

Week #3

Recall A_1, A_2 are independent if

$$P(A_1, A_2) = P(A_1)P(A_2)$$

Def'n A_1, A_2, \dots are independent if for every $i_1 < i_2 < \dots < i_k$

$$(*) \quad P(A_{i_1}, A_{i_2}, \dots, A_{i_k}) = P(A_{i_1})P(A_{i_2}) \dots P(A_{i_k})$$

Note $I_{A_1} I_{A_2} = I_{A_1 A_2}$

$$I_{A_{i_1} \dots A_{i_k}} = I_{A_{i_1}} \dots I_{A_{i_k}}$$

So (*) is

$$E(I_{A_{i_1} \dots A_{i_k}}) = E(I_{A_{i_1}} \dots I_{A_{i_k}}) = E(I_{A_{i_1}}) \dots E(I_{A_{i_k}})$$

Def'n X_1, X_2, \dots are independent if every " X_1 event", " X_2 event", \dots are independent

Theorem If X_1, X_2, \dots are independent then

$$E[h_1(X_1) h_2(X_2) \dots] = E[h_1(X_1)] E[h_2(X_2)] \dots$$

H: Not here.

"A" h_1, h_2, \dots

Let range of $X \subset \{0, 1, \dots\}$. This is a special rv called a counting rv.

eg Let A be an event & I_A its indicator. This is a counting rv (possible values are 0 or 1). Suppose $p = P(A)$ & $q = 1-p$ & assume $0 < p < 1$.

$$\# \begin{cases} P(I_A = x) = p^x q^{1-x}, & x=0, 1 \\ = 0, & \text{ow} \end{cases}$$

$$E(I_A) = 0 \times q + 1 \times p = p$$

$$E(I_A^k) = 0^k \times q + 1^k \times p = p \quad (k > 0 \text{ \& an integer.})$$

$$\text{Var}(I_A) = E(I_A^2) - (E(I_A))^2 = p - p^2 = pq$$

Note $\text{Var}(X) = E[(X - \underbrace{\mu}_{E(X)})^2] = E(X^2) - \mu^2$

Terminology Call X a Bernoulli(p) rv if $X \in \{0, 1\}$ & $P(X=1) = p$. $X \sim \text{Bernoulli}(p)$

Let X_1, X_2, \dots be iid Bernoulli(p)
rv's. ↑
ind identically
distributed

Let $Y = \#$ of 1's until "Time" m .
 $= X_1 + X_2 + \dots + X_m$

Possible values for Y are $0, 1, \dots, m$. Y is
called a binomial(m, p) rv.

$$P(Y=k) ?$$

Sol'n #1 Count & use independence (see text)

Sol'n #2 Use probability generating f'ns.

Def'n If Y is a counting rv its pgf

is
$$G(s) = E(s^Y) = \sum_{k=0}^{\infty} s^k P(Y=k)$$

Notice $|G(s)| \leq \sum_{k=0}^{\infty} |s|^k P(Y=k) \leq \sum_{k=0}^{\infty} P(Y=k) = 1$,
if $|s| \leq 1$. ↑
 Δ inequality ($|a+b| \leq |a| + |b|$)

$$G(\Delta) = P(Y=0) + P(Y=1)\Delta + P(Y=2)\Delta^2 + \dots$$

Since a polynomial determines all the coefficients, knowing $G \Rightarrow$ know the probabilities.

Application to the calculation of the binomial (n, p) probabilities.

$$Y \sim \text{binomial}(n, p)$$

$$= X_1 + \dots + X_n$$

\uparrow i.i.d Bernoulli(p)

PGF of X_1

$$G_{X_1}(\Delta) = E(\Delta^{X_1}) = \overbrace{P(X_1=0)}^q + \overbrace{P(X_1=1)}^p \Delta$$

$$= q + p\Delta$$

PGF of Y

$$G_Y(\Delta) = E(\Delta^Y) = \sum_{k=0}^n P(Y=k) \Delta^k$$

||

$$\begin{aligned}
 & E(\Delta^{X_1 + \dots + X_m}) \\
 &= E(\Delta^{X_1} \Delta^{X_2} \dots \Delta^{X_m}) = E(\Delta^{X_1}) E(\Delta^{X_2}) \dots E(\Delta^{X_m}) \\
 &= G_{X_1}(\Delta) G_{X_2}(\Delta) \dots G_{X_m}(\Delta)
 \end{aligned}$$

Aside

Note The above shows that the pgf of a finite sum of ind rv's = the product of the pgf's;

$$\begin{aligned}
 &= (g + p\Delta)^m = \sum_{k=0}^m \binom{m}{k} (p\Delta)^k g^{m-k} \\
 &= \sum_{k=0}^m \binom{m}{k} p^k g^{m-k} \Delta^k \\
 &\qquad\qquad\qquad \underbrace{\hspace{10em}}_{P(Y=k)}
 \end{aligned}$$

So if $Y \sim \text{binomial}(m, p)$

probabilities $P(Y=k) = \binom{m}{k} p^k g^{m-k}, \quad k=0, \dots, m$

pgf $G(\Delta) = (g + p\Delta)^m = (1 - p + p\Delta)^m = (1 + p(\Delta - 1))^m$

$E(Y)?$

Easiest way

$$Y = X_1 + \dots + X_m$$

$$\Rightarrow E(Y) = E(X_1) + \dots + E(X_m) = mp$$

Another way

$$E(Y) = \sum_{k=0}^m k \binom{m}{k} p^k q^{m-k} \stackrel{\text{diff}}{=} mp$$

Var(Y)? = $E(Y^2) - [E(Y)]^2$

Method #1

$$E(Y^2) = \sum_{k=0}^m k^2 \binom{m}{k} p^k q^{m-k} \stackrel{\text{diff}}{=}$$

Method #2 - use ~~pgf~~

$$G(s) = E(s^Y)$$

$$G^{(1)}(s) = E\left(\frac{d}{ds} s^Y\right) = E(Y s^{Y-1})$$

$$G^{(2)}(s) = E(Y(Y-1) s^{Y-2})$$

o
o

$$E(Y) = G^{(1)}(1)$$

$$E[Y(Y-1)] = G^{(2)}(1)$$

$$\text{So } \begin{cases} G^{(2)}(1) = E(Y^2) - E(Y) \\ G^{(1)}(1) = E(Y) \end{cases}$$

$$\hookrightarrow E(Y^2) = G^{(1)}(1) + G^{(2)}(1)$$

Here

$$G(s) = (q + ps)^m$$

$$\Rightarrow G^{(1)}(s) = m(q + ps)^{m-1} p \stackrel{s=1}{=} mp$$

$$G^{(2)}(s) = m(m-1)(q + ps)^{m-2} p^2 \stackrel{s=1}{=} m(m-1)p^2$$

$$\therefore E(Y^2) = m(m-1)p^2 + mp$$

∴ so

$$\text{Var}(Y) = m(m-1)p^2 + mp - (mp)^2 = mp - mp^2$$

$$= mpq$$

$$\underbrace{SD(Y)}_{\sigma} = \sqrt{\text{Var}(Y)} = \sqrt{mpq}$$

One last thing. If $Y \sim \text{binomial}(n, p)$

$$G(s) = [1 + p(s-1)]^n$$

$$= \left(1 + \frac{np}{n}(s-1)\right)^n$$

$$= \left(1 + \frac{\lambda(\lambda-1)}{m}\right)^m \approx e^{\lambda(\lambda-1)},$$

$$\left(1 + \frac{x}{m}\right)^m \rightarrow e^x \quad \text{for large } m \text{ + } \lambda \text{ fixed.}$$

What kind of rv has pgf $e^{\lambda(\lambda-1)}$?

Call it X .

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

$$X = e^{-\lambda} e^{\lambda\lambda}$$

$$= e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda\lambda)^k}{k!}$$

$$= \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k \lambda^k}{k!}$$

so

$$P(X=k) = e^{-\lambda} \frac{\lambda^k}{k!}, \quad k=0, 1, \dots$$

These are the Poisson(λ) probabilities.

Back to iid Bernoulli(p) sequence

$$X_1, X_2, \dots$$

Let $Y =$ "time" until the first 1. This is a geometric(p) rv & clearly

$$P(Y=k) = P(X_1=0, X_2=0, \dots, X_{k-1}=0, X_k=1)$$

means

and (same as intersection)

$$= P(X_1=0) P(X_2=0) \dots P(X_{k-1}=0) P(X_k=1)$$

$$= q^{k-1} p, \quad k=1, 2, \dots$$

These are the geometric(p) probabilities and the corresponding P.F. (probability function) is

$$f(x) = \begin{cases} q^{x-1} p, & x=1, 2, \dots \\ 0, & \text{ow} \end{cases}$$

Similarly, for the Poisson(λ) the p.f. is

$$f(x) = \begin{cases} e^{-\lambda} \frac{\lambda^x}{x!}, & x=0, 1, \dots \\ 0, & \text{ow} \end{cases}$$

The time to the r th 1 is a negative binomial rv. Call it S_r . Clearly S_r is the sum of r iid geometric(p) rv's. Hence the p.f. of S_r is
[p.f. of a geometric(p)] ^{r}

pdf of a geometric (p)

If $Y \sim \text{geometric}(p)$ then

$$G(\lambda) = E(\lambda^Y) = \sum_y \lambda^y f(y) = \sum_{k=1}^{\infty} \lambda^k q^{k-1} p$$

$$= \frac{p}{q} \sum_{k=1}^{\infty} (q\lambda)^{k-1}$$

$$= \frac{p}{q} \frac{q\lambda}{1-q\lambda}$$

$$= \frac{p\lambda}{1-q\lambda}$$

$$, \quad \underbrace{|q\lambda| < 1}_{|\lambda| < \frac{1}{q}}$$

Aside

Note $\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}$, $|x| < 1$

$$\sum_{k=1}^{\infty} x^k = \frac{x}{1-x}, \quad |x| < 1$$

* we can differentiate to get related series

If $S_r \sim \text{negative binomial}(r, p)$
negbinomial (r, p)

$$\Rightarrow G_{S_r}(\lambda) = \left(\frac{p\lambda}{1-q\lambda} \right)^r, \quad |\lambda| < \frac{1}{q}$$

Also $P(S_r = k) = P((r-1) \text{ 1's in the first } k-1 \text{ trials + 1 on the } k\text{th})$
 $= P((r-1) \text{ 1's in the first } k-1 \text{ trials}) P(1 \text{ on the } k\text{th})$
 $= \binom{k-1}{r-1} p^{r-1} q^{k-r} p = \binom{k-1}{r-1} p^r q^{k-r}, \quad k = r, r+1, \dots$

The mean & variance of these distributions may be obtained directly or via the pdf. Direct calculations are often harder. An alternative way of obtaining the moments is to use the moment generating function (mgf). For a rv X this is defined as

$$m(t) = E(e^{tX}) \left\{ \begin{array}{l} = \sum_x e^{tx} f(x) \text{ in the discrete case} \end{array} \right.$$

Note: $m(0) = 1$ but $m(t)$ may be ∞ for other t 's. The nice case is when $m(t) < \infty$ for $-\epsilon < t < \epsilon$ with $\epsilon > 0$.

2 For counting rv's with pdf $G(s)$

$$m(t) = G(e^t)$$

3 $m^{(k)}(0) = E(X^k)$

eg The pdf of a Poisson(λ) rv is

$$G(s) = e^{-\lambda} \sum_{x=0}^{\infty} \frac{\lambda^x}{x!} s^x$$

& the mgf is

$$m(t) = e^{-\lambda} \sum_{x=0}^{\infty} \frac{\lambda^x}{x!} (e^t)^x = e^{-\lambda} e^{\lambda e^t} = e^{\lambda(e^t - 1)}$$

Hypergeometric rv

$$\begin{array}{|l} N_1 \text{ b's} \\ N_2 \text{ w's} \end{array}$$

select m chips without replacement
 $Y = \#$ of b's

$$P(Y=k) = \frac{\binom{N_1}{k} \binom{N_2}{m-k}}{\binom{N}{m}}$$

where $N = N_1 + N_2$. Had the chips been selected with replacement then $Y \sim \text{binomial}(m, p)$, where $p = \frac{N_1}{N}$.

The hypergeometric completes our introduction to the main discrete distributions.