

Machine Learning

Session 2 - T

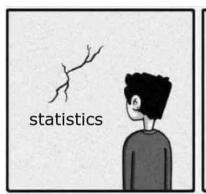
Data Preprocessing

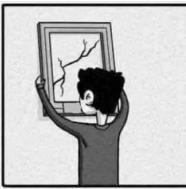
Ciência de Dados Aplicada 2023/2024

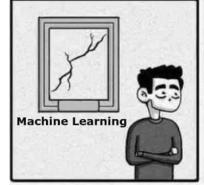
What is Machine Learning?

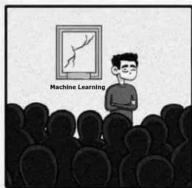


- It's similar to statistics...
 - Both aim to uncover patterns within data.
 - Both heavily rely on calculus, probability, and linear algebra, and share many common algorithms.
- But it's not statistics!
 - Statistics primarily helps drawing reliable conclusions;
 ML focuses on building autonomous agents.
 - Statistics gives greater importance on interpretability and mathematical rigor; ML prioritizes predictive performance, scalability, and autonomy.







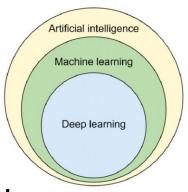


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Machine Learning and Artificial Intelligence



• Machine Learning is a subset of Artificial Intelligence (AI).

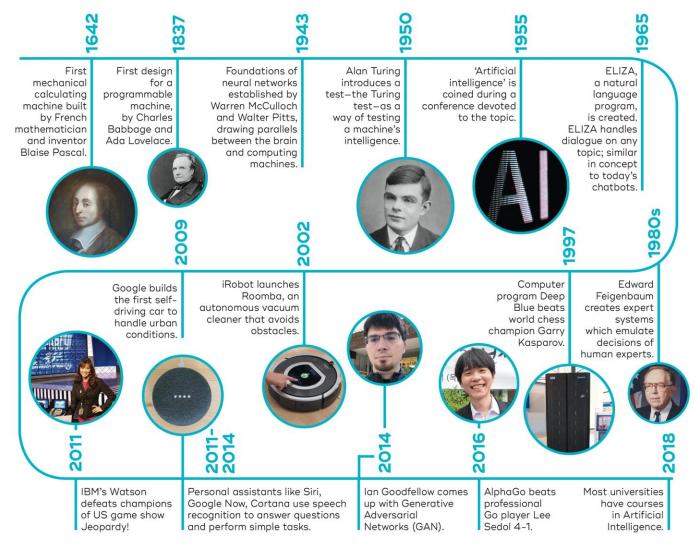


- Al encompasses various approaches beyond learning-based systems:
 - Symbolic reasoning;
 - Rule-based systems;
 - Tree search;

 Learning-based systems, such as Machine Learning, are more flexible and proficient in solving problems through data-driven learning processes.

Brief History of Machine Learning





https://qbi.uq.edu.au/brain/intelligent-machines/history-artificial-intelligence

The importance of data



- Most Machine Learning courses primarily focus on algorithms, operating under the assumption of high-quality and sufficient data to create robust models;
- Real-world data often **contains errors**, highlighting the need for data curation. Even widely-used benchmark datasets frequently contain errors in assigned labels (<u>labelerrors.com/</u>);
- The quality of the output is determined by the quality of the input (garbage-in, garbage-out);
- The emerging trend of "data-centric AI" focuses on enhancing datasets to improve model outcomes.

Data Representation



- We will assume datasets to be organized in the following way:
 - Data is organized in a tabular format;
 - Rows represent samples (aka records, entities, or examples) and columns variables (aka attributes or features);

Variables can be categorized as either numerical (or continuous) or

discrete (or nominal).

Player	Minutes	Points	Rebounds	Assists
А	39	20	6	150
В	30	29	7	6
С	22	7	7	2
D	20	3	3	14
E	9	19	5	5
•••	•••	•••	•••	•••

Raw vs Processed Data

■ Pranrocassing needs.



Raw data:

- The original source of the data;
- Often challenging for direct analysis;

i reprocessing needs.
☐ Handling missing values;
☐ Rescaling variables;
Detecting and managing outliers;
☐ Correcting errors;

May come from different sources:
Data integration from multiple sources;
☐ Data cleaning;
☐ Data transformations;
☐ Data selection;
☐ Data enrichment;

Player	Minutes	Points	Rebounds	Assists
Α	39	20	6	150
В	30	29	7	6
С	22	7	7	2
D	20	three	3	14
Е	-9	19	?	5
F	14	6	1	3
G	22		4	

Raw vs Processed Data



Processed data:

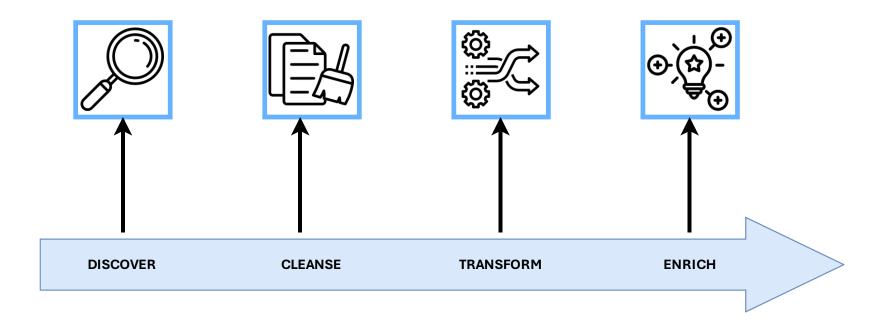
- Data is in a structure ready for analysis;
- Usually represented in a matrix or vector format.

Player	Minutes	Points	Rebounds	Assists
Α	39	20	6	14
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Data Preparation



• The differnet stages involved in data preparation, leading from raw to processed data, heavily rely on the **domain of the data** and the unique **characteristics of the datasets**.



Data Structure and Content Verification



- Exploring the structure and content of data involves various tasks, including:
 - Checking the number of samples and variables;
 - Verifying data types (numerical, discrete);
 - Checking value ranges for numerical variables or the set of possible values for discrete variables;
 - Identifying missing or unknown values;
 - Identifying duplicates;

- ...

Data Sumarization



- Characterization of large datasets using global metrics;
- Aims to identify preprocessing needs like handling outliers, missing values, and errors;
- Tasks include checking value distributions and applying summary statistics to variables.

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count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333	1.000000
std	0.828066	0.435866	1.765298	0.762238	0.819232
min	4.300000	2.000000	1.000000	0.100000	0.000000
25%	5.100000	2.800000	1.600000	0.300000	0.000000
50%	5.800000	3.000000	4.350000	1.300000	1.000000
75%	6.400000	3.300000	5.100000	1.800000	2.000000
max	7.900000	4.400000	6.900000	2.500000	2.000000

Data Transformation



- Data transformation can play a crucial role in preparing datasets for effective use in machine learning applications.
 - Typical operations:
 - □ Feature engineering: Creating new features from existing ones to enhance the predictive power of the model;
 - □ Imputation: Handling missing values by filling them in with estimated or imputed values;
 - **Feature Scaling/Normalization:** Rescaling features to a similar scale to ensure that no single feature dominates the learning process.
 - ☐ Feature Encoding: Converting categorical variables into numerical representations that machine learning algorithms can interpret;
 - □ Dimensionality Reduction: Reducing the number of features in the dataset while preserving important information.



- Missing values refers to values or information that are not stored or absent for certain variables within a given dataset.
- In Pandas, missing values are typically represented by NaN, which stands for "Not a Number."
- Why is data missing from the dataset?
 - Past data can become corrupted due to inadequate maintenance practices;
 - Recording failures from human error;
 - Intentional omission;

- ...



Why do I need to care about missing values?

- Some machine learning algorithms fail with missing values;
- Failure to handle missing values can lead to biased models and inaccurate results;
- Missing data can reduce precision in statistical analysis;

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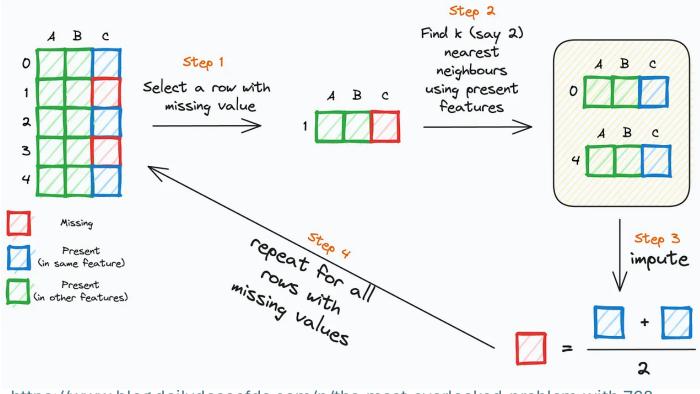


- Addressing missing values involves various approaches that can be specific to different data types and analysis scenarios:
 - Keep missing values in the data if the analysis methods can handle them;
 - Disregarding missing values by removing rows and/or columns containing them.
 - Substituting missing values with other values, which can be achieved through methods such as:
 - □ Imputation with a constant value (specific value, mean, median, mode) per column (or row).

Utilizing more sophisticated techniques like **k-nearest neighbors**, leveraging information from neighboring data points.



Handling missing values with the k-nearest neighbor algorithm:



https://www.blog.dailvdoseofds.com/p/the-most-overlooked-problem-with-768

Resources



 McCallum, Q. E. (2013). Bad Data Handbook Mapping the World of Data Problems. O'Reilly.

• Rattenbury, T., Hellerstein, J. M., Heer, J. M., Kandel, S., & Carreras, C. (2017). Principles of data wrangling: Practical Techniques for Data Preparation. O'Reilly.