

Independence

$\Pr(A \cap B) = \Pr(A) \Pr(B)$

Bays Theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$
$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_{j=0} P(B|A_j)P(A_j)}$$

Law of total probability

$\Pr(B) = \sum_j \Pr(B|A_j) \Pr(A_j)$

Density function

A function f is a density function of a random variable only if $f(x) \geq 0 \forall x$ and $\sum_{allx} f(x) = 1$

Expected value

$\text{Discrete expected value } \mathbb{E}[X] = \sum_{allx} x f(x)$
 $\mu = \mathbb{E}[c] = c$
 $\mathbb{E}[cX] = c\mathbb{E}[X]$

$\mathbb{E}[X + Y] = \mathbb{E}[X] + \mathbb{E}[Y]$

$\text{Var}[X] = \mathbb{E}[(X - \mu)^2]$

Variance and Standard deviation

$\sigma = \text{Sd}[X] = \sqrt{\text{Var}[X]}$

$\text{Var}[X] = \mathbb{E}[X^2] - \mathbb{E}[X]^2$

$\text{Var}[c] = 0$

$\text{Var}[cX] = c^2 \text{Var}[X]$

$\text{Sd}[cX] = c \text{Sd}[X]$

$\text{Var}(X) = \text{Cov}(X, X)$

$\text{Var}(X) = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$

Bernoulli

$$f(x) = \begin{cases} p, & \text{if } x = 1 \\ 1 - p, & \text{if } x = 0 \\ 0, & \text{otherwise} \end{cases}$$

$\mathbb{E}[X] = p$

$\text{Var}[X] = p(1 - p)$

Important series

For $|s| < 1$ it holds:

$\sum_{k=0}^{\infty} s^k = \frac{1}{1-s}$

$\sum_{k=0}^n s^k = \frac{1-s^{n+1}}{1-s}$

$(a + b)^n = \sum_{k=0}^n \binom{n}{k} a^k b^{n-k}$

Geometric random variable

$$f(x) = \begin{cases} p(1 - p)^{x-1}, & \text{if } x \in \mathbb{N} \\ 0, & \text{otherwise} \end{cases}$$

$\mathbb{E}[X] = \frac{1}{p}$

$\text{Var}[X] = \frac{1-p}{p^2}$

Binomial random variable

$$f(x) = \begin{cases} \binom{n}{x} p^x (1 - p)^{n-x}, & \text{if } x \in \mathbb{N} \\ 0, & \text{otherwise} \end{cases}$$

$\mathbb{E}[X] = np$

$\text{Var}[X] = np(1 - p)$

* Constant p, * independent

$X \sim \text{Bin}(\#total, P(success))$

Moment Generating Functions

The moments of a r.v. are $\mathbb{E}[X], \mathbb{E}[X^2], \dots$

$m_X(t) = \mathbb{E}[e^{tX}]$

Provided the RHS is finite $\forall t$ in some open interval.

Normal distribution

X is this if $\mu \in \mathbb{R}$ and $\sigma > 0$ if

$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \forall x \in \mathbb{R}$

Notated as $X \sim N(\mu, \sigma^2)$

$\mathbb{E}[X] = \mu$

$\text{Var}[X] = \sigma^2$

Standardization

$X \sim N(\mu, \sigma^2)$ then $\frac{X-\mu}{\sigma} \sim N(0, 1)$.

Joint distribution

bivariate discrete random variable

$f_{XY}(x, y) = \Pr[X = x, Y = y], \forall (x, y) \in \mathbb{R}^2$

joint density for the vector (X, Y)

$f(x, y) \geq 0$

$\sum_{all(x,y)} f(x, y) = 1$

The marginal density f

$f_X(x) = \sum_{ally} f_{XY}(x, y)$

$f_Y(y) = \sum_{allx} f_{XY}(x, y)$

Two X and Y with joint f_{XY} and marginal densities f_X, f_Y is independent iff

$f_{XY}(x, y) = f_X(x) f_Y(y), \forall x \forall y$

Expected value

$\mathbb{E}[H(X, Y)] = \sum_{all(x,y)} H(x, y) f_{XY}(x, y)$

Iff X, Y is independent $\Rightarrow \mathbb{E}[XY] =$

$\mathbb{E}[X] \mathbb{E}[Y]$

Definition: Covariance

$\text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])]$

$\text{Cov}(X, Y) = \mathbb{E}[XY] - \mathbb{E}[X] \mathbb{E}[Y]$

Iff X, Y is independent \Rightarrow

$\mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y] \Rightarrow \text{Cov}(X, Y) = 0$

$\text{Cov}(X, Y)$ indicates association of X, Y

$\text{Cov}(X, Y) \in \mathbb{R} \Rightarrow$ no information about the

strength of the dependence?

Definition (Correlation)

$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}[X] \text{Var}[Y]}}$

ρ_{XY} mesures linear dependance and $\rho_{XY} \in$

$[-1, 1]$

$|\rho_{XY}| = 1$ iff $Y = \beta_0 + \beta_1 X$ where $\beta_0, \beta_1 \neq 0$

Definition (conditional density) X, Y

with f_{XY} and f_X, f_Y , then for X with $Y = y$

the

$f_{X|y} = \frac{f_{XY}(x, y)}{f_Y(y)}, \text{ if } f_Y(y) > 0$

Poisson distribution

$f(x) = \frac{e^{-\lambda} \lambda^x}{x!}, x \in \mathbb{N}, \lambda > 0$

$\mathbb{E}[X] = \lambda, \text{Var}(X) = \lambda,$

λ is avg events in 1 unit of time

Iff $X_1 \sim \text{Poisson}(\lambda_1), X_2 \sim \text{Poisson}(\lambda_2)$

are independent then $X_1 + X_2 \sim$

$\text{Poisson}(\lambda_1 + \lambda_2)$

Hypergeometric distribution

$f(x) = \frac{\binom{r}{x} \binom{N-r}{n-x}}{\binom{N}{n}}$

$\max\{0, n - (N - r)\} \leq x \leq \min\{n, r\}$

$\mathbb{E}[X] = n \frac{r}{N}, \text{Var}(X) = n \frac{r}{N} \frac{N-r}{N} \frac{N-n}{N-1}$

We select n objects from N objects, of which r has a trait. X counts how many of the selected objects have the trait

Exponential distribution

$f(x) = \frac{1}{\beta} e^{-\frac{x}{\beta}}$

$\mathbb{E}[X] = \beta$

$\text{Var}(X) = \beta^2$

$F_X(X) = 1 - e^{-\frac{x}{\beta}}, \lambda = \frac{1}{\beta}$

negative Binomial distribution

$p \in [1, 0], r \in \mathbb{N} \setminus \{0\}$

$f(x) = \binom{x-1}{r-1} (1-p)^{x-r} p^r, x = r, r+1, r+2, \dots$

$\mathbb{E}[X] = \frac{r}{p}, \text{Var}(X) = \frac{r(1-p)}{p^2}$

Consider a sequence of independent and identical experiments, each one with probability p of success. X models the number of trails needed to obtain r successes.

Generating function

given $\{a_n\}_{n=0}^{\infty}$ then $g(x) = \sum_{n=0}^{\infty} a_n x^n$

let $a_n = c^n$ then $\sum_{n=0}^{\infty} c^n x^n = \sum_{n=0}^{\infty} (cx)^n = \frac{1}{1-cx}$

$\binom{n}{k} = \frac{n!}{k!(n-k)!} = \prod_{i=1}^k \frac{n-i+1}{i}$

See binom theorem: $\sum_{k=0}^n \binom{n}{k} x^k = (1+x)^n$

Let $a_n = \binom{n+k}{k}$ then $\sum_{n=0}^{\infty} a_n x^n = \frac{1}{(1-x)^{k+1}}$

Chebychev's inequality:

Let $X \ni \mathbb{E} = \mu \wedge \text{Var}(X) = \sigma^2$, iff $0 < \sigma^2 < \infty$ then $\forall a > 0$ it holds $P(|X - \mu| \geq a) \leq \frac{\sigma^2}{a^2}$

Let $Y = |X - \mu|$. $\forall a > 0$ define

$$Z = \begin{cases} a^2, & Y \geq a \\ 0, & \text{otherwise} \end{cases}$$

then $Z \leq Y^2 \Rightarrow \mathbb{E}[Z] \leq \mathbb{E}[Y^2] (1)$

see $\mathbb{E}[Z] = a^2 P(Y \geq a) = a^2 P(|X - \mu| \geq a)$

see $\mathbb{E}[Y^2] = \mathbb{E}[|X - \mu|^2] = \text{Var}(X) = \sigma^2$

substitute into (1): $a^2 P(|X - \mu| \geq a) \leq \sigma^2$

$\text{Var}(X) \Leftrightarrow P(|X - \mu| \geq a) \geq \frac{\text{Var}(X)}{a^2} = \frac{\sigma^2}{a^2}$

Marcov chain

$P(X_n = x_n | X_{n-1} = x_{n-1}) = P(X_n =$

$x_n | X_{n-1} = x_{n-1}, \dots, X_0 = x_0)$

$P = \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix}$

$N = (I - Q)^{-1}$ then $B = NR$

Characteristic function

$\phi_X(t) = \mathbb{E}[e^{itX}], \phi(0) = 1, |\phi(t)| \leq 1$

Wilcoxs?

$\mathbb{E}(W_m) = \frac{m(m+n+1)}{2}$

$\text{Var}(W_m) = \frac{m(m+n+1)}{12}$

$\frac{W_m - \mathbb{E}(W_m)}{\sqrt{\text{Var}(W_m)}} \sim N(0, 1)$

Central limit theorem

Confidence Interval

The $100(1 - \alpha)\%$ for $\forall \mu$ is given by

$I_\alpha = [\bar{X} - z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}, \bar{X} + z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}]$

where $z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}$ is the point such that

$P(N(0, 1)) \geq z_{\frac{\alpha}{2}} = \frac{\alpha}{2}$. The interval I_α has

width of $I_\alpha = 2z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}$

Iff $\alpha \rightarrow 1$, $I_\alpha \rightarrow 0$ visavi.

Misc

Given two events A, B (if $\Pr[B] > 0$) we

have $\Pr[A|B] = \frac{\Pr[A \cap B]}{\Pr[B]}$,

$X \geq 1$

$\mathbb{E}[U] = \frac{b+a}{2} \forall U \in [a, b]$

then $\mathbb{E}[V] = s + t \cdot \frac{b+a}{2} \forall V = s + tU$

Demorgans law

$P(A^c \cap B^c) = P((A \cup B)^c)$.