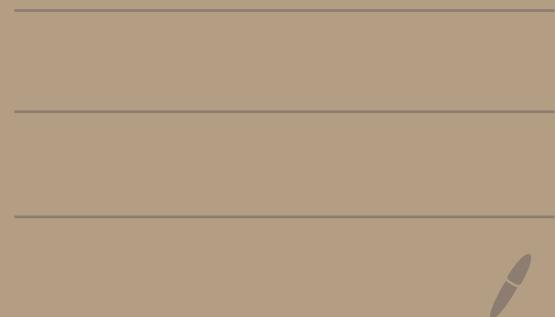


Lecture 9 Naive Bayes, MLE

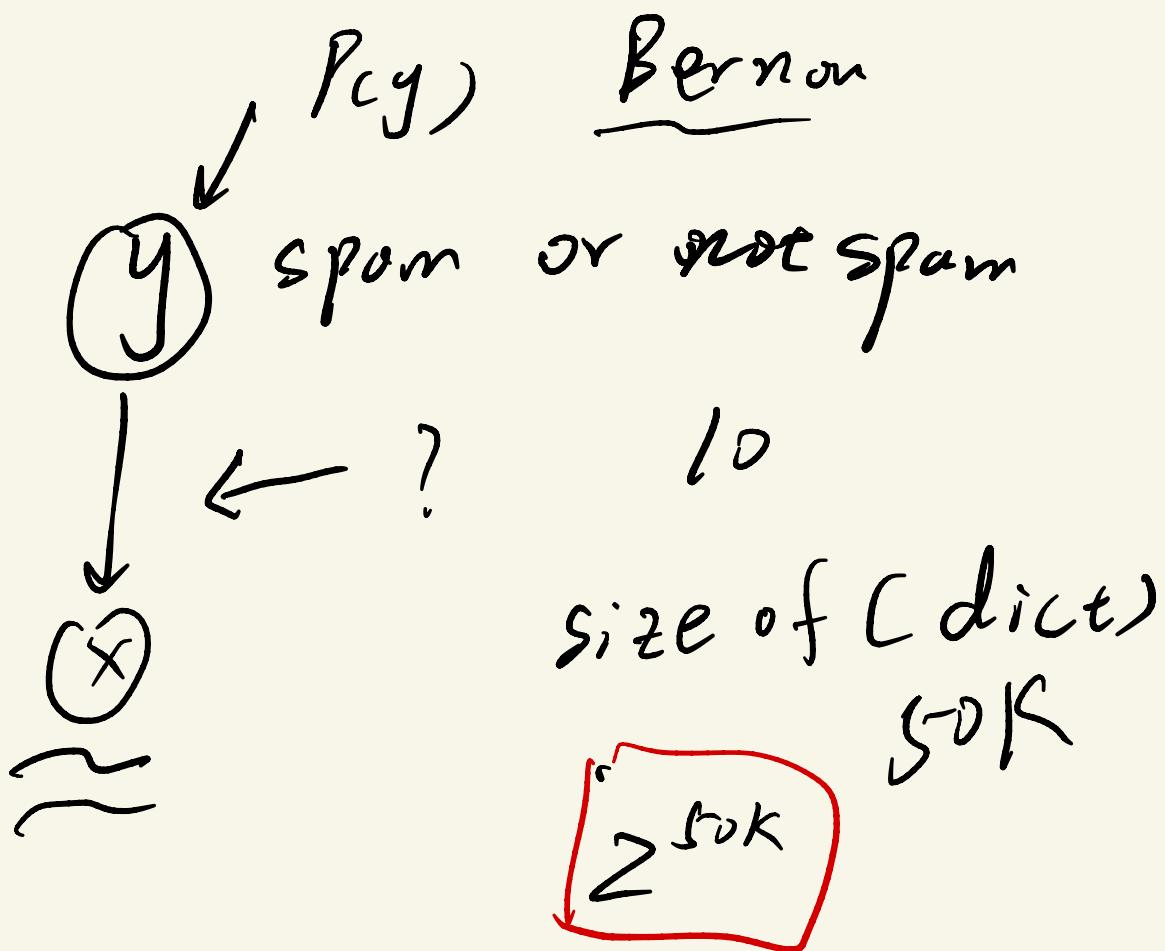


$$P(x|y) \quad P(y)$$

$$\underline{P(y|x)} \propto P(x|y) P(y)$$

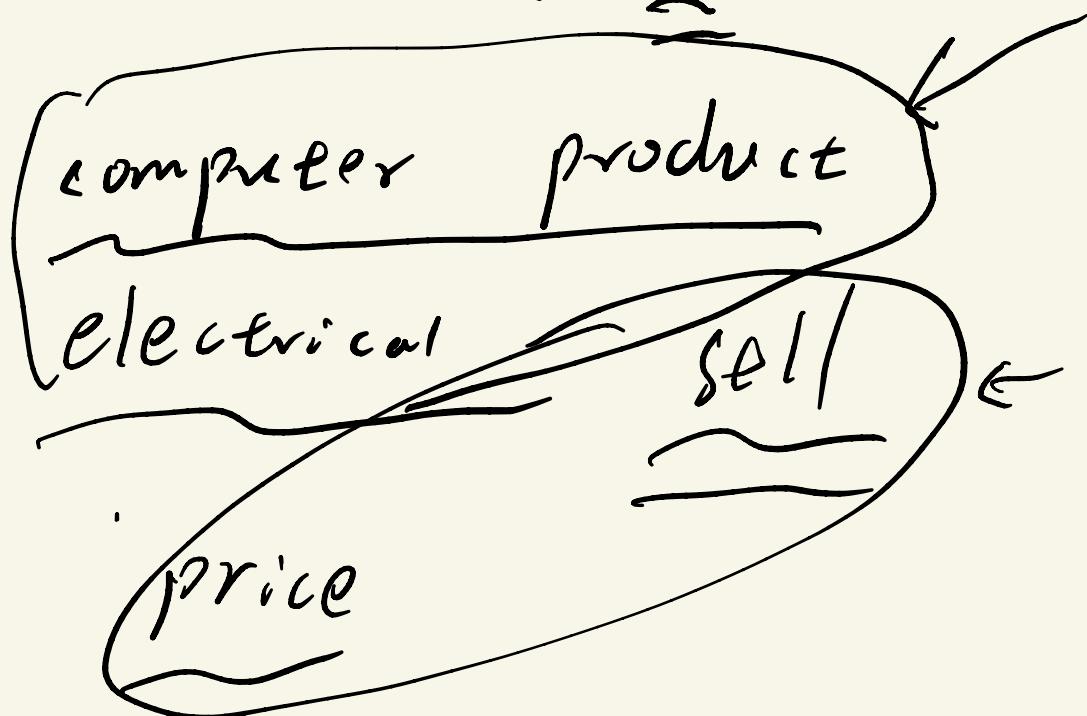
1. count of the words

2. order



y

$$P(x_i | \underline{y_j}) = P(x_i | y_j, \underline{x_j})$$



$$P(x_1, x_2, x_3, \dots, x_n | c_1, c_2, c_3)$$

$$= P(x_1 | c_1, c_2, c_3) P(x_2 | x_1, c_1, c_2, c_3) P(x_3 | x_1, x_2, c_1, c_2, c_3) \dots P(x_n | x_1, \dots, x_{n-1})$$

$$= P(x_5) P(x_2 | x_5) P(x_3 | x_2, x_5)$$

$$P(x_n | x_3, x_2, x_5) \dots$$

$$P(x_1 | y, \dots, x_2, \dots, x_3, \dots)$$

$$= P(x, y)$$

2^{50K}

$$I(\text{true}) = 1$$

$$I(\text{false}) = 0$$

① and

P("computer" is present | spam)

=

$$\phi_y =$$

normalization

$$\sum_{j=1}^K \phi_j = 1$$



$$\log P_\theta(x) + L(\theta)$$

$P_{\text{data}}(x)$ no parameter

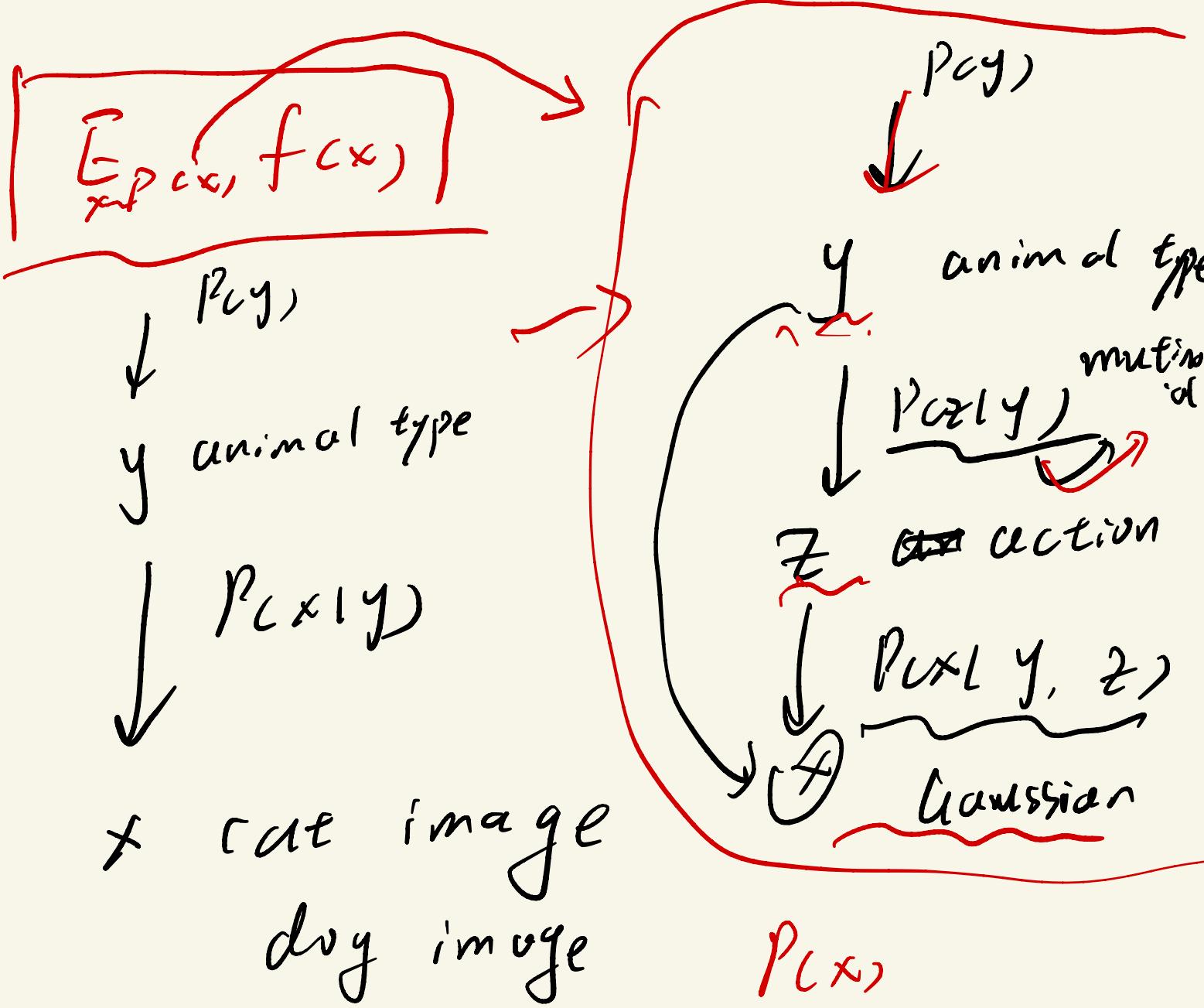
$$E_{x \sim p(x)} \underbrace{f(x)}$$

$$\overbrace{E\left[\frac{1}{n} \sum_{i=1}^n f(x^{(i)})\right]} = \underbrace{E_{x \sim p(x)} f(x)}$$

what if $\text{Var}\left[\frac{1}{n} \sum_{i=1}^n f(x^{(i)})\right] = 1$

$$\text{Var} = \frac{\text{Var}(f(x))}{n} \xrightarrow{n \rightarrow \infty}$$

$$\lim_{n \rightarrow \infty} \text{Var} = 0$$



$$P(x) = \sum_{y, z} P(y, z, x)$$

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

folk

\hat{x}_0

ancestral sampling

$$f(x) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

inverse CDF

$$CDF = \int_{-\infty}^x P(x) dx$$

$$\underbrace{P(x)}$$

$$bias = \frac{1}{n}$$

$$\text{mean}(x) = \left(\frac{\sum_i^n x_i}{n} \right) \hat{\mu}$$

$\text{Var}(x)$

\rightarrow biased

$$E\left[\frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2\right] = \text{Var}(x)$$

unbiased

$\text{Var}(x)$

central limit theorem

$$= E[(x - \mu)^2]$$

theorem

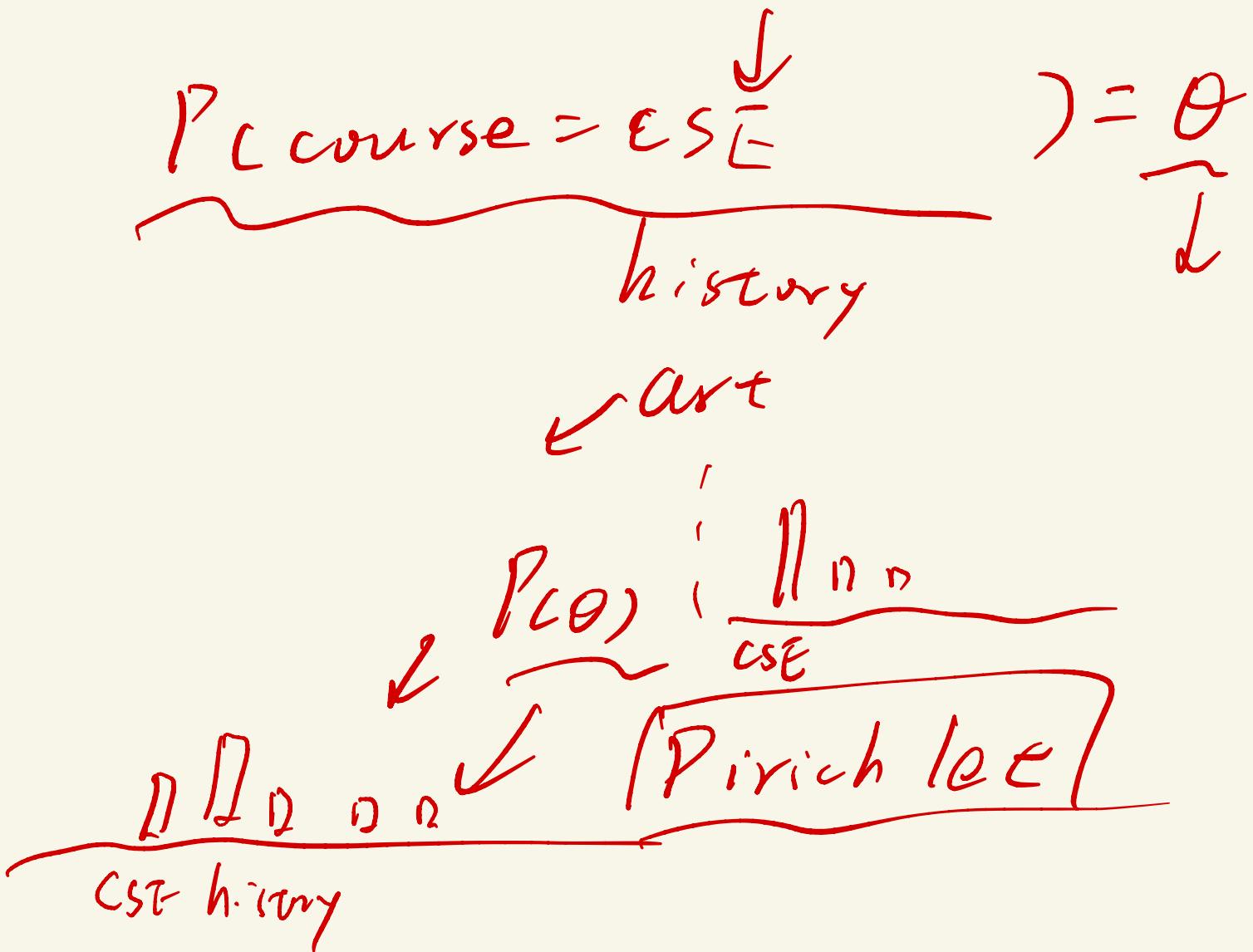
bias or unbiased?

$$E\left[\frac{\sum_i^n x_i}{n}\right] = \text{mean}(x)$$

μ, σ^2

↓
random variable

$$\underbrace{P(\mu), P(\sigma^2)}_{N(0,1)}$$



$$P(\theta), P(D|\theta)$$

