LABORATORIO 6

In [1]:

```
import pandas as pd
import numpy as np
from typing import List, Callable, Any
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import scipy.optimize as opt
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

DATOS

In [2]:

```
x = pd.read_csv('/Users/maria/OneDrive/Documentos/mle_laboratorios/Lab6/Lab6/wine_data.csv',
                names=["1", "2", "3", "4","5", "6", "7", "8","9", "10", "11", "12", "13","14'

print(type(x), x.shape)
```

```
<class 'pandas.core.frame.DataFrame'> (178, 14)
```

In [3]:

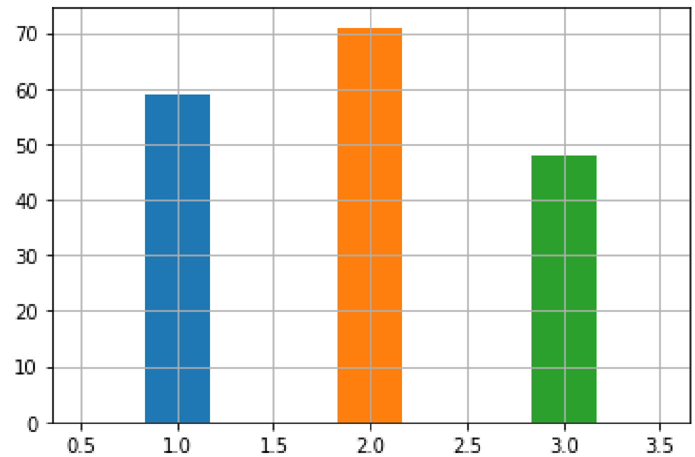
```
x.describe()
```

Out[3]:

	1	2	3	4	5	6	7	8	
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.00(
mean	1.938202	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.36
std	0.775035	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.12
min	1.000000	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.13(
25%	1.000000	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.27(
50%	2.000000	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.34(
75%	3.000000	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.43
max	3.000000	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.66(

In [4]:

```
#visualizacion datos de cada tipo de vino
x.groupby('1')['1'].hist(bins=3)
plt.show()
```



In [5]:

```
#Separacion de dataset en variable dependiente e independientes
Y = x['1']
X = x.iloc[:, [1,2,3,4,5,6,7,8,9,10,11,12,13]]
print(X.shape, Y.shape)
```

```
(178, 13) (178,)
```

In [6]:

```
X.head()
```

Out[6]:

	2	3	4	5	6	7	8	9	10	11	12	13	14
0	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065
1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050
2	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185
3	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480
4	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735

ESTANDARIZACION DE VARIABLES INDEPENDIENTES

In [7]:

```
sc = StandardScaler()
est = sc.fit_transform(X)
est = pd.DataFrame(est)
```

In [8]:

```
est.head()
```

Out[8]:

	0	1	2	3	4	5	6	7	8	9	
0	1.518613	-0.562250	0.232053	-1.169593	1.913905	0.808997	1.034819	-0.659563	1.224884	0.251717	0.3
1	0.246290	-0.499413	-0.827996	-2.490847	0.018145	0.568648	0.733629	-0.820719	-0.544721	-0.293321	0.4
2	0.196879	0.021231	1.109334	-0.268738	0.088358	0.808997	1.215533	-0.498407	2.135968	0.269020	0.3
3	1.691550	-0.346811	0.487926	-0.809251	0.930918	2.491446	1.466525	-0.981875	1.032155	1.186068	-0.4
4	0.295700	0.227694	1.840403	0.451946	1.281985	0.808997	0.663351	0.226796	0.401404	-0.319276	0.3

In [9]:

```
est = pd.concat([pd.Series(1, index = est.index, name = '13'), est], axis=1)
print(type(est), est.shape)
```

```
<class 'pandas.core.frame.DataFrame'> (178, 14)
```

In [10]:

```
Y_procesado = np.array(Y).T
Y_procesado = Y_procesado.reshape(178,1)
X_procesado = np.array(est)

m,n = X_procesado.shape
print(X_procesado.shape, Y_procesado.shape)
```

```
(178, 14) (178, 1)
```

In [11]:

```
x_train, x_test = train_test_split(X_procesado, test_size=0.33)
y_train, y_test = train_test_split(Y_procesado, test_size=0.33)
```

FUNCIONES

Se realiza una prueba general del algoritmo con el dataset entero, se validara la funcionalidad para cada clase mas adelante

In [12]:

```
theta_0 = np.random.rand(n, 1).T
```

In [13]:

```
def hyp(X, theta):
    z = np.dot(theta, X.T)
    return 1/(1+np.exp(-(z))) - 0.0000001
```

In [14]:

```
def log_cost(X, y, theta):
    y1 = hyp(X, theta)
    return -(1/len(X)) * np.sum(y*np.log(y1) + (1-y)*np.log(1-y1))
```

In [15]:

```
def gradient_descent(X, y, theta, learning_rate, max_iter):
    m =len(X)
    J = [log_cost(X, y, theta)]
    for i in range(0, max_iter):
        h = hyp(X, theta)
        for i in range(0, len(X)):
            theta = theta - (learning_rate * log_cost(X, y, theta))
        J.append(log_cost(X, y, theta))
    return J, theta
```

In [16]:

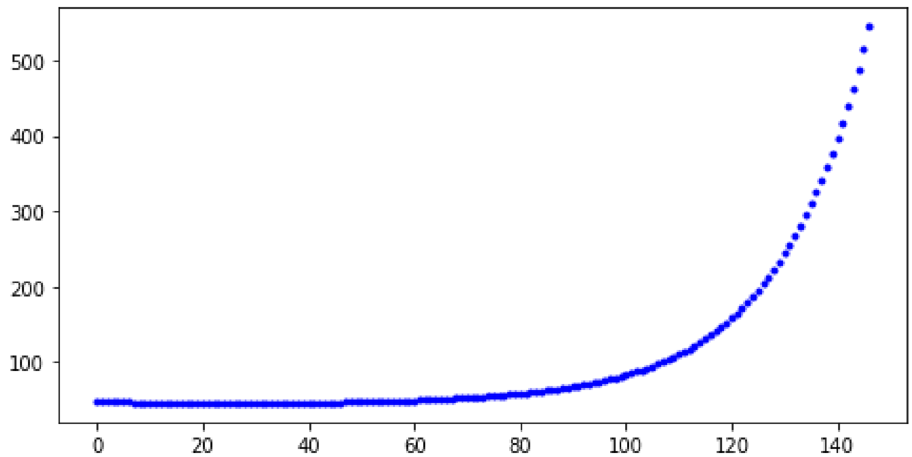
```
costs, theta = gradient_descent(X_procesado, Y_procesado, theta_0, learning_rate = 0.0001, ma
```

In [17]:

```
c, t = gradient_descent(x_train, y_train, theta_0, learning_rate = 0.000001, max_iter = 1000(
```

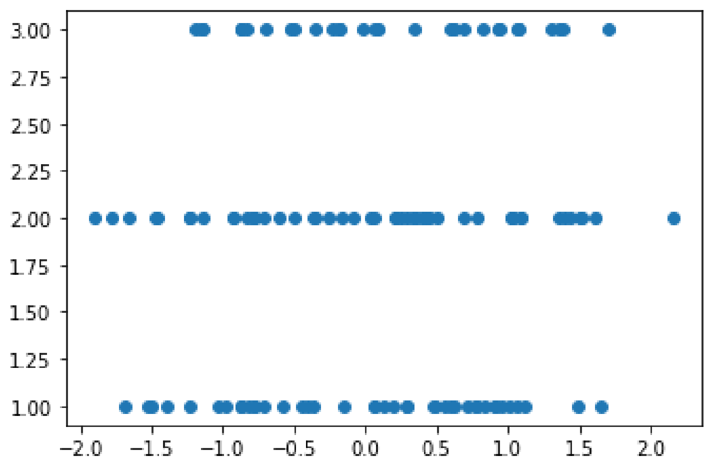
In [18]:

```
fig,ax = plt.subplots(figsize=(8,4))
_=ax.plot(range(10001),c,'b.')
```



In [19]:

```
pred = hyp(x_test,theta)
plt.figure()
plt.scatter(x=x_train[:,1],y= y_train)
plt.scatter(x=x_test[:,1], y=pred)
plt.show()
```



In [20]:

```
uno = x[x['1']==1]
dos = x[x['1']==2]
tres = x[x['1']==3]
```

CLASE 1

In [21]:

```
Y1 = uno['1']
X1 = uno.iloc[:, [1,2,3,4,5,6,7,8,9,10,11,12,13]]
print(X1.shape, Y1.shape)
```

```
(59, 13) (59,)
```

In [22]:

```
sc1 = StandardScaler()
est1 = sc.fit_transform(X1)
est1 = pd.DataFrame(est1)

Y_procesado1 = np.array(Y1).T
Y_procesado1 = Y_procesado1.reshape(59,1)
X_procesado1 = np.array(est1)

m1,n1 = X_procesado1.shape
```

```
x_train1, x_test1 = train_test_split(X_procesado1, test_size=0.33)
y_train1, y_test1 = train_test_split(Y_procesado1, test_size=0.33)

theta_01 = np.random.rand(n1, 1).T
```

In [23]:

```
c1, t1 = gradient_descent(x_train1, y_train1, theta_01, learning_rate = 0.00001, max_iter = 1
```

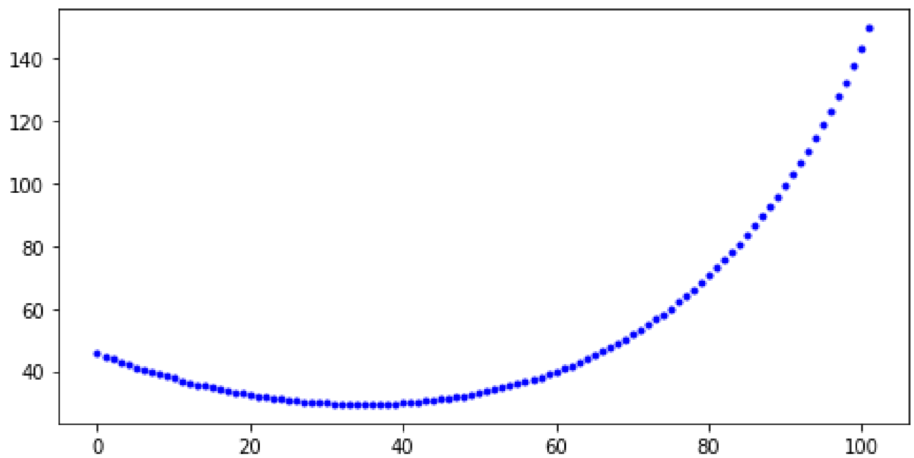
In [36]:

```
print(min(c1))
```

```
29.458007153676018
```

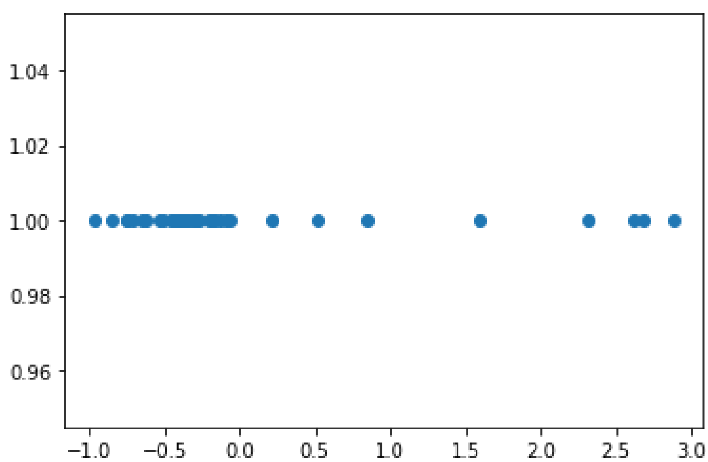
In [24]:

```
fig,ax = plt.subplots(figsize=(8,4))
_=ax.plot(range(1001),c1,'b.')
```



In [25]:

```
pred1 = hyp(x_test1,t1)
plt.figure()
plt.scatter(x=x_train1[:,1],y= y_train1)
plt.scatter(x=x_test1[:,1], y=pred1)
plt.show()
```



CLASE 2

In [26]:

```
Y2 = dos['1']
X2 = dos.iloc[:, [1,2,3,4,5,6,7,8,9,10,11,12,13]]
print(X2.shape, Y2.shape)
```

```
(71, 13) (71,)
```

In [27]:

```
sc2 = StandardScaler()
est2 = sc.fit_transform(X2)
est2 = pd.DataFrame(est2)

Y_procesado2 = np.array(Y2).T
Y_procesado2 = Y_procesado2.reshape(71,1)
X_procesado2 = np.array(est2)

m2,n2 = X_procesado2.shape
x_train2, x_test2 = train_test_split(X_procesado2, test_size=0.33)
y_train2, y_test2 = train_test_split(Y_procesado2, test_size=0.33)

theta_02 = np.random.rand(n2, 1).T
```

In [28]:

```
c2, t2 = gradient_descent(x_train2, y_train2, theta_02, learning_rate = 0.00001, max_iter = 1
```

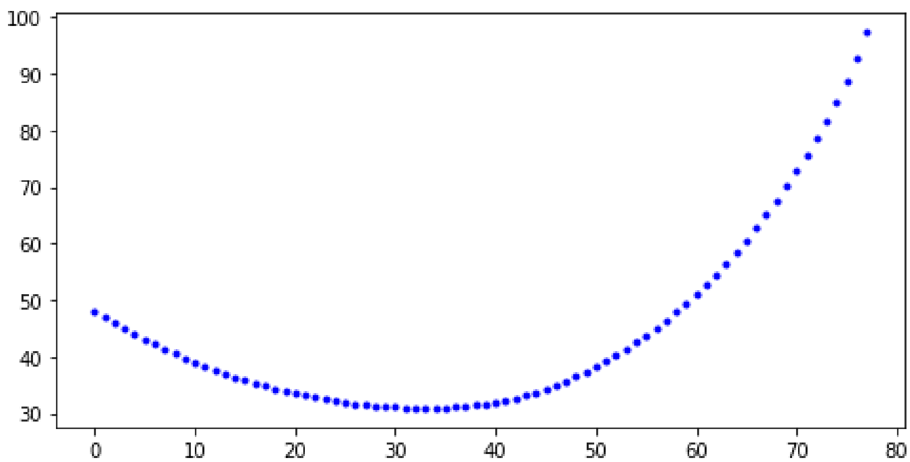
In [37]:

```
print(min(c2))
```

```
30.90927264602434
```

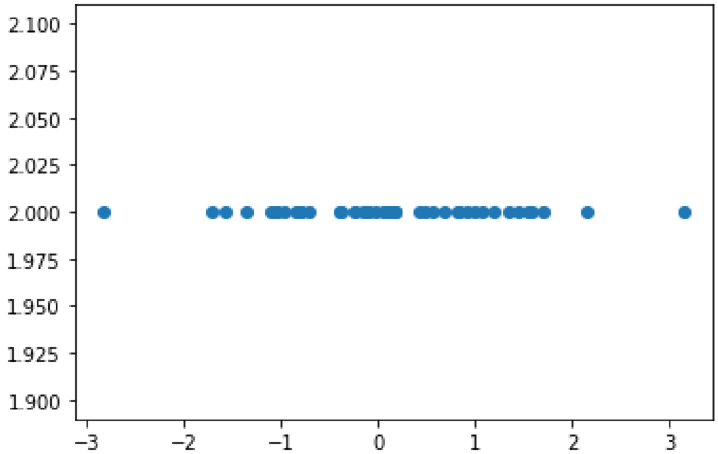
In [29]:

```
fig,ax = plt.subplots(figsize=(8,4))
_=ax.plot(range(1001),c2,'b.')
```



In [30]:

```
pred2 = hyp(x_test2,t2)
plt.figure()
plt.scatter(x=x_train2[:,2],y= y_train2)
plt.scatter(x=x_test2[:,2], y=pred2)
plt.show()
```



CLASE 3

In [31]:
```
Y3 = tres['1']
X3 = tres.iloc[:, [1,2,3,4,5,6,7,8,9,10,11,12,13]]
print(X3.shape, Y3.shape)
```

```
(48, 13) (48,)
```

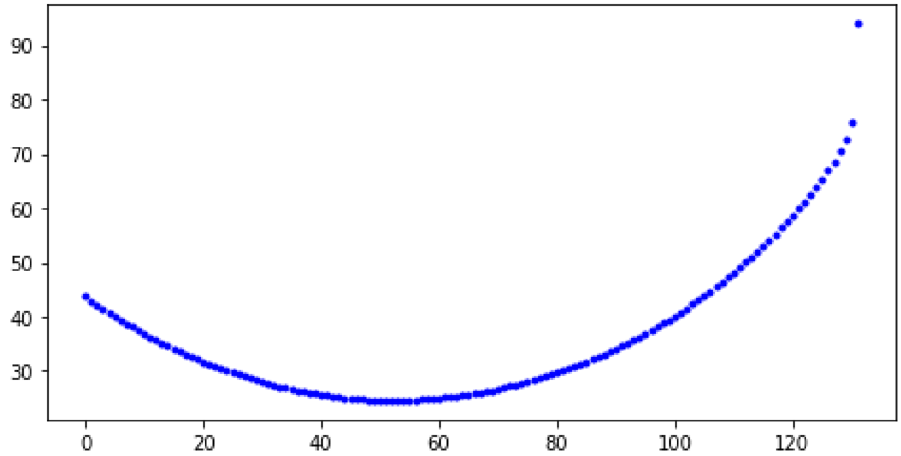
In [32]:
```
sc3 = StandardScaler()
est3 = sc.fit_transform(X3)
est3 = pd.DataFrame(est3)

Y_procesado3 = np.array(Y3).T
Y_procesado3 = Y_procesado3.reshape(48,1)
X_procesado3 = np.array(est3)

m3,n3 = X_procesado3.shape
x_train3, x_test3 = train_test_split(X_procesado3, test_size=0.33)
y_train3, y_test3 = train_test_split(Y_procesado3, test_size=0.33)

theta_03 = np.random.rand(n3, 1).T
```

In [45]:
```
c3, t3 = gradient_descent(x_train3, y_train3, theta_03, learning_rate = 0.00001, max_iter = 1
```

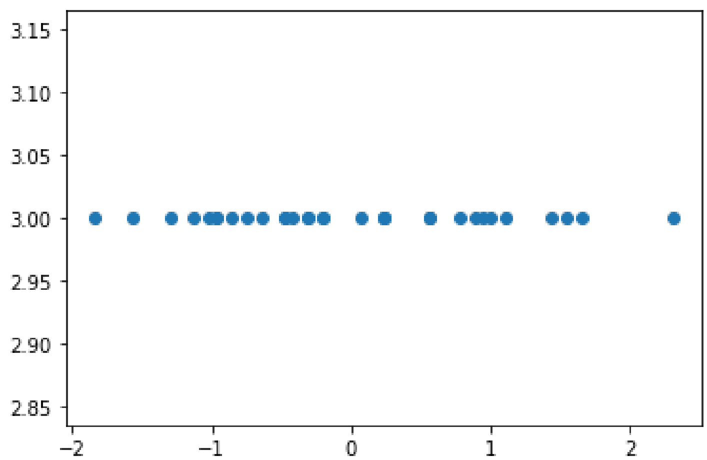
In [46]:
```
print(min(c3))
```

```
24.585881746473916
```

In [47]:
```
fig,ax = plt.subplots(figsize=(8,4))
_=ax.plot(range(1001),c3,'b.')
```



In [40]:
```
pred3 = hyp(x_test3,t3)
plt.figure()
plt.scatter(x=x_train3[:,2],y= y_train3)
plt.scatter(x=x_test3[:,2], y=pred3)
plt.show()
```



ANALISIS RESULTADOS

Aunque los graficos de gradient descent convergieron demasiado pronto, era la mejor forma de observar el comportamiento, ya que al reducir las iteraciones se perdia la caida y quedaba como una recta, por ende solo se busco el minimo de los resultados que realmente es lo que se buscaba.

Los modelos para las 3 clases obtuvieron resultados bastante similares, aunque el de la clase 2 se considera el mejor. Puesto que logro el menor resultado del decenso del gradiente y la nube de datos se ve mas centralizada.

La nube de datos con el comportamiento mas similar a una funcion logistica fue el que contaba con las tres caracteristicas, aunque por tener tres lineas se podria suponer que es una de cada clase.

Aunque fue bastante complejo lograr un modelo que funcionara realmente, se considera que este es el mejor debido a su capacidad de predecir los resultados y al comportamiento tanto en las nubes de datos como en el decenso del gradiente.