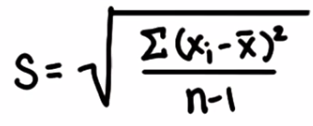
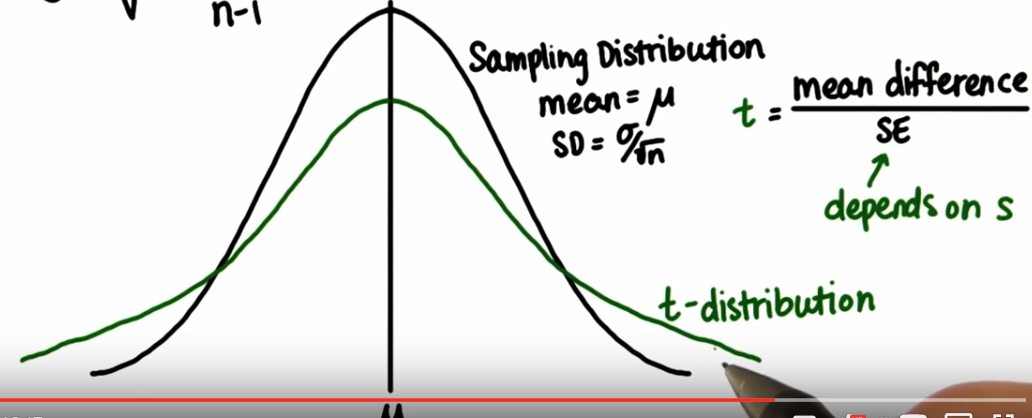
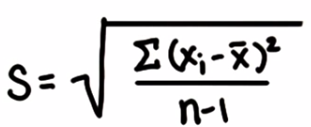
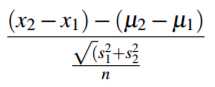
***Udacity Data Analyst Track***

**I. Into to Inferential Stats**

4. T-tests Part 1

* Much of the time we actually do NOT know the population mean and SD, and only have samples
* But we can use these samples to figure out how different a sample mean is from the population and from other sample means (can be **dependent** or **independent**)
* When working w/ samples, we need to *estimate* the pop SD using sigma w/ **Bessel’s correction = sqrt(sum(xi – x)^2/(n-1)) =** 
* Before, we found where a sample mean was in the distribution of sample means (whose shape we know from the population parameters)
* For any sample mean, we could find where it was in the distribution by **standardizing** (finding z-score = mean difference / SE)
* But SE depends on the sample in this case since we don’t know sigma 🡪 end up w/ a distribution more prone to error (**t-distribution**) = more spread out + thicker @ tails
*  
* Just like before when larger sample sizes = skinnier distributions 🡪 as n increases here, t-distribution gets skinner, t-distribution approaches a normal distribution, SE decreases (larger sample size = less error), and SE approaches SD
* The **t-Test** is best to use when we DON’T know the population SD + we instead use sample SD (SE)
* The **t-Test statistic** can be computed similarly to the **z-score** 🡪 **t = x - µ / sigma/sqrt(n) = x - µ / SE**
* We also have to compute **degrees of freedom (df)** for the sample 🡪 **df = n - 1**
* How many numbers we are free to choose before we are forced to choose (4 numbers to add up to 10 🡪 can pick 1st 3, 4th # is forced to sum up to 10, or sudoku, where we pick #’s in a row, but the last one must be forced to be the remaining # in a row/column)
* **dF** = # of pieces of info that can be freely varied w/out violating any given restrictions/@ of independent pieces of info available to estimate another piece of info
* Only n-1 pieces of info are available after we know the mean
* The sum of x1 to xn values *must* = mean(x) \*n, so we have the freedom to choose n-1 values for x, but the last one must make it such that the sum of all x’s = mean(x)\*n
* As dF increases the t-distribution better approximates the normal distribution
* **n – 1 = effective sample size 🡪** n - 1 values may vary, but the last value must make the sum = mean(x)
* Like the Z-score, we can use the t-table to get the proportion below or between a specific value
* T-table tells us the **t critical values**
* When t-statistic is far from 0 in either direction (sample mean is far from pop mean), reject the NULL
* T statistic = (smpl mean – pop mean) / sample error 🡪 (smpl mean – pop mean) / (smpl SD/sqrt(n))
* When comparing sample mean to initial population mean, center the t-distribution at pop mean and find where the sample mean lies on the distribution
* Further away, more significant chance it comes from a population w/ a significantly different intervention population mean (
* larger s mean = new pop mean > old pop mean, smaller s mean = new pop mean < old pop mean
* 1 sample t-test:
* Null = pop mean = old pop mean (mu = mu(0))
* Alternative 🡪 mu < m(0), or mu > mu(0), or just mu =/= mu(0)
* t numerator = point estimate for population mean mu/sample mean minus mu(0) (difference between)
* t denominator = measures difference between mu and mu(0) that we expect by chance
* To increase t (the t statistic), we can have a larger difference between x and mu(0) or a larger sample size
* Larger t = higher on distribution = lower probability of obtaining that t value
* 1 tailed t-test 🡪 p-value = probability of being above/below t-statistics (if positive/negative)
* 2-tailed t-test 🡪 p-value probability above and below positive and negative t-statistics
* *Reject Null when p < alpha*
* CANNOT use t-table to find *EXACT* p-values 🡪 only for interval estimate for p-values
* **Cohen’s d** is a standardized mean difference that measures the distance between 2 means in standard deviation units (divide by SD of sample rather than SE)
* i.e. measures the **effect size** of the strength of a phenomenon + gives us the distance between means in standardized units + is computed by 🡪 **d = (x1 - x2) / s**
* where s = sqrt((n1 - 1)\*s1^2 + (n2 - 1)\*s2^2)/(n1 + n2 – 2) =
* The larger Cohen’s d is, the further x is from mu(0), in terms of the sample SD
* In addition to deciding if a sample from a new population is significantly different than the original population, we want a CI in which the new pop mean will probably lie
* *i.e.* interval that most likely contains the true average rent for all Rental CA Co.’s rental units
* T-tests are also great for testing 2 sample means (**dependent** **paired t-tests**) where we modify the formula to become: **(x2 - x1) - (µ2 - µ1) / (sqrt(s1^2 + s2^2)/n) =**  
* **Dependent samples** –> sample subject takes the same test twice
* A **within-subject design** examples
* Each subject is assigned 2 conditions in random order (control + treatment, 2 treatments)
* Pre-test + post-test
* Growth over time (**longitudinal study)** w/ variable measurement at different points in time
* Use D(i) = x(i) – y(i) as our values for a sample + proceed w/ the same procedure as a 1 sample t-test
* Ex: **repeated measures design** where each subject gets both treatments (2 phones w/ different keyboard configurations)
* Interested in effects of keyboard configs on text msg errors
* 25 people use each keyboard and created 20-word txt w/in 30 seconds and we recorded each error for each person for each keyboard, with each person randomly assigned to which keyboard they used 1st
* 2 different populations and their samples (# of errors made)
* Types of 2 sample t-tests
* **repeated measures design** 🡪 NULL = the 2 populations/population means are the same
* h(0) = mu(1) – mu(2)
* **longitudinal** 🡪 measure variable for a subject at 1 time and measure same variable for same subject at later time and check for sig differences
* h(0) = mu(early) = mu(later)
* **pre-test/post-test** 🡪 measure same variable for same subject before and after some intervention to check for significant effect from the treatment
* **h(0) =** mu (pre) = mu(post)
* Ex: Researchers took random sample of 1k 4-year olds in the US + had them say a few sentences
* On average, the 4-year olds said 3 words per sentence w/ SD = 1.2. 4 years later, researchers repeated this w/ the same kids to get a 12 words/sentence average w/ SD = 2.7
* This is both a longitudinal AND dependent-samples t-test (same sample subjects takes the same test twice)
* IV = Age, DV = average# of words/sentence
* H(0) = Kid’s vocabs does not change from age 4 to age 8 🡪 mu(2) – mu(1) = 0
* H(A) = Kid’s vocabs increase from age 4 to age 8 🡪 mu(2) – mu(1) > 0
* Use a 1-tailed t-test (only care about improving)
* T-critical values w/ alpha 0.05 + dF = 999 🡪 **1.646**
* Mean of differnces 🡪 mu(d) = mu(2) – mu(1) = 12 – 3 = **9**
* SD of differences 🡪 Sqrt(s(2)^2 + s(1)^2) 🡪 Sqrt(2.7^2 + 1.2^2) = **2.954657**
* t 🡪 [ mu(d) – 0 ] / [ s(d) / sqrt(n) ] 🡪 **96.32419486**
* **t much higher than t-crit 🡪 reject null 🡪 new mean definitely not due to chance**
* **Age significantly improves vocab**