

Naive Bayesian(cont.) && confidence interval

1. Naive Bayesian \rightarrow alphabet (cont.)

a. Prior

$$p(x) \propto \exp \left\{ \frac{1}{2} \sum_{i \neq j} \beta_{ij} (x_i x_j + (1 - x_i)(1 - x_j)) \right\}$$

b. Likelihood \rightarrow try to fit the data well

$$p(y|x) = \prod_{i=1}^n f(y_i|1)^{x_i} f(y_i|0)^{1-x_i}.$$

2. Exact Map Estimation for Binary images

a. Our map inference becomes equivalent to minimizing

$$\sum_{i=1}^n x_i \max(0, -\lambda_i) + \sum_{i=1}^n \max(0, \lambda_i)(1 - x_i) + \frac{1}{2} \sum_{i \sim j} \beta_{ij} (x_i - x_j)^2,$$

$$\text{where } \lambda_i = \frac{f(y_i|1)}{f(y_i|0)}.$$

b. We have $n * m$ binary matrix

c. We impose a grid structure

d. WE call two neighboring nodes bad if they have different values. We pay K units for each such pair

e. We are allowed to flip the value of any node, but we have to pay R units

f. The total cost is the sum of these two terms. How do we find the best assignment of values to nodes?

i. $R(\# \text{ pixels flipped}) + k(\# \text{ disagreements})$

g. Max flow problem!

i. Source s, sink t

ii. Arc of capacity R from s to each node u with value 0

iii. Arc of capacity R from each u node with value 1 to sink t

iv. Directed arcs from each node u to its neighbors with capacity K

3. Convolution

a. Suppose X and Y are independent, with known distributions, and $Z = X + Y$. What is distribution of Z?

$$p_Z(z) = \sum_q p_X(q)p_Y(z - q)$$

- i. Case 1 (discrete): the pmf is given by
- ii. Case 2 (continuous): the pdf is given by

$$f_Z(z) = \int_{-\infty}^{+\infty} f_X(q)f_Y(z - q)dq$$

4. Convolution of normal distribution

- a. The normal distribution satisfies a nice convolution identity:

if $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$, $X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$, then $X_1 + X_2 \sim \mathcal{N}(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

- b. Inductively we obtain the following fact:

if $X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), \dots, X_n \sim \mathcal{N}(\mu_n, \sigma_n^2)$, then $\sum_{i=1}^n X_i \sim \mathcal{N}\left(\sum_{i=1}^n \mu_i, \sum_{i=1}^n \sigma_i^2\right)$

- c. If all $X_i \sim \mathcal{N}(\mu, \sigma^2)$, then by standardizing (setting mean to 0 and std to 1), we obtain

$$\frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}} \sim \mathcal{N}(0, 1)$$

5. Moments

- a. We define the k-th moment of a random variable as follows:

$$M_k(X) = \mathbb{E}[X^k]$$

- i. When $k = 0$, $M(x) = 1$
- ii. When $k = 1$, $M(x) = \mathbb{E}[x]$
- iii. When $k = 2$, $M(x) = \text{Var}(x) + M_{k-1}(x)^2$
- b. We define the k-th central moment of a random variable as

$$\mu_k(X) = \mathbb{E}\left[(X - \mathbb{E}X)^k\right]$$

- i. Therefore, $\mu_2(X) = \text{Var}(X)$

6. Standardized moments of a RV

- a. Given a variable X with mean μ , and variance σ^2 , we define the standardized RV

$$Z = \frac{X - \mu}{\sigma}$$

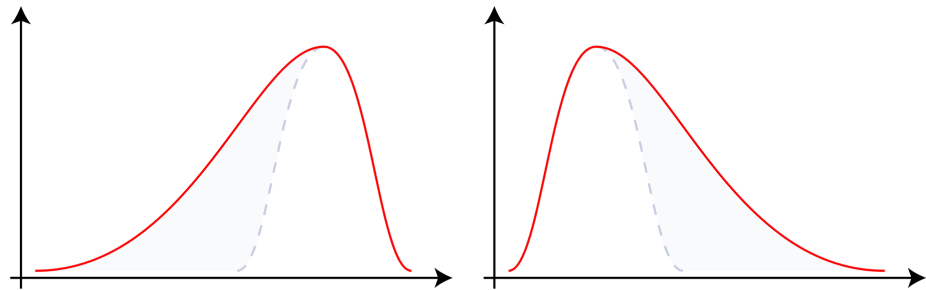
- b. The standardized moments of X are defined as the k-th moments of Z

$$\bar{\mu}_k(X) = \mathbb{E}\left[\left(\frac{X - \mu}{\sigma}\right)^k\right]$$

7. Skewness and Kurtosis

- a. Skewness → measures the symmetry of the distribution about mean:

$$\bar{\mu}_3(X) = \frac{\mu_3(X)}{\sigma^3}$$



- i. Negative Skew
- ii. Positive Skew
- ii. Negative skew: when left tail is longer (mean < median)
- iii. Positive skew: when right tail is longer (mean > median)

$$\bar{\mu}_4(X) = \frac{\mu_4(X)}{\sigma^4}$$

- b. Kurtosis:

8. Applications: confidence intervals

- a. Suppose we have 100 points from an unknown distribution, for which we know that the true population mean is 500, and the standard deviation is 80

- i. Find probability that the sample mean will be inside the interval (490, 510)

1. CLT:

$$S_n - n\mu$$

$$\sim N(0,1)$$

$$\sigma \cdot \sqrt{n}$$

$$= S_n - n\mu \sim N(0, \sigma^2 \cdot n)$$

$$= S_n - n\mu$$

$$\sim N(0, \sigma^2/n)$$

$$n$$

$$= S_n/n \sim N(\mu, \sigma^2/n)$$

2. By the CLT we know that the sample mean converges to

$$\bar{X}_n \rightarrow N\left(500, \left(\frac{80}{\sqrt{100}}\right)^2\right) \text{ in distribution. Therefore,}$$

$$\Pr(490 \leq \bar{X}_n \leq 510) = \Pr\left(\frac{490 - 500}{\frac{80}{\sqrt{n}}} \leq \bar{Z}_n \leq \frac{510 - 500}{\frac{80}{\sqrt{n}}}\right) = \Phi(1.25) - \Phi(-1.25) = 0.789$$

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-\frac{x^2}{2}} dx$$

3. Here,

is the usual cdf

- ii. Find an interval such that 95% of the sample average is covered

1. The mass on each side of the tails is at most $(1-0.95)/2 = 0.025$
2. Let's find the value z for which $\Phi(z)=1-0.025=0.975$
3. Using calculator, the upper z value is 1.96, lower z value is -1.96
4. $\sqrt{100} \frac{z - 500}{80} = \pm 1.96 \Rightarrow z_{low} = 484.32, z_{up} = 515.68$
5. In other words, the interval of 95% confidence is

$$\Pr(484.32 \leq \bar{X}_n \leq 515.68) = 0.95$$