

Frequency Distributions

Technical Supplement: Iterated Expectations

Fall 2017

Iterated Expectations

In some situations, we only observe a single outcome but can conceptualize an outcome as resulting from a two (or more) stage process. These are called **two-stage**, or “**hierarchical**,” type situations. Some special cases include:

- problems where the parameters of the distribution are random variables,
- mixture problems, where stage 1 represents the type of subpopulation and stage 2 represents a random variable with a distribution that depends on population type
- an aggregate distribution, where stage 1 represents the number of events and stage two represents the amount per event.

In these situations, the law of iterated expectations can be useful. The law of total variation is a special case that is particularly helpful for variance calculations.

To apply these rules,

- 1 Identify the random variable that is being conditioned upon, typically a stage 1 outcome (that is not observed).
- 2 Conditional on the stage 1 outcome, calculate summary measures such as a mean, variance, and the like.
- 3 There are several results of the step (ii), one for each stage 1 outcome. Then, combine these results using the iterated expectations or total variation rules.

Iterated Expectations

- Consider two random variables, X and Y , and a function $h(X, Y)$. Assuming expectations exist and are finite, a rule/theorem from probability states that

$$E h(X, Y) = E \{E (h(X, Y)|X)\}.$$

- This result is known as the *law of iterated expectations*.
- Here, the random variables may be discrete, continuous, or a hybrid combination of the two.
- Similarly, the *law of total variation* is

$$\text{Var } h(X, Y) = E \{ \text{Var } (h(X, Y)|X) \} + \text{Var } \{E (h(X, Y)|X)\},$$

the expectation of the conditional variance plus the variance of the conditional expectation.

Discrete Iterated Expectations

- To illustrate, suppose that X and Y are both discrete random variables with joint probability

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

- Further, let $p(y|x) = \frac{p(x,y)}{\Pr(X=x)}$ be the conditional probability mass function.
- The conditional expectation is

$$E(h(X, Y)|X = x) = \sum_y h(x, y)p(y|x)$$

- You can use the conditional expectation to get the unconditional expectation using

$$\begin{aligned} E\{E(h(X, Y)|X)\} &= \sum_x \left\{ \sum_y h(x, y)p(y|x) \right\} \Pr(X = x) \\ &= \sum_x \sum_y h(x, y)p(y|x) \Pr(X = x) \\ &= \sum_x \sum_y h(x, y)p(x, y) = E h(X, Y) \end{aligned}$$

- The proofs of the law of iterated expectations for the continuous and hybrid cases are similar.

Law of Total Variation

- To see this rule, first note that we can calculate a conditional variance as

$$\text{Var } (h(X, Y)|X) = E \left(h(X, Y)^2 | X \right) - \{E (h(X, Y)|X)\}^2.$$

- From this, the expectation of the conditional variance is

$$E \text{Var } (h(X, Y)|X) = E \left(h(X, Y)^2 \right) - E \{E (h(X, Y)|X)\}^2. \quad (1)$$

- Further, note that the conditional expectation, $E (h(X, Y)|X = x)$, is a function of x , say, $g(x)$.
- Now, $g(X)$ is a random variable with mean $E h(X, Y)$ and variance

$$\begin{aligned} \text{Var } \{E (h(X, Y)|X)\} &= \text{Var } g(X) \\ &= E g(X)^2 - (E h(X, Y))^2 \\ &= E \{E (h(X, Y)|X)\}^2 - (E h(X, Y))^2 \end{aligned} \quad (2)$$

- Adding the variance of the conditional expectation in equation (2) to the expectation of conditional variance in equation (1) gives the law of total variation.

Mixtures of Finite Populations: Example

- For example, suppose that N_1 represents claims from “good” drivers and N_2 represents claims from “bad” drivers. We draw

$$N = \begin{cases} N_1 & \text{with prob } \alpha \\ N_2 & \text{with prob } (1 - \alpha). \end{cases}$$

- Here, α represents the probability of drawing a “good” driver.
- Let T be the type, so $T = 1$ with prob α and $T = 2$ with prob $1 - \alpha$.
- From the law of iterated expectations, we have

$$\begin{aligned} E N &= E \{E (N|T)\} \\ &= E N_1 \times \alpha + E N_2 \times (1 - \alpha). \end{aligned}$$

- From the law of total variation

$$\text{Var } N = E \{ \text{Var } (N|T) \} + \text{Var } \{ E (N|T) \},$$

Mixtures of Finite Populations: Example 2

- To be more concrete, suppose that N_j is Poisson with parameter λ_j .
Then

$$\text{Var } N_j|T = \text{E } N_j|T = \begin{cases} \lambda_1 & T = 1 \\ \lambda_2 & T = 2 \end{cases}$$

- Thus

$$\text{E } \{\text{Var } (N|T)\} = \alpha\lambda_1 + (1 - \alpha)\lambda_2$$

and

$$\text{Var } \{\text{E } (N|T)\} = (\lambda_1 - \lambda_2)^2\alpha(1 - \alpha)$$

(Recall: for a Bernoulli with outcomes a and b and prob α , the variance is $(b - a)^2\alpha(1 - \alpha)$).

- Thus,

$$\text{Var } N = \alpha\lambda_1 + (1 - \alpha)\lambda_2 + (\lambda_1 - \lambda_2)^2\alpha(1 - \alpha)$$