3.Ocean Proximity. Logistic Regression

1 Ocean Proximity as a Logistic Regression Problem (Batch update)

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

```
In [12]: n_epochs = 20000
         learning_rate = 0.1
```

1.3 Build the model: logistic classifier

```
In [13]: X = tf.placeholder (dtype=tf.float32, shape=(None,INPUTS),name="X")
         t = tf.placeholder (dtype=tf.float32, shape=(None,OUTPUTS), name="t")
```

```
In [14]: 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 [15]: 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 [16]: cross_entropy = tf.nn.softmax_cross_entropy_with_logits_v2 (labels=t, logits=net)
         mean_log_loss = tf.reduce_mean (cross_entropy, name="cost")
```

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

```
In [17]: train_step = tf.train.GradientDescentOptimizer (learning_rate).minimize(mean_log_loss)
```

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

```
In [18]: 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 (batch pproach)

```
In [19]: init = tf.global_variables_initializer()
         accuracy_train_history = []
         with tf.Session() as sess:
             sess.run(init)
             for epoch in tqdm(range(n_epochs)):
                 sess.run (train_step, feed_dict={X: x_train[:NUM_TRAINING_EXAMPLES],
                                                  t: t_train[:NUM_TRAINING_EXAMPLES]})
                 accuracy_train_history.append (accuracy.eval(feed_dict={X: x_train[:NUM_TRAININ
                                                                         t: t_train[:NUM_TRAININ
             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%|| 20000/20000 [03:52<00:00, 86.04it/s]
```

```
In [20]: "Final accuracy in training: " + str(accuracy_train)
```

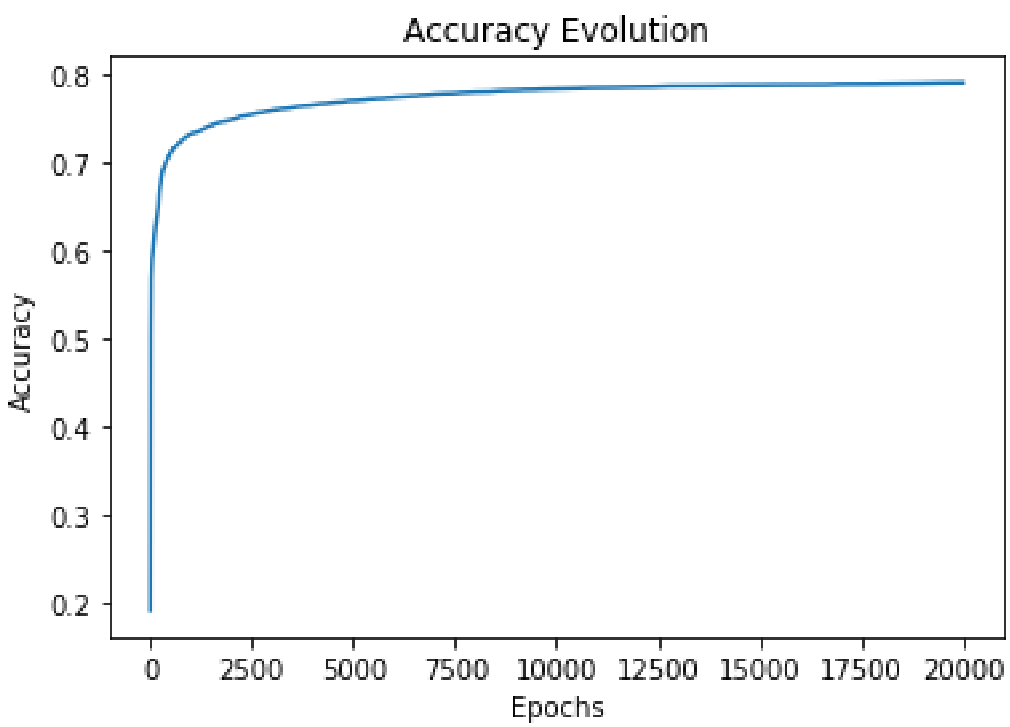
```
Out[20]: 'Final accuracy in training: 0.7898666'
```

```
In [21]: "Accuracy for the development set: " + str(accuracy_dev)
```

```
Out[21]: 'Accuracy for the development set: 0.7914831'
```

```
In [22]: plt.title ("Accuracy Evolution")
         plt.xlabel ("Epochs")
         plt.ylabel ("Accuracy")
         plt.plot (range(n_epochs),accuracy_train_history)
```

```
Out[22]: [<matplotlib.lines.Line2D at 0xb37dcc0b8>]
```




```
In [23]: predictions
```

```
Out[23]: array([[3.2244977e-02, 9.6210325e-01, 2.0898040e-03, 3.5620250e-03],
                [5.1652497e-01, 1.5065208e-02, 1.8596150e-01, 2.8244838e-01],
                [1.4083046e-01, 4.9856969e-04, 7.6692057e-01, 9.1750368e-02],
                ...,
                [4.6194196e-01, 1.8944679e-01, 2.1744657e-01, 1.3116471e-01],
```

```
             [1.8539132e-01, 5.9627473e-01, 2.0724732e-01, 1.1086642e-02],
             [6.7923743e-01, 1.8258539e-01, 2.8578560e-03, 1.3531925e-01]],
            dtype=float32)
```

```
In [24]: 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[24]: 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 [25]: t_dev[:10]
```

```
Out[25]: 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 [26]: final_correct_preditions[:10]
```

```
Out[26]: array([ True,  True,  True, False,  True,  True,  True,  True,  True,
                 True])
```

```
In [27]: final_train_mean_log_loss
```

```
Out[27]: 0.6051138
```

```
In [28]: final_dev_mean_log_loss
```

```
Out[28]: 0.59014726
```

The accuracy is up to 79% in the training and development (unseen data) datasets. Dev samples has been employed to adjust the learning rate to $\alpha = 0.1$ and the number of epochs to 20,000. Note that 3 minutes and 52 secs. have been taken to train a simple model without hidden layers. There are 9 inputs x 4 outputs = 36 weights (the kernel size) + 4 bias = 40 parameters to adjust for each sample in each epoch: 16,342 training samples * 20,000 epochs = 326,840,000 weight variation calculations.

No GPU has been used in this study case, just a 2,7 GHz intel Core i7.