

**Probability distributions:** A probability distribution is a mathematical function that describes the probability of different possible values of a variable. Probability distributions are often depicted using graphs or probability tables.

**Discrete probability distributions:** A random variable  $X$  is said to have a discrete distribution if the sample space of  $X$  is countable.

**Discrete uniform distribution:** A random variable  $X$  is said to have a discrete *uniform*( $k$ ) distribution, denoted by  $X \sim Uniform(N)$ , if its PMF has the following form:

$$f(x) = \begin{cases} \frac{1}{N} & x = 1, 2, \dots, N \\ 0 & \text{otherwise} \end{cases}$$

where  $N$  is a specified positive integer, and it is called the parameter of the distribution. This distribution puts equal mass on each of the possible outcomes  $1, 2, \dots, N$ .

**Mean and variance:** By definition of the mean and variance, we have

$$E[X] = \sum_{x=1}^N x f(x) = \frac{1}{N} \sum_{x=1}^N x = \frac{1}{N} \left( \frac{N(N+1)}{2} \right) = \frac{N+1}{2}$$

$$E[X^2] = \sum_{x=1}^N x^2 f(x) = \frac{1}{N} \sum_{x=1}^N x^2 = \frac{1}{N} \left( \frac{N(N+1)(2N+1)}{6} \right) = \frac{(N+1)(2N+1)}{6}$$

$$\begin{aligned}
\text{Var}(X) &= E[X^2] - E[X]^2 \\
&= \frac{(N+1)(2N+1)}{6} - \left(\frac{N+1}{2}\right)^2 \\
&= \frac{N+1}{2} \left(\frac{2N+1}{3} - \frac{N+1}{2}\right) \\
&= \frac{N+1}{2} \left(\frac{2(2N+1) - 3(N+1)}{6}\right) \\
&= \frac{N+1}{2} \left(\frac{4N+2 - 3N-3}{6}\right) \\
&= \frac{(N+1)(N-1)}{12} = \frac{N^2-1}{12}
\end{aligned}$$

**Moment generating function:**

$$\begin{aligned}
M_X(t) &= E[e^{tX}] \\
&= \frac{1}{N} \sum_{x=1}^N e^{tx} \\
&= \frac{1}{N} [e^t + e^{2t} + e^{3t} + \dots + e^{Nt}] \\
&= \frac{1}{N} [(e^t)^1 + (e^t)^2 + (e^t)^3 + \dots + (e^t)^N] \\
&= \frac{1}{N} e^t [(e^t)^0 + (e^t)^1 + (e^t)^2 + \dots + (e^t)^{N-1}] \\
&= \frac{1}{N} e^t \sum_{x=0}^{N-1} (e^t)^x \\
&= \frac{1}{N} \left( \frac{e^t (1 - e^{Nt})}{1 - e^t} \right)
\end{aligned}$$

notice that for any  $r \neq 1$  the following geometric series can be written as:

$$\begin{aligned}s_N &= ar^0 + ar^1 + ar^2 + \dots + ar^{N-1} \\ &= a \left( \frac{1 - r^N}{1 - r} \right)\end{aligned}$$

**Cumulative distribution function:** The CDF of a discrete uniform random variable is given by

$$F(x) = \sum_{k=1}^x f(k) = \sum_{k=1}^x \frac{1}{N} = \frac{1}{N} \sum_{k=1}^x (1) = \frac{1}{N} (1 + 1 + \dots + 1) = \frac{x}{N}$$

hence

$$F(x) = \begin{cases} \frac{x}{N} & x = 1, 2, \dots, N \\ 1 & x \geq N \\ 0 & \text{otherwise} \end{cases}$$

**Example 1.1 (Homework):** Let  $X \sim \text{uniform}(N)$ . Use the MGF of  $X$  to find the mean and variance of  $X$ .

**Example 1.2 (Homework):** Let  $X \sim \text{uniform}(5)$

1- Write down the PMF of  $X$ .

2- Find the mean, the variance, the CDF, and the MGF of  $X$ .

3- Find  $P(2 < X \leq 4)$ .

**Example 1.3:** If  $X \sim \text{Uniform}(N)$ , find the value of  $N$ , such that  $P(X \leq E[X]) = 0.65$ .

**Solution:** We have  $E[X] = \frac{N+1}{2}$ . Hence

$$\begin{aligned} P(X \leq E[X]) &= P\left(X \leq \frac{N+1}{2}\right) \\ &= F\left(\frac{N+1}{2}\right) \end{aligned}$$

We also have  $F(x) = \frac{x}{N}$ , so that

$$\begin{aligned} F\left(\frac{N+1}{2}\right) &= \frac{(N+1)/2}{N} \\ &= \frac{N+1}{2N} \end{aligned}$$

therefore

$$\begin{aligned} P(X \leq E[X]) &= 0.65 \\ \implies \frac{N+1}{2N} &= 0.65 \\ \implies N+1 &= 1.3N \\ \implies 1.3N - N &= 1 \\ \implies 0.3N &= 1 \\ \implies N &= \frac{1}{0.3} \implies N \approx 3 \end{aligned}$$

Find  $N$  such that  $F(x) \leq \frac{N}{2}$  (**Homework**).

**Bernoulli distribution:** A random variable  $X$  is said to have a *Bernoulli*( $p$ ) distribution, denoted by  $X \sim \text{Bernoulli}(p)$ , if its PMF has the following

form:

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

where  $p$  is called the probability of success ( $1-p$  here is called the probability of failure). This distribution is used with the experiments that have only two possible outcomes. If  $X = 1$ , then the experiment turned a “success”. While if  $X = 0$ , then the experiment turned a “failure”.

**Mean and variance:** By definition of the mean and variance, we have

$$\begin{aligned} E[X] &= \sum_{x=0}^1 xf(x) = \sum_{x=0}^1 xp^x(1-p)^{1-x} = (0)p^0(1-p)^{1-0} + (1)p^1(1-p)^{1-1} = p \\ E[X^2] &= \sum_{x=0}^1 x^2f(x) = \sum_{x=0}^1 x^2p^x(1-p)^{1-x} = (0)p^0(1-p)^{1-0} + (1)p^1(1-p)^{1-1} = p \end{aligned}$$

notice that the  $r$ th moment about the origin is  $E[X^r] = p$ , for  $r = 1, 2, 3, \dots$

$$\begin{aligned} \text{Var}(X) &= E[X^2] - E[X]^2 \\ &= p - p^2 = p(1-p) \end{aligned}$$

## Moment generating function:

$$\begin{aligned}M_X(t) &= E[e^{tX}] \\&= \sum_{x=0}^1 e^{tx} p^x (1-p)^{1-x} \\&= \sum_{x=0}^1 e^{tx} p^x (1-p)^{1-x} \\&= e^{t(0)} p^0 (1-p)^{1-0} + e^{t(1)} p^1 (1-p)^{1-1} \\&= e^t p + (1-p)\end{aligned}$$

Find the characteristic function of  $X \sim \text{Bernoulli}(p)$  (**Homework**)

**Example 1.4:** Let  $X_1$  and  $X_2$  have the following joint probability function:

$$f_{X_1, X_2}(x_1, x_2) = \begin{cases} p^{x_1+x_2} (1-p)^{2-x_1-x_2} & x_1, x_2 = 0, 1 \text{ and } 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

- 1- Show that  $f_{X_1, X_2}(x_1, x_2)$  is a joint PMF.
- 2- Find the marginal PMFs.
- 3- Find the conditional PMFs, and check if  $X_1$  and  $X_2$  are dependent or not.

**Solution:** 1- Show that  $f_{X_1, X_2}(x_1, x_2)$  is a joint PMF

$$\begin{aligned}
 \sum_{x_2=0}^1 \sum_{x_1=0}^1 f_{X_1, X_2}(x_1, x_2) &= \sum_{x_2=0}^1 \sum_{x_1=0}^1 p^{x_1+x_2} (1-p)^{2-x_1-x_2} \\
 &= (1-p)^2 + p(1-p) + p(1-p) + p^2 \\
 &= (1-p)((1-p) + p + p) + p^2 \\
 &= (1-p)(1+p) + p^2 \\
 &= 1 - p^2 + p^2 = 1
 \end{aligned}$$

therefore  $f_{X_1, X_2}(x_1, x_2)$  is a joint PMF.

2- The marginals

$$\begin{aligned}
 f_{X_1}(x_1) &= \sum_{x_2=0}^1 f_{X_1, X_2}(x_1, x_2) \\
 &= \sum_{x_2=0}^1 p^{x_1+x_2} (1-p)^{2-x_1-x_2} \\
 &= p^{x_1+0} (1-p)^{2-x_1-0} + p^{x_1+1} (1-p)^{2-x_1-1} \\
 &= p^{x_1} (1-p)^{2-x_1} + p^{x_1+1} (1-p)^{1-x_1} \\
 &= p^{x_1} (1-p)^{1-x_1} ((1-p) + p) = p^{x_1} (1-p)^{1-x_1}
 \end{aligned}$$

so that  $X_1 \sim \text{Bernoulli}(p)$

$$f_{X_1}(x_1) = \begin{cases} p^{x_1} (1-p)^{1-x_1} & x_1 = 0, 1 \text{ and } 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

show that  $X_2 \sim \text{Bernoulli}(p)$  (**Homework**).

3- The conditional PMFs:

$$\begin{aligned} f_{X_2|X_1}(x_2|x_1) &= \frac{f_{X_1,X_2}(x_1, x_2)}{f_{X_1}(x_1)} \\ &= \frac{p^{x_1+x_2}(1-p)^{2-x_1-x_2}}{p^{x_1}(1-p)^{1-x_1}} \\ &= p^{x_1+x_2}(1-p)^{2-x_1-x_2}p^{-x_1}(1-p)^{-1+x_1} \\ &= p^{x_1+x_2-x_1}(1-p)^{2-x_1-x_2-1+x_1} = p^{x_2}(1-p)^{1-x_2} \end{aligned}$$

hence

$$f_{X_2|X_1}(x_2|x_1) = \begin{cases} p^{x_2}(1-p)^{1-x_2} & x_2 = 0, 1 \text{ and } 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

similarly (**Homework**)

$$f_{X_1|X_2}(x_1|x_2) = \begin{cases} p^{x_1}(1-p)^{1-x_1} & x_1 = 0, 1 \text{ and } 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

since

$$f_{X_2|X_1}(x_2|x_1) = f_{X_2}(x_2) = p^{x_2}(1-p)^{1-x_2}$$

$$f_{X_1|X_2}(x_1|x_2) = f_{X_1}(x_1) = p^{x_1}(1-p)^{1-x_1}$$

we can say that  $X_1$  and  $X_2$  are independent. Notice that we can prove



that  $X_1$  and  $X_2$  are independent by

$$f_{X_1, X_2}(x_1, x_2) = f_{X_1}(x_1)f_{X_2}(x_2)$$

**Example 1.5:** Let  $X \sim \text{Bernoulli}(0.97)$ .

1- Find the mean, the variance, and the MGF of  $Y = 2X + 3$ .

2- Then find  $P(Y \leq 4)$

**Solution:**

$$\begin{aligned} E[Y] &= E[2X + 3] \\ &= 2E[X] + 3 = 2(0.97) + 3 = 4.94 \end{aligned}$$

$$\begin{aligned} \text{Var}(Y) &= \text{Var}(2X + 3) \\ &= 4\text{Var}(X) \\ &= 4(0.97)(1 - 0.97) = 0.1164 \end{aligned}$$

$$\begin{aligned}
M_{(Y)}(t) &= E[e^{tY}] \\
&= E[e^{t(2X+3)}] \\
&= E[e^{2tX+3t}] \\
&= e^{3t} E[e^{2tX}] \\
&= e^{3t} M_{(X)}(2t) \\
&= e^{3t} (0.97e^{2t} + (1 - 0.97)) \\
&= 0.97e^{5t} + 0.03e^{3t}
\end{aligned}$$

find  $P(Y \leq 4)$

$$\begin{aligned}
P(Y \leq 4) &= P(2X + 3 \leq 4) \\
&= P(X \leq \frac{4-3}{2}) \\
&= P(X \leq 1/2) \\
&= P(X = 0) \\
&= 0.97^0(1 - 0.97)^{1-0} = 0.03
\end{aligned}$$

**Binomial distribution:** A random variable  $Y$  is said to have a *Binomial*( $n, p$ ) distribution, denoted by  $Y \sim \text{Binomial}(n, p)$ , if its PMF has

the following form:

$$f(y) = \begin{cases} \binom{n}{y} p^y (1-p)^{n-y} & y = 0, 1, \dots, n \text{ and } 0 \leq p \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

where  $p$  is called the probability of success ( $1 - p$  here is called the probability of failure), and  $n$  is a positive integer represents the total number of trials. **Here  $Y$  represents the number of successes out of  $n$  independent Bernoulli trials.** That is, if  $X_1, X_2, \dots, X_n$  are  $n$  independent Bernoulli random variables (or Bernoulli trials), each takes the values 0 or 1, then  $Y = \sum_{j=1}^n X_j$  has a binomial distribution with parameters  $n$  and  $p$ .

**The binomial expansion:** For any two real numbers  $a$  and  $b$ , the polynomial  $(a + b)^n$  can be written as:

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

now if  $a = p$  and  $b = 1 - p$ , then

$$\begin{aligned} (p + (1 - p))^n &= \sum_{y=0}^n \binom{n}{y} p^y (1 - p)^{n-y} \\ \implies 1 &= \sum_{y=0}^n \binom{n}{y} p^y (1 - p)^{n-y} \end{aligned}$$

**Mean and variance:** By definition of the mean and variance, we have

$$\begin{aligned}
E[Y] &= \sum_{y=0}^n y f(y) \\
&= \sum_{y=0}^n y \binom{n}{y} p^y (1-p)^{n-y} \\
&= \sum_{y=1}^n y \binom{n}{y} p^y (1-p)^{n-y}, \quad \text{because the first term is zero} \\
&= \sum_{y=1}^n y \frac{n!}{y!(n-y)!} p^y (1-p)^{n-y} \\
&= \sum_{y=1}^n y \frac{n(n-1)!}{y(y-1)!(n-y)!} p^y (1-p)^{n-y} \\
&= np \sum_{y=1}^n \frac{(n-1)!}{(y-1)!(n-y)!} p^{y-1} (1-p)^{n-y} \\
&= np \sum_{y=1}^n \binom{n-1}{y-1} p^{y-1} (1-p)^{n-y}
\end{aligned}$$

let  $k = y - 1 \implies y = k + 1$ , then  $k$  takes the values  $0, 1, 2, \dots, n - 1$ .

Then

$$\begin{aligned}
E[Y] &= np \sum_{k=0}^{n-1} \binom{n-1}{k} p^k (1-p)^{n-1-k} \\
&= np (p + (1-p))^{n-1}, \quad \text{by the binomial expansion} \\
&= np
\end{aligned}$$

Now to find  $E[Y^2]$ , we calculate  $E[Y(Y-1)] = E[Y^2] - E[Y]$ , then  $E[Y^2] = E[Y(Y-1)] + E[Y]$

$$\begin{aligned}
E[Y(Y-1)] &= \sum_{y=0}^n y(y-1)f(y) \\
&= \sum_{y=0}^n y(y-1) \binom{n}{y} p^y (1-p)^{n-y} \\
&= \sum_{y=2}^n y(y-1) \binom{n}{y} p^y (1-p)^{n-y}, \quad \text{because the first two terms are zeros} \\
&= \sum_{y=2}^n y(y-1) \frac{n!}{y!(n-y)!} p^y (1-p)^{n-y} \\
&= \sum_{y=2}^n y(y-1) \frac{n(n-1)(n-2)!}{y(y-1)(y-2)!(n-y)!} p^y (1-p)^{n-y} \\
&= n(n-1)p^2 \sum_{y=2}^n \frac{(n-2)!}{(y-2)!(n-y)!} p^{y-2} (1-p)^{n-y} \\
&= n(n-1)p^2 \sum_{y=2}^n \binom{n-2}{y-2} p^{y-2} (1-p)^{n-y}
\end{aligned}$$

let  $k = y - 2 \implies y = k + 2$ , then  $k$  takes the values  $0, 1, 2, \dots, n-2$ .

Then

$$\begin{aligned}
E[Y(Y-1)] &= n(n-1)p^2 \sum_{k=0}^{n-2} \binom{n-2}{k} p^k (1-p)^{n-2-k} \\
&= n(n-1)p^2 (p + (1-p))^{n-2}, \quad \text{by the binomial expansion} \\
&= n(n-1)p^2 = n^2p^2 - np^2
\end{aligned}$$

$$\begin{aligned}
E[Y^2] &= E[Y(Y-1)] + E[Y] \\
&= n^2p^2 - np^2 + np
\end{aligned}$$

$$\begin{aligned}
\text{Var}(Y) &= E[Y^2] - E[Y]^2 \\
&= n^2 p^2 - np^2 + np - n^2 p^2 \\
&= np(1 - p)
\end{aligned}$$

**Moment generating function:**

$$\begin{aligned}
M_Y(t) &= E[e^{tY}] \\
&= \sum_{y=0}^n e^{ty} \binom{n}{y} p^y (1-p)^{n-y} \\
&= \sum_{y=0}^n \binom{n}{y} (pe^t)^y (1-p)^{n-y} \\
&= (pe^t + (1-p))^n, \quad \text{by the binomial expansion}
\end{aligned}$$

**Example 1.6:** Let  $Y$  be a discrete random variable with the following MGF:

$$M_Y(t) = (0.6e^t + 0.4)^3$$

- 1- What is the distribution of  $Y$ ? Write down the PMF of  $Y$ .
- 2- Use the MGF to find the mean and variance of  $Y$ . Then find the mean and variance of  $W = \frac{Y - E[Y]}{\sqrt{\text{Var}(Y)}}$ .
- 3- Find the MGF of  $W$ .

**Solution:**

1- The distribution of  $Y$  is binomial with  $n = 3$  and  $p = 0.6$ ; That is,  $Y$  has the following PMF

$$f(y) = \begin{cases} \binom{3}{y} 0.6^y 0.4^{3-y} & y = 0, 1, 2, 3 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} E[X] &= \left. \frac{d}{dt} M_X(t) \right|_{t=0} \\ &= \left. \frac{d}{dt} (0.6e^t + 0.4)^3 \right|_{t=0} \\ &= 3(0.6e^t + 0.4)^2 (0.6e^t) \Big|_{t=0} \\ &= 1.8e^0 (0.6e^0 + 0.4)^2 \\ &= 1.8 \end{aligned}$$

$$\begin{aligned} E[X^2] &= \left. \frac{d^2}{dt^2} M_X(t) \right|_{t=0} \\ &= \left. \frac{d}{dt} 1.8e^t (0.6e^t + 0.4)^2 \right|_{t=0} \\ &= 1.8e^t (2(0.6e^t + 0.4)(0.6e^t)) + 1.8e^t (0.6e^t + 0.4)^2 \Big|_{t=0} \\ &= 1.8e^0 (2(0.6e^0 + 0.4)(0.6e^0)) + 1.8e^0 (0.6e^0 + 0.4)^2 \\ &= 1.8(2(0.6)) + 1.8 = 3.96 \end{aligned}$$

$$\begin{aligned} \text{Var}(X) &= E[X^2] - E[X]^2 \\ &= 3.96 - (1.8)^2 = 0.72 \end{aligned}$$

Now the mean and variance of  $W = \frac{Y - E[Y]}{\sqrt{\text{Var}(Y)}}$

$$\begin{aligned} E[W] &= E \left[ \frac{Y - E[Y]}{\sqrt{\text{Var}(Y)}} \right] \\ &= E \left[ \frac{Y - 1.8}{0.72} \right] \\ &= \frac{E[Y] - 1.8}{0.72} \\ &= \frac{1.8 - 1.8}{0.72} = 0 \end{aligned}$$

$$\begin{aligned} \text{Var}(W) &= \text{Var} \left( \frac{Y - E[Y]}{\sqrt{\text{Var}(Y)}} \right) \\ &= \text{Var} \left( \frac{Y - 1.8}{\sqrt{0.72}} \right) \\ &= \frac{1}{0.72} (\text{Var}(Y) + \text{Var}(1.8)) \\ &= \frac{1}{0.72} (0.72 + 0) = 1 \end{aligned}$$



MGF of  $W$

$$\begin{aligned}M_W(t) &= E[e^{tW}] \\&= E \left[ e^{t \left( \frac{Y - E[Y]}{\sqrt{\text{Var}(Y)}} \right)} \right] \\&= E \left[ e^{t \left( \frac{Y - 1.8}{\sqrt{0.72}} \right)} \right] \\&= E \left[ e^{-\frac{1.8t}{\sqrt{0.72}}} e^{\frac{t}{\sqrt{0.72}} Y} \right] \\&= e^{-\frac{1.8t}{\sqrt{0.72}}} E \left[ e^{\frac{t}{\sqrt{0.72}} Y} \right] \\&= e^{-\frac{1.8t}{\sqrt{0.72}}} M_Y \left( t / \sqrt{0.72} \right) \\&= e^{-\frac{1.8t}{\sqrt{0.72}}} \left( 0.6e^{t/\sqrt{0.72}} + 0.4 \right)^3\end{aligned}$$

**Example 1.7:** Write down the probability functions and MGFs of each of the following distributions:

1-  $X \sim \text{Uniform}(5)$

$$f(x) = \begin{cases} \frac{1}{5} & x = 1, 2, \dots, 5 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned}M_X(t) &= \frac{1}{5}(e^t + e^{2t} + \dots + e^{5t}) \\&= \frac{1}{5} \left( \frac{e^t (1 - e^{5t})}{1 - e^t} \right)\end{aligned}$$

2-  $X \sim \text{Bernoulli}(0.7)$

$$f(x) = \begin{cases} 0.7^x 0.3^{1-x} & x = 0, 1 \\ 0 & \text{otherwise} \end{cases}$$

$$M_X(t) = 0.7e^t + 0.3$$

3-  $Y \sim \text{Binomial}(5, 0.8)$

$$f(x) = \begin{cases} \binom{5}{y} 0.8^y 0.2^{5-y} & y = 0, 1, \dots, 5 \\ 0 & \text{otherwise} \end{cases}$$

$$M_X(t) = (0.8e^t + 0.2)^5$$