

PROBABILITY REVIEW

(not all of it... just
interesting parts)

$$E[X] = \begin{bmatrix} E[X_1] = m_{X_1} \\ \vdots \\ E[X_n] = m_{X_n} \end{bmatrix}$$

• Covariance matrix

$$\Sigma = E[(X - m_X)(X - m_X)^T] = \begin{bmatrix} \sigma_{X_1}^2 & \sigma_{X_1 X_2} & \dots & \sigma_{X_1 X_n} \\ \vdots & & \ddots & \vdots \\ & \sigma_{X_i X_j} & & \\ \sigma_{X_n X_1} & \dots & & \sigma_{X_n}^2 \end{bmatrix}$$

$$\sigma_{X_i X_j} = \text{Cov}(X_i, X_j) = E[(X_i - m_{X_i})(X_j - m_{X_j})]$$

If X_i and X_j are independent, $\sigma_{X_i X_j} = 0$ (not true the other direction)

!
proof on module

Linearity of Expectation

$$E[X_1 + X_2] = E[X_1] + E[X_2]$$

$\text{Var}[aX + b] = a^2 \text{Var}[X]$

constants

$$\text{Var}[X_1 + X_2] = \text{Var}[X_1] + \text{Var}[X_2] + 2\sigma_{X_1, X_2}$$

\hookrightarrow If $\sigma_{X_1, X_2} = 0$ then $\text{Var}[X_1 + X_2] = \text{Var}[X_1] + \text{Var}[X_2]$

\Downarrow

If X_1, X_2 are independent then

$$\text{Var}[X_1 + X_2] = \text{Var}[X_1] + \text{Var}[X_2]$$

Relative frequency: $f_n(A) = \frac{S_n}{n}$ ($S_n = \sum_{i=1}^n X_i$) $X_i(z) = \begin{cases} 1 & \text{if } z \in A \\ 0 & \text{if } z \notin A \end{cases}$

\downarrow # of fav. outcomes outcome
 \downarrow # of outcomes \downarrow event we're interested in

Each X_i is a Bernoulli r.v. of parameter p : $X_i \sim B(p)$

$$p = P[X_i = 1] = P[z \in A]$$

Then $S_n = \sum_{i=1}^n X_i$ is a Binomial r.v. of parameters n, p

$$S_n \sim \text{Bin}(n, p)$$

$$\underline{\underline{P(S_n = k) = \binom{n}{k} p^k (1-p)^{n-k}}}$$

$$\underline{E[\text{Bin}(n, p)]} = np \quad \text{Var}[\text{Bin}(n, p)] = np(1-p)$$

$$f_n(A) = \frac{S_n}{n}, \quad S_n \sim \text{Bin}(n, p)$$

$$\underline{E[f(A)] = p} \quad \left(= E\left[\frac{S_n}{n}\right] = \frac{1}{n} E[S_n] = \frac{np}{n} \right)$$

$$\underline{\text{Var}[f(A)] = \frac{p(1-p)}{n}} \quad \left(= \text{Var}\left[\frac{S_n}{n}\right] = \frac{1}{n^2} \text{Var}[S_n] = \frac{1}{n^2} np(1-p) \right)$$

↙ The more tries, the lower the variance

Chebyshev's inequality:

X is a r.v. $\rightarrow E[X] = \mu \quad \text{Var}[X] = \sigma^2$ then:

$P[|X - \mu| > \varepsilon] < \frac{\sigma^2}{\varepsilon^2} \rightarrow$ The further i want to be from the expectation, the more improbable it is.



$$P[|f_n(A) - p| > \varepsilon] \leq \frac{p(1-p)}{n\varepsilon^2}$$

\Rightarrow the larger n , the closer is my frequency to the true probability
 $\left(\lim_{n \rightarrow \infty} f_n(A) = p \right)$

$$P[A|B] = \frac{P(A \cap B)}{P(B)} = \lim_{n \rightarrow \infty} \frac{f_n(A \cap B)}{f_n(B)} = \lim_{n \rightarrow \infty} \frac{S_n(A \cap B)}{S_n(B)}$$

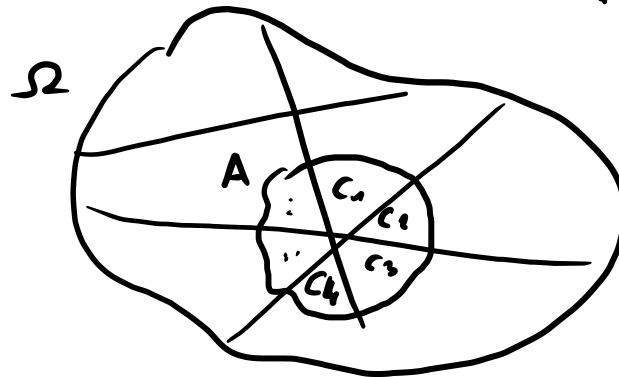
↓

$P[A|B]$ = fraction of times that A and B happens over the times B happens

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

↓ combined with the law of total probability

$$P(A) = \sum_{i=1}^n P(A|C_i) P(C_i) \quad \left(\begin{array}{l} \cdot \bigcup_{i=1}^n C_i = \Omega \\ \cdot C_i \cap C_j = \emptyset \quad \forall i, j \end{array} \right)$$



Ex: $P(B) = P(B|A)P(A) + P(B|A^c)P(A^c)$