UNSW
SYDNEY

COMP9444

Homework 1

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Part 1 Question 1

Final Confusion matrix =

[[765. 7. 7. 4. 59. 8. 5. 16. 11. 8.]

[5. 671. 65. 37. 51. 26. 23. 29. 37. 52.]

[8. 109. 689. 61. 84. 125. 150. 26. 94. 85.]

[12. 18. 26. 759. 21. 17. 10. 12. 42. 3.]

[31. 27. 27. 14. 623. 20. 27. 89. 6. 51.]

[65. 22. 21. 56. 20. 726. 25. 19. 32. 34.]

[2. 58. 45. 14. 33. 27. 719. 53. 45. 19.]

[61. 14. 37. 17. 34. 8. 21. 620. 6. 31.]

[32. 25. 44. 26. 19. 32. 9. 89. 704. 39.]

[19. 49. 39. 12. 56. 11. 11. 47. 23. 678.]]

Final → Test set: Average loss: 1.0107, **Accuracy:** 6954/10000 (70%)

Part 1 Question 2

1) **Num_id** = 500 **accuracy** = 85%
2) **Num_id** = 1000 **accuracy** = 85%
3) **Num_id** = 1500 **accuracy** = 84%
4) **Num_id** = 2000 **accuracy** = 84%
5) **Num_id** = 3000 **accuracy** = 84%

Final Confusion matrix =

[[850. 6. 7. 2. 37. 11. 3. 17. 11. 4.]

[5. 814. 13. 8. 31. 17. 14. 11. 28. 19.]

[2. 37. 831. 24. 16. 84. 40. 20. 29. 49.]

[6. 2. 46. 927. 7. 6. 10. 6. 55. 4.]

[26. 20. 10. 3. 823. 11. 16. 16. 4. 28.]

[36. 10. 19. 15. 6. 832. 6. 8. 8. 4.]

[2. 58. 26. 5. 28. 17. 894. 33. 28. 21.]

[42. 5. 13. 2. 14. 1. 7. 836. 2. 17.]

[28. 17. 20.   6. 23. 15.   2. 23. 830.   9.]

[3. 31. 15.   8. 15.   6.   8. 30.   5. 845.]]

Final -> **Test set: Average loss:** 0.4935, **Accuracy:** 8482/10000 (85%)

Part 1 Question 3

Training No	**Accuracy (%)**
1	93
2	93
3	93
4	93
5	93

Final Confusion Matrix =

[[939.   3. 11.   3. 19.   6.   5.   5.   3.   6.]

[7. 926. 11.   1. 14. 19. 10. 12. 22. 12.]

[3.   4. 894. 18.   4. 50. 21. 10. 15. 11.]

[1.   0. 36. 957.   3.   9.   3.   2. 11.   2.]

[28.   3.   2.   2. 912.   3.   7.   8.   5.   5.]

[3.   2. 10.   6.   4. 887.   3.   1.   5.   0.]

[2. 46. 19.   3. 17. 14. 946. 16. 10.   5.]

[11.   3.   3.   5. 10.   6.   2. 926.   4.   3.]

[2.   2.   7.   1.   9.   2.   1.   2. 922.   2.]

[4. 11.   7.   4.   8.   4.   2. 18.   3. 954.]]

Test set: Average loss: 0.2747, **Accuracy:** 9263/10000 (93%)

Part 1 Question 4

My major takeaway from the above activity is to always start with the simplest model for the problem at hand, so that we can set a baseline (accuracy) which is also the suggested approach according to occam's razor. The simplest model can consist of a single linear layer along with a softmax activation function and mostly commonly used values for metaparameters. We can then start to add a layer and vary the number of hidden nodes at the hidden layer to see how well the model can fit the data before adding any more layers.

Part a

When talking about accuracy we can see from the above results that the CNN network performs best to perform the image classification task as the convolutional layers extract more features from the images which can then be learned in fully connected layers part of the network. While increasing the number of hidden nodes in the hidden layer of fully connected 2-layer network did not have any effect on the accuracy. CNN network hits 93% accuracy consistently.

Part b

If we do a comparison between the three confusion matrixes, we notice that the diagonal values are increasing as we move from NetLin towards NetConv indicating the increase in the performance of the model. As if we look at NetLin confusion matrix, we see that the confusion matrix has high values when it makes a prediction of 2 for target values of 1,3,4,5,6,8,9 characters and it is possible that the model will most likely make a wrong prediction for these characters.

If we look at the confusion matrix for NetFull model, the diagonal values have increased and the most likely character this model might classify wrong is 5 where the model is predicting 2.

Part c

NetLin

1) **Learning rate** = 0.1 **num_hid** = 10
   Test set: Average loss: 1.3255, **Accuracy:** 6722/10000 (67%)
2) **Learning rate** = 0.001 **num_hid** = 10
   Test set: Average loss: 1.0467, **Accuracy:** 6725/10000 (67%)

1) **Num_id** = 500
   Test set: Average loss: 1.0096, **Accuracy:** 6972/10000 (70%)
2) **Num_id** = 1000
   Test set: Average loss: 1.0101, **Accuracy:** 6960/10000 (70%)
3) **Num_id** = 1500
   Test set: Average loss: 1.0096, **Accuracy:** 6971/10000 (70%)

   First I changed the learning rate parameter while keeping the number of hidden nodes same to try to see if our model is not stuck in a local minima but as you can see from the above result that it decreased the accuracy rather than increasing it which means 0.01 learning rate is performing best for this model. Second parameter I changed for this model is number of hidden

nodes while keeping learning rate to 0.01 and it turns out there is no change from my original result and therefore it could mean that our model is not complex enough to learn and generalize better.

NetFull

1) **Learning rate** = 0.1 **num_hid** = 500
   Test set: Average loss: 0.4343, **Accuracy:** 8936/10000 (89%)
2) **Learning rate** = 0.001 **num_id =** 500
   Test set: Average loss: 0.4978, **Accuracy:** 8489/10000 (85%)

First I tried to change the number of hidden nodes as you can refer Part 1 Question 2 had no change in the accuracy of the model which could mean that the model might be getting stuck in a local minima and therefore I changed the learning rate to 0.1 which proved to improve the accuracy while changing the learning rate to 0.0001 proved to be slower when compared with other learning rates hence had less accuracy than before.

NetConv

1) **Conv2d in-channels** = 1 **Conv2d out-channels** = 4
   Conv2d in-channels = 4 **Conv2d out-channels** = 6
   Test set: Average loss: 0.4224, **Accuracy:** 8769/10000 (88%)

2) **Conv2d in-channels** = 1 **Conv2d out-channels** = 6
   Conv2d in-channels = 6 **Conv2d out-channels** = 12
   Test set: Average loss: 0.3663, **Accuracy:** 9023/10000 (90%)

While keeping kernel size of convolutional layers to 5 and max pooling of kernel size to 2, we can see as we increase the number of out-channels of the convolutional layer the accuracy of the model is increasing which is the result of more features for the fully connected layers to learn.

Part 2 Question 2

Num_hid = 6

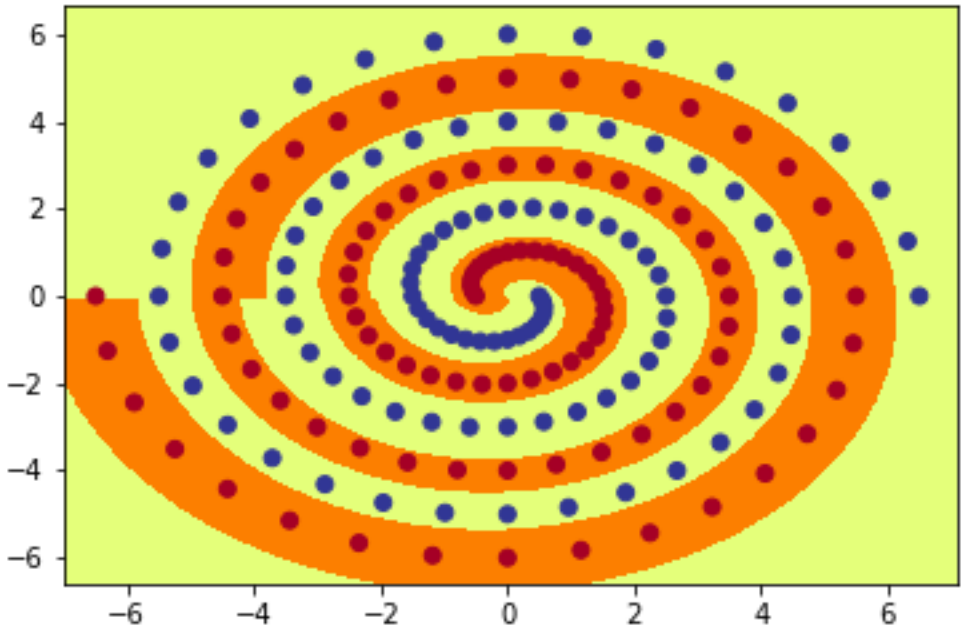
Training no	**Epoch No**	**Percentage (%)**
1	14400	100
2	6500	100
3	17500	100
4	3400	100
5	20,000	98.48
6	6300	100

7	20,000	98.48
8	20,000	91.75
9	5900	100
10	20,000	99.48

Num_hid = 7

Training no	**Epoch No**	**Percentage (%)**
1	20,000	91.75
2	12100	100
3	4100	100
4	5300	100
5	20,000	77.84
6	10400	100
7	9200	100
8	5000	100
9	11800	100
10	20,000	91.75

The minimum number of hidden nodes in hidden layer of PolarNet which enables the model to learn to correctly classify all the training data within 20000 epochs, on almost all runs are 7. We can see that 7 number of hidden nodes model correctly classifies all the training data within 20000 epochs 7/10 times.



Part 2 Question 4

Learning Rate = 0.01 **Number of hidden nodes** = 10 are constant for all runs in this section.

Initial weight size = 0.1

Training No	**Epochs**	**Percentage (%)**
1	20,000	92.27
2	20,000	50.52
3	20,000	53.61
4	20,000	53.61
5	20,000	53.61
6	4,600	100
7	9,300	100
8	17,000	100
9	6,800	100
10	20,000	50.52

Initial weight size = 0.2

Training No	Epochs	Percentage (%)
1	6700	100
2	20,000	97.94
3	20,000	98.94
4	9,800	100
5	20,000	97.94
6	6,800	100
7	11,700	100
8	9,100	100
9	5,700	100
10	10,100	100

Initial weight size = 0.3

Training No	Epochs	Percentage (%)
1	20,000	92.27
2	20,000	97.94
3	20,000	97.94
4	20,000	97.94
5	20,000	97.42
6	20,000	96.91
7	20,000	99.84
8	20,000	99.48
9	20,000	96.39
10	10,000	100

Initial weight size = 0.01

Training No	Epochs	Percentage (%)
1	20,000	50.52
2	20,000	50.52
3	20,000	50.52
4	20,000	50.52

5	20,000	50.52
6	20,000	50.52
7	20,000	50.52
8	20,000	50.52
9	20,000	50.52
10	20,000	50.52

Initial weight size = 0.001

Training No	**Epochs**	**Percentage (%)**
1	20,000	50.52
2	20,000	50.52
3	20,000	50.52
4	20,000	50.52
5	20,000	50.52

Initial weight size = 0.25

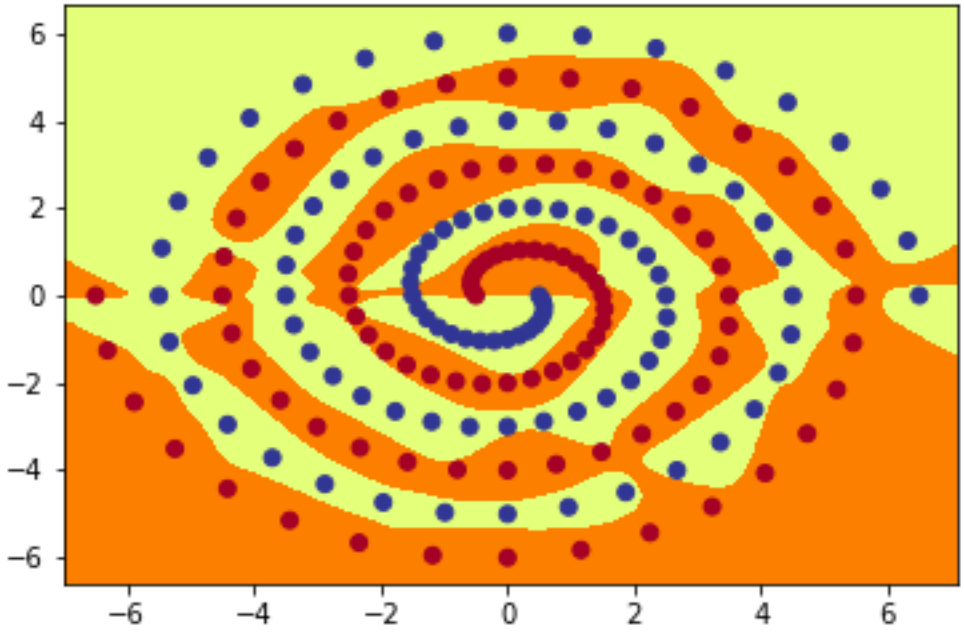
Training No	**Epochs**	**Percentage (%)**
1	20,000	96.39
2	20,000	98.45
3	9,700	100
4	20,000	94.85
5	20,000	89.69
6	8,300	100
7	20,000	99.48
8	20.000	94.85

Initial weight size = 0.21

Training No	**Epochs**	**Percentage (%)**
1	7,900	100
2	4,900	100
3	8,000	100
4	20,000	98.97

5	4,100	100
6	20,000	95.88
7	8,700	100
8	9,000	100
9	9,300	100
10	20,000	97.42

The minimum size of initial weights which enables the model to learn to correctly classify all the training data within 20000 epochs, on almost all runs are 0.21. We can see that 0.21 size of initial weight gives correctly classifies all the training examples within 20,000 epochs 7/10 times.



Part 2 Question 6

Num_hid = 5

Initial weight = 0.1

Training No	**Epochs**	**Percentage (%)**
1	20,000	94.85
2	20,000	99.85

3	20,000	88.66
4	20,000	87.63
5	20,000	76.80
6	20,000	87.63
7	20,000	90.72
8	20,000	83.51
9	20,000	83.51
10	20,000	83.51

Num_hid = 5

Initial weight = 0.2

Training No	**Epochs**	**Percentage (%)**
1	20,000	91.24
2	20,000	92.78
3	20,000	75.77
4	20,000	83.51
5	20,000	78.35
6	20,000	94.85
7	20,000	93.30
8	20,000	77.32
9	20,000	94.85
10	20,000	86.60

Num_hid = 5

Initial weight = 0.3

Training No	**Epochs**	**Percentage (%)**
1	20,000	82.47
2	20,000	73.20
3	20,000	82.47
4	20,000	83.51
5	20,000	84.02
6	6400	100

7	20,000	89.69
8	20,000	84.54
9	20,000	74.74
10	20,000	71.13

Num_hid = 5

Initial weight = 0.01

Training No	**Epochs**	**Percentage (%)**
1	20,000	86.60
2	20,000	50.52
3	19,100	100
4	20,000	80.93
5	20,000	50.52
6	20,000	50.52

Num_hid = 5

Initial weight = 0.001

Training No	**Epochs**	**Percentage (%)**
1	20,000	50.52
2	20,000	91.75
3	20,000	87.63
4	20,000	84.02
5	20,000	50.52

Num_hid = 5

Initial weight = 0.21

Training No	**Epochs**	**Percentage (%)**
1	20,000	79.38
2	20,000	90.72
3	20,000	88.66
4	20,000	86.60
5	20,000	84.54

Num_hid = 5

Initial weight = 0.25

Training No	Epochs	Percentage (%)
1	20,000	97.94
2	20,000	77.32
3	20,000	96.91
4	20,000	74.74
5	5,500	94.85
6	20,000	91.75

Num_hid = 6

Initial weight = 0.1

Training No	Epochs	Percentage (%)
1	20,000	94.85
2	20,000	99.48
3	9,900	100
4	8,200	100
5	17,300	100
6	20,000	84.54
7	20,000	90.72

Num_hid = 6

Initial weight = 0.2

Training No	Epochs	Percentage (%)
1	20,000	84.54
2	20,000	84.02
3	10,000	100
4	15,000	92.78
5	20,000	97.94

Num_hid = 6

Initial weight = 0.21

Training No	**Epochs**	**Percentage (%)**
1	20,000	86.08
2	20,000	91.75
3	20,000	82.47
4	20,000	93.81
5	10,200	100

Num_hid = 6

Initial weight = 0.25

Training No	**Epochs**	**Percentage (%)**
1	20,000	89.69
2	20,000	90.72
3	8,500	100
4	20,000	98.97
5	20,000	94.85

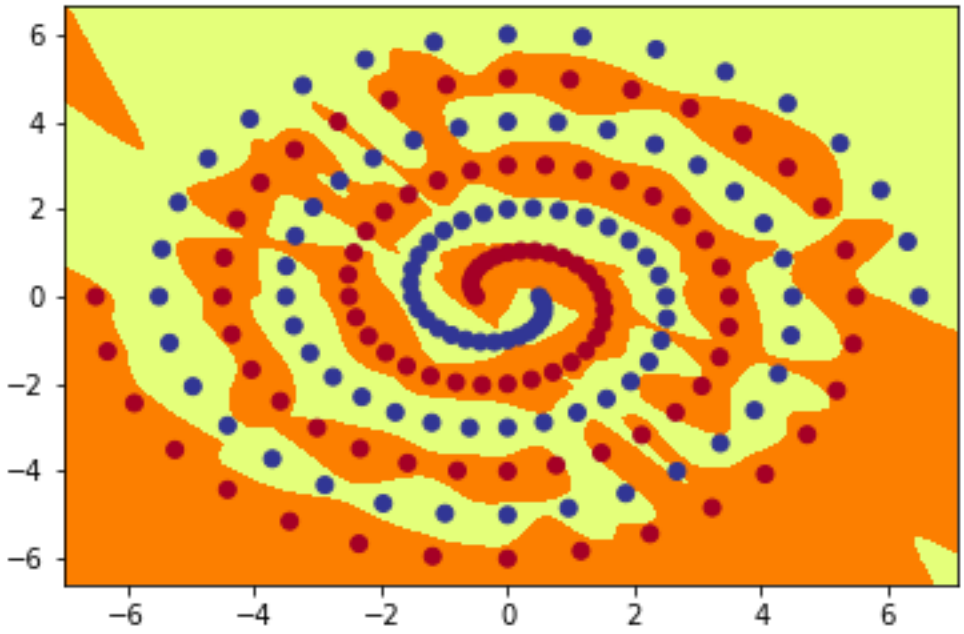
Num_hid = 7

Initial weight = 0.20

Training No	**Epochs**	**Percentage (%)**
1	11,900	100
2	9,000	100
3	12,700	100
4	9,300	100
5	20,000	92.78
6	20,000	92.78
7	8,300	100
8	20,000	94.33
9	3,900	100
10	9,200	100

The minimum number of hidden nodes and value of initial weight size which enables the model to learn to correctly classify all the training data within 20000 epochs, on almost all runs are 7 and 0.20. We can

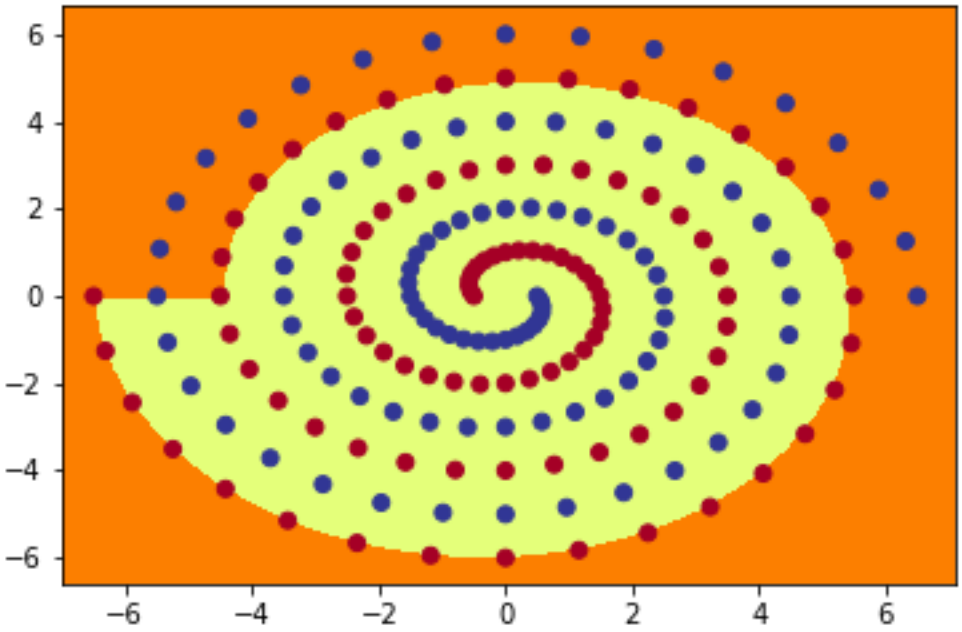
see that 7 number of hidden nodes correctly classifies all the training data within 20,000 epochs 7/10 times.



Part 2 Question 7

PolarNet

Layer 1 nodes in sequence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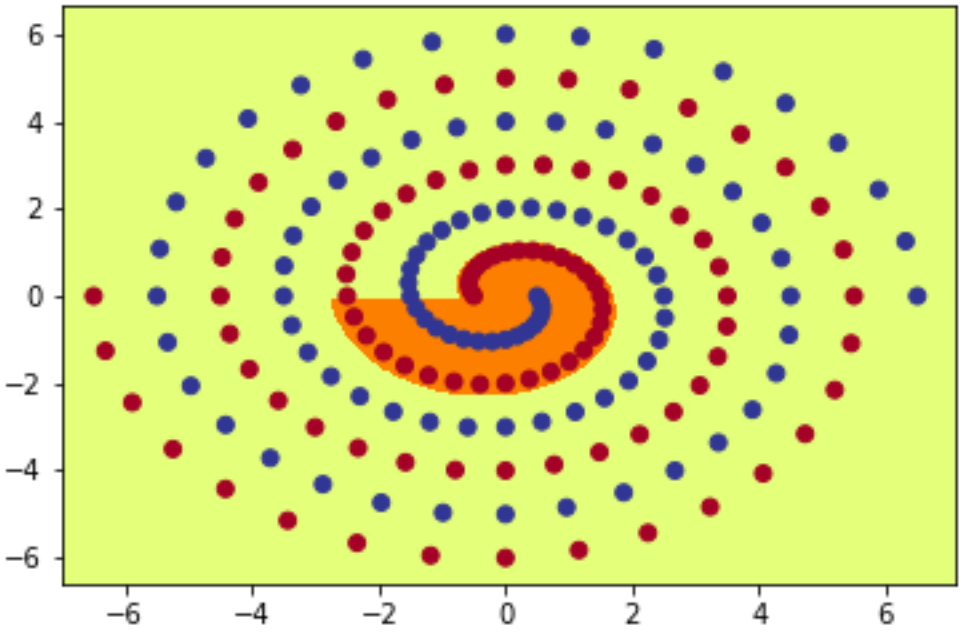
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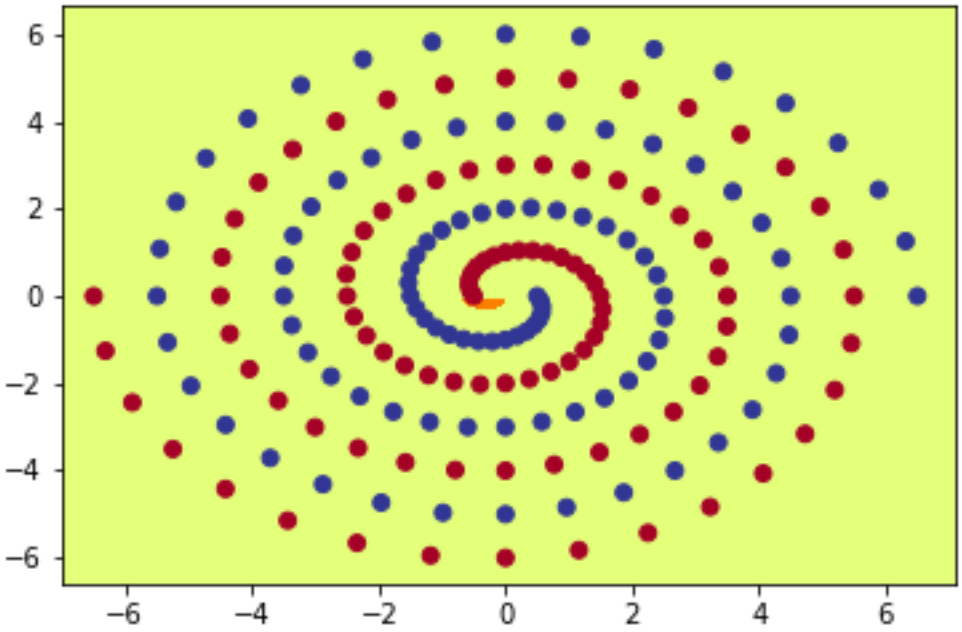
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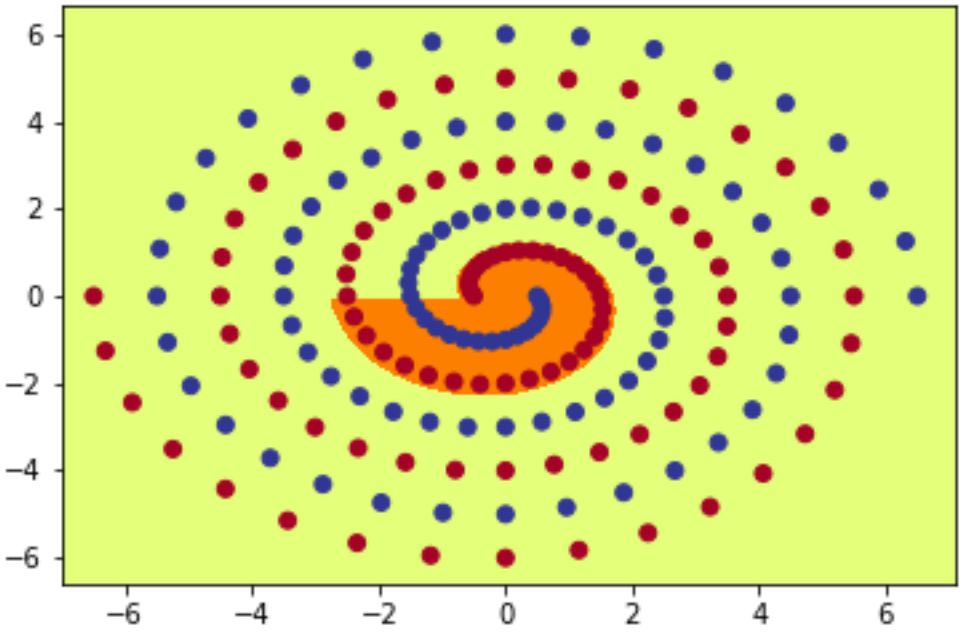
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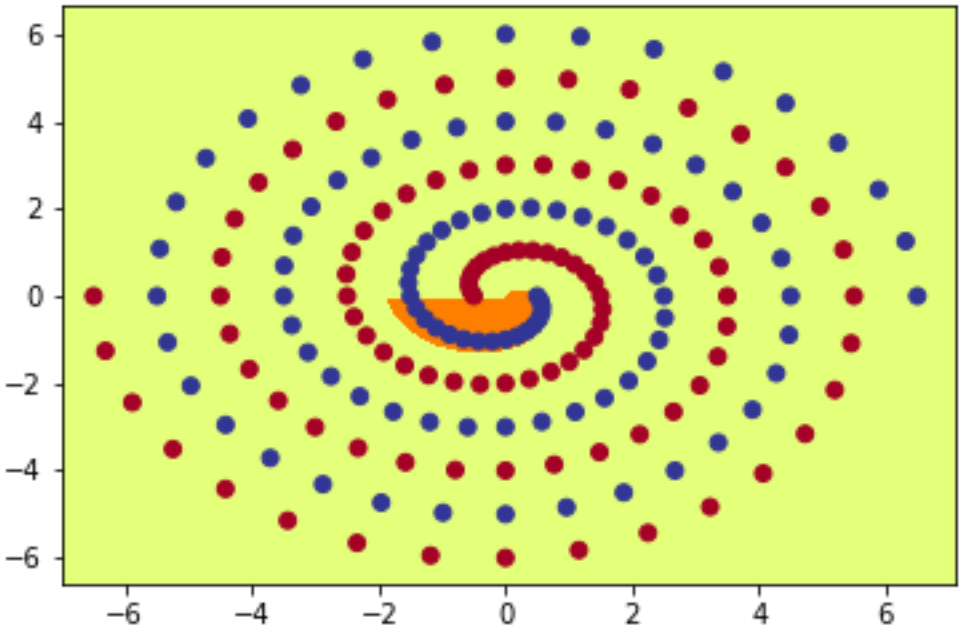
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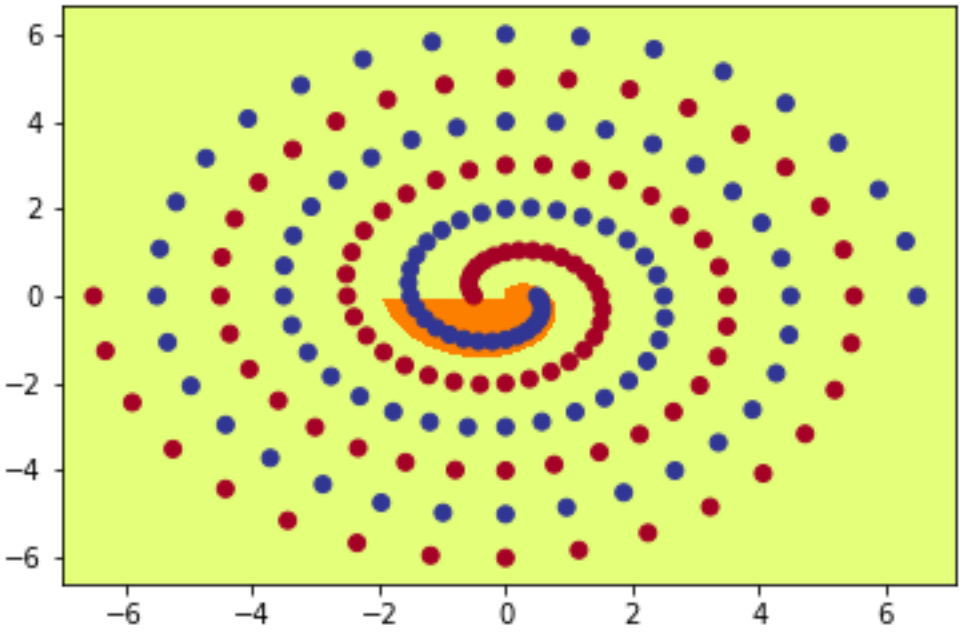
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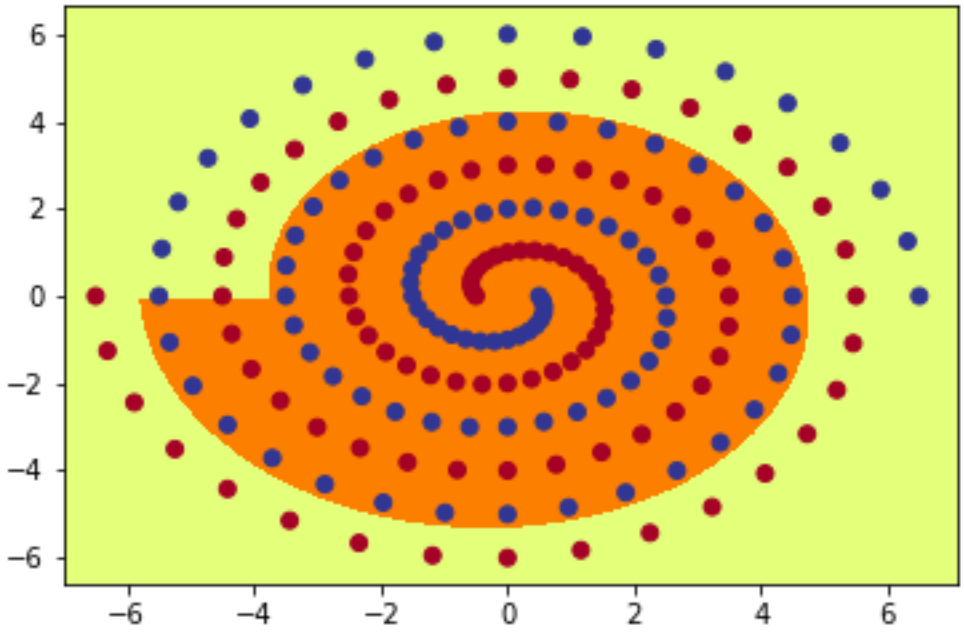
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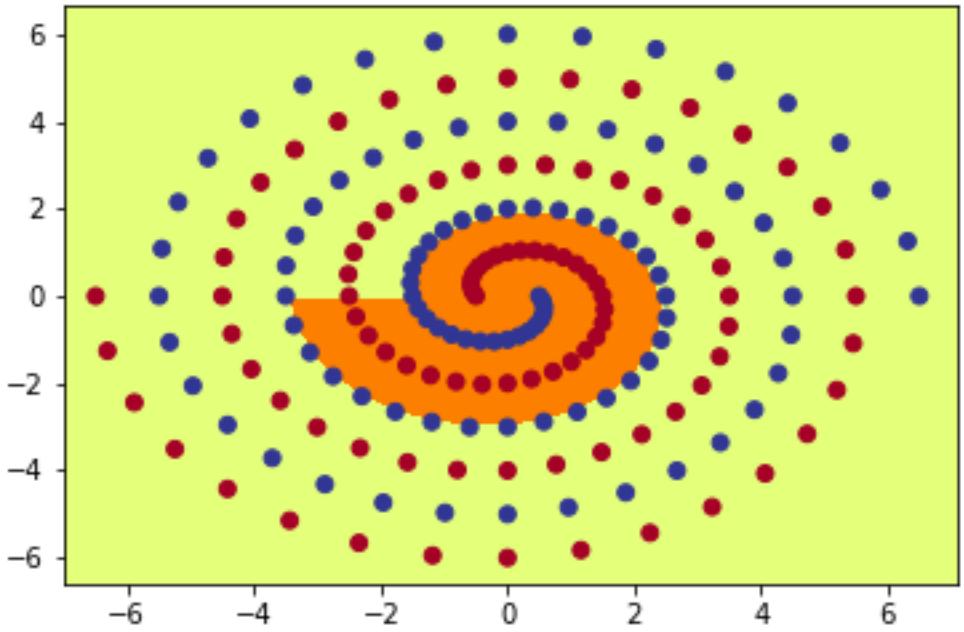
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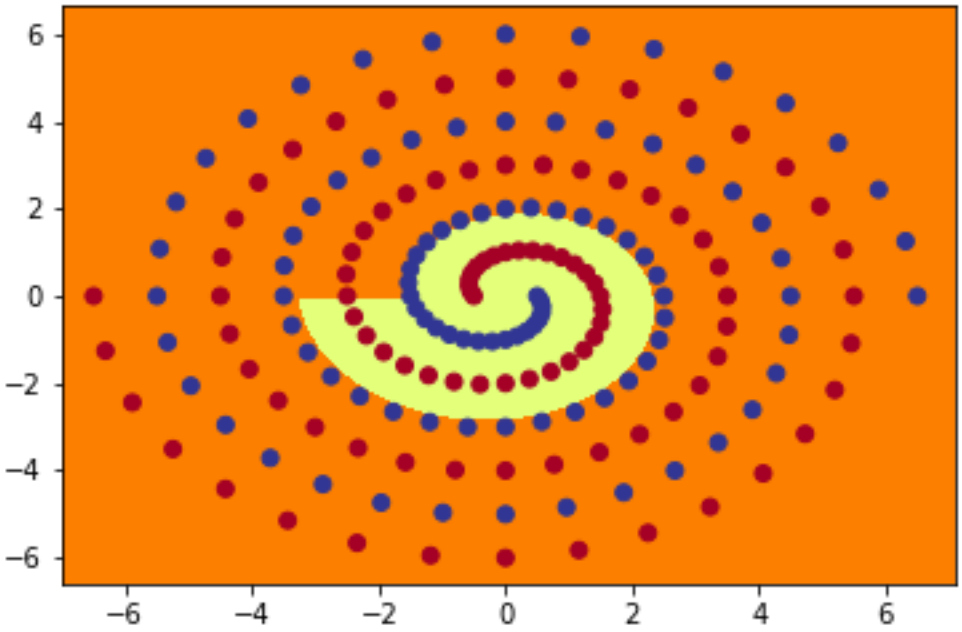
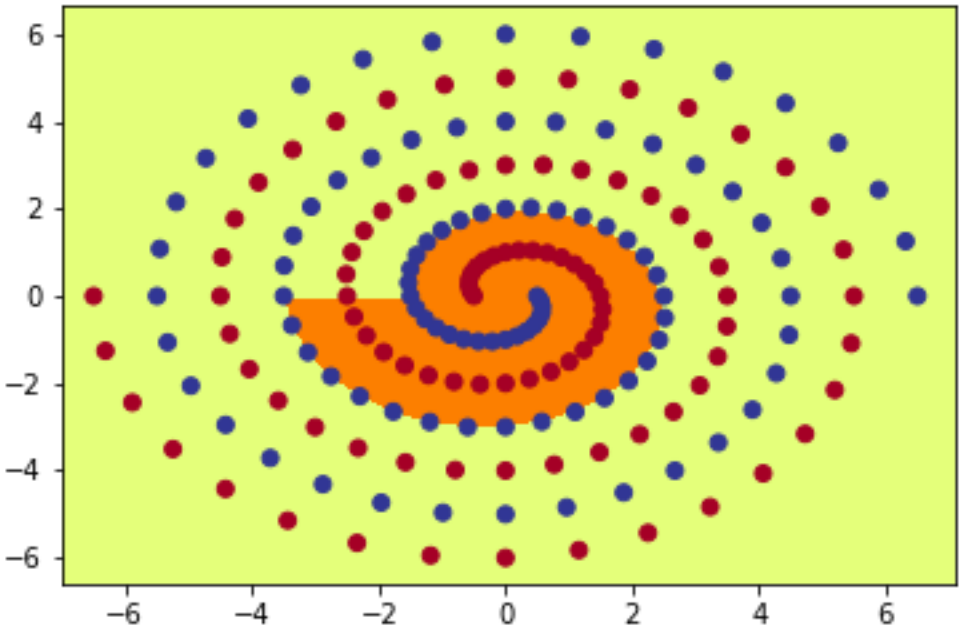
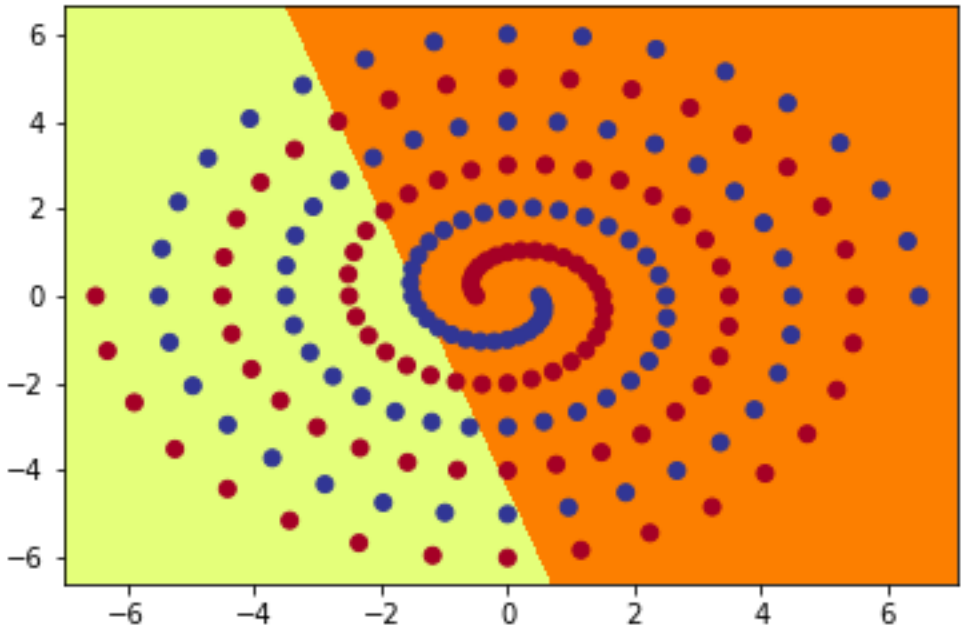




RawNet:

Layer 1 nodes in sequence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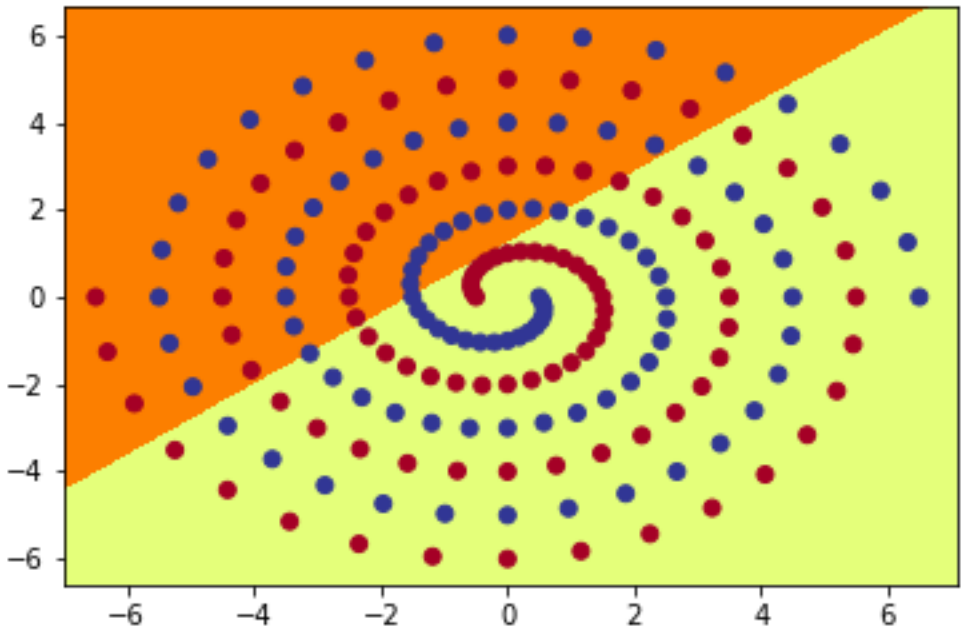
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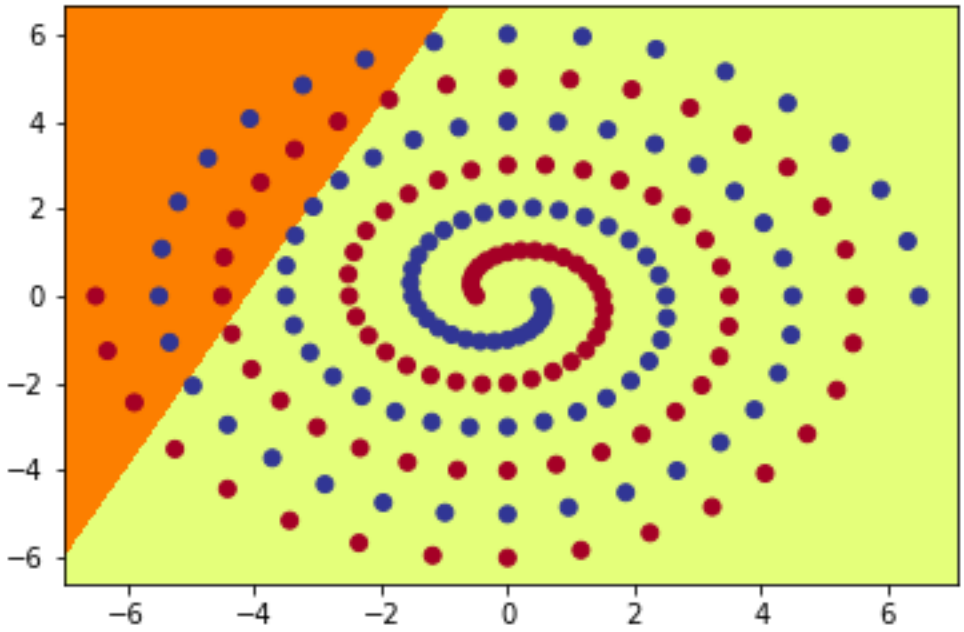
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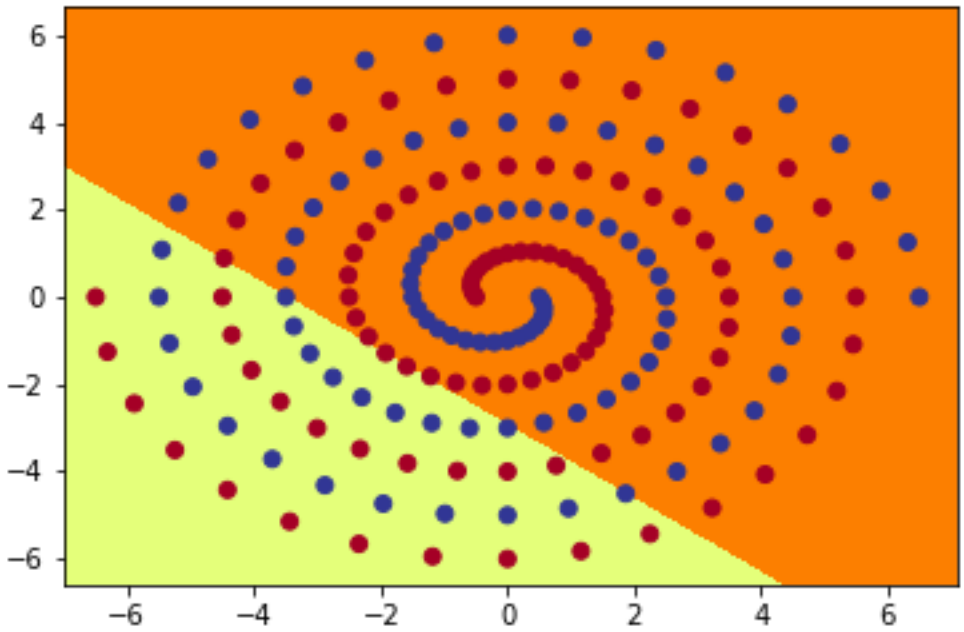
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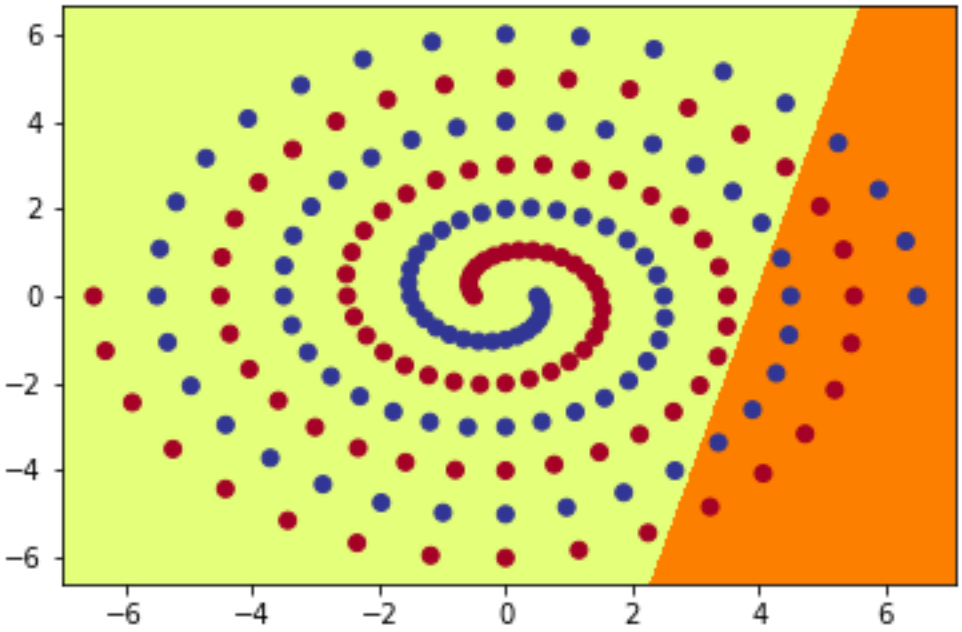
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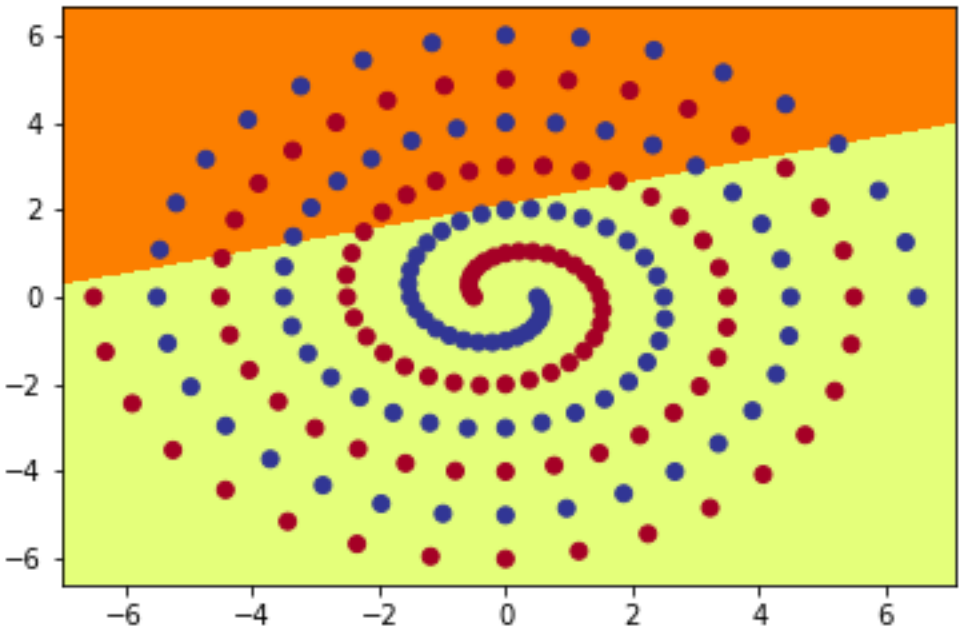
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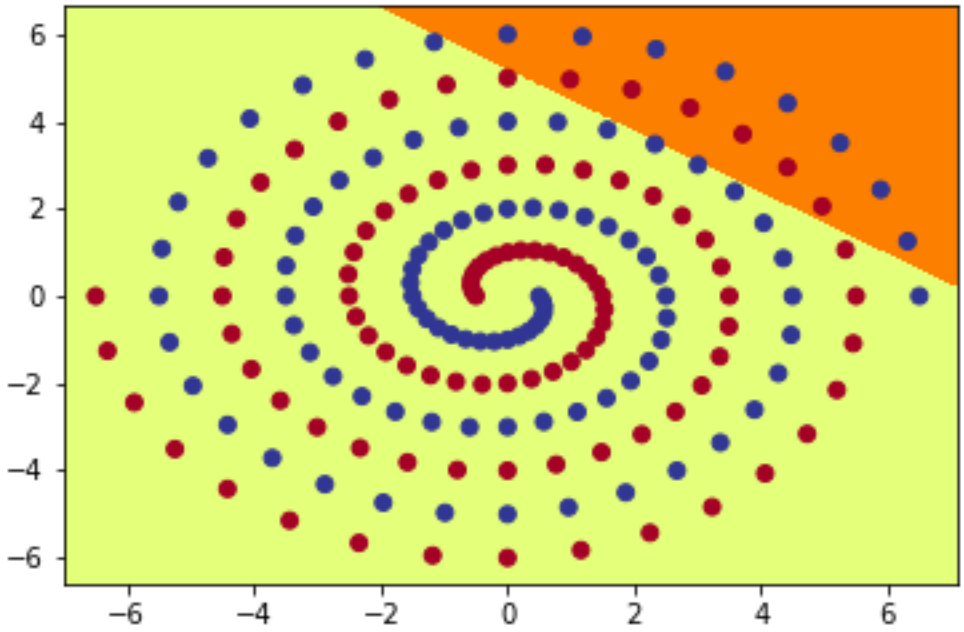
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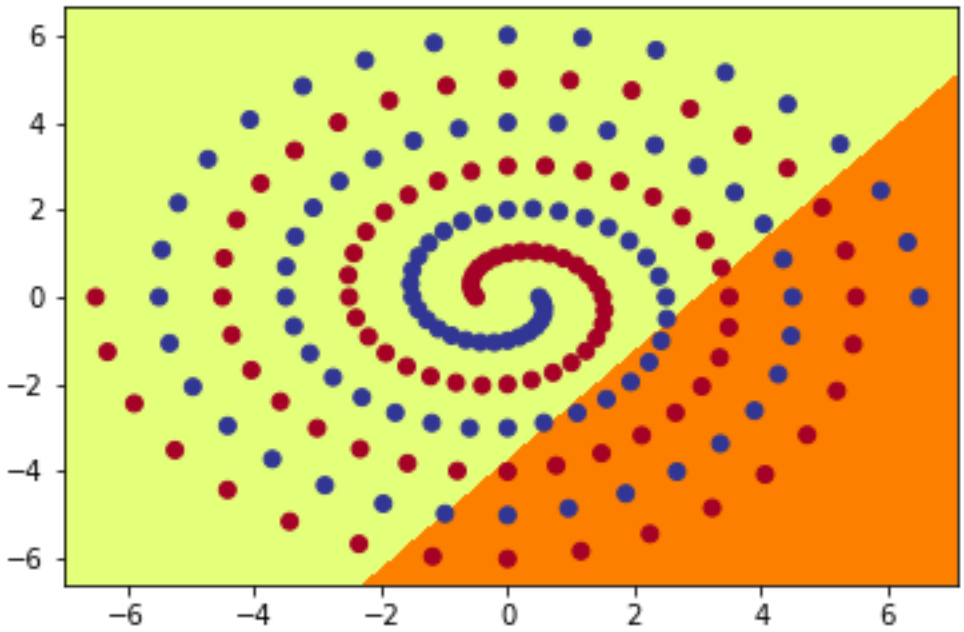
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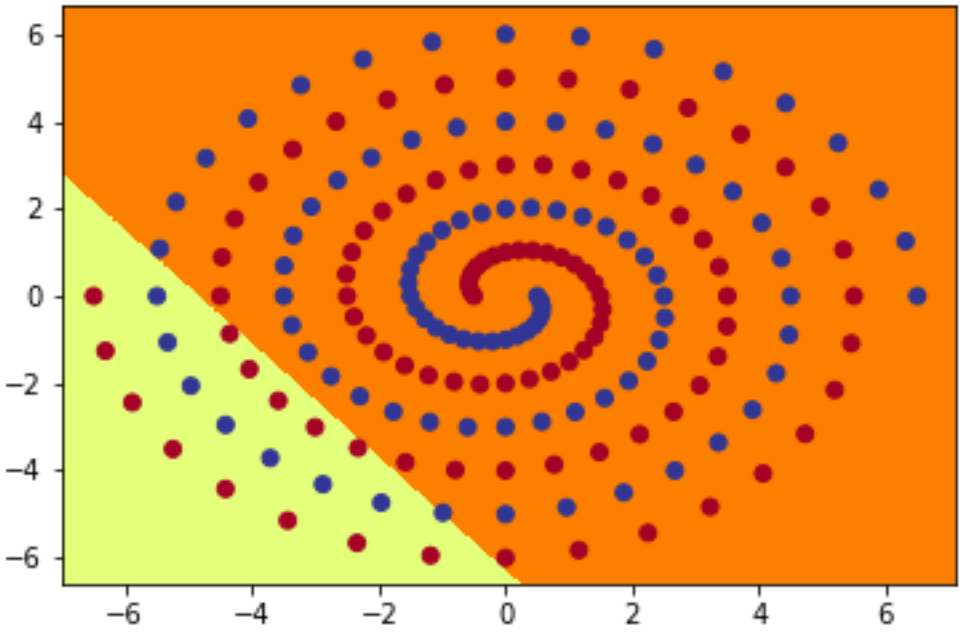

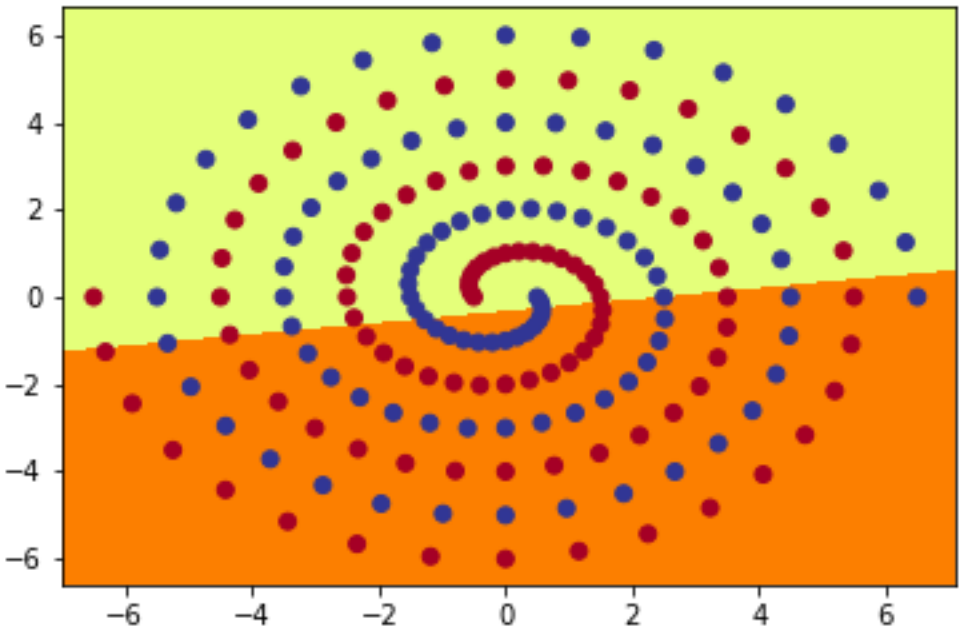

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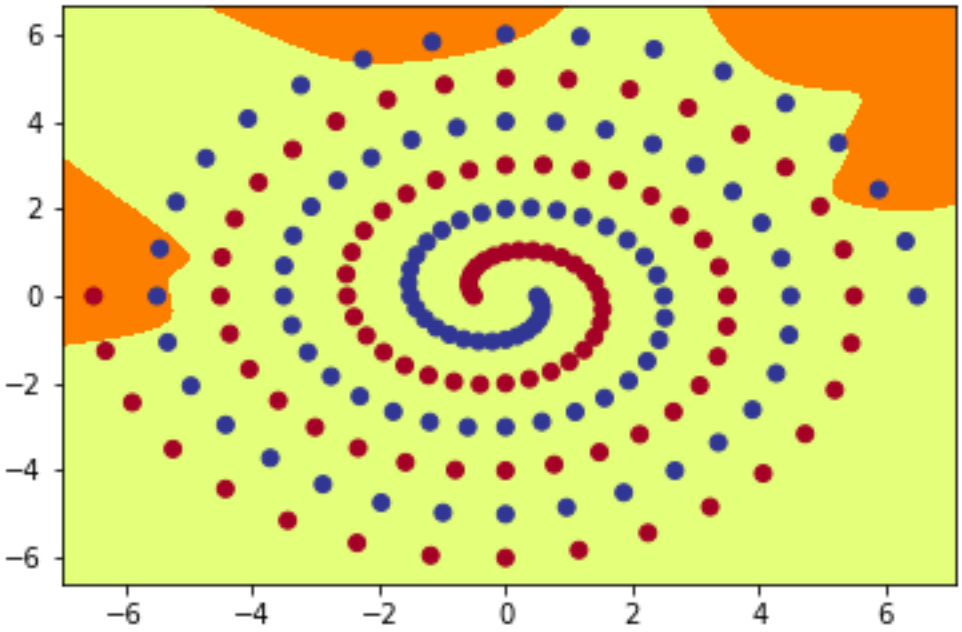
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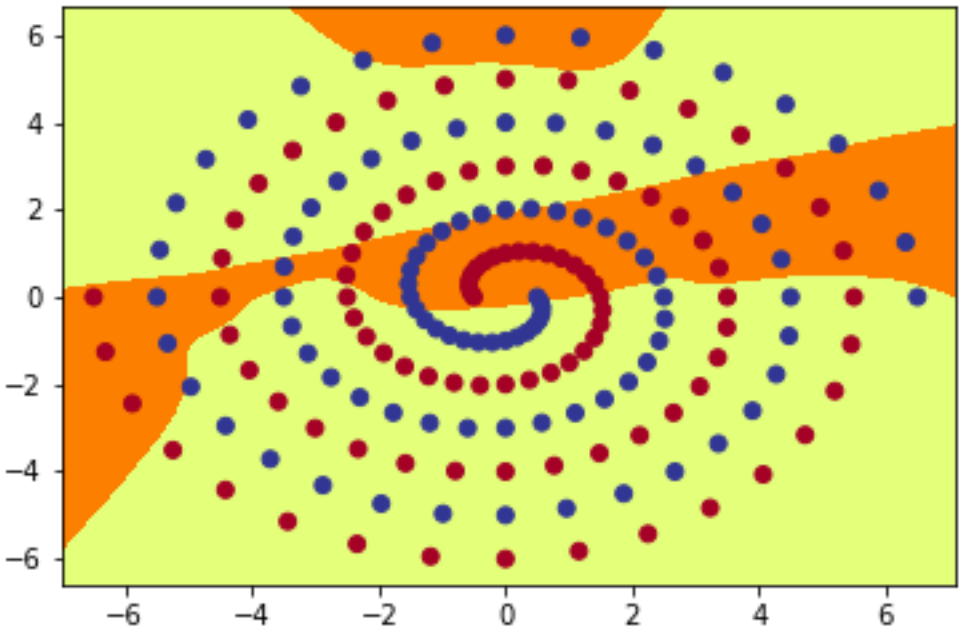
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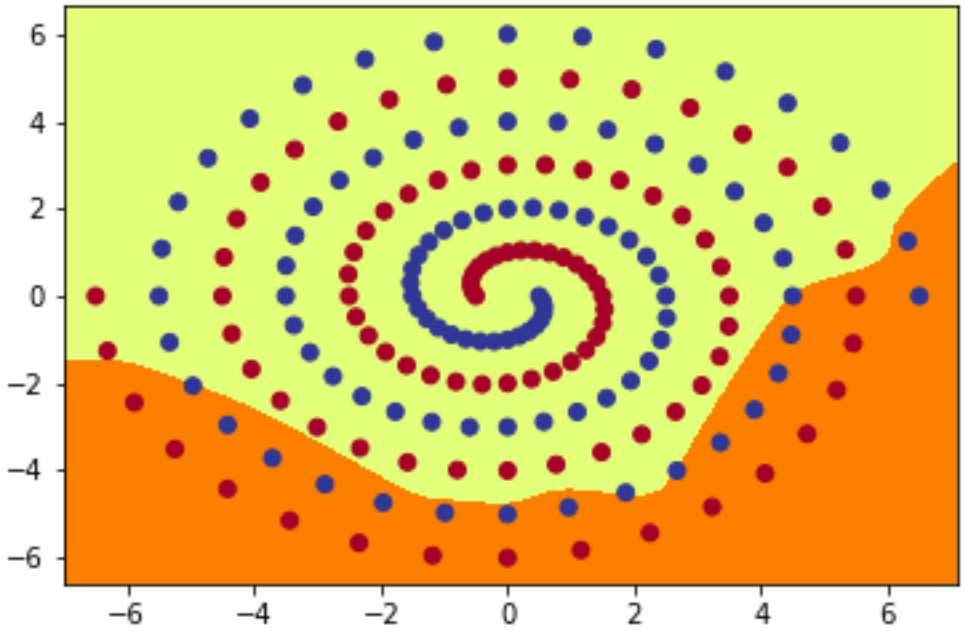
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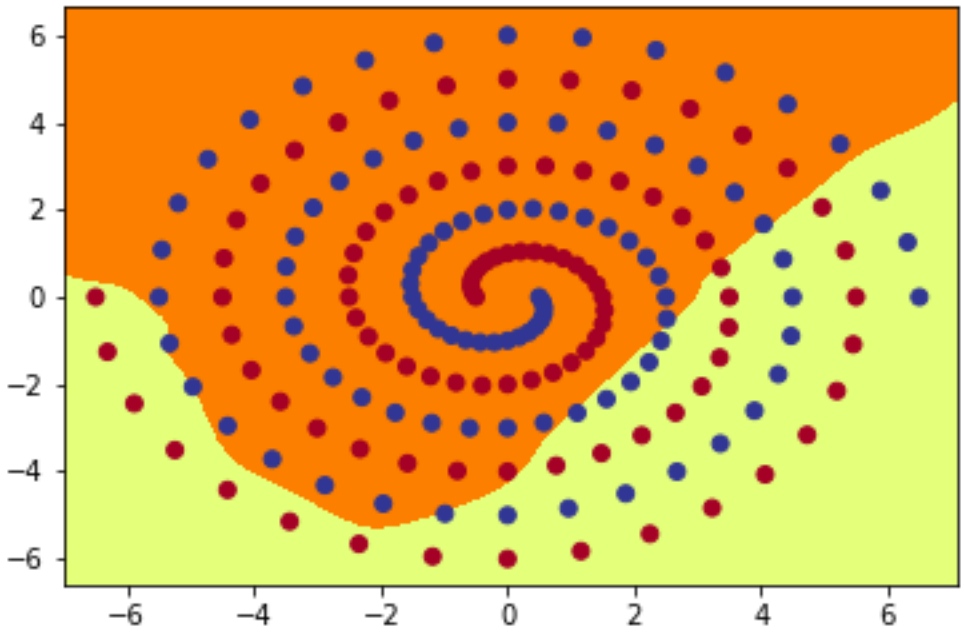
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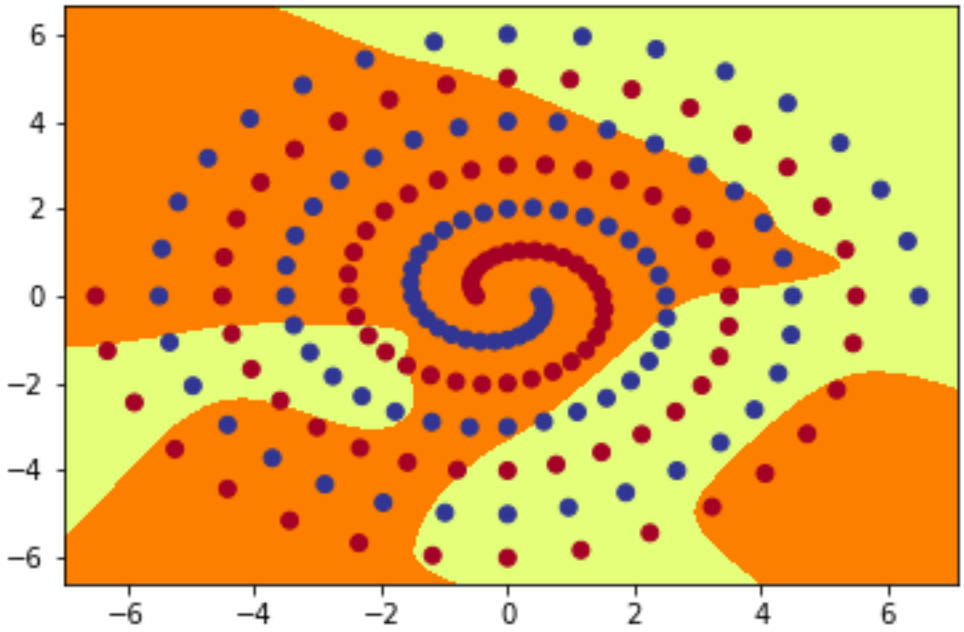
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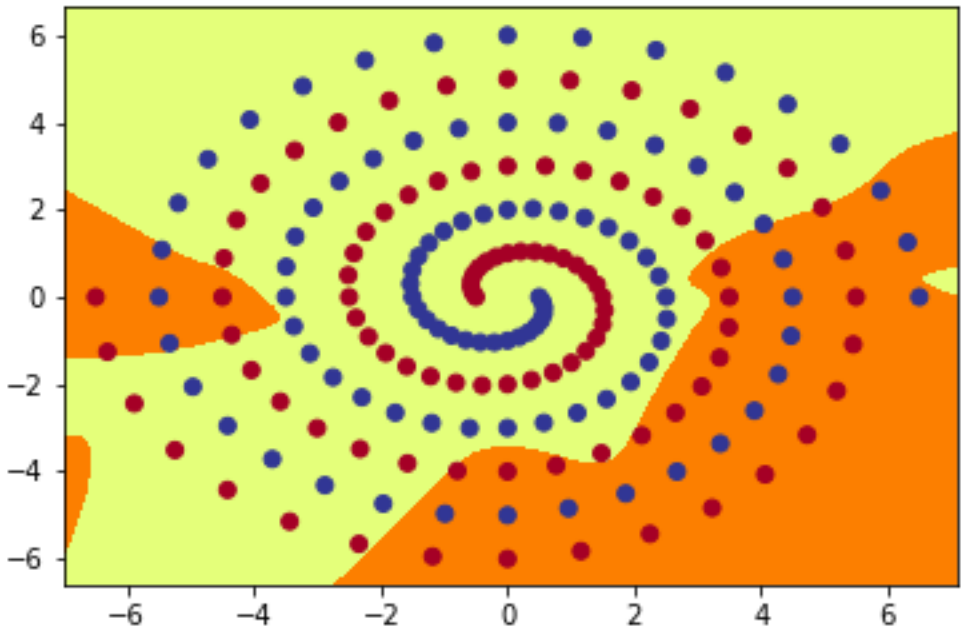
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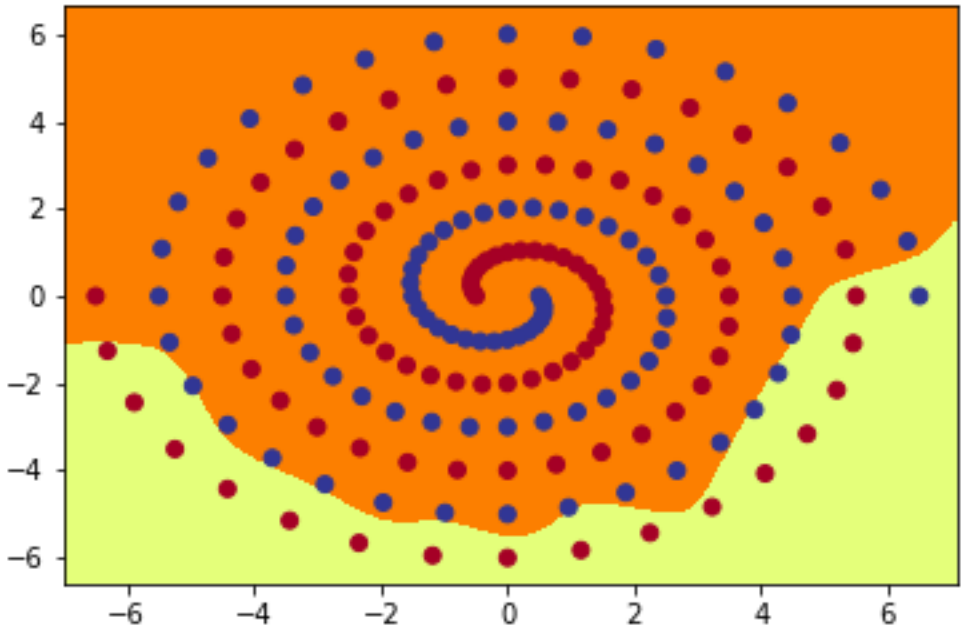
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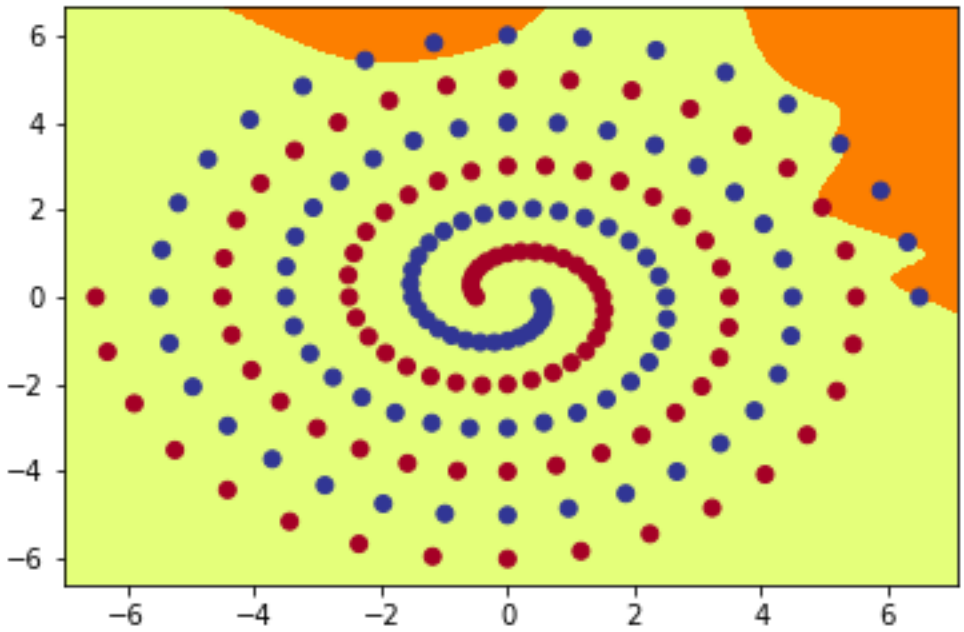
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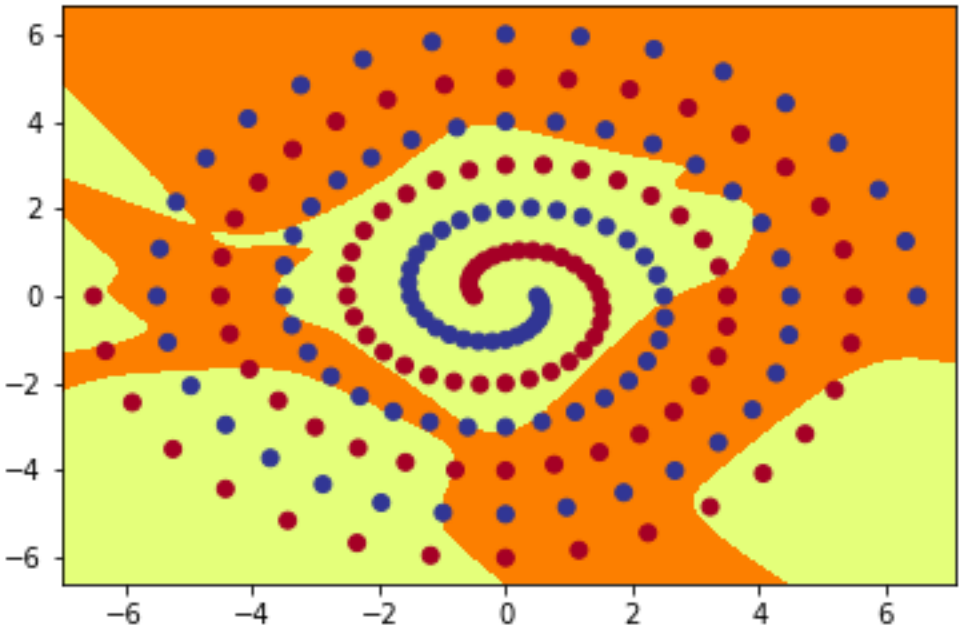

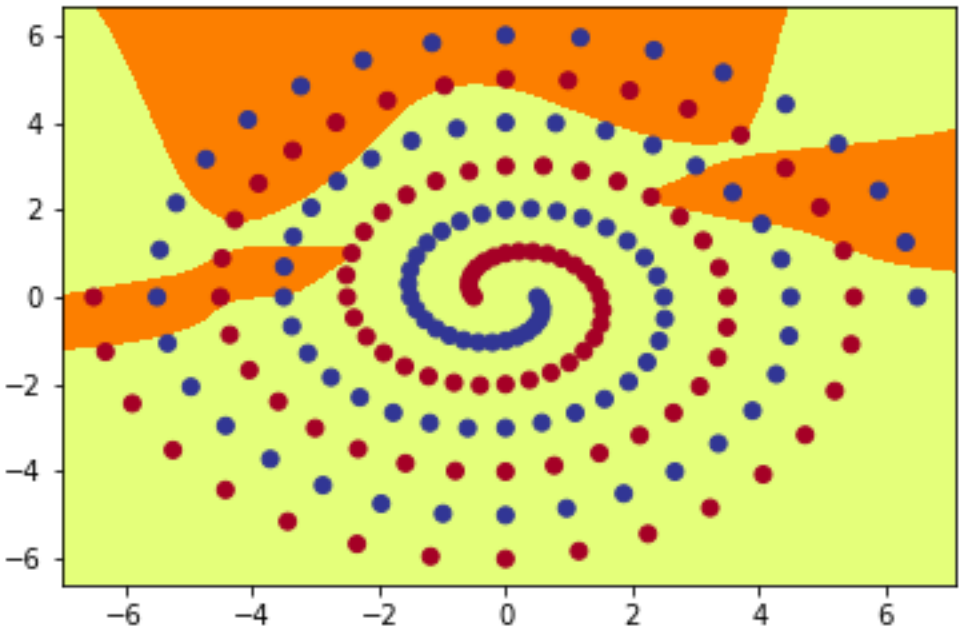

ShortNet:

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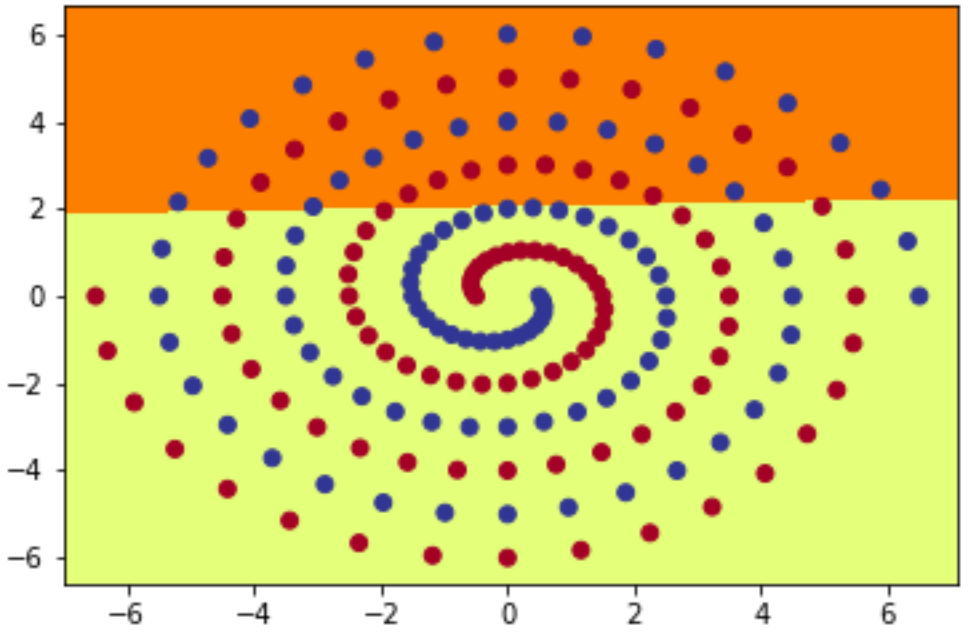
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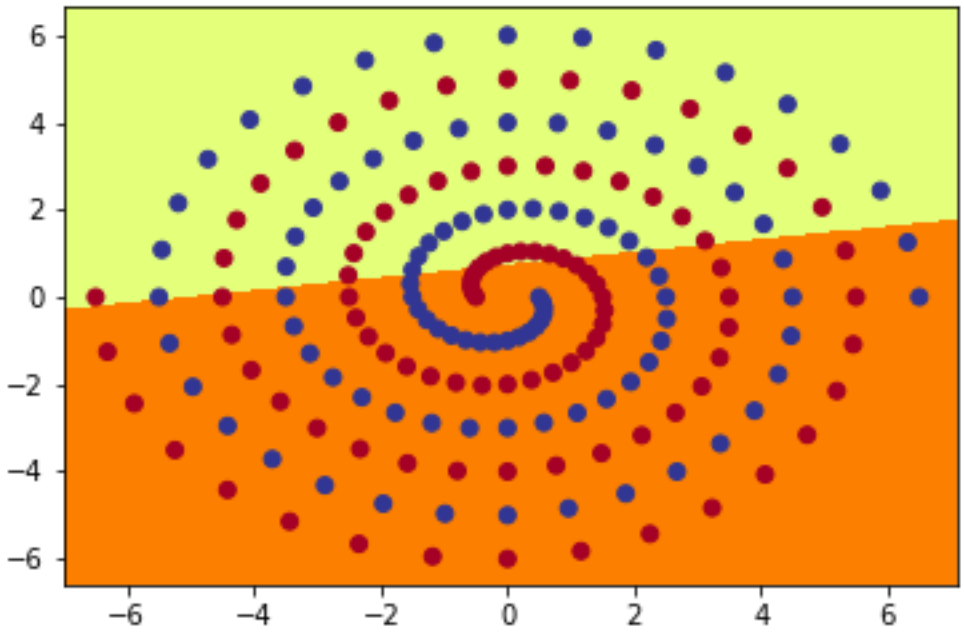
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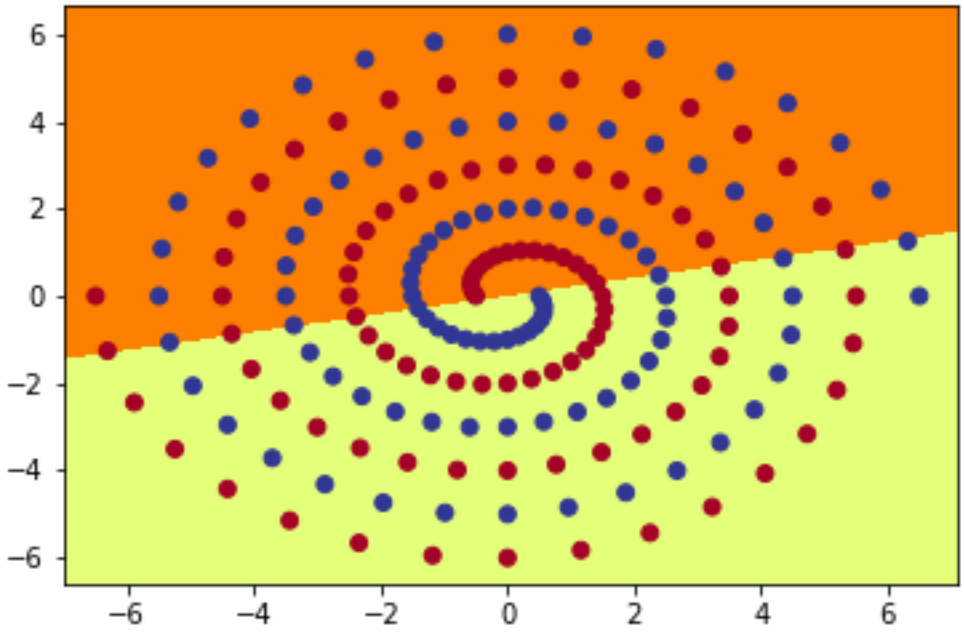
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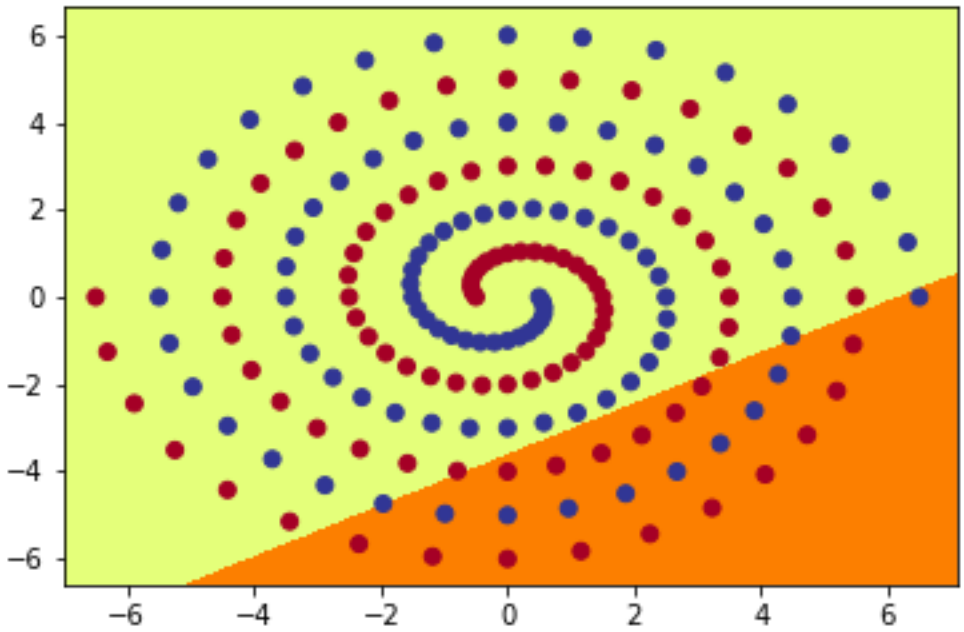
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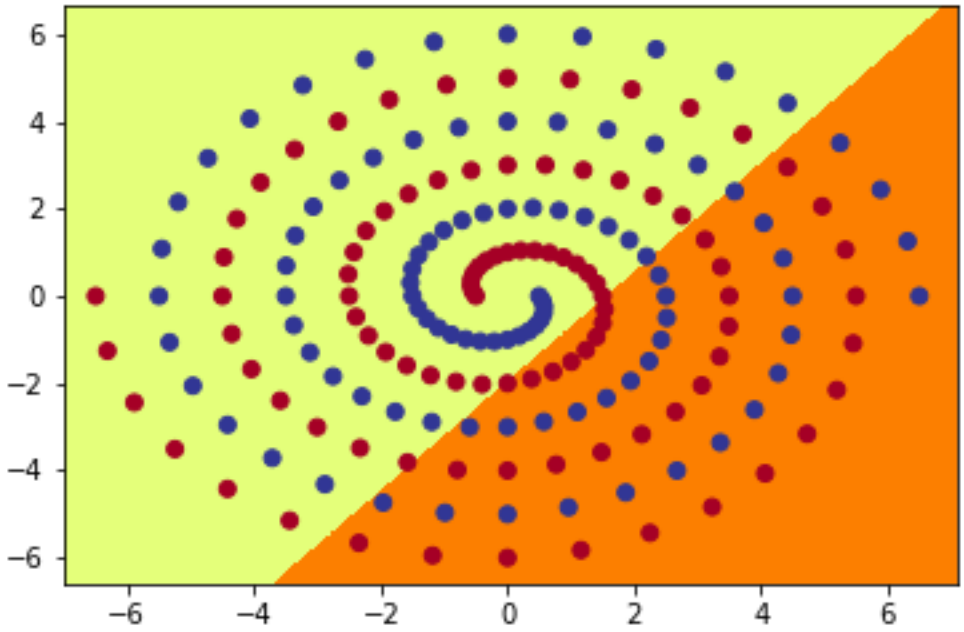
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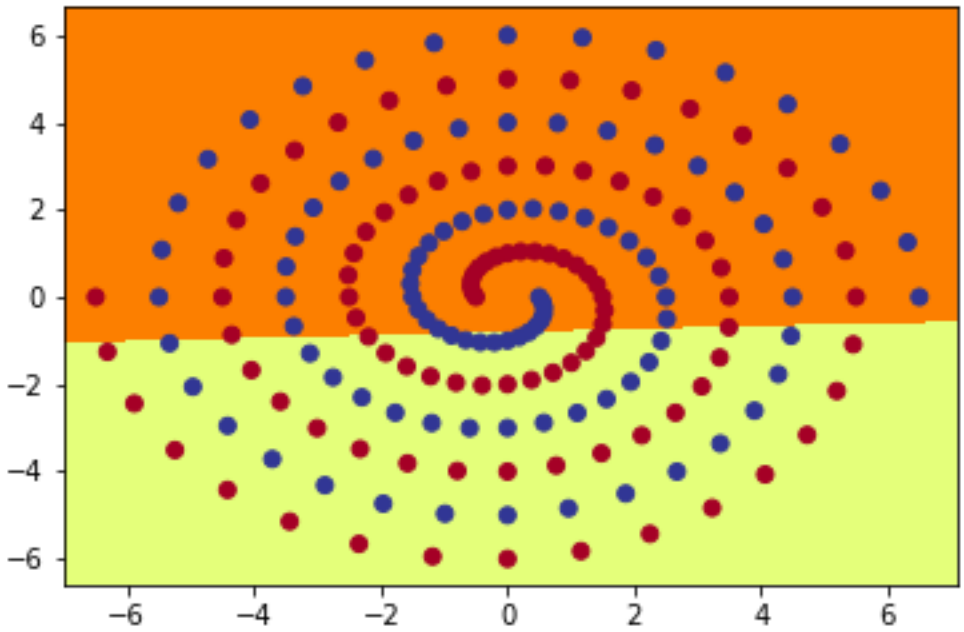
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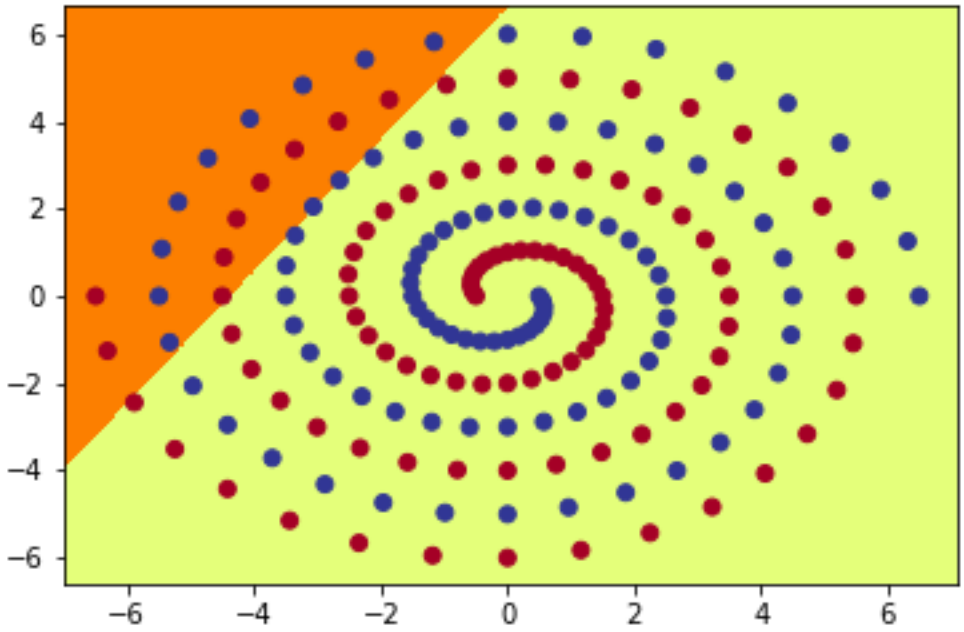
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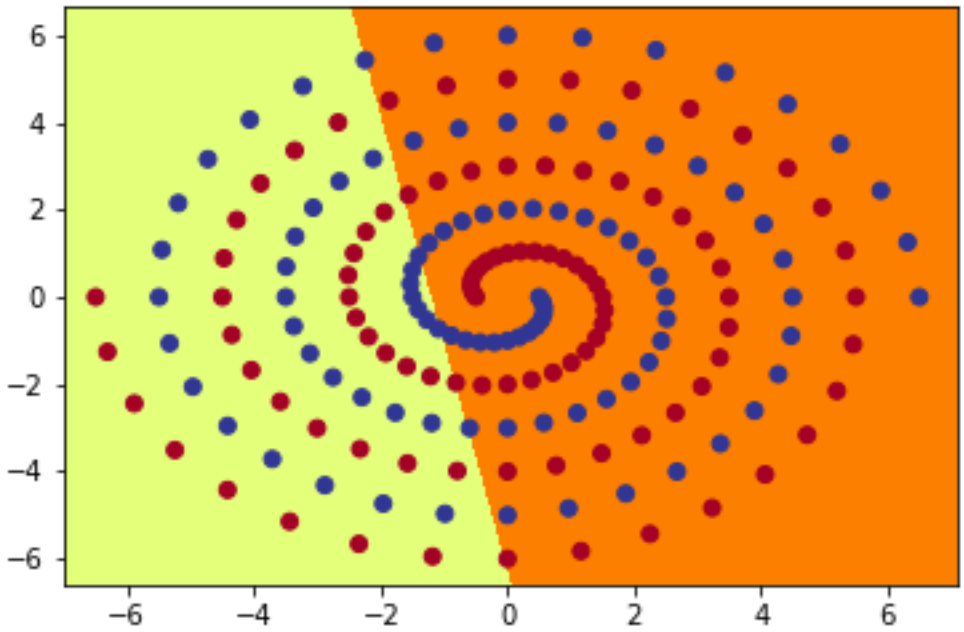
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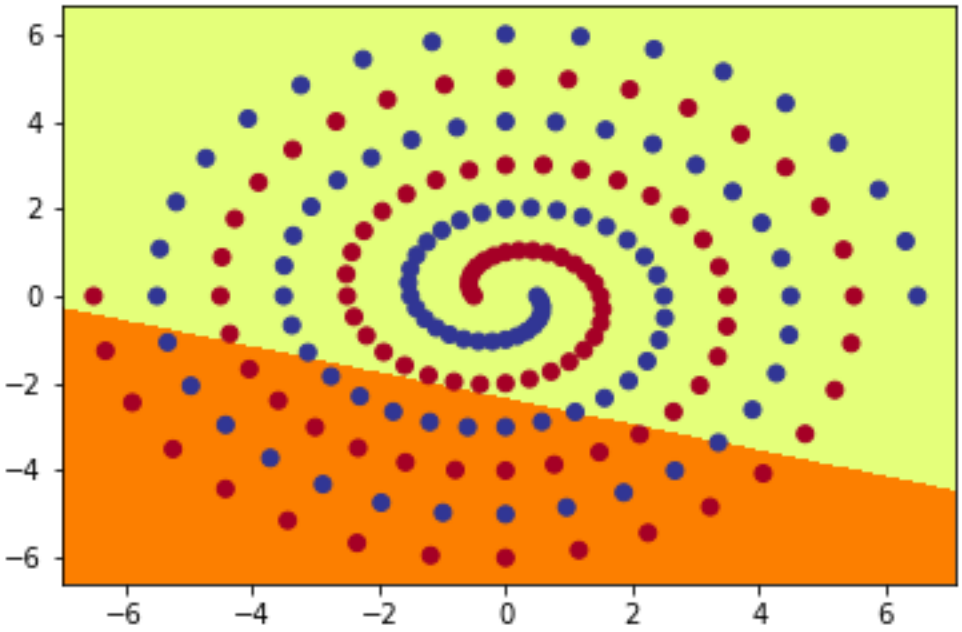

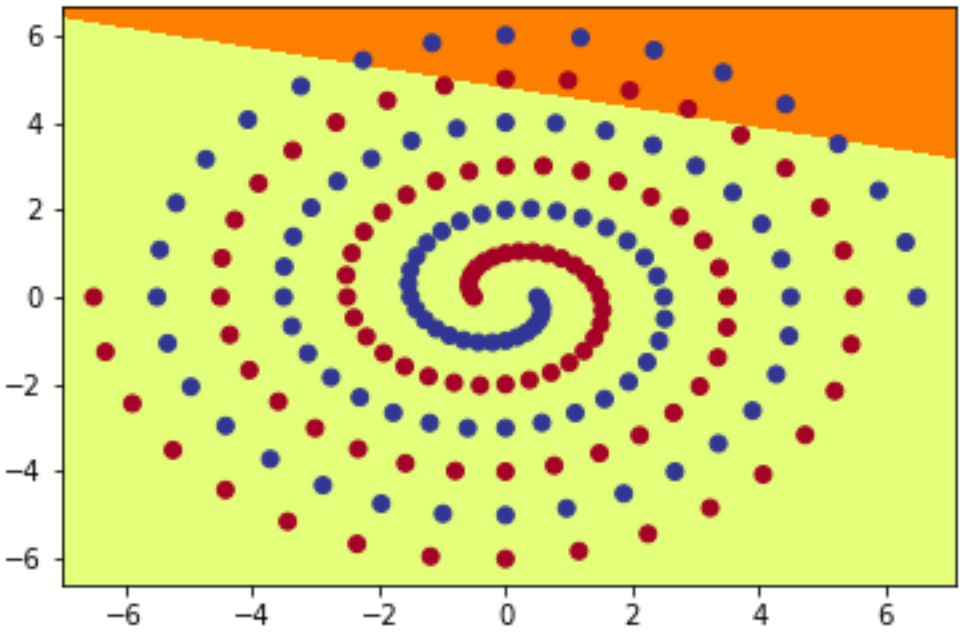

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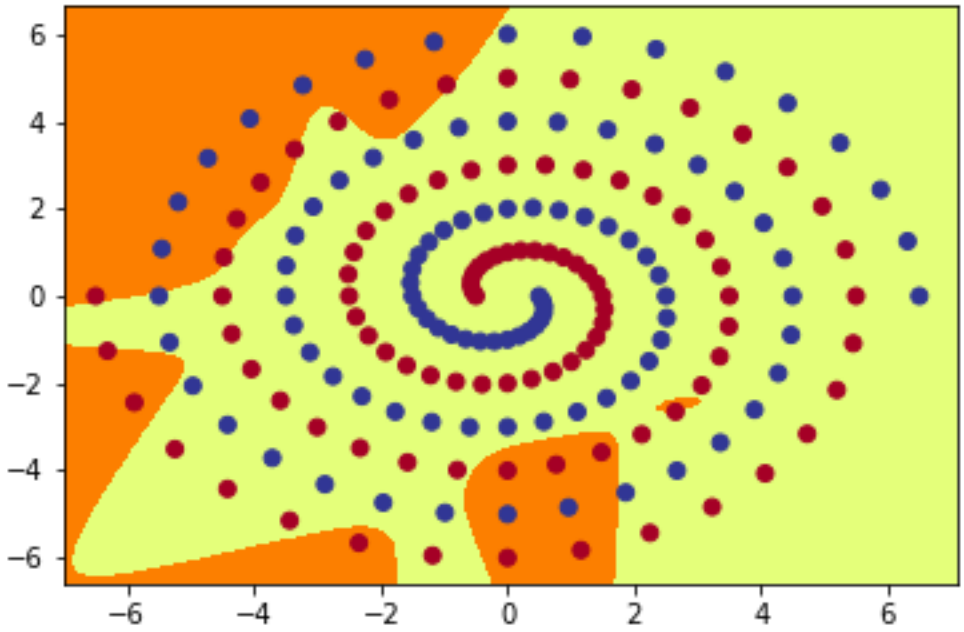
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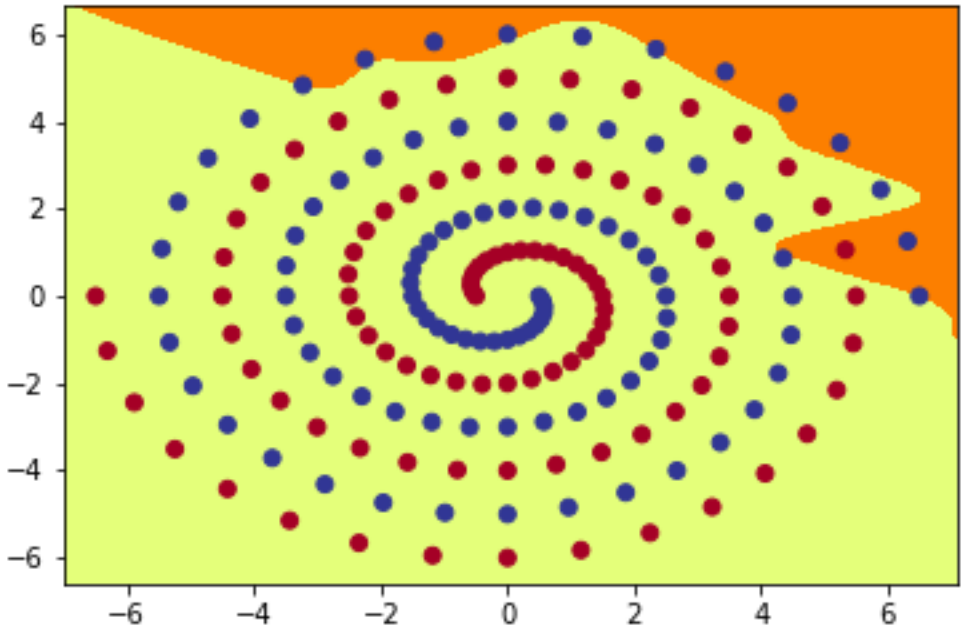
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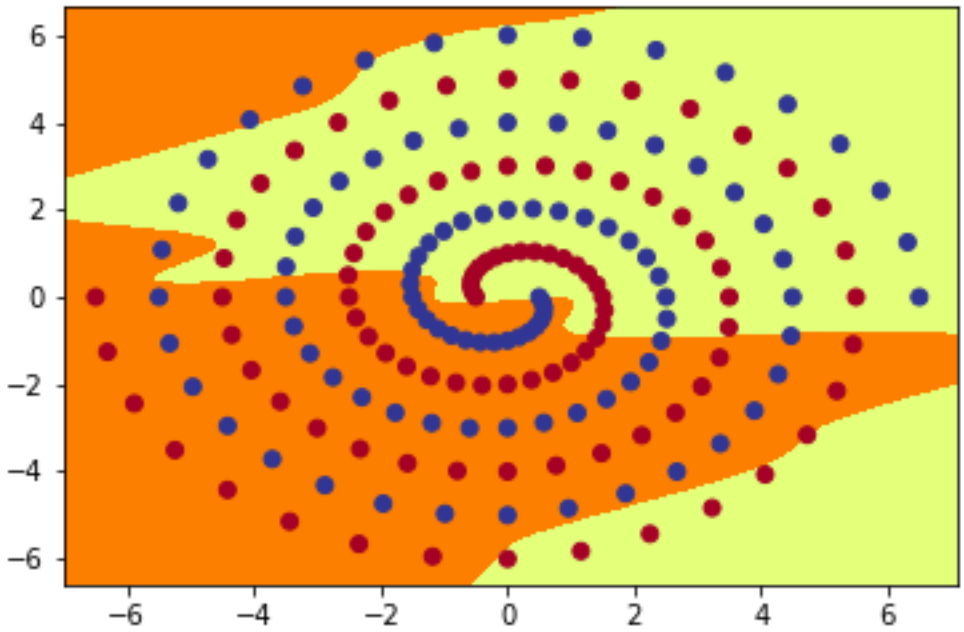
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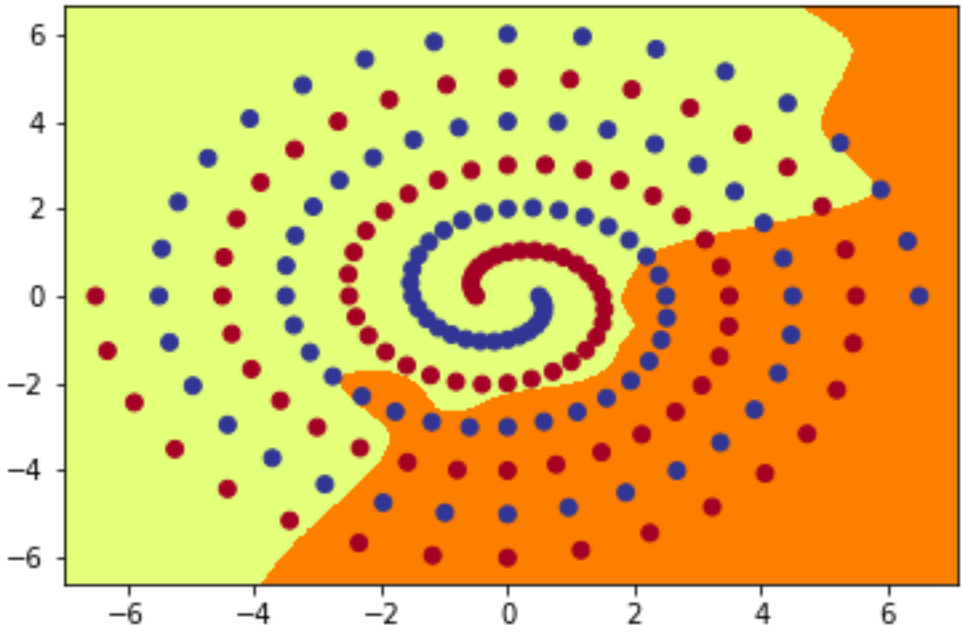
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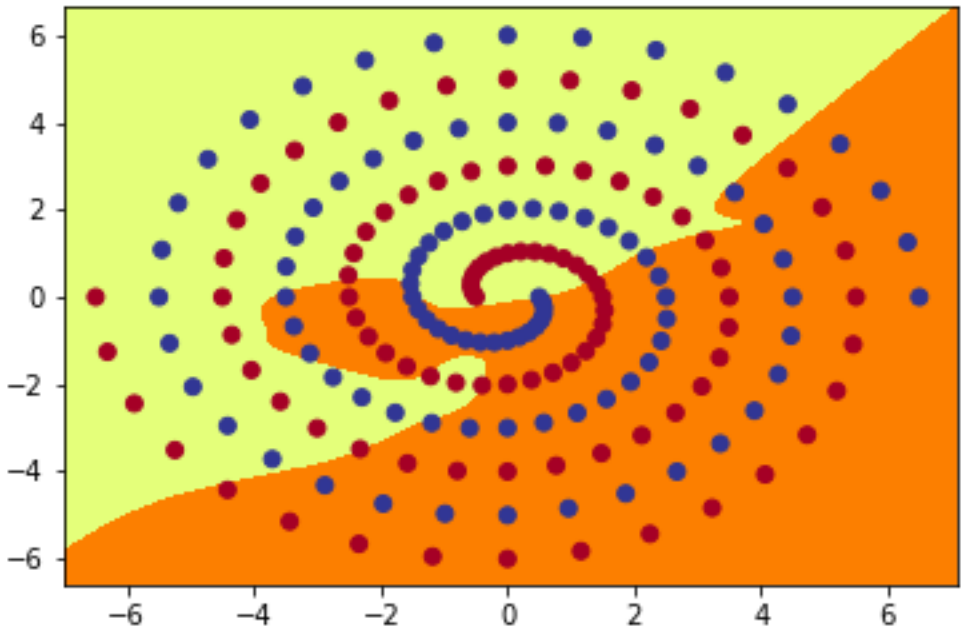
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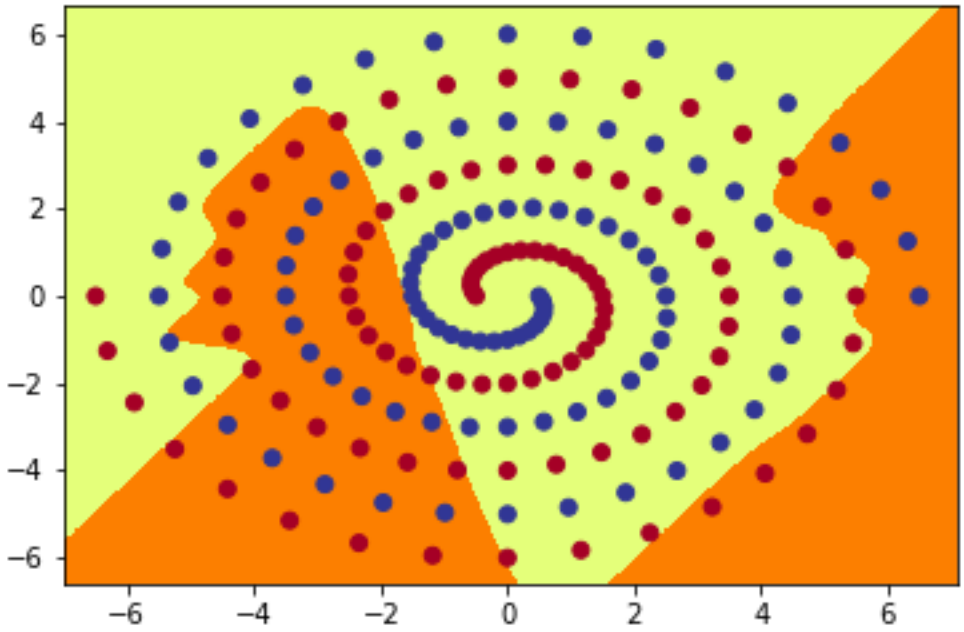
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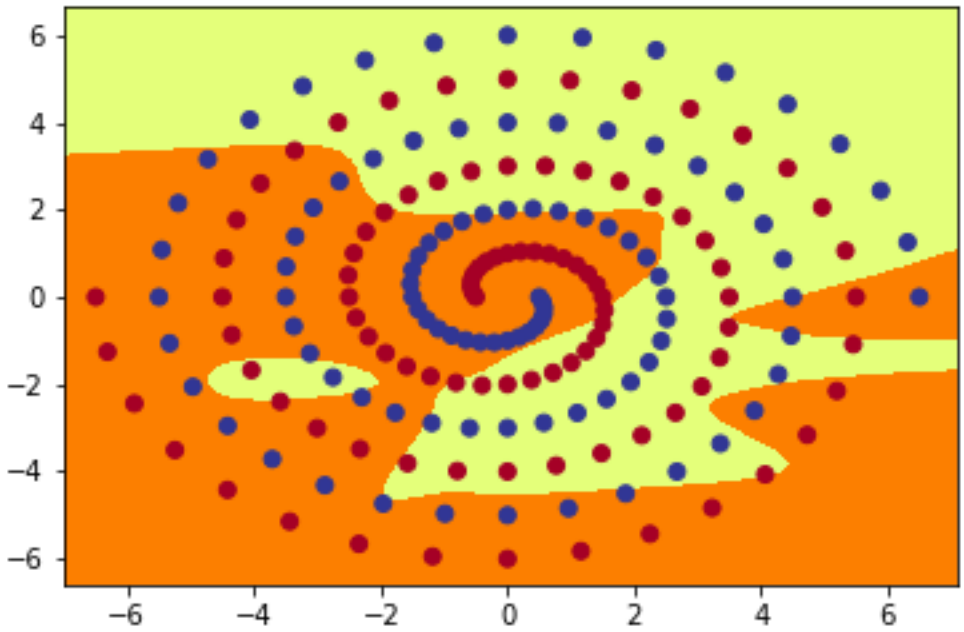
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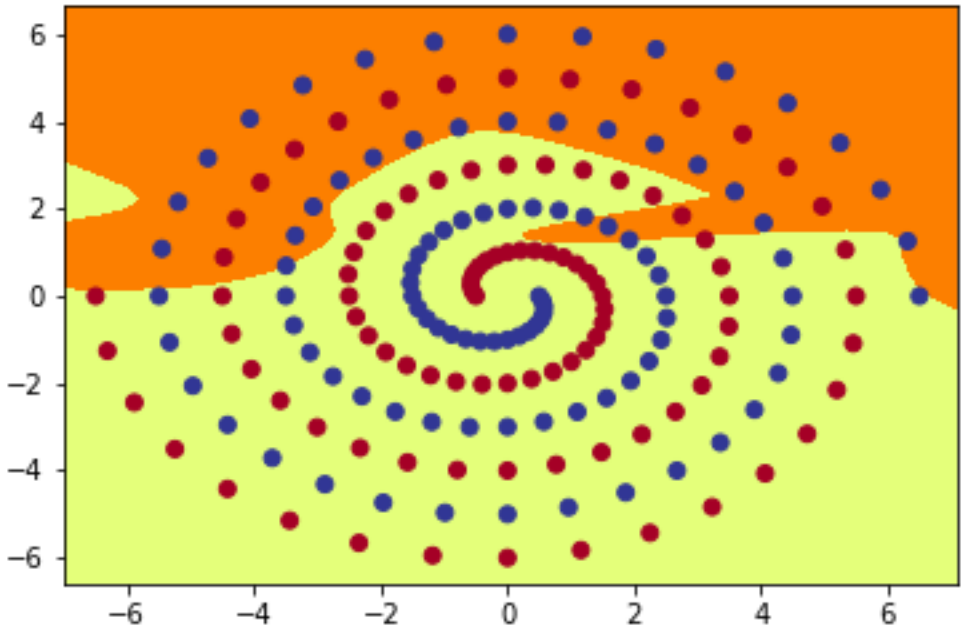
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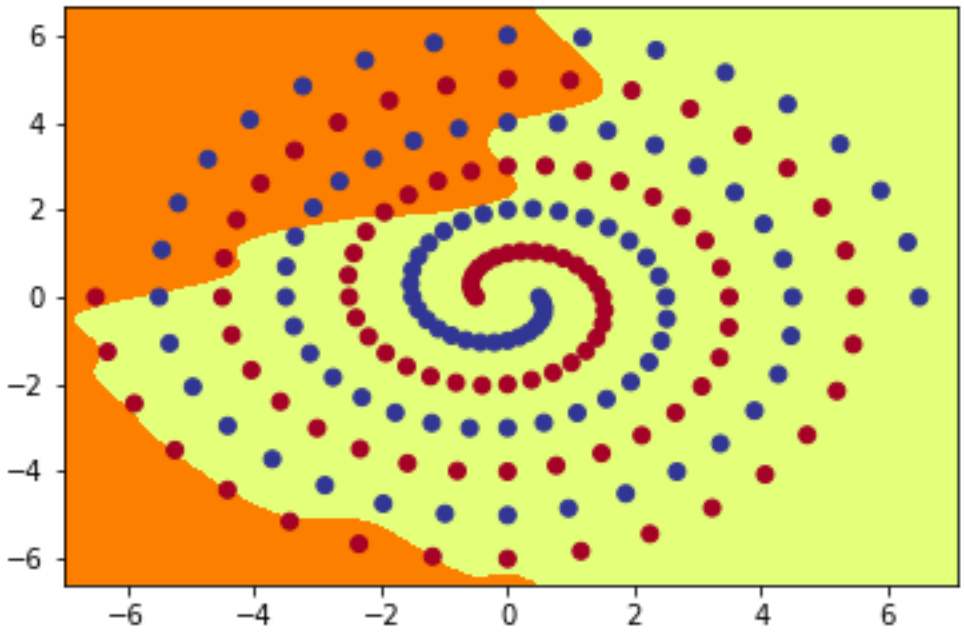
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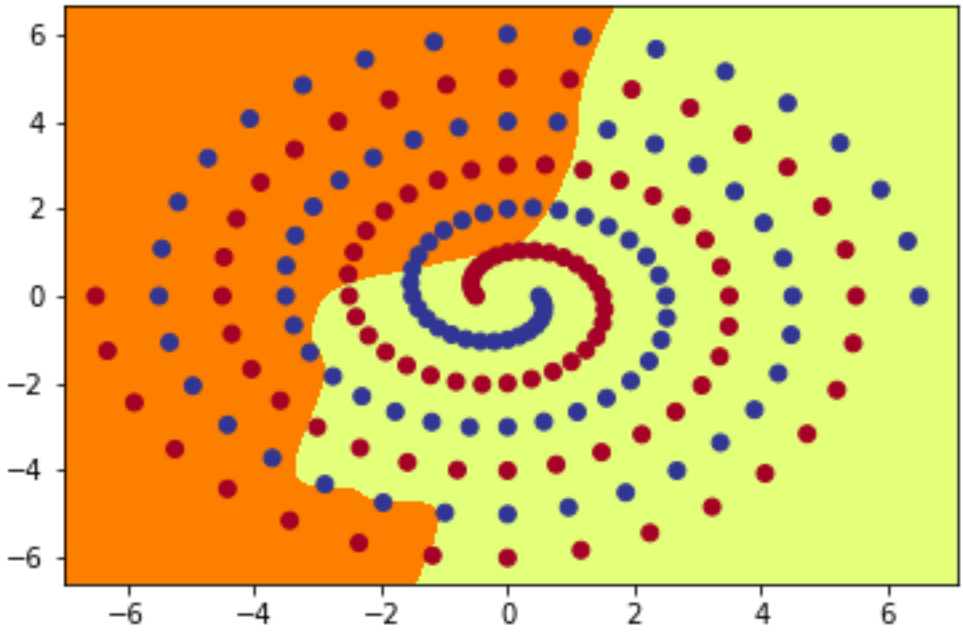

Part 2 Question 9 Part a

As we know that in PolarNet, first we are converting the coordinates to polar coordinates and then sending the input to the network to learn the two-spiral problem. The network is trying to learn different parts of the two spirals patterns by learning the polar coordinates and that's why if we notice the images of the hidden layers we see the model learning parts of spiral pattern. These patterns are then combined in the output layer to produce the model which we can see that correctly classifies most training examples and close to the actual spiral pattern. While RawNet and ShortNet both in the first hidden layer are learning simple linear features of the spiral pattern and that is why we see straight lines. The second hidden layer of RawNet and ShortNet try to learn complex parts of the spiral pattern rather than straight lines. In the output layer of RawNet and ShortNet both combine the results of the hidden layers and produce a classifier for the spiral pattern.

Part 2 Question 9 Part b

We see from the results in the previous questions that for RawNet if we consider initial weight size of 0.1 as our baseline, then smaller weights give us very low accuracy maybe because the weights are diminishing while if we are increase the weight size to 0.2, it gives us a better accuracy than 0.1 but setting to 0.3 gives us a lower accuracy than 0.2. Only when we set our weights to 0.21, we can get 100% accuracy in 7/10 runs. Similarly, if we see the previous results for ShortNet, while considering the values of 5,6 for number of hidden nodes we see a similar trend of 0.2 initial weight size performing

better than 0.1 and 0.3 not performing better than 0.2. Only when we set the number of hidden nodes to 7 and initial size of 0.2 than ShortNet can correctly classify 7/10 times.

Part 2 Question 9 Part C

Looking at the relative "naturalness" of the output function computed by the three networks, we see that PolarNet output function is very close to the actual function which generated the two-spiral pattern. While we look at the output function of RawNet and ShortNet, the output function not as good as PolarNet but if we compare RawNet and ShortNet, ShortNet does a better job than RawNet. The reason PolarNet's output function is very close to the actual output function is the conversion of input to polar coordinates which is enables PolarNet model to learn the function correctly. The correct representation of input for deep learning task is important because if we represent the input correctly, the model will be able to extract more features and learn the function better. We can also see this from our two spiral pattern that when we converted the input to polar coordinates, the hidden layers in PolarNet were able to learn parts of spiral patterns and ultimately learn the function while this was not the case in RawNet and ShortNet

Part 2 Question 9 Part D

PolarNet batchsize = 194

Num_id = 7

Training No	**Epochs**	**Percentage (%)**
1	1700	100
2	3300	100
3	600	100
4	4200	100
5	5800	100
6	1600	100
7	20,000	68.40
8	2000	100
9	20,000	82.99
10	20,000	91.75

RawNet batchsize = 194

Initial weight size = 0.21

Training No	**Epochs**	**Percentage (%)**
1	20,000	97.94
2	2,400	100
3	20,000	98.97
4	4,100	100
5	1,600	100
6	20,000	98.45
7	20,000	99.48
8	5,500	100
9	12,900	100
10	20,000	97.94

ShortNet batchsize = 194

Num_id = 7

Initial weight size = 0.20

Training No	**Epochs**	**Percentage (%)**
1	2,100	100
2	20,000	93.81
3	20,000	96.39
4	3,400	100
5	3,900	100
6	2,000	100
7	1,100	100
8	1,400	100
9	3,200	100
10	6,600	100

While observing the results of all the three models and changing batch size to 194 and keeping other parameters the same, we can observer that whenever the model achieves 100% accuracy, it does it in less epochs than previous results.

Optimizer = SGD

Batchsize = 97

Num_id = 7

PolarNet

Training No	**Epochs**	**Percentage (%)**
1	20,000	73.20
2	20,000	69.07
3	20,000	71.65
4	19,300	70.10
5	20,000	67.01
6	20,000	67.01
7	20,000	66.49
8	20,000	66.49
9	20,000	63.92
10	20,000	68.04

Optimizer = SGD

Batchsize = 97

Initial weight size = 0.21

RawNet

Training No	**Epochs**	**Percentage (%)**
1	20,000	52.58
2	20,000	52.58

3	20,000	52.06
4	20,000	60.82
5	20,000	59.79
6	20,000	56.70
7	20,000	63.92
8	20,000	61.86
9	20,000	57.22
10	20,000	54.11

Optimizer = SGD

Batchsize = 97

Initial weight size = 0.20

Num_id = 7

ShortNet

Training No	**Epochs**	**Percentage (%)**
1	20,000	60.31
2	20,000	64.95
3	20,000	64.43
4	20,000	56.70
5	20,000	62.37
6	20,000	58.25
7	20,000	61.34
8	20,000	60.31
9	20,000	56.70
10	20,000	79.38

From the above results of SGD and keeping all the other parameters same, we see that Adam performs much better than SGD on this set of data.