataset
```
Out[52]:

customer_id	age	Closing_bal

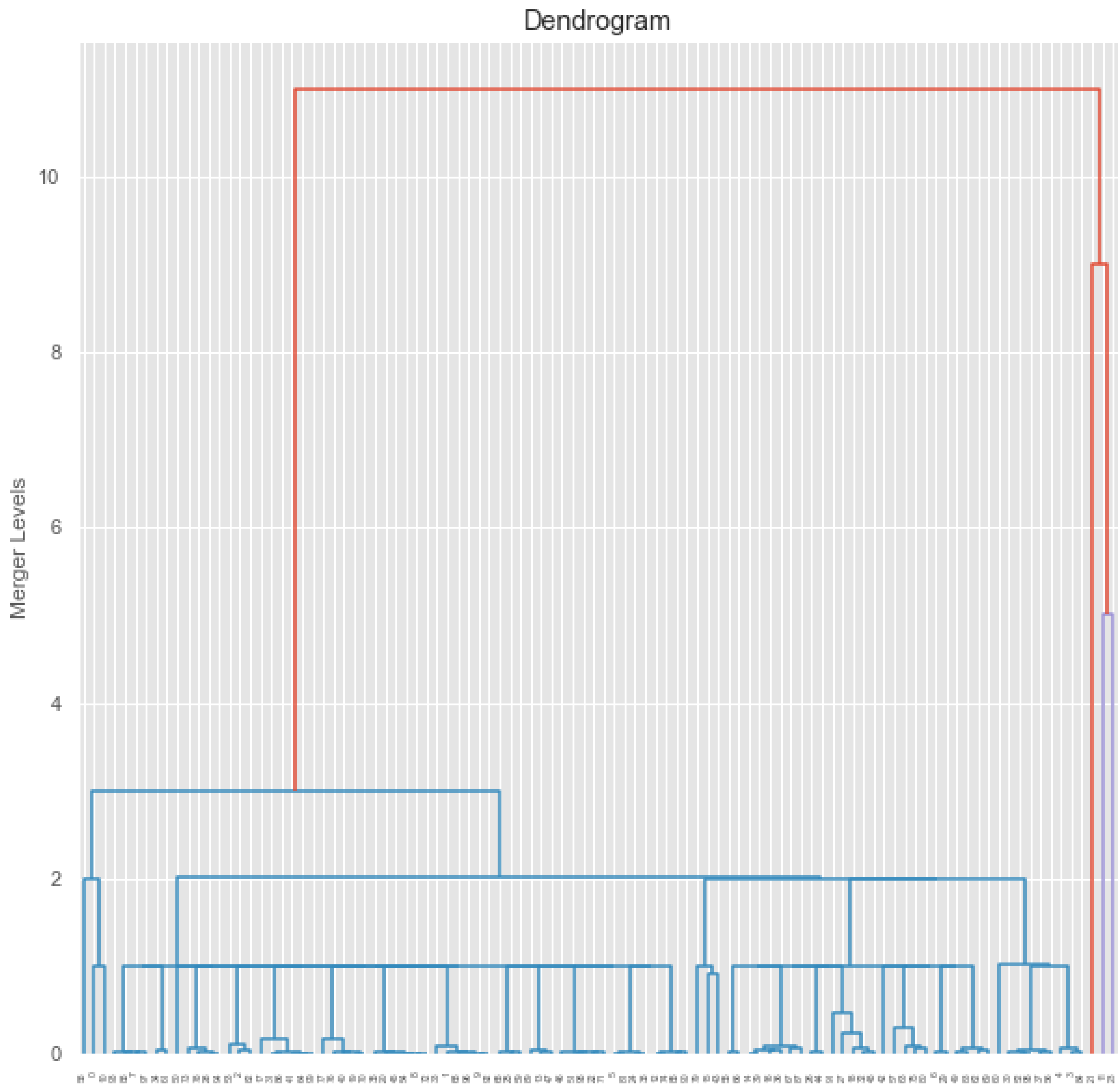
CUS-1005756958	53	0.027127
CUS-1117979751	21	0.061445
CUS-1140341822	28	0.017714
CUS-1147642491	34	0.050102
CUS-1196156254	34	0.108749
...	...	...
CUS-72755508	35	0.018532
CUS-809013380	21	0.029252
CUS-860700529	30	0.011754
CUS-880898248	26	0.038607
CUS-883482547	19	0.070188

100 rows × 2 columns

Implementing Hierarchical Clustering Algorithm

In [53]:
```
plt.figure(figsize = (10,10))
import scipy.cluster.hierarchy as hc
dendrogram = hc.dendrogram(hc.linkage(c_age_sal, method = 'single'))

plt.title('Dendrogram')
plt.ylabel('Merger Levels')
plt.show()
```



In [54]:
```
from sklearn.cluster import AgglomerativeClustering
ahc = AgglomerativeClustering(n_clusters = 3  , affinity = 'euclidean', l
inkage = 'single')
y_ahc = ahc.fit_predict(c_age_sal)
print(y_ahc)
```

```
[1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 2 1 0 1 1 1 1 1 1 1 1 1 1 1 1
1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```

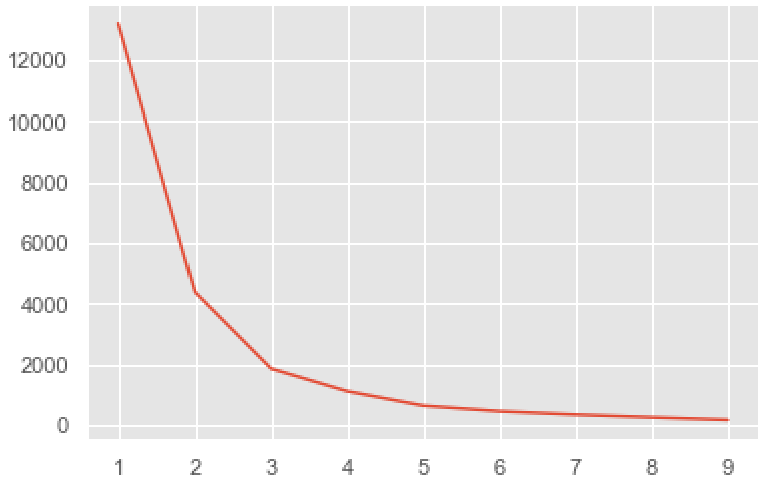
In [55]:
```
np.unique(y_ahc, return_counts = True)
```

Out[55]:
```
(array([0, 1, 2], dtype=int64), array([ 2, 97,  1], dtype=int64))
```

From the above output,we can conclude Hierarchical clustering performed very poorly. Hence, we proceed to do clustering using a non-hierarchical algorithm namely k-means clustering.

K-Means Clustering Algorithm

In [56]:
```
from sklearn.cluster import KMeans
wcss = []
for i in range(1,10):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 10000,
n_init = 20,
                   random_state = 0)
    kmeans.fit(c_age_sal)
    wcss.append(kmeans.inertia_)
plt.plot(range(1,10), wcss)
# plt.title()
# plt.xlabel()
# plt.ylabel()
plt.show()
```



In order to find the optimal number of clusters we use the elbow method where within cluster sum of squares is plotted against number of clusters. From the above figure, we can conclude that 3 clusters can be considered as the optimum number of clusters as there is a elbow formation near the value 3.

In [57]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 1000, n_in
it = 10, random_state = 42)
y_kmeans = kmeans.fit_predict(c_age_sal)
```

In [58]:
```
print(np.unique(y_kmeans, return_counts = True))
```

```
(array([0, 1, 2]), array([56, 41,  3], dtype=int64))
```

In [59]:
```
print(wcss)
```

```
[13195.56442041737, 4377.717974287569, 1859.101080561276, 1115.7228432666
263, 640.9358425487203, 457.9258719408131, 346.2506640443445, 257.6951897
0426236, 173.84115116141723]
```

In [60]:
```
c_age_sal['cluster'] = y_kmeans
```

In [61]:
```
c_age_sal[c_age_sal['cluster'] == 0 ].sort_values('Closing_bal')
```

Out[61]:

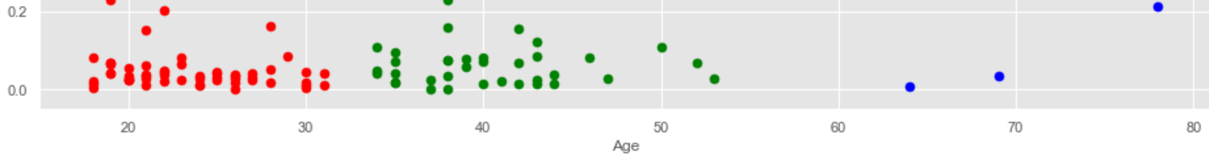
	age	Closing_bal	cluster
customer_id			
CUS-2487424745	26	0.000000	0
CUS-3702001629	18	0.003510	0
CUS-1271030853	30	0.004934	0
CUS-325142416	21	0.010630	0
CUS-860700529	30	0.011754	0
...	...	...	...
CUS-261674136	29	0.085597	0
CUS-2059096722	21	0.152010	0
CUS-2663907001	28	0.163550	0
CUS-3462882033	22	0.205496	0
CUS-1609060617	19	0.231023	0

56 rows × 3 columns

Visualizing the output

In [63]:
```
plt.figure(figsize = (16,6))
plt.scatter((c_age_sal[c_age_sal.cluster == 0 ]).age,
            (c_age_sal[c_age_sal.cluster == 0 ]).Closing_bal, s = 50, c=
'red', label = 'Middle Aged')
plt.scatter((c_age_sal[c_age_sal.cluster == 1 ]).age,
            (c_age_sal[c_age_sal.cluster == 1 ]).Closing_bal, s = 50, c=
'green', label = 'Young Aged')
plt.scatter((c_age_sal[c_age_sal.cluster == 2 ]).age,
            (c_age_sal[c_age_sal.cluster == 2 ]).Closing_bal, s = 50, c=
'blue', label = 'Old Aged')

plt.title('Clustering of customer based on age and closing balance')
plt.xlabel('Age')
plt.ylabel('Scaled Closing Balance')
plt.legend()
plt.show()
```



From the above output, we can see that based on age and closing balance, we have done the data segmentation quite successfully.Most of the persons have low closing balance, which is a bit unusual and it happened may be because of the synthesisation of the dataset.