
Midterm Review

03/28/2023

Part I: Loss Fn Based Approaches

$$L(y, \hat{y}), \hat{y} = h_{\theta}(x)$$

↓

$$L(y, h_{\theta}(x))$$

Training:

$$D = \{(x^{(1)}, y^{(1)}), \dots, (x^{(M)}, y^{(M)})\}$$

$$\min_{\theta} \sum_{i=1}^M L(y^{(i)}, h_{\theta}(x^{(i)}))$$

optimize using GD

$$\theta^{(0)} = \text{Something}$$

for $t = 1:T$

$$\theta^{(t+1)} = \theta^t - \alpha \nabla L(\theta)$$

Regularization

$$\min_{\theta} L(\theta) + \frac{\lambda}{2} \|\theta\|^2$$

low $\|\theta\| \rightarrow$ Reduce overfit

① Regression: $L(y, \hat{y}) = [y - \hat{y}]^2$

② Classifⁿ: $L(y, \hat{y}) = 1(y \neq \hat{y})$

Problem: cannot optimize.

Perceptron.

$$L(y, \hat{y}) = \max(0, -y \cdot \hat{y})$$

SVM

$$L(y, \hat{y}) = \max(0, 1 - y \cdot \hat{y})$$

Part II: Non-Parametric Approaches

kNN

No training

(Store Data in Mem)

Test: $\hat{y} = y^{(i^*)}$

where $i^* = \underset{i}{\operatorname{argmin}} \|x^{(i)} - x\|^2$

- Normalization important
- Careful with irrelevant attributes
- High inference time/cost, High memory

→ kD trees to reduce inf. time

Decision Trees



Loss fn: $\min_T \sum_L(h_T(\tilde{x}), y)$

DT Algo: Greedy Algo

Achieve Certainty or instances of "same class" on the same side after splitting

— Entropy

$\underset{i, t}{\operatorname{argmax}} H(Y) - H(Y | \{x_i \leq t\})$

Part III: Probabilistic Models

$$p(y|x, \theta), p(x, y|\theta)$$

↑
Conditional

↑
Joint

Generative Models
(NB)

$$\text{Model } p(x, y|\theta) = p(x|y, \theta) \underbrace{p(y|\theta)}$$

Learning:

Max Likelihood

$$\text{NB: } p(x|y) = \prod_{i=1}^d p(x_i|y)$$

Inference:

$$\underset{y}{\operatorname{argmax}} p(y|x)$$

Discriminative Models
(LR)

$$\text{Model: } p(y|x, \theta)$$

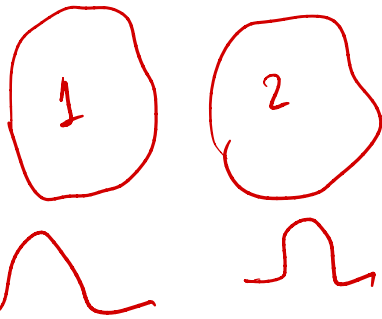
$$\text{Ideal: } p(y = \hat{y} | x, \theta) = 1 \text{ (if } y \text{ is } \hat{y} \text{ else 0)}$$

Since above is non-diff,

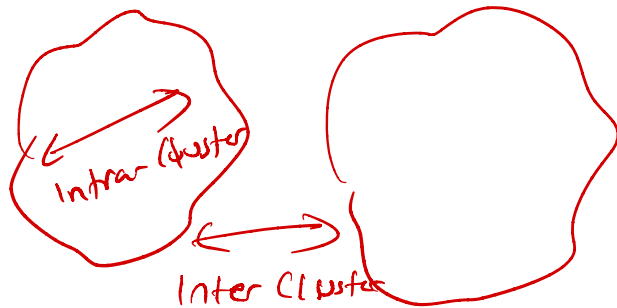
$$p(y|x, \theta) = \sigma(y, x, \theta)$$

Learning: Cond log Likelihood

$$\text{Inference: } \underset{y}{\operatorname{argmax}} p(y|x, \theta)$$



Part IV: Unsupervised Learning



K-Means

- Assignment Step (AS)
- Means Step (MS)

Alternating Minimization

$$\min_{S_1, \dots, S_K, \mu_1, \dots, \mu_K}$$

$$\sum_{i=1}^K \sum_{j \in S_i} \|x_j - \mu_i\|^2$$

↓

AS: Fix μ , optimize S

MS: Fix S , optimize μ