

Deep Learning: Theory and Practice

Linear and Logistic Models for Classification

14-02-2019

deeplearning.cce2019@gmail.com



Logistic Regression

- ❖ 2- class logistic regression

$$p(\mathcal{C}_1|\phi) = y(\phi) = \sigma(\mathbf{w}^T \phi)$$

- ❖ Maximum likelihood solution

$$\nabla E(\mathbf{w}) = \sum_{n=1}^N (y_n - t_n) \phi_n$$

- ❖ K-class logistic regression

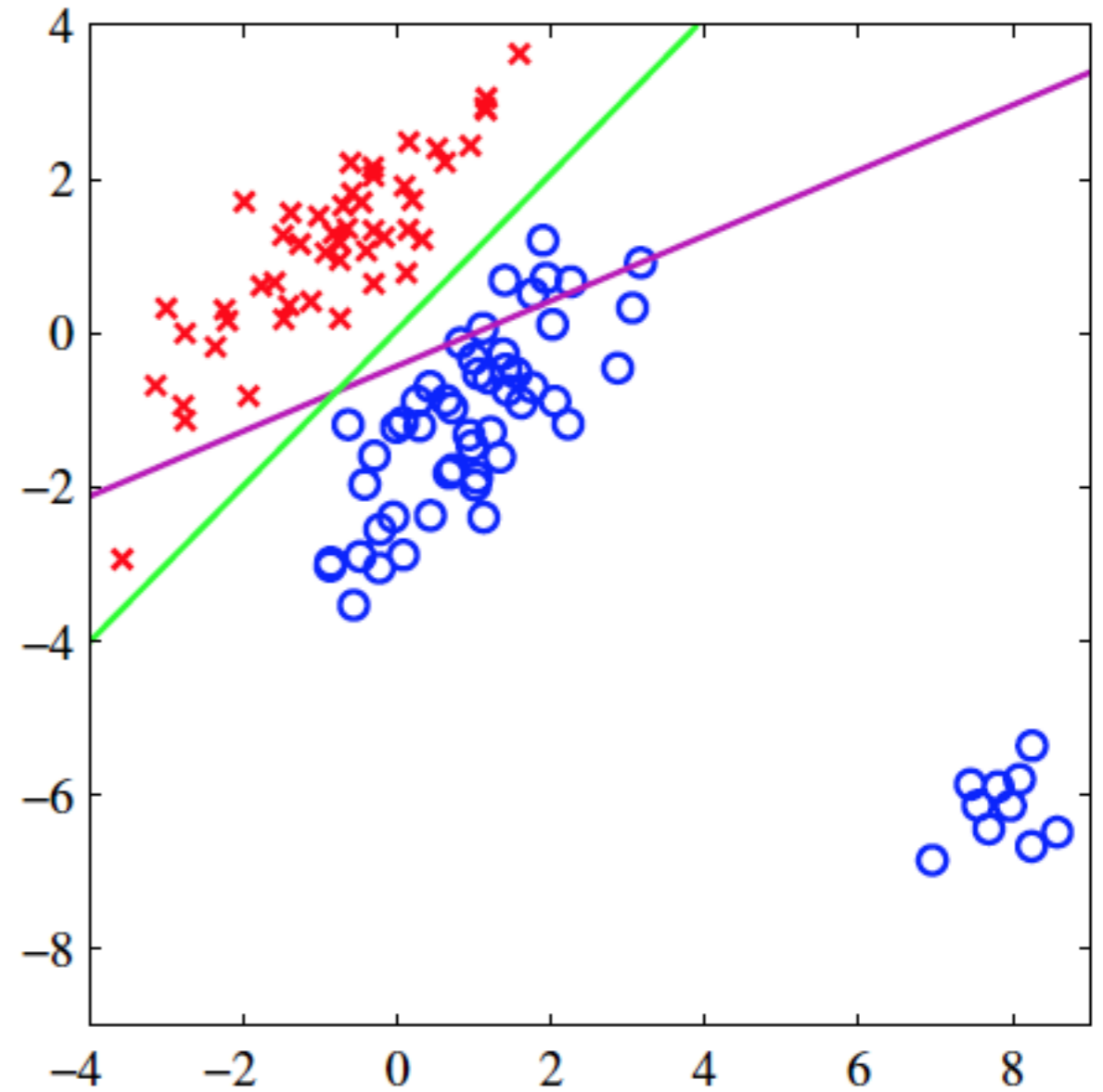
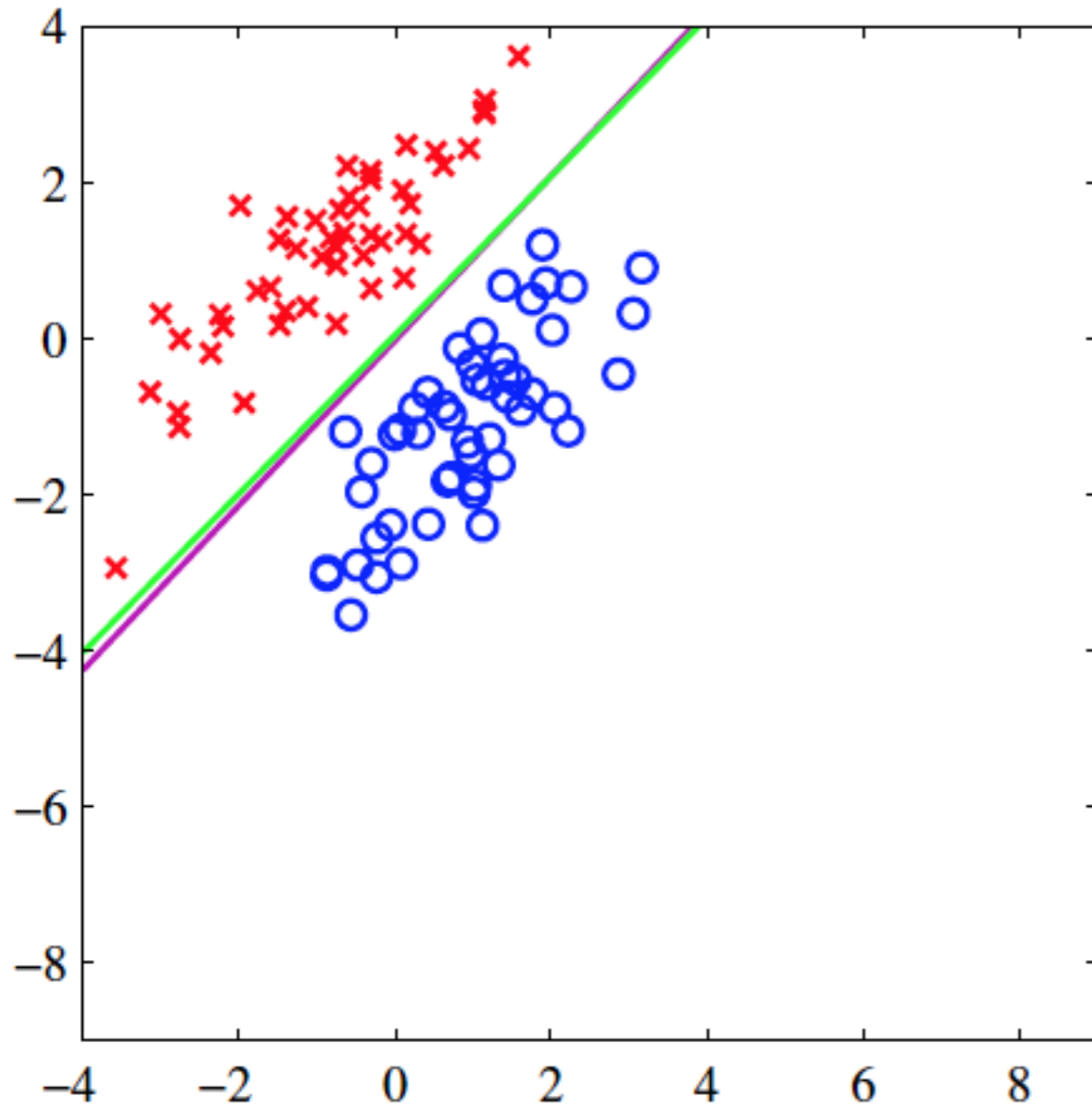
$$p(\mathcal{C}_k|\phi) = y_k(\phi) = \frac{\exp(a_k)}{\sum_j \exp(a_j)}$$

- ❖ Maximum likelihood solution

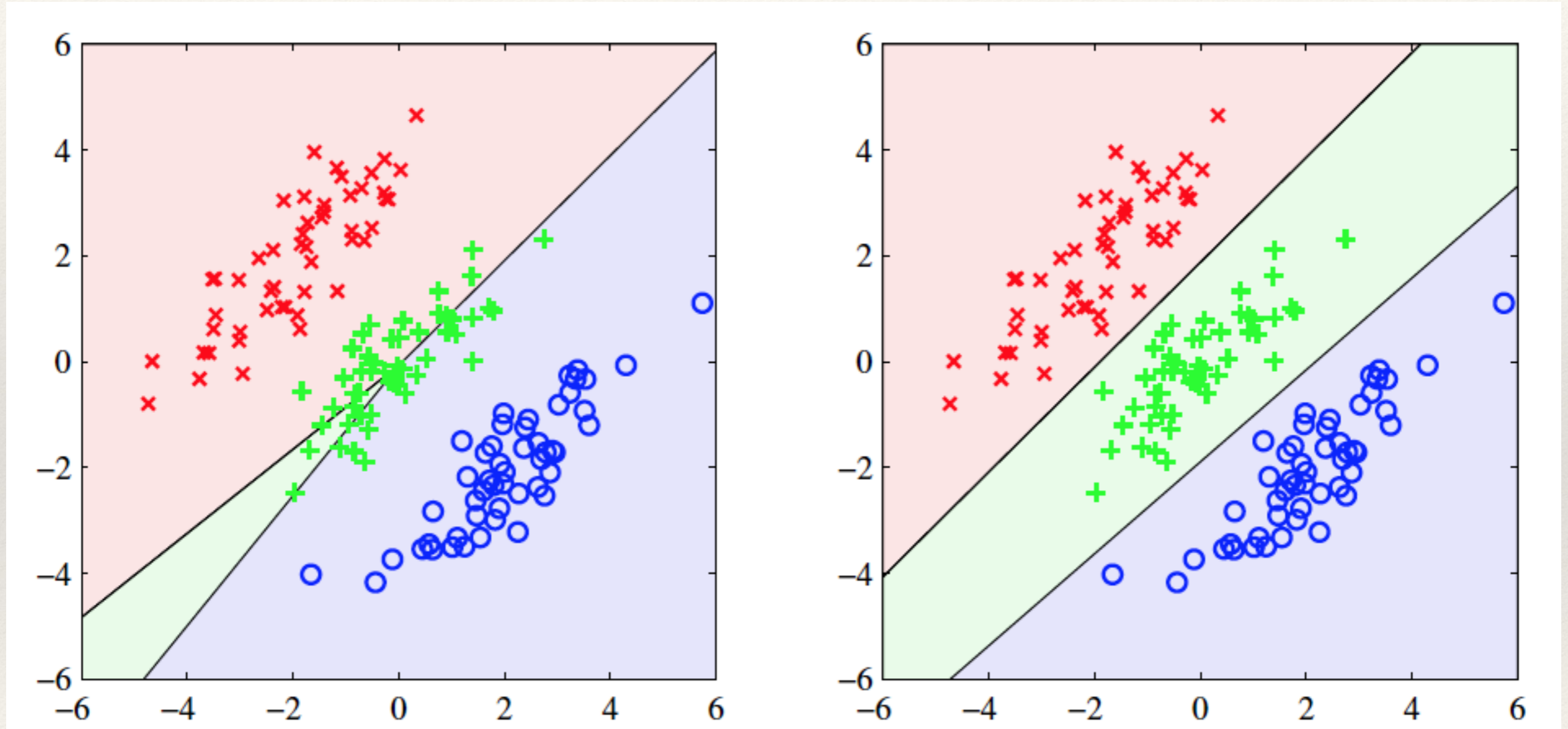
$$a_k = \mathbf{w}_k^T \phi.$$

$$\nabla_{\mathbf{w}_j} E(\mathbf{w}_1, \dots, \mathbf{w}_K) = \sum_{n=1}^N (y_{nj} - t_{nj}) \phi_n$$

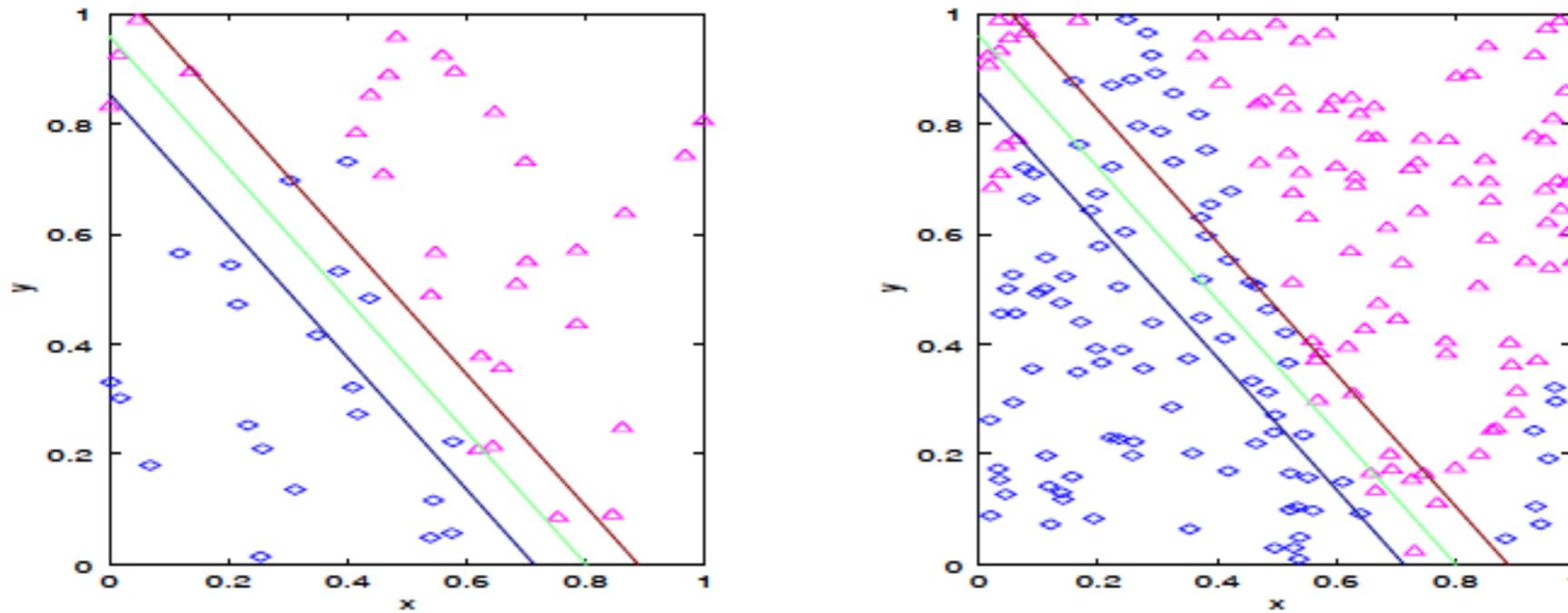
Least Squares versus Logistic Regression



Least Squares versus Logistic Regression

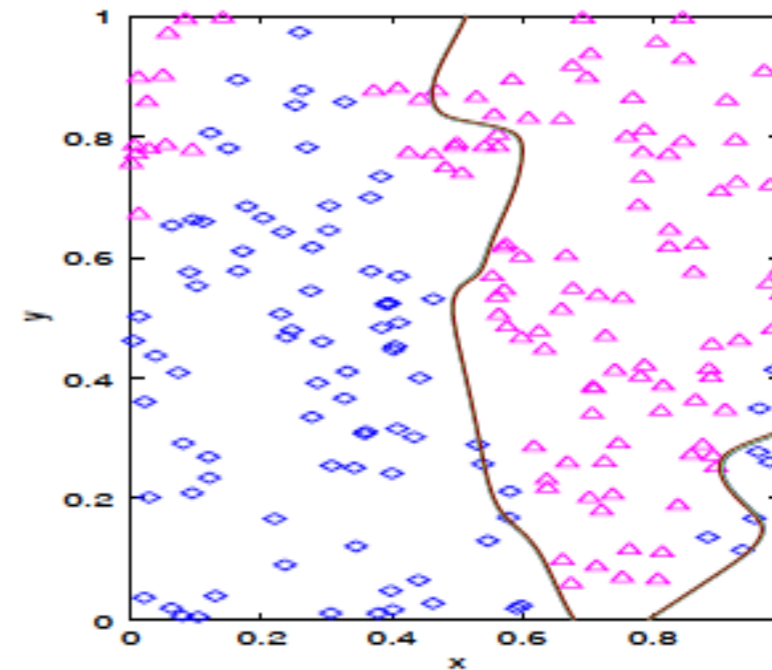
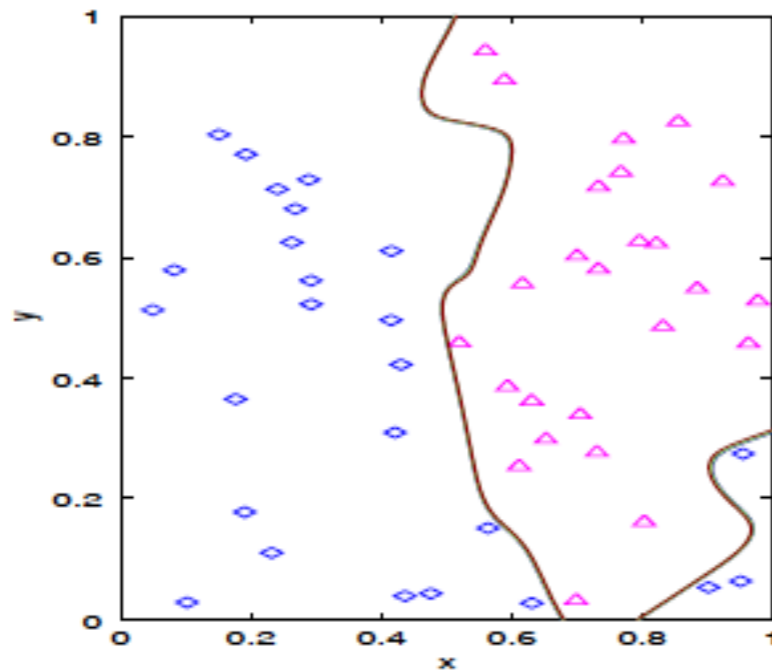


Underfit



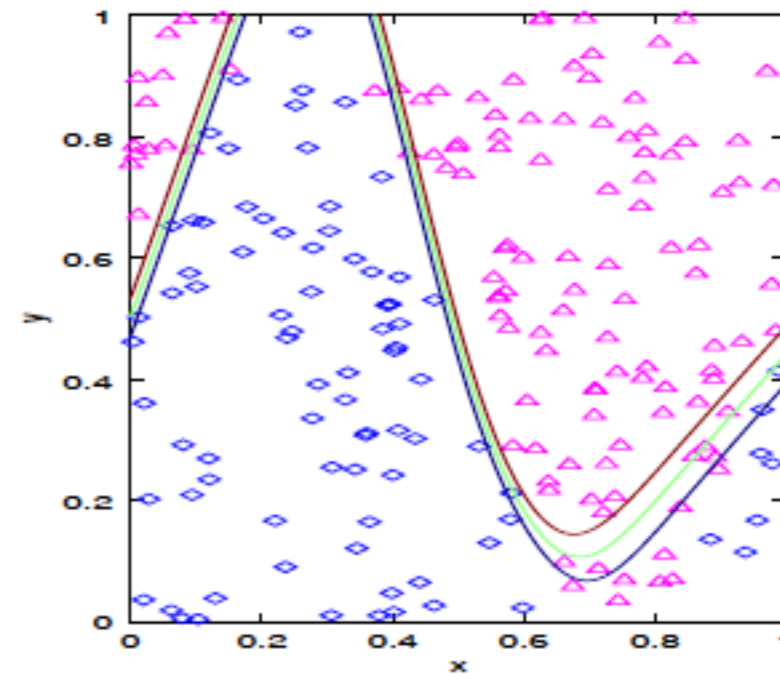
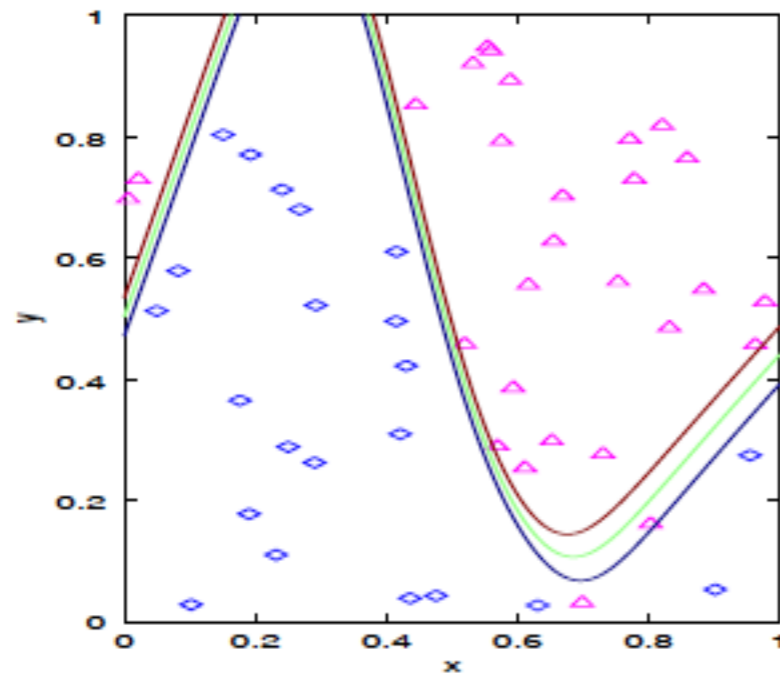
- The model is not able to capture the variability in the data (Linear Model)
- Both the training and testing error are high (15%,20%)
- Try to learn a more complex model – more features, more hidden neurons, decrease regularization
- More data would not help

Overfit



- The model is capturing data as well as accidental variations (100 hidden neurons)
- Training error is too low and testing error is too high (0%, and 16%)
- Try to learn a simpler model – less features, less hidden neurons, increase regularization
- More data would help

Compromise



- Reasonable training and test errors – (4%, 8%)
- Appropriate model – capturing only the global characteristics not details

Summary so far ...

- ❖ Maximum Likelihood
- ❖ Linear Least Squares Classifiers
- ❖ Logistic Regression
 - ❖ Application of ML to Logistic Regression
 - ❖ Gradient Descent
 - ❖ Coding Logistic regression

Training, Validation and Test Set

Original Set

Training

Testing

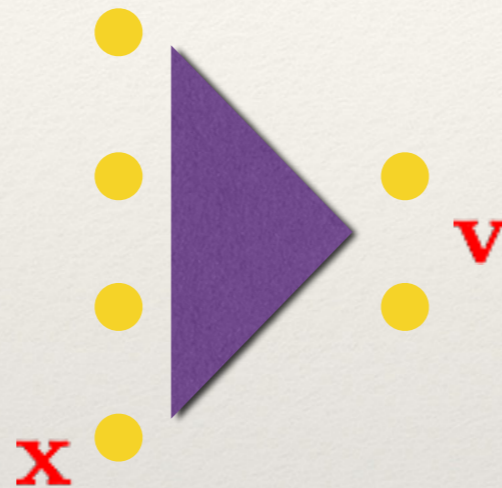
Training

Validation

Testing

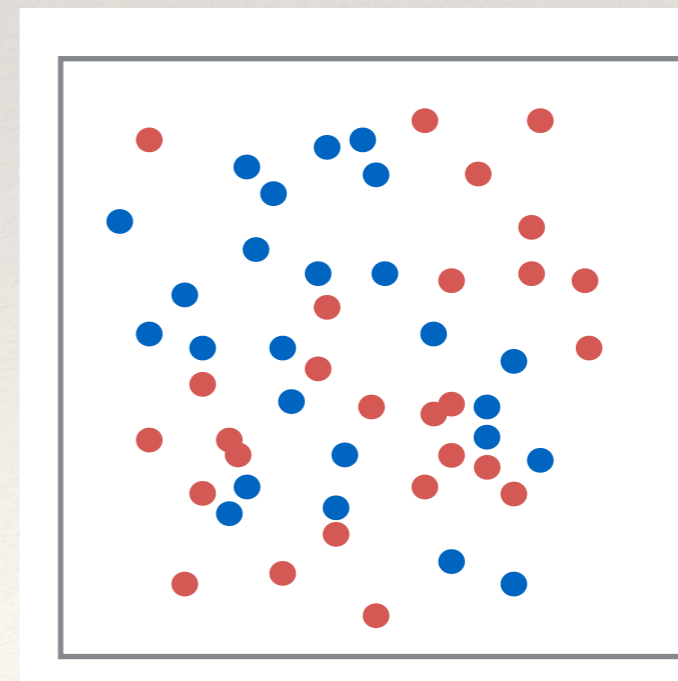
Perceptron Algorithm

Perceptron Model [McCulloch, 1943, Rosenblatt, 1957]



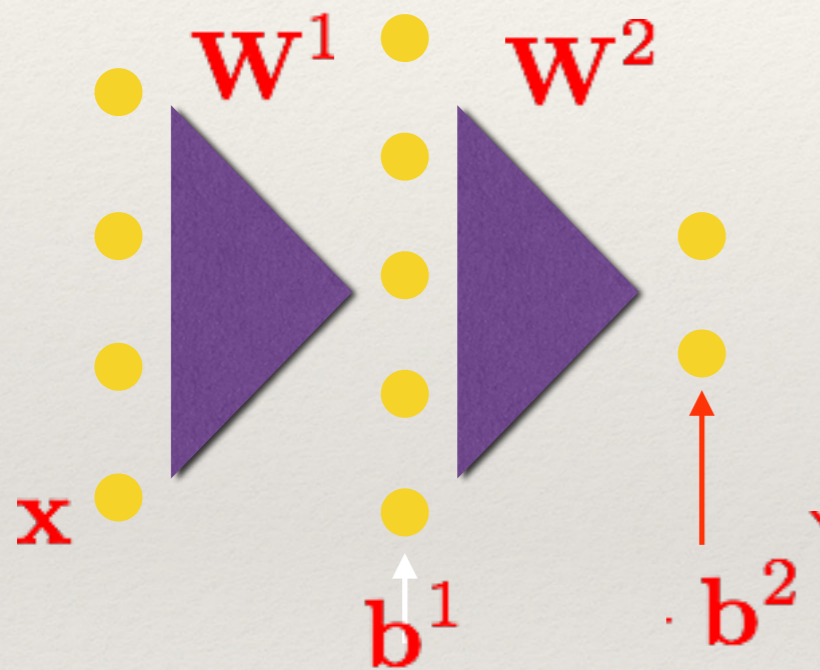
Targets are binary classes $[-1, 1]$

What if the data is not
linearly separable



Multi-layer Perceptron

Multi-layer Perceptron [Hopfield, 1982]



$$\mathbf{v}^2 = \psi \left(\mathbf{W}^2 \phi(\mathbf{W}^1 \mathbf{x} + \mathbf{b}^1) + \mathbf{b}^2 \right)$$

ϕ non-linear function (*tanh, sigmoid*)

ψ thresholding function