

Week 2 QCB 408 / 508 Spring 2020

Continuous RV's (continued)

Normal (Gaussian) distribution

$$X \sim \text{Normal}(\mu, \sigma^2)$$

$$X = (-\infty, \infty)$$

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

$$E[X] = \mu, \quad \text{Var}(X) = \sigma^2 > 0$$

dnorm(x, mean=2, sd=3)

Multivariate RV's

Two RV's X and Y

$$\text{Joint cdf } F(a, b) = \Pr(X \leq a, Y \leq b)$$

$$= \Pr(\{\omega : X(\omega) \leq a\} \cap \{\omega : Y(\omega) \leq b\})$$

Suppose continuous.

$$\frac{\partial^2}{\partial x \partial y} F(x, y) = f(x, y) \rightarrow \text{joint pdf}$$

Suppose discrete

joint pmf $f(x, y) = \Pr(X=x, Y=y)$

Marginal distributions

$$f(x) = \sum_{y \in Q_y} f(x, y)$$

$$f(x) = \int f(x, y) dy$$

See Law of Total Probability.

Independent rvs

If X and Y are independent

then:

$$f(x, y) = f(x)f(y) \checkmark$$

$$\begin{aligned} F_{X,Y}(a, b) &= \Pr(X \leq a, Y \leq b) \\ &= \Pr(X \leq a) \Pr(Y \leq b) \\ &= F_X(a) F_Y(b) \end{aligned}$$

Conditional Distributions

$$\Pr(X \leq a | Y \leq b) = \frac{\Pr(X \leq a, Y \leq b)}{\Pr(Y \leq b)}$$

$$\{\omega : X(\omega) \leq a\} \quad \{\omega : Y(\omega) \leq b\}$$

$$F_{X|Y}(a | Y \leq b) = \frac{F_{X,Y}(a, b)}{F_Y(b)}$$

$$f(x|y) = \frac{f(x,y)}{f(y)}$$

Bayes Theorem $f(y|x) = \frac{f(x|y) f(y)}{f(x)}$

All of the above extends to

e.g. X_1, X_2, \dots, X_n

$$f(x_1, x_2 | x_3, x_4, x_5) = \frac{f(x_1, x_2, x_3, x_4, x_5)}{f(x_3, x_4, x_5)}$$

$$f(x_3, x_4, x_5) = \iint f(x_1, x_2, x_3, x_4, x_5) dx_1 dx_2$$

If x_1, x_2, \dots, x_n are independent then

$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n f(x_i)$$

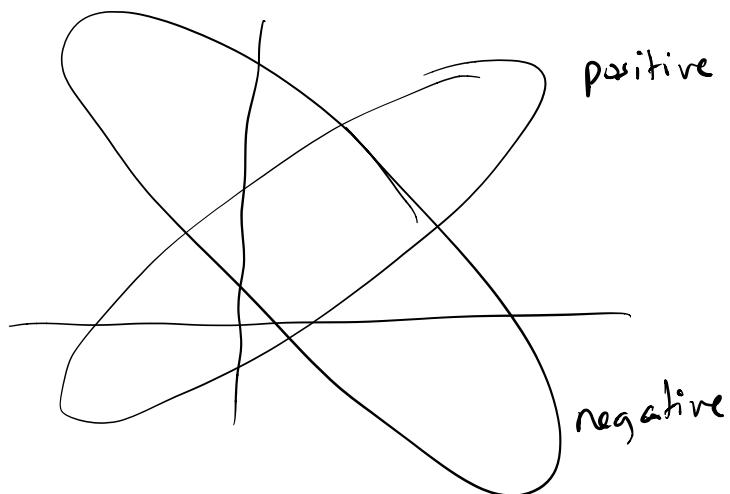
Moments of Joint Distributions

For a single rv, X :

$E[X^k]$ is the k^{th} moment

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

$$\text{Cov}(X, Y) = \underline{E[(X - E[X])(Y - E[Y])]} \checkmark$$



First set $E[X], E[Y]$

$$\text{Cov}(X, Y) = \iint (x - E[X])(y - E[Y]) f(x, y) dx dy$$

or

$$= \sum_x \sum_y (x - E[X])(y - E[Y]) \frac{f(x, y)}{\downarrow}$$

$$\Pr(X=x, Y=y)$$

Linear Transformations of RV's

X is a RV

a and b are constants

$$E[a + bX] = a + bE[X]$$

$$\text{Var}(a + bX) = b^2 \text{Var}(X)$$

$$E[\underline{a + bX}] = \int (a + bx) f(x) dx$$

$$= \int a f(x) dx + \int bx f(x) dx$$

$$= a \underbrace{\int f(x) dx}_{\substack{x \\ 1}} + b \frac{\int x f(x) dx}{E[X]}$$

$$= a + bE[X]$$

Exercise: $\text{Var}(a+bx) = b^2 \text{Var}(x)$

Law of Total Variance

Jointly distributed rv's X and Y

$$\rightarrow \text{Var}(X) = \underbrace{\text{Var}(E[X|Y])}_{\rightarrow} + \underbrace{E[\text{Var}(X|Y)]}_{\rightarrow}$$

$$E[X|Y] \rightarrow ?$$

$$E[X|Y=y] = \underbrace{\int x f(x|y) dx}_{\text{function of } y},$$

Have a pmf or pdf for y

$$E[X|Y] = \underbrace{\int x f(x|Y) dx}_{\text{function of } Y}$$

$$E[E[X|Y]] = \underbrace{\iint x f(x|y) dx f(y) dy}_{E[X|Y=y]}$$

$$= \iint x f(x|y) \underbrace{f(y)}_{\rightarrow} dx dy$$

$$\begin{aligned}
 &= \iint x f(x,y) dx dy \\
 &= \int \int x f(x,y) dy dx \\
 &= \int x \underbrace{\int f(x,y) dy}_{\downarrow} dx \\
 &= \int x f(x) dx \\
 &= E[X]
 \end{aligned}$$

$$f(x) = \int f(x,y) dy$$

$$\text{Var}(X|Y) = E\{(X - E[X|Y])^2 | Y\}$$

Exercise : Prove Law of Total Variance

↓
or
read

Hardy-Weinberg Equilibrium

$$\text{SNP} \quad CC, CT, TT$$

$$\downarrow \quad \downarrow \quad \downarrow$$

$$0 \quad 1 \quad 2$$

Genotype $X \in \{0, 1, 2\}$

$$\Pr(X=k) = r_k \quad k=0, 1, 2$$

$$E[X] = r_0 + 2r_1 \quad E\left[\frac{X}{2}\right] = \underbrace{\frac{r_1}{2} + r_2}_\text{freq. of T} \equiv p$$

$Y \in \{0, 1\}$ is the transmitted

$$\Pr(Y=1 | X=k) = \begin{cases} 0 & k=0 \\ 1/2 & k=1 \\ 1 & k=2 \end{cases}$$

$$\Pr(Y=1) = \sum_{k=0}^2 \Pr(Y=1 | X=k) \Pr(X=k)$$

$$= 0 \cdot r_0 + \frac{1}{2} r_1 + r_2$$

$$= p$$

$$\Rightarrow Y \sim \text{Bernoulli}(p)$$

$Z \in \{0, 1, 2\}$ is next generation genotype

$Y_1, Y_2 \stackrel{\text{iid}}{\sim} \text{Bernoulli}(p)$

iid = independent, identically distributed

$$Z = Y_1 + Y_2$$

$$\Rightarrow Z \sim \text{Binomial}(2, p)$$

$$E[Z] = 2p = E[X] \Rightarrow \begin{aligned} &\text{transmission} \\ &\text{probs for } Z \\ &\text{are identical} \\ &\text{to } X \end{aligned}$$

\Rightarrow equilibrium

\Rightarrow all ^{future} generations' genotypes are drawn from $\text{Binomial}(2, p)$

$$\Pr(Z=0) = (1-p)^2$$

$$\Pr(Z=1) = 2p(1-p) \leftarrow$$

$$\Pr(Z=2) = p^2$$

Typically $\Pr(z=1) < 2\rho(1-\rho)$ when HWE is violated.

Inbreeding

IBD = identical by descent

Two alleles are IBD if they are copies from a common ancestor

Let I be a rv such that it indicates whether two randomly drawn alleles are IBD or not.

Y_1 and Y_2 :

$$\begin{array}{ll} \xrightarrow{\hspace{1cm}} & I=1 \Rightarrow Y_1=Y_2 \sim \text{Bernoulli}(\rho) \\ & I=0 \Rightarrow Y_1, Y_2 \stackrel{\text{iid}}{\sim} \text{Bernoulli}(\rho) \end{array}$$

$I \sim \text{Bernoulli}(f)$

f is the inbreeding coefficient (usually F)

$Z | I=0 \sim \text{Binomial}(2, \rho)$

$Z_{1/2} | I=1 \sim \text{Bernoulli}(\rho)$

$Y_1, Y_2, Y_3 \stackrel{iid}{\sim} \text{Bernoulli}(p)$

$Z|I=0 \sim \text{Binomial}(2, p)$

$Z|I=1 \sim \text{Bernoulli}(p)$

$$Z = (Y_1 + Y_2)(1 - I) + 2Y_3 I$$

thus \rightarrow

$$\Pr(Z=k | I=0) = \begin{cases} (1-p)^2 & k=0 \\ 2p(1-p) & k=1 \\ p^2 & k=2 \end{cases}$$

$$\Pr(Z=k | I=1) = \begin{cases} 1-p & k=0 \\ 0 & k=1 \\ p & k=2 \end{cases}$$

i.e., $Z|I=1 \sim 2\text{-Bernoulli}(p)$

$$Pr(Z=0) = Pr(Z=0 | I=0) Pr(I=0) + \\ Pr(Z=0 | I=1) Pr(I=1)$$

$$= \overbrace{(1-p)^2 (1-f) + (1-p)f}$$

$$= \overbrace{(1-p)^2 + \cancel{p(1-p)f}}$$

$$Pr(Z=1) = \overbrace{2p(1-p)(1-f) + 0 \cdot f} \\ = \overbrace{2p(1-p)(1-f)} < 2p(1-p)$$

$$Pr(Z=2) = \overbrace{p^2 (1-f) + pf} \\ = \overbrace{p^2 + \cancel{p(1-p)f}}$$

$$E[Z] = E[E[Z|I]] =$$

$$\text{Note: } 2p(1-p) = 2p(1-p)(1-f) +$$

$$2p(1-p)f$$

$$= 2p(1-p)(1-f) f$$

$$\rightarrow p((1-p)f +$$

$$\rightarrow p(1-p)f$$

$$\text{Var}(Z) = \underbrace{E[\text{Var}(Z|I)]}_{\text{Var}(Z|I=0)} + \text{Var}(E[Z|I])$$

$$\text{Var}(Z|I=0) = 2p(1-p) \quad [\text{Binomial}(2,p)]$$

$$\begin{aligned}\text{Var}(Z|I=1) &= \text{Var}(2Y_3) \\ &= 4\text{Var}(Y_3) \\ &= 4p(1-p)\end{aligned}$$

$$\text{Var}(Z|I) = 2p(1-p)(1-I) + 4p(1-p)I$$

$$\begin{aligned}E[\text{Var}(Z|I)] &= 2p(1-p)(1-f) + 4p(1-p)f \\ &= 2p(1-p)(1+f)\end{aligned}$$

$$Z|I=0 = Y_1 + Y_2$$

$$Z|I=1 = 2Y_3$$

$$E[Z|I=0] = 2p$$

$$E[Z|I=1] = 2E[Y_3] = 2p$$

$$E[Z|I] = 2p$$

$$\text{Var}(E[Z|I]) = 0$$

$$\Rightarrow \text{Var}(Z) = 2p(1-p)(1+f)$$

$$f = \frac{\text{Var}(Z) - \text{Var}(Z|I=0)}{\text{Var}(Z|I=0)}$$

$$f = 1 - \frac{\Pr(Z=1)}{\Pr(Z=1|I=0)}$$

Drift

Make allele frequency random.

Then allow for HWE style mating.

$$Z|Q \sim \text{Binomial}(2, Q)$$

Q is a random variable

$$Z|Q=q \sim \text{Binomial}(2, q) \quad \checkmark$$

Q changes according to a distribution

p = ancestral allele frequency

f = fixation index, "inbreeding"

$$Q \sim \text{Beta} \left(\frac{1-f}{f} p, \frac{1-f}{f} (1-p) \right)$$

↗ α ↗ β

$$= BN(p, f)$$

Balding - Nichols

$$Q \sim BN(p, f)$$

$$E[Q] = p, \quad \text{Var}(Q) = p(1-p)f$$

$$E[Z] = E[E[Z|Q]] = E[2Q] = 2p$$

$$\begin{aligned}
 \Pr(Z=2) &= \int \Pr(Z=2|Q=q) f(q) dq \\
 &= \int q^2 f(q) dq \\
 &= \boxed{E[Q^2]} \\
 &= \frac{\text{Var}(Q) + E[Q]^2}{p(1-p)f + p^2}
 \end{aligned}$$

Var(Q)
 = E(Q^2) - E(Q)^2

$$\text{Verify: } \Pr(Z=0) = p(1-p)f + (1-p)^2$$

$$\Pr(Z=1) = 2p(1-p)(1-f)$$

$$\begin{aligned} \nearrow \text{Var}(Z) &= E[\text{Var}(Z|Q)] + \text{Var}(E[Z|Q]) \\ &= E[2Q(1-Q)] + \text{Var}(2Q) \\ &= E[2Q] - E[2Q^2] + 4p(1-p)f \\ &= 2p - 2E[Q^2] + 4p(1-p)f \\ &= 2p - 2[\text{Var}(Q) + E(Q)^2] + 4p(1-p)f \\ &= 2p - 2p(1-p)f - 2p^2 + 4p(1-p)f \\ &= 2p(1-p) + 2p(1-p)f \\ &= 2[p(1-p) + p(1-p)f] \\ &= 2p(1-p)(1+f) \end{aligned}$$

Model of RNA-seq Data

Assume $i = 1, 2, \dots, m$ genes
 $j = 1, 2, \dots, n$ observations

Consider a single biological condition or population.

Observe RNA-seq read counts y_{ij} for gene i in observation j .

Target: True proportion of gene i expression, call it a_i

The proportion of mRNA for gene i in this population is a_i .

$$\sum_{i=1}^m a_i = 1, \text{ most } a_i \text{ are small.}$$

Instructive, idealized example to follow.

Step 1. Sample cells and mRNA molecules

Step 2. Sequence mRNA molecules and obtain counts.

Step 1:

M_j is the number of mRNA molecules sampled for observation j

X_{ij} is the number of mRNA molecules sampled for gene i in observation j

Assume completely random sampling of mRNA molecules.

$\Rightarrow X_{ij} | M_j \sim \text{Binomial}(M_j, a_i)$

M_j is large, a_i is small

$$\Rightarrow x_{ij} \sim \text{Poisson}(M_j a_i)$$

$$\text{Var}(x_{ij} | M_j) = M_j a_i \underbrace{(1-a_i)}_{\approx 1}$$

$$\pi_{ij} = \frac{x_{ij}}{M_j} \quad \text{random proportion of gene } i \text{ mRNA in observation } j$$

$E[\pi_{ij}] =$ to be continued next week (week 3)...