

Math 302.102 Fall 2010  
Summary of Discrete Random Variables

A random variable  $X$  is called *discrete* if it can assume at most countably many values. A discrete random variable can be completely described by its *probability mass function* (also called its *probability function* or *mass function* or *probability density function* or *density function*) which is just the values of

$$\mathbf{P}\{X = k\}$$

for  $k \in \mathbb{Z}$ .

**Example.** We say that a random variable  $X$  has a *Bernoulli distribution* with parameter  $p$  for some  $0 \leq p \leq 1$  if

$$\mathbf{P}\{X = 1\} = p \quad \text{and} \quad \mathbf{P}\{X = 0\} = 1 - p.$$

Note that

$$\mathbb{E}(X) = p \quad \text{and} \quad \text{Var}(X) = p(1 - p).$$

Often we write  $X \sim \text{Bernoulli}(p)$  for such a random variable.

**Example.** We say that a random variable  $X$  has a *binomial distribution* with parameters  $n$  and  $p$  for some positive integer  $n$  and some  $0 \leq p \leq 1$  if

$$\mathbf{P}\{X = k\} = \binom{n}{k} p^k (1 - p)^{n-k}$$

for  $k = 0, 1, 2, \dots, n$ . Note that

$$\mathbb{E}(X) = np \quad \text{and} \quad \text{Var}(X) = np(1 - p).$$

Often we write  $X \sim \text{Bin}(n, p)$  for such a random variable.

**Example.** We say that a random variable  $X$  has a *Poisson distribution* with parameter  $\lambda$  for some  $\lambda > 0$  if

$$\mathbf{P}\{X = k\} = \frac{\lambda^k}{k!} e^{-\lambda}$$

for  $k = 0, 1, 2, \dots, n$ . Note that

$$\mathbb{E}(X) = \lambda \quad \text{and} \quad \text{Var}(X) = \lambda.$$

Often we write  $X \sim \text{Poisson}(\lambda)$  for such a random variable.

**Example.** We say that a random variable  $X$  has a *geometric distribution* with parameter  $p$  for some  $0 < p < 1$  if

$$\mathbf{P}\{X = k\} = (1 - p)^{k-1} p$$

for  $k = 1, 2, \dots, n$ . Note that

$$\mathbb{E}(X) = \frac{1}{p} \quad \text{and} \quad \text{Var}(X) = \frac{1 - p}{p^2}.$$

Often we write  $X \sim \text{Geometric}(p)$  for such a random variable.

Math 302.102 Fall 2010

Calculations of Means and Variances for Discrete Random Variables

If  $X$  is a discrete random variable, then its expected value  $\mathbb{E}(X)$  is just the weighted average of its possible values; that is,

$$E(X) = \sum_{k=-\infty}^{\infty} k \mathbf{P}\{X = k\}.$$

Its second moment  $\mathbb{E}(X^2)$  is just the weighted average of its possible values squared; that is,

$$E(X^2) = \sum_{k=-\infty}^{\infty} k^2 \mathbf{P}\{X = k\}.$$

Furthermore,  $\text{Var}(X)$  can be computed as  $\text{Var}(X) = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2$ .

**Example.** If  $X \sim \text{Bernoulli}(p)$ , then

$$E(X) = 0 \cdot \mathbf{P}\{X = 0\} + 1 \cdot \mathbf{P}\{X = 1\} = 0 \cdot (1 - p) + 1 \cdot p = p$$

and

$$E(X^2) = 0^2 \cdot \mathbf{P}\{X = 0\} + 1^2 \cdot \mathbf{P}\{X = 1\} = 0^2 \cdot (1 - p) + 1^2 \cdot p = p.$$

so that

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

**Example.** If  $X \sim \text{Bin}(n, p)$ , then we can express  $X$  as  $X = X_1 + X_2 + \cdots + X_n$  where  $X_1, \dots, X_n$  are iid  $\text{Bernoulli}(p)$  random variables. Thus,

$$\mathbb{E}(X) = \mathbb{E}(X_1 + \cdots + X_n) = \mathbb{E}(X_1) + \cdots + \mathbb{E}(X_n) = p + \cdots + p = np$$

and

$$\text{Var}(X) = \text{Var}(X_1 + \cdots + X_n) = \text{Var}(X_1) + \cdots + \text{Var}(X_n) = p(1 - p) + \cdots + p(1 - p) = np(1 - p).$$

In order to calculate the variance of both a geometric random variable and a Poisson random variable, it turns out that it is not so easy to calculate the second moment directly. Instead, it turns out to be easier to consider  $\mathbb{E}[X(X - 1)]$ . This is not a problem since

$$\mathbb{E}[X(X - 1)] = \mathbb{E}(X^2 - X) = \mathbb{E}(X^2) - \mathbb{E}(X).$$

Thus, if we can calculate  $\mathbb{E}[X(X - 1)]$ , then we can find  $\mathbb{E}(X^2) = \mathbb{E}[X(X - 1)] + \mathbb{E}(X)$ .

**Example.** If  $X \sim \text{Poisson}(\lambda)$ , then

$$\mathbb{E}(X) = \sum_{k=0}^{\infty} k \cdot \frac{\lambda^k}{k!} e^{-\lambda} = e^{-\lambda} \sum_{k=1}^{\infty} k \cdot \frac{\lambda^k}{k!} = \lambda e^{-\lambda} \sum_{k=1}^{\infty} \frac{\lambda^{k-1}}{(k-1)!} = \lambda e^{-\lambda} \sum_{j=0}^{\infty} \frac{\lambda^j}{j!} = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

and

$$\begin{aligned}
\mathbb{E}[X(X-1)] &= \sum_{k=0}^{\infty} k(k-1) \cdot \frac{\lambda^k}{k!} e^{-\lambda} = e^{-\lambda} \sum_{k=2}^{\infty} k(k-1) \cdot \frac{\lambda^k}{k!} = e^{-\lambda} \sum_{k=2}^{\infty} \frac{\lambda^k}{(k-2)!} \\
&= \lambda^2 e^{-\lambda} \sum_{k=2}^{\infty} \frac{\lambda^{k-2}}{(k-2)!} \\
&= \lambda^2 e^{-\lambda} \sum_{j=0}^{\infty} \frac{\lambda^j}{j!} \\
&= \lambda^2 e^{-\lambda} e^{\lambda} \\
&= \lambda^2
\end{aligned}$$

so that

$$\text{Var}(X) = \mathbb{E}(X^2) - [\mathbb{E}(X)]^2 = \mathbb{E}[X(X-1)] + \mathbb{E}(X) - [\mathbb{E}(X)]^2 = \lambda^2 + \lambda - \lambda^2 = \lambda.$$

**Example.** If  $X \sim \text{Geometric}(p)$ , then in order to compute  $\mathbb{E}(X)$  and  $\text{Var}(X)$ , we need to sum up some particular series. To begin, note that if  $0 < q < 1$ , then

$$\sum_{k=1}^{\infty} kq^{k-1} = \sum_{k=1}^{\infty} \frac{d}{dq} q^k = \frac{d}{dq} \sum_{k=1}^{\infty} q^k = \frac{d}{dq} \left[ \left( \sum_{k=0}^{\infty} q^k \right) - 1 \right] = \frac{d}{dq} \left[ \frac{1}{1-q} - 1 \right] = \frac{1}{(1-q)^2}.$$

Furthermore,

$$\begin{aligned}
\sum_{k=2}^{\infty} k(k-1)q^{k-2} &= \sum_{k=2}^{\infty} \frac{d^2}{dq^2} q^k = \frac{d^2}{dq^2} \sum_{k=2}^{\infty} q^k = \frac{d^2}{dq^2} \left[ \left( \sum_{k=0}^{\infty} q^k \right) - 1 - q \right] = \frac{d^2}{dq^2} \left[ \frac{1}{1-q} - 1 - q \right] \\
&= \frac{2}{(1-q)^3}.
\end{aligned}$$

Thus, we see that

$$\mathbb{E}(X) = \sum_{k=1}^{\infty} k \cdot (1-p)^{k-1} p = p \sum_{k=1}^{\infty} k(1-p)^{k-1} = \frac{p}{(1-(1-p))^2} = \frac{p}{p^2} = \frac{1}{p}$$

and

$$\begin{aligned}
\mathbb{E}[X(X-1)] &= \sum_{k=1}^{\infty} k(k-1) \cdot (1-p)^{k-1} p = p \sum_{k=2}^{\infty} k(k-1)(1-p)^{k-1} = p(1-p) \sum_{k=2}^{\infty} k(k-1)(1-p)^{k-2} \\
&= \frac{2p(1-p)}{(1-(1-p))^3} \\
&= \frac{2p(1-p)}{p^3} \\
&= \frac{2(1-p)}{p^2}
\end{aligned}$$

so that

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