TP2_MachineLearning_BIM_0part_toy_classification

December 2, 2020

Toy examples

In this part of the practical session, you will play with some toy data to better understand the classification algorithms seen this morning.

Please answer all questions

Deadline: Upload this notebook and the one about Emotion Recognition as a single .zip file to the Moodle. Please name it 'TP2-Supervised-YOUR-SURNAME.zip'. You have one week.

Let's first load the needed packages.

[1]:
```
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt  # for plots
from matplotlib.colors import ListedColormap
from matplotlib import rc

import seaborn as sns
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score
import time

%matplotlib inline
np.random.seed(seed=666)
```

Here, we define some functions useful for generating and plotting the data

[2]:
```
def gaussian_data_generation(n, mean, cov, noise_std):
    # create data which follows a multivariate Gaussian distribution
    # a white (Gaussian) noise is then added to the data

    assert cov.shape[0] == cov.shape[1], "Please use only square covariance␣
↪matrix"
```

```python
    assert len(mean) == cov.shape[0], "the dimension of the mean should be␣
↪equal to the dimension of the covariance matrix"

    X = np.random.multivariate_normal(mean, cov, n) # actual data
    X = X + np.random.multivariate_normal(np.zeros(len(mean)), noise_std ** 2␣
↪*np.eye(len(mean)), n)  # we add white noise to the data

    return X

def frontiere(f, X, y, step=50):
    # decision boundary of classifier f
    # construct cmap

    min_tot = np.min(X)
    max_tot = np.max(X)
    delta = (max_tot - min_tot) / step
    xx, yy = np.meshgrid(np.arange(min_tot, max_tot, delta),
                         np.arange(min_tot, max_tot, delta))
    z = np.array([f(vec) for vec in np.c_[xx.ravel(), yy.ravel()]])
    z = z.reshape(xx.shape)
    labels = np.unique(z)
    color_blind_list = sns.color_palette("colorblind", labels.shape[0])
    sns.set_palette(color_blind_list)
    my_cmap = ListedColormap(color_blind_list)
    plt.imshow(z, origin='lower', extent=[min_tot, max_tot, min_tot, max_tot],
               interpolation="mitchell", alpha=0.80, cmap=my_cmap)

    ax = plt.gca()
    cbar = plt.colorbar(ticks=labels)
    cbar.ax.set_yticklabels(labels)

    k = np.unique(y).shape[0]
    color_blind_list = sns.color_palette("colorblind", k)
    for i, label in enumerate(y):
        plt.scatter(X[i, 0], X[i, 1], c=[color_blind_list[int(y[i])]],
                    s=80, marker=symlist[int(label)])
    plt.ylim([min_tot, max_tot])
    plt.xlim([min_tot, max_tot])
    ax.get_yaxis().set_ticks([])
    ax.get_xaxis().set_ticks([])

def class_int_round(z, n_class):
    # rounding needed to go from real to integer values
    output = np.round(z).astype(int)
    if isinstance(z, np.ndarray):
        j = z < 0
        output[j] = 0
```

```
        k = z > n_class - 1
        output[k] = n_class - 1
    else:
        if output < 0:
            output = 0
        else:
            if output > n_class - 1:
                output = n_class - 1
    return output
```

The next function is the one you will use to crete the toy data. You can choose among three scenarios: 2, 3 or 4 classes. Each class is composed of 2D points sampled from a multivariate Gaussian distribution. You can choose the number of samples, average and covariance matrix for each class.

[3]:
```
def generate_scenario(n_classes=3, n_0=80, n_1=80, n_2=80):
    if n_classes == 2:
        # Example with 2 classes

        n_0=80 # you can modify here
        mean_0 = [0, 0]  # you can modify here
        cov_0 = np.array([[1, 0.1], [0.1, 0.9]]) # you can modify here
        X_0=gaussian_data_generation(n_0, mean_0, cov_0, 0.1)
        y_0=np.zeros(n_0)

        n_1=80 # you can modify here
        mean_1 = [3, 2] # you can modify here
        cov_1 = np.array([[0.1, 0], [0, 0.5]]) # you can modify here
        X_1=gaussian_data_generation(n_1, mean_1, cov_1, 0.1)
        y_1=np.ones(n_1)

        X=np.concatenate((X_0,X_1))
        y=np.concatenate((y_0,y_1))

    elif n_classes == 3:
        # Example with 3 classes

        n_0=n_0 # you can modify here
        mean_0 = [0, 0]  # you can modify here
        cov_0 = np.array([[1, 0.1], [0.1, 0.9]]) # you can modify here
        X_0=gaussian_data_generation(n_0, mean_0, cov_0, 0.1)
        y_0=np.zeros(n_0)

        n_1=n_1 # you can modify here
        mean_1 = [2, 2] # you can modify here
        cov_1 = np.array([[0.1, 0], [0, 0.5]]) # you can modify here
        X_1=gaussian_data_generation(n_1, mean_1, cov_1, 0.1)
```

```
        y_1=np.ones(n_1)

        n_2=n_2 # you can modify here
        mean_2 = [3, 3] # you can modify here
        cov_2 = np.array([[0.5, 0.1], [0.1, 1]]) # you can modify here
        X_2=gaussian_data_generation(n_2, mean_2, cov_2, 0.1)
        y_2=2*np.ones(n_2)

        X=np.concatenate((X_0,X_1,X_2))
        y=np.concatenate((y_0,y_1,y_2))
    elif n_classes == 4:
        # Example with 4 classes

        n_0=80 # you can modify here
        mean_0 = [0, 0] # you can modify here
        cov_0 = np.array([[1, 0.1], [0.1, 0.9]]) # you can modify here
        X_0=gaussian_data_generation(n_0, mean_0, cov_0, 0.1)
        y_0=np.zeros(n_0)

        n_1=80 # you can modify here
        mean_1 = [3, 3] # you can modify here
        cov_1 = np.array([[0.1, 0], [0, 0.5]]) # you can modify here
        X_1=gaussian_data_generation(n_1, mean_1, cov_1, 0.1)
        y_1=np.ones(n_1)

        n_2=80 # you can modify here
        mean_2 = [0, 3] # you can modify here
        cov_2 = np.array([[0.5, 0.1], [0.1, 1]]) # you can modify here
        X_2=gaussian_data_generation(n_2, mean_2, cov_2, 0.1)
        y_2=2*np.ones(n_2)

        n_3=80 # you can modify here
        mean_3 = [3, 0] # you can modify here
        cov_3 = np.array([[0.9, 0.15], [0.15, 0.8]]) # you can modify here
        X_3=gaussian_data_generation(n_3, mean_3, cov_3, 0.1)
        y_3=3*np.ones(n_3)

        X=np.concatenate((X_0,X_1,X_2,X_3))
        y=np.concatenate((y_0,y_1,y_2,y_3))

    return X, y
```

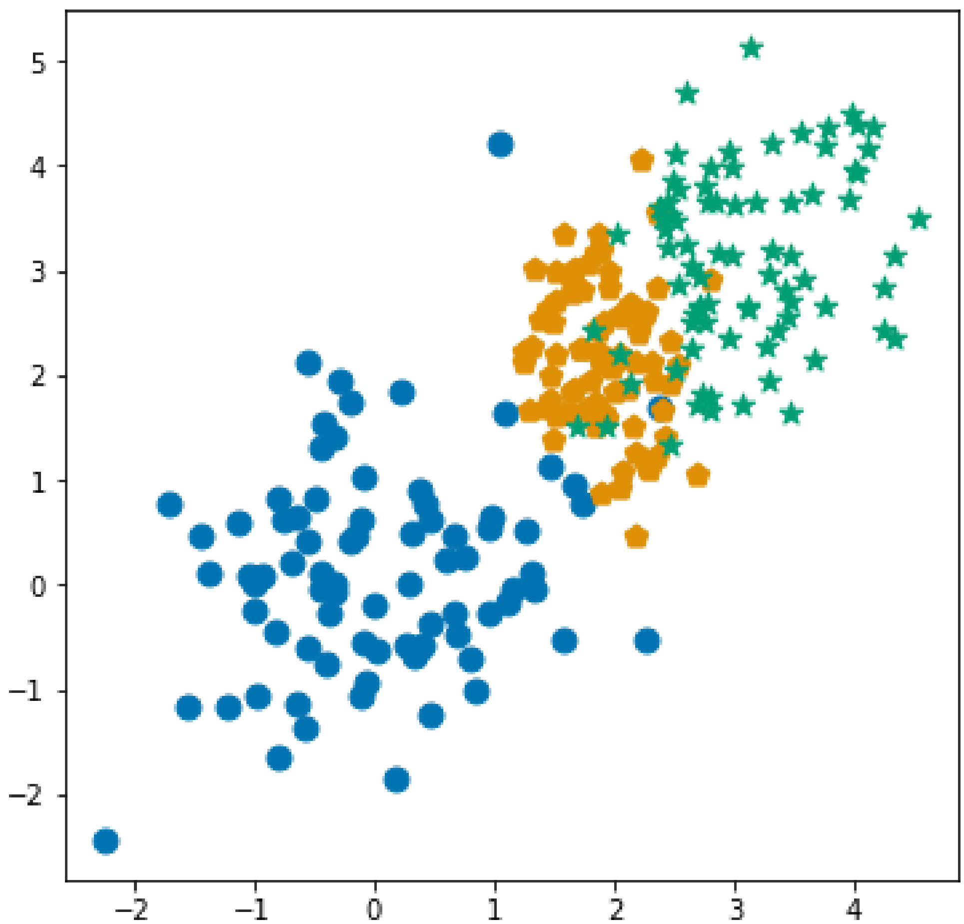
Let's choose a scenario and generate some data

[4]:
```
######## PARAMETER TO CHOOSE THE SCENARIO (number of classes) #######
n_classes=3
####################################################################
```

```
X, y = generate_scenario(n_classes, 80 ,80, 80)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=42)
```

Let's plot the data

[5]:
```
fig1 = plt.figure(figsize=(6, 6))
ax = plt.gca()
min_tot = np.min(X)
max_tot = np.max(X)
symlist = ['o', 'p', '*', 's', '+', 'x', 'D', 'v', '-', '^']
k = np.unique(y).shape[0]
color_blind_list = sns.color_palette("colorblind", k)
for i, label in enumerate(y):
    plt.scatter(X[i, 0], X[i, 1], c=[color_blind_list[int(y[i])]],
                s=80, marker=symlist[int(label)])
#ax.get_yaxis().set_ticks([])
#ax.get_xaxis().set_ticks([])
```



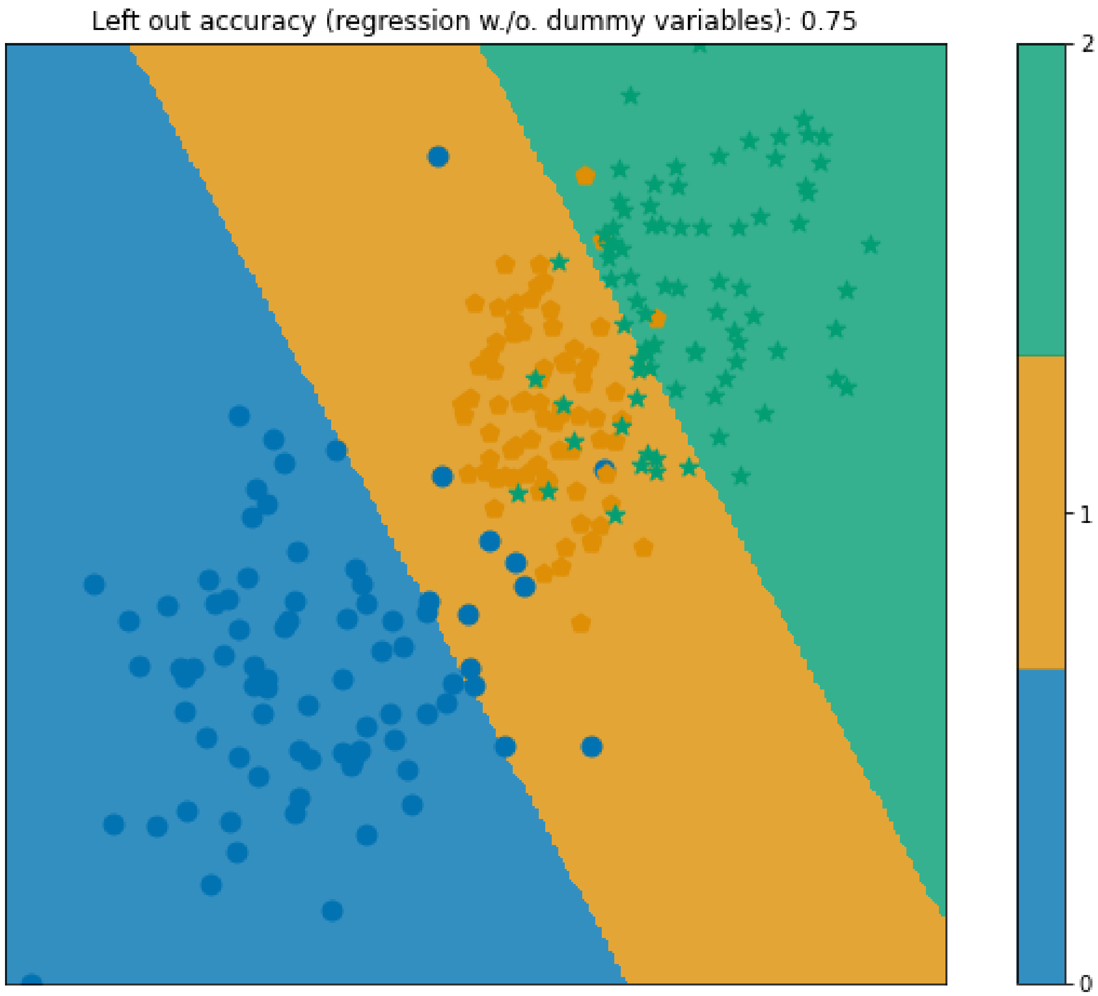
As first classifier, we can use a simple linear regression where we transform in integers the predictions.

Question (IMH+IMP): look at the function 'class_int_round' and try to understand what it does

Answer:

It divided the z matrix into classes first he rounds all the data and makes it as int, since int will make negative numbers to positive it reassign all the negative numbers to the lowest class and then make sure that no number it above the maximum number of classes and if it doses it reassign them to the last class.

[6]:
```
###############################################################################
# Naive linear regression on raw observations
###############################################################################

resolution_param = 150  # 500 for nice plotting, 50 for fast version
regr = LinearRegression()
regr.fit(X_train, y_train)
y_pred_test = class_int_round(regr.predict(X_test), n_classes)

# Plotting part
fig0 = plt.figure(figsize=(12, 8))
title = "Left out accuracy (regression w./o. dummy variables)" + \
        ": {:.2f}".format(accuracy_score(y_test, y_pred_test))
plt.title(title)

def f(xx):
    """Classifier"""
    return class_int_round(regr.predict(xx.reshape(1, -1)), n_classes)
frontiere(f, X, y, step=resolution_param)

plt.show()
```



Instead than using this simple strategy, we can also use a *OneHotEncoder*.

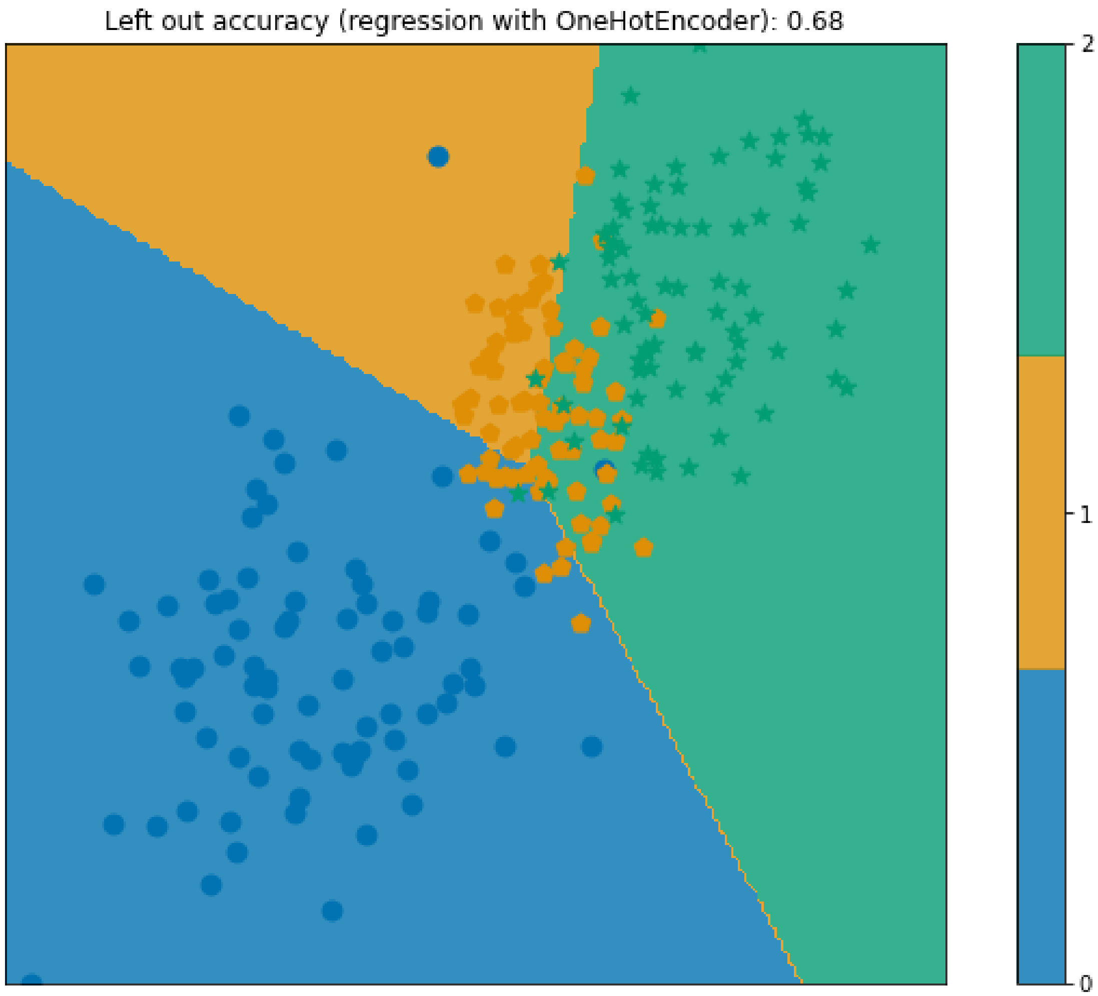
Question (IMP+IMH): Do you see any difference in the resulting decision boundaries ? Which is the best strategy in your opinion ? Why ?

Answer:

There is a difference the OneHotEncoder looks like its overfitting to class 0 and 2 and as a result, class 1 is miss calculate so OneHotEncoder overfit and do not do the general case.

[7]:
```
##############################################################################
# Naive linear regression on dummy variables (OneHotEncoder)
##############################################################################
resolution_param = 150
enc = OneHotEncoder(categories='auto')
enc.fit(y_train.reshape(-1, 1))
Y = enc.transform(y_train.reshape(-1, 1)).toarray()
regr_multi = LinearRegression()
```

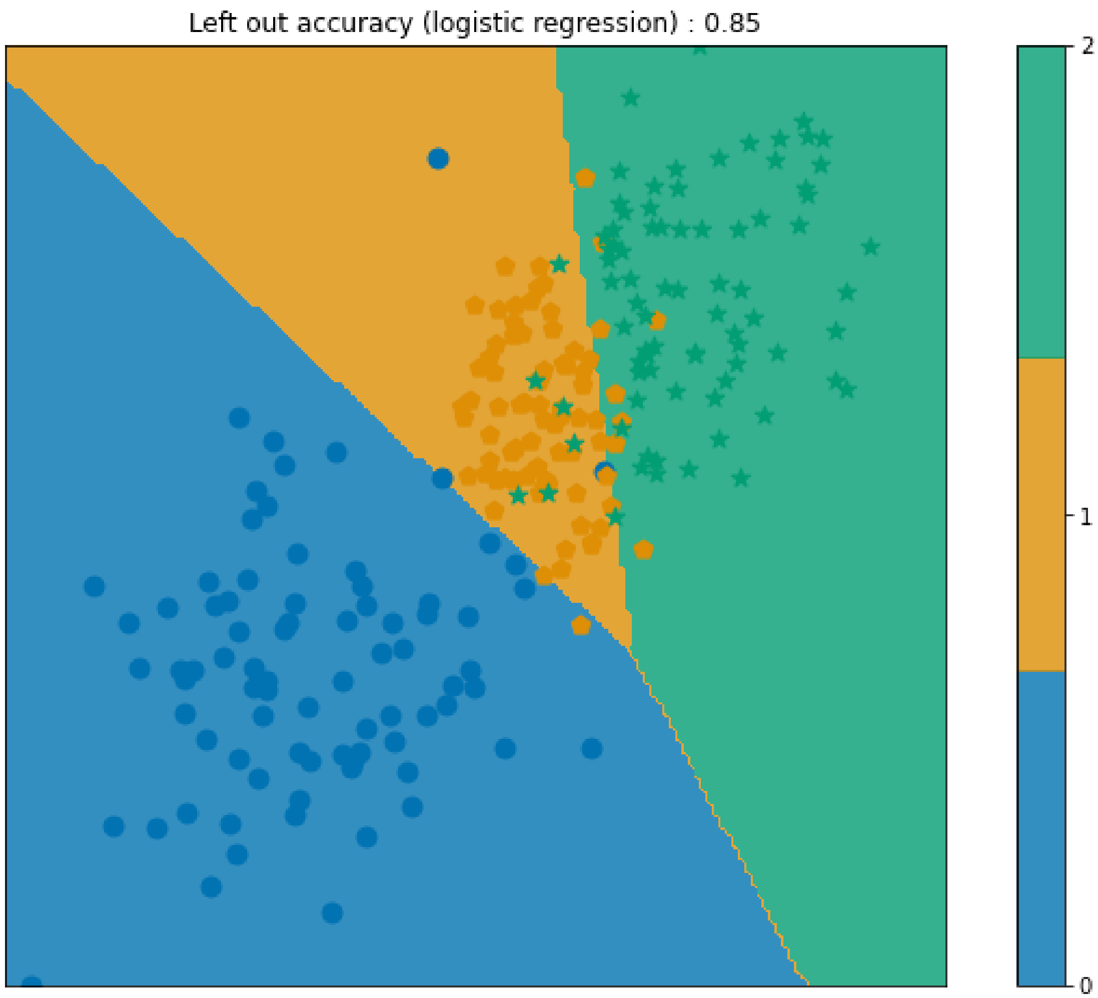
```python
regr_multi.fit(X_train, Y)
proba_vector_test = regr_multi.predict(X_test)
y_pred_test = class_int_round(regr.predict(X_test), n_classes)

# performance evaluation on new dataset
y_pred_test = np.argmax(proba_vector_test, axis=1)
title = "Left out accuracy (regression with OneHotEncoder)" + \
        ": {:.2f}".format(accuracy_score(y_test, y_pred_test))

# Plotting part
fig1 = plt.figure(figsize=(12, 8))
plt.title(title)


def f(xx):
    """Classifier"""
    return np.argmax(regr_multi.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



Let's use the other strategies seen this morning.

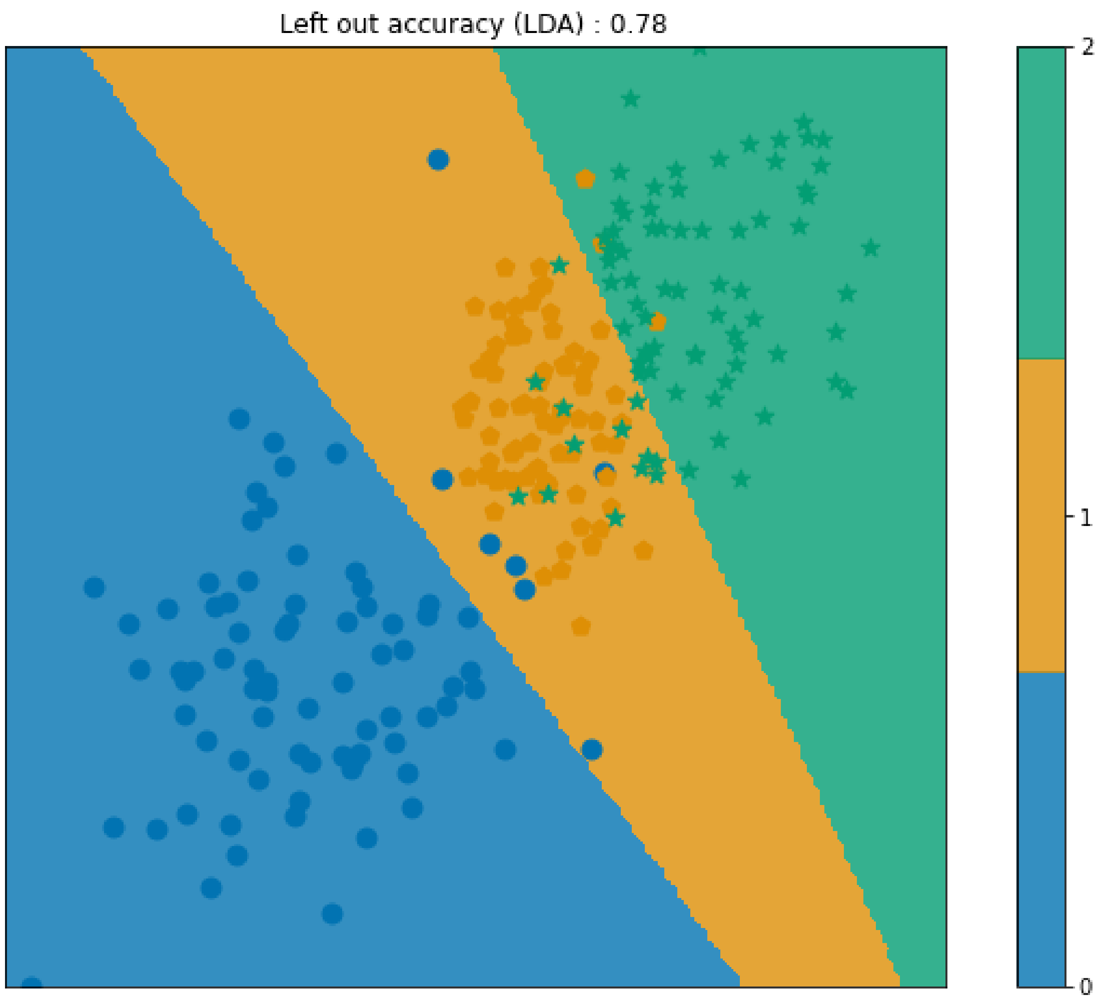
[8]:
```
###############################################################################
# Logistic regression
###############################################################################
resolution_param = 150
clf = LogisticRegression(solver='lbfgs',multi_class='ovr') # you can also try␣
 ↪multi_class='multinomial',
clf.fit(X_train, y_train)
y_logit_test = clf.predict(X_test)
title = "Left out accuracy (logistic regression) " + \
        ": {:.2f}".format(accuracy_score(y_test, y_logit_test))
fig2 = plt.figure(figsize=(12, 8))
plt.title(title)
```

```python
def f(xx):
    """Classifier"""
    return int(clf.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



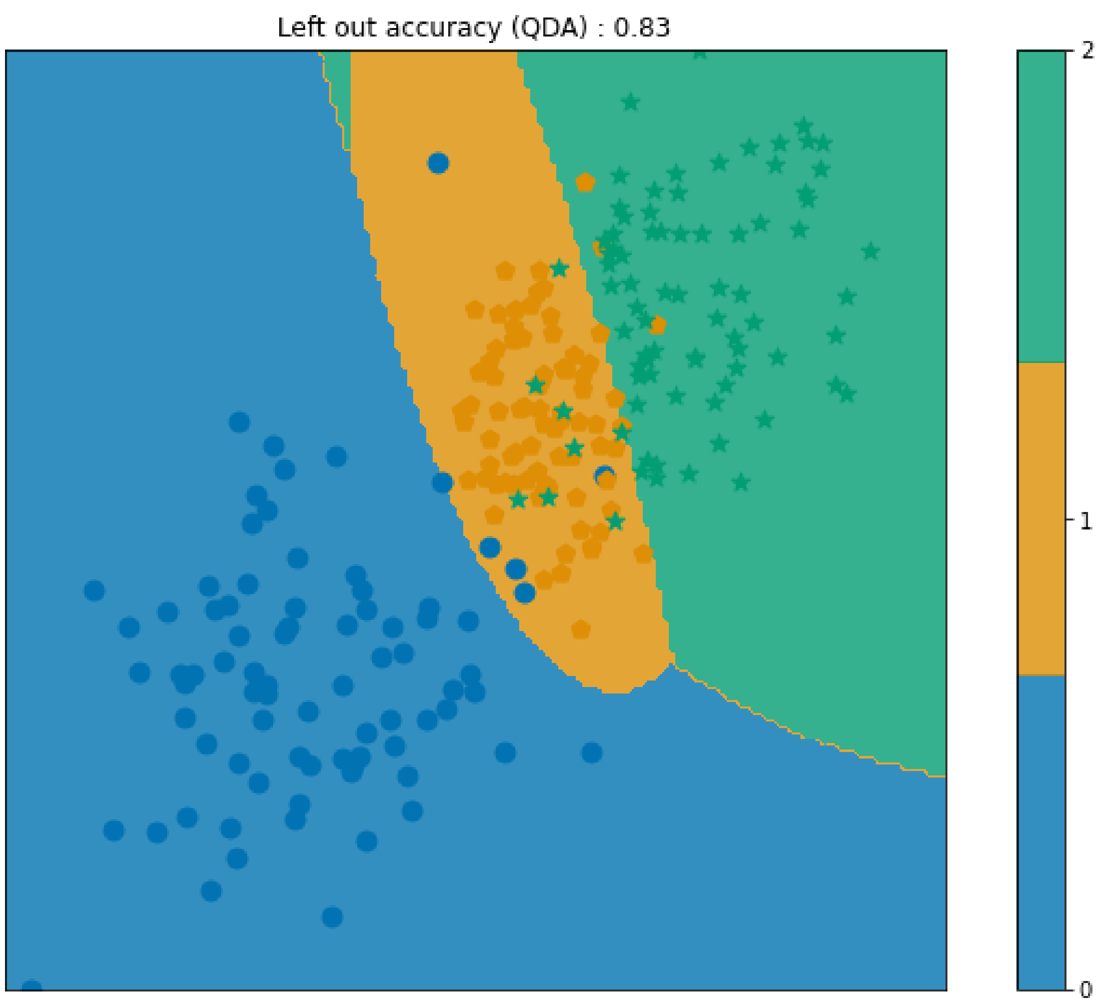
[9]:
```python
###############################################################################
# LDA
###############################################################################
resolution_param = 150
clf_LDA = LinearDiscriminantAnalysis()
clf_LDA.fit(X_train, y_train)
y_LDA_test = clf_LDA.predict(X_test)
```

```python
title = "Left out accuracy (LDA) " + \
        ": {:.2f}".format(accuracy_score(y_test, y_LDA_test))
fig2 = plt.figure(figsize=(12, 8))
plt.title(title)


def f(xx):
    """Classifier"""
    return int(clf_LDA.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



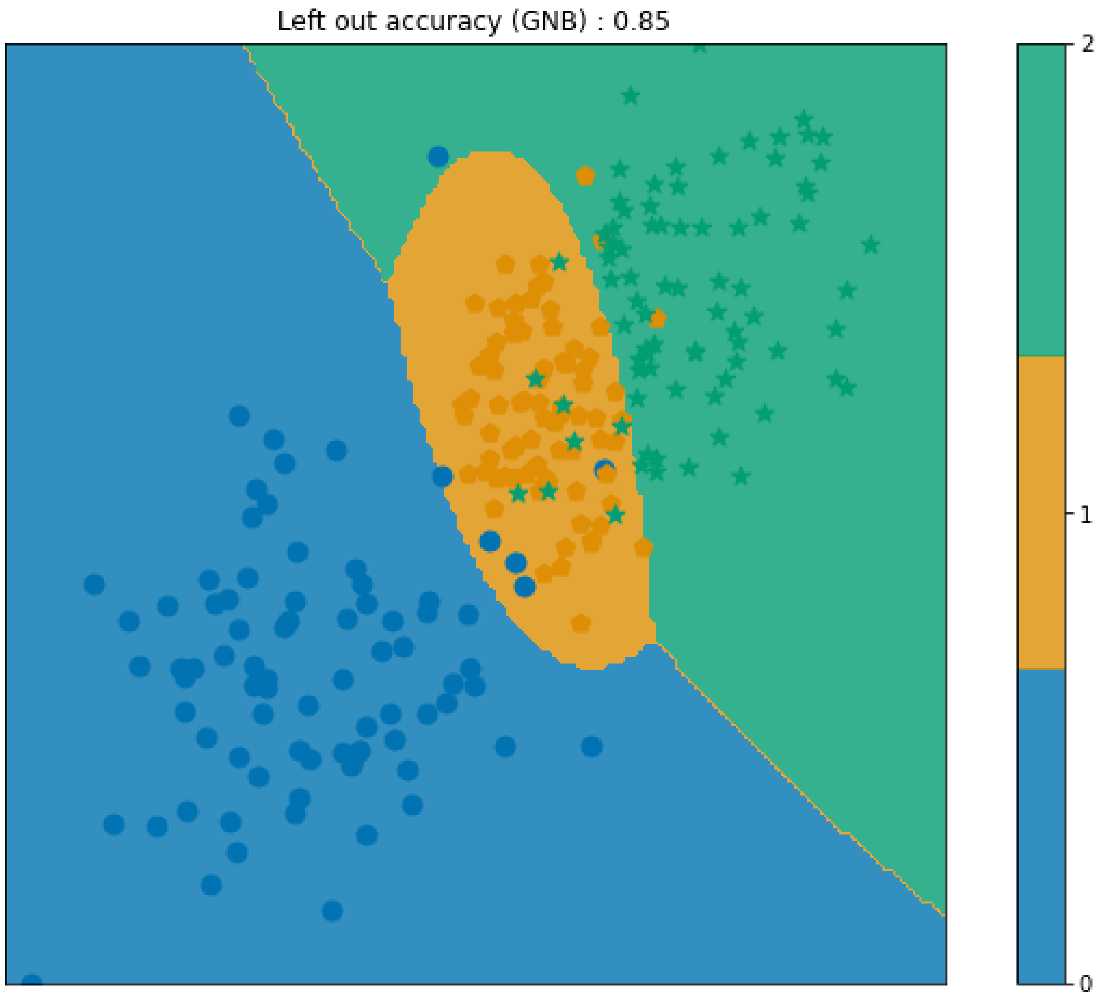
[10]:
```python
##############################################################################
# QDA
```

```python
##############################################################################
resolution_param = 150
clf_QDA = QuadraticDiscriminantAnalysis()
clf_QDA.fit(X_train, y_train)
y_QDA_test = clf_QDA.predict(X_test)
title = "Left out accuracy (QDA) " + \
        ": {:.2f}".format(accuracy_score(y_test, y_QDA_test))
fig2 = plt.figure(figsize=(12, 8))
plt.title(title)


def f(xx):
    """Classifier"""
    return int(clf_QDA.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



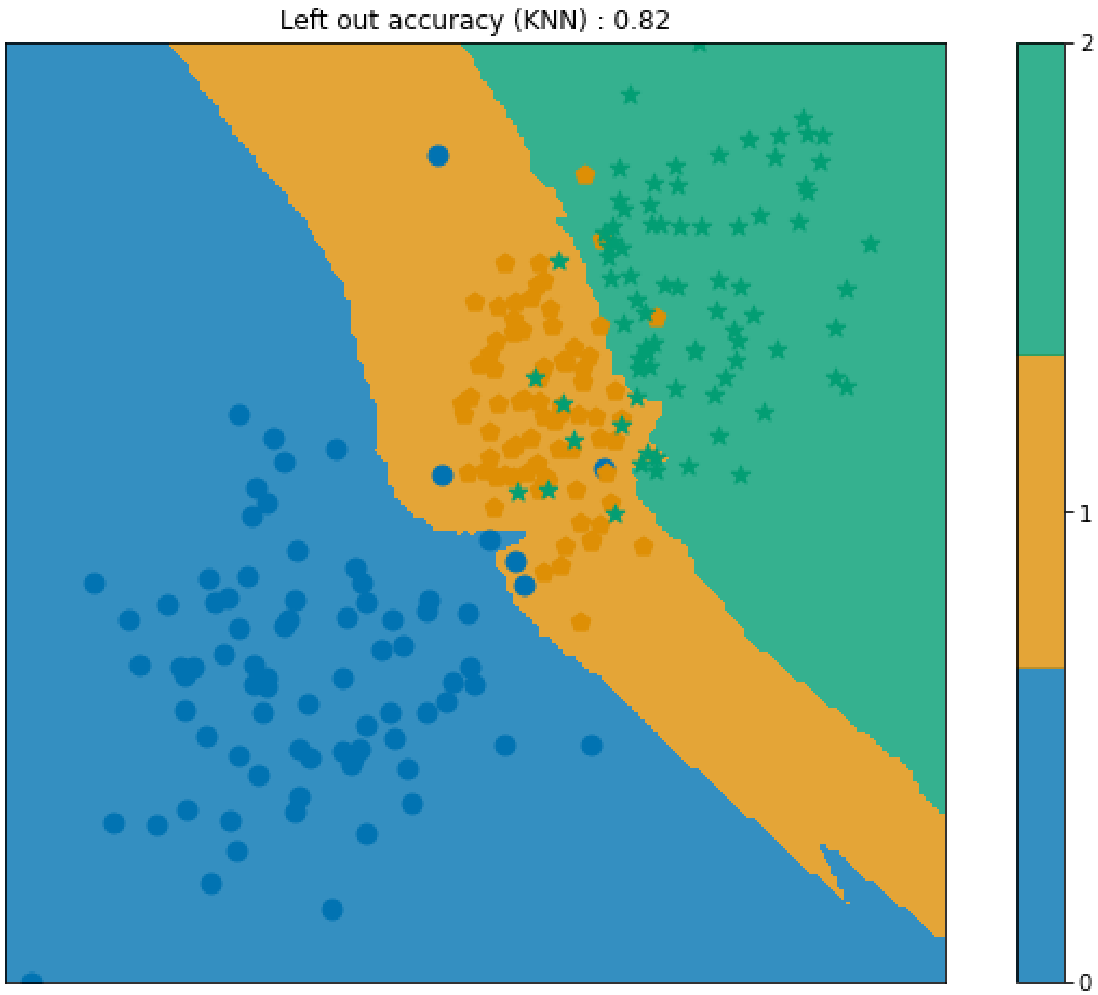
[11]:

```python
#############################################################################
# Naive Bayes
#############################################################################
resolution_param = 150
clf_GNB = GaussianNB()
clf_GNB.fit(X_train, y_train)

y_test_GNB = clf_GNB.predict(X_test)

title = "Left out accuracy (GNB) " + \
        ": {:.2f}".format(accuracy_score(y_test, y_test_GNB))
fig2 = plt.figure(figsize=(12, 8))
plt.title(title)


def f(xx):
    """Classifier"""
    return int(clf_GNB.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



[12]:
```
################################################################################
# KNN
################################################################################
resolution_param = 150
clf_KNN = KNeighborsClassifier()
clf_KNN.n_neighbors=5

clf_KNN.fit(X_train, y_train)
y_KNN_test = clf_KNN.predict(X_test)

title = "Left out accuracy (KNN) " + \
        ": {:.2f}".format(accuracy_score(y_test, y_KNN_test))
fig2 = plt.figure(figsize=(12, 8))
plt.title(title)

def f(xx):
```

```
    """Classifier"""
    return int(clf_KNN.predict(xx.reshape(1, -1)))
frontiere(f, X, y, step=resolution_param)

plt.show()
```



Questions:

1. Describe the decision boundaries of the methods. Are all linear ?
2. Using the following code, compare the computational time and the test accuracy of the different methods in the three scenarios. Comment the results.
3. (Optional) If you change the number of samples per class, do the results vary ?

Answers:

1. Not all are linear, K Nearest Neighbors (KNN) and Quadratic Discriminant Analysis (QDA) are non-linear. It is easy to see that Linear discriminant analysis and linear regression are linear, Naive Bayes is less obvious but it is linear.

2. We can see that KNN was the slowest we might have lower computational time if we lower the number of iterations but the model might not be able to convert. Not surprisingly LDA GNB and QDA have very similar computational time since they are from the same family of algorithms (Gaussian Discriminant Analysis).
3. Yes, the computational time is directly influenced by the number of samples more samples means longer computational time and the other way around. if we have more samples the accuracy of the model gets better. I also checked imbalance dataset and got better accuracy than each class is equal to 80 scenario.

[19]:
```
# each class is 80
clf_KNN = KNeighborsClassifier()
clf_KNN.n_neighbors=5
clf_GNB = GaussianNB()
clf_QDA = QuadraticDiscriminantAnalysis()
clf_LDA = LinearDiscriminantAnalysis()
######## PARAMETER TO CHOOSE THE SCENARIO (number of classes) #######
n_classes=3
####################################################################

X, y = generate_scenario(n_classes, 80 ,80, 80)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=42)

# example using KNN
time_start = time.perf_counter()
clf_KNN.fit(X_train, y_train)
y_KNN_test = clf_KNN.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy KNN', "%.
↪2f" %accuracy_score(y_test, y_KNN_test))
# using LDA
time_start = time.perf_counter()
clf_LDA.fit(X_train, y_train)
y_LDA_test = clf_LDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy LDA', "%.
↪2f" %accuracy_score(y_test, y_LDA_test))
# using GNB
time_start = time.perf_counter()
clf_GNB.fit(X_train, y_train)
y_GNB_test = clf_GNB.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy GNB', "%.
↪2f" %accuracy_score(y_test, y_GNB_test))
# using QDA
time_start = time.perf_counter()
clf_QDA.fit(X_train, y_train)
```

```
y_QDA_test = clf_QDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy QDA', "%.
↪2f" %accuracy_score(y_test, y_QDA_test))
```

```
Computational time: 0.00610 s ; Test accuracy KNN 0.78
Computational time: 0.00214 s ; Test accuracy LDA 0.78
Computational time: 0.00156 s ; Test accuracy GNB 0.80
Computational time: 0.00160 s ; Test accuracy QDA 0.80
```

[20]:
```
# each class is 150
clf_KNN = KNeighborsClassifier()
clf_KNN.n_neighbors=5
clf_GNB = GaussianNB()
clf_QDA = QuadraticDiscriminantAnalysis()
clf_LDA = LinearDiscriminantAnalysis()
######## PARAMETER TO CHOOSE THE SCENARIO (number of classes) #######
n_classes=3
####################################################################

X, y = generate_scenario(n_classes, 150 ,150, 150)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
↪random_state=42)

# example using KNN
time_start = time.perf_counter()
clf_KNN.fit(X_train, y_train)
y_KNN_test = clf_KNN.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy KNN', "%.
↪2f" %accuracy_score(y_test, y_KNN_test))
# using LDA
time_start = time.perf_counter()
clf_LDA.fit(X_train, y_train)
y_LDA_test = clf_LDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy LDA', "%.
↪2f" %accuracy_score(y_test, y_LDA_test))
# using GNB
time_start = time.perf_counter()
clf_GNB.fit(X_train, y_train)
y_GNB_test = clf_GNB.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy GNB', "%.
↪2f" %accuracy_score(y_test, y_GNB_test))
# using QDA
time_start = time.perf_counter()
```

```python
clf_QDA.fit(X_train, y_train)
y_QDA_test = clf_QDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy QDA', "%.
 ↪2f" %accuracy_score(y_test, y_QDA_test))
```

```
Computational time: 0.00902 s ; Test accuracy KNN 0.86
Computational time: 0.00245 s ; Test accuracy LDA 0.88
Computational time: 0.00153 s ; Test accuracy GNB 0.89
Computational time: 0.00084 s ; Test accuracy QDA 0.89
```

[21]:

```python
# imbalanced dataset, n0=50, n1=150,n2=80
clf_KNN = KNeighborsClassifier()
clf_KNN.n_neighbors=5
clf_GNB = GaussianNB()
clf_QDA = QuadraticDiscriminantAnalysis()
clf_LDA = LinearDiscriminantAnalysis()
######## PARAMETER TO CHOOSE THE SCENARIO (number of classes) #######
n_classes=3
####################################################################

X, y = generate_scenario(n_classes, 50 ,150, 80)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)

# example using KNN
time_start = time.perf_counter()
clf_KNN.fit(X_train, y_train)
y_KNN_test = clf_KNN.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy KNN', "%.
 ↪2f" %accuracy_score(y_test, y_KNN_test))
# using LDA
time_start = time.perf_counter()
clf_LDA.fit(X_train, y_train)
y_LDA_test = clf_LDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy LDA', "%.
 ↪2f" %accuracy_score(y_test, y_LDA_test))
# using GNB
time_start = time.perf_counter()
clf_GNB.fit(X_train, y_train)
y_GNB_test = clf_GNB.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy GNB', "%.
 ↪2f" %accuracy_score(y_test, y_GNB_test))
# using QDA
```

```
time_start = time.perf_counter()
clf_QDA.fit(X_train, y_train)
y_QDA_test = clf_QDA.predict(X_test)
time_elapsed = (time.perf_counter() - time_start)
print('Computational time:', "%.5f" %time_elapsed, 's ; Test accuracy QDA', "%.
↪2f" %accuracy_score(y_test, y_QDA_test))
```

```
Computational time: 0.00468 s ; Test accuracy KNN 0.91
Computational time: 0.00182 s ; Test accuracy LDA 0.84
Computational time: 0.00204 s ; Test accuracy GNB 0.93
Computational time: 0.00143 s ; Test accuracy QDA 0.91
```

[ ]:

```

```

[ ]:

```

```