A Practical Introduction to Data Science

Part 2

Business and Data Understanding

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Course Agenda

I.	Introduction to Data Science
II.	Business and Data Understanding
III.	Introduction to Supervised Learning
IV.	Advanced Supervised Learning
V.	Unsupervised Learning
VI.	Time Series Analysis
VII.	Deep Learning
VIII.	Machine Learning Operations

Business and Data Understanding

- The Importance of B&D Understanding
- Data Collection
- Exploratory Data Analysis
- Statistical Inference
- Confidence Intervals
- Hypothesis Testing
- Common Mistakes
- Case Studies

The Importance of B&D Understanding

The Importance of B&D Understanding

A lack of business/data understanding can lead to:

- Wasted time and resources
- Poor adoption of the model
- Useless model (bad generalization)
- Unsatisfied stakeholders (e.g. lack of explainability)

The Importance of B&D Understanding

Good business/data understanding leads to:

- Faster project delivery
- Early discovery of limitations or even blockers
- Better decisions at later steps
- Setting the focus of the analysis
- Better overall solution

The Importance of B&D Understanding

Requirements:

- Understand business objective, desired outcomes and KPIs
- Understand processes, model integration and consequences
- Understand constraints (time, budget, resources)
- Iterative thinking, multiple Q&A sessions with the business
- Stakeholder engagement
- Documentation

Data Collection

Data Collection

Common Data Sources

- On-prem / Cloud Data Warehouse
  - Customer data
  - Product data
  - Transactional data
  - Financial data
- Sensor data (IoT)
- Third-Party data
- Web scraping

Challenges

- Quality
- Volume
- Security
- Privacy
- Integration
- Processing
- Governance

Data Collection

Extract > Transform > Load (ETL)

Tools for data ingestion, processing and storing:

- Apache: Kafka, Hive, Spark, Hadoop
- GCP: Data Fusion, Dataproc, Dataflow, BigQuery

Data Collection itself is usually the responsibility of the ***Data Engineer****. However, the* ***Data Scientist*** *is responsible for*

- *specifying data needs and the required format*
- *monitoring data quality*
- *collaborating with Data Engineers to solve data issues*

Data Collection

Requirements:

- Data source reliability
- Proper data collection methodology
- Availability and consistency over time
- Data ingestion automation
- Data completeness, bias and limitations
- Process Documentation and Data Dictionary

Exploratory Data Analysis

Exploratory Data Analysis (EDA)

1. Data Structure Assessment

- Table Relations & Joining
- Number of rows & columns (observations & features)
- Data Types
- Column Descriptions
- Data Granularity & IDs
- Long and Wide Format
- Aggregation

2. Data Quality Assessment

- Data Errors
- Duplications
- Missing Values
- Outliers
- Label Correctness
- Data Inconsistencies

Exploratory Data Analysis (EDA)

3. Looking for Patterns

- Distributions
- Relationships
- Data Bias
- Trend and Cointegration
- Data Drift
- Data Segments

4. Methods

- Data Visualization
  - Gain insights: understand patterns, detect anomalies
  - Communicate results to non-technical stakeholders: enhanced storytelling
- Statistical Analysis
  - Descriptive
  - Inferential
- Ask business/data owner

Exploratory Data Analysis (EDA)

Univariate Analysis

- Feature distributions
  - Histogram
  - Bar plot
  - Box plot
- Descriptive statistics:
  - mean, std
  - median, IQR
  - min, max

Multivariate Analysis

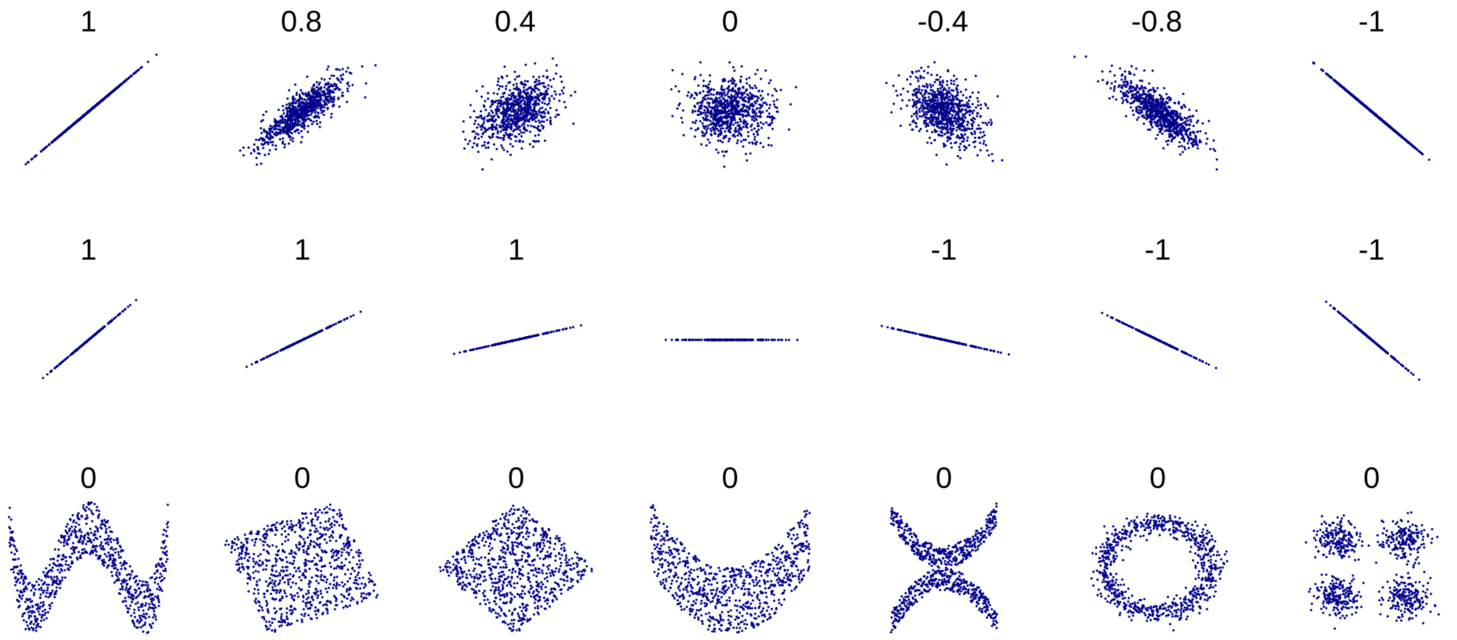
- Correlations (Pearson, Spearman)
- Contingency tables (crosstabs)
- Joint distributions
  - scatter plot
  - box plot
  - heatmap

Correlation

Pearson correlation

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$$

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}}$$



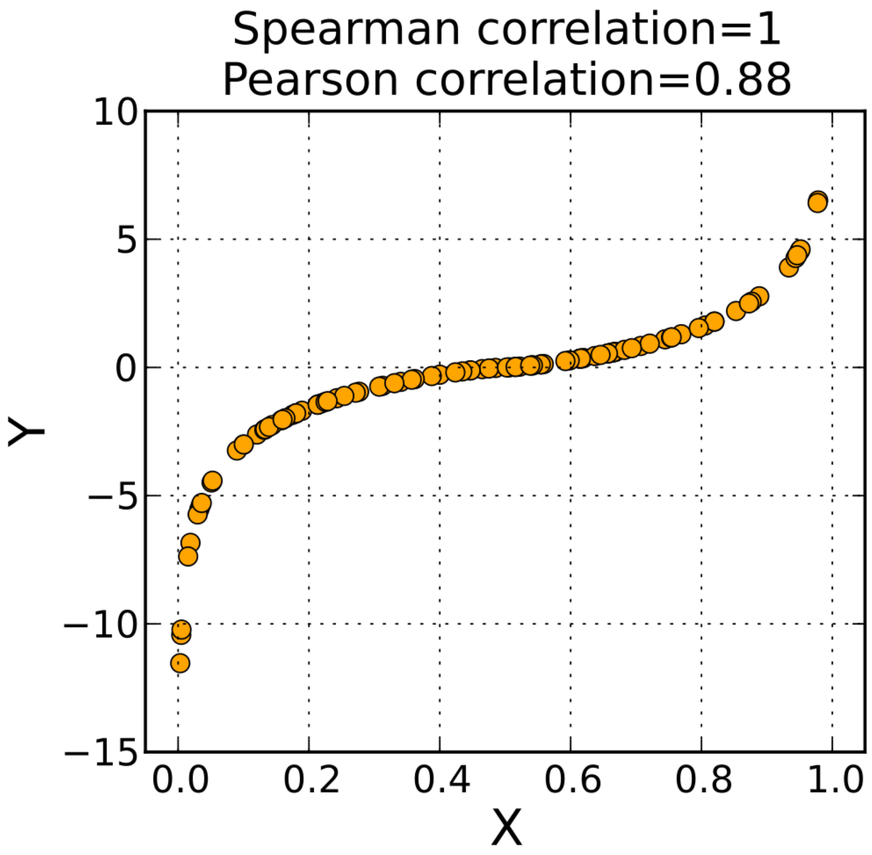
- The correlation reflects the strength and direction of a linear relationship (top row),
- but not the slope of that relationship (middle),
- nor many aspects of nonlinear relationships (bottom)

Source: Pearson correlation coefficient – Wikipedia

Correlation

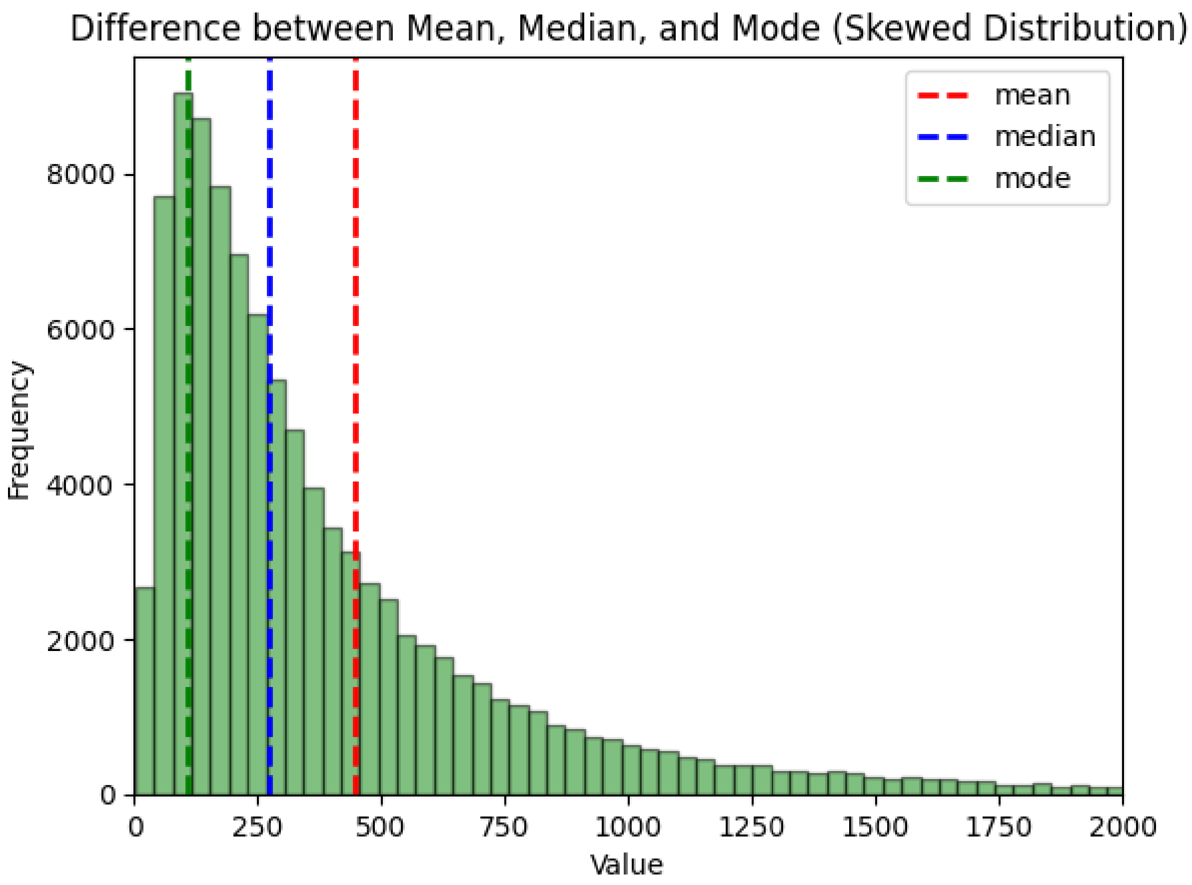
Spearman's rank correlation

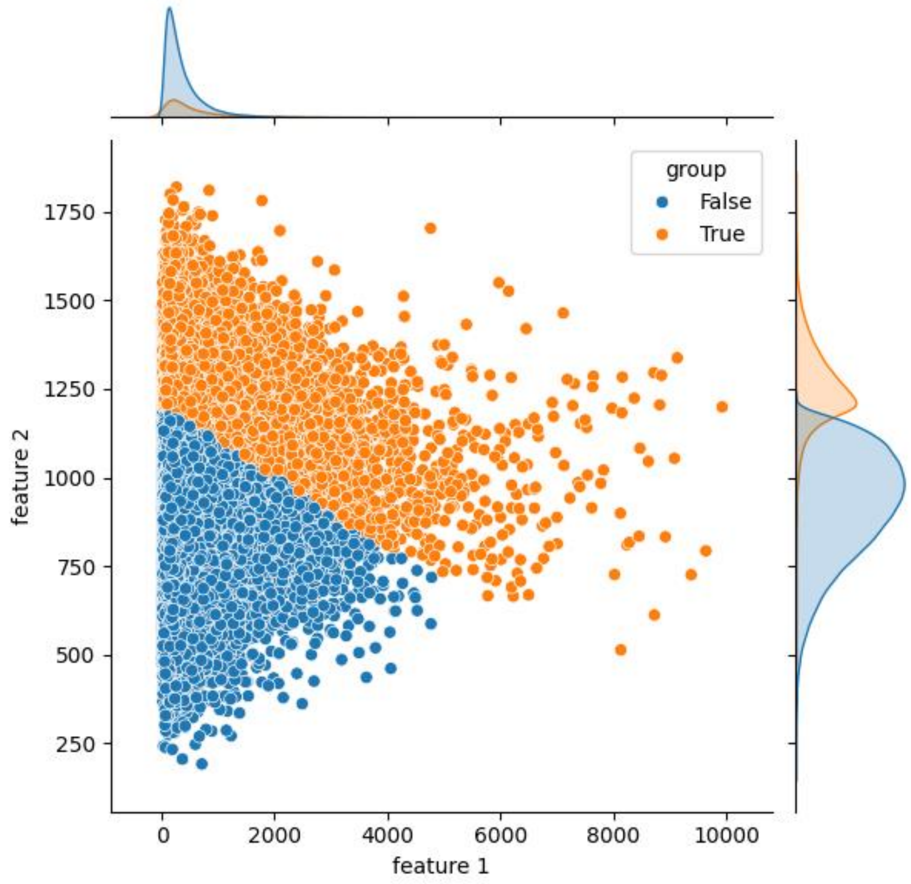
- Spearman's correlation assesses monotonic relationships (whether linear or not)
- The Spearman correlation between two variables is equal to the Pearson correlation between the rank values of those two variables
- $r_S = \rho(R[X], R[Y])$



Source: [Spearman's rank correlation coefficient – Wikipedia]

Exploratory Data Analysis (EDA)



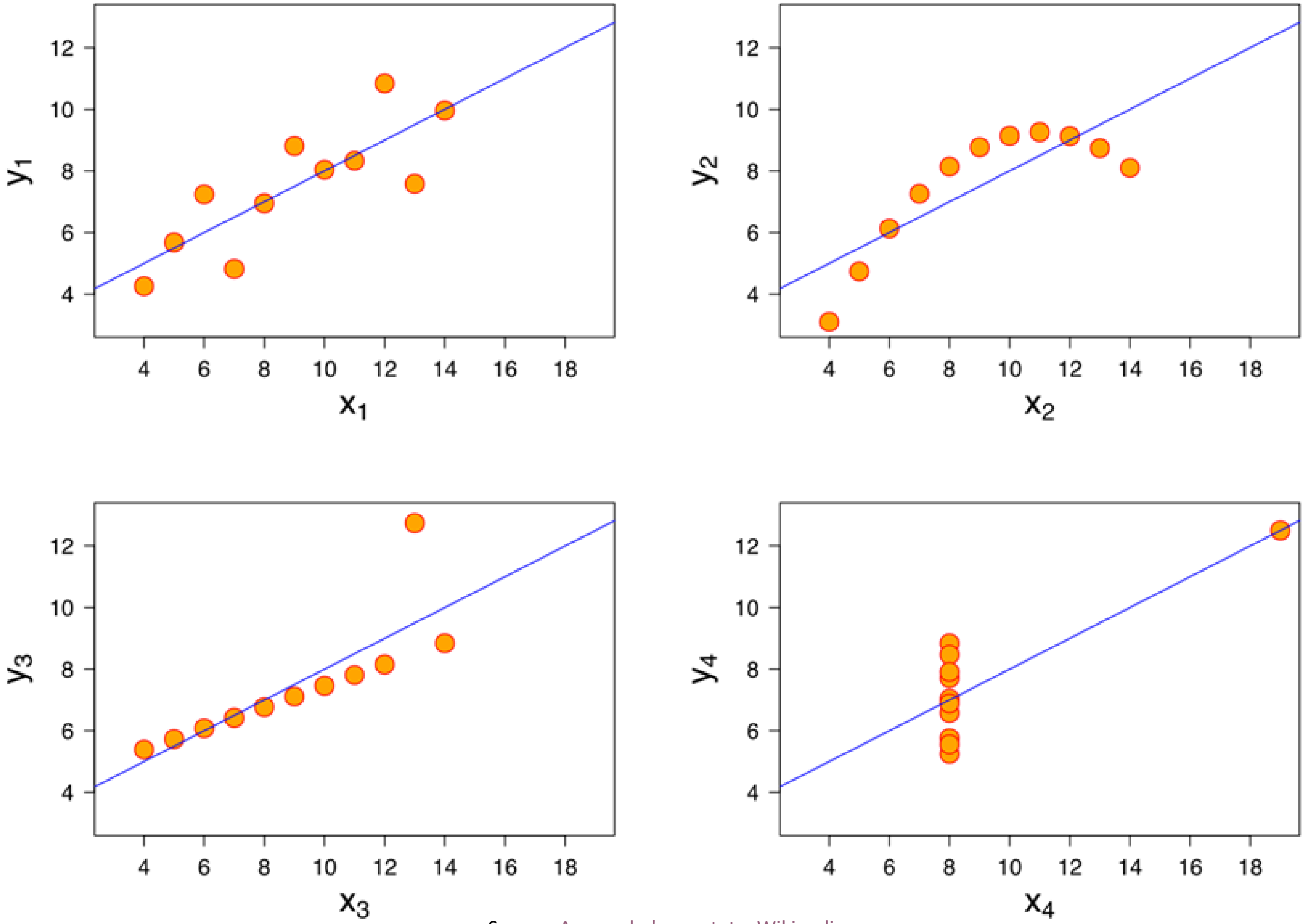


Exploratory Data Analysis (EDA)

Anscombe's quartet

Same mean, variance and correlation

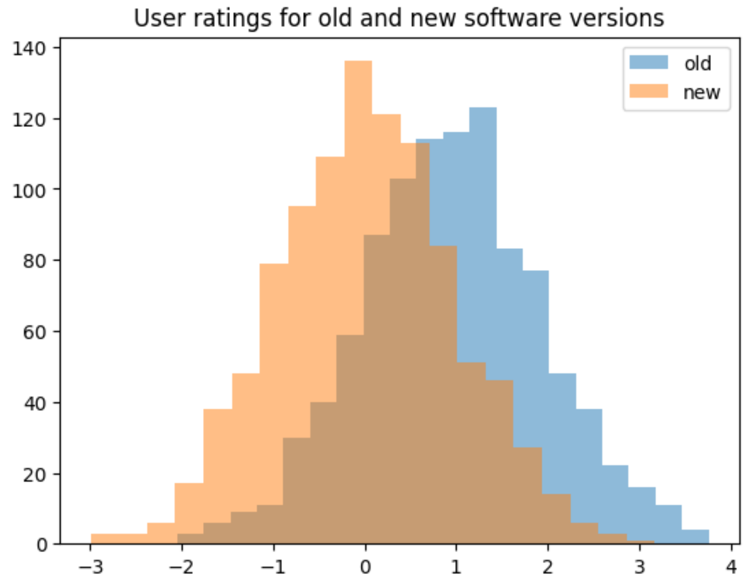
- The importance of visualization
- Pearson vs Spearman correlation
- OLS vs Robust regression
- Outliers and influential points



Source: [Anscombe's quartet – Wikipedia]

Hand’s paradox

	Old version	New version
Distribution	Normal	Normal
Mean	1	0
Std	1	1

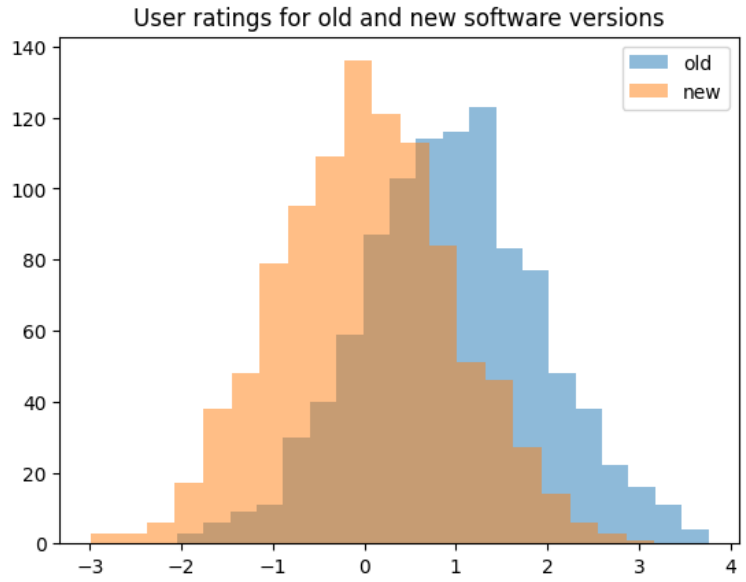


At first glance:

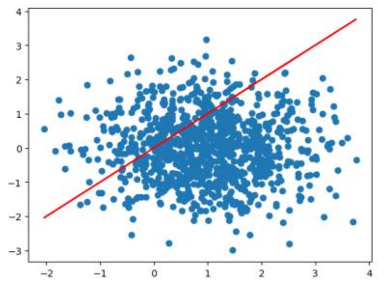
- People liked the old version better on average
- In healthcare: patients responded better to the old treatment

Hand's paradox

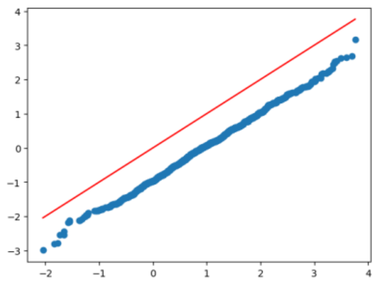
	Old version	New version
Distribution	Normal	Normal
Mean	1	0
Std	1	1



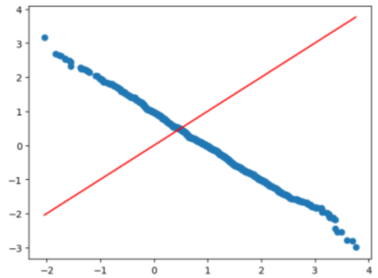
Correlation 0
Positive change rate 24%



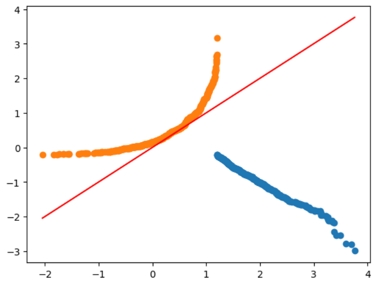
Correlation 1
Positive change rate 0%



Correlation -1
Positive change rate 30%



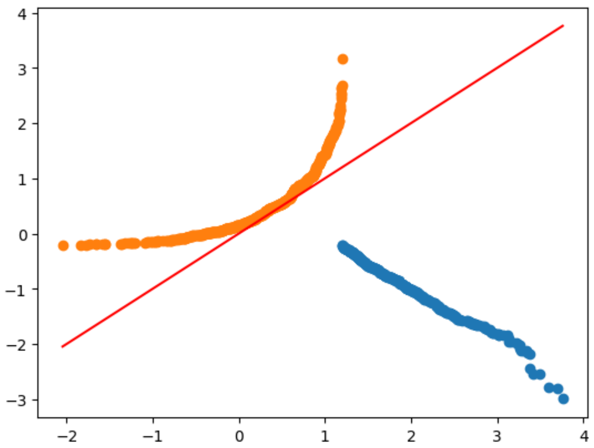
Correlation -0.5
Positive change rate 60%

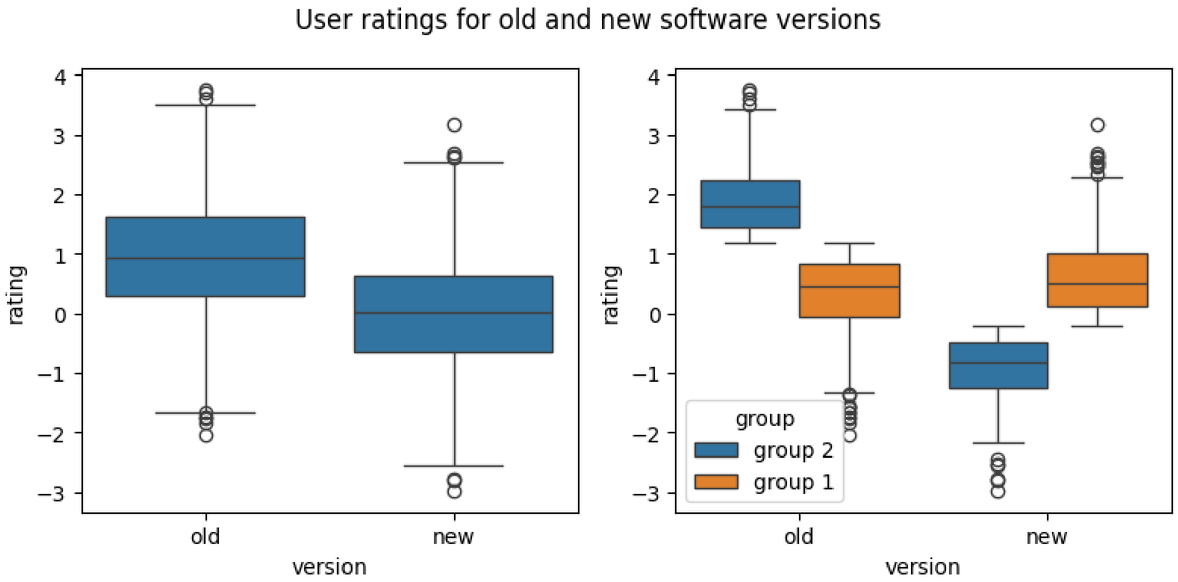


Hand’s paradox

	Old version	New version
Overall mean	1	0
Group 1 mean	0.3	0.6
Group 2 mean	1.9	-0.9

Correlation	-0.5
Positive change rate	60%





- Old version has a higher average rating
- However, more users prefer the new version
- Moreover, results are different in business segments
- What is the business goal?

A comparison between two randomly chosen patients, one from each group, and a comparison of treatment effects on a randomly chosen patient, can lead to different conclusions. (Hand's paradox)

Exploratory Data Analysis (EDA)

Conclusions:

- Identify issues and limitations
- Find insights
- Collaborate with business stakeholders and data owners
- Document findings and communicate to stakeholders
- Guide data cleaning
- Guide feature selection and engineering
- Guide model selection

Statistical Inference

Statistical Inference

Statistical inference helps to determine if observed differences or relationships are ***statistically significant or due to random chance****. Useful for validating research hypotheses, making data-driven decisions, and avoiding false conclusions.*

- Prerequisite: Probability Theory
- Methods:
  - Estimation (Point and Interval)
  - Hypothesis Testing
  - Regression Analysis
- Python packages: scipy, statsmodels
- There are many use cases that don't need ML, only EDA and statistical testing

Conditional Probability and Bayes' Theorem

Conditional Probability

The probability of an event occurring given that another event has already occurred.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Law of total probability

The total probability of an outcome which can be realized via several distinct events (scenarios).

$$\mathrm{P(B)} = \sum_n P(B \cap A_n) = \\ = \sum_n P(B|A_n)P(A_n)$$

Bayes' Theorem

A mathematical rule for inverting conditional probabilities.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{\sum_n P(B|A_n)P(A_n)}$$

Three prisoners problem

- Three prisoners are sentenced to death. The governor has selected one of them at random to be pardoned. The warden knows which one is pardoned. Prisoner A begs the warden to let him know the identity of one of the two who are going to be executed.
- "If B is to be pardoned, give me C's name. If C is to be pardoned, give me B's name. And if I'm to be pardoned, secretly flip a coin to decide whether to give me name B or C."
- The warden gives him B's name.
- What is the probability that A / C will be pardoned?

Three prisoners problem

- A_n is the event that the corresponding prisoner will be pardoned
- b is the event that the warden tells A that prisoner B is to be executed

$$P(A_1|b) = \frac{P(b|A_1)P(A_1)}{P(b|A_1)P(A_1) + P(b|A_2)P(A_2) + P(b|A_3)P(A_3)} = \frac{\left(\frac{1}{2} * \frac{1}{3}\right)}{\left(\frac{1}{2} * \frac{1}{3}\right) + \left(0 * \frac{1}{3}\right) + \left(1 * \frac{1}{3}\right)} = \frac{1}{3}$$

$$P(A_3|b) = \frac{P(b|A_3)P(A_3)}{P(b|A_1)P(A_1) + P(b|A_2)P(A_2) + P(b|A_3)P(A_3)} = \frac{\left(1 * \frac{1}{3}\right)}{\left(\frac{1}{2} * \frac{1}{3}\right) + \left(0 * \frac{1}{3}\right) + \left(1 * \frac{1}{3}\right)} = \frac{2}{3}$$

More details: [Wikipedia – Three prisoners problem]

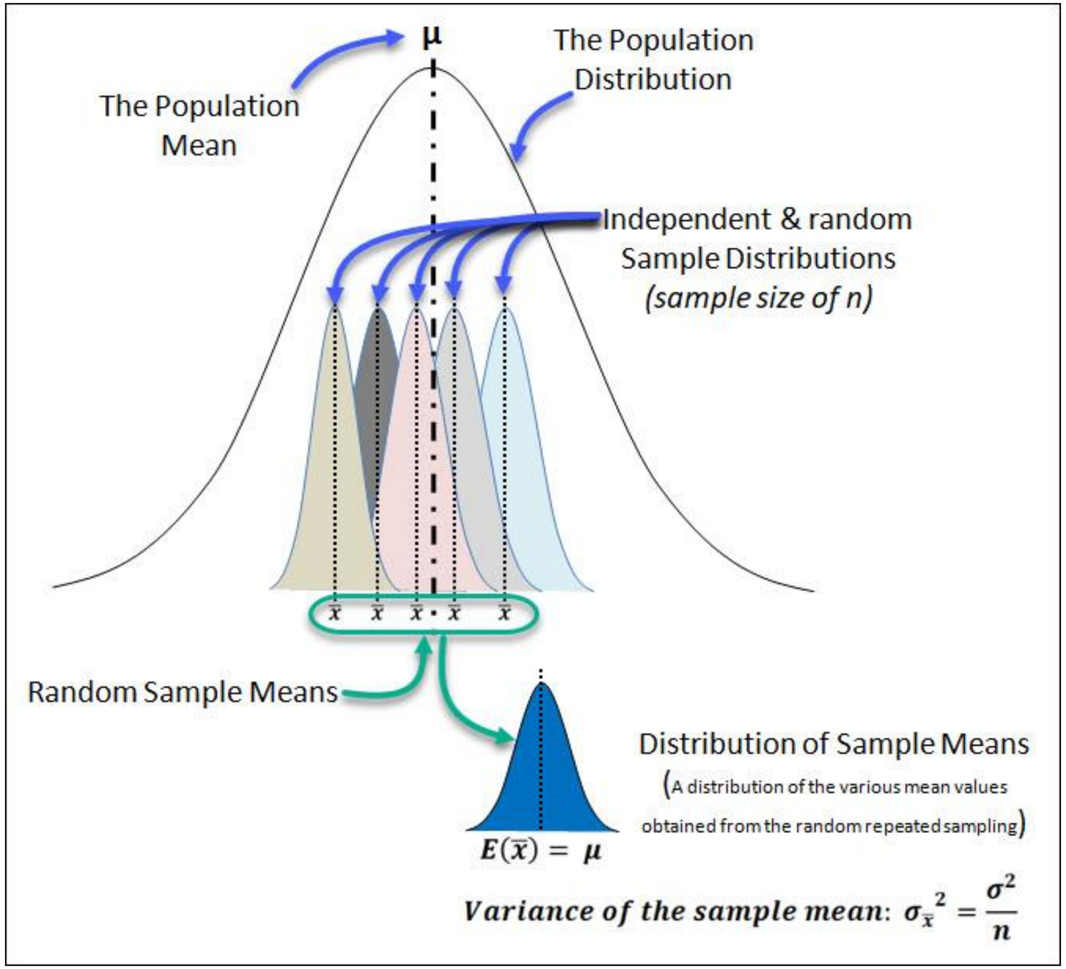
Confidence Intervals

Interval Estimation

Central Limit Theorem (CLT)

- The sample mean is approx. normally distributed around the population mean (regardless of the original distribution)
- As the sample size increases, the variance of the sample mean decreases

$$\bar{X} \rightarrow N\left(\mu, \frac{\sigma}{\sqrt{n}}\right)$$

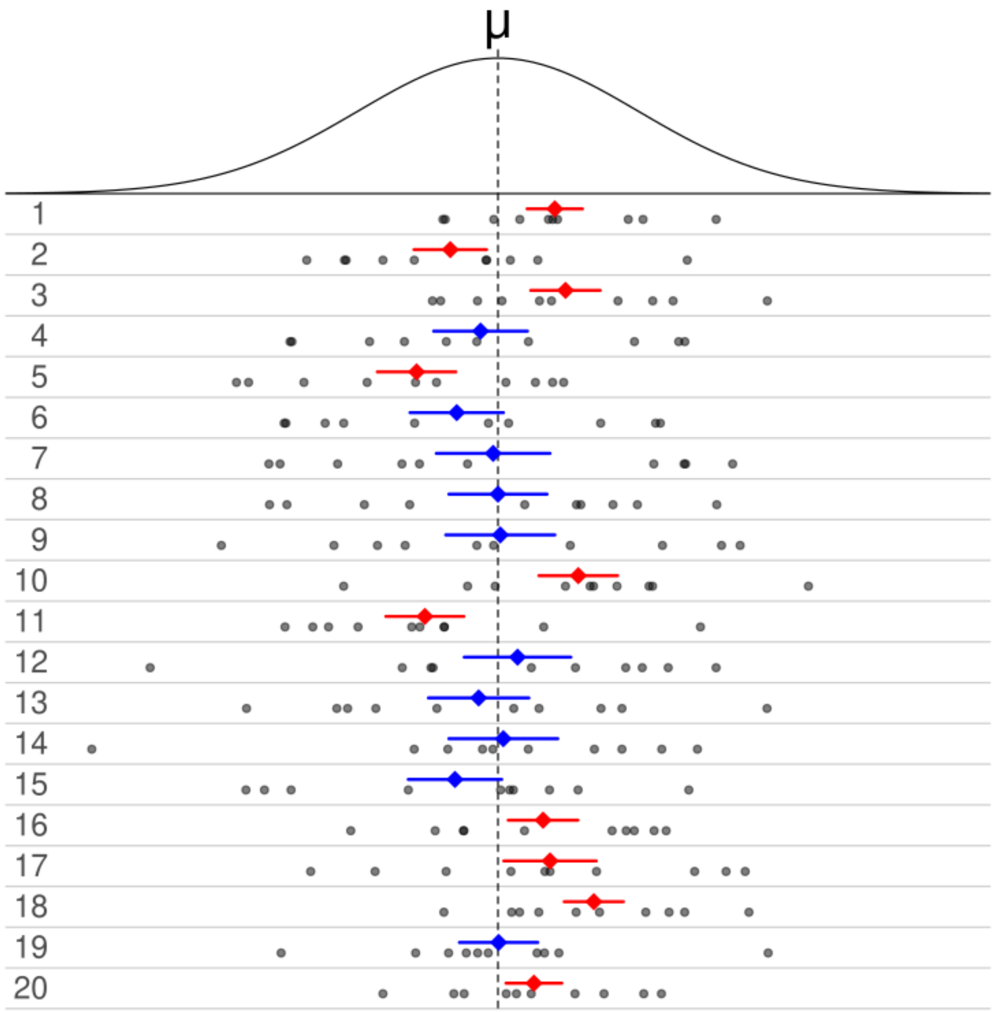


Source: Point Estimates and Confidence Intervals - CQE Academy

Interval Estimation

95% Confidence Interval:

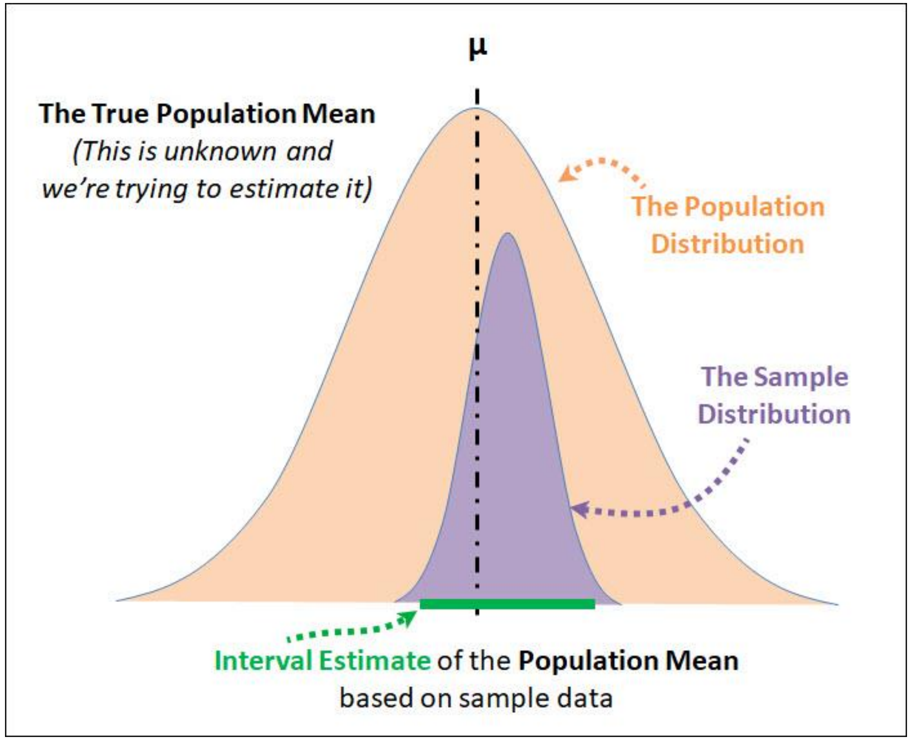
- If we repeated the sampling process many times, 95% of the confidence intervals would include the true population mean.
- The higher the confidence level, the wider the confidence interval



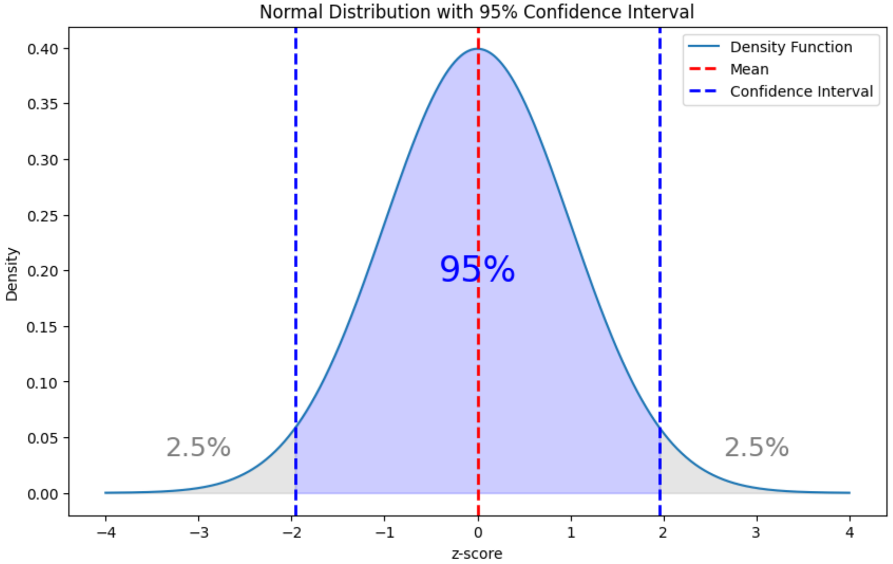
Source: Confidence interval - Wikipedia

Interval Estimation

The ***z-score*** *is the* ***quantile function*** *(or inverse cumulative distribution function) of the* ***standard normal distribution****. For a normal distribution, the z-score measures how far a given quantile is from the* ***mean****, in units of the* ***standard deviation****.*



Source: Point Estimates and Confidence Intervals - CQE Academy



For a 95% ***confidence level*** *we calculate z(0.975) = 1.96. This means that 95% of the possible* ***sample means*** *fall within 1.96* ***standard error*** *from the true* ***population mean****. So, the* ***interval estimate*** *equals the* ***point estimate*** *plus/minus 1.96 times the standard error:*

$$CI = \left(x - z_{1-\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}}, x + z_{1-\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} \right)$$

Hypothesis Testing

Hypothesis Testing

Steps:

1. Formulate **Null and Alternative Hypotheses**
   - *Null Hypothesis (H_0): There is no effect or difference.*
   - *Alternative Hypothesis (H_1): There is an effect or a difference.*
2. Choose a **significance level** (α)
3. Calculate the test statistic and the p-value

   *The **test statistic** is a value derived from the sample data, that follows a specific distribution under the null hypothesis. It helps determine the **p-value**, which is:*

   the probability of observing the sample data, or something more extreme, given that the null hypothesis is true
4. Based on the p-value, **accept or reject H_0**

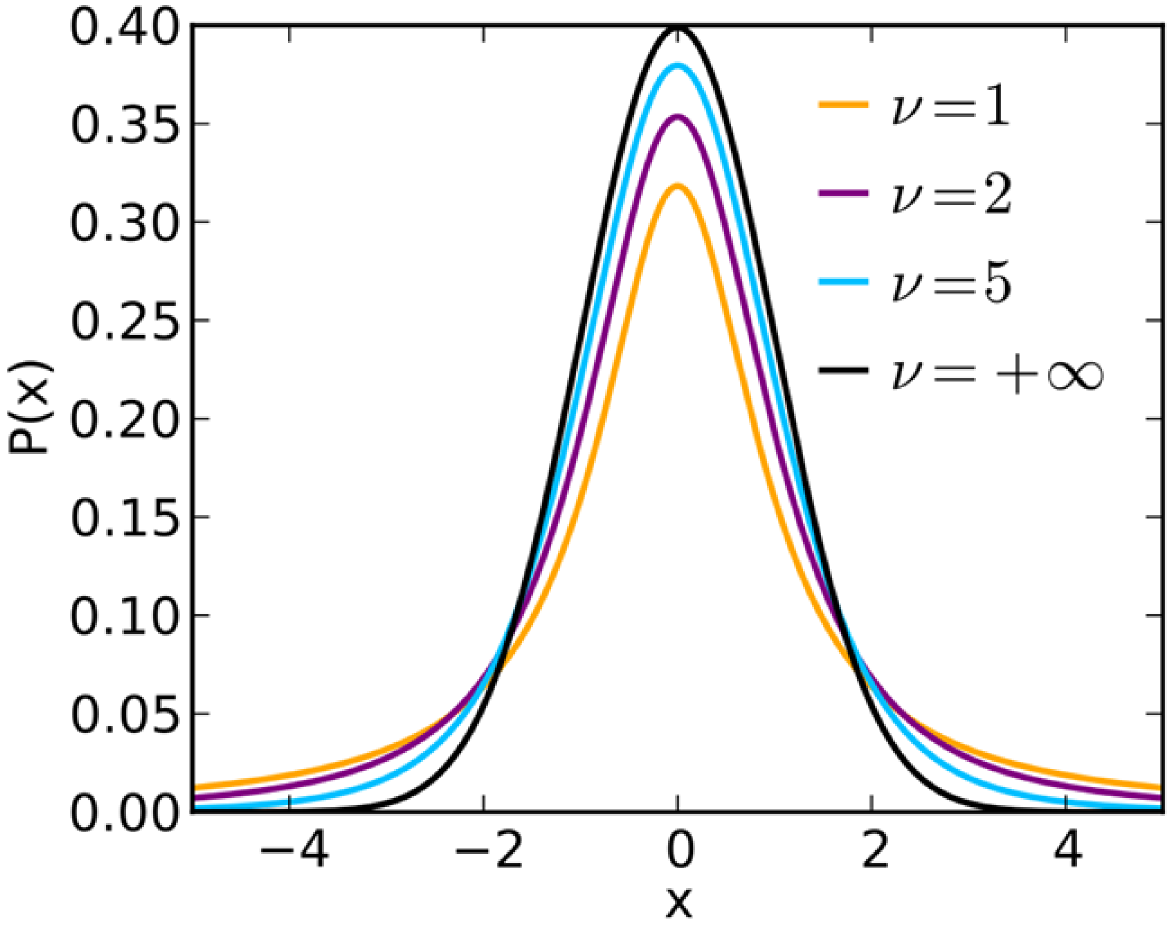
   Reject H_0 if $p < \alpha$

Student’s t-distribution

- The t-distribution is the generalization of the standard normal distribution (with heavier tails)
- It is used when the sample size is small, and the population variance is unknown

Student’s t-test

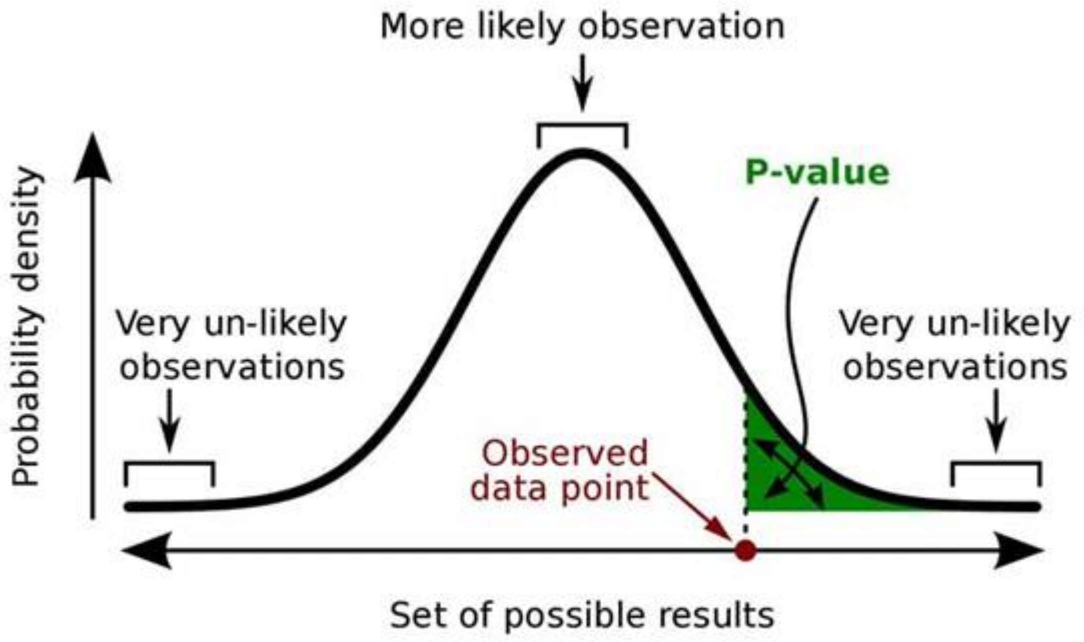
- The test statistic follows the t-distribution under the null hypothesis:
- $t = \frac{\bar{x} - \mu}{\sqrt{\frac{s^2}{n}}} \sim t_{n-1}$
- It measures the distance between the sample mean and the assumed population mean in units of the standard error.



Source: [Student's t-distribution - Wikipedia]

Understanding the p-value

- If the p-value is very low, then we can conclude that a difference exists (we reject H_0) because it would be unlikely to get this sample if H_0 was true.
- If the p-value is high, it means that our sample would not be extreme if H_0 was true. Hence, we cannot reject H_0
- We determine alpha before testing, as a threshold for the p-value
- Note: the p-value is not the probability of H_0 being true! A high p-value does not mean that H_0 is proven, only that we can't reject it based on the data.



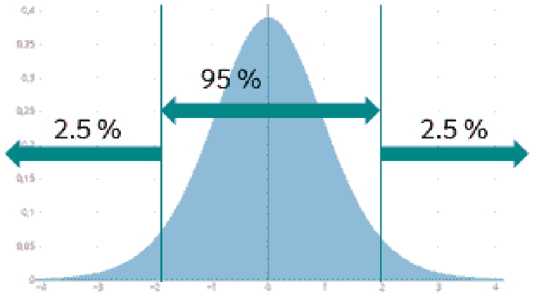
A **p-value** (shaded green area) is the probability of an observed (or more extreme) result assuming that the null hypothesis is true.

Source: [Understanding P-Values and Statistical Significance]

One-sample t-test

$H_0 : \mu = 28$
$H_1 : \mu \neq 28$
$\alpha = 0.05$

Two tailed (non-directional)



Student	Score
1	28
2	29
3	35
4	37
5	32
6	26
7	37
8	39
9	22
10	29
11	36
12	38

Significance level

$$\alpha = 0.05$$

Number of sample values

$$n = 12$$

Mean value

$$\bar{x} = 32.33$$

Standard deviation

$$s = 5.47$$

Standard error of the mean

$$s_{\bar{x}} = \frac{s}{\sqrt{n}} = \frac{5{,}47}{\sqrt{12}} = 1.58$$

t-value

$$t = \frac{\bar{x} - \mu}{s_{\bar{x}}} = \frac{32.33 - 28}{1.58} = 2.75$$

Degrees of freedom

$$df = n - 1 = 11$$

We calculate the p-value from the test statistics (t-value) based on the Student's t-distribution.
p-value = 0.02 which means that the probability of a sample like this (or more extreme), if the null hypothesis is true, is 2%. **We reject the null hypothesis.**

Source: [One-Sample t-Test: Step-by-Step Guide]

Common Tests

t-tests:

1. One-Sample t-test: Compares the sample mean to a known or hypothesized population mean.
2. Two-Sample t-test: Compares the means of two independent samples
3. Paired Sample t-test: Compares the means from the same group at different times or under different conditions.

F-tests:

1. F-test of equality of variances: Compares the variances of two samples
2. ANOVA (Analysis of Variance): Compares the means of three or more independent samples

Chi-squared tests:

1. Goodness of Fit Test: Determines if a sample data matches a population with a specific distribution.
2. Test of Independence: Assesses whether two categorical variables are independent of each other.

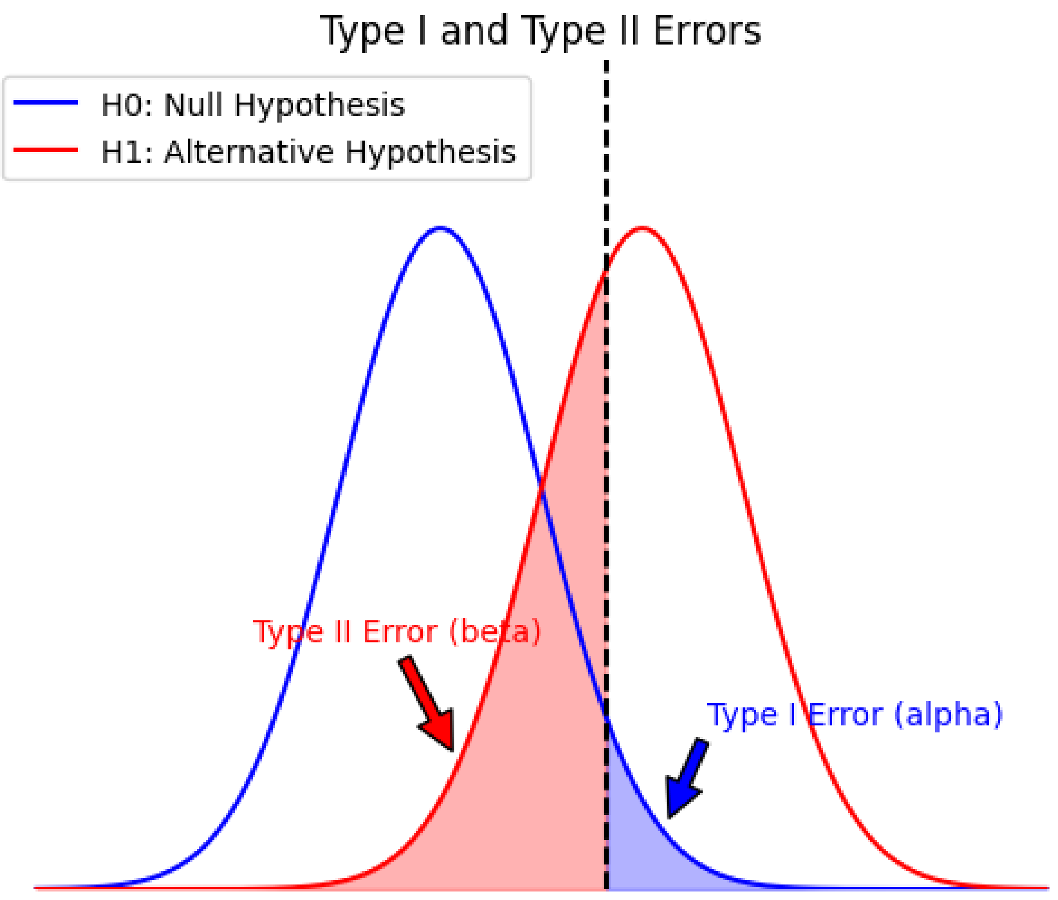
Statistical tests are widely used to test hypotheses and validate results in medical studies and surveys, as well as for EDA, feature selection, evaluation and time series analysis.

Common Mistakes

Common Mistakes in Statistics

Misinterpreting the p-value

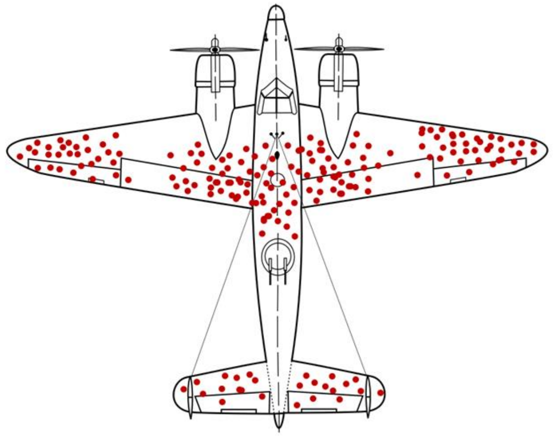
- p-value is *not* the probability of the null hypothesis being true
- p-value is *not* the probability of making a mistake
- p-value does *not* indicate the size of the observed effect
- alpha and beta are conditional probabilities
- p-hacking or data dredging
    - Multiple comparisons (look-elsewhere effect) and selective reporting

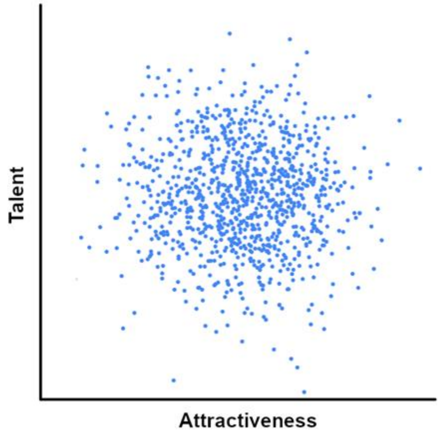


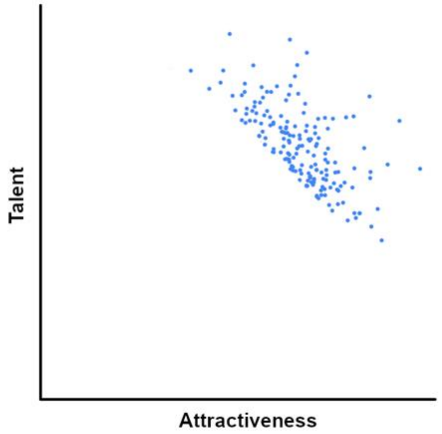
Common Mistakes in Statistics

Incorrect conclusions

- Small sample size, low statistical power
- Ignoring the Assumptions of Statistical Tests
  - e.g. normality, independence, equal variances
- Overgeneralization due to Selection/Sampling bias
  - Participation bias
  - Survivorship bias
  - Berkson’s paradox







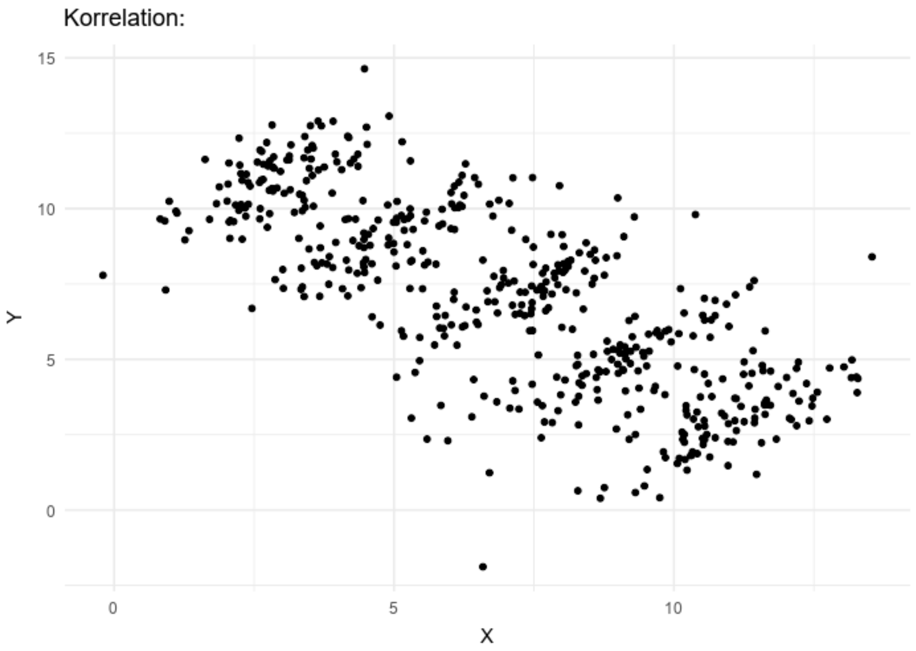
Source: Survivorship bias – Wikipedia

Source: Berkson's paradox – Wikipedia

Common Mistakes in Statistics

Incorrect conclusions

- Small sample size, low statistical power
- Ignoring the Assumptions of Statistical Tests
  - e.g. normality, independence, equal variances
- Overgeneralization due to Selection/Sampling bias
  - Participation bias
  - Survivorship bias
  - Berkson’s paradox
- Correlation does not imply causation
  - False correlation
  - Simpson's paradox
  - Confounder variables
- Confirmation bias
- Post hoc analysis (Texas sharpshooter fallacy)



Stone size \ Treatment	Treatment A	Treatment B
Small stones	*Group 1* **93% (81/87)**	*Group 2* 87% (234/270)
Large stones	*Group 3* **73% (192/263)**	*Group 4* 69% (55/80)
Both	78% (273/350)	**83% (289/350)**

Source: Simpson's paradox – Wikipedia

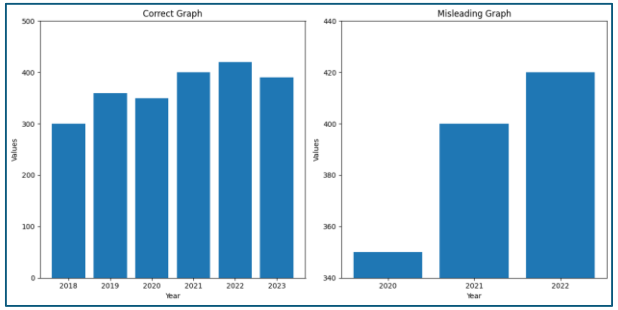
Source: Origin of the Texas Sharpshooter – Bayesian Spectacles

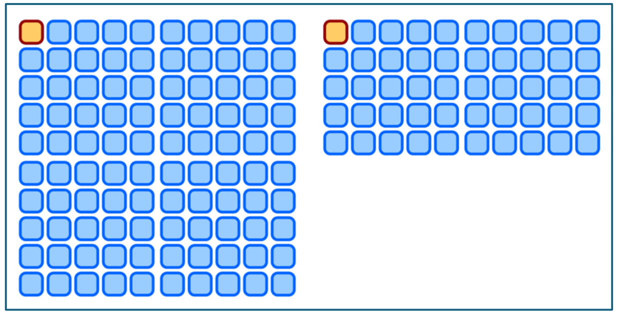
Common Mistakes in Statistics

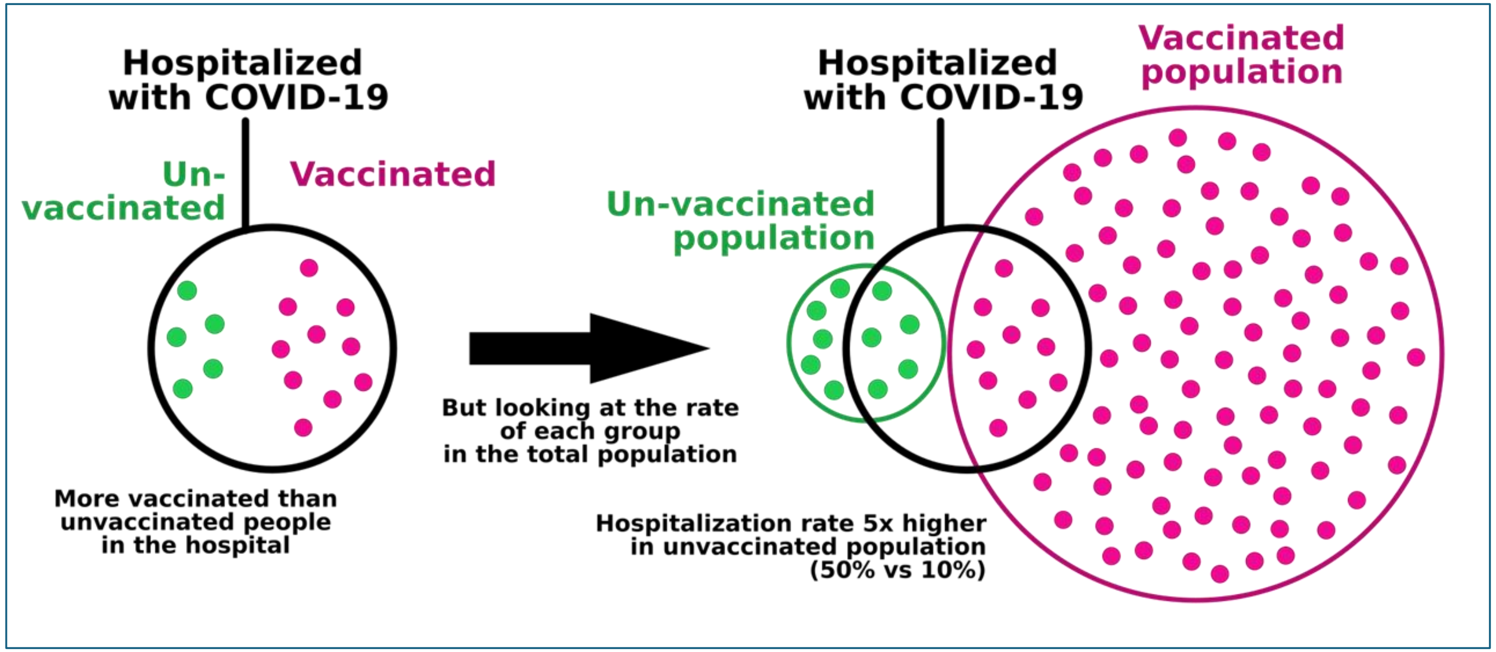
Misinterpretations

- Data (e.g. outliers, skewness)
- Statistical Significance (p-values) versus Practical Significance (effect size)
- Loaded questions
- Misleading graph
- Potato paradox
- Preparedness paradox
- Base Rate Fallacy
  - Prevention paradox
  - False positive paradox

	Positive	Negative
Drunk	2	0
Sober	100	1900





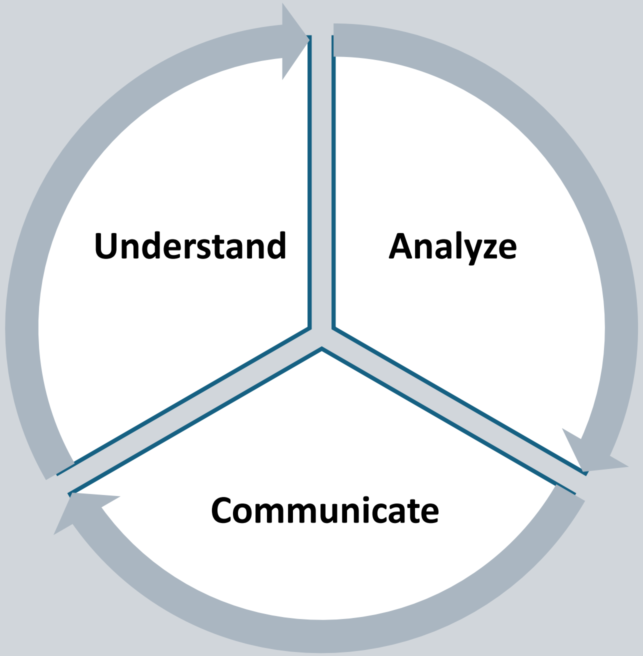


Source: Base rate fallacy – Wikipedia   Source: Potato paradox – Wikipedia

Case Studies

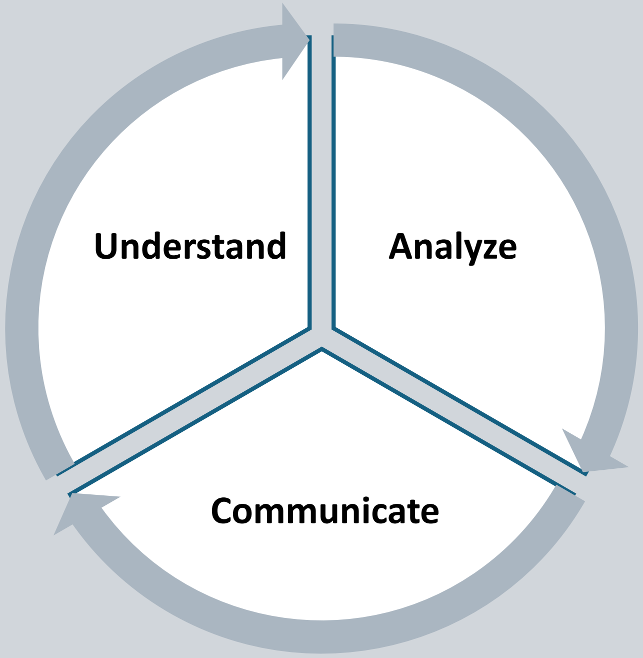
Case Study – Customer churn

1. Business target
   - Churn in the given month
   - Churn in the next 6 months
2. Data availability at inference time
   - When was the data collected?
   - Usage data of the last month
3. Historical data
   - What to collect, what to calculate?
   - Storing data
   - New customers
4. Actions
   - No improvements?



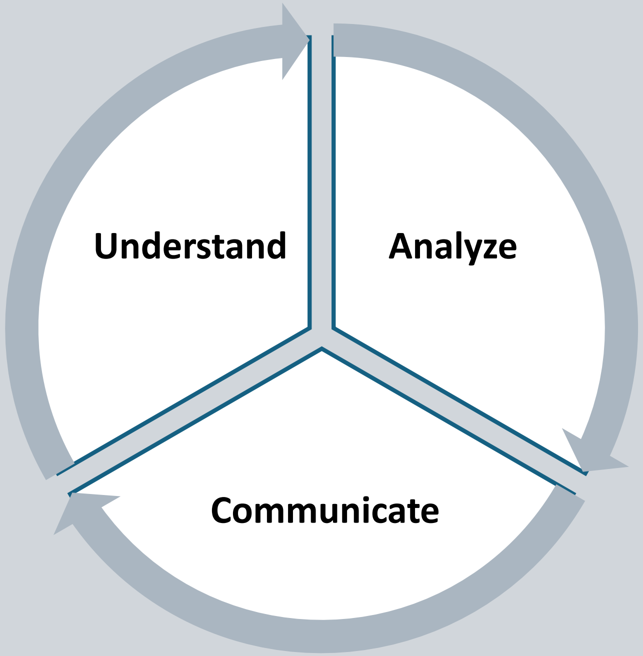
Case Study – Movie popularity prediction

1. Business target
   - Views or ratings
   - Base drift
   - Introduce – Where?
   - Introduce – Which?
2. Data availability at inference time
   - External ratings, popularity
3. Historical data
   - Representativeness
4. Actions
   - Marketing: self-fulfilling predictions



Case Study – Anomaly Detection

1. Business target
   - Types: outlier, shift, variance, interactions
   - Special events
   - Seasonality
2. Link between data sources



Business and Data Understanding

- The Importance of B&D Understanding
- Data Collection
- Exploratory Data Analysis
- Statistical Inference
- Confidence Intervals
- Hypothesis Testing
- Common Mistakes
- Case Studies

Thank you for your attention!

Your feedback would be much appreciated:

Any Questions?

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