

Statistical Distributions and Their Use cases



<https://github.com/learn-co-curriculum/dsc-stat-distributions-use-cases>



<https://github.com/learn-co-curriculum/dsc-stat-distributions-use-cases/issues/new/choose>

Introduction

As a data scientist, you'll often have to work with statistical distributions. This includes selecting which distribution is most representative of a given set of data. A typical use case includes A/B testing, where understanding the process that generated the data is important. You can think of distributions in relation to statistical analysis as to data structures to computer programming.

There are an enormous amount of distributions out there, but you'll see about a handful of distributions that can represent the vast majority of situations you'll come across. In the upcoming series of lessons, you'll look at ways to analyze common distributions you will encounter most frequently.

Objectives

You will be able to:

- Define statistical distributions
- Differentiate between discrete and continuous distributions
- List the common distributions and their use cases

What is a Statistical Distribution?

A statistical distribution is a **representation of the frequencies of potential events** or the percentage of time each event occurs. Here we will focus on a particular kind of statistical distribution: a **probability distribution**.

Returning to set theory, a probability distribution mathematically represents the probabilities of sets of variables X and sets of events E such that $X \in E$ (X is a member of E), fully written as $P(X \in E)$. So, for a given x value and a given event, a probability distribution gives you the probability that x belongs to that event.

Because they mathematically represent probabilities of events, rules applying to probabilities in general also apply to probability distributions:

$$1. P(X \in E) \in \mathbb{R}, P(X \in E) \geq 0$$

- The probability that a certain X belongs to a certain E is a non-negative real number
- This corresponds to the **positivity** axiom from probability theory

$$2. P(X \in E) \leq 1, P(\Omega) = 1$$

- The probability that a certain X belongs to a certain E is less than or equal to 1, and the probability of some event within the sample space occurring is 1
- This corresponds to the **unitarity** axiom (probability of a certain event)

$$3. P(X \in \bigcup_i E_i) = \sum_i P(X \in E_i) \text{ for any disjoint family of sets } E_i$$

- The probability that a certain X belongs to the union of these disjoint (mutually exclusive) events is equal to the sum of the probability that X belongs to each event, added together
- This corresponds to the **additivity** axiom (for mutually exclusive events). ***In a probability distribution, all events must be mutually exclusive.***

This may feel pretty vague and theoretical, which is why we'll use two examples to clarify this concept.

Initial Probability Distribution Examples

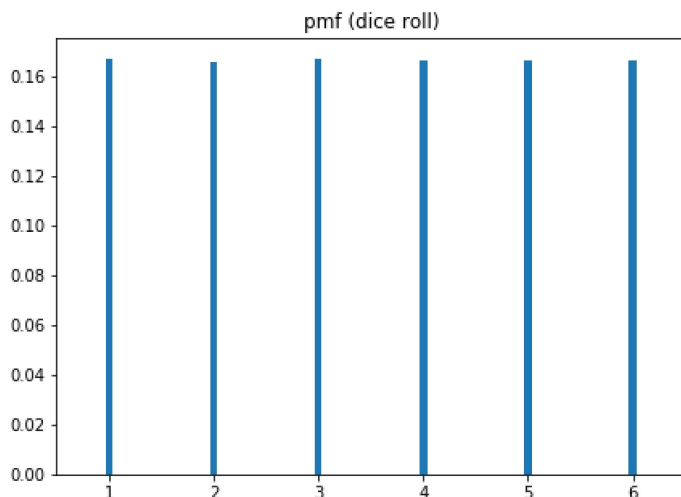
We'll start with one example of a discrete distribution, and one example of a continuous distribution.

Rolling Dice Distribution

Let's think back about our example of rolling dice. You know that when rolling a single die, you will obtain a number between 1 and 6, with each outcome to be as likely, as denoted in this table:

outcome	1	2	3	4	5	6
probability	1/6	1/6	1/6	1/6	1/6	1/6

You can also represent this graphically as follows:

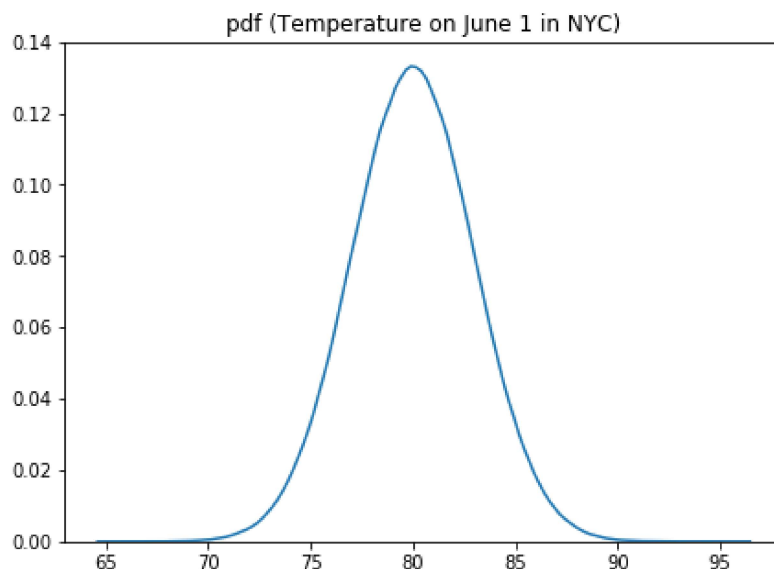


Note how, with a fair die, the chance of throwing each number is *exactly* $1/6$ (or 0.1666). The number of outcomes is finite and the outcome is a set of values. In this case, you are dealing with a **discrete distribution**.

Temperature Distribution

Let's look at another situation. Imagine we want to think of the distribution of the temperature in New York on June 1st. Thinking about this, you could say that the temperature would generally range between 65 and 95 degrees Fahrenheit (more extreme values would be exceptional), with the average around 80 degrees.

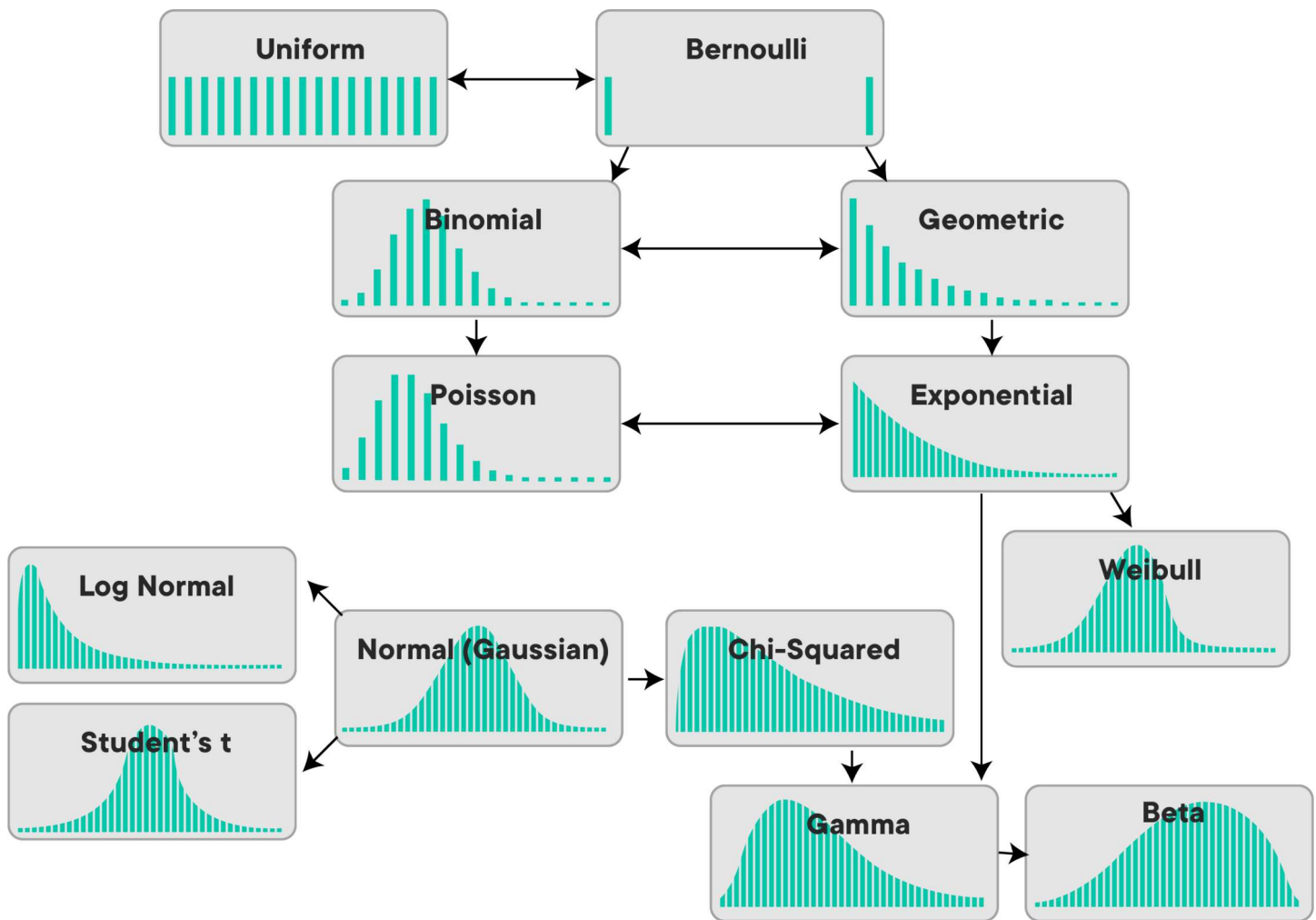
A potential distribution looks like this:



Note that instead of bars, which we had for the dice example, we have *continuous* lines here. Our distribution is a **continuous distribution** because temperature is a continuous value (we can have a temperature of 80 degrees, of 80.5 degrees, of 80.0034 degrees, etc.).

Common Distributions

In this image, you can see the general shapes of some common distributions. The horizontal axis in each chart represents the set of possible numeric outcomes. The vertical axis describes the probability of the respective outcomes.



You'll get a more in-depth overview of some important distributions in the next few lessons, but to give you an initial idea of some applications, we'll give you a quick overview below. Let's quickly talk about some common distributions and their use cases below.

Discrete vs Continuous Distributions

When dealing with **discrete** data you use a **Probability Mass Function (PMF)** (as in our dice example). When dealing with **continuous** data, you use a **Probability Density Function (PDF)** (see our temperature example).

Based on the variation of their attributes, data distributions can take many shapes and forms. In the next few lessons, you'll learn how to describe data distributions. Very often, distributions are described using their statistical mean (or **expected value**) and variance of the data, but this is not always the case. You'll see more on this in the next few lessons.

Examples of Discrete Distributions

The Bernoulli Distribution

The Bernoulli distribution represents the probability of success for a certain experiment (the outcome being "success or not", so there are two possible outcomes). A coin toss is a classic example of a Bernoulli experiment with a probability of success 0.5 or 50%, but a Bernoulli experiment can have any probability of success between 0 and 1.

The Poisson Distribution

The Poisson distribution represents the probability of n events in a given time period when the overall rate of occurrence is constant. A typical example is pieces of mail. If your overall mail received is constant, the number of items received on a single day (or month) follows a Poisson distribution. Other examples might include visitors to a website, or customers arriving at a store, or clients waiting to be served in a queue.

The Uniform Distribution

The uniform distribution occurs when all possible outcomes are equally likely. The dice example shown before follows a uniform distribution with equal probabilities for throwing values from 1 to 6. The dice example follows a discrete uniform distribution, but continuous uniform distributions exist as well.

Examples of Continuous Distributions

The Normal or Gaussian Distribution

A normal distribution is the single most important distribution; you'll come across it very often. The normal distribution follows a bell shape and is a foundational distribution for many models and theories in statistics and data science. A normal distribution turns up very often when dealing with real-world data including heights, weights of different people, errors in some measurement or grades on a test. Our temperature example above follows a normal distribution as well!

Summary

In this lesson, you learned about the concept of (discrete and continuous) probability distributions, as well as some common ones. You'll learn more about distributions and their properties in the next few lessons!

How do you feel about this lesson?



Have specific feedback?

[Tell us here! \(https://github.com/learn-co-curriculum/dsc-stat-distributions-use-cases/issues/new/choose\)](https://github.com/learn-co-curriculum/dsc-stat-distributions-use-cases/issues/new/choose)