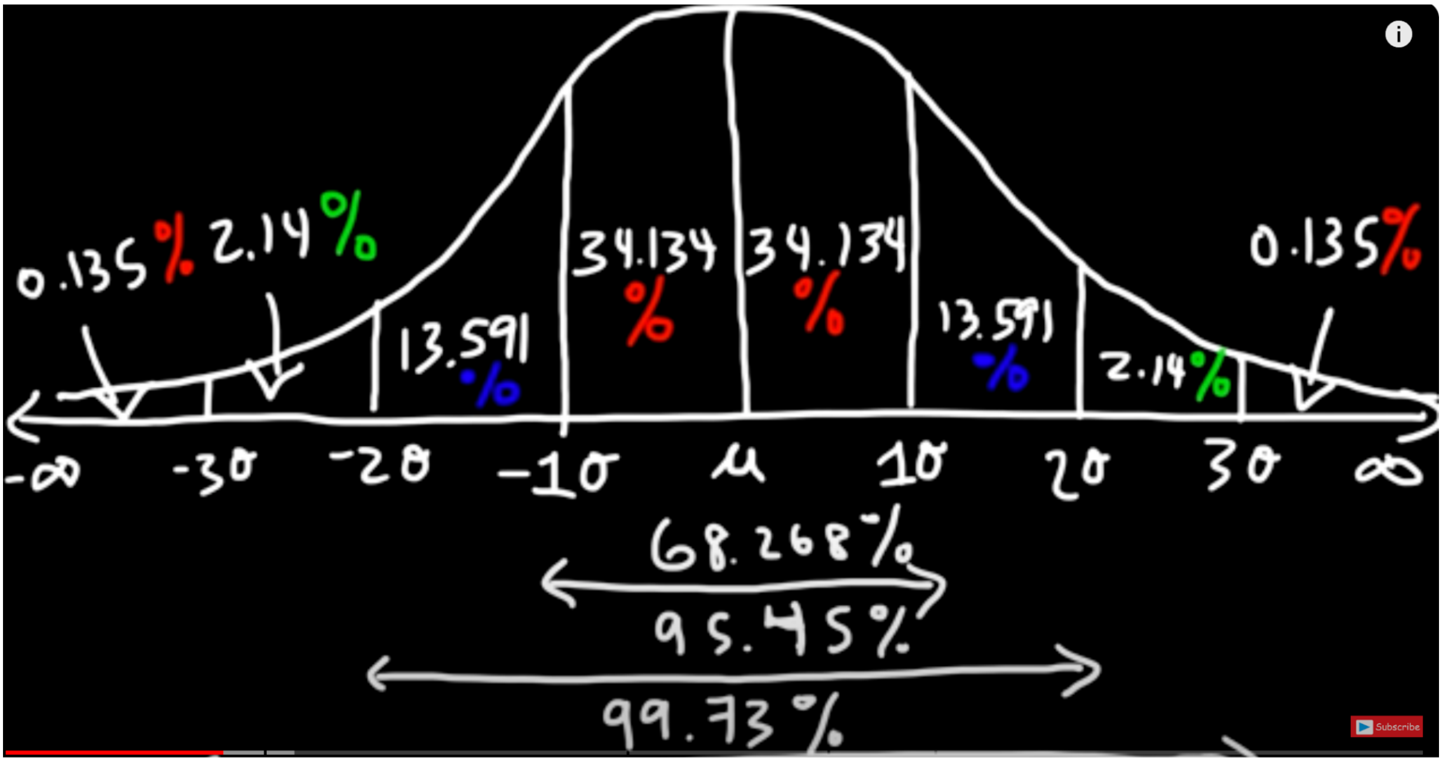
Probability

Normal (Gaussin) Distributions
1 standard deviation - 68.268%
2 standard deviations - 95.45%
3 standard deviations - 99.73%



To find the percentage of finding an event between the mean and the **1st standard deviation** apply formula:

68.268% / 2 = 34.134%

The area of both regions **-1σ and 1σ** is the area 34.134 as a percentage (see above). The **area** is the same as the **probability** of an event happening within a certain region.

To find the percentage of an event happening between the **1st and 2nd standard deviation** subtract **95.45% from 68.268%= 27.182%**
Now take 27.182% and divide by 2. = **13.591%**

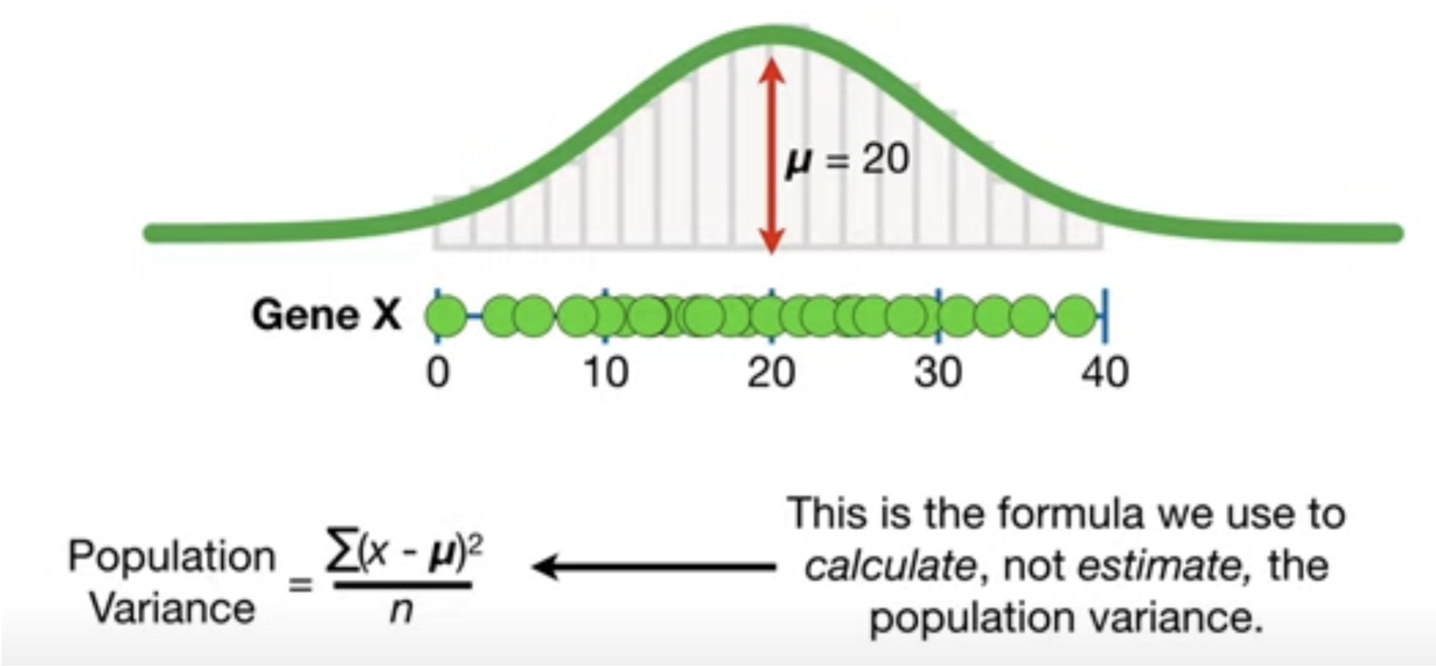
To find the percentage of an event happening between the **2nd and 3rd standard deviation** subtract **99.73% from 95.45% = 4.28%**, Now divide **4.28%** by 2 = **2.14%**

To find the last region we base the graph on 100%. So take **(100% - 99.73%) / 2 = .135%**

σ - sigma
μ - population mean

To determine how wide to make the curve we calculate the standard deviation and the variance. In other words how the data is spread around the population mean.

Formula to calculate the population variance:



https://www.youtube.com/watch?v=SzZ6GpcfoQY (Explanation)

Gaussian Distribution Formulas

probability density function

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

where:

μ is the mean

σ is the standard deviation

σ^2 is the variance

Binomial Distribution Formulas

mean

$$\mu = n * p$$

In other words, a fair coin has a probability of a positive outcome (heads) p = 0.5. If you flip a coin 20 times, the mean would be 20 * 0.5 = 10; you'd expect to get 10 heads.

variance

$$\sigma^2 = n * p * (1 - p)$$

Continuing with the coin example, n would be the number of coin tosses and p would be the probability of getting heads.

standard deviation

$$\sigma = \sqrt{n * p * (1 - p)}$$

or in other words, the standard deviation is the square root of the variance.

probability density function

$$f(k, n, p) = \frac{n!}{k!(n-k)!} p^k (1 - p)^{(n-k)}$$

Video on mean, variance and standard deviation

Text: Recap + Next Steps

The Binomial Distribution

The **Binomial Distribution** helps us determine the probability of a string of independent 'coin flip like events'.

The probability mass function associated with the binomial distribution is of the following form:

$$P(X = x) = \frac{n!}{x!(n-x)!}p^x(1-p)^{n-x}$$

where **n** is the number of events, **x** is the number of "successes", and **p** is the probability of "success".

We can now use this distribution to determine the probability of things like:

- The probability of 3 heads occurring in 10 flips.
- The probability of observing 8 or more heads occurring in 10 flips.
- The probability of not observing any heads in 20 flips.

Looking Ahead

The truth is that in practice, you will commonly be working with data, which might follow a binomial distribution. So it is less important to calculate these probabilities (though this can be useful in some cases), and it is more important that you understand what the Binomial Distribution is used for, as it shows up in a lot of modeling techniques in machine learning, and it can sneak up in our datasets with tracking any outcome with two possible events. You will get some practice with this in the **Python Probability Practice** lesson.

One of the most popular places you see the Binomial distribution is in logistic regression, which you will learn about in the last lesson of this statistics course.

In the next section, you will begin to work with events that aren't independent. The events we have seen so far haven't influenced one another, but it turns out the real world is usually more complicated than this. The next section will introduce the idea of dependence, and you will learn even more with Bayes rule in the following section.

Text: Summary

Conditional Probability

In this lesson you learned about conditional probability. Often events are not independent like with coin flips and dice rolling. Instead, the outcome of one event depends on an earlier event.

For example, the probability of obtaining a positive test result is dependent on whether or not you have a particular condition. If you have a condition, it is more likely that a test result is positive. We can formulate conditional probabilities for any two events in the following way:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

In this case, we could have this as:

$$P(positive|disease) = \frac{P(\text{positive} \cap \text{disease})}{P(disease)}$$

where $|$ represents "given" and $\cap$ represents "and".

Looking Ahead

You will get more practice with conditional probability using Bayes rule in the lesson. If you are comfortable with the examples here, the next lesson should be a breeze. And if you are still feeling a bit uncomfortable with these ideas, the next lesson should be good practice to reinforce the topics here with some more examples.

← Previous Next →