Part B: Practice

Logistic Regression on Synthetic and Real-World Data

In [15]:

```
import numpy as np
from scipy.special import expit
from scipy.optimize import minimize
from sklearn.datasets import make_classification
from sklearn.datasets import make_moons
from matplotlib import pyplot as plt
from seaborn import scatterplot
```

In [16]:

```
class LogisticRegression:
    def __init__(self):
        return

    def cross_entropy(self):
        return np.sum(- self.y * np.log(expit(np.dot

    def g(self, w, x):
        return expit(np.dot(x, w))

    def gradient_descent(self):
        w_new = self.w
        for i in range(self.iterations):
            w_old = w_new
            w_new = w_old - self.learning_rate * np.
        return w_new

    def SGD(self):
        w_new = self.w
        for i in range(self.iterations):
            n = np.random.randint(0, self.N, 1)
            xi = self.x[n]
            yi = self.y[n]
            w_old = w_new
            w_new = w_old - self.learning_rate * np.
        return w_new

    def fit(self, x, y, w0=None, learning_rate=0.1,
        self.x = x
        self.y = y
        self.N = np.size(y)
        self.learning_rate = learning_rate
        self.iterations = iterations
        if w0 is not None:
            self.w = w0
        else:
            self.w = np.random.rand(np.size(x, 1))

        self.w = self.SGD()
        return self.w
```

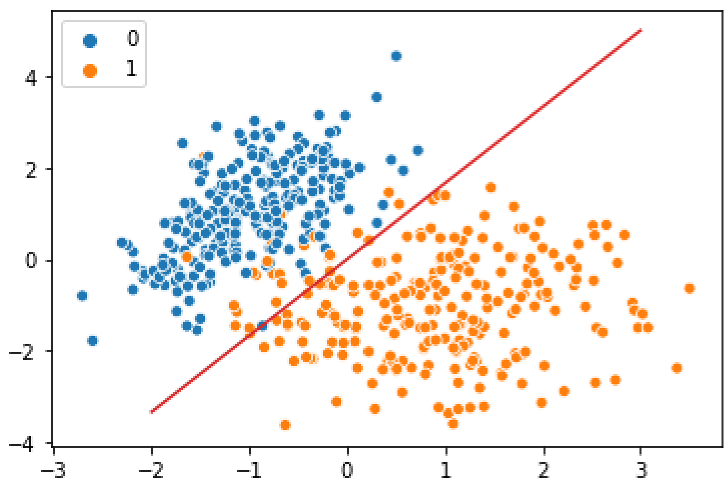
```python
    def predict(self, x):
        return np.round(self.g(self.w, x))

    def score(self, x, y):
        ypredict = self.predict(x)
        return np.sum(ypredict == y) / np.size(y)
```

In [21]:

```python
x, y = make_classification(n_samples=500, n_features
clf = LogisticRegression()
w = clf.fit(x, y)
scatterplot(x[:, 0], x[:, 1], hue=y.reshape(-1))
x1 = np.linspace(-2, 3, num=100)
y1 = (- w[0] * x1) / w[1]
plt.plot(x1, y1, color="tab:red")
```

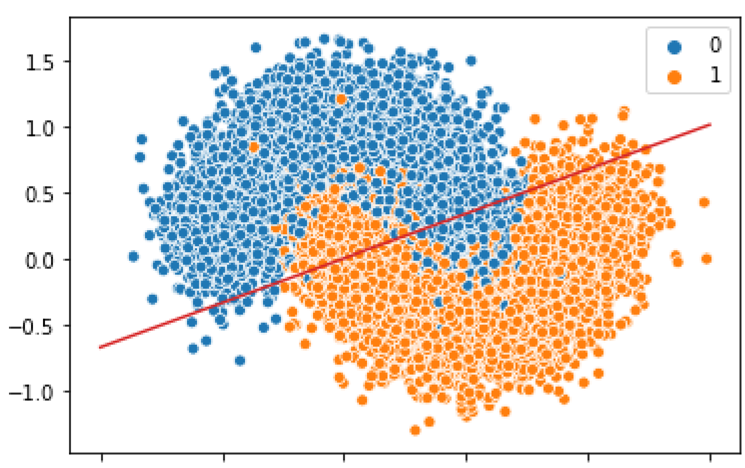
Out[21]: [<matplotlib.lines.Line2D at 0x7f34950d3bd0>]



In [4]:

```python
x, y = make_moons(n_samples=10000, noise=0.25, rando
clf = LogisticRegression()
w = clf.fit(x, y)
scatterplot(x[:, 0], x[:, 1], hue=y.reshape(-1))
x1 = np.linspace(-2, 3, num=100)
y1 = (- w[0] * x1) / w[1]
plt.plot(x1, y1, color="tab:red")
```

Out[4]: [<matplotlib.lines.Line2D at 0x7f34c84df8d0>]



Dimensionality Reduction

In [5]:

```
import pandas as pd
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from scipy.stats import wilcoxon
from sklearn.model_selection import cross_val_score
import warnings
warnings.filterwarnings('ignore')
```

In [6]:

```
datasets = ["abalone", "acute-inflammation", "acute-
               "car", "cardiotocography-3clases", "c
path = "../UA-ECE523-EngrAppMLData/data/" + datasets
data = np.loadtxt(path, delimiter=",")
X, y = data[:, :-1], data[:, -1]
```

In [7]:

```
def score_dataset(X, y, clf):
    pca = PCA(n_components=0.90)
    pcaX = pca.fit_transform(X)

    score0 = np.mean(cross_val_score(clf, X, y, cv=5
    score1 = np.mean(cross_val_score(clf, pcaX, y, c

    return score0, score1
```

The following code tests whether PCA does better than not using a preprocessing technique with a Logistic Regression classifier.

In [8]:

```
scores = np.zeros((len(datasets), 2))
i = 0
for dataset in datasets:
    path = "../UA-ECE523-EngrAppMLData/data/" + data
    data = np.loadtxt(path, delimiter=",")
    X, y = data[:, :-1], data[:, -1]

    clf = LogisticRegression()

    scores[i] = score_dataset(X, y, clf)
    i += 1

print(scores)

w, p = wilcoxon(scores[:, 1], scores[:, 0], alternat
print(w, p)
if p < 0.1:
    print("There is strong evidence that using PCA t
else:
    print("There is not strong evidence to say that
```

```
[[0.64424639 0.54895606]
```

```
 [1.         1.        ]
 [1.         1.        ]
 [0.63279761 0.63712768]
 [0.89493571 0.89117636]
 [0.70278282 0.68523896]
 [0.75279944 0.75279944]
 [0.85137586 0.85797073]
 [0.6161041  0.62064956]
 [0.84212625 0.84649554]
 [0.90666667 0.86666667]]
14.0 0.7122984885436232
There is not strong evidence to say that using PCA t
o preprocess the data does better than not using it
at the 0.05 level.
```

The following code tests whether PCA does better than not using a preprocessing technique with a Naive Bayes Gaussian classifier.

In [9]:

```
scores = np.zeros((len(datasets), 2))
i = 0
for dataset in datasets:
    path = "../UA-ECE523-EngrAppMLData/data/" + data
    data = np.loadtxt(path, delimiter=",")
    X, y = data[:, :-1], data[:, -1]

    clf = GaussianNB()

    scores[i] = score_dataset(X, y, clf)
    i += 1

print(scores)

w, p = wilcoxon(scores[:, 1], scores[:, 0], alternat
print(w, p)
if p < 0.1:
    print("There is strong evidence that using PCA t
```

```
[[0.57052789 0.55591593]
 [0.82282609 0.94166667]
 [0.91666667 1.        ]
 [0.14167139 0.33788957]
 [0.82504327 0.88608786]
 [0.67120387 0.66067756]
 [0.69498252 0.77774566]
 [0.71309473 0.85422038]
 [0.55881267 0.57496051]
 [0.79724011 0.80878173]
 [0.95333333 0.89333333]]
57.0 0.016427109964321847
There is strong evidence that using PCA to preproces
s the data does better than not using it at the 0.05
level.
```

Density Estimation in Practice

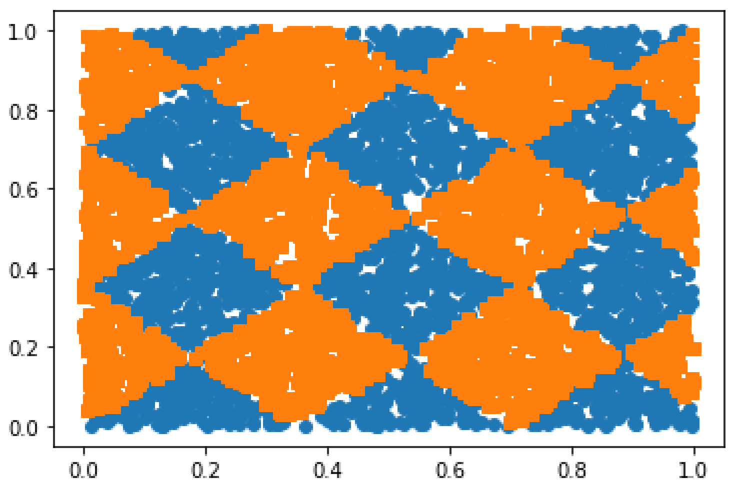
In [10]:

```
from sklearn.neighbors import KernelDensity
```

In [11]:

```
def gen_cb(N, a, alpha):
    """
    N: number of points on the checkerboard
    a: width of the checker board (0<a<1)
    alpha: rotation of the checkerboard in radians
    """
    d = np.random.rand(N, 2).T
    d_transformed = np.array([d[0]*np.cos(alpha)-d[1
                              d[0]*np.sin(alpha)+d[1
    s = np.ceil(d_transformed[:,0]/a)+np.floor(d_tra
    lab = 2 - (s%2)
    data = d.T
    return data, lab


X, y = gen_cb(5000, .25, np.pi/4)
y -= 1
plt.figure()
plt.plot(X[y==0, 0], X[y==0, 1], 'o')
plt.plot(X[y==1, 0], X[y==1, 1], 's')
plt.show()
plt.clf()
```



<Figure size 432x288 with 0 Axes>

In [12]:

```
prior = np.array([(y == 0).sum() / np.size(y), (y ==

x_min, x_max = X[:, 0].min(), X[:, 0].max()
y_min, y_max = X[:, 1].min(), X[:, 1].max()
h = .02  # step size in the mesh
xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.
zz = np.stack((xx.ravel(), yy.ravel()), axis=1)

like = [0, 0]
kerneldensity = KernelDensity(bandwidth=0.05)
kerneldensity.fit(X[y==0])
like[0] = np.exp(kerneldensity.score_samples(zz)).re

kerneldensity = KernelDensity(bandwidth=0.05)
kerneldensity.fit(X[y==1])
like[1] = np.exp(kerneldensity.score_samples(zz)).re

evid = like[0] * prior[0] + like[1] * prior[1]
```

```
post = np.zeros((2, np.size(xx, 0), np.size(xx, 0)))
post[0] = like[0] * prior[0] / evid
post[1] = like[1] * prior[1] / evid

plt.pcolormesh(xx, yy, post[0], cmap="coolwarm")
plt.show()
plt.pcolormesh(xx, yy, post[1], cmap="coolwarm")
plt.show()
```