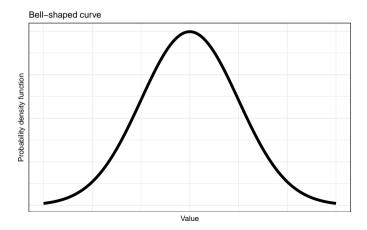
#### P4 - Central Limit Theorem

STAT 587 (Engineering) Iowa State University

August 27, 2020

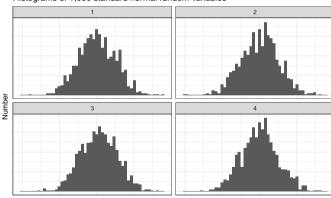
# Bell-shaped curve

The term bell-shaped curve typically refers to the probability density function for a normal random variable:



# Histograms of samples from bell-shaped curves

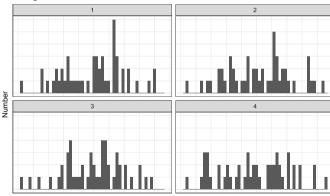




Value

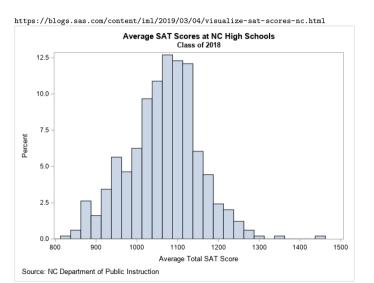
# Histograms of samples from bell-shaped curves

#### Histograms of 50 standard normal random variables

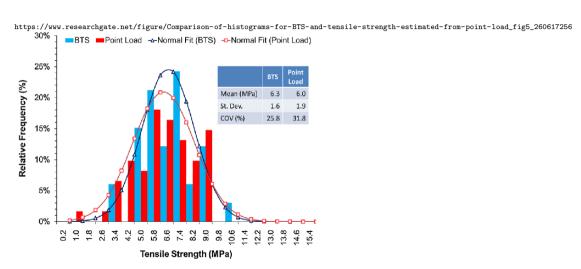


Value

#### SAT scores

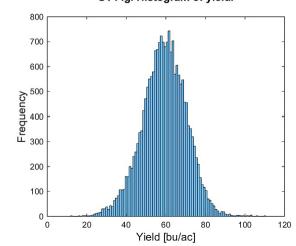


## Tensile strength



## Yield

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0184198 S1 Fig. Histogram of yield.



# Sums and averages of iid random variables

Suppose  $X_1, X_2, \ldots$  are iid random variables with

$$E[X_i] = \mu \quad Var[X_i] = \sigma^2.$$

Define

$$\begin{array}{ll} \text{Sample Sum: } S_n &= X_1 + X_2 + \cdots + X_n \\ \text{Sample Average: } \overline{X}_n &= S_n/n. \end{array}$$

For  $S_n$ , we know

$$E[S_n] = n\mu, \quad Var[S_n] = n\sigma^2, \quad \text{and} \quad SD[S_n] = \sqrt{n}\sigma.$$

For  $\overline{X}_n$ , we know

$$E[\overline{X}_n] = \mu, \quad Var[\overline{X}_n] = \sigma^2/n, \quad \text{and} \quad SD[\overline{X}_n] = \sigma/\sqrt{n}.$$

# Central Limit Theorem (CLT)

Suppose  $X_1, X_2, \ldots$  are iid random variables with

$$E[X_i] = \mu \quad Var[X_i] = \sigma^2.$$

Define

$$\begin{array}{ll} \text{Sample Sum: } S_n &= X_1 + X_2 + \cdots + X_n \\ \text{Sample Average: } \overline{X}_n &= S_n/n. \end{array}$$

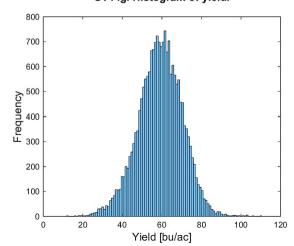
Then the Central Limit Theorem says

$$\lim_{n \to \infty} \frac{\overline{X}_n - \mu}{\sigma / \sqrt{n}} \xrightarrow{d} N(0, 1) \quad \text{and} \quad \lim_{n \to \infty} \frac{S_n - n\mu}{\sqrt{n}\sigma} \xrightarrow{d} N(0, 1).$$

Main Idea: Sums and averages of iid random variables from any distribution have approximate normal distributions for sufficiently large sample sizes.

## Yield

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0184198 S1 Fig. Histogram of yield.



# Approximating distributions

Rather than considering the limit, I typically think of the following approximations as n gets large.

For the sample average,

$$\overline{X}_n \stackrel{.}{\sim} N(\mu, \sigma^2/n).$$

where  $\stackrel{.}{\sim}$  indicates approximately distributed because

$$E\left[\overline{X}_n\right] = \mu$$
 and  $Var\left[\overline{X}_n\right] = \sigma^2/n$ .

For the sample sum,

$$S_n \stackrel{\cdot}{\sim} N(n\mu, n\sigma^2)$$

because

$$E[S_n] = n\mu$$

$$Var[S_n] = n\sigma^2.$$

# Averages and sums of uniforms

Let  $X_i \stackrel{ind}{\sim} Unif(0,1)$ . Then

$$\mu = E[X_i] = \frac{1}{2}$$
 and  $\sigma^2 = Var[X_i] = \frac{1}{12}$ .

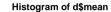
Thus

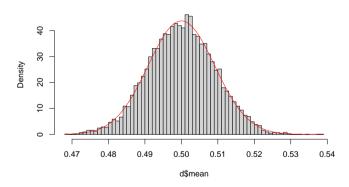
$$\overline{X}_n \stackrel{\cdot}{\sim} N\left(\frac{1}{2}, \frac{1}{12n}\right)$$

and

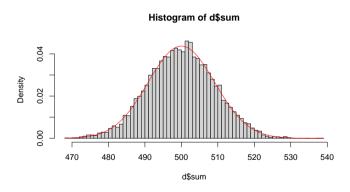
$$S_n \stackrel{\cdot}{\sim} N\left(\frac{n}{2}, \frac{n}{12}\right)$$
.

# Averages of uniforms





## Sums of uniforms



## Normal approximation to a binomial

Recall if  $Y_n = \sum_{i=1}^n X_i$  where  $X_i \stackrel{ind}{\sim} Ber(p)$ , then

$$Y_n \sim Bin(n,p).$$

For a binomial random variable, we have

$$E[Y_n] = np \qquad \text{and} \qquad Var[Y_n] = np(1-p).$$

By the CLT,

$$\lim_{n \to \infty} \frac{Y_n - np}{\sqrt{np(1-p)}} \to N(0,1),$$

 $\quad \text{if } n \text{ is large,} \\$ 

$$Y_n \stackrel{\cdot}{\sim} N(np, np[1-p]).$$

## Roulette example

A European roulette wheel has 39 slots: one green, 19 black, and 19 red. If I play black every time, what is the probability that I will have won more than I lost after 99 spins of the wheel?

Let Y indicate the total number of wins and assume  $Y \sim Bin(n,p)$  with n=99 and p=19/39. The desired probability is  $P(Y \geq 50)$ . Then

$$P(Y \ge 50) = 1 - P(Y < 50) = 1 - P(Y \le 49)$$

```
n = 99
p = 19/39
1-pbinom(49, n, p)
[1] 0.399048
```

## Roulette example

A European roulette wheel has 39 slots: one green, 19 black, and 19 red. If I play black every time, what is the probability that I will have won more than I lost after 99 spins of the wheel?

Let Y indicate the total number of wins. We can approximate Y using  $X \sim N(np, np(1-p)).$ 

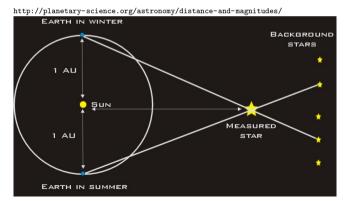
$$P(Y \ge 50) \approx 1 - P(X < 50)$$

```
1-pnorm(50, n*p, sqrt(n*p*(1-p)))
[1] 0.3610155
```

A better approximation can be found using a continuity correction.

# Astronomy example

An astronomer wants to measure the distance, d, from Earth to a star. Suppose the procedure has a known standard deviation of 2 parsecs. The astronomer takes 30 iid measurements and finds the average of these measurements to be 29.4 parsecs. What is the probability the average is within 0.5 parsecs?



## Astronomy example

Let  $X_i$  be the  $i^{th}$  measurement. The astronomer assumes that  $X_1, X_2, \dots X_n$  are iid with  $E[X_i] = d$  and  $Var[X_i] = \sigma^2 = 4$ . The estimate of d is

$$\overline{X}_n = \frac{(X_1 + X_2 + \dots + X_n)}{n} = 29.4.$$

and, by the Central Limit Theorem, we believe  $\overline{X}_n \stackrel{.}{\sim} N(d, \sigma^2/n)$  where n=30. We want to find

$$P(|\overline{X}_n - d| < 0.5) = P(-0.5 < \overline{X}_n - d < 0.5)$$

$$= P(\frac{-0.5}{\sigma/\sqrt{n}} < \frac{\overline{X}_n - d}{\sigma/\sqrt{n}} < \frac{0.5}{\sigma/\sqrt{n}})$$

$$\approx P(-1.37 < Z < 1.37)$$

```
diff(pnorm(c(-1.37,1.37)))
```

[1] 0.8293131

# Astronomy example (cont.)

Suppose the astronomer wants to be within 0.5 parsecs with at least 95% probability. How many more samples would she need to take?

We solve

$$0.95 \le P\left(\left|\overline{X}_n - d\right| < .5\right) = P\left(-0.5 < \overline{X}_n - d < 0.5\right)$$

$$= P\left(\frac{-0.5}{\sigma/\sqrt{n}} < \frac{\overline{X}_n - d}{\sigma/\sqrt{n}} < \frac{0.5}{\sigma/\sqrt{n}}\right)$$

$$= P(-z < Z < z)$$

$$= 1 - [P(Z < -z) + P(Z > z)]$$

$$= 1 - 2P(Z < -z)$$

where  $z=0.5/(\sigma/\sqrt{n})=1.96$  since

```
-qnorm(.025)
```

[1] 1.959964

and thus n=61.47 which we round up to n=62 to ensure

# Summary

- Central Limit Theorem
  - Sums
  - Averages
- Examples
  - Uniforms
  - Binomial
  - Roulette
- Sample size
  - Astronomy