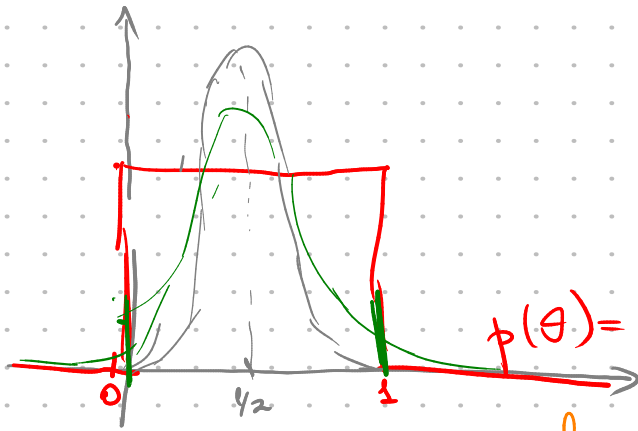


$D = htthhh$        $\theta = p(\text{open})$

$P(D|\theta) = \theta^n (1-\theta)^m$

$\theta_{ML} = \frac{n}{n+m}$



$p(\theta|D) \propto p(\theta)p(D|\theta)$

$\theta_{MAP} = \theta_{ML}$

$p(\theta) = \begin{cases} 1, & \theta \in [0,1] \\ 0, & \theta \notin [0,1] \end{cases}$

$p(\text{open} | D) = \int p(\text{open}, \theta | D) d\theta = \int p(\text{open} | \theta) p(\theta | D) d\theta$

$p(\text{open} | D) = \frac{n+1}{n+m+2}$

$p(\theta) = \begin{cases} \propto \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(\theta - \frac{1}{2})^2} \\ 0, & \theta \notin [0,1] \end{cases}$

$\times p(D|\theta) = \theta^n (1-\theta)^m$

бета-распределение:

$p(\theta | \alpha, \beta) = \frac{1}{B(\alpha, \beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1}, \theta \in [0,1]$

на  $[0,1]$

$p(\theta|D) \propto p(D|\theta) p(\theta | \alpha, \beta) \propto \theta^n (1-\theta)^m \cdot \theta^{\alpha-1} (1-\theta)^{\beta-1} =$   
 $= \theta^{n+\alpha-1} (1-\theta)^{m+\beta-1}$

$p(\theta|D) = \text{Beta}(\theta | \alpha+n, \beta+m)$

$p(\theta) \times p(D|\theta) \propto p(\theta|D)$

$\text{Beta}(\theta | \alpha, \beta)$

$\theta^n (1-\theta)^m$

$\text{Beta}(\theta | \alpha+n, \beta+m)$

$D', n', m'$  - любые значения

$$p(\theta | \underline{D}, \underline{D}') \propto p(\theta) p(\underline{D}, \underline{D}' | \theta)$$

$$\propto \underline{p(\theta | \underline{D})} \cdot p(\underline{D}' | \theta)$$

### Conjugate priors

$p(\theta | \bar{x})$  - con. conj. exp. p.  $\Rightarrow$  con. conj. p.  $p(\underline{D} | \theta)$ , even  
 $\Rightarrow p(\theta | \bar{x}) \cdot p(\underline{D} | \theta) \propto p(\theta | \bar{x}')$

$$\theta^{\alpha-1} (1-\theta)^{\beta-1} \quad \frac{\alpha-1}{\alpha+\beta-2}$$

Equivalent sample size

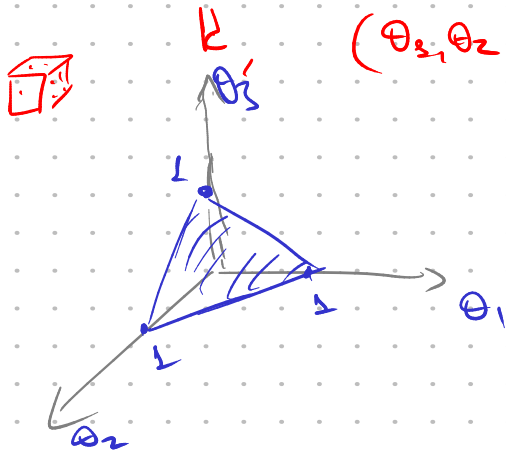
$$p(\theta) = \text{Beta}(\theta | 1, 1)$$

$\Leftrightarrow$

$$p(\theta) = \text{Beta}(1, 1)$$

$$p(\underline{D} | \theta) = \theta^{10} (1-\theta)^{10}$$

$$\text{Beta}(\theta | \frac{1}{2}, \frac{1}{2}) \propto \theta^{-\frac{1}{2}} (1-\theta)^{-\frac{1}{2}}$$



$$(\theta_1, \theta_2, \dots, \theta_k) = \bar{\theta} \quad 0 \leq \theta_k \leq 1$$

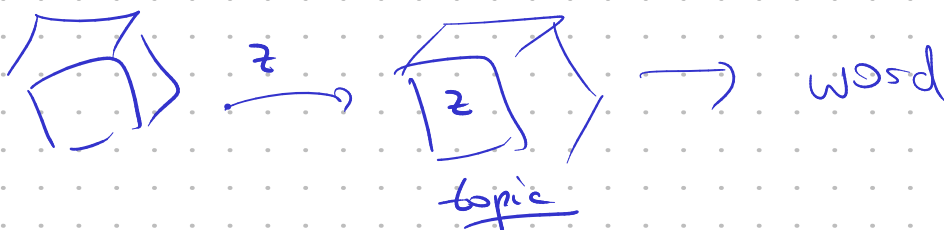
$$\theta_k = 1 - \sum_{i=1}^{k-1} \theta_i \quad \sum \theta_k = 1$$

$$p(\underline{D} | \bar{\theta}) = \theta_1^{n_1} \theta_2^{n_2} \dots \theta_k^{n_k}$$

$$p(\bar{\theta} | \bar{x}) = \frac{1}{\text{Dir}(\bar{x})} \theta_1^{d_1-1} \theta_2^{d_2-1} \dots \theta_k^{d_k-1}$$

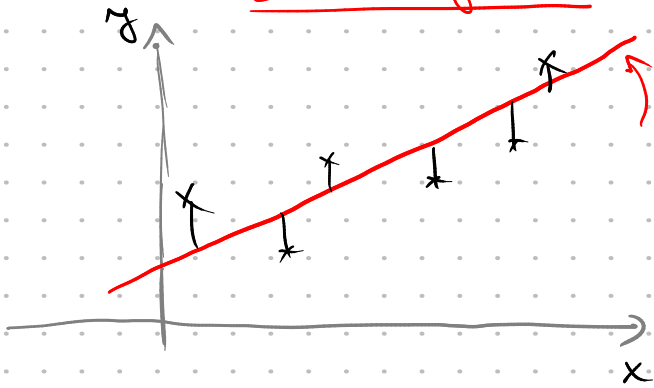
$$p(\bar{\theta} | \underline{D}) \propto p(\bar{\theta}) p(\underline{D} | \bar{\theta}) \propto \theta_1^{\alpha_1+n_1-1} \dots \theta_k^{\alpha_k+n_k-1}$$

$$p(\bar{\theta} | (\frac{1}{10}, \dots, \frac{1}{10})) = \frac{1}{\text{Dir}(\bar{x})} \theta_1^{-\frac{9}{10}} \theta_2^{-\frac{9}{10}} \dots \theta_k^{-\frac{9}{10}}$$



$$p(\theta|D) \propto p(\theta) p(D|\theta)$$

Linear regression



$$D = \{(x_n, y_n)\}_{n=1}^N$$

$$y = w_0 + w_1 x$$

$$D = \{(x_n, y_n)\}_{n=1}^N$$

$$y \sim w_0 + w_1 x + \dots + w_d x^d$$

$$\boxed{y \sim \bar{w}^T \bar{x}} = \begin{pmatrix} x \\ 1 \end{pmatrix}$$

$$L = \sum_{n=1}^N (y_n - \bar{w}^T \bar{x}_n)^2$$

$$\rightarrow \min_{\bar{x}_i^T \bar{w}}$$

$$\begin{pmatrix} y_1 - \bar{w}^T \bar{x}_1 \\ \vdots \\ y_N - \bar{w}^T \bar{x}_N \end{pmatrix}^T \begin{pmatrix} y_1 - \bar{w}^T \bar{x}_1 \\ \vdots \\ y_N - \bar{w}^T \bar{x}_N \end{pmatrix} =$$

$N \times 1 \quad N \times d \quad d \times 1$

$$= (\bar{y} - X\bar{w})^T (\bar{y} - X\bar{w}) = \bar{y}^T \bar{y} - \underbrace{(X\bar{w})^T \bar{y}} - \underbrace{\bar{y}^T X\bar{w}} + \underbrace{(X\bar{w})^T X\bar{w}} =$$

$$\begin{pmatrix} - & x_1 & - \\ - & x_2 & - \\ \vdots & \vdots & \vdots \\ - & x_N & - \end{pmatrix} \begin{pmatrix} \bar{w}_1 \\ \vdots \\ \bar{w}_d \end{pmatrix}$$

$$= \bar{w}^T (X^T X) \bar{w} - 2 \bar{y}^T X \bar{w} + \bar{y}^T \bar{y} \rightarrow \min$$

$w_1 a_1 + \dots + w_d a_d$

$$\nabla_{\bar{w}} L = 0$$

$$\nabla_{\bar{w}} L = \begin{pmatrix} \partial L / \partial w_1 \\ \vdots \\ \partial L / \partial w_d \end{pmatrix}$$

$$\nabla_{\bar{w}} (\bar{w}^T \bar{a}) = \begin{pmatrix} a_1 \\ \vdots \\ a_d \end{pmatrix} = \bar{a}$$

$$\nabla_{\bar{w}} (\bar{w}^T \bar{w}) = 2\bar{w}$$

$$\nabla_{\bar{w}} (\bar{w}^T A \bar{w}) = (A + A^T) \bar{w}$$

$$= \bar{a}_{k \times k}^T \bar{w} + \bar{a}_{k \times k}^T \bar{w}$$

$$\partial \left( \sum_{i=1}^d \sum_{j=1}^d a_{ij} w_i w_j \right) = \sum_{j \neq k} a_{kj} w_j + \sum_{i \neq k} a_{ik} w_i + 2a_{kk} w_k =$$

$$\nabla_{\bar{w}} L = 2X^T X \bar{w} - 2X^T \bar{y} = 0$$

$$X^T X \bar{w} = X^T \bar{y}$$

$$\bar{w}^* = (X^T X)^{-1} X^T \bar{y}$$

Moore-Penrose  
pseudoinverse

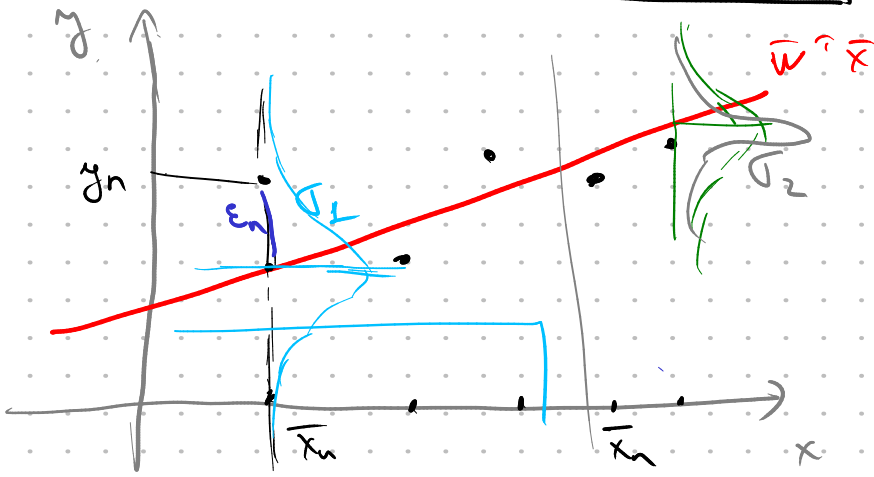
~~p(x)~~ discriminative

$$p(y | \bar{w}(\bar{x}))$$

$$p(D | \bar{w}, X)$$

$$y = (\bar{w}^T \bar{x} + \varepsilon)$$

$$\varepsilon \sim \mathcal{N}(0, \sigma^2)$$



likelihood

$$p(D | \bar{w}, X) = \prod_{n=1}^N p(y_n | \bar{w}, \bar{x}_n) = \prod_{n=1}^N \mathcal{N}(y_n | \bar{w}^T \bar{x}_n, \sigma^2) =$$

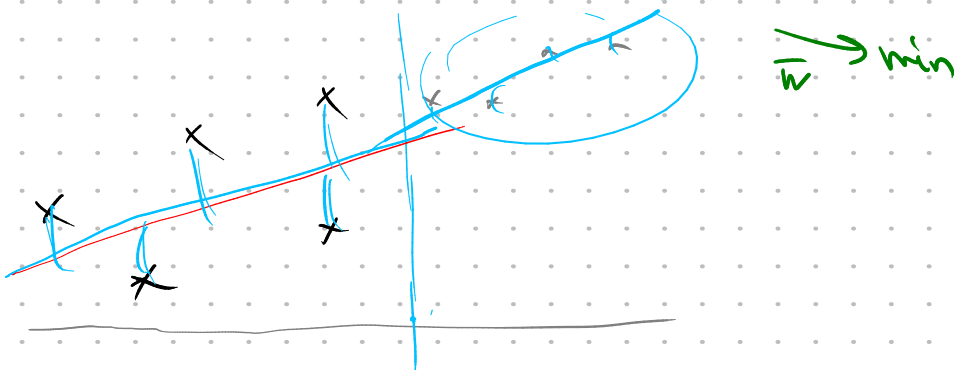
$$= \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} (y_n - \bar{w}^T \bar{x}_n)^2}$$

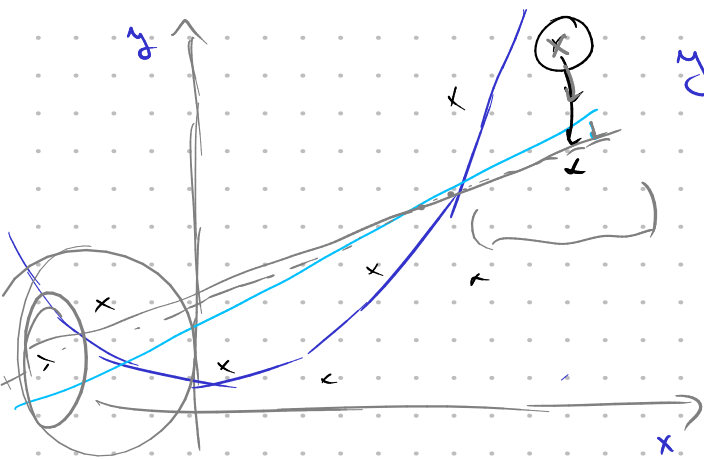
$\bar{w} \rightarrow \max$

$$\ln p(D | \bar{w}, X) = \sum_{n=1}^N \left( -\frac{1}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} (y_n - \bar{w}^T \bar{x}_n)^2 \right) =$$

$$= \text{const} - \frac{1}{2\sigma^2} \sum_{n=1}^N (y_n - \bar{w}^T \bar{x}_n)^2$$

$\bar{w} \rightarrow \max$

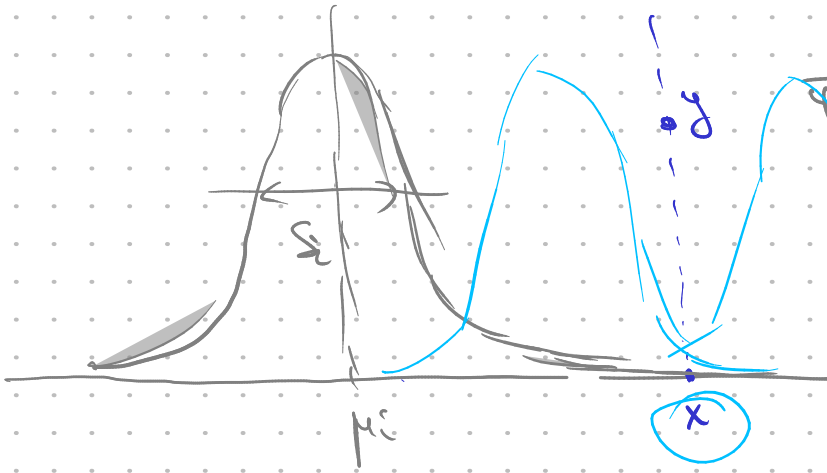




$$y \sim w_0 + w_1 x + w_2 x^2 = \begin{pmatrix} w_0 \\ w_1 \\ w_2 \end{pmatrix}^T \begin{pmatrix} 1 \\ x \\ x^2 \end{pmatrix}$$

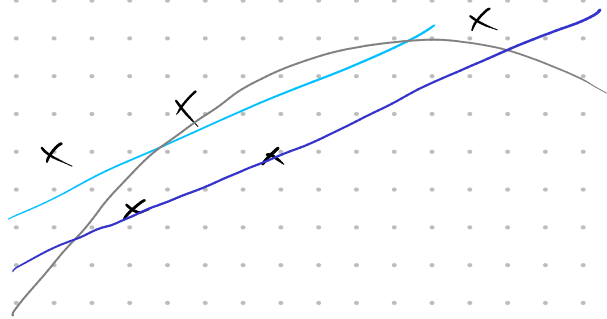
$$y \sim \bar{w}^T \varphi(x)$$

$$x \mapsto \varphi(x)$$



$$\varphi_i(x) = e^{-\frac{1}{2\sigma_i^2}(x-\mu_i)^2}$$

$$y \sim \sum_i w_i \varphi_i(x)$$



$$p(d_1, d_2 | \theta) = p(d_1 | \theta) p(d_2 | \theta)$$

$$p(d_1 | d_2)$$

$$p(x | \theta)$$

$$p(x | D) = \int p(\theta | D) p(x | \theta) d\theta$$

$$p(x | D, \theta) \equiv p(x | \theta)$$

Model selection

$$p(D | \theta) = \prod p(d_i | \theta)$$

↑  
noisy