

# Random Independent variables<sup>1</sup>

STA302 Fall 2014

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<sup>1</sup>See last slide for copyright information.

# Overview

## Preparation: Indicator functions

### Conditional expectation and the Law of Total Probability

$I_A(x)$  is the *indicator function* for the set  $A$ . It is defined by

$$I_A(x) = \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases}$$

Also sometimes written  $I(x \in A)$

$$\begin{aligned} E(I_A(X)) &= \sum_x I_A(x)p(x), \text{ or} \\ &\int_{-\infty}^{\infty} I_A(x)f(x) dx \\ &= P\{X \in A\} \end{aligned}$$

So the expected value of an indicator is a probability.

## Applies to conditional probabilities too

$$\begin{aligned} E(I_A(X)|Y) &= \sum_x I_A(x)p(x|Y), \text{ or} \\ &\int_{-\infty}^{\infty} I_A(x)f(x|Y) dx \\ &= Pr\{X \in A|Y\} \end{aligned}$$

So the conditional expected value of an indicator is a *conditional* probability.

$$E(X) = E(E[X|Y]) = E(g(Y))$$

$$E(X) = E(E[X|Y])$$

$$\begin{aligned} E(E[X|Y]) &= \int E[X|Y = y] f_y(y) dy \\ &= \int \left( \int x f_{x|y}(x|y) dx \right) f_y(y) dy \\ &= \int \left( \int x \frac{f_{x,y}(x,y)}{f_y(y)} dx \right) f_y(y) dy \\ &= \int \int x f_{x,y}(x,y) dx dy \\ &= E(X) \end{aligned}$$

Double expectation:  $E(g(X)) = E(E[g(X)|Y])$

$E(E[I_A(X)|Y]) = E[I_A(X)] = Pr\{X \in A\}$ , so

$$\begin{aligned} Pr\{X \in A\} &= E(E[I_A(X)|Y]) \\ &= E(Pr\{X \in A|Y\}) \\ &= \int_{-\infty}^{\infty} Pr\{X \in A|Y = y\} f_Y(y) dy, \text{ or} \\ &\quad \sum_y Pr\{X \in A|Y = y\} p_Y(y) \end{aligned}$$

This is known as the *Law of Total Probability*

## Don't you think its strange?

- In the general linear regression model, the  $\mathbf{X}$  matrix is supposed to be full of fixed constants.
- This is convenient mathematically. Think of  $E(\hat{\beta})$ .
- But in any non-experimental study, if you selected another sample, youd get different  $\mathbf{X}$  values, because of random sampling.
- So  $\mathbf{X}$  should be at least partly random variables, not fixed.
- View the usual model as *conditional* on  $\mathbf{X} = \mathbf{x}$ .
- All the probabilities and expected values so far in this course are *conditional* probabilities and *conditional* expected values.
- Does this make sense?



$\hat{\beta}$  is (conditionally) unbiased

$$E(\hat{\beta} | \mathbf{X} = \mathbf{x}) = \beta \text{ for any fixed } \mathbf{x}$$

It's *unconditionally* unbiased too.

$$E\{\hat{\beta}\} = E\{E\{\hat{\beta} | \mathbf{X}\}\} = E\{\beta\} = \beta$$

$$\begin{aligned} E\{\widehat{\boldsymbol{\beta}}\} &= E\{E\{\widehat{\boldsymbol{\beta}}|\mathbf{X}\}\} \\ &= \int \cdots \int E\{\widehat{\boldsymbol{\beta}}|\mathbf{X} = \mathbf{x}\} f(\mathbf{x}) d\mathbf{x} \\ &= \int \cdots \int \boldsymbol{\beta} f(\mathbf{x}) d\mathbf{x} \\ &= \boldsymbol{\beta} \int \cdots \int f(\mathbf{x}) d\mathbf{x} \\ &= \boldsymbol{\beta} \cdot 1 = \boldsymbol{\beta}. \end{aligned}$$

## Conditional size $\alpha$ test, Critical region $A$

$$Pr\{F \in A | \mathbf{X} = \mathbf{x}\} = \alpha$$

$$\begin{aligned} Pr\{F \in A\} &= \int \cdots \int Pr\{F \in A | \mathbf{X} = \mathbf{x}\} f(\mathbf{x}) d\mathbf{x} \\ &= \int \cdots \int \alpha f(\mathbf{x}) d\mathbf{x} \\ &= \alpha \int \cdots \int f(\mathbf{x}) d\mathbf{x} \\ &= \alpha \end{aligned}$$

## The moral of the story

- Don't worry.
- Even though  $X$  variables are often random, we can apply the usual fixed- $x$  model without fear.
- Estimators are still unbiased.
- Tests have the right Type I error probability.
- Similar arguments apply to confidence intervals and prediction intervals.
- And its all distribution-free with respect to  $X$ .

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