$$P(A,B) = P(A|B)P(B) = P(B|A)P(A)$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$\mathcal{T} = \{x_i, y_i\} \quad i=1 \ldots N$$

$$P(\theta,\mathcal{T}) = P(\theta|\mathcal{T})P(\mathcal{T}) = P(\mathcal{T}|\theta)P(\theta)$$

$$P(\theta|\mathcal{T}) = \frac{P(\mathcal{T}|\theta)P(\theta)}{P(\mathcal{T})}$$ — evidence

$P(\theta)$ — априорное распр-е θ

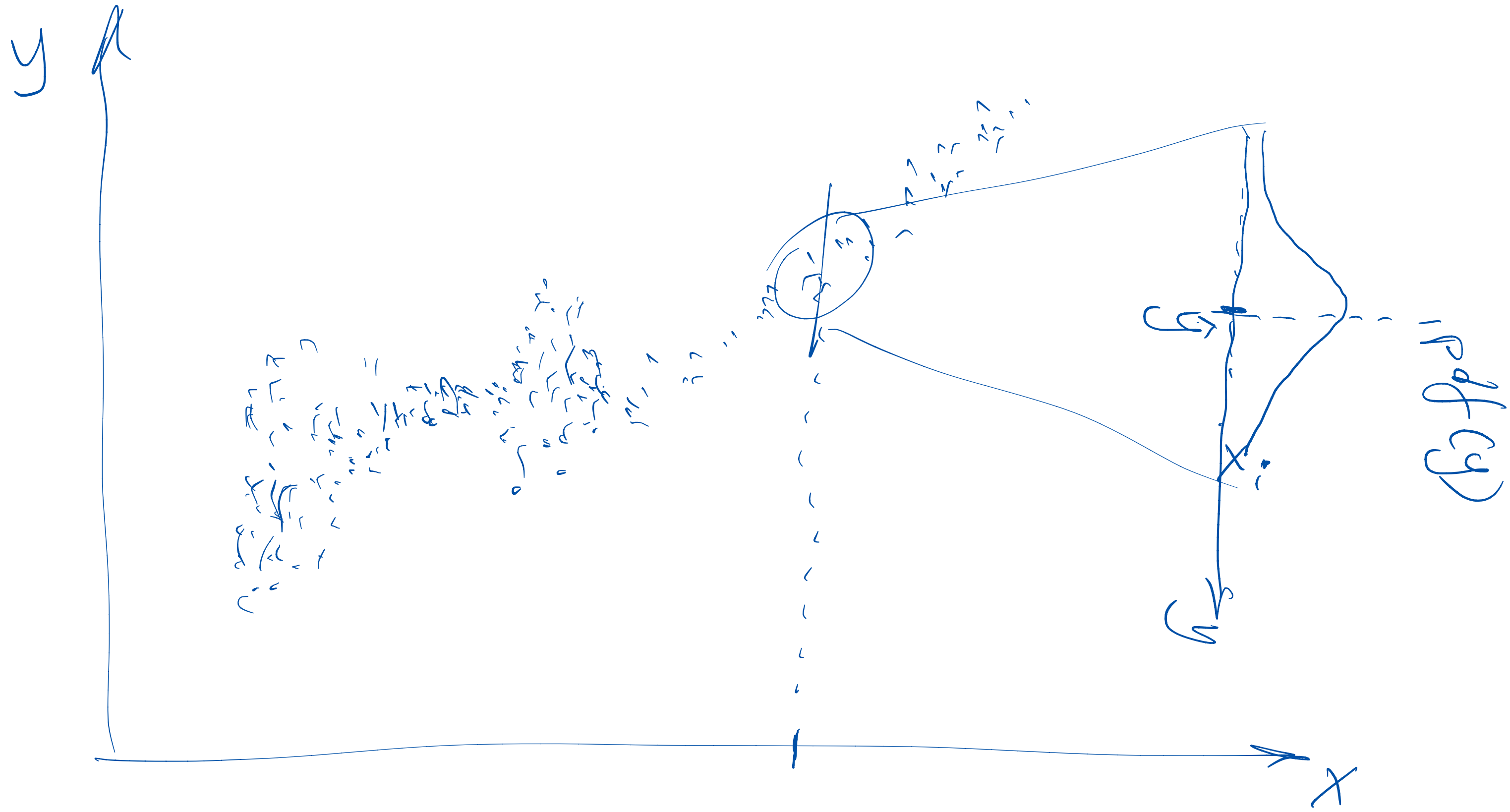
prior

$P(\mathcal{T}|\theta)$ — likelihood

правдоподобие выборки

$P(\theta|\mathcal{T})$ — апостериорное распр-е θ

$$\theta^* = \underset{\Theta}{\operatorname{argmax}}\, P(\mathcal{T}|\theta)$$



$\mu(x_i)$

$\sigma^2(x_i)$

$y_i \sim \mathcal{N}(\mu, \sigma^2)$

LINE

L: $\mu_i = \theta^T x_i$ linear

I: i.i.d.

N: $y \sim \mathcal{N}(\mu, \sigma^2)$ normal

E: $\sigma_i^2 = \sigma^2$ equivariance

$$P(x_i, y_i, \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \mu_i)^2}{2\sigma^2}}$$

$$L(Y, \theta) = P(Y|\theta) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \mu_i)^2}{2\sigma^2}}$$

$$\theta^* = \underset{\Theta}{\operatorname{argmax}}\, P(Y|\theta) = \underset{\Theta}{\operatorname{argmax}}\, \underline{\ln P(Y|\theta)}$$

$$\ell(Y|\theta) = \ln \prod \ldots = \sum_{i=1}^{N} \ln \ldots =$$

$$= \sum_{i=1}^{N} \left[\ln \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) + \ln e^{-\frac{(y_i - \mu_i)^2}{2\sigma^2}} \right) =$$

$$= N \cdot \ln \frac{1}{\sqrt{2\pi\sigma^2}} - \sum_{i=1}^{N} \left(\frac{(y_i - \mu_i)^2}{2\sigma^2} \right)$$

$$\underset{\Theta}{\operatorname{argmax}}\, \ell(Y|\theta) = \underset{\Theta}{\operatorname{argmin}} \sum_{i=1}^{N} (y_i - \mu_i)^2 =$$

$$= \boxed{\underset{\Theta}{\operatorname{argmin}} \sum_{i=1}^{N} (y_i - \theta^T x_i)^2}$$

$$\mathcal{L} = \sum_{i=1}^{N} (y_i - \theta^T x_i)^2$$