Associated Reading: Wackerly 7, Chapter 6, Sections 1-4

Let's start by establishing the point of this chapter. You've conducted an experiment which yields observed data Y_1, \dots, Y_n , and now you need to analyze these data. What do you do?

- 1. You determine what property of the underlying conceptual population that you want to statistically infer. (For instance, your Y's may all be drawn from some known or unknown distribution whose mean is μ , and you want to use your data to infer μ .)
- 2. You select an *estimator* of the property you want to infer. (For instance, you might select the sample mean as an estimator of the population mean.)
- 3. As your chosen estimator is a function of the random variables *Y*, it itself is a random variable, sampled from some distribution. In order to perform precise statistical inference, you need to determine this distribution. Not just its mean, or its mean and variance, but its actual shape. (Up until now, we've fallen back on imprecise inference using Tchebysheff's Theorem. No more!)

Here's a motivating example:

② We wish to infer mean of population: up
⇒) estimator
$$\overline{Y} = \frac{Y_1 + \cdots + Y_n}{n} = \frac{1}{n} \stackrel{?}{\underset{i=1}{\sum}} Y_i$$
.

We can't compute precisely
$$P(M_Q - 60 \le Y \le MQ + 60)$$
.

without knowing dist Q.

What we will look at in Chapter 6 are three methods that one can use to try to determine the pmf/pdf of an estimator (or any other function of random variables, for that matter):

• the *method of transformations* (which is really just a simplified form of the preceding method); and

• the method of moment-generating functions (or mgfs).

In this notes set, we'll work through examples of the first two methods, and in the next set of notes, we'll turn to mgfs.

The method of distribution functions applies methods that you have already learned up to now in this class. The main issue with it is its apparent complexity. I'll break it down into steps here:

$$[pdf] f_{\mathcal{V}}(u) = \frac{dF_{\mathcal{V}}}{du}$$

$$P(u) = P(U \le u) = P(g(\cdot) \le u).$$

$$P(y) = P(y) \text{ find jump point of } f(y) \text{ for } f(y) \text{ dy } f(y) \text{ dy } f(y) \text{ for } f(y) \text{ dy } f(y) \text$$

(ii) if
$$U = g(Y_1, Y_2)$$
 $p(g(Y_1, Y_2) \leq u) = \sum_{y_1, y_2 \in g(y_1, y_2) \leq \mu} p(y_1, y_2) dy_1$

$$g(y_1, y_2) \leq \mu \qquad g(y_1, y_2) \leq \mu \qquad g(y_1, y_2) \leq \mu$$

$$g(y_1, y_2) \leq \mu$$

To internalize these details, there is, as usual, no substitute to working through problems.

 \rightarrow **EXAMPLE.** Wackerly 7, Exercise 6.3(a,b)

6.3 A supplier of kerosene has a weekly demand
$$Y$$
 possessing a probability density function given by
$$f(y) = \begin{cases} y, & 0 \le y \le 1, \\ 1, & 1 < y \le 1.5, \\ 0, & \text{elsewhere,} \end{cases}$$

$$= \int_{-4}^{6} u \frac{u+4}{100} du$$

with measurements in hundreds of gallons. (This problem was introduced in Exercise 4.13.) The supplier's profit is given by U = 10Y - 4.

 $+\int_{6}^{N}u_{10}^{+}du=\xi_{12}^{-7}$

a Find the probability density function for
$$U$$
.

b Use the answer to part (a) to find
$$E(U)$$
.

c Find
$$E(U)$$
 by the methods of Chapter 4.

a).
$$V = 10Y - 4$$
 method of dist furtion.

$$\sqrt{EU = E[10Y-4]}$$

Let divide into cases.

Cose 1:
$$\frac{u+\psi}{10} \leq 0$$
 $P[U \leq u] = 0$

$$\frac{1}{10} \leq 0 \qquad \text{Plusu} = 0$$

Case 2:
$$\frac{u+b}{10} \in [0,1], \quad P(Y \leq \frac{u+b}{10}) = \int_{0}^{u+b} y$$

$$\frac{12(\sqrt{10})^2}{100} = \int_0^1 g \, dg$$

Case 3:
$$\frac{\mu+\mu}{10}$$
 $\in [1,1,1]$ $P(\underline{Y} \leq \frac{\mu+\mu}{10}) = P(\underline{Y} \leq 1) + P(\underline{I} \leq \frac{\mu+\mu}{10})$.

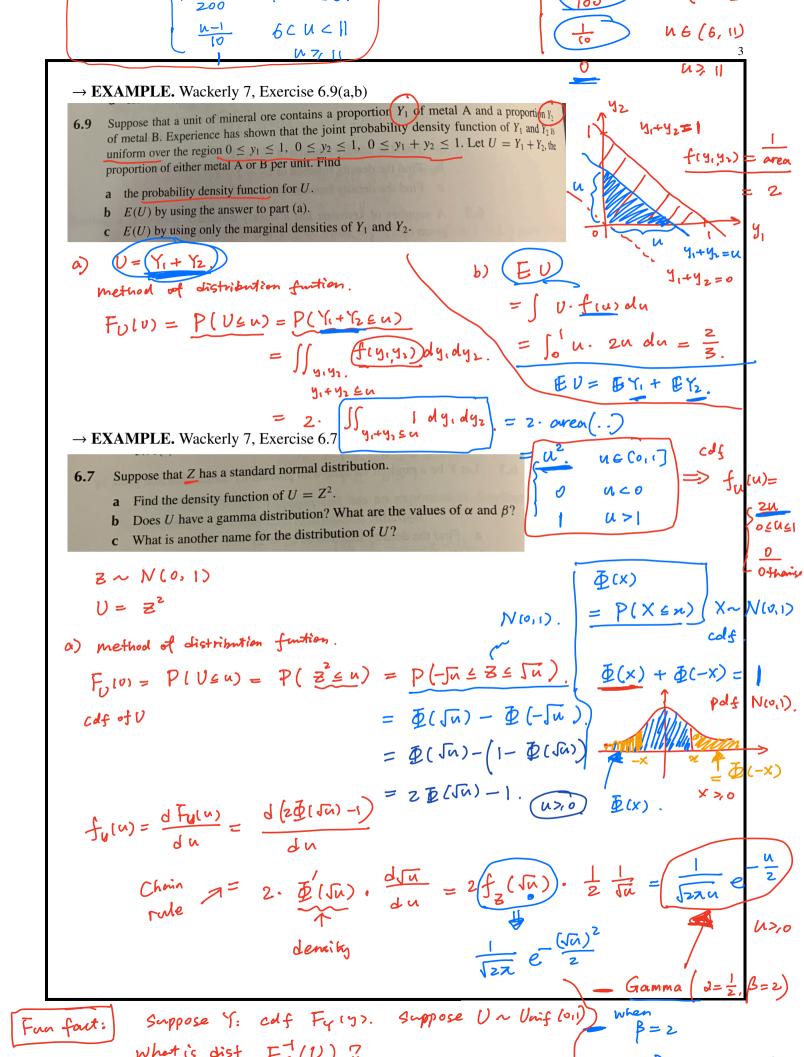
$$= P(121) + P(1212 - 0).$$

$$= \frac{10^{2}}{200} + \int_{0}^{u+4} dy = \frac{u-1}{10}$$

Set u=6 in Case 2

Case 4:
$$\frac{h+\mu}{10} > 1.5$$
 Plys $\frac{u+\mu}{10}$

$$F_{U}(u) = \begin{cases} 0 & u \leq -\psi \\ (u+\psi)^{2} & -\psi \leq u \leq 6 \end{cases} \Rightarrow f_{U}(v) = \begin{cases} 0 & u \leq -\psi \\ u+\psi & u \in [-\psi, 6] \end{cases}$$



There is another application of this methodology that is useful for simulating usea. Let's say you want to simulate a datum Y from an arbitrary distribution. One way to do this is to simulate a datum U from a Uniform(0,1) distribution (which is easy to do given any random number generator), and then transform that datum such that Y = g(U) is sampled from the distribution of your choice.

→ **EXAMPLE.** Wackerly 7, Exercise 6.15

6.15 Let Y have a distribution function given by
$$F(y) = \begin{cases} 0, & y < 0, \\ 1 - e^{-y^2}, & y \ge 0. \end{cases}$$
 Find a transformation $G(U)$ such that, if U has a uniform distribution on the interval $(0, 1)$, $G(U)$ has the same distribution as Y .

let
$$U = F(Y) \Rightarrow Y \Rightarrow F^{\dagger}(U)$$
.
 $U = 1 - e^{-Y^2}$
 $e^{-y^2} = 1 - U$
 $y = \sqrt{\log(1-U)}$.

if we wond to generate distribution whose colfis Fy. then,

O generate U~ Vinf (ou)

@ find Fr

3 Fy(U), has

The method of transformations is, as mentioned, a simplified version of the method of distribution functions that one can apply when the function U = h(Y) is *strictly increasing* or *strictly decreasing* over the support of f(y). For instance, if the support of f(y) is the range $-1 \le y \le 1$ and $U = Y^2$, you cannot use the method of transformations, because h(Y) decreases over the range $-1 \le y < 0$ and increases over the range $0 < y \le 1$. But if the support of f(y) is the range $0 \le y \le 1$ and $U = Y^2$, you *can* use the method of transformations, as h(Y) is strictly increasing.

The method of transformations is based on the following algorithm:

odf
$$F_{U}(u) = P(U \leq u) = P(h(Y) \leq u) = P(Y \leq h^{T}(u)) = F_{Y}(h^{T}(u)).$$

poly, $f_{U}(u) = f_{Y}(h^{T}(u)) = f_{Y}(h^{T}(u)) = f_{Y}(h^{T}(u)).$

Chain rule.

Suppose $h \downarrow h$

$$F_{U}(u) = f_{Y}(h^{T}(u)) = f_{Y}(h^{T}(u)) = f_{Y}(h^{T}(u)) = f_{Y}(h^{T}(u))$$

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