

ECE 30 Project

1- Loss Function

In the loss function, we explore a method of finding the accuracy of our estimation (relative to the given data); we must find the distance between every data point and the line that we created. After taking the distance between the dataset values and the estimated points, we square the differences $((y_i - \hat{y}_i)^2)$, then sum them all up for the entire dataset, before multiplying that sum with $(1/n)$ to normalize the number to find the loss.

```
////////////////////
// Write the loss function
////////////////////
//Calculate the loss against a set of data
// Int Input: X0: arraySize, X1: array address
// Single Input: S0: m, S1: c

loss:
    // LDA X1, array
    LDA X6, inverseN
    ADD X2, X1, XZR // X2 holdes array address
    LDA X7, zeroFloat // load in 0 float value
    LDURS S7, [X7, #0]
    ADDI X5, XZR, #0 // counter

loop2: LDURS S3, [X2, #0] // loads x-value dataset[i][0]
        LDURS S4, [X2, #4] // loads y-value dataset[i][1]
        FMULS S4, S4, S0 // m*xi
        FADDS S4, S4, S1 // +c
        FSUBS S4, S3, S4 // y-yexpected
        FMULS S4, S4, S4 // pow(base,2)
        ADDI X5, X5, #1
        ADDI X2, X2, #8
        FADDS S7, S7, S4
        B check

check: SUBS XZR, X5, X0
        B.LT loop2
```

```
LDURS S4, [X6,#0]
FMULS S7, S7, S4
BR LR
```

2- Training Function

In the training function, we loop through the dataset while calculating the gradient throughout it (to see how we can make the line fit the data better); subsequently, we implement the gradient into the M and C values in order to get a better line. After repeating this step, we have our line!

```
////////////////////
// Write the train function //
////////////////////
// Int Input: X0: arraySize, X1: array address, X2: epoch number
// Single Input: S0: m, S1: c, S2: learning rate, S3: -2/arraySize
// Output: S0: m, S1: c, S2: loss
train:
    //Initialize stack frame for needed variables

    //LDURS S7, [X3, #0]
    LDURS S0, [X3, #0] // set M to 0.0
    LDURS S1, [X3, #0] // set c to 0.0
    LDA X4, epsilon
    LDURS S4, [X4, #0] // setting epsilon to S4
    ADDI X5, XZR, #0 // counter

loop1:

    LDURS S4, [X3, #0] // set D_m = 0
    LDURS S5, [X3, #0] // set D_c = 0
    ADDI X6, XZR, #0 // counter for loop 3
    ADDI X7, X1, #0 // array address counter

loop3:
```

```
LDURS S6, [X7, #0] // loads dataset [j][0]
LDURS S8, [X7, #4] // loads dataset[j][1]

ADDI X7, X7, #8 // sets up X7 for next iteration.
FMULS S9, S0, S6 // M*dataset [j][0]
FADDS S9, S9, S1 // M*dataset [j][0]+C
FSUBS S9, S8, S9 // ( dataset[j][1] - (M*dataset[j][0] + C ) )
FMULS S9, S9, S6 // dataset[j][0] * ( dataset[j][1] - (M*dataset[j][0] + C ) )
FADDS S4, S4, S9 // D_m += dataset[j][0] * ( dataset[j][1] - (M*dataset[j][0] + C ) )
FMULS S9, S0, S6 // M*dataset[j][0]
FADDS S9, S9, S1 // M*dataset[j][0] + c
FSUBS S9, S8, S9 // dataset[j][1] - ( M*dataset[j][0] + C )
FADDS S5, S5, S9 // D_C += dataset[j][1] - ( M*dataset[j][0] + C )
ADDI X6, X6, #1 // COUNTER +1
SUBS XZR, X0, X6 // checker
B.GT loop3
```

```
FMULS S4, S3, S4 // D_m *= -2/dataset.size()
FMULS S5, S3, S5 // D_c *= -2/dataset.size()
FMULS S9, S4, S2 // lr *D_m
FSUBS S0, S0, S9 // M - lr *D_m /
FMULS S9, S5, S2 // lr*D_c
FSUBS S1, S1, S9 // C = C - lr*D_c
```

SUBI SP, SP, #80 // the number depends on how many instructions we wanna save (40 is temp for 5)

```
STUR FP [SP, #72]
STUR LR [SP, #64]
STUR X6 [SP, #8]
STUR X7 [SP, #16]
STURS S4 [SP, #24]
STUR X5 [SP, #32]
STURS S2 [SP, #40]
STURS S3 [SP, #48]
STUR X2 [SP, #56]
ADDI FP, SP, #80
```

BL loss

```
LDUR FP [SP, #72]
LDUR LR [SP, #64]
LDUR X6 [SP, #8]
LDUR X7 [SP, #16]
LDURS S4 [SP, #24]
LDUR X5 [SP, #32]
LDURS S2 [SP, #40]
LDURS S3 [SP, #48]
LDUR X2 [SP, #56]
ADDI SP, SP, #80
```

```
//SUBIS XZR, X5, #0
//B.EQ past
//LDURS S9 [SP, #0]
//FSUBS S9, S7, S9
//FCMPS S9, S4
//B.LT end
```

```
SUBS XZR, X7, X10
B.GT end
```

past:

```
STURS S7 [SP, #0] // store last loss value
ADDI X5, X5, #1 // add to counter
SUBS XZR, X2, X5 // checker
B.GT loop1
```

```
//Call loss function at end of each epoch
//Call loss function at the end of the function return the loss
```

3- Visualization

Using the Desmos online calculator, we visualize our model. After inputting our data and equation, we can see how our line fits into our data! The attached graph (**Figure 1**) depicts our estimation line going through our data.

Loss Number: ~0.45

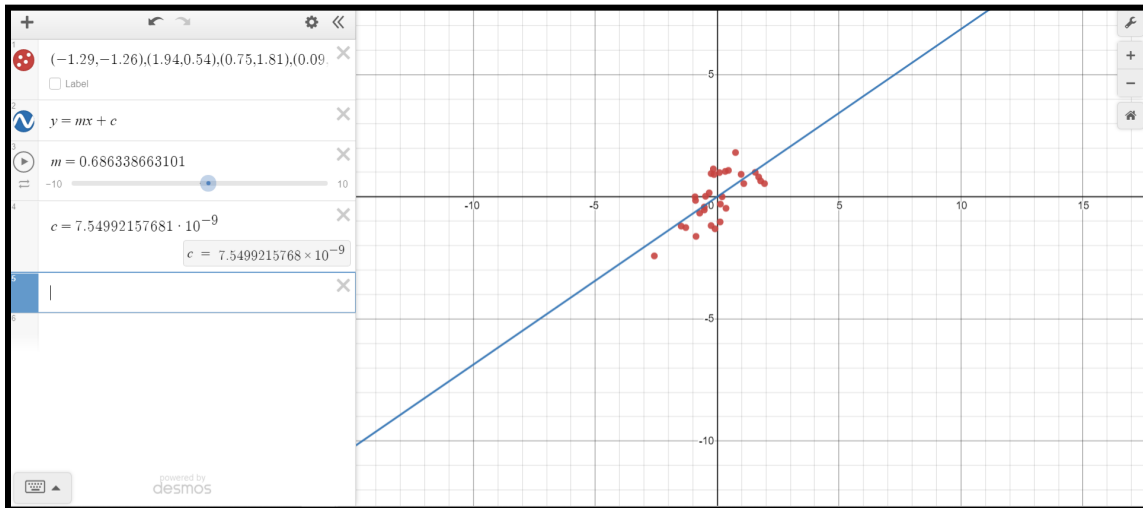


Figure 1: Graph with Data and Estimation Line

4- Early Stop of Training Using Absolute Values

Here, we implemented an if-statement that detects whether our loss gets lower than a threshold that matches our dataset (this statement is placed before the epoch iterations). If the loss is lower than the threshold, the program breaks. We were able to implement this with two lines of code.

FCMPS S14, S7

B.GT end

5- Early Stop of Training Using Difference in Losses

Similar to the previous section, this function calculates the difference between the current loss and the last iteration's loss, to see if it is less than the given *epsilon* value. If it is, the training function is halted.

```
        SUBIS XZR, X5, #0
        B.EQ past
        LDURS S9 [SP, #0]
        FSUBS S9, S7, S9
        FCMPS S9, S4
        B.LT end

past:
        STURS S7 [SP, #0] // store last loss value
        ADDI X5, X5, #1 // add to counter
        SUBS XZR, X2, X5 // checker
        B.GT loop1
```

6- Normalization of Dataset

After running the linear regression algorithm on “RawSOCRdata.txt” and we realize that the results look strange and are not matched with our line (the slope was off); we believe that this went wrong because we didn’t normalize the points prior to running the algorithm, so our graph below shows what it looks like when we have a normalized estimation without a normalized dataset. This equation ensures that our data is consistent and in the same format, and is essential for us to be able to accurately analyze and interpret data.

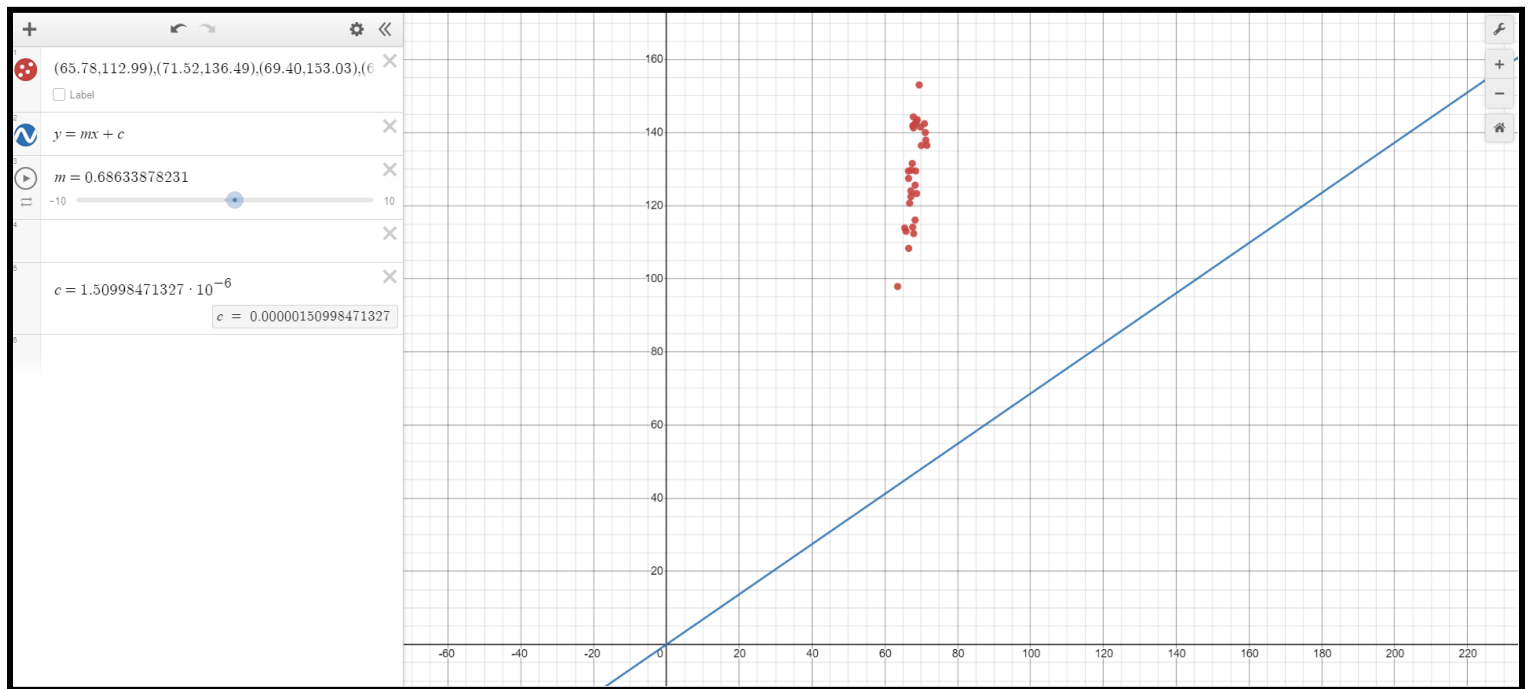


Figure 2: Graph Depicting Unnormalized Data

Here, we use data standardization by taking our data point, subtracting the average, and dividing that difference by the standard deviation (σ). Doing this to normalize the data solved the issue that is depicted in the above image (**Figure 2**). The following is the graph after we fixed the data (**Figure 3**):

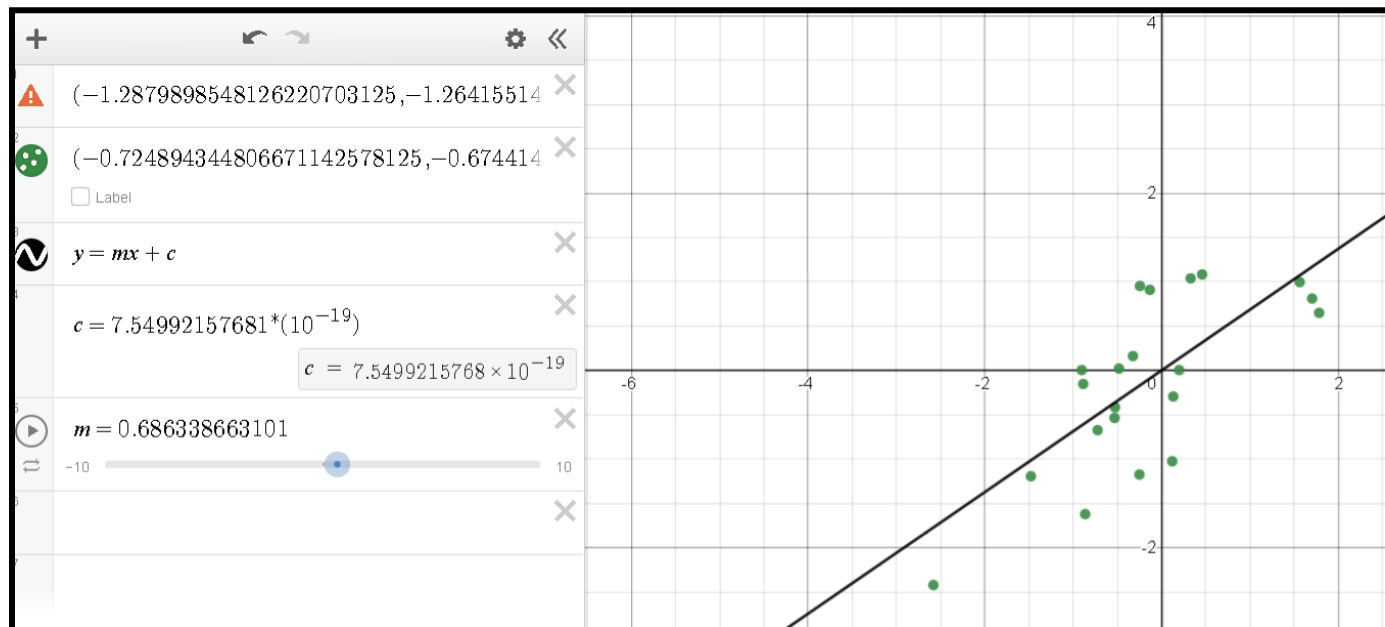


Figure 3: Graph with Normalized Data

The following (**Figure 4**) is a graph with both datasets (normalized in green and unnormalized in blue):

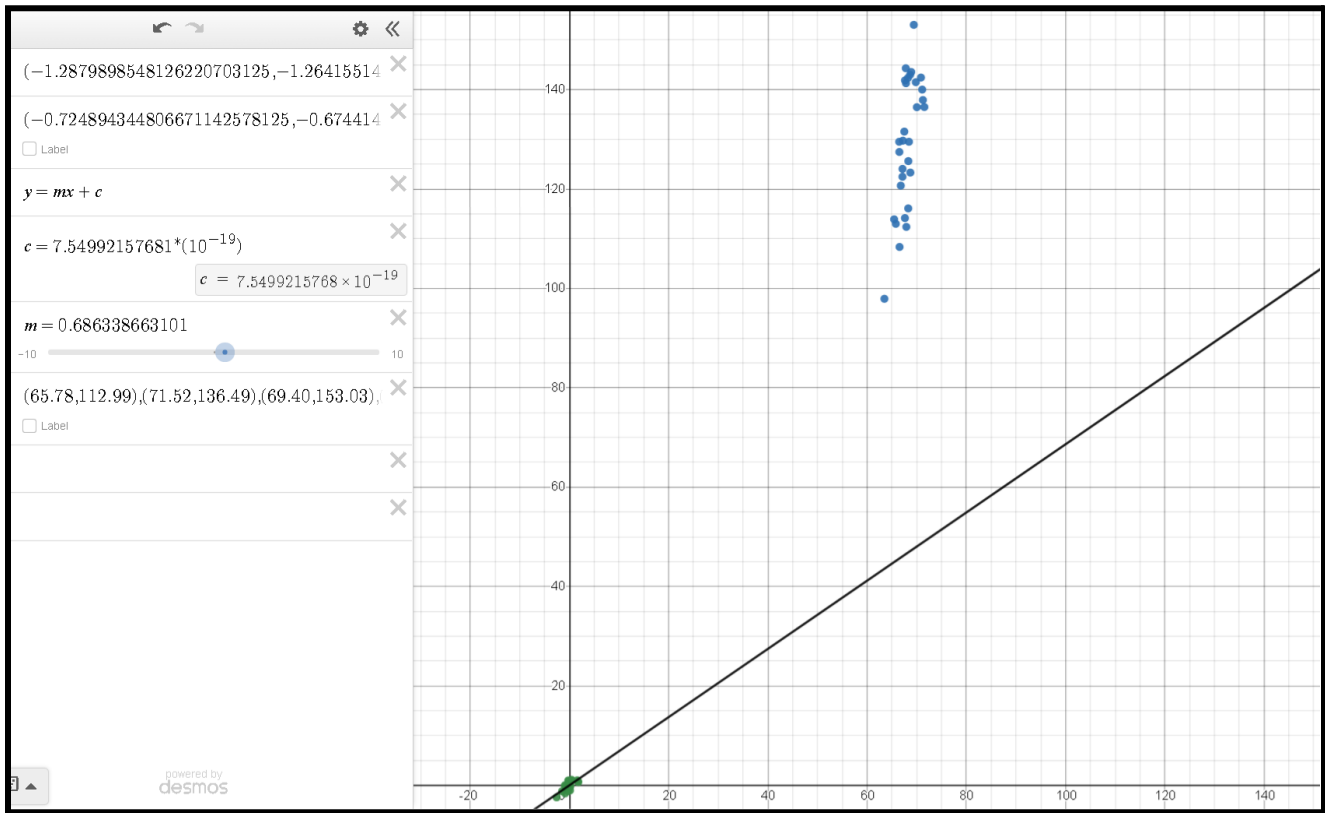


Figure 4: Graph Depicting Unnormalized and Normalized Data

M: NAN (7FC00000)

C: NAN (7FC00000)

Loss: NAN (7FC00000)

Normal:

LDURS S6, [X15, #0] // loads dataset [j][0]

LDURS S8, [X15, #4] // loads dataset[j][1]

FSUBS S6, S6, S10

FDIVS S6, S6, S12

FSUBS S8, S8, S11

FDIVS S8, S8, S13

STURS S6, [X15, #0]

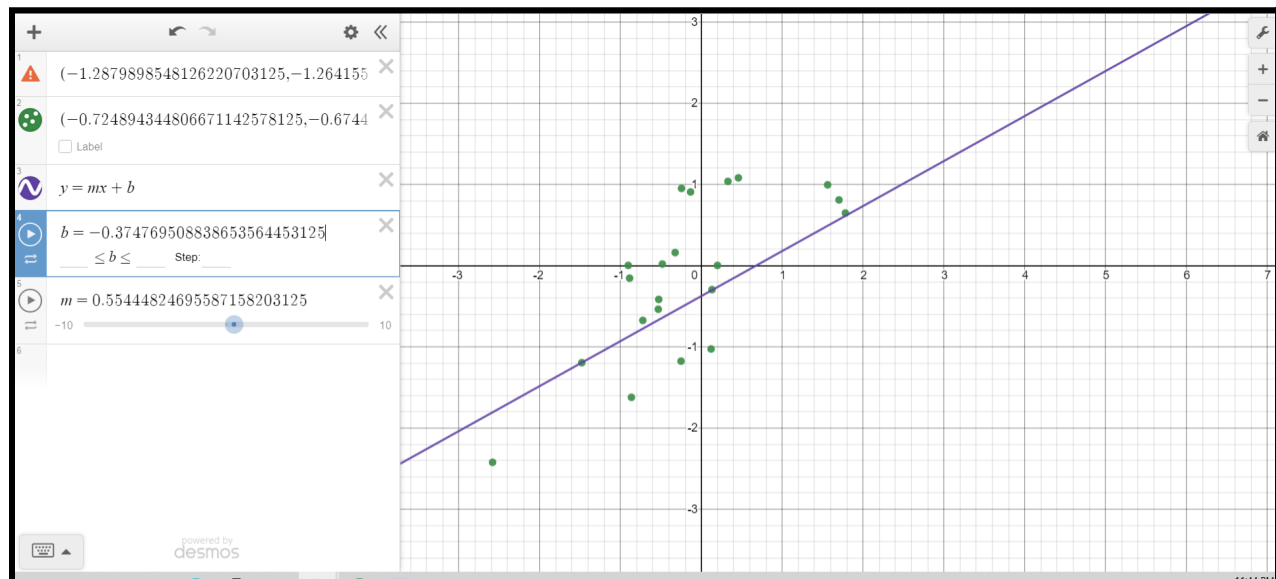
STURS S8, [X15, #4]

```
ADDI X15, X15, #8 // sets up X15 for the next iteration.  
ADDI X16, X16, #1  
SUBS XZR, X0, X16 // checker  
B.GT Normal  
Br LR
```

Normalization Conversions:

(-1.2879898548126220703125 , -1.2641551494598388671875) ,
(1.94417703151702880859375 , 0.540391564369),
(0.75041735172271728515625, 1.810484409332275390625),
(0.08596451580524444580078125, 0.98960769176483154296875) ,
(-0.15616671741008758544921875, 1.14012658596038818359375) ,
(0.3562479317188262939453125, -0.4724581539630889892578125),
(0.97565639019012451171875, 0.924337565898895263671875),
(1.093905925750732421875, 0.53808796405792236328125) ,
(-0.09422586858272552490234375, -1.31176412105560302734375) ,
(-0.724894344806671142578125, -0.674414098262786865234375) ,
(-0.888192594051361083984375, -0.15378344058990478515625),
(-0.251891911029815673828125, -1.175847530364990234375),
(0.1310131847858428955078125, -0.29507529735565185546875) ,
(-0.53343963623046875, -0.536961376667022705078125) ,
(0.119748868048191070556640625, -1.02610874176025390625),

(1.70204579830169677734375, 0.809921205043792724609375),
(-0.90508472919464111328125, 0.00363464490510523319244384765625),
(0.328095734119415283203125, 1.03798520565032958984375),
(1.7808830738067626953125, 0.648663461208343505859375),
(-0.527811825275421142578125, -0.4156343042850494384765625),
(-0.133642375469207763671875, 0.908211290836334228515625),
(0.457605302333831787109375, 1.0817544460296630859375),
(-2.5831091403961181640625, -2.4229037761688232421875),
(0.19858188927173614501953125, 0.00363464490510523319244384765625),
(-0.24626405537128448486328125, 0.951981723308563232421875),
(-0.4827631413936614990234375, 0.02052836306393146514892578125),
(1.5612719058990478515625, 0.995750963687896728515625),
(-0.32509708404541015625, 0.1610527336597442626953125),
(-0.865668237209320068359375, -1.621992588043212890625),
(-1.479440212249755859375, -1.1950447559356689453125)

**Figure 5: New Normalized Data****Normalized Results:**

m: 0.55444824695587158203125

c:-0.374769508838653564453125

Loss: 48.793376922607421875

We were able to successfully normalize the data but ended up getting a high loss value. When we attempted to fix the issue we had problems with running Legiss (kept stalling out). This could be due to an infinite loop somewhere but the only thing we added was the normalization part and I couldn't find anything through debugging.