

Probabilistic Prediction

- To handle ambiguous cases

Probability Distribution: $P(y|x, D)$

= a Vector of length C ;

- If $C=2$; $P(y=1|x, D) + P(y=0|x, D) = 1$

$$\hat{y} = \hat{f}(x) = \underset{c=1}{\operatorname{argmax}} P(y=c|x, D)$$

\sim most probable class label

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Regression

- Response variable is continuous

$$x_i \in \mathbb{R} \rightarrow y_i \in \mathbb{R}$$

Unsupervised Learning

\sim density estimation i.e. Build a model

a model of form $P(\underline{x}_i | \theta)$; unconditional density estimation.

\downarrow
vector of features

So we need to create multivariate prob. models.

- First task is to estimate the distribution over the number of clusters $p(K|D) \Rightarrow$ any subpopulation there or not

- for dimensionality reduction we use principal components analysis or PCA .

① parametric vs non-parametric model

probabilistic model ne of form $p(y|x)$ or $p(x)$
 \downarrow supervised \downarrow unsupervised

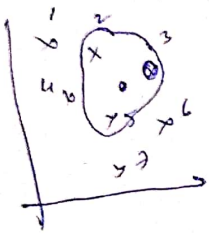
faster \leftarrow (parametric) parameters of the model is fixed?

flexible \leftarrow (non-parametric) grows or with the amount of training data?

$$\downarrow \text{exp} \quad \text{KNN} = p(y=c | x, D, K) = \frac{1}{K} \sum_{i \in N_K(x, D)} \mathbb{I}(y_i = c)$$

$N_K(x, D) =$ indices of K nearest points to x in D

$\mathbb{I}(e) =$ indicator funⁿ = $\begin{cases} 1 & \text{if } e = \text{true} \\ 0 & \text{if } e \text{ is false} \end{cases}$



$$p(y=0 | x, D, K) = \frac{1}{K} \sum_{i \in N_K} \mathbb{I}(y_i = 0)$$

$$N_K(x, D) = \{2, 3, 5\}$$

$$= \frac{1}{3} \{0, 1, 0\} = \frac{1}{3}$$

$$p(y=1 | x, D, K) = \frac{1}{K} \sum \frac{1}{3} \{1, 0, 1\} = \frac{2}{3}$$

② linear regression;

response is linear funⁿ of input

$$y(x) = \underline{w}^T \underline{x} + \epsilon = \sum_{j=1}^D w_j x_j + \epsilon$$

\downarrow residual error

Gaussian or normal distribution $N(\mu, \sigma^2)$

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