1. Outlier

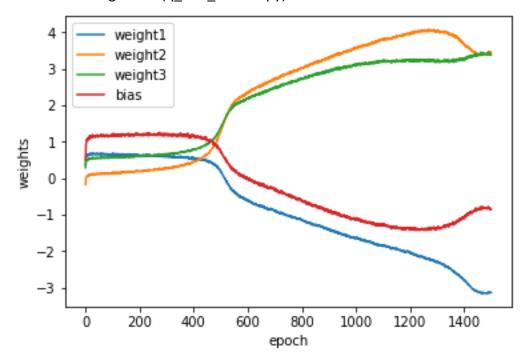
- a. Yes, there are outliers in the dataset
- b. no, the isolation forest and LOF don't agree each other. I think the reason why they disagree is that the ways they detect outliers are different. LOF will draw circles from each point and see how many other points are included. This is called k numbers. IsoForest tries to draw random lines to separate data points. If a point takes fewer lines to separate, it would be an outlier.
- c. The local outlier factor (LOF) method scores points in a multivariate dataset whose rows are assumed to be generated independently from the same probability distribution.

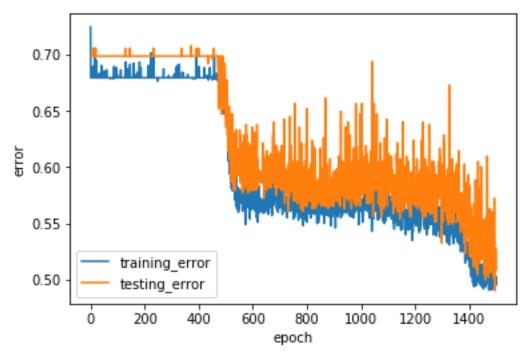
The isolation-based approach measures how isolated a point is without any assumption on the data distribution

I used Isolation forest to detect outliers. I separated the ERL data out and run outlier algorithm in the rest data because there are only five of ERL, and they are pretty far from the rest of other classes. As a result, the outlier detector will consider them as outliers and wipe out all ERL classes. I append the data of ERL class after the removal of outliers in the rest data and do the fitting.

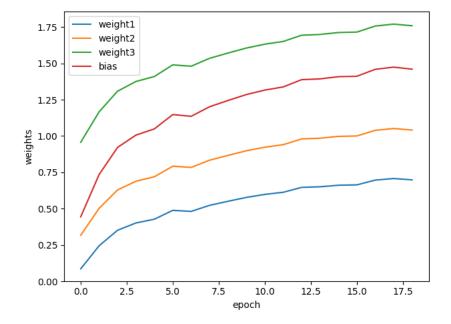
2. Graph

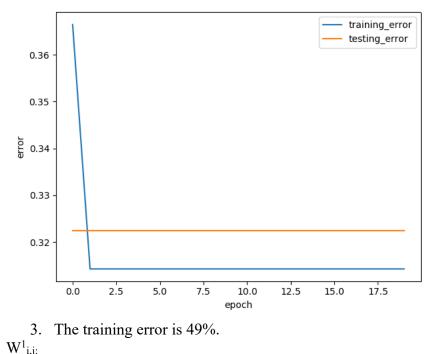
I am not sure which method to use, I used normal 10 classes classification and get the following result.(q_two_normal.py)





I also used CYT class versus all method which sets CYT class to 1 and anything else to $0.(q_two_nevsall.py)$ Here is the graph:





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** 1,J:			
i∖j	1	2	3
1	-2.1102152	-1.4224404	-6.1384377
2	-0.95252943	-2.258863	-0.5459768
3	[-2.2399316	-1.5370386	-2.4138312
4	1.7532674	-2.2792144	3.2550364
5	1.2469106	3.9437149	1.2858084
6	-0.92298543	1.9879668	-1.9019877
7	2.1192098	-1.0134993	3.371361
8	0.65852046	1.9403076	1.36866
Bias weights	-0.26492488	1.042711	-1.2803181

W²ji:

i∖j	1	2	3
1	1.5685434	2.3213522	2.5931113
2	3.6316113	3.2313075	-3.910231
3	6.425479	3.610899	6.657158
Bias weights	-3.2191505	-5.2541513	-3.000276

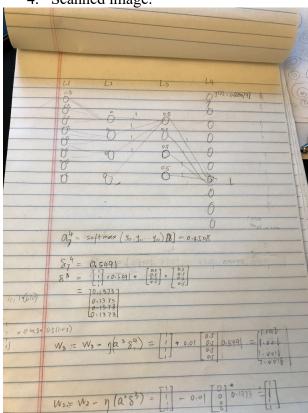
i∖j	1	2	3	4	5	6	7	8	9	10
1	3.4098 232	- 2.24657 96	- 5.45992 02	- 4.7452 083	- 1.43674 47	4.45700 74	1.5751 253	1.76955 84	- 1.53918 23	5.35187 66
2	3.3591 673	- 1.60118 28	- 2.20178 03	3.7939 258	- 1.12325 70	- 1.43227 12	- 1.8251 935	5.81427 19	- 4.70038 50	1.28935 86
3	2.1966 605	9.26064 25e-01	9.56915 39e-02	- 3.7555 292	- 6.50380 25e-01	- 5.45279 17	6.8054 771	5.59640 11e-01	8.41094 61e-01	1.16239 59e-01
Bias weig hts	- 3.1517 823	0.13407 792	1.13979 35	3.3757 99	1.99953 46	0.13785 586	- 0.8446 069	- 2.44316 3	0.50435 436	- 0.85184 35

The formula of activation function is

$$P(y = j \mid \mathbf{x}) = rac{e^{\mathbf{x}^\mathsf{T} \mathbf{w}_j}}{\sum_{k=1}^K e^{\mathbf{x}^\mathsf{T} \mathbf{w}_k}}$$

Where $w_{j}\, is$ (W11, W12, W13, Bias1) $Wk\; is\; W^{3}{}_{\text{ij}}$

4. Scanned image:



It matches the output:

5. Table:

Layer\Node	3	6	9	12
1	0.464953	0.455607	0.448598	0.436915
2	0.577102	0.492990	0.483644	0.483644
3	0.698598	0.628504	0.642523	0.602803

The optimal config is 1 hidden layer with 12 hidden nodes. The relationship between number of layers, number of nodes and generalization error is that the more layer, the higher the error. The more nodes, the less the error.

- 6. The predicted class is 7, so it's NUC
- 7. We can use the error rate which will tell us the miss predicted of the model. The uncertainty is 0.43