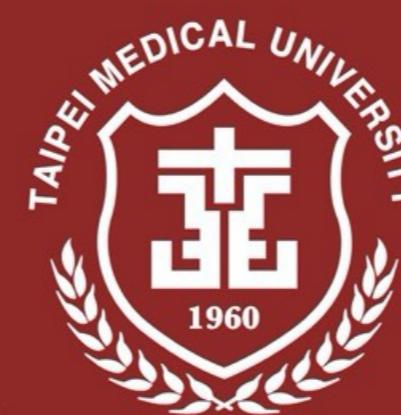


Psychol. Statistics using R



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Nonparametric Testing

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Statistics

1. Recap of Distribution & Assumptions

- Violation of assumptions, Nonparametric: Ranks & Sign Test

2. Nonparametric Tests

- Wilcoxon signed-rank & rank-sum tests

3. [R] Hands-on Practices

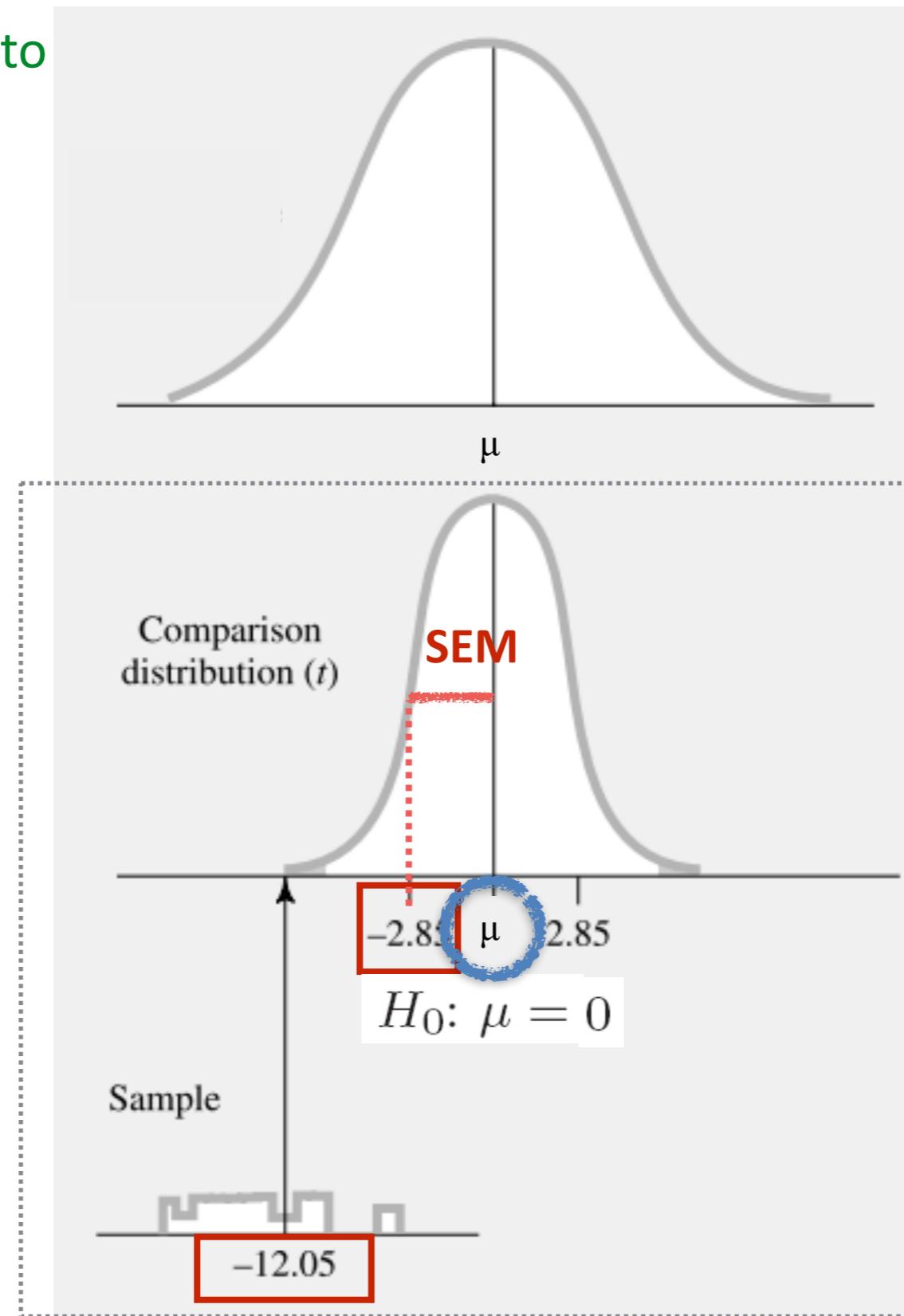
Theories

Practice

Assignment

Parametric Statistics

- Use the sample mean to compare with the population mean in **H₀ distribution**



- ▶ Compare the sample mean to 0 according to the SEM

$$\frac{-12.05}{2.85} = -4.2$$

Population
null hypothesis (H_0)

from current data for inference

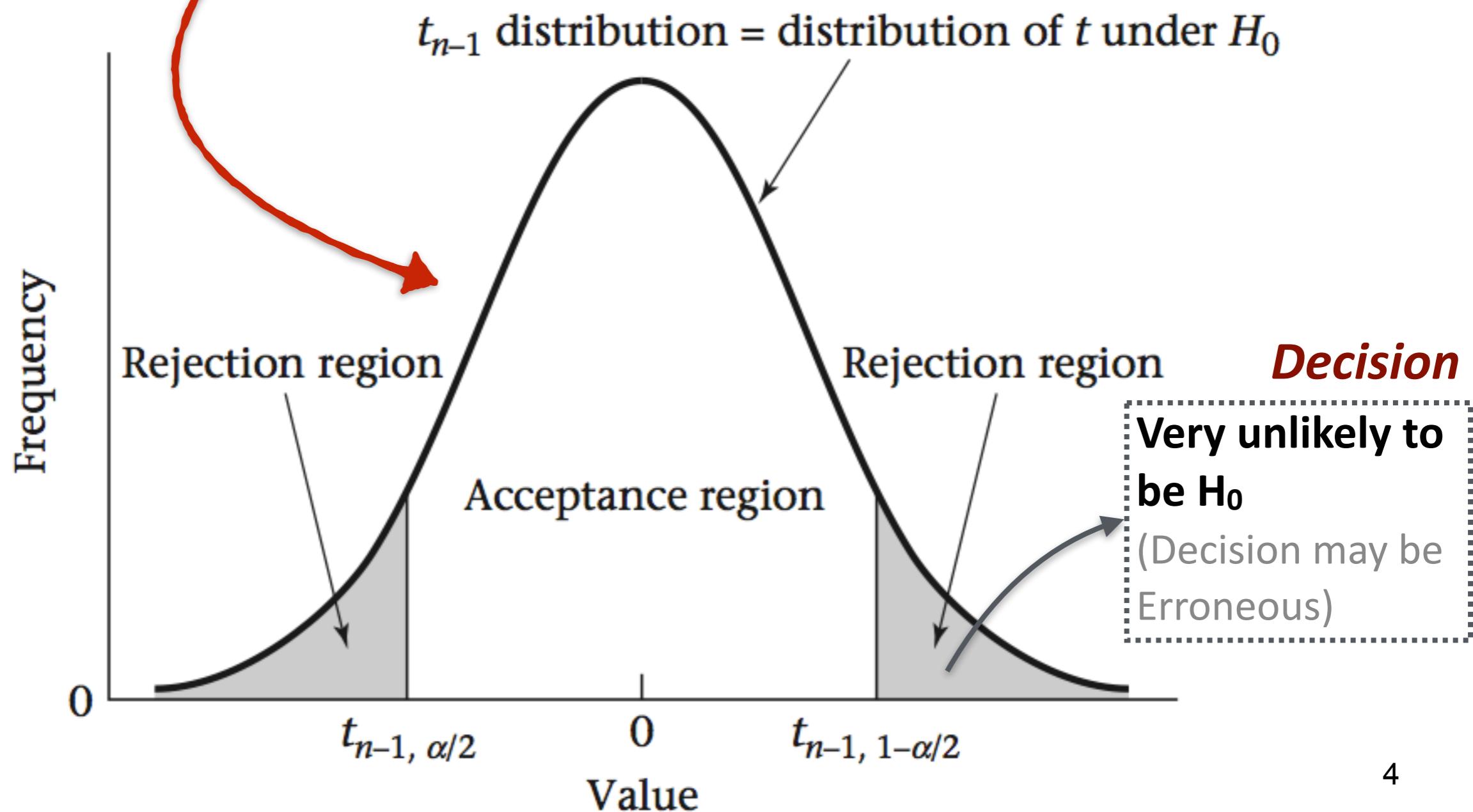
Estimation
*unreliability for estimation
from the presumed sampling distribution (e.g., *t*-distribution)*

Sample
descriptive stat.

Parametric Testing

This prob. distribution corresponds to H_0

$H_0: \mu = c$	$E(t) = 0$
$H_a: \mu \neq c$	$E(t) \neq 0$



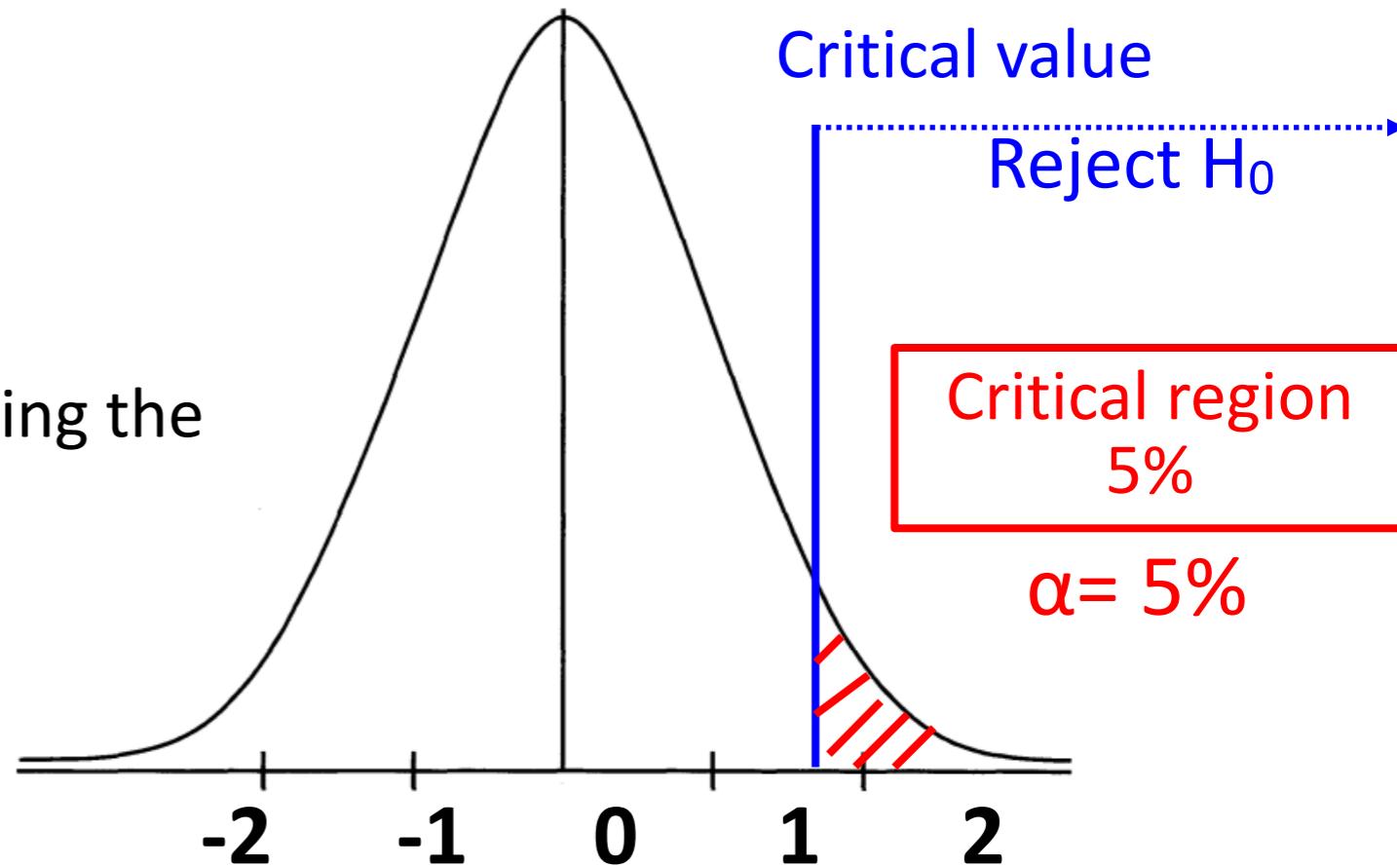
Types of decision errors

The probability of a **type I error** is the probability of rejecting the null hypothesis when H_0 is true.

- **Type I error (α)**

- ➔ Falsely support the research hypothesis
- ➔ The chance of finding significant effects when no effects are in reality.
- ➔ Control the probability by establishing the cutoff (critical value) or alpha level
($p=.05$, $\alpha=.05$, critical region = 5%)

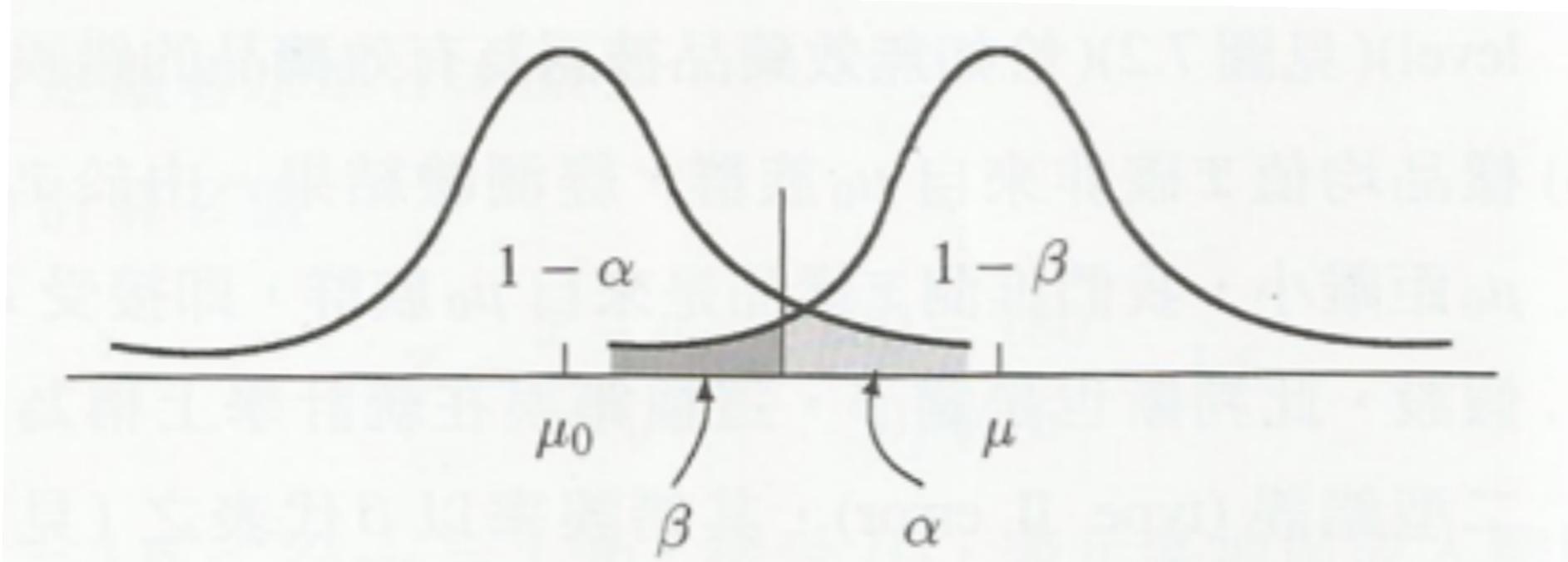
- ▶ We are willing to risk falsely supporting the research hypothesis 5% of the time.



Types of decision errors

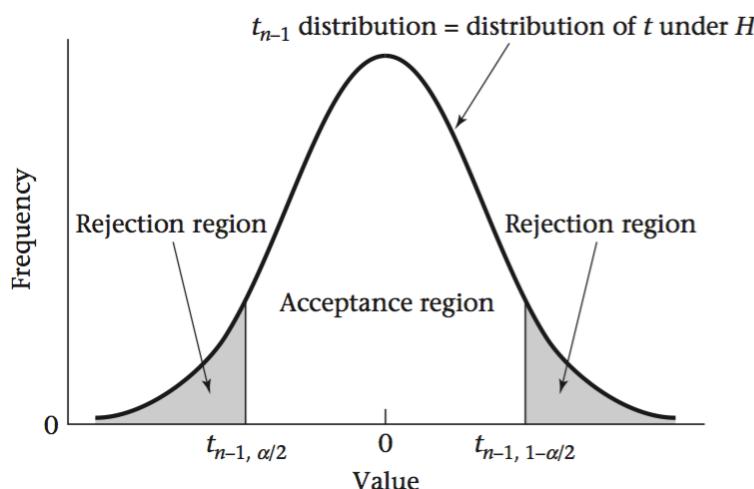
The probability of a **type II error** is the probability of accepting the null hypothesis when H_1 is true. This probability is a function of μ as well as other factors.

- **Type II error (β)**
 - Missing an effect that actually exists.
 - The chance of accepting no effect when difference exists in reality.
 - We know that α and β are inversely related:
 - When α increases, β decreases.
 - When α decreases, β increases.
 - There is always a **trade-off** between two types of errors



Decision in Hypothesis Testing

- Type I error
 - Falsely support the alternative hypothesis when there is no effect in reality.
- Power (1 - Type II error)
 - Testing can detect differences when there is actually an effect.



Real Situation

Research Hypothesis is True	Null Hypothesis is True
Right	Wrong Type I error
Wrong Type II error	Right

Decision

Reject the Null Support Research	
Accept the Null Inconclusive	

Assumptions of *t*-test

● Parametric tests

- ▶ Based on Normal distribution (from original population);
- ▶ Data are measured at the **interval scales**.
- ▶ (independent *t*-test) Scores in different conditions are independent.

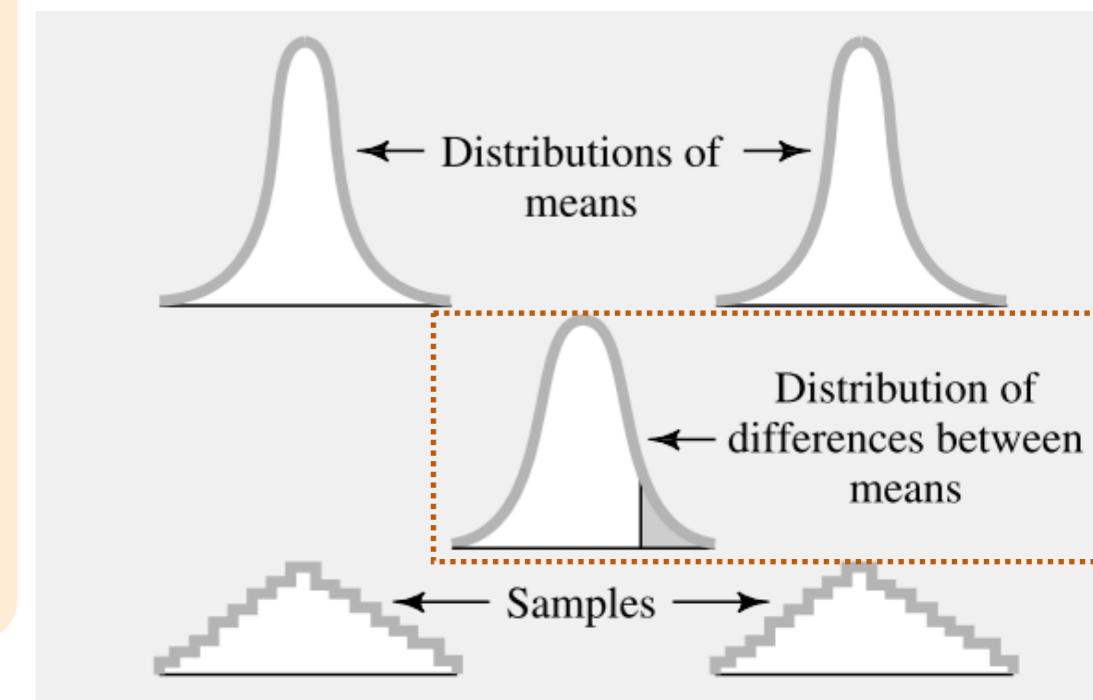
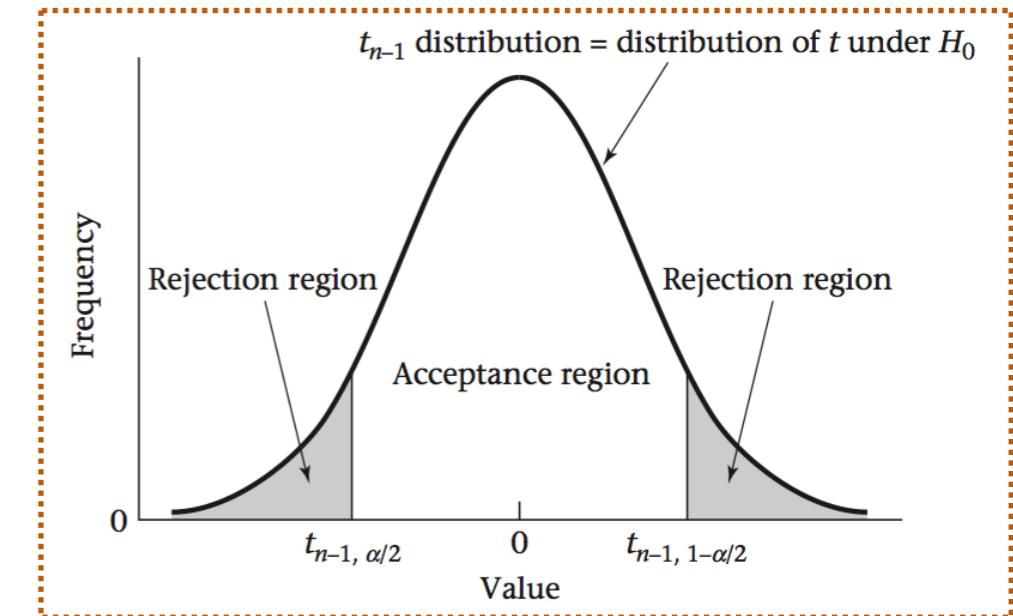
● Normality:

- ▶ (independent *t*-test) Sampling distribution should be normally distributed.
- ▶ (paired *t*-test) Sampling distribution of the differences should be normal.

● Homogeneity of variance:

- ▶ (independent *t*-test) Theoretically, variance shall be equal.

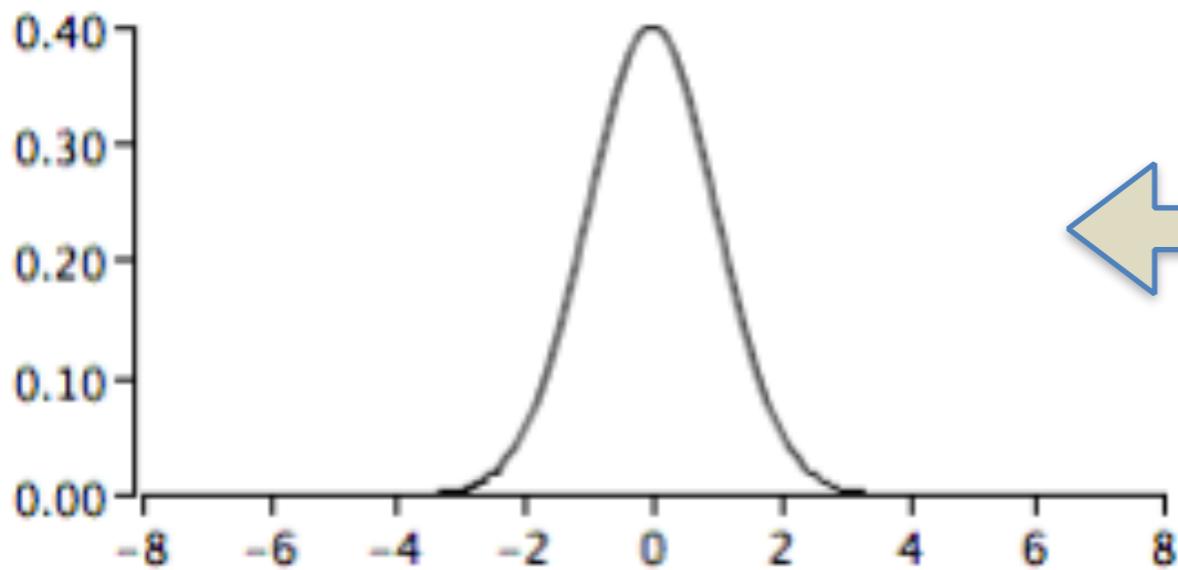
How large the unreliability is...



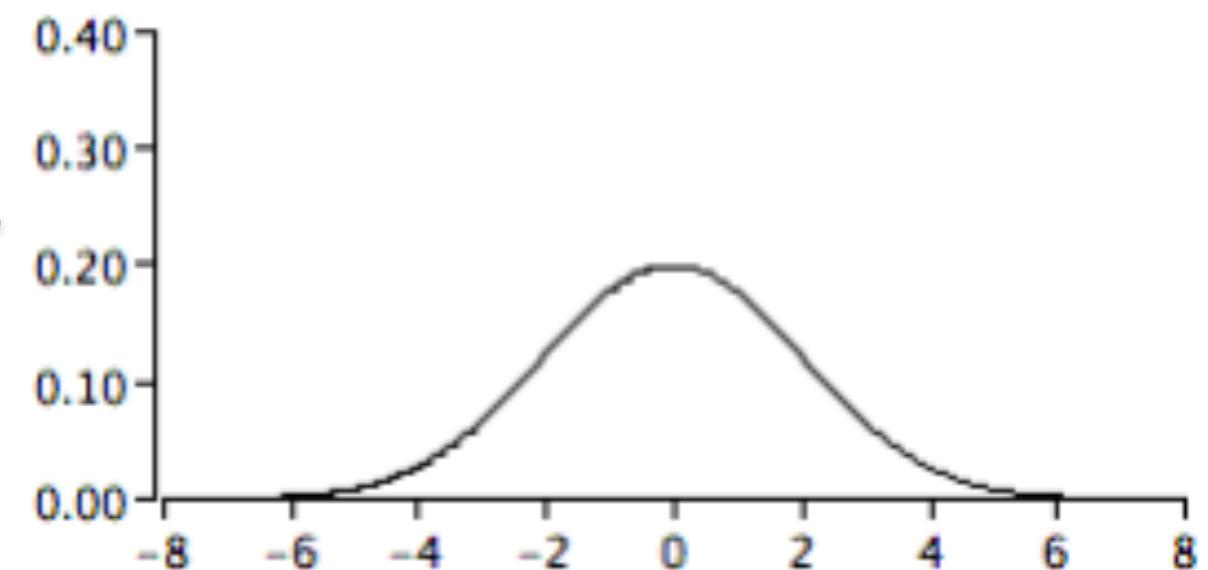
Violation of Assumptions

- Violation of Variance Homogeneity
 - (t-test) **Welch's approximation** to adjust degree of freedom
 - (f-test) **Welch's F test** for adjustments (*oneway.test* in R)
 - (f-test) → **Non-parametric counterparts**

Population 1



Population 2



Violation of Assumptions

- Violation of Normality Assumption

- Data Transformation

(changes distribution, such as *log* or *sqrt*)

- (t-test or f-test) → Non-parametric tests

Data Transformation

Log transformation ($\log(X_i)$): Taking the logarithm of a set of numbers squashes the right tail of the distribution. As such it's a good way to reduce positive skew. However, you can't take the log of zero or negative numbers, so if your data tend to zero or produce negative numbers you need to add a constant to all of the data before you do the transformation. For example, if you have zeros in the data then do $\log(X_i + 1)$, or if you have negative numbers add whatever value makes the smallest number in the data set positive.

Square root transformation ($\sqrt{X_i}$): Taking the square root of large values has more of an effect than taking the square root of small values. Consequently, taking the square root of each of your scores will bring any large scores closer to the centre – rather like the log transformation. As such, this can be a useful way to reduce positive skew; however, you still have the same problem with negative numbers (negative numbers don't have a square root).

Reciprocal transformation ($1/X_i$): Dividing 1 by each score also reduces the impact of large scores. The transformed variable will have a lower limit of 0 (very large numbers will become close to 0). One thing to bear in mind with this transformation is that it reverses the scores: scores that were originally large in the data set become small (close to zero) after

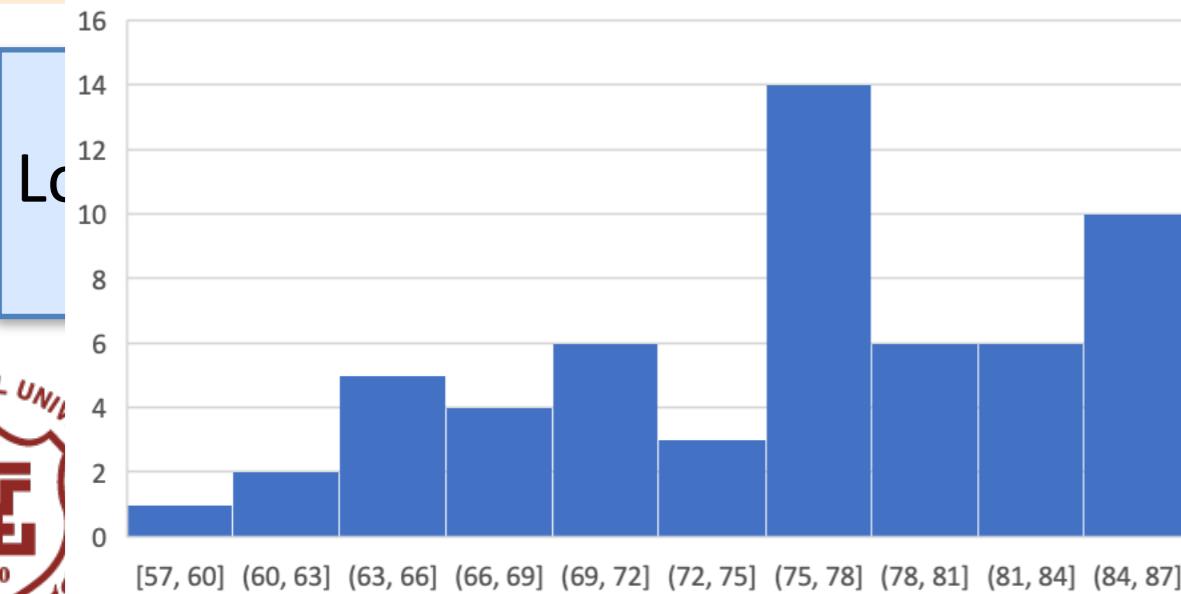
Can Correct For

Positive skew,
unequal variances

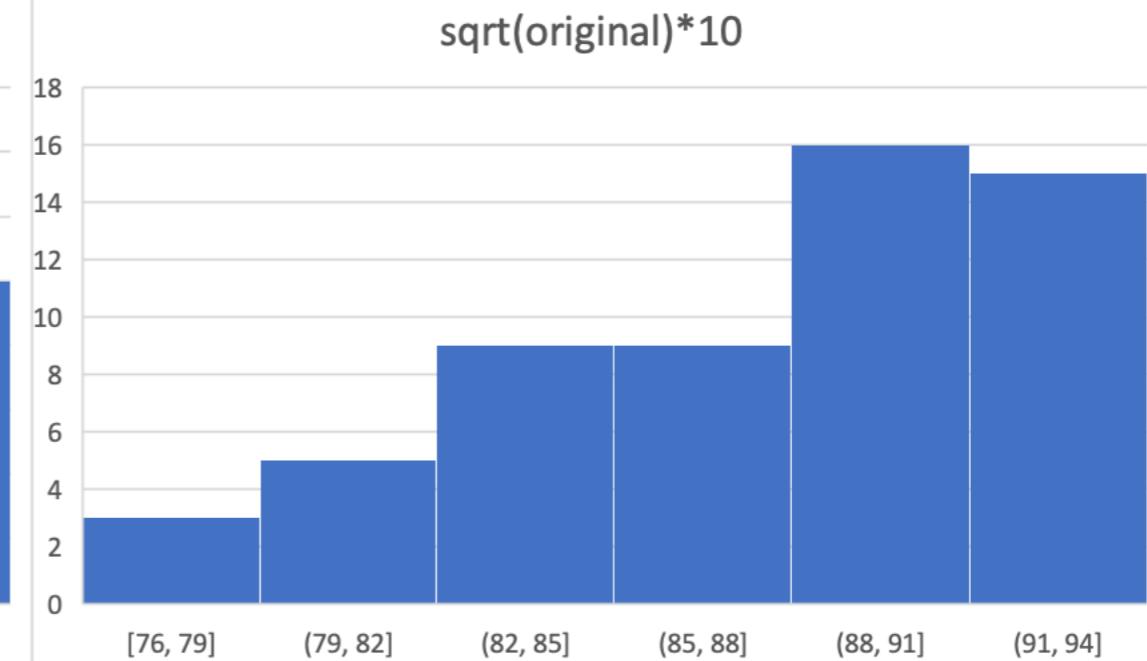
Positive skew,
unequal variances

Positive skew,
unequal variances

original



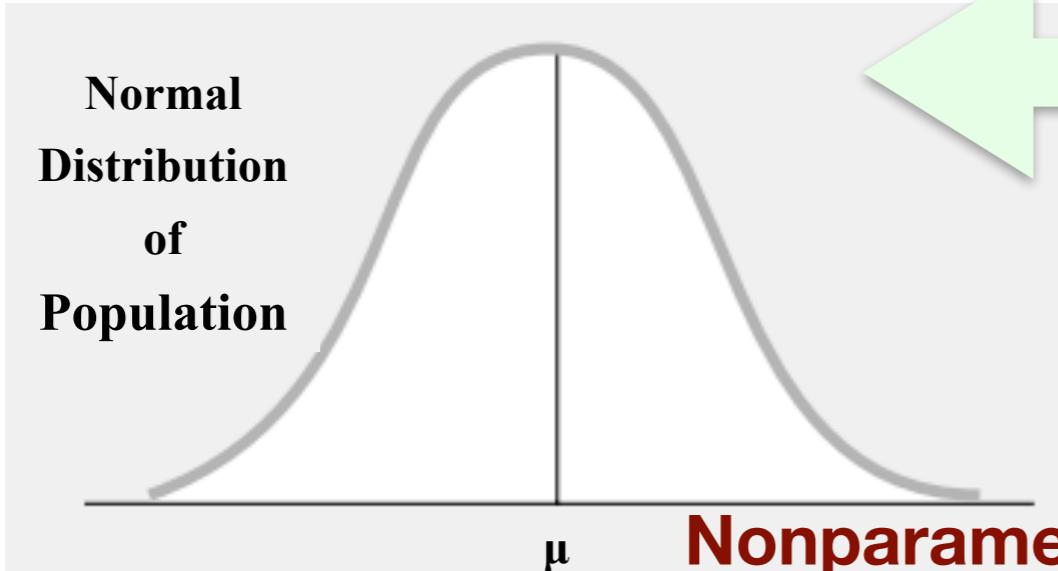
$\sqrt{\text{original}} * 10$



Big scores have become small and small scores have become big!

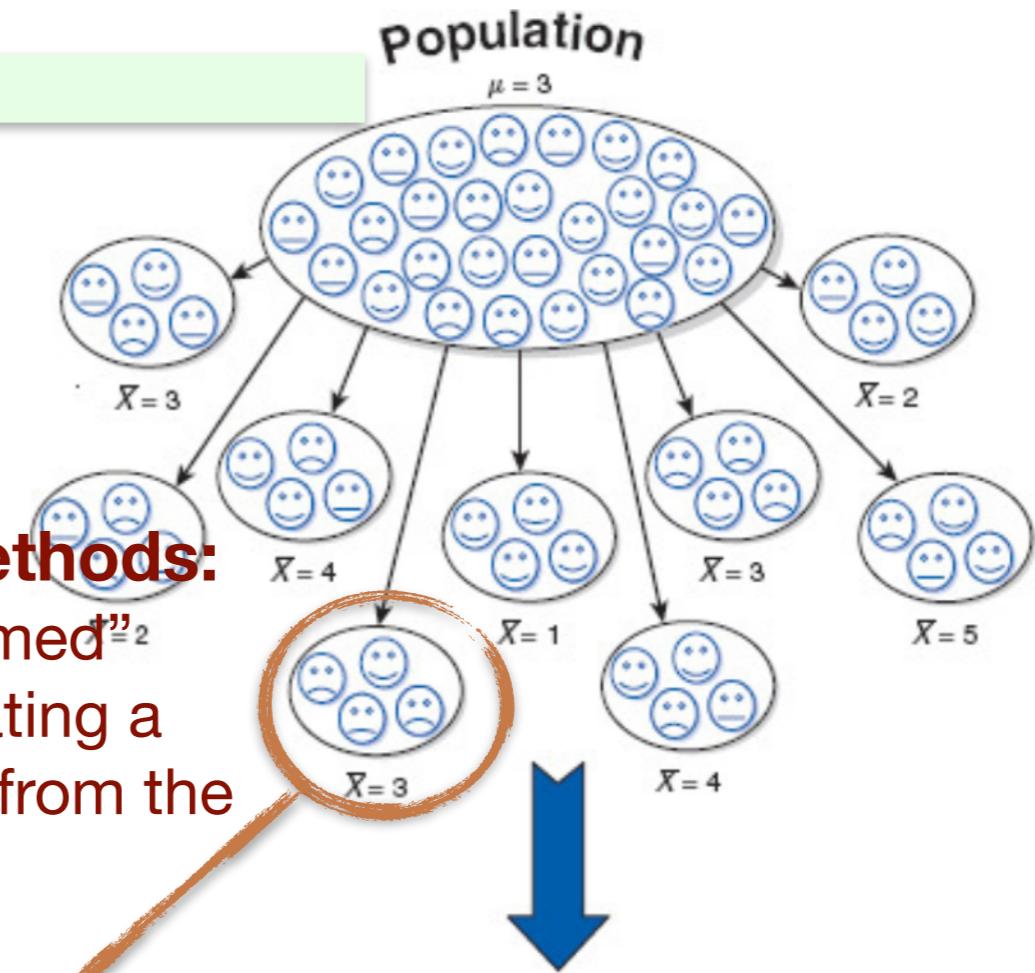


Parametric vs. Nonparametric



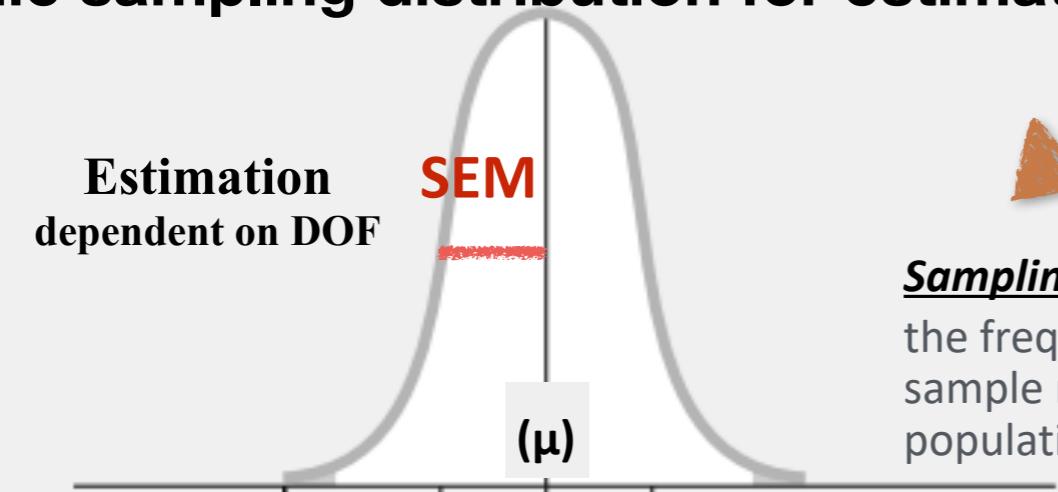
$$H_0: \mu = 0$$

Nonparametric methods:
No use of "presumed" distribution, generating a sampling distribution from the single data



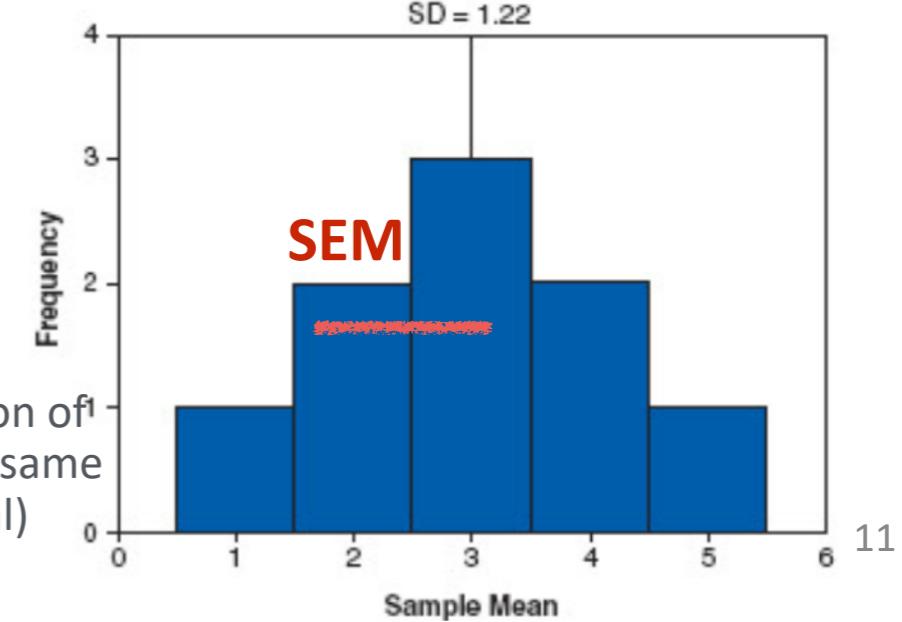
Parametric methods:

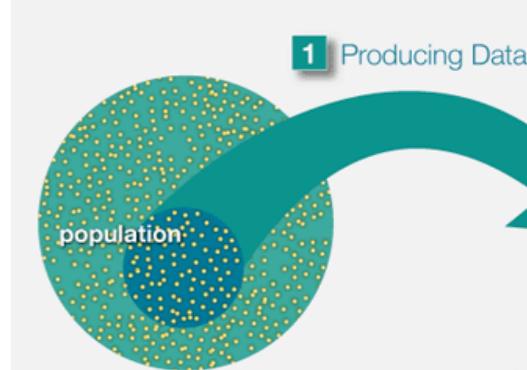
With single data, we use a "presumed" distribution to mimic sampling distribution for estimation



Sampling distribution:

the frequency distribution of sample means from the same population. (symmetrical)





Types of Variables

- **Numeric variables**

- Equal-interval variables (interval scales)

- Continuous variable: e.g., GPA; height
 - Discrete counts: e.g., the number of time visiting dentist
 - Proportions: e.g., percentage, rate

- Rank-order variables (ordinal/discrete scales)

- e.g., order of finishing a race; birth order of children
 - Physical activity level (low, moderate and high)

- **Nominal variables**

- Gender (male, female)
 - Ethnicity (Caucasian, African American, Asian and Hispanic)
 - Profession (surgeon, doctor, nurse, dentist)

Non-Parametric Statistics

- Does not require the assumption of **Normality**
 - **Distribution-free tests**, fewer assumptions, broader applicability
 - Useful when the sample size < 30 (non-Gaussian dist.)
 - Uses **ranks** (1 as the lowest value) instead of the values
 - Less susceptible to the outliers
 - Remove 0 difference (remove it from DOF as well)
 - Average generated ranks for equal difference values
- While parametric stat. focuses on the **mean** of a population, nonparametric stat. focuses on the **median**.
- Even though it is **robust**, nonparametric tests suffer from **Less power** than the parametric statistics. (Because we lost some information because of ranking)



Non-Parametric Tests

	Parametric	Nonparametric
Assumed distribution	normal	any
Assumed variance	homogenous	any
Type of variables	interval or ratio	nominal or ordinal
Data set relationships	independent	any
Central measure	mean	median
Advantage	more powerful	simple, less affected by outliers

https://maxstat.de/images/Dokumentation/parametric_vs_nonparametric_tests.htm#:~:text=Nonparametric%20tests%20are%20less%20powerful,position%20of%20pairs%20of%20scores.

Non-Parametric Statistics & Hypothesis Testing

$P(w \neq M)$

Non-Parametric

test probability away from median

1-Sample or 2-samples (dep.)

2-samples (indep.)

Sign Test

Wilcoxon Signed-Rank

Mann-Whitney U

Binomial dist. on
 $(+)$ & $(-)$

check **pbinom**
& **binom.test**

Sign + Ranking,
test probability away
from median

check **psignrank**
& **wilcox.test**

Pooled ranking,
test probability away
from median

check **pwilcox** &
wilcox.test

Hypothesis

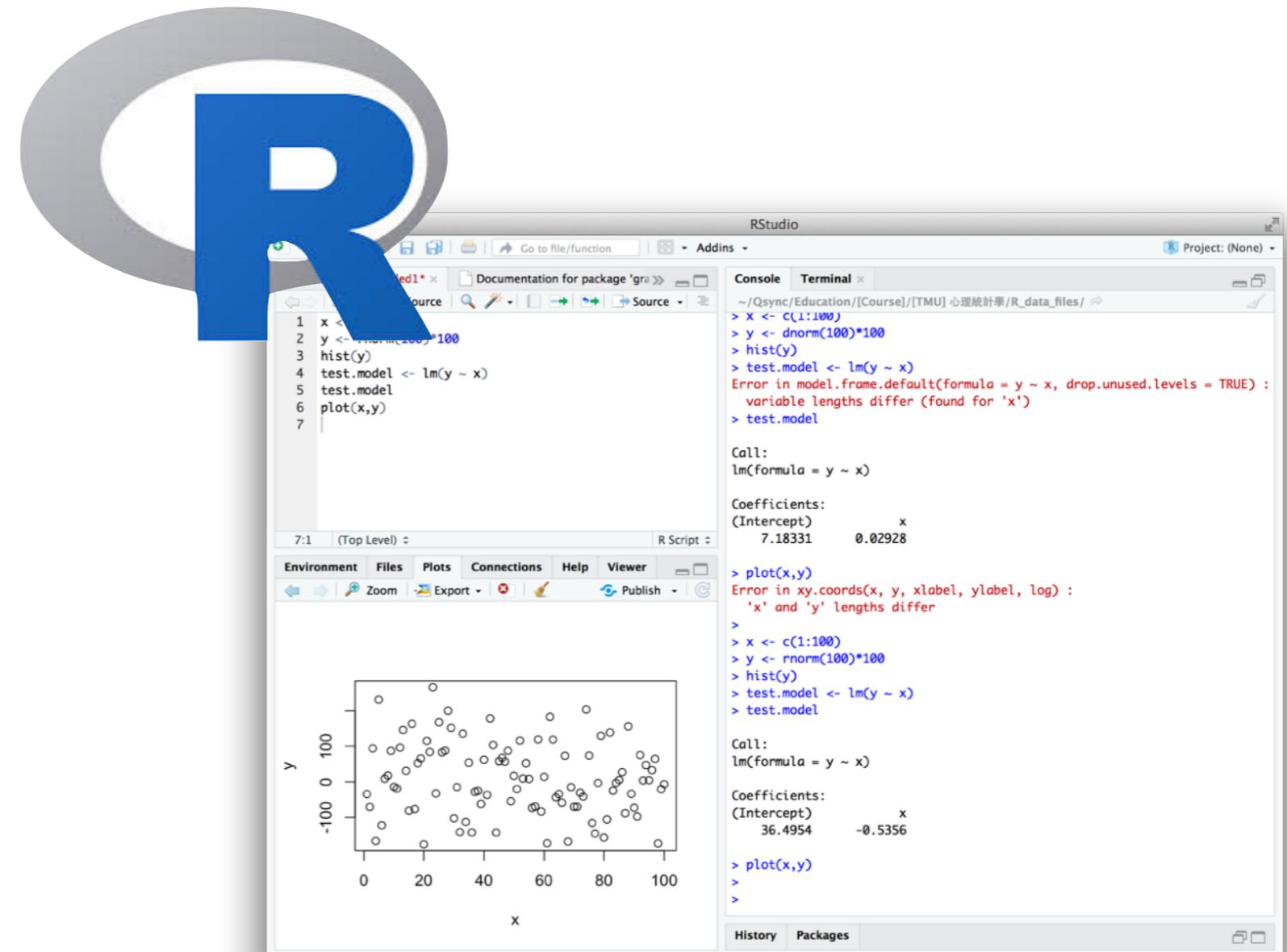
Testing

Non-Parametric Tests

- **Sign test** requires no assumption on the datasets.
- **Wilcoxon signed-rank test** compares two **repeated-measure** conditions and the data violate any assumption of the paired t-test.
 - Report the W-statistic, the significance value and the effect size.
 - Draw a box plot to present the medians and corresponding ranges.
- **Wilcoxon rank-sum (Mann-Whitney U) test** compares two **independent-measure** conditions and the data violate any assumption of the independent t-test.
 - Report the U-statistic, the significance value, and the effect size.
 - Draw a box plot to present the medians and corresponding ranges.

Counterpart of One-sample t-test

① SIGN TEST



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Signed Test

①
Hypothesis

The hypotheses are the same as for the sign test:

- *Two-tailed.* $H_0: M = M_0$ versus $H_a: M \neq M_0$.
- *Left-tailed.* $H_0: M \geq M_0$ versus $H_a: M < M_0$.
- *Right-tailed.* $H_0: M \leq M_0$ versus $H_a: M > M_0$.

②
Assumption

The assumptions of this test are more restrictive than those of the sign test.

1. The continuous random variable X is *symmetric* about a median M .
2. $X_1, \dots, X_{n'}$ denotes a random sample of size n' from the distribution of X .
3. M_0 denotes a hypothesized median for X .

(1) Exact Method

(2) Normal Approximation

Monte Carlo approach:

'Generate' a distribution by the sample itself ("Sign" compared with Median)

IF sample size is large or ties exist, we need to use normal approximation.



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(1) Exact Method

Monte Carlo approach:

'Generate' a distribution by the sample itself ("Sign" only)

Original data: [50 25 30 24 18]

Binarize by 20: [+ + + + -]

1. [- - - - -]
2. [+ - - - -]
3. [- + - - -]
4. [- - + - -]
5. [- - - + -]
6. [- - - - +]
7. [- - - + +]
8. [- - + + -]
- ...

Example. A bank manager claims that the median number of customers per day is no more than 750. A teller doubts the accuracy of this claim. The numbers of bank customers per day for 16 randomly selected days are listed below. At $\alpha = 0.05$, can the teller reject the bank manager's claim.

775	765	801	742	754	753	739	751
745	750	777	769	756	760	782	789

H_0 : median ≤ 750 . This is the claim.

H_a : median > 750 . Right tailed test

Compare the data to the hypothesized median 750.

+	+	+	-	+	+	-	+
-	0	+	+	+	+	+	+

How many possibilities do we have?

→ all signed conditions $= 2^5 = 32$

What is the chance with 5 + ?

(2) Normal Approximation

If the sample size is large (>40) enough:

Use normal (z) distribution for approximation

To find a 95% confidence interval with a larger sample ($n > 20$), again list the elementary estimates in order. To find the endpoint depth d for the confidence interval limits, use the normal approximation discussed earlier. In particular, for a 95% confidence interval d is chosen so that

Continuity correction

$$P(S \leq d) = P\left(Z \leq \frac{d + 0.5 - \mu}{\sigma}\right) = P\left(Z \leq \frac{d + 0.5 - \frac{n}{2}}{\frac{\sqrt{n}}{2}}\right) = 0.025.$$

From Table C.3, for the standard normal curve, $P(Z \leq -1.96) = 0.025$, so we can solve for d in the previous equation:

$$\frac{d + 0.5 - \frac{n}{2}}{\frac{\sqrt{n}}{2}} = -1.96,$$

which is equivalent to

$$d = \frac{n - 1 - 1.96\sqrt{n}}{2}.$$

Signed Test

EXAMPLE 6.8. Southeastern Queensland is home to more than 40 species of frogs. Among them are several species of *Crinia*, which are small, highly variable brownish or grayish froglets usually found in soaks, swamps, or temporary ponds. One way to distinguish these froglets is by their lengths. A population of froglets from a single pond appear to be of the same species. You tentatively identify them as clicking froglets *C. signifera*, a species known to have a median length of 30 mm. To be honest, you are not really sure that's what they are. A random sample of 18 froglets is captured and their lengths (in mm) are recorded in the table below. Is it reasonable to assume that these are clicking froglets?

24.1	22.9	23.0	26.1	25.0	30.8	27.1	23.2	22.8
23.7	24.6	30.3	23.9	21.8	28.1	25.4	31.2	30.9

→ all signed conditions = 2^{18}

difference = [-5.9 -7.1 -7.0 -3.9 -5.0 0.8 -2.9 -6.8 -7.2 -6.3 -5.4 0.3 -6.1 -8.2 -1.9
-4.6 1.2 0.9]

Signed Test

SOLUTION TO EXAMPLE 6.8. Since we decided on a two-tailed test, we have $H_0: M = 30 \text{ mm}$ versus $H_a: M \neq 30 \text{ mm}$. Perform the test with $\alpha = 0.05$. Of the 18 observations only 4 exceeded 30 mm so $S_+ = 4$ and 14 were smaller so $S_- = 14$. The test statistic is the smaller of these two, $S_+ = 4$. From Table C.1, the P value is

$$F(4) = P(S_+ \leq 4) = 0.0154.$$

How to calculate the CDF?

→ Use binomial distribution

Since 0.0154 is smaller than $\frac{\alpha}{2} = 0.025$, we reject H_0 . If H_0 were true, $E(S_+) = E(S_-) = \frac{18}{2} = 9$. But $S_+ = 4$ and $S_- = 14$ and are sufficiently far from this expectation to reject H_0 . Based on the evidence, it is reasonable to conclude that these are *not* clicking froglets.

→ Use SIGN.test in R

> SIGN.test(a, md=30)

E68<-c(24.1, 22.9, 23.0, 26.1, 25, 30.8, 27.1, 23.2, 22.8,
23.7, 24.6, 30.3, 23.9, 21.8, 28.1, 25.4, 31.2, 30.9)

Practice

Signed Test

EXAMPLE 6.9. In June of 1996 in the Finger Lakes region of New York, a series of warm days in the middle of the month caused people to comment that it was “unusually” warm. The median normal maximum temperature for Ithaca in June is 75°F. Do the data (the daily maximum temperatures for all 30 days in June) support the notion that June was unusually warm? (Based on data reported in The Ithaca Climate Page, http://snow.cit.cornell.edu/climate/ithaca/moncrt_06-96.html, July 2000.)

72	78	79	75	74	70	77	83	85	85
84	85	80	78	82	83	83	77	68	69
76	76	80	72	73	70	70	78	78	78

E69<-c(72, 78, 79, 75, 74, 70, 77, 83, 85, 85, 84, 85, 80, 78,
82, 83, 83, 77, 68, 69, 76, 76, 80, 72, 73, 70, 70, 78, 78, 78)

Signed Test

EXAMPLE 6.9. In June of 1996 in the Finger Lakes region of New York, a series of warm days in the middle of the month caused people to comment that it was “unusually” warm. The median normal maximum temperature for Ithaca in June is 75°F . Do the data (the daily maximum temperatures for all 30 days in June) support the notion that June was unusually warm? (Based on data reported in The Ithaca Climate Page, http://snow.cit.cornell.edu/climate/ithaca/moncrt_06-96.html, July 2000.)

72	78	79	75	74	70	77	83	85	85
84	85	80	78	82	83	83	77	68	69
76	76	80	72	73	70	70	78	78	78

SOLUTION. There are 30 observations, but one of them equals $M_0 = 75^{\circ}$. So the reduced sample size is $n = 29$. Since there is some reason to believe that temperatures were higher than normal, we perform a right-tailed test with $H_0: M \leq 75^{\circ}$ versus $H_a: M > 75^{\circ}$, with $\alpha = 0.05$. The test statistic is $S_- = 9$, the number of observations below the median. Then the P value using the normal approximation with $\mu = \frac{29}{2}$ and $\sigma = \frac{\sqrt{29}}{2}$ is

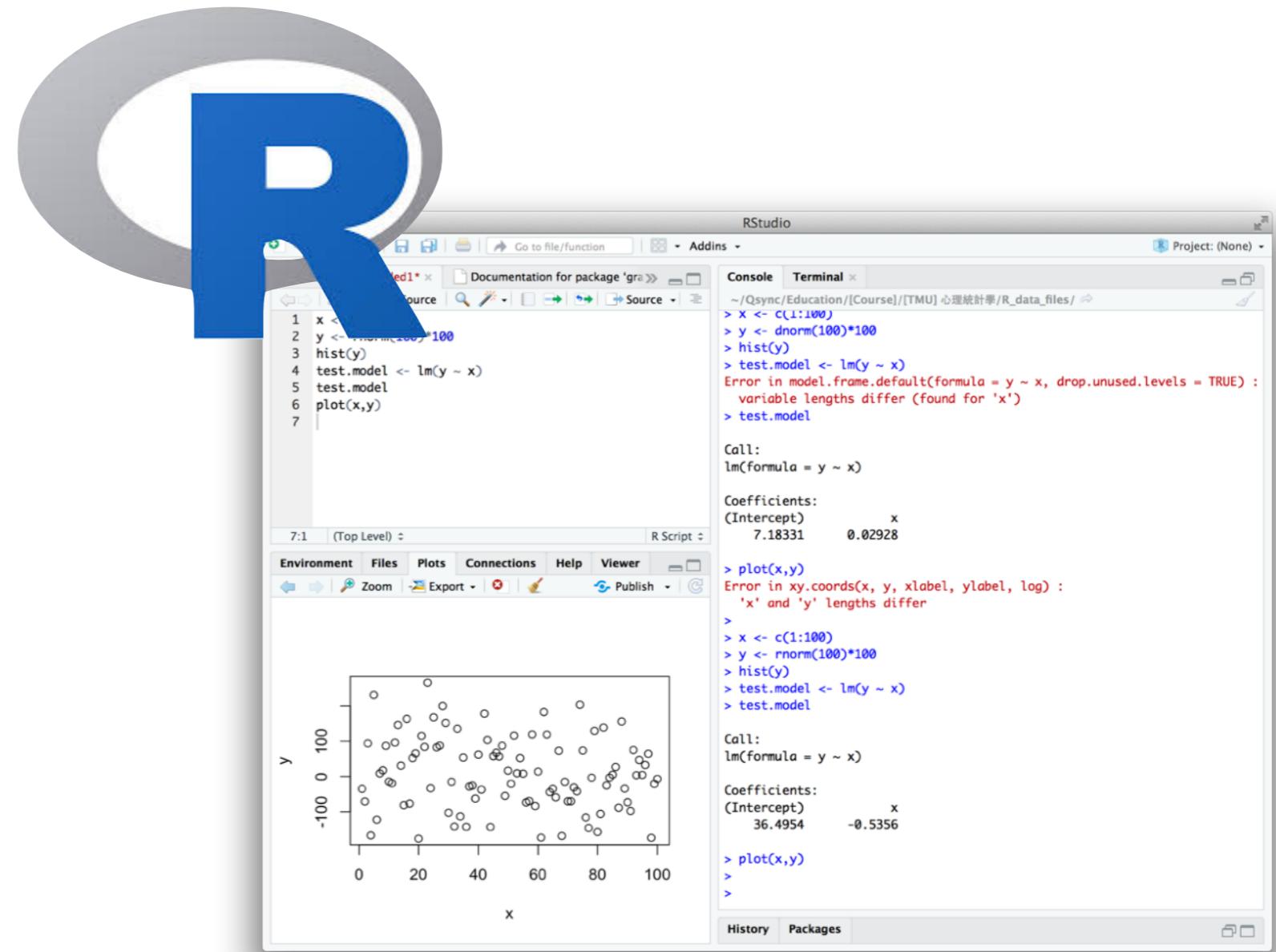
$$F(9) = P(S \leq 9) = P\left(Z \leq \frac{9.5 - \frac{29}{2}}{\frac{\sqrt{29}}{2}}\right) = P(Z \leq -1.86) = 0.0314 < 0.05.$$

There is sufficient evidence to reject H_0 . June of 1996 was unusually warm.



Counterpart of paired t-test

② WILCOXON SIGNED-RANK TEST



Wilcoxon Signed-Rank Test

Again the hypothesis test can take one of three forms:

①
Hypothesis

- *Two-tailed.* $H_0: M_{X-Y} = 0$ and $H_a: M_{X-Y} \neq 0$. The alternative hypothesis means that X_i tends to be different from Y_i .
- *Left-tailed.* $H_0: M_{X-Y} \geq 0$ and $H_a: M_{X-Y} < 0$. The alternative hypothesis means that X_i tends to be smaller than Y_i .
- *Right-tailed.* $H_0: M_{X-Y} \leq 0$ and $H_a: M_{X-Y} > 0$. The alternative hypothesis means that X_i tends to be larger than Y_i .

②
Assumption

1. X and Y are continuous random variables.
2. $(X_1, Y_1), \dots, (X_{n'}, Y_{n'})$ denotes a random sample of size n' from the distribution of (X, Y) .
3. Consider the n' continuous differences $X_1 - Y_1, \dots, X_{n'} - Y_{n'}$. The underlying assumption is that there is no difference between X and Y . More precisely, the assumption is that the median difference $M_{X-Y} = 0$.

The elementary estimates for the paired sign test are just the observed differences $X_i - Y_i$ in pairs.



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Exact Method

Monte Carlo approach:

'Generate' a distribution by the sample itself ("Sign" or "Rank")

five observations and the corresponding values of (+) & (-)

+1, -2, -3, +4, +5

$W_+ = 10$

$W_- = 5$

→ How to test on this?

→ all signed conditions = $2^5 = 32$

Ranking	W_+	Ranking	W_+
-1, -2, -3, -4, -5	0	+1, +2, +3, -4, -5	6
+1, -2, -3, -4, -5	1	+1, +2, -3, +4, -5	7
-1, +2, -3, -4, -5	2	+1, +2, -3, -4, +5	8
-1, -2, +3, -4, -5	3	+1, -2, +3, +4, -5	8
-1, -2, -3, +4, -5	4	+1, -2, +3, -4, +5	9
-1, -2, -3, -4, +5	5	+1, -2, -3, +4, +5	10
+1, +2, -3, -4, -5	3	-1, +2, +3, +4, -5	9
+1, -2, +3, -4, -5	4	-1, +2, +3, -4, +5	10
+1, -2, -3, +4, -5	5	-1, +2, -3, +4, +5	11
+1, -2, -3, -4, +5	6	-1, -2, +3, +4, +5	12
-1, +2, +3, -4, -5	5	+1, +2, +3, +4, -5	10
-1, +2, -3, +4, -5	6	+1, +2, +3, -4, +5	11
-1, +2, -3, -4, +5	7	+1, +2, -3, +4, +5	12
-1, -2, +3, +4, -5	7	+1, -2, +3, +4, +5	13
-1, -2, +3, -4, +5	8	-1, +2, +3, +4, +5	14
-1, -2, -3, +4, +5	9	+1, +2, +3, +4, +5	15

Probability density function (PDF):

w	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$P(W = w)$	$\frac{1}{32}$	$\frac{1}{32}$	$\frac{1}{32}$	$\frac{2}{32}$	$\frac{2}{32}$	$\frac{3}{32}$	$\frac{3}{32}$	$\frac{3}{32}$	$\frac{3}{32}$	$\frac{3}{32}$	$\frac{2}{32}$	$\frac{2}{32}$	$\frac{1}{32}$	$\frac{1}{32}$	$\frac{1}{32}$	
$P(W \leq w)$	$\frac{1}{32}$	$\frac{2}{32}$	$\frac{3}{32}$	$\frac{5}{32}$	$\frac{7}{32}$	$\frac{10}{32}$	$\frac{13}{32}$	$\frac{16}{32}$	$\frac{19}{32}$	$\frac{22}{32}$	$\frac{25}{32}$	$\frac{27}{32}$	$\frac{29}{32}$	$\frac{30}{32}$	$\frac{31}{32}$	$\frac{32}{32}$

Wilcoxon Signed-Rank Test

- **Wilcoxon signed-rank test** compares two conditions when the same participants take part in each condition and the resulting data violate any assumption of the dependent t-test.
- Look at the p-value. If the value $< .05$ then two groups are different.
- Report the W-statistic and the significance value. Also report the medians and their corresponding ranges (with boxplot).
- Calculate the effect size if possible.

Wilcoxon Signed-Rank Test

EXAMPLE 6.13. Adult heights are known to be symmetrically distributed. We measured the heights of 10 male faculty in the science division at Hobart and William Smith Colleges. The median male adult height in the U.S. is supposedly 178 cm. Do the data collected support this assertion? Set up the appropriate two-tailed hypothesis and determine whether H_0 can be rejected at the $\alpha = 0.05$ level.

171 175 177 178 180 182 190 192 195 202

SOLUTION. The null hypothesis is $H_0: M = 178$ versus the two-sided alternative $H_a: M \neq 178$. Note that one of the observations is the same as the suspected median so it must be removed. The differences of the remaining nine sample values are calculated and their absolute values are ranked.

X_i	171	175	177	180	182	190	192	195	202
$X_i - 178$	-7	-3	-1	2	4	12	14	17	24
$ X_i - 178 $	7	3	1	2	4	12	14	17	24
Signed rank	-5	-3	-1	+2	+4	+6	+7	+8	+9

Under symmetry assumption, we expect $W_- \sim W_+$



Wilcoxon Signed-Rank Test

SOLUTION. The null hypothesis is $H_0: M = 178$ versus the two-sided alternative $H_a: M \neq 178$. Note that one of the observations is the same as the suspected median so it must be removed. The differences of the remaining nine sample values are calculated and their absolute values are ranked.

X_i	171	175	177	180	182	190	192	195	202
$X_i - 178$	-7	-3	-1	2	4	12	14	17	24
$ X_i - 178 $	7	3	1	2	4	12	14	17	24
Signed rank	-5	-3	-1	+2	+4	+6	+7	+8	+9

From the ranks we see that

$$W_+ = 9 + 8 + 7 + 6 + 4 + 2 = 36 \quad W_- = |-5 - 3 - 1| = 9.$$

As a check, $W_+ + W_- = 45 = \frac{9(9+1)}{2} = \frac{n(n+1)}{2}$.

→ What is the p-value and the decision?

For a two-sided test, the test statistic is the minimum of W_+ and W_- ; so $W = W_- = 9$. From Table C.6, the P value for the test statistic $W = 9$ with $n = 9$ is 0.0645. Since $0.0645 > 0.025 = \frac{\alpha}{2}$, we cannot reject H_0 . There is no evidence that the median male height is different from 178 cm.



Wilcoxon Signed-Rank Test

EXAMPLE 7.13. Body height and arm span are related quantities; taller people generally have longer arms. One rule of thumb says that adult height is nearly equal to adult span. The arm spans of the 10 science faculty in Example 6.13 were also measured. Do the data support the contention? (Height and span data are symmetric.)

Height	171	175	177	178	180	182	190	192	195	202
Span	173	178	182	182	188	185	186	198	193	202

- Use R to test on the dataset.
(PASWR package)

Practice

Wilcoxon Signed-Rank Test

SOLUTION. Test the null hypothesis $H_0: M_{H-S} = 0$ versus the two-sided alternative hypothesis, $H_a: M_{H-S} \neq 0$ at the $\alpha = 0.05$ level using the Wilcoxon signed-rank test because of the symmetry assumption. Calculate the 10 differences and rank them using signed ranks. Note the use of midranks and that the observation with a 0 difference has not been ranked:

$H_i - S_i$	-2	-3	-5	-4	-8	-3	4	-6	2	0
$ H_i - S_i $	2	3	5	4	8	3	4	6	2	0
Signed rank	-1.5	-3.5	-7	-5.5	-9	-3.5	+5.5	-8	+1.5	*

The test statistic is $W_+ = 7$, which is the smaller of W_- and W_+ . Using Table C.6 with $n = 9$, the P value is 0.0371. Since $0.0371 > 0.025 = \frac{\alpha}{2}$, we cannot reject H_0 in favor of the alternative hypothesis in this two-sided test. The data support the claim that adult height and arm span are nearly equal.

DEMO

Ecstasy vs. Alcohol

- **Background:** We want to test the depression levels between ecstasy and alcohol users.
- Here we hypothesize that ecstasy users' depression level changes between Wednesday and Sunday. Let's test whether there will be no difference between days.

Load: Drug.dat

Participant	Drug	BDI (Sunday)	BDI (Wednesday)
1	Ecstasy	15	28
2	Ecstasy	35	35
3	Ecstasy	16	35
4	Ecstasy	18	24
5	Ecstasy	19	39
6	Ecstasy	17	32
7	Ecstasy	27	27
8	Ecstasy	16	29
9	Ecstasy	13	36
10	Ecstasy	20	35
11	Alcohol	16	5
12	Alcohol	15	6
13	Alcohol	20	30
14	Alcohol	15	8
15	Alcohol	16	9
16	Alcohol	13	7
17	Alcohol	14	6
18	Alcohol	19	17
19	Alcohol	18	3
20	Alcohol	18	10

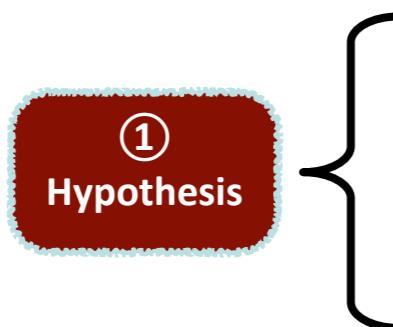
Ecstasy vs. Alcohol

- **Background:** We want to test the change of depression levels between Wednesday and Sunday for ecstasy users. Let's hypothesize that there will be no difference between days.

Dependent measure of ecstasy users over Wedn/Sun

Measure: Beck's Depression Inventory (BDI)

- **Set up Hypothesis:**



$$\left. \begin{array}{l} H_0: \text{BDI}_{\text{(Wednesday)}} = \text{BDI}_{\text{(Sunday)}} \\ H_a: \text{BDI}_{\text{(Wednesday)}} \neq \text{BDI}_{\text{(Sunday)}} \end{array} \right\}$$

DEMO

Ecstasy vs. Alcohol

- Hypothesis:

$$\left\{ \begin{array}{l} H_0: BDI_{(Wednesday)} = BDI_{(Sunday)} \\ H_a: BDI_{(Wednesday)} \neq BDI_{(Sunday)} \end{array} \right.$$

- Data import:

▶ `drugData <- read.delim("Drug.dat", header = TRUE)`

- Assumption check:

▶ `by(drugData$BDIchange, drugData$drug, stat.desc, basic = FALSE, norm = TRUE)`

drugData\$drug:	Alcohol		
kurt.2SE	0.36973617	normtest.W	normtest.p 0.03161929

- Let's focus on Ecstasy data →

drugData\$drug:	Ecstasy		
kurt.2SE	-0.5128991	normtest.W	normtest.p 0.2727175

②

Assumption



DEMO

Ecstasy vs. Alcohol

Exclude zero diff.

Split ranks for equal values

<i>BDI Sunday</i>	<i>BDI Wednesday</i>	<i>Difference</i>	<i>Sign</i>	<i>Rank</i>	<i>Positive ranks</i>	<i>Negative ranks</i>
Ecstasy						
15	28	13	+	2.5	2.5	
35	35	0	Exclude			
16	35	19	+	6	6	
18	24	6	+	1	1	
19	39	20	+	7	7	
17	32	15	+	4.5	4.5	
27	27	0	Exclude			
16	29	13	+	2.5	2.5	
13	36	23	+	8	8	
20	35	15	+	4.5	4.5	
Total =				36	0	
Alcohol						
16	5	-11	-	9	9	
15	6	-9	-	7	7	
20	30	10	+	8	8	
15	8	-7	-	3.5	3.5	
16	9	-7	-	3.5	3.5	
13	7	-6	-	2	2	
14	6	-8	-	5.5	5.5	
19	17	-2	-	1	1	
18	3	-15	-	10	10	
18	10	-8	-	5.5	5.5	
Total =				8	47	



Ecstasy vs. Alcohol

General form:

- ▶ **wilcox.test(outcome ~ predictor, data=dataframe, paired=FALSE/TRUE)**
- ▶ **wilcox.test(data1, data2, paired=FALSE/TRUE)**

- Parameters:

- **alternative**=("two.sided" / "less" / "greater"): choose one.
- **mu=0**: difference between means = 0 is default null hypothesis
- **exact=TRUE**: normal approximation is used if n>50 or if ties exist.
- **correct=TRUE**: by default it performs a continuity correction
- **conf.level=0.95**: by default setting confidence interval = 95%
- **na.action**: exclude the missing data by default (=na.exclude)

- Usage:

- ▶ **wilcox.test(wedsBDI ~ drug, data = drugData, exact = FALSE, correct= FALSE, conf.int = T)**



Ecstasy vs. Alcohol

(3)

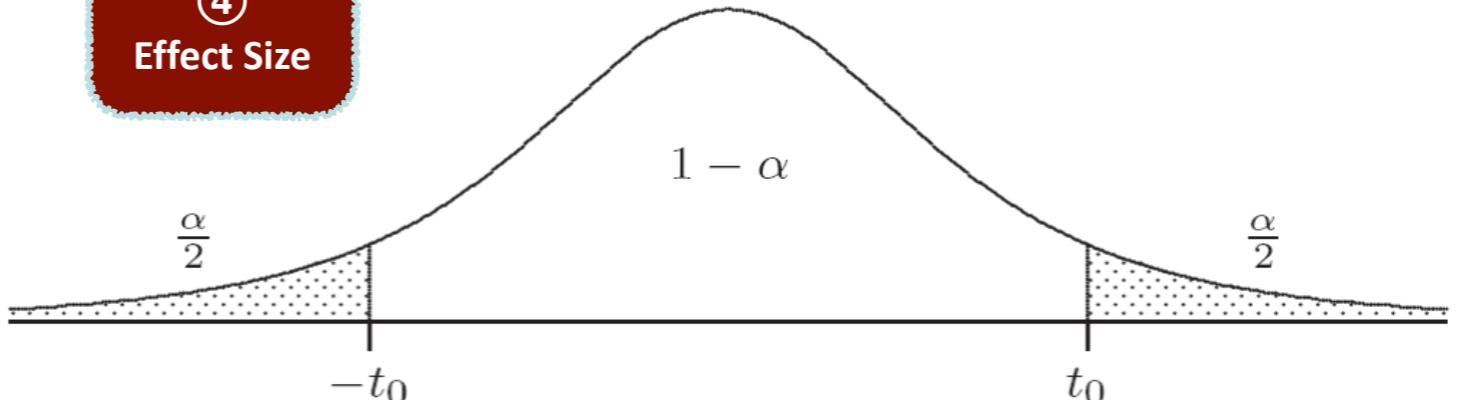
Testing

- Usage:
 - ▶ `wilcox.test(ecstasyData$wedsBDI, ecstasyData$sundayBDI, paired = TRUE, correct = FALSE, conf.int = T)`
- Results: Wilcoxon signed rank test

```
data: ecstasyData$wedsBDI and ecstasyData$sundayBDI
V = 36, p-value = 0.01151
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 10.50007 19.50002
sample estimates:
(pseudo)median
 15.95848
```

`z<- qnorm(wilcoxModel$p.value/2)
r<- z/sqrt(N)`

④
Effect Size



Ecstasy vs. Alcohol

④

Effect Size

- **Effect size:** assume the distribution as ideal, using $z \rightarrow r$ transform: ([recover z value from the p-value](#), Rosenthal, 1991, p.19)

`ecstasyData$wedsBDI` and `ecstasyData$sundayBDI` Effect Size, $r = -0.5649$

⑤

Decision

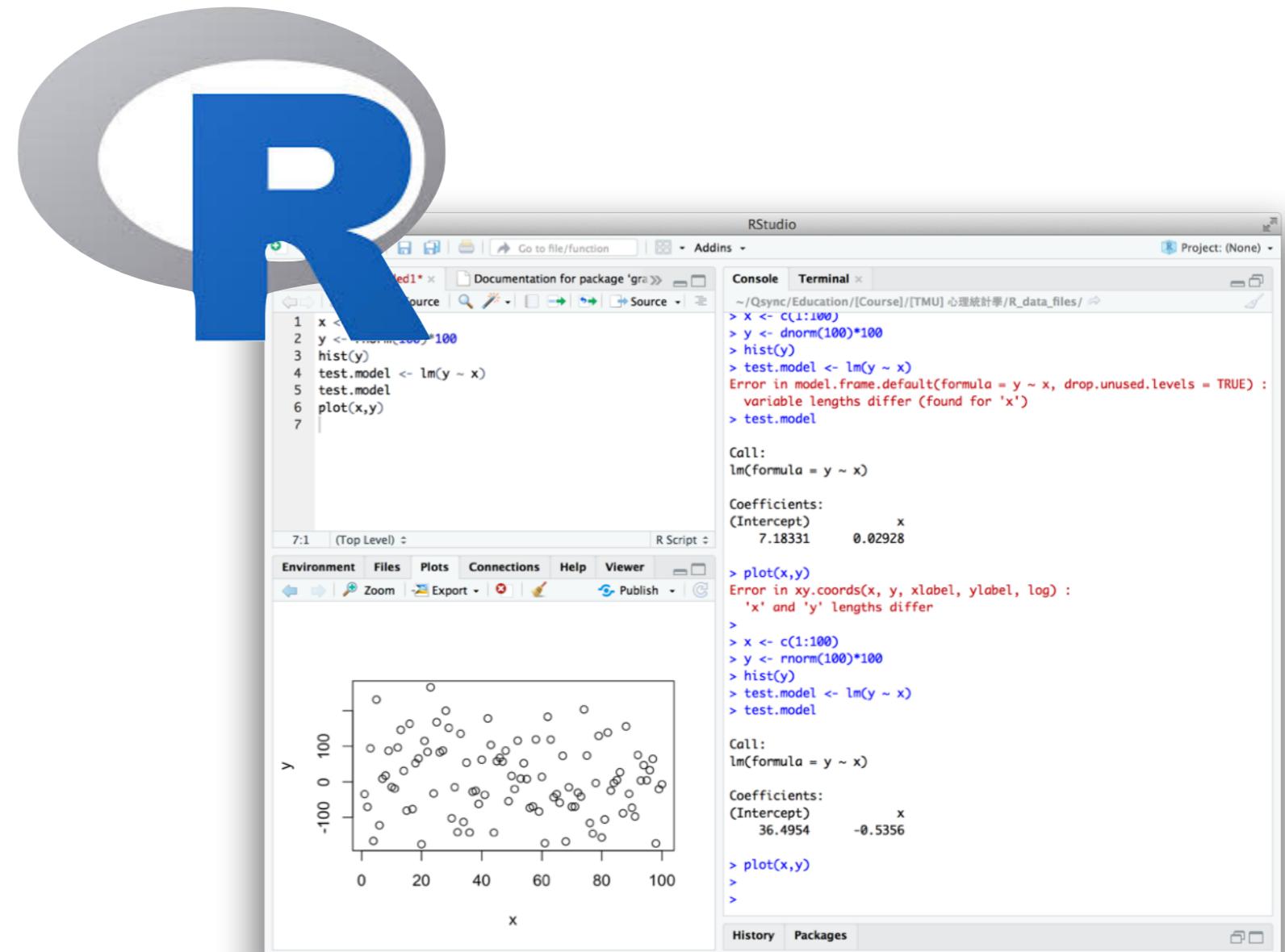
- **Reporting decision:**

For ecstasy users, depression levels were significantly higher on Wednesday (median=33.5) than on Sunday (median=17.5), $p = .012$, effect size (r) = -0.56.

- How about Alcohol users?

Counterpart of independent t-test

③ WILCOXON RANK-SUM TEST (MANN-WHITNEY U TEST)



Wilcoxon Rank-Sum Test

Mann-Whitney U Test

Let M_X and M_Y denote the medians of X and Y , respectively. The hypothesis test can take one of three forms:

① Hypothesis

- *Two-tailed.* $H_0: M_X = M_Y$ versus $H_a: M_X \neq M_Y$. This tests whether the X 's tend to be different from the Y 's.
- *Left-tailed.* $H_0: M_X \geq M_Y$ versus $H_a: M_X < M_Y$. This tests whether the X 's tend to be smaller than the Y 's.
- *Right-tailed.* $H_0: M_X \leq M_Y$ versus $H_a: M_X > M_Y$. This tests whether the X 's tend to be larger than the Y 's.

② Assumption

The assumptions for the Wilcoxon rank-sum test are the following:

1. X and Y are continuous random variables.
2. The data consist of two *independent*, random samples. X_1, \dots, X_m denotes a random sample of size m from the distribution of X , and Y_1, \dots, Y_n denotes a random sample of size n from the distribution of Y . Note that m and n are often, but not always, different.
3. The null hypothesis is that the X and Y populations are identical.

For convenience, we will assume that the X 's represent the smaller sample, that is, $m \leq n$. This makes listing critical values of the test statistic easier. The Wilcoxon rank-sum test examines whether the populations differ in location (median).



Wilcoxon Rank-Sum Test

(Mann-Whitney U Test)

- **Wilcoxon rank-sum test** compares two conditions when different participants take part in each condition and the resulting data violate any assumption of the independent t-test.
- Look at the p-value. If the value $< .05$ then two groups are different.
- Calculate the mean rank.
- Report the **U-statistic** and the significance value. Also report the medians and their corresponding ranges (with boxplot).
- Calculate the effect size and report it.

Mann-Whitney U Test

EXAMPLE 7.10. Two color morphs (green and red) of the same species of sea star were found at Polka Point, North Stradbroke Island. One might suppose that the red color morph is more liable to predation and, hence, those found might be smaller than the green color morph. The following data are the radial lengths of two random samples of these sea stars (in mm). Are red color morphs significantly smaller than green color morphs?

Red	108	64	80	92	40
Green	102	116	98	132	104

SOLUTION. Let $X = R$ represent the red sea star morphs since this sample has the smaller number of observations and $Y = G$ represent the green morphs. To test whether red color morphs tend to be smaller than the green, the appropriate test is left-tailed with $H_0: M_R \geq M_G$ versus $H_a: M_R < M_G$. The test is done at the $\alpha = 0.05$ level. The first step is to rank the combined data set. We denote the red sea star observations and ranks in **bold** for convenience:

Mann-Whitney U Test

SOLUTION. Let $X = R$ represent the red sea star morphs since this sample has the smaller number of observations and $Y = G$ represent the green morphs. To test whether red color morphs tend to be smaller than the green, the appropriate test is left-tailed with $H_0: M_R \geq M_G$ versus $H_a: M_R < M_G$. The test is done at the $\alpha = 0.05$ level. The first step is to rank the combined data set. We denote the red sea star observations and ranks in **bold** for convenience:

Size	40	64	80	92	98	102	104	108	116	124	132
Rank	1	2	3	4	5	6	7	8	9	10	11

The test statistic is the sum of the red sea star ranks,

$$W_X = W_R = 1 + 2 + 3 + 4 + 8 = 18.$$

$$U_1 = R_1 - \frac{n_1(n_1 + 1)}{2}$$

$$U_1 + U_2 = n_1 n_2.$$

$$U_2 = R_2 - \frac{n_2(n_2 + 1)}{2}$$

Sum of ranks assigned to the Red group: $U_1 = R_1 - \frac{n_1(n_1 + 1)}{2} = 18 - 15 = 3$

→ What is the p-value and the decision? (report U instead of W)

data: r and g
W = 3, p-value = 0.01515
alternative hypothesis: true location shift is less than 0

Ecstasy vs. Alcohol

- **Background:** We want to test the depression levels between ecstasy and alcohol users. Let's imagine that the **ecstasy group is more depressed than the alcohol group**. What is the working hypothesis to be tested?

Independent measure over 2 groups

Measure: Beck's Depression Inventory (BDI)

- Set up Hypothesis:


$$\left. \begin{array}{l} \text{① Hypothesis} \\ H_0: \text{BDI}_{(\text{ecstasy})} = \text{BDI}_{(\text{alcohol})} \\ H_a: \text{BDI}_{(\text{ecstasy})} \neq \text{BDI}_{(\text{alcohol})} \end{array} \right\}$$

DEMO

Ecstasy vs. Alcohol

- Hypothesis: $\left\{ \begin{array}{l} H_0: BDI_{(ecstasy)} = BDI_{(alcohol)} \\ H_a: BDI_{(ecstasy)} \neq BDI_{(alcohol)} \end{array} \right.$

Load: Drug.dat

- **Data import:**

```
► drugData <- read.delim("Drug.dat", header = TRUE)
```

- Assumption check:

```
▶ by(drugData[,c(2:3)], drugData$drug, stat.desc, basic=FALSE,  
norm=TRUE)
```

```
drugData$drug: Alcohol  
                      sundayBDI          wedsBDI  
normtest.W      0.95946584  0.753466511  
normtest.p      0.77976459  0.003933024
```

```
drugData$drug: Ecstasy  
              sundayBDI      wedsBDI  
normtest.W    0.81063991  0.9411413  
normtest.p    0.01952060  0.5657814
```



DEMO

Ecstasy vs. Alcohol

Wednesday Data																				
Score	3	5	6	6	7	8	9	10	17	24	27	28	29	30	32	35	35	35	36	39
Potential Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Actual Rank	1	2	3.5	3.5	5	6	7	8	9	10	11	12	13	14	15	17	17	17	19	20
Group	A	A	A	A	A	A	A	A	E	E	E	E	A	E	E	E	E	E	E	
Sum of Ranks for Alcohol (A) = 59										Sum of Ranks for Ecstasy (E) = 151										
Sunday Data																				
Score	13	13	14	15	15	15	16	16	16	16	17	18	18	18	19	19	20	20	27	35
Potential Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Actual Rank	1.5	1.5	3	5	5	5	8.5	8.5	8.5	8.5	11	13	13	13	15.5	15.5	17.5	17.5	19	20
Group	A	E	A	A	A	E	A	A	E	E	E	A	A	A	E	A	E	E	E	
Sum of Ranks for Alcohol (A) = 90.5										Sum of Ranks for Ecstasy (E) = 119.5										



DEMO

Ecstasy vs. Alcohol

Wilcoxon rank sum test

- Results:** data: wedsBDI by drug
 $W = 4$, p-value = 0.0004943
 alternative hypothesis: true location shift is not equal to 0

(4)

Effect Size

- Effect size:** assume the distribution as ideal, using $z \rightarrow r$ transform: (Rosenthal, 1991)

$$r = 1 - \frac{2U}{n_1 n_2}$$

*U is the smaller of the two*wedsBDI by drug Effect Size, $r = -0.779$ **(5)**

Decision

- Reporting decision:**

Depression levels in ecstasy users on Wednesday (median=33.5) were significantly more depressed than alcohol users (median=7.5), $U = 4$, $p < .001$, effect size (r) = -0.78.



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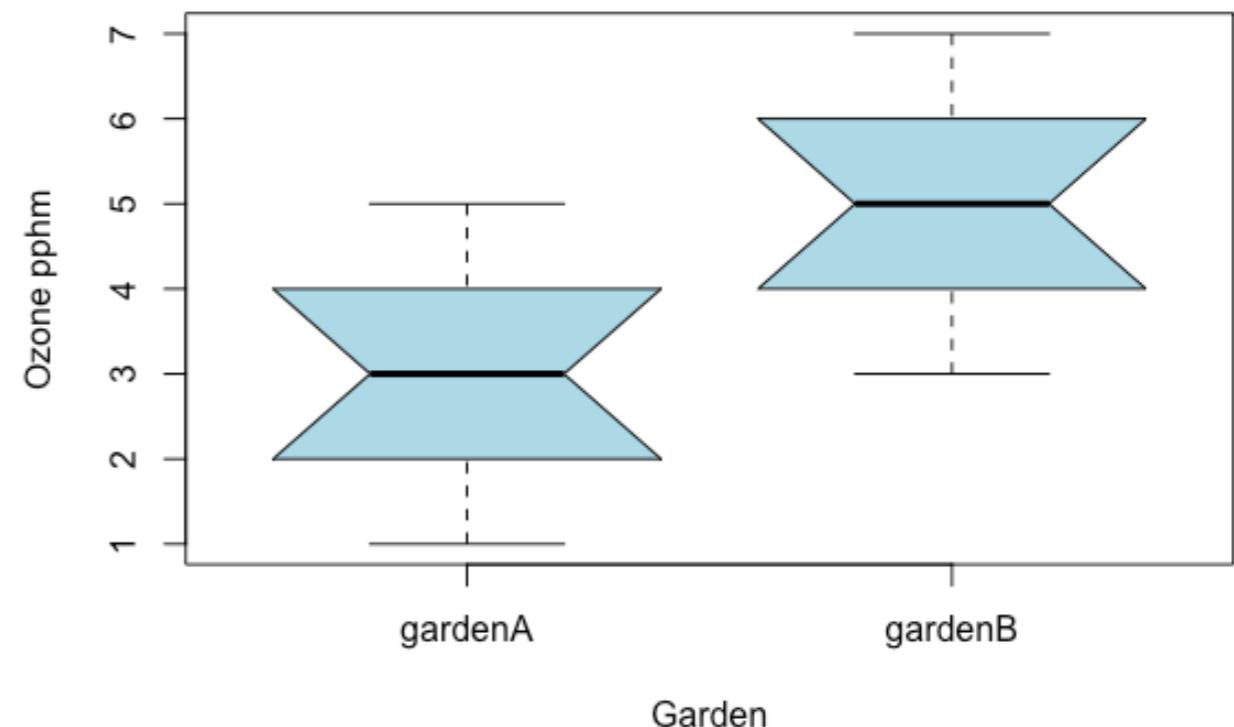
- How about using wedsDay in t-test?

Practice

Ozone Levels

- **Background:** We have atmospheric ozone concentrations measured in parts per hundred million (pphm) in two commercial lettuce-growing gardens (we shall call the gardens A and B for simplicity).
- Based on the collected data, do the two gardens have different ozone concentrations?
- **Check the assumptions**
- **Use both t-test & nonparametric method to test it.**
- **What is the difference in results?**

Load: ozone.csv



Discussion

1. Violation of Assumptions

- Nonparametric, Ranks & Signed Tests

1. Nonparametric Tests: Two Samples

- Wilcoxon signed-rank & rank-sum tests

2. [R] Hands-on Practices

One-Sample Tests

One-sample tests of hypothesis with continuous variables

Hypothesis	Sampling assumptions	Test statistic
$H_0: \sigma^2 = c$	None	χ^2 test
$H_0: \sigma = c; H_0: \sigma^2 = c^2$		
$H_0: \mu = c$	Normal population or approximately normal under Central Limit Theorem	t test
$H_0: \mu \text{ or } M = c$	Symmetrical distribution	One-sample Wilcoxon signed-rank test
$H_0: M = c$	None	One-sample sign test

Two-Sample Tests

Two-sample tests of hypothesis with continuous variables

Hypothesis	Sampling assumptions	Test statistic
$H_0: \sigma_1^2 = \sigma_2^2$	Independent samples Normal populations	F test
$H_0: \mu_1 = \mu_2$	Independent samples Normal populations Equal variances	Unpaired t test with pooled variance
$H_0: \mu_1 = \mu_2$	Independent samples Normal populations Unequal variances	Welch's approximate t test
$H_0: \mu_d = c$	Paired data Normal populations	Paired t test
$H_0: M_X = M_Y$	Independent samples	Wilcoxon rank-sum test
$H_0: M_{X-Y} = 0$	Paired data	Sign test
$H_0: M_{X-Y} = 0$	Paired data Symmetric populations	Wilcoxon signed-rank test for paired data





THANK YOU FOR YOUR ATTENTION

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