

COL774
Machine Learning
Oct 20, 2021

Unsupervised Learning :-

Till Now:- Supervised setting

$\{x^{(i)}, y^{(i)}\}_{i=1}^m$:- Training data

$h_\theta(x) = ?$

$x^{(i)} \in \mathbb{R}^n$ | $x^{(i)} \in \{ \dots \}$
 $\{0, 1\}$

Classification $y^{(i)} \in \{0, 1\}$

Regression $y^{(i)} \in \{ \dots \}$
 $y^{(i)} \in \mathbb{R}$

Neural Networks, Deep Networks

Linear Reg., Logistic Reg.

Unsupervised Learning $\{x^{(i)}\}_{i=1}^m$

Data:- $\{x^{(i)}\}_{i=1}^m$ $x^{(i)} \in \mathbb{R}^n$

"Learning" / Pattern finding.

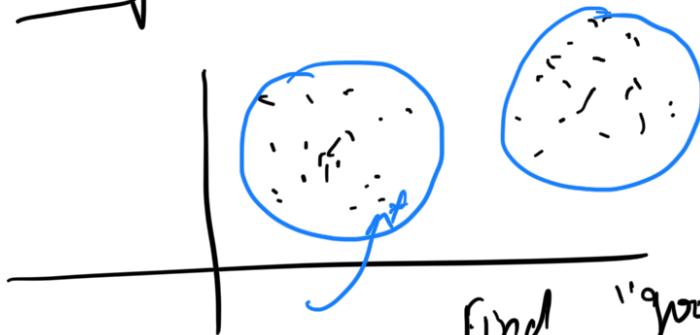
Semi-supervised setting

$\{x^{(i)}, y^{(i)}\}_{i=1}^m$

As subset of variables some are available others are not

$\{x^{(i)}\}_{i=1}^m$
 $\{x^{(i)}, z^{(i)}\}_{i=1}^m$
4 models
 $p(x^{(i)}, z^{(i)}; \theta)$

① Clustering :- $\{x^{(i)}\}_{i=1}^m$ $x^{(i)} \in \mathbb{R}^n$

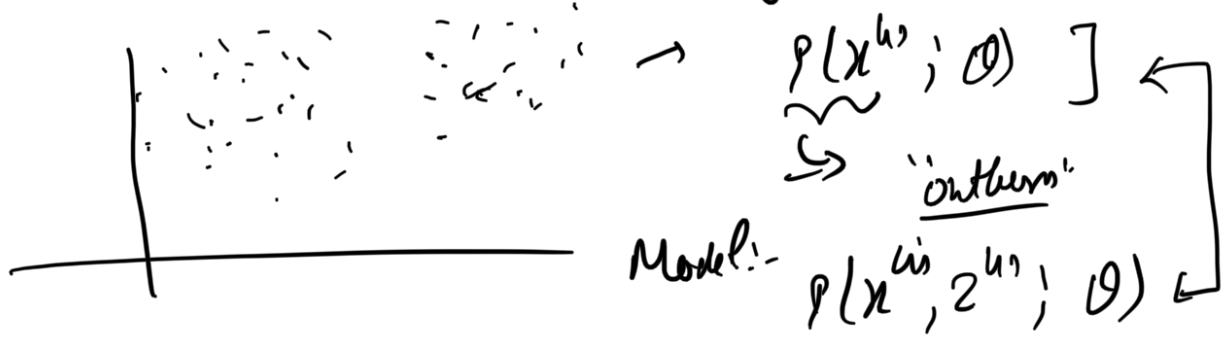


$K=2$
K-Means

find "good" clusters
↳ what is good?

② Density Estimation :-

- ✓ GMM (Gaussian Mixture Model) ← Prob D.H
 ✓ EM (Expectation Maximization)
 ↳ To deal with missing data



$$P(x^{(i)}; \theta) = \sum_{z^{(i)}} \underbrace{P(x^{(i)}, z^{(i)}; \theta)}_{\text{Joint Distribution}}$$

$$P(x^{(i)}; \theta) = \sum_{z^{(i)}} P(x^{(i)}, z^{(i)}; \theta) = \sum_{z^{(i)}} \underbrace{P(x^{(i)} | z^{(i)}; \theta)}_{\text{Gaussian}} P(z^{(i)}; \theta)$$

↳ Gaussian
 GMM: - Gaussian
 Mixture
 Model

→ "iterative
 algorithm"
 $z^{(i)}$'s & θ

⇒ EM: - Expectation Maximization

$$P(x^{(i)}, z^{(i)}; \theta)$$

$$\{x^{(i)}\}_{i=1}^m$$

$$\log \left[\prod_{i=1}^m P(x^{(i)}; \theta) \right] = \log \prod_{i=1}^m \left[\sum_{z^{(i)}} P(x^{(i)}, z^{(i)}; \theta) \right]$$

$$= \sum_{i=1}^m \log \sum_{z^{(i)}} P(x^{(i)}, z^{(i)}; \theta)$$

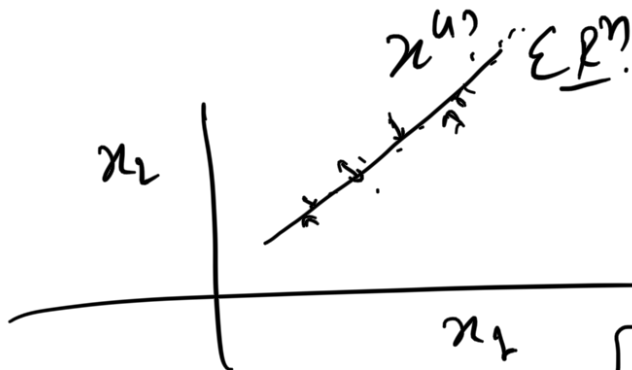
$$\geq \sum_{i=1}^m \sum_{z^{(i)}} h(z^{(i)}) \log \frac{P(x^{(i)}, z^{(i)}; \theta)}{q_i(z^{(i)})}$$

Jensen's
inequality

E:- Expectation
M:- Maximization

Estimate of distribution
over hidden variables

PCA:- Principal Component Analysis



:- Project the data
onto a lower
dimensional
subspace.

- ① Compact Rep
(Noise free)
- ② :- Small Feature

$\left[\mu_1 \dots \mu_K \right] :-$ principal components

$$x^{(u)} = \sum_{k=1}^K z_k^{(u)} \frac{\mu_k}{\|\mu_k\|}$$

FINALLY:-

Learning Theory.

Theoretical Foundations of Machine Learning

$\{x^{(i)}, y^{(i)}\}_{i=1}^m :-$ (holdn)
Generate with

$$Pr \left(\underbrace{|\hat{G}(S) - G(S)|}_{\substack{\downarrow \\ \text{Training} \\ \text{error}}} \geq S \right) \leq \underbrace{2e^{-2\gamma^2 m}}_{\substack{\downarrow \\ \text{Parameter}}} \quad \downarrow \quad 0 \leq S \leq 1$$

where $G(S)$ is the error on unseen data

PAC:- Probably Approximately Correct

K-Means clustering :- # of clusters Given:-



$K \quad \{x^{(i)}\}_{i=1}^m \quad x^{(i)} \in \mathbb{R}^n$

Find:-

① $\mu_1 \dots \mu_K$:- cluster centroids

$\mu_k \in \mathbb{R}^n$

② $\{c^{(i)}\}_{i=1}^m \in \{1 \dots K\}$
 \hookrightarrow cluster assignment for $x^{(i)}$
"good" clusters.

Notion of a good clustering:-

- (a) Intra cluster distance is minimized
- (b) Inter cluster distance will be maximized

argmin $\sum_{i=1}^m \|x^{(i)} - \mu_{c^{(i)}}\|^2$ is minimized

$\{ \mu_k \}_{k=1}^K$
 $\{ c^{(i)} \}_{i=1}^m$

$\{\mu_1 \dots \mu_K\}$
 $\{c^{(1)} \dots c^{(m)}\}$

Mixed optimization problem.
 (Discrete + Cont.)

K-Means Algorithm:-

(Iteration)

(A) If μ_k 's are known:-

$\therefore c^{(i)} = \argmin_k \|x^{(i)} - \mu_k\|^2$

(B) If $c^{(i)}$'s are known:-

$\mu_k = \frac{\sum_{i=1}^m 1_{\{c^{(i)}=k\}} x^{(i)}}{\sum_{i=1}^m 1_{\{c^{(i)}=k\}}}$

$$\mu_k = \underset{\mu_k}{\operatorname{argmin}} \frac{\sum_{i=1}^m \mathbb{1}_{\{C^w = k\}} \|x^{(i)} - \mu_k\|^2}{\sum_{i=1}^m \mathbb{1}_{\{C^w = k\}}}$$