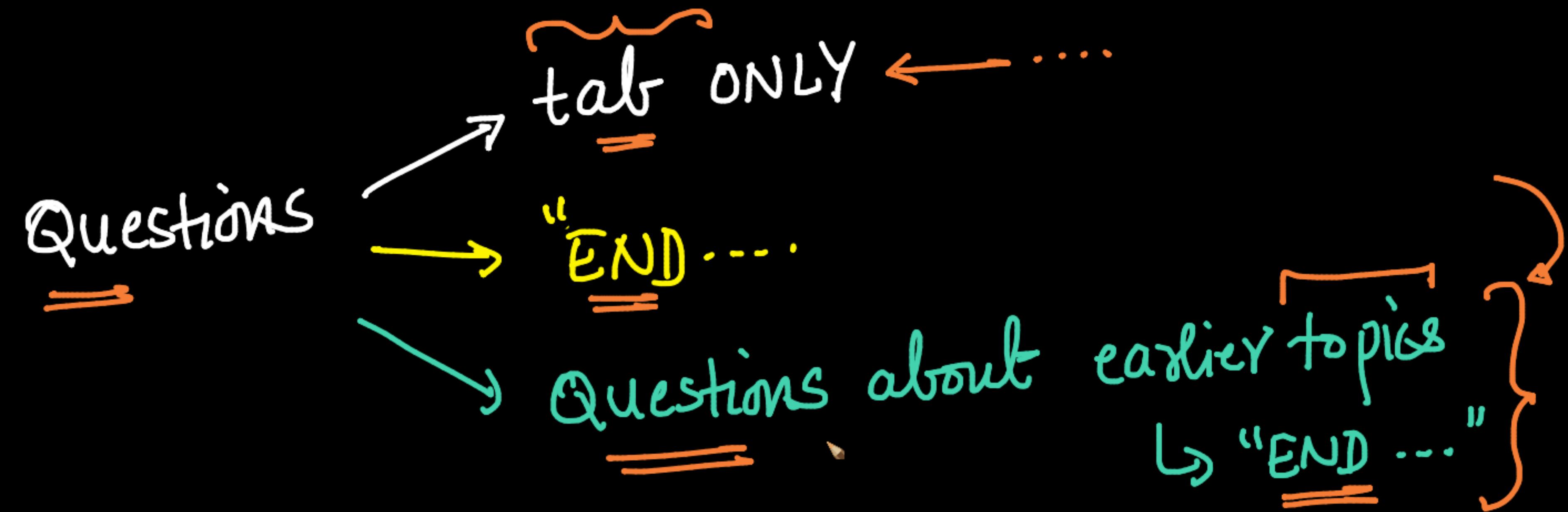


Topics:

- ✓ ① One-sample T-test ✓
- ✓ ② Paired T-test ✓
- ✓ ③ KS-test
- ✓ ④ Z-proportions test
- ✓ ⑤ χ^2 -test

Same framework
as earlier

Ops:



chat → Interactive & Yes/No

{ TA's
= } → [video chat] — Tricky, follow-up
= o = o =

A hand-drawn diagram illustrating a cycle. On the left, a blue bracket groups the text "Problem-solving sessions" and "Next week". An arrow points from "Problem-solving sessions" to the right. On the right, a pink bracket groups the text "least answered" and "questions". An arrow points from "least answered" back to "Problem-solving sessions". Below the main text, there is a large green double-headed curved arrow spanning the distance between the two brackets.

Problem-solving sessions → least answered
questions

~~Q~~

Med 1

 $\rightarrow \mu_1$
 $S_1^{n_1}:$ x_1, x_2, \dots, x_{n_1}
 $\overrightarrow{S_2^{n_2}}:$ $x_1^1, x_2^1, \dots, x_{n_2}^1$

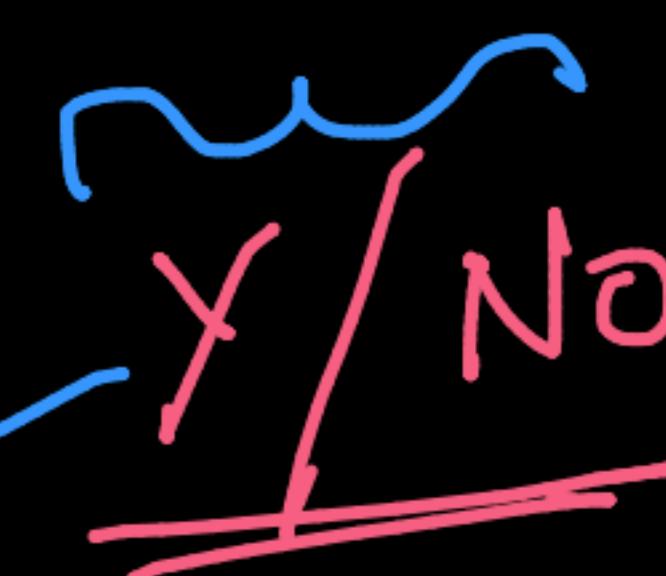
Med 2

 μ_2

Compare means

 $\mu_1 = \mu_2$

Transform



2-sample T-test

non-gaussian

pop mean & std-dev
are finite

Y 6
N 34

- T-test
- obs are indep ✓
 - compare means ✓
 - n_1 & n_2 are small; do NOT know σ_1 & σ_2
 - CLT. pop mean & std-dev are finite

Two sample T-test

$$\rightarrow \left[\text{ML} | \text{stats} \right] \quad \begin{matrix} (n_1 + n_2) - \\ \# \text{indep obs} \end{matrix} - \begin{matrix} (2) \\ \# \text{params to estimate} \end{matrix}$$

DOF

{ 2-Sample T-test

n_1 obs

m_1 ✓

n_2 obs

m_2 ↗

Ques: $\mu_1 = \mu_2$
or not

{ 2-Sample T-test

$$\text{Test-statistik} = \frac{m_1 - M_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \sim t\text{ dist}(v)$$

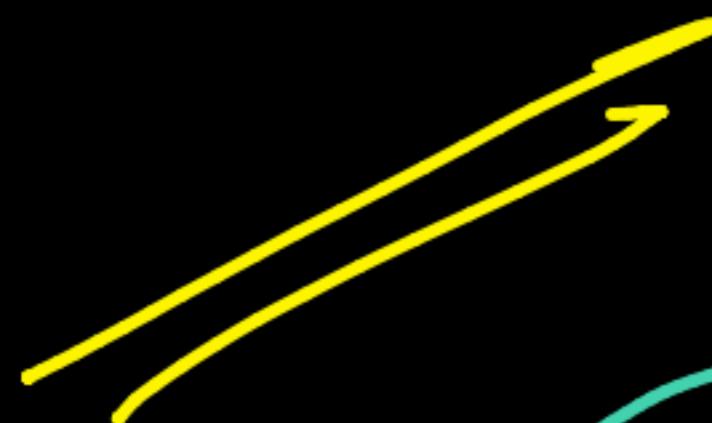
\downarrow

$$\underline{n_1 + n_2 - 2}$$

(e.g.) $\checkmark \overbrace{x_1 x_2 \dots}^{\rightarrow m = \text{sample-mean}} x_n \leftarrow n \text{ obs}$

$$\underline{\text{sample-var}} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \underline{\underline{m}})^2$$

DOF \rightarrow $n-1$ \nwarrow obs $\hookrightarrow \text{sample mean}$



x

baby weights in India
 $x_1 \ x_2 \ \dots \ x_n$

1-Sample
T-test

[Given :-

Task: check if Indian babies have a mean weight of $\underline{\underline{\mu_0 = 2.8 \text{ kgs}}}$ (WHO)

\bar{x} : sample mean μ = Mean Indian baby weight

Framework:

✓ ①

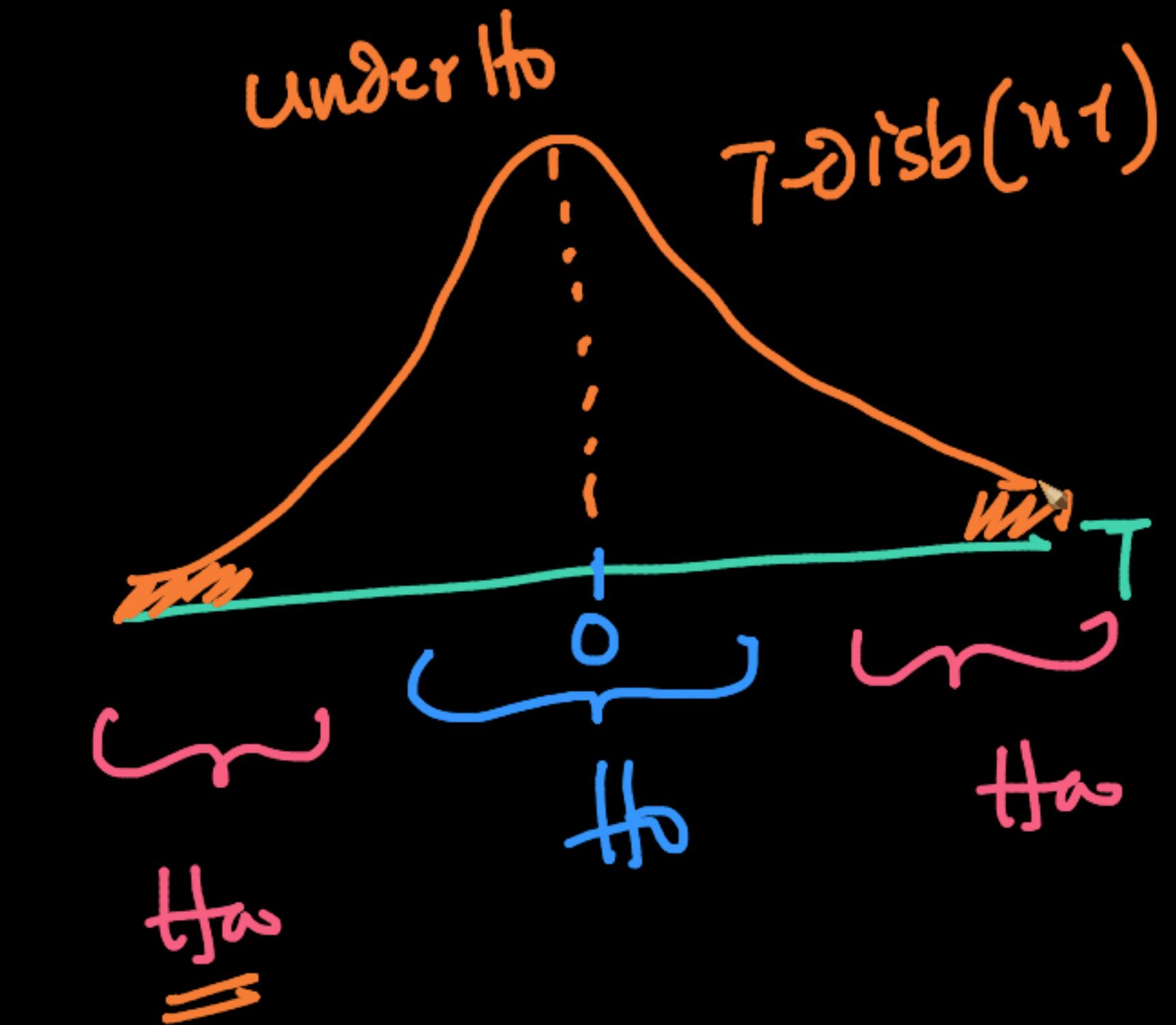
$$\left\{ \begin{array}{l} H_0: \mu = \mu_0 \\ H_a: \mu \neq \mu_0 \end{array} \right.$$

↑ 2.8 kgs
sample mean

②

$$T = \frac{\bar{X} - \mu_0}{S/\sqrt{n}}$$

↑ 2.8
Sample Std. Dev of n obs



$$T \sim t(\nu = n-1)$$

③

2-sided or 1-sided

$t_{\text{dist}}(n-1)$

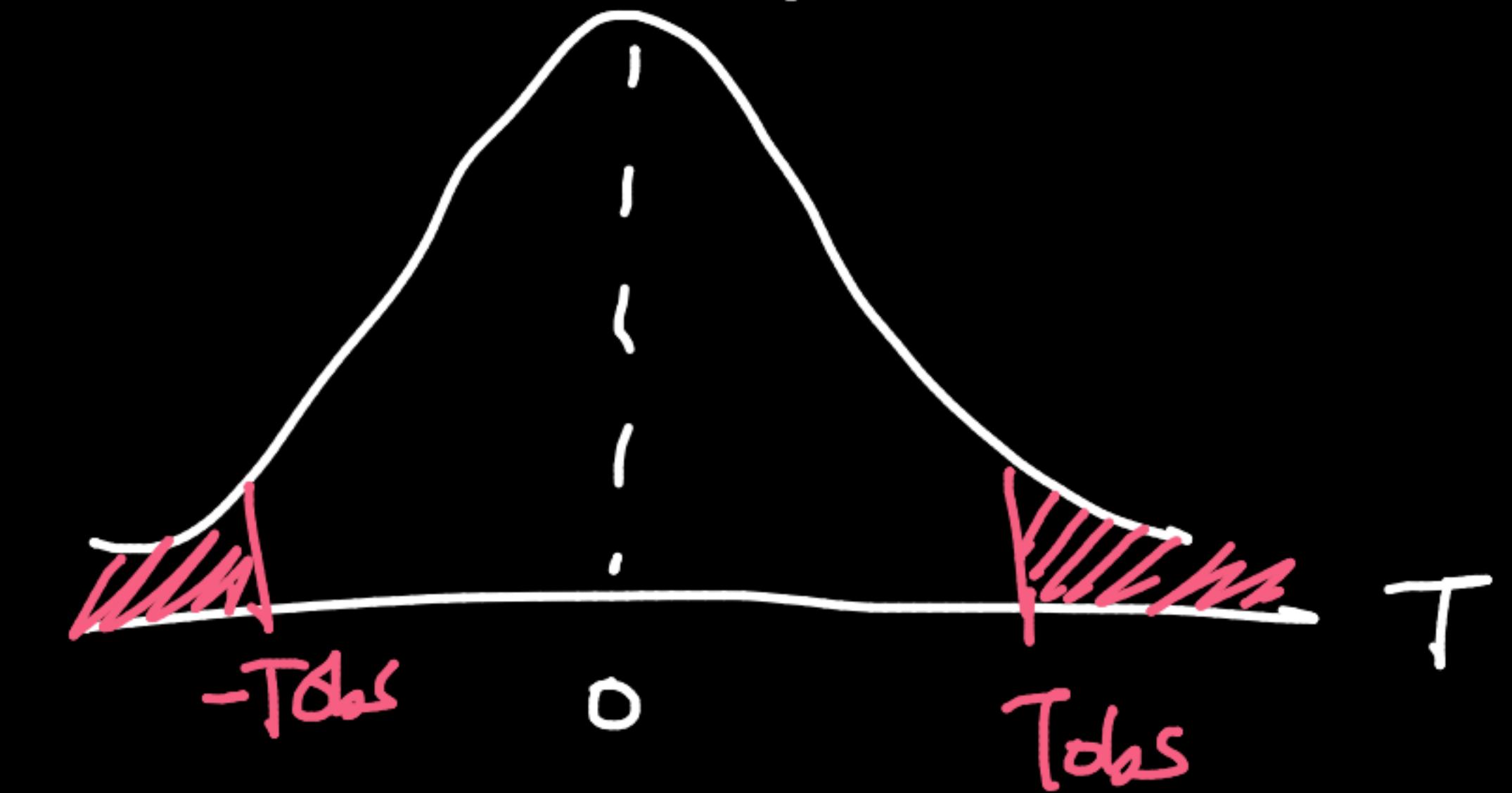
④

p-val

⑤

$\alpha = 5\%$

p-val vs α



Dependent $\sqrt{\text{"Paired" T-test}}$

Task!

①

$\bar{d} = \frac{d_1 + d_2 + \dots + d_n}{n}$

pop. mean of diff. μ_d

$H_0: \underline{\text{mean-diff}} \text{ is } \underline{\mu_d}$

$\{ H_a: \text{mean-diff} \neq \mu_d \}$

②

$$T = \frac{\bar{d} - \mu_d}{S_d / \sqrt{n}} \sim t(v=n-1)$$

ST ID	Test 1	Test 2	Diff: d
1	80	82	-2 $\rightarrow d_1$
2	85	81	5 $\rightarrow d_2$
.	.	.	.
.	50	89	-39
.	56	58	-2 $\rightarrow d_n$

↳ Remedial PS

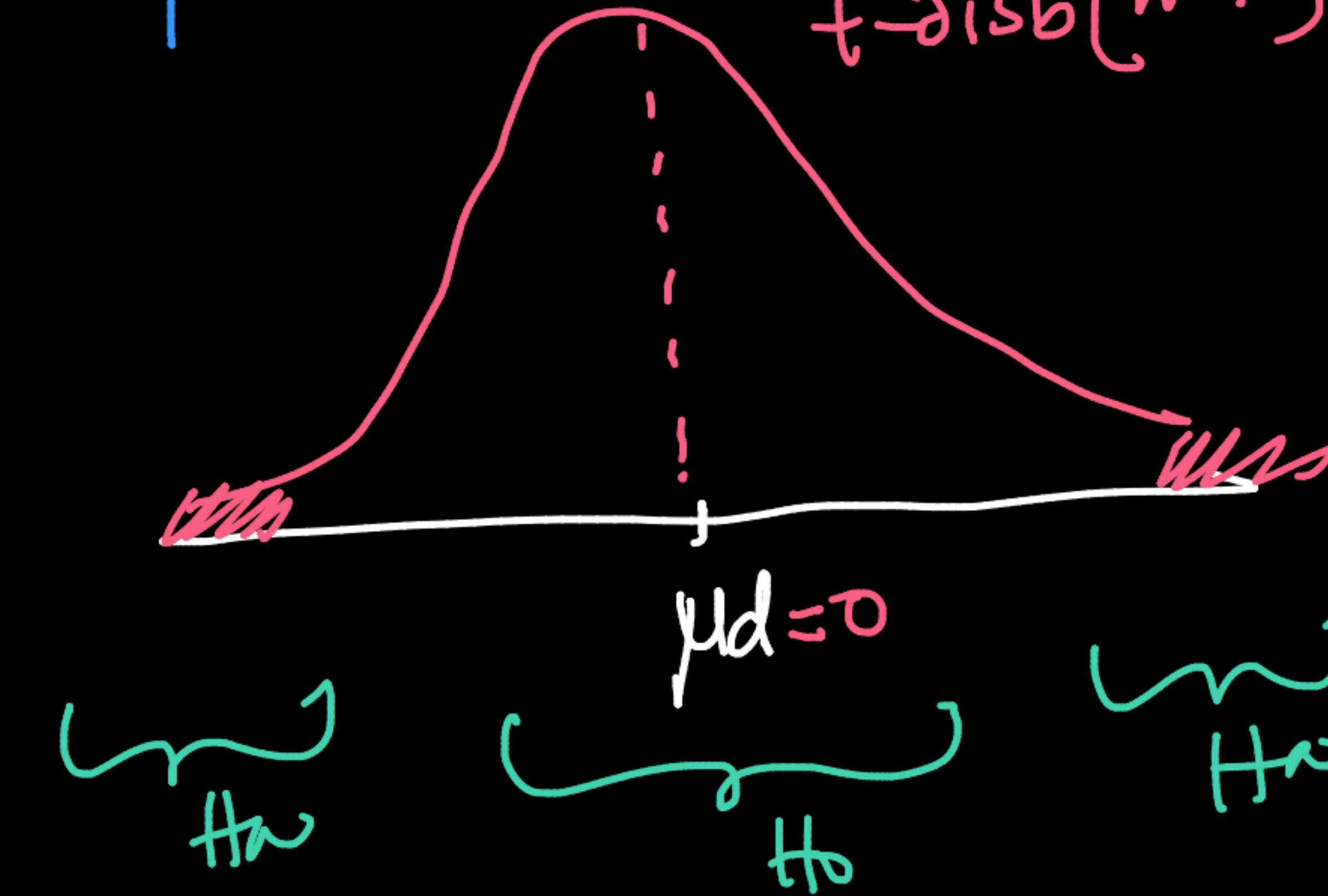
\bar{d} : sample mean of diff

s_d : sample std. dev of diff
 $t \sim t\text{-dist}(n-1)$

③ 2-sided

④ p-val

⑤ $d = \bar{d} - \mu_d$.
p-val vs d



$$\left\{ \begin{array}{l} H_0: \mu_1 = \mu_2 \Rightarrow \mu_d = 0 \\ H_a: \mu_d \neq 0 \Rightarrow \mu_1 \neq \mu_2 \rightarrow \text{2-sided} \end{array} \right.$$

diff = 1st - 2nd

=====

$$H_0: \mu_d = 0 \Rightarrow \mu_1 = \mu_2$$

$$H_a: \mu_2 > \underline{\mu_1} \Rightarrow \mu_d < 0$$

=====

Q:

t-test

$\mu_x = \mu_y$?



$$T = \frac{\mu_x - \mu_y}{\sqrt{\frac{s_x^2}{n_1} + \frac{s_y^2}{n_2}}} =$$

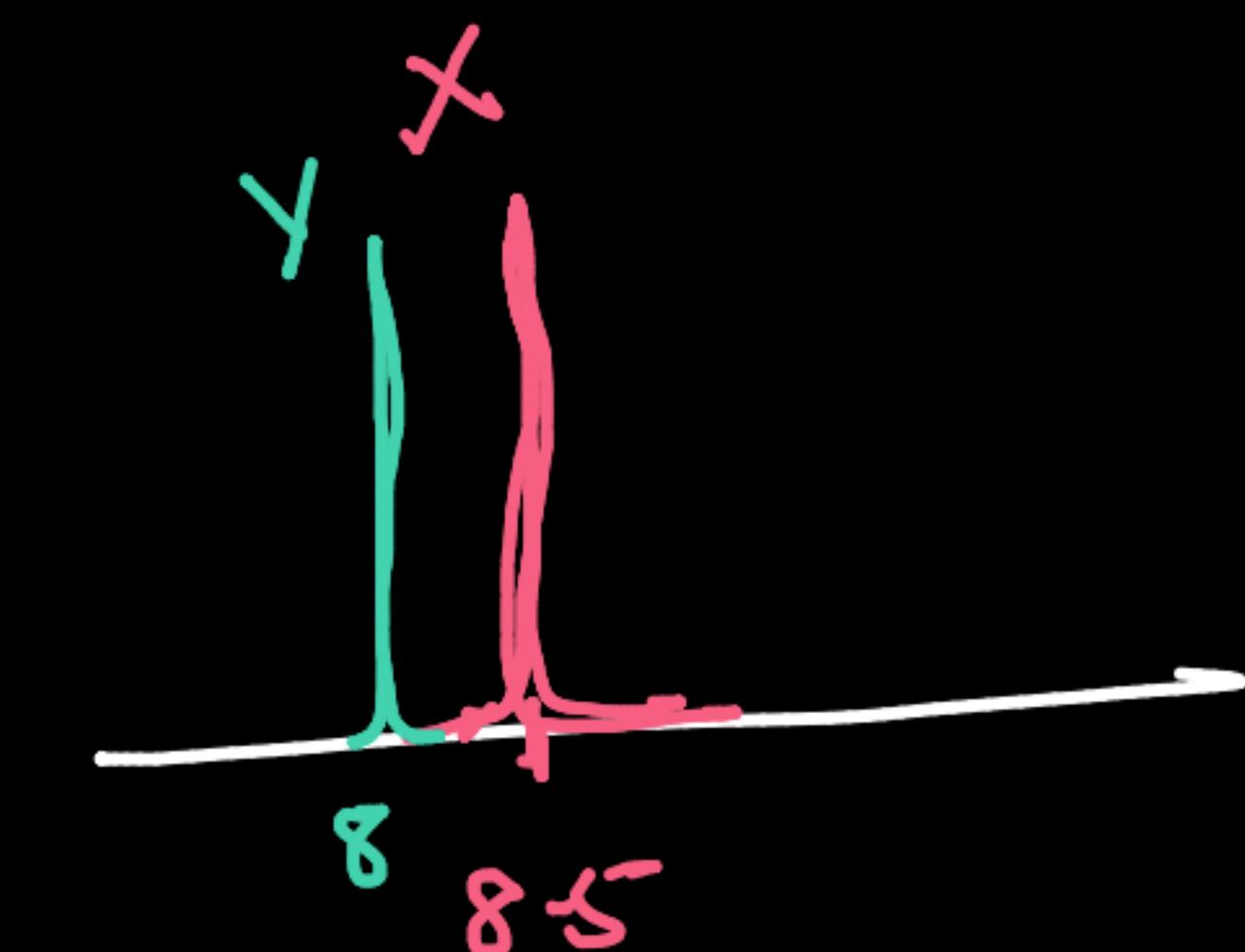
$$\frac{\mu_x - \mu_y}{\sqrt{\frac{s_x^2}{n_1} + \frac{s_y^2}{n_2}}}$$

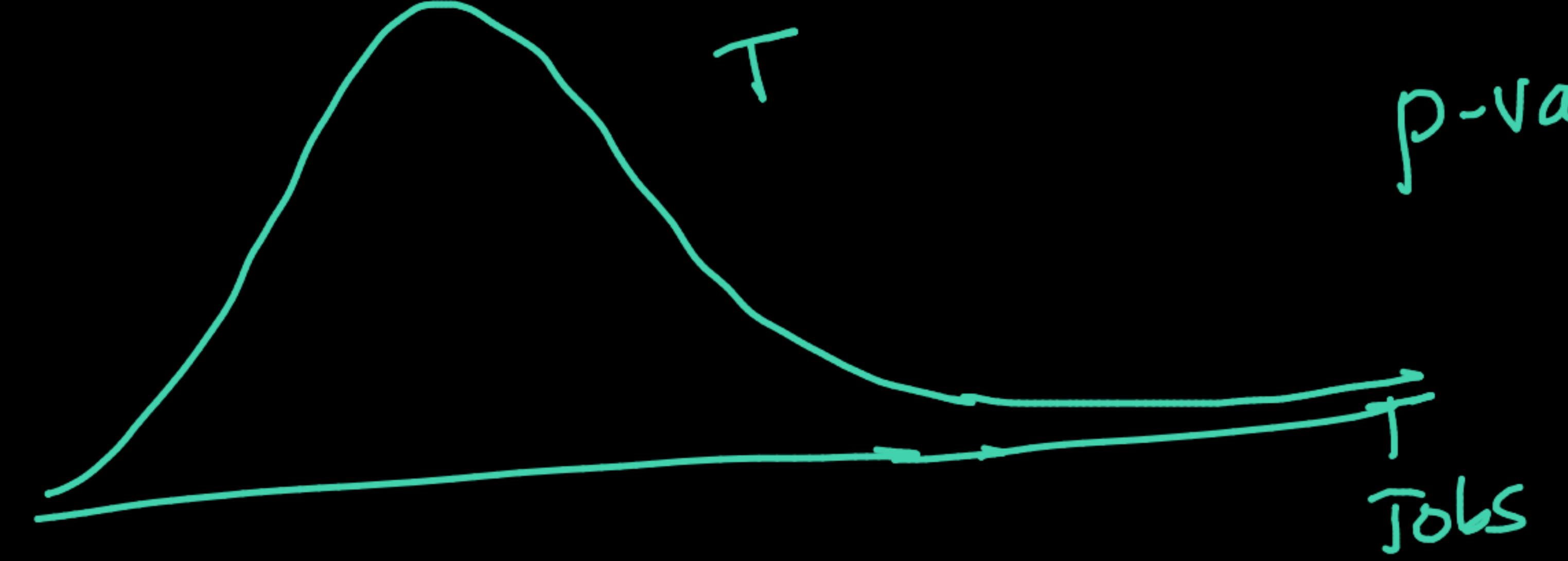
\rightarrow Undefined

$$X = [8.5, 8.5, \dots, 8.5] \quad n_1 = 20$$

$$Y = [8, 8, \dots, 8] \quad n_2 = 25$$

$$Z = [1, 1, \dots, 1]$$

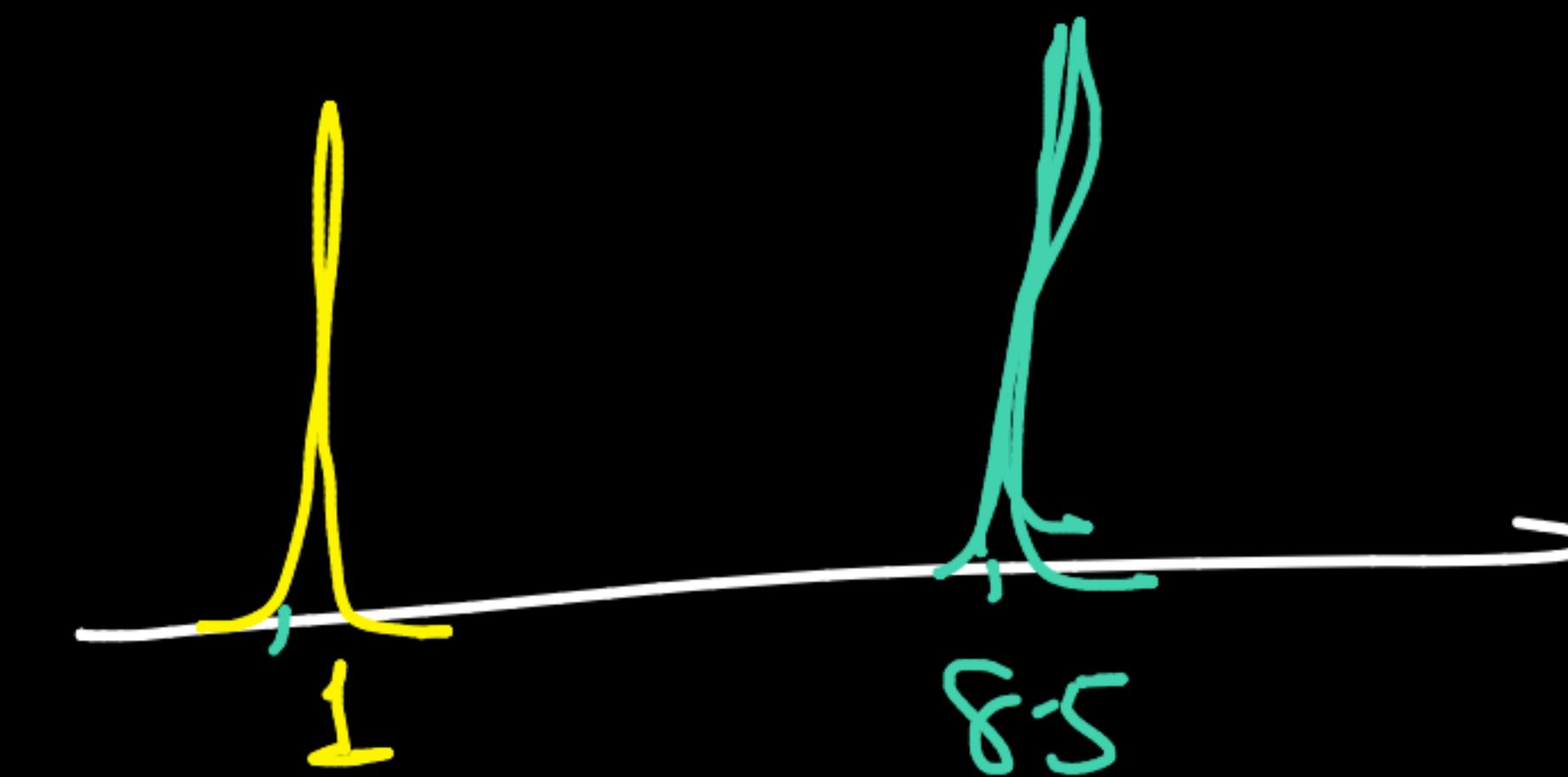


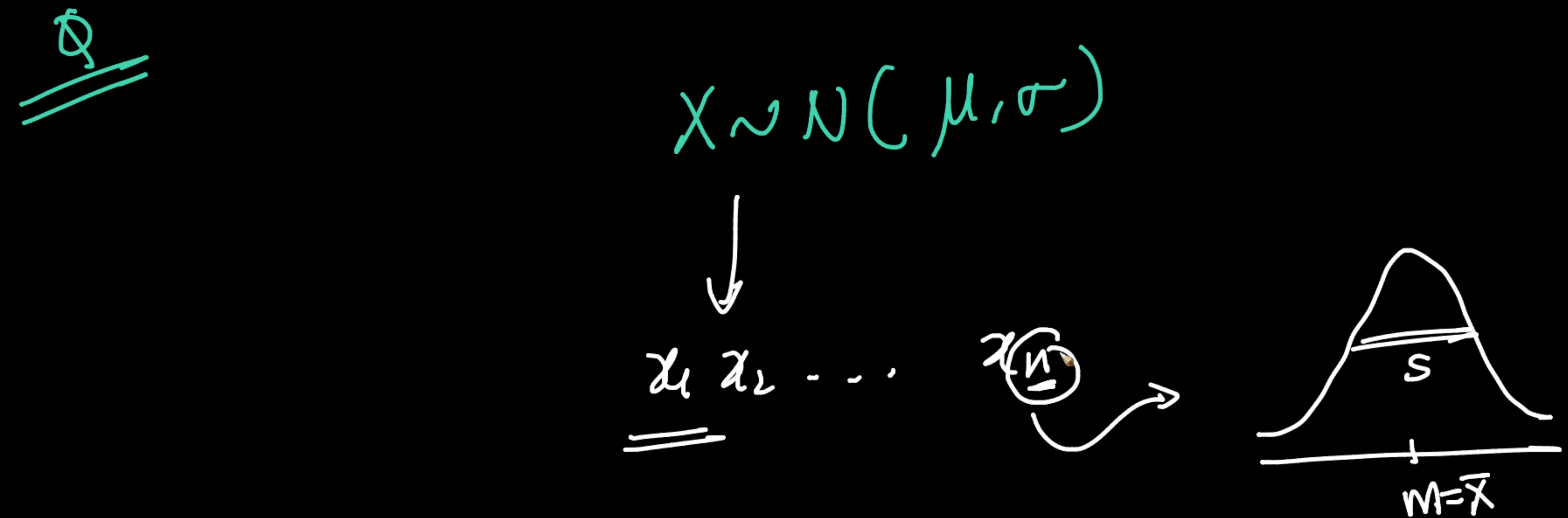


$T_{obs} \rightarrow \infty$; $p\text{-val} \rightarrow 0 \Rightarrow$
reject H_0

$$\mu_X \neq \mu_Z$$
$$X = \begin{bmatrix} 8.5 & 8.5 & \dots & 8.5 \end{bmatrix} \rightarrow 25 \text{ times}$$

$$Z = \begin{bmatrix} 1 & 1 & 1 & 1 & \dots & 1 \end{bmatrix} \rightarrow 30 \text{ times}$$





as $n \rightarrow \infty$

$S \rightarrow \Gamma$

$m = \bar{x} \rightarrow \mu$

Q
|||

2-Sample

Indep T-test
→

obj Med1 Med2
 $\mu_1 = \mu_2$ or not
=

paired t-test
→

obj diff 1st 2nd → 0
↳ Is the diff = 0 or not

St-Id Test 1 Test 2

diff ?
↓

~~paired~~

~~dependent~~

i j

80 ←→ 85

55 ←→ 65

KTest_Ttest.ipynb - Colaboratory | Kolmogorov-Smirnov test - Wikipedia | Chi-squared distribution - Wikipedia | One-Sample z-test

cliffsnotes.com/study-guides/statistics/univariate-inferential-tests/one-sample-z-test

Numerical Measures >

Probability >

Sampling >

Principles of Testing >

Univariate Inferential Tests > **Current**

Bivariate Relationships >

Common Mistakes and Tables >

Cummulative Reviews >

Statistics Quizzes >

Test for population mean

Hypothesis test

Formula: $z = \frac{\bar{x} - \mu}{\sigma / \sqrt{n}}$

where \bar{x} is the sample mean, μ is a specified value to be tested, σ is the population standard deviation, and n is the size of the sample. Look up the significance level of the z -value in the standard normal table (Table in Appendix B).

A herd of 1,500 steer was fed a special high-protein grain for a month. A random sample of 29 were weighed and had gained an average of 6.7 pounds. If the standard deviation of weight gain for the entire herd is 7.1, test the hypothesis that the average weight gain per steer for the month was more than 5 pounds.

null hypothesis: $H_0: \mu = 5$

alternative hypothesis: $H_a: \mu > 5$

$$z = \frac{6.7 - 5}{7.1 / \sqrt{29}} = \frac{1.7}{1.318} = 1.289$$

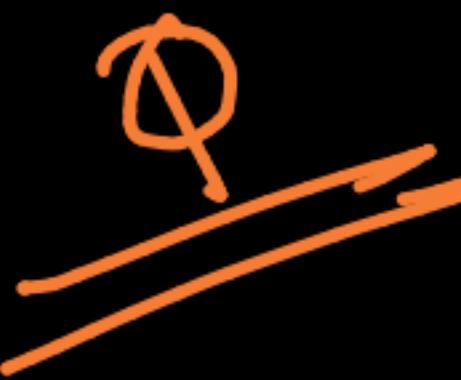
Tabled value for $z \leq 1.28$ is 0.8997

$1 - 0.8997 = 0.1003$

Handwritten notes:

- Population mean μ (circled)
- Sample mean \bar{x} (circled)
- Sample size n (circled)
- Standard deviation σ (circled)
- Null hypothesis: $H_0: \mu = 5$
- Alternative hypothesis: $H_a: \mu \neq 5$
- Test statistic: $T = \frac{\bar{x} - 5}{\sigma / \sqrt{n}}$
- Standardized test statistic: $z(\bar{o}, 1)$

Back to Top



T-test

$H_0:$

$$\mu_1 = \mu_2$$



$H_0: \mu_1 \neq \mu_2$



$$T = \frac{M_1 - M_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

distrib of T under H_0 ?

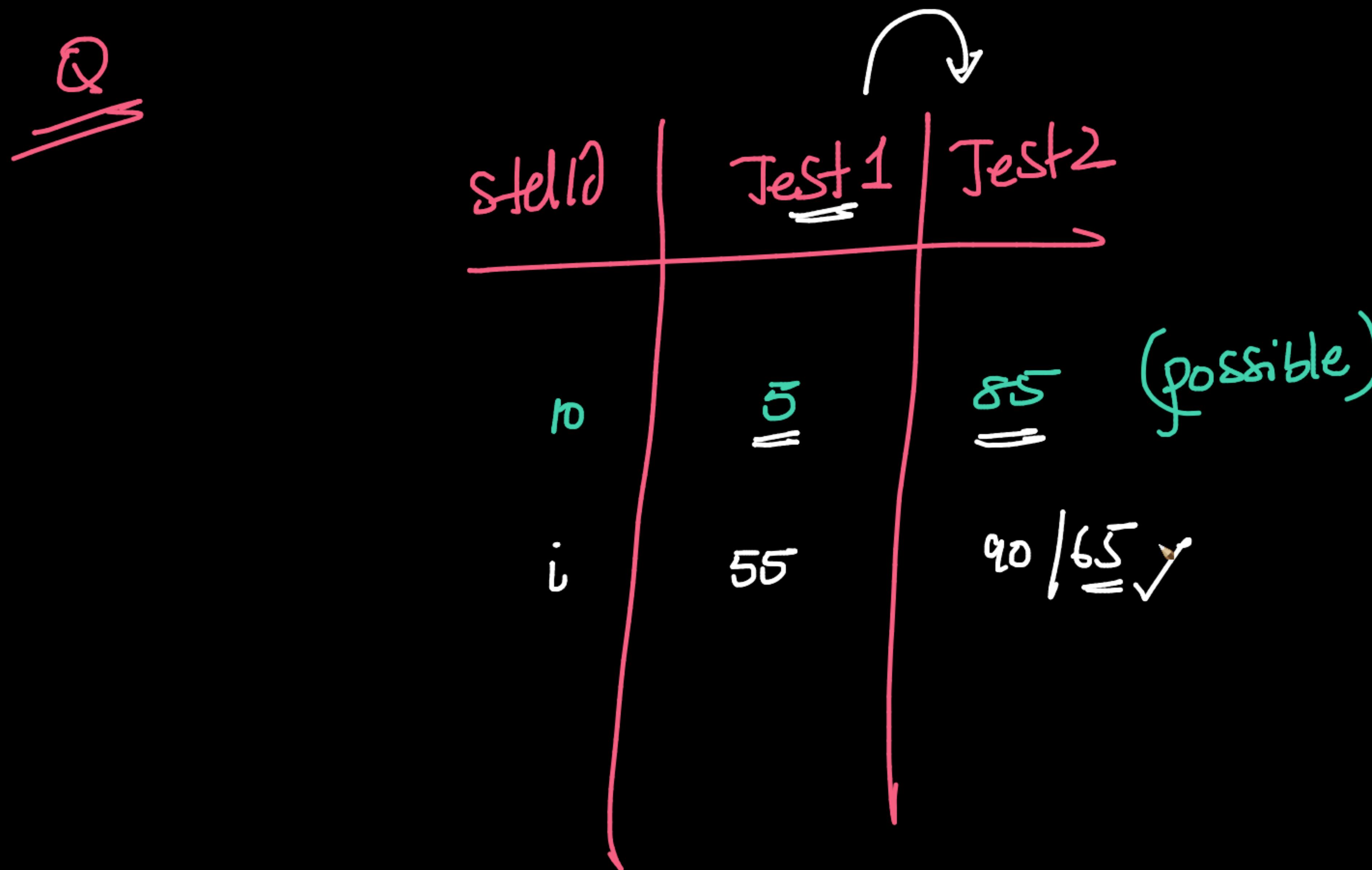
Q

μ_d = pop. mean of differences Test 1 & Test 2

as cl. 1 of
this
CLT + BS

$d_1, d_2, \dots, d_n \rightarrow n \text{ obs of diff}$

\bar{d} : sample mean of diff



\varnothing
Z-test

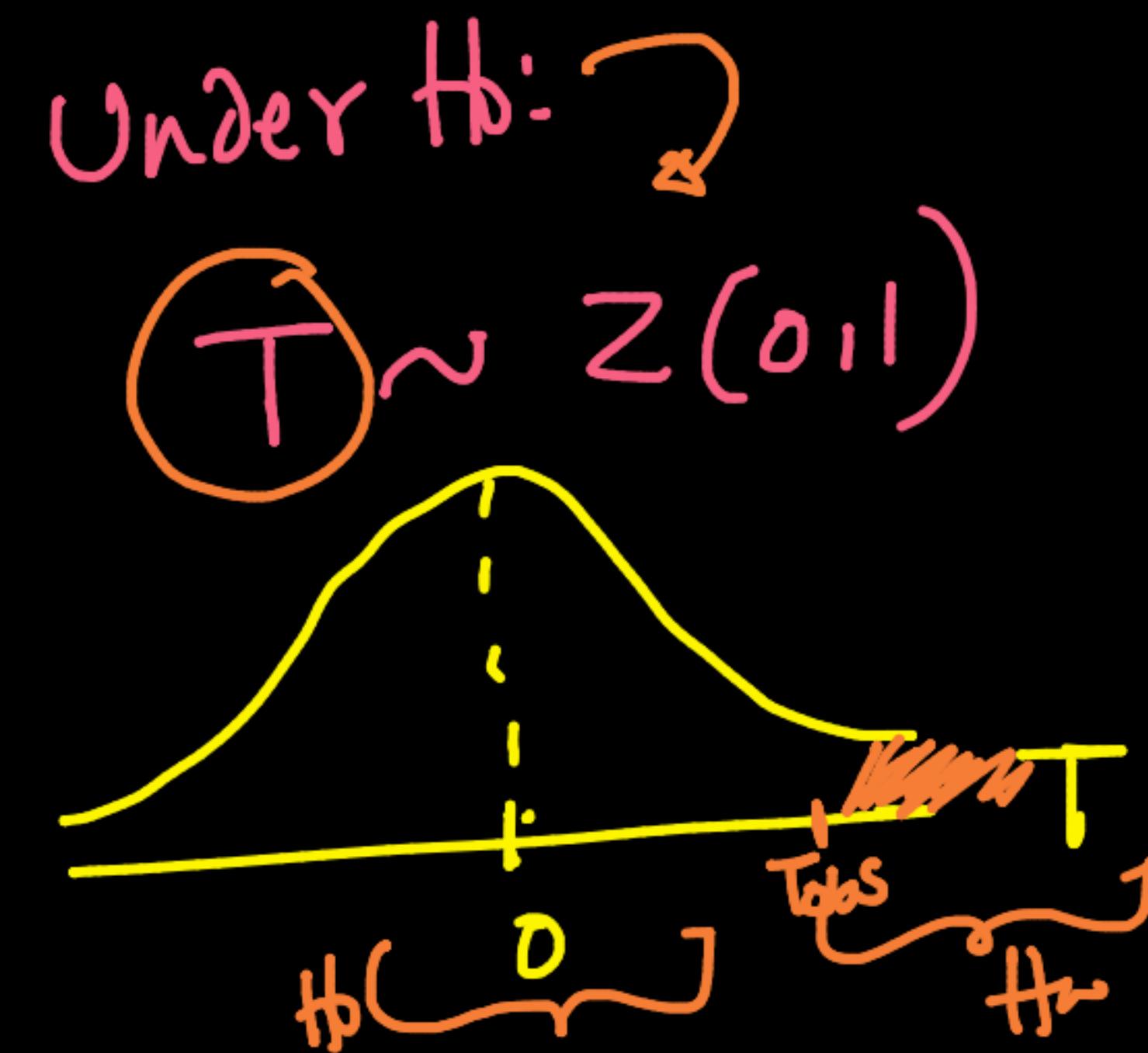
$$\mu_1 \rightarrow \boxed{X} \rightarrow m_1, s_1$$

$$\mu_2 \rightarrow \boxed{Y} \rightarrow m_2, s_2$$

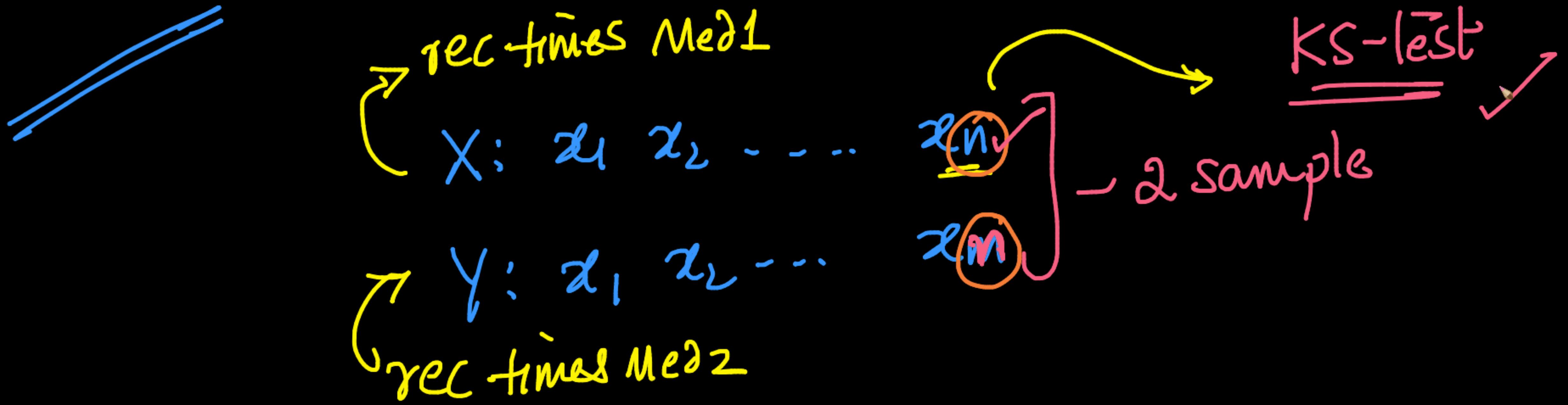
$$T = \frac{m_1 - m_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 > \mu_2$$

✓ Z-test }
 T-test } → Comparison of Means



Task:

$\text{disb } \underline{\underline{X}} = \text{disb } \underline{\underline{Y}}$

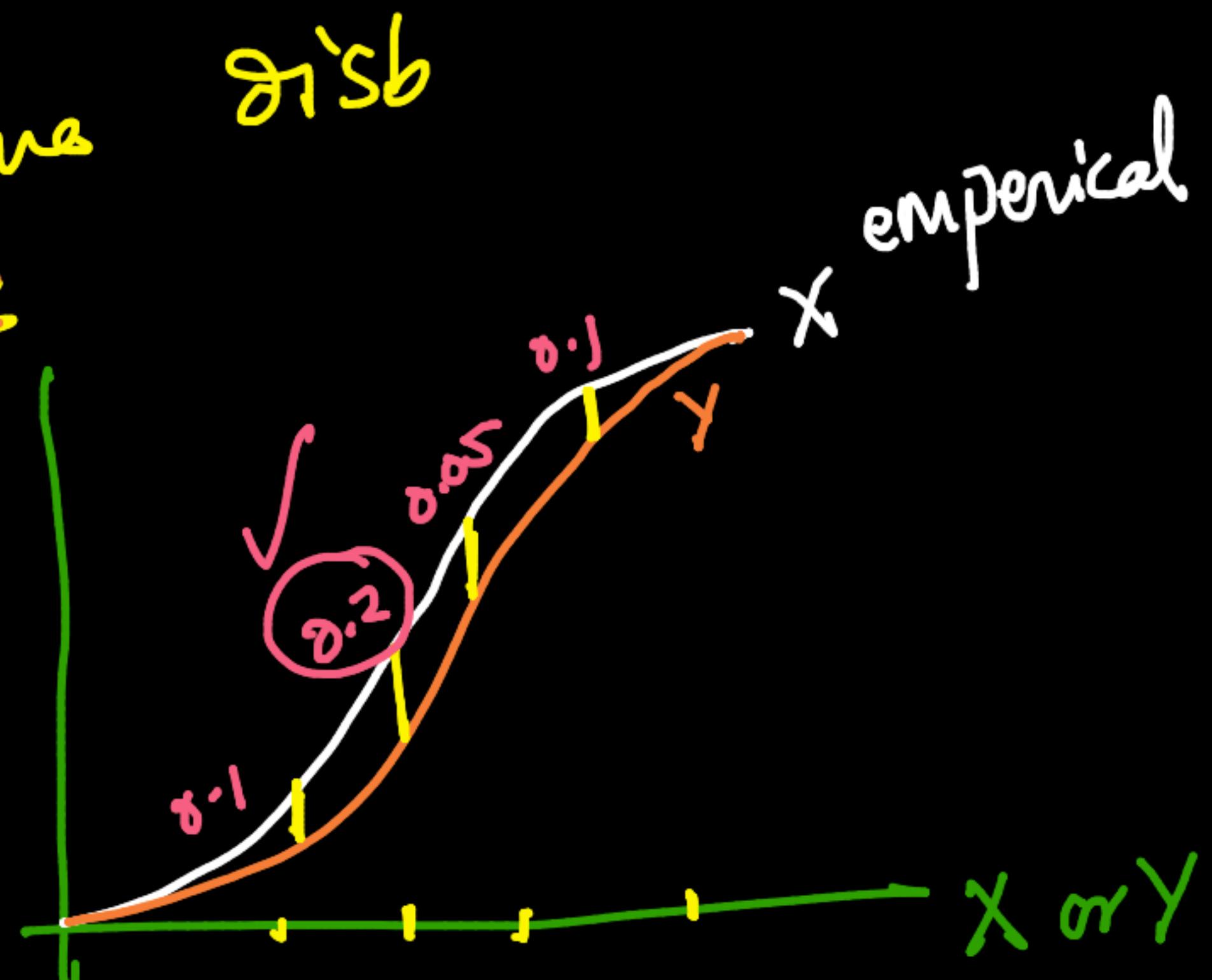
① $H_0: X \sim Y$ have same dist's
 $H_a: X \neq Y$ not same dist's

X empirical

emp-CDF

$$\text{② } T = \max \left| \text{gap b/w CDFs} \right|_{X \text{ & } Y}$$

$$= \text{Supremum} \left| \text{gap b/w CDFs} \right|$$



T_{KS}



Under H₀: closer to zero

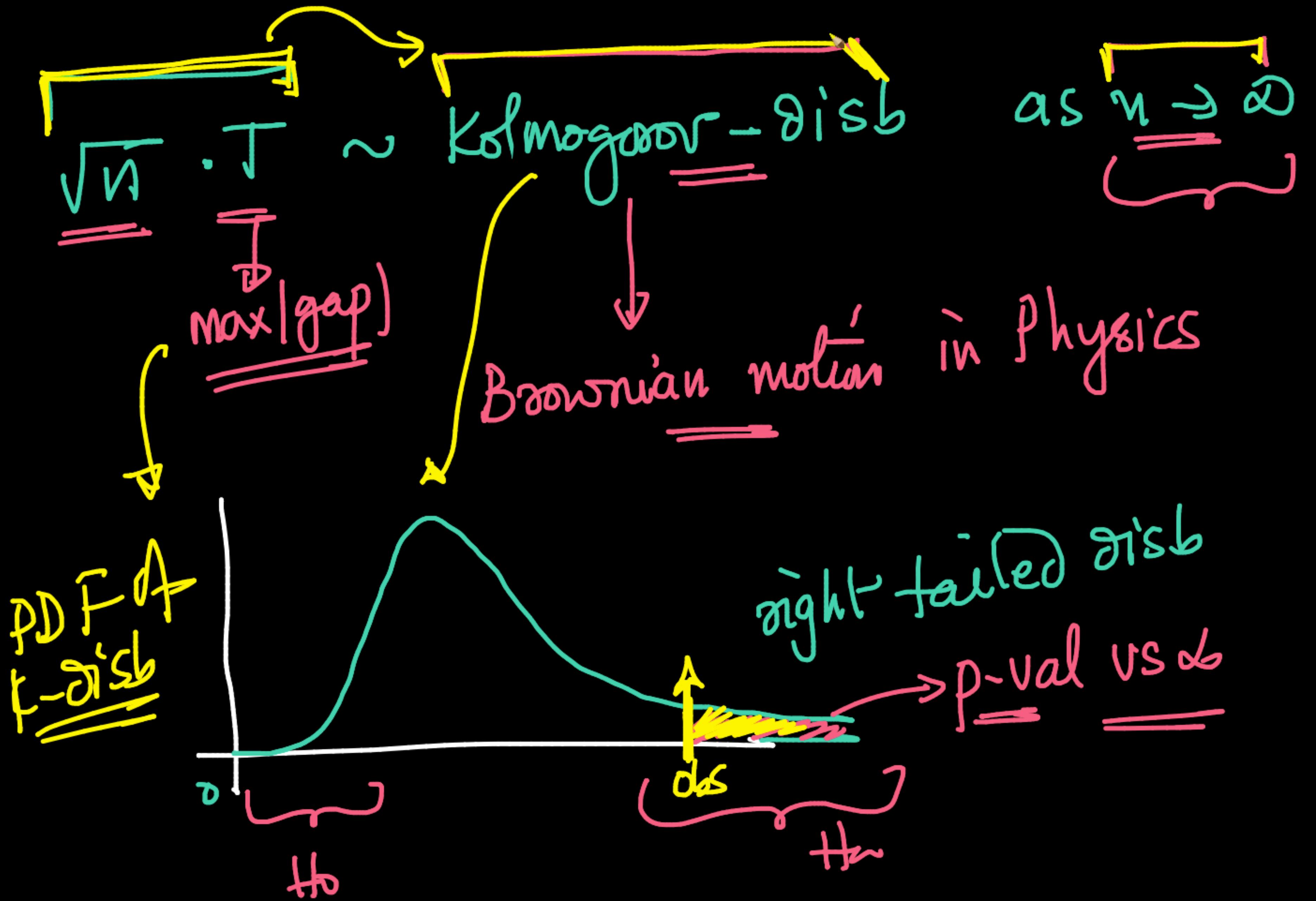
Under H_a: larger +ve values

③

↓
right tailed test

$\sqrt{n} \cdot T_{obs}$

KS-test



KTest_Ttest.ipynb - Colaboratory | Kolmogorov-Smirnov test - Wikipedia | Chi-squared distribution - Wikipedia | One-Sample z-test | +

en.wikipedia.org/wiki/Kolmogorov-Smirnov_test

Major statistical packages among which [SAS](#) PROC NPAR1WAY, [\[14\]](#) [Stata](#) ksmirnov [\[15\]](#) implement the KS test under the assumption that $F(x)$ is continuous, which is more conservative if the null distribution is actually not continuous (see [\[16\]](#) [\[17\]](#) [\[18\]](#)).

Two-sample Kolmogorov–Smirnov test [\[edit\]](#)

The Kolmogorov–Smirnov test may also be used to test whether two underlying one-dimensional probability distributions differ. In this case, the Kolmogorov–Smirnov statistic is

$$D_{n,m} = \sup_x |F_{1,n}(x) - F_{2,m}(x)|,$$

where $F_{1,n}$ and $F_{2,m}$ are the empirical distribution functions of the first and the second sample respectively, and \sup is the supremum function.

For large samples, the null hypothesis is rejected at level α if

$$D_{n,m} > c(\alpha) \sqrt{\frac{n+m}{n \cdot m}}.$$

Where n and m are the sizes of first and second sample respectively. The value of $c(\alpha)$ is given in the table below for the most common levels of α

α	0.20	0.15	0.10	0.05	0.025	0.01	0.005	0.001
$c(\alpha)$	1.073	1.138	1.224	1.358	1.48	1.628	1.731	1.949

and in general [\[19\]](#) by

$$c(\alpha) = \sqrt{-\ln\left(\frac{\alpha}{2}\right) \cdot \frac{1}{2}},$$

so that the condition reads

$$D_{n,m} > \sqrt{-\ln\left(\frac{\alpha}{2}\right) \cdot \frac{1+\frac{m}{n}}{2m}}.$$

Here, again, the larger the sample sizes (e.g. $m = n$), the minimal bound scales in the size of either of the samples according to the formula.

Illustration of the two-sample Kolmogorov–Smirnov statistic. Red and blue lines each correspond to an empirical distribution function, and the black arrow is the two-sample KS statistic.

Where n_1 and n_2 are the sizes of first and second sample respectively. The value of $c(\alpha)$ is given in the table below for the most common levels of α

α	0.20	0.15	0.10	0.05	0.025	0.01	0.005	0.001
$c(\alpha)$	1.073	1.138	1.224	1.358	1.48	1.628	1.731	1.949

Illustration of the two-sample Kolmogorov–Smirnov statistic. Red and blue lines each correspond to an empirical distribution function, and the black arrow is the two-sample KS statistic.

and in general^[19] by

$$c(\alpha) = \sqrt{-\ln\left(\frac{\alpha}{2}\right)} \cdot \frac{1}{2},$$

so that the condition reads

$$D_{n,m} > \sqrt{-\ln\left(\frac{\alpha}{2}\right)} \cdot \frac{1 + \frac{m}{n}}{2m}.$$

Here, again, the larger the sample sizes, the more sensitive the minimal bound: For a given ratio of sample sizes (e.g. $m = n$), the minimal bound scales in the size of either of the samples according to its inverse square root.

Note that the two-sample test checks whether the two data samples come from the same distribution. This does not specify what that common distribution is (e.g. whether it's normal or not normal). Again, tables of critical values have been published. A shortcoming of the univariate Kolmogorov–Smirnov test is that it is not very powerful because it is devised to be sensitive against all possible types of differences between two distribution functions. Some argue^{[20][21]} that the Cucconi test, originally proposed for simultaneously comparing location and scale, can be much more powerful than the Kolmogorov–Smirnov test when comparing two distribution functions.

Setting confidence limits for the shape of a distribution function [edit]

Main article: [Dvoretzky–Kiefer–Wolfowitz inequality](#)

While the Kolmogorov–Smirnov test is usually used to test whether a given $F(x)$ is the underlying probability distribution of $F_n(x)$, the procedure may be inverted to give confidence limits on $F(x)$ itself. If one chooses a critical value of the test statistic D_α such that $P(D_n > D_\alpha) = \alpha$, then a band of width $\pm D_\alpha$ around $F_n(x)$ will entirely contain $F(x)$ with probability $1 - \alpha$.

The Kolmogorov–





+ Code + Text

```
[ ] 9.53931977, 9.02602273, 6.79374185, 8.59715131, 8.37747338,  
8.78161815, 6.78716383, 8.28473394, 8.20283798, 12.50518811,  
10.19772574, 8.93758457, 8.9540311, 8.28927558, 6.28935098,  
7.69447559, 9.66777701, 10.33898342, 8.71199578, 5.12781581,  
9.70954569, 9.13685031, 7.28989718, 8.0868909, 7.42937556,  
7.31356749, 9.92345816, 8.60211814, 9.33228465, 8.14132658,  
6.17871495, 10.28358242, 7.31898597, 7.95085527, 6.20331719,  
9.19119762, 6.98600628, 7.05314883, 10.57921482, 6.83637574,  
7.86199283, 8.23350975, 5.87625665, 7.78945364, 8.83612492]
```

```
[ ] ✓d1 = np.array(r1)  
✓d2 = np.array(r2)
```

```
[ ] n1 = len(d1)  
n2 = len(d2)
```

```
[ ] n1
```

100

```
[ ] n2
```

120

+ Code + Text

Connect ▾

1

[] n1

100

[] n2

120

[] #2-sample KS Test

```
stats.ks_2samp(d1, d2)
```

May
gap

-5x10⁻⁵

```
KstestResult(statistic=0.3233333333333333, pvalue=1.5163387982131127e-05)
```

p-value = 0.00001516 < 0.001 = 0.1% = alpha

=> Reject H₀ (r₁ and r₂ same distribution)

=> Accept H_a (the distributions of r_1 and r_2 are different)

```
[ ] plt.grid()
a = plt.hist(d1, bins=100, cumulative=True, label='CDF', density=True, histtype='step')
b = plt.hist(d2, bins=100, cumulative=True, label='CDF', density=True, histtype='step')
plt.show()
```

+ Code + Text

Connect

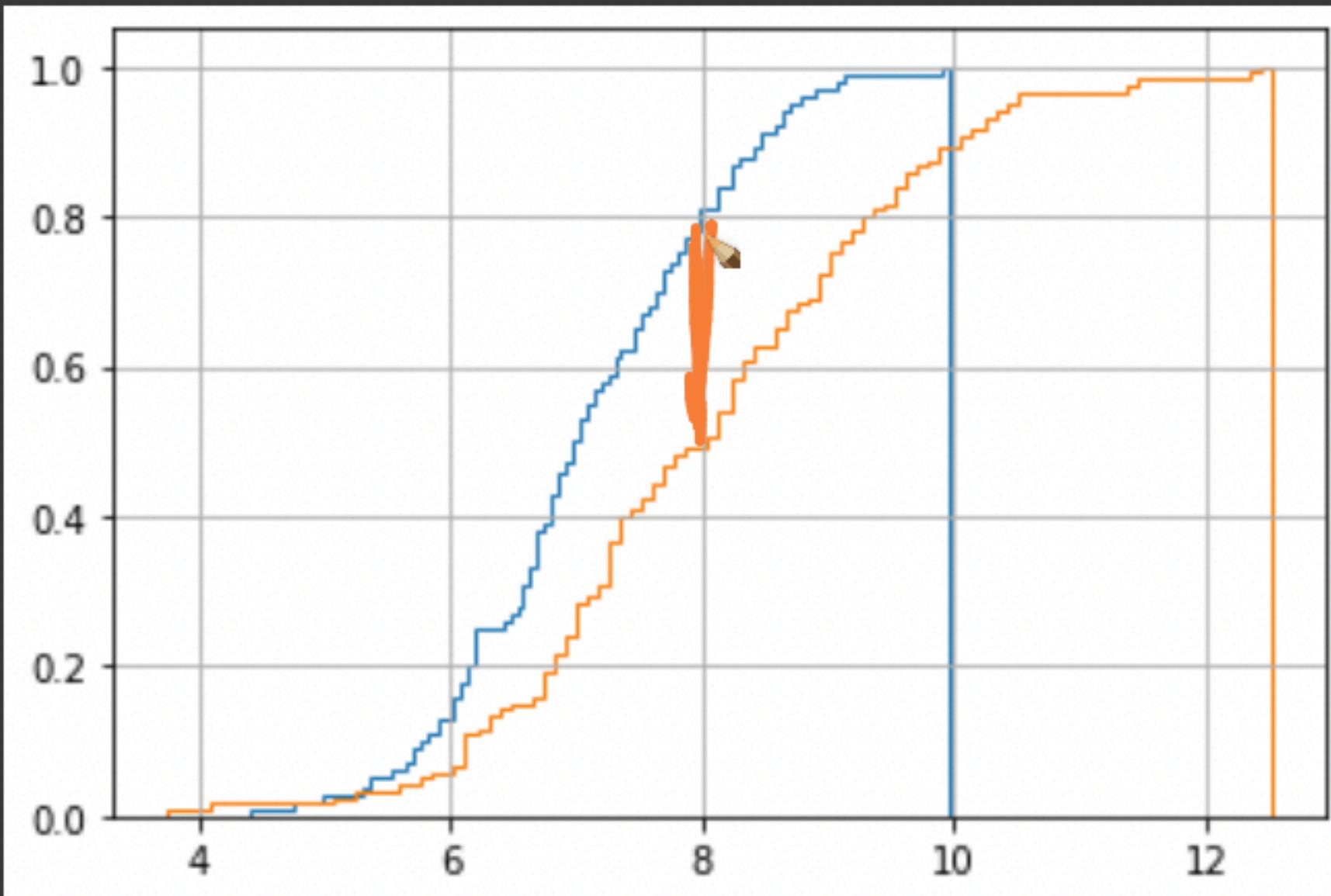


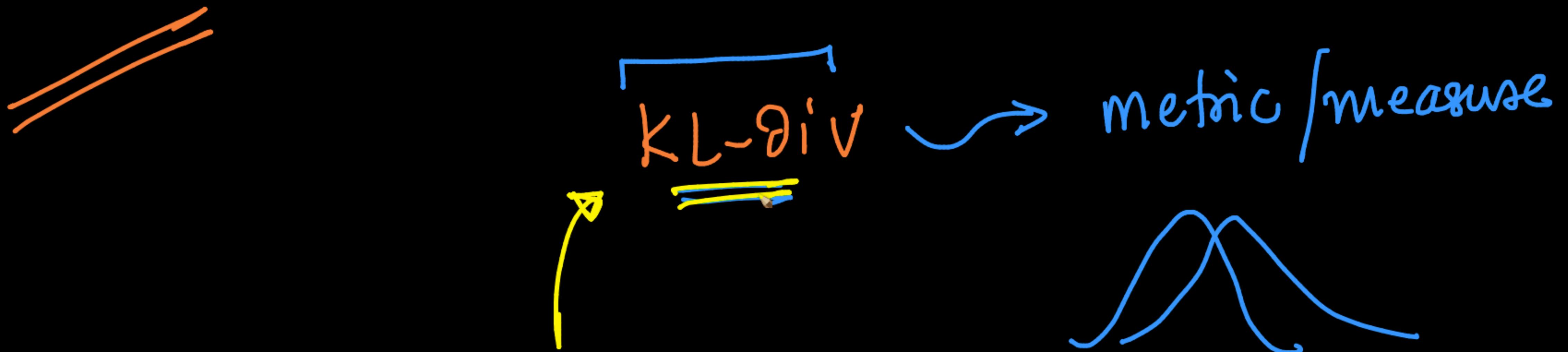
p-value = 0.00001516 < 0.001 = 0.1% = alpha

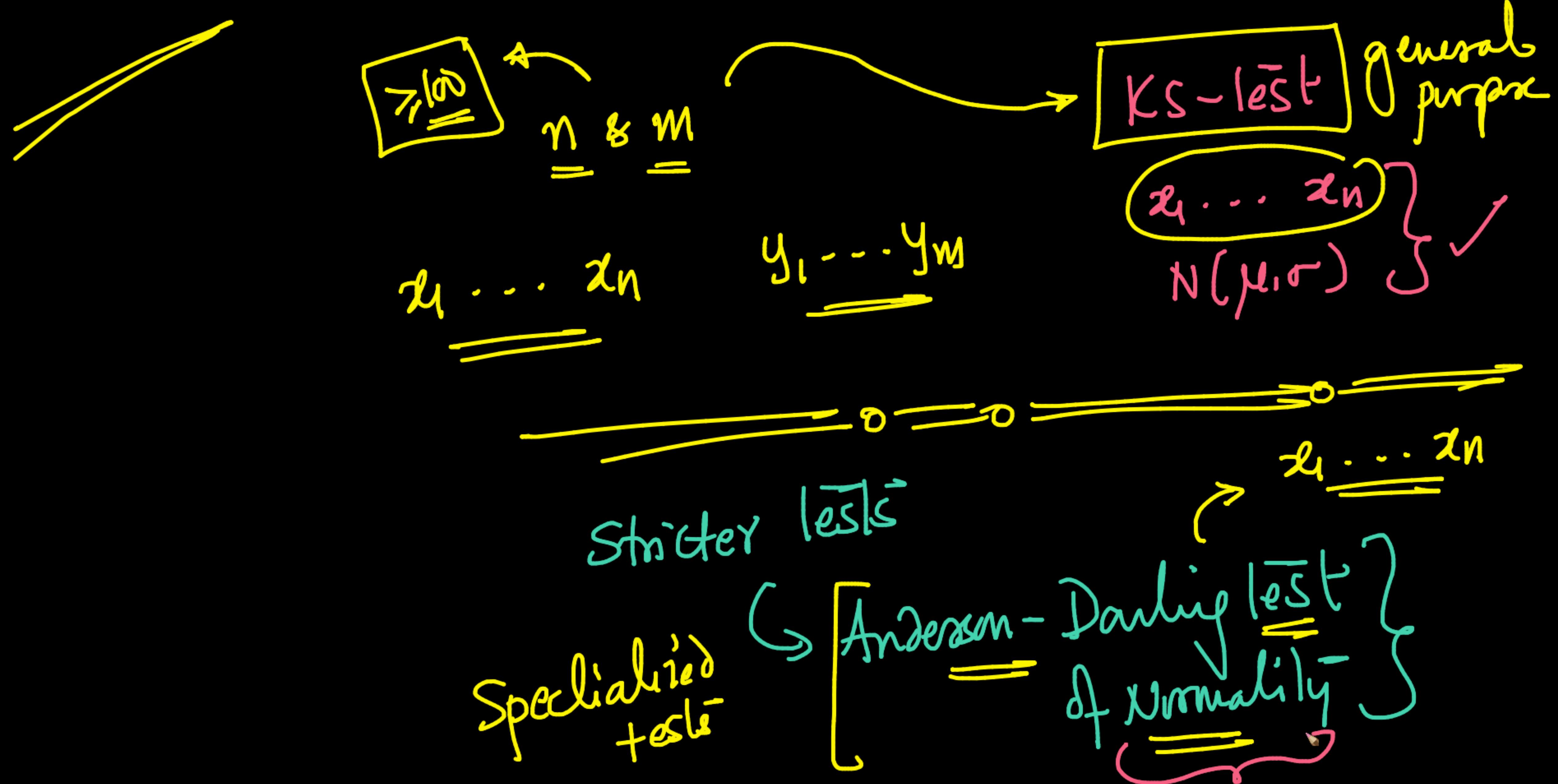
=> Reject H0 (r1 and r2 same distribution)

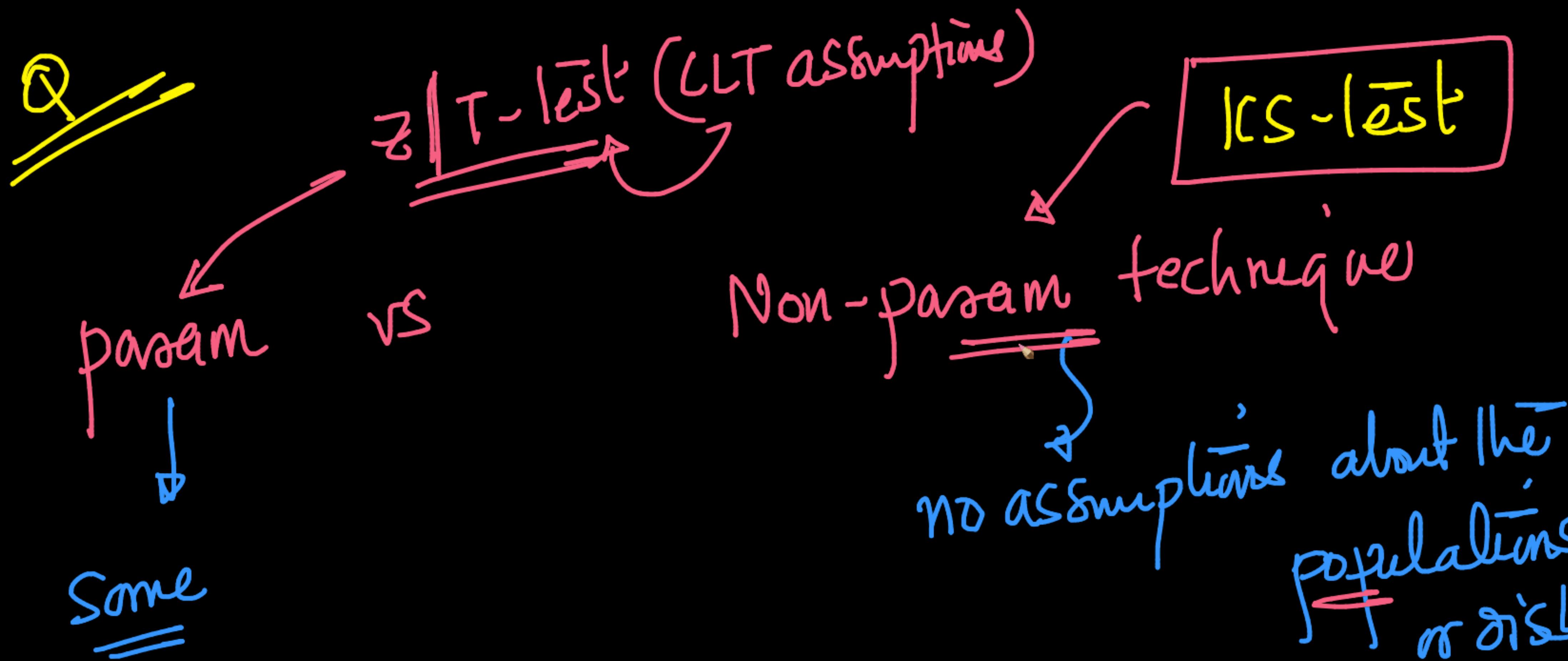
=> Accept Ha (the distributions of r1 and r2 are different)

```
[ ] plt.grid()
    a = plt.hist(d1, bins=100, cumulative=True, label='CDF', density=True, histtype='step')
    b = plt.hist(d2, bins=100, cumulative=True, label='CDF', density=True, histtype='step')
    plt.show()
```



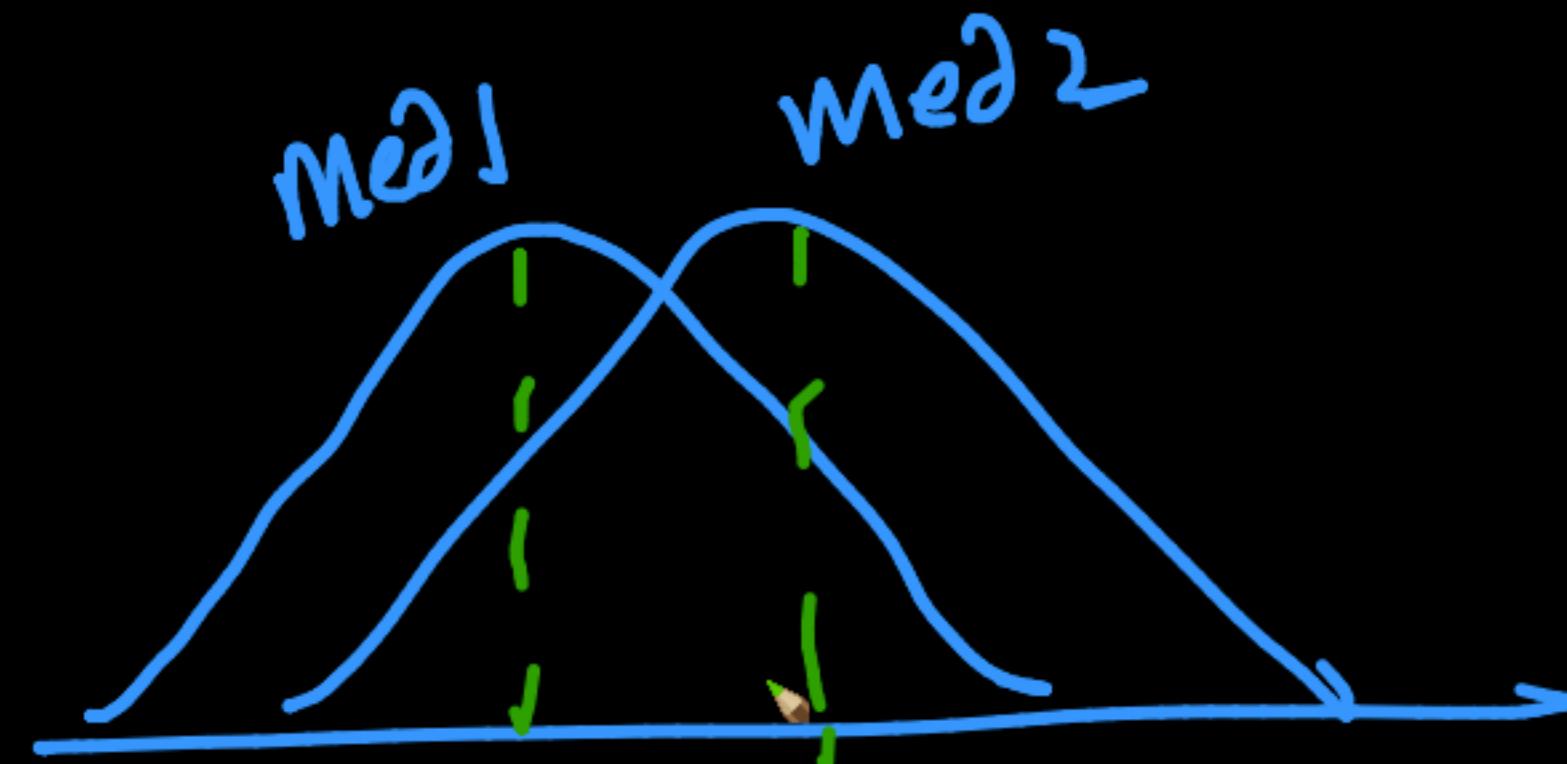








$M_1 \sim N_2$

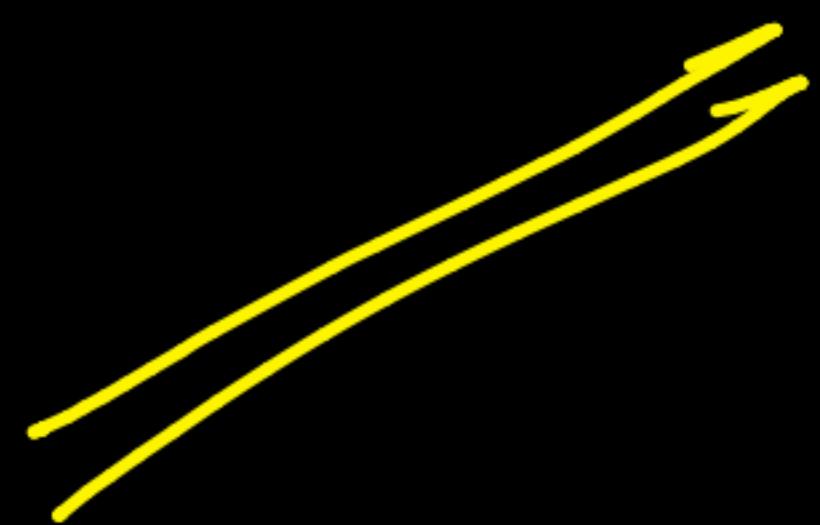


p-val

Q

$x_1 \ x_2 \ \dots \ x_{200} \sim \text{expo}(\lambda)$

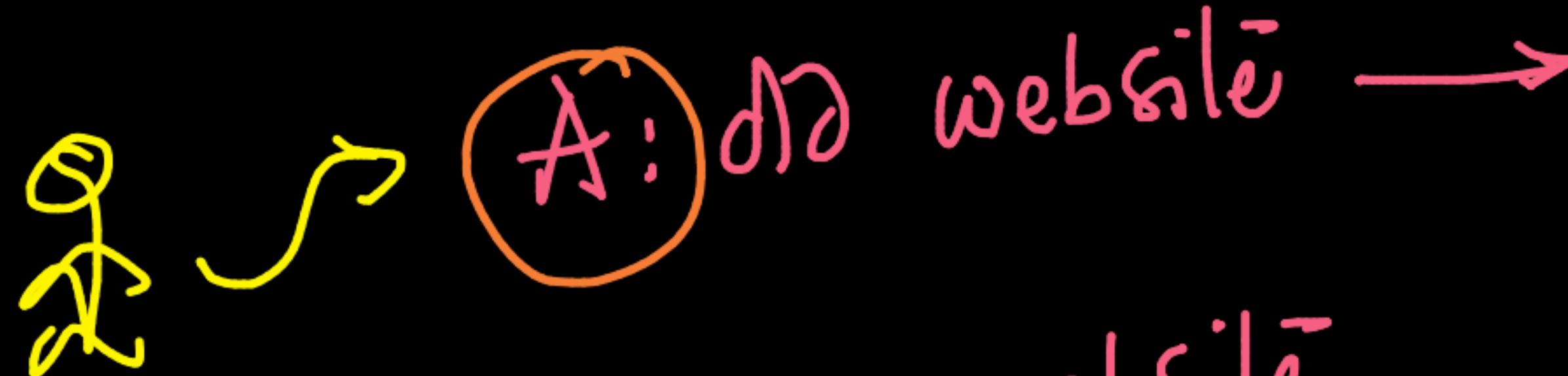
QQ-plot
KS-test $p\text{-val}$ ✓



$$n_1 \text{ & } n_2 > 30$$

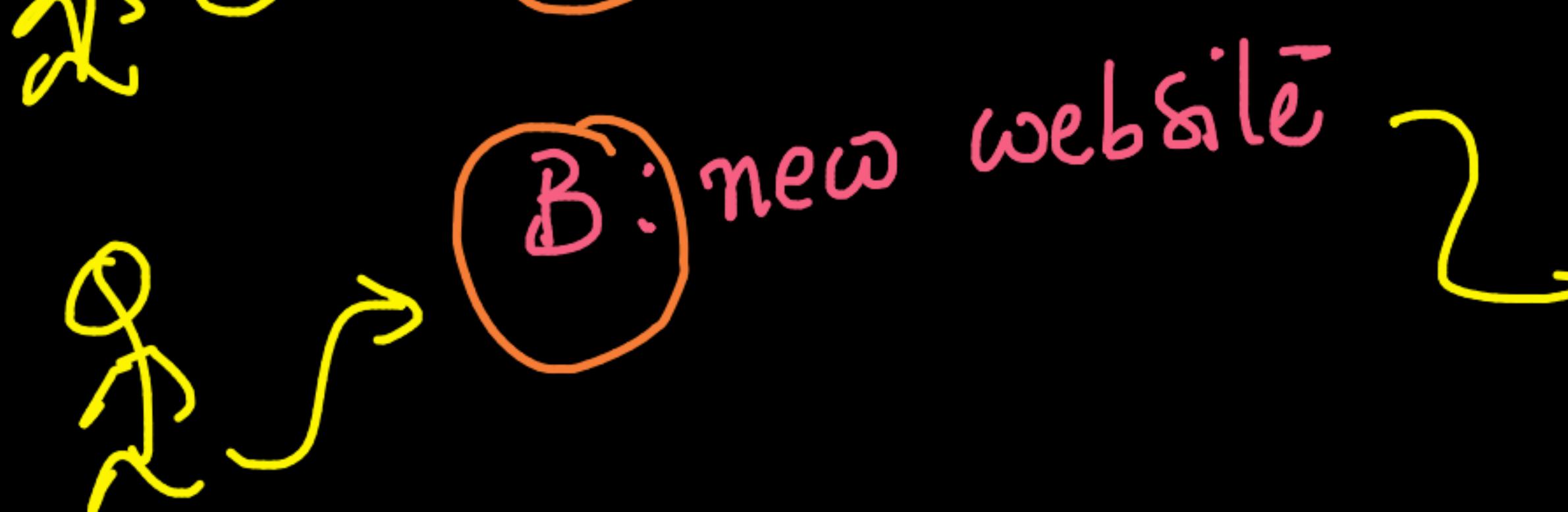
Z - proportions Test
~~p =~~

Retail-website



conv. rate

$$\frac{\text{conv}_1}{\text{visits}_1} = \frac{p_1}{n_1}$$



$$\frac{\text{conv}_2}{\text{visits}_2} = \frac{p_2}{n_2}$$

Observed proportion

\hat{P}_1 & \hat{P}_2 : sample observed proportions

n_1 & n_2 obs

{ Task!
Compare the population proportions
 P_1 P_2

(1)

$$H_0: \hat{P}_1 = \hat{P}_2$$

$$H_a: \hat{P}_1 \neq \hat{P}_2$$

(2)

$$T_{\text{obs}} = \frac{\hat{P}_1 - \hat{P}_2}{\sqrt{\hat{P}(\hat{P})(\frac{1}{n_1} + \frac{1}{n_2})}}$$

$$X \sim \text{Bin}(n, p)$$

$$\text{Var}(X) = p(1-p)$$

$$\hat{P}_1 = \frac{\text{conv}_1}{\text{visits}_1} = n_1$$

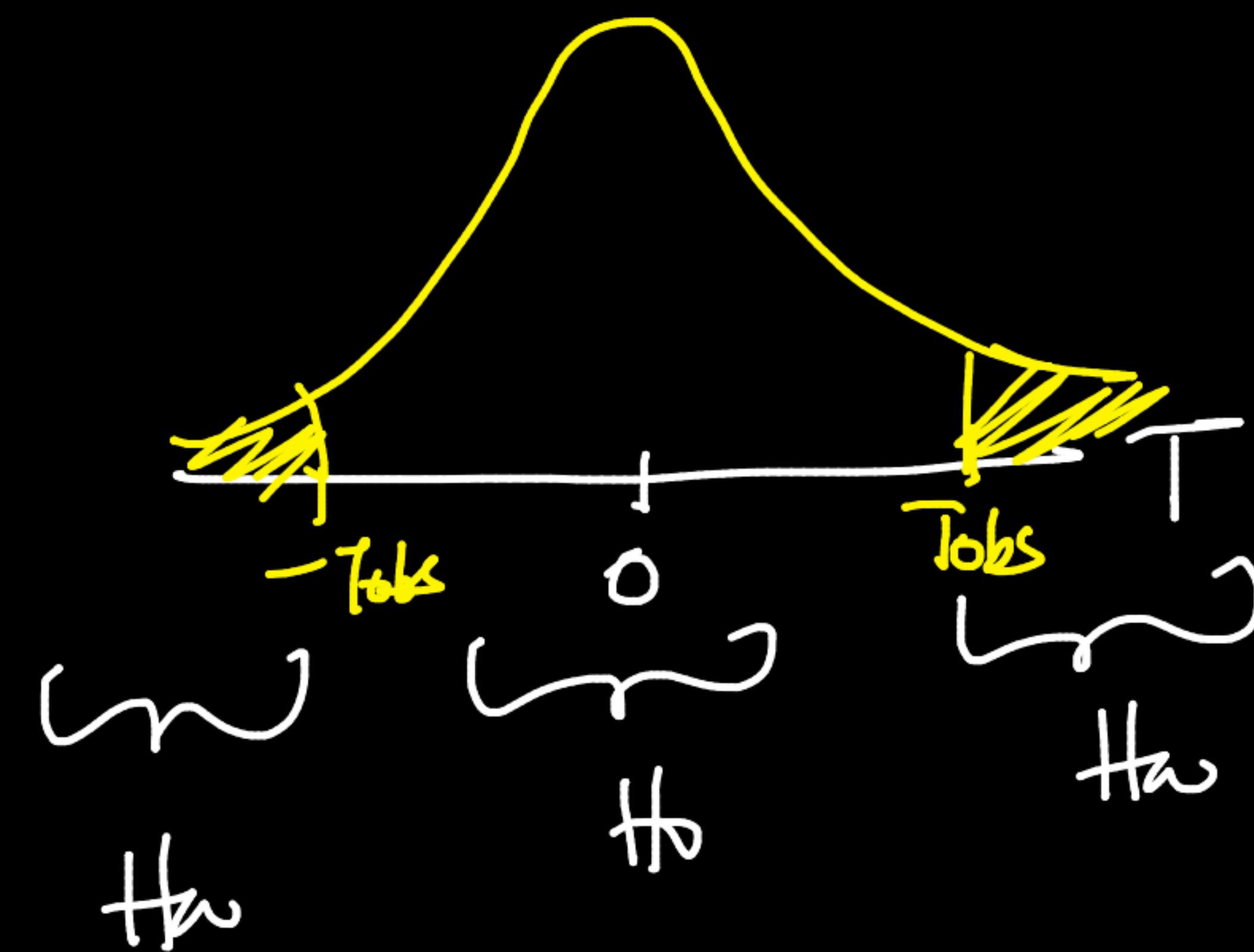
$$\hat{P}_2 = \frac{\text{conv}_2}{\text{visits}_2} = n_2$$

$$\hat{P} = \frac{\text{conv}_1 + \text{conv}_2}{\text{visits}_1 + \text{visits}_2}$$

aggregate conv. rate

$$T \sim Z(0,1)$$

2-sided
p-val
 $\alpha = 5\%$
p-val vs α



will assess whether or not a sample from a population represents the true proportion from the entire population.

Critical Value Approach

The steps to perform a test of proportion using the critical value approach are as follows:

1. State the null hypothesis H_0 and the alternative hypothesis H_A .
2. Calculate the test statistic:

$$z = \frac{\hat{p} - p_0}{\sqrt{\frac{p_0(1-p_0)}{n}}} \rightarrow$$

$H_0: \hat{p} = p_0 = 0.1 = 10\%$

where p_0 is the null hypothesized proportion i.e., when $H_0: p = p_0$

3. Determine the critical region.
4. Make a decision. Determine if the test statistic falls in the critical region. If it does, reject the null hypothesis. If it does not, do not reject the null hypothesis.

Example S.6.1

Newborn babies are more likely to be boys than girls. A random sample found 13,173 boys were born

BASIC STATISTICAL CONCEPTS

- S.1 Basic Terminology
- S.2 Confidence Intervals
- ▶ S.3 Hypothesis Testing
- S.4 Chi-Square Tests
- S.5 Power Analysis
- S.6 Test of Proportion
- S.7 Self-Assess
- ▶ Calculus Review
- ▶ Matrix Algebra Review
- ▶ Ethics and Statistics
- ▶ Technology Tutorials

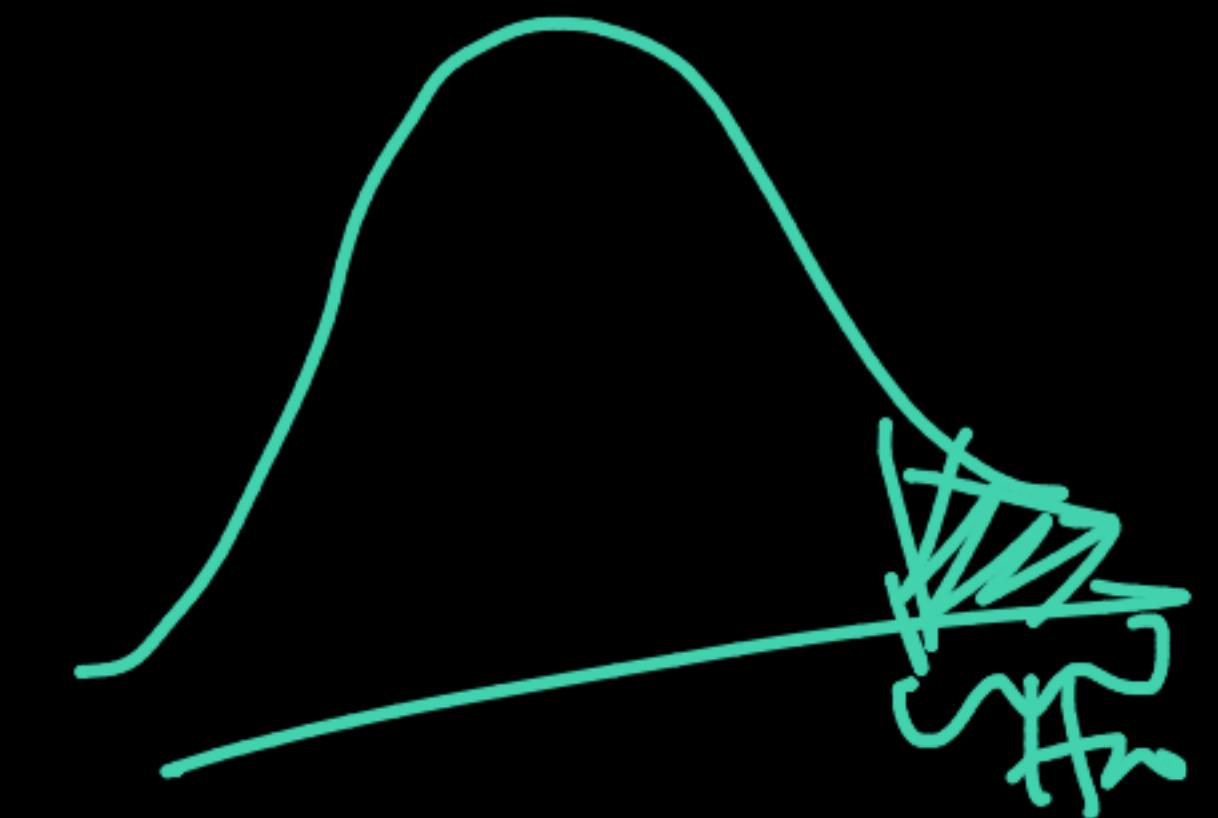
$$H_0: p_1 = p_2$$

$H_a: p_1 \neq p_2 \rightarrow \text{2-sided}$

{ also have

$H_a: p_1 > p_2 \rightarrow \text{right-tailed test}$

$H_a: p_1 < p_2 \rightarrow \text{left-tailed test}$



χ^2 -test

Test of independence

Youtube

BIZ:

regular → premium

✓ [Q does gender matter in converting from
reg to premium

Biz:

Does

discrete
premium - sub

Depend on

discrete
gender or
not?

1
0

		Contingency Table	
		0	1
Gender	0	346	149
	1	339	165

Data:

$$P(P=0 \text{ and } G=F)$$

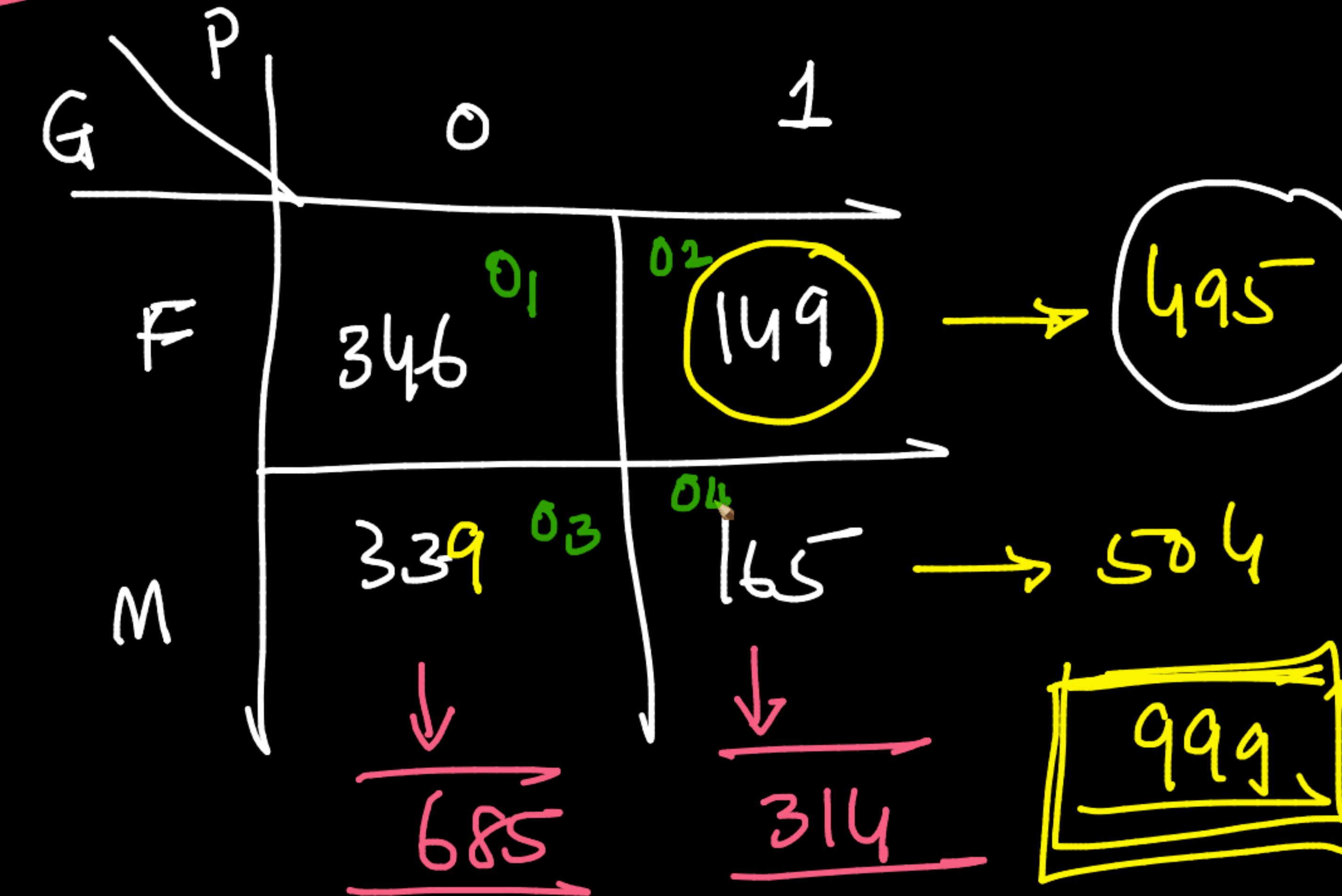
i

$H_0:$ Gender is indep of Premium

\Rightarrow Gender doesn't impact Premium sub..

$H_a:$ Gender impacts premium for

Obs:

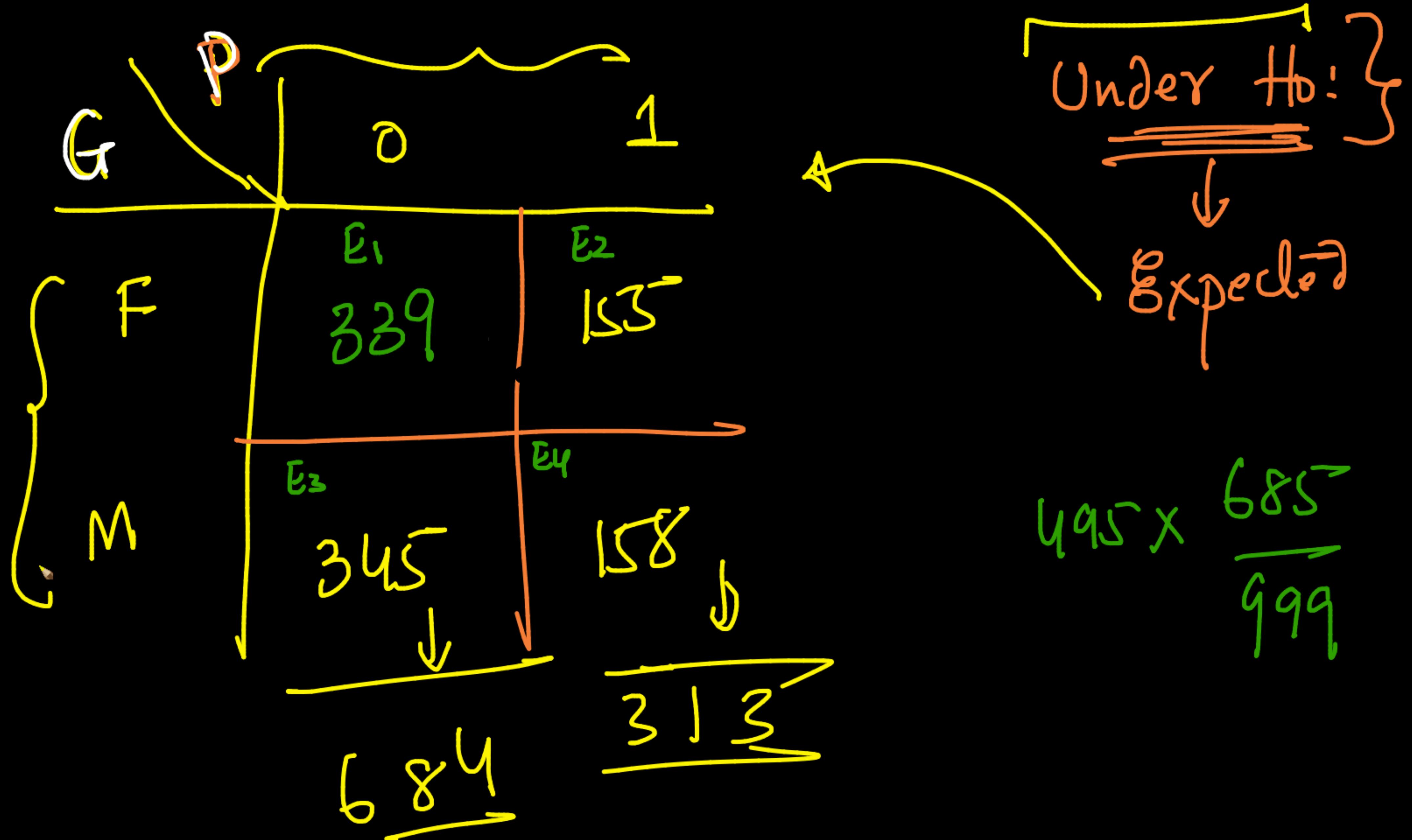


$P(\text{non-sub})$

$$\frac{685}{999}$$

$P(\text{sub})$

$$\frac{314}{999}$$

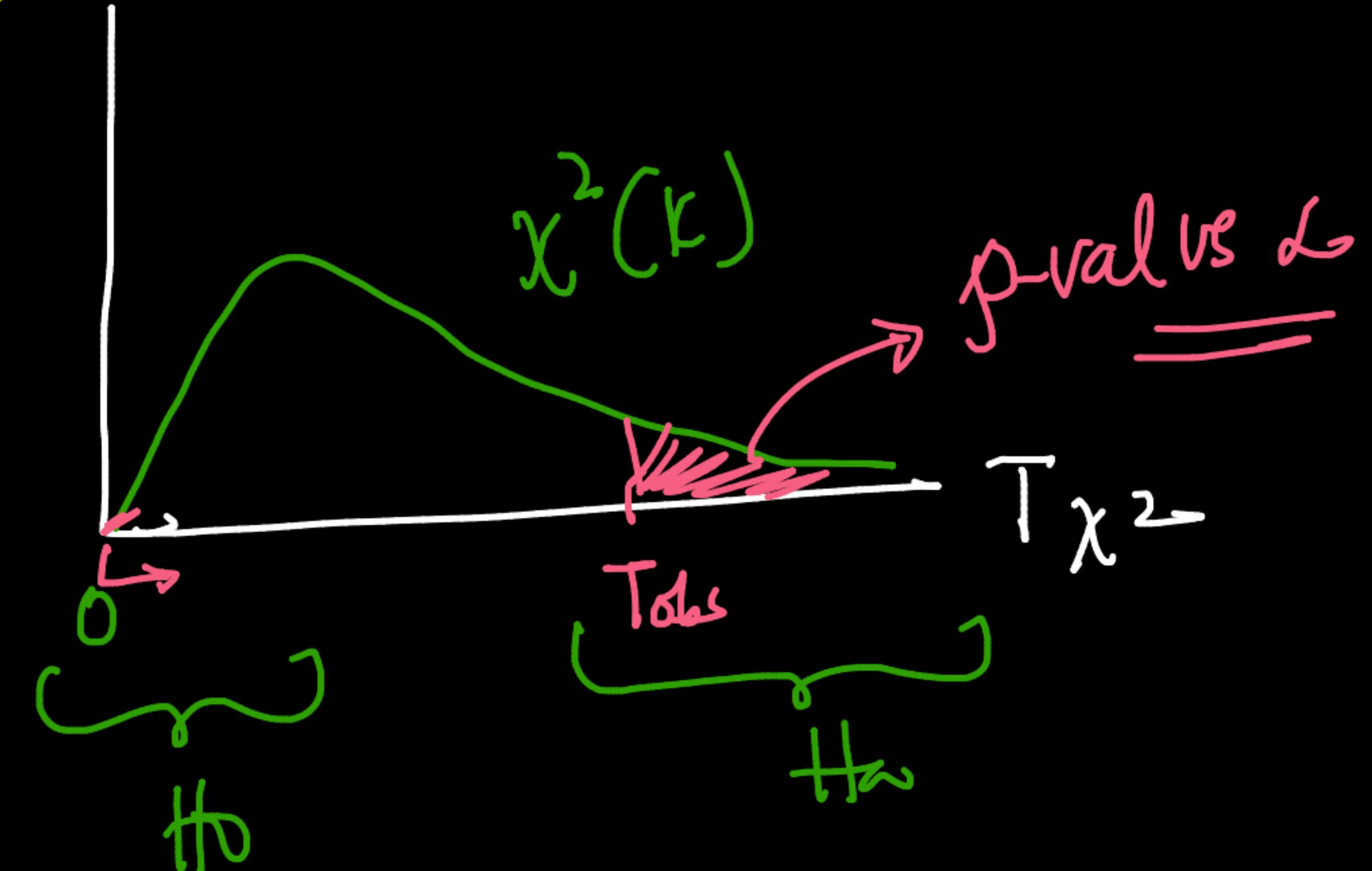


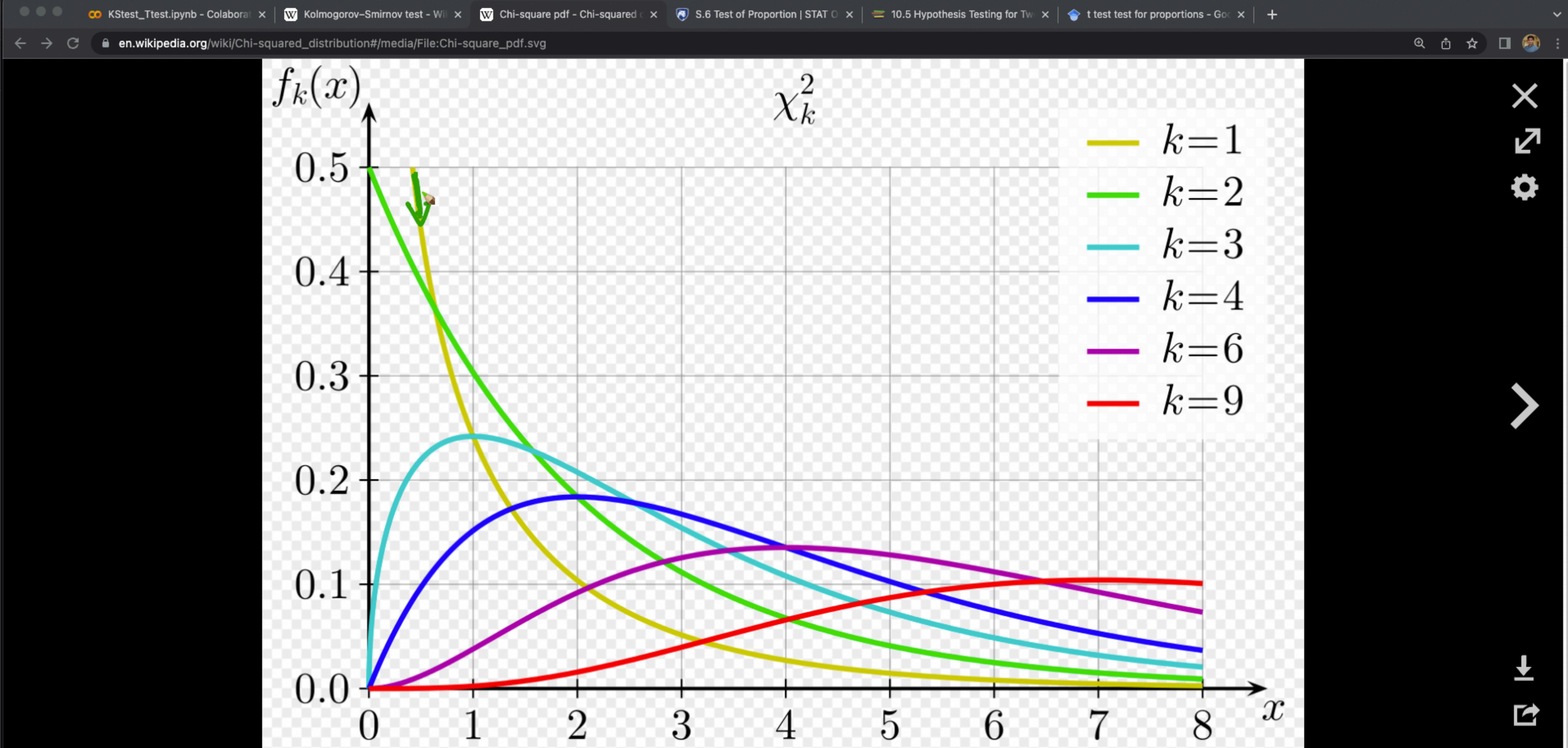
② $\chi^2 = \sum_{i=1}^{\# \text{cells}} \frac{(O_i - E_i)^2}{E_i}$

$\chi^2 \rightarrow \text{logical}$

$\chi^2 \sim \chi^2(k)$

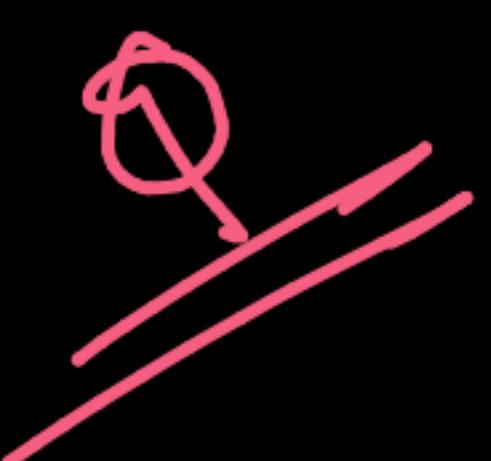
$\left(\frac{n_{rows}-1}{2} \right) \left(\frac{n_{cols}-1}{2} \right)$





Plot of the chi-square distribution for values of $k = \{1, 2, 3, 4, 6, 9\}$. Accurate plotcurves. Labels are embedded in Computer-Modern font.

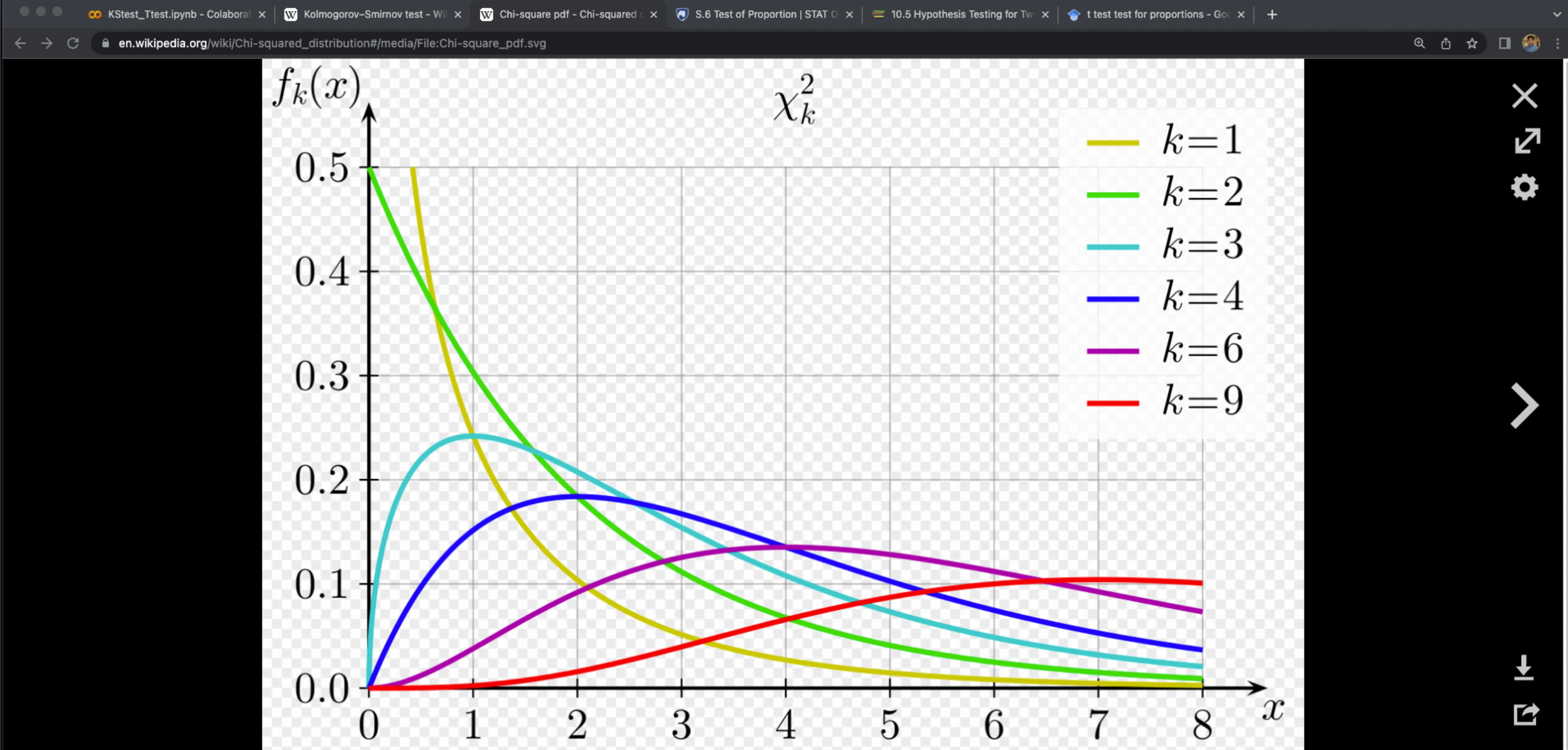
More details



{ H_0 : G is indep of P

Test-statistik = $\sum_{i=1}^{\text{#cells}} \frac{(O_i - E_i)^2}{E_i}$

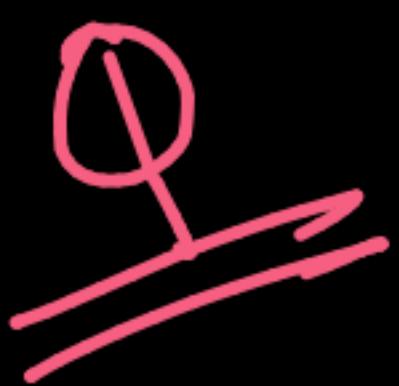
$\chi^2(k)$



Plot of the chi-square distribution for values of $k = \{1, 2, 3, 4, 6, 9\}$. Accurate plotcurves. Labels are embedded in Computer-Modern font.

More details





Gender vs Poem.

V - good

Z-pop-test

Female →

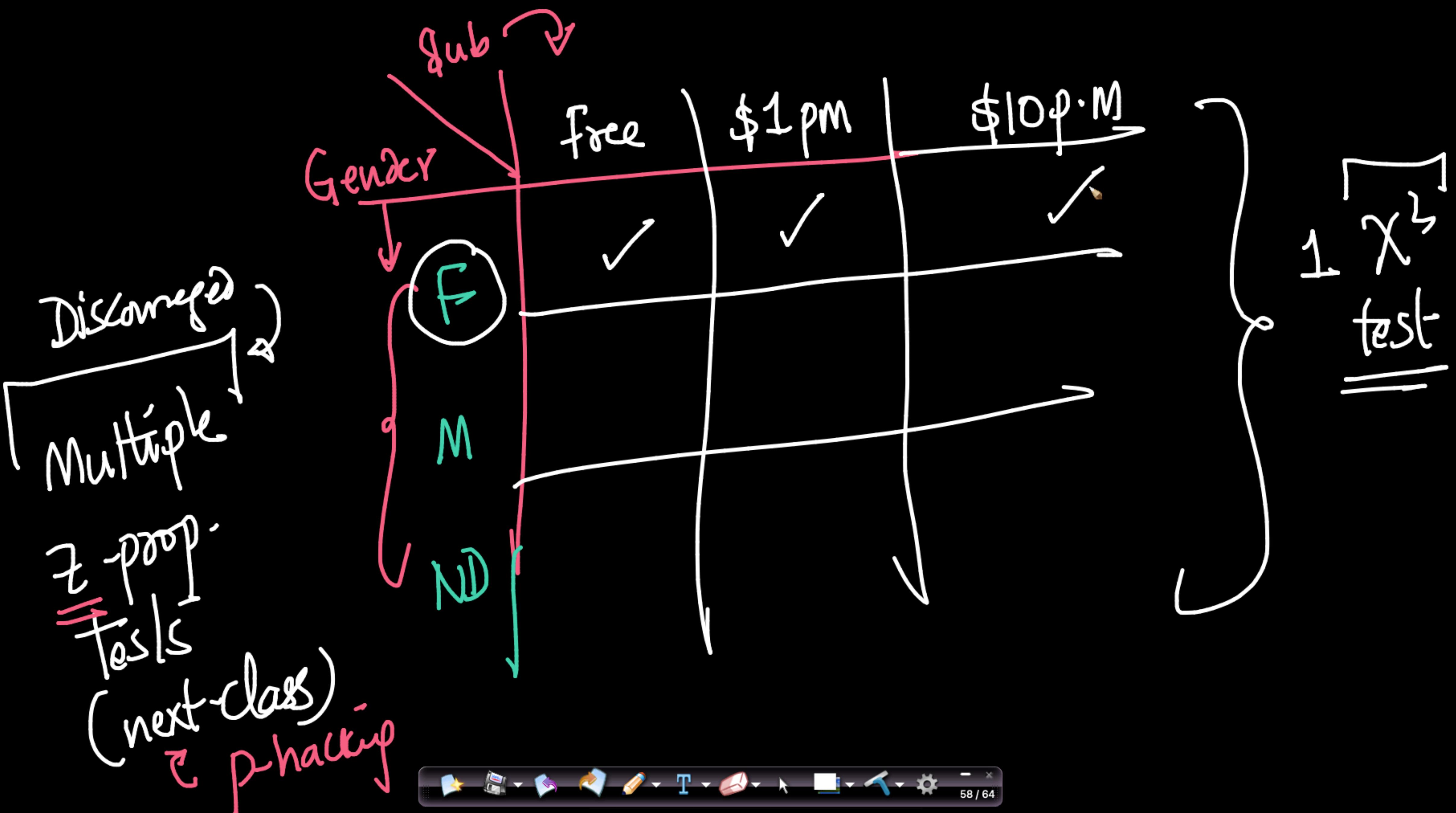
Males →

$\hat{P}_1 = \frac{\# \text{poem}}{\# \text{total-fem}}$

$\hat{P}_2 = \frac{\# \text{poem}}{\# \text{total males}}$

$\hat{P}_1 = \hat{P}_2 \text{ or } \text{not}$

A yellow checkmark is next to the 'V - good' text. A curly brace groups 'Female' and 'Males'.





χ^2 test



Gender impacts

P_{sub}
 P_{M}



$H_0: P_F = P_M$

$H_a: P_F > P_M$

Z-test



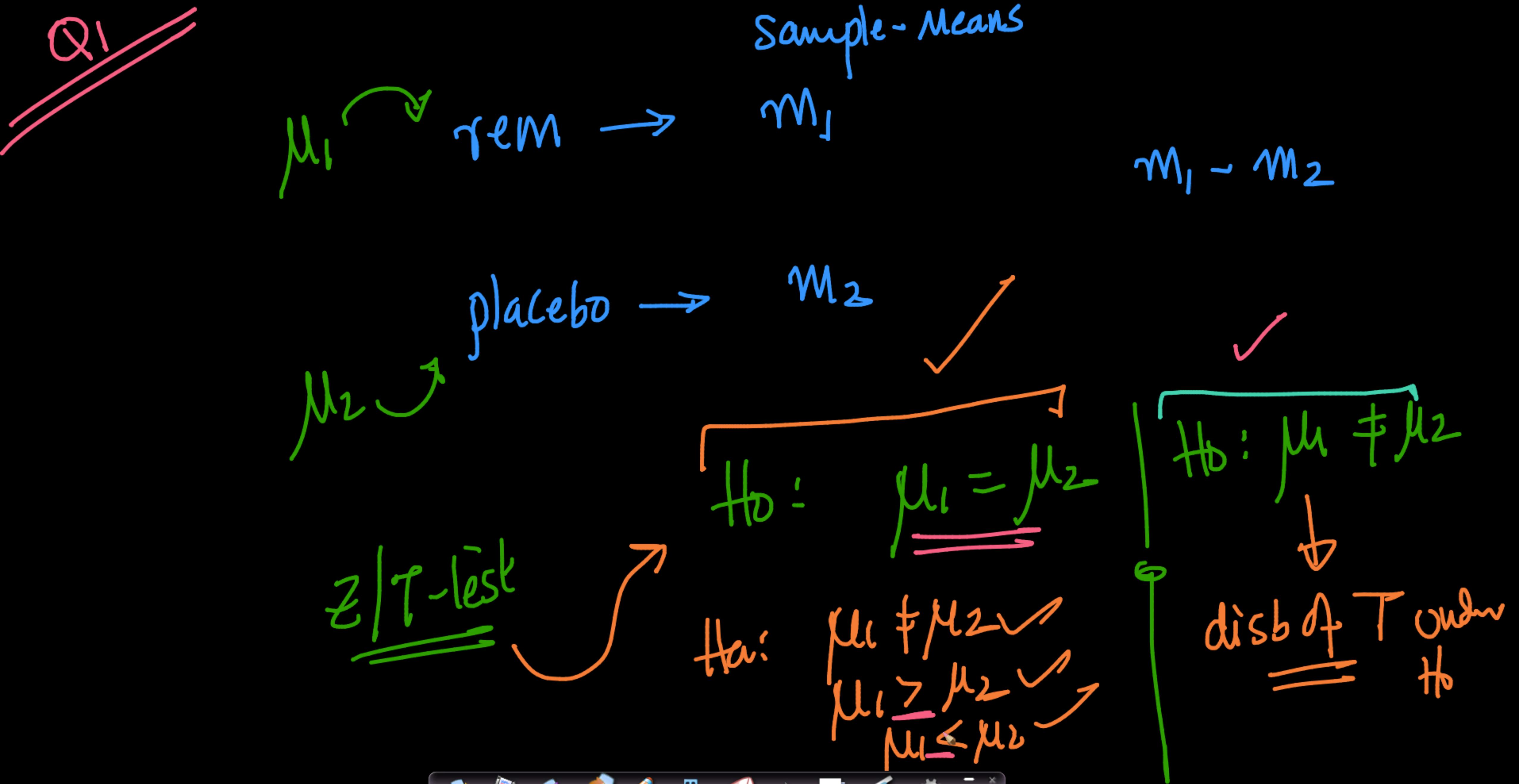
95% C.I. of

95% C.I. of

Two parallel red arrows pointing upwards.

χ^2 -test → Non-param tests

KS-test



Let

if $T = M_1 - M_2$

distrib of T under

$$\mu_1 \neq \mu_2$$



$$\begin{matrix} \uparrow \\ H_0 \checkmark \end{matrix}$$

$T = \bar{M}_1 - \bar{M}_2$

disb ΔT under H_0

$H_0: \mu_1 = \mu_2$

rem $\Rightarrow \mu_1 > \mu_2$

$\Rightarrow \mu_1 - \mu_2 > 0$

$H_a: \mu_1 - \mu_2 \leq 0$

placebo is better

disb ΔT under H_0

$H_0: \mu_1 \leq \mu_2$

$\Rightarrow \mu_1 - \mu_2 \leq 0$

$H_a: \mu_1 - \mu_2 > 0$

Rem .. is better

Q

χ^2 -test

$$\left\{ \begin{array}{l} H_0: \underline{p_F} = \underline{p_M} \\ H_a: \underline{p_F} > \underline{p_M} \end{array} \right.$$

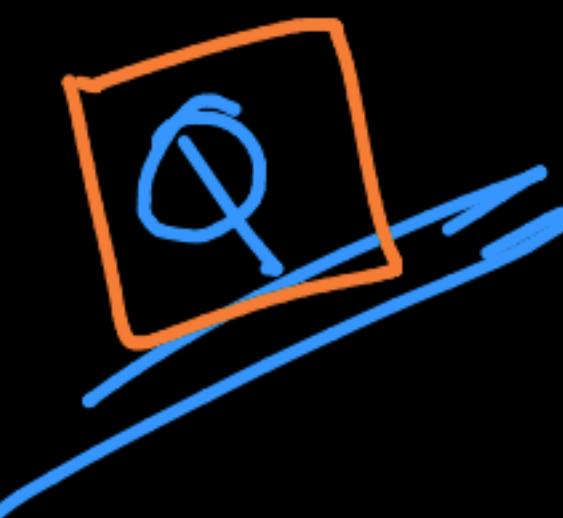
$H_0: G$ is indep of Poer

Cells

$$T = \sum_{i=1}^{\text{cells}} \frac{(O_i - E_i)^2}{E_i}$$

$$\chi^2(k)$$

T under $H_0 \sim \chi^2(k)$



Z-test :

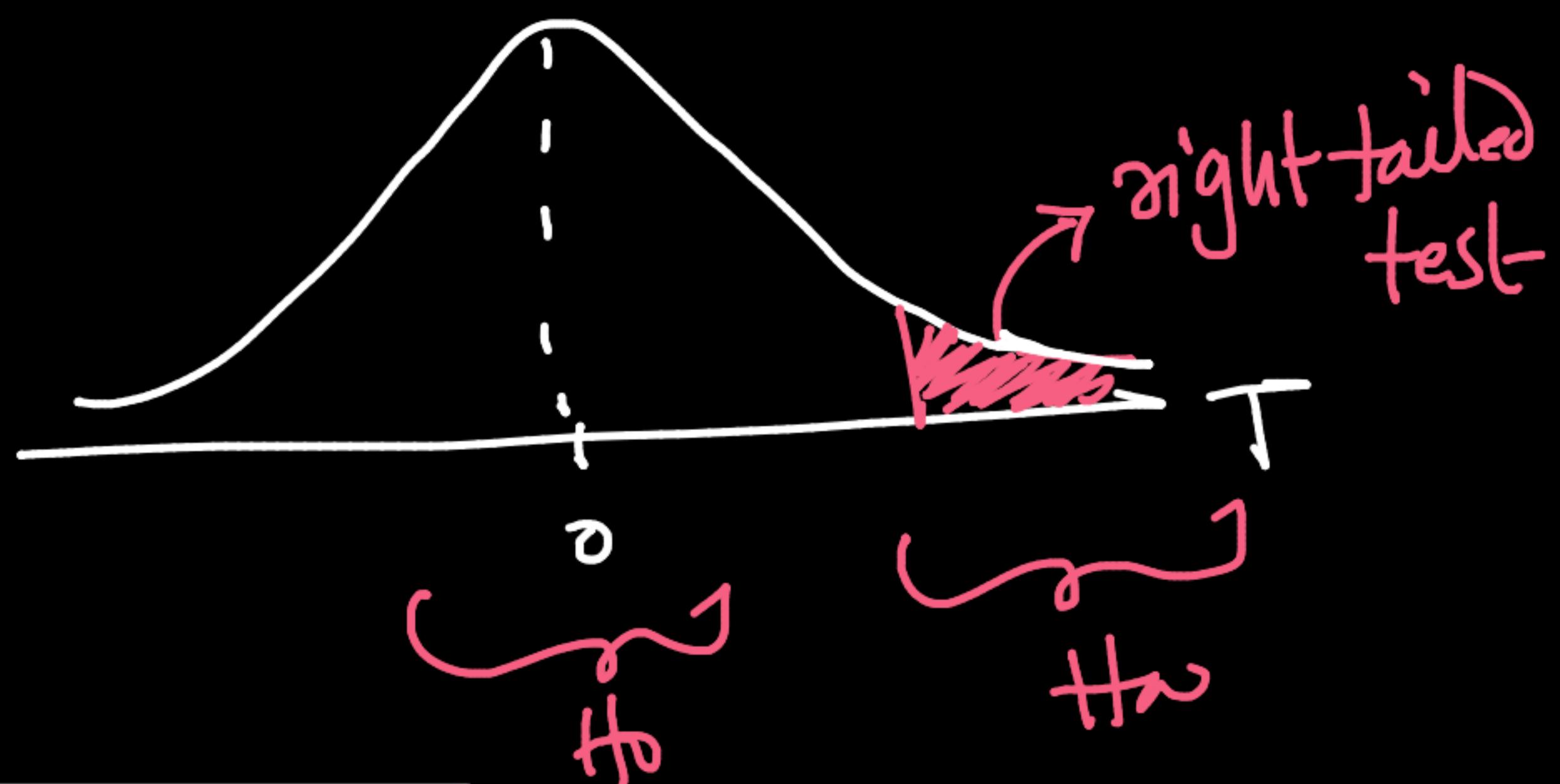
$$\left\{ \begin{array}{l} H_0: \mu_1 = \mu_2 \\ H_a: \mu_1 > \mu_2 \end{array} \right.$$

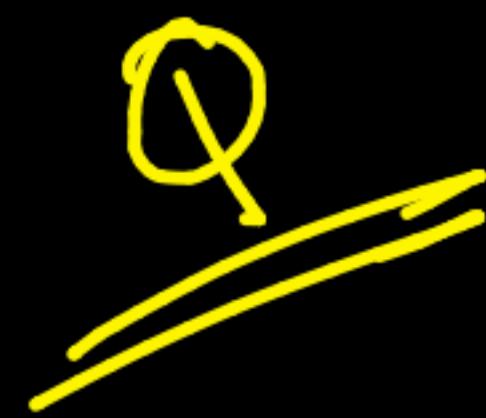
default

$$\tilde{T} = \frac{\bar{M}_1 - \bar{M}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \sim Z(0,1)$$

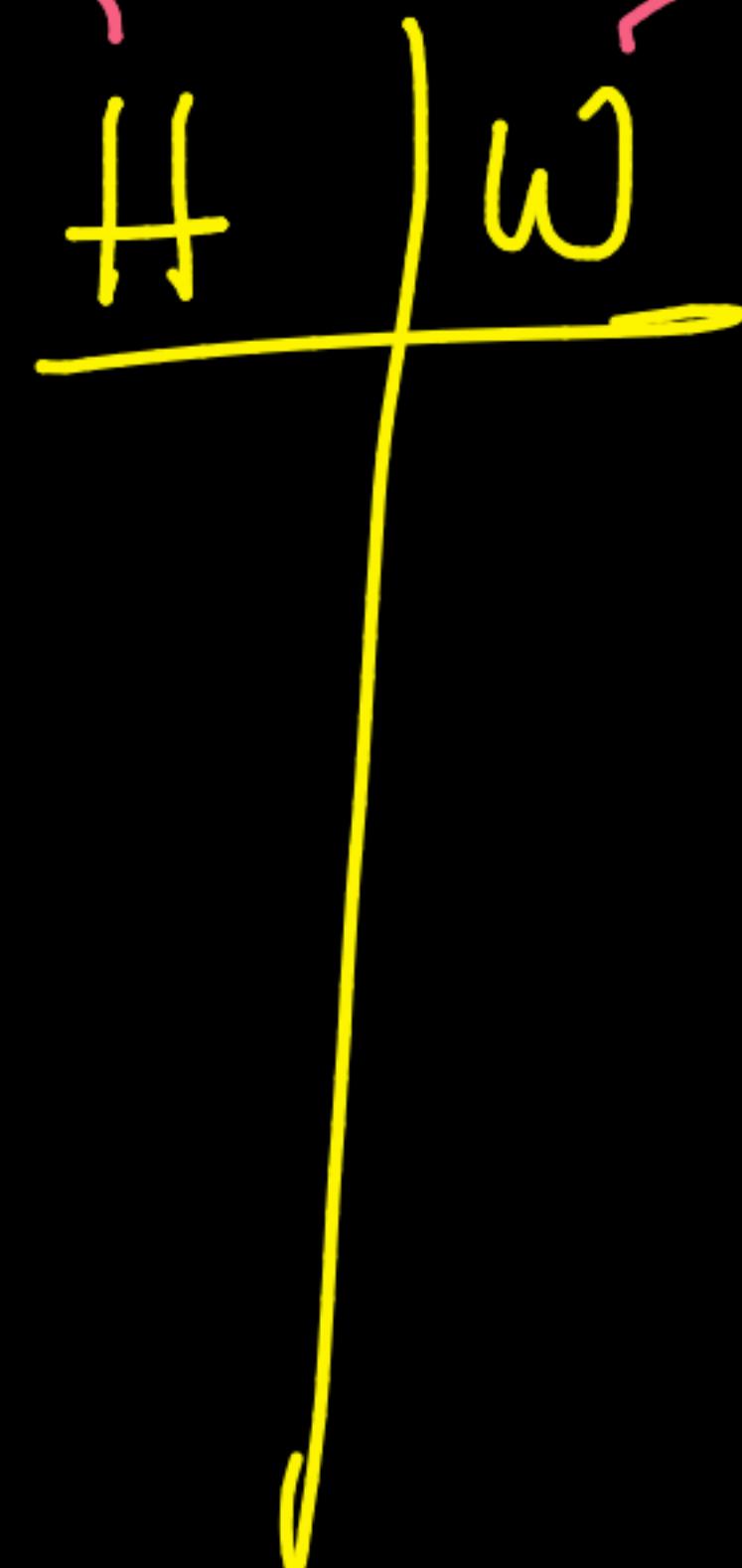
if

$$\left\{ \begin{array}{l} T = \frac{\bar{M}_2 - \bar{M}_1}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \rightarrow \text{left-tailed} \\ \end{array} \right.$$





cont r.v.

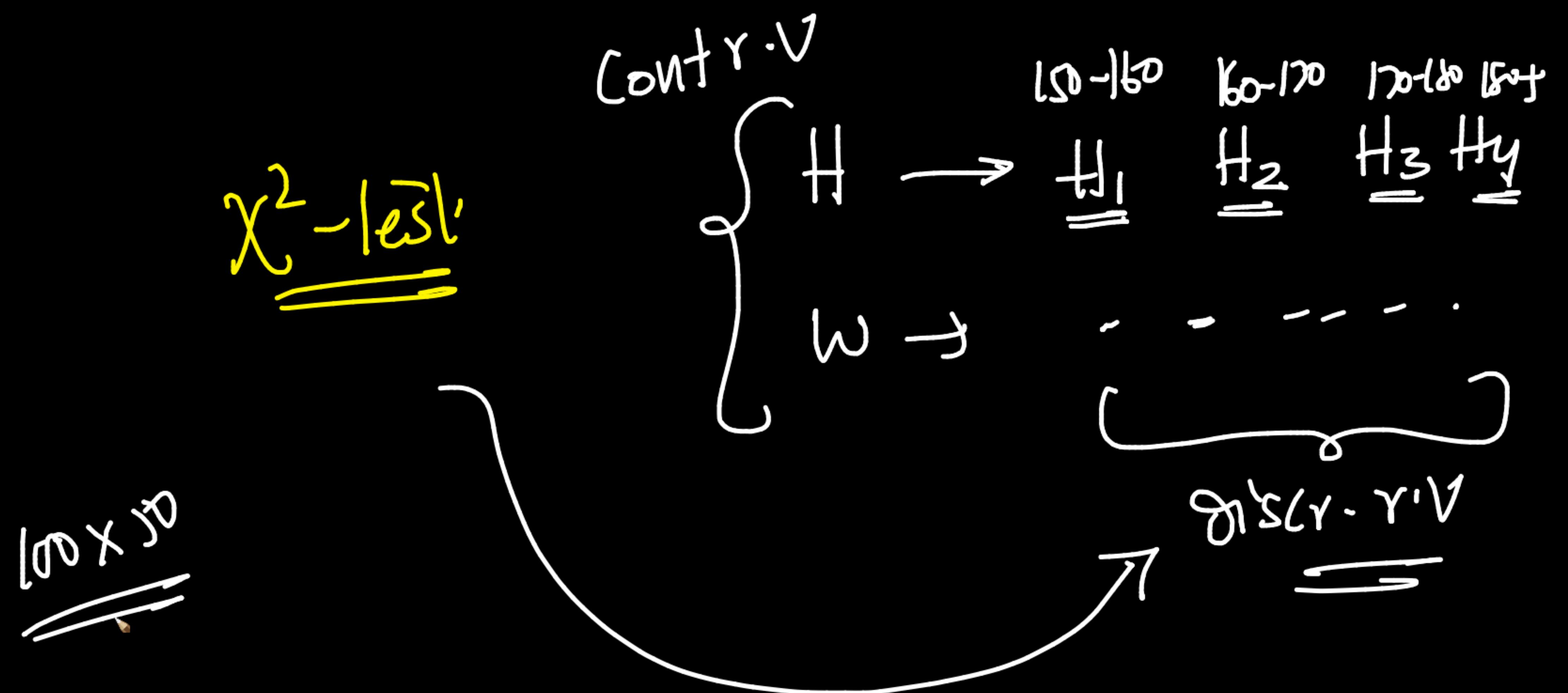


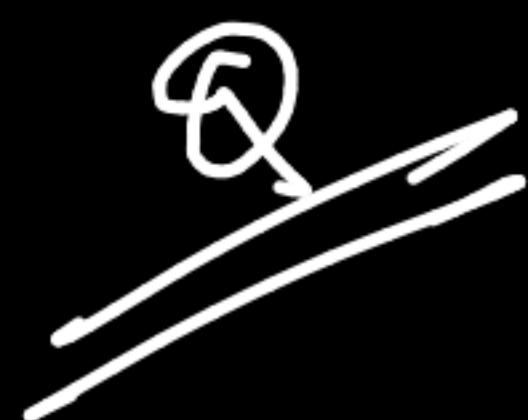
cont r.v

Is w dependent
on H?

Pearson CC
&
Spearman rank CC

Cannot use χ^2 -test





Compare means

Z-test ($\sigma_1 \& \sigma_2 \text{ or}$
 $n_1 \& n_2 \text{ are large}$)

T-test ✓

Compare prop \rightarrow Z-prop. test

χ^2 -test (Cat. & V)

Test for indep

disb-dim

KS-test or AD-test
(Gaussianity)

$X = [8 \cdot 5 \quad \dots \quad 8 \cdot 5]$

$Y = [8, 8 \quad \dots \quad 8]$

$Z = [1, 1 \quad \dots \quad 1]$

$C.lmX$

$C.lmY$

$C.lmZ$

$[8; 8]$

$[1, 1]$

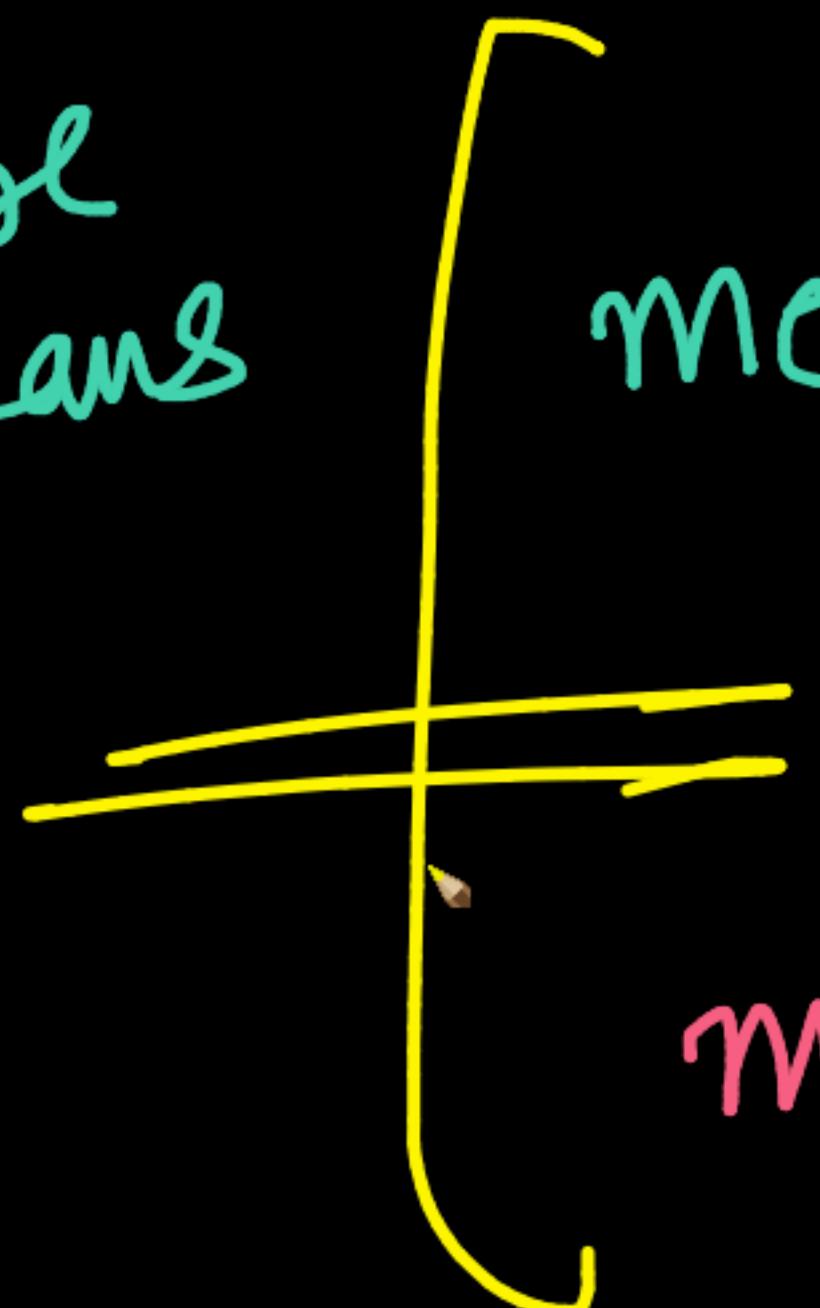
$[8, 8]$

$[8, 8; 8; 1, 1]$

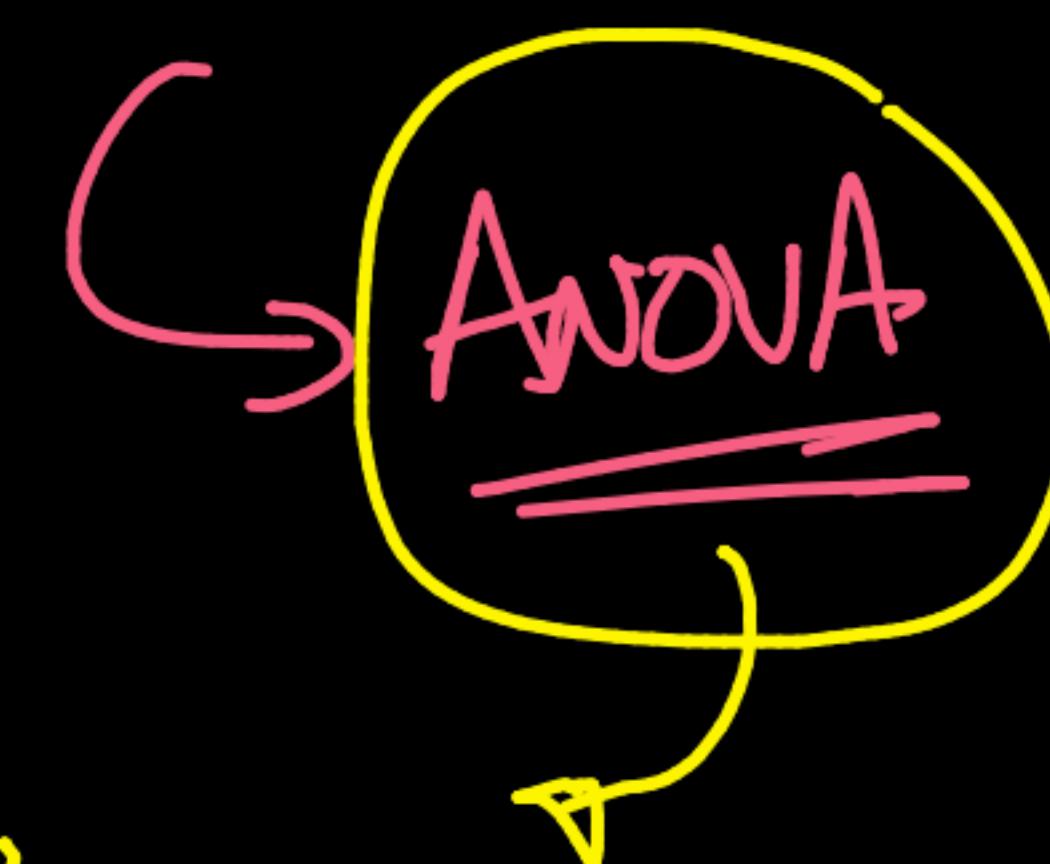
$[8 \cdot 5]$

$[8, 5]$

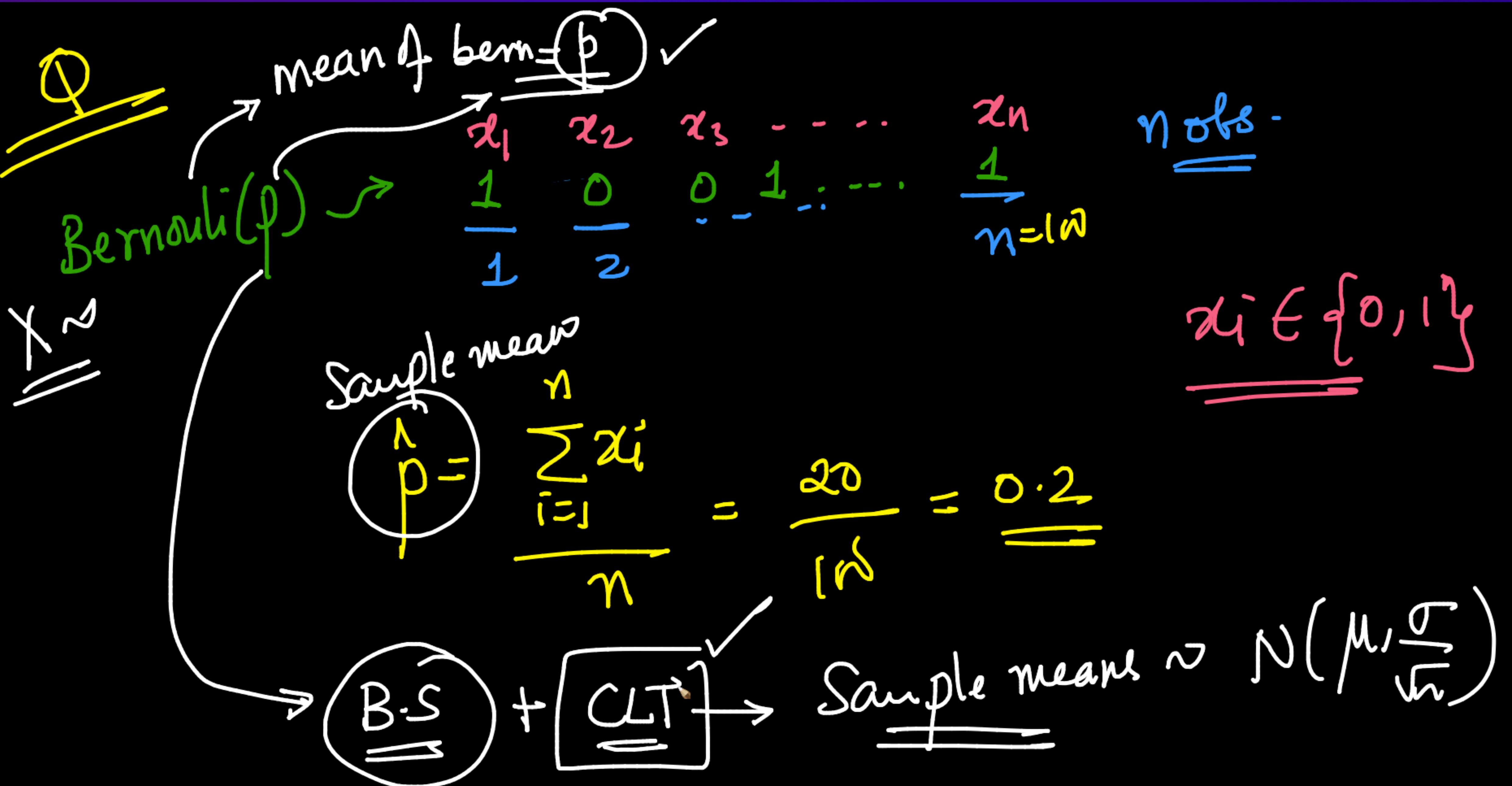
Compare means
Med 1 vs Med 2 → T-test



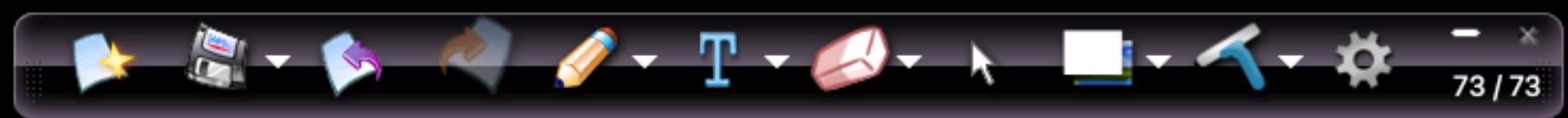
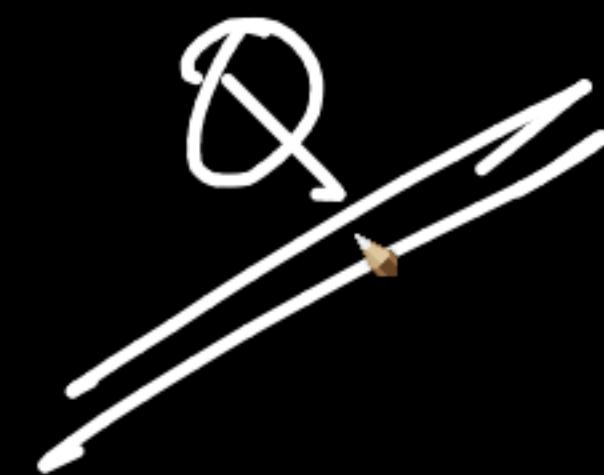
Med 1 vs Med 2 vs Med 3 ...



[assump: rectangles area
gaussian distr]



X ~ b



KStest_Ttest.ipynb - Colaboratory | Kolmogorov-Smirnov test - Wikipedia | Bernoulli distribution - Wikipedia | S.6 Test of Proportion | STATO | 10.5 Hypothesis Testing for Two Proportions | t test test for proportions - Google Sheets | scipy.stats.ks_1samp - SciPy | +

docs.scipy.org/doc/scipy/reference/generated/scipy.stats.ks_1samp.html

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x₁, x₂, ..., x_n

```
>>> x = np.linspace(-15, 15, 9)
>>> stats.ks_1samp(x, stats.norm.cdf)
(0.44435602715924361, 0.038850142705171065)
```

```
>>> stats.ks_1samp(stats.norm.rvs(size=100, random_state=rng),
...                  stats.norm.cdf)
KstestResult(statistic=0.165471391799..., pvalue=0.007331283245...)
```

Test against one-sided alternative hypothesis

Shift distribution to larger values, so that ``CDF(x) < norm.cdf(x)``:

```
>>> x = stats.norm.rvs(loc=0.2, size=100, random_state=rng)
>>> stats.ks_1samp(x, stats.norm.cdf, alternative='less')
KstestResult(statistic=0.100203351482..., pvalue=0.125544644447...)
```

Reject null hypothesis in favor of alternative hypothesis: less

```
>>> stats.ks_1samp(x, stats.norm.cdf, alternative='greater')
```

0.920581859791...

KStest_Ttest.ipynb - Colaborat | W Kolmogorov-Smirnov test - Wiki | W Bernoulli distribution - Wikipedia | S.6 Test of Proportion | STATO | 10.5 Hypothesis Testing for Two Proportions | t test test for proportions - Google Sheets | scipy.stats.ks_1samp - SciPy | +

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```

Reject null hypothesis in favor of alternative hypothesis: less

```
>>> stats.ks_1samp(x, stats.norm.cdf, alternative='greater')
```

0.920581859791...

$x_1 \dots x_n$

C.I on tP_{99} \rightarrow B-S \rightarrow middle 95%.

2.5 97.5

L ↗

KStest_Ttest.ipynb - Colaborat | W Kolmogorov-Smirnov test - Wiki | W Bernoulli distribution - Wikipedia | S.6 Test of Proportion | STATO | 10.5 Hypothesis Testing for Two Proportions | t test test for proportions - Google Sheets | scipy.stats.ks_1samp — SciPy v1.8.1

docs.scipy.org/doc/scipy/reference/generated/scipy.stats.ks_1samp.html

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Statistical functions ([scipy.stats](#))

scipy.stats.ks_1samp

```
scipy.stats.ks_1samp(x, cdf, args=(), alternative='two-sided', mode='auto')
```

[\[source\]](#)

Performs the one-sample Kolmogorov-Smirnov test for goodness of fit.

This test compares the underlying distribution $F(x)$ of a sample against a given continuous distribution $G(x)$. See Notes for a description of the available null and alternative hypotheses.

Parameters:

- x : array_like**
a 1-D array of observations of iid random variables.
- cdf : callable**
callable used to calculate the cdf.
- args : tuple, sequence, optional**
Distribution parameters, used with *cdf*.
- alternative : {‘two-sided’, ‘less’, ‘greater’}, optional**
Defines the null and alternative hypotheses. Default is ‘two-sided’. Please
- mode : {‘auto’, ‘exact’, ‘approx’, ‘asymp’}, optional**
Defines the distribution used for calculating the p-value. The following