

Machine Learning and AI

Jour 2 : Développement et Intégration de Projets IA

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Doing Data Science

Perspectives

- Data science is iterative
- Start simple, get better

Perspectives

- Data science is iterative
- Start simple, get better

Sometimes there's no business case to do more.
You want to know where that threshold is so you can stop.

Risks

- Nothing is guaranteed, but competitors are innovating and experimenting
- Examples from past projects can help, but often leads to “this is different”

Success

Think early about how to measure success.

Success

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The definition of success will evolve.

Andrew Ng Methodology — Lifecycle of an ML Project

Four phases:

- 1 Project scope definition
- 2 Data management
- 3 Modeling
- 4 Deployment

Each phase has its own particular challenges.

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1. Project Scope Definition

Keypoints:

- Delimitation of the task to be accomplished
- Definition of success indicators
- Budget in terms of time, personnel, etc.

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2. Data Management

Keypoints:

- Unbiased data collection method
- Clear definition of inputs and outputs
- Robust data processing pipeline without training/production disparities
- Reproducibility and experiment management

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3. Modeling

Keypoints:

- Training that takes into account production needs (model size, speed, etc.)
- Error analysis, often by significant data slices
- Reproducibility and experiment management

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4. Deployment

Keypoints:

- Scaling
- Detection of data and concept drifts
- Monitoring
- Retraining process

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CRISP-DM

The cross-industry standard process for data mining.

The major phases:

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment

Technical standpoint — MLOps

From a technical standpoint, Data Science projects management is called MLOps:

- Tools bridging the gap from proof of concept to production
- Techniques to comply with regulatory obligations
- Methods for mitigating ethical issues

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State of MLOps

It's still a young practice, even if it's grown enormously in ten years.

- Rapid evolution, many competing libraries
- Much less stable than DevOps
- Adoption much less homogeneous than DevOps
- Co-evolution with legislation and regulation

Given the instability of the domain, broad principles are more important than specific techniques.

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Data

Data Management Phases

Two distinct phases:

- Definition and calibration
- Retrieval, labeling and organisation

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Data Management Phases

Two distinct phases:

- Definition and calibration (*what's needed, how collected, accuracy*)
- Retrieval, labeling and organisation (*extraction, labeling, organising*)

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Data Management Phases

Two distinct phases:

- Definition and calibration
- Retrieval, labeling and organisation

Definition:

- Identify Data Requirements
- Data Sources
- Data Standards (*formats, naming conventions, ...*)

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Data Management Phases

Two distinct phases:

- Definition and calibration
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Calibration

- Data Quality Metrics (*accuracy, completeness, consistency, timeliness, . . .*)
- Validation Rules
- Data Integration
- Tools and Technologies

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Data Management Phases

Two distinct phases:

- Definition and calibration
- Retrieval, labeling and organisation

Retrieval:

- Data Extraction
- Data Aggregation

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Data Management Phases

Two distinct phases:

- Definition and calibration
- Retrieval, labeling and organisation

Labeling:

- Metadata assignment
- Data Tagging
- Annotations

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Data Management Phases

Two distinct phases:

- Definition and calibration
- Retrieval, labeling and organisation

Organisation:

- Data Structuring
- Data Storage
- Data Indexing
- Data Management

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Objectives

We want primarily to address two questions:

- What are the relevant inputs and outputs?
- What level of performance can we expect?

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Trash in Trash out Principle

Fundamental Principle of Machine Learning:

Data definition is the *central* point of a machine learning system.

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Research vs Industry

$$\text{Research System} = \text{Data} + \overbrace{\text{Parameters} + \text{Model}}^{\text{Work}}$$

$$\text{Industry System} = \overbrace{\text{Data} + \text{Parameters}}^{\text{Work}} + \text{Model}$$

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Definition Example – Translation

How to define the output?

- ① I was overwhelmed with joy. → J'ai été submergé par la joie.
- ② I was overwhelmed with joy. → Je fus submergé de joie.
- ③ I was overwhelmed with joy. → Je fus terrassé par la joie.

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Definition Example – Audio

How to define the input?

- 1 Um... I'll be there in 5 minutes
- 2 Um, I'll be there in 5 minutes
- 3 I'll be there in 5 minutes

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Definition Example – Identity Fusion

How to define the output?

- Martin Durant, 44000, ..., <martin@durant.fr>
- Martin Durant, 44000, ..., <martin.durant@gmail.com>

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What is at stake?

All these decisions change the function that the model will approximate.

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Types of Data

Two primary criteria:

- Size of the dataset
- Structured or unstructured data

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Size of the Dataset

How much data we have influences what is important.

Small Quality of annotations is crucial

Large Quality of data processing processes is crucial

A subset of a large dataset can behave like a small dataset (especially a critical slice).

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Structured / Unstructured Data

Data structure affects what's easy and hard.

Structured Hard to annotate for humans. Hard to augment.

Unstructured Likely easy to annotate for humans. Often augmentable.

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Annotation Guide

For annotators:

- Should be as robust as possible
- Ideally written by a mix of domain experts / ML
- Written iteratively:
 - Write a version
 - Annotate
 - Detect ambiguous points
 - Write a new version

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Coverage of Input Data

Data coverage principles:

- All cases to be handled must be represented in the data
- All cases to be handled must be represented in sufficient quantities
- It's particularly important to avoid discrimination on protected attributes

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Calibration

Estimating expected performance:

- Bibliographic research on existing approaches
- Estimation of human performance

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Human Level Performance (HLP)

Human Level Performance (HLP) refers to the capability of AI systems or models to perform tasks at a level comparable to that of a human.

Achieving HLP means that the AI can handle specific tasks with a similar degree of accuracy, efficiency, and reliability as a human expert in that domain.

Human Level Performance

- **Benchmark for Performance:** HLP serves as a benchmark to estimate the potential maximum performance of a system.
- **Bayes' Error Estimation:** It helps in estimating the Bayes' error, which is the minimum possible error due to the inherent randomness in the data.
- **Annotation by External Processes:** HLP is crucial when annotations are generated by external processes rather than human annotators.
- **Unstructured Data:** Particularly relevant for tasks involving unstructured data (e.g., images, audio, text).
- **Achievable Performance:** Provides an idea of the best possible performance that can be achieved by a system.

Improving Human Level Performance

- **Underestimating HLP:** Sometimes, HLP is underestimated to make it easier for AI models to surpass human performance.
- **Impact on Orientation:** Poorly defined HLP can mislead the direction of development efforts, resulting in suboptimal performance improvements.

Improving Human Level Performance — Example

Example of HLP in Action:

- ① “Um. . . I’ll be there in 5 minutes.”
 - ② “I’ll be there in 5 minutes.”
- If 80% of annotators prefer the first transcription and 20% prefer the second, the agreement between two random annotators is calculated as:
 $0.8^2 + 0.2^2 = 68\%$ agreement.
 - An algorithm that always chooses the most common transcription can achieve 80% agreement.
 - Significant errors may be obscured by these seemingly high agreement rates, highlighting the need for deeper analysis beyond superficial gains.

Documentation

Things to track during the definition and calibration process:

- Potential biases in the data that you suspect
- Real data coverage issues
- Regulatory issues related to the data

This information is crucial for properly documenting the model in the long run.

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Data Processing

Data Organization

Many options:

- Structuring (schema, description, ...)
- Scaling (SQL, NoSQL, distributed file system, ...)

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Feature Store

In an MLOps context, feature stores are often an intermediate step between the original source and processing.

- Allows storage optimized for ML
- Avoids recomputing the same features
- Enables discoverability

See *Feast* for example.

<https://docs.feast.dev/>

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Data Acquisition

- Aim for a short first iteration to get feedback for subsequent phases
- List potential sources and their time/money budget
- Potentially have the ML team do initial annotation
- Define competent profiles

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Iterations on Data

- Order of magnitude: not more than x10 at once
- Work jointly on source quality, processes, volume
- Very different in prototyping and production phases:

Prototyping Gathering enough data to decide go/no-go

Production Deep work as the main vector to reach performance ceiling

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Metadata

Because data is the heart of an ML system, follow good practices.

- Track provenance
- Track transformations
- Maintain reproducibility of data acquisition and transformations:
 - Increasingly important for regulation
 - Essential for debugging

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Metadata — Consequences

Think about preserving metadata.

- Define data acquisition processes
- Define data transformations
- Implement dedicated systems

This leads to many architecture decisions.

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Processing Pipelines

- Provide reproducibility and process automation
- Often are directed acyclic graphs of operations
- Many solutions exist

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Desirable Characteristics

Strengths of a processing pipeline

- Adaptation to batch (development) as well as real-time (production)
- Faithfulness of development/production processing
- Scalability
- Deployment on various targets
- Ease of development
- Integration with the ecosystem

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Main Processing Pipeline Solutions

Strong points of each solution:

Deployment options, dev/prod parity, performance

<https://www.tensorflow.org/tfx>

Kubernetes integration <https://www.kubeflow.org/>

Reproducibility and “low tech” solution <https://dvc.org/>

Flexible, easy to adopt, supported by clouds

<https://mlflow.org/>

Kubernetes integration <https://www.pachyderm.com/>

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Modeling

Model Engineering

Several key aspects to consider:

- Performance in production
- Various deployments with very distinct characteristics
- Interpretability
- Maintainability
- Compliance with regulations (non-discrimination, . . .)

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Best Practices

In an industrial context, the focus is on the data, not the model :

- Start simple (heuristic, simple model)
- Use the industry standard for the task given your performance and deployment requirements
- Improve data first, model second

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Model Card

Model cards were introduced in *Model Cards for Model Reporting*

<https://arxiv.org/abs/1810.03993>

- Specifies ethical and regulatory decisions related to the model
- Provides transparency
- Goal is informing both the public and internal teams

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Model Registry

Centralized place to store and retrieve models and associated meta-data :

- Eases deployment
- Solidifies reproducibility

`https://mlflow.org/docs/latest/model-registry.html`

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Models and Error Analysis

Introduction

Error analysis is crucial during development:

- Guides future work
- Determines potential progress

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Link between error analysis and interpretability

- Interpretability enables error analysis
- Transparency (sometimes a regulatory or functional requirement in production)
- Interpretability-performance continuum:
 - Interpretable models often insufficient to approximate desired functions
 - Modern performant models are black boxes

Often a dilemma in choosing a model.

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Link between error analysis and interpretability

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Often a dilemma in choosing a model.

Useless tip: humans are often not explainable.

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Recommended Approach

Some heuristics for error analysis:

- Determine relevant data slices
- Estimate model performance and achievable performance on each slice
- Prioritize work on slices offering the most impact

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Data Slices

Idea popularized by Apple in their paper *Overton: A Data System for Monitoring and Improving Machine-Learned Products* and *Snorkel*

<https://www.snorkel.org/>.

Excellent Snorkel blog on the subject.

<https://www.snorkel.org/blog/slicing>

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Recommended Approach — Example

Let's consider working on an image classification system.

Suppose we distinguish the following slices in our image data:

- Presence of mountains
- Presence of humans
- Presence of cars

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Recommended Approach — Example, Continued

We estimate the following performances:

Slice	HLP	Model
Mountains	65%	60%
Humans	96%	90%
Cars	80%	40%

Which slice is most important for improvements in the next iteration?

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Recommended Approach — Example, Conclusion

Using proportions in the dataset to quantify impact:

Slice	HLP	Model	Proportion	Potential Impact
Mountains	65%	60%	10%	0.5%
Humans	96%	90%	85%	5.1%
Cars	80%	40%	1%	0.4%

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Error Analysis

Once relevant slices are identified, some options:

- Find explanatory examples of the model
- Use a simpler model that globally or locally explains the complex model

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Explanatory Examples

Things to look for:

- **Prototypes** Representative examples of model behavior
- **Counterfactual examples** Modification of existing instances to see how prediction evolves
- **Adversarial examples** Counterfactual examples with a significant impact on prediction
- **Influential examples** Examples that have had the most impact on the model

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Explanatory Models

Training models:

- Simple
- Interpretable (linear regression, simple trees, etc.)
- Approximating the complex model
- Helping to understand important features
- Globally (multiple examples, broad coverage)
- Or locally (one example)

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Measures

Once the analysis is done:

- Data augmentation
- Feature engineering
- Exploration of new parameters

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Further Reading

Interpretable Machine Learning book

<https://christophm.github.io/interpretable-ml-book/>

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Intro to Production Deployment

Deployment Challenges

- Providing a trained model to a diverse and large crowd
- With ML performance observed in quality tests
- With good classical performance (latency, throughput, ...)

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Common Pitfalls

What can go wrong? (*Or: what often goes wrong?*)

- Different code in development vs production
- Poor dependency management
- Inadequate or inappropriate architecture

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Deployment Best Practices

Deployment Strategies

Several criteria allow for choosing a deployment strategy:

- Service traffic
- Audience (public, internal, other services, ...)
- Deployment frequency
- ...

Key concepts:

- Progressive deployment
- Rollback (ability to return to the previous state of the system)

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Shadow Deployment

- Deployment of the model alongside the existing system
- Model outputs are not used by the application
- Analysis of model outputs and decision to continue deployment or not

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Blue/Green Deployment

- Deployment of the new model (green) alongside the existing system (blue)
- When tests are successful on the green system, traffic is redirected there
- Allows for rollback if issues arise

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Canary Deployment

- Similar to blue/green, two parallel systems
- Gradual ramp-up of the green system

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Implementation

The two most popular options:

- Kubernetes + istio
- Internal tooling

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The launch of these deployments can be done via git tags and operations in CI/CD.

This is the gitops approach with gto project from DVC, for example

<https://www.atlassian.com/git/tutorials/gitops>

<https://dvc.org/doc/gto>

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Monitoring

Challenges

- Model drift
- Ensuring proper behavior of a model
- Knowing when to retrain a model
- Understanding the data of a model

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Common Issues

Data Drift: the evolution of the input data distribution.

Gradually makes models obsolete, so need to retrain.

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Common Issues

Concept Drift: the evolution of the correspondence between outputs and inputs.

Gradually makes models obsolete, so need to retrain.

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Speed of Data Evolution

Different data sets evolve at different rates.

- **User Data** often changes slowly but fundamentally
- **Enterprise Data** often changes more markedly and abruptly

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Common Issues

Data Quality:

- Missing values
- Outliers
- Schema changes
- ...

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Tools — Test Suites

Automated execution for detection of all these challenges:

- Data drift
- Concept drift
- Poor data quality
- Drop in prediction performance

The most widely used library for this is `evidently`.

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Tools — Dashboard

The human-facing counterpart of test suites:

- To fuel discussion on data within the Machine Learning team
- To complement more general dashboards

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Classic Monitoring

In addition to these Machine Learning-specific issues, a production system needs usual monitoring.

E.g., the four "golden signals" in Site Reliability Engineering:

- Latency
- Traffic
- Errors
- Saturation

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Implementation

Several solutions are common:

- **Evidently** <https://www.evidentlyai.com/>
- **Seldon Core** <https://www.seldon.io/solutions/core-plus>
- **TFX ExampleValidator**
<https://www.tensorflow.org/tfx/guide/exampleval>
- **Great Expectations**
<https://docs.greatexpectations.io/docs/home/>

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Case Study

Let's talk about you