Kaushik Mondal Data@ANZ (Task 2)

In [1]:
```python
# Data wrangling
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from statistics import mode

# Machine learning
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.compose import make_column_transformer
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error
```

1. Load data

Load the data that we have saved from the previous exercise.

In [2]:
```python
data = pd.read_pickle("C:/Users/HP/Documents/data.pkl")
data.head()
```

Out[2]:

	status	card_present_flag	account	long_lat	txn_description	merchant_id	first_name	balance	date	gender	...	extraction	amc
0	authorized	1.0	ACC-1598451071	153.41 -27.95	POS	81c48296-73be-44a7-befa-d053f48ce7cd	Diana	35.39	2018-08-01	F	...	01:01:15	1(
1	authorized	0.0	ACC-1598451071	153.41 -27.95	SALES-POS	830a451c-316e-4a6a-bf25-e37caedca49e	Diana	21.20	2018-08-01	F	...	01:13:45	1
2	authorized	1.0	ACC-1222300524	151.23 -33.94	POS	835c231d-8cdf-4e96-859d-e9d571760cf0	Michael	5.71	2018-08-01	M	...	01:26:15	(
3	authorized	1.0	ACC-1037050564	153.10 -27.66	SALES-POS	48514682-c78a-4a88-b0da-2d6302e64673	Rhonda	2117.22	2018-08-01	F	...	01:38:45	4(
4	authorized	1.0	ACC-1598451071	153.41 -27.95	SALES-POS	b4e02c10-0852-4273-b8fd-7b3395e32eb0	Diana	17.95	2018-08-01	F	...	01:51:15	:

5 rows × 23 columns

In [3]:
```python
# Dataframe columns
pd.DataFrame({"Columns": data.columns})
```

Out[3]:

	Columns
0	status
1	card_present_flag
2	account
3	long_lat
4	txn_description
5	merchant_id
6	first_name
7	balance
8	date
9	gender
10	age
11	merchant_suburb
12	merchant_state
13	extraction
14	amount
15	transaction_id
16	customer_id
17	merchant_long_lat
18	movement
19	month
20	dayofweek
21	hour
22	category

2. Feature engineering

In order to model annual salary, we first need to compute the annual salary for each customer as well as create features that can help us predict those salaries.

2.1 Target variable (customers' annual salary)

A target variable, or sometimes called a response variable, is the variable that we are trying to predict and in our case, this is the annual salary for each customer.

In [4]:

```
# Check the salary payment frequency of each customer
salary_df = pd.DataFrame({"customer_id": data.customer_id.unique()})
salary_df.head()
```

Out[4]:

	customer_id
0	CUS-2487424745
1	CUS-2142601169
2	CUS-1614226872
3	CUS-2688605418
4	CUS-4123612273

In [5]:

```
example = data.loc[(data.customer_id == salary_df.customer_id[0]) & (data.txn_description == "PAY/SALARY"), ["d
example
```

Out[5]:

	date	amount
0	2018-08-01	1013.67
1	2018-08-08	1013.67
2	2018-08-15	1013.67
3	2018-08-22	1013.67
4	2018-08-29	1013.67
5	2018-09-05	1013.67
6	2018-09-12	1013.67
7	2018-09-19	1013.67
8	2018-09-26	1013.67
9	2018-10-03	1013.67
10	2018-10-10	1013.67
11	2018-10-17	1013.67
12	2018-10-24	1013.67
13	2018-10-31	1013.67

In [6]:

```
# Loop through all salary payments for each customer
# Assume the salary level is constant for each customer over the observed period
df_freq = []
df_amount = []

for customer in range(len(salary_df)):
    salary = data.loc[(data.customer_id == salary_df.customer_id[customer]) & (data.txn_description == "PAY/SAL
    count = len(salary)
    if count == 0:
        df_amount.append(np.nan)
        df_freq.append(np.nan)
    else:
        days_between_payments = []
        for date in range(len(salary)-1):
            days_between_payments.append((salary.date[date + 1] - salary.date[date]).days)
        df_freq.append(max(days_between_payments))
        df_amount.append(mode(salary.amount))

salary_df["salary_freq"] = df_freq
salary_df["salary_amount"] = df_amount
salary_df["annual_salary"] = salary_df["salary_amount"] / salary_df["salary_freq"] * 365.25
salary_df.head()
```

Out[6]:

	customer_id	salary_freq	salary_amount	annual_salary
0	CUS-2487424745	7	1013.67	52891.852500
1	CUS-2142601169	7	1002.13	52289.711786
2	CUS-1614226872	7	892.09	46547.981786
3	CUS-2688605418	14	2320.30	60534.969643
4	CUS-4123612273	7	1068.04	55728.801429

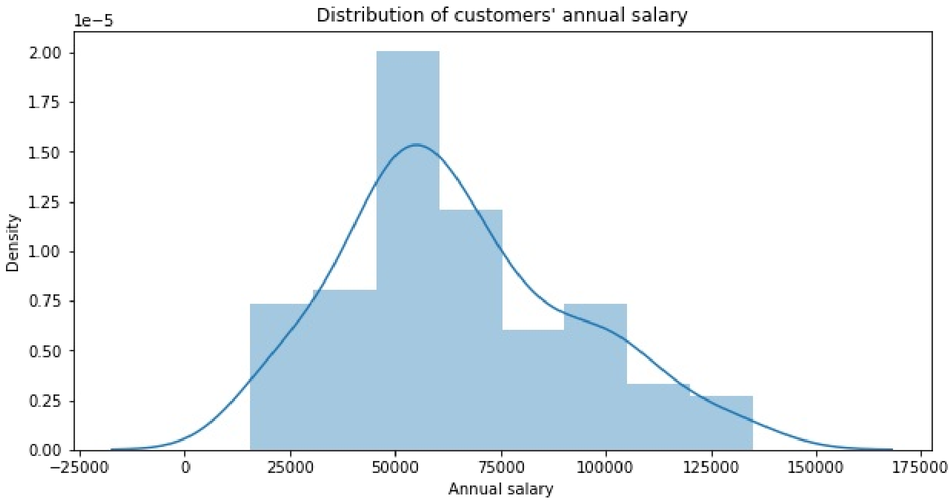
In [7]:

```
# Plot customer's annual salary distribution
plt.figure(figsize = (10, 5))
sns.distplot(salary_df.annual_salary)
plt.title("Distribution of customers' annual salary")
plt.xlabel("Annual salary")
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecate
d function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-le
vel function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[7]:

```
Text(0.5, 0, 'Annual salary')
```



2.2 Predictor variables

Predictor variables or features are variables that will help us predict the salaries for each customer.

In this section, we will create the following features each customer:

Average number of weekly transactions
Maximum transaction amount
Number of large transactions (over $100)
Number of days with transactions
Average transaction amount
Median balance
State of residence
By no means this is an exhaustive list of features we can create. Feel free to come up with your own features!

Also, not to forget from our original dataframe:

Age
Gender

In [8]:
```
# Unique customer id's
unique_id = data.customer_id.unique()
len(unique_id)
```

Out[8]:
```
100
```

In [9]:
```
unique_id[:5]
```

Out[9]:
```
array(['CUS-2487424745', 'CUS-2142601169', 'CUS-1614226872',
       'CUS-2688605418', 'CUS-4123612273'], dtype=object)
```

2.2.1 Average number of weekly transactions

In [10]:
```
avg_no_weekly_trans = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "date"]
    avg_no_weekly_trans.append(round(len(array)/array.nunique()*7))
avg_no_weekly_trans[:5]
```

Out[10]:
```
[48, 29, 24, 14, 21]
```

2.2.2 Maximum amount

In [11]:
```
max_amount = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "amount"]
    max_amount.append(max(array))
max_amount[:5]
```

Out[11]:
```
[1452.21, 2349.55, 892.09, 2320.3, 1068.04]
```

2.2.3 Number of large transactions

In [12]:
```
no_large_trans = []
for id_ in unique_id:
    count = 0
    array = data.loc[data.customer_id == id_, "amount"]
    for amount in array:
        if amount > 100:
            count += 1
    no_large_trans.append(count)
no_large_trans[:5]
```

Out[12]:
```
[22, 23, 22, 25, 32]
```

2.2.4 Number of days with transactions

In [13]:
```
no_days_with_trans = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "date"]
    no_days_with_trans.append(array.nunique())
no_days_with_trans[:5]
```

Out[13]:
```
[85, 74, 76, 63, 44]
```

2.2.5 Average transaction amount

In [14]:
```
avg_trans_amount = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "amount"]
    avg_trans_amount.append(array.mean())
avg_trans_amount[:5]
```

Out[14]:
```
[45.34877162629756,
 78.20610561056101,
 74.46501930501928,
 159.3041860465116,
 166.50835820895517]
```

2.2.6 Median balance

In [15]:
```
median_balance = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "balance"]
    median_balance.append(array.median())
median_balance[:5]
```

Out[15]:
```
[1580.4, 1132.66, 3618.5, 5616.63, 6162.45]
```

2.2.7 State of residence

In [16]:
```
# Assume customers live in the state where most of their transactions occured
state = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "merchant_state"]
    state.append(mode(array))
state[:5]
```

Out[16]:
```
['QLD', 'NSW', 'QLD', 'NSW', 'VIC']
```

2.2.8 Include age and gender from original dataframe

In [17]:
```python
age = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "age"]
    age.append(mode(array))
age[:5]
```

Out[17]:
```
[26, 38, 40, 20, 43]
```

In [18]:
```python
gender = []
for id_ in unique_id:
    array = data.loc[data.customer_id == id_, "gender"]
    gender.append(mode(array))
gender[:5]
```

Out[18]:
```
['F', 'M', 'F', 'M', 'F']
```

2.2.9 Putting everything together

Here, we will put together all the features that we have created into a dataframe called features_df and subsequently concatenate the annual salary for each customer to form a final dataframe called df.

In [19]:
```python
# Predictor variables
features_df = pd.DataFrame({"customer_id": unique_id,
                            "avg_no_weekly_trans": avg_no_weekly_trans,
                            "max_amount": max_amount,
                            "no_large_trans": no_large_trans,
                            "avg_trans_amount": avg_trans_amount,
                            "median_balance": median_balance,
                            "state": state,
                            "age": age,
                            "gender": gender})
features_df.head()
```

Out[19]:

	customer_id	avg_no_weekly_trans	max_amount	no_large_trans	avg_trans_amount	median_balance	state	age	gender
0	CUS-2487424745	48	1452.21	22	45.348772	1580.40	QLD	26	F
1	CUS-2142601169	29	2349.55	23	78.206106	1132.66	NSW	38	M
2	CUS-1614226872	24	892.09	22	74.465019	3618.50	QLD	40	F
3	CUS-2688605418	14	2320.30	25	159.304186	5616.63	NSW	20	M
4	CUS-4123612273	21	1068.04	32	166.508358	6162.45	VIC	43	F

In [20]:
```python
# Target variable
salary_df.head()
```

Out[20]:

	customer_id	salary_freq	salary_amount	annual_salary
0	CUS-2487424745	7	1013.67	52891.852500
1	CUS-2142601169	7	1002.13	52289.711786
2	CUS-1614226872	7	892.09	46547.981786
3	CUS-2688605418	14	2320.30	60534.969643
4	CUS-4123612273	7	1068.04	55728.801429

In [21]:
```python
# Concat annual salary column to features dataframe
df = pd.concat([features_df, salary_df.annual_salary], axis = 1)
df.head()
```

Out[21]:

	customer_id	avg_no_weekly_trans	max_amount	no_large_trans	avg_trans_amount	median_balance	state	age	gender	annual_salary
0	CUS-2487424745	48	1452.21	22	45.348772	1580.40	QLD	26	F	52891.852500
1	CUS-2142601169	29	2349.55	23	78.206106	1132.66	NSW	38	M	52289.711786
2	CUS-1614226872	24	892.09	22	74.465019	3618.50	QLD	40	F	46547.981786
3	CUS-2688605418	14	2320.30	25	159.304186	5616.63	NSW	20	M	60534.969643
4	CUS-4123612273	21	1068.04	32	166.508358	6162.45	VIC	43	F	55728.801429

In [22]:
```python
# Check for missing values
df.isnull().sum()
```

Out[22]:
```
customer_id          0
avg_no_weekly_trans  0
max_amount           0
no_large_trans       0
avg_trans_amount     0
median_balance       0
state                0
age                  0
gender               0
annual_salary        0
dtype: int64
```

Great, there are no missing values!

Our final dataframe is now ready for some minor preprocessing and then we are good to go with modelling.

3. Preprocessing

In this section, we will perform train and test split on our final dataframe as well as construct a column transformer which consists of one-hot-encoder and standard scaler.

3.1 Train test split

Here, we will split 70% of the dataframe into training set, which is used to train our model and 30% of the dataframe into test set, which is used to assess model predictions.

In [23]:
```
X = df.drop(["customer_id", "annual_salary"], axis = 1)
Y = df.annual_salary
print("X shape: ", X.shape)
print("Y shape: ", Y.shape)
```

```
X shape:  (100, 8)
Y shape:  (100,)
```

In [24]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.3, random_state = 42)

print("X_train shape: ", X_train.shape)
print("Y_train shape: ", Y_train.shape)
print("X_test shape: ", X_test.shape)
print("Y_test shape: ", Y_test.shape)
```

```
X_train shape:  (70, 8)
Y_train shape:  (70,)
X_test shape:  (30, 8)
Y_test shape:  (30,)
```

3.2 Column transformer with one-hot encoder and standard scaler

Models cannot train on variables that contain text, therefore we need to encode both the state and gender columns using one-hot encoder. Furthermore, to ensure that each feature contributes proportionally to the final prediction, we need to scale all the numerical variables using standard scaler.

We will include both the one-hot encoder and the standard scaler into a single column transformer.

In [26]:
```
# Crete column transformer
ohe = OneHotEncoder(sparse = False)
scaler = StandardScaler()
column_transform = make_column_transformer((ohe, ["state", "gender"]), (scaler, ["avg_no_weekly_trans", "max_am
```

4. Predict customers' annual salary

Now that our column transformer is ready, we can build a pipeline using the column transformer and a machine learning model to predict customers' annual salary.

Here, we will try two models:

Linear regression
Decision tree regressor

4.1 Linear regression

In [27]:
```
# Instantiate model and pipeline
```

```
lm = LinearRegression()
lm_pipeline = make_pipeline(column_transform, lm)
```

In [28]:
```
# Fit pipeline and make predictions
lm_pipeline.fit(X_train, Y_train)
lm_pred = lm_pipeline.predict(X_test)
```

In [29]:
```
# RMSE
print("RMSE: ", round(np.sqrt(mean_squared_error(lm_pred, Y_test))))
```

```
RMSE:  28039
```

4.2 Decision tree

In [30]:
```
# Instantiate model and pipeline
tree = DecisionTreeRegressor()
tree_pipeline = make_pipeline(column_transform, tree)
```

In [31]:
```
# Fit pipeline and make predictions
tree_pipeline.fit(X_train, Y_train)
tree_pred = tree_pipeline.predict(X_test)
```

In [32]:
```
# RMSE
print("RMSE: ", round(np.sqrt(mean_squared_error(tree_pred, Y_test))))
```

```
RMSE:  23989
```

5. Conclusion

The RMSE for both models are over $20,000 and although decision tree performed better than linear regression by having a smaller RMSE, both models still appear to be highly inaccurate. Therefore, it is risky to use them to predict customers' income bracket. More data is required to develop a more reliable model.

Nevertheless, one can invest more time into coming up with more features and selecting the best ones using backward elimination by optimising for a specific metric like AIC, however I doubt the result will be materially different as we only have a very limited amount of data (100 salaries) available.

In [ ]: