Logistic Regression

In [1]:
```
# This code appears in every demonstration Notebook.
# By default, when you run each cell, only the last output of the codes will show.
# This code makes all outputs of a cell show.
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

1. Import libraries

In [2]:
```
import pandas as pd
import statsmodels.api as sm
# api submodule gives access to the most commonly used
# classes and functions directly.
```

```
C:\Users\shanm\AppData\Local\Temp\ipykernel_24360\867986546.py:1: DeprecationWarnin
g:
Pyarrow will become a required dependency of pandas in the next major release of pan
das (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better inte
roperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

2. Import Default dataset

In [3]:
```
default = pd.read_csv('Default.csv')
```

In [4]:
```
default.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 4 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   default  10000 non-null  object
 1   student  10000 non-null  object
 2   balance  10000 non-null  float64
 3   income   10000 non-null  float64
dtypes: float64(2), object(2)
memory usage: 312.6+ KB
```

In [5]:
```
default.head()
```

Out[5]:

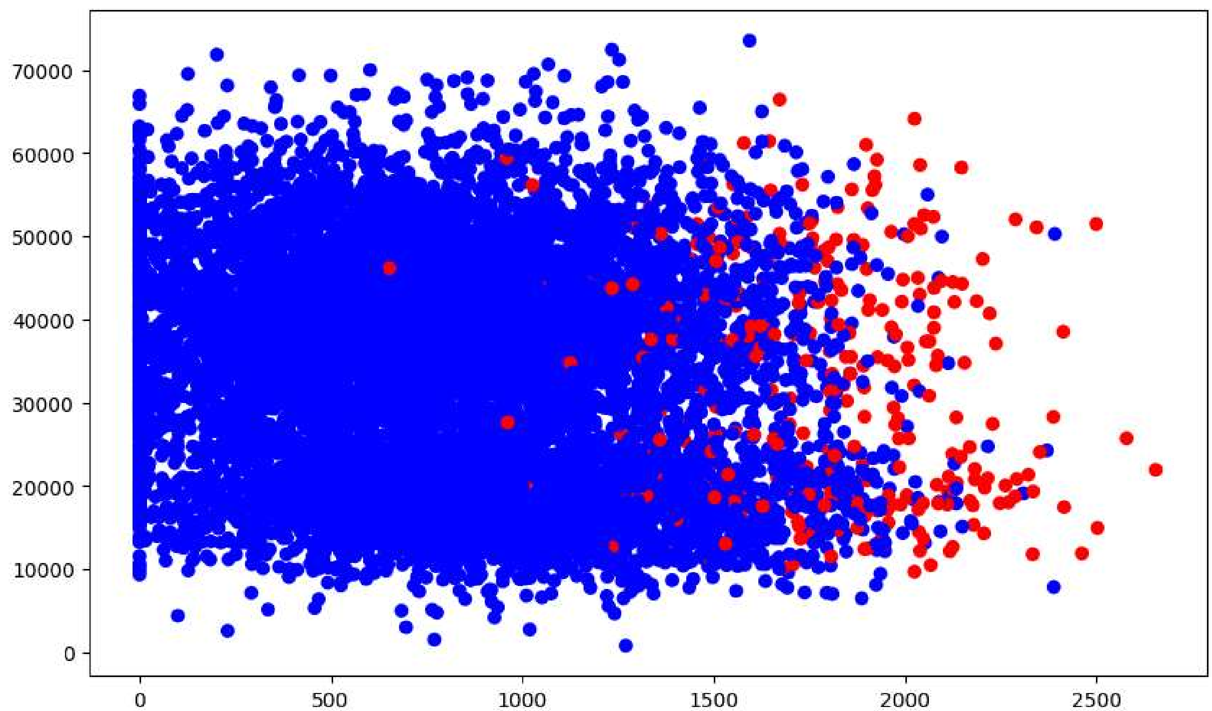
	default	student	balance	income
0	No	No	729.526495	44361.625074
1	No	Yes	817.180407	12106.134700
2	No	No	1073.549164	31767.138947
3	No	No	529.250605	35704.493935
4	No	No	785.655883	38463.495879

In [6]:
```
# Color dictionary
colors = {'No': 'blue', 'Yes': 'red'}
markers = {'No': 's', 'Yes': 'o'}
```

In [7]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,6))
plt.scatter(default['balance'], default['income'],
            c = default['default'].map(colors))
```

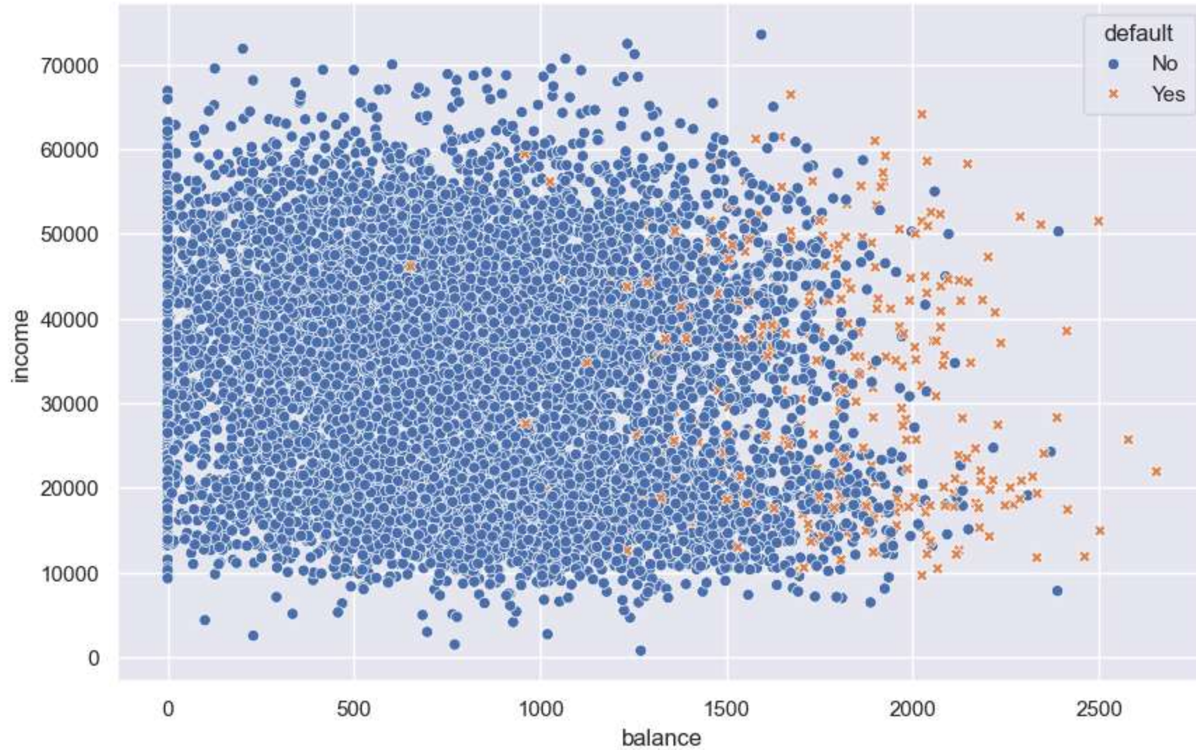
Out[7]: <Figure size 1000x600 with 0 Axes>

Out[7]: <matplotlib.collections.PathCollection at 0x2b5033f2f50>



In [8]:
```
import seaborn as sns
sns.set(rc={'figure.figsize':(10,6.27)})
sns.scatterplot(data = default, x = default['balance'], y = default['income'],
                style = default['default'], hue = default['default'])
```

Out[8]: <Axes: xlabel='balance', ylabel='income'>



In [9]:
```python
import statsmodels.api as sm

# Models in statsmodels require design matrices, which mean that the data
# need to be represented in a way that is compatible with model building

# We can use patsy library to create design matrices more easily, e.g.
# create dummy variables
import patsy

y, X = patsy.dmatrices('default ~ balance + income + student',
                       data = default,
                       return_type = 'dataframe')
```

In [10]:
```python
y.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 10000 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   default[No]   10000 non-null  float64
 1   default[Yes]  10000 non-null  float64
dtypes: float64(2)
memory usage: 234.4 KB
```

In [11]:
```python
# pd.concat([y,default.default],axis=1)[default.default=='Yes']
```

In [12]:
```python
##y.head()
X.head()
```

Out[12]:

	Intercept	student[T.Yes]	balance	income
0	1.0	0.0	729.526495	44361.625074
1	1.0	1.0	817.180407	12106.134700
2	1.0	0.0	1073.549164	31767.138947
3	1.0	0.0	529.250605	35704.493935
4	1.0	0.0	785.655883	38463.495879

In [13]:
```
# Fit a single variable model - balance
logit_model_1 = sm.Logit(y['default[Yes]'], X[['Intercept','balance']])
logit_res_1 =  logit_model_1.fit()
logit_res_1.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.079823
         Iterations 10
```

Out[13]:

Logit Regression Results

Dep. Variable:	default[Yes]	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9998
Method:	MLE	**Df Model:**	1
Date:	Tue, 27 Feb 2024	**Pseudo R-squ.:**	0.4534
Time:	13:37:15	**Log-Likelihood:**	-798.23
converged:	True	**LL-Null:**	-1460.3
Covariance Type:	nonrobust	**LLR p-value:**	6.233e-290

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-10.6513	0.361	-29.491	0.000	-11.359	-9.943
balance	0.0055	0.000	24.952	0.000	0.005	0.006

Possibly complete quasi-separation: A fraction 0.13 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case some parameters will not be identified.

In [14]:
```
b1000 = pd.DataFrame({'Intercept':[1], 'balance':[1000]})
```

In [15]:
```
b1100 = pd.DataFrame({'Intercept':[1], 'balance':[1100]})
```

In [16]:
```
b2000 = pd.DataFrame({'Intercept':[1], 'balance':[2000]})
```

In [17]:
```
b2000
```

Out[17]:

	Intercept	balance
0	1	2000

In [18]:
```
logit_res_1.predict(b1000)
```

Out[18]:
```
0    0.005752
dtype: float64
```

In [19]:
```
logit_res_1.predict(b1100)
```

Out[19]:
```
0    0.009927
dtype: float64
```

In [20]:
```
def odds_ratio(p1,p2):
    return (p2/(1-p2))/(p1/(1-p1))
```

In [23]:
```
odds_ratio(logit_res_1.predict(b1000),logit_res_1.predict(b1100))
```

Out[23]:
```
0    1.733065
dtype: float64
```

odds_ratio(0.005752,0.009927)

In [ ]:
```
math.exp(0.55)
```

In [ ]:
```
logit_res_1.predict(b2000)
```

In [ ]:
```
import math
math.exp(5.5)
```

In [ ]:
```
# Fit a single variable model - student
logit_model_2 = sm.Logit(y['default[Yes]'], X[['Intercept','student[T.Yes]']])
logit_res_2 =  logit_model_2.fit()
logit_res_2.summary()
```

In [27]:
```
# Fit a full model
logit_model_3 = sm.Logit(y['default[Yes]'], X)
logit_res_3 =  logit_model_3.fit()
logit_res_3.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.078577
         Iterations 10
```

Out[27]:

Logit Regression Results

Dep. Variable:	default[Yes]	**No. Observations:**	10000
Model:	Logit	**Df Residuals:**	9996
Method:	MLE	**Df Model:**	3
Date:	Tue, 27 Feb 2024	**Pseudo R-squ.:**	0.4619
Time:	13:37:45	**Log-Likelihood:**	-785.77
converged:	True	**LL-Null:**	-1460.3
Covariance Type:	nonrobust	**LLR p-value:**	3.257e-292

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-10.8690	0.492	-22.079	0.000	-11.834	-9.904
student[T.Yes]	-0.6468	0.236	-2.738	0.006	-1.110	-0.184
balance	0.0057	0.000	24.737	0.000	0.005	0.006
income	3.033e-06	8.2e-06	0.370	0.712	-1.3e-05	1.91e-05

Possibly complete quasi-separation: A fraction 0.15 of observations can be perfectly predicted. This might indicate that there is complete quasi-separation. In this case some parameters will not be identified.

In [29]:

```
# Make predictions for the dataset
predicted_p = logit_res_3.predict(X)
```

In [30]:

```
predicted_p
```

Out[30]:

```
0       0.001429
1       0.001122
2       0.009812
3       0.000442
4       0.001936
          ...
9995    0.001323
9996    0.001560
9997    0.002896
9998    0.147144
9999    0.000033
Length: 10000, dtype: float64
```

In [34]:

```
# Classification based on threshold
predicted_classes = (predicted_p >= 0.5).astype(int)
predicted_classes[:10000]
```

Out[34]:
```
0       0
1       0
2       0
3       0
4       0
       ..
9995    0
9996    0
9997    0
9998    0
9999    0
Length: 10000, dtype: int32
```

In [32]:
```python
# Evaluate the classification performance

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy = accuracy_score(y['default[Yes]'], predicted_classes)
conf_matrix = confusion_matrix(y['default[Yes]'], predicted_classes)
classification_report_str = classification_report(y['default[Yes]'], predicted_clas
```

In [33]:
```python
print(accuracy)
print(conf_matrix)
print(classification_report_str)
```

```
0.9732
[[9627   40]
 [ 228  105]]
              precision    recall  f1-score   support

         0.0       0.98      1.00      0.99      9667
         1.0       0.72      0.32      0.44       333

    accuracy                           0.97     10000
   macro avg       0.85      0.66      0.71     10000
weighted avg       0.97      0.97      0.97     10000
```

In [ ]:
```python
# Change the base case
y, X = patsy.dmatrices('default ~ balance + income + C(student,Treatment(reference
                      data = default,
                      return_type = 'dataframe')
```

In [ ]:
```
jupyter nbconvert --to pdf DSCI 5240 Logistic Regression.ipynb
```