

DATA ANALYSIS

Week 4: Sampling

today's agenda



probability and inference



sampling



class survey

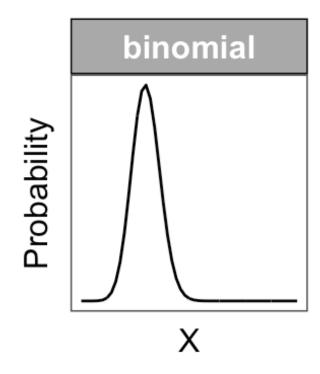
recap: binomial distribution

- data can only take two possible values (bi = two, nomial = names)
- a sequence of "bernoulli trials" (with only 2 possible outcomes)
- question of interest: how often does an outcome (A or B) occur in a sample of observations?

$$p = p(A) \text{ and } q = p(B)$$

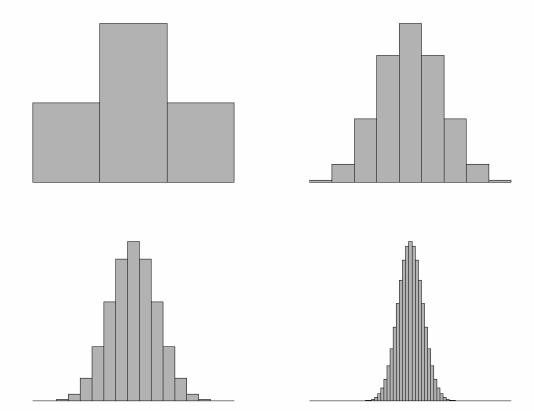
 $p + q = 1 \text{ i.e., } q = 1 - p(A) \text{ and } p = 1 - p(B)$

- *n* : number of observations/individuals in the sample
- *X*: number of times that A occurs in the sample
 - X ranges between 0 and n
- the binomial distribution shows the probability associated with each X
 value from X=0 to X=n



increasing n...

- play with the coin toss simulator
 - increase number of coin tosses (n)
 - simulate flips!
- as the number of coin tosses (n) increases, the distribution starts to resemble a normal distribution!
- rule of thumb: when pn and $qn \ge 10$, the binomial distribution approximates the normal distribution
 - mean: $\mu = pn$
 - standard deviation: $\sigma = \sqrt{npq}$
 - z-score: $z = \frac{X \mu}{\sigma} = \frac{X pn}{\sqrt{npq}}$



example 1

- using a balanced coin, what is the probability of obtaining more than 30 heads in 50 tosses?
- balanced coin, i.e., p = p(head) = 0.5, q = p (tail) = 0.5

-
$$n = 50, X = 30$$

-
$$\mu = pn = 0.5 (50) = 25$$
, $qn = 0.5 (50) = 25$, i.e., ≥ 10

$$- \sigma = \sqrt{npq} = \sqrt{50(0.5)(0.5)} = 3.54$$

$$-z = \frac{X-\mu}{\sigma} = \frac{30-25}{3.54} = 1.41$$

- look up probability in visual calculator
- p(X > 30) = more than .0793



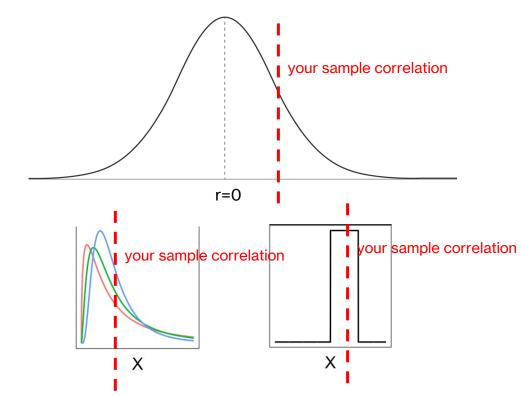
example 2

- a friend bets you that he can draw a king more than 8 times in 20 draws (with replacement) of a fair deck of cards, and he does it. Is this a likely outcome, or should you conclude that the deck is not "fair"?



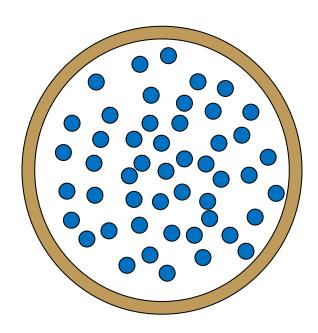
three outstanding questions

- question 1: how do I calculate probabilities if I don't have access to ALL the scores?
- question 2: how do we know what the distribution of the null hypothesis looks like? If we don't know the <u>form</u> of the distribution, we cannot calculate probabilities
- question 3: how do we know whether the probability we obtained, i.e., P(data | null hypothesis) is small enough?



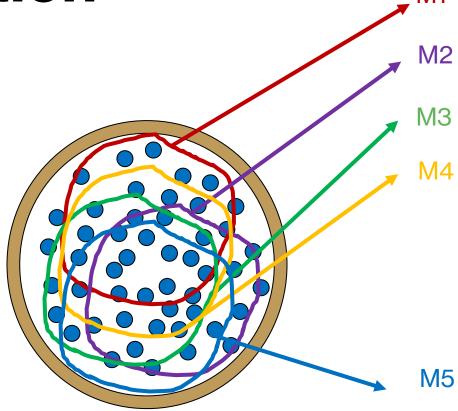
sampling from a population

- sampling error: the discrepancy between the sample statistic and the true population parameter it is estimating
- each time we sample, we compute some type of statistic (e.g., mean, correlation, etc.)
- sampling distribution: distribution of all possible values of the <u>statistic</u> obtained from multiple samples of a given size
- distribution of sample means contains all sample means of a size n that can be obtained from a population



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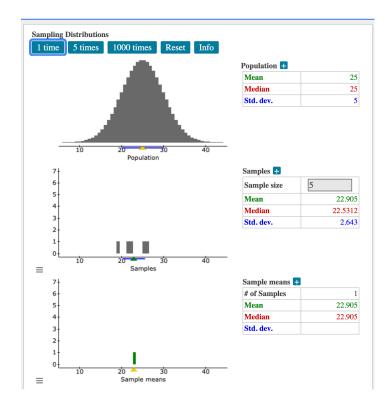


what does the sampling distribution of means look like??

sampling distribution

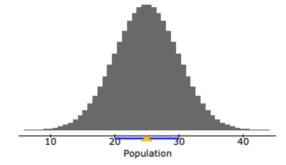
- simulator
- change the distribution to bell-shaped and make sure the first statistic is the "mean" and the second statistic is "none"
- start with a single sample of size 5 and play it 1 time vs. 5 times vs. 1000 times
- explore what the three graphs are showing



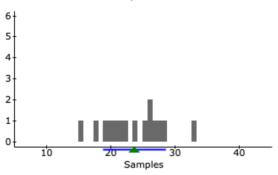


sampling distribution

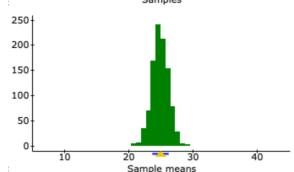
- three distributions
 - the population distribution
 - the sample distribution
 - the sampling distribution (of all means)
- mean of sample means = population mean (unbiased estimator!)
- the sampling distribution of means approximates the normal distribution as n (sample size) increases



Population 🛨	
Mean	25
Median	25
Std. dev.	5



Samples +	
Sample size	15
Mean	23.68
Median	24.1384
Std. dev.	4.8149



Sample means 🛨	
# of Samples	1000
Mean	24.9524
Median	24.9226
Std. dev.	1.2832

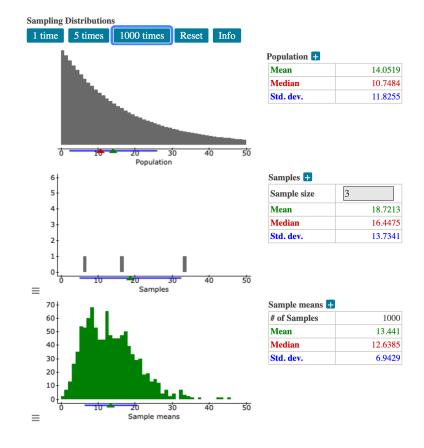
from all samples to few samples

- in practice, we cannot compute <u>all</u> possible samples of size n
- the central limit theorem states that for <u>any</u> population with mean μ and standard deviation σ , the distribution of sample means for sample size n will have:
 - a mean of $\mu_M = \mu$ = expected value of M
 - a standard deviation of $\sigma_M = \frac{\sigma}{\sqrt{n}}$ = standard error of the mean or M
 - will approach a normal distribution as n approaches infinity
 - distribution of sample means will be normally distributed **even if the population was not normally distributed (if n is large enough!)**
 - typically n (number of scores in a sample) around 30 yields a reasonably normal distribution

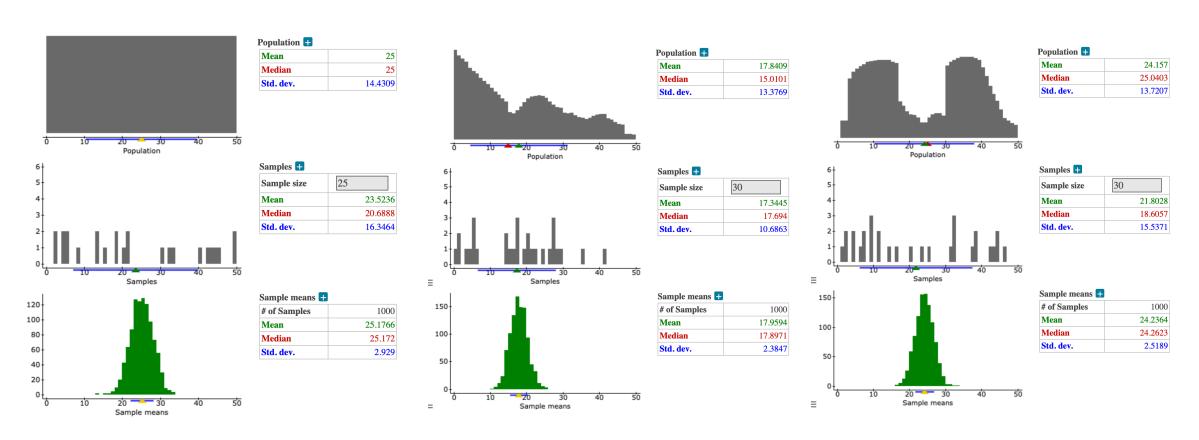
any distribution?

- simulator
- change the population distribution to any non-normal distribution
- make sure the first statistic is the "mean" and the second statistic is "none"
- explore what the sampling distribution looks like for small and large samples



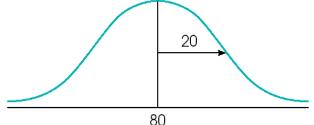


distribution of sample means

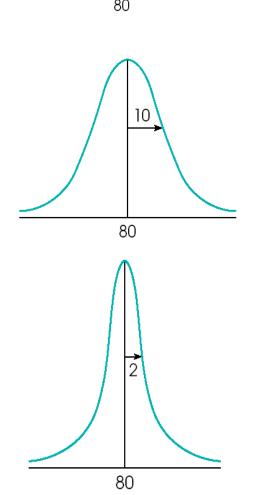


for a large n, distribution of sample means will be normally distributed even if the population was not normally distributed!

standard error of the mean



- standard error of the mean: $\sigma_M = \sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$
- how different a mean from one sample could be from another on "average"
- also measures reliability: how well an individual sample's mean represents the entire distribution of sample means
- law of large numbers: the larger the sample size (n), the more likely that the sample mean is closer to the population mean, and smaller the σ_M
- insight: we cannot control the population standard deviation but we can control the sample size!
- if we want our standard error of the mean to be low, we can use larger samples



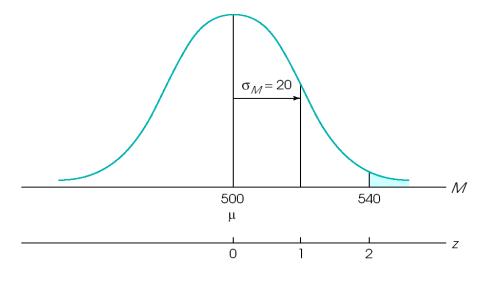
example

- SAT-scores population (μ =500, σ =100). If you take a random sample of n = 16 students, what is the **probability that the** sample mean will be greater than M = 540?
- we are talking about the sample mean, not an individual score anymore! i.e., we use the <u>distribution of sample means (i.e., the sampling distribution)</u> which approaches the normal distribution for large n
- represent the problem graphically
- calculate σ_M and z

$$\sigma_M = \frac{\sigma}{\sqrt{n}} = \frac{100}{\sqrt{16}} = \frac{100}{4} = 20$$
$$z = \frac{M - \mu}{\sigma} = \frac{540 - 500}{20} = 2$$

- visual calculator
- p (M > 540) = .0228

distribution of sample means

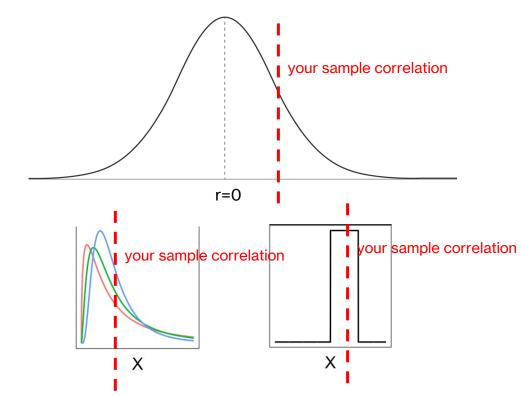


activity

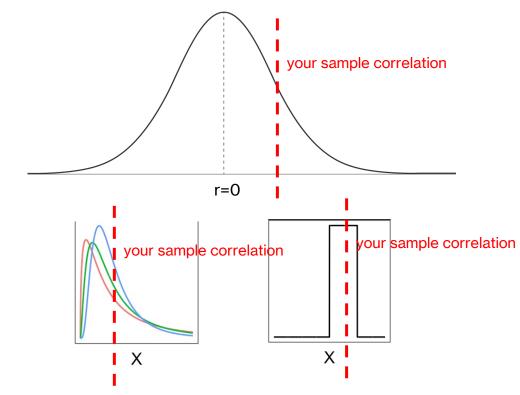
Jumbo shrimp are those that require 10–15 shrimp to make a pound. Suppose that the number of jumbo shrimp in a 1-pound bag averages μ = 12.5 with a standard deviation of σ = 1, and forms a normal distribution. What is the probability of randomly picking a sample of n = 25 1-pound bags that average more than M = 13 shrimp per bag?

three outstanding questions

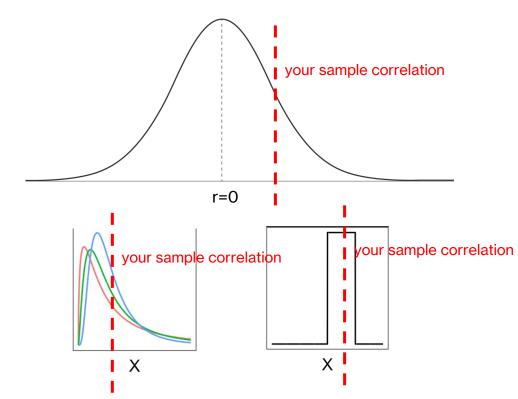
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- question 3: how do we know whether the probability we obtained, i.e., P(data | null hypothesis) is small enough?



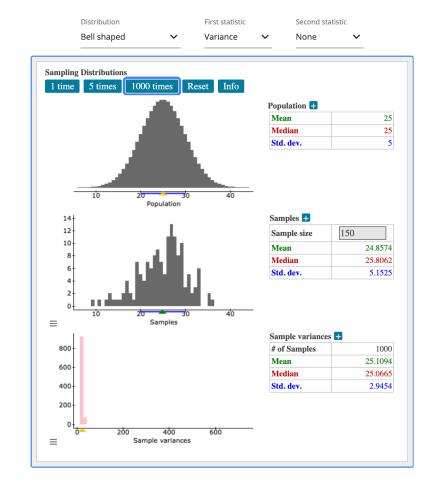
- question 1: how do I calculate probabilities if I don't have access to ALL the scores?
- if I know that the distribution of the sample statistic is normal, or approaches normal, then I can calculate probabilities!



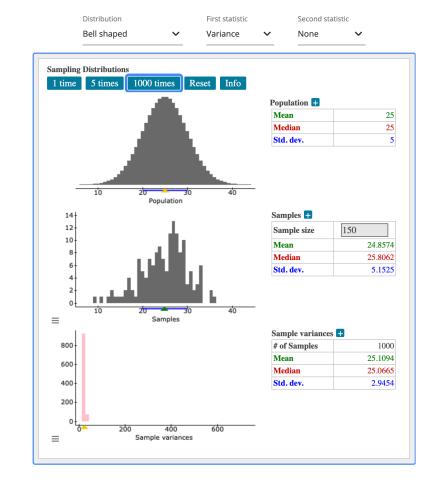
- question 2: how do we know what the distribution of the null hypothesis looks like? If we don't know the <u>form</u> of the distribution, we cannot calculate probabilities
- the central limit theorem states that for any population, the distribution of sample means will be normal for large sample (n > 30)
- caveat: CLT only applies to sample means, NOT other sample statistics!



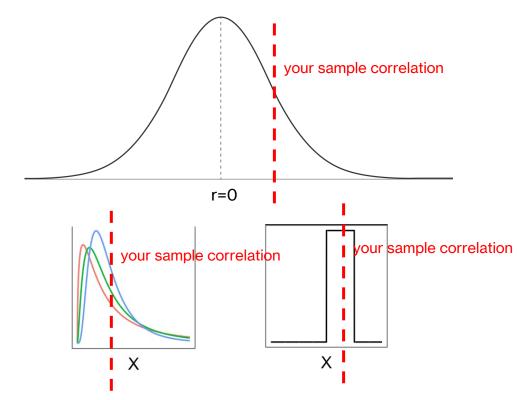
- simulator
- change the distribution to bell-shaped and make sure the first statistic is the "variance" and the second statistic is "none"
- start with a single sample of size 5 and play it 1 time vs. 5 times vs. 1000 times
- explore what the three graphs are showing
- the sampling distribution of variances is NOT normally distributed
- sampling distribution of several other statistics (e.g., correlation) may also NOT be normally distributed!



- question 2: how do we know what the distribution of the null hypothesis looks like? If we don't know the <u>form</u> of the distribution, we cannot calculate probabilities
- if we can figure out the sampling distribution of the sample statistic (e.g., means, variances, correlations, etc.), and we know the mathematical form of these distributions, we can find probabilities



- <u>question 3</u>: how do we know whether the probability we obtained, i.e., P(data | null hypothesis) is <u>small enough?</u>
- we need to set thresholds in place BEFORE we look at our data (no peeking!)
- all researchers/scientists must follow the same framework when testing hypotheses
- enter: null hypothesis significance testing (NHST)



today's agenda



probability and inference



sampling



class survey

some changes

- problem sets now due Tuesday night
 - PS4 is due March 11
 - PS4 revision is due March 27
- quizzes will still be due Monday night
- pace will be slower
- more practice problems using Sheets (but, we have limited time)
- PLEASE watch the videos (when they are listed on the website!)
- rethinking office hour times (TBD)
- thanks for your feedback!

next time

- **before** class
 - *prep*: textbook readings
 - *try*: week 6 quiz
 - apply: PS4 problems (chapters 6 and 7)
 - apply: optional meme
- during class
 - hypothesis testing