Larson and Marx Section 3.4

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Problems where this is not the case arise often, so we need to extend our definitions accordingly.

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Fortunately, this is neither necessary nor desirable.

Interval Functions

One way around the problem is to consider only a certain class of subsets when assigning probabilities.

For example, we can consider only subsets that qualify as **intervals**:

For $a, b \in \mathcal{R}$, with a < b, these are sets of the form:

 $\begin{array}{ll} (a,b) & I = \{x \ : \ a < x < b\} \\ \\ [a,b) & I = \{x \ : \ a \le x < b\} \\ \\ (a,b] & I = \{x \ : \ a < x \le b\} \\ \\ \\ [a,b] & I = \{x \ : \ a \le x \le b\} \end{array}$

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We also allow the limiting cases where one or both of a and b are $\pm \infty$,

 $(a,\infty), (-\infty,b], , (-\infty,\infty),$ etc.

Now consider the experiment:

A real number is selected randomly from the interval [0,1]

We will define the continuous random variable X to be simply the number selected, so the function defining our random variable is:

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according to the rule:

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Definition: (3.4.2) A function *X* that maps a subset of the real numbers into the real numbers is called a **continuous random variable**.

The **probability density function** (pdf) of X is defined to be the function

 $f_X(x)$

having the property that for any numbers a and b,

$$P(a \le X \le b) \quad = \quad \int_{a}^{b} f_X(x) dx$$

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- If we assume that every number in the interval is equally likely to be selected, a reasonable **probability density function** is:

$$f_X(x) = \begin{cases} 0 & x < 0\\ 1 & 0 \le x \le 1\\ 0 & x > 1 \end{cases}$$

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A probability density function is said to have **support** on the subset of \mathcal{R} where it is positive.

The above probability density function has support on [0, 1].

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This is true for our density function,

$$\int_0^1 1 dx = x]_0^1 = 1$$

and in fact the probability distrubution associated with this density function is known as the **uniform distribution**.

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So, if *X* has the uniform distribution, the probability that $a \le X \le b$ is just the length of the interval [a, b].

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Solution: The probability is given by:

$$P(X \le 0.7) = \int_0^{0.7} 1dx = x]_0^{0.7} = 0.7$$

Definition: (3.4.3) The **cumulative distribution function** (cdf) of a continuous random variable *X* is defined to be

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Note that outside of its support, the integral of the density function is zero.

So, while stating the lower limit of integration as $-\infty$ produces the most general answer, in practice we can ignore values outside the support of $f_X(x)$.

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Since $f_X(x)$ only has support on [0, 1], we can ignore the rest of the real line, so

$$F_X(x) = \int_0^x 1dr = r]_0^x = x = P(X \le x)$$

Relationship Between the pdf and cdf

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It follows immediately from the Fundamental Theorem of Calculus that:

Theorem: (3.4.1) Let $F_X(x)$ be the cdf of a continuous random variable *X*. Then

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That is, the derivative of a continuous cumulative distribution function is the corresponding probability density function.

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$$d) \quad \lim_{x \to -\infty} F_X(s) = 0$$

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Then the probability density function of Y is

$$f_Y(y) = \frac{1}{|a|} f_X\left(\frac{y-b}{a}\right)$$

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- Suppose instead we are choosing a real number at random from the interval [3, 7].
- Most calculators would not have this function built in, but we can produce the same result by drawing a number randomly from [0, 1], multiplying it by 4, and adding 3:

$$Y = 4X + 3$$

Theorem 3.4.3 says that the probability density function of Y = 4X + 3 will be given by:

$$f_Y(y) = \frac{1}{|4|} f_X\left(\frac{y-3}{4}\right), \quad 3 \le y \le 7$$

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For these values, $f_X(x) = 1$, so by substitution $f_Y(y)$ reduces to:

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Generalizations of the uniform distribution that arise in this way are called a **rectangular** distributions.

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This is indeed a pdf, since $f_X(x) \ge 0$ everywhere, and, following the convention that outside of its support, the interval [0, 1], we assume $f_X(x) = 0$,

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The cdf for this probability distribution is

$$F_X(x) = \int_0^x f_X(r)dr = \frac{2r^2}{2} \bigg|_0^x = x^2, \quad 0 \le x \le 1$$

The probability distribution with pdf

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Clearly $f_X(x) \ge 0$ everywhere, and, since

$$\int_0^t \frac{1}{\mu} e^{-x/\mu} dx = -\frac{\mu e^{-x/\mu}}{\mu} \Big]_0^t = 1 - e^{-t/\mu}$$

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$$F_X(x) = \int_0^x \frac{1}{\mu} e^{-r/\mu} dr = 1 - e^{-x/\mu}, \quad 0 \le x$$

Suppose the time to failure of a light bulb has an exponential distribution with $\mu = 500$ (hours). Then the pdf of the time to failure is:

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What is the probability that a given light bulb lasts less than 400 hours?

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$$F_X(x) = = 1 - e^{-x/500}, \quad 0 \le x$$

SO

$$P(X \le 400) = F_X(400) = 1 - e^{-400/500} = 0.551$$

Again suppose the time to failure of a light bulb has an exponential distribution with $\mu = 500$ (hours).

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What is the probability that a given light bulb lasts more than 600 hours?

The probability that it lasts 600 hours or less is $F_X(600)$, so the probability that it lasts longer than 600 hours is

 $1 - P(X \le 600) = 1 - F_X(600) = 1 - (1 - e^{-600/500}) = 0.301$