sheet_2

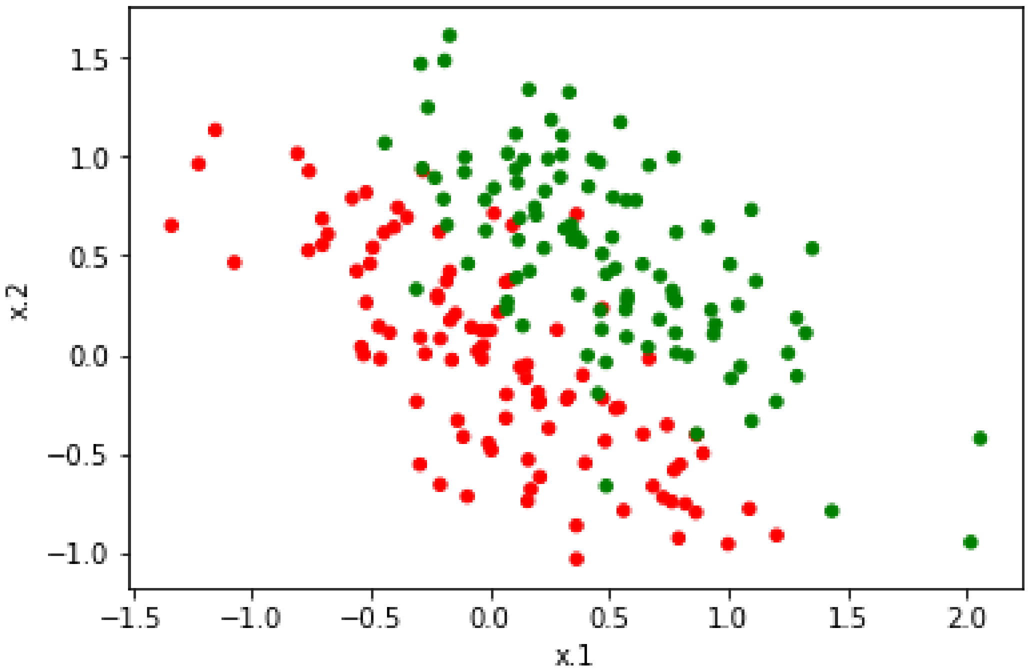
October 29, 2017

0.1 # Exercise 1

a)

```
In [3]: import pandas as pd
        import numpy as np
        % matplotlib inline
        #x.1     x.2   y
        df = pd.read_csv('applesOranges.csv')

        colors = np.where(df["y"]==0,'r','-')
        colors[df["y"]==1] = 'g'

        df.plot(kind='scatter', x='x.1', y='x.2', c=colors,)
```

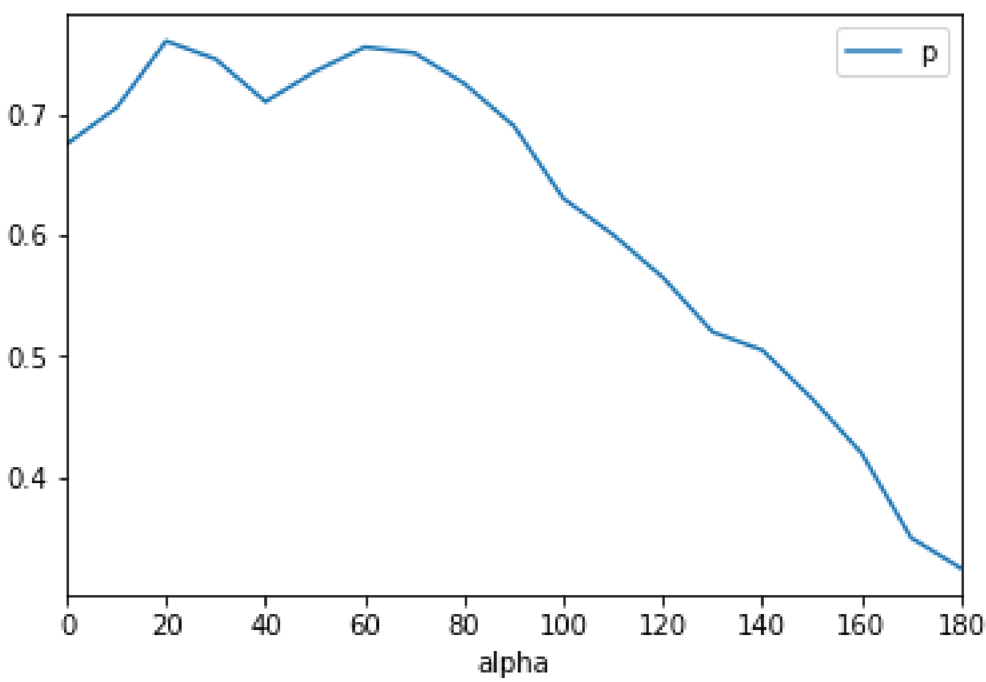
```
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4f502f2a58>
```



b)

In [4]:
```
alphas = np.arange(0, 190, 10)
w0 = np.cos(alphas * np.pi / 180)
w1 = np.sin(alphas * np.pi / 180)
ws = np.column_stack((w0, w1))
#print(df[["x.1", "x.2"]])


#sign = lambda h: 1 if h > 0 else 0

def predict(w, bias):
    y_pred = np.sign(np.array(np.dot(df[["x.1", "x.2"]], w)) - bias)
    y_pred[y_pred == -1] = 0
    return y_pred
def getAccuracy(w, bias):
    y_pred = predict(w, bias)
    #print(y_pred)
    return 1 - np.count_nonzero(y_pred - df["y"]) / y_pred.size

def getAccuracyForW(w):
    return getAccuracy(w, 0)
accs = np.apply_along_axis(getAccuracyForW, 1, ws)
acc_df = pd.DataFrame(data=np.array([alphas, accs]).T, columns=["alpha", "p"])
acc_df.plot(x='alpha', y='p')
```

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4f48439cf8>



c)

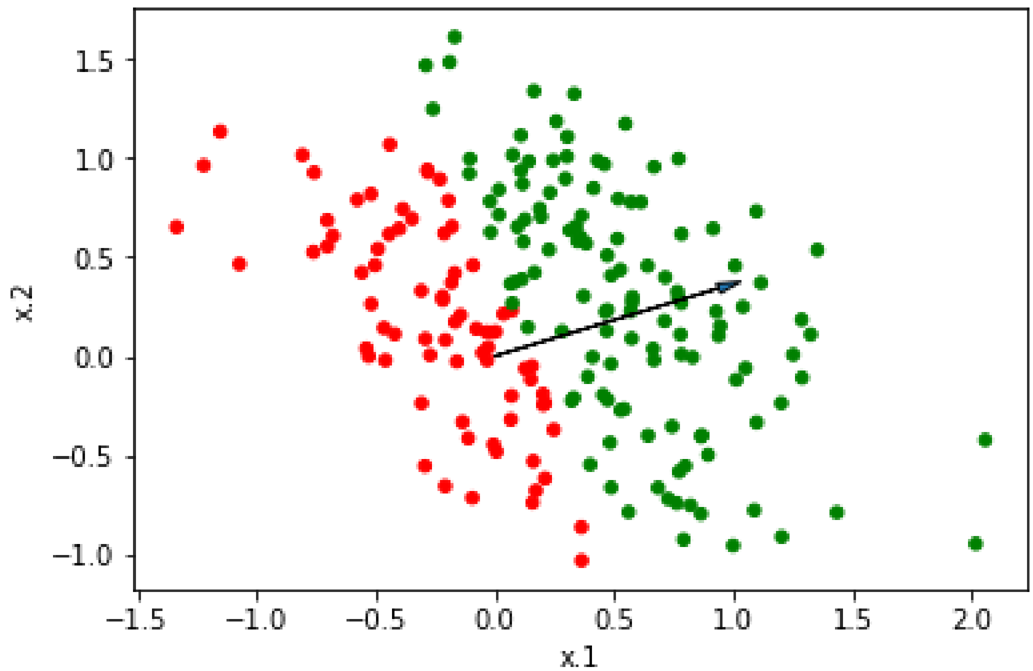
```
In [5]: w_best = ws[np.argmax(accs)]

        bias = np.arange(-3, 3, 0.05)

        #print(bias)
        def getAccuracyForBias(b):
            return getAccuracy(w_best, b)
        getAccuracyForBias = np.vectorize(getAccuracyForBias)
        accs_b = getAccuracyForBias(bias)

        bias_best = bias[np.argmax(accs_b)]
        print("The best bias is "+str(bias_best))
```

```
The best bias is :0.15
```

d)

```
In [101]: y_pred = predict(w_best, bias_best)

          pred_colors = np.where(y_pred==0,'r','-')
          pred_colors[y_pred==1] = 'g'

          ax = df_pred.plot(kind='scatter', x='x.1', y='x.2', c=pred_colors)
          ax.arrow(0, 0, w_best[0], w_best[1], head_width=0.05, head_length=0.1)
```

```
Out[101]: <matplotlib.patches.FancyArrow at 0x7fba679e5048>
```



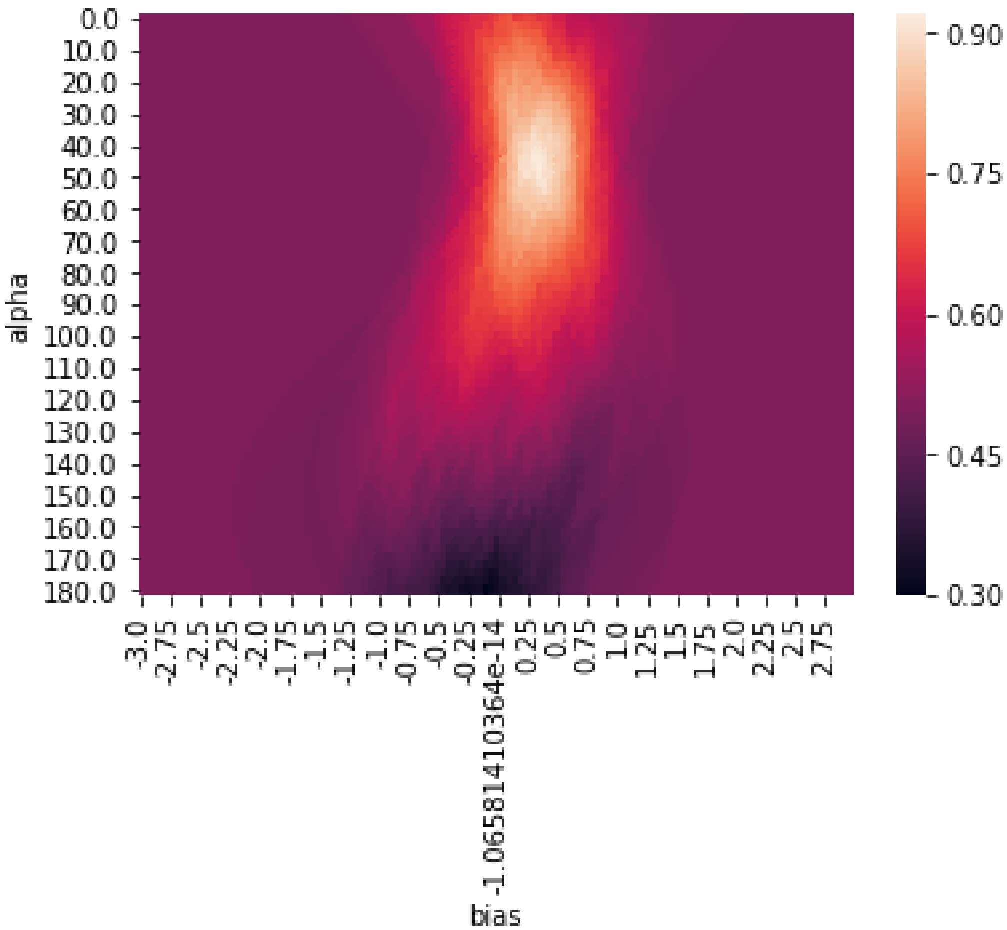
the vector w stands orthogonal to the line of seperation between apples and oranges

e)

In [6]:
```
alphas_many = np.arange(0, 181, 2.5)
bias_many = np.arange(-3, 3, 0.05)

alpha_bias = np.transpose([np.tile(bias_many, len(alphas_many)), np.repeat(alphas_many,


w0 = np.cos(alpha_bias[:,1] * np.pi / 180)
w1 = np.sin(alpha_bias[:,1] * np.pi / 180)
parameters = np.column_stack((w0, w1, alpha_bias[:,0]))

#print(parameters)

def getAccuracyForVector(p):
    return getAccuracy(p[[0,1]],p[2])

#print(getAccuracy(np.array([0,1]), 3))
#print(getAccuracyForVector(np.array([0,1,3])))

accs_many = np.apply_along_axis(getAccuracyForVector, 1, parameters)
#print(accs_many)

import matplotlib.pyplot as plt
```

```python
heatmap = pd.DataFrame(data=np.column_stack((alpha_bias[:,1], alpha_bias[:,0], accs_many
heatmap = heatmap.pivot("alpha", "bias", "acc")
#print(heatmap)
import seaborn as sns
sns.heatmap(heatmap)
#plt.imshow(heatmap, cmap='hot', interpolation='nearest')
#plt.show()
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4f3f7cbd68>

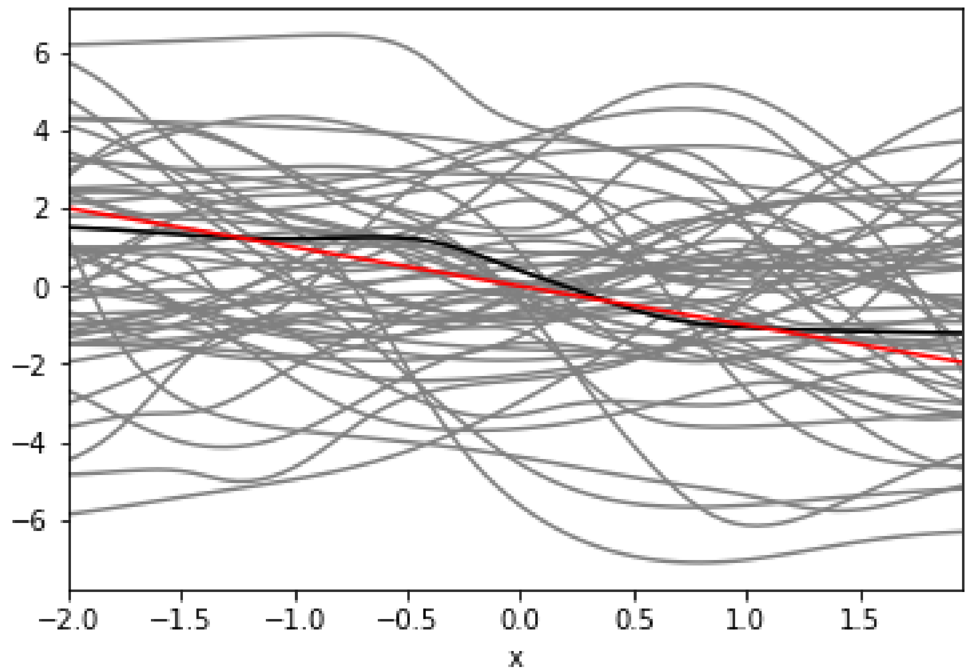


f) The optimization method can not be applied to any problem, because the number of configuration to test increases exponentially with the number of parameters. It would for example not be possible to classify pictures regarding whether or not they show a dog.

0.2 # Exercise 2

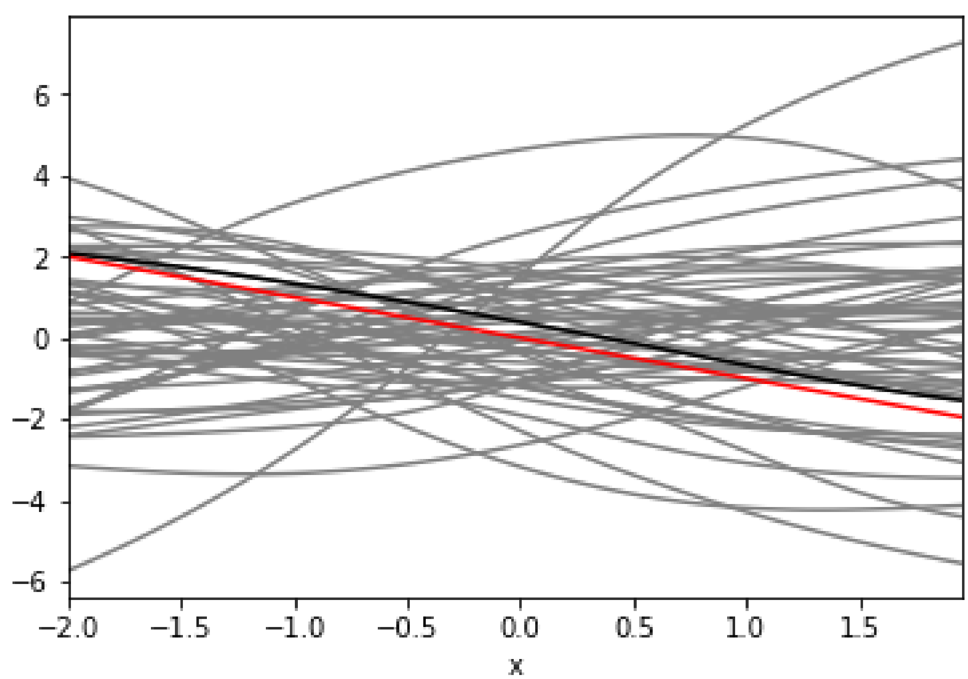
a)

In [7]:
```
def multilayer(a, w, b):
    def y_pred(x):
        return np.sum(np.tanh(a*(x - b))*w)
    y_pred = np.vectorize(y_pred)
    return y_pred

def plotFunction(x, y, ax, color="gray"):
    x_y = pd.DataFrame(data=np.array([x, y]).T, columns=["x", "y"])
    return x_y.plot(x="x", y="y", ax=ax, legend=False, color=color)


def plotRandoms(a_mean, a_std):
    ax = None
    y_best = None
    err_best = 10000000000

    x = np.arange(-2, 2, 0.05)
    for i in range(0,50):
        a = np.random.normal(a_mean, a_std, 10)
        w = np.random.normal(0, 1, 10)
        b = np.random.uniform(-2, 2, 10)

        y_pred = multilayer(a, w, b)
        y= y_pred(x)

        err = 0.5 * np.sum((y + x) ** 2)
        if (err < err_best):
            y_best = y
            err_best = err

        ax = plotFunction(x, y, ax)
    ax = plotFunction(x, y_best, ax, color="black")
    plotFunction(x, x*-1, ax, color="red")
plotRandoms(0, 2)
```



b)

```
In [8]: plotRandoms(0, 0.5)
```



With a smaller a the term $h = a(x - b)$ becomes smaller. For smaller h $tanh(h)$ is more linear, thus the overall function output is more linear

c) See the black line in the above graphs