ANZ synthesized transaction
(Task 2)

By: Atefeh Gholipour

Project Description

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	status	card_pres	bpay_	account	currency	long_lat	txn_descr	merchant_	merchant_	first_nam	balance	date	gend	age	merchant_	merchant_	extraction	amount	transactio	country	customer_	merchant_	movemen
2	authorize	1		ACC-1598	AUD	153.41 -27	POS	81c48296-73be-44a7-		Diana	35.39	8/1/2018	F	26	Ashmore	QLD	2018-08-0	16.25	a623070bf	Australia	CUS-2487	153.38 -27	debit
3	authorize	0		ACC-1598	AUD	153.41 -27	SALES-PO	830a451c-316e-4a6a-		Diana	21.2	8/1/2018	F	26	Sydney	NSW	2018-08-0	14.19	13270a2a	Australia	CUS-2487	151.21 -33	debit
4	authorize	1		ACC-1222	AUD	151.23 -33	POS	835c231d-8cdf-4e96-		Michael	5.71	8/1/2018	M	38	Sydney	NSW	2018-08-0	6.42	feb79e7e	Australia	CUS-2142	151.21 -33	debit
5	authorize	1		ACC-1037	AUD	153.10 -27	SALES-PO	48514682-c78a-4a88-		Rhonda	2117.22	8/1/2018	F	40	Buderim	QLD	2018-08-0	40.9	2698170d	Australia	CUS-1614	153.05 -26	debit
6	authorize	1		ACC-1598	AUD	153.41 -27	SALES-PO	b4e02c10-0852-4273-		Diana	17.95	8/1/2018	F	26	Mermaid	QLD	2018-08-0	3.25	329adf798	Australia	CUS-2487	153.44 -28	debit

Objective:

- Build a simple regression model to predict the annual salary for each customer

Dataset:

- Contains synthesised transaction of 3 months for 100 customers including inter bank, payment, phone bank, POS, sales-POS and salary transactions.

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12043 entries, 0 to 12042
Data columns (total 23 columns):
status               12043 non-null object
card_present_flag    7717 non-null float64
bpay_biller_code     885 non-null object
account              12043 non-null object
currency             12043 non-null object
long_lat             12043 non-null object
txn_description      12043 non-null object
merchant_id          7717 non-null object
merchant_code        883 non-null float64
first_name           12043 non-null object
balance              12043 non-null float64
date                 12043 non-null datetime64[ns]
gender               12043 non-null object
age                  12043 non-null int64
merchant_suburb      7717 non-null object
merchant_state       7717 non-null object
extraction           12043 non-null object
amount               12043 non-null float64
transaction_id       12043 non-null object
country              12043 non-null object
customer_id          12043 non-null object
merchant_long_lat    7717 non-null object
movement             12043 non-null object
dtypes: datetime64[ns](1), float64(4), int64(1), object(17)
memory usage: 2.1+ MB
```

Analysis Steps:
Step 1: Preliminary analysis and feature selection

- Drop some irrelevant features
- Check for null data (there is no null in remaining dataset)

[10]:
```
# drop irrelevant columns

df = dataset.drop(['status', 'card_present_flag', 'bpay_biller_code',␣
↪'account', 'currency', 'merchant_id',
                   'merchant_code', 'first_name', 'date', 'merchant_suburb',␣
↪'merchant_state', 'extraction',
                   'transaction_id', 'country', 'merchant_long_lat',␣
↪'movement'], axis = 1)
```

[11]:
```
df.head()
```

[11]:

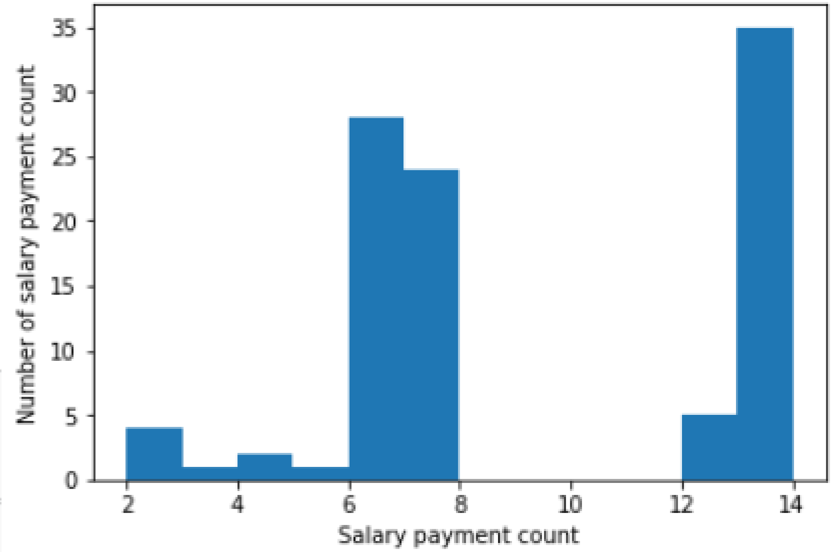
	long_lat	txn_description	balance	gender	age	amount	customer_id
0	153.41 -27.95	POS	35.39	F	26	16.25	CUS-2487424745
1	153.41 -27.95	SALES-POS	21.20	F	26	14.19	CUS-2487424745
2	151.23 -33.94	POS	5.71	M	38	6.42	CUS-2142601169
3	153.10 -27.66	SALES-POS	2117.22	F	40	40.90	CUS-1614226872
4	153.41 -27.95	SALES-POS	17.95	F	26	3.25	CUS-2487424745

[12]:
```
# check for nulls
df.isnull().sum()
```

[12]:
```
long_lat           0
txn_description    0
balance            0
gender             0
age                0
amount             0
customer_id        0
dtype: int64
```

Analysis Steps:
Step 2: Data Extraction (annual salary)

- Annual salary should be extracted from txn_description column
- Distribution of the salary of the customers are shown as:



  - There is no data for 16-08-2018.
  - For finding annual salary from 3 month payment three:

[20]:
```
# Calculate annual salary
# if Salary_Count >= 12 then payment is weekly
# if Salary_Count <= 5 then payment is monthly
# if other value then payment is fortnightly
```

[21]:
```
df_CI_S ['Annual_Salary'] = 0
for i in range (0, len(df_CI_S)):
    if int(df_CI_S.Salary_Count[i]) >= 12:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) / 7 * 356
    elif int(df_CI_S.Salary_Count[i]) <= 5:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) * 12
    else:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) / 14 * 356

# all transaction multipy 4 to obtain for one year

df_CI_S [['INTER BANK', 'PAYMENT', 'PHONE BANK', 'POS',
          'SALES-POS']] =4 * df_CI_S [['INTER BANK','PAYMENT', 'PHONE BANK',␣
 ↪'POS', 'SALES-POS']]
```

Analysis Steps:
Step 2: Data Extraction (customers' location)

- State of each customer are found based on latitude and longitude information.
- There is one out-of-range latitude. So, remove it (row number 2036).

```
# find state of each customer base on longitude and latitude information

import geopy
from geopy.geocoders import Nominatim
def LoctoState(LOC):
    locator = Nominatim(user_agent="myGeocoder")
    coordinates = LOC
    location = locator.reverse(coordinates, exactly_one = True, timeout = 10)
    address = location.raw['address']
    state = address.get('state','')
    return state
#print (LoctoState( "-27.51,153.03"))

df_S_B['state'] = ''
for i in range (0, len(df_S_B)):
    df_S_B['state'][i] = LoctoState(df_S_B['lat_long'][i])
```

Analysis Steps:
Step 2: Data Extraction

- Attribute 'total spend' is defined which includes inter bank, payment, phone bank, POS and sales-POS.
- Initial balance of each account has been added.

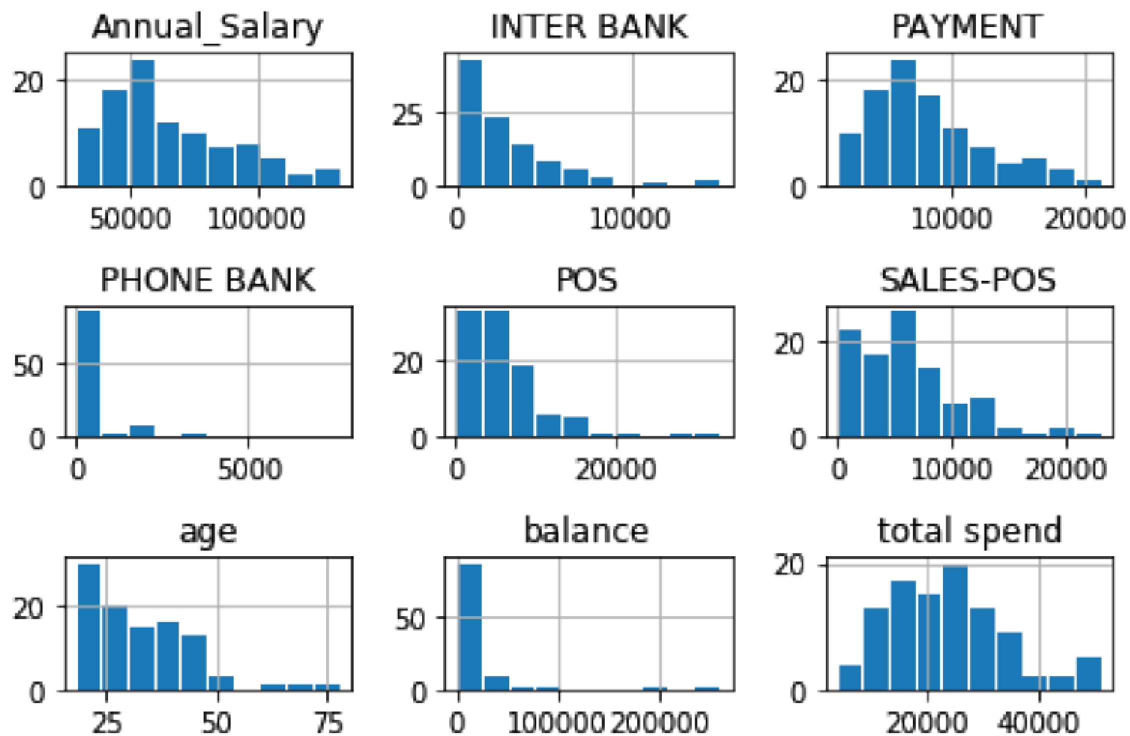
- The final dataset for analysis is as below:

	age	gender	INTER BANK	PAYMENT	PHONE BANK	POS	SALES-POS	Annual_Salary	balance	total spend	state
0	53	F	0	5184	2184	2992.04	4251.40	49355	463.96	14611.44	Queensland
1	21	M	4004	15828	0	2425.48	13477.80	90999	2335.35	35735.28	Western Australia
2	28	M	1080	3408	0	5425.88	12132.28	48734	823.53	22046.16	Victoria
3	34	F	1000	10388	0	8249.24	7293.76	87036	1726.28	26931.00	New South Wales
4	34	F	3068	12068	0	9222.60	10539.84	99266	12529.59	34898.44	South Australia

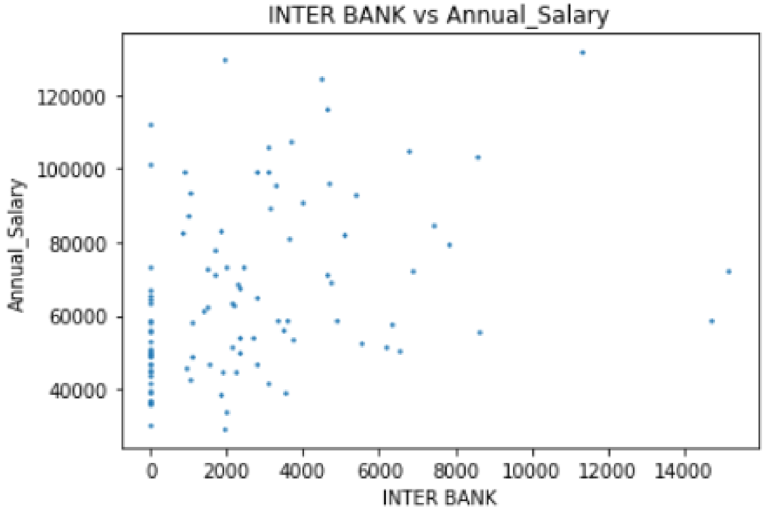
Analysis Steps:
Step 3: Data visualisation

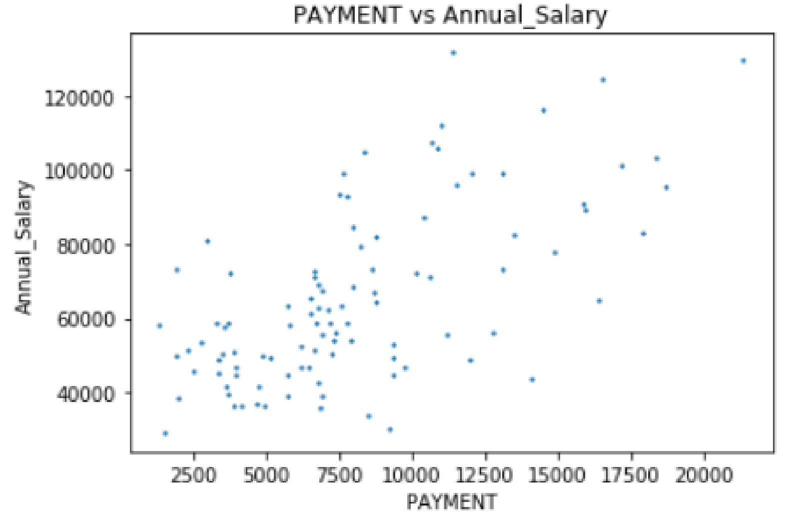
- Distribution of features

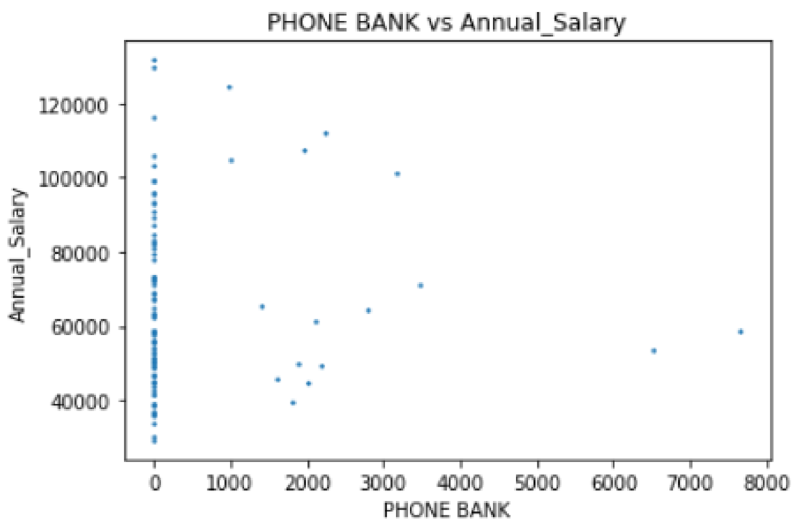
[25]:
```
# Histogram of Data visulisation
df_F.hist(rwidth = 0.9)
plt.tight_layout()
```

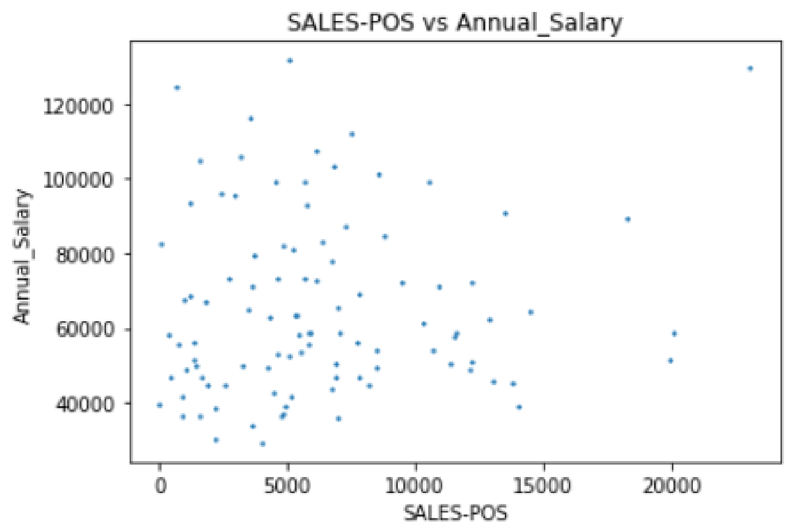


Analysis Steps:
Step 3: Data visualisation (continuous features)

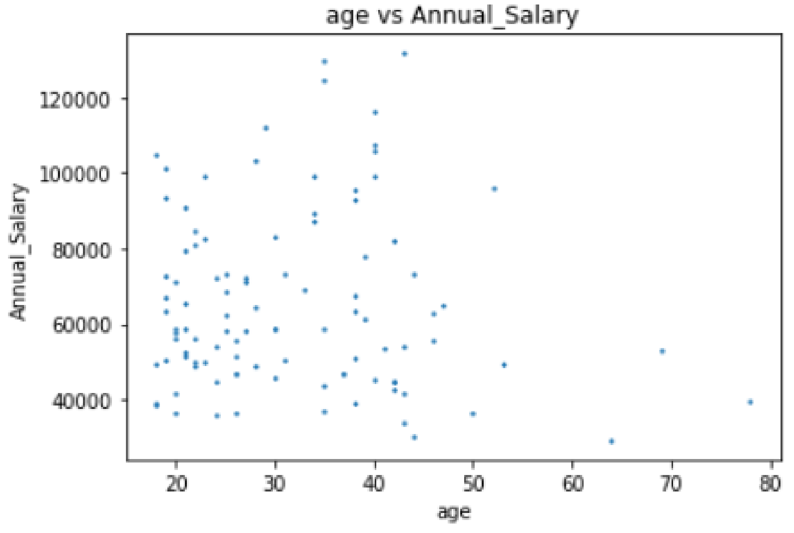


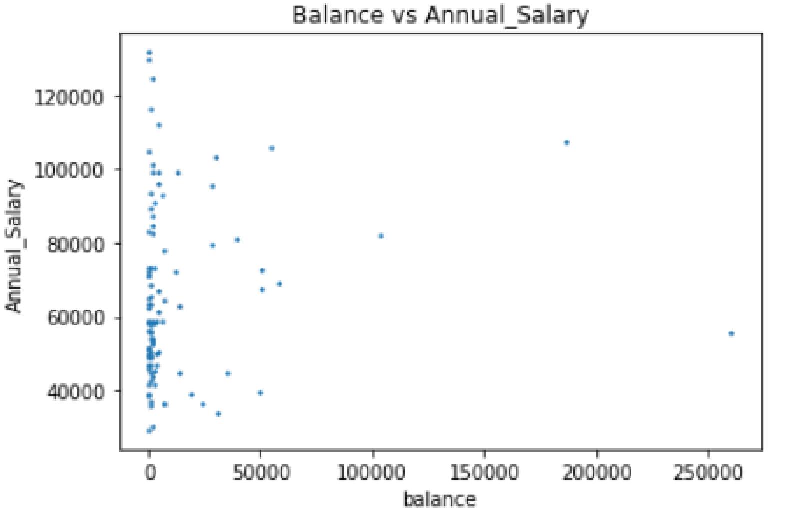


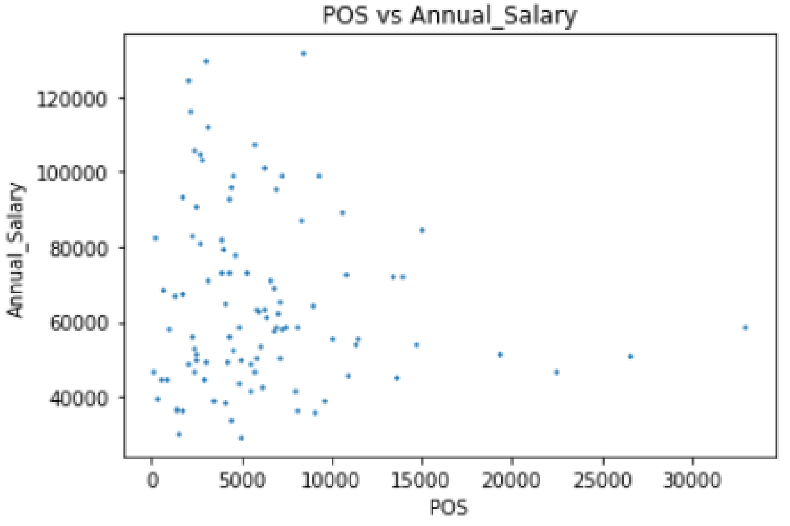


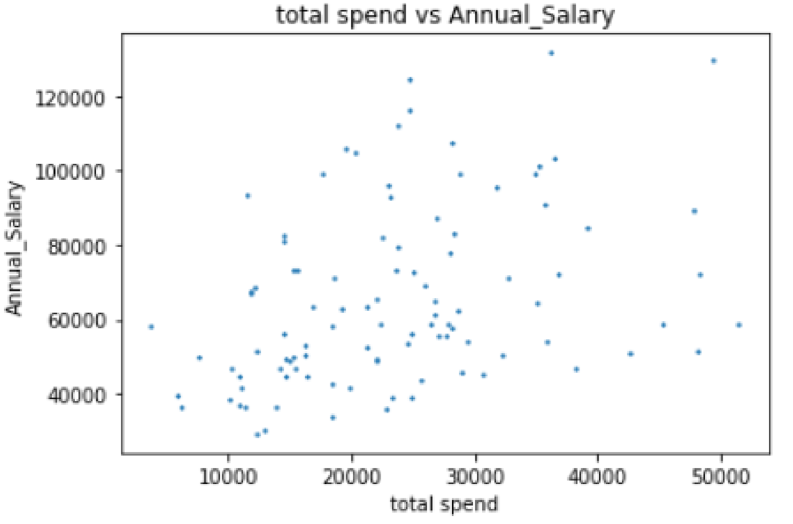


Analysis Steps:
Step 3: Data visualisation (continuous features)

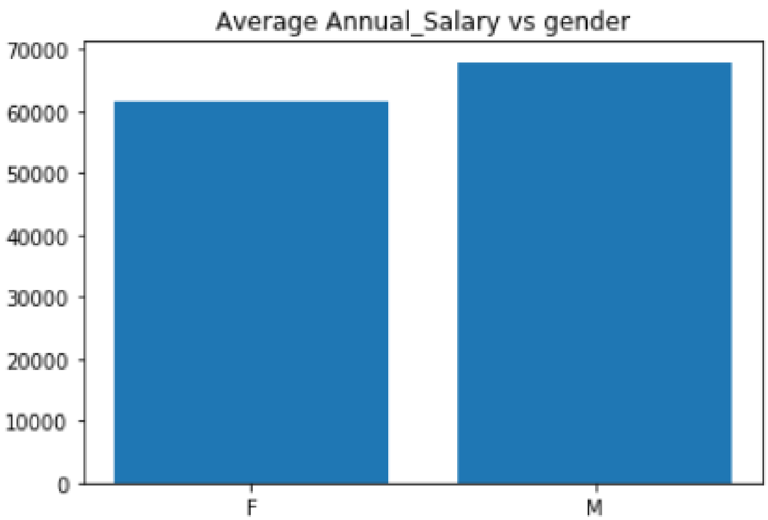


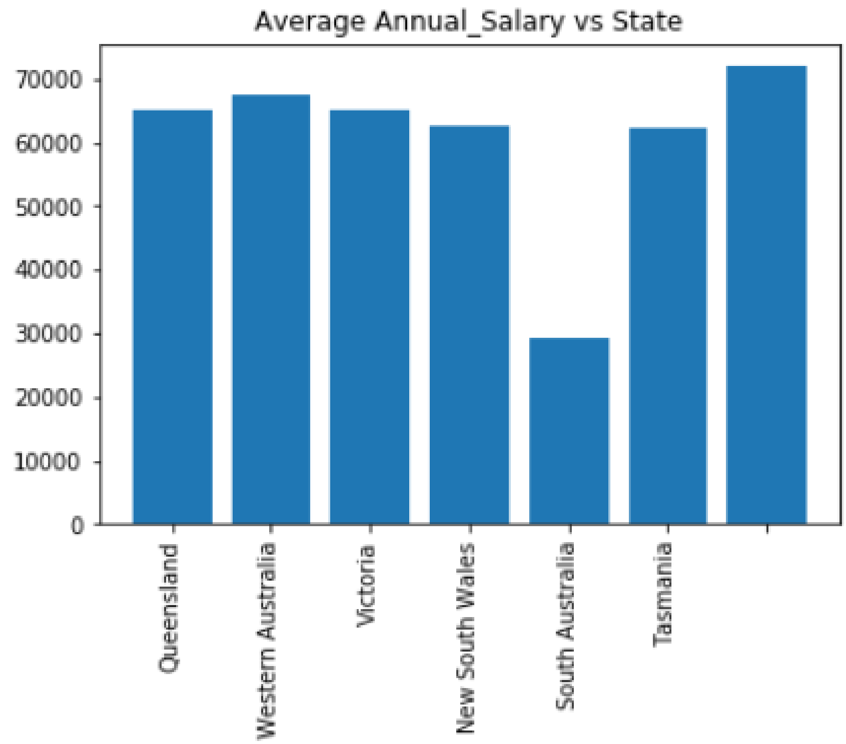






Analysis Steps:
Step 3: Data visualisation (categorical features)





Analysis Steps:
Step 4: Feature selection (correlation calculation)

- Drop features with lower correlation

```
# Check linearity using correlation coeficient matrix
correlation = df_F[['Annual_Salary', 'age', 'INTER BANK', 'PAYMENT', 'PHONE␣
↪BANK', 'POS', 'SALES-POS',
                    'balance', 'total spend']].corr()
print(correlation)
```

```
              Annual_Salary       age  INTER BANK   PAYMENT  PHONE BANK  \
Annual_Salary      1.000000 -0.061377    0.352362  0.639631    0.033414
age               -0.061377  1.000000   -0.099233  0.026884    0.103961
INTER BANK         0.352362 -0.099233    1.000000  0.087386   -0.081680
PAYMENT            0.639631  0.026884    0.087386  1.000000   -0.132095
PHONE BANK         0.033414  0.103961   -0.081680 -0.132095    1.000000
POS               -0.086938 -0.036929    0.181437 -0.123618   -0.052313
SALES-POS          0.100400 -0.139284    0.158792  0.121610    0.007496
balance            0.110321  0.237992    0.211241  0.018268    0.026537
total spend        0.371378 -0.086176    0.476295  0.416710    0.015633

                    POS  SALES-POS   balance  total spend
Annual_Salary -0.086938   0.100400  0.110321     0.371378
age           -0.036929  -0.139284  0.237992    -0.086176
INTER BANK     0.181437   0.158792  0.211241     0.476295
PAYMENT       -0.123618   0.121610  0.018268     0.416710
PHONE BANK    -0.052313   0.007496  0.026537     0.015633
POS            1.000000   0.418105 -0.000239     0.689232
SALES-POS      0.418105   1.000000 -0.153300     0.756790
balance       -0.000239  -0.153300  1.000000     0.002437
total spend    0.689232   0.756790  0.002437     1.000000
```

Analysis Steps:
Step 4: Feature selection (f_regression)

- get_dummies for categorical variables and StandardScaler for continuous variables
- Use f_regression to calculate F-score and P-value
- Feature with lower F_score has been removed

```
# feature selection
from sklearn.feature_selection import f_regression
result = f_regression(X,Y)
f_score = result [0]
p_value = result [1]

columns = list(X.columns)
print("  Feature   ", "                        F_score   " , "                  P_value   ")
print("  -------                        -------                         ------- ")
for i in range(0, len(columns)):
    f1=  f_score[i]
    p1=  p_value[i]
    print(" ", columns[i].ljust(20),"   " , f1, "   ", p1)
```

```
  Feature                          F_score                        P_value
  -------                         -------                         -------
  INTER BANK               13.077682186681905    0.00047643710935370927
  PAYMENT                  68.01558513144904    7.985674327460962e-13
  SALES-POS                0.9104035219992912    0.34237914303848604
  balance                  1.2633164571082347    0.26379816386664495
  total spend              14.845159693260255    0.00020959410709466692
  gender_M                 1.7205564326030651    0.19271752801591077
  state_New South Wales     0.3735928480105821    0.5424821000548368
  state_Queensland         0.0010899400623479772    0.9737310705621645
  state_South Australia     0.07316966142052807    0.7873511721337136
  state_Tasmania           2.350633544897465    0.12848730409545903
  state_Victoria           0.8304095476594371    0.3644132122518978
  state_Western Australia    1.337959517193049    0.25023486278067525
```

Analysis Steps:
Step 4: Linear Regression

- Final dataset is as follows:

	gender	INTER BANK	PAYMENT	Annual_Salary	total spend
0	F	0	5184	49355	14611.44
1	M	4004	15828	90999	35735.28
2	M	1080	3408	48734	22046.16
3	F	1000	10388	87036	26931.00
4	F	3068	12068	99266	34898.44

- After splitting data to test and train datasets and fitting the model:

```
score_test = LR.score(X_test, Y_test)
RMSE = math.sqrt(mean_squared_error(Y_test, Y_Predicted))

print('r2 score for Linear Regression is:' ,score_test)
print('RMSE for Linear Regression is:' ,RMSE)
```

```
r2 score for Linear Regression is: 0.6173311697006681
RMSE for Linear Regression is: 0.615533613440O503
```

- However some method such as KFold can slightly improve the r2_value.

```
# KFold
from sklearn.model_selection import KFold
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)
scores = cross_val_score(LR, X_train, Y_train, scoring='r2', cv=folds)
scores
```

```
array([ 0.40019539,  0.68358956,  0.58267536, -0.19175429, -0.09101695])
```

Summary

- Even with using feature selection method, the selected feature can not leads to a good model and r2_value is not high enough (r2_score = 0.61).

- As the number of customer was very low, obtaining the model with low accuracy was predictable.

ANZ_regression

January 29, 2021

[97]:
```python
# import libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
```

[98]:
```python
# read dataset
dataset = pd.read_excel("ANZ synthesised transaction dataset.xlsx")
dataset.head()
```

[98]:
```
       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

        long_lat txn_description                           merchant_id  \
0  153.41 -27.95             POS  81c48296-73be-44a7-befa-d053f48ce7cd
1  153.41 -27.95       SALES-POS  830a451c-316e-4a6a-bf25-e37caedca49e
2  151.23 -33.94             POS  835c231d-8cdf-4e96-859d-e9d571760cf0
3  153.10 -27.66       SALES-POS  48514682-c78a-4a88-b0da-2d6302e64673
4  153.41 -27.95       SALES-POS  b4e02c10-0852-4273-b8fd-7b3395e32eb0

   merchant_code first_name  ...  age merchant_suburb merchant_state  \
0            NaN      Diana  ...   26         Ashmore            QLD
1            NaN      Diana  ...   26          Sydney            NSW
2            NaN    Michael  ...   38          Sydney            NSW
3            NaN     Rhonda  ...   40         Buderim            QLD
4            NaN      Diana  ...   26   Mermaid Beach            QLD

                    extraction amount                    transaction_id  \
0  2018-08-01T01:01:15.000+0000  16.25  a623070bfead4541a6b0fff8a09e706c
1  2018-08-01T01:13:45.000+0000  14.19  13270a2a902145da9db4c951e04b51b9
2  2018-08-01T01:26:15.000+0000   6.42  feb79e7ecd7048a5a36ec889d1a94270
3  2018-08-01T01:38:45.000+0000  40.90  2698170da3704fd981b15e64a006079e
4  2018-08-01T01:51:15.000+0000   3.25  329adf79878c4cf0aeb4188b4691c266
```

```
     country     customer_id merchant_long_lat movement
0  Australia  CUS-2487424745     153.38 -27.99    debit
1  Australia  CUS-2487424745     151.21 -33.87    debit
2  Australia  CUS-2142601169     151.21 -33.87    debit
3  Australia  CUS-1614226872     153.05 -26.68    debit
4  Australia  CUS-2487424745     153.44 -28.06    debit

[5 rows x 23 columns]
```

[99]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12043 entries, 0 to 12042
Data columns (total 23 columns):
status               12043 non-null object
card_present_flag    7717 non-null float64
bpay_biller_code     885 non-null object
account              12043 non-null object
currency             12043 non-null object
long_lat             12043 non-null object
txn_description      12043 non-null object
merchant_id          7717 non-null object
merchant_code        883 non-null float64
first_name           12043 non-null object
balance              12043 non-null float64
date                 12043 non-null datetime64[ns]
gender               12043 non-null object
age                  12043 non-null int64
merchant_suburb      7717 non-null object
merchant_state       7717 non-null object
extraction           12043 non-null object
amount               12043 non-null float64
transaction_id       12043 non-null object
country              12043 non-null object
customer_id          12043 non-null object
merchant_long_lat    7717 non-null object
movement             12043 non-null object
dtypes: datetime64[ns](1), float64(4), int64(1), object(17)
memory usage: 2.1+ MB
```

[100]:
```
#dataset.columns
```

[101]:
```
#print(dataset.date.dtype)
# There is no data for 16-08-2018 so ingore this month
#sub_dataset = dataset[(dataset['date'] >= '2018-09-01')]
#sub_dataset = dataset
```

[102]:
```
# drop irrelevant columns

df = dataset.drop(['status', 'card_present_flag', 'bpay_biller_code',␣
↪'account', 'currency', 'merchant_id',
                   'merchant_code', 'first_name', 'date', 'merchant_suburb',␣
↪'merchant_state', 'extraction',
                   'transaction_id', 'country', 'merchant_long_lat',␣
↪'movement'], axis = 1)
```

[103]:
```
df.head()
```

[103]:

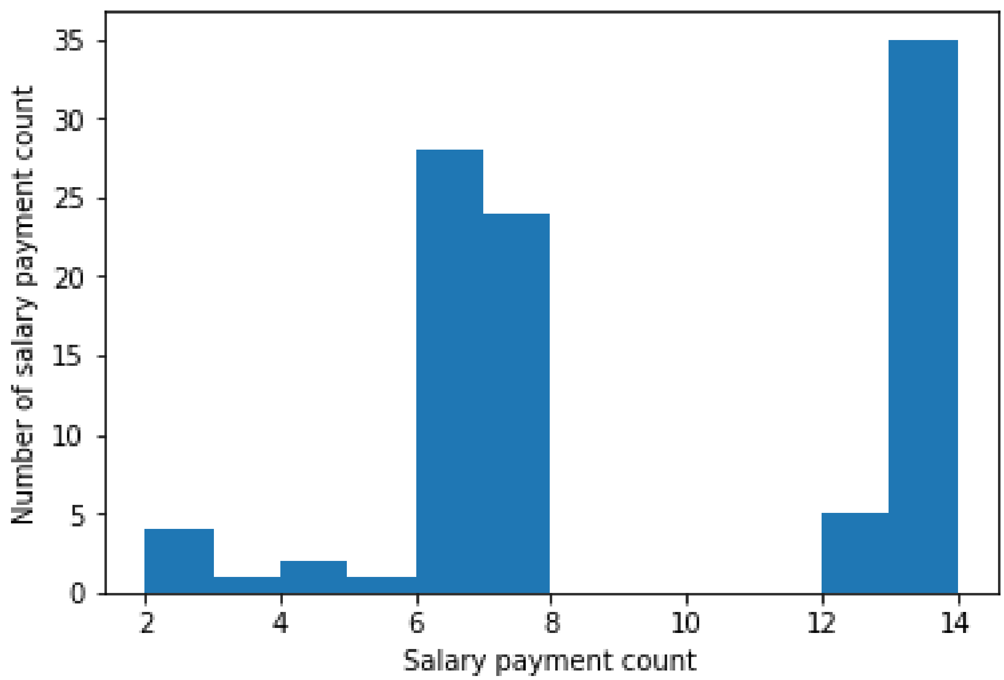
	long_lat	txn_description	balance	gender	age	amount	customer_id
0	153.41 -27.95	POS	35.39	F	26	16.25	CUS-2487424745
1	153.41 -27.95	SALES-POS	21.20	F	26	14.19	CUS-2487424745
2	151.23 -33.94	POS	5.71	M	38	6.42	CUS-2142601169
3	153.10 -27.66	SALES-POS	2117.22	F	40	40.90	CUS-1614226872
4	153.41 -27.95	SALES-POS	17.95	F	26	3.25	CUS-2487424745

[104]:
```
# check for nulls
df.isnull().sum()
```

[104]:
```
long_lat           0
txn_description    0
balance            0
gender             0
age                0
amount             0
customer_id        0
dtype: int64
```

[105]:
```
# Count the number of PAY/SALARY for each customer

df_salary = dataset[['customer_id', 'txn_description', 'amount', 'date']]
df_salary = df_salary[(df['txn_description'] == 'PAY/SALARY')]

#df_salary_sort = df_salary.sort_values(by = ['customer_id', 'date'], ascending␣
↪= False)
#df_salary_sort

df_salary_count = df_salary.pivot_table(index=['customer_id'], aggfunc='size')
type(df_salary_count)
df_count_S = pd.DataFrame(df_salary_count)
df_count_S = df_count_S.reset_index()
df_count_S.rename(columns = {0 :'Salary_Count'}, inplace = True)
#type(df_count)
plt.hist(df_salary_count, bins = 12)
plt.ylabel('Number of salary payment count')
plt.xlabel('Salary payment count')
#df_count
```

[105]: Text(0.5, 0, 'Salary payment count')



[106]:
```
# pivot table to find unique customers and their salary and other kind of␣
↪transactions
df_CI = pd.pivot_table(df, values = 'amount',
                       index = ['customer_id', 'age', 'long_lat', 'gender' ],
                       columns = ['txn_description'], aggfunc = np.sum,␣
↪fill_value = 0)
df_CI.head()
```

[106]:
```
txn_description                                  INTER BANK  PAY/SALARY  PAYMENT  \
customer_id    age long_lat      gender
CUS-1005756958 53  153.03 -27.51 F                        0    12616.11     1296
CUS-1117979751 21  115.81 -31.82 M                     1001    25050.55     3957
CUS-1140341822 28  144.97 -37.42 M                      270    11499.06      852
CUS-1147642491 34  151.04 -33.77 F                      250    22248.07     2597
CUS-1196156254 34  138.52 -35.01 F                      767    27326.11     3017

txn_description                                  PHONE BANK      POS  SALES-POS
customer_id    age long_lat      gender
CUS-1005756958 53  153.03 -27.51 F                      546   748.01    1062.85
CUS-1117979751 21  115.81 -31.82 M                        0   606.37    3369.45
CUS-1140341822 28  144.97 -37.42 M                        0  1356.47    3033.07
CUS-1147642491 34  151.04 -33.77 F                        0  2062.31    1823.44
CUS-1196156254 34  138.52 -35.01 F                        0  2305.65    2634.96
```

[107]:
```
#df_CI.columns
```

[108]:
```
#df_CI.info()
```

[109]:
```
# Turn Pandas Multi-Index into column
df_CI = df_CI.reset_index()
df_CI.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 10 columns):
customer_id    100 non-null object
age            100 non-null int64
long_lat       100 non-null object
gender         100 non-null object
INTER BANK     100 non-null int64
PAY/SALARY     100 non-null float64
PAYMENT        100 non-null int64
PHONE BANK     100 non-null int64
POS            100 non-null float64
SALES-POS      100 non-null float64
dtypes: float64(3), int64(4), object(3)
memory usage: 7.9+ KB
```

[110]:
```
df_CI.head()
```

[110]:
```
txn_description     customer_id  age        long_lat gender  INTER BANK  \
0                CUS-1005756958   53  153.03 -27.51      F           0
1                CUS-1117979751   21  115.81 -31.82      M        1001
2                CUS-1140341822   28  144.97 -37.42      M         270
3                CUS-1147642491   34  151.04 -33.77      F         250
4                CUS-1196156254   34  138.52 -35.01      F         767

txn_description  PAY/SALARY  PAYMENT  PHONE BANK      POS  SALES-POS
0                  12616.11     1296         546   748.01    1062.85
1                  25050.55     3957           0   606.37    3369.45
2                  11499.06      852           0  1356.47    3033.07
3                  22248.07     2597           0  2062.31    1823.44
4                  27326.11     3017           0  2305.65    2634.96
```

[111]:
```
# Add Salary Count to dataset
df_CI_S = df_CI.merge(df_count_S, left_on = 'customer_id', right_on =␣
↪'customer_id', how = 'inner')
df_CI_S.head()
```

[111]:
```
      customer_id  age        long_lat gender  INTER BANK  PAY/SALARY  PAYMENT  \
0  CUS-1005756958   53  153.03 -27.51      F           0    12616.11     1296
1  CUS-1117979751   21  115.81 -31.82      M        1001    25050.55     3957
2  CUS-1140341822   28  144.97 -37.42      M         270    11499.06      852
3  CUS-1147642491   34  151.04 -33.77      F         250    22248.07     2597
```

```
4  CUS-1196156254   34  138.52 -35.01      F          767     27326.11     3017

   PHONE BANK      POS  SALES-POS  Salary_Count
0         546   748.01    1062.85            13
1           0   606.37    3369.45             7
2           0  1356.47    3033.07             6
3           0  2062.31    1823.44            13
4           0  2305.65    2634.96             7
```

[112]:

```
# Calculate annual salary
# if Salary_Count >= 12 then payment is weekly
# if Salary_Count <= 5 then payment is monthly
# if other value then payment is fortnightly
```

[113]:

```
df_CI_S ['Annual_Salary'] = 0
for i in range (0, len(df_CI_S)):
    if int(df_CI_S.Salary_Count[i]) >= 12:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) / 7 * 356
    elif int(df_CI_S.Salary_Count[i]) <= 5:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) * 12
    else:
        df_CI_S.Annual_Salary[i] = df_CI_S ['PAY/SALARY'][i]/(df_CI_S.
 ↪Salary_Count[i]) / 14 * 356

# all transaction multipy 4 to obtain for one year

df_CI_S [['INTER BANK', 'PAYMENT', 'PHONE BANK', 'POS',
          'SALES-POS']] =4 * df_CI_S [['INTER BANK','PAYMENT', 'PHONE BANK',␣
 ↪'POS', 'SALES-POS']]

df_CI_S.head()
```

```
C:\Users\atefeh\Anaconda3\lib\site-packages\ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
C:\Users\atefeh\Anaconda3\lib\site-packages\ipykernel_launcher.py:8:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

```
C:\Users\atefeh\Anaconda3\lib\site-packages\ipykernel_launcher.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
```

[113]:

```
      customer_id  age       long_lat gender  INTER BANK  PAY/SALARY  PAYMENT  \
0  CUS-1005756958   53  153.03 -27.51      F           0    12616.11     5184
1  CUS-1117979751   21  115.81 -31.82      M        4004    25050.55    15828
2  CUS-1140341822   28  144.97 -37.42      M        1080    11499.06     3408
3  CUS-1147642491   34  151.04 -33.77      F        1000    22248.07    10388
4  CUS-1196156254   34  138.52 -35.01      F        3068    27326.11    12068

   PHONE BANK      POS  SALES-POS  Salary_Count  Annual_Salary
0        2184  2992.04    4251.40            13          49355
1           0  2425.48   13477.80             7          90999
2           0  5425.88   12132.28             6          48734
3           0  8249.24    7293.76            13          87036
4           0  9222.60   10539.84             7          99266
```

[114]:

```python
# find the initial balance of each customer
df_B = dataset[['customer_id','balance']]
df_CI_B = df_B.drop_duplicates(subset = ['customer_id'], keep = 'first')


# merge with previous dataframe
df_S_B = df_CI_S.merge(df_CI_B , left_on = 'customer_id', right_on =␣
↪'customer_id', how = 'inner')

# adding a column for total spend
df_S_B['total spend'] = df_S_B['INTER BANK']+ df_S_B['PAYMENT']+ df_S_B['PHONE␣
↪BANK']+ df_S_B['POS']+ df_S_B['SALES-POS']

df_S_B.head()
```

[114]:

```
      customer_id  age       long_lat gender  INTER BANK  PAY/SALARY  PAYMENT  \
0  CUS-1005756958   53  153.03 -27.51      F           0    12616.11     5184
1  CUS-1117979751   21  115.81 -31.82      M        4004    25050.55    15828
2  CUS-1140341822   28  144.97 -37.42      M        1080    11499.06     3408
3  CUS-1147642491   34  151.04 -33.77      F        1000    22248.07    10388
4  CUS-1196156254   34  138.52 -35.01      F        3068    27326.11    12068

   PHONE BANK      POS  SALES-POS  Salary_Count  Annual_Salary  balance  \
0        2184  2992.04    4251.40            13          49355   463.96
1           0  2425.48   13477.80             7          90999  2335.35
2           0  5425.88   12132.28             6          48734   823.53
```

```
3            0  8249.24    7293.76            13           87036   1726.28
4            0  9222.60   10539.84             7           99266  12529.59

   total spend
0     14611.44
1     35735.28
2     22046.16
3     26931.00
4     34898.44
```

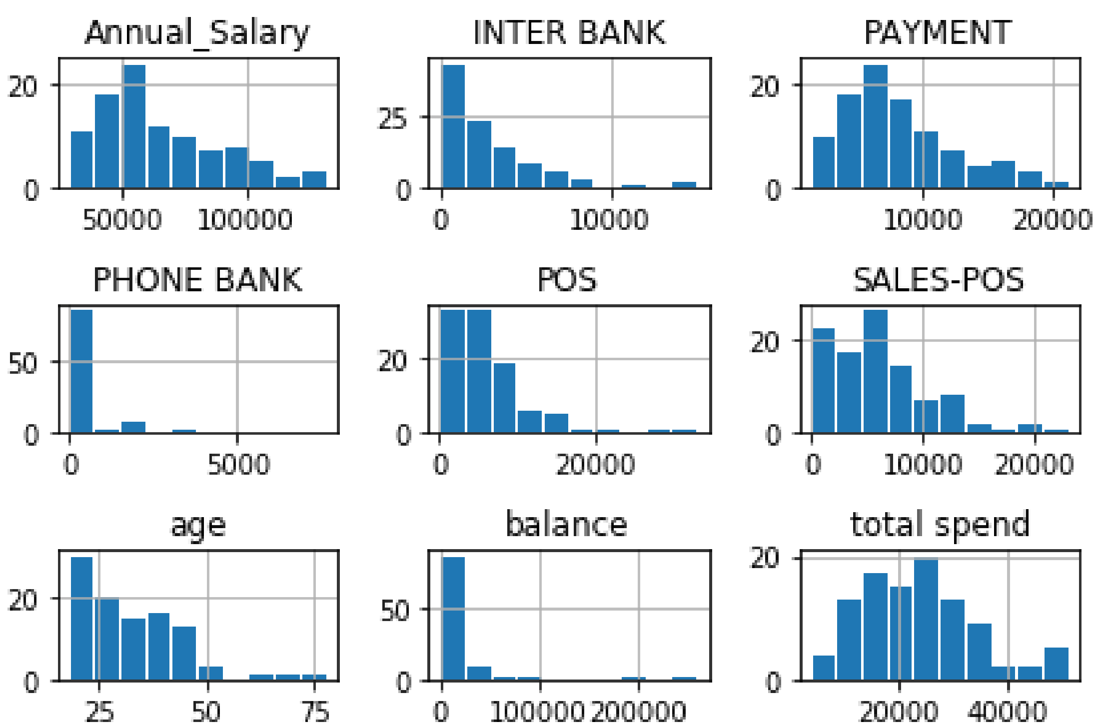
[115]:
```
# find state of each customer base on longitude and latitude information
"""
df_S_B[['long', 'lat']] = df_S_B.long_lat.str.split(' ', expand = True)
df_S_B['lat_long'] = df_S_B['lat'].map(str) + ',' + df_S_B['long'].map(str)

import geopy
from geopy.geocoders import Nominatim
def LoctoState(LOC):
    locator = Nominatim(user_agent="myGeocoder")
    coordinates = LOC
    location = locator.reverse(coordinates, exactly_one = True, timeout = 10)
    address = location.raw['address']
    state = address.get('state')
    return state
#print (LoctoState( "-27.51,153.03"))

df_S_B['state'] = ''
for i in range (0, len(df_S_B)):
    df_S_B['state'][i] = LoctoState(df_S_B['lat_long'][i])

df_S_B.head()
"""
```

[115]:
```
'\ndf_S_B[[\'long\', \'lat\']] = df_S_B.long_lat.str.split(\' \', expand =
True)\ndf_S_B[\'lat_long\'] = df_S_B[\'lat\'].map(str) + \',\' +
df_S_B[\'long\'].map(str)\n\nimport geopy\nfrom geopy.geocoders import
Nominatim\ndef LoctoState(LOC):\n    locator =
Nominatim(user_agent="myGeocoder")\n    coordinates = LOC\n    location =
locator.reverse(coordinates, exactly_one = True, timeout = 10)\n    address =
location.raw[\'address\']\n    state = address.get(\'state\')\n    return
state\n#print (LoctoState( "-27.51,153.03"))\n\ndf_S_B[\'state\'] = \'\'\nfor i
in range (0, len(df_S_B)):\n    df_S_B[\'state\'][i] =
LoctoState(df_S_B[\'lat_long\'][i])\n    \ndf_S_B.head()\n'
```

[116]:
```
df_F = df_S_B.drop(['customer_id', 'long_lat', 'PAY/SALARY', 'Salary_Count'],
 axis = 1)
df_F.head()
```

[116]:
```
    age gender  INTER BANK  PAYMENT  PHONE BANK      POS  SALES-POS  \
0    53      F           0     5184        2184  2992.04    4251.40
1    21      M        4004    15828           0  2425.48   13477.80
2    28      M        1080     3408           0  5425.88   12132.28
3    34      F        1000    10388           0  8249.24    7293.76
4    34      F        3068    12068           0  9222.60   10539.84

   Annual_Salary   balance  total spend
0          49355    463.96     14611.44
1          90999   2335.35     35735.28
2          48734    823.53     22046.16
3          87036   1726.28     26931.00
4          99266  12529.59     34898.44
```

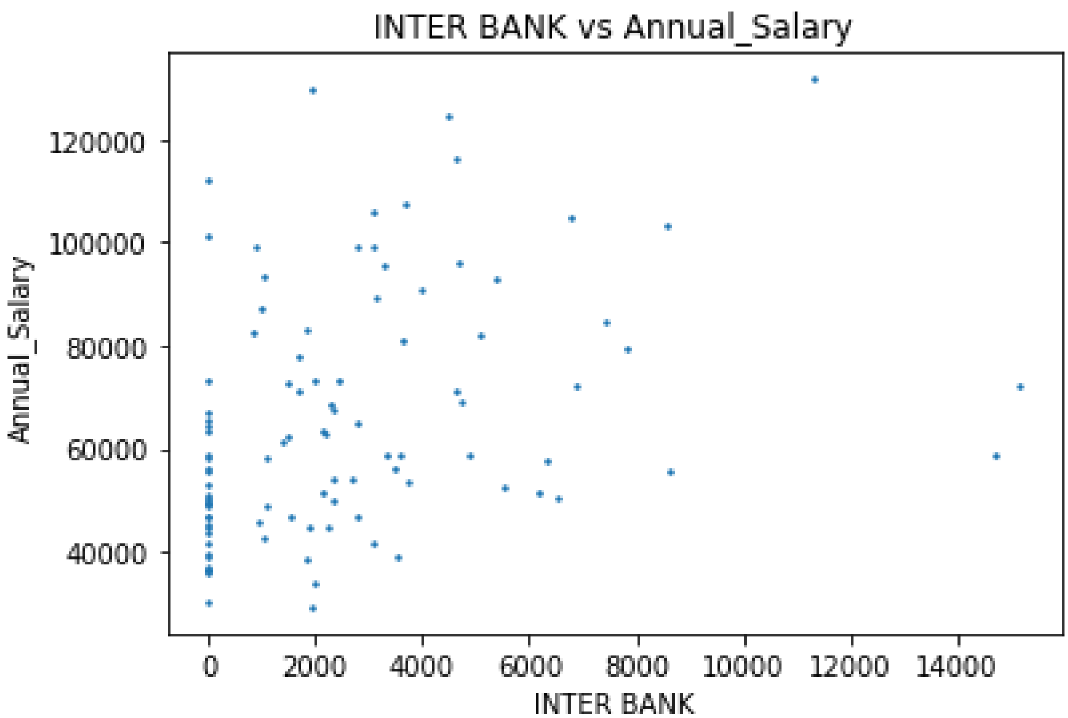
[117]:
```python
# Histogram of Data visulisation
df_F.hist(rwidth = 0.9)
plt.tight_layout()
```



[118]:
```python
# Data visulisation
# Visualise the continuous features vs PAY/SALARY
#plt.subplot(8,1,1)
plt.title('INTER BANK vs Annual_Salary')
plt.scatter(df_F['INTER BANK'], df_F['Annual_Salary'], s = 2)
plt.xlabel('INTER BANK')
```

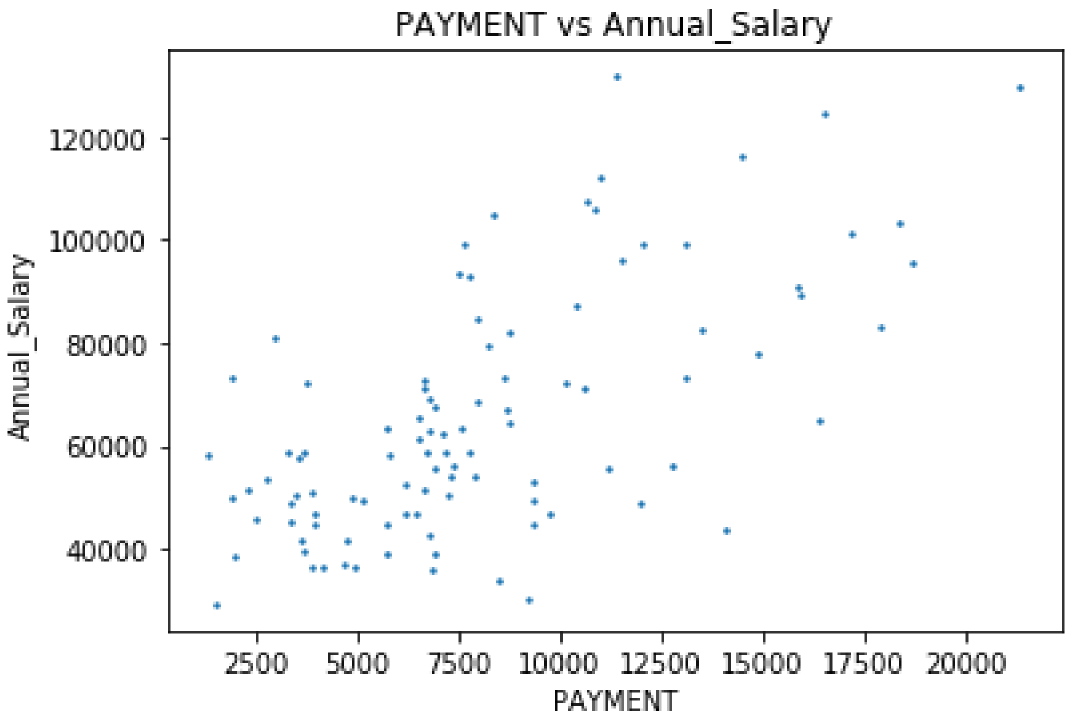
```
plt.ylabel('Annual_Salary')

#plt.tight_layout()
```

[118]: Text(0, 0.5, 'Annual_Salary')



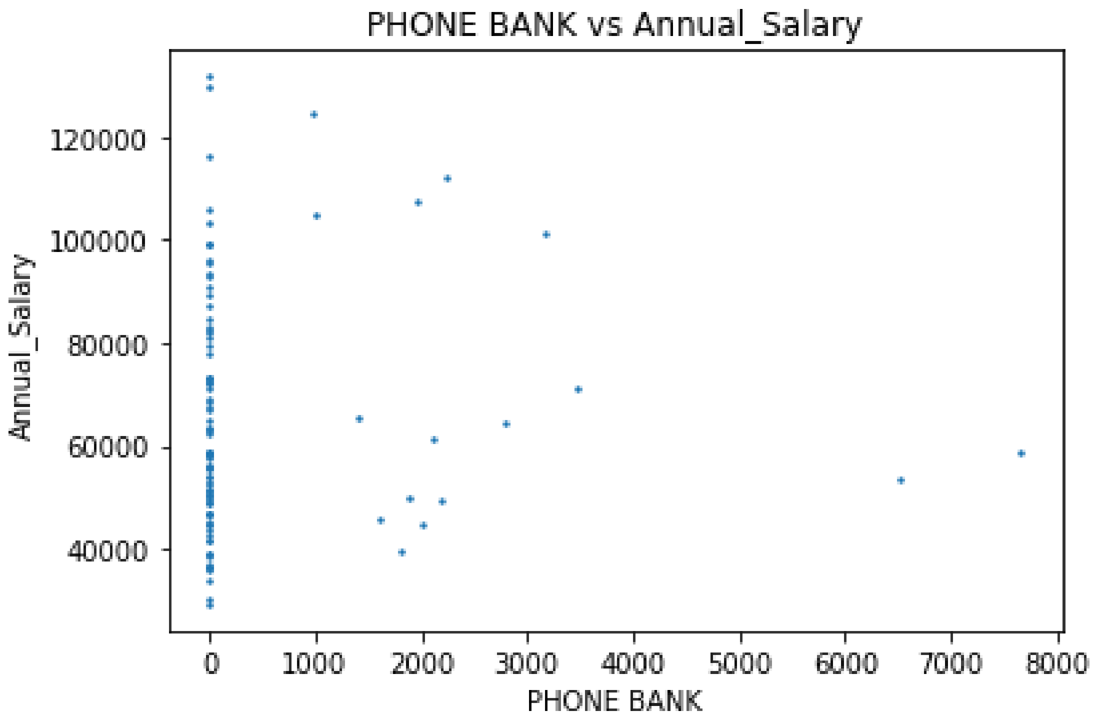
[119]:
```
#plt.subplot(8,1,2)
plt.title('PAYMENT vs Annual_Salary')
plt.scatter(df_F['PAYMENT'], df_F['Annual_Salary'], s = 2)
plt.xlabel('PAYMENT')
plt.ylabel('Annual_Salary')
```

[119]: Text(0, 0.5, 'Annual_Salary')



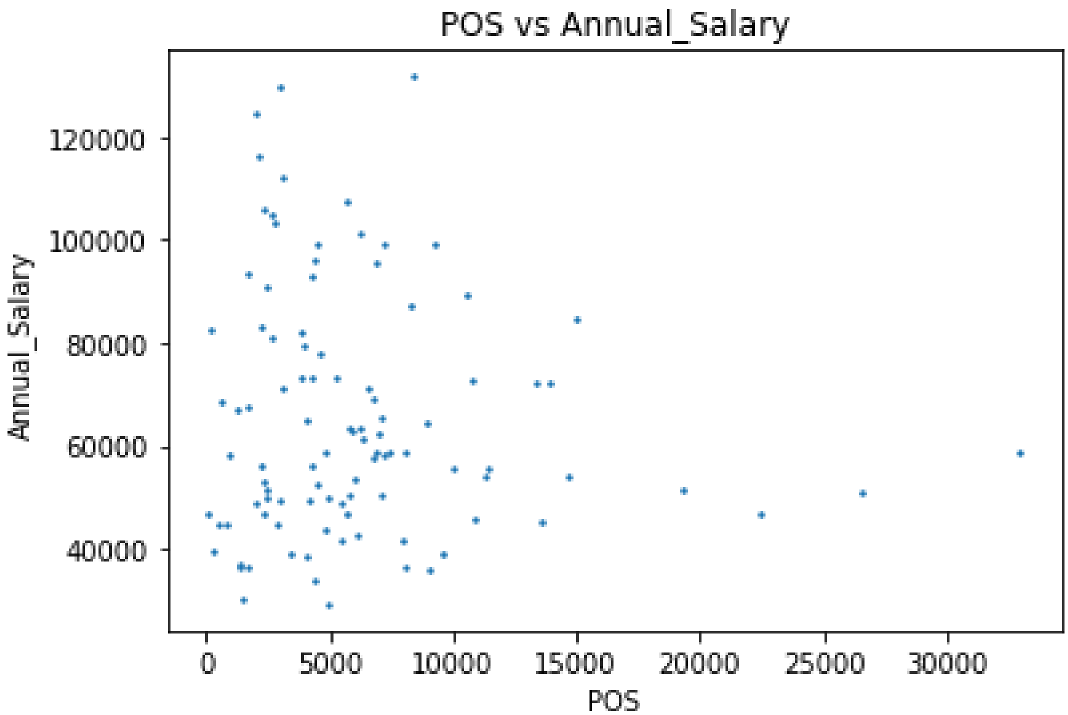
[120]:
```
#plt.subplot(8,1,3)
plt.title('PHONE BANK vs Annual_Salary')
plt.scatter(df_F['PHONE BANK'], df_F['Annual_Salary'], s = 2)
plt.xlabel('PHONE BANK')
plt.ylabel('Annual_Salary')
```

[120]:
```
Text(0, 0.5, 'Annual_Salary')
```



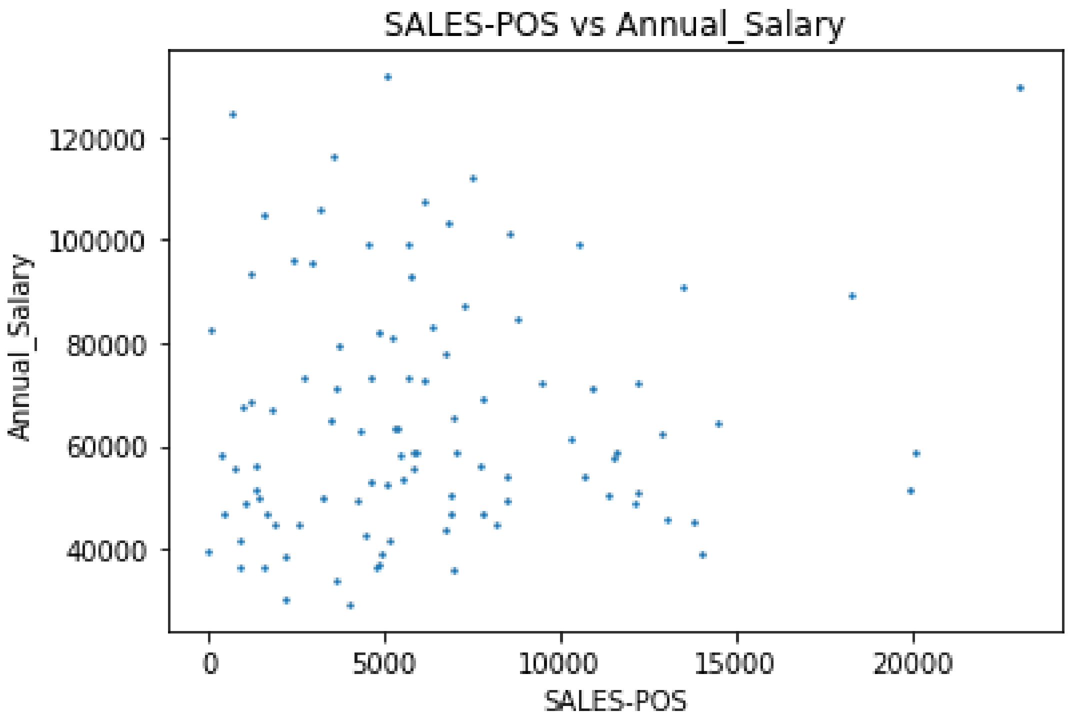
[121]:
```
#plt.subplot(8,1,4)
plt.title('POS vs Annual_Salary')
plt.scatter(df_F['POS'], df_F['Annual_Salary'], s = 2)
plt.xlabel('POS')
plt.ylabel('Annual_Salary')
```

[121]:
```
Text(0, 0.5, 'Annual_Salary')
```



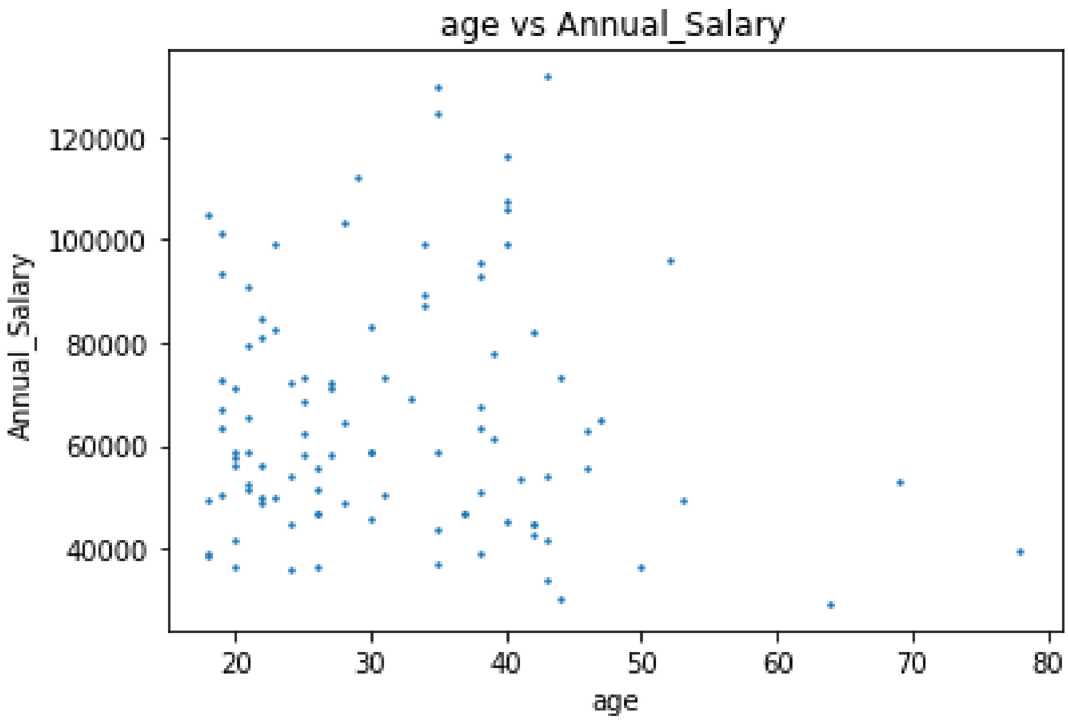
[122]:
```
#plt.subplot(8,1,5)
plt.title('SALES-POS vs Annual_Salary')
plt.scatter(df_F['SALES-POS'], df_F['Annual_Salary'], s = 2)
plt.xlabel('SALES-POS')
plt.ylabel('Annual_Salary')
```

[122]:
```
Text(0, 0.5, 'Annual_Salary')
```



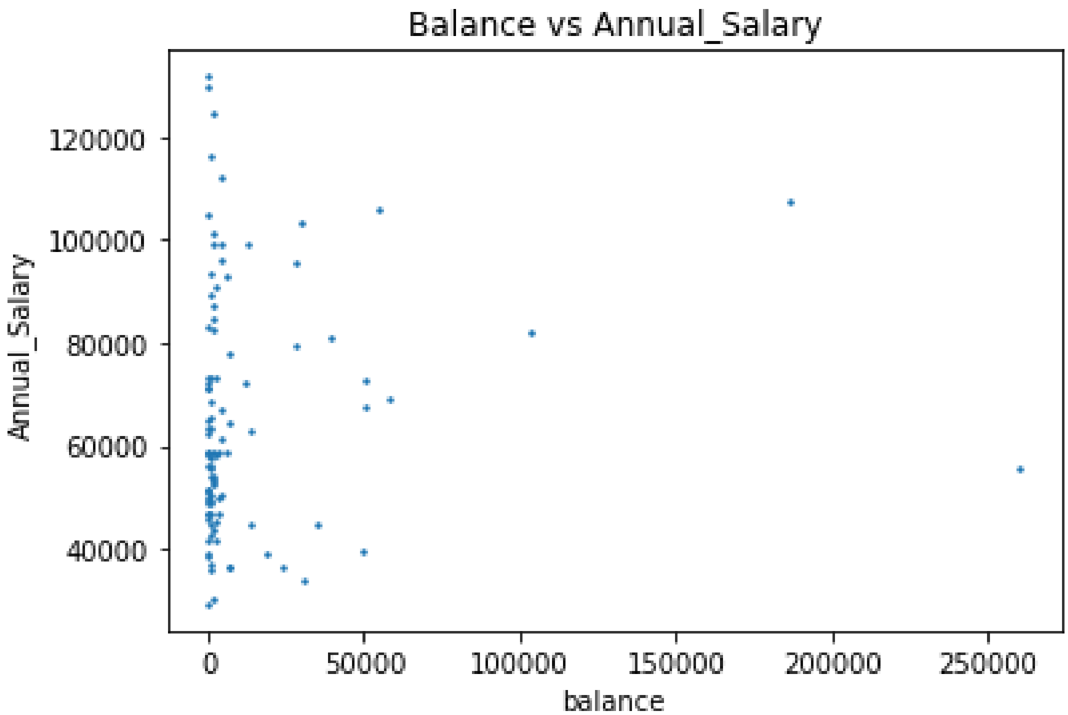
[123]:
```
#plt.subplot(8,1,6)
plt.title('age vs Annual_Salary')
plt.scatter(df_F['age'], df_F['Annual_Salary'], s = 2)
plt.xlabel('age')
plt.ylabel('Annual_Salary')
```

[123]: Text(0, 0.5, 'Annual_Salary')



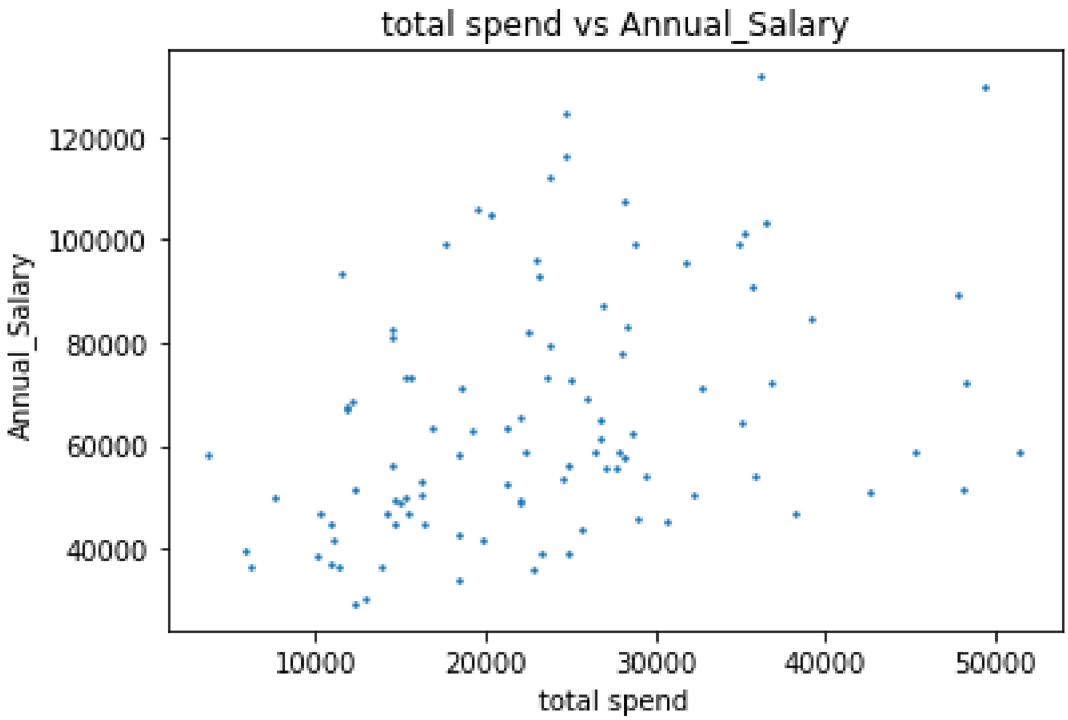
[124]:
```
#plt.subplot(8,1,7)
plt.title('Balance vs Annual_Salary')
plt.scatter(df_F['balance'], df_F['Annual_Salary'], s = 2)
plt.xlabel('balance')
plt.ylabel('Annual_Salary')
```

[124]:
```
Text(0, 0.5, 'Annual_Salary')
```



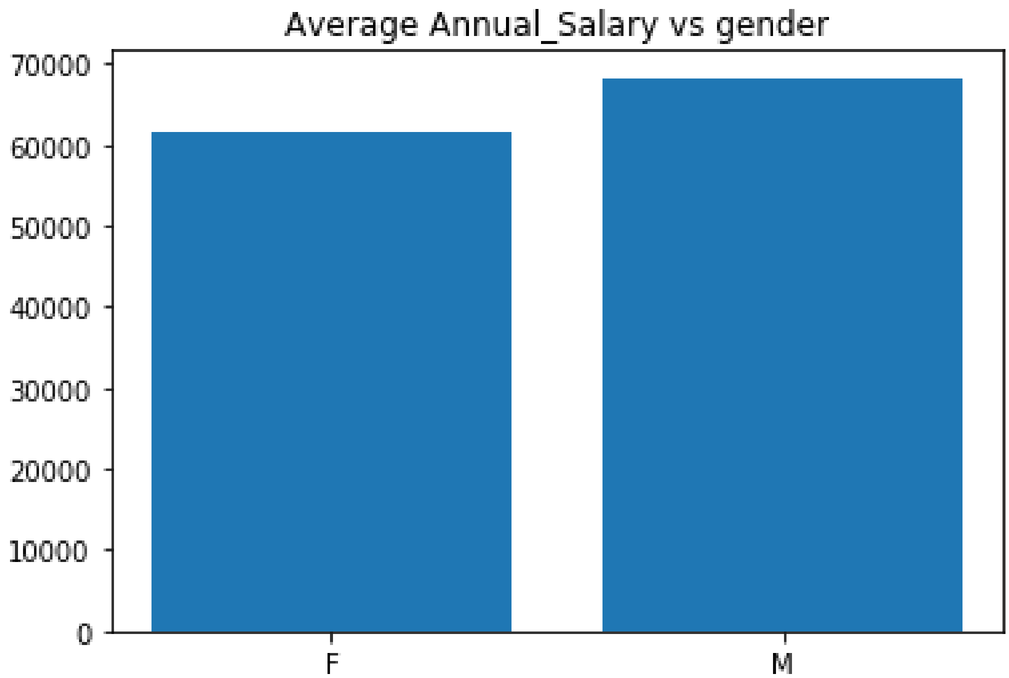
[125]:
```
#plt.subplot(8,1,8)
plt.title('total spend vs Annual_Salary')
plt.scatter(df_F['total spend'], df_F['Annual_Salary'], s = 2)
plt.xlabel('total spend')
plt.ylabel('Annual_Salary')
```

[125]: Text(0, 0.5, 'Annual_Salary')



[126]:
```
# Data visulisation
# Visualise the categorical feature vs PAY/SALARY

cat_list = df_F['gender'].unique()
cat_average = df_F.groupby('gender')['Annual_Salary'].mean()
#cat_average = df_F.groupby('gender').mean()['Annual_Salary']
plt.title('Average Annual_Salary vs gender')
plt.bar(cat_list, cat_average)
```

[126]:
```
<BarContainer object of 2 artists>
```



[127]:
```
# Check for outlier
df_F['Annual_Salary'].describe()
#df_F['Annual_Salary'].quantile([0.05, 0.1, 0.15, 0.9, 0.95, 0.99])
```

[127]:
```
count       100.000000
mean      65352.270000
std       23633.324404
min       29293.000000
25%       48267.500000
50%       58803.000000
75%       79821.250000
max      131618.000000
Name: Annual_Salary, dtype: float64
```

[128]:
```
# Check linearity using correlation coeficient matrix
correlation = df_F[['Annual_Salary', 'age', 'INTER BANK', 'PAYMENT', 'PHONE␣
 ↪BANK', 'POS', 'SALES-POS',
                   'balance', 'total spend']].corr()
print(correlation)
```

```
               Annual_Salary       age  INTER BANK   PAYMENT  PHONE BANK  \
Annual_Salary       1.000000 -0.061377    0.352362  0.639631    0.033414
age                -0.061377  1.000000   -0.099233  0.026884    0.103961
INTER BANK          0.352362 -0.099233    1.000000  0.087386   -0.081680
PAYMENT             0.639631  0.026884    0.087386  1.000000   -0.132095
PHONE BANK          0.033414  0.103961   -0.081680 -0.132095    1.000000
```

```
POS                 -0.086938 -0.036929    0.181437 -0.123618   -0.052313
SALES-POS            0.100400 -0.139284    0.158792  0.121610    0.007496
balance              0.110321  0.237992    0.211241  0.018268    0.026537
total spend          0.371378 -0.086176    0.476295  0.416710    0.015633

                    POS  SALES-POS   balance  total spend
Annual_Salary -0.086938   0.100400  0.110321     0.371378
age           -0.036929  -0.139284  0.237992    -0.086176
INTER BANK     0.181437   0.158792  0.211241     0.476295
PAYMENT       -0.123618   0.121610  0.018268     0.416710
PHONE BANK    -0.052313   0.007496  0.026537     0.015633
POS            1.000000   0.418105 -0.000239     0.689232
SALES-POS      0.418105   1.000000 -0.153300     0.756790
balance       -0.000239  -0.153300  1.000000     0.002437
total spend    0.689232   0.756790  0.002437     1.000000
```

[129]:
```
# Drop irrelevant features
df_ss = df_F.drop([ 'age','PHONE BANK','POS'], axis = 1)
df_ss.head()
```

[129]:

	gender	INTER BANK	PAYMENT	SALES-POS	Annual_Salary	balance	total spend
0	F	0	5184	4251.40	49355	463.96	14611.44
1	M	4004	15828	13477.80	90999	2335.35	35735.28
2	M	1080	3408	12132.28	48734	823.53	22046.16
3	F	1000	10388	7293.76	87036	1726.28	26931.00
4	F	3068	12068	10539.84	99266	12529.59	34898.44

[130]:
```
# Create dummy variable
df_ss['gender'].dtype
df_sm = pd.get_dummies(df_ss, drop_first = True)
#df_sm = df_ss
```

[131]:
```
# Normalise the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_sm['INTER BANK'] = scaler.fit_transform(df_sm[['INTER BANK']])
df_sm['PAYMENT'] = scaler.fit_transform(df_sm[['PAYMENT']])
df_sm['SALES-POS'] = scaler.fit_transform(df_sm[['SALES-POS']])
df_sm['balance'] = scaler.fit_transform(df_sm[['balance']])
df_sm['total spend'] = scaler.fit_transform(df_sm[['total spend']])
df_sm['Annual_Salary'] = scaler.fit_transform(df_sm[['Annual_Salary']])
```

```
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
```

```
  return self.fit(X, **fit_params).transform(X)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

[132]:
```
# Split into train and test
from sklearn.model_selection import train_test_split

X = df_sm.drop(['Annual_Salary'], axis = 1)
Y = df_sm[['Annual_Salary']]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state = 1234)
```

1 Linear Regression

[133]:
```
# Fit and score the model
# Linear regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

LR = LinearRegression()
LR.fit(X_train, Y_train)
Y_Predicted = LR.predict(X_test)

score_train = LR.score(X_train, Y_train)
score_test = LR.score(X_test, Y_test)
#r2_score = r2_score(Y_test, Y_Predicted)
RMSE = math.sqrt(mean_squared_error(Y_test, Y_Predicted))


print('r2 score for Linear Regression is:' ,score_test)
```

```
print('RMSE for Linear Regression is:' ,RMSE)
```

```
r2 score for Linear Regression is: 0.5763367529452759
RMSE for Linear Regression is: 0.6476652932203193
```

[134]:
```
# cross_val_score
from sklearn.model_selection import cross_val_score
scores = cross_val_score(LR, X_train, Y_train, scoring='r2', cv=5)
scores
```

[134]:
```
array([ 0.2288959 , -0.13826055,  0.34843882,  0.44948336, -0.89811154])
```

[135]:
```
# KFold
from sklearn.model_selection import KFold
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)
scores = cross_val_score(LR, X_train, Y_train, scoring='r2', cv=folds)
scores
```

[135]:
```
array([ 0.2989966 ,  0.64696935,  0.57678064, -0.17722345, -0.11800458])
```

2 Feature Selection

[136]:
```
# feature selection
from sklearn.feature_selection import f_regression
result = f_regression(X,Y)
f_score = result [0]
p_value = result [1]

columns = list(X.columns)
print("  Feature   ", "         F_score   " , "          P_value  ")
print("  --------           --------             -------- ")
for i in range(0, len(columns)):
    f1=  f_score[i]
    p1=  p_value[i]
    print(" ", columns[i].ljust(10),"   " , f1, "  ", p1)
```

```
  Feature            F_score            P_value
  --------          --------           --------
  INTER BANK     13.892456810874593    0.00032395470010236047
  PAYMENT        67.85635791948742    7.878230949637538e-13
  SALES-POS      0.997918573516517    0.32027489509276974
  balance        1.2074184722859997    0.2745362021940989
  total spend     15.678767795365692    0.00014233394008753423
  gender_M       1.9135367414106539    0.16971417787004986
```

```
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761:
DataConversionWarning: A column-vector y was passed when a 1d array was
```

```
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

3 Linear Regression after FS

[137]:
```python
# Drop irrelevant features
df_ss = df_F.drop([ 'age','PHONE BANK','POS', 'balance','SALES-POS'], axis = 1)
df_ss.head()
```

[137]:

	gender	INTER BANK	PAYMENT	Annual_Salary	total spend
0	F	0	5184	49355	14611.44
1	M	4004	15828	90999	35735.28
2	M	1080	3408	48734	22046.16
3	F	1000	10388	87036	26931.00
4	F	3068	12068	99266	34898.44

[138]:
```python
# Create dummy variable
df_ss['gender'].dtype
df_sm = pd.get_dummies(df_ss, drop_first = True)
```

[139]:
```python
# Normalise the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_sm['INTER BANK'] = scaler.fit_transform(df_sm[['INTER BANK']])
df_sm['PAYMENT'] = scaler.fit_transform(df_sm[['PAYMENT']])
df_sm['total spend'] = scaler.fit_transform(df_sm[['total spend']])
df_sm['Annual_Salary'] = scaler.fit_transform(df_sm[['Annual_Salary']])
```

```
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
```

```
  return self.partial_fit(X, y)
C:\Users\atefeh\Anaconda3\lib\site-packages\sklearn\base.py:464:
DataConversionWarning: Data with input dtype int64 were all converted to float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

[140]:
```
# Split into train and test
from sklearn.model_selection import train_test_split

X = df_sm.drop(['Annual_Salary'], axis = 1)
Y = df_sm[['Annual_Salary']]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state = 1234)
```

[141]:
```
# Fit and score the model
# Linear regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

LR = LinearRegression()
LR.fit(X_train, Y_train)
Y_Predicted = LR.predict(X_test)

score_train = LR.score(X_train, Y_train)
score_test = LR.score(X_test, Y_test)
RMSE = math.sqrt(mean_squared_error(Y_test, Y_Predicted))

print('r2 score for Linear Regression is:' ,score_test)
print('RMSE for Linear Regression is:' ,RMSE)
```

```
r2 score for Linear Regression is: 0.6173311697006681
RMSE for Linear Regression is: 0.6155336134400503
```

[142]:
```
# cross_val_score
from sklearn.model_selection import cross_val_score
scores = cross_val_score(LR, X_train, Y_train, scoring='r2', cv=5)
scores
```

[142]:
```
array([ 0.23932364, -0.12905291,  0.44972776,  0.49994856, -0.49757349])
```

[143]:
```
# KFold
from sklearn.model_selection import KFold
folds = KFold(n_splits = 5, shuffle = True, random_state = 100)
scores = cross_val_score(LR, X_train, Y_train, scoring='r2', cv=folds)
scores
```

[143]:
```
array([ 0.40019539,  0.68358956,  0.58267536, -0.19175429, -0.09101695])
```

```
[ ]:
```

```
[ ]:
```