Random Variables

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1 Discrete Random Variables

1.1 Bernoulli

An experiment that results in "success" or "failure."

$$X \sim \text{Ber}(p)$$

$$P(X = 0) = 1 - p$$

$$P(X = 1) = p$$

$$E[X] = p$$

$$Var(X) = p(1 - p)$$

$$M(t) = e^{t}p + 1 - p$$

1.2 Binomial

The number of successes in an experiment with n trials and p probability of success on each trial.

$$X \sim \operatorname{Bin}(n, p)$$

$$P(X = i) = p(i) = \binom{n}{i} p^{i} (1 - p)^{n - i} \text{ where } i = 0, 1, \dots, n$$

$$E[X] = np$$

$$\operatorname{Var}(X) = np(1 - p)$$

$$M(t) = (pe^{t} + 1 - p)^{n}$$

If $X_i \sim \text{Bin}(n_i, p)$ for $1 \le i \le N$, then

$$\left(\sum_{i=1}^{N} X_i\right) \sim \operatorname{Bin}\left(\sum_{i=1}^{N} n_i, p\right)$$

1.3 Poisson

Approximates the binomial random variable when n is large and p is small enough to make np "moderate"—generally when n > 20 and p < 0.05.

$$X \sim \operatorname{Poi}(\lambda)$$
 where $\lambda = np$
$$P(X = i) = e^{-\lambda} \frac{\lambda^{i}}{i!} \text{ where } i = 0, 1, 2, \dots$$

$$E[X] = \lambda$$

$$\operatorname{Var}(X) = \lambda$$

$$M(t) = e^{\lambda(e^{t} - 1)}$$

The approximations also works to a certain extent when the successes in the trials are not entirely independent, and when the probability of success in each trial varies slightly.

If $X_i \sim \text{Poi}(\lambda_i)$ for $1 \le i \le N$, then

$$\left(\sum_{i=1}^{N} X_i\right) \sim \operatorname{Poi}\left(\sum_{i=1}^{N} \lambda_i\right)$$

1.4 Geometric

The number of independent trials until a success, where the probability of success is p.

$$X \sim \text{Geo}(p)$$

$$P(X = n) = (1 - p)^{n-1}p \text{ where } n = 1, 2, \dots$$

$$E[X] = 1/p$$

$$Var(X) = (1 - p)/p^2$$

1.5 Negative Binomial

The number of independent trials until r successes, with probability p of success.

$$X \sim \text{NegBin}(r, p)$$

$$P(X = n) = \binom{n-1}{r-1} p^r (1-p)^{n-r} \text{ where } n = r, r+1, \dots$$

$$E[X] = r/p$$

$$\text{Var}(x) = r(1-p)/p^2$$

$$\text{Geo}(p) \sim \text{NegBin}(1, p)$$

1.6 Hypergeometric

The number of white balls drawn after drawing n balls (without replacement) from an urn containing N balls, with m white balls and N-m other ("black") balls.

$$X \sim \operatorname{HypG}(n, N, m)$$

$$P(X = i) = \frac{\binom{m}{i} \binom{N-m}{n-i}}{\binom{N}{n}} \quad \text{where } i = 0, 1, \dots, n$$

$$E[X] = n(m/N)$$

$$\operatorname{Var}(X) = \frac{nm(N-n)(N-m)}{N^2(N-1)}$$

$$\operatorname{HypG}(n, N, m) \rightarrow Bin(n, m/N) \text{ , as } N \rightarrow \infty \text{ and } m/N \text{ stays constant}$$

1.7 Multinomial

Given an experiment with n independent trials, where each trial results in one of m outcomes, with respective probabilities p_1, p_2, \ldots, p_m such that $\sum_{i=1}^m p_i = 1$, then if X_i denotes the number of trials with outcome i we have

$$P(X_1 = c_1, X_2 = c_2, \dots, X_m = c_m) = \binom{n}{c_1, c_2, \dots, c_m} p_1^{c_1} p_2^{c_2} \cdots p_m^{c_m}$$

where $\sum_{i=1}^m c_i = n$ and $\binom{n}{c_1, c_2, \dots, c_m} = \frac{n!}{c_1! c_2! \cdots c_m!}$.

2 Continuous Random Variables

If Y is a non-negative continuous random variable

$$E[Y] = \int_{0}^{\infty} P(Y > y) dy$$

2.1 Uniform

$$X \sim \text{Uni}(\alpha, \beta)$$

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \alpha \le x \le \beta \\ 0 & \text{otherwise} \end{cases}$$

$$E[X] = \frac{\alpha + \beta}{2}$$

$$\text{Var}(X) = \frac{(\beta - \alpha)^2}{12}$$

2.2 Normal

For values in common natural phenomena, especially when resulting from the sum of multiple variables.

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

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

$$E[X] = \mu$$

$$Var(X) = \sigma^2$$

$$M(t) = e^{\left(\frac{\sigma^2 t^2}{2} + \mu t\right)}$$

Letting $X \sim N(\mu, \sigma^2)$ and Y = aX + b, we have

$$Y \sim N(a\mu + b, a^2\sigma^2)$$
$$F_Y(x) = F_X(\frac{x - b}{a})$$

The Standard (Unit) Normal Random Variable $Z \sim N(0,1)$ has a cumulative distribution function (CDF) commonly labeled $\Phi(x) = P(Z \le z)$ that has some useful properties.

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

$$\Phi(-z) = 1 - \Phi(z)$$

$$P(Z \ge -z) = P(Z > z)$$

Given $X \sim N(\mu, \sigma^2)$ where $\sigma > 0$, we can then compute the CDF of X using the CDF of the standard normal variable.

$$F_X(x) = \Phi(\frac{x-\mu}{\sigma})$$

By the de Moivre-Laplace Limit Theorem, the normal variable can approximate the binomial when $Var(X) = np(1-p) \ge 10$. If we let S_n denote the number of successes (with probability p) in n independent trials, then

$$P\left(a \le \frac{S_n - np}{\sqrt{np(1-p)}} \le b\right) \stackrel{n \to \infty}{\to} \Phi(b) - \Phi(a)$$

If $X_i \sim N(\mu_i, \sigma_i^2)$ for i = 1, 2, ..., n, then

$$\left(\sum_{i=1}^{n} X_i\right) \sim N\left(\sum_{i=1}^{n} \mu_i, \sum_{i=1}^{n} \sigma_i^2\right)$$

2.3 Exponential

Represents time until some event, with rate $\lambda > 0$.

$$X \sim \text{Exp}(\lambda)$$

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \ge 0 \\ 0 & \text{if } x < 0 \end{cases}$$

$$E[X] = \frac{1}{\lambda}$$

$$\text{Var}(X) = \frac{1}{\lambda^2}$$

$$F(x) = 1 - e^{-\lambda x} \text{ where } x \ge 0$$

Exponentially distributed random variables are memoryless.

$$P(X > s + t | X > s) = P(X > t)$$

2.4 Beta

$$X \sim \text{Beta}(a, b)$$

$$f(x) = \begin{cases} \frac{1}{B(a, b)} x^{a-1} (1 - x)^{b-1} & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$B(a, b) = \int_{0}^{1} x^{a-1} (1 - x)^{b-1} dx$$

$$E[X] = \frac{a}{a + b}$$

$$\text{Var}(X) = \frac{ab}{(a + b)^{2} (a + b + 1)}$$

If $X \sim \text{Uni}(0,1)$ and N denotes the number of heads resulting from a number of coin flips with some unknown probability of getting heads, then

$$X|(N = n, m + n \text{ trials}) \sim \text{Beta}(n + 1, m + 1)$$