Data Science Essentials

Simulations and Confidence Intervals

Simulations and confidence intervals are both concerned with estimating real-world data distributions from statistical suppositions or data samples.

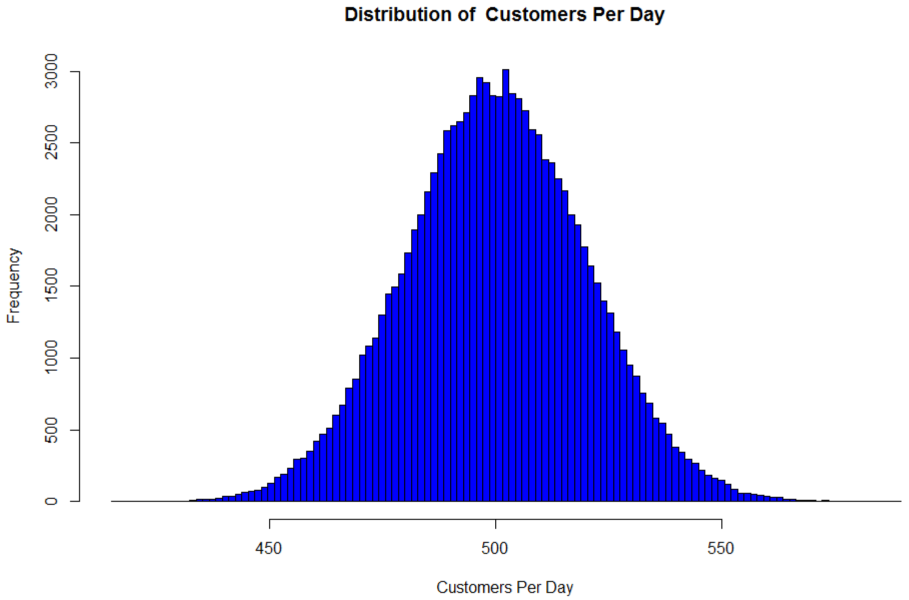
Simulations

Data scientists often need to use statistical methods to experiment with data and model real-world scenarios. When the data consists of a known number of independent random variables, the models can be calculated relatively simply. However, many real-world scenarios are more complex, and cannot be easily modeled using a single standard distribution. In these cases, you can use a *simulation* to model the variables and gain an understanding of how the scenario is likely to work in reality.

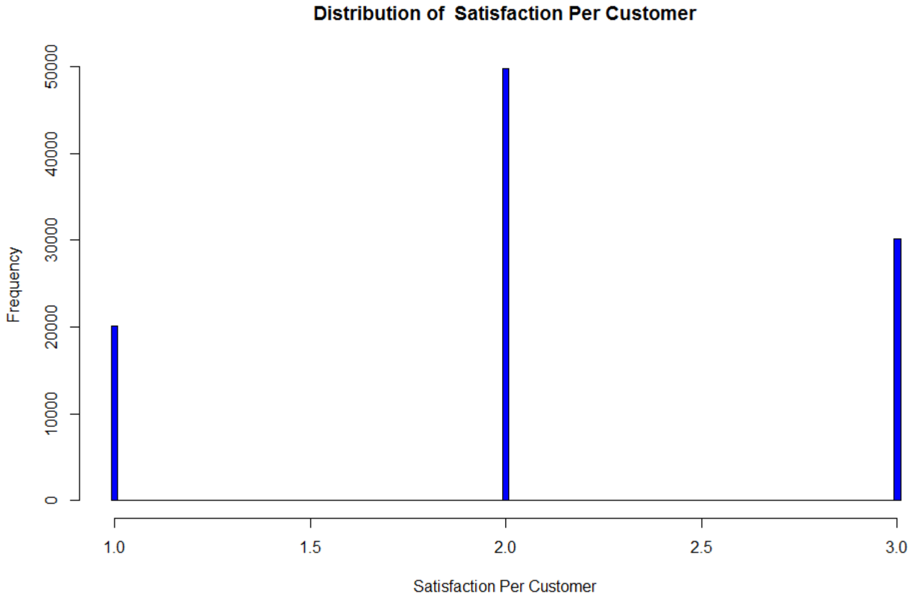
To run a simulation, you must identify the possible outcomes for each variable in the scenario along with their probability, and then draw a number of random variables that represent these outcomes. For example, suppose you need to model customer satisfaction at a store where each customer can rate service as 1 for poor, 2 for acceptable, and 3 for excellent. The individual ratings are then totaled each day to give an overall satisfaction score. There are two variables that need to be taken into consideration for the scenario: the number of customers and the ratings they give.

For this example, we'll assume that the number of customers can be represented as a normal distribution with a mean of 500 and a standard deviation of 20; and that 50% of the time these customers tend to give a rating of 2, 20% of the time they give a rating of 1, and 30% of the time they give a rating of 3.

Using these suppositions, you can run the simulation a number of times, generating random values for the two variables based on their probability distributions, and use the results to model the likely distribution of total satisfaction scores. In this case, the distribution of customers for 100,000 runs (or *realizations*) of the simulation looks like this:

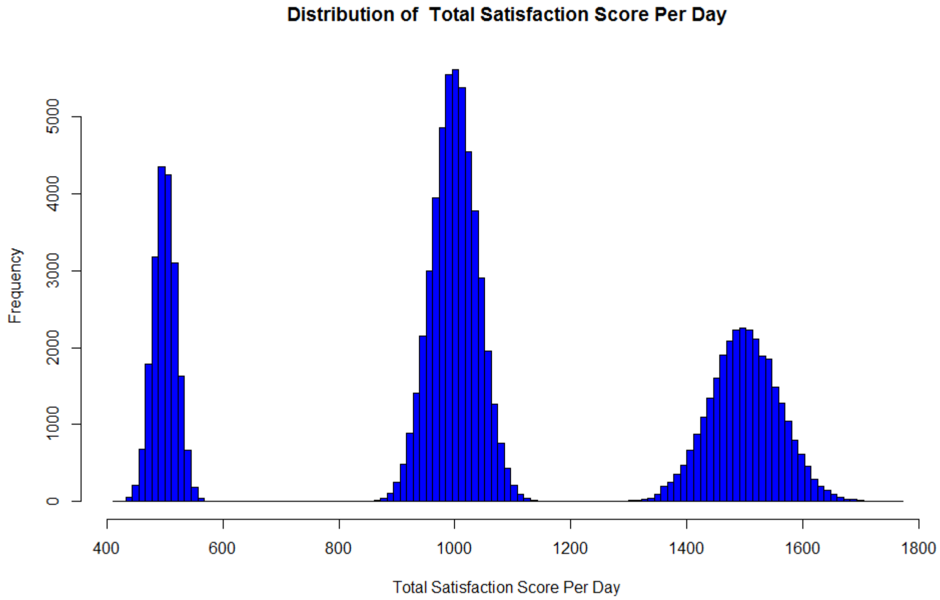


The mean number of customers per day is 500, and this was achieved around 3,000 days out of the total 100,000 simulated. The ratings given by those customers looks like this:



Out of 100,000 realizations, around half of them (50,000) produce a rating of 2. There are 2,000 instances of a rating of 1, and 3,000 instances of a rating of 3. This corresponds with the probability we assumed for customer ratings.

When we combine the results of the simulations for both variables, we can see the likely distribution of total satisfactions scores below:



This distribution indicates that around 4,500 days out of 100,000, the total score will be around 500, around 5,000 days will achieve a total score of 1,000, and around 2,000 days will achieve a total score of 2,000. These peaks (*modes*) in the distribution are the result of combining the number of customers and customer scores generated in 100,000 realizations of the simulation based on the expected distribution of those individual variables.

Confidence Intervals

When you are working with a sample of data, you can easily calculate the sample mean (x̄), and determine intervals in the distribution. However, without having access to the total population of the data, you need to be able to determine how closely the sample mean is likely to approximate the population mean (μ), or how the intervals in your sample will match the true intervals in the total population. A *confidence interval* is a way to express how often we can expect a true population parameter to fall within an interval estimate if we use the same sampling method to select different samples and compute an interval estimate for each sample.