

CSL407 Machine Learning

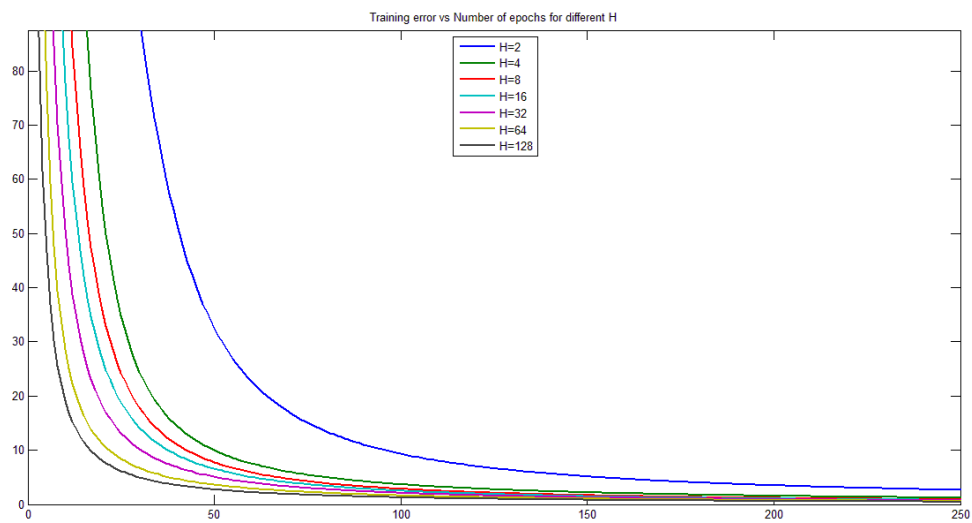
Homework3

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Ans1

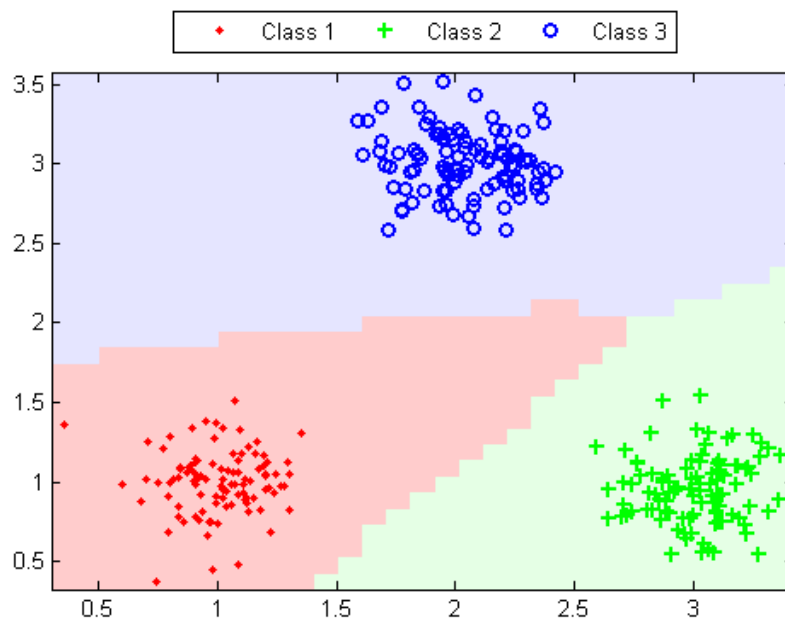
d)

Training error vs Number of Epochs for different number of hidden layer units

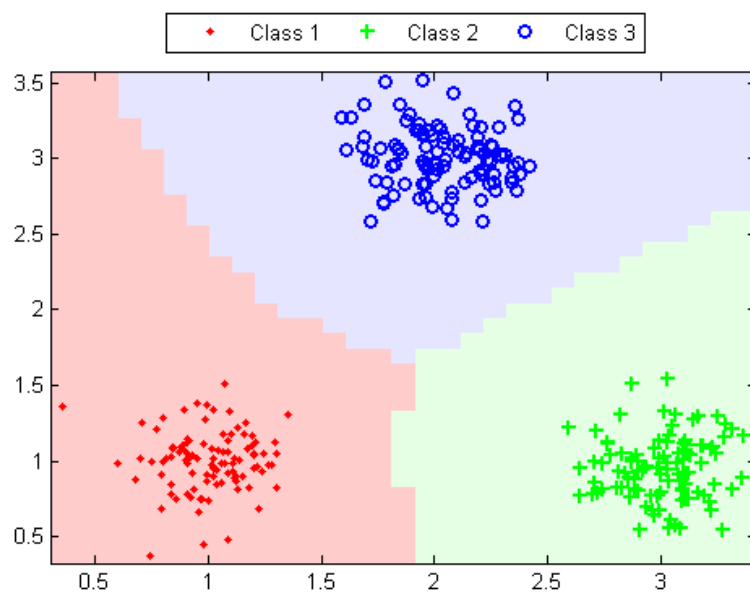


Conclusion: More the number of hidden layer units, lower the training error for a fixed number of epochs.

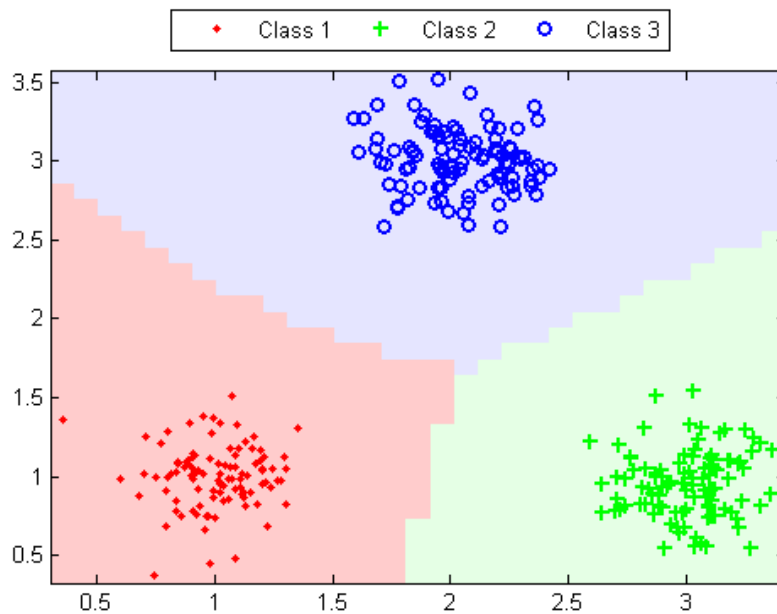
Decision boundary for H=2



Decision boundary for $H=4$



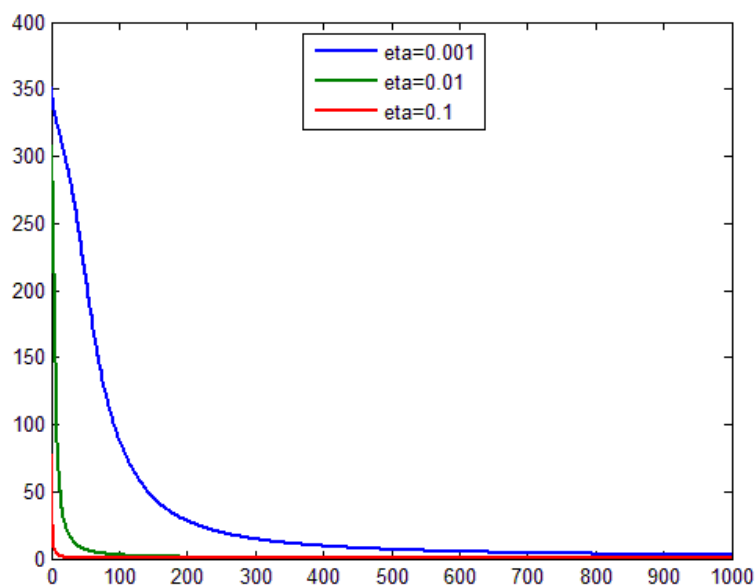
Decision boundary for H=64



Conclusion: More the number of hidden layer units , more the overfitting. Thus ,tighter the decision boundary around a particular training class. For H=64, the decision boundary of the red class is much tighter as compared to the boundary for H=2.

e)

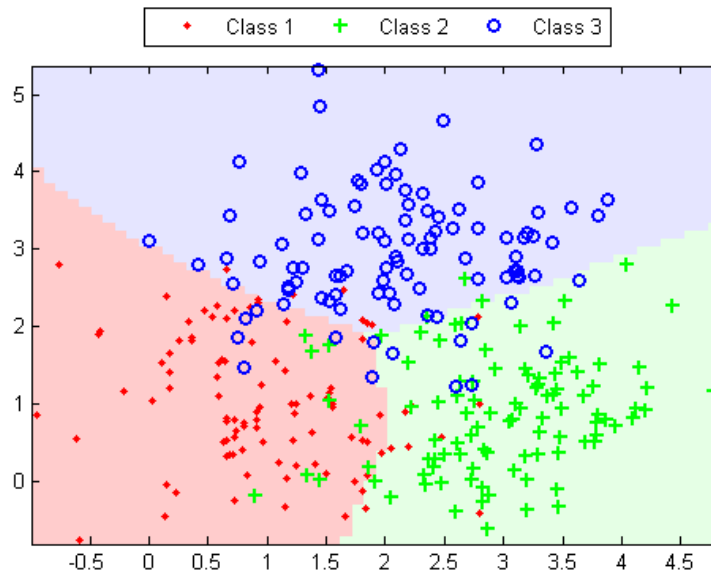
Training error Vs Number of Epochs for different values of learning rates



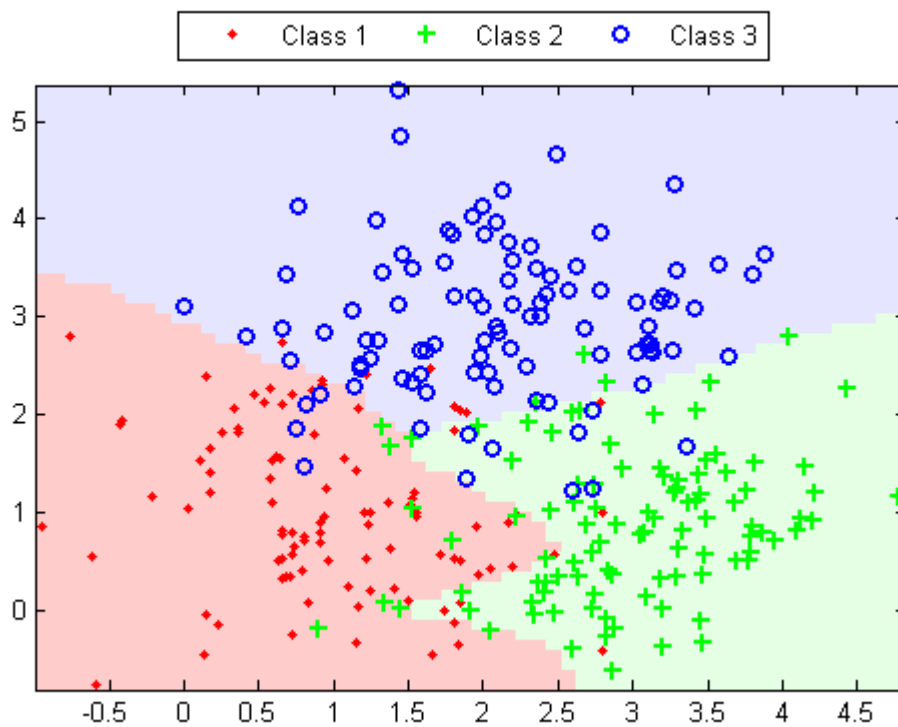
Conclusion: Greater the learning rate, faster the convergence. With $\eta=0.1$, error becomes almost 0 at the start itself, whereas with $\eta=0.001$, error becomes 0 after 800 epochs.

f)

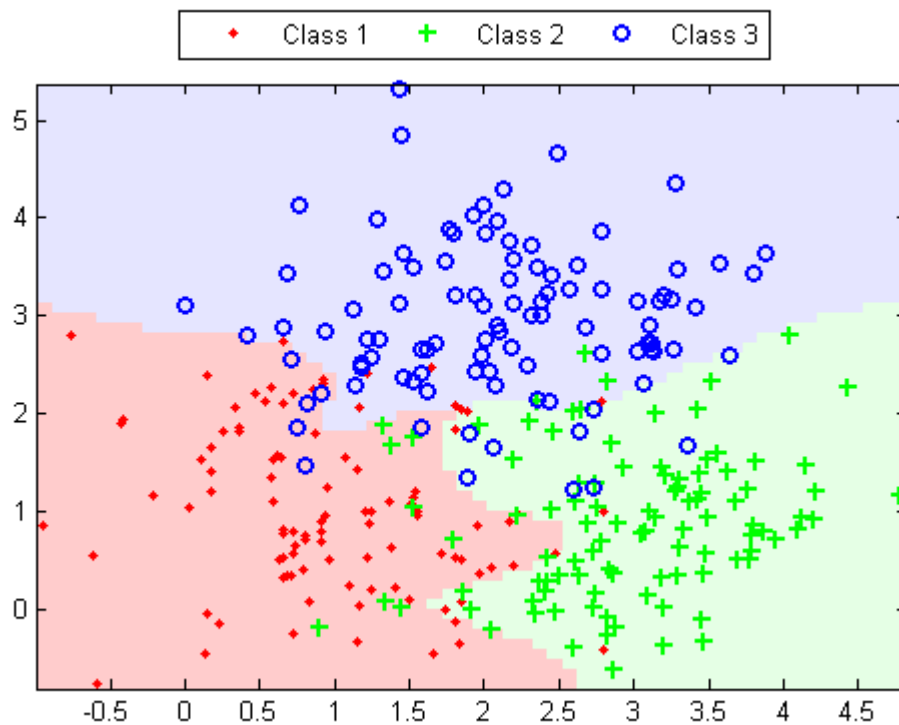
Training error at 1000 epochs=108.3275



Training error at 5000 epochs=91.6284



Training error at 10000 epochs=86.3546



Conclusion: As the number of epochs increases the decision boundaries overfits the training examples which shows that the complexity of the hypothesis learnt increases.

Ans2

Epoch 1

Forward propagation for training example 1:

$$c_1 = \text{sigmoid}(0.1*1 + 0.1*1 + 0.1*0 = 0.2) = 0.5498$$

$$y_1 = d_1 = \text{sigmoid}(0.1*1 + 0.1*0.5498 = 0.15498) = 0.5387$$

Forward propagation for training example 2:

$$c_2 = \text{sigmoid}(0.1*1 + 0.1*0 + 0.1*1 = 0.2) = 0.5498$$

$$y_2 = d_2 = \text{sigmoid}(0.1*1 + 0.1*0.5498 = 0.15498) = 0.5387$$

$$\text{Error} = \frac{1}{2*(2)} * \sum_{i=1}^2 (t_i - y_i)^2$$

$$\mathbf{vd0_new} = \mathbf{vd0_old} + \mathbf{delta_vd0} = 0.1 + (0.3 * (1 - 0.5387) * 0.5387 * (1 - 0.5387) * 1 + 0.3 * (0 - 0.5387) * 0.5387 * (1 - 0.5387) * 1) / 2 = 0.0971$$

$$\mathbf{vdc_new} = \mathbf{vdc_old} + \mathbf{delta_vdc} = 0.1 + (0.3 * (1 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.5498 + 0.3 * (0 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.5498) / 2 = 0.0984$$

$$\mathbf{wc0_new} = \mathbf{wc0_old} + \mathbf{delta_wc0} =$$

$$0.1 + 0.3 * ((1 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.1 * 0.5498 * (1 - 0.5498) * 1 + (0 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.1 * 0.5498 * (1 - 0.5498) * 1) / 2 = 0.0999$$

$$\mathbf{wca_new} = 0.1 + 0.3 * ((1 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.1 * 0.5498 * (1 - 0.5498) * 1 + 0) / 2 = 0.1004$$

$$\mathbf{wcb_new} = 0.1 + 0.3 * (0 + (0 - 0.5387) * 0.5387 * (1 - 0.5387) * 0.1 * 0.5498 * (1 - 0.5498) * 1) / 2 = 0.0995$$

Epoch2

$$\mathbf{c_1} = \text{sigmoid}(0.0999 * 1 + 0.1004 * 1 + 0.0995 * 0) = 0.5499$$

$$\mathbf{y_1} = \mathbf{d_1} = \text{sigmoid}(0.0971 * 1 + 0.0984 * .5499) = 0.5377$$

$$\mathbf{c_2} = \text{sigmoid}(0.0999 * 1 + 0.1004 * 0 + 0.0995 * 1) = 0.5497$$

$$\mathbf{y_2} = \mathbf{d_2} = \text{sigmoid}(0.0971 * 1 + 0.0984 * .5497) = 0.5377$$

$$\mathbf{vd0_new} = \mathbf{vd0_old} + \mathbf{delta_vd0} + \mathbf{alpha} * \mathbf{delta_vd0_old} = 0.0971 + (0.3 * (1 - 0.5377) * 0.5377 * (1 - 0.5377) * 1 + 0.3 * (0 - 0.5377) * 0.5377 * (1 - 0.5377) * 1) / 2 + 0.9 * (-.0029) = \mathbf{0.0940}$$

$$\mathbf{vdc_new} = \mathbf{vdc_old} + \mathbf{delta_vdc} + \mathbf{alpha} * \mathbf{delta_vdc_old} = 0.0984 + (0.3 * (1 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.5499 + 0.3 * (0 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.5497) / 2 + 0.9 * (-.0016) = \mathbf{0.0954}$$

$$\mathbf{wc0_new} = \mathbf{wc0_old} + \mathbf{delta_wc0} + \mathbf{alpha} * \mathbf{delta_wc0_old} =$$

$$0.0999 + 0.3 * ((1 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.0984 * 0.5499 * (1 - 0.5499) * 1 + (0 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.0984 * 0.5497 * (1 - 0.5497) * 1) / 2 + 0.9 * (-0.0001) = \mathbf{0.0999}$$

$$\mathbf{wca_new} = 0.1004 + 0.3 * ((1 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.0984 * 0.5499 * (1 - 0.5499) * 1 + 0) / 2 + 0.9 * (0.0004) = \mathbf{0.1011}$$

$$\mathbf{wcb_new} = 0.0995 + 0.3 * (0 + (0 - 0.5377) * 0.5377 * (1 - 0.5377) * 0.0984 * 0.5497 * (1 - 0.5497) * 1) / 2 + 0.9 * (-0.9005) = \mathbf{-0.7114}$$

Ans3

$$\mathbf{R} = \mathbf{A} \sim \mathbf{B}$$

A	B	R
0	0	0
0	1	0
1	0	1
1	1	0

Points belonging to class R=0 are {(0,0) (0,1) (1,1)}

Points belonging to class R=1 are (1,0)

Both the classes are linearly separable.

The line $A-B-0.5=0$ separates both the classes.

Since points belonging to class 0 when substituted in the equation give -ve value

And point (1,0) gives positive value.

Thus, the weights of the perceptron are:

$$W_{y0} = -0.5$$

$$W_{yA} = 1$$

$$W_{yB} = -1$$

Ans4

Derivation

$$E(w, v) = -\sum_{i=1}^K t_i \log(y_i) \text{ (Cross Entropy error function)}$$

$$y_i = \frac{e^{(zv_i^T)}}{\sum_{j=1}^K e^{(zv_j^T)}} \text{ (Softmax function)}$$

$$z_h = \tanh\left(\sum_{j=0}^D x_j w_{hj}\right)$$

$$\frac{\partial E}{\partial v_{ih}} = \sum_{j=1}^K \frac{\partial E}{\partial y_j} * \frac{\partial y_j}{\partial v_{ih}} = \frac{\partial E}{\partial y_i} * \frac{\partial y_i}{\partial v_{ih}} + \sum_{j=1, j \neq i}^K \frac{\partial E}{\partial y_j} * \frac{\partial y_j}{\partial v_{ih}}$$

$$1) \frac{\partial y_i}{\partial v_{ih}} = y_i(1 - y_i)z_h$$

$$2) \frac{\partial E}{\partial y_i} = -\frac{t_i}{y_i}$$

$$3) \frac{\partial E}{\partial y_i} * \frac{\partial y_i}{\partial v_{ih}} = -t_i(1 - y_i)z_h$$

$$4) \frac{\partial y_j}{\partial v_{ih}} = -y_j y_i z_h$$

$$5) \frac{\partial E}{\partial y_j} * \frac{\partial y_j}{\partial v_{ih}} = t_j y_i z_h$$

$$\begin{aligned}\frac{\partial E}{\partial v_{ih}} &= -t_i(1 - y_i)z_h + \sum_{j=1, j \neq i}^K t_j y_i z_h = -t_i(1 - y_i)z_h + y_i z_h(1 - t_i) \\ &= -z_h(t_i - y_i) \{ \text{using equations 1,2,3,4,5 and } \sum_{i=1}^K t_i = 1 \}\end{aligned}$$

(Weight update equation for v_{ih})

$$v_{ih} = v_{ih} - \text{eta} * \frac{\partial E}{\partial v_{ih}} = v_{ih} + \text{eta} * (t_i - y_i)z_h$$

$$\frac{\partial E}{\partial w_{hj}} = \sum_{i=1}^K \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial z_h} \frac{\partial z_h}{\partial w_{hj}}$$

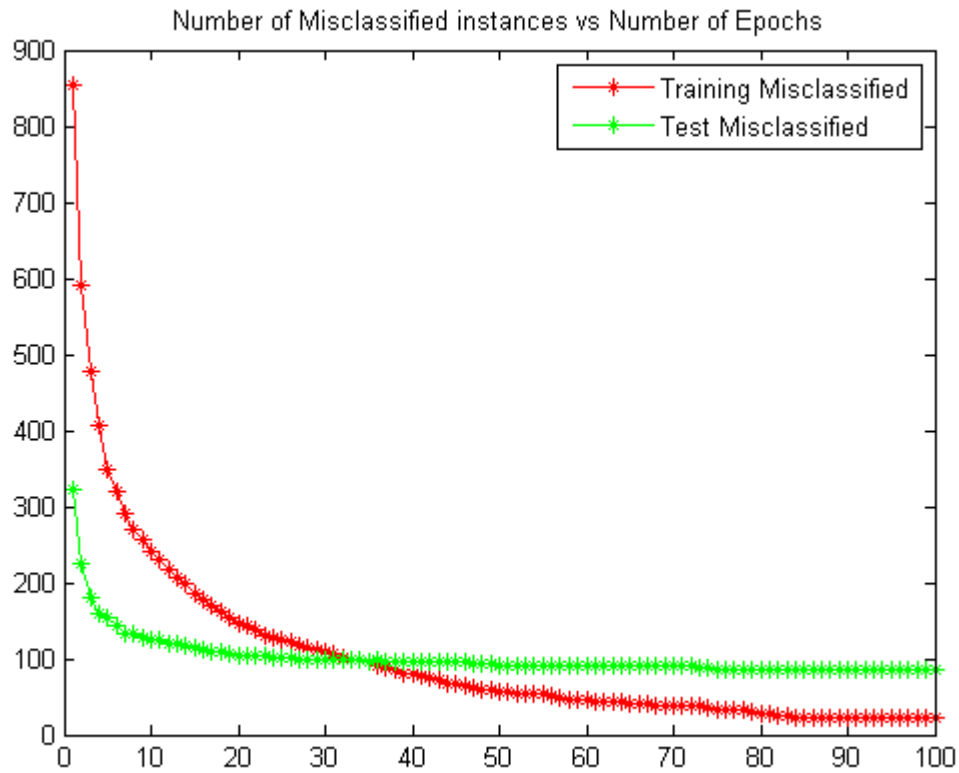
$$6) \frac{\partial y_i}{\partial z_h} = y_i v_{ih} - y_i \left(\sum_{j=1}^K y_j v_{jh} \right)$$

$$7) \frac{\partial z_h}{\partial w_{hj}} = (1 - z_h^2) x_j$$

$$\begin{aligned}\frac{\partial E}{\partial w_{hj}} &= \sum_{i=1}^K \frac{\partial E}{\partial y_i} \frac{\partial y_i}{\partial z_h} \frac{\partial z_h}{\partial w_{hj}} = \frac{\partial E}{\partial w_{hj}} = \sum_{i=1}^K \frac{-t_i}{y_i} * (y_i v_{ih} - y_i \left(\sum_{j=1}^K y_j v_{jh} \right)) * (1 - z_h^2) x_j \\ &= (1 - z_h^2) x_j \left(- \sum_{i=1}^K t_i v_{ih} + \sum_{j=1}^K y_j v_{jh} * \sum_{i=1}^K t_i \right) = (1 - z_h^2) x_j \left(\sum_{i=1}^K (-t_i v_{ih} + y_i v_{ih}) \right) \\ &= -(1 - z_h^2) x_j \left(\sum_{i=1}^K (t_i - y_i) v_{ih} \right) \{ \text{using equations 2,6,7 and } \sum_{i=1}^K t_i = 1 \}\end{aligned}$$

(Weight update equation for w_{hj})

$$w_{hj} = w_{hj} - \text{eta} * \frac{\partial E}{\partial w_{hj}} = w_{hj} + \text{eta} * (1 - z_h^2) x_j \left(\sum_{i=1}^K (t_i - y_i) v_{ih} \right)$$

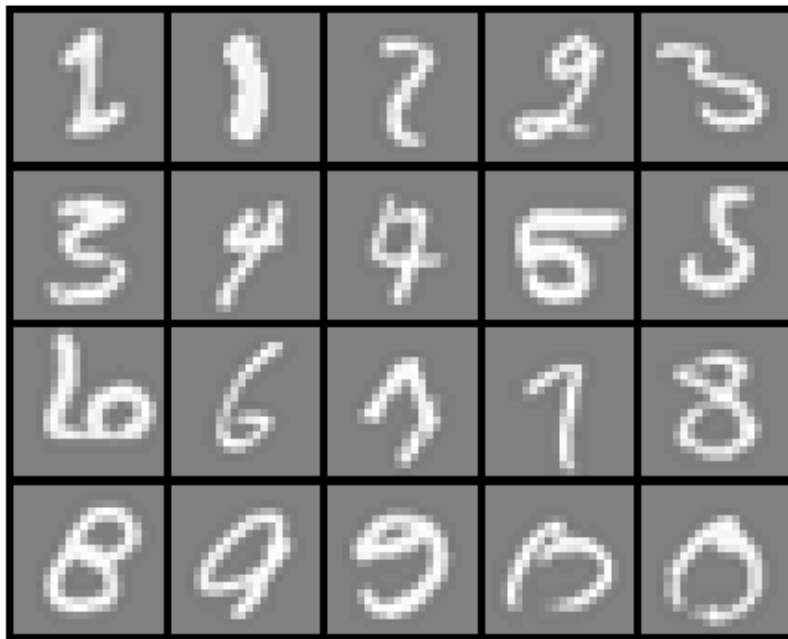


Misclassified examples out of 2990 training examples=22

Misclassified examples out of 1010 validation examples=86

Misclassified examples out of 1000 test examples=71

These are the 20 misclassified examples(row-wise starting from 1st row).



The labels and the prediction for the 20 misclassified examples shown above are :

1. label of example=1
predicted label of example=2
2. label of example=1
predicted label of example=7
3. label of example=2
predicted label of example=8
4. label of example=2
predicted label of example=3
5. label of example=3
predicted label of example=6
6. label of example=3
predicted label of example=5
7. label of example=4
predicted label of example=9
8. label of example=4
predicted label of example=7
9. label of example=5
predicted label of example=8
10. label of example=5
predicted label of example=2
11. label of example=6
predicted label of example=2
12. label of example=6

- predicted label of example=5
- 13. label of example=7
 - predicted label of example=10
- 14. label of example=7
 - predicted label of example=9
- 15. label of example=8
 - predicted label of example=3
- 16. label of example=8
 - predicted label of example=5
- 17. label of example=9
 - predicted label of example=10
- 18. label of example=9
 - predicted label of example=10
- 19. label of example=10
 - predicted label of example=9
- 20. label of example=10
 - predicted label of example=7