Exercise 1 - Simple rules

First name: Brian

Last name: Schweigler

Matriculation number: 16-102-071

(1a) What is the best default rule for this dataset? (Default means without any evidence about the person)?

Without prior knowledge, all we know is whether a person died or not. For this, we can test the two rules "all dead" or all "survived":

In [80]:

```
%load_ext autoreload
%autoreload 2
%matplotlib inline

import os
import math
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
from sklearn.feature_selection import chi2
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn import preprocessing
import scipy
from mlxtend.classifier import OneRClassifier
from mlxtend.evaluate import accuracy_score

clf = GaussianNB()
le = preprocessing.LabelEncoder()
df = pd.read_csv("data/titanic.csv", index_col='Name')
pd.set_option('display.max_colwidth', None)
print(df.head(10))
# df.describe(include='all')
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
                                                    Survived  Pclass     Sex  \
Name
Mr. Owen Harris Braund                                     0       3    male
Mrs. John Bradley (Florence Briggs Thayer) Cumings         1       1  female
Miss. Laina Heikkinen                                      1       3  female
Mrs. Jacques Heath (Lily May Peel) Futrelle                1       1  female
Mr. William Henry Allen                                    0       3    male
Mr. James Moran                                            0       3    male
Mr. Timothy J McCarthy                                     0       1    male
Master. Gosta Leonard Palsson                              0       3    male
Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson           1       3  female
Mrs. Nicholas (Adele Achem) Nasser                         1       2  female

                                                     Age  \
Name
Mr. Owen Harris Braund                              22.0
Mrs. John Bradley (Florence Briggs Thayer) Cumings  38.0
Miss. Laina Heikkinen                               26.0
Mrs. Jacques Heath (Lily May Peel) Futrelle         35.0
Mr. William Henry Allen                             35.0
Mr. James Moran                                     27.0
Mr. Timothy J McCarthy                              54.0
Master. Gosta Leonard Palsson                        2.0
Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson    27.0
Mrs. Nicholas (Adele Achem) Nasser                  14.0

                                                    Siblings/Spouses Aboard  \
Name
Mr. Owen Harris Braund                                                    1
Mrs. John Bradley (Florence Briggs Thayer) Cumings                        1
Miss. Laina Heikkinen                                                     0
Mrs. Jacques Heath (Lily May Peel) Futrelle                               1
Mr. William Henry Allen                                                   0
Mr. James Moran                                                           0
Mr. Timothy J McCarthy                                                    0
Master. Gosta Leonard Palsson                                             3
Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson                          0
Mrs. Nicholas (Adele Achem) Nasser                                        1

                                                    Parents/Children Aboard  \
Name
Mr. Owen Harris Braund                                                    0
Mrs. John Bradley (Florence Briggs Thayer) Cumings                        0
Miss. Laina Heikkinen                                                     0
Mrs. Jacques Heath (Lily May Peel) Futrelle                               0
Mr. William Henry Allen                                                   0
Mr. James Moran                                                           0
Mr. Timothy J McCarthy                                                    0
Master. Gosta Leonard Palsson                                             1
Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson                          2
Mrs. Nicholas (Adele Achem) Nasser                                        0

                                                       Fare
Name
Mr. Owen Harris Braund                               7.2500
Mrs. John Bradley (Florence Briggs Thayer) Cumings  71.2833
Miss. Laina Heikkinen                                7.9250
```

```
Mrs. Jacques Heath (Lily May Peel) Futrelle        53.1000
Mr. William Henry Allen                             8.0500
Mr. James Moran                                     8.4583
Mr. Timothy J McCarthy                             51.8625
Master. Gosta Leonard Palsson                      21.0750
Mrs. Oscar W (Elisabeth Vilhelmina Berg) Johnson   11.1333
Mrs. Nicholas (Adele Achem) Nasser                 30.0708
```

In [69]:

```
survived = 0
died = 0
for index, row in df.iterrows():
    if row["Survived"] == 1:
        survived += 1
    else:
        died += 1

print("Accuracy if assuming everyone survived :", survived/(survived+died))
print("Accuracy if assuming everyone died :", died/(survived+died))
```

```
Accuracy if assuming everyone survived : 0.3855693348365276
Accuracy if assuming everyone died : 0.6144306651634723
```

In general, "choose most frequent to be the default rule". In this case, assuming that everyone died is the best default rule, and we should aim to beat with our prediction approaches.

(1b) What is the best 1R for this dataset?

Very likely, without prior information, we can assume that due to "mothers and children first" when the titanic sank, that those are most likely to have survived, thus gender (Sex) or if they are a parent/child.

So let's test this:

In [70]:

```
X_d = df[["Sex"]]
y = df["Survived"]
Xd_train, Xd_test, y_train, y_test = train_test_split(X_d, y, test_size=0.3, random_state=2)
oner = OneRClassifier()
oner.fit(Xd_train.to_numpy(), y_train)
y_pred = oner.predict(Xd_test.to_numpy())

accuracy = accuracy_score(y_test, y_pred)
print("Accuracy using outdated binary gender: ", accuracy)

X_d_fam = df[["Parents/Children Aboard"]]
y_fam = df["Survived"]
Xd_train_fam, Xd_test_fam, y_train_fam, y_test_fam = train_test_split(X_d_fam, y_fam, test_size=0.3, random_state=2)
oner_fam = OneRClassifier()
oner_fam.fit(Xd_train_fam.to_numpy(), y_train_fam)
y_pred_fam = oner_fam.predict(Xd_test_fam.to_numpy())

accuracy_fam = accuracy_score(y_test_fam, y_pred_fam)
print("Parents/Children accuracy: ", accuracy_fam)
```

```
Accuracy using outdated binary gender:  0.8014981273408239
Parents/Children accuracy:  0.602996254681648
```

Thus the outdated binary gender within this dataset (M/F) is the best 1R.

(1c) Can you produce a second rule based on a single attribute with a good effectiveness?

For this we can simply look at all the variants:

In [71]:

```
X_d_fare = df[["Fare"]]
y_fare = df["Survived"]
Xd_train_fare, Xd_test_fare, y_train_fare, y_test_fare = train_test_split(X_d_fare, y_fare, test_size=0.3, random_state=2)
oner_fare = OneRClassifier()
oner_fare.fit(Xd_train_fare.to_numpy(), y_train_fare)
y_pred_fare = oner_fare.predict(Xd_test_fare.to_numpy())
accuracy_fare = accuracy_score(y_test_fare, y_pred_fare)
print("Fare Accuracy: ", accuracy_fare)

X_d_pclass = df[["Pclass"]]
y_pclass = df["Survived"]
Xd_train_pclass, Xd_test_pclass, y_train_pclass, y_test_pclass = train_test_split(X_d_pclass, y_pclass, test_size=0.3, random_state=2)
oner_pclass = OneRClassifier()
oner_pclass.fit(Xd_train_pclass.to_numpy(), y_train_pclass)
y_pred_pclass = oner_pclass.predict(Xd_test_pclass.to_numpy())

accuracy_pclass = accuracy_score(y_test_pclass, y_pred_pclass)
print("Pclass Accuracy: ", accuracy_pclass)

X_d_age = df[["Age"]]
y_age = df["Survived"]
Xd_train_age, Xd_test_age, y_train_age, y_test_age = train_test_split(X_d_age, y_age, test_size=0.3, random_state=2)
oner_age = OneRClassifier()
oner_age.fit(Xd_train_age.to_numpy(), y_train_age)
y_pred_age = oner_age.predict(Xd_test_age.to_numpy())

accuracy_age = accuracy_score(y_test_age, y_pred_age)
print("Age accuracy: ", accuracy_age)

X_d_sib = df[["Siblings/Spouses Aboard"]]
y_sib = df["Survived"]
Xd_train_sib, Xd_test_sib, y_train_sib, y_test_sib = train_test_split(X_d_sib, y_sib, test_size=0.3, random_state=2)
oner_sib = OneRClassifier()
oner_sib.fit(Xd_train_sib.to_numpy(), y_train_sib)
```

```
y_pred_sib = oner_sib.predict(Xd_test_sib.to_numpy())

accuracy_sib = accuracy_score(y_test_sib, y_pred_sib)
print("Sibling/Spouse accuracy: ", accuracy_sib)
```

```
Fare Accuracy:  0.6853932584269663
Pclass Accuracy:  0.6853932584269663
Age accuracy:  0.5917602996254682
Sibling/Spouse accuracy:  0.6367041198501873
```

Thus, we can conclude that using the Pclass (or Fare which correlates with it) are the best ones. This is likely due to the fact that those who payed more (or are in a better class) are higher up on the ship, farther away from the engines. Thus they had more time to escape.

---

(2) Use a stock / market index for daily return of the day

First we simply load the dataset

In [72]:

```
pd.set_option('display.max_colwidth', None)
stock_df = pd.read_csv("data/Nasdaq.csv", index_col='Date')
print(stock_df.head(10))
# stock_df['Date'] = stock_df['Date'].apply(pd.to_datetime)
stock_df.describe(include='all')
```

```
                  Open        High         Low       Close   Adj Close  Volume
Date
1971-02-05  100.000000  100.000000  100.000000  100.000000  100.000000       0
1971-02-08  100.839996  100.839996  100.839996  100.839996  100.839996       0
1971-02-09  100.760002  100.760002  100.760002  100.760002  100.760002       0
1971-02-10  100.690002  100.690002  100.690002  100.690002  100.690002       0
1971-02-11  101.449997  101.449997  101.449997  101.449997  101.449997       0
1971-02-12  102.050003  102.050003  102.050003  102.050003  102.050003       0
1971-02-16  102.190002  102.190002  102.190002  102.190002  102.190002       0
1971-02-17  101.739998  101.739998  101.739998  101.739998  101.739998       0
1971-02-18  101.419998  101.419998  101.419998  101.419998  101.419998       0
1971-02-19  100.699997  100.699997  100.699997  100.699997  100.699997       0
```

Out[72]:

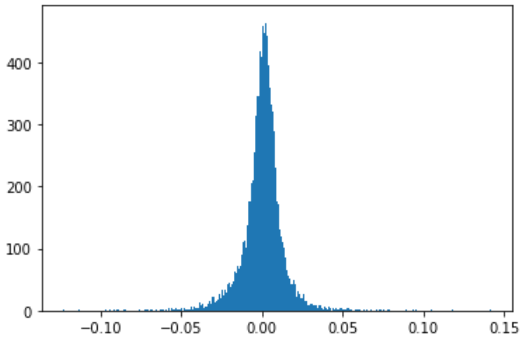
	Open	High	Low	Close	Adj Close	Volume
count	12402.000000	12402.000000	12402.000000	12402.000000	12402.000000	1.240200e+04
mean	2120.657774	2134.377615	2104.791436	2120.585484	2120.585484	1.042295e+09
std	2692.888884	2709.482136	2673.491669	2693.171132	2693.171132	1.145532e+09
min	54.869999	54.869999	54.869999	54.869999	54.869999	0.000000e+00
25%	284.700012	284.857498	284.150002	284.477501	284.477501	5.035250e+07
50%	1262.969971	1268.849976	1250.440002	1259.405029	1259.405029	5.930600e+08
75%	2623.209961	2642.297607	2599.407410	2619.670044	2619.670044	1.870712e+09
max	15375.980469	15403.440430	15343.280273	15374.330078	15374.330078	1.110216e+10

Look at daily return histograms:

In [73]:

```
daily_return = np.empty(stock_df['Close'].shape)
#  From Slides: Daily return (r): Difference in percentage between the price at time t+1 and at time t
daily_return[0] = float('NaN') # The first
daily_return[1:] = np.ediff1d(stock_df['Close']) / stock_df['Close'][:-1]
stock_df.insert(loc=len(stock_df.columns), column='Daily Return', value=daily_return)

bins = int(len(daily_return) / 32)
plt.hist(daily_return, bins=bins)
plt.show()
```



An approach to compare binary and ternary solution.

In [74]:

```
binary = (daily_return > 0).astype(float)
stock_df.insert(loc=len(stock_df.columns), column='Binary Decision', value=binary)

limit = 0.001
ternary = np.zeros(daily_return.shape)
ternary[np.where(daily_return > limit)] = 2
ternary[np.where(daily_return < limit)] = 1
stock_df.insert(loc=len(stock_df.columns), column='Ternary Decision', value=ternary)

print(stock_df.head(20))
```

```
                  Open        High         Low       Close   Adj Close  \
```

```
Date
1971-02-05  100.000000  100.000000  100.000000  100.000000  100.000000
1971-02-08  100.839996  100.839996  100.839996  100.839996  100.839996
1971-02-09  100.760002  100.760002  100.760002  100.760002  100.760002
1971-02-10  100.690002  100.690002  100.690002  100.690002  100.690002
1971-02-11  101.449997  101.449997  101.449997  101.449997  101.449997
1971-02-12  102.050003  102.050003  102.050003  102.050003  102.050003
1971-02-16  102.190002  102.190002  102.190002  102.190002  102.190002
1971-02-17  101.739998  101.739998  101.739998  101.739998  101.739998
1971-02-18  101.419998  101.419998  101.419998  101.419998  101.419998
1971-02-19  100.699997  100.699997  100.699997  100.699997  100.699997
1971-02-22   99.680000   99.680000   99.680000   99.680000   99.680000
1971-02-23   99.720001   99.720001   99.720001   99.720001   99.720001
1971-02-24  100.639999  100.639999  100.639999  100.639999  100.639999
1971-02-25  101.230003  101.230003  101.230003  101.230003  101.230003
1971-02-26  101.339996  101.339996  101.339996  101.339996  101.339996
1971-03-01  101.779999  101.779999  101.779999  101.779999  101.779999
1971-03-02  101.839996  101.839996  101.839996  101.839996  101.839996
1971-03-03  102.070000  102.070000  102.070000  102.070000  102.070000
1971-03-04  102.779999  102.779999  102.779999  102.779999  102.779999
1971-03-05  103.000000  103.000000  103.000000  103.000000  103.000000

            Volume  Daily Return  Binary Decision  Ternary Decision
Date
1971-02-05       0           NaN              0.0               0.0
1971-02-08       0      0.008400              1.0               2.0
1971-02-09       0     -0.000793              0.0               1.0
1971-02-10       0     -0.000695              0.0               1.0
1971-02-11       0      0.007548              1.0               2.0
1971-02-12       0      0.005914              1.0               2.0
1971-02-16       0      0.001372              1.0               2.0
1971-02-17       0     -0.004404              0.0               1.0
1971-02-18       0     -0.003145              0.0               1.0
1971-02-19       0     -0.007099              0.0               1.0
1971-02-22       0     -0.010129              0.0               1.0
1971-02-23       0      0.000401              1.0               1.0
1971-02-24       0      0.009226              1.0               2.0
1971-02-25       0      0.005863              1.0               2.0
1971-02-26       0      0.001087              1.0               2.0
1971-03-01       0      0.004342              1.0               2.0
1971-03-02       0      0.000589              1.0               1.0
1971-03-03       0      0.002258              1.0               2.0
1971-03-04       0      0.006956              1.0               2.0
1971-03-05       0      0.002141              1.0               2.0
```

Create 1R model using volume:

In [75]:

```python
X_d_stock = stock_df[["Volume"]]
y_stock = stock_df["Binary Decision"]
print("Length of DF: ", stock_df.shape[0])
test_size = 100/stock_df.shape[0]
print("Percentage of test_size to use last 100 days: ", test_size)
Xd_train_stock, Xd_test_stock, y_train_stock, y_test_stock = train_test_split(X_d_stock, y_stock, test_size=test_size, random_state=2, shuffle
oner_stock = OneRClassifier()
oner_stock.fit(Xd_train_stock.to_numpy(), y_train_stock)
y_pred_stock = oner_stock.predict(Xd_test_stock.to_numpy())
accuracy_stock_bi = accuracy_score(y_test_stock, y_pred_stock)
print("Binary Accuracy: ", accuracy_stock_bi)

# As ternary does not play nicely with OneR, using binary only
# X_d_stock_ter = stock_df[["Volume"]]
# y_stock_ter = stock_df["Ternary Decision"]
# Xd_train_stock_ter, Xd_test_stock_ter, y_train_stock_ter, y_test_stock_ter = train_test_split(X_d_stock_ter, y_stock_ter, test_size=0.3)
# oner_stock_ter = OneRClassifier()
# oner_stock_ter.fit(Xd_train_stock_ter.to_numpy(), y_train_stock_ter)
# y_pred_stock_ter = oner_stock_ter.predict(Xd_test_stock_ter.to_numpy())
# accuracy_stock_ter = accuracy_score(y_test_stock_ter, y_pred_stock_ter)
# print("Ternary Accuracy: ", accuracy_stock_ter)
```

```
Length of DF:  12402
Percentage of test_size to use last 100 days:  0.008063215610385421
Binary Accuracy:  0.44
```

Create 1R model using volume and rolling averages:

In [76]:

```python
stock_df['Rolling Mean 5'] = stock_df['Close'].rolling(5).mean()
stock_df['Rolling Mean 10'] = stock_df['Close'].rolling(10).mean()
stock_df['Rolling Mean 20'] = stock_df['Close'].rolling(20).mean()
stock_df['Rolling Mean 50'] = stock_df['Close'].rolling(50).mean()
stock_df['Rolling Mean 200'] = stock_df['Close'].rolling(200).mean()
```

In [79]:

```python
X_d_stock_5 = stock_df[["Volume", "Rolling Mean 5"]]
y_stock_5 = stock_df["Binary Decision"]
test_size = 100/stock_df.shape[0]
Xd_train_stock_5, Xd_test_stock_5, y_train_stock_5, y_test_stock_5 = train_test_split(X_d_stock_5, y_stock_5, test_size=test_size, random_stat
oner_stock_5 = OneRClassifier()
oner_stock_5.fit(Xd_train_stock_5.to_numpy(), y_train_stock_5)
y_pred_stock_5 = oner_stock_5.predict(Xd_test_stock_5.to_numpy())
accuracy_stock_bi_5 = accuracy_score(y_test_stock_5, y_pred_stock_5)
print("Rolling Mean 5 Accuracy: ", accuracy_stock_bi_5)

X_d_stock_10 = stock_df[["Volume", "Rolling Mean 10"]]
y_stock_10 = stock_df["Binary Decision"]
Xd_train_stock_10, Xd_test_stock_10, y_train_stock_10, y_test_stock_10 = train_test_split(X_d_stock_10, y_stock_10, test_size=test_size, rando
oner_stock_10 = OneRClassifier()
oner_stock_10.fit(Xd_train_stock_10.to_numpy(), y_train_stock_10)
```

```
y_pred_stock_10 = oner_stock.predict(Xd_test_stock_10.to_numpy())
accuracy_stock_bi_10 = accuracy_score(y_test_stock_10, y_pred_stock_10)
print("Rolling Mean 10 Accuracy: ", accuracy_stock_bi_10)

X_d_stock_20 = stock_df[["Volume", "Rolling Mean 20"]]
y_stock_20 = stock_df["Binary Decision"]
Xd_train_stock_20, Xd_test_stock_20, y_train_stock_20, y_test_stock_20 = train_test_split(X_d_stock_20, y_stock_20, test_size=test_size, rando
oner_stock_20 = OneRClassifier()
oner_stock_20.fit(Xd_train_stock_20.to_numpy(), y_train_stock_20)
y_pred_stock_20 = oner_stock_20.predict(Xd_test_stock_20.to_numpy())
accuracy_stock_bi_20 = accuracy_score(y_test_stock_20, y_pred_stock_20)
print("Rolling Mean 20 Accuracy: ", accuracy_stock_bi_20)

X_d_stock_50 = stock_df[["Volume", "Rolling Mean 50"]]
y_stock_50 = stock_df["Binary Decision"]
Xd_train_stock_50, Xd_test_stock_50, y_train_stock_50, y_test_stock_50 = train_test_split(X_d_stock_50, y_stock_50, test_size=test_size, rando
oner_stock_50 = OneRClassifier()
oner_stock_50.fit(Xd_train_stock_50.to_numpy(), y_train_stock_50)
y_pred_stock_50 = oner_stock_50.predict(Xd_test_stock_50.to_numpy())
accuracy_stock_bi_50 = accuracy_score(y_test_stock_50, y_pred_stock_50)
print("Rolling Mean 50 Accuracy: ", accuracy_stock_bi_50)

X_d_stock_200 = stock_df[["Volume", "Rolling Mean 200"]]
y_stock_200 = stock_df["Binary Decision"]
Xd_train_stock_200, Xd_test_stock_200, y_train_stock_200, y_test_stock_200 = train_test_split(X_d_stock_200, y_stock_200, test_size=test_size,
oner_stock_200 = OneRClassifier()
oner_stock_200.fit(Xd_train_stock_200.to_numpy(), y_train_stock_200)
y_pred_stock_200 = oner_stock_200.predict(Xd_test_stock_200.to_numpy())
accuracy_stock_bi_200 = accuracy_score(y_test_stock_200, y_pred_stock_200)
print("Rolling Mean 200 Accuracy: ", accuracy_stock_bi_200)
```

```
Rolling Mean 5 Accuracy:  0.44
Rolling Mean 10 Accuracy:  0.44
Rolling Mean 20 Accuracy:  0.44
Rolling Mean 50 Accuracy:  0.44
Rolling Mean 200 Accuracy:  0.44
```

Weirdly enough, no matter what the rolling average, we seem to receive the same results.