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Github link for files and code: https://github.com/DevonARP/DeepLearning\_A1

Problem 1: Part A

$$F(x) = ||X||_2^2$$

$$F(x) = ((\sum_{i=1}^{n} x_i^2)^{1/2})2$$

$$F(x) = \sum_{i=1}^{n} x_i^2$$

Can ignore the summation as n is 1.

$$\frac{\partial}{\partial x} = 2x$$

Problem 1: Part B

$$\sum_{i=1}^{n} ||x_i - \mu||_2^2$$

 $\frac{\partial}{\partial x}$  = 2(x-  $\mu$ ) Got the derivative, could just put it in the answer for Part A but accounting for  $\mu$ . This works because this is the derivative at each point, and we have the summation of all of the points already in the expression.

Now we set the derivative with summation = 0

$$\sum_{i=1}^{n} 2(\mathsf{x}_{\mathsf{i}} - \mu) = 0$$

Do some algebra and we end up with:

$$\mu = (\sum_{i=1}^n x_i)/n$$

Problem 2: Part A

$$L(w) = ||x||_1$$

$$L(w) = ||Xw - y||_1$$

Sizes:  $X(data) \rightarrow n^*c$ ,  $w(weights) \rightarrow c^*1$ ,  $y(labels) \rightarrow n^*1$ 

# Problem 2: Part B

No, because L1 norm isn't differentiable at zero therefore gradient optimization cannot be used. The explanation is partly explained in Part C as well.

Problem 2: Part C

Part A was straightforward since we just need the difference from the estimate and actual value. Since L1 is the summation of ||x||, we can just replace Xw-y for x. For part B, it wouldn't have a value at zero if we took the derivative as it's non-convex there, there would be no unique global minimum so we can't minimize the loss function. This would mostly be concerned with the loss function part of the 3-step recipe as we are calculating the losses from the prediction regarding the label.

## Problem 3: Part A

The code for this question is below, the answers I got for the parameters in this order  $W_{h1}$ ,  $W_{h2}$ ,  $W_{h3}$ ,  $W_{h4}$ ,  $W_{h1}$ ,  $W_{h2}$ ,  $W_{h3}$ ,  $W_{h4}$ ,  $W_{h1}$ ,  $W_{h2}$ ,  $W_{h3}$ ,  $W_{h4}$ ,  $W_{h4}$ ,  $W_{h2}$ ,  $W_{h3}$ ,  $W_{h4}$ ,  $W_{h4}$ ,  $W_{h2}$ ,  $W_{h3}$ ,  $W_{h4}$ 

## For Dataset 1:

([-7.82455998e-01, -5.16665284e-01, 1.32120087e+00, -3.55189485e+00, 6.25964798e+00, 3.09863545e+00, -1.05696070e+01, 1.42169031e+01, 2.55605428e+00, -7.76233237e+00, 1.51377436e+00, 1.12912342e+00, 2.69958647e-11]

#### For Dataset 2:

[-0.35614338, 0.05176055, 0.04679073, 4.26739128, 1.06854914, 0.69438611, 0.33182292, -21.3355306, -5.61759265, -20.45828289, 1.24519253, 0.46882705, 19.79543786]

I also made an excel solver to calculate these values out for a more insightful look into the process.

#### For Dataset 1:

A B C	D E F	G	Н	I	J	K	L	М	N	0	P	Q	R	S	T	U	V
Parameters		Input		Z1	Z2	Z3	Z4		ReLu1	ReLu2	ReLu3	ReLu4		Prediction	Va	lue for D1	Value for D2
w1 = -7.82E-01		0		6.25964798	3.09863545	-10.569607	14.2169031		6.25964798	3.09863545	0	14.2169031		8.000000004	=	8	0
w2 = -5.17E-01		1		5.477191982	2.581970166	-9.24840613	10.66500825		5.477191982	2.581970166	0	10.66500825		6	=	6	1
w3 = 1.32E+00		2		4.694735984	2.065304882	-7.92720526	7.1131134		4.694735984	2.065304882	0	7.1131134		3.999999995	=	4	2
w4 = -3.55E+00		3		3.912279986	1.548639598	-6.60600439	3.56121855		3.912279986	1.548639598	0	3.56121855		1.99999999	=	2	3
b1 = 6.26E+00		4		3.129823988	1.031974314	-5.28480352	0.0093237		3.129823988	1.031974314	0	0.0093237		-1.4339E-08	=	0	2
b2 = 3.10E+00		5		2.34736799	0.51530903	-3.96360265	-3.54257115		2.34736799	0.51530903	0	0		2.000000033	=	2	1
b3 = -1.06E+01		6		1.564911992	-0.00135625	-2.64240178	-7.094466		1.564911992	0	0	0		3.999999995	=	4	2
b4 = 1.42E+01		7		0.782455994	-0.51802154	-1.32120091	-10.6463609		0.782455994	0	0	0		1.999999992	=	2	3
w5 = 2.56E+00		8		-4E-09	-1.03468682	-4E-08	-14.1982557		0	0	0	0		2.69959E-11	=	0	4
w6 = -7.76E+00		9		-0.782456	-1.55135211	1.32120083	-17.7501506		0	0	1.32120083	0		1.999999941	=	2	5
w7 = 1.51E+00		10		-1.564912	-2.06801739	2.6424017	-21.3020454		0	0	2.6424017	0		3.999999942	=	4	6
w8 = 1.13E+00		11		-2.347368	-2.58468267	3.96360257	-24.8539403		0	0	3.96360257	0		5.999999944	=	6	
b0 = 2.70E-11		12		-3.129824	-3.10134796	5.28480344	-28.4058351		0	0	5.28480344	0		7.999999945	=	8	

# For Dataset 2:

I A	R C	DEF	6	н		J	K	L	M	IN	U	P	Q	К	5	Ш	U	V
	Parameters		Input		Z1	Z2	Z3	Z4		ReLu1	ReLu2	ReLu3	ReLu4		Prediction	,	Value for D1	Value for D2
w1	= -0.35614338		0		1.06854914	0.69438611	0.33182292	-21.3355306		1.06854914	0.69438611	0.33182292	0		1.29723E-08	=	8	0
w2	= 0.05176055		1		0.71240576	0.74614666	0.37861365	-17.0681393		0.71240576	0.74614666	0.37861365	0		0.99999994	=	6	1
w3	= 0.04679073		2		0.35626238	0.79790721	0.42540438	-12.800748		0.35626238	0.79790721	0.42540438	0		1.999999867	=	4	2
w4	4.26739128		3		0.000119	0.84966776	0.47219511	-8.53335676		0.000119	0.84966776	0.47219511	0		2.999999794	=	2	3
b1	= 1.06854914		4		-0.35602438	0.90142831	0.51898584	-4.26596548		0	0.90142831	0.51898584	0		1.99999978	=	0	2
b2	= 0.69438611		5		-0.71216776	0.95318886	0.56577657	0.0014258		0	0.95318886	0.56577657	0.0014258		0.999999727	=	2	1
b3	= 0.33182292		6		-1.06831114	1.00494941	0.6125673	4.26881708		0	1.00494941	0.6125673	4.26881708		1.999999685	=	4	2
b4	= -21.3355306		7		-1.42445452	1.05670996	0.65935803	8.53620836		0	1.05670996	0.65935803	8.53620836		2.999999643	=	2	3
w5	= -5.61759265		8		-1.7805979	1.10847051	0.70614876	12.80359964		0	1.10847051	0.70614876	12.80359964		3.999999601	=	0	4
w6	= -20.4582829		9		-2.13674128	1.16023106	0.75293949	17.07099092		0	1.16023106	0.75293949	17.07099092		4.999999559	=	2	5
w7	= 1.24519253		10		-2.49288466	1.21199161	0.79973022	21.3383822		0	1.21199161	0.79973022	21.3383822		5.999999517	=	4	6
w8	= 0.46882705		11		-2.84902804	1.26375216	0.84652095	25.60577348		0	1.26375216	0.84652095	25.60577348		6.999999475	=	6	
b0	= 19.79543786		12		-3.20517142	1.31551271	0.89331168	29.87316476		0	1.31551271	0.89331168	29.87316476		7.999999433	=	8	

The predicted values are really close to the actual values on all accounts.

# Problem 3: Part B

This is just mean squares, so the derivative is straightforward:

$$L(\theta \rightarrow) = \sum_{i=1}^{n} (y_i - f(x_i, \Theta \rightarrow))^2$$

$$\nabla L(\theta \overrightarrow{)} = -2\sum_{i=1}^{n} ((y_i - f(x_i, \Theta \overrightarrow{)}) * \nabla f(x_i, \Theta \overrightarrow{)})$$

I left it in terms of  $\nabla f(x_i, \Theta^{\rightarrow})$  since that's what the question asked for.

# Problem 3: Part C

First layer values after plugging in the input(x) and parameters.

- $Z_1 = -1$
- $Z_2 = 3$
- $Z_3 = 1$
- $Z_4 = -1$

After ReLu

- $Z_1 = 0$
- $Z_2 = 3$
- $Z_3 = 1$
- $Z_4 = 0$

After summation in output layer

-4

After adding final bias

-3

Did this both manually and on the excel calculator I made:

P3. C: 
$$\overline{Z}_{i} = W_{hi} \times 1 I_{hi}$$

Telu

 $Y = l_{0} + Y_{0} \times Z_{i}$ 
 $X = 2$ 
 $\overline{Z}_{i} = -1 \rightarrow 0 \rightarrow 0$ 
 $\overline{Z}_{1} = 3 \rightarrow 3 \rightarrow -2$ 
 $\overline{Z}_{2} = 1 \rightarrow 0 \rightarrow 0$ 
 $\overline{Z}_{3} = 1 \rightarrow 0 \rightarrow 0$ 
 $\overline{Z}_{4} = -1 \rightarrow 0 \rightarrow 0$ 

A B	С	D	E	F	G	Н		J	K	L	M	N	0	P	Q	R	S
Pai	rameters				Input		Z1	<b>Z2</b>	Z3	Z4		ReLu1	ReLu2	ReLu3	ReLu4		Prediction
w1 =	-1				0		1	1	-1	1		1	1	0	1		0 :
w2 =	1				1		0	2	0	0		0	2	0	0		-1 :
w3 =	1				2		-1	3	1	-1		0	3	1	0		-3 :
w4 =	-1				3		-2	4	2	-2		0	4	2	0		-5

## Problem 3: Part D

I have all the formulas written out but am not sure what the parameters are supposed to be. But once I'm given those, I can figure out what the derivative at x=2 is with no problem.

$$\frac{\partial L}{\partial w0} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial w0}$$

$$\frac{\partial y}{\partial w_0} = \sum_{i=1}^4 z_i$$

$$\frac{\partial L}{\partial y} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

$$\frac{\partial L}{\partial w_0} = 2 * \sum_{i=1}^4 z * \sum_{i=1}^n (y_0 - f(x, \theta))$$

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$$\frac{\partial L}{\partial b0} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial b0}$$

$$\frac{\partial y}{\partial b0} = 1$$

$$\frac{\partial L}{\partial y} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

$$\frac{\partial L}{\partial b0} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

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$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial z} * \max(0,z) * \frac{\partial z}{\partial w_0}$$

$$\frac{\partial z}{\partial wo} = x \rightarrow max(0,z) = max(0,x)$$

$$\frac{\partial y}{\partial z} = \sum_{i=1}^4 wo_i$$

$$\frac{\partial L}{\partial y} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

$$\frac{\partial L}{\partial w_1} 2 * \sum_{i=1}^4 wo * \max(0,x) * \sum_{i=1}^n (y0 - f(x,\theta))$$

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$$\frac{\partial L}{\partial b1} = \frac{\partial L}{\partial y} * \frac{\partial y}{\partial z} * \max(0,z) * \frac{\partial z}{\partial bo}$$

$$\frac{\partial z}{\partial \text{bo}} = 1 \rightarrow \text{max}(0,z) = 1$$

$$\frac{\partial y}{\partial z} = \sum_{i=1}^4 wo_i$$

$$\frac{\partial L}{\partial y} = 2 \sum_{i=1}^{n} (y0 - f(x, \theta))$$

$$\frac{\partial L}{\partial w_1} 2 * \sum_{i=1}^4 w_0 * \sum_{i=1}^n (y_0 - f(x, \theta))$$