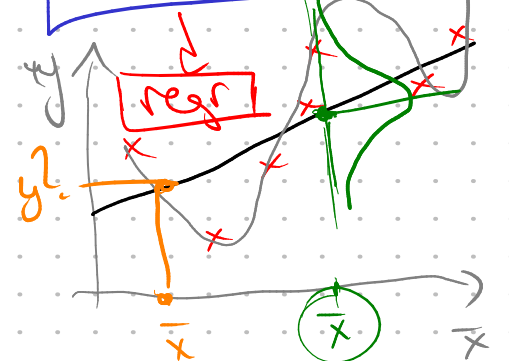


ML

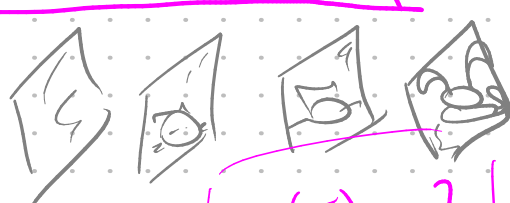
Reinforcement learning

Unsupervised learning

Supervised learning

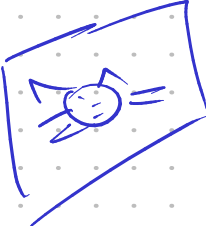


Classification



$P(\bar{x}) = ?$

clustering

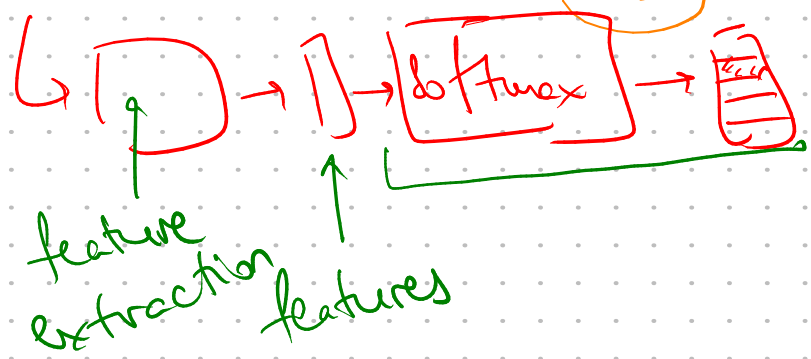


cat?
dog?

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

$$f: \bar{x} \rightarrow y$$

$$P(y|\bar{x}) = ?$$



$$P(x=a, y=b)$$

$$P(x) = \int P(x,y) dy$$

$$P(x|y) = \frac{P(x,y)}{P(y)}$$

← marginalization
 conditional independence
 $P(x,y|z) = P(x|z)P(y|z)$
 $P(x,y) = P(x)P(y)$
 independence

$$P(x,y) = P(x|y)P(y) = P(y|x)P(x)$$

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

Bayes Theorem

MAP - posterior
MLE - evidence

$$p(\theta | D) = \frac{\overbrace{p(D|\theta)}^{\text{likelihood}} \overbrace{p(\theta)}^{\text{prior}}}{\underbrace{p(D)}_{\text{evidence}}}$$

posterior distribution

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

(1) ML - max likelihood

$$\theta_{ML} = \underset{\theta}{\operatorname{argmax}} p(D|\theta)$$

(2) MAP - maximum a posteriori

$$\theta_{MAP} = \underset{\theta}{\operatorname{argmax}} p(\theta | D) = \underset{\theta}{\operatorname{argmax}} p(D|\theta)p(\theta)$$

(3) Predictive distribution

$$p(x | D) = \int p(x, \theta | D) d\theta = \int p(x | \theta, D) \cdot \underbrace{p(\theta | D)}_{\text{posterior}} d\theta = \int \underbrace{p(x | \theta)}_{\text{likelihood}} \underbrace{p(\theta | D)}_{\text{posterior}} d\theta$$

Bayesian inference

$$p(D|\theta) = \prod_{d \in D} p(d|\theta)$$

$$\begin{aligned} \mathbb{E}_{p(x)}[f(x)] &= \\ &= \int f(x) p(x) dx \end{aligned}$$

$$p(x|D) = \mathbb{E}_{p(\theta|D)} [p(x|\theta)] \approx$$

$$\approx \frac{1}{R} \sum_{z=1}^R p(x|\theta^{(z)}) \quad \text{use } \theta^{(z)} \sim p(\theta|D)$$

Moneta

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

$$1-\theta = p(\text{reverse})$$

D = htthhttt

$$p(D|\theta) = \prod_{d \in D} p(d|\theta) = \theta^n (1-\theta)^m \quad \text{use}$$

$$\theta_{ML} = \arg \max_{\theta} p(D|\theta) \stackrel{h}{=} \frac{n}{n+m}$$

n = # opens
m = # reverses

$$\frac{\partial p(D|\theta)}{\partial \theta} = n \theta^{n-1} (1-\theta)^m - m \theta^n (1-\theta)^{m-1} = 0$$

$$\theta^{n-1} (1-\theta)^{m-1} (n(1-\theta) - m\theta) = 0$$

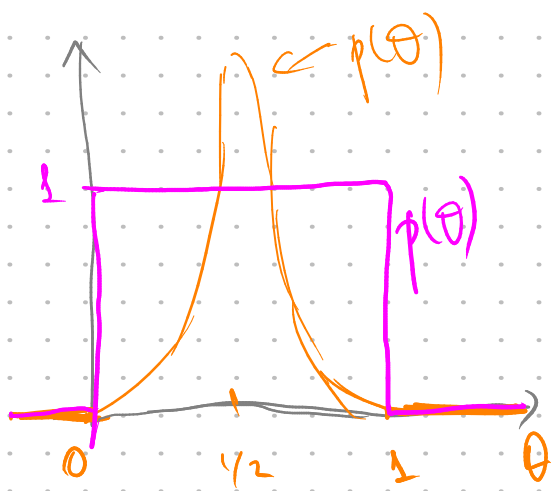
$$\theta = 0, 1, \frac{n}{n+m}$$

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

D = h

$$p(D|\theta) = \theta \rightarrow \max$$

$$\theta_{ML} = 1$$



prior
 $p(\theta)$

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

$$p(\theta | D) \propto p(D | \theta) p(\theta) = \begin{cases} \theta^n (1-\theta)^m, & \theta \in [0, 1] \\ 0, & \theta \notin [0, 1] \end{cases}$$

$$p(\theta) = \int_{-\infty}^{\infty} p(D | \theta) p(\theta) d\theta = \int_0^1 \theta^n (1-\theta)^m d\theta = B(n+1, m+1)$$

$$= \frac{\Gamma(n+1) \Gamma(m+1)}{\Gamma(n+m+2)} = \frac{n! m!}{(n+m+1)!}$$

$$B(\alpha, \beta) = \frac{\Gamma(\alpha) \Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

$$p(\theta | D) = \begin{cases} \frac{(n+m+1)!}{n! m!} \theta^n (1-\theta)^m, & \theta \in [0, 1] \\ 0, & \theta \notin [0, 1] \end{cases}$$

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

$$b = h$$



$$(3) p(\text{opřen} | D) = \int \underline{p(\text{opřen} | \theta)} p(\theta | D) d\theta =$$

$$= \int_0^1 \theta \cdot \frac{(n+m+1)!}{n!m!} \theta^n (1-\theta)^m d\theta =$$

$$= \frac{(n+m+1)!}{n!m!} \int_0^1 \theta^{n+1} (1-\theta)^m d\theta =$$

$$= \frac{\cancel{(n+m+1)!}}{\cancel{n!m!}} \cdot \frac{\cancel{(n+1)!} \cdot \cancel{m!}}{(n+m+2)!}$$

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

Laplace's
rule