2.Ocean Proximity. Linear Regression

1 Ocean Proximity as a Linear Regression Problem

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

After importing the libraries, the datasets are loaded: the *magic command* %run executes a .py file

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

```
Name of the label file: OceanProximityDiscretizedClasses.csv
x_train: (16342, 9)
t_train: (16342, 1)
x_dev: (2043, 9)
t_dev: (2043, 1)
x_test: (2043, 9)
t_test: (2043, 1)
```

```
In [3]: t_train = t_train.reshape((1,-1))[0]
        t_dev = t_dev.reshape((1,-1))[0]
        t_test = t_test.reshape((1,-1))[0]
```

1.1 Initialization

```
In [4]: INPUTS = x_train.shape[1]
        OUTPUTS = 1
        NUM_TRAINING_EXAMPLES = round(x_train.shape[0]/10) # training and dev examples are
        NUM_DEV_EXAMPLES = round (x_dev.shape[0]/10) # reduced to avoid excessive time spent
```

Some data is displayed:

```
In [5]: x_train[:5]
```

```
Out[5]: 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 [6]: t_train[:5]
```

```
Out[6]: array([1, 3, 0, 1, 1])
```

```
In [7]: x_dev[:5]
```

```
Out[7]: 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 [8]: t_dev[:5]
```

```
Out[8]: array([1, 0, 2, 3, 0])
```

1.2 Hyperparameters

```
In [9]: n_epochs = 2000
        learning_rate = 0.1
```

1.3 Definition of the neural network tensor graph

A placeholder is a special variable whose value will be assigned later. X stands for the input tensor, the inputs to the neural network, y is the output, and t is the target output of the supervised learning.

```
In [10]: X = tf.placeholder (dtype=tf.float32, shape=[None,INPUTS], name="X")
         t = tf.placeholder (dtype=tf.float32, shape=[None], name="t")
```

A variable can change its value during the execution phase. W is a matrix of weights (kernel). In this case, a column vector since there is just one output. b is the bias vector, an scalar in this study case.

```
In [11]: W = tf.Variable (tf.random_uniform([INPUTS,1], -1.0,1.0), name="W")
         b = tf.Variable (.0, name="bias")
```

Now, the output y is computed:

```
In [12]: y = tf.matmul(X,W)+b
```

The loss function is the SSE, defined by $E_p(W) = (y_p - t_p)^2$. The cost function is defined by $MSE = \frac{1}{P}\sum_{i=1}^{P}(y_i - t_i)^2$

```
In [13]: loss = tf.square(y-t)
         mse = tf.reduce_mean(loss,name="cost")
```

The learning method is the gradient descent to minimize the cost MSE, with the previously defined (hyperparameter) learning rate α:

```
In [14]: optimizer = tf.train.GradientDescentOptimizer(learning_rate) #LMS in this case
         training_op = optimizer.minimize(mse)
```

Finally, all variables are initialized prior to executing the graph:

```
In [15]: init = tf.global_variables_initializer()
```

1.4 Running the tensorflow graph

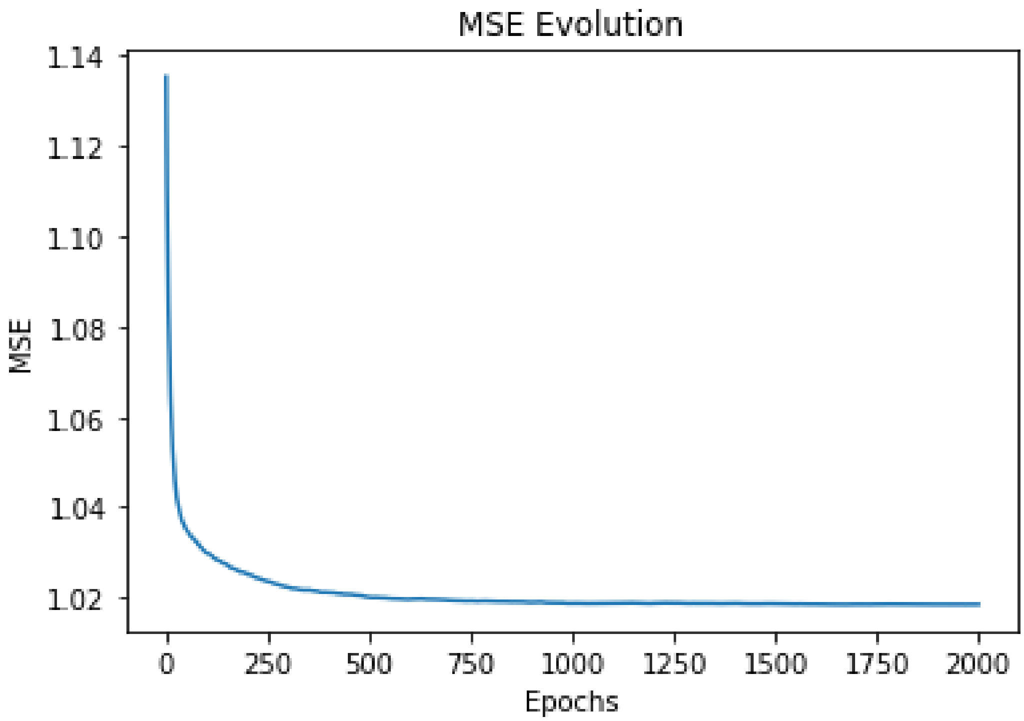
```
In [16]: mse_array = []

         # First, a session is executed
         with tf.Session() as sess:
             sess.run(init)
             for epoch in tqdm(range(n_epochs)): #for each epoch a learning iteration is compute
                 sess.run(training_op, feed_dict={X: x_train[:NUM_TRAINING_EXAMPLES],
                                                  t: t_train[:NUM_TRAINING_EXAMPLES]})
                 mse_array.append (mse.eval(feed_dict={X: x_train[:NUM_TRAINING_EXAMPLES],
                                                       t: t_train[:NUM_TRAINING_EXAMPLES]}))
             final_training_mse = mse.eval(feed_dict={X: x_train[:NUM_TRAINING_EXAMPLES],
                                                      t: t_train[:NUM_TRAINING_EXAMPLES]})
             dev_mse = mse.eval(feed_dict={X: x_dev[:NUM_DEV_EXAMPLES],
                                           t: t_dev[:NUM_DEV_EXAMPLES]})
             computed_outputs = y.eval(feed_dict={X: x_dev[:NUM_DEV_EXAMPLES]})

100%|| 2000/2000 [02:04<00:00, 16.06it/s]
```

```
In [17]: plt.title("MSE Evolution")
         plt.xlabel("Epochs")
         plt.ylabel("MSE");
         plt.plot(range(n_epochs),mse_array)

Out[17]: [<matplotlib.lines.Line2D at 0xb292fdbe0>]
```



The learning process falls into a local optimum in a MSE of about 1. The MSE evolution turns into a flat line from 1,500 epochs. A non-linear problem is tried to be solved with linear regression.

```
In [18]: "Final training MSE: " + str(final_training_mse)

Out[18]: 'Final training MSE: 1.0184555'

In [19]: "Dev MSE: " + str(dev_mse)

Out[19]: 'Dev MSE: 0.97868484'
```

The final MSE for both the training and development datasets are too high. Good results were not expected even though a small subset of the training samples are involved since a linear regression algorithm is being used to solve a non-linear problem. Next, the comparison between computed and target outputs is shown for the 10 first develoment examples.

```
In [20]: comparison = pd.DataFrame([[computed,dev] for computed, dev
                    in zip(computed_outputs.reshape([computed_outputs.shape[0]]),
                           t_dev[:NUM_DEV_EXAMPLES])], columns=["y","t"])

In [21]: comparison[:10]

Out[21]:           y  t
         0  0.887487  1
         1  0.883364  0
         2  0.880687  2
```

```
3  0.885280  3
4  0.891493  0
5  0.885119  0
6  0.882976  0
7  0.885779  0
8  0.882598  1
9  0.890736  1
```

Note that the computed values are all around 0.9, the mean value of the discretized target outputs, considering that the class 0 contains most of the examples, to achieve the lowest error. More accurate results can not be computed since this is a linear neural network