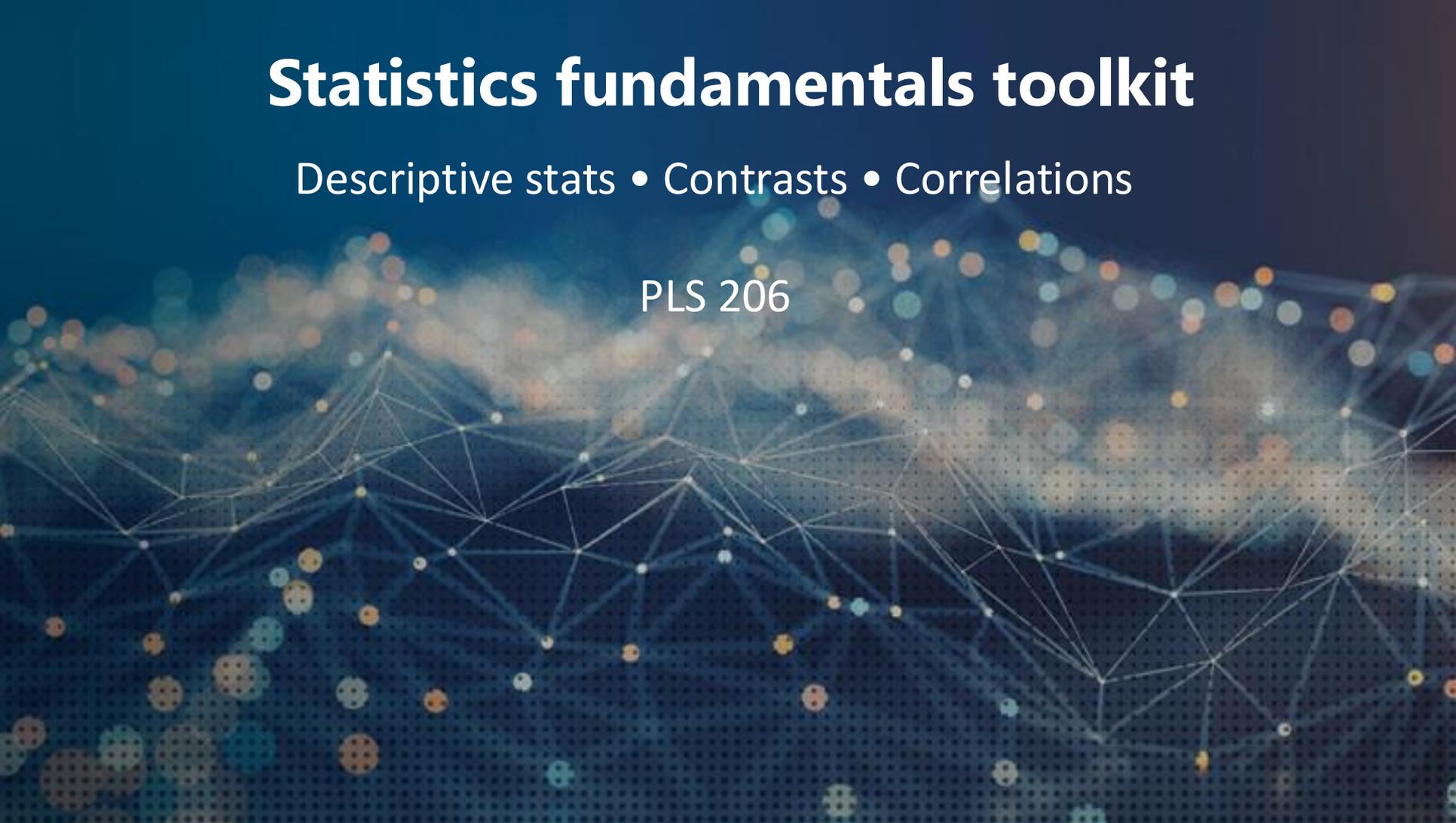


Statistics fundamentals toolkit

Descriptive stats • Contrasts • Correlations

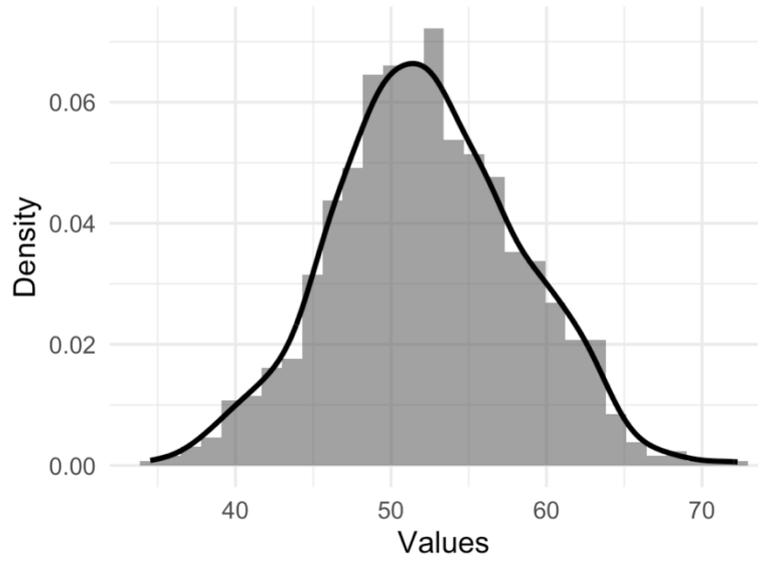
PLS 206



Goals for Today

- Summaries (mean, SD, SE, CI)
- Group comparisons (t-tests, ANOVA; non-parametric)
- Correlation (Pearson, Spearman)
- Test choice guidelines

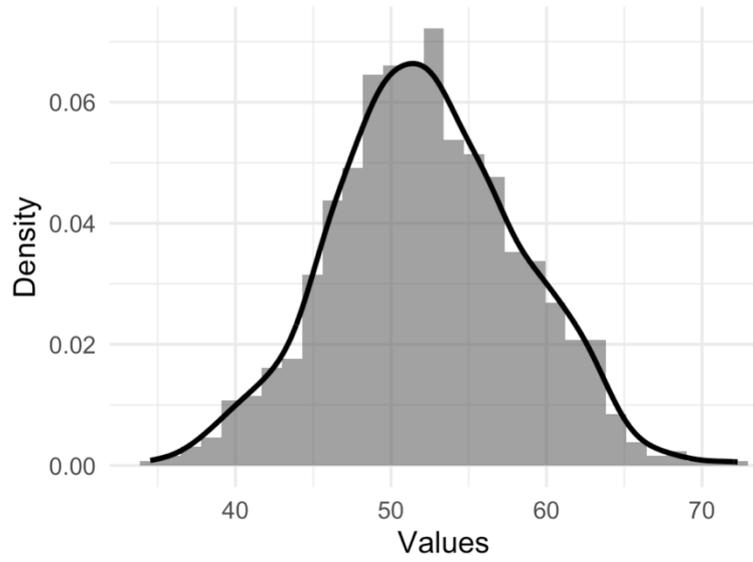
```
x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
[15] 48.66495 62.72148 54.98710 40.20030 56.20814 49.16325 45.59306
[22] 50.69215 45.84397 47.62665 48.24976 41.87984 57.02672 52.92024
[29] 45.17118 59.52289 54.55879 50.22957 57.37075 57.26880 56.92949
[36] 56.13184 55.32351 51.62853 50.16422 49.71717 47.83176 50.75250
[43] 44.40762 65.01374 59.24777 45.26135 49.58269 49.20007 56.67979
[50] 51.49979 53.51991 51.82872 51.74278 60.21161 50.64537 61.09882
[57] 42.70748 55.50768 52.74313 53.29565 54.27784 48.98606 50.00076
[64] 45.88855 45.56925 53.82117 54.68926 52.31803 57.53360 64.30051
[71] 49.05381 38.14499 58.03443 47.74480 47.87195 58.15343 50.29136
[78] 44.67569 53.08782 51.16665 52.03459 54.31168 49.77604 55.86626
[85] 50.67708 53.99069 58.58103 54.61109 50.04441 58.89285 57.96102
[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147
```



```

> x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
[15] 48.66495 62.72148 54.98710 40.20030 56.20814 49.16325 45.59306
[22] 50.69215 45.84397 47.62665 48.24976 41.87984 57.02672 52.92024
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566

```



```

> mean(x)
[1] 52.23827
> sum(x)/length(x)
[1] 52.23827
> sd(x)
[1] 6.027895
> sqrt(sum((mean(x)-x)^2)/(length(x)-1))
[1] 6.027895
> (se=sd(x)/sqrt(length(x)))
[1] 0.1906188
> var(x)
[1] 36.33552
> sum((x - mean(x))^2) / (length(x) - 1)
[1] 36.33552
> median(x)
[1] 52.0056
> min(x)
[1] 34.52097
> max(x)
[1] 72.28588
> quantile(x, probs = c(0, 0.25, 0.5, 0.75, 1))
      0%      25%      50%      75%     100%
34.52097 48.25772 52.00560 56.30350 72.28588
> summary(x)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 34.52  48.26   52.01   52.24  56.30   72.29

```

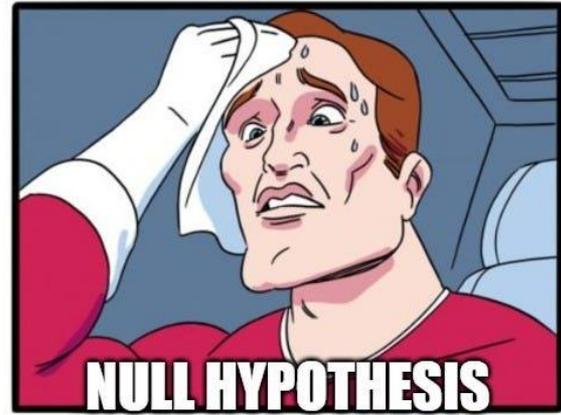
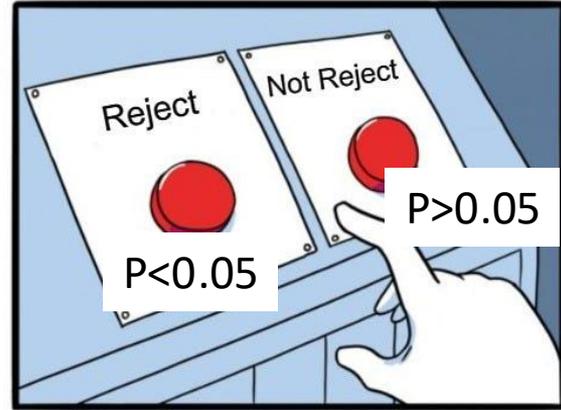
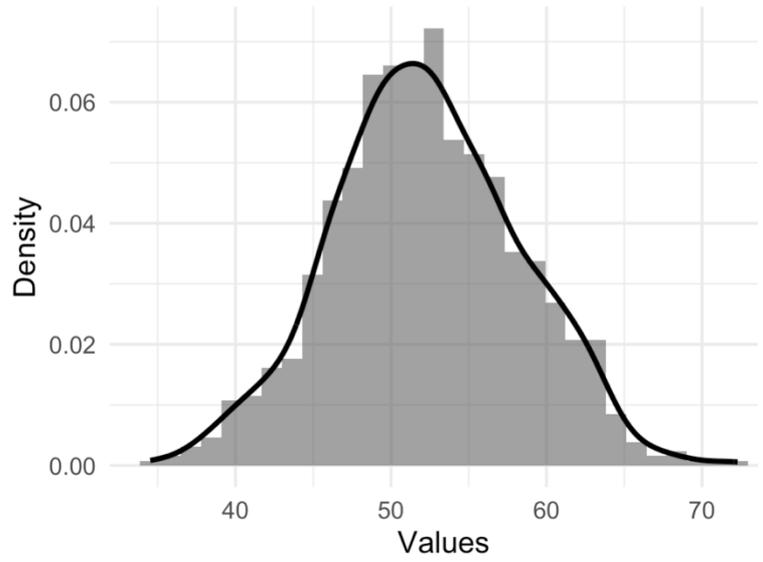
$$s = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}}$$

$$SE = \frac{s}{\sqrt{n}}$$

$$s^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}$$

\bar{x} = sample mean
 μ_0 = hypothesized mean
 s = sample standard deviation
 n = sample size

```
x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147
```



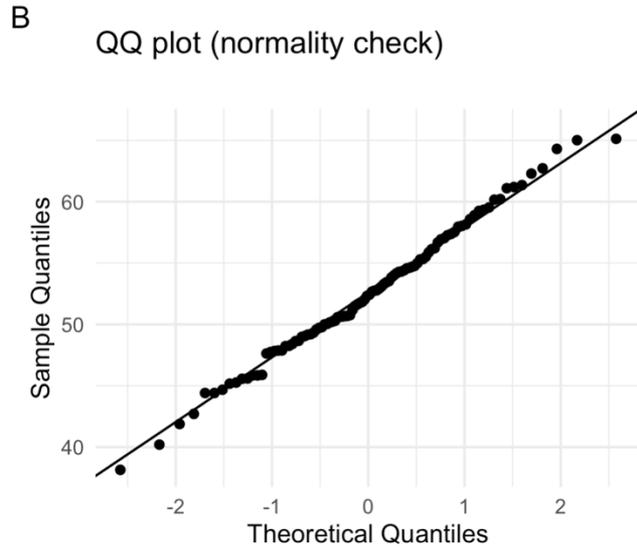
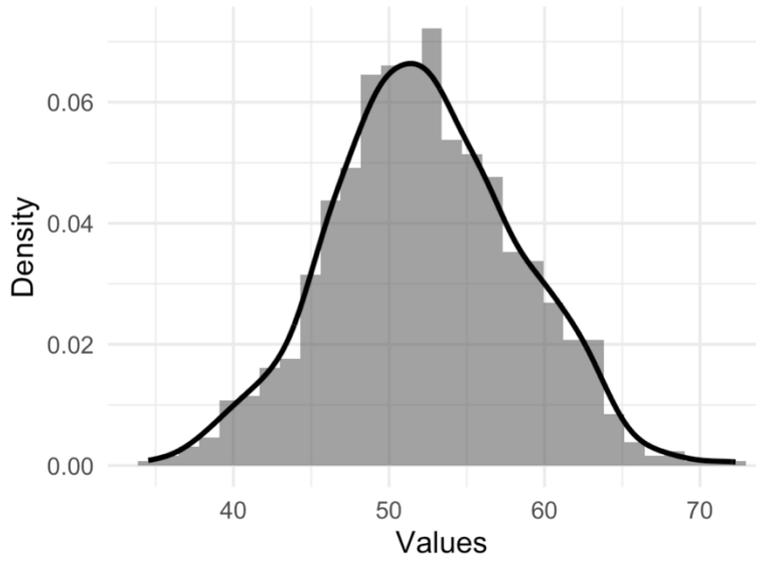
```
x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147
```

Null hypothesis (H_0): The data are normally distributed.
Alternative hypothesis (H_1): The data are not normally distributed.

```
> shapiro.test(x)

Shapiro-Wilk normality test

data: x
W = 0.99388, p-value = 0.9349
```

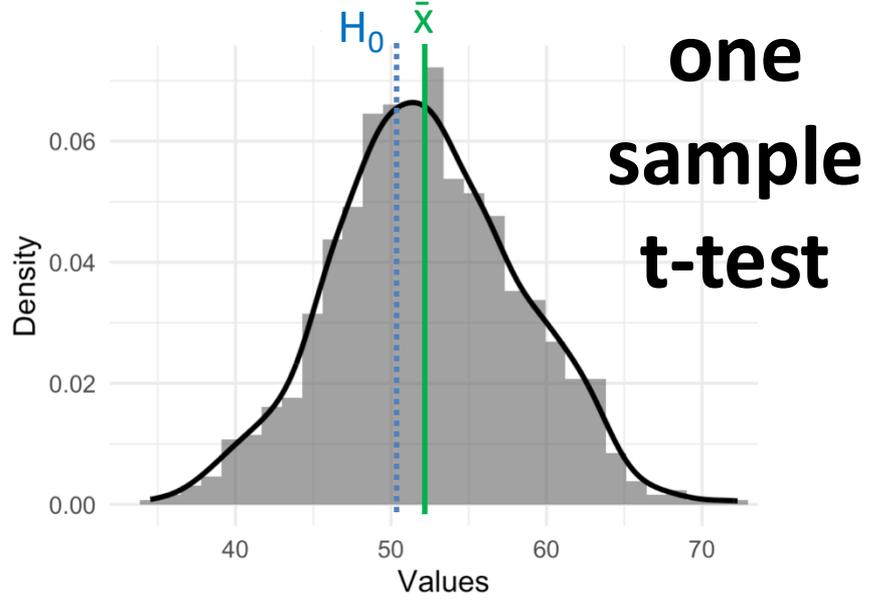


```

x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
[15] 48.66495 62.72148 54.98710 40.20030 56.20814 49.16325 45.59306
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[57] 42.70748 55.50768 52.74313 53.29565 54.27784 48.98606 50.00076
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[78] 44.67569 53.08782 51.16665 52.03459 54.31168 49.77604 55.86626
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147

```

Null hypothesis (H₀): The population mean = some value (μ_0)
Alternative hypothesis (H₁): The population mean $\neq \mu_0$ (two-sided), or $>$ / $<$ (one-sided)



```

> t.test(x, mu = 50)

```

$$t = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$$

One Sample t-test

$$df = n - 1$$

```

data: x
t = 4.8026, df = 99, p-value = 5.569e-06
alternative hypothesis: true mean is not equal to 50
95 percent confidence interval:
 51.74424 54.20026
sample estimates:
mean of x
 52.97225

```

\bar{x} = sample mean
 μ_0 = hypothesized mean
s = sample standard deviation
n = sample size

```

> t<-(mean(x)-50)/(sd(x)/sqrt(length(x))) ##t
> t
[1] 4.802567
> df<-length(x)-1
> pval <- 2 * (1 - pt(abs(t), df))
> pval
[1] 5.568592e-06

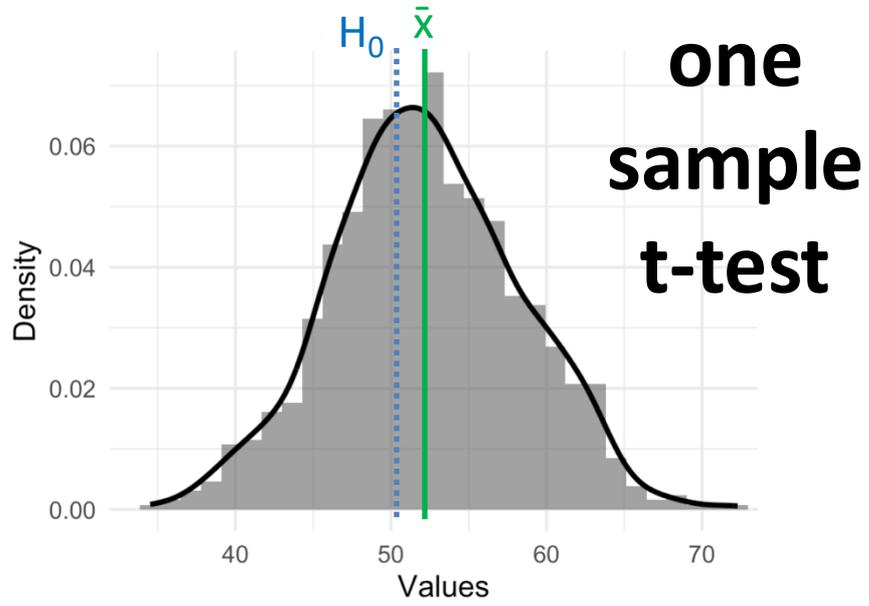
```

```

x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
[15] 48.66495 62.72148 54.98710 40.20030 56.20814 49.16325 45.59306
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[43] 44.40762 65.01374 59.24777 45.26135 49.58269 49.20007 56.67979
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147

```

Null hypothesis (H_0): The population mean = some value (μ_0)
 Alternative hypothesis (H_1): The population mean $\neq \mu_0$ (two-sided), or $>$ / $<$ (one-sided)



```

> t.test(x, mu = 50)

data: x
t = 4.8026, df = 99, p-value = 5.569e-06
alternative hypothesis: true mean is not equal to 50
95 percent confidence interval:
 51.74424 54.20026
sample estimates:
mean of x
52.97225

```

$$CI = \bar{x} \pm t^* \times SE$$

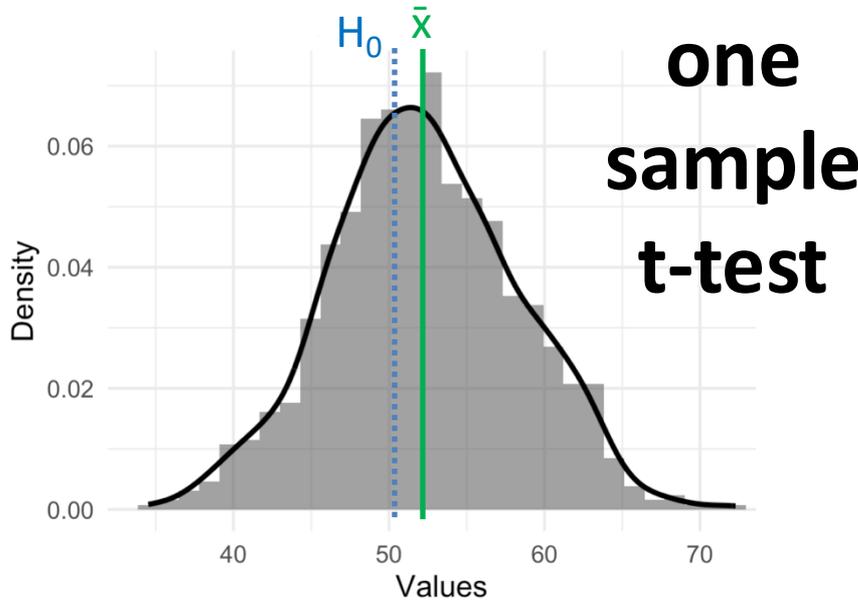
```

> alpha <- 0.05
> df <- length(x) - 1
> t_star <- qt(1 - alpha/2, df) # two-tailed critical value
> mean(x)-sd(x)/sqrt(length(x))*t_star
[1] 51.74424
> mean(x)+sd(x)/sqrt(length(x))*t_star
[1] 54.20026

```

```
x
[1] 48.63715 50.61894 61.35225 52.42305 52.77573 62.29039 54.76550
[8] 44.40963 47.87888 49.32603 59.34449 54.15888 54.40463 52.66410
[15] 48.66495 62.72148 54.98710 40.20030 56.20814 49.16325 45.59306
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[36] 56.13184 55.32351 51.62853 50.16422 49.71717 47.83176 50.75250
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[92] 55.29038 53.43239 48.23256 60.16391 48.39844 65.12400 61.19566
[99] 50.58580 45.84147
```

Null hypothesis (H_0): The population mean = some value (μ_0)
Alternative hypothesis (H_1): The population mean $\neq \mu_0$ (two-sided), or $>$ / $<$ (one-sided)



```
> t.test(x, mu = 50)

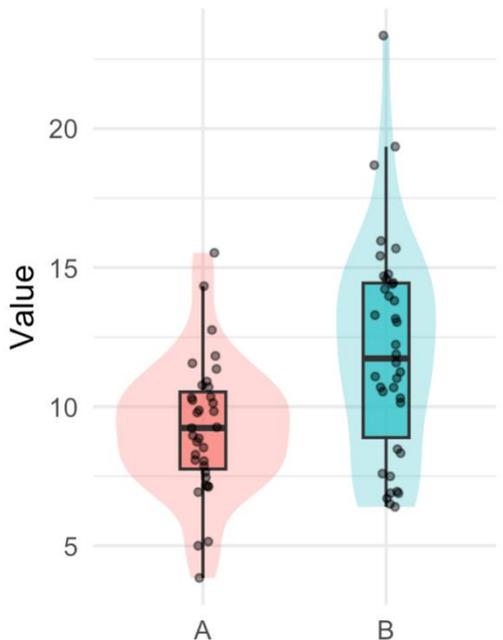
One Sample t-test

data: x
t = 4.8026, df = 99, p-value = 5.569e-06
alternative hypothesis: true mean is not equal to 50
95 percent confidence interval:
 51.74424 54.20026
sample estimates:
mean of x
 52.97225
```

Two sample t-test

```
> df_two
```

	group	value
1	B	15.684490
2	B	10.696464
3	A	5.146352
4	A	7.145144
5	B	11.082309
6	A	9.231723
7	A	8.859320
8	A	9.786076
9	B	6.883855
10	A	12.756990
11	A	10.706160
12	B	6.698663
13	A	4.996174
14	B	14.589816
15	B	11.246168
16	A	7.645287
17	B	13.043797
18	B	7.580457



```
> tt_two <- t.test(value ~ group, data = df_two)
> tt_two
```

Welch Two Sample t-test

data: value by group

t = -3.6613, df = 62.644, p-value = 0.0005172

alternative hypothesis: true difference in means between group A and group B is not equal to 0

95 percent confidence interval:

-4.280188 -1.257436

sample estimates:

mean in group A mean in group B

9.243104

12.011917

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{(s_1^2/n_1)^2}{n_1-1} + \frac{(s_2^2/n_2)^2}{n_2-1}}$$

\bar{x}_1, \bar{x}_2 = sample means

s_1^2, s_2^2 = sample variances

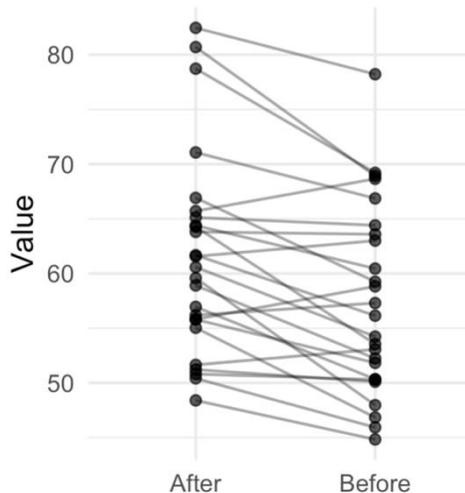
n_1, n_2 = sample sizes

Alternate syntax note:

```
t.test(x1, x2, var.equal = FALSE)
```

Paired t-test

```
> df
  after  before
1  65.70457 68.65839
2  56.94951 50.33579
3  59.58114 47.96439
4  56.18829 57.29763
5  63.80180 63.58607
6  55.03589 46.83742
7  82.45742 78.21918
8  55.79342 51.82677
9  66.91447 59.24740
10 50.41310 45.92759
11 61.68081 56.14247
12 61.56274 63.00493
13 64.39138 60.44929
14 55.81577 58.82193
15 51.21642 50.10190
```



```
> df<-data.frame(after, before)
> tt_paired <- t.test(df$after, df$before, paired = TRUE)
> tt_paired
```

Paired t-test

```
data: df$after and df$before
t = 4.5693, df = 24, p-value = 0.0001242
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 2.231368 5.907615
sample estimates:
mean difference
 4.069491
```

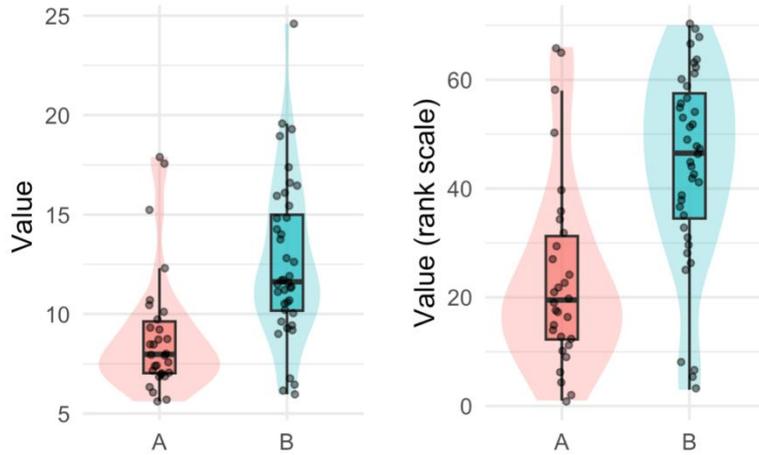
(Same as one sample t-test on difference)

```
> t.test(df$after- df$before)
```

One Sample t-test

```
data: df$after - df$before
t = 4.5693, df = 24, p-value = 0.0001242
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 2.231368 5.907615
sample estimates:
mean of x
 4.069491
```

Wilcoxon test ("non parametric *t*-test")



```
> df_wilx
  group  value
1     B  5.960864
2     A  5.607224
3     B  6.446158
4     B  9.428198
5     A  7.946408
6     B 11.691042
7     A  9.315445
8     B 16.458500
9     B 10.593346
10    A  8.711629
11    A  6.969304
12    B 10.044467
13    B 16.091317
14    A  8.001500
```

```
> wx_rs <- wilcox.test(value ~ group, data = df_wilx)
> wx_rs
```

Wilcoxon rank sum exact test

data: value by group

W = 249, p-value = 1.596e-05

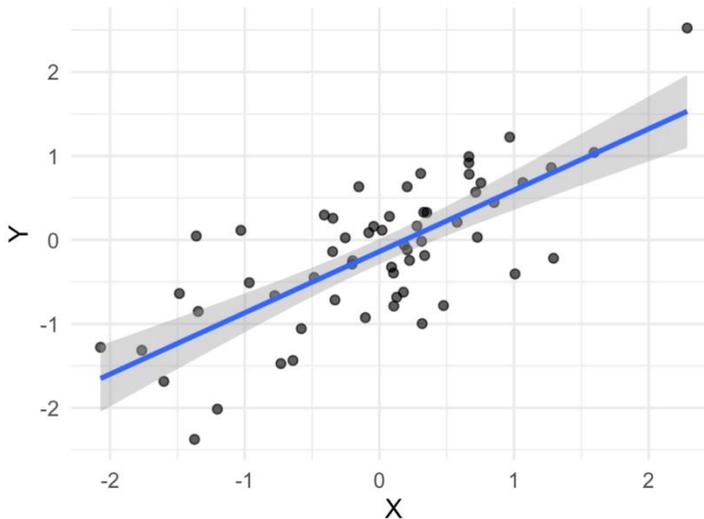
alternative hypothesis: true location shift is not equal to 0

```

> df
      xC      yC
1 -0.34778693 -0.13858920
2  0.66671889  0.78298571
3  0.66478866  0.99223687
4 -1.60079686 -1.68439178
5 -0.20319713 -0.28725030
6 -0.15295493  0.63394353
7  0.07441540  0.28013303
8  1.59382310  1.04195056
9 -2.07130493 -1.27841449
10 0.20650953 -0.11749842
11 -0.10440737 -0.92468670
12 -1.48556503 -0.63764525
13 -0.19935287 -0.24739595
14 -1.02915229  0.11441361

```

Pearson correlation



```

> ct_pear <- cor.test(xC, yC, method = "pearson")
> ct_pear

```

Pearson's product-moment correlation

```

data: xC and yC
t = 8.2438, df = 58, p-value = 2.393e-11
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.5908006 0.8330748
sample estimates:
 cor
0.7345317

```

Spearman correlation (non-parametric)

```
> cor_spear <- cor.test(df_cor_s$x, df_cor_s$y, method = "spearman")
> cor_spear
```

Spearman's rank correlation rho

data: df_cor_s\$x and df_cor_s\$y

S = 22610, p-value < 2.2e-16

alternative hypothesis: true rho is not equal to 0

sample estimates:

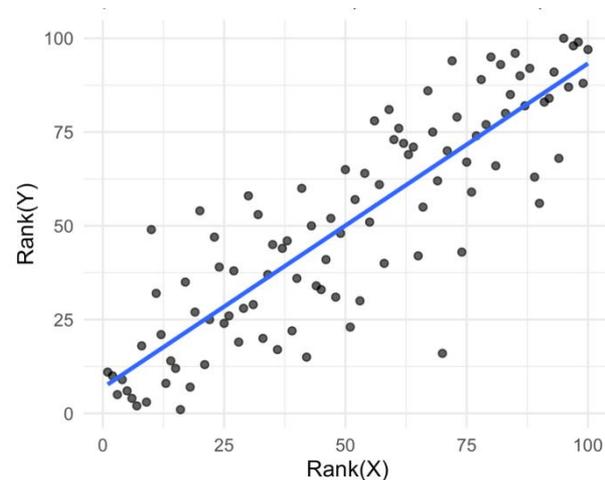
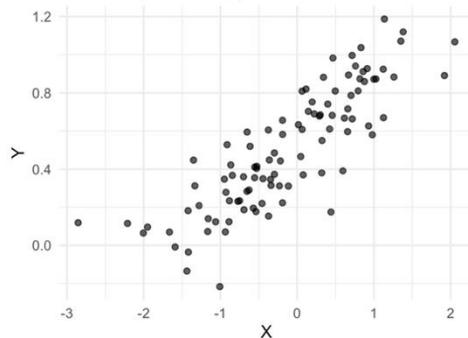
rho

0.8643264

```
> df_cor_s
```

	x	y	rank_x	rank_y
1	-0.65299176	0.594404400	30	58
2	1.35050938	1.070701180	97	98
3	-0.52991148	0.402799808	37	44
4	-0.92826260	0.278389803	19	27
5	-0.36435588	0.448172637	43	50
6	0.14544443	0.702384925	60	73
7	0.30126605	0.684225086	64	71
8	-2.85561802	0.118934330	1	11
9	1.13652272	1.187260760	95	100
10	0.65905478	0.715439229	77	74

Ranked >>>



Spearman correlation (non-parametric)

```
> cor_spear <- cor.test(df_cor_s$x, df_cor_s$y, method = "spearman")  
> cor_spear
```

Spearman's rank correlation rho

data: df_cor_s\$x and df_cor_s\$y

S = 22610, p-value < 2.2e-16

alternative hypothesis: true rho is not equal to 0

sample estimates:

rho

0.8643264

```
> cor.test(df_cor_s$rank_x, df_cor_s$rank_y, method = "pearson")
```

Pearson's product-moment correlation

data: df_cor_s\$rank_x and df_cor_s\$rank_y

t = 17.013, df = 98, p-value < 2.2e-16

alternative hypothesis: true correlation is not equal to 0

95 percent confidence interval:

0.8044853 0.9067980

sample estimates:

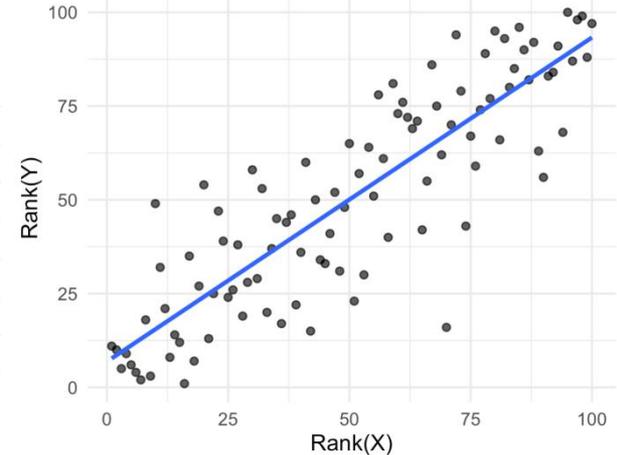
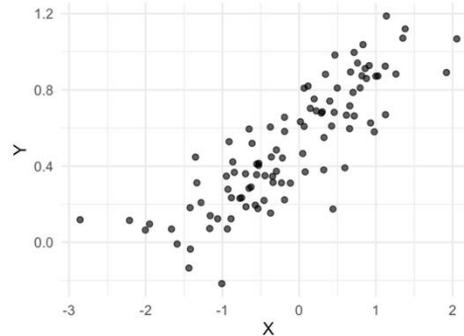
cor

0.8643264

```
> df_cor_s
```

	x	y	rank_x	rank_y
1	-0.65299176	0.594404400	30	58
2	1.35050938	1.070701180	97	98
3	-0.52991148	0.402799808	37	44
4	-0.92826260	0.278389803	19	27
5	-0.36435588	0.448172637	43	50
6	0.14544443	0.702384925	60	73
7	0.30126605	0.684225086	64	71
8	-2.85561802	0.118934330	1	11
9	1.13652272	1.187260760	95	100
10	0.65905478	0.715439229	77	74

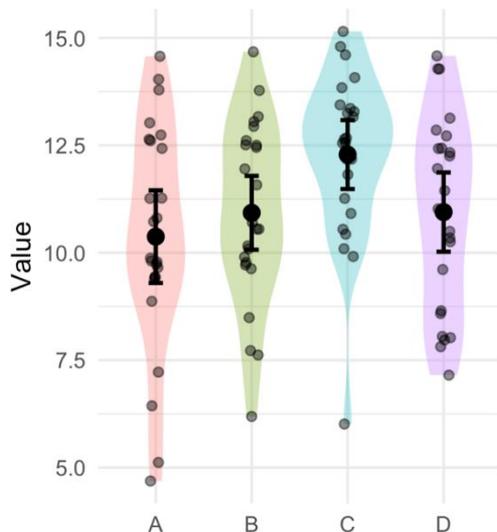
Ranked >>>



One way analysis of variance (ANOVA)

```
> df_aov
```

	group	value
1	A	13.790387
2	D	9.609565
3	C	11.265531
4	C	12.370461
5	A	9.442422
6	B	10.160362
7	C	14.605085
8	B	13.050642
9	B	10.934007
10	A	9.874572



```
> anovafit <- aov(value ~ group, data = df_aov)
> summary(anovafit)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
group	3	49.5	16.487	3.308	0.0234 *
Residuals	96	478.5	4.985		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> fit
```

```
Call:
```

```
aov(formula = value ~ group, data = df_aov)
```

```
Terms:
```

	group	Residuals
Sum of Squares	49.4604	478.5241
Deg. of Freedom	3	96

```
Residual standard error: 2.232628
```

```
Estimated effects may be unbalanced
```

```
> TukeyHSD(fit)
```

```
Tukey multiple comparisons of means
95% family-wise confidence level
```

```
Fit: aov(formula = value ~ group, data = df_aov)
```

\$group	diff	lwr	upr	p adj
B-A	0.55539226	-1.0956860	2.2064706	0.8154664
C-A	1.91041309	0.2593348	3.5614914	0.0165497
D-A	0.57157795	-1.0795003	2.2226563	0.8021317
C-B	1.35502083	-0.2960575	3.0060991	0.1462149
D-B	0.01618569	-1.6348926	1.6672640	0.9999939
D-C	-1.33883514	-2.9899134	0.3122432	0.1540804

```
> str(df_aov)
```

```
'data.frame': 100 obs. of 2 variables:
```

```
$ group: Factor w/ 4 levels
```

```
"A","B","C","D": 1 4 3 3 1 2 3 2 2 1 ...
```

```
$ value: num 13.79 9.61 11.27 12.37 9.44
```

Binomial test

```
# survival data  
survived <- 23  
total <- 30
```

```
> binom.test(survived, total, p = 0.5, alternative = "two.sided")
```

Exact binomial test

data: survived and total

number of successes = 23, number of trials = 30, p-value = 0.005223

alternative hypothesis: true probability of success is not equal to 0.5

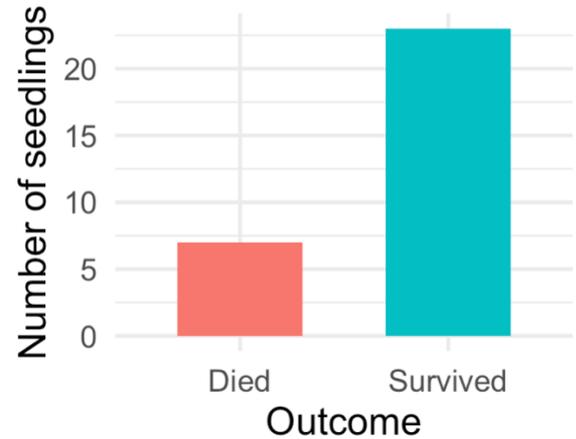
95 percent confidence interval:

0.5771635 0.9006621

sample estimates:

probability of success

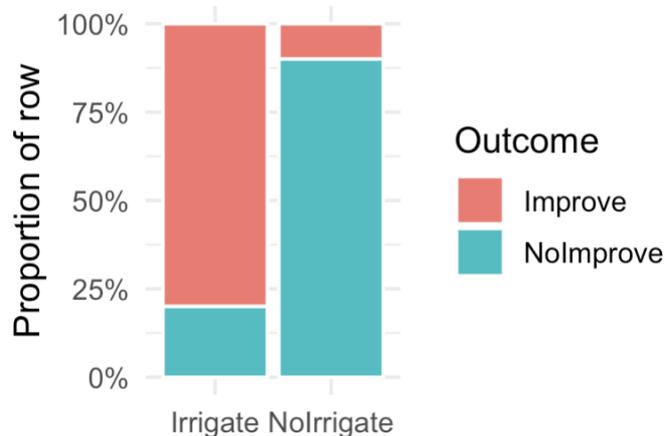
0.7666667



Fishers Test

```
> tab_2x2
```

Treatment	Outcome	
	Improve	NoImprove
Irrigate	8	2
NoIrrigate	1	9



```
> fish_2x2 <- fisher.test(tab_2x2)
```

```
> fish_2x2
```

Fisher's Exact Test for Count Data

```
data: tab_2x2
```

```
p-value = 0.005477
```

```
alternative hypothesis: true odds ratio is not equal to 1
```

```
95 percent confidence interval:
```

```
2.057999 1740.081669
```

```
sample estimates:
```

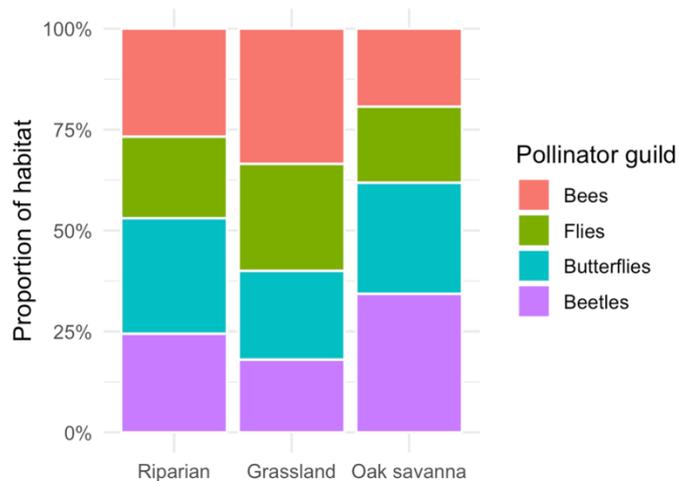
```
odds ratio
```

```
27.32632
```

Chi-squared test

```
> tab_rc
```

Habitat	Guild			
	Bees	Flies	Butterflies	Beetles
Riparian	57	43	61	52
Grassland	67	53	44	36
Oak savanna	40	39	57	71



```
> chi_rc <- chisq.test(tab_rc)
```

```
> chi_rc
```

Pearson's Chi-squared test

```
data: tab_rc
```

```
X-squared = 23.561, df = 6, p-value = 0.0006289
```

Parametric tests

Assume your data follow a certain distribution (i.e. normal).

They use the **actual values** (means, variances).

Examples:

- **t-test** (compares means between groups)
- **Pearson correlation** (measures strength of a straight-line relationship)

 Advantages: More powerful if the assumptions hold (they can detect smaller effects).

 Drawback: Can give misleading results if assumptions are badly violated (e.g., very skewed data, outliers, small sample sizes).

Non-parametric tests

Do not assume normality.

They use **ranks or order of the data** instead of raw values.

Examples:

- **Wilcoxon tests** (rank-based alternative to the t-test)
- **Spearman correlation** (rank-based alternative to Pearson)

 Advantages: Work with skewed data, outliers, small samples, or ordinal data (e.g., ratings 1–5).

 Drawback: Less powerful than parametric tests when data actually *are* normal.

Correlation (Pearson vs. non-normal data)

- **Pearson correlation** assumes bivariate normality (both variables normally distributed with a linear relationship).
- **Violations** (skew, heavy tails, outliers):
 - Outliers can **inflate correlation** spuriously → **false positives** (detecting significance when no real relationship).
 - Nonlinear but monotonic relationships can give **low Pearson r** even if association is strong → **false negatives**.
- **Spearman correlation** (rank-based) is robust to non-normality and monotonic-but-nonlinear patterns.

Side-by-side

t-test vs. Wilcoxon

- *t-test*: compares group means, assumes data \approx normal.
- *Wilcoxon*: compares group ranks/medians, no normality assumption.

Pearson vs. Spearman

- *Pearson*: checks linear relationship, sensitive to outliers, needs numeric data with normal-like distribution.
- *Spearman*: checks monotonic relationship (just whether values go up or down together), based on ranks, robust to outliers.

◆ t-test (two groups)

- Assumes each group is normally distributed with equal variances (Welch's version relaxes equal variance).
- **Violations:**
 - With **large samples** ($n > \sim 30$ per group), the Central Limit Theorem helps → type I error (false positives) stays near 5%.
 - With **small samples:**
 - **Heavy tails / outliers:** can inflate type I error → **false positives**.
 - **Skewness:** reduces power → **false negatives** (harder to detect real differences).
- In practice: non-normality is more likely to cause **loss of power** (false negatives) unless outliers dominate, in which case **false positives** can rise.

◆ ANOVA (more than 2 groups)

- Assumes **normal residuals** and **homogeneity of variances**.
- **Violations:**
 - **Unequal variances + unequal group sizes** → especially dangerous, can lead to **inflated type I error (false positives)**.
 - **Pure non-normality with equal variances** → mainly reduces power → **false negatives**.
- That's why we often check with **Levene's / Fligner–Killeen tests** for variance equality, and use **Kruskal–Wallis** when assumptions fail.

Rough summary and guide (green discussed in lecture):

Goal	Parametric test	Non-parametric alternative	When to use parametric	When to use non-parametric
Compare one sample mean vs. a value	One-sample t-test	Wilcoxon signed-rank	Data \approx normal	Data skewed, ordinal, outliers
Compare two independent groups	Two-sample t-test	Mann–Whitney U (a.k.a. Wilcoxon rank-sum)	Normal-ish distribution, equal variances	Skewed, ordinal data, unequal variances, outliers
Compare two paired samples (before/after)	Paired t-test	Wilcoxon signed-rank	Normal-ish differences	Non-normal differences, small N, outliers
Compare >2 groups	ANOVA	Kruskal–Wallis	Normal-ish, equal variances	Skewed/ordinal, unequal variances
Compare >2 repeated measures	Repeated-measures ANOVA	Friedman test	Normal-ish, sphericity assumption	Non-normal, ordinal, violations of sphericity
Test correlation	Pearson correlation	Spearman correlation	Linear relationship, normal data	Monotonic (not necessarily linear), skewed/outliers, ordinal
Test association in counts	Chi-squared test	Fisher's exact test	Large sample, expected counts >5	Small sample, expected counts <5
Test a sample proportion vs. expected probability	Large-sample z-test for proportions (normal approx)	Binomial test	Large n (so normal approximation to binomial is valid, expected successes/failures >5)	Small n, skewed proportions, exact inference needed