ECT_HW6_108403523

一. python 實作

1. 載入 Churn_Modelling.csv 資料集，並印出哪些欄位含有遺漏值 (missing value)

1.1 Gender、Age、EstimatedSalary 各有 4、6、4 筆缺失值

In [116…

```
import pandas as pd
df = pd.read_csv('Churn_Modelling.csv')
df.isna().sum()
```

Out[116…

```
CustomerId         0
CredRate           0
Geography          0
Gender             4
Age                6
Tenure             0
Balance            0
Prod Number        0
HasCrCard          0
ActMem             0
EstimatedSalary    4
Exited             0
dtype: int64
```

2. 以平均值填入 EstimatedSalary 的遺漏值，以眾數填入 Age 與 Gender的遺漏值

2.1 按照題義填補缺失值

(下面先取得Age、Gender欄位的眾數才做缺失值回填)

In [117…
```
df['Age'].mode()
```

Out[117…
```
0    37.0
dtype: float64
```

In [118…
```
df['Gender'].mode()
```

Out[118…
```
0    Male
dtype: object
```

In [119…
```
# 填入眾數
df['Gender'] = df['Gender'].fillna('Male')
df['Age'] = df['Age'].fillna(37)
# 填入平均數
df['EstimatedSalary'] = df['EstimatedSalary'].fillna(df['EstimatedSalary'].mean())
```

2.2 檢查是否還有缺失值

In [120…
```
# 檢查缺失值
df.isna().sum()
```

Out[120…
```
CustomerId         0
CredRate           0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
Prod Number        0
HasCrCard          0
ActMem             0
EstimatedSalary    0
Exited             0
dtype: int64
```

3. 修改欄位名稱，將 CredRate 改成 CreditScore、ActMem 改成 IsActiveMember、Prod Number 改成 NumOfProducts、Exited 改成 Churn，以利後續分析資料

3.1 重新命名欄位

In [121…
```
df.rename(columns = {'CredRate':'CreditScore',
                     'ActMem':'IsActiveMember',
                     'Prod Number':'NumOfProducts',
                     'Exited':'Churn'}, inplace = True)
```

3.2 檢查重新命名後的結果

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerId       10000 non-null  int64
 1   CreditScore      10000 non-null  int64
 2   Geography        10000 non-null  object
 3   Gender           10000 non-null  object
 4   Age              10000 non-null  float64
 5   Tenure           10000 non-null  int64
 6   Balance          10000 non-null  float64
 7   NumOfProducts    10000 non-null  int64
 8   HasCrCard        10000 non-null  int64
 9   IsActiveMember   10000 non-null  int64
 10  EstimatedSalary  10000 non-null  float64
 11  Churn            10000 non-null  int64
dtypes: float64(3), int64(7), object(2)
memory usage: 937.6+ KB
```

4. 去除 CustomerId,欄位，並將Geography、Gender、HasCrCard、Churn、IsActiveMember 修改資料型態為 category，印出所有欄位的資料型態，並存成新的 CSV 檔 (設定 index=False)

4.1 去除 CustomerId 欄位

In [123…

```
df = df.drop(['CustomerId'],axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  float64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Churn            10000 non-null  int64
dtypes: float64(3), int64(6), object(2)
memory usage: 859.5+ KB
```

4.2 將Geography、Gender、HasCrCard、Churn、IsActiveMember 修改資料型態為 category

In [124…

```
df['Geography'] = df['Geography'].astype('category')
df['Gender'] = df['Gender'].astype('category')
df['HasCrCard'] = df['HasCrCard'].astype('category')
df['Churn'] = df['Churn'].astype('category')
df['IsActiveMember'] = df['IsActiveMember'].astype('category')
```

4.3 印出所有欄位的資料型態，並存成新的 CSV 檔 (index=False)

In [125…

```
df.info()
df.to_csv('Churn_Modelling_Modified.csv',index=False)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype   
---  ------           --------------  -----   
 0   CreditScore      10000 non-null  int64   
 1   Geography        10000 non-null  category
 2   Gender           10000 non-null  category
 3   Age              10000 non-null  float64 
 4   Tenure           10000 non-null  int64   
 5   Balance          10000 non-null  float64 
 6   NumOfProducts    10000 non-null  int64   
 7   HasCrCard        10000 non-null  category
 8   IsActiveMember   10000 non-null  category
 9   EstimatedSalary  10000 non-null  float64 
 10  Churn            10000 non-null  category
dtypes: category(5), float64(3), int64(3)
memory usage: 518.3 KB
```

5. 對各個欄位進行分析，了解目前銀行客戶的概況：

5.1 對 HasCrCard 欄位進行分析，說明有多少比例的人持有信用卡，多少比例的人不持有信用卡

有持卡: 70.55%、沒持卡: 29.45%

In [126…

```
# 查看有多少人有/沒有卡
print(df.groupby('HasCrCard').size())
# 計算持卡比例
print("有持卡的比例: "+str(705500/10000)+'%')
print("沒有持卡的比例: "+str(294500/10000)+'%')
```

```
HasCrCard
0    2945
1    7055
dtype: int64
有持卡的比例: 70.55%
沒有持卡的比例: 29.45%
```

5.2 對 Churn 欄位進行分析，說明有多少比例的客戶流失

流失比例: 20.37%

In [127…

```
# 查看有多少人流失
print(df.groupby('Churn').size())
# 計算持卡比例
print("流失的比例: "+str(203700/10000)+'%')
```

```
Churn
0    7963
1    2037
dtype: int64
流失的比例: 20.37%
```

5.3 對 IsActiveMember 欄位進行分析，說明有多少比例的客戶仍是活躍狀態

活躍狀態比例: 51.51%

In [128…

```
# 查看有多少人流失
print(df.groupby('IsActiveMember').size())
# 計算持卡比例
print("活躍用戶的比例: "+str(515100/10000)+'%')
```

```
IsActiveMember
0    4849
1    5151
dtype: int64
活躍用戶的比例: 51.51%
```

5.4 對 Churn 進行分析，觀察流失客戶跟未流失客戶的資料平均值

未流失客戶的 CreditScore 平均比流失客戶略高，Age 則比流失客戶低蠻多的。
流失客戶的 Balance、EstimatedSalary 平均都較未流失客戶高。

In [129…

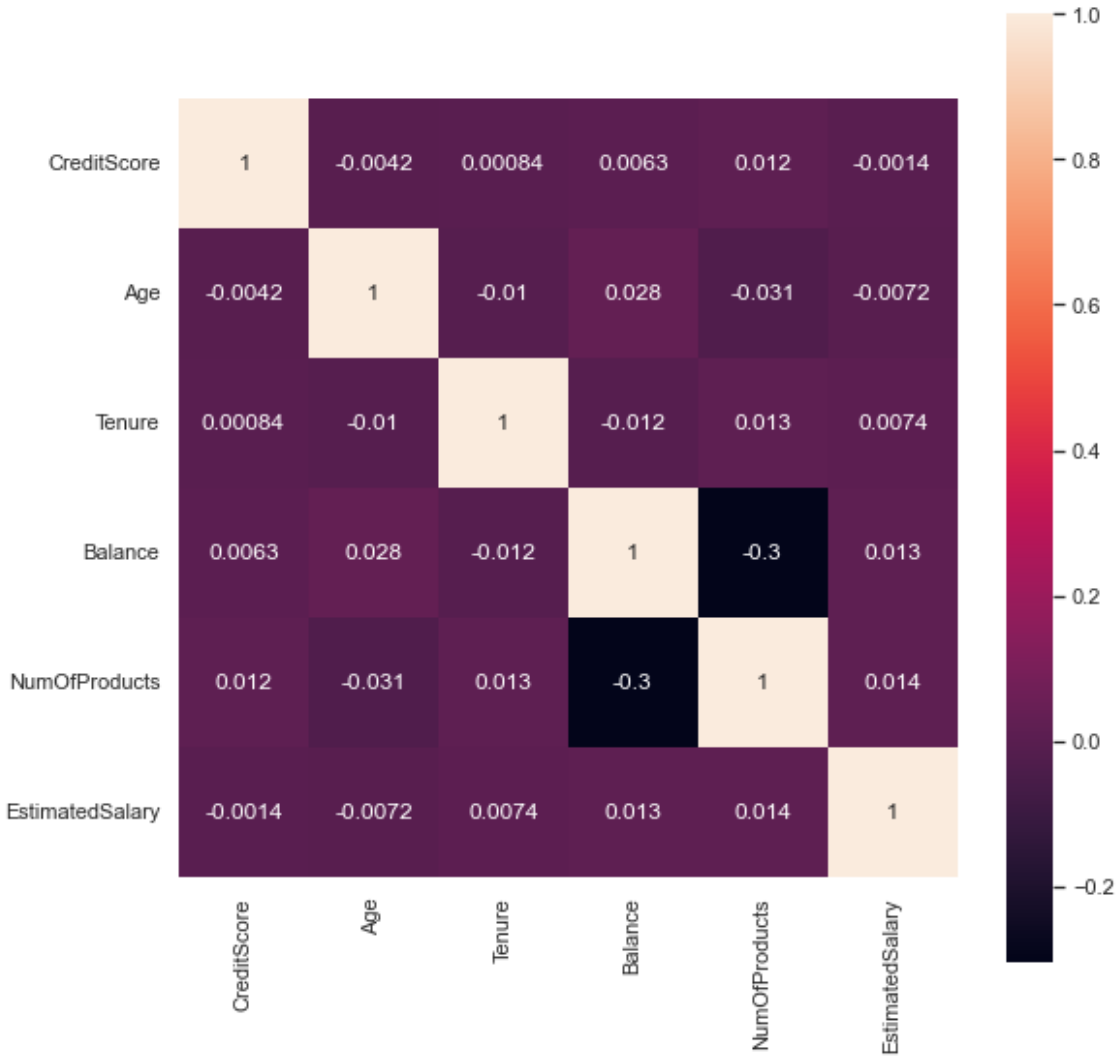
```
print("未流失客戶的資料平均值:")
print(df[df['Churn']==0].mean())
print('='*30)
print("流失客戶的資料平均值:")
print(df[df['Churn']==1].mean())
```

```
未流失客戶的資料平均值:
CreditScore          651.853196
Age                   37.411277
Tenure                 5.033279
Balance            72745.296779
NumOfProducts          1.544267
EstimatedSalary    99718.932023
dtype: float64
==============================
流失客戶的資料平均值:
CreditScore          645.351497
Age                   44.837997
Tenure                 4.932744
Balance            91108.539337
NumOfProducts          1.475209
EstimatedSalary    101465.677531
dtype: float64
```

5.5 計算屬性間的相關係數，並用 seaborn 繪製出熱力圖 (heatmap)

In [130…

```
import seaborn as sns
import matplotlib.pyplot as plt
def test(df):
    dfData = df.corr()
    plt.subplots(figsize=(9, 9)) # 設定畫面大小
    sns.heatmap(dfData, annot=True, vmax=1, square=True)
    plt.savefig('./BluesStateRelation.png')
    plt.show()
test(df)
```



6. 運用資料視覺化來幫助分析：

6.1 繪出 Gender 與 Churn 的數量關係，分析不同性別於客戶流失的關係

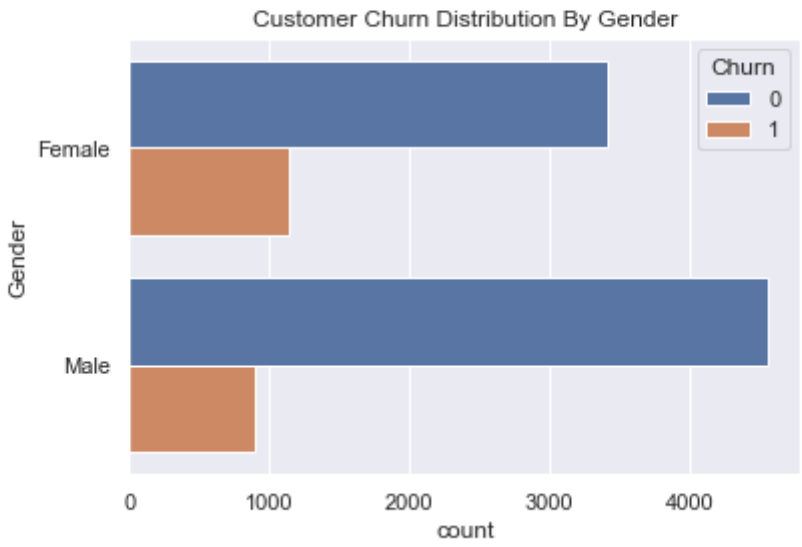
女性客戶流失的數量比男性客戶來得多

In [131…

```
import seaborn as sns
sns.set_theme(style="darkgrid")
ax = sns.countplot(y="Gender", hue="Churn", data=df)
ax.set_title("Customer Churn Distribution By Gender")
```

Out[131…

```
Text(0.5, 1.0, 'Customer Churn Distribution By Gender')
```



6.2 繪出 Geography 與 Churn 的數量關係，分析不同地區於客戶流失的關係

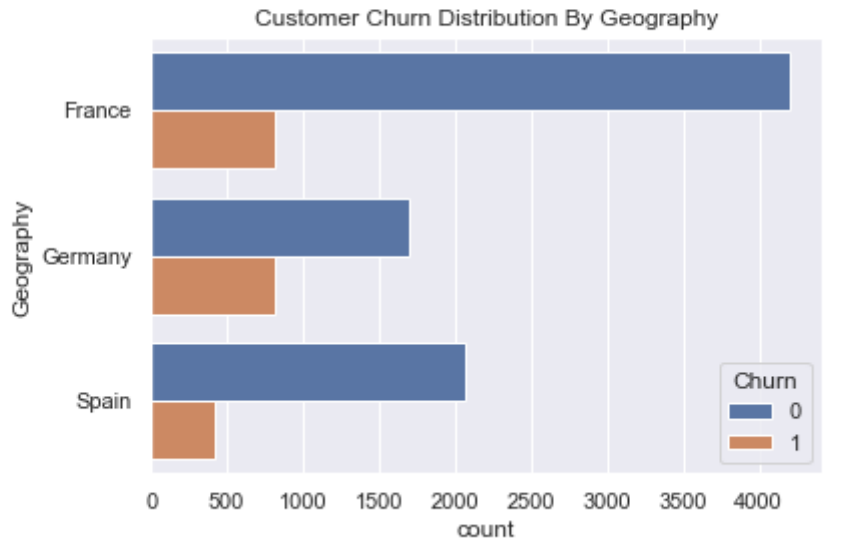
France、Germany 流失的客戶量基本相同，留下的客戶又以 France 最多。
Spain 是客戶流失量最少的地區。

In [132…

```
import seaborn as sns
sns.set_theme(style="darkgrid")
ax = sns.countplot(y="Geography", hue="Churn", data=df)
ax.set_title("Customer Churn Distribution By Geography")
```

Out[132…

```
Text(0.5, 1.0, 'Customer Churn Distribution By Geography')
```



6.3 繪出 Age 分布與 Churn 的關係，分析不同年齡於客戶流失率的關係

從圖中可以驗證流失的客戶年紀很大一部分都大於未流失客戶的年紀。

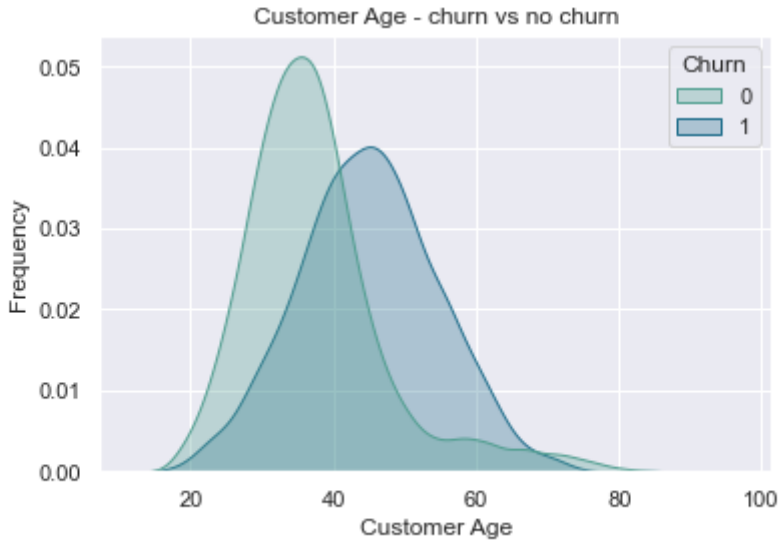
In [133…

```
ax2 = sns.kdeplot(
   data=df, x="Age", hue="Churn",
   fill=True, common_norm=False, palette="crest",
   alpha=.3, linewidth=1,
)

ax2.set_ylabel('Frequency')
ax2.set_xlabel('Customer Age')
ax2.set_title('Customer Age - churn vs no churn')
```

Out[133…

```
Text(0.5, 1.0, 'Customer Age - churn vs no churn')
```



6.4 繪出 CreditScore 與 Churn 的關係，分析客戶信用分數於客戶流失率的關係

CreditScore 與 Churn 的關係圖形中，未流失、流失客戶基本疊在一起，可以說明並驗證"5.4"中，流失與未流失客戶的平均 CreditScore 沒有太大的差別，我們僅能說某 CreditScore 區間的客戶流失比較多，但無法說明 CreditScore 與客戶流失與否的關係。

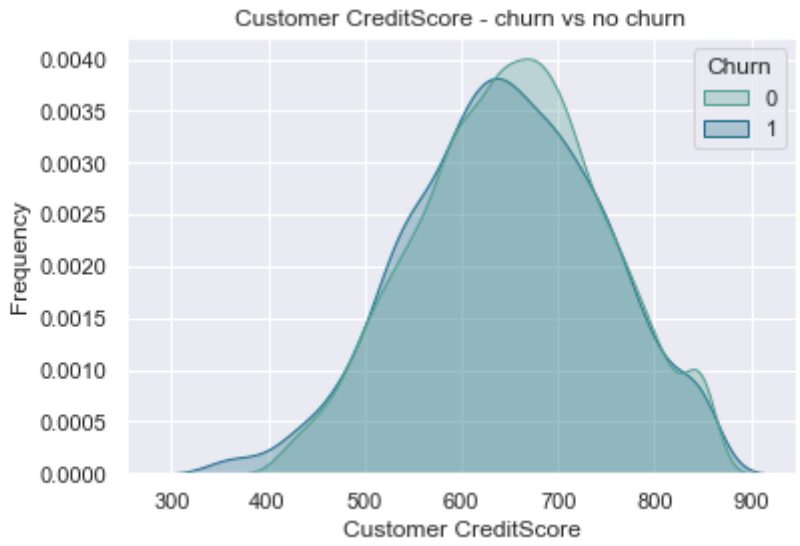
In [134…

```
ax2 = sns.kdeplot(
   data=df, x="CreditScore", hue="Churn",
   fill=True, common_norm=False, palette="crest",
   alpha=.3, linewidth=1,
)

ax2.set_ylabel('Frequency')
ax2.set_xlabel('Customer CreditScore')
ax2.set_title('Customer CreditScore - churn vs no churn')
```

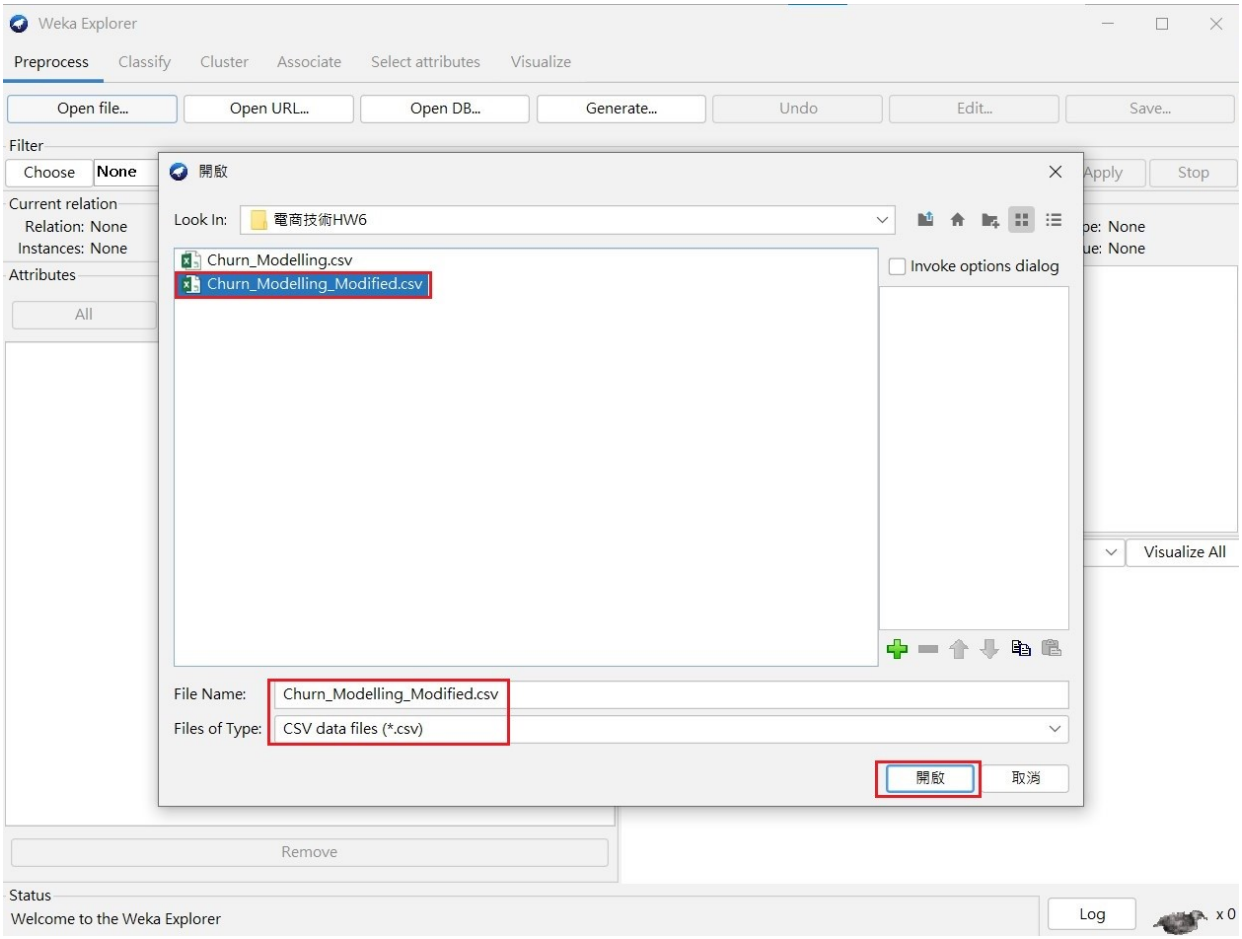
Out[134…

```
Text(0.5, 1.0, 'Customer CreditScore - churn vs no churn')
```

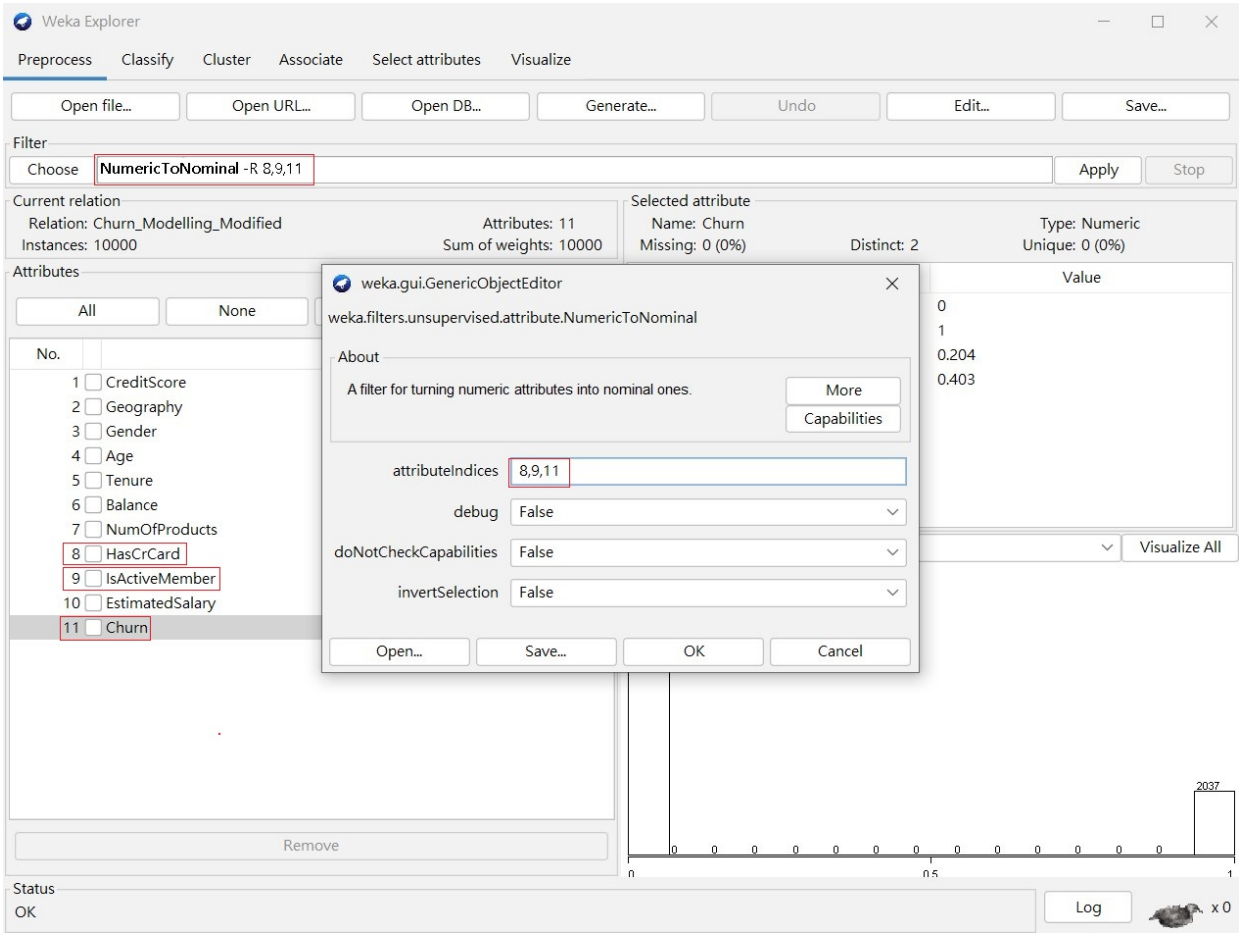


二. Weka 實作

0. 載入 Python 儲存的新的 CSV 檔



1. 將 HasCrCard, IsActiveMember, Churn 轉成 Nominal 屬性



2. 使用 Attribute Selection，以 CfsSubsetEval 及 BestFirst 來篩選屬性，並說明屬性篩選結果

   CfsSubsetEval評估器使用相關分析的方式，找出屬性本身與分類結果(class)最相關、屬性與其他屬性最不相關的屬性。BestFirst是貪婪演算法的爬山法，它會儘可能找出局部最佳結果，速度快，但不能從整體大局找到最佳結果，圖片中的Start Set 是 Empty。

   特徵篩選完後，最終找到 CreditScore、Geography、Gender、Age、NumOfProducts、IsActiveMember 共 6 個屬性。