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## F. Distribution.

Let  $Y_1$  and  $Y_2$  be two independent  $\chi^2$ -distributed r.v.s. w/  $df=1$

For both  $Y_1$  and  $Y_2$ , the pdf is

$$f_Y(y) = \frac{1}{\sqrt{2\pi y}} e^{-\frac{y}{2}} \mathbb{1}_{(0, \infty)}(y) \quad \leftarrow$$

Define  $W = \frac{Y_2}{Y_1}$ , i.e.,  $w = g(Y_1, Y_2)$  w/  $g(y_1, y_2) = \frac{y_2}{y_1}$

Goal: Density of  $W$ :  $f_W$ !

Start by figuring out the cdf  $F_W$ .

$$w > 0: \quad F_W(w) = \mathbb{P}[W \leq w] = \mathbb{P}\left[\frac{Y_2}{Y_1} \leq w\right] = \mathbb{P}[Y_2 \leq w \cdot Y_1]$$

$$= \int_0^\infty \int_0^{w \cdot y_1} f_{Y_1, Y_2}(y_1, y_2) dy_2 dy_1$$

$$= \int_0^\infty \int_0^{w \cdot y_1} \frac{1}{\sqrt{2\pi y_1}} e^{-\frac{y_1}{2}} \cdot \frac{1}{\sqrt{2\pi y_2}} e^{-\frac{y_2}{2}} dy_2 dy_1$$

$$= \int_0^\infty \frac{1}{\sqrt{2\pi y_1}} e^{-\frac{y_1}{2}} \left( \int_0^{w \cdot y_1} \frac{1}{\sqrt{2\pi y_2}} e^{-\frac{y_2}{2}} dy_2 \right) dy_1$$

$F_{Y_2}(w \cdot y_1)$

$f_W(w)$

$$F_W(w) = \int_0^\infty \frac{1}{\sqrt{2\pi y_1}} e^{-\frac{y_1}{2}} F_{Y_2}(w \cdot y_1) dy_1$$

$$F_W'(w) = \frac{d}{dw} F_W(w)$$

$$\rightarrow f_W(w) = F_W'(w) = \int_0^\infty \frac{1}{\sqrt{2\pi y_1}} e^{-\frac{y_1}{2}} f_Y(w \cdot y_1) \cdot y_1 dy_1$$

$$\begin{aligned}
 f_w(w) &= \int_0^{\infty} \left( \frac{1}{\sqrt{2\pi} y_1} \right) e^{-\frac{y_1}{2}} \cdot \left( \frac{1}{\sqrt{2\pi w \cdot y_1}} \right) e^{-\frac{w \cdot y_1}{2}} \cdot y_1 dy_1 \\
 &= \frac{1}{2\pi \sqrt{w}} \int_0^{\infty} e^{-\frac{1}{2} y_1 (1+w)} dy_1 = \\
 &= \frac{1}{2\pi \sqrt{w}} \left( -\frac{2}{1+w} e^{-\frac{1}{2} y_1 (1+w)} \right) \Big|_{y_1=0}^{\infty} \\
 &= \frac{1}{\cancel{2}\pi \sqrt{w}} \cdot \frac{\cancel{2}}{1+w} = \frac{1}{\pi \sqrt{w} (1+w)}
 \end{aligned}$$

is the density  $F(1,1)$ , i.e.,

the F distribution w/ 1 numerator degree of freedom  
and 1 denominator degree of freedom



## M378K Introduction to Mathematical Statistics

### Problem Set #7

#### Moment generating functions.

**Definition 7.1.** The  $k^{\text{th}}$  moment of a random variable  $Y$  taken about the origin is defined as  $\mathbb{E}[Y^k]$  provided that the expectation exists. We write

$$\mu_k = \mathbb{E}[Y^k]$$



when there is no ambiguity about the random variable in question.

**Remark 7.2.**  $\mu_k$  is also referred to as the  $k^{\text{th}}$  raw moment.

**Remark 7.3.** In particular,  $\mu_1 = \mu$  happens to be the **mean** of the random variable  $Y$ .

**Definition 7.4.** The  $k^{\text{th}}$  central moment of a random variable  $Y$  is defined as  $\mathbb{E}[(Y - \mu)^k]$  provided that the expectation exists. We write

$$\mu_k^c = \mathbb{E}[(Y - \mu)^k]$$

when there is no ambiguity about the random variable in question.

**Remark 7.5.**  $\mu_k^c$  is also referred to as the  $k^{\text{th}}$  moment of a random variable  $Y$  taken about its mean.

**Definition 7.6.** The moment-generating function (mgf)  $m_Y$  for a random variable  $Y$  is defined as

$$m_Y(t) = \mathbb{E}[e^{tY}]$$

$$\mathbb{E}[e^{tY}]$$

for all  $t$  for which the above expectation exists. In fact, we say that the moment-generating function **exists** if there exists a positive number  $b$  such that  $m_Y(t)$  is finite for all  $t$  such that  $|t| \leq b$ .

**Problem 7.1.** How much is  $m_Y(0)$ ?

$$m_Y(0) = \mathbb{E}[e^{0 \cdot Y}] = 1$$

**Remark 7.7.** On the choice of terminology ...

Step 1.

$$\frac{d}{dt} m_Y(t) = ?$$

$$\begin{aligned} \frac{d}{dt} m_Y(t) &= \frac{d}{dt} \mathbb{E}[e^{tY}] = \mathbb{E}\left[\frac{d}{dt} e^{tY}\right] = \\ &= \mathbb{E}[Y e^{tY}] \end{aligned}$$

Step 2.

$$m'_Y(0) = ?$$

$$m'_Y(0) = \mathbb{E}[Y e^{0 \cdot Y}] = \mathbb{E}[Y] = \mu_Y$$

Step 3.

$$\frac{d^2}{dt^2} m_Y(t) = ?$$

$$\frac{d}{dt} \left( \frac{d}{dt} m_Y(t) \right) = \frac{d}{dt} \mathbb{E}[Y e^{tY}] = \mathbb{E}[Y^2 e^{tY}]$$

Step 4.

$$m''_Y(0) = ?$$

$$m''_Y(0) = \mathbb{E}[Y^2]$$

Step 5. What do you suspect the **generalization** of the above would be?

**Theorem 7.8.** If  $m_Y$  exists, then for  $k \in \mathbb{N}$ , we have

$$m_Y^{(k)}(0) = \mu_k.$$

**Example 7.9.** Let  $Y \sim b(n=1, p)$ , i.e., let  $Y$  model a Bernoulli trial with the probability of success denoted by  $p$ . Find  $m_Y$ .

$$\begin{aligned} \rightarrow: m_Y(t) &= \mathbb{E}[e^{tY}] = e^{t \cdot 0} \cdot (1-p) + e^{t \cdot 1} \cdot p \\ &= 1-p + pe^t \quad t \in \mathbb{R} \end{aligned}$$

**Proposition 7.10.** Let  $Y_1$  and  $Y_2$  be independent random variables with m.g.f.s denoted by  $m_{Y_1}$  and  $m_{Y_2}$ . Define  $Y = Y_1 + Y_2$ . Then, for every  $t$  for which both  $m_{Y_1}$  and  $m_{Y_2}$  are well defined, we have

$$m_Y(t) = ?$$

*Proof.* By definition:

$$m_Y(t) = \mathbb{E}[e^{tY}]$$

Using  $Y = Y_1 + Y_2$ , we can substitute  $Y_1 + Y_2$  for  $Y$  in the expression above. So,

$$m_Y(t) = \mathbb{E}[e^{t(Y_1+Y_2)}]$$

One of the properties of the exponential function is that  $e^{A+B} = e^A \times e^B$ . Thus, the above becomes:

$$m_Y(t) = \mathbb{E}[e^{tY_1} \cdot e^{tY_2}]$$

Recall that  $Y_1$  and  $Y_2$  are assumed to be independent random variables. With this in mind, we get:

$$m_Y(t) = \mathbb{E}[e^{tY_1}] \cdot \mathbb{E}[e^{tY_2}]$$

Finally, using the definition of a m.g.f., we have

$$m_Y(t) = m_{Y_1}(t) \cdot m_{Y_2}(t)$$

□

**Example 7.11.** Let  $Y \sim b(n, p)$ . What is the moment generating function of  $Y$ ?

**Example 7.12.** Let  $N \sim \text{Poisson}(\lambda)$ . What is the moment generating function  $m_N$  of  $N$ ?

**Example 7.13.** Let  $Z \sim N(0, 1)$ . What is the moment generating function  $m_Z$  of  $Z$ ?