

Final Review (cont'd)

3 Classification

3.1 Perceptron: an algorithm for learning a binary classifier of the form

$$h(x) = \text{sign}(w^T x + b)$$

where $w \in \mathbb{R}^D$ is the weight and $b \in \mathbb{R}$ is the bias. (WLOG, $b=0$)

Setting: Given labeled sample pts $(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$ with $y_i = \pm 1$.

If $\exists i$ s.t. $y_i (x^{(i)T} w^{(k)}) < 0$,

update $w^{(k+1)} = w^{(k)} + y_i x^{(i)}$.

Algorithm: Lecture 26

Related Topics: convergence under linear separability assumption.
(HW8 #1)

3.2 SVM: a linear binary classifier based on margin maximization.

Setting: Given labeled sample pts
 $(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$ with $y_i = \pm 1$,
solve the convex optimization problem:

$$\min_{w \in \mathbb{R}^d} \|w\|^2$$

s.t. $y_i (x^{(i)T} w + b) \geq 1, \quad i=1, \dots, n.$

(margin $= \frac{2}{\|w\|^2}$)

3.3 LDA: a dimension reduction method that maximizes projected data separability.

Setting: Given labeled sample pts
 $(x^{(1)}, y_1), \dots, (x^{(n)}, y_n)$ with $y_i = \pm 1$,
two classes: $\mathcal{C}_1 = \{x^{(i)} : y_i = 1\}$ $\mathcal{C}_2 = \{x^{(i)} : y_i = -1\}$

of sample pts: n_1 n_2

means $\mu^{(1)} = \frac{1}{n_1} \sum_{x^{(i)} \in \mathcal{C}_1} x^{(i)}$ $\mu^{(2)} = \frac{1}{n_2} \sum_{x^{(i)} \in \mathcal{C}_2} x^{(i)}$

sample covariance matrix

$$C^{(1)} = \frac{1}{n_1} \sum_{x^{(i)} \in \mathcal{C}_1} (x^{(i)} - \mu^{(1)}) (x^{(i)} - \mu^{(1)})^T \quad C^{(2)} = \frac{1}{n_2} \sum_{x^{(i)} \in \mathcal{C}_2} (x^{(i)} - \mu^{(2)}) (x^{(i)} - \mu^{(2)})^T$$

Solve $\arg \max_{\|u\|=1} \frac{u^T S_B u}{u^T S_W u}$ ($=$ eigenvector associated to the largest eigenvalue of $S_W^{-1} S_B$)

where $S_B \stackrel{\text{def}}{=} (\mu^{(1)} - \mu^{(2)})(\mu^{(1)} - \mu^{(2)})^T$ is the
between-class scatter matrix.

and $S_W \stackrel{\text{def}}{=} n_1 c^{(1)} + n_2 c^{(2)}$ is the
within-class scatter matrix.

Algorithm : Lecture 32

Related Topics : generalized Rayleigh quotient
(HW9 #2 #3)

4 Linear Methods in Regression: Statistical Point of View.

- Formulation of three linear models with
noise
- Def of bias, variance, MSE
and their relations (bias-variance tradeoff)

$$MSE(\beta) = \|\text{Bias}(\beta)\|^2 + \text{tr Cov}(\beta)$$

- Def and derivation of β^{blue} , β^{map} , and

their relations with β^{ls} , β^{ridge} , β^{lasso} .

(HW10 #3 #4)