HW3

October 14, 2023

0.1 # Homework #3

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GitHub: https://github.com/samofuture/Intro-to-ML

```
[ ]: import numpy as np
     import matplotlib.pyplot as plt
     import pandas as pd
     from sklearn.model_selection import train_test_split
     from sklearn.preprocessing import StandardScaler
```

0.2 Problem 1

```
[ ]: df = pd.read_csv('diabetes.csv')

     X = df.iloc[:, 0:7].values
     Y = df.iloc[:, 8].values

     #Now we'll split our Data set into Training Data and Test Data. Training data␣
      ↪will be used to train our
     #Logistic model and Test data will be used to validate our model. We'll use␣
      ↪Sklearn to split our data. We'll import  train_test_split from sklearn.
      ↪model_selection
     X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
      ↪random_state = 7)
```

```
[ ]: sc_X = StandardScaler()
     X_train = sc_X.fit_transform(X_train)
     X_test = sc_X.transform(X_test)
```

```
[ ]: #Import LogisticRegression from sklearn.linear_model
     #Make an instance classifier of the object LogisticRegression and give␣
      ↪random_state =  0
     from sklearn.linear_model import LogisticRegression
     from sklearn.metrics import accuracy_score
```

```
classifier = LogisticRegression(random_state=10)
classifier.fit(X_train, Y_train)
```

[ ]: LogisticRegression(random_state=10)

[ ]:
```
#Using Confusion matrix we can get accuracy of our model.

from sklearn.metrics import confusion_matrix
Y_pred = classifier.predict(X_test)
cnf_matrix = confusion_matrix(Y_test, Y_pred)
cnf_matrix
```

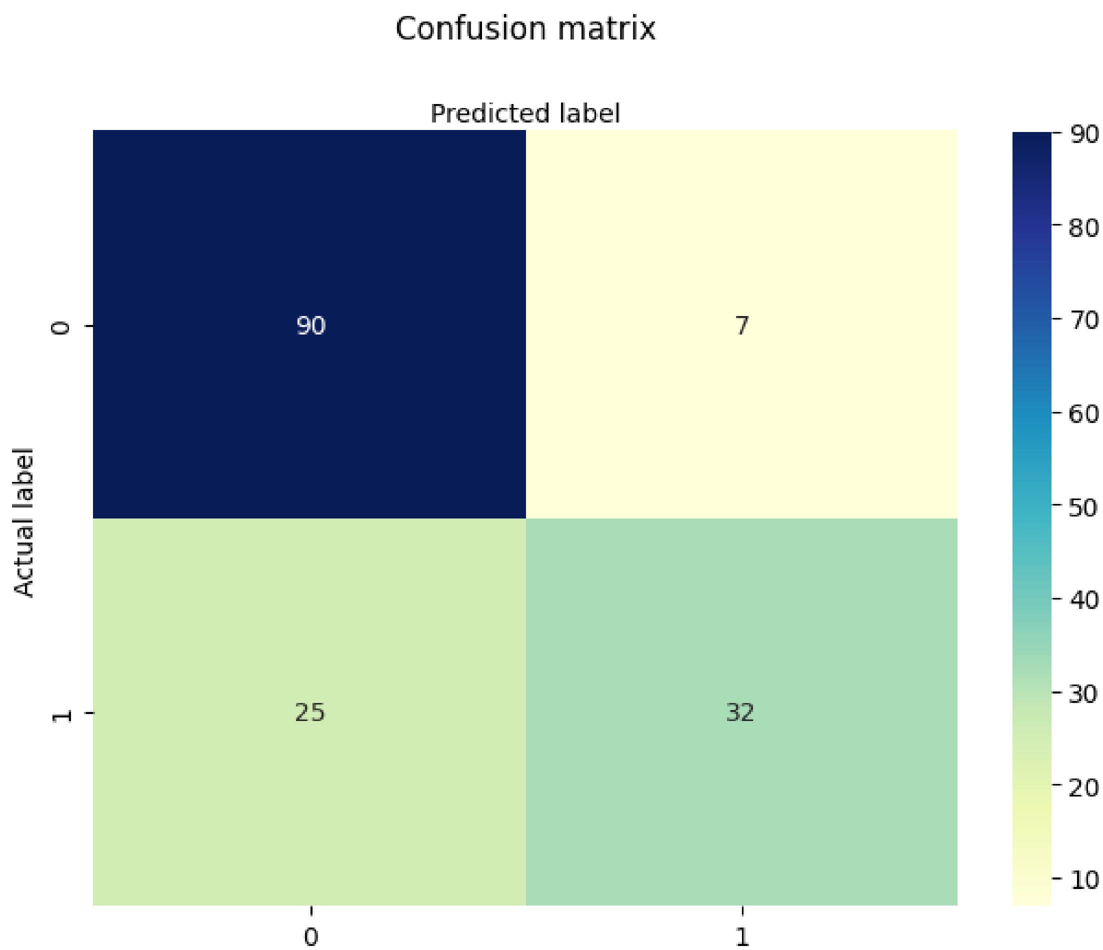
[ ]:
```
array([[90,  7],
       [25, 32]])
```

[ ]:
```
#Let's evaluate the model using model evaluation metrics such as accuracy,␣
↪precision, and recall.
from sklearn import metrics
print(metrics.classification_report(Y_test, Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.93      0.85        97
           1       0.82      0.56      0.67        57

    accuracy                           0.79       154
   macro avg       0.80      0.74      0.76       154
weighted avg       0.80      0.79      0.78       154
```

[ ]:
```
#Let's visualize the results of the model in the form of a co#nfusion matrix␣
↪using matplotlib and seaborn.
#Here, you will visualize the confusion matrix using Heatmap.
import seaborn as sns
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]: Text(0.5, 427.9555555555555, 'Predicted label')



0.3 Problem 2a

```
[ ]: df = pd.read_csv('cancer.csv')
df['diagnosis'] = df['diagnosis'].apply(lambda x: 1 if x == 'M' else 0)
Y = df.iloc[:, 1].values
df = df.drop(columns='diagnosis', axis=1)
X = df.iloc[:, 1:].values

#Now we'll split our Data set into Training Data and Test Data. Training data␣
 ↪will be used to train our
#Logistic model and Test data will be used to validate our model. We'll use␣
 ↪Sklearn to split our data. We'll import  train_test_split from sklearn.
 ↪model_selection
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state = 7)
```

[ ]:
```
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

[ ]:
```
classifier = LogisticRegression(random_state=10)
classifier.fit(X_train, Y_train)
```

[ ]:
```
LogisticRegression(random_state=10)
```

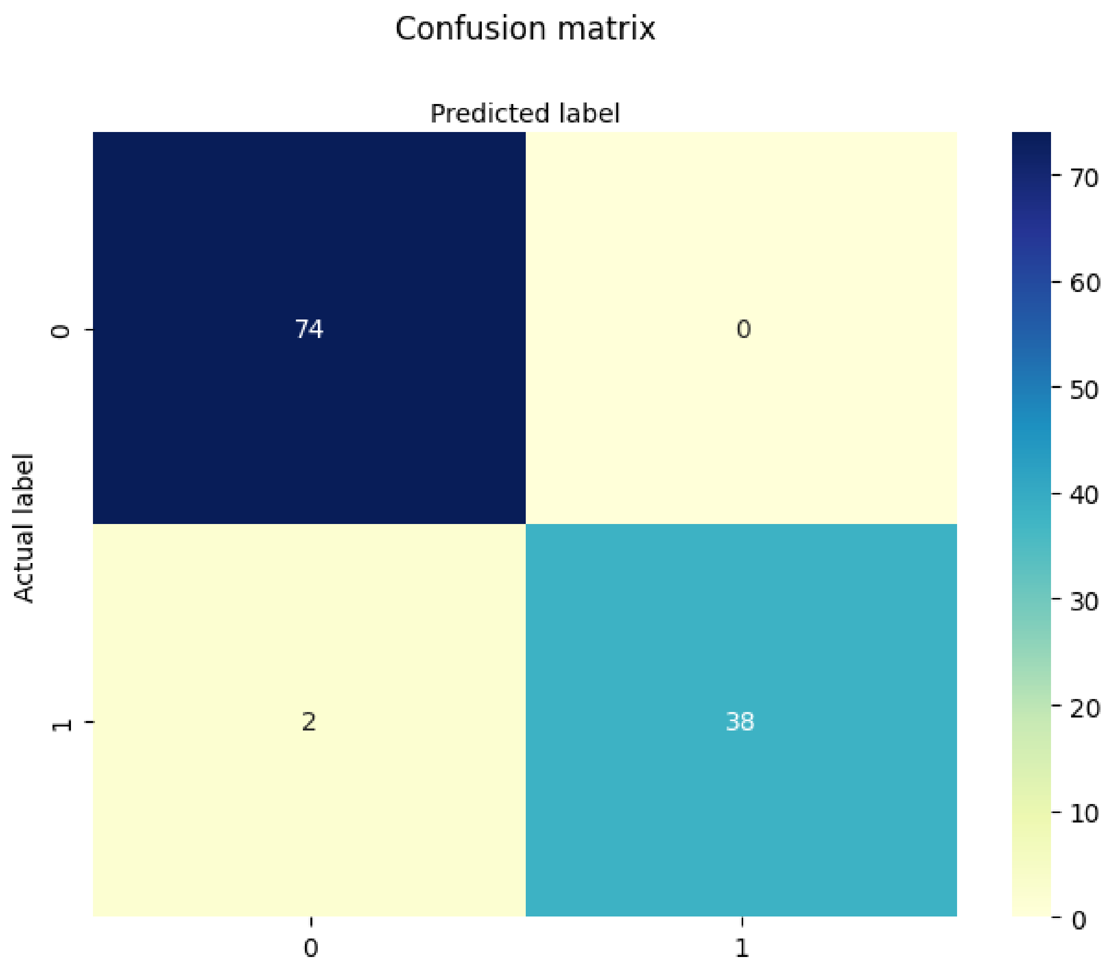
[ ]:
```
#Using Confusion matrix we can get accuracy of our model.

Y_pred = classifier.predict(X_test)
cnf_matrix = confusion_matrix(Y_test, Y_pred)
```

[ ]:
```
print(metrics.classification_report(Y_test, Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        74
           1       1.00      0.95      0.97        40

    accuracy                           0.98       114
   macro avg       0.99      0.97      0.98       114
weighted avg       0.98      0.98      0.98       114
```

[ ]:
```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]:
```
Text(0.5, 427.9555555555555, 'Predicted label')
```



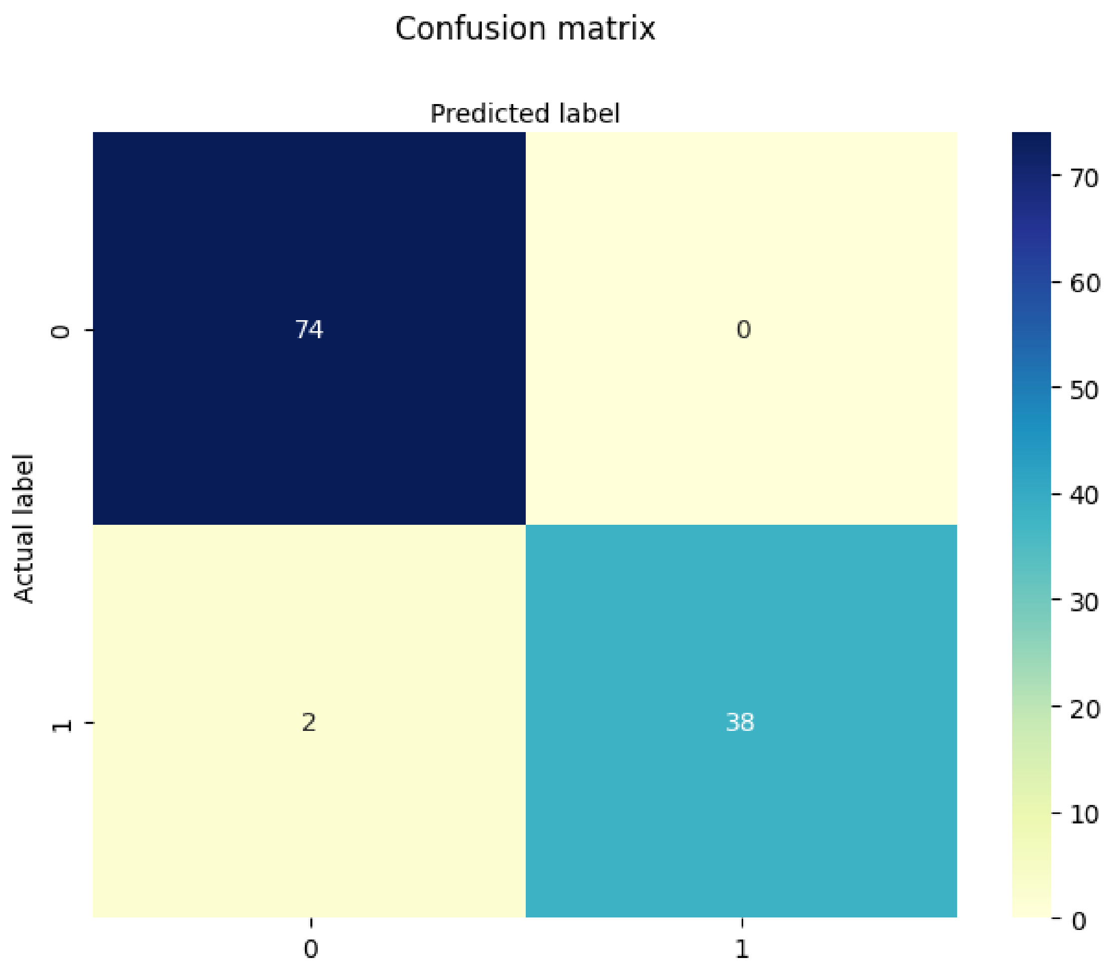
0.4 Problem 2b

```
[ ]: classifier = LogisticRegression(random_state=10, penalty='l2', C=0.8)
     classifier.fit(X_train, Y_train)
     Y_pred = classifier.predict(X_test)
     cnf_matrix = confusion_matrix(Y_test, Y_pred)

     print(metrics.classification_report(Y_test, Y_pred))

     class_names=[0,1] # name  of classes
     fig, ax = plt.subplots()
     tick_marks = np.arange(len(class_names))
     plt.xticks(tick_marks, class_names)
     plt.yticks(tick_marks, class_names)
     # create heatmap
     sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
     ax.xaxis.set_label_position("top")
```

```python
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        74
           1       1.00      0.95      0.97        40

    accuracy                           0.98       114
   macro avg       0.99      0.97      0.98       114
weighted avg       0.98      0.98      0.98       114
```

[ ]: Text(0.5, 427.9555555555555, 'Predicted label')



0.5 Problem 3

[ ]:
```
df = pd.read_csv('cancer.csv')
df['diagnosis'] = df['diagnosis'].apply(lambda x: 1 if x == 'M' else 0)
Y = df.iloc[:, 1].values
df = df.drop(columns='diagnosis', axis=1)
X = df.iloc[:, 1:].values

#Now we'll split our Data set into Training Data and Test Data. Training data␣
 ↪will be used to train our
#Logistic model and Test data will be used to validate our model. We'll use␣
 ↪Sklearn to split our data. We'll import  train_test_split from sklearn.
 ↪model_selection
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state = 7)
```

[ ]:
```
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)
```

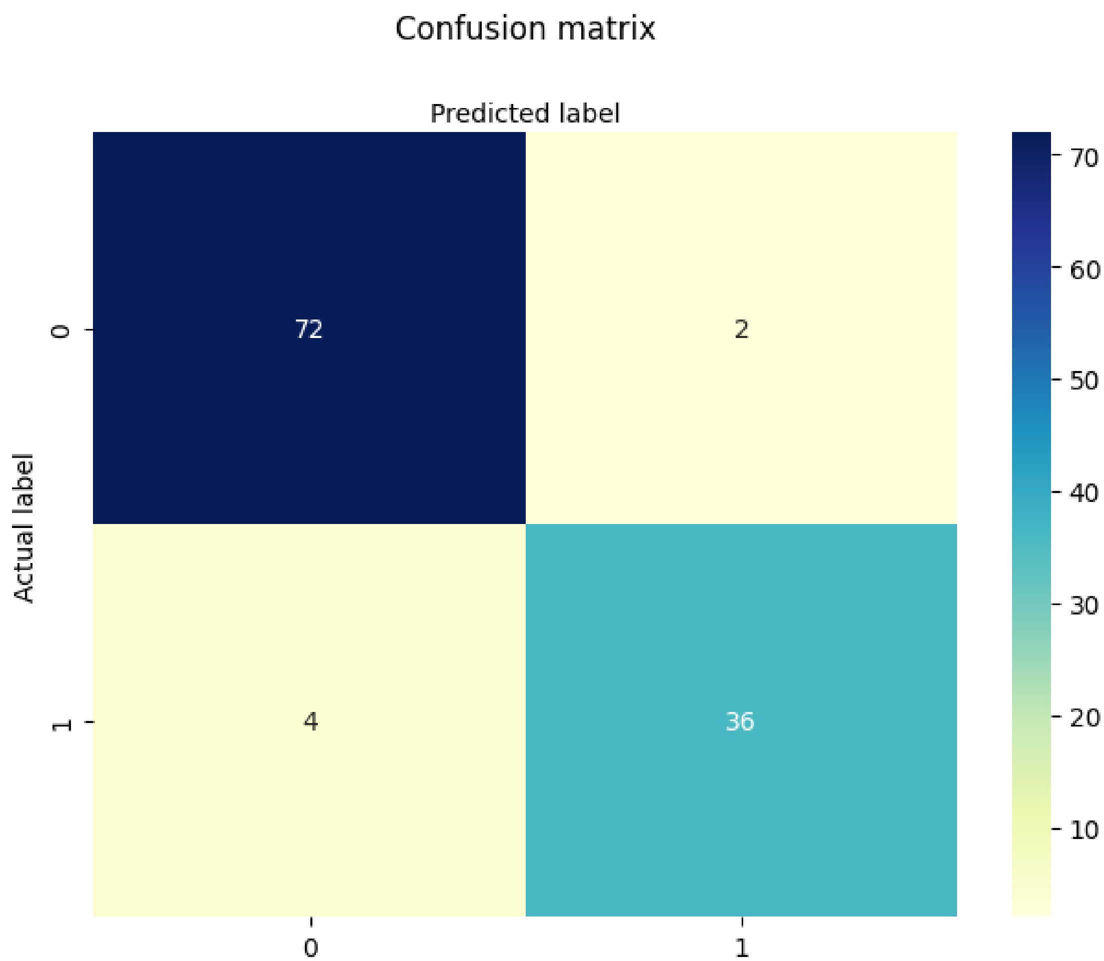
[ ]:
```
from sklearn.naive_bayes import GaussianNB

# fit a Naive Bayes model to the data
model = GaussianNB()

model.fit(X_train, Y_train)
# make predictions
expected = Y_test
predicted = model.predict(X_test)
# summarize the fit of the model
print(metrics.classification_report(expected, predicted))
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96        74
           1       0.95      0.90      0.92        40

    accuracy                           0.95       114
   macro avg       0.95      0.94      0.94       114
weighted avg       0.95      0.95      0.95       114
```

[ ]:
```
cnf_matrix = metrics.confusion_matrix(expected, predicted)
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
```

```python
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]: Text(0.5, 427.9555555555555, 'Predicted label')



The Bayesian classifier performed worse than the normal Logistic Regression in problem 2a. Although, it outperformed Problem 2b in recall and precision. These conclusions are also supported by the f1 score, where 2a has the highest, 3 is second highest, and 2b is lowest.

0.6 Problem 4

[ ]:
```
df = pd.read_csv('cancer.csv')
df['diagnosis'] = df['diagnosis'].apply(lambda x: 1 if x == 'M' else 0)
Y = df.iloc[:, 1].values
df = df.drop(columns='diagnosis', axis=1)
X = df.iloc[:, 1:].values
```

[ ]:
```
from sklearn.decomposition import PCA
k = 30
max_accuracy = 0
max_acc_index = 0
for n in range(1, k+1):
    pc_list = [f'pc{i}' for i in range(n)]
    pca = PCA(n_components=n)
    principalComponents = pca.fit_transform(X)
    principalDf = pd.DataFrame(data = principalComponents
                 , columns = pc_list)

    X_train, X_test, Y_train, Y_test = train_test_split(principalDf, Y,␣
 ↪test_size = 0.2, random_state = 7)
    sc_X = StandardScaler()
    X_train = sc_X.fit_transform(X_train)
    X_test = sc_X.transform(X_test)

    classifier = LogisticRegression(random_state=10)
    classifier.fit(X_train, Y_train)
    Y_pred = classifier.predict(X_test)
    cnf_matrix = confusion_matrix(Y_test, Y_pred)

    acc = metrics.accuracy_score(Y_test, Y_pred)
    if acc > max_accuracy:
        max_accuracy = acc
        max_acc_index = n
    # print(f'{n} PC:', acc)
    print(metrics.classification_report(Y_test, Y_pred))
print(f'{max_acc_index}: {max_accuracy}')
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94        74
           1       0.97      0.80      0.88        40

    accuracy                           0.92       114
   macro avg       0.94      0.89      0.91       114
weighted avg       0.93      0.92      0.92       114

              precision    recall  f1-score   support
```

```
           0       0.89      1.00      0.94        74
           1       1.00      0.78      0.87        40

    accuracy                           0.92       114
   macro avg       0.95      0.89      0.91       114
weighted avg       0.93      0.92      0.92       114

              precision    recall  f1-score   support

           0       0.89      1.00      0.94        74
           1       1.00      0.78      0.87        40

    accuracy                           0.92       114
   macro avg       0.95      0.89      0.91       114
weighted avg       0.93      0.92      0.92       114

              precision    recall  f1-score   support

           0       0.91      0.99      0.95        74
           1       0.97      0.82      0.89        40

    accuracy                           0.93       114
   macro avg       0.94      0.91      0.92       114
weighted avg       0.93      0.93      0.93       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40

    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40

    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40
```

```
    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40

    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40

    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
```

```
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.91      1.00      0.95        74
           1       1.00      0.82      0.90        40

    accuracy                           0.94       114
   macro avg       0.96      0.91      0.93       114
weighted avg       0.94      0.94      0.94       114

              precision    recall  f1-score   support

           0       0.94      0.99      0.96        74
           1       0.97      0.88      0.92        40

    accuracy                           0.95       114
   macro avg       0.95      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support
```

```
           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.93      1.00      0.96        74
           1       1.00      0.85      0.92        40

    accuracy                           0.95       114
   macro avg       0.96      0.93      0.94       114
weighted avg       0.95      0.95      0.95       114

              precision    recall  f1-score   support

           0       0.95      1.00      0.97        74
           1       1.00      0.90      0.95        40

    accuracy                           0.96       114
   macro avg       0.97      0.95      0.96       114
weighted avg       0.97      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.96      1.00      0.98        74
           1       1.00      0.93      0.96        40

    accuracy                           0.97       114
   macro avg       0.98      0.96      0.97       114
weighted avg       0.97      0.97      0.97       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40
```

```
    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
```

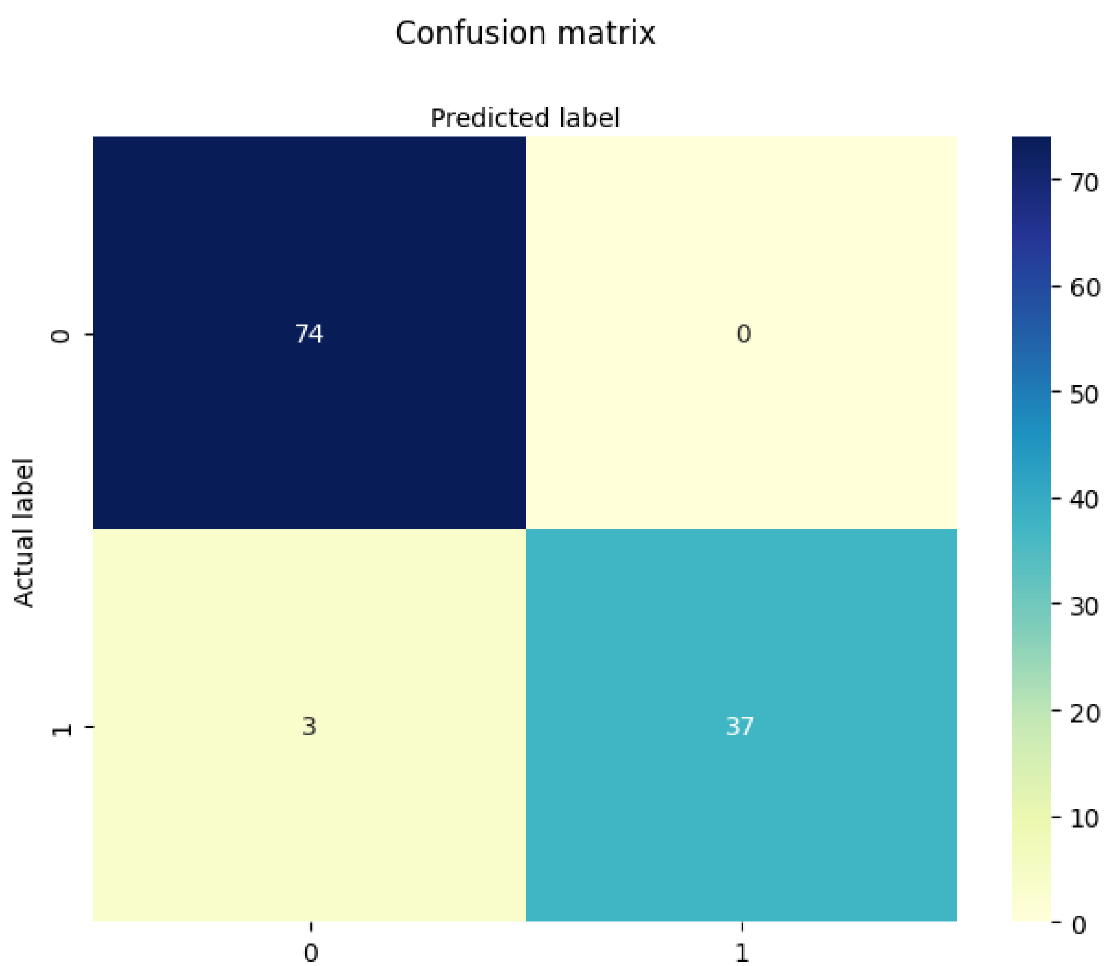
```
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.94      1.00      0.97        74
           1       1.00      0.88      0.93        40

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114

              precision    recall  f1-score   support

           0       0.95      1.00      0.97        74
           1       1.00      0.90      0.95        40

    accuracy                           0.96       114
   macro avg       0.97      0.95      0.96       114
weighted avg       0.97      0.96      0.96       114

22: 0.9736842105263158
```

[ ]:
```
pc_list = [f'pc{i}' for i in range(max_acc_index)]
pca = PCA(n_components=max_acc_index)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data=principalComponents, columns=pc_list)

X_train, X_test, Y_train, Y_test = train_test_split(principalDf, Y, test_size =
 ↪0.2, random_state = 7)
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)

classifier = LogisticRegression(random_state=10)
classifier.fit(X_train, Y_train)
Y_pred = classifier.predict(X_test)
cnf_matrix = confusion_matrix(Y_test, Y_pred)

print(metrics.classification_report(Y_test, Y_pred))
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        74
           1       1.00      0.93      0.96        40

    accuracy                           0.97       114
   macro avg       0.98      0.96      0.97       114
weighted avg       0.97      0.97      0.97       114
```

[ ]:
```python
cnf_matrix = metrics.confusion_matrix(Y_test, Y_pred)
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]:
```
Text(0.5, 427.9555555555555, 'Predicted label')
```



Compared to the previous questions, based on the f1 scores, this model is slightly worse than 2a, being above 3 and 2b in performance.

0.7 Problem 5

```
[ ]: df = pd.read_csv('cancer.csv')
df['diagnosis'] = df['diagnosis'].apply(lambda x: 1 if x == 'M' else 0)
Y = df.iloc[:, 1].values
df = df.drop(columns='diagnosis', axis=1)
X = df.iloc[:, 1:].values
```

```
[ ]: k = 30
max_accuracy = 0
max_acc_index = 0
for n in range(1, k+1):
    pc_list = [f'pc{i}' for i in range(n)]
    pca = PCA(n_components=n)
    principalComponents = pca.fit_transform(X)
    principalDf = pd.DataFrame(data = principalComponents
                 , columns = pc_list)

    X_train, X_test, Y_train, Y_test = train_test_split(principalDf, Y,␣
 ↪test_size = 0.2, random_state = 7)
    sc_X = StandardScaler()
    X_train = sc_X.fit_transform(X_train)
    X_test = sc_X.transform(X_test)

    model = GaussianNB()
    model.fit(X_train, Y_train)

    predicted = model.predict(X_test)
    cnf_matrix = confusion_matrix(Y_test, predicted)

    acc = metrics.accuracy_score(Y_test, predicted)
    if acc > max_accuracy:
        max_accuracy = acc
        max_acc_index = n

    print(metrics.classification_report(Y_test, predicted))
print(f'{max_acc_index}: {max_accuracy}')
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94        74
           1       0.97      0.78      0.86        40

    accuracy                           0.91       114
   macro avg       0.93      0.88      0.90       114
```

```
weighted avg       0.92      0.91      0.91       114

              precision    recall  f1-score   support

           0       0.87      0.99      0.92        74
           1       0.97      0.72      0.83        40

    accuracy                           0.89       114
   macro avg       0.92      0.86      0.88       114
weighted avg       0.90      0.89      0.89       114

              precision    recall  f1-score   support

           0       0.87      0.99      0.92        74
           1       0.97      0.72      0.83        40

    accuracy                           0.89       114
   macro avg       0.92      0.86      0.88       114
weighted avg       0.90      0.89      0.89       114

              precision    recall  f1-score   support

           0       0.88      0.97      0.92        74
           1       0.94      0.75      0.83        40

    accuracy                           0.89       114
   macro avg       0.91      0.86      0.88       114
weighted avg       0.90      0.89      0.89       114

              precision    recall  f1-score   support

           0       0.89      0.99      0.94        74
           1       0.97      0.78      0.86        40

    accuracy                           0.91       114
   macro avg       0.93      0.88      0.90       114
weighted avg       0.92      0.91      0.91       114

              precision    recall  f1-score   support

           0       0.89      0.97      0.93        74
           1       0.94      0.78      0.85        40

    accuracy                           0.90       114
   macro avg       0.91      0.87      0.89       114
weighted avg       0.91      0.90      0.90       114

              precision    recall  f1-score   support
```

```
           0       0.89      0.97      0.93        74
           1       0.94      0.78      0.85        40

    accuracy                           0.90       114
   macro avg       0.91      0.87      0.89       114
weighted avg       0.91      0.90      0.90       114

              precision    recall  f1-score   support

           0       0.86      0.93      0.90        74
           1       0.85      0.72      0.78        40

    accuracy                           0.86       114
   macro avg       0.86      0.83      0.84       114
weighted avg       0.86      0.86      0.86       114

              precision    recall  f1-score   support

           0       0.86      0.92      0.89        74
           1       0.83      0.72      0.77        40

    accuracy                           0.85       114
   macro avg       0.84      0.82      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.85      0.91      0.88        74
           1       0.80      0.70      0.75        40

    accuracy                           0.83       114
   macro avg       0.82      0.80      0.81       114
weighted avg       0.83      0.83      0.83       114

              precision    recall  f1-score   support

           0       0.87      0.91      0.89        74
           1       0.81      0.75      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.86      0.89      0.87        74
           1       0.78      0.72      0.75        40
```

```
    accuracy                           0.83       114
   macro avg       0.82      0.81      0.81       114
weighted avg       0.83      0.83      0.83       114

              precision    recall  f1-score   support

           0       0.86      0.91      0.88        74
           1       0.81      0.72      0.76        40

    accuracy                           0.84       114
   macro avg       0.83      0.82      0.82       114
weighted avg       0.84      0.84      0.84       114

              precision    recall  f1-score   support

           0       0.89      0.91      0.90        74
           1       0.82      0.80      0.81        40

    accuracy                           0.87       114
   macro avg       0.86      0.85      0.85       114
weighted avg       0.87      0.87      0.87       114

              precision    recall  f1-score   support

           0       0.87      0.91      0.89        74
           1       0.81      0.75      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.86      0.91      0.88        74
           1       0.81      0.72      0.76        40

    accuracy                           0.84       114
   macro avg       0.83      0.82      0.82       114
weighted avg       0.84      0.84      0.84       114

              precision    recall  f1-score   support

           0       0.86      0.89      0.87        74
           1       0.78      0.72      0.75        40

    accuracy                           0.83       114
   macro avg       0.82      0.81      0.81       114
```

weighted avg	0.83	0.83	0.83	114

	precision	recall	f1-score	support
0	0.86	0.89	0.87	74
1	0.78	0.72	0.75	40
accuracy			0.83	114
macro avg	0.82	0.81	0.81	114
weighted avg	0.83	0.83	0.83	114

	precision	recall	f1-score	support
0	0.85	0.91	0.88	74
1	0.80	0.70	0.75	40
accuracy			0.83	114
macro avg	0.82	0.80	0.81	114
weighted avg	0.83	0.83	0.83	114

	precision	recall	f1-score	support
0	0.86	0.89	0.87	74
1	0.78	0.72	0.75	40
accuracy			0.83	114
macro avg	0.82	0.81	0.81	114
weighted avg	0.83	0.83	0.83	114

	precision	recall	f1-score	support
0	0.86	0.89	0.87	74
1	0.78	0.72	0.75	40
accuracy			0.83	114
macro avg	0.82	0.81	0.81	114
weighted avg	0.83	0.83	0.83	114

	precision	recall	f1-score	support
0	0.87	0.89	0.88	74
1	0.79	0.75	0.77	40
accuracy			0.84	114
macro avg	0.83	0.82	0.82	114
weighted avg	0.84	0.84	0.84	114

	precision	recall	f1-score	support

```
           0       0.87      0.91      0.89        74
           1       0.81      0.75      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.87      0.91      0.89        74
           1       0.81      0.75      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.87      0.91      0.89        74
           1       0.81      0.75      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.83       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.87      0.89      0.88        74
           1       0.79      0.75      0.77        40

    accuracy                           0.84       114
   macro avg       0.83      0.82      0.82       114
weighted avg       0.84      0.84      0.84       114

              precision    recall  f1-score   support

           0       0.88      0.91      0.89        74
           1       0.82      0.78      0.79        40

    accuracy                           0.86       114
   macro avg       0.85      0.84      0.84       114
weighted avg       0.86      0.86      0.86       114

              precision    recall  f1-score   support

           0       0.88      0.91      0.89        74
           1       0.82      0.78      0.79        40
```

```
    accuracy                           0.86       114
   macro avg       0.85      0.84      0.84       114
weighted avg       0.86      0.86      0.86       114

              precision    recall  f1-score   support

           0       0.88      0.89      0.89        74
           1       0.79      0.78      0.78        40

    accuracy                           0.85       114
   macro avg       0.84      0.83      0.84       114
weighted avg       0.85      0.85      0.85       114

              precision    recall  f1-score   support

           0       0.88      0.91      0.89        74
           1       0.82      0.78      0.79        40

    accuracy                           0.86       114
   macro avg       0.85      0.84      0.84       114
weighted avg       0.86      0.86      0.86       114

1: 0.9122807017543859
```

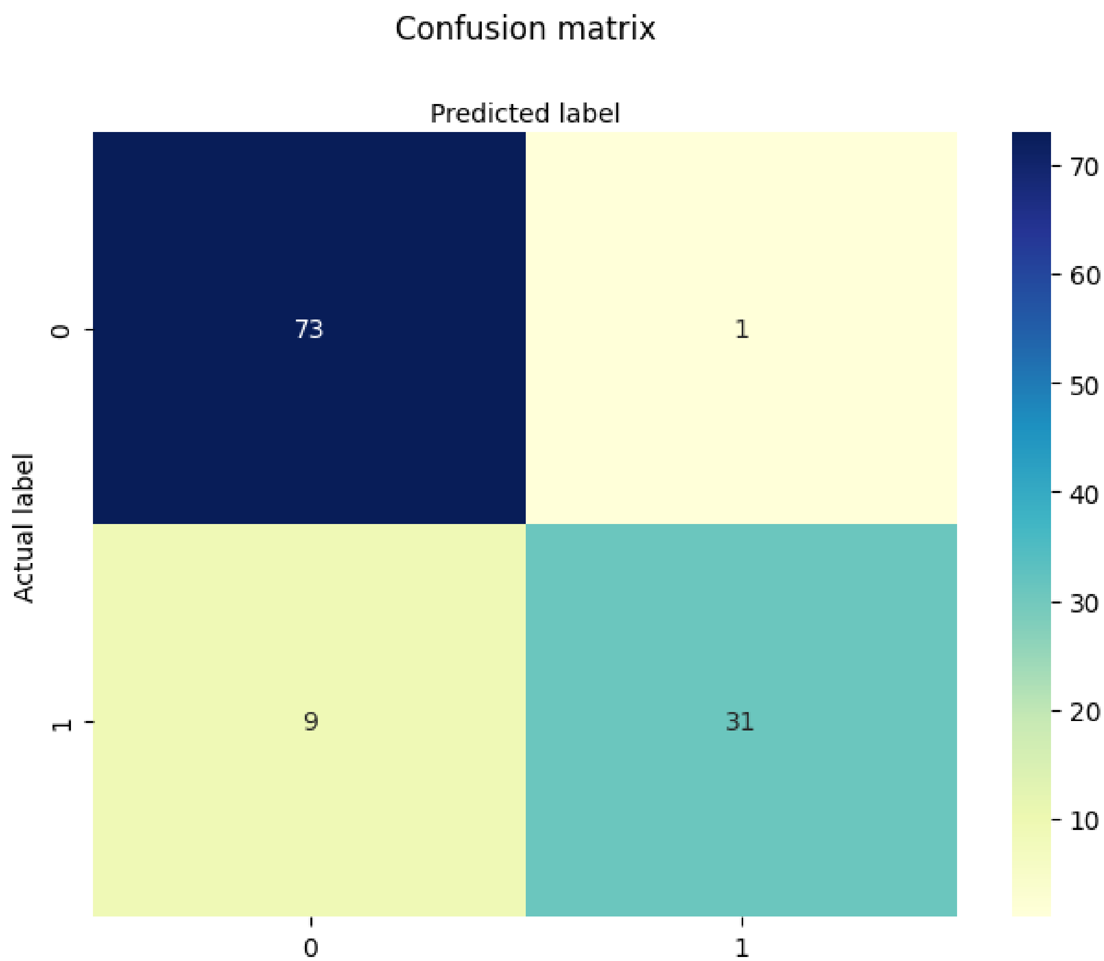
[ ]:
```
pc_list = [f'pc{i}' for i in range(max_acc_index)]
pca = PCA(n_components=max_acc_index)
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data=principalComponents, columns=pc_list)

X_train, X_test, Y_train, Y_test = train_test_split(principalDf, Y, test_size =␣
 ↪0.2, random_state = 7)
sc_X = StandardScaler()
X_train = sc_X.fit_transform(X_train)
X_test = sc_X.transform(X_test)

model = GaussianNB()
model.fit(X_train, Y_train)

predicted = model.predict(X_test)
cnf_matrix = confusion_matrix(Y_test, predicted)

print(metrics.classification_report(Y_test, predicted))
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94        74
           1       0.97      0.78      0.86        40
```

```
    accuracy                           0.91       114
   macro avg       0.93      0.88      0.90       114
weighted avg       0.92      0.91      0.91       114
```

[ ]:
```
cnf_matrix = metrics.confusion_matrix(Y_test, predicted)
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

[ ]:
```
Text(0.5, 427.9555555555555, 'Predicted label')
```



This model had the worst f1 scores, being slightly below 2b.