STA286 Lecture 05

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Equality vs. inequality not really important in a "continuous" probability model.

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As an example of the latter, consider the time-to-failure of an electronic component that:

- ▶ fails immediately the first time you try it, with probability 0.01
- works immediately with probability 0.99 and subsequently fails according to some continuous probability model TBA.

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Example: Let X be the number of tosses of a coin until the first H appears. This function maps individual outcomes to probabilities:

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- "probability function" (name already taken by P!)
- "probability distribution" (name already being used for a fundamental concept!)

more pmf examples

See if a product is defective: A factory makes a defective item with probability p. Select an item at random from a factory. Let X=1 if the item is defective, and let X=0 otherwise.

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More compact version: $p(x) = p^x (1-p)^{1-x}$

defining properties of pmf

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A function p(x) is a pmf if and only if:

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$$\sum_{\{x \mid P(X=x) > 0\}} p(x) = 1$$

checking if a function is a valid pmf

I said this function is a pmf. Is it?

$$p(x) = f(x) = P(X = x) = \left(\frac{1}{2}\right)^{x}, \quad x \in \{1, 2, 3, \ldots\}$$

Verify:

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Verify:

1.
$$p(x) \ge 0$$

2. Fact: $\sum_{n=0}^{\infty} ar^n = \frac{a}{1-r}$ for 0 < r < 1. So:

$$\sum_{x=1}^{\infty} \left(\frac{1}{2}\right)^x = \sum_{x=0}^{\infty} \frac{1}{2} \left(\frac{1}{2}\right)^x = 1$$

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Yes, because you can compute a cdf from a pdf and vice versa. Obviously:

$$F(x) = \sum_{y \leqslant x} p(y)$$

For the reverse direction you take the jump points of the cdf and determine the magnitude of the jump.