



Université
de Technologie
Tarbes
Occitanie Pyrénées

THE COMPLETE GUIDE TO

INFERENTIAL STATISTICS

< By Raymond HOUÉ NGOUNA />

</SECTION 4>

TWO-SAMPLE T-TEST

SECTION OUTLINE



- Case study
- Key concepts
 - ✓ Dependent variable and Independent variable
 - ✓ Test for normality
 - ✓ Test for equality of variance
 - ✓ Paired two-sample t-test
- Summary
 - ✓ Two-sample t-test implementation





CASE STUDY

27/09/2024

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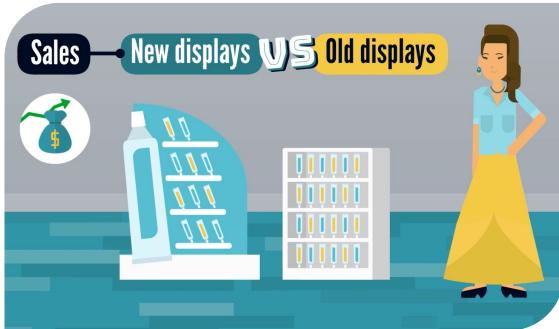
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CASE STUDY

- ✓ Carmen works in the **trade marketing department** of a company that sells toothpaste.
 - The products are distributed through **hypermarkets**, **supermarkets**, and **convenience stores**.
 - She wants to introduce a new type of in-store display but is unsure if the **concept will be effective**.
 - Instead of rolling out the visual merchandising solution across the entire retail network, she decides to first **conduct an experiment**.

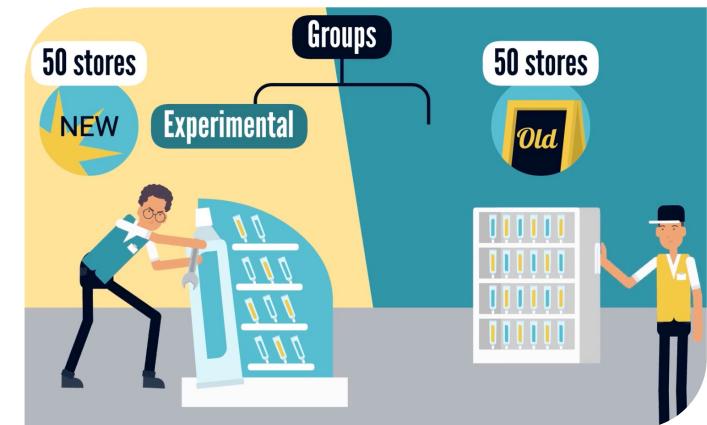


CARMEN'S EXPERIMENT

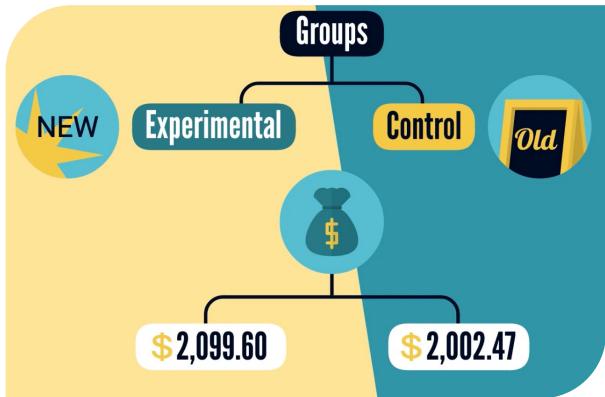


✓ Carmen aims to determine whether there's a difference in sales volume between stores using **new display** setups and those with **traditional displays**.

- Her team installed the new displays in 50 stores across the country, forming the **experimental group**.
- Meanwhile, another 50 stores within the company's distribution network kept the regular displays, serving as the **control group**.
- Over several days, Carmen and her manager monitored **sales volume** as the **dependent variable**.



OUTCOME OF THE EXPERIMENT



- ✓ The data shows that the **new display** type averages \$2,099.60 in sales:
 - outperforming the **old display** type's average of \$2,002.47,
 - suggesting that the newer displays lead to **higher sales** volumes.

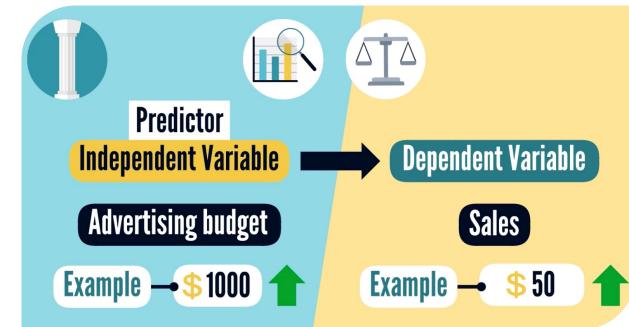
- ✓ To ensure the difference is **statistically significant**, Carmen conducts a two-sample t-test with a significance level of 0.05:
 - $t = 1.7693$ with 98 degrees of freedom.
 - $p\text{-value} = 0.0400 \rightarrow$ Carmen is happy (**why?**).



DEPENDENT / INDEP. VARIABLES

DEPENDENT & INDEPENDENT VARIABLES

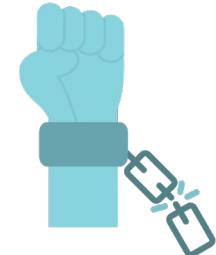
✓ In statistics, the **dependent** and **independent** variables are the two primary variables studied to understand their **relationship**.



✓ The connection between these variables is one of the focus of **statistical analysis**.

INDEPENDENT VARIABLES

- ✓ The **independent variable** (IV), also known as the **predictor** or **explanatory variable**, is **manipulated** or controlled in an experiment or study.
 - Its values are **deliberately changed** or varied to observe their **effect** on the dependent variable.
 - It is called "independent" because it stands alone and is **not influenced** or **altered** by other measured variables.
 - In a cause-and-effect relationship, independent variables are expected to **cause changes** in the dependent variable.
- ✓ In visual analyses, IVs are represented on a chart's **x-axis**.

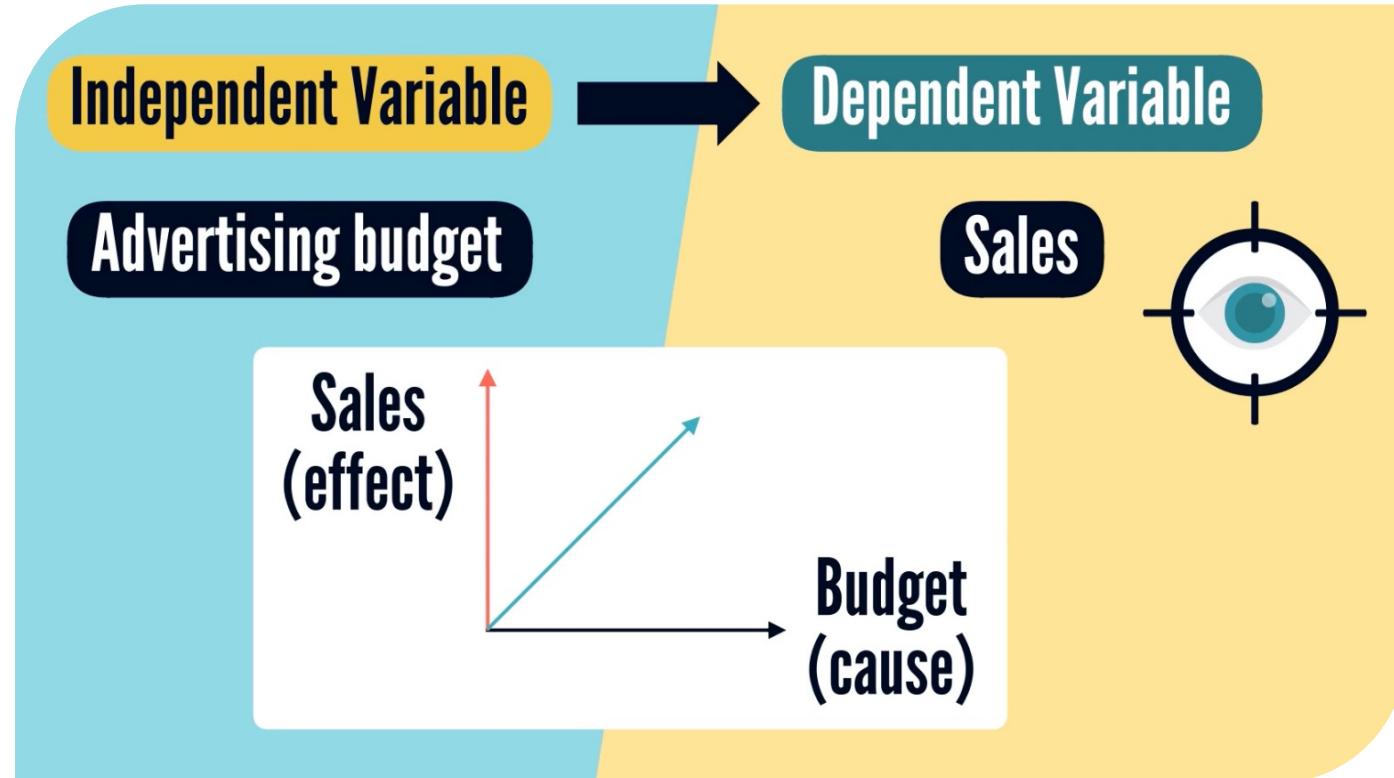


DEPENDENT VARIABLES

- ✓ The **dependent variable** (DV), also known as the response or outcome variable, is the **primary focus of observation** in an experiment or study.
 - It is what the researcher measures and is **influenced** by the experimental conditions, with its **variation** depending on changes in the independent variable in a cause-and-effect relationship.
- ✓ The dependent variable **responds to changes** in the independent variable and is plotted on the **y-axis**.



VISUALIZATION OF DV AND IV





NORMALITY TEST

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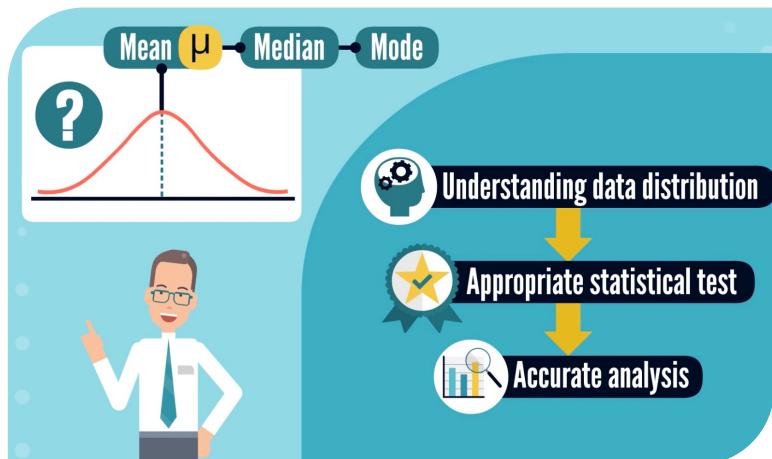
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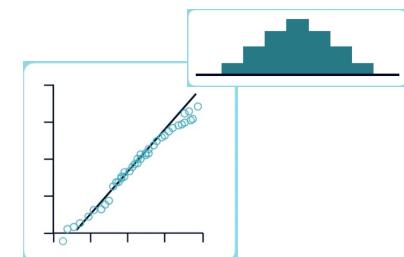
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NORMALITY TEST



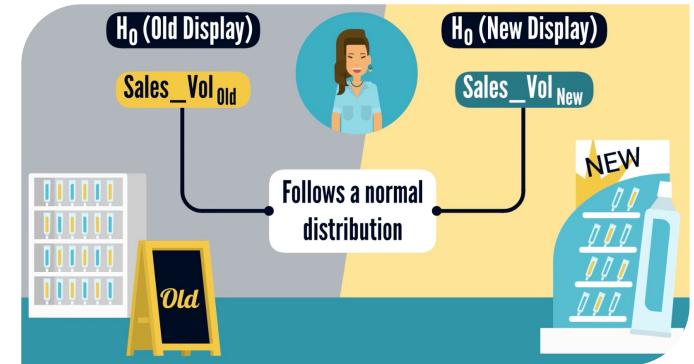
- ✓ This section presents another technique to determine whether a dataset follows a **normal distribution**.
 - This knowledge is crucial because understanding the **distribution of data** can significantly influence the **choice of statistical methods** and the **accuracy** of your analyses.

- As described earlier, normality can be **visually** assessed using a histogram or a **QQ-plot**.
- Additionally, it can be evaluated **mathematically** using the **Shapiro-Wilk test**, a specific statistical test for normality.



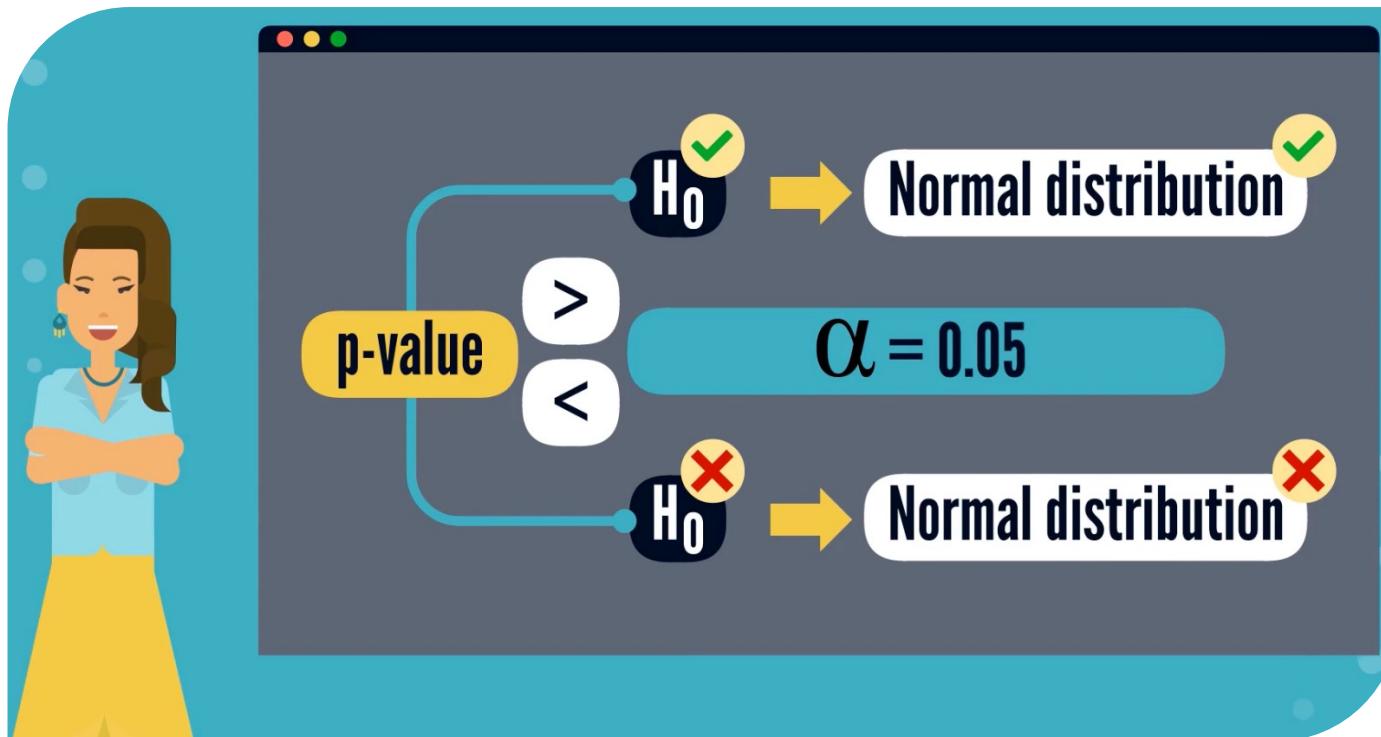
SHAPIRO-WILK TEST

- ✓ The **Shapiro-Wilk** test is a dedicated statistical test for assessing normality.
- ✓ Its primary objective is to quantitatively evaluate the likelihood that the data in a sample were drawn from a **normal distribution**.
 - The **null hypothesis** of the test suggests that the data follow a normal distribution.

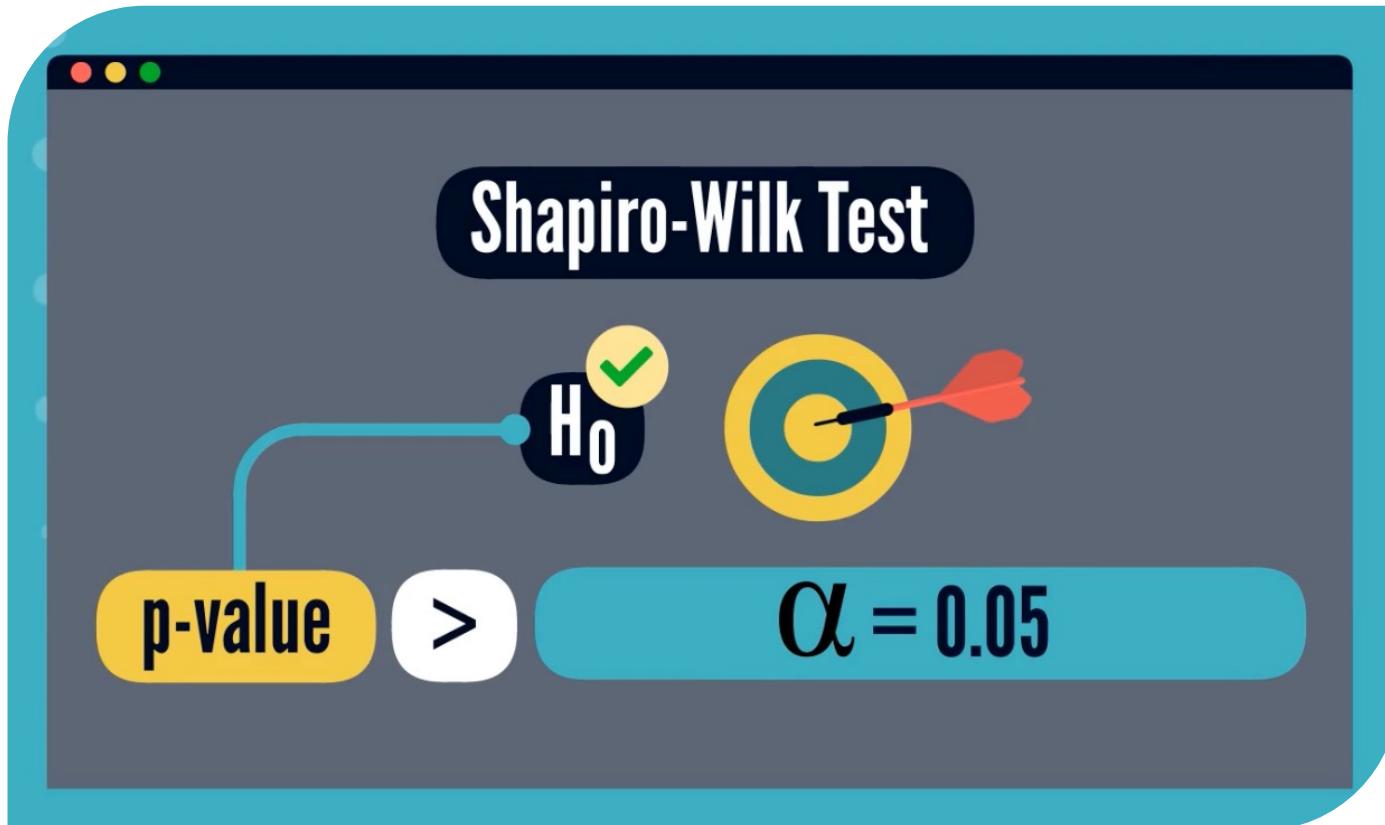


Carmen's case study

CARMEN'S STUDY TEST FOR NORMALITY



EXPECTATION IN APPLYING SHAPIRO-WILK TEST





TEST FOR EQUALITY OF VARIANCE

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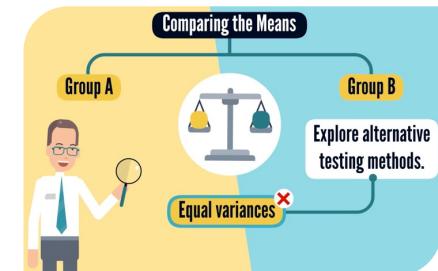
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RELIABILITY OF A MEAN COMPARISON TEST

✓ The **reliability** of certain statistical tests, including mean comparisons, depends on a key assumption:

- The 2 samples must have **equal variances**.
- This means that the **variability** within each group from which the samples are drawn should be similar.

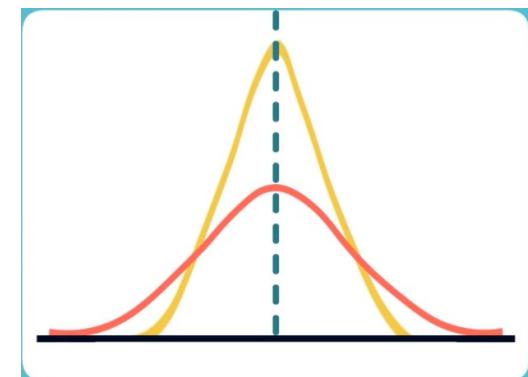


- If this condition is not met, the test's p-value may be unreliable.
- In situations where variances are unequal, alternative testing methods may be necessary to address this discrepancy and yield more robust results.

LEVENE'S TEST FOR EQUALITY OF VARIANCES

✓ One commonly used technique to assess whether the variances of two or more groups differ significantly is **Levene's test** for **equality of variances**.

- Variance is a **measure of spread** that quantifies how data points are dispersed around their mean value.
- It captures the **variability** within a data set, highlighting how much the data points differ from the average.



LINK WITH STANDARD DEVIATION

Variance

Quantifies the dispersion of a set of data points around their mean value

Standard Deviation

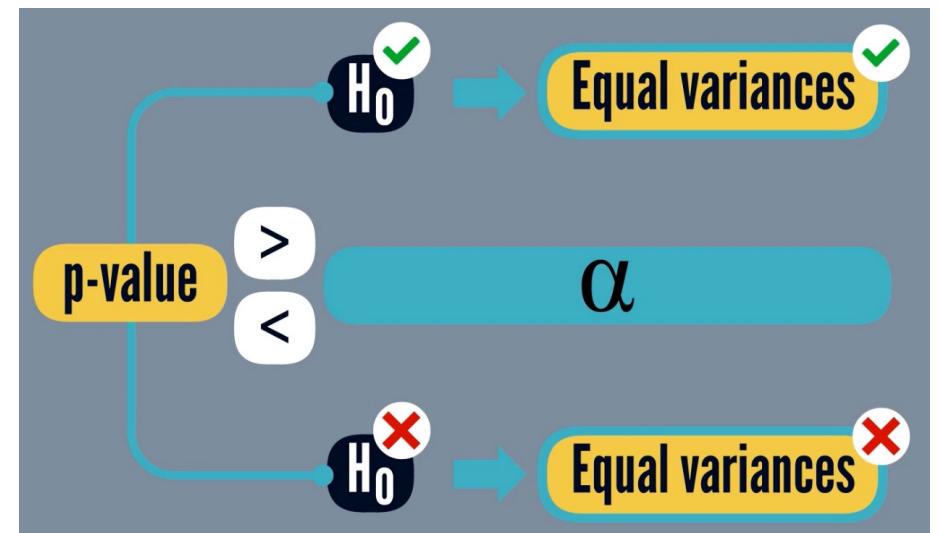
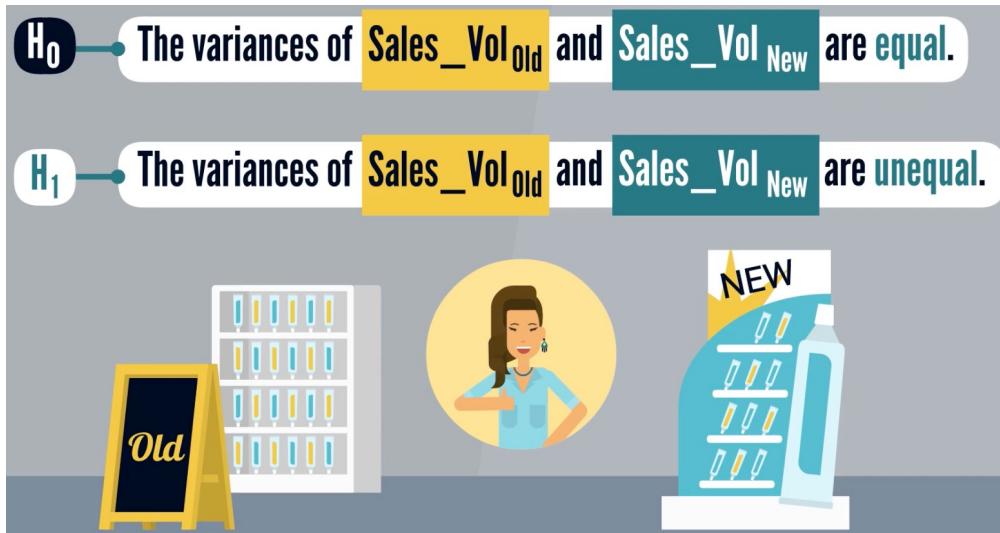
The average distance of the data points from the mean

$$S^2 = \frac{\sum(\bar{x} - x_i)^2}{N}$$



$$S = \sqrt{\frac{\sum(\bar{x} - x_i)^2}{N}}$$

LEVENE'S TEST APPLIED TO CARMEN'S STUDY

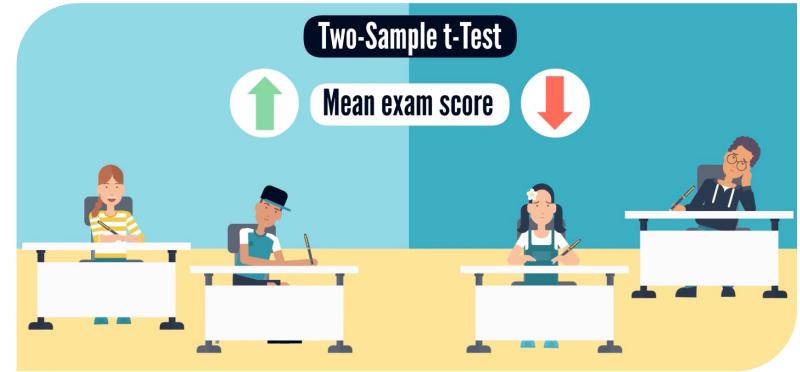




TWO-SAMPLE T-TEST

TWO-SAMPLE T-TEST

- ✓ The two-sample t-test is a statistical hypothesis test used to assess whether there is a significant **difference between the means** of 2 independent groups or samples.
 - This test is commonly applied when comparing the means of two populations or treatment groups, to determine whether the **observed difference** reflects a true **effect** or is simply due to **chance**.
- ✓ In essence, it helps evaluate whether the **differences in mean** values are statistically significant.



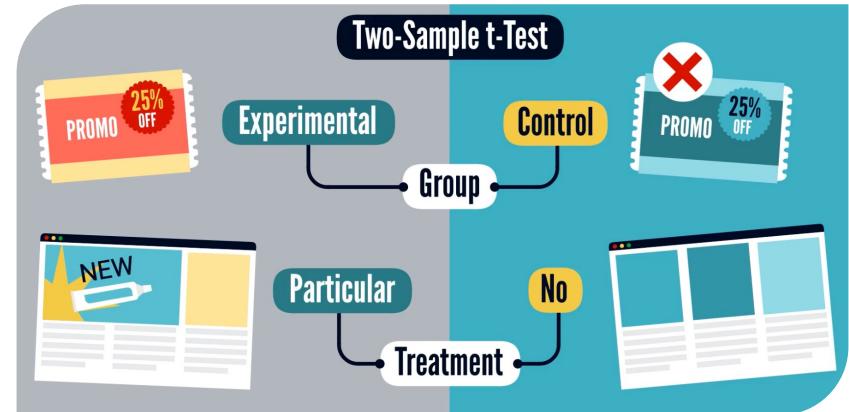
BRIEF HISTORY



- ✓ There are two main types of t-tests:
 - The two-sample (**unpaired**) t-test, also known as Student's t-test is named after **William Sealy Gosset**, who introduced the t-distribution in 1908 in an article published under the pseudonym "Student".
 - The **paired** samples t-test.
- ✓ The **independent** or **unpaired** samples t-test is used to determine whether the means of two unrelated groups are the same.
 - This test requires that the subjects in each group be distinct,
 - Ensuring that the observations in one group do not influence or directly relate to those in the other group.

EXPERIMENTS USING A TWO-SAMPLE T-TEST

- ✓ Experiments using a two-sample t-test typically divide the sample into two distinct groups:
 - The **experimental group** receives a specific treatment e.g. a promotional coupon or a modified version of a website.
 - The **control group** receives no treatment e.g. they do not get coupons or see the modified website, but instead interact with the existing version.

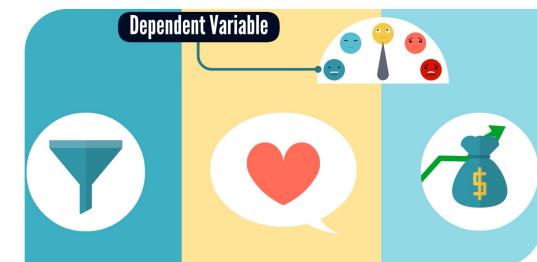


→ Because the two groups are unrelated, we obtain two **independent samples**.

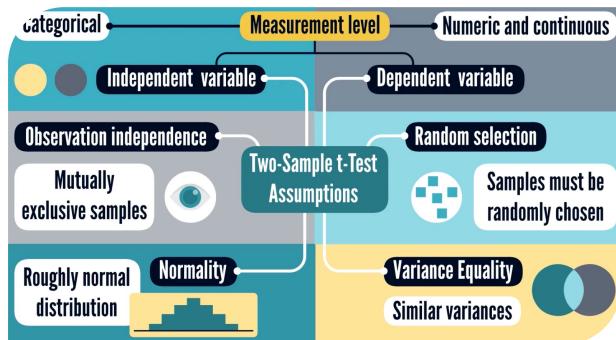
TYPES OF VARIABLE INVOLVED

✓ The two-sample t-test involves 2 variables.

- The **independent variable**, which defines and distinguishes the **2 groups**,
 - Ex.: *Design A* versus *Design B*, men versus women, the new versus the old display...
- The **dependent variable**, which represents the **measurement of interest**,
 - Such as the conversion rate, brand affinity, the sales volume, etc.



TWO-SAMPLE T-TEST ASSUMPTIONS



✓ Measurement Level:

- The **IV** should be **categorical**, either nominal or ordinal, with exactly 2 categories.
- The **DV** should be **numeric** and continuous in both samples.

- ✓ **Independence of Observations:** The samples must be mutually exclusive, with no overlapping values between them.
- ✓ **Random Selection:** The samples should be randomly selected to ensure that the test results can be generalized to the population.
- ✓ **Normality:** The distributions of the dependent variable in both sample and population should be approximately normal.
- ✓ **Equality of Variances:** The variances of the two samples should be similar.

HYPOTHESES OF THE TWO-SAMPLE T-TEST

H_0

No significant difference between
the means of the two groups

H_1

A notable difference in the
means of the two groups

IN CARMEN'S CASE STUDY

- ✓ The vendor assured Carmen that the **new in-store (IV)** displays were **more visually appealing** than the previous ones, leading her to believe they would **increase sales (DV)**.



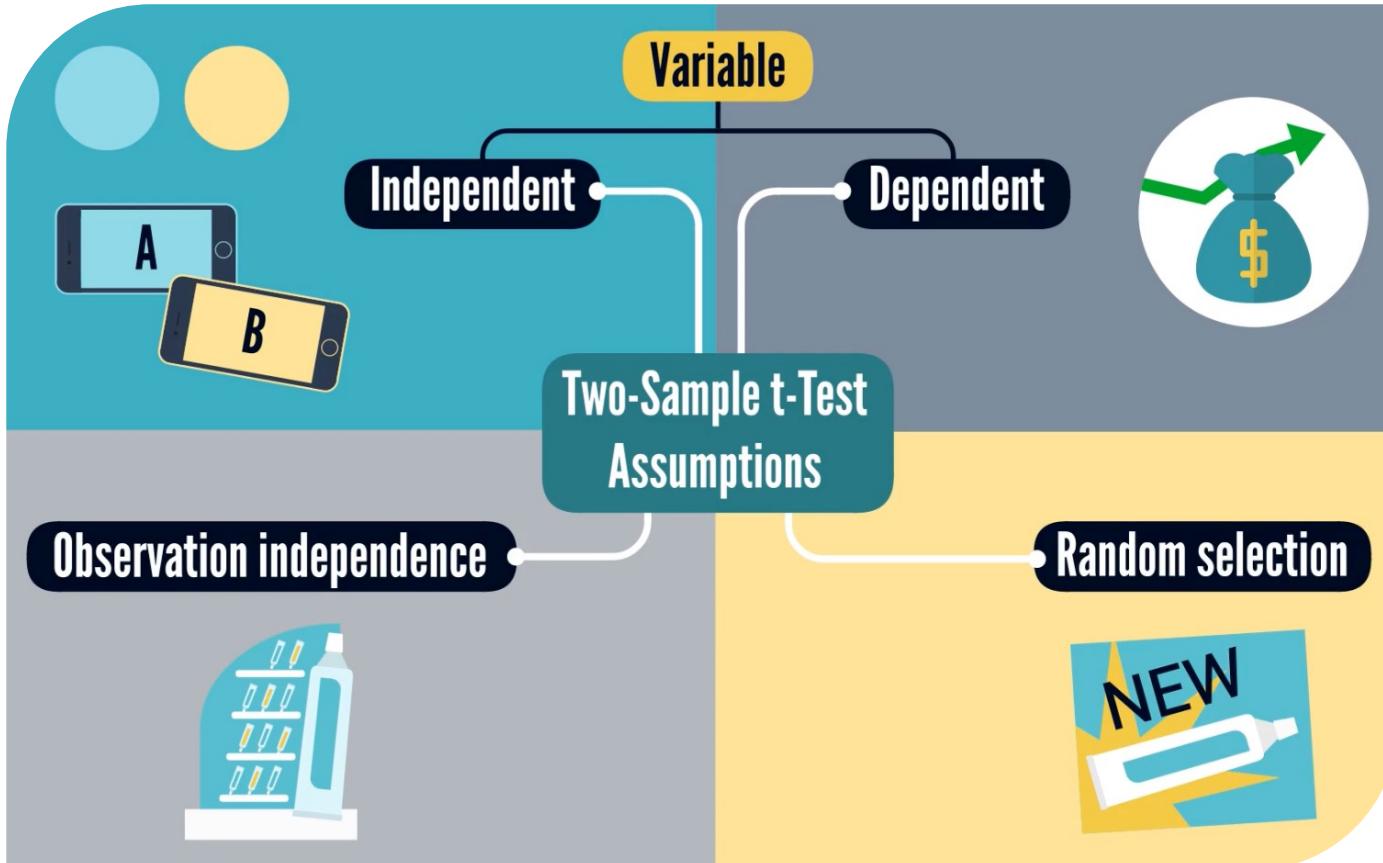
- She sought statistical evidence to support this belief, which would justify their widespread adoption throughout the company's retail network.
- To this end, a one-tailed alternative hypothesis could be used:
the difference between the mean sales volumes for the new and old displays is greater than zero.



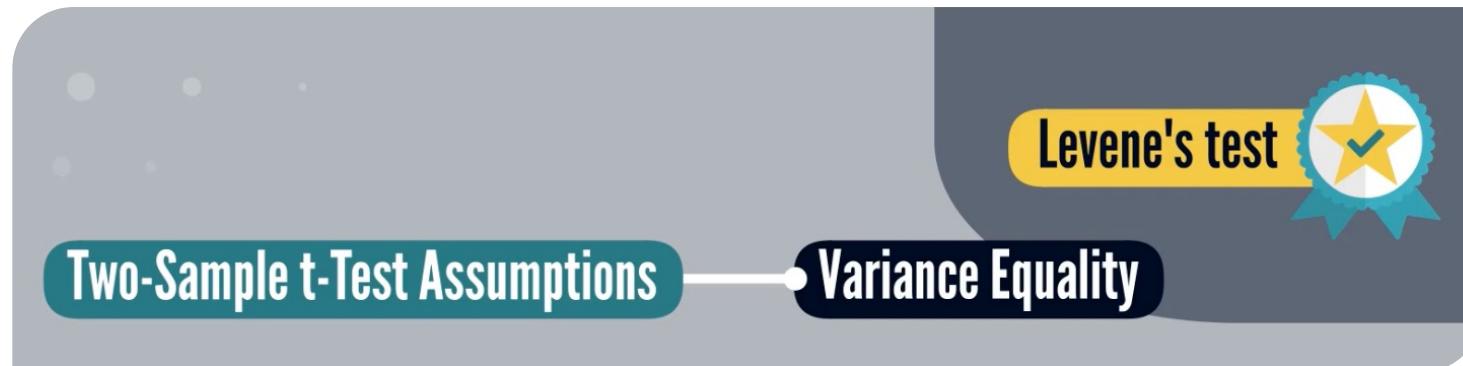
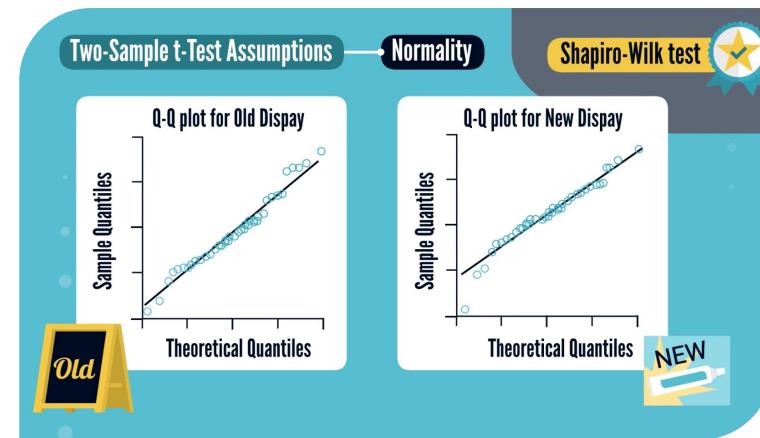
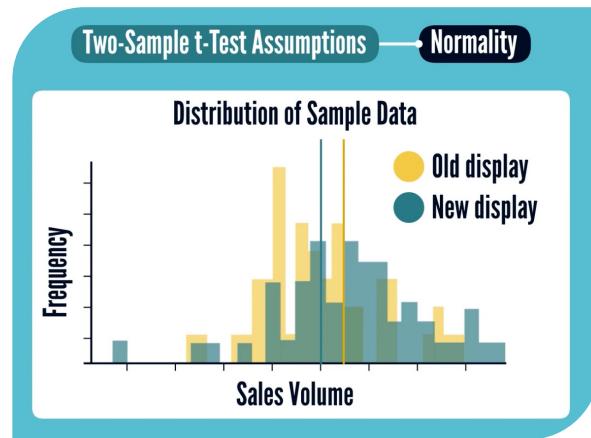
SUMMARY



VERIFICATION OF THE ASSUMPTIONS



NORMALITY AND VARIANCE ASSUMPTIONS



HYPOTHESES OF THE TEST

$$H_0: \mu(\text{Sales_Vol}_{\text{New}}) - \mu(\text{Sales_Vol}_{\text{Old}}) = 0$$

$$H_1: \mu(\text{Sales_Vol}_{\text{New}}) - \mu(\text{Sales_Vol}_{\text{Old}}) > 0$$



CONCLUSION OF THE STUDY

```
from scipy.stats import shapiro
import matplotlib.pyplot as plt
import statsmodels.api as sm

pd.options.display.float_format = "{:.2f}".format

# Read case data
df = pd.read_excel("4. Case 3 - Two-sample t-test.xlsx")

df.head()

      Store Id  Display Type  Sales Volume
0  3846186  Old_display_type    2038.31
1  1083410  Old_display_type    2017.29
2  4278951  Old_display_type    1746.47
3  6670048  Old_display_type    2061.78
4  5054220  Old_display_type    2253.76

# Create arrays with units sold for 'Old_display_type' and 'New_display_type'
data_o = df[df["Display Type"] == "Old_display_type"]["Sales Volume"].values
data_n = df[df["Display Type"] == "New_display_type"]["Sales Volume"].values

# Perform Shapiro-Wilk test on both variables
print("Old display: " + str(shapiro(data_o)))
print("New display: " + str(shapiro(data_n)))

Old display: ShapiroResult(statistic=0.9745517373085022, pvalue=0.3508000373840332)
New display: ShapiroResult(statistic=0.9707477688789368, pvalue=0.2481728047132492)
```

EQUALITY OF VARIANCE TEST

```
import pandas as pd
import numpy as np
from scipy import stats
from scipy.stats import levene

pd.options.display.float_format = "{:.2f}".format

# Read case data
df = pd.read_excel("4. Case 3 - Two-sample t-test.xlsx")

df.head()

      Store Id  Display Type  Sales Volume
0  3846186  Old_display_type     2038.31
1  1083410  Old_display_type     2017.29
2  4278951  Old_display_type     1746.47
3  6670048  Old_display_type     2061.78
4  5054220  Old_display_type     2253.76

# Create arrays with units sold for 'old_display_type' and 'New_display_type'
data_o = df[df["Display Type"] == "Old_display_type"]["Sales Volume"].values
data_n = df[df["Display Type"] == "New_display_type"]["Sales Volume"].values

# Levene's test centered at the mean
print(stats.levene(data_o, data_n, center='mean'))
```

TOW-SAMPLE T-TEST

```
df.head()
```

	Store Id	Display Type	Sales Volume
0	3846186	Old_display_type	2038.31
1	1083410	Old_display_type	2017.29
2	4278951	Old_display_type	1746.47
3	6670048	Old_display_type	2061.78
4	5054220	Old_display_type	2253.76

```
# Create arrays with units sold for 'old_display_type' and 'New_display_type'
data_o = df[df["Display Type"] == "Old_display_type"]["Sales Volume"].values
data_n = df[df["Display Type"] == "New_display_type"]["Sales Volume"].values
```

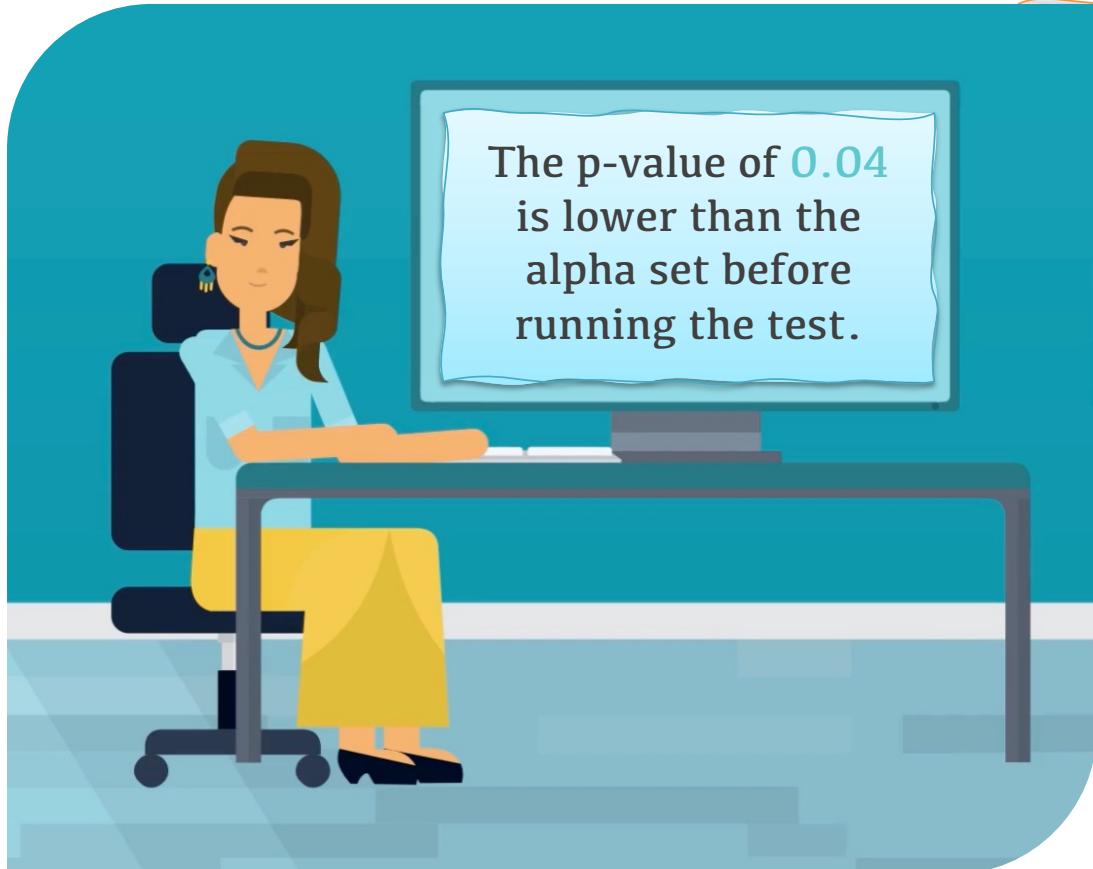
```
# Mean sales for old and new display types
print("Mean Old: " + str(np.mean(data_o)))
print("Mean New: " + str(np.mean(data_n)))
```

```
Mean Old: 2002.471400000001
Mean New: 2099.604999999996
```

```
# Run the two-sample t-test
stats.ttest_ind(data_n, data_o, equal_var=True, alternative = "greater")
```

```
Ttest_indResult(statistic=1.7693132318181237, pvalue=0.0399761880616222)
```

THE RESULT OF THE TEST



- Based on this result, we can reject the null hypothesis.
- Although the mean sales volume for the new in-store display is only slightly higher than for the old one.
- The results indicate that the difference is statistically significant at the 0.05 level.