

HCAI5DS02 – Data Analytics and Visualization. Lecture – 08

Statistical Inference and Hypothesis Testing – Part -II. Chi – Square and ANOVA

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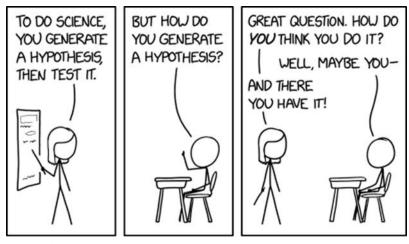


From Last Week ...

{A. Basics of Hypothesis Testing ...}

A.1 Statistical Inference and Hypothesis Testing.

- Statistical inference allows us to evaluate claims about a population parameter using observed data.
 - This is done through hypothesis testing, where we:
 - 1. Formulate a null hypothesis (e.g. no effect, no difference)
 - 2. Collect sample data
 - 3. Calculate a test statistic (e.g. t value, z score)
 - 4. Evaluate the evidence against the null hypothesis using probability (p values)
 - 5. Make a decision: reject or fail to reject the null.



©Explain xkcd.



A.2 Setting up Hypothesis ...

1. Setup the null Hypothesis:

• The null Hypothesis always states that there is no difference, no relationship between variables in a study.

2. Setup Alternate Hypothesis:

- The alternative hypothesis (denoted as H_1 or H_a) is the statement that researchers
 - aim to provide evidence for in a statistical hypothesis test.
- It is the opposite of the null hypothesis and represents:
 - the presence of an effect, difference, or relationship that the researcher expects or hopes to find.

Example 1:	The new drug has no effect on the disease compared to a placebo.		
Scenario	Null Hypothesis	Alternate Hypothesis	In Practice
Clinical Trial: New Drug vs. Placebo	 No difference in effect. H₀: μ_{drug} = μ_{placebo} 	 H_a: μ_{drug} ≠ μ_{placebo} Two-sided test. 	 H₁: μ_{drug} > μ_{placebo} We are only interested in improvement. One – sided alternative.



A.3 Hypothesis Testing → Making Decisions.

- The **hypothesis** we want to test is **whether H_a is likely true**.
 - So, there are two possible outcomes:
 - Reject H₀ and accept H_a because of sufficient evidence in the sample in favor of H_a.
 - Do not reject H₀ because of insufficient evidence to support H_a.

Very important!!!

Note that failure to **reject** H_0 does not mean the null hypothesis is true. There is no formal outcome that says "accept H_0 ". It only means that we do not have sufficient evidence to **support** H_a .

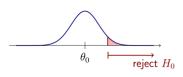




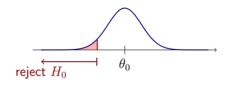
A.4 One vs. Two Tailed Test

One – Tailed Test:

- A one tailed test is used when you are interested in
 - detecting a difference in a specific direction.
- You **hypothesize** that:
 - the true parameter is
 - either greater than or less than a certain value,
 - but not both.



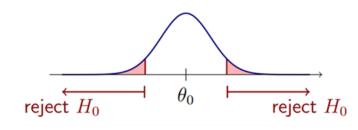
- Right Tailed:
 - $H_0: \mu \leq \mu_0$ $H_a: \mu > \mu_0$



- Left Tailed:
 - $H_0: \mu \geq \mu_0$ $H_a: \mu < \mu_0$

Two – Tailed Test:

- A two tailed test is used when you are interested in
 - detecting any significant difference.
 - From null hypothesis, regardless of the direction.



• Two Tailed: $H_0 \colon \mu = \mu_0 \\ H_a \colon \mu \neq \mu_0$



A.5 Understanding What a Hypothesis Can Test?

- 1. Single Sample Hypothesis (One Group vs. a value):
 - You are testing whether the population mean of one group is equal to some fixed number or benchmark.
 - Example: Is the average delivery time less than 30 minutes?
 - Hypothesis:
 - null \rightarrow H₀: $\mu = 30$; alternate \rightarrow H_a: $\mu < 30$
- 2. Two Sample Hypothesis (Between two Groups):
 - You are testing whether two different groups have the same mean, proportion etc.
 - Example: Do male and female employees earn the same average salary?
 - Hypothesis:
 - null \rightarrow H₀: $\mu_1 = \mu_2$; alternate \rightarrow H_a: $\mu_1 \neq \mu_2$
- 3. Hypothesis about relationships (Between Variables):
 - You are testing whether two variables are related (not necessarily groups).
 - Example: Is there a correlation between study time and exam score?
 - Hypothesis:
 - null \rightarrow H₀: $\rho = 0$ (no correlation); alternate \rightarrow H_a: $\rho \neq 0$
 - This tests for **association**, not difference between groups.



B. Various Approaches to Hypothesis Testing.

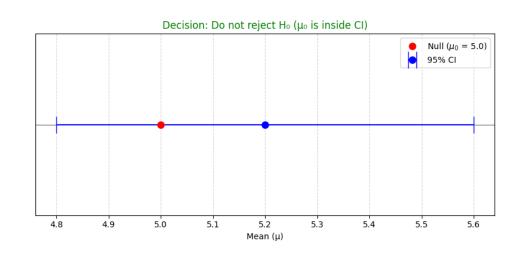


B.1 Confidence Interval Approach.

- We can use a confidence interval to help us weigh the evidence against the null hypothesis.
 - A confidence interval gives us a range of *plausible* values for μ .
 - If the **null value** is **in the interval**, then μ_0 is *plausible value* for μ .
 - If the null value is not in the interval, then μ_0 is not a plausible value for μ .

```
1. State Hypotheses:
                                         • \mathbf{H_0}: \mu = \mu_0 (NullHypothesis)
                                      • H_1: \mu \neq \mu_0 (AlternativeHypothesis)
2. Choose Significance Level:
                                      • \alpha = 0.05(95\%CI) or \alpha = 0.01(99\%CI)
3. Check Assumptions:
                           · Sample size, normality, data conditions for CI method
4. Find Critical Value:
                                • Using z^* (normal) or t^* (t-distribution) for given \alpha
5. Compute Confidence Interval:
                                          • CI = \bar{x} \pm (critical \ value \times SE)
6. Decision Rule:
        if \mu_0 \notin CI then
 Reject H_0
 \Rightarrow Evidence for H_1 (\mu \neq \mu_0)
 Fail to reject H_0
⇒ No significant difference found
7. Interpretation:

    State conclusion in context of the research question
```







B.2 Critical Value Approach.

1. State Hypotheses:

• $\mathbf{H_0} : \mu = \mu_0$

• $\mathbf{H_1} : \mu \neq \mu_0$

2. Choose Significance Level:

• $\alpha = 0.05 \text{ or } 0.01$

3. Check Assumptions:

• Normality, sample size requirements

4. Calculate Test Statistic:

•
$$\mathbf{z} = \frac{\bar{\mathbf{x}} - \mu_0}{\mathbf{SE}}$$
 or **t**-statistic

5. Find Critical Value:

• \mathbf{z}^* or \mathbf{t}^* for given α

6. Decision Rule:

if
$$|z| > z^*$$
 or $|t| > t^*$ then

 \Rightarrow Statistically significant

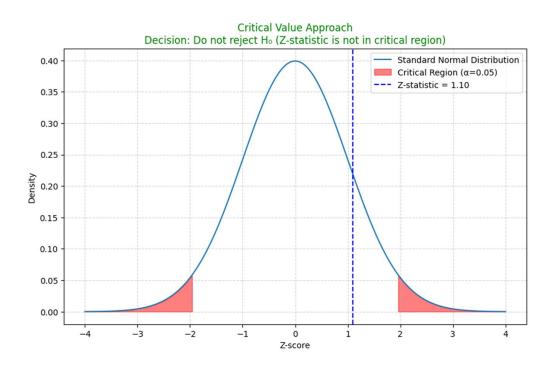
else

Fail to reject H_0

 \Rightarrow Not significant

7. Interpretation:

• Compare test statistic to critical value

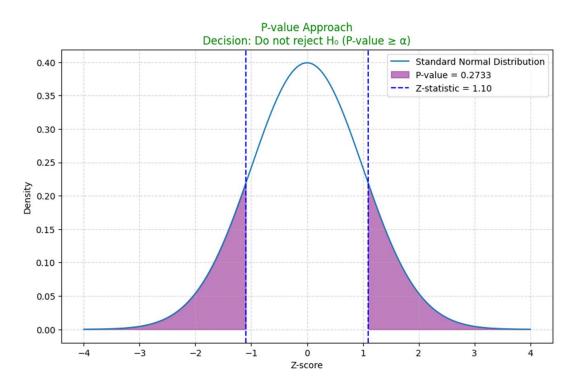






B.3 p – value Approach.

1. State Hypotheses: • $\mathbf{H_0} : \mu = \mu_0$ • $\mathbf{H_1} : \mu \neq \mu_0$ 2. Choose Significance Level: • $\alpha = 0.05 \text{ or } 0.01$ 3. Check Assumptions: • Normality, sample size requirements 4. Calculate Test Statistic: • $\mathbf{z} = \frac{\bar{\mathbf{x}} - \mu_0}{\mathbf{SE}}$ or **t**-statistic 5. Find p-value: • $P(|\mathbf{Z}| > |\mathbf{z}|)$ or $P(|\mathbf{T}| > |\mathbf{t}|)$ 6. Decision Rule: if p-value $< \alpha$ then Reject H_0 ⇒ Statistically significant Fail to reject H_0 ⇒ Not significant 7. Interpretation: • p-value represents strength of evidence against H_0





1. Variance Based Testing. {Chi – Square Distribution}



1.1 Motivation: Why Test Variance?

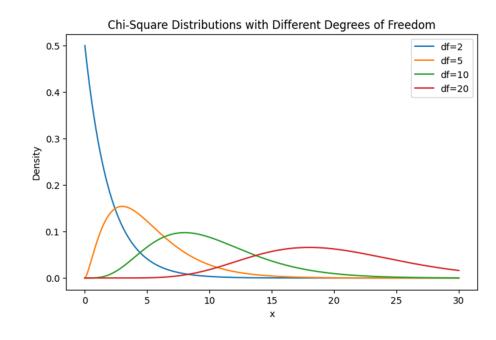
- In business, we rarely care only about the *average*:
 - we **often also want to know** whether **differences** between groups or categories are
 - real or just due to chance.
 - Example 1 Customer Satisfaction:
 - You run a survey for 3 service channels (Phone, Email, Live Chat)
 - Average ratings: Phone = 4.3; Email = 4.0, Live Chat = 4.1;
 - Question: Are these differences meaningful or random?
 - Example 2 Market Segmentation:
 - You test if product preference depends on region.
 - Data is categorical: **North**, **South**, **East**, **West**.
 - Question: Is there an association between region and product choice?
- Sometimes differences in sample data are due to *natural random variation*.
 - We need **statistical tools** to decide whether **these differences are significant**.





1.2 Chi – square Distribution.

- Numerically, the variance is different from the mean because
 - it can not be negative, so it won't make sense to use a normal or t distribution.
- In order to do hypothesis testing for a variance,
 - we need to learn a little bit about a new distribution, the **chi-square distribution**.
- Key properties of the **chi square Distribution**:
 - If $X_1, X_2, ..., X_n$ are independent standard normal variables then:
 - Chi Square $(\chi^2) = X_1^2 + X_2^2 + \cdots + X_k^2$
 - follows a chi square distribution with df = k.
 - Notations $\rightarrow \chi_{\rm df}^2$
 - Shape Right skewed, starts at 0, extends to $+\infty$
 - Parameters:
 - Degrees of freedom (df) determines the shape.
 - Mean: $\mu = df$
 - Variance: $\sigma^2 = 2 \times df$







1.3 Two Main Tools.

Test	When to Use	Data Type
Chi – square Test	Relationship between categorical variables	Categorical
ANOVA	Compare means across 3 + groups	Continuous (numerical) outcome,categorical group variable.



2. Variance Based Testing. {Chi – Square Test}

2.1 Chi – Square Test – Core Idea.

- Motivation:
 - The chi square (χ^2) test measures how different observed counts are from expected counts.
 - If differences are too large to be explained by chance,
 - we conclude that the distribution or relationship is statistically significant.
- Types of Chi Square Test:
 - 1. Goodness of Fit Test:
 - Purpose: Tests if sample data matches a hypothesized distribution.
 - When to use:
 - Comparing one categorical variable to a theoretical distribution.
 - Testing proportions against benchmarks.
 - Examples:
 - Marketing: "Do our website visitors follow the expected 40%/30%/30% split by age group?
 - Operations: "Is our defect rate (3%) consistent across all products?
 - HR: "Does our hiring ratio match the applicant pool's demographics?"
 - In General: "Does our observed data fit what we expected?"



2.1 Chi – Square Test – Core Idea.

- Motivation:
 - The chi square (χ^2) test measures how different observed counts are from expected counts.
 - If differences are too large to be explained by chance,
 - we conclude that the distribution or relationship is statistically significant.
- Types of Chi Square Test:
 - 2. Test of Independence:
 - **Purpose:** Tests if two categorical variables are related.
 - When to use:
 - Analyzing two categorical variables simultaneously.
 - Checking for dependencies between two factors.
 - Examples:
 - Retail: "Is purchase frequency (low/med/high) related to customer region?"
 - Heatlcare: "Does treatment outcome (success/failure) depend on clinic location?"
 - In General: "Are these two factors associated.?"





2.2 Case: Goodness of Fit

- Derivation of Chi square Statistic:
 - In Goodness of fit:
 - We want to compare observed frequencies O_i and expected frequencies E_i for k categories.
 - Step 1 Measure difference for each category:
 - Difference = $O_i E_i$
 - But difference can be positive or negative.
 - To avoid them cancelling out → square them.
 - Difference = $(O_i E_i)^2$
 - Step 2 Weight by expected count:
 - Large differences in categories with small expected counts are more unusual than in large counts.
 - So, we normalize by E_i , i.e.
 - $\bullet \quad \frac{(O_i E_i)^2}{E_i}$





2.2.1 Case: Goodness of Fit

- Step 3 Sum across Categories:
 - The chi square statistic is:

•
$$\chi^2 = \sum_{i=1}^k \frac{(0_i - E_i)^2}{E_i}$$

- Step 4 Sampling distribution:
 - Under the null hypothesis, χ^2 follows a chi square distribution with:
 - df = k 1



2.2.2 Example – Goodness – of – fit Test.

- Scenario:
 - An e commerce business claims that
 - 50% of purchase come from mobile, 30% from desktop, and 20% from tablet.
 - You collect a **random sample of 400 purchases**:

Device	Observed (O _i)
Mobile	220
Desktop	120
Tablet	60

- Null Hypothesis (H₀):
 - The distribution of purchases by device matches the company's claim:
 - $p_{Mobile} = 0.50$; $p_{Desktop} = 0.30$; $p_{Tablet} = 0.20$
- Alternative Hypothesis (H_a):
 - The distribution of purchases by device does not match the company's claim:
 - At least one of p_{Mobile} , $p_{Desktop}$, p_{Tablet} differs from the claim.





1. Data & Claimed proportions:

• Claimed proportions:

•
$$p_{Mobile} = 0.50$$
; $p_{Desktop} = 0.30$; $p_{Tablet} = 0.20$

- Sample Size: n = 400
- Observed Counts: O_i : Mobile = 220; Desktop = 120; Tablet = 60.

2. Expected counts under H_0 :

• $E_i = n \times p_i$ (Why?)

Device	Observed (0 _i)	Expected $(E_i = n \times p_i)$
Mobile	220	$E_{Mobile} = 400 \times 0.50 = 200.$
Desktop	120	$E_{Desktop} = 400 \times 0.30 = 120.$
Tablet	60	$E_{Tablet} = 400 \times 0.20 = 80.$





3. Compute the **chi – square statistic**:

•
$$\chi^2 = \sum_{i=1}^k \frac{(0_i - E_i)^2}{E_i}$$

• Compute Each term:

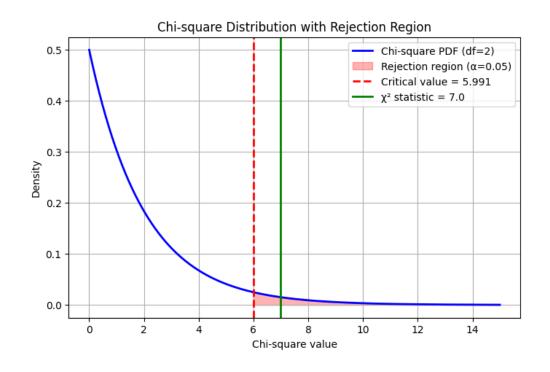
Device	Observed (0 _i)	Expected ($\mathbf{E_i} = \mathbf{n} \times \mathbf{p_i}$)	$(\mathbf{O_i} - \mathbf{E_i})^2$	$(\mathbf{O_i} - \mathbf{E_i})^2$
				$\overline{E_i}$
Mobile	220	$E_{Mobile} = 400 \times 0.50 = 200.$	$(220 - 200)^2 = 400$	$\frac{400}{200} = 2$
Desktop	120	$E_{Desktop} = 400 \times 0.30 = 120.$	$(120 - 120)^2 = 0$	0
Tablet	60	$E_{Tablet} = 400 \times 0.20 = 80.$	$(60 - 80)^2 = 400$	$\frac{400}{80}=5$
			$\chi^2 \Rightarrow$	2+0+5=7.0





4. Degrees of Freedom:

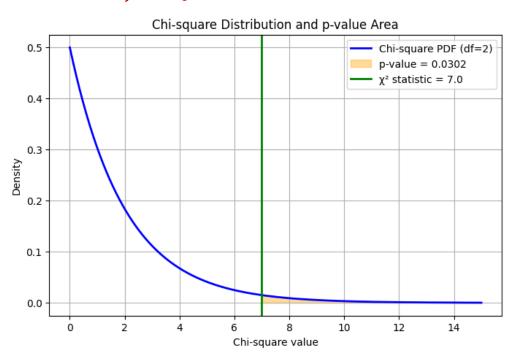
- For goodness of fit with k categories:
 - df = k 1 = 3 1 = 2
- 5. Critical value ($\alpha = 0.05$) and decision rule:
 - Critical value from $\chi_{df=2}^2$ distribution at 0.05 significance:
 - $\chi^2_{0.95,df=2} \approx 5.991$
 - Decision rule $@ \alpha = 0.05$:
 - If $\chi^2 > 5.991 \rightarrow \text{reject H}_0$
 - Here $\chi^2 = 7.0 > 5.991 \rightarrow \text{reject H}_0$





6. p – value :

- p-value is the probability of observing a chi-square at least as large a 7 under H₀
 - $p value = P(\chi^2_{df=2} \ge 7.0) \approx 0.0302$
- Because 0.0302 < 0.05 this agrees with the decision to reject H_0 .





- 7. Conclusion & Business Interpretation:
 - i. Statistical conclusion:
 - Reject the null hypothesis.
 - The observed device distribution (220,120,60) is
 - significantly different from the claimed (50%, 30%, 20%) at the 5% level.
 - ii. Business insight:
 - Mobile purchases are higher than claimed (220 vs 200 expected);
 - tablet purchases are lower (60 vs 80 expected).
 - iii. The company should investigate:
 - Why mobile appears stronger (better UX, targeting, or promotion)?
 - Why tablet underperforms (poor UI, tracking issues, or lower traffic)?
 - iv. Actionable next steps:
 - drill down by segments (region, time, campaign),
 - check tracking,
 - consider reallocating optimization resources.

2.3 Case: Test of Independence.

- Derivation of Chi square Statistic:
 - While the **Goodness-of-Fit** test checks whether a **single categorical variable** matches an expected distribution,

the Test of Independence examines whether two categorical variables are related.

- Step 1 Setup:
 - We **collect data** in an $\mathbf{r} \times \mathbf{c}$ **contingency table**:

	Category 1	Category 2	•••	Total
Group 1	0 ₁₁	0 ₁₂		$\sum \mathbf{O}_{11} + \mathbf{O}_{12} + \cdots$
Group 2	0 ₂₁	0 ₂₂		$\Sigma 0_{21} + 0_{22} + \cdots$
Total	$\Sigma \mathbf{O}_{11} + \mathbf{O}_{21} + \cdots$	$\Sigma \mathbf{O}_{12} + \mathbf{O}_{22} + \cdots$		
Table: r × c contigency Table.				

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2.3.1 Case: Test of Independence.

- Step 2 Expected Counts:
 - If the variables are independent:
 - $E_{ij} = \frac{(Row Total_i) \times (Column Total_j)}{Grand Total}$
 - If the variables are not independent:
 - then the above formula no longer represents the expected counts,
 - because this formula is derived under the null hypothesis H₀
 - Why?
 - **Under independence**, the probability of being in **cell(i, j)** is simply:
 - $P(Row_i) \times P(Column_i)$
 - Which leads to the **above multiplication formula**.
 - If the variables are dependent,
 - the probability of being in (i, j) is not the product of marginal probabilities
 - it depends on the joint distribution.





2.3.1 Case: Test of Independence.

- Step 3 Chi square Statistic:
 - Same formula, but applied to all cells:

•
$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(o_{ij} - E_{ij})^2}{E_{ij}}$$

- Degrees of freedom:
 - $df = (r-1) \cdot (c-1)$
- When variables are not independent,
 - the actual observed counts Oii will systematically deviate from these expected counts.
 - The chi square statistic:

•
$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(o_{ij} - E_{ij})^2}{E_{ij}}$$

• will be large, leading us to reject H_0 .



2.3.2 Example – Test of Independence.

- Scenario:
 - A retailer wants to know if the device type is related to purchase completion.

Device	Purchased (Yes)	Purchased (No)	Total
Mobile	180	120	300
Desktop	140	160	300
Tablet	60	40	100
Total	380	320	700

- Null and Alternative Hypothesis:
 - H_0 : Device type and purchase completion are independent (no relationship).
 - H_a: Device type and purchase completion are not independent (there is a relationship).





2.3.3 Solution – Test – of – Independence.

1. Observed Frequencies Table (From Data) \Rightarrow

	Device	Purchased (Yes)	Purchased (N	No) Total	
$)\Rightarrow$	Mobile	180	120	300	
	Desktop	140	160	300	
	Tablet	60	40	100	
	Total	380	320	700	
Device		\sim E_{ij}	ow Total)×(Colu Grand Tot Ited for each	al cell.	urchased (N
Mobile	E ₁₁	$=\frac{300\times380}{700}\approx$	162.857	$\mathbf{E_{12}} = \frac{30}{}$	$\frac{00\times320}{700}\approx$
Desktop	E ₂₁ :	$=\frac{300\times380}{700}\approx$	162.857	$E_{22}=\frac{30}{}$	$\frac{00\times320}{700}\approx$
Tablet		100×380		1	00×320

2. Expected Frequencies $(E_{ij}) \Rightarrow$

Mobile	$E_{11} = \frac{300 \times 380}{700} \approx 162.857$	$E_{12} = \frac{300 \times 320}{700} \approx 137.143$	
Desktop	$E_{21} = \frac{300 \times 380}{700} \approx 162.857$	$E_{22} = \frac{300 \times 320}{700} \approx 137.143$	
Tablet	$E_{31} = \frac{100 \times 380}{700} \approx 54.286$	$E_{32} = \frac{100 \times 320}{700} \approx 45.714$	
	Expected Table.		



2.3.3 Solution – Test – of – Independence.

Device	Purchased (Yes)	Purchased (No)	Total
Mobile	180 —	120	300
Desktop	140	160	300
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Total	380	320	700

Device	Purchased (Yes)	Purchased (No)
Mobile	$E_{11} = \frac{300 \times 380}{700} \approx 162.857$	$E_{12} = \frac{300 \times 320}{700} \approx 137.143$
Desktop	$E_{21} = \frac{300 \times 380}{700} \approx 162.857$	$E_{22} = \frac{300 \times 320}{700} \approx 137.143$
Tablet	$E_{31} = \frac{100 \times 380}{700} \approx 54.286$	$E_{32} = \frac{100 \times 320}{700} \approx 45.714$
Expected Table.		

3. Compute Chi – square Statistic ⇒

4. Degrees of Freedom:

•
$$df = (r - 1) \times (C - 1) = (3 - 1) \times (2 - 1) = 2.$$

Device	Purchased (Yes)	Purchased (No)
Mobile	$\frac{(180 - 162.857)^2}{162.857} \approx 1.800$	$\frac{(120-137.143)^2}{137.143}\approx 2.145$
Desktop	$\frac{(140 - 162.857)^2}{162.857} \approx 3.207$	$\frac{(160-137.143)^2}{137.143} \approx 3.807$
Tablet	$\frac{(60-54.286)^2}{54.286}\approx 0.603$	$\frac{(40-45.714)^2}{45.714}\approx 0.714$
	$\chi^2 \rightarrow Each cell va$	lue
Grand T	otal $\Rightarrow \chi^2 = 1.800 + 2.145 + 3.207 + 3.300 +$	3.807 + 0.603 + 0.714 = 12.276.

{Repeat for each cell with correct value.}





2.3.3 Solution – Test – of – Independence.

5. Critical Value & Decision:

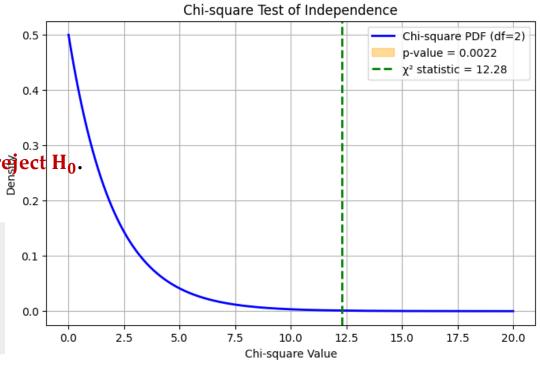
- At $\alpha = 0.05$, $\chi^2_{0.95,df=2} \approx 5.991$
- Since: $12.276 > 5.991 \rightarrow \text{we reject H}_0$

6. p – value:

- Formula:
 - $p = P(\chi_{df=2}^2 \ge 12.276) \approx 0.0021$
- Because 0.0021 < 0.05 this agrees with the decision to reject H_0 .

7. Interpretation (Business Context)

- Since p≈0.0021<0.05, there is strong evidence that
 - device type and purchase completion are related.
- · From a business standpoint,
 - this means user experience and conversion strategy may need to be tailored
 - **differently** for mobile, desktop, and tablet users.





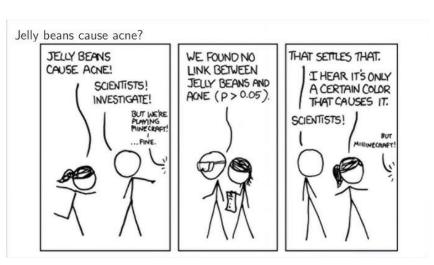
"Chi-Square works for categorical data, but what if we want to test differences in means across multiple groups?"

{ 3. ANOVA Test}



3.1 Motivation for ANOVA.

- In **business analytics**, you often want to **compare more than two groups**.
 - Does **average sales** differ between regions?
 - Do **conversion rates** differ across multiple website designs?
 - Does average customer satisfaction vary between service channels?
- If you only **had two groups**, you could **use a t test**.
 - But what if you have 3 or more groups?
 - Doing multiple t tests increase the risk of Type I error (false positives).
 - ANOVA solves this by testing all groups at once.





3.2 What is ANOVA?

- ANOVA Analysis of Variance checks whether the means of multiple groups are significantly different.
 - Null Hypothesis H₀: All group means are equal.
 - Alternative Hypothesis H_a: At least one group is different.
- Key Idea:
 - ANOVA compares:
 - Between-group variability: how far group means are from the overall mean.
 - Within-group variability: how spread-out values are inside each group.
 - If between-group variability is large compared to within-group variability,
 - the means are probably different.



3.3 Special Distribution for ANOVA.

- Why not t distribution?
 - The **t-distribution** is used to compare **means of two groups** (or a sample mean against a known mean)
 - basically, one variance estimate is involved in the denominator (the estimate of standard error).
 - ANOVA compares more than two groups, so the simple two-group comparison logic doesn't hold.
 - Also, the ANOVA test statistic is a ratio of two variances,
 - not a difference of means standardized by a standard error.
 - The **t-distribution** arises when you have a **single sample variance estimate**
 - and want to **standardize a mean difference**, not when comparing **ratios** of **two variance estimates**.
- Why not chi square distribution?
 - The **chi-square distribution** describes the distribution of a **single variance estimate** (sum of squared deviations normalized) based on **normally distributed data**.
 - In **ANOVA**, we have **two variance estimates**:
 - Variance between groups (based on differences of group means from overall mean)
 - Variance within groups (based on variability inside groups)
 - The **chi-square distribution** describes **only one** variance estimate at a time, not the ratio of two.





3.3.1 Why the F – distribution?

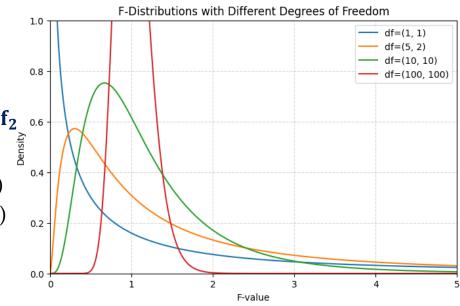
- The **F distribution** models the distribution of the ratio of
 - two independent chi square variables,
 - each divided by their degrees of freedom exactly what the **ANOVA test statistic** is:
 - Formally if:

•
$$X \sim \frac{\chi_{df_1}^2}{df_1}$$
 and $Y \sim \frac{\chi_{df_2}^2}{df_2}$

• are independent, then

•
$$\mathbf{F} = \frac{\mathbf{X}}{\mathbf{Y}}$$

- follows an F distribution with degrees of freedom df₁ and df₂ 0.69
- This perfectly matches the ANOVA setup where:
 - Numerator = variance estimate between groups (scaled chi square)
 - Denominator = variance estimate within groups (scaled chi square)







3.4 Statistic for ANOVA.

- F statistics Formula:
 - $\mathbf{F} = \frac{\text{Variance Between Groups}}{\text{Variance Within Groups}}$
- Where:
 - Variance Between Groups = $MSB = \frac{SSB}{df_{between}}$
 - Variance Between Groups = $MSW = \frac{SSW}{df_{within}}$



3.5 Types of ANOVA.

- There are several types of ANOVA, each suited to different experimental designs and data structures.
 - Here's a **quick overview** of the **two main types**:
 - 1. One way ANOVA:
 - Purpose:
 - Compare means across one categorical independent variable with 3 or more groups.
 - Example:
 - Comparing average sales across
 - 3 marketing channels (Social Media, Email, Organic Search).
 - 2. Two way ANOVA:
 - Purpose:
 - Compare means across two categorical independent variables simultaneously,
 - and check for **interaction effects** between them.
 - Example:
 - Comparing average sales across marketing channel and region
 - (e.g., Social Media vs Email, across North and South regions).
 - Allows you to see:
 - Main effect of each factor
 - Interaction effect between factors



3.6 Example – One Way ANOVA.

- Derivation:
 - Theory and Formulas for ONE Way ANOVA:
 - Suppose you have **k** groups with sample sizes $n_1, n_2 \dots, n_k$ and observations X_{ij} ,
 - where i indexes' groups and j indexes observations within groups.
 - Goal:
 - Test:
 - H_0 : $\mu_1 = \mu_2 = \cdots = \mu_k$
 - Vs.
 - H_a: At least one group mean differs.





Steps a) Compute group means and overall mean: fonttitle

1. Group mean:

$$\bar{\mathbf{X}}_{\mathbf{i}} = \frac{1}{n_{\mathbf{i}}} \sum_{\mathbf{j}=1}^{n_{\mathbf{i}}} \mathbf{X}_{\mathbf{i}\mathbf{j}}$$

2. Overall mean:

$$\bar{X} = \frac{1}{N} \sum_{i=1}^k \sum_{j=1}^{n_i} X_{ij}$$

where:

$$N = \sum_{i=1}^k n_i$$



Steps b) Compute Sum of Squares

1. Between Groups (SSB):

$$\mathbf{SSB} = \sum_{i=1}^k \mathbf{n}_i (\mathbf{\bar{X}_i} - \mathbf{\bar{X}})^2$$

2. Within Groups (SSW):

$$\mathbf{SSW} = \sum_{i=1}^k \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2$$

3. Total (SST):

$$\mathbf{SST} = \sum_{i=1}^k \sum_{j=1}^{\mathbf{n_i}} (\mathbf{X_{ij}} - \mathbf{\bar{X}})^2 = \mathbf{SSB} + \mathbf{SSW}$$





Steps c) Degrees of Freedom	
1. Between Groups:	$\mathbf{df_{between}} = \mathbf{k} - 1$
2. Within Groups:	$df_{within} = N - k$
3. Total:	$\mathbf{df_{total}} = \mathbf{N} - 1$





Steps d) Mean Squares

1. Mean Square Between (MSB):

$$\mathbf{MSB} = rac{\mathbf{SSB}}{\mathbf{df_{between}}}$$

2. Mean Square Within (MSW):

$$\mathbf{MSW} = \frac{\mathbf{SSW}}{\mathbf{df_{within}}}$$





Steps e) Compute the F-statistic

$$\mathbf{F} = rac{\mathbf{MSB}}{\mathbf{MSW}}$$

Steps f) Decision Rule

• Compare **F** to the critical value $F_{-}\alpha$, $df_{-}between$, $df_{-}within$ or compute the p-value:

$$p = P(F_{df_{between}, df_{within}} \ge F_{obs})$$

• Reject $\mathbf{H_0}$ if $\mathbf{p} < \alpha$. Otherwise, do not reject $\mathbf{H_0}$.





3.7 Example – Two Way ANOVA.

Definition and Goal of Two-Way ANOVA

Two-way ANOVA is used to examine the influence of two categorical factors on a continuous response variable, including possible interaction effects between the factors.

Null hypotheses:

$$\begin{cases} H_{0A}: \mu_1 = \mu_2 = \dots = \mu_a. & \text{(No effect of Factor A)} \\ H_{0B}: \mu_{\cdot 1} = \mu_{\cdot 2} = \dots = \mu_{\cdot b} & \text{(No effect of Factor B)} \\ H_{0AB}: \text{No interaction between Factors A and B} \end{cases}$$

Alternate hypotheses: At least one group mean differs for Factor A or Factor B, or there is an interaction effect.





Step a) Compute Marginal Means

• Row means:

$$\mathbf{\bar{X}_{i\cdot}} = \frac{1}{n_{i\cdot}} \sum_{j=1}^{b} \sum_{k=1}^{n_{ij}} \mathbf{X_{ijk}}$$

• Column means:

$$\bar{X}_{\cdot j} = \frac{1}{n_{\cdot j}} \sum_{i=1}^a \sum_{k=1}^{n_{ij}} X_{ijk}$$

• Overall mean:

$$ar{ ext{X}} = rac{1}{ ext{N}} \sum_{ ext{i}=1}^{ ext{a}} \sum_{ ext{j}=1}^{ ext{b}} \sum_{ ext{k}=1}^{ ext{n}_{ ext{ijk}}} ext{X}_{ ext{ijk}}$$



Step b) Compute Sums of Squares

Total SS:
$$SST = \sum_{i=1}^{a} \sum_{j=1}^{b} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X})^2$$

Factor A SS:
$$SSA = \sum_{i=1}^{a} n_i \cdot (\bar{X}_{i\cdot} - \bar{X})^2$$

Factor B SS:
$$SSB = \sum_{j=1}^{o} n_{\cdot j} (\bar{X}_{\cdot j} - \bar{X})^2$$

Interaction SS:
$$SSAB = \sum_{i=1}^{a} \sum_{j=1}^{b} n_{ij} (\bar{X}_{ij} - \bar{X}_{i.} - \bar{X}_{.j} + \bar{X})^{2}$$

$$= \sum_{i=1}^{a} \sum_{j=1}^{b} n_{ij} (\bar{X}_{ij} - \bar{X}_{i.} - \bar{X}_{.j} + \bar{X})^{2}$$

Within SS:
$$SSW = \sum_{i=1}^{a} \sum_{j=1}^{b} \sum_{k=1}^{n_{ij}} (X_{ijk} - \bar{X}_{ij})^2$$





Step c) Degrees of Freedom $df_A=a-1$ $df_B=b-1$ $df_{AB}=(a-1)(b-1)$ $df_{within}=N-ab$ $df_{total}=N-1$





Step d) Compute Mean Squares $MS_A = \frac{SSA}{df_A}$ $MS_B = \frac{SSB}{df_B}$ $MS_{AB} = \frac{SSAB}{df_{AB}}$ $MS_{within} = \frac{SSW}{df_{within}}$





Step e) Compute F-Statistics

$$F_A = \frac{MS_A}{MS_{within}}, \quad F_B = \frac{MS_B}{MS_{within}}, \quad F_{AB} = \frac{MS_{AB}}{MS_{within}}$$

Step f) Decision Rule

- For each factor and the interaction, compare the F statistic to the critical value F_{α,df_1,df_2} or compute the p-value.
- Reject the null hypothesis for that factor or interaction if $p < \alpha$.
- Interpret the main effects and interaction effects accordingly.





Thank You.