

# *Deep Learning: Theory and Practice*

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Matrix Calculus  
Linear and Logistic Regression Models

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# Matrix Derivatives

$$\left( \frac{\partial \mathbf{a}}{\partial x} \right)_i = \frac{\partial a_i}{\partial x}$$

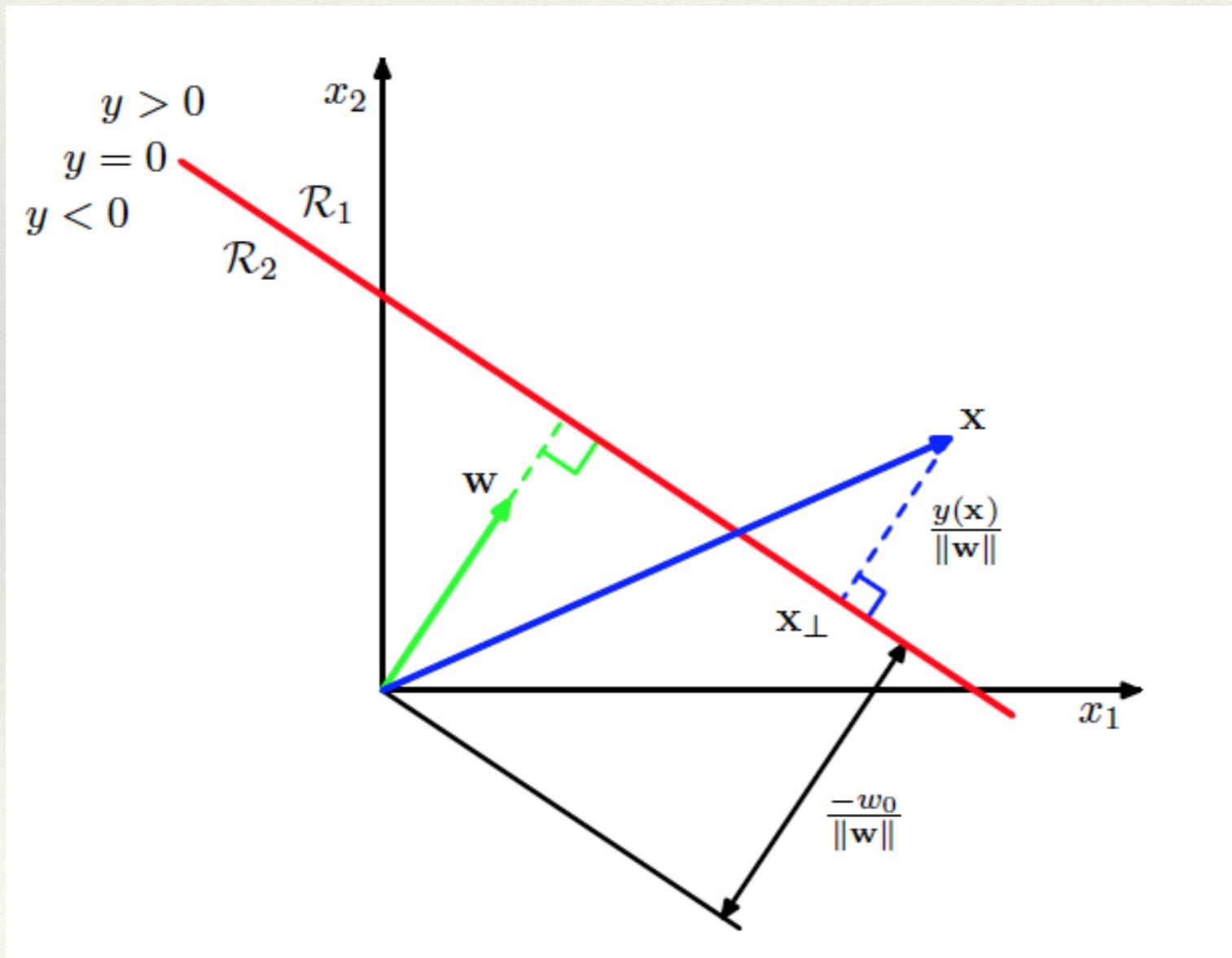
$$\left( \frac{\partial x}{\partial \mathbf{a}} \right)_i = \frac{\partial x}{\partial a_i}$$

$$\left( \frac{\partial \mathbf{a}}{\partial \mathbf{b}} \right)_{ij} = \frac{\partial a_i}{\partial b_j}.$$

# Linear Models for Classification

- ❖ Optimize a modified cost function

$$y(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + w_0$$



# Least Squares for Classification

- ❖ K-class classification problem

$$y_k(\mathbf{x}) = \mathbf{w}_k^T \mathbf{x} + w_{k0}$$

$$\mathbf{y}(\mathbf{x}) = \widetilde{\mathbf{W}}^T \widetilde{\mathbf{x}}$$

- ❖ With 1-of-K hot encoding, and least squares regression

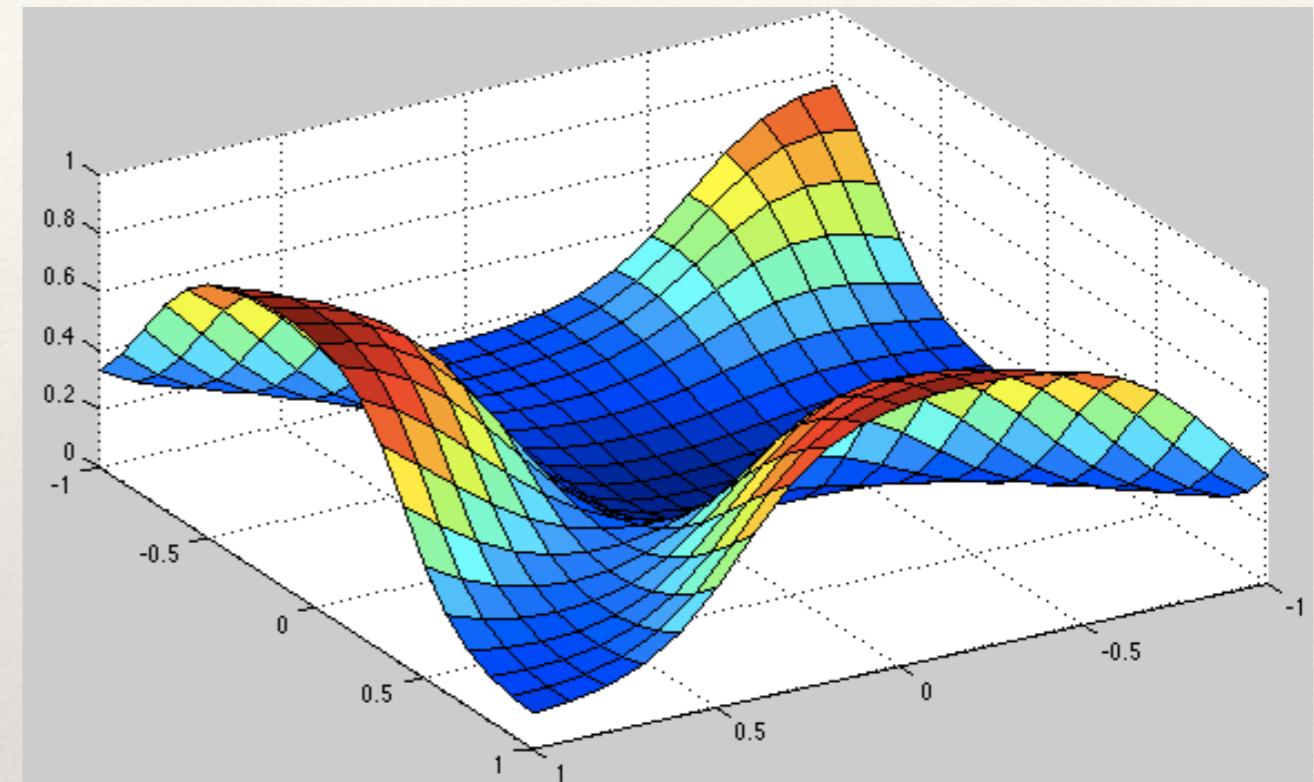
$$E_D(\widetilde{\mathbf{W}}) = \frac{1}{2} \text{Tr} \left\{ (\widetilde{\mathbf{X}} \widetilde{\mathbf{W}} - \mathbf{T})^T (\widetilde{\mathbf{X}} \widetilde{\mathbf{W}} - \mathbf{T}) \right\}$$

# Gradient Descent For Function Minimization

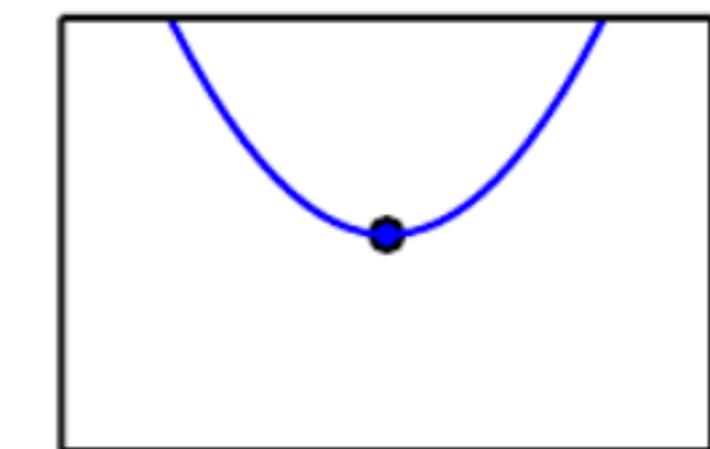
# Non-linear Optimization

Typical Error Surface as a function of parameters (weights)

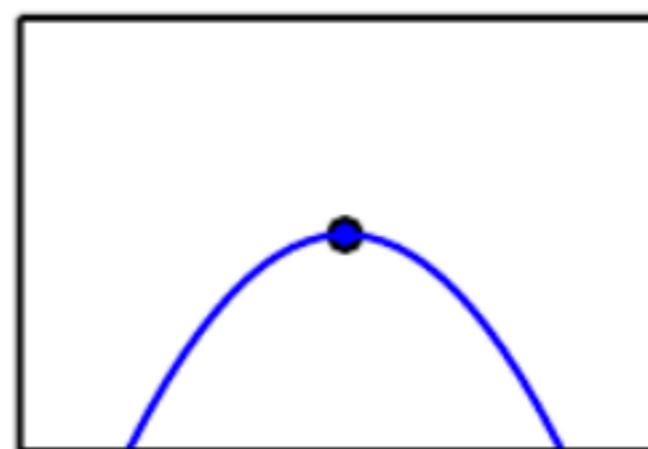
Highly Non-linear



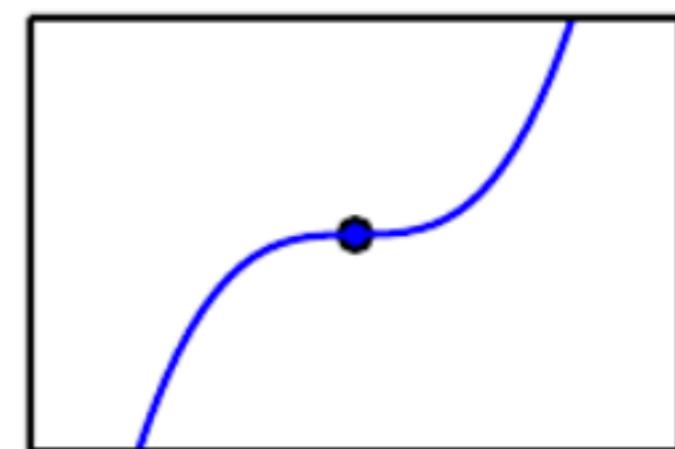
Minimum



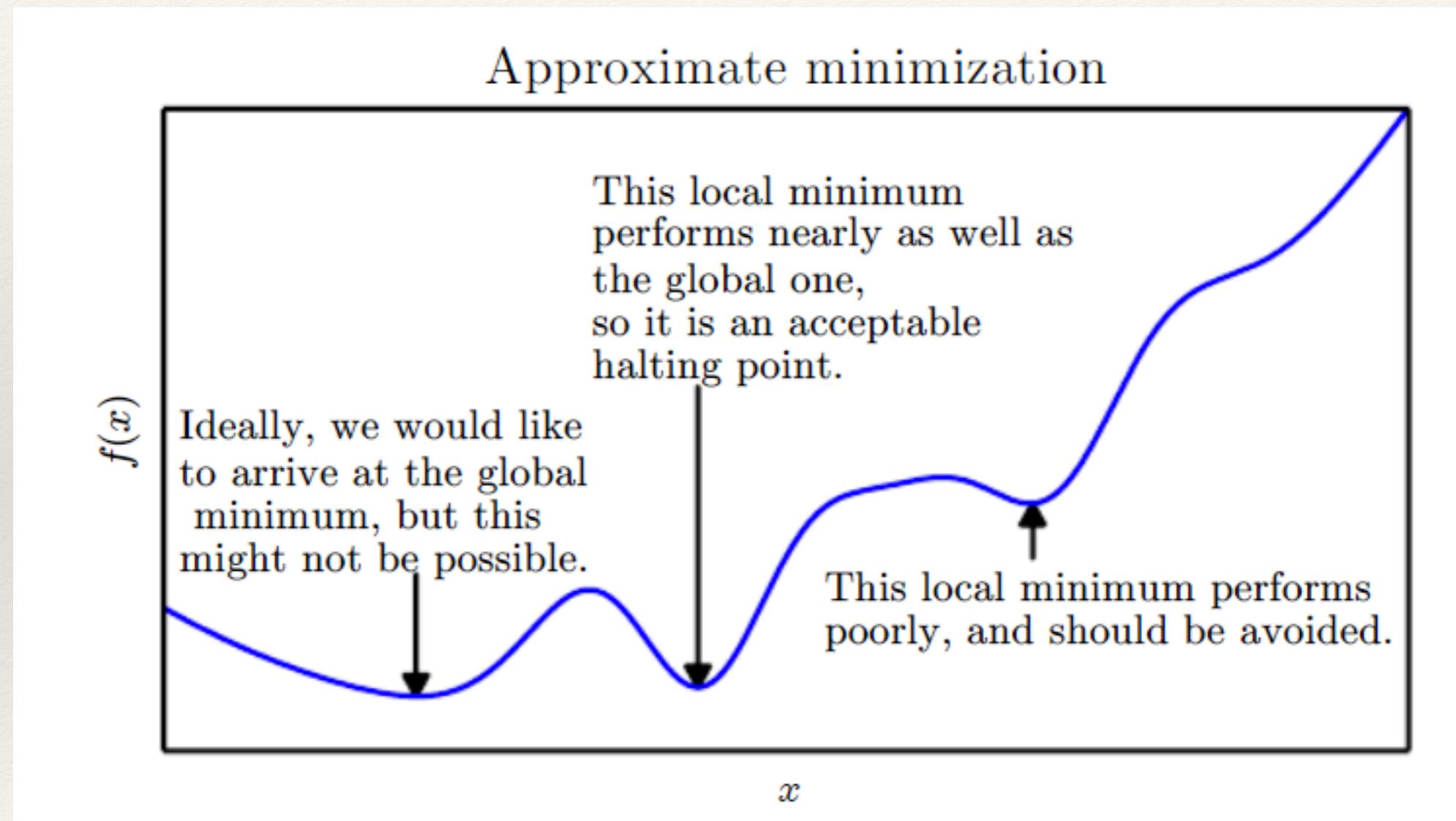
Maximum



Saddle point



# Approximate Minimization



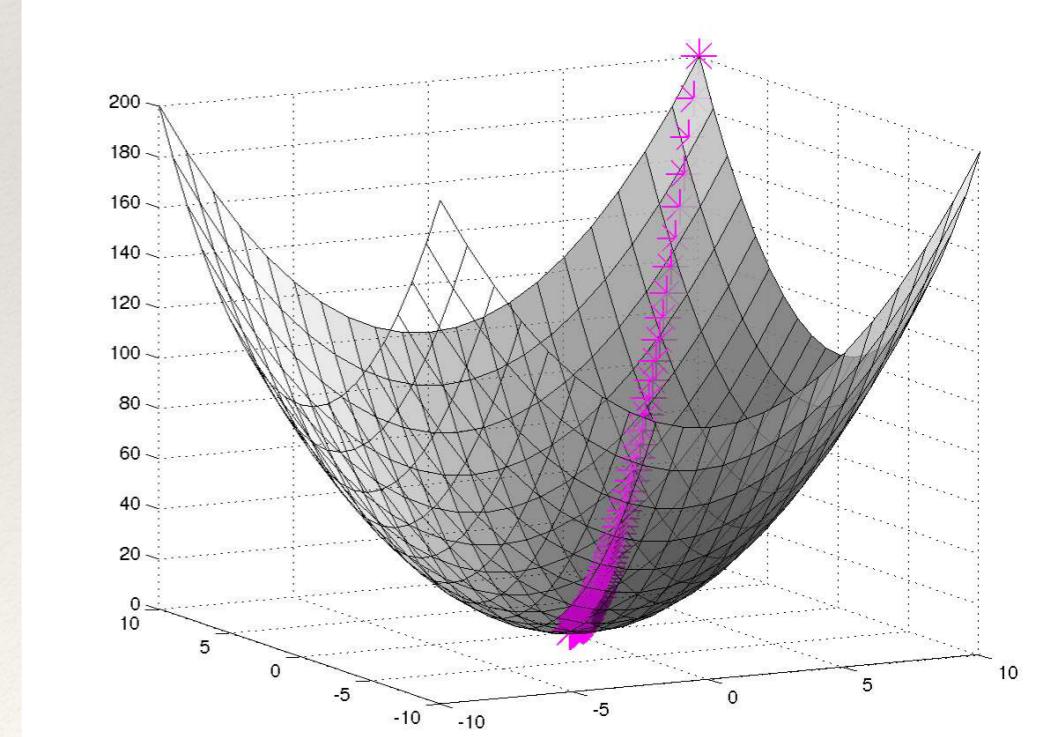
# Approximate Minimization

## Method of Steepest Descent

$$\mathbf{x}' = \mathbf{x} - \epsilon \nabla_{\mathbf{x}} f(\mathbf{x})$$

Error surface close to a local optima

Move to local optima



# 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

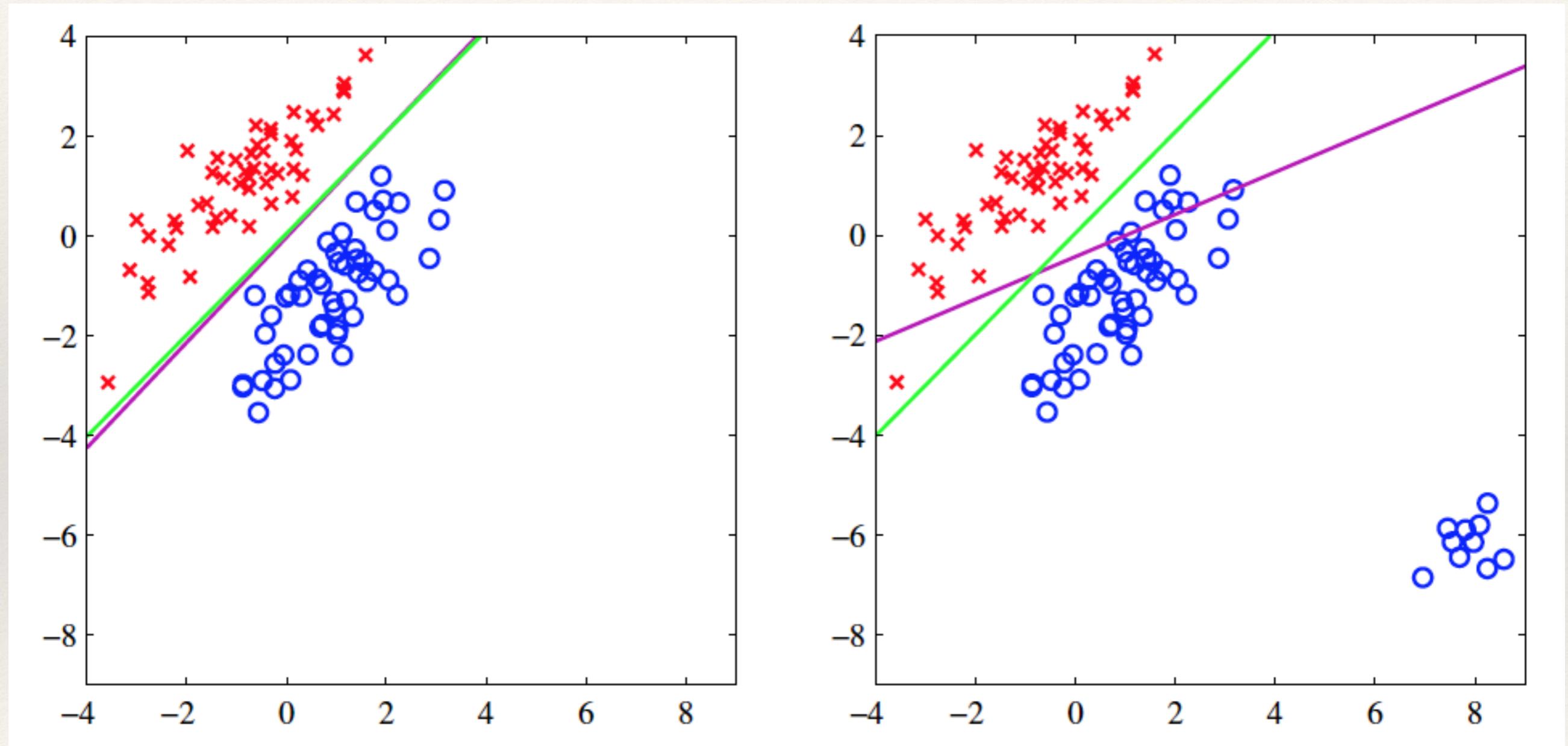
$$p(\mathcal{C}_k|\phi) = y_k(\phi) = \frac{\exp(a_k)}{\sum_j \exp(a_j)}$$

- ❖ 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

