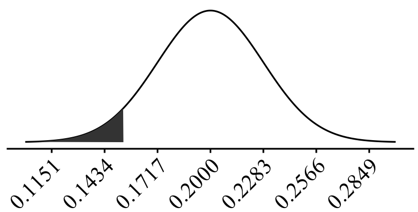
# Lesson 8.2.2

8-37. a. $H_0$: $p = 0.20$, $H_A$: $p < 0.20$

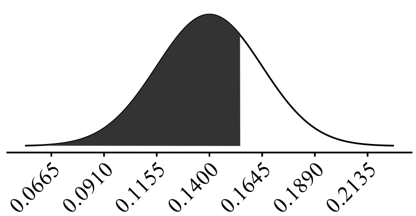
b. A Type I error would be if the null hypothesis of $p = 0.20$ (or greater) is rejected even though it is true. This would allow the drug to be approved even though it should not be. A Type II error would occur if the true proportion of severe side effects is less than 20% but that is not shown and the drug is not approved, keeping the drug off the market and resulting in lost revenue for the company.

c. Hypothesis $\hat{p}$ sampling distribution




d. The left tail below $\hat{p}$ needs to be no more than 5% of the curve, so this is found using InvNorm(0.05, 0.2, 0.0283) command or equivalent. The minimum $\hat{p}$ for rejection is 0.1535. See diagram above.

e. Suspected $\hat{p}$ sampling distribution



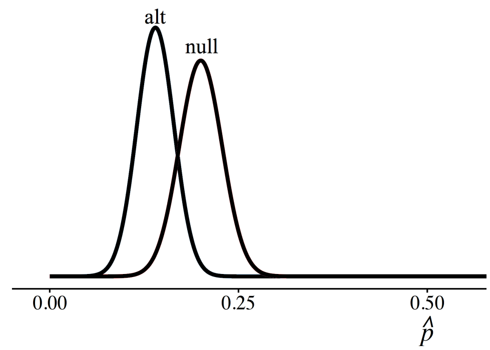

f. This sampling distribution has $\mu_{\hat{p}} = 0.14$, $\sigma_{\hat{p}} = \sqrt{\frac{0.14(0.86)}{200}} \approx 0.0245$,

$P(\hat{p} < 0.1535 \mid p = 0.14) \approx$ normalcdf(–10^99, 0.1535, 0.14, 0.0245) $\approx 0.709$.

g. A Type II error occurs when the value is *not* rejected, so $P(\text{Type II error} \mid p = 0.14) \approx 0.291$.

8-38. a. See example sketch at right. The calculations should match if all went well in problem 8-35.




b. Between the two of them they fill the entire alternative sampling distribution under the alternative hypothesis; this makes sense, since their sum is 1!

c. *i*. Change $p_A$ to 0.12, increases power to 93%.

*ii*. Change $p_0$ to 0.22, increases power to 90%.

*iii*. Change $\alpha$ as described, increases power to 83%.

*iv*. Change $n$ to 300, increases power to 86%.

d. Increase sample size!

8-39. a. This will increase power if the stratification is on a well-chosen variable, since it decreases sampling variability. Drawbacks are that the math is more complicated AND that it is simply more work.

b. The blocking will also reduce variability within each blocking group, making the differences more obvious and more detectable, increasing power. Again, this is more work, and blocking decreases the sample size of the individual comparisons, so it can backfire if the variable does not matter.

c. Cluster sampling does not decrease variability in most cases, certainly not reliably, so power would not change or would decrease. However, it can be much more feasible to actually do!

d. Could increase power. If more variables are controlled for, it will reduce the variability caused by them.

e. This will likely decrease power, since it will increase sampling variation. However, any differences successfully detected will be applicable to a larger audience.

f. This will likely increase power of tests, since it will decrease sampling variation. However, any results can only be extrapolated out to the population the study or experiment drew from.

8-40. a. 0.255 to 0.336, or $0.2955 \pm 0.040$

b. Based on this 95% confidence interval, this claim cannot be rejected. $\frac{1}{3}$, or 0.333, is in this confidence interval, so it is believable based on this interval that the claim could be true.

c. The new interval is from 0.262 to 0.329. Based on this interval, you can reject the claim, since no values greater than $\frac{1}{3}$ are in the confidence interval.

d. Test statistic is –1.78, resulting in a $p$-value of 0.037, so the one-tailed test rejects the null hypothesis, matching with the 90% interval.

e. If it were a two-tailed test, the $p$-value would double to 0.074, so the hypothesis test would no longer be rejected and the test would match the 95% interval.

8-41. The probability of winning is $\frac{1}{200} = 0.005$, which means the probability of losing is 0.995. $\sum xP(x) = -100(0.995) + 16900(0.005) = -\$15$,

$\sigma = \sqrt{\sum (x-\bar{x})^2 P(x)} = \sqrt{(-100)-(-15))^2(0.995)+(16900-(-15))^2(0.005)} = \$1199.07$,

or you could put winnings in L1 and probabilities in L2 and run 1-Var Stats L1, L2.

8-42. a. $r = -0.6705$, indicating a moderate negative linear association between the oxygen percentage versus carbon dioxide levels in air samples, which is confirmed by an inspection of the residual plot where there is no discernable pattern in the residuals.

b. $r^2 = 0.4496$, meaning that 45% of the variation observed in oxygen percentage is explained by a linear relationship with carbon dioxide levels. In other words, knowing the carbon dioxide level associated with each oxygen percentage reduces the error in predicting oxygen percentage by 45% over using just the mean oxygen percentage as a predictor.

c. When making predictions about air sample oxygen percentages by using carbon dioxide levels, one can expect to typically be off by 0.642%.