ZAD 1

```
import tensorflow as tf
```

```
x = tf.Variable(4.0)
y = tf.Variable(3.0)

with tf.GradientTape() as tape:
    f = (x**3)+(y**2)
    df_dx,df_dy = tape.gradient(f,(x,y))

print(df_dx.numpy())
print(df_dy.numpy())
```

```
48.0
6.0
```

ZAD 2

```
x = tf.Variable(1.0)
y = tf.Variable(2.0)

with tf.GradientTape() as tape:
    f = 4*(x**3)+11*(y**2)+9*y*x+10
    df_dx,df_dy = tape.gradient(f,(x,y))

print(df_dx.numpy())
print(df_dy.numpy())
```



```
53.0
```

Zad 3

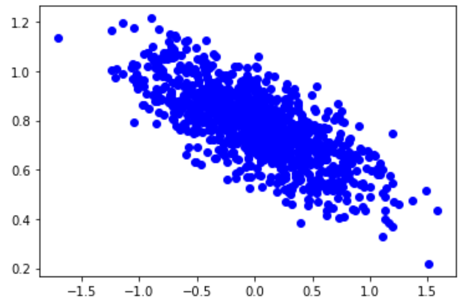
```
import matplotlib.pyplot as plt
import numpy as np
```

```
number_of_points = 1000
x_point = []
y_point = []
```

```
a = -0.22
b = 0.78
```

```
for i in range(number_of_points):
    x = np.random.normal(0.0,0.5)
    y = (a*x+b)+np.random.normal(0.0,0.1)
    x_point.append(x)
    y_point.append(y)
```

```
plt.scatter(x_point,y_point,c='b')
plt.show()
```




```
real_x = np.array(x_point)
real_y = np.array(y_point)
```

```
def loss_fn(real_y, pred_y):
    return tf.reduce_mean((real_y - pred_y)**2)
```

```
import·random
a·=·tf.Variable(random.random())
b·=·tf.Variable(random.random())
```

```
Loss = []
epochs = 1000
learning_rate = 0.01

for _ in range(epochs):
                                   :
    loss = loss_fn(real_y, pred_y)
    Loss.append(loss.numpy())

  dloss_da, dloss_db = tape.gradient(loss,(a, b))

  a.assign_sub(learning_rate*dloss_da)  #a = a - alpha*dloss_da
  b.assign_sub(learning_rate*dloss_db)  #b = b - alpha*dloss_db
```

Zapisano pomyślnie.

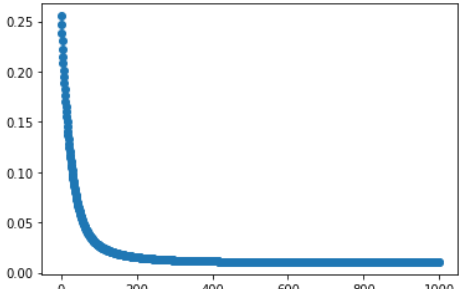
```
np.max(Loss),np.min(Loss)
```

    (0.2553488, 0.010641033)

```
print(a.numpy())
print(b.numpy())
```

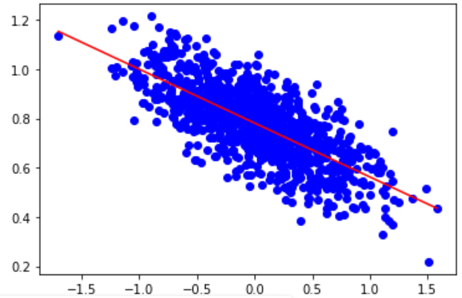
    -0.21870963
    0.78094

```
plt.scatter(np.arange(epochs),Loss)
plt.show()
```




```
max = np.max(x_point)
min = np.min(x_point)


X = np.linspace(min, max, num=10)
plt.plot(X,a.numpy()*X+b.numpy(),c='r')
plt.scatter(x_point,y_point,c="b")
plt.show()
```




```
def subset_dataset(x_dataset, y_dataset, subset_size):
    arr = np.arange(len(x_dataset))
    np.random.shuffle(arr)
    x_train = x_dataset[arr[0:subset_size]]
    y_train = y_dataset[arr[0:subset_size]]
    return x_train,y_train


a = tf.Variable(random.random())
b = tf.Variable(random.random())


Loss = []
epochs = 1000
learning_rate = 0.2
batch_size = 50

for i in range(epochs):
  real_x_batch,real_y_batch = subset_dataset(real_x,real_y,batch_size)
  with tf.GradientTape() as tape:
    pred_y = a * real_x_batch + b
    loss = loss_fn(real_y_batch, pred_y)
    Loss.append(loss.numpy())
```

```
  dloss_da, dloss_db = tape.gradient(loss,(a, b))

  a.assign_sub(learning_rate*dloss_da)  #a = a - alpha*dloss_da
  b.assign_sub(learning_rate*dloss_db)  #b = b - alpha*dloss_db
```

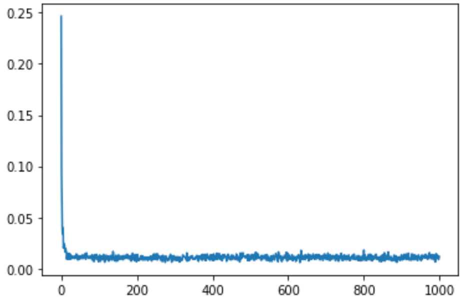
```
np.max(Loss),np.min(Loss)
```

```
(0.24657296, 0.0058904802)
```

```
print(a.numpy())
print(b.numpy())
```

```
-0.20982282
0.77441996
```

```
plt.plot(Loss)
plt.show()
```



Zapisano pomyślnie.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
df = pd.read_csv('Boston.csv')
print(df)
```

```
     Unnamed: 0     crim    zn  indus  chas    nox     rm   age     dis  rad  \
0             1  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1
1             2  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2
2             3  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2
3             4  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3
4             5  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3
..          ...      ...   ...    ...   ...    ...    ...   ...     ...  ...
501         502  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1
502         503  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1
503         504  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1
504         505  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1
505         506  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1

     tax  ptratio   black  lstat  medv
0    296     15.3  396.90   4.98  24.0
1    242     17.8  396.90   9.14  21.6
2    242     17.8  392.83   4.03  34.7
```

```
3    222     18.7  394.63   2.94  33.4
4    222     18.7  396.90   5.33  36.2
..   ...      ...     ...    ...   ...
501  273     21.0  391.99   9.67  22.4
502  273     21.0  396.90   9.08  20.6
503  273     21.0  396.90   5.64  23.9
504  273     21.0  393.45   6.48  22.0
505  273     21.0  396.90   7.88  11.9

[506 rows x 15 columns]
```

```
df.head()
```

	Unnamed: 0	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	1	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	2	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	3	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	4	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	5	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

```
rm=df.iloc[:,6]
```

```
rm
```

```
0      6.575
1      6.421
2      7.185
3      6.998
4      7.147
```

Zapisano pomyślnie.

```
503    6.976
504    6.794
505    6.030
Name: rm, Length: 506, dtype: float64
```

```
medv=df.iloc[:,14]
```

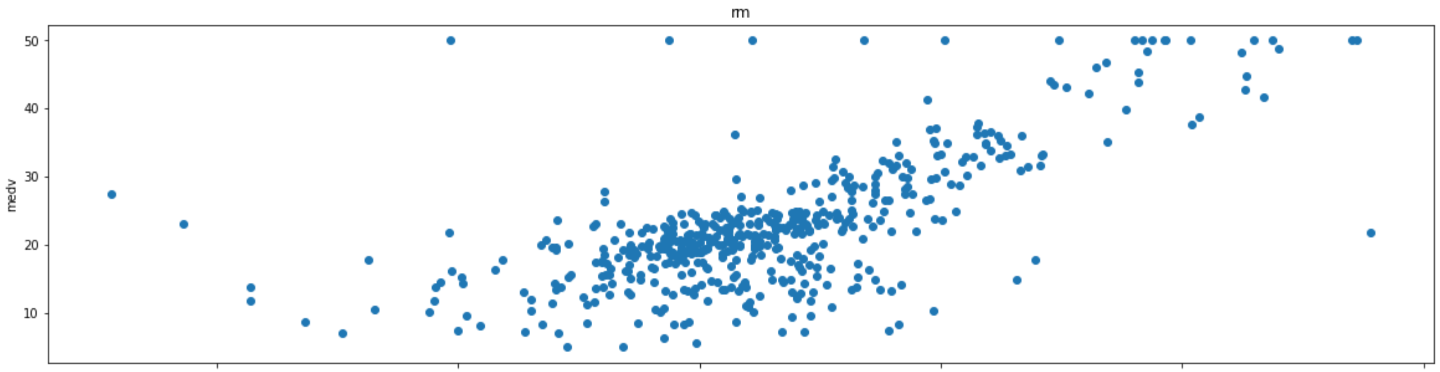
```
medv
```

```
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ...
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: medv, Length: 506, dtype: float64
```

```
plt.figure(figsize=(20, 5))

features = ['rm']
target = df['medv']

for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = df[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('medv')
```




```
real_rm = np.array(rm)
real_medv = np.array(medv)
```

Zapisano pomyślnie.

```
                      6.998, 7.147, 6.43 , 6.012, 6.172, 5.631,
       6.004, 6.377, 6.009, 5.889, 5.949, 6.096, 5.834, 5.935, 5.99 ,
       5.456, 5.727, 5.57 , 5.965, 6.142, 5.813, 5.924, 5.599, 5.813,
       6.047, 6.495, 6.674, 5.713, 6.072, 5.95 , 5.701, 6.096, 5.933,
       5.841, 5.85 , 5.966, 6.595, 7.024, 6.77 , 6.169, 6.211, 6.069,
       5.682, 5.786, 6.03 , 5.399, 5.602, 5.963, 6.115, 6.511, 5.998,
       5.888, 7.249, 6.383, 6.816, 6.145, 5.927, 5.741, 5.966, 6.456,
       6.762, 7.104, 6.29 , 5.787, 5.878, 5.594, 5.885, 6.417, 5.961,
       6.065, 6.245, 6.273, 6.286, 6.279, 6.14 , 6.232, 5.874, 6.727,
       6.619, 6.302, 6.167, 6.389, 6.63 , 6.015, 6.121, 7.007, 7.079,
       6.417, 6.405, 6.442, 6.211, 6.249, 6.625, 6.163, 8.069, 7.82 ,
       7.416, 6.727, 6.781, 6.405, 6.137, 6.167, 5.851, 5.836, 6.127,
       6.474, 6.229, 6.195, 6.715, 5.913, 6.092, 6.254, 5.928, 6.176,
       6.021, 5.872, 5.731, 5.87 , 6.004, 5.961, 5.856, 5.879, 5.986,
       5.613, 5.693, 6.431, 5.637, 6.458, 6.326, 6.372, 5.822, 5.757,
       6.335, 5.942, 6.454, 5.857, 6.151, 6.174, 5.019, 5.403, 5.468,
       4.903, 6.13 , 5.628, 4.926, 5.186, 5.597, 6.122, 5.404, 5.012,
       5.709, 6.129, 6.152, 5.272, 6.943, 6.066, 6.51 , 6.25 , 7.489,
       7.802, 8.375, 5.854, 6.101, 7.929, 5.877, 6.319, 6.402, 5.875,
       5.88 , 5.572, 6.416, 5.859, 6.546, 6.02 , 6.315, 6.86 , 6.98 ,
       7.765, 6.144, 7.155, 6.563, 5.604, 6.153, 7.831, 6.782, 6.556,
       7.185, 6.951, 6.739, 7.178, 6.8  , 6.604, 7.875, 7.287, 7.107,
       7.274, 6.975, 7.135, 6.162, 7.61 , 7.853, 8.034, 5.891, 6.326,
       5.783, 6.064, 5.344, 5.96 , 5.404, 5.807, 6.375, 5.412, 6.182,
       5.888, 6.642, 5.951, 6.373, 6.951, 6.164, 6.879, 6.618, 8.266,
       8.725, 8.04 , 7.163, 7.686, 6.552, 5.981, 7.412, 8.337, 8.247,
```

```
            6.726, 6.086, 6.631, 7.358, 6.481, 6.606, 6.897, 6.095, 6.358,
            6.393, 5.593, 5.605, 6.108, 6.226, 6.433, 6.718, 6.487, 6.438,
            6.957, 8.259, 6.108, 5.876, 7.454, 8.704, 7.333, 6.842, 7.203,
            7.52 , 8.398, 7.327, 7.206, 5.56 , 7.014, 8.297, 7.47 , 5.92 ,
            5.856, 6.24 , 6.538, 7.691, 6.758, 6.854, 7.267, 6.826, 6.482,
            6.812, 7.82 , 6.968, 7.645, 7.923, 7.088, 6.453, 6.23 , 6.209,
            6.315, 6.565, 6.861, 7.148, 6.63 , 6.127, 6.009, 6.678, 6.549,
            5.79 , 6.345, 7.041, 6.871, 6.59 , 6.495, 6.982, 7.236, 6.616,
            7.42 , 6.849, 6.635, 5.972, 4.973, 6.122, 6.023, 6.266, 6.567,
            5.705, 5.914, 5.782, 6.382, 6.113, 6.426, 6.376, 6.041, 5.708,
            6.415, 6.431, 6.312, 6.083, 5.868, 6.333, 6.144, 5.706, 6.031,
            6.316, 6.31 , 6.037, 5.869, 5.895, 6.059, 5.985, 5.968, 7.241,
            6.54 , 6.696, 6.874, 6.014, 5.898, 6.516, 6.635, 6.939, 6.49 ,
            6.579, 5.884, 6.728, 5.663, 5.936, 6.212, 6.395, 6.127, 6.112,
            6.398, 6.251, 5.362, 5.803, 8.78 , 3.561, 4.963, 3.863, 4.97 ,
            6.683, 7.016, 6.216, 5.875, 4.906, 4.138, 7.313, 6.649, 6.794,
            6.38 , 6.223, 6.968, 6.545, 5.536, 5.52 , 4.368, 5.277, 4.652,
            5.   , 4.88 , 5.39 , 5.713, 6.051, 5.036, 6.193, 5.887, 6.471,
            6.405, 5.747, 5.453, 5.852, 5.987, 6.343, 6.404, 5.349, 5.531,
            5.683, 4.138, 5.608, 5.617, 6.852, 5.757, 6.657, 4.628, 5.155,
            4.519, 6.434, 6.782, 5.304, 5.957, 6.824, 6.411, 6.006, 5.648,
            6.103, 5.565, 5.896, 5.837, 6.202, 6.193, 6.38 , 6.348, 6.833,
            6.425, 6.436, 6.208, 6.629, 6.461, 6.152, 5.935, 5.627, 5.818,
            6.406, 6.219, 6.485, 5.854, 6.459, 6.341, 6.251, 6.185, 6.417,
            6.749, 6.655, 6.297, 7.393, 6.728, 6.525, 5.976, 5.936, 6.301,
            6.081, 6.701, 6.376, 6.317, 6.513, 6.209, 5.759, 5.952, 6.003,
            5.926, 5.713, 6.167, 6.229, 6.437, 6.98 , 5.427, 6.162, 6.484,
            5.304, 6.185, 6.229, 6.242, 6.75 , 7.061, 5.762, 5.871, 6.312,
            6.114, 5.905, 5.454, 5.414, 5.093, 5.983, 5.983, 5.707, 5.926,
            5.67 , 5.39 , 5.794, 6.019, 5.569, 6.027, 6.593, 6.12 , 6.976,
            6.794, 6.03 ])
```

```
import random
a = tf.Variable(random.random())
b = tf.Variable(random.random())
```

Zapisano pomyślnie.

```
                               dataset, subset_size):
                               t))
    x_train = x_dataset[arr[0:subset_size]]
    y_train = y_dataset[arr[0:subset_size]]
    return x_train,y_train
```

```
def loss_fn(real_y, pred_y):
    return tf.reduce_mean((real_y - pred_y)**2)
```

```
Loss = []
epochs = 1000
learning_rate = 0.01
batch_size = 50
a = tf.Variable(random.random())
b = tf.Variable(random.random())
for _ in range(epochs):
  real_rm_batch,real_medv_batch = subset_dataset(real_rm,real_medv,batch_size)
  with tf.GradientTape() as tape:
    pred_medv = a * real_rm_batch + b
    loss = loss_fn(real_medv_batch, pred_medv)
    Loss.append(loss.numpy())
```

```
    dloss_da, dloss_db = tape.gradient(loss,(a, b))

    a.assign_sub(learning_rate*dloss_da)  #a = a - alpha*dloss_da
    b.assign_sub(learning_rate*dloss_db)  #b = b - alpha*dloss_db
```

```
  Loss
```

Zapisano pomyślnie.

```
 48.695568]
```

```
np.max(Loss),np.min(Loss)
```

```
(226.16956, 17.60775)
```

```
print(a.numpy())
print(b.numpy())
```

```
4.855049
-6.8641143
```

```
import tensorflow as tf
import keras
from keras.layers import Dense
from keras.models import Sequential
```

```
model=Sequential()
```

```
model.add(Dense(units = 3, use_bias=True, input_dim=1, activation = "linear"))
model.add(Dense(units = 1, use_bias=True,  activation = "linear"))
```

```
opt = tf.keras.optimizers.Adam()
```

```
model.compile(loss='MSE',optimizer=opt)
```

```
model.summary()
```

Zapisano pomyślnie.

```
Model: "sequential_2"
_________________________________________________________________
                             Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 3)                 6

 dense_5 (Dense)             (None, 1)                 4

=================================================================
Total params: 10
Trainable params: 10
Non-trainable params: 0
_________________________________________________________________
```

```
epochs = 200
h = model.fit(real_rm,real_medv, verbose=1, epochs=epochs, batch_size=100, validation_split=0.3)
```

```
Epoch 1978/2000
4/4 [==============================] - 0s 14ms/step - loss: 31.8383 - val_loss: 117.2317
Epoch 1979/2000
4/4 [==============================] - 0s 14ms/step - loss: 31.8297 - val_loss: 117.3754
Epoch 1980/2000
4/4 [==============================] - 0s 13ms/step - loss: 31.8108 - val_loss: 117.2357
Epoch 1981/2000
4/4 [==============================] - 0s 13ms/step - loss: 31.7972 - val_loss: 117.0044
Epoch 1982/2000
4/4 [==============================] - 0s 14ms/step - loss: 31.7866 - val_loss: 116.8757
Epoch 1983/2000
4/4 [==============================] - 0s 26ms/step - loss: 31.7723 - val_loss: 116.7933
Epoch 1984/2000
4/4 [==============================] - 0s 16ms/step - loss: 31.7638 - val_loss: 116.7077
Epoch 1985/2000
4/4 [==============================] - 0s 13ms/step - loss: 31.7491 - val_loss: 116.5757
Epoch 1986/2000
4/4 [==============================] - 0s 20ms/step - loss: 31.7377 - val_loss: 116.3435
Epoch 1987/2000
4/4 [==============================] - 0s 18ms/step - loss: 31.7256 - val_loss: 116.3480
Epoch 1988/2000
4/4 [==============================] - 0s 13ms/step - loss: 31.7122 - val_loss: 116.4285
Epoch 1989/2000
4/4 [==============================] - 0s 14ms/step - loss: 31.6996 - val_loss: 116.4728
Epoch 1990/2000
4/4 [==============================] - 0s 13ms/step - loss: 31.6871 - val_loss: 116.4474
Epoch 1991/2000
4/4 [==============================] - 0s 12ms/step - loss: 31.6710 - val_loss: 116.3184
Epoch 1992/2000
4/4 [==============================] - 0s 20ms/step - loss: 31.6593 - val_loss: 116.2374
Epoch 1993/2000
4/4 [==============================] - 0s 14ms/step - loss: 31.6477 - val_loss: 116.2057
Epoch 1994/2000
4/4 [==============================] - 0s 16ms/step - loss: 31.6423 - val_loss: 116.3429
Epoch 1995/2000
4/4 [==============================] - 0s 21ms/step - loss: 31.6209 - val_loss: 116.3812
Epoch 1996/2000
4/4 [==============================] - 0s 15ms/step - loss: 31.6100 - val_loss: 116.4358
Epoch 1997/2000
=======] - 0s 19ms/step - loss: 31.6124 - val_loss: 116.1545
4/4 [==============================] - 0s 14ms/step - loss: 31.5878 - val_loss: 116.3866
Epoch 1999/2000
4/4 [==============================] - 0s 22ms/step - loss: 31.5705 - val_loss: 116.5085
Epoch 2000/2000
4/4 [==============================] - 0s 23ms/step - loss: 31.5529 - val_loss: 116.4900
```



```
#Loss = h.history['loss']
#Loss


plt.scatter(np.arange(epochs),h.history['loss'])
plt.scatter(np.arange(epochs),h.history['val_loss'],c='r')
plt.show()
```

Zadanie 5

```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
```

```
import keras
from keras.models import Sequential
from keras.layers import Dense
```

Dwa gangi

Zbiór danych:

```
[0]*10+[1]*10
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
```

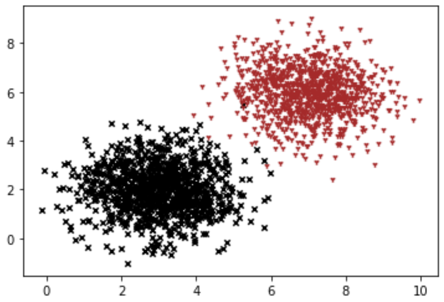
```
x_label1 = np.random.normal(3, 1, 1000)
y_label1 = np.random.normal(2, 1, 1000)
x_label2 = np.random.normal(7, 1, 1000)
y_label2 = np.random.normal(6, 1, 1000)

xs = np.append(x_label1, x_label2)
ys = np.append(y_label1, y_label2)
labels = np.asarray([0.]*len(x_label1)+[1.]*len(x_label2))
```

Zapisano pomyślnie.

```
array([0., 0., 0., ..., 1., 1., 1.])
```

```
plt.scatter(x_label1, y_label1, c='black', marker='x', s=20)
plt.scatter(x_label2, y_label2, c='brown', marker='1', s=20)
plt.show()
```




```
x_label1
```

```
       2.87281707,  1.58367747,  3.88420014,  2.55478095,  2.15807149,
       3.68333439,  1.72726028,  3.5687913 ,  4.11233697,  3.4268136 ,
       4.34640378,  1.11017676,  4.72302785,  2.38920203,  1.72423622,
       2.6277729 ,  1.90169701,  3.88267508,  3.19224728,  2.80271136,
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       1.02610678,  3.25838022,  3.51232235,  2.57539136,  1.9215747 ])
```



```
def loss_fn_grad(y, y_model):
 return tf.reduce_mean(-y*tf.math.log(y_model)-(1-y)*tf.math.log(1-y_model))
```

```
def subset_dataset_2(x_dataset, y_dataset,label,subset_size):
    arr = np.arange(len(x_dataset))
```

```
    np.random.shuffle(arr)
    x_train = x_dataset[arr[0:subset_size]]
    y_train = y_dataset[arr[0:subset_size]]
    label_train = label[arr[0:subset_size]]
    return x_train,y_train,label_train
```

```
labels.shape
```

```
(2000,)
```

```
Loss = []
epochs = 1000
learning_rate = 0.01
batch_size = 50
a = tf.Variable(random.random())
b = tf.Variable(random.random())
c = tf.Variable(random.random())
for _ in range(epochs):
  xs_batch,ys_batch,labels_batch = subset_dataset_2(xs,ys,labels,batch_size)
  with tf.GradientTape() as tape:
    pred_l = tf.sigmoid(a * xs_batch + b * ys_batch + c)
    #print(label_batch.shape)
    loss = loss_fn_grad(labels_batch, pred_l)
    Loss.append(loss.numpy())

  dloss_da, dloss_db, dloss_dc = tape.gradient(loss,(a, b,c))

  a.assign_sub(learning_rate*dloss_da)  #a = a - alpha*dloss_da
  b.assign_sub(learning_rate*dloss_db)  #b = b - alpha*dloss_db
  c.assign_sub(learning_rate*dloss_dc)
```

```
np.max(Loss),np.min(Loss)
```

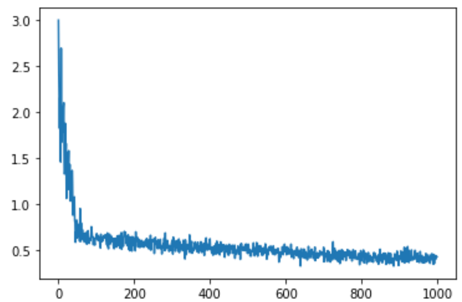
```
(2.9938192, 0.32082856)
```

Zapisano pomyślnie.

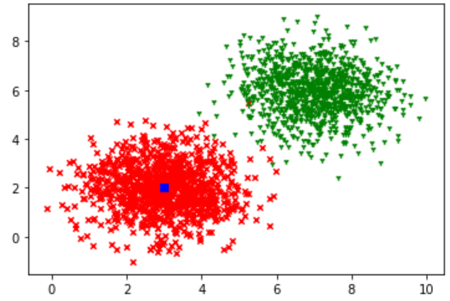
```
print(a.numpy())
print(b.numpy())
```

```
-0.058886457
0.52488345
```

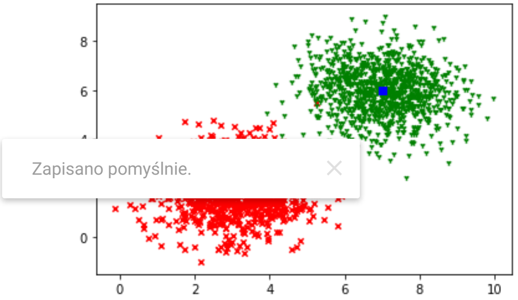
```
plt.plot(Loss)
plt.show()
```



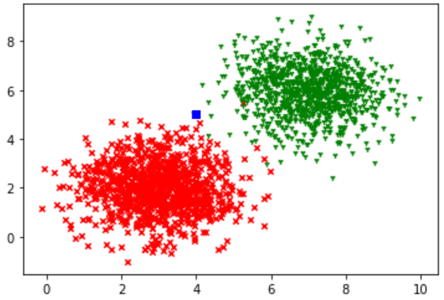
```
x=3.0
y=2.0
plt.scatter(x_label1, y_label1, c='r', marker='x', s=20)
plt.scatter(x_label2, y_label2, c='g', marker='1', s=20)
plt.scatter(x,y,c='b', marker='s')
plt.show()
```




```
x=7.0
y=6.0
plt.scatter(x_label1, y_label1, c='r', marker='x', s=20)
plt.scatter(x_label2, y_label2, c='g', marker='1', s=20)
plt.scatter(x,y,c='b', marker='s')
plt.show()
```




```
x=4.0
y=5.0
plt.scatter(x_label1, y_label1, c='r', marker='x', s=20)
plt.scatter(x_label2, y_label2, c='g', marker='1', s=20)
plt.scatter(x,y,c='b', marker='s')
plt.show()
```



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Zapisano pomyślnie.