

عنوان: F.R. 7154 جدولی: تاریخ: ۱۳۹۸/۰۵/۰۵

موضوع: VC dimension و shattering

VC dimension: VC dimension of a set of points H is the maximum number of points that can be shattered by H .
 $H = \{h_1, h_2, \dots, h_n\}$ is a set of points in \mathbb{R}^d .
 H is shattered by H if and only if there exists a function $f: H \rightarrow \{0, 1\}$ such that $f(h_i) = 1$ if and only if h_i is in the set defined by f .

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minimizing the loss function (MSE) gives the

$$w^* = \underset{w}{\operatorname{argmin}} \sum_{i=1}^m (y_i - w^T x_i)^2$$

one can also consider the Gaussian likelihood of each y_i given x_i and w

$$y_i = w^T x_i + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

the joint likelihood is

$$w^* = \underset{w}{\operatorname{argmax}} \prod_{i=1}^m \mathcal{L}(y_i | x_i, w, \sigma^2) = \underset{w}{\operatorname{argmax}} \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i - w^T x_i)^2}{2\sigma^2}} =$$

$$\underset{w}{\operatorname{argmax}} \log \left(\prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y_i - w^T x_i)^2}{2\sigma^2}} \right) = \underset{w}{\operatorname{argmax}} \sum_{i=1}^m \left(\log \left(\frac{1}{\sqrt{2\pi}\sigma} \right) - \frac{(y_i - w^T x_i)^2}{2\sigma^2} \right) =$$

$$\underset{w}{\operatorname{argmax}} \sum_{i=1}^m \left(-\frac{(y_i - w^T x_i)^2}{2\sigma^2} \right) = \underset{w}{\operatorname{argmax}} \sum_{i=1}^m (y_i - w^T x_i)^2 = \underset{w}{\operatorname{argmin}} \sum_{i=1}^m (y_i - w^T x_i)^2$$

the same as minimizing the MSE

the ML estimate of σ^2 is the variance of the

$$(\mu^*, \sigma^{*2}) = \underset{\mu, \sigma^2}{\operatorname{argmax}} \prod_{i=1}^m \mathcal{L}(x_i | \mu, \sigma^2) = \underset{\mu, \sigma^2}{\operatorname{argmax}} \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}} =$$

$$\underset{\mu, \sigma^2}{\operatorname{argmax}} \sum_{i=1}^m \left(\log \left(\frac{1}{\sqrt{2\pi}\sigma} \right) - \frac{(x_i - \mu)^2}{2\sigma^2} \right) =$$

$$\frac{\partial}{\partial \mu} \sum_{i=1}^m \left(-\frac{(x_i - \mu)^2}{2\sigma^2} \right) = 0 \implies \mu = \frac{1}{m} \sum_{i=1}^m x_i$$

$$\frac{\partial}{\partial \sigma^2} \sum_{i=1}^m \left(-\frac{(x_i - \mu)^2}{2\sigma^2} \right) = 0 \implies \sigma^{*2} = \frac{1}{m} \sum_{i=1}^m (x_i - \mu)^2$$

the Regression line will be

$$w^* = \underset{w}{\operatorname{argmin}} \|Y - KW\|_2^2$$

where K is the matrix of features and Y is the vector of targets

$$w^* = \underset{w}{\operatorname{argmin}} (Y - KW)^T (Y - KW) = \underset{w}{\operatorname{argmin}} Y^T Y - Y^T K W - W^T K^T Y + W^T K^T K W$$

$$\frac{\partial}{\partial w} \left(Y^T Y - Y^T K W - W^T K^T Y + W^T K^T K W \right) = 0 \implies -Y^T K + 2W^T K^T K = 0 \implies W = (K^T K)^{-1} K^T Y$$

with regularization

$$w^* = \underset{w}{\operatorname{argmin}} \|Y - KW\|_2^2 + \lambda \|w\|_2^2 =$$

$$\underset{w}{\operatorname{argmin}} Y^T Y - Y^T K W - W^T K^T Y + W^T K^T K W + \lambda W^T W$$

$$\frac{\partial}{\partial w} \left(Y^T Y - Y^T K W - W^T K^T Y + W^T K^T K W + \lambda W^T W \right) = 0 \implies (K^T K + \lambda I) W = K^T Y$$

$$w = (K^T K + \lambda I)^{-1} K^T Y$$