## 1 Discrete probability

• Expectation value: For a discrete random variable X (this can also be replaced by a function h(x)) and probability mass function p(x)

$$E(x) = \mu_x = \sum_{x \in D} x p(x)$$

Some properties:

1. 
$$E(C) = C$$

2. 
$$E(CX) = CE(X)$$

3. 
$$E(CX+d) = CE(X) + d$$

• Variance: Assume the discrete random variable X to have an expected value  $\mu$ . Then

$$V(X) = \sum_{D} (x - \mu)^{2} \cdot p(x) = E[(x - \mu)^{2}]$$

This can also be rewritten as  $V(X) = \sigma^2 = E(X^2) - [E(X)]^2$ . For any arbitrary function h(X) of the form (aX + b), we have  $V(h(X)) = a^2V(X)$ 

• Moment Generating Function (MGF): For a discrete random variable X,  $m_X(t) = E(e^{tX})$ . Using this, we have the following

$$\left. \frac{d^r m_X(t)}{dt^r} \right|_{t=0} = E(X^r)$$

• Bernoulli Distribution: Consider a random variable X which takes Boolean values (0 and 1). Let the probability of obtaining the value 1 be p and 0 be q = (1 - p)

1. 
$$f(x,p) = p^x (1-p)^{1-x}$$

2. 
$$E(X) = p$$

3. 
$$Var(X) = pq$$

4. 
$$m_X(t) = q + pe^t$$

• Binomial Distribution: For a random variable X with parameters n and p (denoted by  $X \sim (n, p)$ )

1. 
$$m_X(t) = (q + pe^t)^n$$

2. 
$$E(X) = np$$

3. 
$$Var(X) = npq$$

4. 
$$p(x) = \binom{n}{x} p^x (1-p)^{n-x}$$

• Geometric Random Variable: Let X denote the random variable representing the number of trials required to get the 1<sup>st</sup> success.

1. 
$$g(n,p) = pq^{n-1}$$

2. 
$$E(X) = \frac{1}{p}$$
 and  $E(X^2) = \frac{1+q}{p^2}$ 

3. 
$$Var(X) = \frac{q}{n^2}$$

4. 
$$m_X(t) = \frac{pe^{-t}}{1-qe^t}$$

• Poisson distribution: For a discrete random variable X with the parameter  $\mu$ 

1. 
$$p(x,\mu) = \frac{e^{-\mu} \cdot \mu^x}{x!}$$

2. 
$$E(X) = Var(X) = \mu$$

3. 
$$m_X(t) = e^{\mu(e^t - 1)}$$

Consider a binomial distribution b(x; n, p) in the limit where  $n \to \infty$  and  $p \to 0$ . In such a scenario,  $b(x; n, p) \to p(x; \mu)$  where  $\mu = np$ 

• Poisson process: Let  $P_k(t)$  denote the probability that k events are observed during a particular time interval of length t, then

$$P_k(t) = e^{-\alpha t} \cdot \frac{(\alpha t)^k}{k!}$$

Where t is the random variable with the parameter  $\mu = \alpha t$  and  $\alpha$  specifies the rate of the process in question.

## 2 Continuous probability

Consider a function f(x) to be a PDF of a continuous random variable x

- $P(a \le x \le b) = \int_a^b f(x) dx$
- CDF =  $F(x) = \int_{-\infty}^{x} f(x) dx$
- Expectation value and MGF:

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx$$

$$E(H(x)) = \int_{-\infty}^{\infty} H(x) f(x) dx$$

$$m_x(t) = E(e^{xt}) = \int_{-\infty}^{\infty} e^{xt} f(x) dx$$

• Moments, mean and variance:

$$\begin{split} E(x^k) &= \int_{-\infty}^{\infty} x^k f(x) dx = \left(\frac{d^k}{dx^k} \left(m_x(t)\right)\right) \bigg|_{t=0} \\ \mu &= E(x) = \int_{-\infty}^{\infty} x f(x) dx \\ \sigma^2 &= \left(\int_{-\infty}^{\infty} x^2 f(x) dx\right) - \left(\int_{-\infty}^{\infty} x f(x) dx\right)^2 \end{split}$$

- Uniform distribution:
  - 1. Probability density function:

$$f(x) = \begin{cases} \frac{1}{b-a} & a \le x \le b \\ 0 & \text{elsewhere} \end{cases}$$

2. MGF, mean and variance:

$$m_x(t) = \frac{e^{bt} - e^{at}}{(b-a)t}$$
$$\mu = \frac{a+b}{2}$$
$$\sigma^2 = \frac{(b-a)^2}{12}$$

- Normal/Gaussian distribution: It is denoted as  $X \sim N(\mu, \sigma^2)$ , where  $\mu(\text{mean})$  and  $\sigma^2$  (variance) are the parameters of the distribution.
  - 1. Probability density function:

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}$$

2. MGF, expectation:

$$m_x(t = e^{\mu t + \frac{t^2 \sigma^2}{2}})$$
  
 $E(x) = m'_x(t)\Big|_{t=0} = \mu$ 

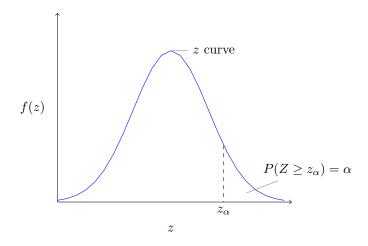
- Standard Normal distribution: Assume  $z = \frac{x-\mu}{\sigma}$ , then E(z) = 0 and V(z) = 1. In such a scenario, z is known as the standard normal variate which is denoted as  $z \sim \mathcal{N}(0,1)$ 
  - 1. Probability density function:

$$\varphi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$$

2. Cumulative density function:

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

3.  $z_{\alpha}$  for z critical values:  $z_{\alpha}$  represents the  $100(1-\alpha)$ th percentile of the standard normal distribution. The values of  $z_{\alpha}$  is often called as the z **critical values**.



• Approximating Binomial distribution: Let X be a random variable based on n trials with a success probability p. If the binomial histogram is not too skewed, then X has  $\approx$  normal distribution with  $\mu = np$  and  $\sigma = \sqrt{npq}$  or

$$P(X \leq x) = B(x;n,p) \approx \Phi\left(\frac{x + 0.5 - np}{\sqrt{npq}}\right)$$

- Exponential and Gamma distribution:
  - 1. Exponential distribution:

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

Mean  $(\mu) = \frac{1}{\lambda}$  and variance  $(\sigma^2) = \frac{1}{\lambda^2}$ 

2. Gamma function: For a parameter  $\alpha > 0$ , we define the **gamma function** as

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha - 1} e^{-x} dx$$

Some important properties:

(a) 
$$\Gamma(\alpha) = (\alpha - 1) \cdot \Gamma(\alpha - 1)$$

(b) 
$$\Gamma(n) = (n-1)!$$

(c) 
$$\Gamma(\frac{1}{2}) = \sqrt{\pi}$$

Gamma distribution:

$$f(x; \alpha, \beta) = \begin{cases} \frac{1}{\beta^{\alpha} \Gamma(\alpha)} x^{\alpha - 1} e^{-x/\beta} & x \ge 0\\ 0 & \text{otherwise} \end{cases}$$

Expectation:  $E(x) = \mu = \alpha \beta$ Variance:  $V(x) = \sigma^2 = \alpha \beta^2$ 

The gamma distribution of a random variable X with parameters  $\alpha$  and  $\beta$  is denoted as:

$$P(X \le x) = F(x; \alpha, \beta) = F\left(\frac{x}{\beta}; \alpha\right)$$

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## 3. Chi-Squared distribution:

For a positive integer  $\nu$  (degrees of freedom of the random variable X), the PDF of this distribution takes the form

$$f(x;\nu) = \begin{cases} \frac{1}{2^{\nu/2}\Gamma(\nu/2)} x^{\left(\frac{\nu}{2}-1\right)} e^{-\frac{x}{2}} & x \ge 0\\ 0 & x < 0 \end{cases}$$

This can be modelled as a gamma distribution with the parameters  $\alpha = \frac{\nu}{2}$  and  $\beta = 2$ .