4.Ocean Proximity. Logistic Regression Mini-Batch

1 Ocean Proximity as a Logistic Regression Problem with Mini_batch

```
In [1]: import numpy as np
        import pandas as pd
        import tensorflow as tf
        import matplotlib.pyplot as plt
        from tqdm import tqdm
```

```
In [2]: %run 1.ReadingData.py
```

```
Name of the label file: OceanProximityOneHotEncodedClasses.csv
x_train: (16342, 9)
t_train: (16342, 4)
x_dev: (2043, 9)
t_dev: (2043, 4)
x_test: (2043, 9)
t_test: (2043, 4)
```

1.1 Initialization

```
In [3]: INPUTS = x_train.shape[1]
        OUTPUTS = t_train.shape[1]
        NUM_TRAINING_EXAMPLES = int(round(x_train.shape[0]/1))
        NUM_DEV_EXAMPLES = int (round (x_dev.shape[0]/1))
```

Some data is displayed to test correctness:

```
In [4]: INPUTS
```

```
Out[4]: 9
```

```
In [5]: OUTPUTS
```

```
Out[5]: 4
```

```
In [6]: NUM_TRAINING_EXAMPLES
```

```
Out[6]: 16342
```

```
In [7]: NUM_DEV_EXAMPLES

Out[7]: 2043

In [8]: x_train[:5]

Out[8]: array([[ 0.42031873, -0.66206164, -0.64705882, -0.69739051, -0.58752328,
                -0.82056672, -0.61914159, -0.69639039, -0.60742018],
               [ 0.43027888, -0.98087141, -0.01960784, -0.91784933, -0.91371819,
                -0.84629614, -0.91810557, -0.58127474, -0.78350192],
               [ 0.26294821, -0.72582359, -0.1372549 , -0.94485986, -0.91713222,
                -0.95392248, -0.91810557, -0.72952097, -0.15628802],
               [-0.44621514, -0.05632306, -0.49019608, -0.73401495, -0.74674115,
                -0.85251829, -0.73754317, -0.3834154 ,  0.09195838],
               [-0.39243028,  0.16471838, -0.41176471, -0.86189532, -0.80757294,
                -0.81277502, -0.78885052, -0.7176039 , -0.62350258]])

In [9]: t_train[:5]

Out[9]: array([[0., 1., 0., 0.],
               [0., 0., 0., 1.],
               [1., 0., 0., 0.],
               [0., 1., 0., 0.],
               [0., 1., 0., 0.]])

In [10]: x_dev[:5]

Out[10]: array([[-0.07171315, -0.10733262, -0.1372549 , -0.89343303, -0.88081937,
                 -0.94910171, -0.86712712, -0.58443332, -0.56041006],
                [-0.4123506 , -0.18384697,  0.49019608, -0.88371738, -0.83612663,
                 -0.91894392, -0.86548265, -0.60979849, -0.27587515],
                [-0.61952191,  0.11583422,  1.        , -0.9123048 , -0.88112973,
                 -0.96575016, -0.88324289, -0.56120605,  0.99999588],
                [ 0.45418327, -0.9957492 , -0.17647059, -0.88961799, -0.82557418,
                 -0.88531069, -0.82798882, -0.79089944, -0.48742067],
                [ 0.15338645, -0.64930925,  0.33333333, -0.96032352, -0.95561763,
                 -0.97634463, -0.95428383, -0.31657494, -0.23133925]])

In [11]: t_dev[:5]

Out[11]: array([[0., 1., 0., 0.],
                [1., 0., 0., 0.],
                [0., 0., 1., 0.],
                [0., 0., 0., 1.],
                [1., 0., 0., 0.]])
```

1.2 Hyperparameters

A new hiperparameter has to be adjuted: the size of the mini-batch

```
In [12]: n_epochs = 40000
         learning_rate = 0.1
         batch_size = 200
```

```
In [13]: n_learning_iterations = batch_size*n_epochs
         n_learning_iterations
```

```
Out[13]: 8000000
```

1.3 Build the model: logistic classifier

```
In [14]: X = tf.placeholder (dtype=tf.float32, shape=(None,INPUTS),name="X")
         t = tf.placeholder (dtype=tf.float32, shape=(None,OUTPUTS), name="t")
```

```
In [15]: W = tf.Variable (tf.random_uniform ([INPUTS,OUTPUTS],-1,1), name="W")
         b = tf.Variable (tf.zeros([OUTPUTS]), name = "bias")
```

Compute the *logits* (net), then the output with the $Softmax$ activation function:

```
In [16]: net = tf.matmul(X,W)+b
         y = tf.nn.softmax (logits=net, name="y")
```

The $log - loss$, $cross - entropy$ (the sun of log-loss is a loss) and and *cost* (the mean of cross-entropy) functions:

```
In [17]: cross_entropy = tf.nn.softmax_cross_entropy_with_logits (labels=t, logits=net)
         mean_log_loss = tf.reduce_mean (cross_entropy, name="cost")
```

```
WARNING:tensorflow:From <ipython-input-17-2f15aa3061b4>:1: softmax_cross_entropy_with_logits (fr
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See @{tf.nn.softmax_cross_entropy_with_logits_v2}.
```

The training algorithm: gradient descent method with a softmax function at the outputs:

```
In [18]: train_step = tf.train.GradientDescentOptimizer (learning_rate).minimize(mean_log_loss)
```

Model evaluation: accuracy. The percentage of correctly classified instances.

```
In [19]: correct_predictions = tf.equal(tf.argmax(y,1),tf.argmax(t,1))
         accuracy = tf.reduce_mean(tf.cast(correct_predictions,tf.float32))
```

1.4 Execute the model M-BGD

```
In [20]: init = tf.global_variables_initializer()
         accuracy_train_history = np.empty([n_epochs])
         with tf.Session() as sess:
             sess.run(init)
             for epoch in tqdm(range(n_epochs)):
                 offset = (epoch * batch_size) % (NUM_TRAINING_EXAMPLES - batch_size)
                 sess.run (train_step, feed_dict={X: x_train[offset:(offset+batch_size)],
                                                  t: t_train[offset:(offset+batch_size)]})
                 accuracy_train_history[epoch] = accuracy.eval(feed_dict={X: x_train[offset:(off
                                                                          t: t_train[offset:(off
             accuracy_train = accuracy.eval(feed_dict={X: x_train[:NUM_TRAINING_EXAMPLES],
                                                       t: t_train[:NUM_TRAINING_EXAMPLES]})
             accuracy_dev = accuracy.eval(feed_dict={X: x_dev[:NUM_DEV_EXAMPLES],
                                                     t: t_dev[:NUM_DEV_EXAMPLES]})
             predictions = y.eval(feed_dict={X: x_dev[:NUM_DEV_EXAMPLES]})
             final_correct_preditions = correct_predictions.eval (feed_dict={X: x_dev[:NUM_DEV_E
                                                                            t: t_dev[:NUM_DEV_E
             final_train_mean_log_loss = mean_log_loss.eval (feed_dict={X: x_train[:NUM_TRAINING
                                                       t: t_train[:NUM_TRAINING_EXAMPLES]})
             final_dev_mean_log_loss = mean_log_loss.eval (feed_dict={X: x_dev[:NUM_DEV_EXAMPLES
                                                       t: t_dev[:NUM_DEV_EXAMPLES]})
```

```
100%|| 40000/40000 [00:39<00:00, 1002.93it/s]
```

```
In [21]: "Final accuracy in training: " + str(accuracy_train)
```

```
Out[21]: 'Final accuracy in training: 0.7961082'
```

```
In [22]: "Maximum accuracy in training: " + str(np.max(accuracy_train_history))
```

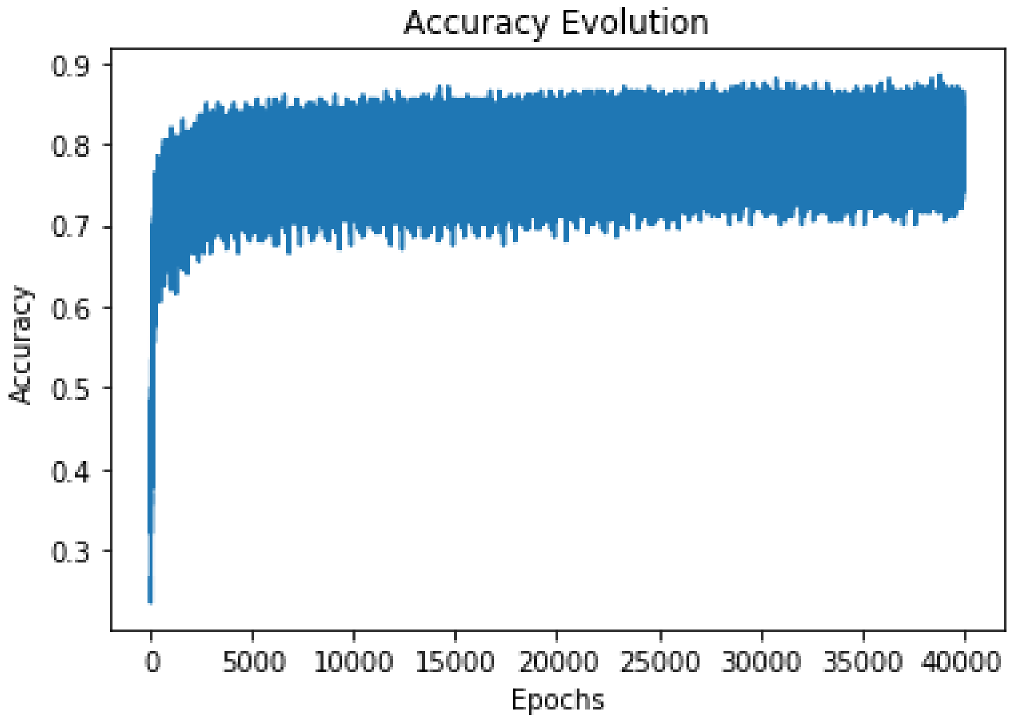
```
Out[22]: 'Maximum accuracy in training: 0.8849999904632568'
```

```
In [23]: "Accuracy for the development set: " + str(accuracy_dev)
```

```
Out[23]: 'Accuracy for the development set: 0.7983358'
```

```
In [24]: plt.title ("Accuracy Evolution")
         plt.xlabel ("Epochs")
         plt.ylabel ("Accuracy")
         plt.plot (range(n_epochs),accuracy_train_history)
```

```
Out[24]: [<matplotlib.lines.Line2D at 0xb36fdeeb8>]
```



Note that accuracy *zig-zags* due to mini-batch *zig-zagging* errors.

```
In [25]: predictions

Out[25]: array([[1.55194625e-02, 9.82724965e-01, 1.10980903e-03, 6.45698048e-04],
                [4.82209116e-01, 5.23199188e-03, 1.62414953e-01, 3.50143880e-01],
                [1.39123917e-01, 6.81051344e-04, 7.77952373e-01, 8.22426453e-02],
                ...,
                [5.33385158e-01, 1.00349545e-01, 2.34790221e-01, 1.31475091e-01],
                [3.24853271e-01, 3.20512027e-01, 3.37372601e-01, 1.72621198e-02],
                [7.17060566e-01, 1.59573972e-01, 3.01069720e-03, 1.20354801e-01]],
               dtype=float32)

In [26]: rounded_predictions=np.round(predictions)
         indices = np.argmax(predictions,1)
         for row, index in zip(rounded_predictions, indices): row[index]=1
         rounded_predictions[:10]

Out[26]: array([[0., 1., 0., 0.],
                [1., 0., 0., 0.],
                [0., 0., 1., 0.],
                [1., 0., 0., 0.],
                [1., 0., 0., 0.],
                [1., 0., 0., 0.],
                [1., 0., 0., 0.],
```

```
       [1., 0., 0., 0.],
       [0., 1., 0., 0.],
       [0., 1., 0., 0.]], dtype=float32)
```

```
In [27]: t_dev[:10]
```

```
Out[27]: array([[0., 1., 0., 0.],
       [1., 0., 0., 0.],
       [0., 0., 1., 0.],
       [0., 0., 0., 1.],
       [1., 0., 0., 0.],
       [1., 0., 0., 0.],
       [1., 0., 0., 0.],
       [1., 0., 0., 0.],
       [0., 1., 0., 0.],
       [0., 1., 0., 0.]])
```

```
In [28]: final_correct_preditions[:10]
```

```
Out[28]: array([ True,  True,  True, False,  True,  True,  True,  True,  True,
        True])
```

```
In [29]: final_train_mean_log_loss
```

```
Out[29]: 0.5683237
```

```
In [30]: final_dev_mean_log_loss
```

```
Out[30]: 0.5543795
```

MBGD takes takes 20 secs. to achieve similar results as those without mini-batch, which takes 1:40 for the same task. 500 epochs correspond to 20,500 iterations