Probability Part 2: Random Variables

Random Variables

A number associated to the outcome of a random experiment.

- The sum of two dice rolls
- The number of heads in 5 flips of a coin
- The average height of a sample of 10 people

Discrete: Outcomes can be listed

Continuous: Can take on any value in an interval

The Binomial Distribution

Binary outcome (yes/no).

A fixed number (n) of repeated **independent** trials with a fixed probability of "success" (p)

Eg. flipping a coin 3 times and recording the number of times it lands on heads.

Here, probability of "success" is 0.5 (if we define "success" as the coin landing on heads)

The Binomial Distribution

The binomial distribution lets us answer questions like “If I flip a coin three times, what is the probability of it landing on heads exactly one time?”

Before getting a general formula, let’s see how we could figure this probability “by hand”.

Here are all of the possible outcomes for a sequence of 3 coins flips:

And the ones that we care about:

How likely is each of these?

(0.5)*(0.5)*(0.5) = 0.125

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How likely is each of these?

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Since we have three cases where there is exactly one coin on heads, each with probability 0.125, the total probability of one heads is

$3*(0.125) = 0.375$

The Binomial Distribution

Let's modify the setup slightly and say that we have a bent coin which has probability of landing on heads equal to 0.7.

This means that the probability of landing on tails is 0.3.

If we flip our bent coin three times, what is the probability of it landing on heads exactly once?

We still have the same three relevant outcomes. How likely is each?

$(0.3)*(0.3)*(0.7) = 0.063$

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We still have the same three relevant outcomes. How likely is each?

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This time, the total probability is

$3*(0.063) =$ 0.189

Let’s break down what went into this calculation:

$(0.3)*(0.3)*(0.7)$ $(0.3)*(0.7)*(0.3)$ $(0.7)*(0.3)*(0.3)$

All of these equal

$$0.063 = (0.7)^1 * (0.3)^2 =$$

$$(\text{probability of heads})^1 * (\text{probability of tails})^2$$

Let’s break down what went into this calculation:

$$3*(0.063) = 0.189$$

The three out front was equal to the number of ways to “choose” one coin out of three to land on heads.

In general, we can calculate the number of ways to choose *x* successes out of *n* trials using the **binomial coefficients:**

$$\binom{n}{x} := \frac{n!}{x! \cdot (n-x)!}$$

The expression on the left is read as “n choose x”.

For example, 3 choose 1:

$$\binom{3}{1} = \frac{3!}{1! \cdot (3-1)!} = \frac{3 \cdot 2 \cdot 1}{1 \cdot 2 \cdot 1} = 3$$

The Binomial Distribution

To recap, for our bent coin (probability of heads = 0.7), if we flip it 3 times, the probability of exactly one flip landing on heads is calculated as

Ans:

$$\binom{3}{1} \cdot (0.7)^1 \cdot (0.3)^2 = 0.189$$

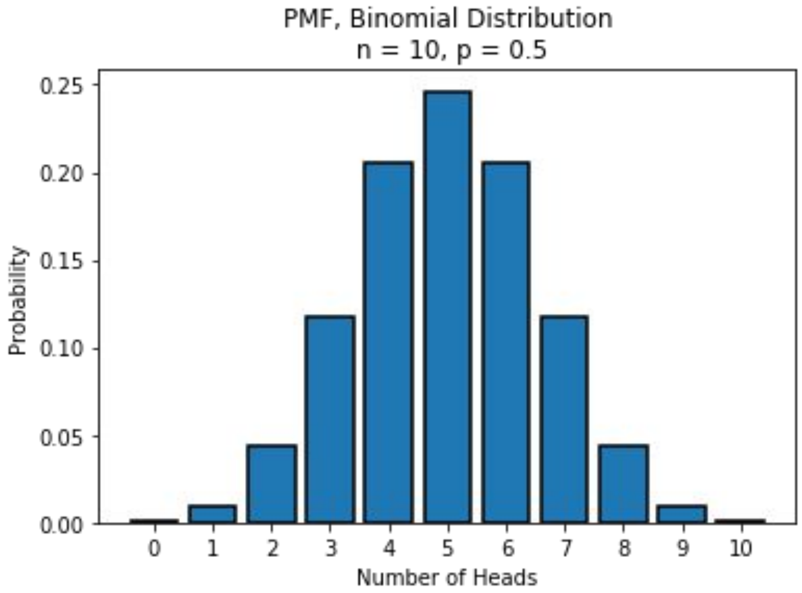
Number of ways to choose 1 successes out of 3 options

Probability of heads

Probability of tails

The Binomial Distribution - Probability Mass Function

By looking at the probability associated with each possible outcome, we obtain the **probability mass function,** or **pmf**.



pmf for ten flips of a fair coin

The Binomial Distribution

In general, a binomial distribution with *n* trials and probability of success *p* was a pmf of:

$$f(x) = \binom{n}{x} \cdot p^x \cdot (1-p)^{n-x}$$

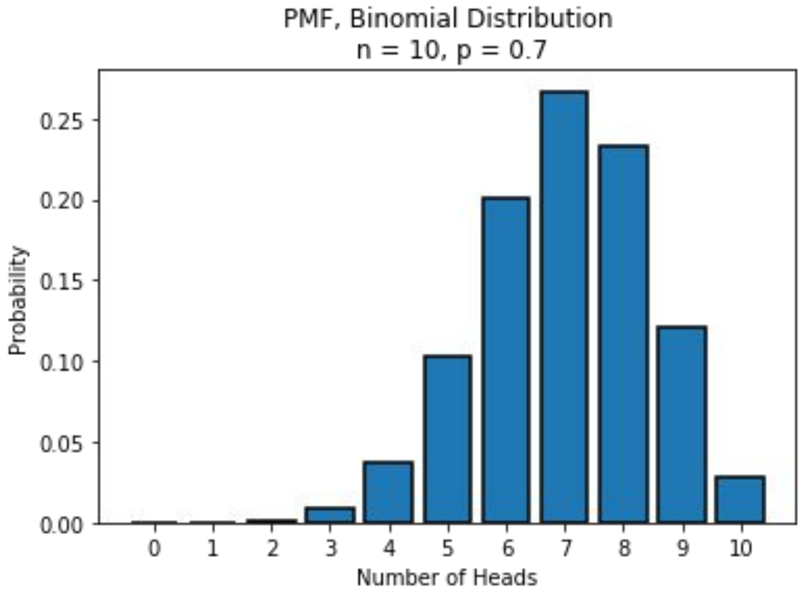
Number of ways to choose *x* success out of *n* trials

Probability of success

Probability of failure

The Binomial Distribution - Probability Mass Function

Let’s say we have a bent coin, where the probability of landing on heads is 0.7. Let’s see how the PMF changes:



The Binomial Distribution

To carry out these types of calculations, we will usually use the *scipy stats* library rather than calculating the probabilities explicitly.

See the corresponding notebook to see what this looks like in practice.

Continuous Random Variables

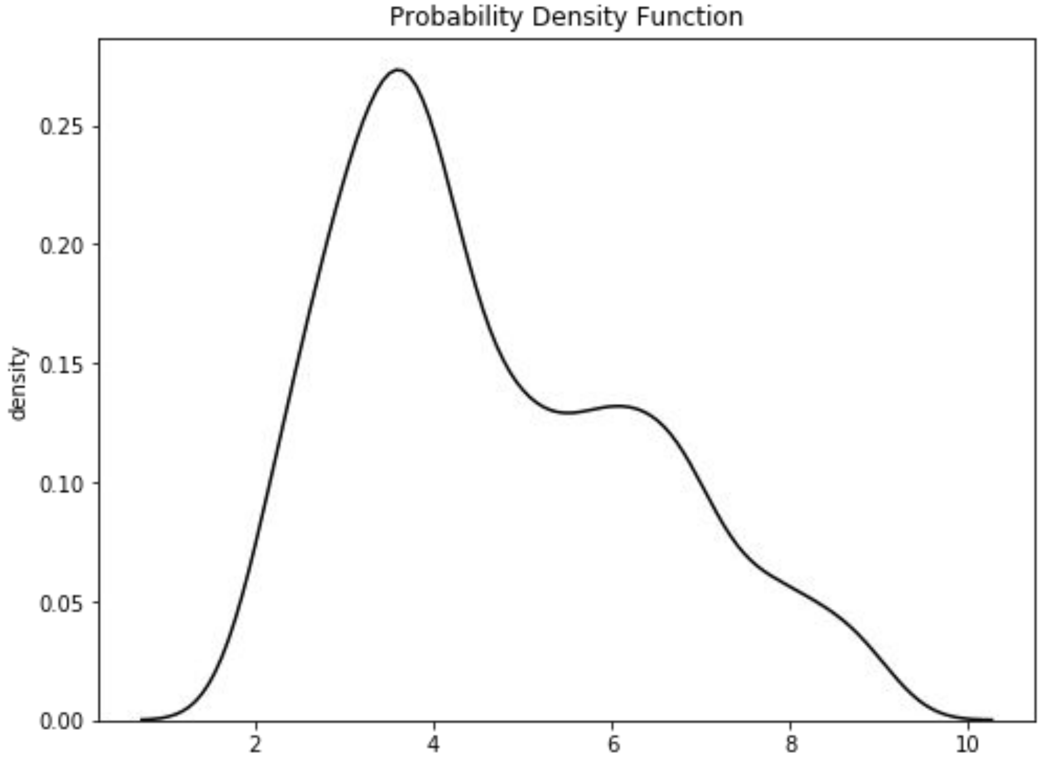
What about random variables which can take on any value in a range?

We can no longer talk about the exact probability for any particular value, but instead can talk about the probability *density* at a particular point.

To find probabilities, we can only find probabilities for the value landing in a particular *range* of values.

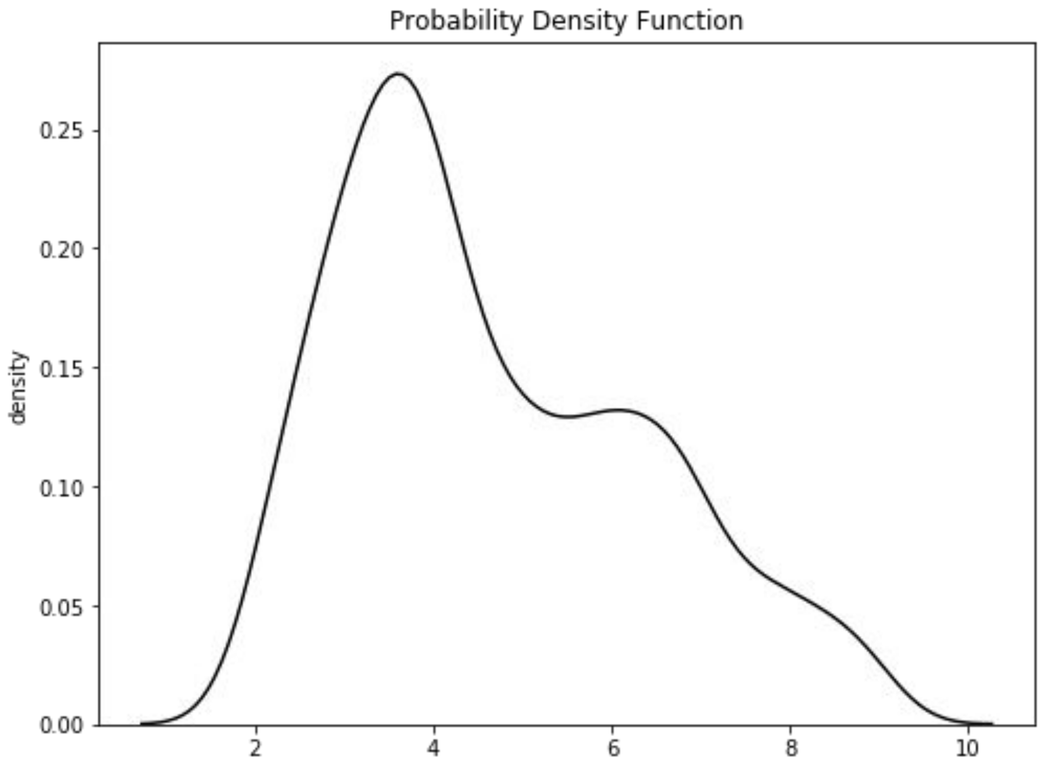
Probability Density Functions

The probability density at each possible value can be specified by a **probability density function**, or **PDF.**



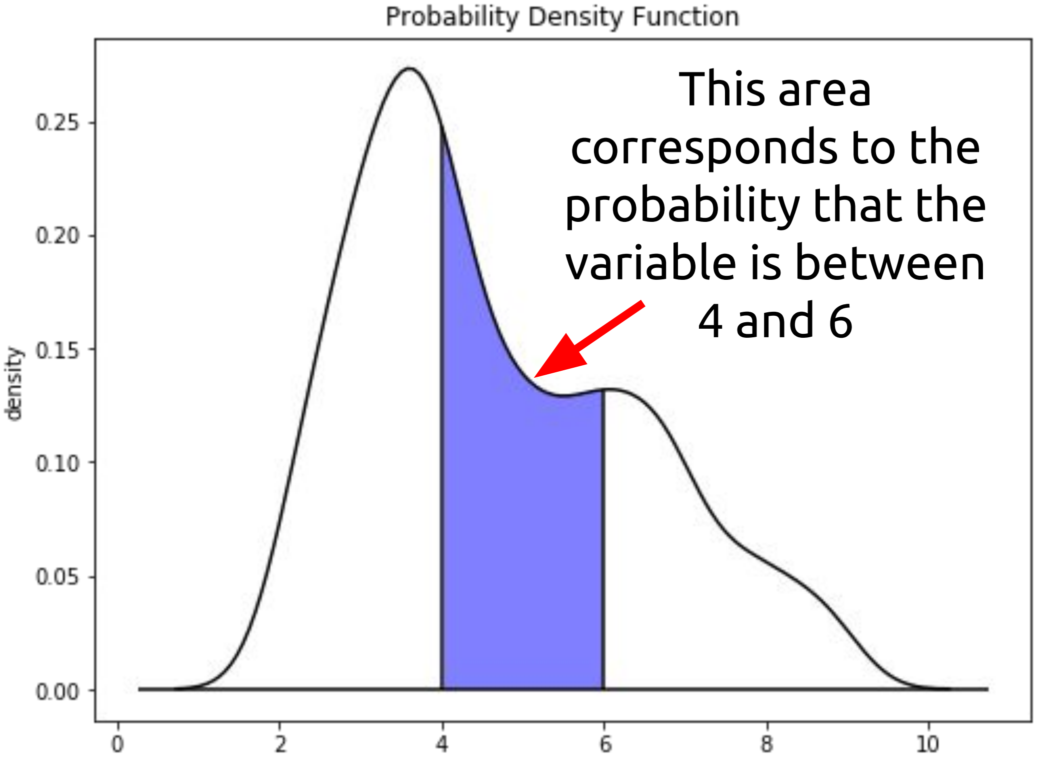
Probability Density Functions

Rather than talk about the probability at a specific value, we can calculate the probability of the variable being in a particular range.



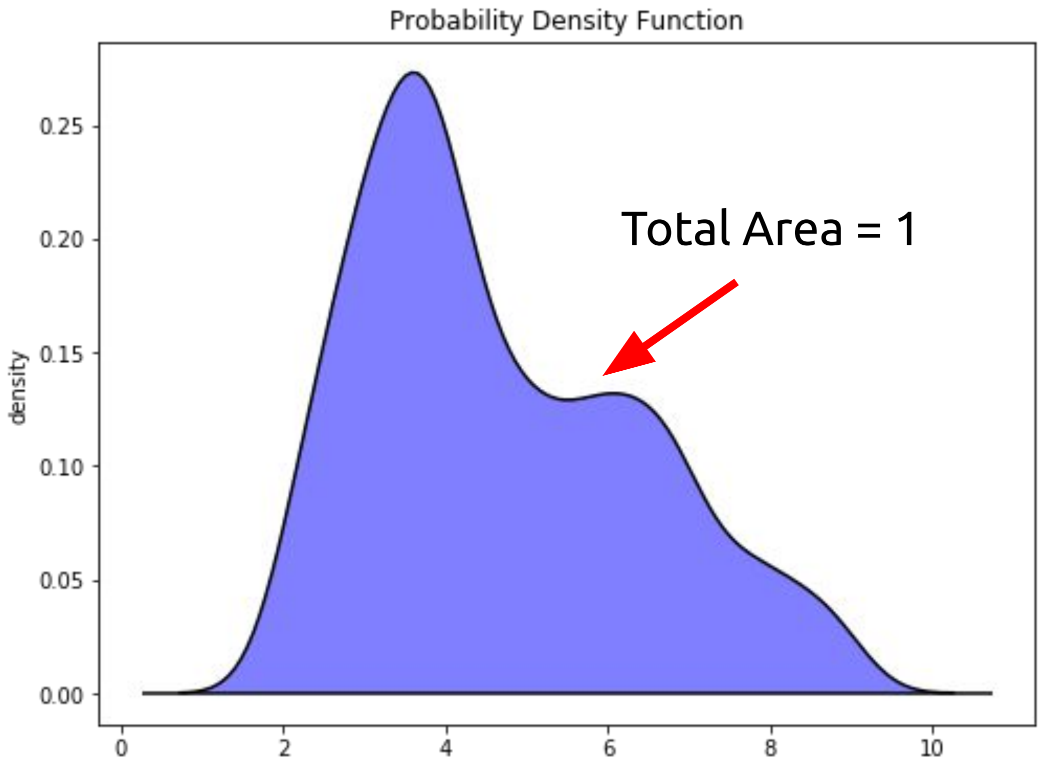
Probability Density Functions

The probability of the variable being in a particular range corresponds to the are under the PDF in that range.



Probability Density Functions

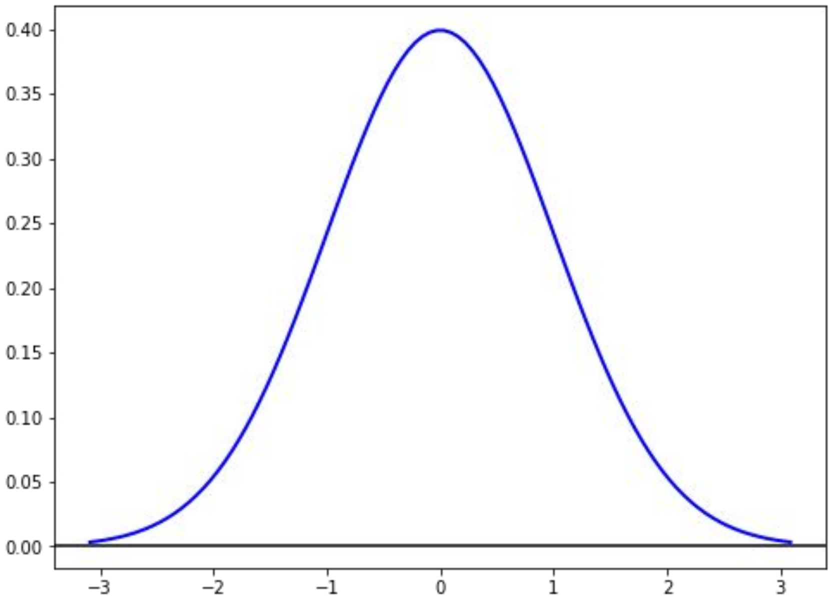
This means that the total area under the curve is 1.



The Normal Distribution

Perhaps the most well-known distribution is the Normal distribution, aka, the "Gaussian" distribution.

It is a symmetric, bell-shaped distribution.



The Standard Normal Distribution

The Normal Distribution

(It is thought that) many things can be described by a normal distribution.

Eg. IQs, test scores, heights, weights, random variations in industrial processes

However, these can only be approximately true (the normal distribution has nonzero density for all real numbers, including negatives)

The Normal Distribution

Bell-shaped distribution, described by two parameters: mean $\boldsymbol{\mu}$ and standard deviation $\boldsymbol{\sigma}$

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

The **standard normal** distribution has mean 0 and standard deviation 1.

See the notebook for a demo of how $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ affect the distribution.