



















# João Magalhães – Short bio jmag@fct.unl.pt

Full Professor, NOVA FCT
Head of the Multimodal Systems Group, NOVA LINCS
PhD, Imperial College London, 2008

My research is focused on text and image understanding AI algorithms and making information accessible through search and conversational systems.

I am keen to solve real-world problems with data-driven NLP, CV and DL methods in different domains.

Throughout the years, my group has collaborated with world leading research institutions, e.g., BBC, Amazon, Google, Farfetch, Vision Box, CMU, Queen Mary.













### Vision and Language AI





























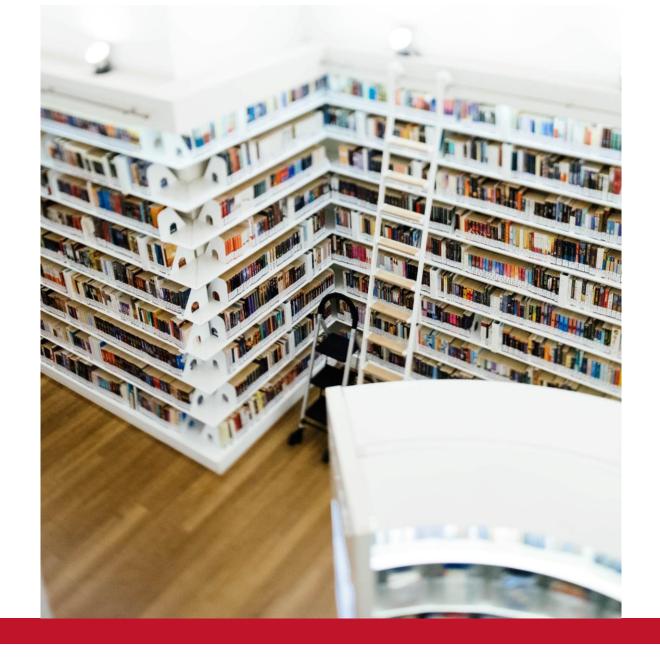


## **Topics**

- 1. PROGRAM STRUCTURE
- 2. WHAT IS AI + ML + DS?
- 3. BRAINSTORM: APPLICATIONS AND USE CASES
- 4. LABORATORY SETUP



Visit to download materials.













# Program Structure











### Learning outcomes: Knowledge

Understand the nature and types of data problems.

- Understand the different challenges in an AI/ML/DS project.
- Understand the capacity and limits of the different family of algorithms.











### Learning outcomes: Know-how

- Identify the challenges of different data types
  - Numerical data / Dates / Categorical data / Text / Natural Language / Geographical data / Vision dat
- Design a data-driven end-to-end solution
- Integrate different algorithms
- Measure progress











### Learning outcomes: Soft-skills

- Understand user needs
  - Set expectations
  - Identify required data
  - Recognize "impossible missions"
- Build a team based on the required skills
- Estimate a project's implementation time, computing budgets and data requirements











### Program structure

- There are 3 core courses.
- These provide you with the basic concepts and tools.
- Each course will have an invited talk by a CMU faculty or industry expert.

| Course                                | Lecturer                            | Teaching hours | ECTS |
|---------------------------------------|-------------------------------------|----------------|------|
| Foundations of<br>Data Science        | David Semedo &<br>Rafael Ferreira   | 30             | 2    |
| Machine Learning                      | Chryssa Zerva &<br>Sweta Agrawal    | 30             | 2    |
| Data Collection and<br>Pre-Processing | Cátia Pesquita &<br>Tiago Guerreiro | 30             | 2    |











### Foundations of Data Science

- Introduction to Data Science
- Python Programming for Data Science
- Statistics and Probability
- Data Preparation and Processing with Pandas
- Machine Learning Fundamentals
- Model Evaluation and Selection
- Data Visualization



Prof. David Semedo



Eng. Rafael Ferreira











### Machine Learning

- Introduction to Machine Learning
- Supervised Learning
- Unsupervised Learning
- Feature Engineering and Selection
- Model Evaluation and Validation
- Regression problems (linear regression)
- Support Vector Machines
- Decision Trees and Random Forests
- Association Rules
- Neural Networks



Prof. Chryssa Zerva



Prof. Sweta Agrawal











### Data Collection and Pre-Processing

- Types of Data and Sources
- Data Collection Techniques
- Data Quality and Validation
- Data Pre-processing Techniques
- Handling Categorical and Numerical Data
- Data Integration and Fusion
- Data Sampling and Imputation
- Best Practices and Case Studies



Prof. Cátia Pesquita











### Program structure

- The optional courses lets you specialize on:
  - Text and language data
  - Complex data
  - Al system engineering
- Capstone Project:
  - Lectured by all lecturers
  - Create and test a real system

| Course                           | Lecturer                          | Teaching hours | ECTS |
|----------------------------------|-----------------------------------|----------------|------|
| Deep Learning                    | Chryssa Zerva &<br>David Semedo   | 18             | 1    |
| Vision and Language              | Bruno Martins &<br>João Magalhães | 18             | 1    |
| Complex Data Analysis            | André Falcão                      | 18             | 1    |
| Cloud-based<br>Data Processing   | Nuno Preguiça & Rodrigo Rodrigues | 18             | 1    |
| Data analytics and visualization | João Moura Pires & Manuel Fonseca | 18             | 1    |
| CapStone                         | Todos                             | 48             | 3    |











### Deep Learning

- Introduction to Deep Learning
- Neural Network Fundamentals
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)
- Generative Adversarial Networks (GANs)
- Attention mechanisms and transformer models
- Large Language Models (LLMs)
- Model Interpretability and Explainability
- Safe deployment, robustness, bias and sustainability



Prof. Chryssa Zerva



Prof. David Semedo











## Language and Vision

- Natural Language Processing (NLP) Fundamentals
- Text Classification and Sentiment Analysis
- Large Language Models
- Computer Vision (CV) fundamentals
- Image Classification and Object Detection
- Large Multimodal Models
- Image Captioning, Visual Question Answering and Multimodal Search
- Advanced Topics and Emerging Trends



Prof. Bruno Martins



Prof. João Magalhães











### Cloud-based Data Processing

- High performance data analytics.
- Large scale data analytics.
- Stream Processing and Real-time Analytics
- Cloud-based Data Storage.
- Machine Learning and AI on the Cloud
- Security, Scalability, Performance, and Cost Optimization



Prof. Rodrigo Rodrigues



Prof. Nuno Preguiça











### Complex Data Analysis

- Graph data
- Social Network Analysis
- Time Series Analysis
- Geospatial Data Analysis



Prof. André Falcão











What is AI + ML + DS?



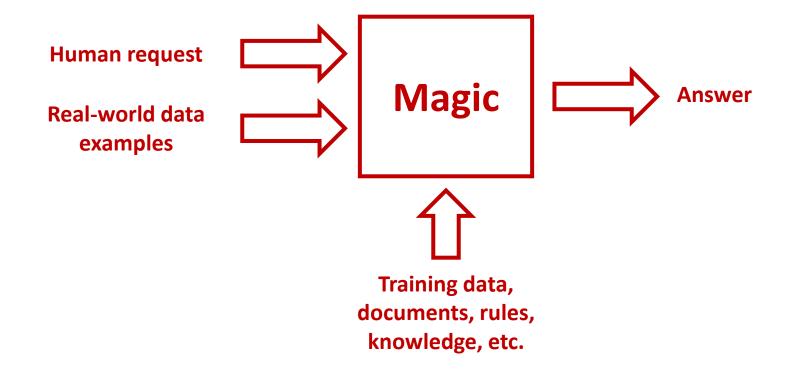








## What is "the" algorithm?



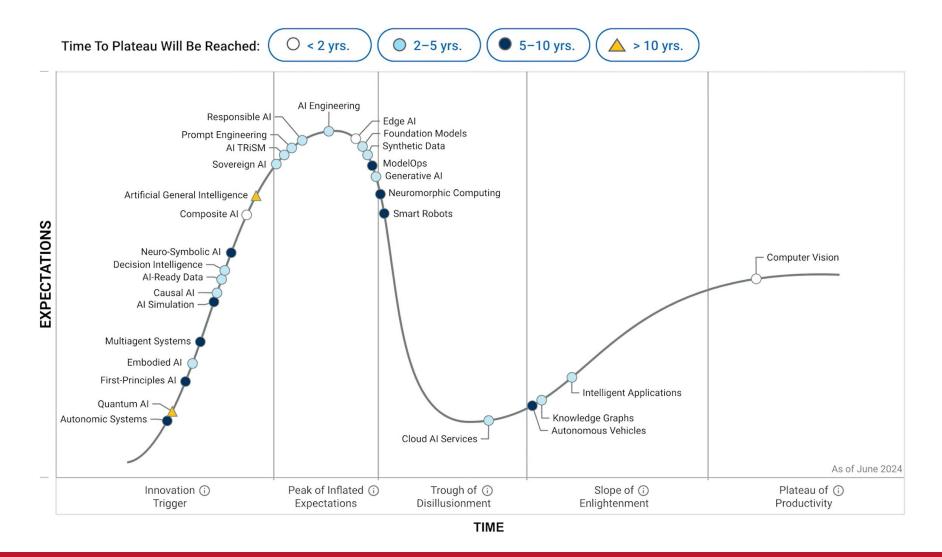














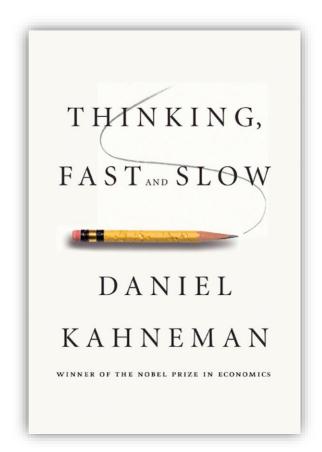






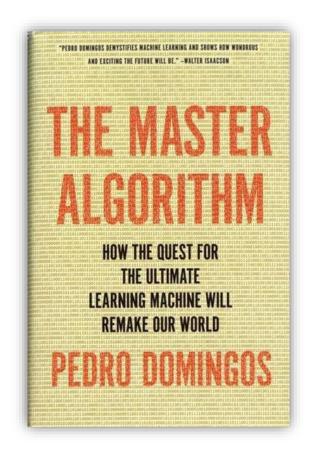


### Readings



### Thinking, Fast and Slow in Al

https://arxiv.org/pdf/2110.01834.pdf https://arxiv.org/pdf/2010.06002.pdf













# Brainstorm: Applications and Use Cases













### Brainstorm

- 1. Identify industry and domain
- 2. Characterize data
- 3. Select end-user
- 4. Identify objectives and write example queries/use cases
- 5. List required AI + ML + DS components
- 6. Measure success and value

Send Miro chart to <a href="mag@fct.unl.pt">jmag@fct.unl.pt</a> by next thursday.











# Laboratory Setup







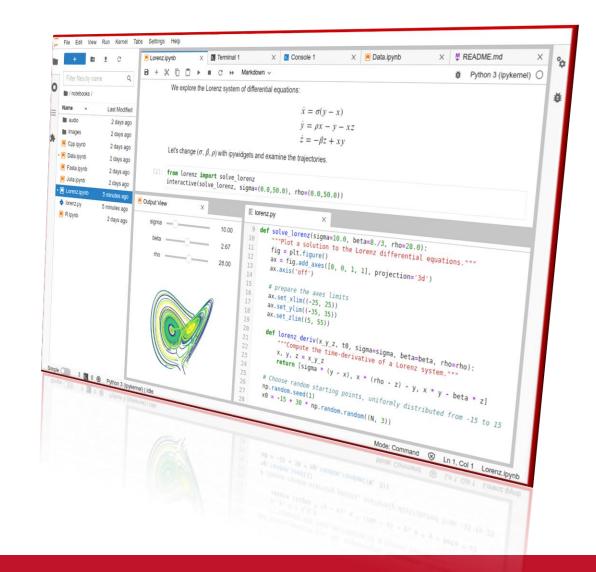




## Laboratory setup

https://wiki.novasearch.org/wiki/lab\_setup















# Measuring Success



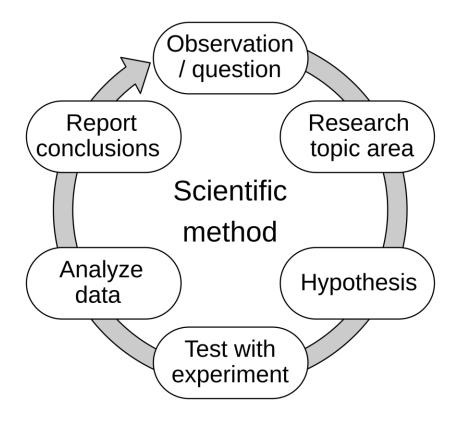








### Scientific method













## Innovation Lifecycle













### From theoretical models to experimental models

- Is the fundamental law known?
  - Yes: Electromagnetism, transistor, have a sound theoretical model.
  - No: shopping patterns, vision, language, etc. have no fundamental laws.











### From experimental model to the deployed model

Every model is flawed by design.

• The true model is unknown.

 The best possible model is the one that best approximates the observed data.











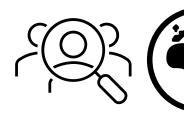
## Validating the model

Laboratory



















### Lab evaluation

- Ad-hoc
- Focus Group
- Toy DatasetsReal World Datasets

Reproducible evaluations











### Ad-hoc

- Developers, Scientists, Quality Assurers and other people dream up data, enter them into the system and eyeball the results.
- Feedback is usually broad and nonspecific, as in "this sample the result was good" or "the results suck".

- Pros: Low initial cost, low startup costs, gives a general overall sense of the system.
- Cons: Not repeatable and not reliable. Doesn't produce measures.











### Focus Groups

 Gather a set of real users and have them interact with the system over some period of time. Log everything they do and explicitly ask them for feedback.

- Pros: Feedback and logs are quite useful, especially if users feel invested in the process.
- Cons: The results may not be extrapolated to broader audience, depending on how well the users represent your target audience.











### Toy Datasets

 Toy datasets usually have a well behaved sample of the real problem.

- Pros: Good for sanity checks and proof of concepts
- Cons: Requires other testing methodologies. Doing well in the dataset doesn't necessarily translate to doing well in real-life











### Real-world Datasets

 Run a relevance study using a set of queries, documents and relevance judgments created by your group or a third-party group.

Pros: Relatively easy to use, test and compare to previous runs.
 Completely repeatable. Good as a part of a larger evaluation.

 Cons: Doing well in the dataset doesn't necessarily translate to doing well in real-life.











### Deployed evaluations

- Log Analysis of a Beta System
- A/B testing

- Empirical Testing a Live SystemMonitoring a Live System











### Log Analysis on a Beta System

- Deploy a live system to a large audience. You should only do this once you are reasonably confident things work well.
- It is imperative to have good logging in place first, which means thinking about the things your want to log, such as queries, results, clickthrough rates, etc.
- Finally, invite feedback from your users.
- Pros: Very close to real-word.
- Cons: Expensive. Maybe difficult to reproduce.











### A/B Testing

- Assign a percentage of users to go to one system, while the other percentage uses an alternate system.
- After the appropriate period of time, evaluate the choices made by those in the A group and those in the B group to see if one group had better results than the other.
- If feasible, have the users in each group rate the results.
- Pros: Combine with log analysis to get a good picture of what people prefer.
- Cons: Requires setting up and maintaining two systems in production.





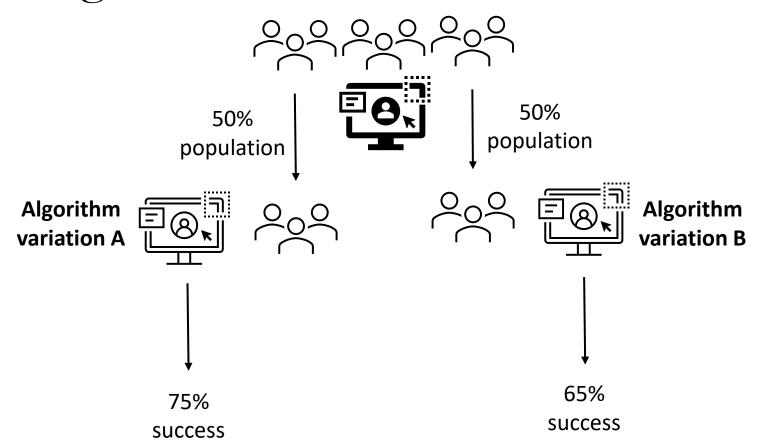






### A/B testing

Full population





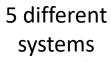








### User ratings of 5 different Amazon Alexa Systems





| Rank    |       | Avg Feed | Number<br>of<br>Conversations | Percentage<br>of |        |                         |
|---------|-------|----------|-------------------------------|------------------|--------|-------------------------|
|         | L7d** | 95% C.I. | Week-Ago                      | L1d              | L7d    | Completed Conversations |
| 1***    | 3.6   | ± 0.26   | 3.23                          | 3.53             | 2894   | 38.5%                   |
| 2       | 3.21  | ± 0.34   | 3.14                          | 2.71             | 2872   | 33.6%                   |
| 3       | 2.98  | ± 0.31   | 3.0                           | 3.36             | 2647   | 29.7%                   |
| 4       | 2.84  | ± 0.60   | 2.93                          | 3.0              | 3141   | 17.1%                   |
| 5       | 2.67  | ± 0.26   | 2.49                          | 3.1              | 2882   | 18.1%                   |
| Average | 3.06  | -        | 2.96                          | 3.14             | 2887.2 | -                       |















### Continuous Testing of a Live System

- Given an existing system, select the top X inputs in terms of volume and Y randomly selected inputs not in the top X.
- Have your Quality Assurance team examine the input/output and rate the top five or ten results as relevant, somewhat relevant and not relevant (and a fourth option: embarrassing).

- Pros: Real queries, real documents, real results.
- Cons: Time consuming. Y becomes too large for long-tail settings.











### Monitoring a Live System

- Return rates
- Conversion rates
- Abandonment rates
- Churn prediction

•











### Validating the model

#### **Development**





- Ad-hoc
- Focus Group
- Toy Datasets
- Real World Datasets

#### **Deployment**



- Log Analysis of a Beta System
- A/B testing
- Empirical Testing a Live System
- Monitoring a Live System





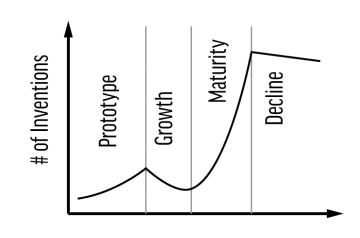






## Impact of an innovation technology

- Prototype phase:
  - Lab experiments are the main drivers
  - Groundbreaking invention unlocks innovation
  - Leading tech companies and academic research
- Growth phase:
  - Real-world experiments are the main drivers
  - Problem is well understood
  - Initial ideas generate high-gains
- Maturity phase:
  - New ideas generate low-gains
  - Mainly industry research
  - Operations optimizations















# Metrics



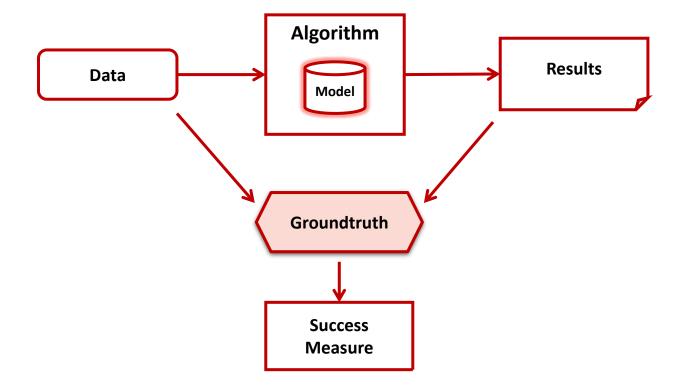








## Evaluation setup













### Ground-truth

• The theoretical "ultimate goal" is to devise a method that produces exactly the same output as the ground-truth.

|        |       | Ground-truth   |                |  |
|--------|-------|----------------|----------------|--|
|        |       | True           | False          |  |
| poq    | True  | True positive  | False positive |  |
| Method | False | False negative | True negative  |  |

Type I error

Type II error

- The practical "ultimate goal" can be very different:
  - ground-truth is incomplete, incorrect and only mirrors a small portion of reality.











### Obtaining groundtruth annotations

- Crowdsourcing system
  - DefinedCrowd, Amazon Mechanical Turk, ...
  - Limesurvey: <a href="https://github.com/LimeSurvey/Li
  - Relevation: <a href="https://github.com/ielab/relevation">https://github.com/ielab/relevation</a>
- Quality annotations
  - Redundant annotations
- Cost reduction strategies
  - Convergence
  - Pooling strategies











### Annotate these pictures with keywords:



















### Groundtruth by annotation



People
Nepal
Mother
Baby
Colorful dress
Fence



Sunset Horizon Clouds Orange Desert



Flowers Yellow Nature



Beach Sea Palm tree White-sand Clear sky

- Groundtruth is incomplete
- Not all groundtruth is of equal importance/relevance.











#### **Evaluation metrics**

- <u>Utility metrics</u> are focused in evaluating the results that are presented to the user
  - Common metrics for binary relevance judgments: Top Precision and Recall

- Stability metrics are focused in evaluating the robustness of the system results.
  - Common metrics: AUC, AP, Precision-Recall curves, ROC curves











### Binary relevance judgments

$$Accuracy = \frac{truePos + trueNeg}{truePos + falsePos + trueNeg + falseNeg}$$

$$Precision = \frac{truePos}{truePos + falsePos}$$

$$Recall = \frac{truePos}{truePos + falseNeg}$$

$$F_1 = \frac{2}{\frac{1}{P} + \frac{1}{R}}$$

|        |       | Ground-truth   |                |  |
|--------|-------|----------------|----------------|--|
|        |       | True           | False          |  |
| Method | True  | True positive  | False positive |  |
| Met    | False | False negative | True negative  |  |

https://developers.google.com/machine-learning/crash-course/classification/accuracy-precision-recall











### Beware of Accuracy

# You easily get 99.99999% by not retrieving non-relevant results!!!

$$Accuracy = \frac{truePos + trueNeg}{truePos + falsePos + trueNeg + falseNeg}$$







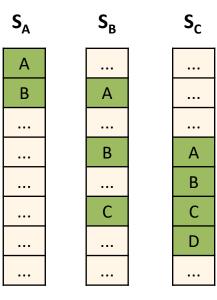


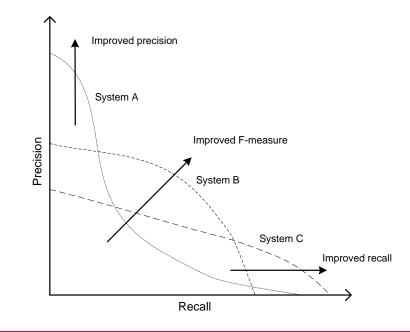


### Precision-recall graphs for ranked results

 The precision-recall curve shows the tradeoff between precision and recall for different thresholds.

Consider three examples:









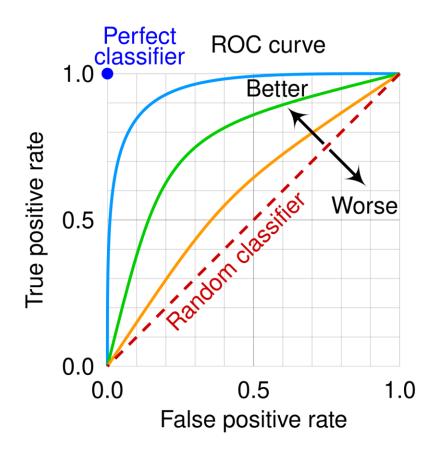






### Receiver operating Curve

 The ROC curve is the plot of the true positive rate (TPR) against the false positive rate (FPR) at each threshold setting.



https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc











### Summary

- Measuring success
  - Metrics (for replicable+repeatable experiments)
  - A/B testing is the best way of measuring success
- Groundtruth
  - Incomplete, incorrect, ambiguous
  - Results pooling is a balanced strategy
- Metrics
  - Accuracy, precision, recall, F1
  - Precision-Recall curves, ROC curve











### Hands-on session

**CMU Data Science Bootcamp** 



