Ec140 - Core Concepts from Statistics

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Housekeeping

- Updated Syllabus
- Unofficial Course Capture!
- What is the weirdest concept you remember from yesterday?
- Switch to finish yesterday's slides

This Lecture

- Introduction to Data
- Mean and Expectation
- Variance and Standard Deviation

What Defines a Data Set?

- Data Set is the collection of any type information (of multiple *Datum*)
- In quantitative analysis we focus on *structured* data sets (unlike, for example, unstructured field notes).
- In econometrics the most commnon way to structure data is in tabular, or rectangular, form.
- A tabular data set is a collection of variables that with information for one or more entities.
- Entities can represent multiple individuals, one individual over time, firms, countries, etc.
- Variables are represented in columns, and observations are represented by rows. (for more on variables The Effect, Ch3)

Data

But What Can We Do With Data?

- We summarized it! (see the great short story by J.L. Borges on why summarizing is essential)
- One of the first thing we do when summarizing data is to look at some type of average.
 - Wait? Type of average? Isn't there just one average? called the mean?

But What Can We Do With Data?

- We summarized it! (see the great short story by J.L. Borges on why summarizing is essential)
- One of the first thing we do when summarizing data is to look at some type of average.
 - Wait? Type of average? Isn't there just one average? called the mean?
- These is also referred as measure of central tendency.
- In this course, we will focus primarily on the mean. **From now on in this course**

average noun



av·er·age | \ˈa-v(ə-)rij **→** \

Definition of average (Entry 1 of 3)

- **a** : a single value (such as a mean, mode, or median) that summarizes or represents the general significance of a set of unequal values
 - **b**: MEAN sense 1b
- **a**: an estimation of or approximation to an arithmetic mean
 - **b** : a level (as of intelligence) typical of a group, class, or series // above the *average*

Mean

 The mean is defined by the sum of a set of values divided by the number of values.

Let's look at the mean from the "hang out with a friend" exercise.

Total over N

$$Average(X) = \frac{1 \times 10 + 2 \times 9 + 3 \times 11}{30} = 2.03$$

- One number, **highly informative** for a variable of interest.
- Always important to keep an eye on the units and magnitude (relevant for PS1).

Mean: Notation (Message to me: draw histogram on the board)

$$Average(X) = rac{1 imes 10 + 2 imes 9 + 3 imes 11}{30} = 2.03$$

$$Ave(X) = 1 imes rac{10}{30} + 2 imes rac{9}{30} + 3 imes rac{11}{30} = 2.03$$

- Let's look at the histogram for the exercise above (drawn in the board) and pretend it is not a sample but the entire population. How can we move from frequencies into probabilities?
- Replace frequencies by probabilities
- The population version of the sample mean is the **expected value**.

Expected Value: Definition (Discrete)

The expected value of a discrete random variable X is the weighted average of its k values $\{x_1,\ldots,x_k\}$ and their associated probabilities:

$$egin{aligned} \mathbb{E}(X) &= x_1 \, \mathbb{P}(X=x_1) + x_2 \, \mathbb{P}(X=x_2) + \cdots + x_k \, \mathbb{P}(X=x_N) \ &= \sum_x x \, \mathbb{P}(X=x) \end{aligned}$$

• Also known as the population mean.

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• Also known as the population mean. Compare it to the sample mean:

$$\overline{X}_n = \sum_x rac{x}{x} imes prop_n(x_1)$$

Example

Rolling a six-sided die once can take values $\{1, 2, 3, 4, 5, 6\}$, each with equal probability. What is the expected value of a roll?

$$\mathbb{E}(\text{Roll}) = 1 \times \frac{1}{6} + 2 \times \frac{1}{6} + 3 \times \frac{1}{6} + 4 \times \frac{1}{6} + 5 \times \frac{1}{6} + 6 \times \frac{1}{6} = 3.5.$$

ullet Note: The expected value can be a number that isn't a possible outcome of X.

Expected Value. Definition (Continuous)

- Compare it to the discrete version
- Continuous

$$\mathbb{E}(X) = \int_{-\infty}^{\infty} x f(x) dx.$$

Discrete

$$\mathbb{E}(X) = \sum_{x} x f(x)$$

Expected Value. Definition (Continuous)

- Compare it to the discrete version
- Continuous

$$\mathbb{E}(X) = \int_{-\infty}^{\infty} \frac{x}{x} f(x) dx.$$

Discrete

$$\mathbb{E}(X) = \sum_{x} \frac{x}{x} f(x)$$

This explanation was inspired by this lecture from Eddie Woo

Expected Value. Definition. One Last Thing 1/2

Let's go back to the mean of our exercise:

$$\overline{X}_n = 1 \times \frac{10}{30} + 2 \times \frac{9}{30} + 3 \times \frac{11}{30} = 2.03$$

But now let's switch the values of the random variables to: 10, 20, 30. How should we compute the mean?

$$\overline{g(X)}_n = 10 \times \frac{10}{30} + 20 \times \frac{9}{30} + \frac{30}{30} \times \frac{11}{30} = 20.33$$

Expected Value. Definition. One Last Thing 2/2

Hence, we can conclude, that for a random variable X, any transformation g(X) has a sample aveage:

$$\overline{X}_n = \sum_x {\color{red} g(x)} imes prop_n(x_1)$$

And an expectation:

$$\mathbb{E}(X) = \sum_{x} g(x) f(x)$$

The same idea applies in the case of a continues random variable

Expected Value: Rules (or Properties)

Rule 1

For any constant c, $\mathbb{E}(c)=c$.

Not-so-exciting examples

$$\mathbb{E}(5)=5$$
.

$$\mathbb{E}(1)=1$$
.

$$\mathbb{E}(4700) = 4700.$$

Rule 2

For any constants a and b, $\mathbb{E}(aX+b)=a\,\mathbb{E}(X)+b$.

Example

Suppose X is the high temperature in degrees Celsius in Eugene during August. The long-run average is $\mathbb{E}(X)=28$. If Y is the temperature in degrees Fahrenheit, then $Y=32+\frac{9}{5}X$. What is $\mathbb{E}(Y)$?

•
$$\mathbb{E}(Y) = 32 + \frac{9}{5}\mathbb{E}(X) = 32 + \frac{9}{5} \times 28 = 82.4.$$

Rule 3: Linearity

If $\{a_1,a_2,\ldots,a_n\}$ are constants and $\{X_1,X_2,\ldots,X_n\}$ are random variables, then

$$\mathbb{E}(a_1X_1 + a_2X_2 + \cdots + a_nX_n) = a_1\mathbb{E}(X_1) + a_2\mathbb{E}(X_2) + \cdots + a_n\mathbb{E}(X_n).$$

In English, the expected value of the sum = the sum of expected values.

Rule 3

The expected value of the sum = the sum of expected values.

Example

Suppose that a coffee shop sells X_1 small, X_2 medium, and X_3 large caffeinated beverages in a day. The quantities sold are random with expected values $\mathbb{E}(X_1)=43$, $\mathbb{E}(X_2)=56$, and $\mathbb{E}(X_3)=21$. The prices of small, medium, and large beverages are 1.75, 2.50, and 3.25 dollars. What is expected revenue?

$$\mathbb{E}(1.75X_1 + 2.50X_2 + 3.35X_n) = 1.75\,\mathbb{E}(X_1) + 2.50\,\mathbb{E}(X_2) + 3.25\,\mathbb{E}(X_3) = 1.75(43) + 2.50(56) + 3.25(21) = 283.5$$

Caution

Previously, we found that the expected value of rolling a six-sided die is $\mathbb{E}(\mathrm{Roll}) = 3.5$.

ullet If we square this number, we get $\left[\mathbb{E}(\mathrm{Roll})
ight]^2=12.25$.

Is
$$\left[\mathbb{E}(\mathrm{Roll})\right]^2$$
 the same as $\mathbb{E}\!\left(\mathrm{Roll}^2\right)$?

No!

Caution

Except in special cases, the transformation of an expected value **is not** the expected value of a transformed random variable.

For some function $g(\cdot)$, it is typically the case that

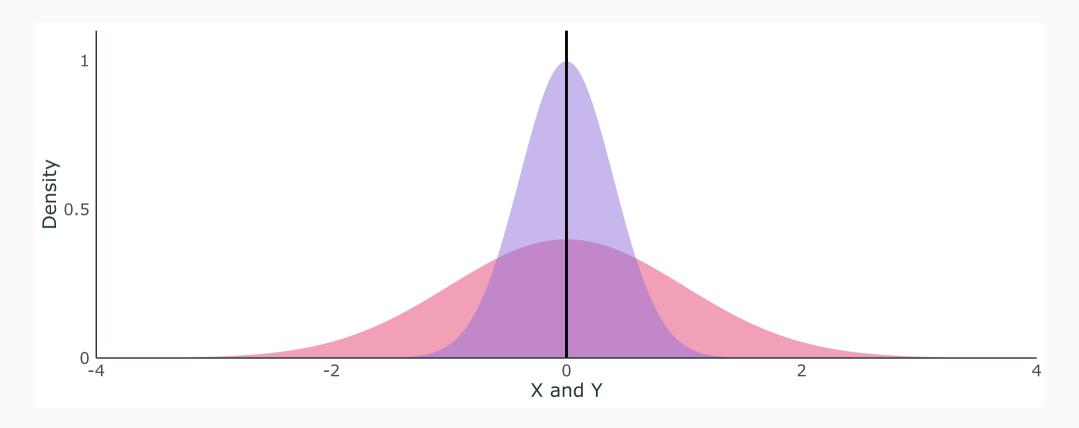
$$g(\mathbb{E}(X)) \neq \mathbb{E}(g(X)).$$

Activity 1

- Let's watch another Stat 110's video. Then get together in groups of 3 and discuss:
 - Don't worry about the law of large numbers yet
 - How does the random variables becomes continuous?
 - How does linearity help with computations?

Variance

Random variables X and Y share the same population mean, but are distributed differently.



Variance¹

How tightly is a random variable distributed about its mean?

- Let $\mu=\mathbb{E}(X)$.
- Describe the distance of X from its population mean μ as the squared difference: $(X-\mu)^2$.

Variance tells us how far X deviates from μ , on average:

$$\operatorname{Var}(X) \equiv \mathbb{E}ig((X-\mu)^2ig) = \sigma^2$$

• σ^2 is shorthand for variance.

Variance

Rule 1

 $\operatorname{Var}(X) = 0 \iff X$ is a constant.

- If a random variable never deviates from its mean, then it has zero variance.
- If a random variable is always equal to its mean, then it's a (not-so-random) constant.

Variance

Rule 2

For any constants a and b, $\mathrm{Var}(aX+b)=a^2\,\mathrm{Var}(X)$.

Example

Suppose X is the high temperature in degrees Celsius in Eugene during August. If Y is the temperature in degrees Fahrenheit, then $Y=32+\frac{9}{5}X$. What is $\overline{\mathrm{Var}(Y)}$?

•
$$Var(Y) = (\frac{9}{5})^2 Var(X) = \frac{81}{25} Var(X)$$
.

Standard Deviation

Standard deviation is the positive square root of the variance:

$$\operatorname{sd}(X) = +\sqrt{\operatorname{Var}(X)} = \sigma$$

• σ is shorthand for standard deviation.

Standard Deviation

Rule 1

For any constant c, $\mathrm{sd}(c)=0$.

Rule 2

For any constants a and b, $\mathrm{sd}(aX+b)=|a|\,\mathrm{sd}(X)$.

Standardizing a Random Variable

When we're working with a random variable $m{X}$ with an unfamiliar scale, it is useful to **standardize** it by defining a new variable $m{Z}$:

$$Z\equiv rac{X-\mu}{\sigma}.$$

 $oldsymbol{Z}$ has mean $oldsymbol{0}$ and standard deviation $oldsymbol{1}$. How?

- ullet First, some simple trickery: Z=aX+b, where $a\equiv rac{1}{\sigma}$ and $b\equiv -rac{\mu}{\sigma}$.
- $\mathbb{E}(Z) = a \, \mathbb{E}(X) + b = \mu \frac{1}{\sigma} \frac{\mu}{\sigma} = 0.$
- $Var(Z) = a^2 Var(X) = \frac{1}{\sigma^2} \sigma^2 = 1.$