

# Continuous Random Variables

Ryan Miller

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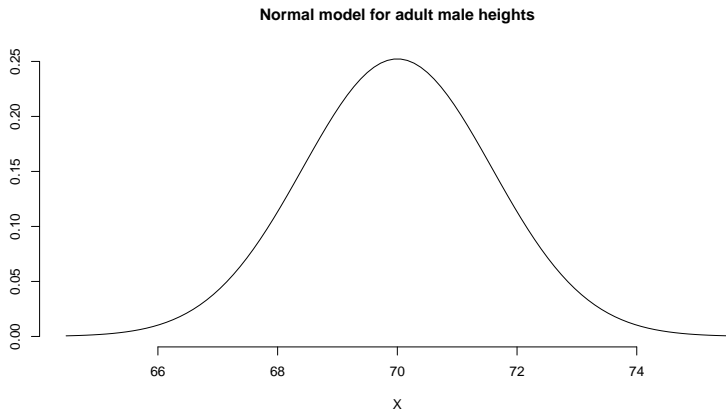
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- ▶ This presentation will focus on *continuous random variables*, or those with infinitely many real-valued outcomes

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  - ▶ Our discussion focused on *discrete random variables*, or those with countable/integer outcomes
- ▶ This presentation will focus on *continuous random variables*, or those with infinitely many real-valued outcomes
- ▶ For example, consider sampling a random adult male and let  $X$  be their height (inches)
  - ▶ Depending on our measurement tool,  $X$  could take on infinitely many values (70.0 inches, 70.01 inches, 70.001 inches, etc.)
  - ▶ This means we cannot use a table to express a probability model for  $X$

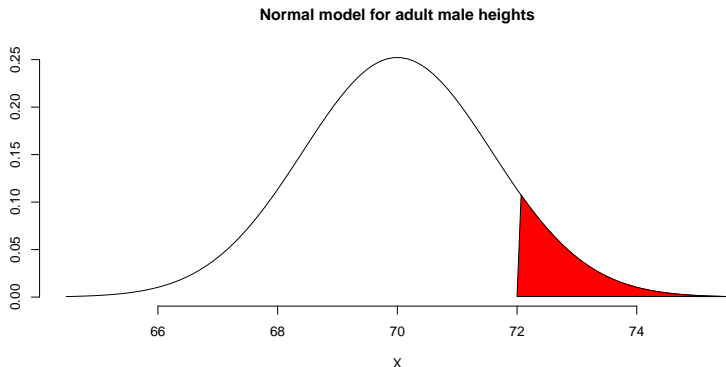
# The Normal Model

- ▶ Continuous random variables necessitate continuous probability models
  - ▶ One of the most widely used is the **Normal model**



# The Normal Model (cont)

- ▶ Under a continuous probability model, the probability of any single value of  $X$  is zero (as there are infinitely many possible values)
  - ▶ Thus, probabilities only make sense for intervals, for example we can represent  $P(X > 72)$  using the *shaded area* shown below:



# The Normal Model (cont)

- ▶ The Normal probability model is defined by the curve:

$$f(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(X-\mu)^2}{2\sigma^2}}$$

- ▶ The parameter  $\mu$  is a constant that defines the *center* of the bell-curve
- ▶ The parameter  $\sigma$  is a constant that defines the *spread* of the bell-curve (how tall or flat it appears)

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- ▶ Note that there are infinitely many Normal curves, one for each combination of  $\mu$  and  $\sigma$ 
  - ▶ We will denote these curves as  $N(\mu, \sigma)$ , for example  $N(70, 2.5)$  might apply to our height example



# Standardization

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  - ▶ This inspired the use of a transformation known as **standardization** to move their data (regardless of its original units) on a unitless, standardized scale

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  - ▶ This inspired the use of a transformation known as **standardization** to move their data (regardless of its original units) on a unitless, standardized scale
- ▶ A common use of standardization is the calculation of  $Z$ -scores
  - ▶ Consider a random variable  $X$  and a Normal model defined by  $\mu$  and  $\sigma$ , under this model  $Z$ -scores are calculated:

$$Z = \frac{X - \mu}{\sigma}$$

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- ▶ For example, suppose  $X$  is a random variable from a  $N(\mu = 70, \sigma = 2.5)$  distribution and we observe  $x = 72$ 
  - ▶ The corresponding Z-score is  $z = (72 - 70)/2.5 = 0.8$
  - ▶ So a height of 72 inches is 0.8 standard deviations above what would be expected (under this probability model)

# The Standard Normal Distribution

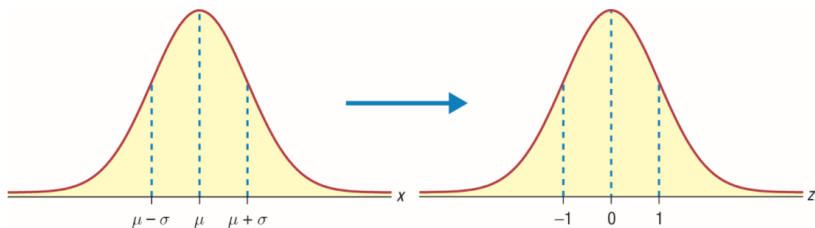
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# The Standard Normal Distribution

- ▶ Standardization allows us to use the **Standard Normal distribution** as a probability model for a wide variety of settings
- ▶ For example, suppose adult male heights follow a Normal distribution centered at 70 inches with a standard deviation of 2.5 inches
  - ▶ This means,  $X \sim N(70, 2.5)$
  - ▶ After standardization,  $Z = \frac{X-70}{2.5} \sim N(0, 1)$

# The Standard Normal Distribution

$$N(\mu, \sigma) \xrightarrow{z\text{-transformation}} N(0, 1)$$



# Example

Let  $X$  denote the height of a randomly chosen adult male, and assume the probability model  $X \sim N(70, 2.5)$

- 1) Determine the probability that this male's height is between 5'10 and 6'0 directly from this model
- 2) Determine the same probability using *standardization*, and the Standard Normal model

For each of these tasks, we'll utilize a new program: StatKey



## Example (solution)

Using Statkey:

- 1) On the  $N(70, 2.5)$  curve, the area to the left of 70 inches (5'10) is 0.5, while the area to the left of 72 inches (6'0) is 0.788; thus, there is a 28% probability of a random adult male being between 5'10 and 6'0 under this model
- 2) To use the Standard Normal model, we'd do the same thing, but with the preliminary step of calculating  $Z$ -scores. The  $Z$ -score for 70 inches is 0, while the  $Z$ -score for 72 inches is 0.8. On the Standard Normal curve, the area to the left of 0 is 0.5, while the area to the left of 0.8 is 0.788; again we find a 28% probability that a random adult male is between 5'10 and 6'0 under this model

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- ▶ The Normal curve is defined by a center,  $\mu$ , and a standard deviation,  $\sigma$ 
  - ▶ By **standardizing**, we can transform our variable onto the unitless  $Z$ -scale, and thereby use the Standard Normal model regardless of the specific situation

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- ▶ The Normal curve is defined by a center,  $\mu$ , and a standard deviation,  $\sigma$ 
  - ▶ By **standardizing**, we can transform our variable onto the unitless  $Z$ -scale, and thereby use the Standard Normal model regardless of the specific situation
- ▶ The next presentation will further explore when the Normal model can be used