

Discrete Random Variables.

1. Discrete random variable: $\sum_{x \in \mathbb{R}} P(X=x) = 1$. (all of its P is on individual values).

1). Probability Function: $p_X(x) = P(X=x)$

① If $\sum_{x \in \mathbb{R}} P(X=x) = 1$, there's a distinct sequence $x_1, x_2, \dots \in \mathbb{R}$, and correspond $P, p_1, p_2, \dots \geq 0$, with $\sum_i p_i = 1$ s.t. $P(X=x_i) = p_i$.

② $p_X(x_i) = p_i$ for all i , with $p_X(x) = 0$ for all $x \notin \{x_1, x_2, \dots\}$.

e.g. Flip 2 coins. Let $X = \#$ of Heads.

$$P(X=0) = \frac{\binom{2}{0}}{2^2} = \frac{1}{4}; P(X=1) = \frac{\binom{2}{1}}{2^2} = \frac{1}{2}; P(X=2) = \frac{\binom{2}{2}}{2^2} = \frac{1}{4}.$$

$$\therefore x_1=0, x_2=1, x_3=2; p_1=\frac{1}{4}, p_2=\frac{1}{2}, p_3=\frac{1}{4}.$$

$$\therefore p_X(0) = \frac{1}{4}, p_X(1) = \frac{1}{2}, p_X(2) = \frac{1}{4}.$$

2. Binomial Distribution: $X \sim \text{Binomial}(n, \theta)$.

1). Bernoulli Distribution: $X \sim \text{Bernoulli}(\theta)$.

e.g. throw a basket ball; $P(\text{score}) = \theta$.

$$P(X=0) = p_X(0) = 1-\theta; P(X=1) = p_X(1) = \theta.$$

$n=1$.

2). Binomial Distribution: $X \sim \text{Binomial}(n, \theta)$.

$$\textcircled{1} p_X(k) = P(X=k) = \binom{n}{k} \theta^k (1-\theta)^{n-k}; \text{ for } k \in \{0, 1, 2, \dots, n\}.$$

\hookrightarrow starts from 0.

$$\textcircled{2} \sum_{k=0}^n P(X=k) = \sum_{k=0}^n \binom{n}{k} \theta^k (1-\theta)^{n-k} = [\theta + (1-\theta)]^n = 1.$$

3). Poisson Distribution: $X \sim \text{Poisson}(\lambda)$, where $\lambda = n \cdot \theta$.

$$\textcircled{1} P(Z=k) = e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

\rightarrow poisson approx. when n is large for Bin.

proof: Since $\lambda = n \cdot \theta \Rightarrow \theta = \frac{\lambda}{n}$, $Z \sim \text{Binomial}(n, \frac{\lambda}{n})$

$$P(Z=k) = \binom{n}{k} \theta^k (1-\theta)^{n-k}.$$

$$= \frac{n!}{(n-k)! \cdot k!} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}.$$

θ : successful rate.

Binomial Theorem:

$$(a+b)^n = \binom{n}{0} a^n b^0 + \binom{n}{1} a^{n-1} b^1 + \dots + \binom{n}{r} a^{n-r} b^r + \dots + \binom{n}{n} a^0 b^n.$$

apply when n is large and θ is small.

$$= \frac{n \cdot (n-1) \cdot (n-2) \cdots (n-k+1)}{k!} \cdot \left(\frac{\lambda}{n}\right)^k \cdot \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

$$= \frac{n \cdot (n-1) \cdot (n-2) \cdots (n-k+1) \cdot \lambda^k}{k! \cdot n^k} \cdot \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

When $n \rightarrow \infty$, for a fixed value k , we have $k \ll n$.

Thus, $\frac{n}{n} \rightarrow 1$, $\frac{n-1}{n} \rightarrow 1$, $\frac{n-2}{n} \rightarrow 1$, $\frac{n-3}{n} \rightarrow 1$, ..., $\frac{n-k+1}{n} \rightarrow 1$, gives.

$$\frac{n \cdot (n-1) \cdot (n-2) \cdots (n-k+1)}{n^k} \rightarrow 1.$$

Also, $\left(1 - \frac{\lambda}{n}\right)^{n-k} \approx \left(1 - \frac{\lambda}{n}\right)^n$

Considering $e^x = 1 + x + \frac{x^2}{2!} + \cdots$, when $x \in \mathbb{R}$, x is small, $e^x \approx 1 + x$.

Take $x = -\frac{\lambda}{n}$, gives $\left(1 - \frac{\lambda}{n}\right)^n \approx \left(e^{-\frac{\lambda}{n}}\right)^n = e^{-\lambda}$

Therefore, we have, when $n \rightarrow \infty$, gives.

$$P(Z=k) = \frac{n \cdot (n-1) \cdot (n-2) \cdots (n-k+1)}{n^k} \cdot \frac{\lambda^k}{k!} \cdot e^{-\lambda}$$

$$= e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

$$\textcircled{2} \sum_{k=0}^{\infty} P(Z=k) = \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k}{k!} = e^{-\lambda} \cdot \left(1 + \lambda + \frac{\lambda^2}{2!} + \cdots\right) = e^{-\lambda} \cdot e^{\lambda} = 1.$$

3. Geometric Distribution: $Z \sim \text{Geometric}(\theta)$.

$$1) P(Z=k) = \theta \cdot (1-\theta)^k$$

$\hookrightarrow k$ starts from 0.

θ : probability for Z .

$$2) \sum_{k=0}^{\infty} P(X=k) = \sum_{k=0}^{\infty} \theta \cdot (1-\theta)^k = \theta \cdot [1 + (1-\theta) + (1-\theta)^2 + \cdots] \quad (0 < \theta < 1).$$

$$= \theta \cdot \frac{1}{1-(1-\theta)} = \theta \cdot \frac{1}{\theta} = 1.$$

3). Always, $\{Z > M\} \searrow \{Z = \infty\}$.

4. Law of Total Probability - Discrete Random Variable Version: If X is a discrete random variable, with possible values x_1, x_2, \dots , and correspond probabilities p_1, p_2, \dots and B be any event, then.

$$P(B) = \sum_i P(X=x_i) \cdot P(B|X=x_i) = \sum_i p_i P(B|X=x_i).$$

e.g. roll a die. flip a number of coins equal to the number showing on the die. Let $X = \#$ of heads. $P(X=3)$.

$B: X=3$; Y : num on die, $Y = \{1, 2, 3, 4, 5, 6\}$. use values of Y as partition

$$\begin{aligned}
P(X=3) &= \sum_{y=3}^6 P(Y=y) \cdot P(X=3|Y=y) \\
&= \sum_{y=3}^6 \frac{1}{2^y} P(X=3|Y=y) \rightarrow \frac{\binom{y}{3}}{2^y} \\
&= P(Y=3) \cdot P(X=3|Y=3) + P(Y=4) \cdot P(X=3|Y=4) + P(Y=5) \cdot P(X=3|Y=5) + \\
&\quad P(Y=6) \cdot P(X=3|Y=6) \\
&= \frac{1}{6} \cdot (P(X=3|Y=3) + P(X=3|Y=4) + P(X=3|Y=5) + P(X=3|Y=6)) \\
&= \frac{1}{6} \cdot \left(\frac{\binom{3}{3}}{2^3} + \frac{\binom{4}{3}}{2^4} + \frac{\binom{5}{3}}{2^5} + \frac{\binom{6}{3}}{2^6} \right) = \frac{1}{6}
\end{aligned}$$

