# Artificial Intelligence & Machine Learning and Pattern Recognition — Perceptron Learning Algorithm



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#### Decision Trees References

- 两个连续变量的线性相关度,用协方差或相关系数来衡量
  - 非线性相关度: Maximal Information Coefficient (MIC). Detecting novel associations in large data sets, *Science*, 2011.
- 两个离散变量的相关度,用互信息度量
  - 互信息倾向于选择取值更多的离散型属性: Adjusted Mutual Information (AMI). Information theoretic measures for clusterings comparison: is a correction for chance necessary? *ICML*, 2009.
  - Standardized mutual information for clustering comparisons: one step further in adjustment for chance, ICML, 2014.
  - Entropy evaluation based on confidence intervals of frequency estimates: application to the learning of decision trees, *ICML*, 2015

# Regression Review

Least-squares solutions

$$n^{-1} \sum_{i=1}^{n} (y_i - w_0 - w_1 x_i) = 0$$
$$n^{-1} \sum_{i=1}^{n} x_i (y_i - w_0 - w_1 x_i) = 0$$

$$Q(w_0, w_1) = \min_{w_0, w_1} \sum_{i=1}^{n} (y_i - w_0 - w_1 x_i)^2$$

$$\partial Q(w_0, w_1) / \partial w_0 = 0 \qquad \qquad \partial Q(w_0, w_1) / \partial w_1 = 0$$

$$-2\sum_{i=1}^{n} (y_i - w_0 - w_1 x_i) = 0 \qquad \qquad -2\sum_{i=1}^{n} x_i (y_i - w_0 - w_1 x_i) = 0$$

# Regression Review

Least-squares solutions

$$w_0 = \overline{y} - w_1 \overline{x}$$

$$w_1 = \frac{\sum_{i=1}^n x_i (y_i - \overline{y})}{\sum_{i=1}^n x_i (x_i - \overline{x})}$$

$$= \frac{\sum_{i=1}^n (x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^n (x_i - \overline{x})^2}$$

- Dealing with all attributes jointly which are continuous variables
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- For  $\mathbf{x}=(x_1,x_2,...,x_d)$  with d features, compute a weighted 'score' and predict +1(good) if  $\sum_{i=1}^d w_i x_i > threshold$  predict -1(bad) if  $\sum_{i=1}^d w_i x_i < threshold$
- $y = \{+1(good), -1(bad)\}$

$$h(\mathbf{x}) = sign\left(\left(\sum_{i=1}^{d} w_i x_i\right) - threshold\right)$$

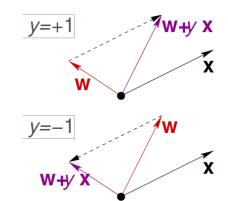
$$h(\mathbf{x}) = sign\left(\left(\sum_{i=1}^{d} w_{i} x_{i}\right) - threshold\right)$$

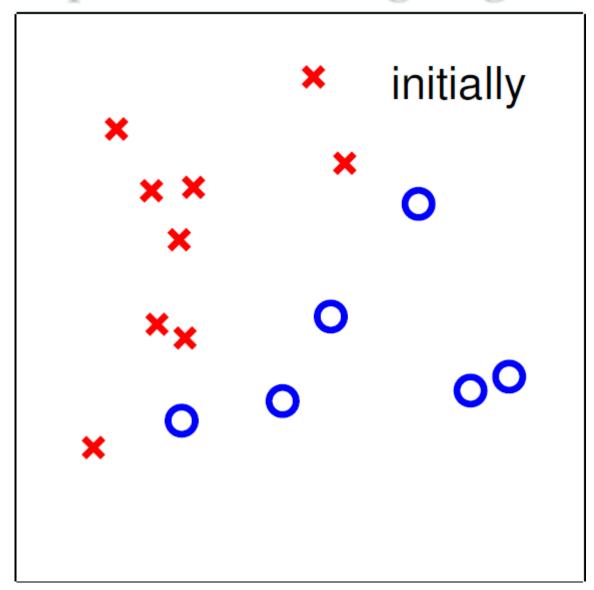
$$= sign\left(\left(\sum_{i=1}^{d} w_{i} x_{i}\right) + \underbrace{(-threshold) \cdot (+1)}_{\mathbf{w}_{0}}\right)$$

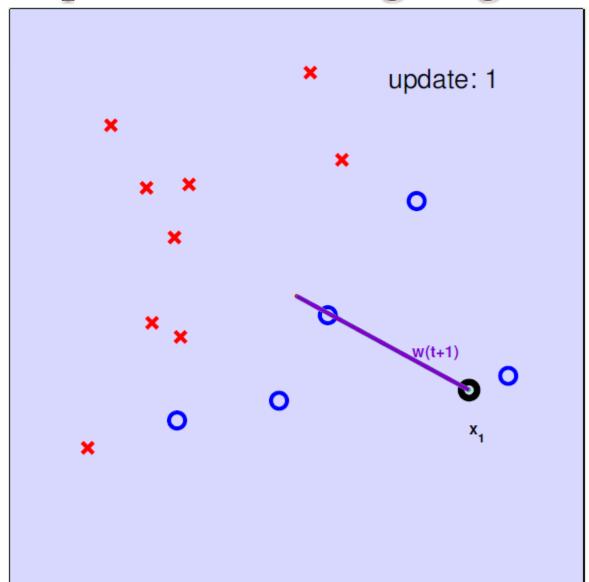
$$= sign\left(\sum_{i=0}^{d} w_{i} x_{i}\right)$$

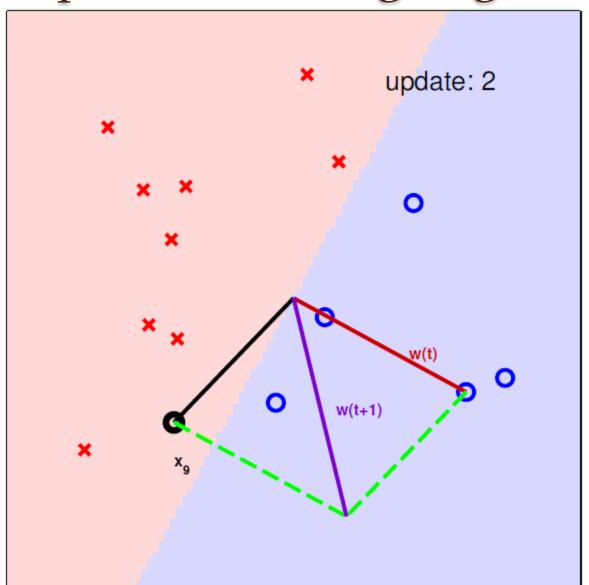
$$= sign\left(\mathbf{W}^{\mathsf{T}} \mathbf{X}\right)$$

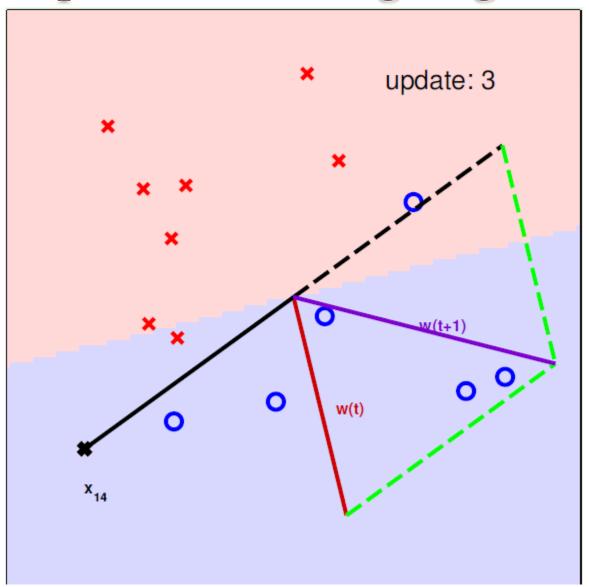
- Difficult: the set of  $h(\mathbf{x})$  is of infinite size
- Idea: start from some initial weight vector  $\mathbf{w}_{(0)}$ , and "correct" its mistakes on D
- For t = 0, 1, ...
  - find a mistake of  $\mathbf{w}_{(t)}$  called  $(\mathbf{x}_{n(t)}, y_{n(t)})$  $sign(\mathbf{w}_{(t)}^{\mathsf{T}} \mathbf{x}_{n(t)}) \neq y_{n(t)}$
  - (try to) correct the mistake by  $\mathbf{w}_{(t+1)} \leftarrow \mathbf{w}_{(t)} + y_{n(t)} \mathbf{x}_{n(t)}$
  - until no more mistakes
- Return last W (called  $W_{PLA}$ )

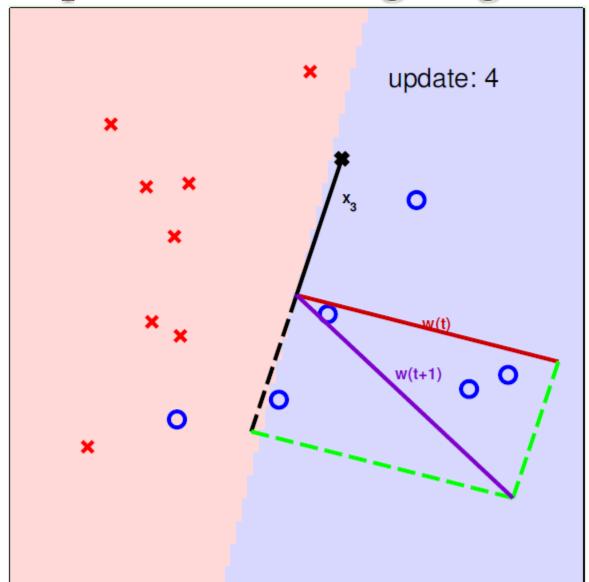


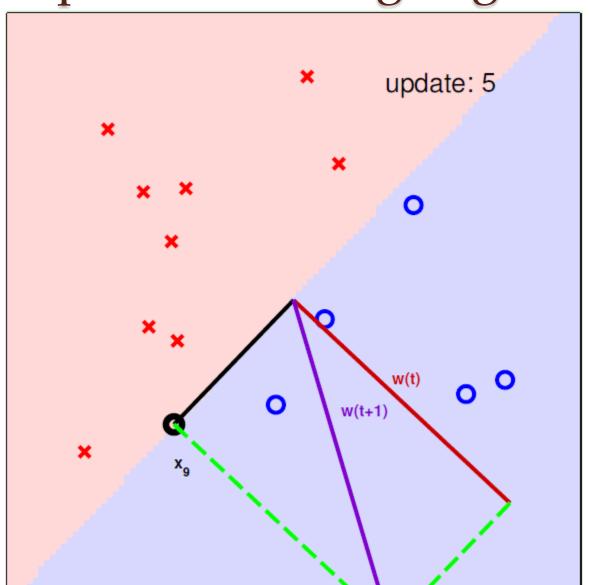


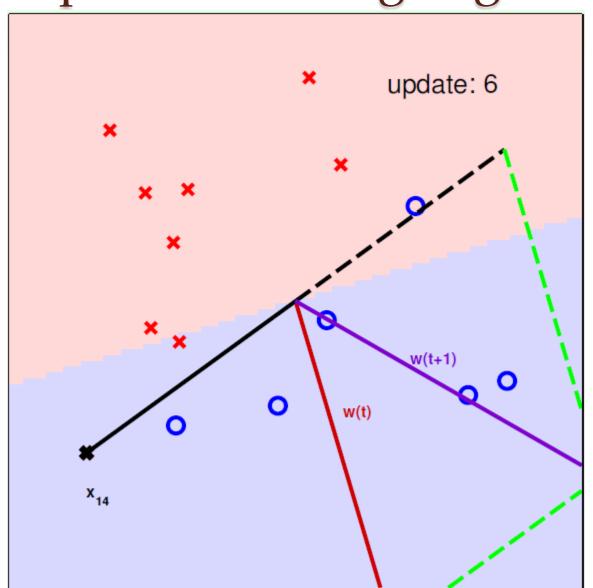


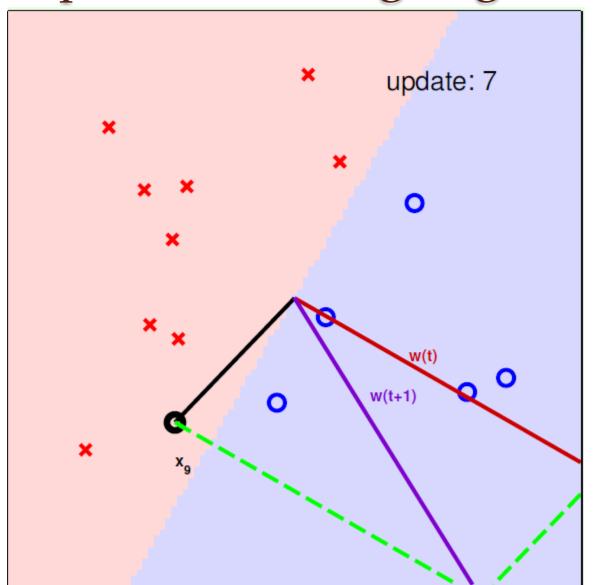


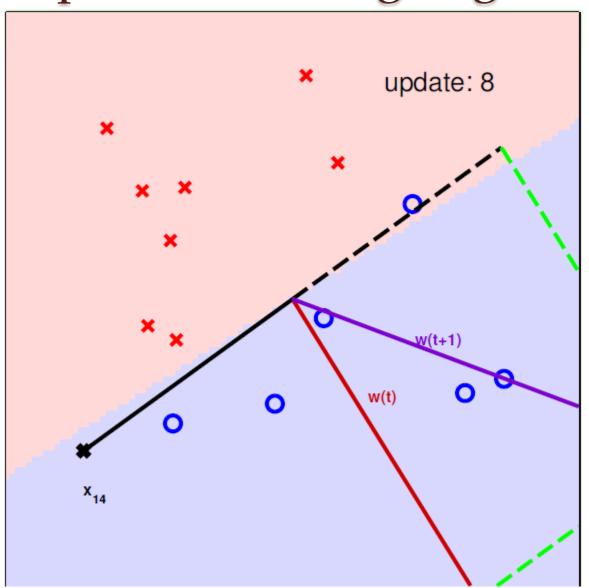


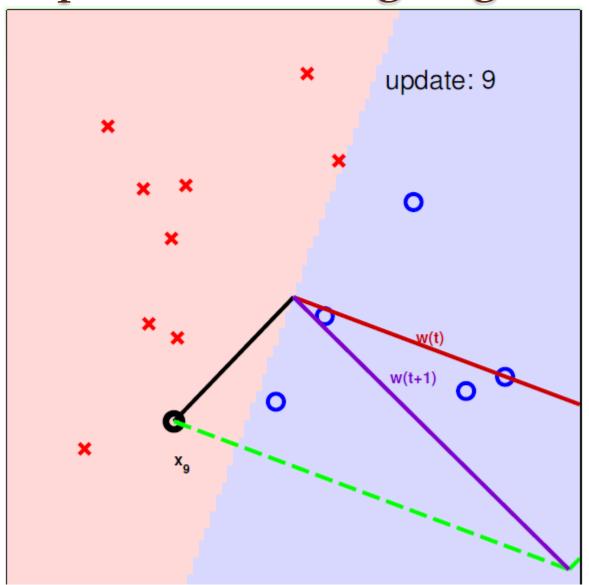


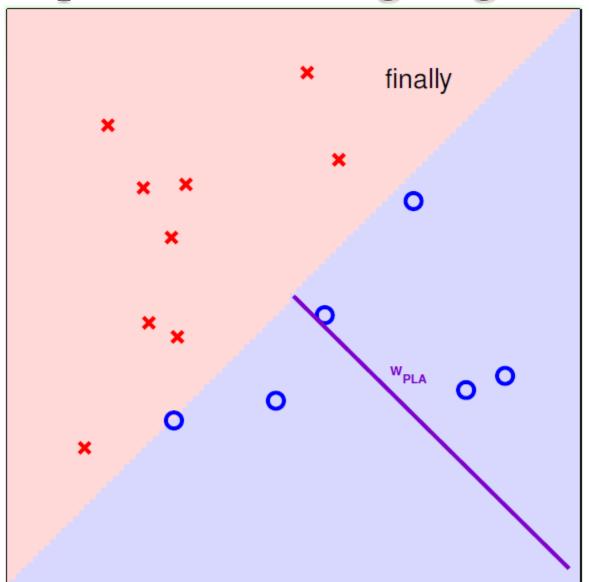


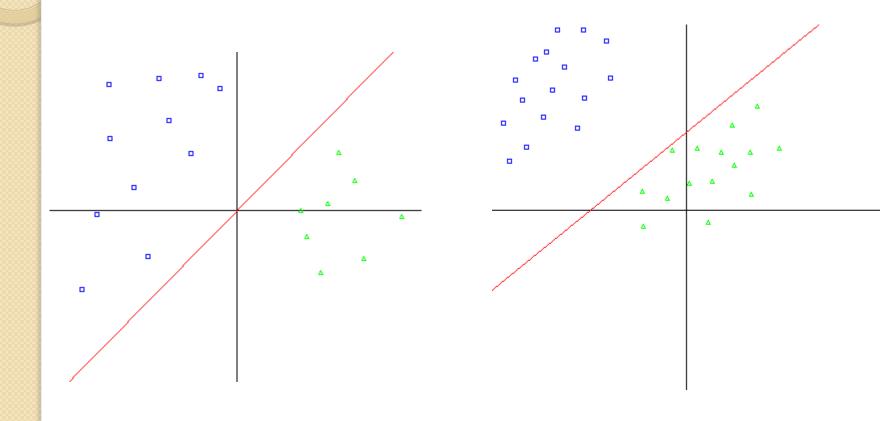












 Only if there exists an hyperplane that correctly classifies the data, the Perceptron procedure is guaranteed to converge; furthermore, the algorithm may give different results depending on the order in which the elements are processed, indeed several different solutions exist.

