# Homework #1

March 9, 2019

0.1 # Homework 1 - Nasir Khalid - 65082

#### 0.2 ### Theoretical Section

Q1: For a 3 dimensional dataset, What is the minimum number of points that are required to fit a hyperplane? For a 3 dimensional dataset we would have:

$$y = w_0 + [w_1 w_2 w_3] * [x_1 x_2 x_3]^T$$

Therefore the hyperplane is a 2D plane which requires a minimum of 3 points.

**Q2:** Write a summary on "Deep Learning" The paper begins by explaining how recent advances in deep learning have allowed machines to teach them selves to identify patterns in high dimensional data. It then discusses supervised learning and explains how a basic neural net works using an error function and then trying to minimize output by using the stochastic gradient descent. The paper explains how this technique only works on shallow data and feature extractors are needed to make it applicable to more complex data as well as invariant to . Before discussing the use of these feature extractors the paper first explains the principle of backpropogation and also discusses briefly that the issue of wrong minima in gradient descent is not a major one. After this it discusses the convolutional neural networks and how they are used to process data that is in the form of multiple arrays. They use pooling and convolution along with certain filter banks, the success of these feedforward networks have made them the standard for image related learning. A network that uses CNN + RNN is discussed which is able to identify objects and features of images using the CNN and after this the RNN creates a caption for the image. The paper then discusses how hidden layers of the network learn to represent the data as a sequential decomposition in to simpler forms, due to these distributed representations the networks are great at prediction and one such example discussed is how computers can predict what a person will type next. The second last section is about the Recurrent neural networks and how they are great for predictive behaviour and their main objective is to learn about long-term dependencies. The final section discusses the future of deep learning and how the authours believe that the way forward for innovation is in unsupervised learning.

**Q3:** What is the difference between deep and shallow learning. Explain with concrete example(s) when shallow learning is suitable as compared to deep learning and vise versa. Shallow learning cases are those where data can be easily segregated in to different classes and the entire network is made up of a single hidden layer containing few neurons. In these cases the dataset provided is already labelled and the computer simply learns how to fit the data with it's labels. Often this is just a binary classification problem.

In deep learning however we provide the network with some data and expect it to identify the patterns and classify the output on its own. This sort of learning often consists of a huge number of hidden layers each consisting of a large number of neurons.

Examples of shallow learning often include linear regression or binary classification problems where the data can be easily split without the need of higher level transformations. One example is guessing the price of a house based on it's square feet. Here we would use previous data of area vs price and linear regression to get a price for given area. It is useful when space can be carved in to half-spaces separated by a hyperplane.

Examples of deep learning are in cases where we have just input data and are looking for our network to learn and find patterns. One example is face recognition or even identifying different breeds of dogs because in both these cases a much higher order transformation is needed to sufficiently identify patterns.

### 0.3 ### Implementation Section

Here we take the error function to be the mean squared error give as:

$$Error = \frac{1}{N} * \sum_{n \in data} (t_n - y_n)^2$$

The derivative of this function with respect to the weights is given by:

$$\Delta w = \frac{1}{N} * \sum_{n \in data} \epsilon * x_n * (t_n - y_n)$$

In this case we have only one weight since we are using a linear neuron so it becomes:

$$\Delta w = \epsilon * x_n * (t_n - y_n)$$

We also have one bias and the input for it is one so  $x_n = 1$  therefore it simplifies to:

$$\Delta b = \epsilon * 1 * (t_n - y_n)$$

```
In [89]: # Importing all required libraries
    import numpy as np
    import matplotlib.pyplot as plt
    import pickle as pkl

# Importing all required datasets
    (x_train_1, y_train_1), (x_test_1, y_test_1) = pkl.load( open( "dataset.pkl", "rb" )
    (x_train_2, y_train_2), (x_test_2, y_test_2) = pkl.load( open( "dataset2.pkl", "rb" )

# Making sure all loaded data is a 1D Tensor
    x_train_1 = x_train_1.flatten()
    y_train_1 = y_train_1.flatten()
    x_test_1 = x_test_1.flatten()
    y_test_1 = y_test_1.flatten()
```

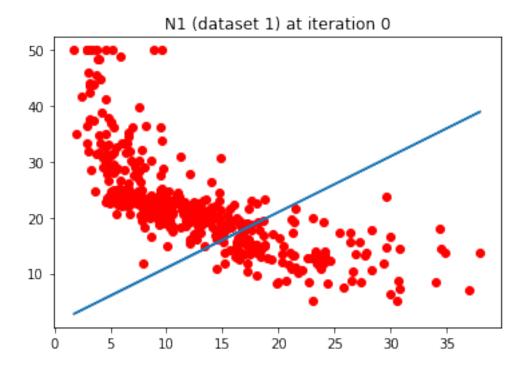
x\_train\_2 = x\_train\_2.flatten()
y\_train\_2 = y\_train\_2.flatten()
x\_test\_2 = x\_test\_2.flatten()

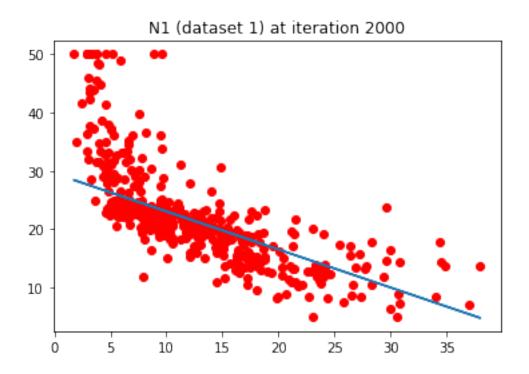
```
# Defining a neuron class
         class neuron:
             def __init__(self, weight, bias):
                 self.weight = weight
                 self.bias = bias
             def fire(self, x):
                 self.output = (self.weight * x) + self.bias
                 return self.output
             def error(self, y_actual):
                 self.err = self.output - y_actual
                 return self.err
             def mse(self, y_actual):
                 return (1/len(y_actual) * ((y_actual - self.output)*(y_actual - self.output))
             def grad_des(self, x, rate):
                 for i, val in enumerate(x):
                     self.weight -= val * self.err[i] * rate
                     self.bias -= self.err[i] * rate
             def plot(self, x, y, title):
                 plt.plot(x, y, 'ro', x, self.output)
                 plt.title(title)
                 plt.show(block=False)
         # Creating a neuron for the first dataset with initialized weight = bias = 1
         N1 = neuron(1, 1)
         # Creating a neuron for the second dataset with initialized weight = bias = 1
         N2 = neuron(1, 1)
         # Learning rate for the first neuron (dataset_1)
         lr_1 = 0.00001
         # Learning rate for the first neuron (dataset_2)
         lr_2 = 0.001
         # Learning rates were decided after a lot of trial and error. Dataset 1 tends
         # to oscillate and eventually 'explode' for a larger learning rate than the one used.
In [90]: # Here we train N1 for dataset 1
```

y\_test\_2 = y\_test\_2.flatten()

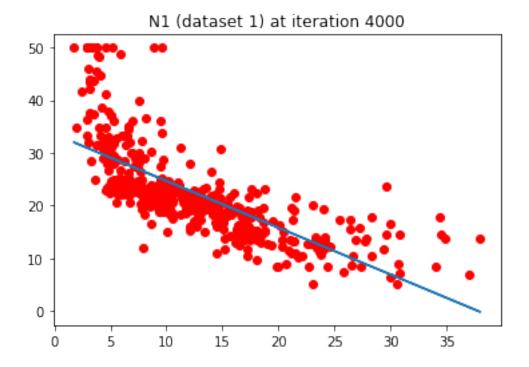
```
loops = 20000
print("Training N1 for Dataset 1")
print("----")
for z in range(0, loops + 1):
    # Activate the first neuron and get an output
   N1.fire(x_train_1)
    # Get the first error based on the previous output
   error_N1 = N1.error(y_train_1)
    # Perform gradient descent using input with learning rate of lr_1
   N1.grad_des(x_train_1, lr_1)
   if (z\%(loops/10)) == 0:
       N1.plot(x_train_1, y_train_1, 'N1 (dataset 1) at iteration ' + str(z))
       print("Error on iteration " + str(z) + " = " + str(error_N1.sum()))
       print("MSE Error on iteration " + str(z) + " = " + str(N1.mse(y_train_1)))
       print("Weight on iteration " + str(z) + " = " + str(N1.weight))
       print("Bias on iteration" + str(z) + " = " + str(N1.bias) + '\n')
```

Training N1 for Dataset 1

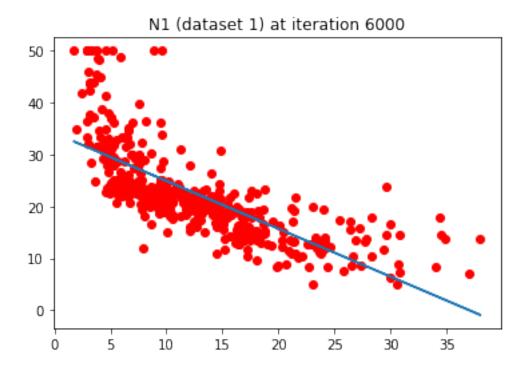




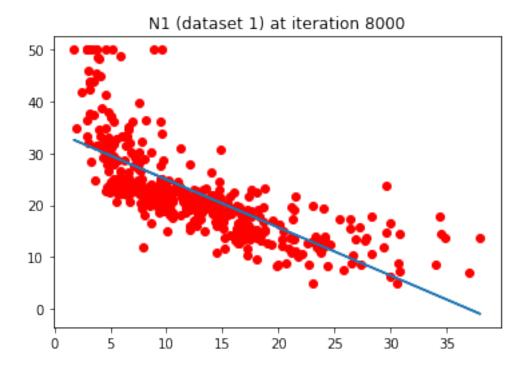
Error on iteration 2000 = -456.3319600354945 MSE Error on iteration 2000 = 44.68678282840193 Weight on iteration 2000 = -0.6526875383272002 Bias on iteration 2000 = 29.582398570769193



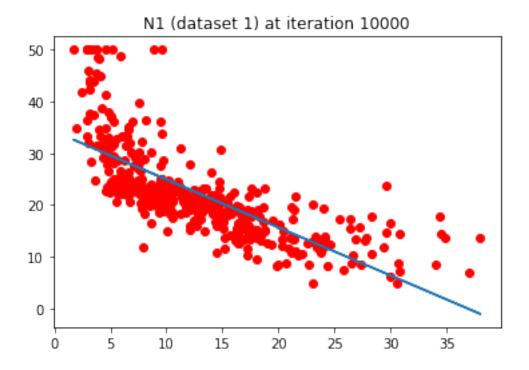
Error on iteration 4000 = -63.7286417233271 MSE Error on iteration 4000 = 39.531599250676464 Weight on iteration 4000 = -0.8893980703034019 Bias on iteration 4000 = 33.56911843657734



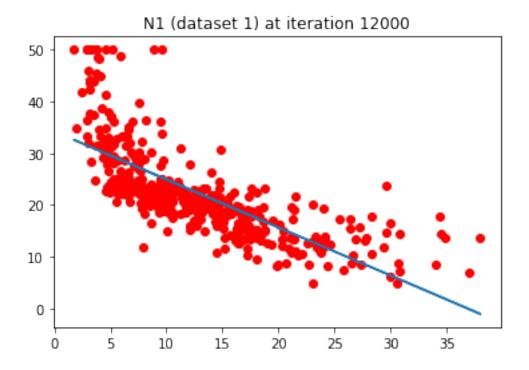
Error on iteration 6000 = -8.899967855930633 MSE Error on iteration 6000 = 39.43105628601307 Weight on iteration 6000 = -0.9224556731135382 Bias on iteration 6000 = 34.12588032097215



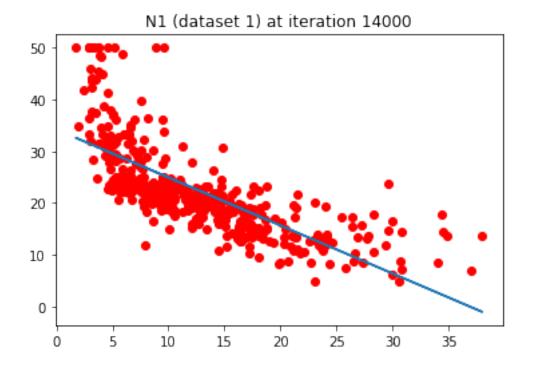
Error on iteration 8000 = -1.2429172454847617 MSE Error on iteration 8000 = 39.42909536889127 Weight on iteration 8000 = -0.9270723037909491 Bias on iteration 8000 = 34.20363441615787



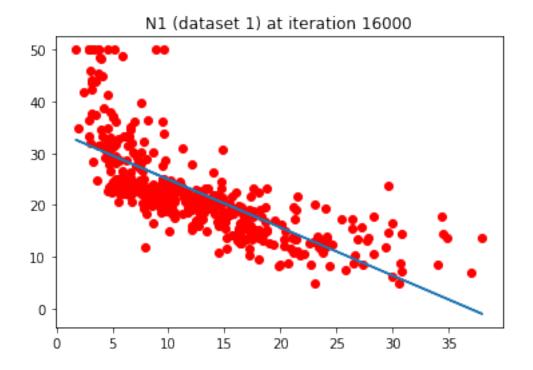
Error on iteration 10000 = -0.17357852353055137 MSE Error on iteration 10000 = 39.42905712458476 Weight on iteration 10000 = -0.9277170353200178 Bias on iteration 10000 = 34.2144930964776



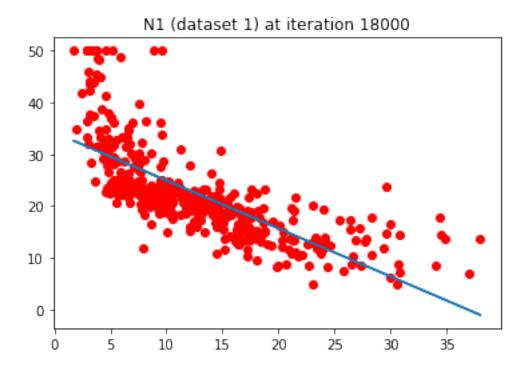
Error on iteration 12000 = -0.02424095739954879 MSE Error on iteration 12000 = 39.42905637869551 Weight on iteration 12000 = -0.9278070747391357 Bias on iteration 12000 = 34.216009556002646



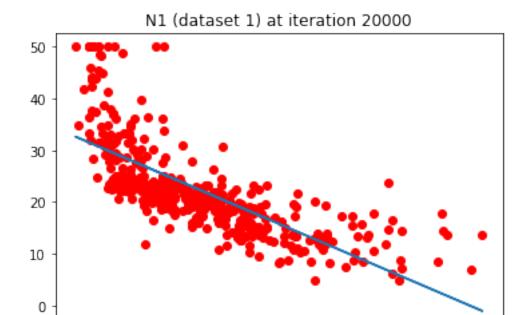
Error on iteration 14000 = -0.0033853499558489375 MSE Error on iteration 14000 = 39.429056364148224 Weight on iteration 14000 = -0.9278196491156276 Bias on iteration 14000 = 34.216221335834035



Error on iteration 16000 = -0.00047277794910627335 MSE Error on iteration 16000 = 39.429056363864504 Weight on iteration 16000 = -0.9278214051793934 Bias on iteration 16000 = 34.21625091176491

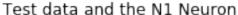


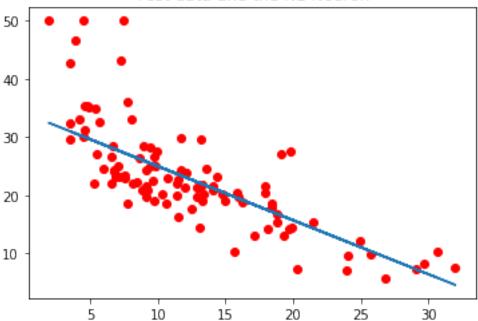
Error on iteration 18000 = -6.602546695688716e-05 MSE Error on iteration 18000 = 39.42905636385897 Weight on iteration 18000 = -0.9278216504208123 Bias on iteration 18000 = 34.21625504216345



Error on iteration 20000 = -9.220773385720804e-06 MSE Error on iteration 20000 = 39.42905636385886 Weight on iteration 20000 = -0.9278216846698336 Bias on iteration 20000 = 34.21625561899132

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Final weight = -0.9278216846698336
Final bias = 34.21625561899132
The MSE error for test data = 34.876196812246626
```

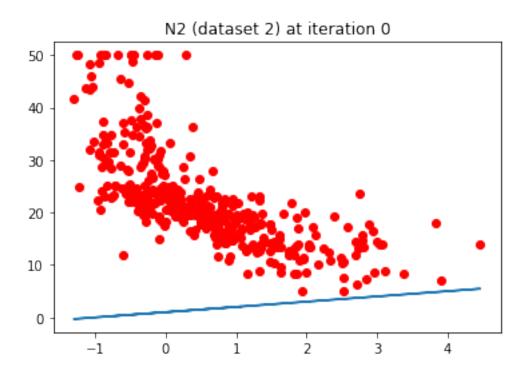
```
In [92]: # Here we train N2 for dataset 2
        loops = 20000
        print("Training N2 for Dataset 2")
        print("-----
        for z in range(0, loops + 1):
             # Activate the first neuron and get an output
            N2.fire(x_train_2)
             # Get the first error based on the previous output
             error_N2 = N2.error(y_train_2)
             # Perform gradient descent using input with learning rate of lr_2
            N2.grad_des(x_train_2, lr_2)
            if (z\%(loops/10)) == 0:
                N2.plot(x_train_2, y_train_2, 'N2 (dataset 2) at iteration ' + str(z))
                print("Error on iteration " + str(z) + " = " + str(error_N2.sum()))
                print("MSE Error on iteration " + str(z) + " = " + str(N2.mse(y_train_1)))
                print("Weight on iteration " + str(z) + " = " + str(N2.weight))
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print("Bias on iteration " + str(z) + " = " + str(N2.bias) + '\n')
```

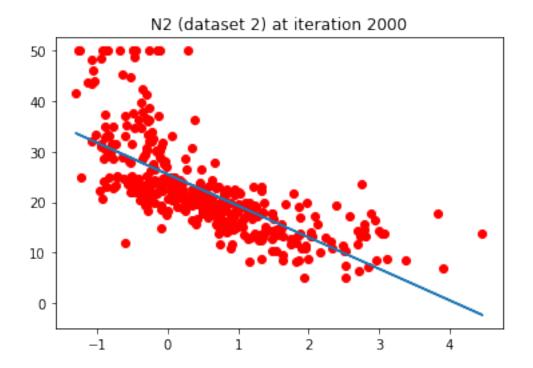
print("-----")

### Training N2 for Dataset 2

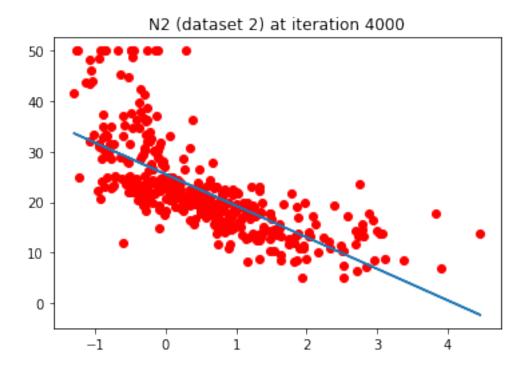
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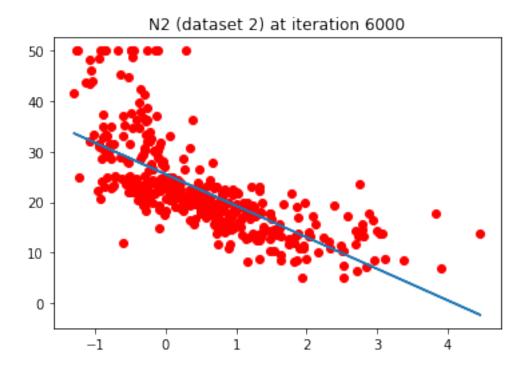
Error on iteration 0 = -8440.80684094769MSE Error on iteration 0 = 535.612696187804Weight on iteration 0 = 2.097271690364214Bias on iteration 0 = 9.440806840947694



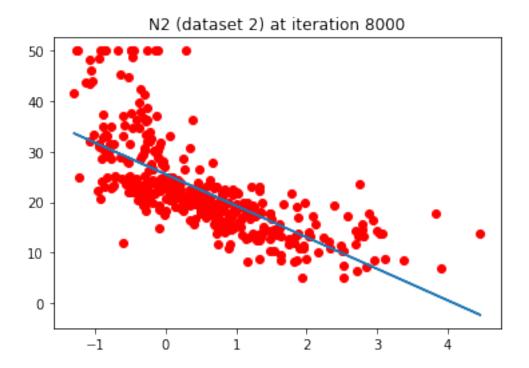
Error on iteration 2000 = -2.9181990157667315e-11 MSE Error on iteration 2000 = 42.840198079698794 Weight on iteration 2000 = -6.238131127132819 Bias on iteration 2000 = 25.526362172905422



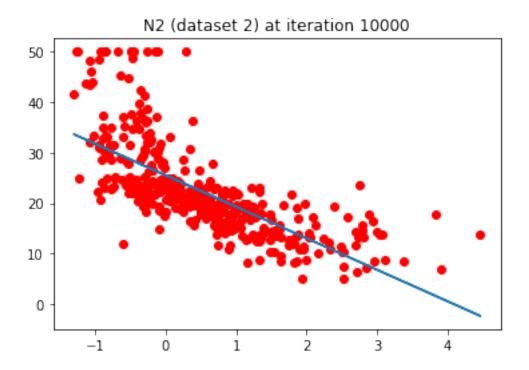
Error on iteration 4000 = -2.9181990157667315e-11 MSE Error on iteration 4000 = 42.840198079698794 Weight on iteration 4000 = -6.238131127132819 Bias on iteration 4000 = 25.526362172905422



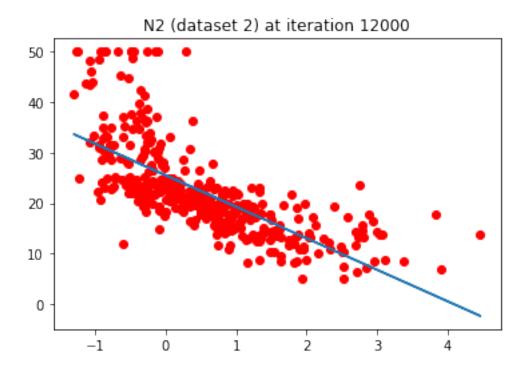
Error on iteration 6000 = -2.9181990157667315e-11 MSE Error on iteration 6000 = 42.840198079698794 Weight on iteration 6000 = -6.238131127132819 Bias on iteration 6000 = 25.526362172905422



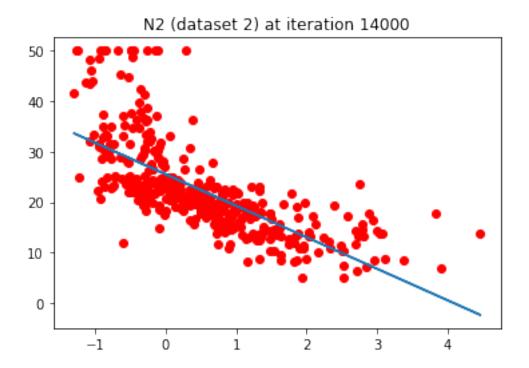
Error on iteration 8000 = -2.9181990157667315e-11 MSE Error on iteration 8000 = 42.840198079698794 Weight on iteration 8000 = -6.238131127132819 Bias on iteration 8000 = 25.526362172905422



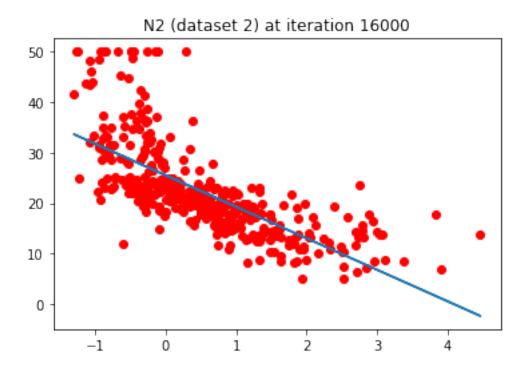
Error on iteration 10000 = -2.9181990157667315e-11 MSE Error on iteration 10000 = 42.840198079698794 Weight on iteration 10000 = -6.238131127132819 Bias on iteration 10000 = 25.526362172905422



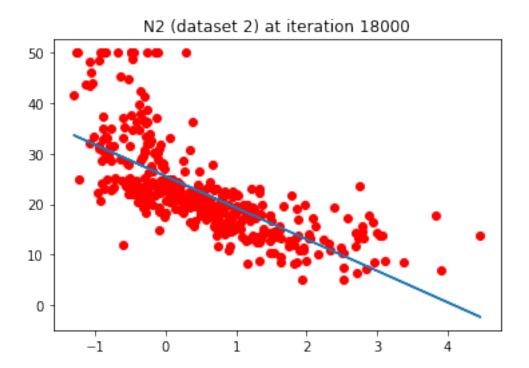
Error on iteration 12000 = -2.9181990157667315e-11 MSE Error on iteration 12000 = 42.840198079698794 Weight on iteration 12000 = -6.238131127132819 Bias on iteration 12000 = 25.526362172905422



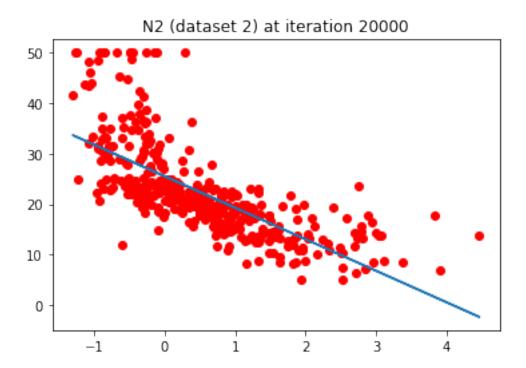
Error on iteration 14000 = -2.9181990157667315e-11 MSE Error on iteration 14000 = 42.840198079698794 Weight on iteration 14000 = -6.238131127132819 Bias on iteration 14000 = 25.526362172905422



Error on iteration 16000 = -2.9181990157667315e-11 MSE Error on iteration 16000 = 42.840198079698794 Weight on iteration 16000 = -6.238131127132819 Bias on iteration 16000 = 25.526362172905422



Error on iteration 18000 = -2.9181990157667315e-11 MSE Error on iteration 18000 = 42.840198079698794 Weight on iteration 18000 = -6.238131127132819 Bias on iteration 18000 = 25.526362172905422



Error on iteration 20000 = -2.9181990157667315e-11 MSE Error on iteration 20000 = 42.840198079698794 Weight on iteration 20000 = -6.238131127132819 Bias on iteration 20000 = 25.526362172905422

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Test data and the N2 Neuron

50 - 40 - 40 - 20 - 10 - 2 - 1 0 1 2

Final weight = -6.238131127132819Final bias = 25.526362172905422The MSE error for test data = 70.80834523792845

## **0.3.1** For Dataset 1

Weight = -0.9278216846698336

Bias = 34.21625561899132

MSE error on Training Dataset = 39.42905636385886

MSE error on Test Dataset = 34.876196812246626

#### 0.3.2 For Dataset 2

Weight = -6.238131127132819

Bias = 25.526362172905422

 $MSE\ error\ on\ Training\ Dataset = 42.840198079698794$ 

MSE error on Test Dataset = 70.80834523792845

In []: