Introduction to MLOps

Sprint 1 | Week 1

INFO9023 - ML Systems Design

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Agenda

1. Introduction to MLOps
    - What is MLOps and why does it matter?
    - Key concepts of MLOps
    - A zoom on LLMOps
    - Real world use case
2. ML project organisation
    - Roles around ML projects
    - Project definition framework
    - Agile way of working
3. MLSD - Course structure

Introduction to the staff

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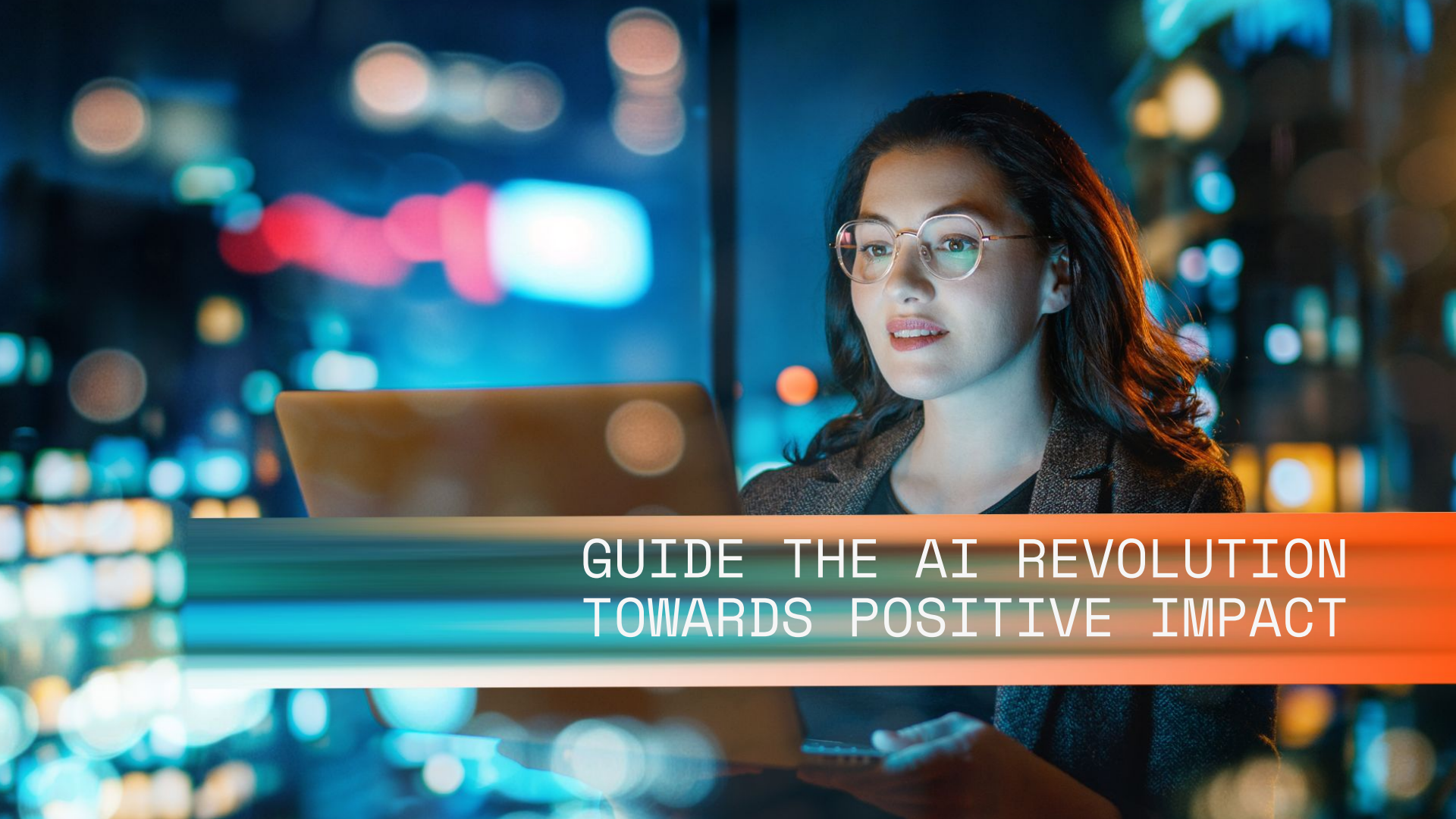

GUIDE THE AI REVOLUTION
TOWARDS POSITIVE IMPACT

INTRODUCTION TO ML6.

One of the largest and fastest growing AI engineering teams since 2013.

120+

Experts spread over 4 different EU locations.

150+

Clients across multiple industries.

300+

Projects delivered.

10+

Applications each day - we are a talent magnet.

100+M

open source downloads p.a., 4.5k stars

250+

Publications & blog posts.

17%

Of engineer time dedicated to research

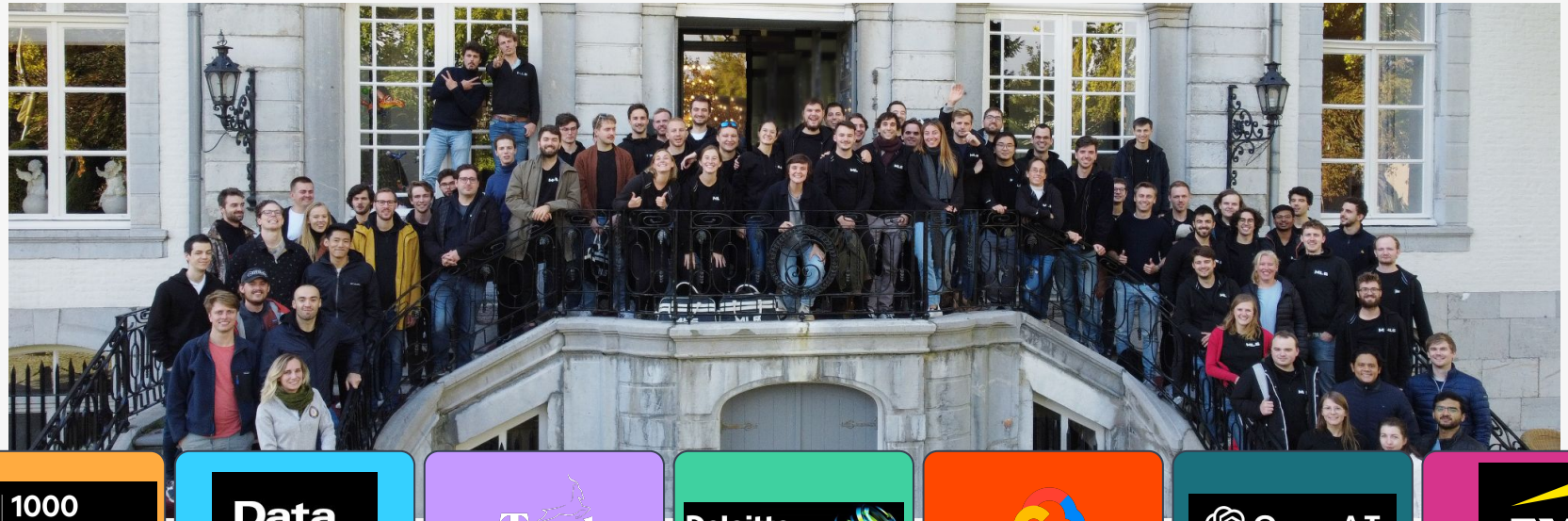
ISO 27001

ISO Certified since 2020 + Security, Legal & Ethical AI experts.

TRUSTED BY LEADERS ACROSS INDUSTRIES.

RECOGNIZED FOR OUR TALENT & GROWTH.

Don't just take our word for it!



FT 1000 Europe's Fastest Growing Companies	Data News	Trends Gazellen 2021	Deloitte. Technology Fast 50	Google Cloud	OpenAI	EY
#386 (EU) | #4 BE	AI Innovator of the year 2020	Multiple nominations & one award win	Nominated in 2022, 2021, 2020, 2019, 2018	Google Cloud partner of the year BeNeLux 2021-2023	1 of the first 6 official service partners of OpenAI in Europe	Scale-up of the year finalists in 2023

What is MLOps and why does it matter?

AI is everywhere!

A few example of ML applications.

Facial recognition

Product recommendation

Email spam filtering

Autocomplete

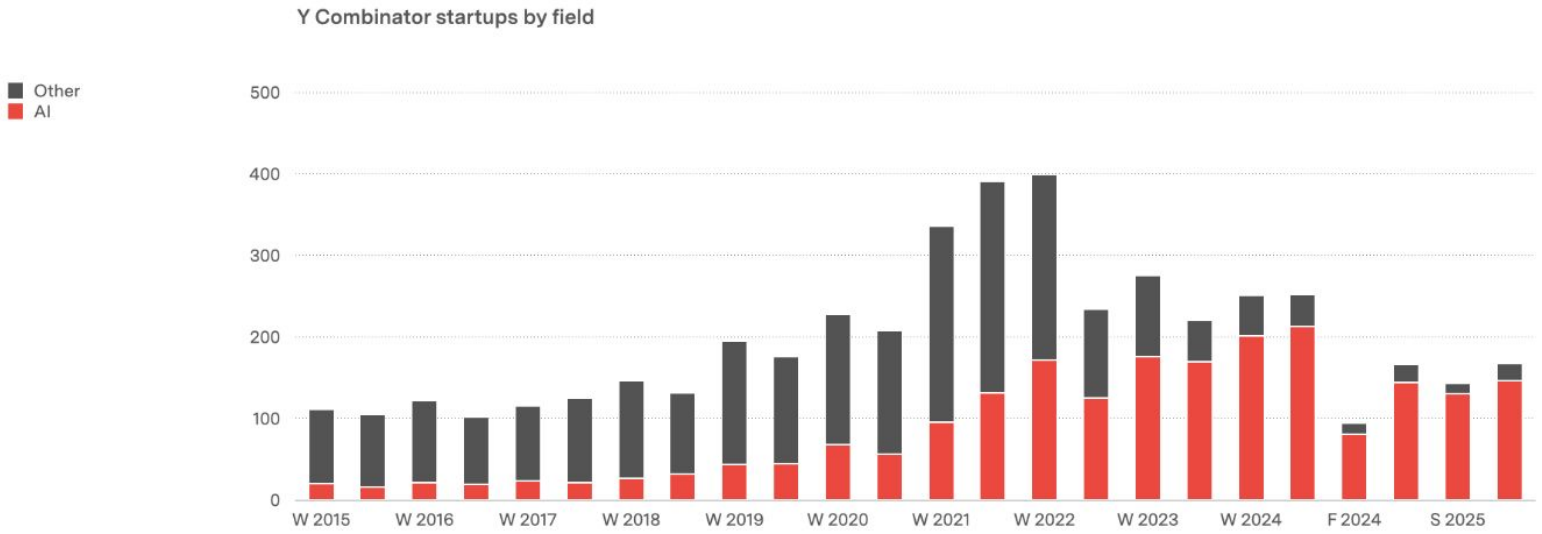
Finance predictions

Healthcare imaging

Weather forecast

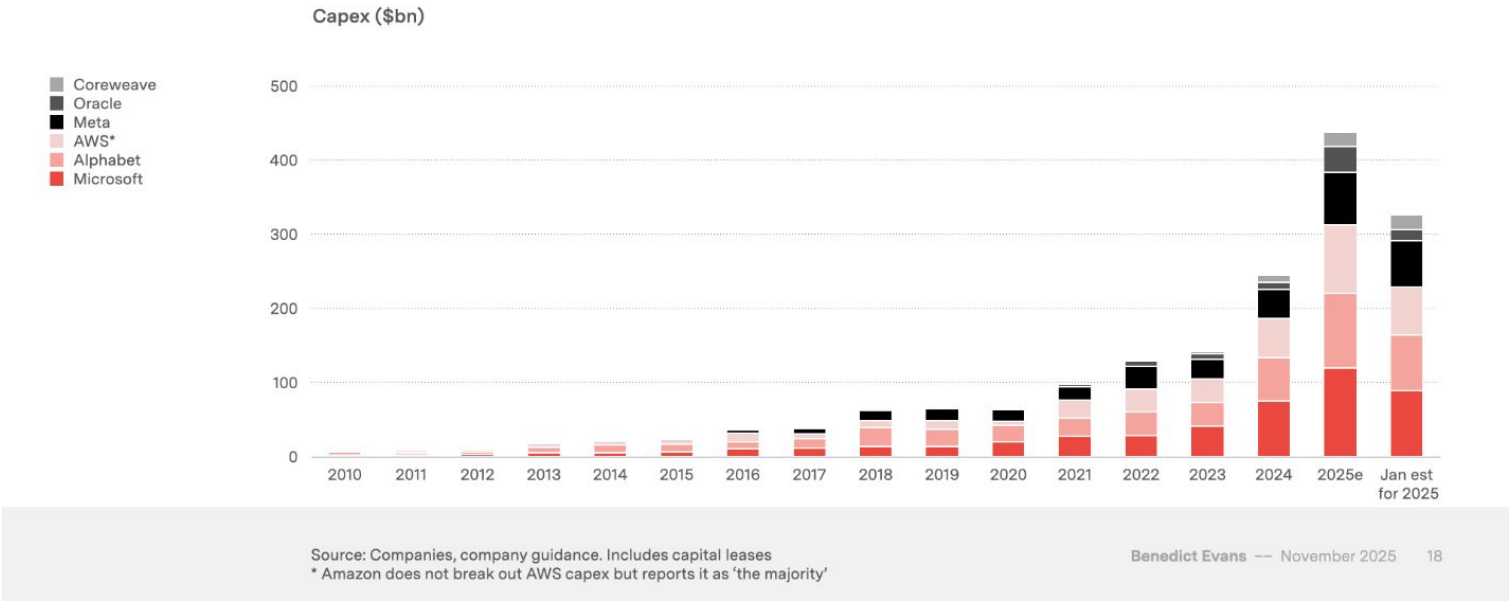
...

Investments are massively focused around AI.



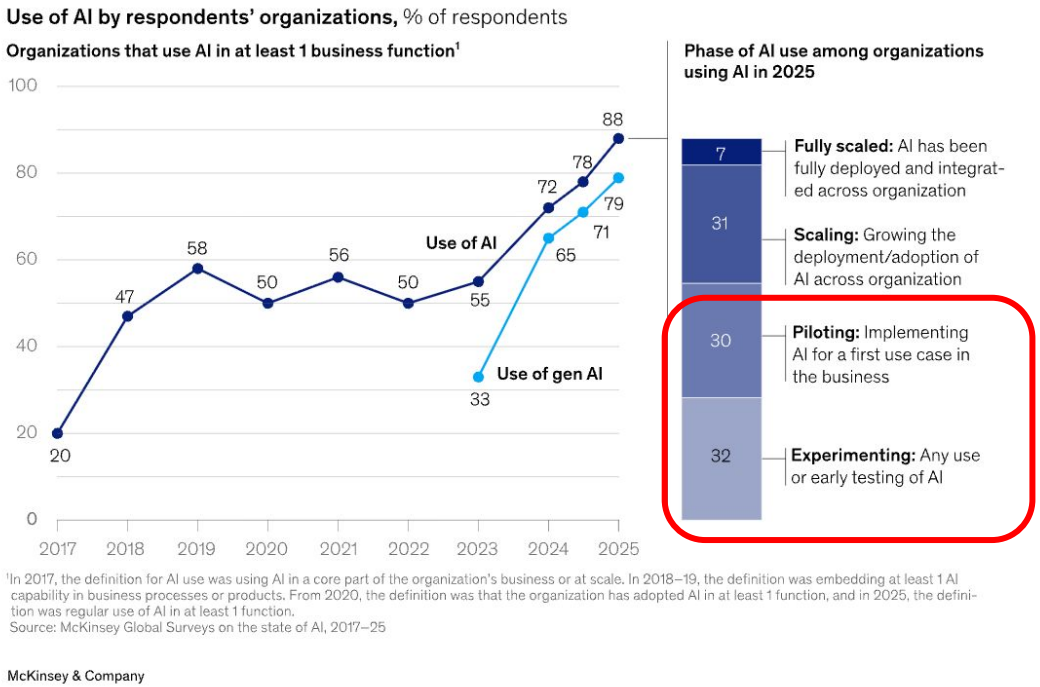
https://www.ben-evans.com/presentations (November 2025) | Source: Y Combinator

As a consequence, there is a growth in investments (expenditures) in cloud (data centers).



https://www.ben-evans.com/presentations (November 2025)

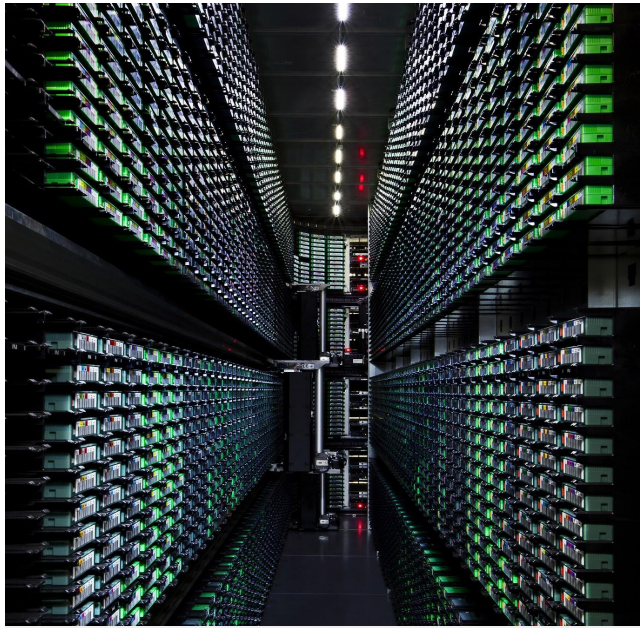
Adoption of AI has skyrocketed in the last years.



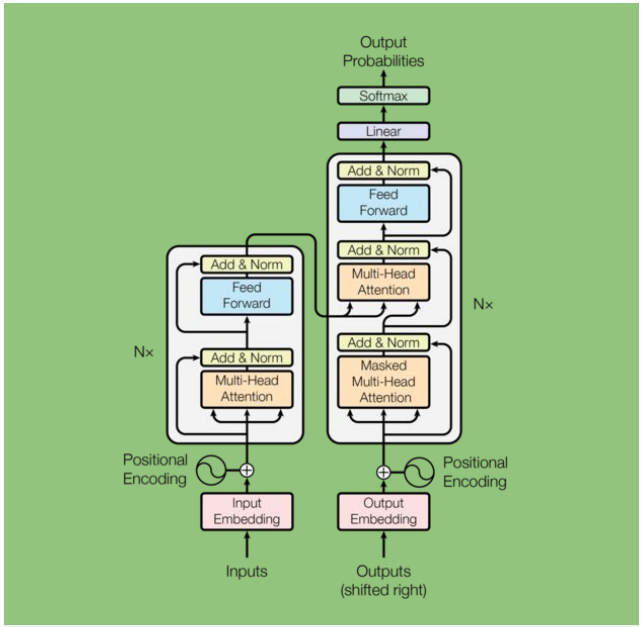
62% are still not in production!

https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai#/

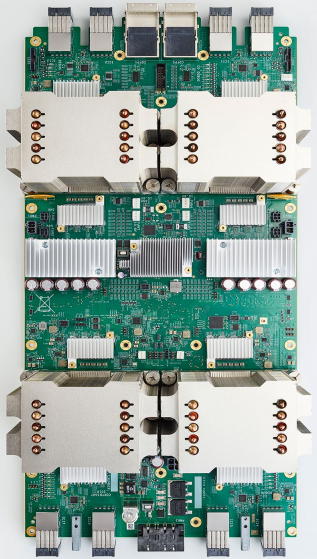
Why now?



Large Datasets

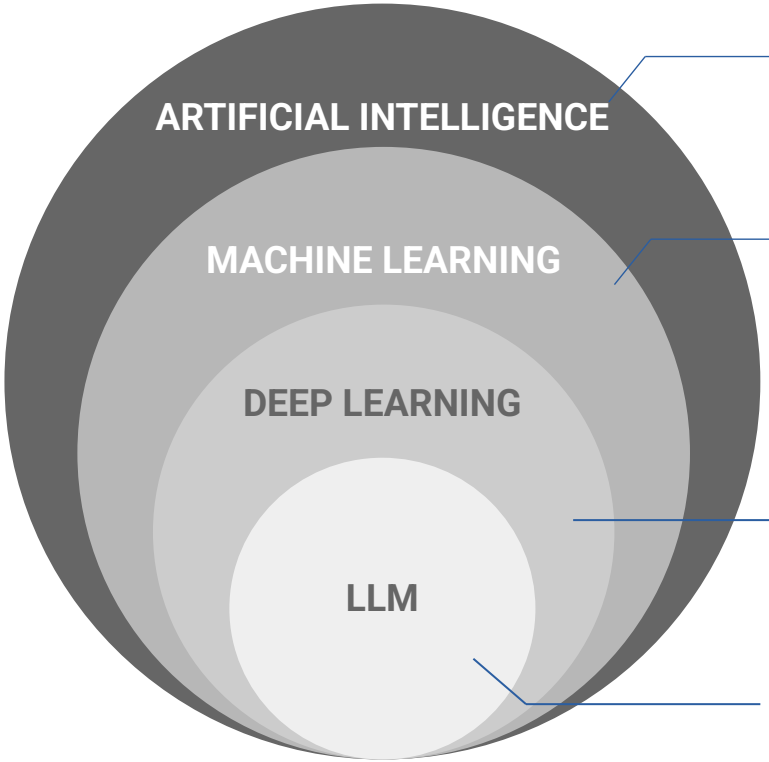


Better Models



Lots of Computation

Declinaisons of AI.



ARTIFICIAL INTELLIGENCE

Ability of a machine to perform cognitive functions.

MACHINE LEARNING

AI techniques that give machines the ability to learn from data without being explicitly programmed,.

DEEP LEARNING

Type of Machine Learning based on deep neural networks or attention mechanisms.

LARGE LANGUAGE MODELS

Generalised models trained on massive amounts of data, mostly used through an API or open sourced model.

Why do we need ML Systems Design?

Building a ML application means implementing much more than just your ML model.

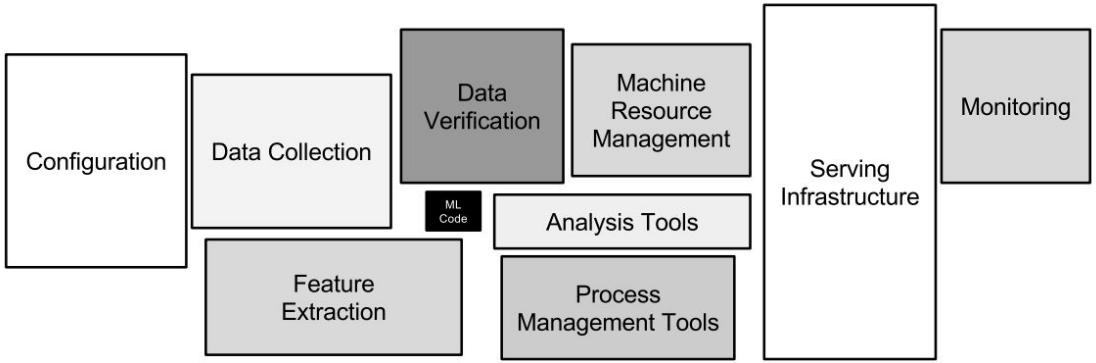


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.

Sculley, D. et al. (2015). Hidden technical debt in machine learning systems. https://papers.nips.cc/paper_files/paper/2015/hash/86df7dcfd896fcaf2674f757a2463eba-Abstract.html

Key definitions.

ML Application: The final solution or program powered by a Machine Learning model.

ML System: All the components responsible for the implementation and management of the data and models powering an ML application.

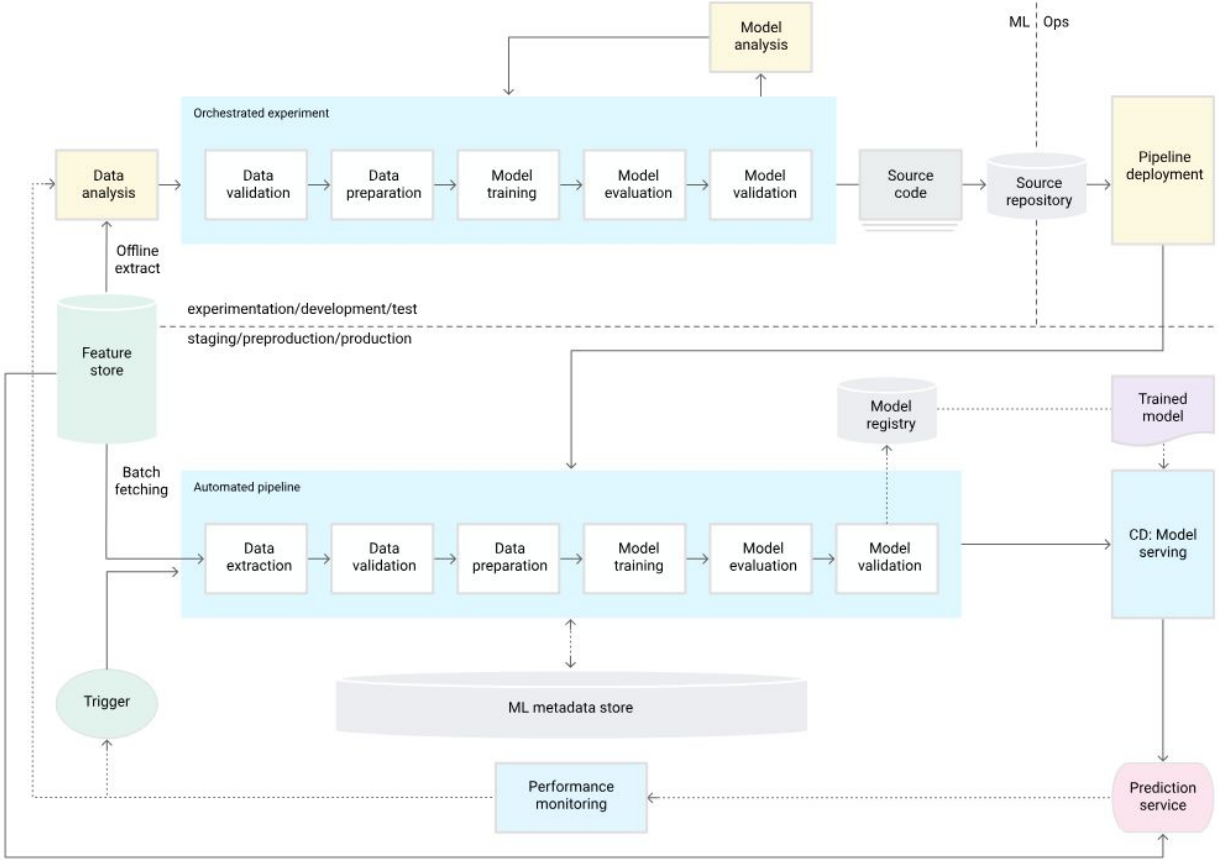
ML Systems Design: The act of designing the architecture and implementing an ML System.

MLOps: A set of practices and tools to enhance and accelerate the entire ML model development life cycle.

LLMOps: A branch of MLOps specifically focusing on LLM application development life cycle.

Key concepts of MLOps

Typical architecture of an ML system



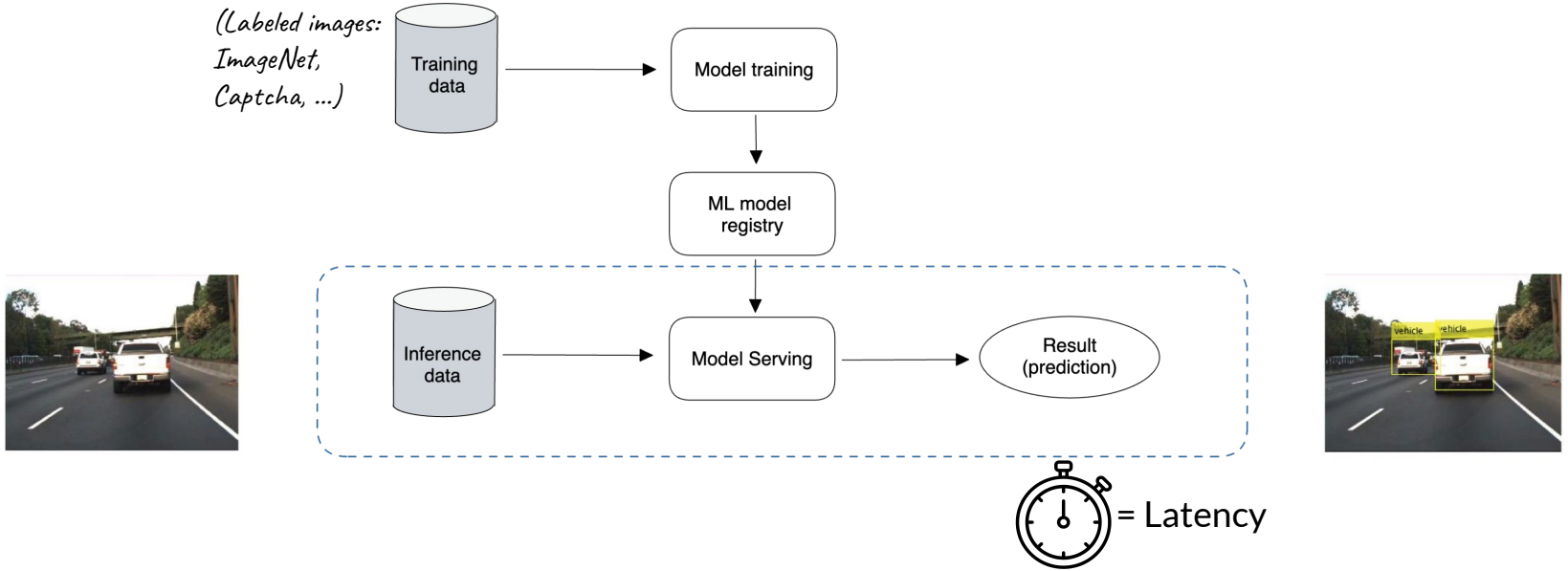
https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

Data preparation

It all starts with data. How to go through all these steps efficiently and effectively.

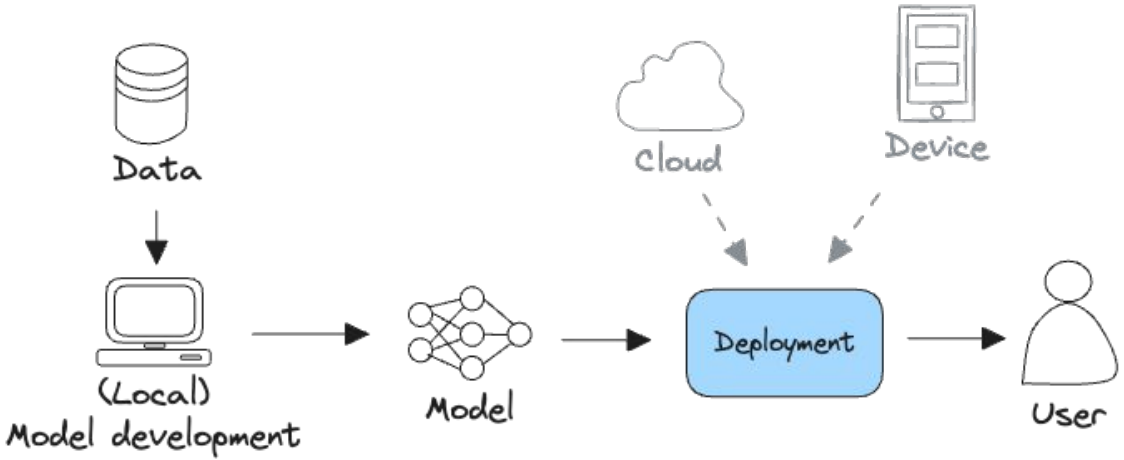
ML model serving

How to efficiently serve ML model to client.



ML model deployment

How to efficiently deploy your model for serving.



Containerisation

Containers encapsulate an application as a **single executable package** that contains all the information to **run it on any hardware**:

- Application code
- configuration files
- libraries
- dependencies

Abstracts the application from its **host operating system.**

Containers can be easily transported from a desktop computer to a virtual machine (VM) operating system, and they will run consistently on virtualized infrastructures or on traditi er on-premise or in the cloud.

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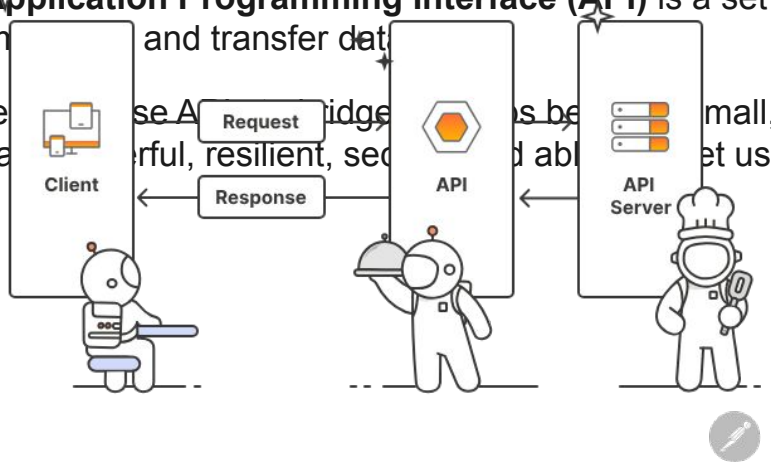
https://www.ibm.com/topics/containerization

APIs

Allow other services to call your model or application.

An **Application Programming Interface (API)** is a set of protocols that enable different software components to comm and transfer dat

Deve se A idge s be mall, discrete chunks of code in order to create applications that a rful, resilient, sec d abl et user needs.



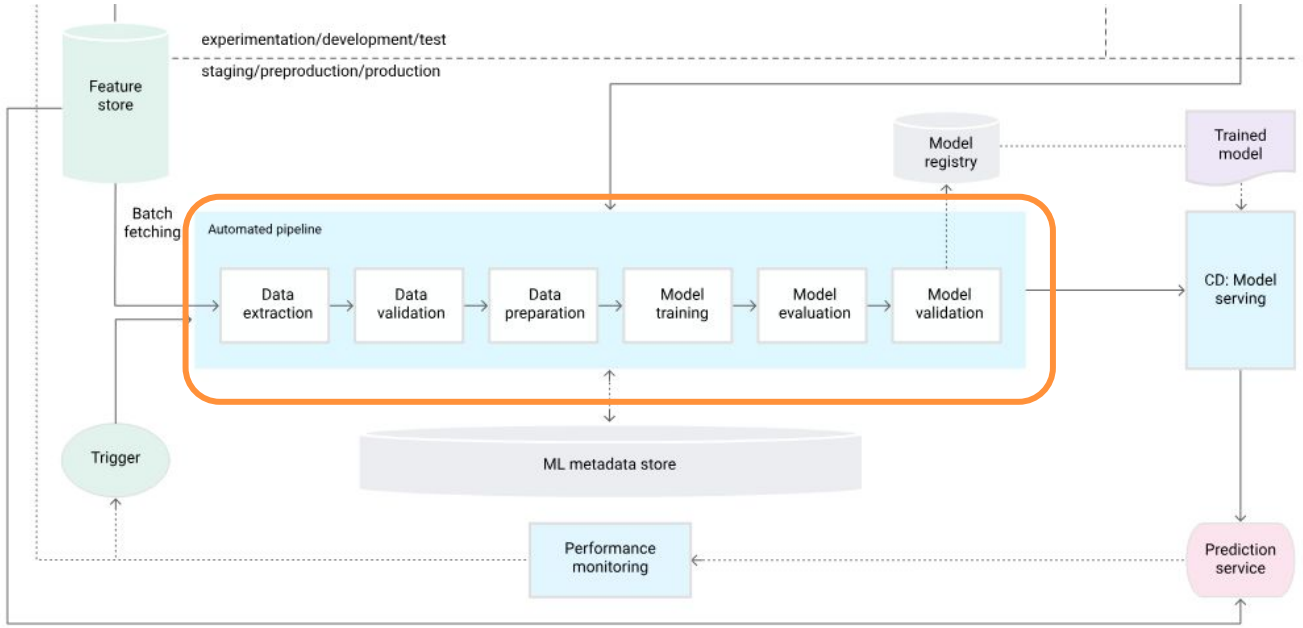
https://www.postman.com/what-is-an-api/

Cloud infrastructure

Cloud infrastructure allow for data storage, compute allocation, training and deploying model, monitoring, …

ML Pipeline

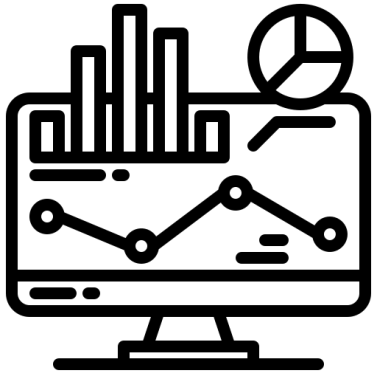
Orchestrates components to prepare data, train, evaluate and deploy ML models (among other things)



https://cloud.google.com/architecture/mlops-continuous-delivery-and-automation-pipelines-in-machine-learning

Monitoring

Ensuring that models in production are performing well.



Resource level (performance and usage of resources)

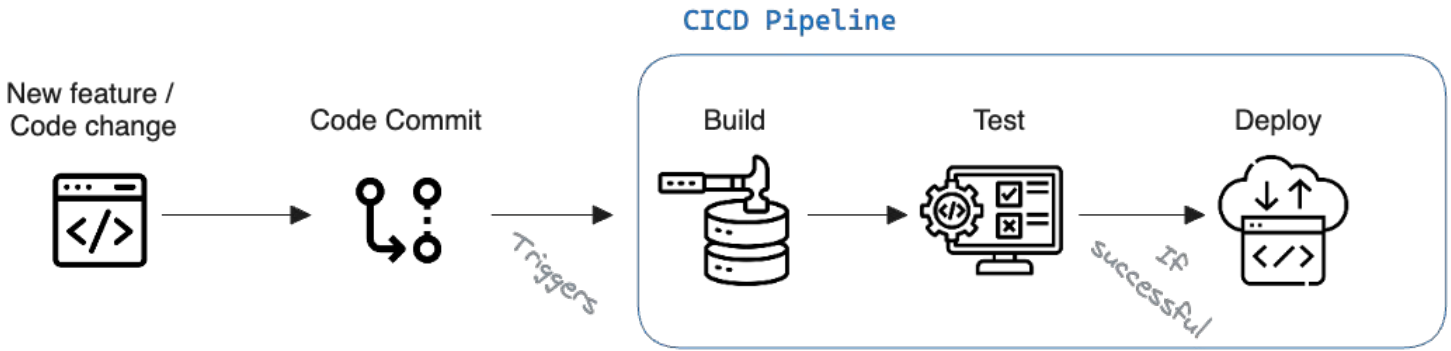
- How much is it being used by users?
- Are the CPU, RAM, network usage, and disk space as expected?
- What are the Cloud costs?
- Are requests being processed at the expected rate?
- What is the system uptime? Some maintenance contract depend on it.

Performance level (performance/accuracy of the model over time)

- Is the model still doing accurate predictions with the new data coming in?
- Is the data distribution changing?
- Is the target variable changing?
- Are concepts around the model changing?

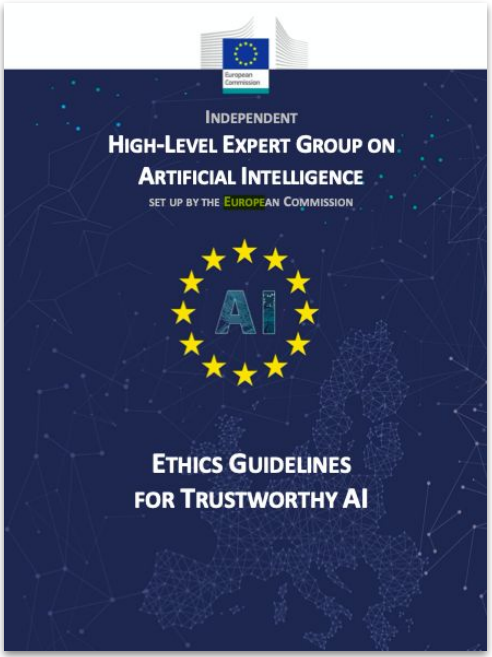
Continuous Integration and Continuous Delivery (CICD)

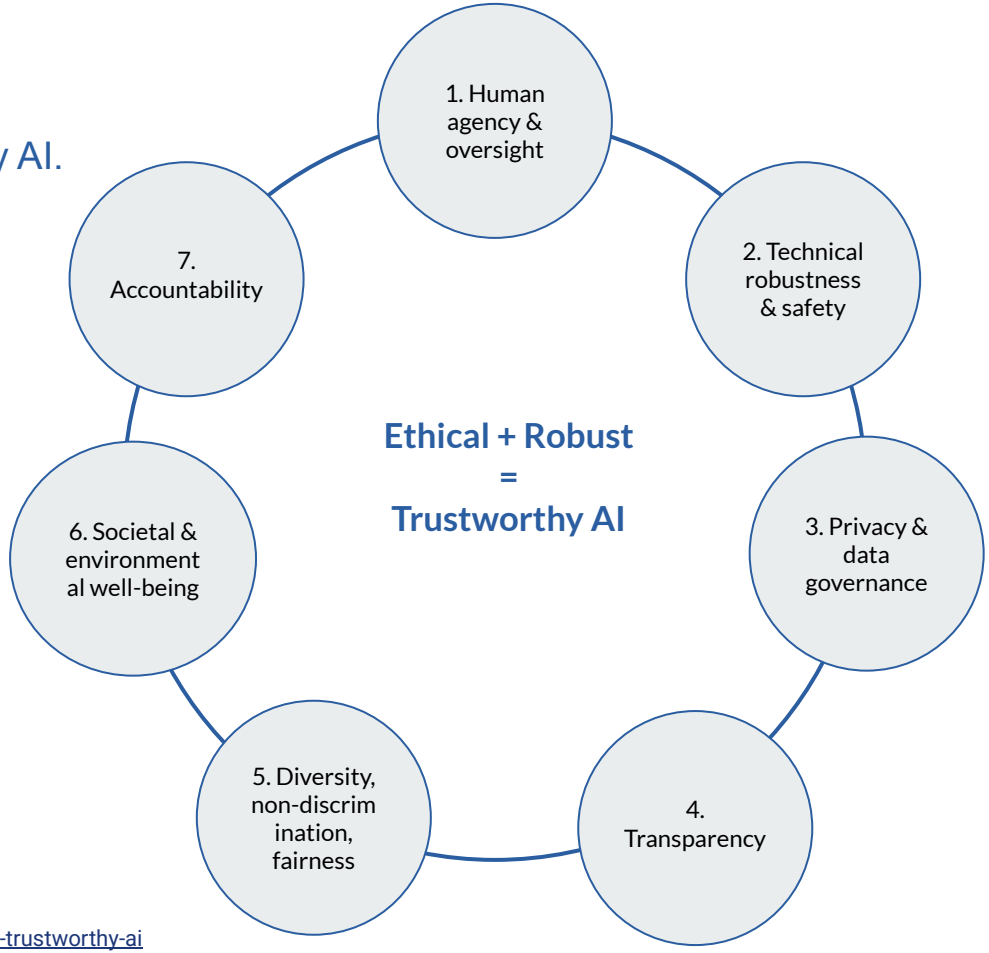
Allows you to continuously work on your application and efficiently deploy new changes to it.



Key concept: Ethical AI

Guidelines & legislation on building trustworthy AI.





https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

Teams can adopt different MLOps maturity levels

Level	Highlights	Technology
Level 0 **No MLOps**	• Difficult to manage full ML model lifecycle • Teams are disparate and releases are painful • "black boxes," little feedback during/post deployment	• Manual training, builds and deployments • Manual testing of model and application • No centralized tracking of model performance
Level 1 **DevOps but no MLOps**	• Releases are less painful than No MLOps • Limited feedback on how well a model performs in production • Difficult to trace/reproduce results	• Automated builds • Automated tests for application cod
Level 2 **Automated Training**	• Training environment is fully managed and traceable • Easy to reproduce model • Releases are manual, but low friction	• Automated model training • Centralized tracking of model training performance • Model management
Level 3 **Automated Deployment**	• Releases are low friction and automatic • Full traceability from deployment back to original data • Entire environment managed: dev > test > production	• Integrated A/B testing of model performance • Automated tests for all code • Centralized tracking of model training performance
Level 4 **Full MLOps**	• Full system automated and easily monitored • Automated feedback collection and retraining • Close to zero-downtime	• Automated model training and testing • Verbose, centralized metrics from deployed model

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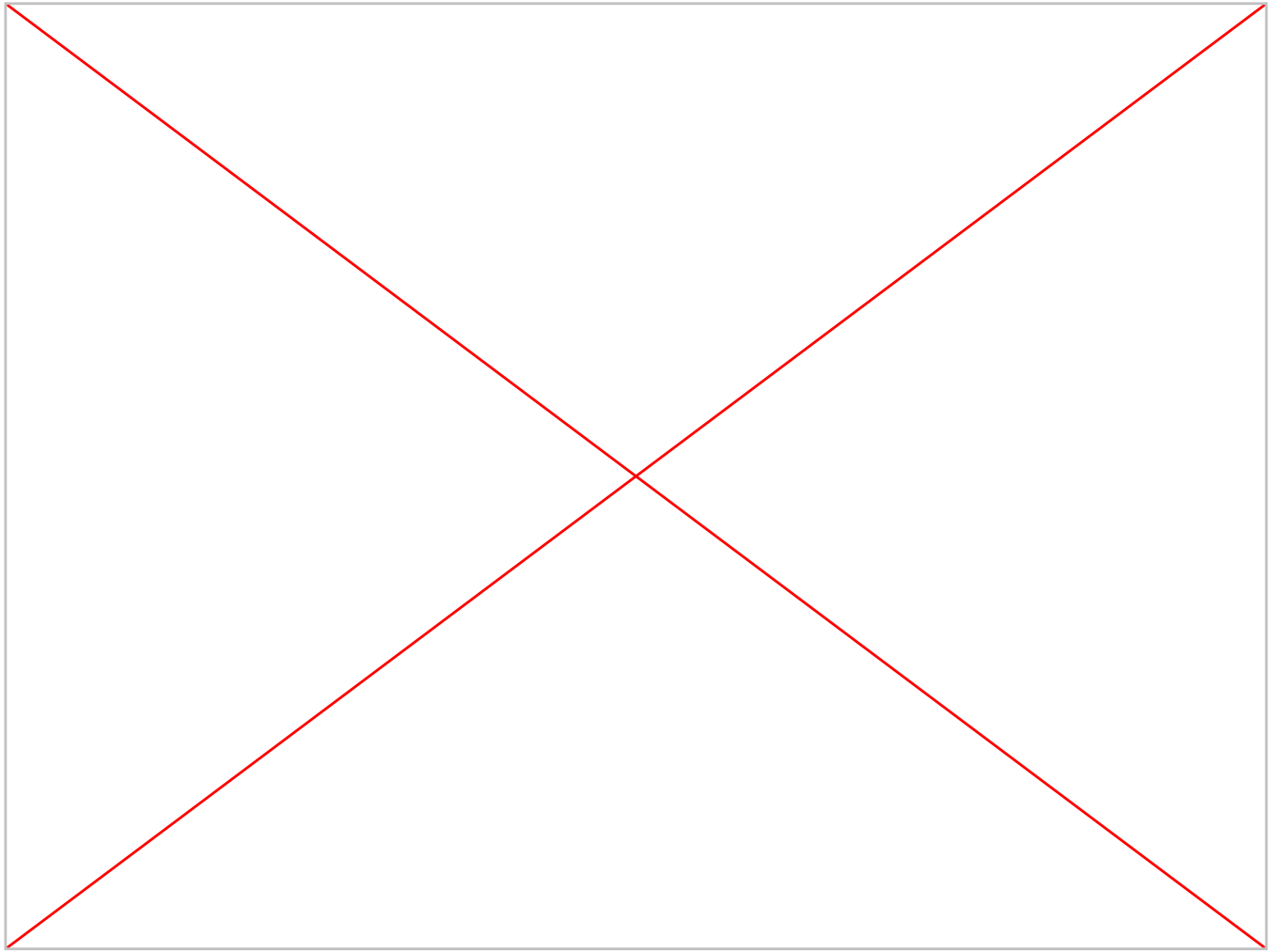
https://learn.microsoft.com/en-us/azure/architecture/ai-ml/guide/mlops-maturity-model#level-0-no-mlops

Going from standard ML Engineer to MLOps master…



A zoom on LLMOps

What defines LLMOps?

LLMOps is a subset of MLOps aimed at Genrative AI (GenAI) and Large Language Model (LLM) applications.

- It aims at unifying LLM system development (LLM/Dev) and operation (Ops).
- It provides **practices** and **tools** to enhance and accelerate the entire LLM application development life cycle.
- It enables developer teams to implement LLM applications in a more **efficient**, **consistent**, **reproducible**, and **secure** way.

Why LLMOps is important now?

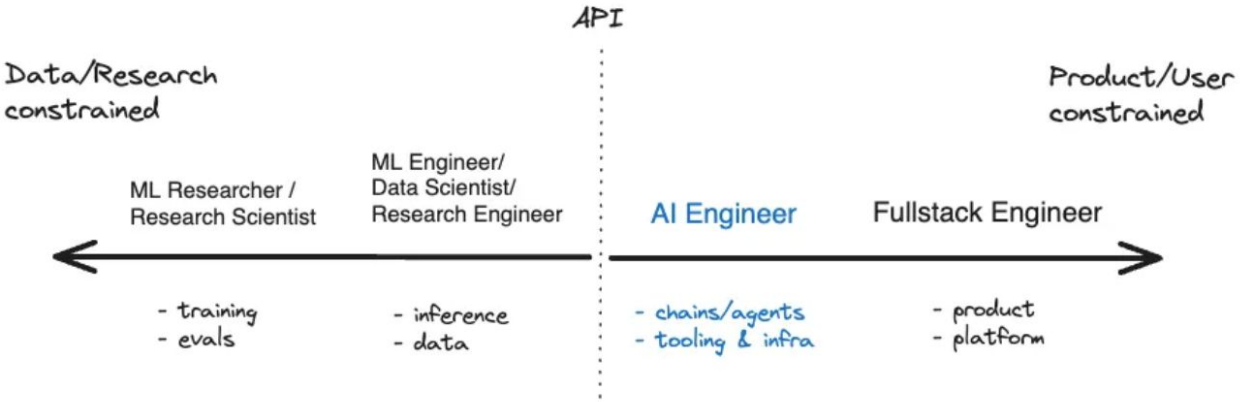
The **potential** and **value** added of GenAI is skyrocketing. Organisations are keen to enable business value by using LLMs in production in an efficient, robust and safe way.

Technologies around GenAI are evolving every day. This is why a proper infrastructure is a must have, to enable an effective and productive ML team

Having a proper ecosystem, enables organizations to **accelerate development** and iterate faster, limits human error and creates a safe and seamless environment to nurture new experiments.

LLMs introduced the need for a new role: AI Engineers.

AI Engineering primarily involves working on GenAI and LLM applications, which uses pre-trained models accessed via APIs or open source. This excludes custom model training, but introduces a new set of unique engineering practices.



https://www.latent.space/p/ai-engineer (2023)

LLMs introduced a new set of engineering practices.

A few examples…

LLM HOSTING

LLMs are heavier and more challenging to host than traditional ML model. Hosting and optimisation requires new techniques.

CONTEXT ENGINEERING

Optimise prompt and context provided to the LLMs can lead to significant differences in latency, cost and performance.

EVALUATION

Evaluating LLM applications is inherently difficult. Different techniques exist for this purpose.

TOOLS / MCP

Implementing tools and and optimising their usage by LLMs agents is key to building modern AI applications.

GENAI GATEWAY

Providing centralized access control, governance and observability for LLM applications.

GUARDRAILS MANAGEMENT

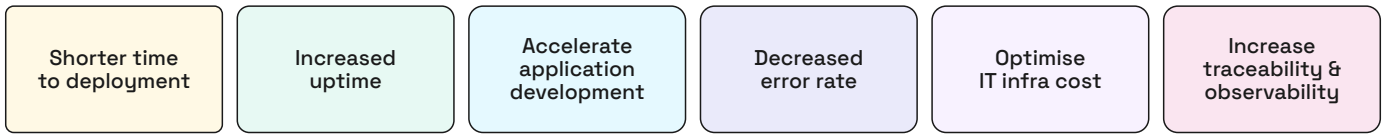
Protect the input and output data of an LLM application with different guardrail techniques.

What defines MLOps?

MLOps in a nutshell:

MLOps aims at unifying ML system development (ML/Dev) and operation (Ops).
It provides practices and tools to enhance and accelerate the entire ML model development life cycle.
It enables developer teams to implement ML applications in a more efficient, consistent, reproducible, and secure way.

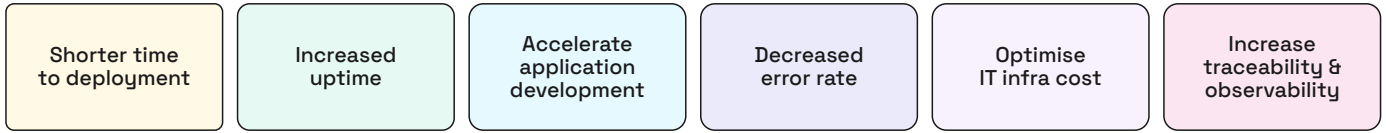
KPIs unlocked by MLOps:



What defines LLMOps?

The core value of MLOps still holds for LLMOps

Just like MLOps, LLMOps is focused on bringing solutions to production efficiently & robustly. The KPIs remain applicable.



GenAI applications have their own dynamics

Unlike traditional ML models, GenAI applications leverage the power of large language models, introducing new challenges across the different development and deployment cycles.

This shift requires adapting your current practices and adopting new ones to ensure effective handling of data, experiments, and deployments.

When comparing LLMOps to MLOps:

→ PRINCIPLES ARE THE SAME

→ BENEFITS ARE THE SAME

→ BUT SKILLS ARE DIFFERENT

When comparing LLMOps to MLOps:

MLOps		LLMOps
• Preparing data for model development (cleaning, feature engineering, etc…) • Sourcing and labelling of data	DATA MANAGEMENT	• New data stack, with elements like vector databases, embedding models, document parsing, etc… • Data access and structure gain relevance for retrieval augmented generation (RAG)
• Experiments focused on altering model parameters and architecture, resulting in new model • Evaluation on hold out test sets with precise metrics	EXPERIMENTS & DEVELOPMENT	• Experiments revolve around prompt engineering and agentic workflows • Importance model choice and future-proofing by enabling model swap • Evaluation is ambiguous and challenging
• Automated deployment of code and models across different environments • Versioning and tracking of models • Set up of A/B experiments	DEPLOYMENT	• Tracing of LLM agents logs • Versioning and tracking of prompts • Guardrails and defensive mechanisms • User testing and validation before release
• Logging and monitoring of data drifts and model performance	CONTINUOUS MONITORING & LOGGING	• Monitoring for biases, hallucination and other risks • Use LLM-as-a-Judge (LAAJ) • Latency & cost optimisation - wide range of motion

Real-world use case:

Grid system imbalance forecasting

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1 **Use case:** What is System Imbalance?

2 Initial **ML model** iteration

3 **MLOps** solution

What is System Imbalance?

Balancing the Grid is Crucial

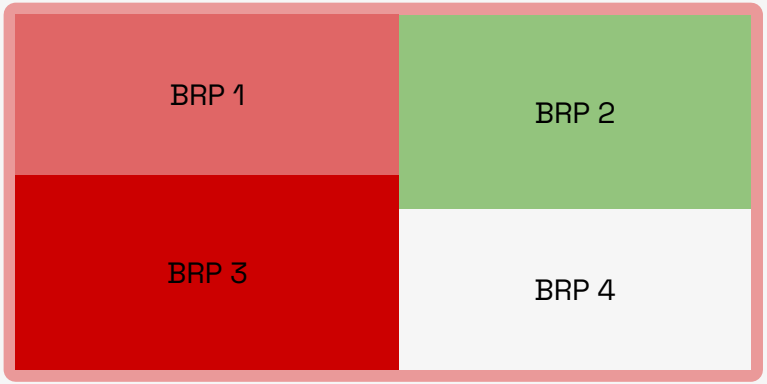
Therefore any imbalance must be counteracted

- Electricity grid frequency must be stable at 50hz
- Task of Belgium's Transmission System Operator → Elia
- System imbalance (SI) is the unintended difference between generation and load after balancing actions were performed

SI Forecasting: What is the purpose?

And why is it relevant for ML6?

- Accurate SI forecasts useful for Balancing Responsible Parties (BRPs)
- BRPs are mainly energy suppliers/retailers (e.g. ENGIE, Luminus)
- BRPs must adapt their own energy asset portfolio based on SI



TSO area

red - negative system imbalance
green - positive system imbalance

System Imbalance Forecasting

Goal of the project:

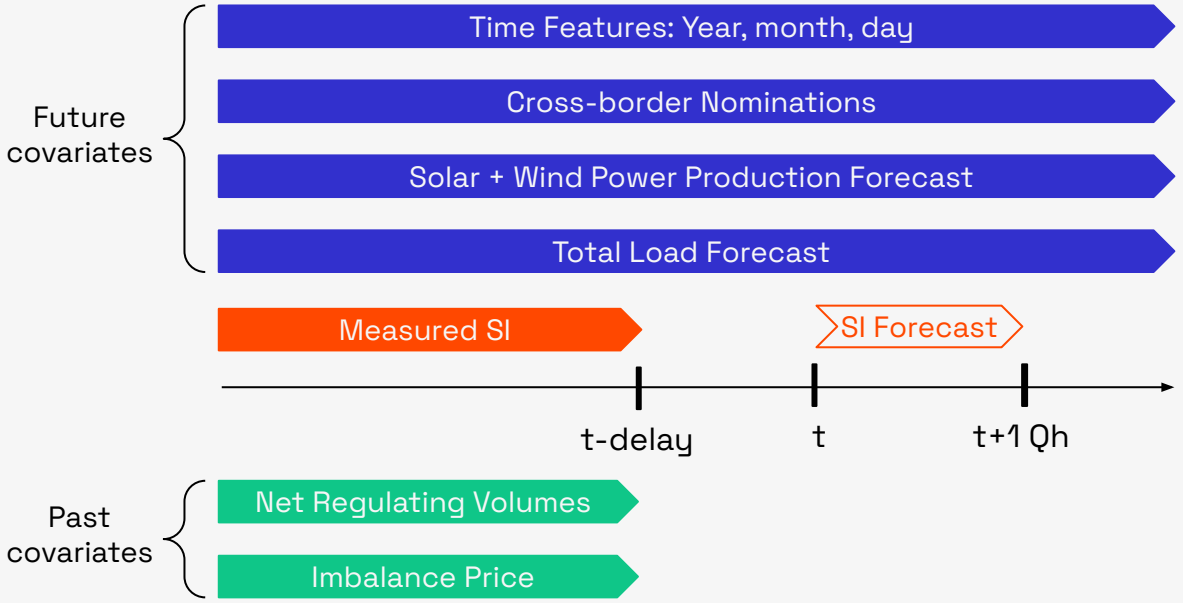
We worked with Luminus to implement ML models that forecast System Imbalance (SI) with higher accuracy than their existing solution.

SI Forecasting: Key Challenges

Initial ML model iteration

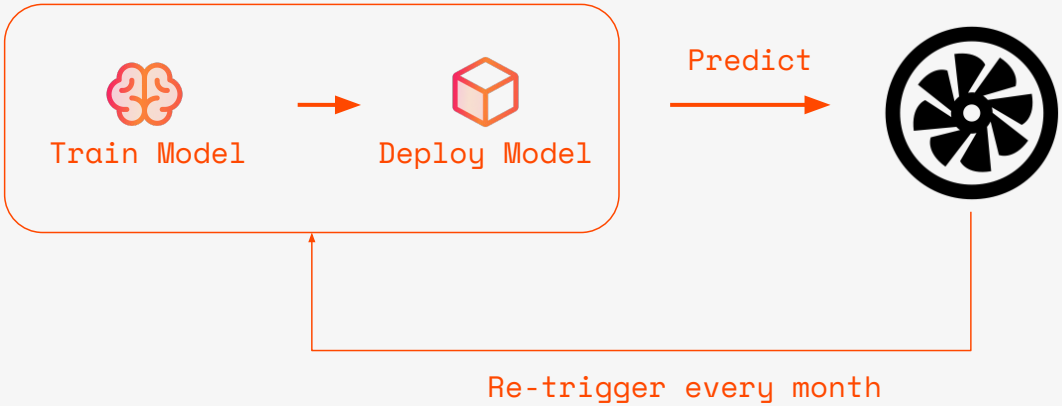
SI Forecasting: Input Data

- Data Source: Elia Open Data Platform
- Past covariates have a data delay
- Goal: Forecast future SI using SI measurement, future and past covariates
- Model: XGBoost



What happens if we don't implement MLOps?

Use case



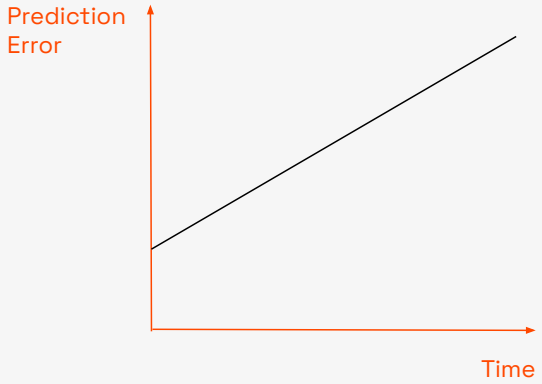
What happens if we don't implement MLOps?

Initially things worked fine

Experimentation

Industrialization

Until they didn't



Setting the scene

What happens if we don't implement MLOps?

When and why did it fail?

- Did the training data start drifting?
- Did the re-training pipeline fail?
- Was the model poorly designed in the first place?

If

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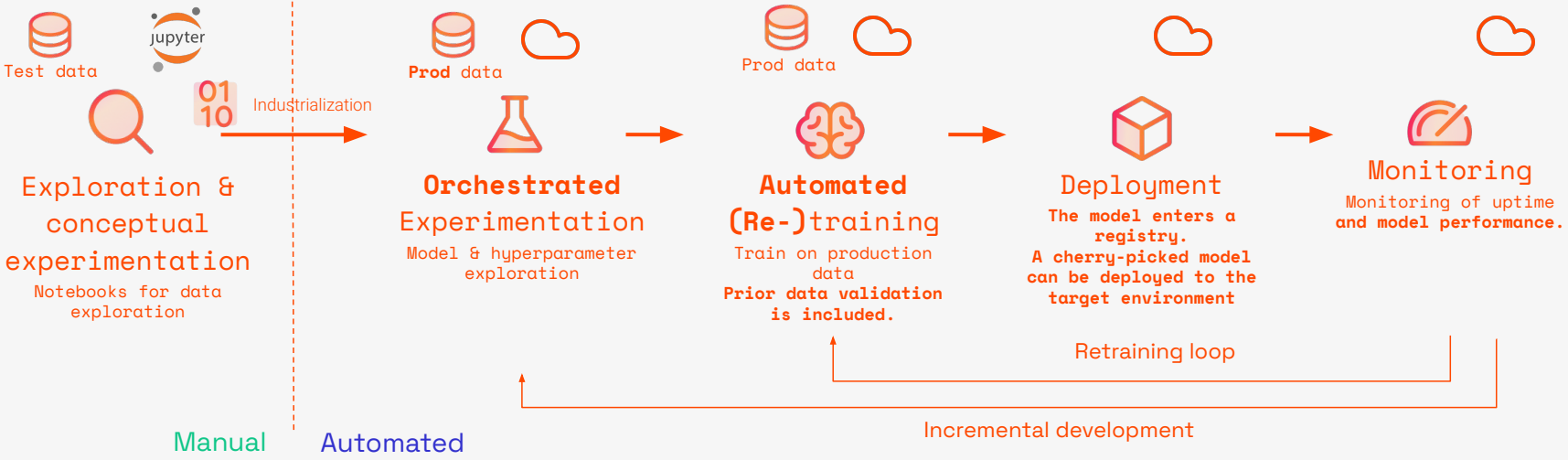
- e our

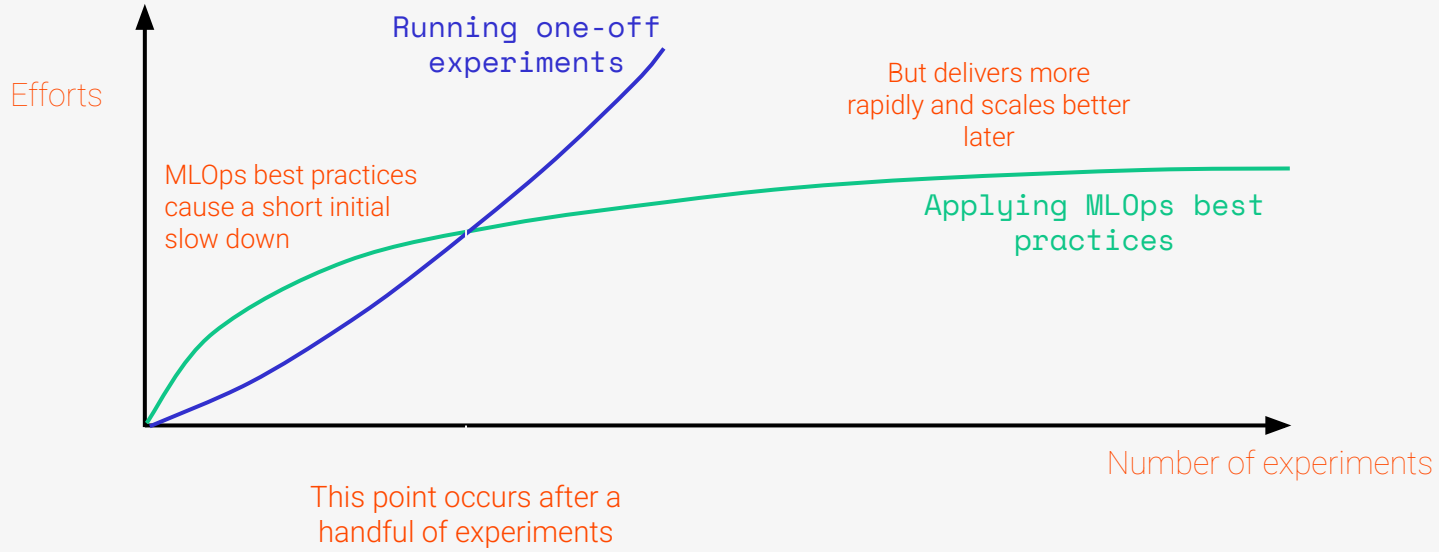
How does MLOps work?

Streamlined MLOps



Why MLOps?

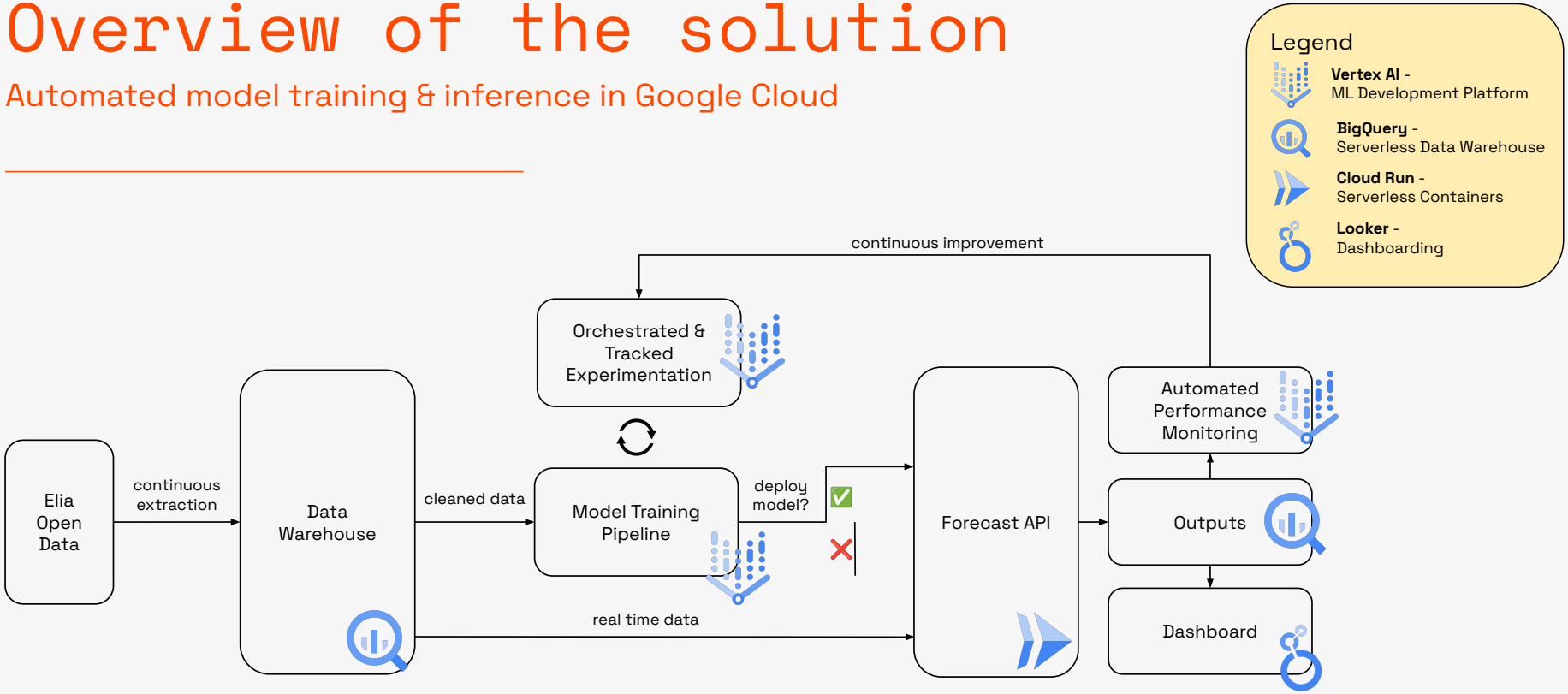
It pays off in the long term!



MLOps solution

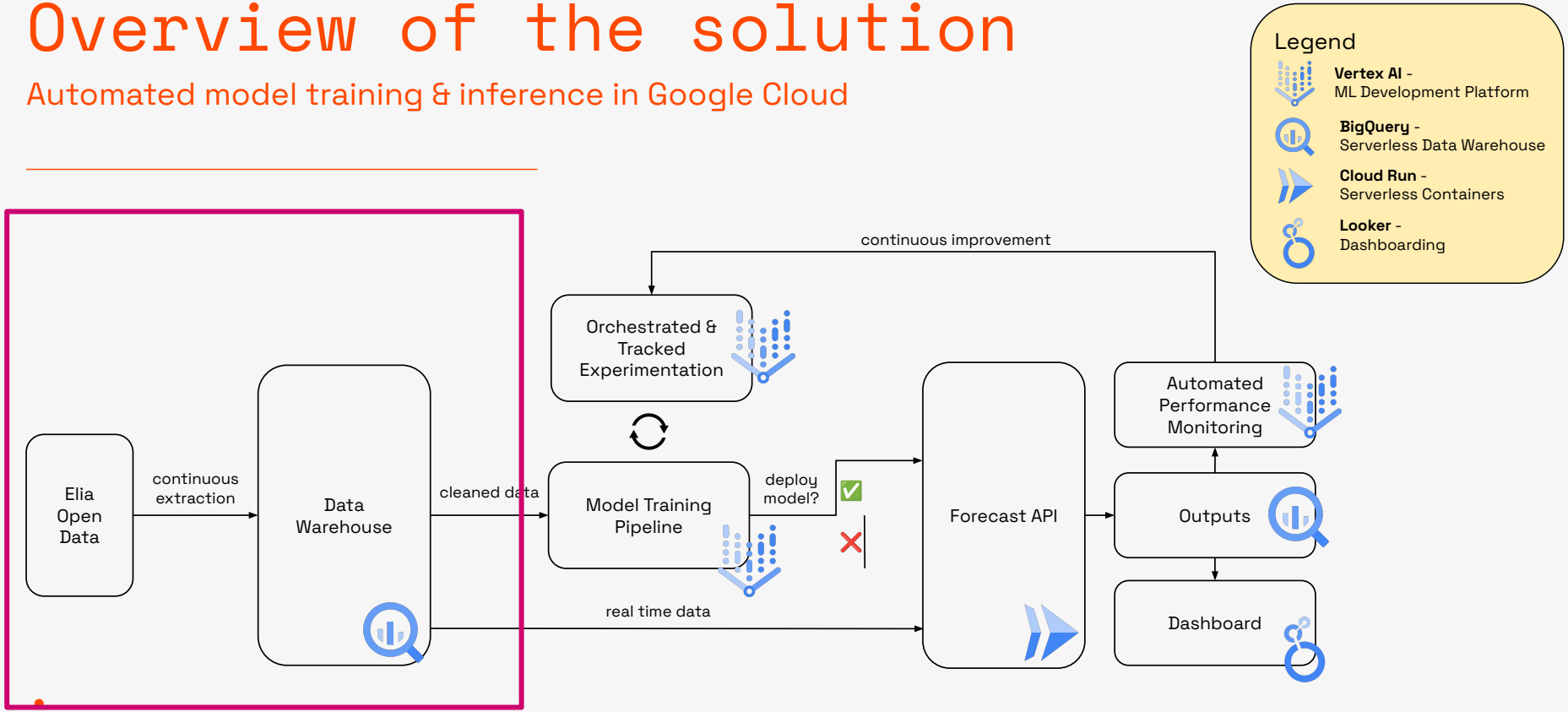
Overview of the solution

Automated model training & inference in Google Cloud

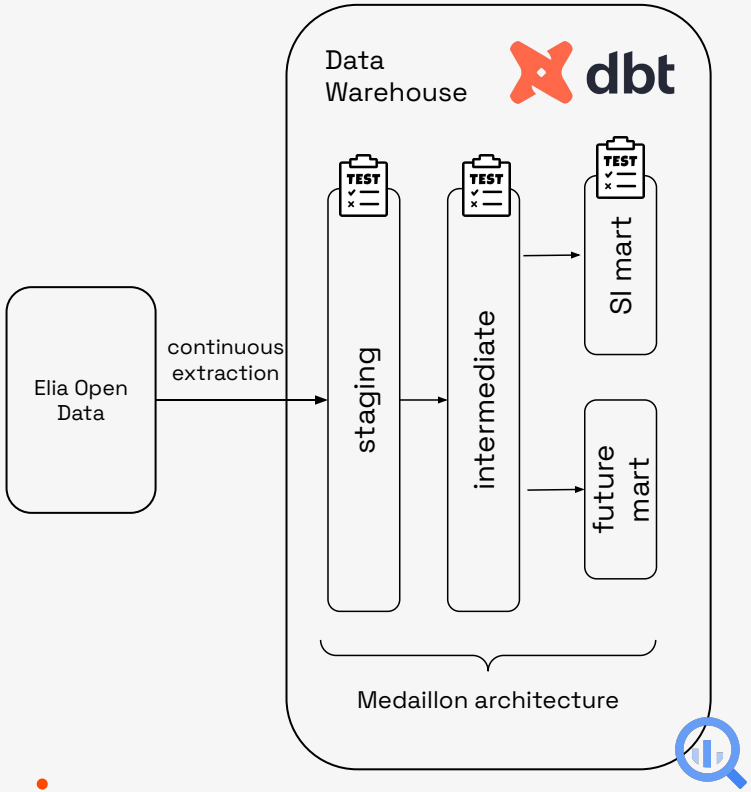


Overview of the solution

Automated model training & inference in Google Cloud



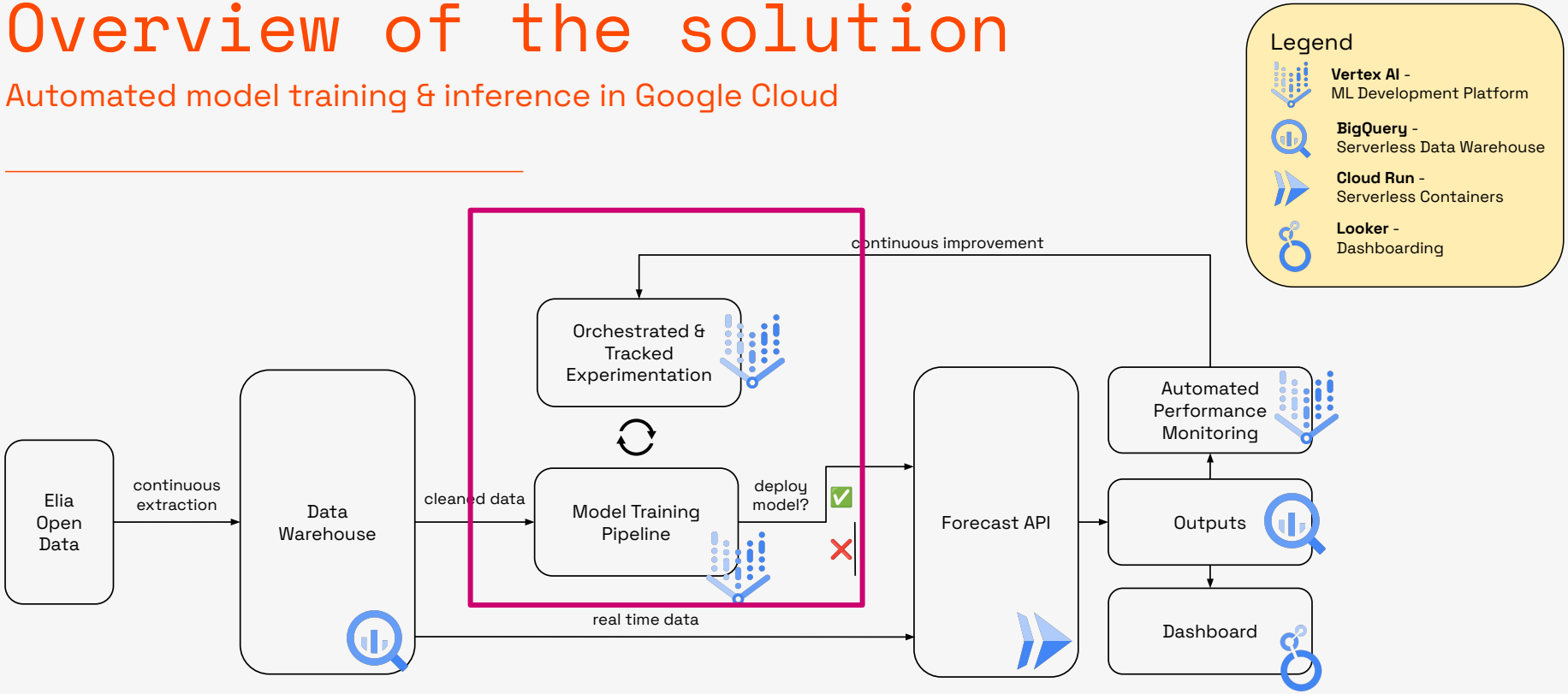
Data Layer



Data Layer Requirements	Solution
Receive live input data	CRON triggered Cloud functions
Data must be cleaned, transformed and exposed	Data warehouse medaillon architecture
Data must have certain formats	Verify via dbt tests

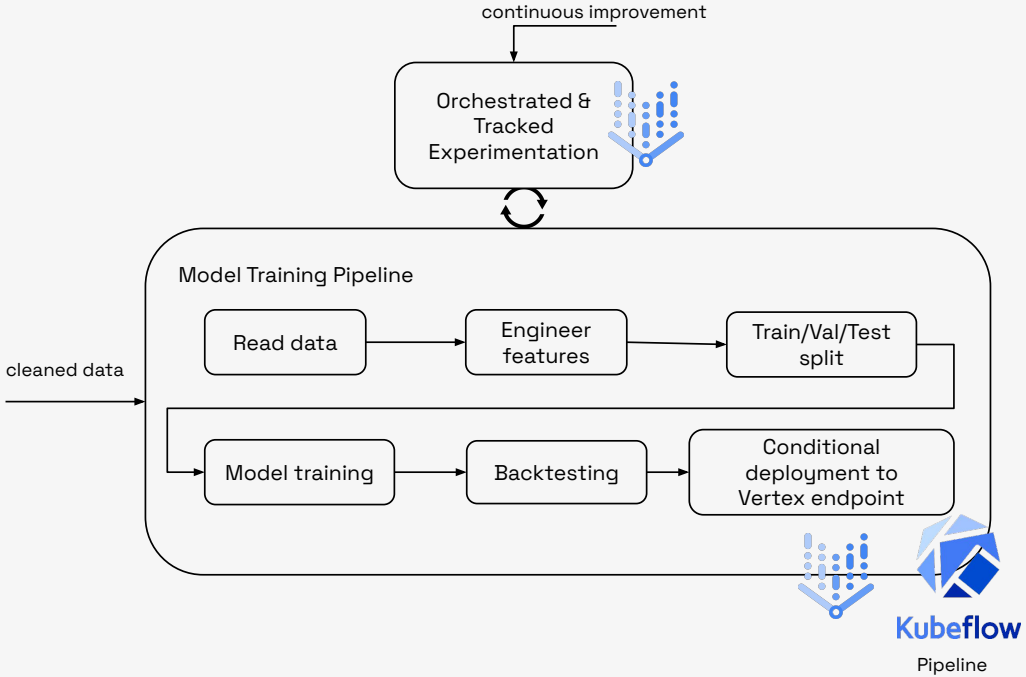
Overview of the solution

Automated model training & inference in Google Cloud

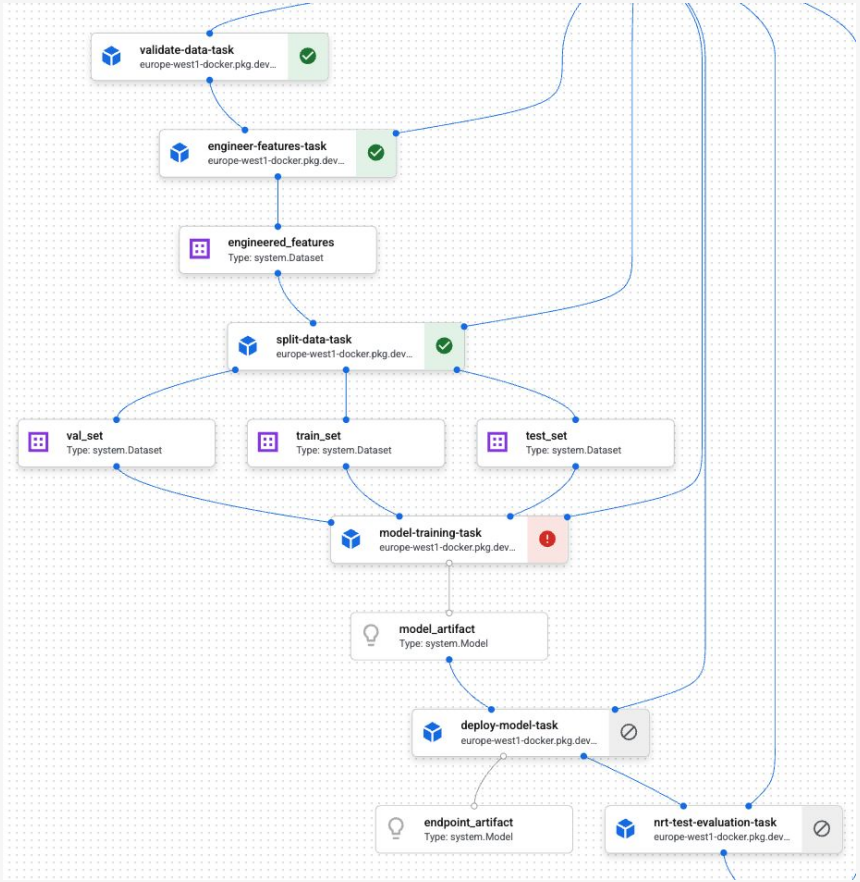


ML Pipeline

Conceptual flow



- Automated
- Reproducible
- Traceable
- Modular
- Improves collaboration

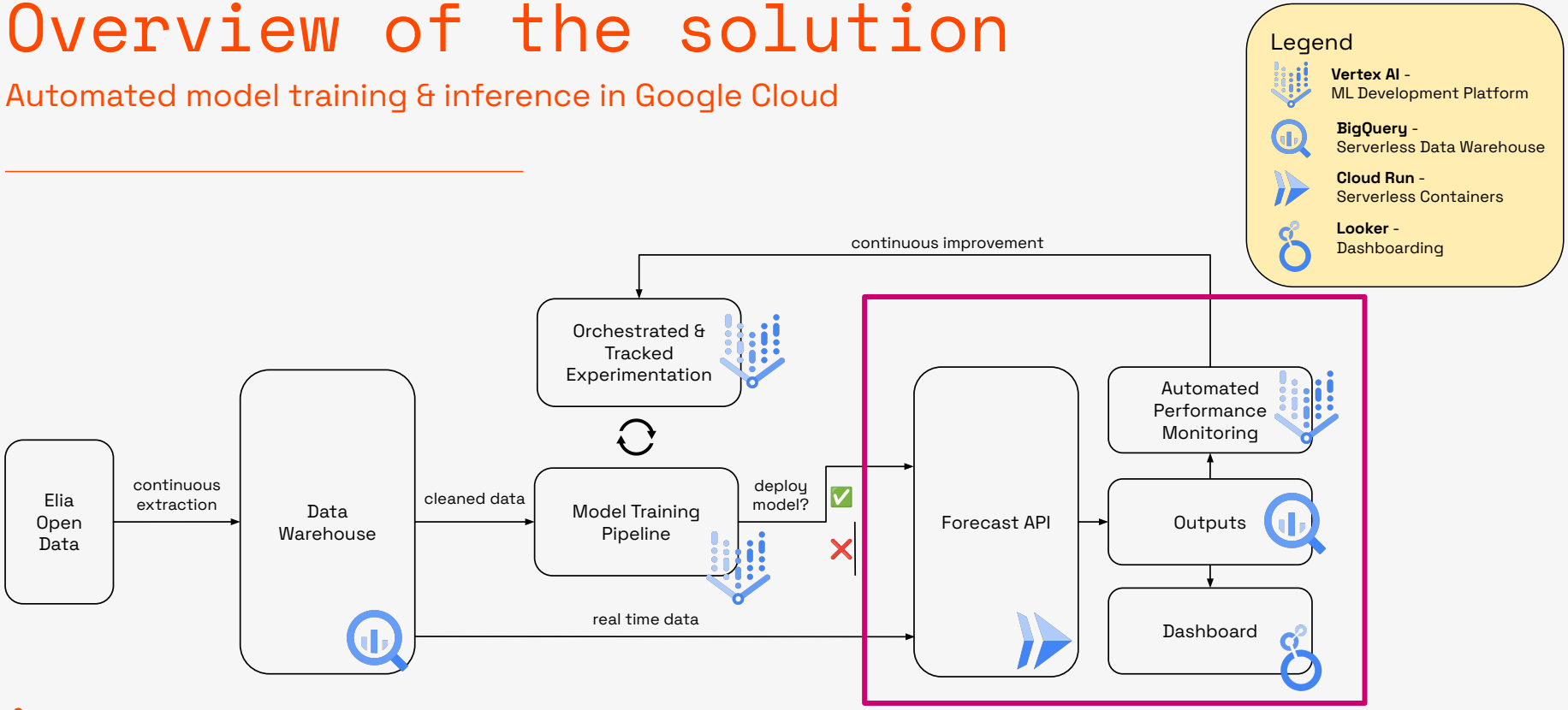


ML Pipeline

Overview of their Vertex Pipeline

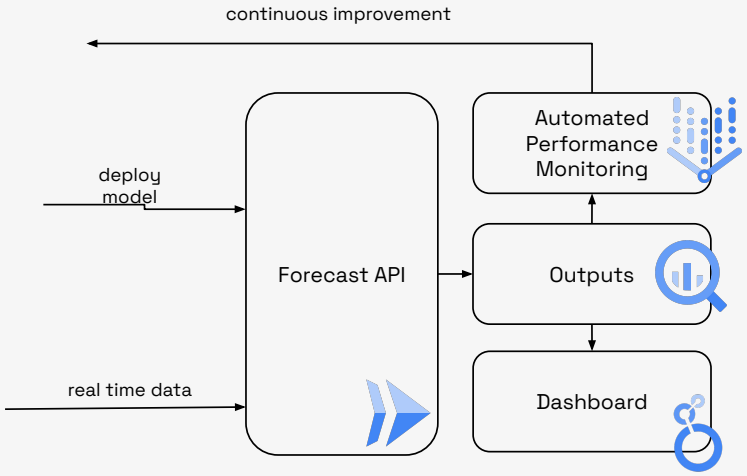
Overview of the solution

Automated model training & inference in Google Cloud



Model serving

REST API - deployed in a Cloud Run instance



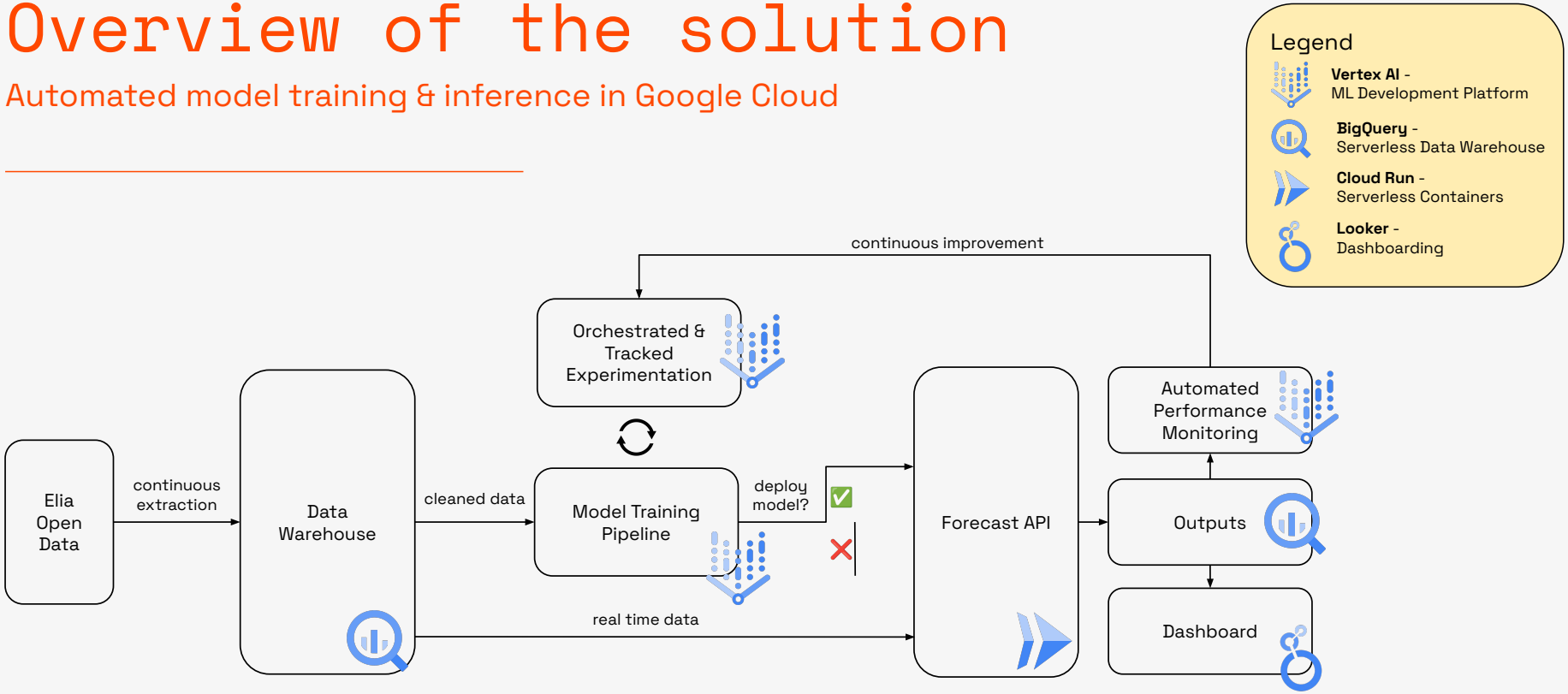
- REST API is used to serve the ML models
- It is packaged in a Docker container
- Which is deployed in a Cloud Run instance

Downstream systems can make a “request” to the API with input data and get forecasts. The API is served in “real time” (online serving).

Each outputs are stored. A monitoring dashboard is built using **Looker**.
(In this course we will see Streamlit for dashboarding)

Overview of the solution

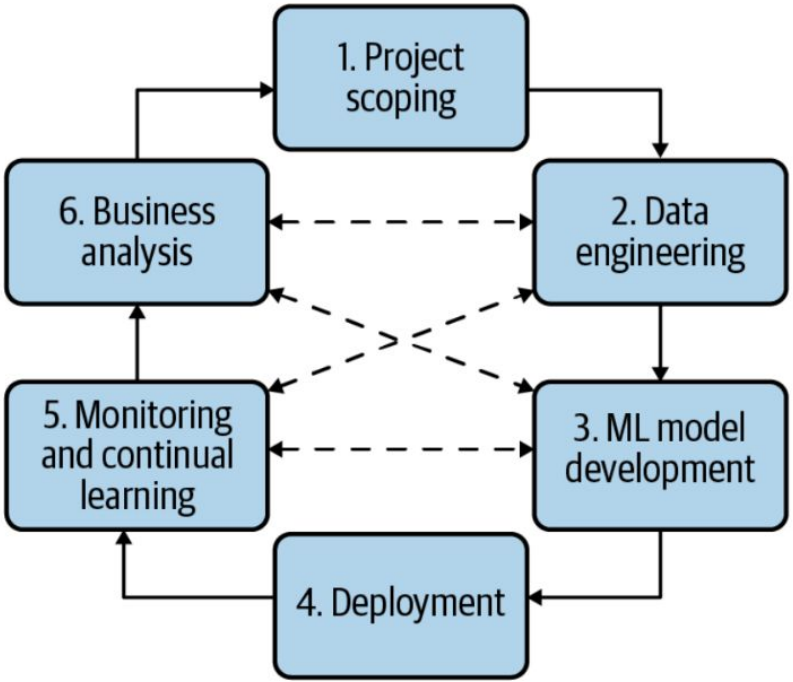
Automated model training & inference in Google Cloud



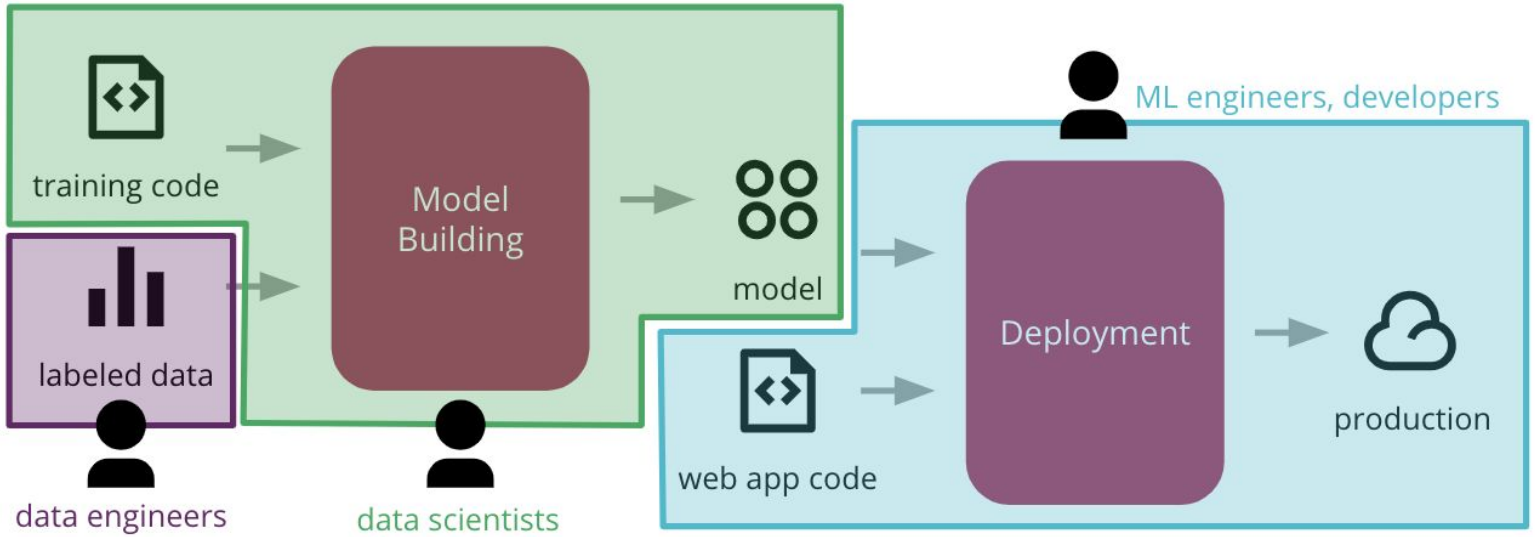
ML project organisation

Roles around ML projects

Typical ML project lifecycle.

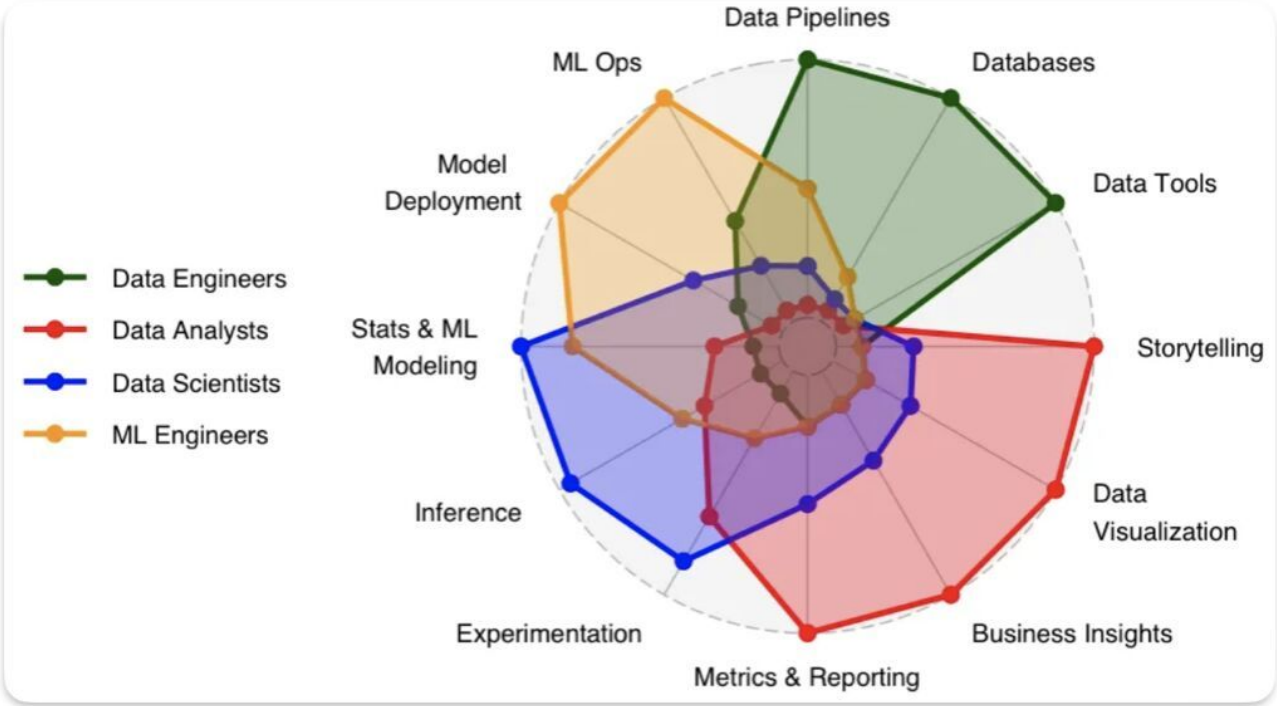


Roles around a ML system implementation.



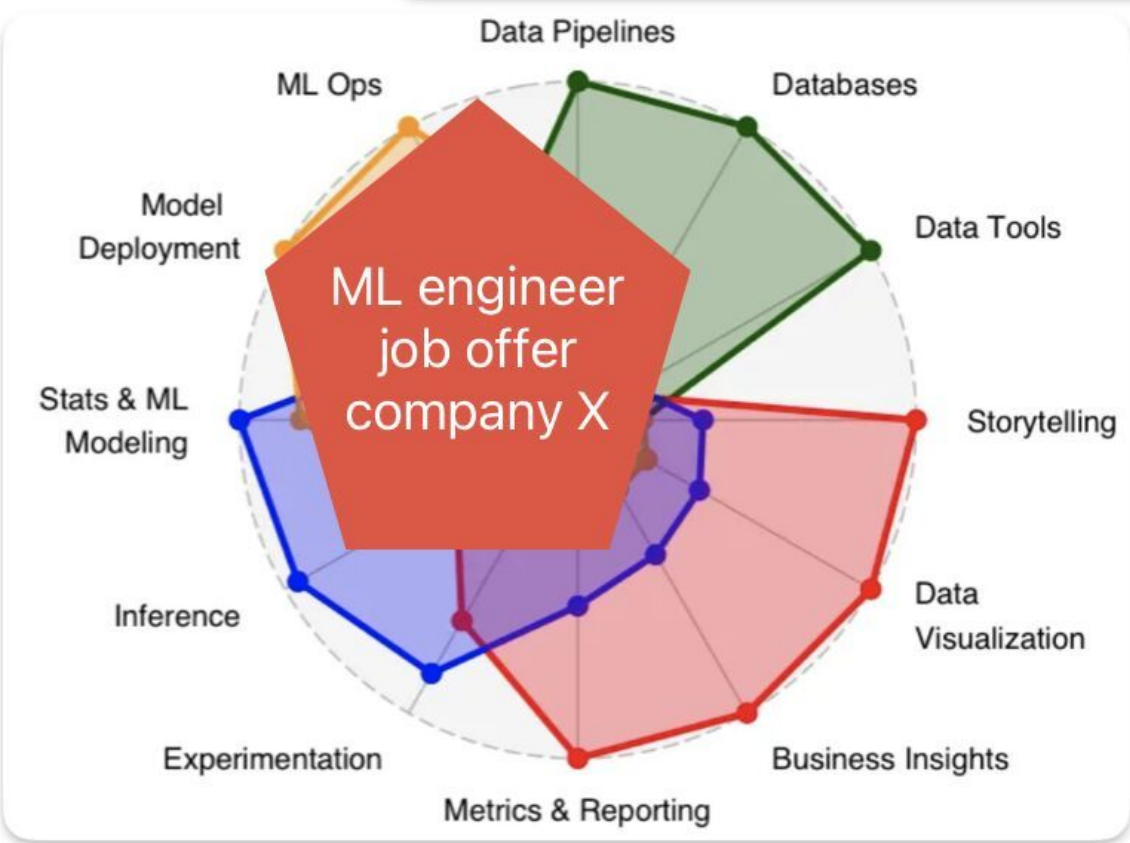
https://martinfowler.com/articles/cd4ml.html

Different set of skills per roles.



https://www.linkedin.com/posts/maria-vechtomova_data-ai-mlops-activity-7125095266403143680-9X-U/

In reality it's a bit blurry…



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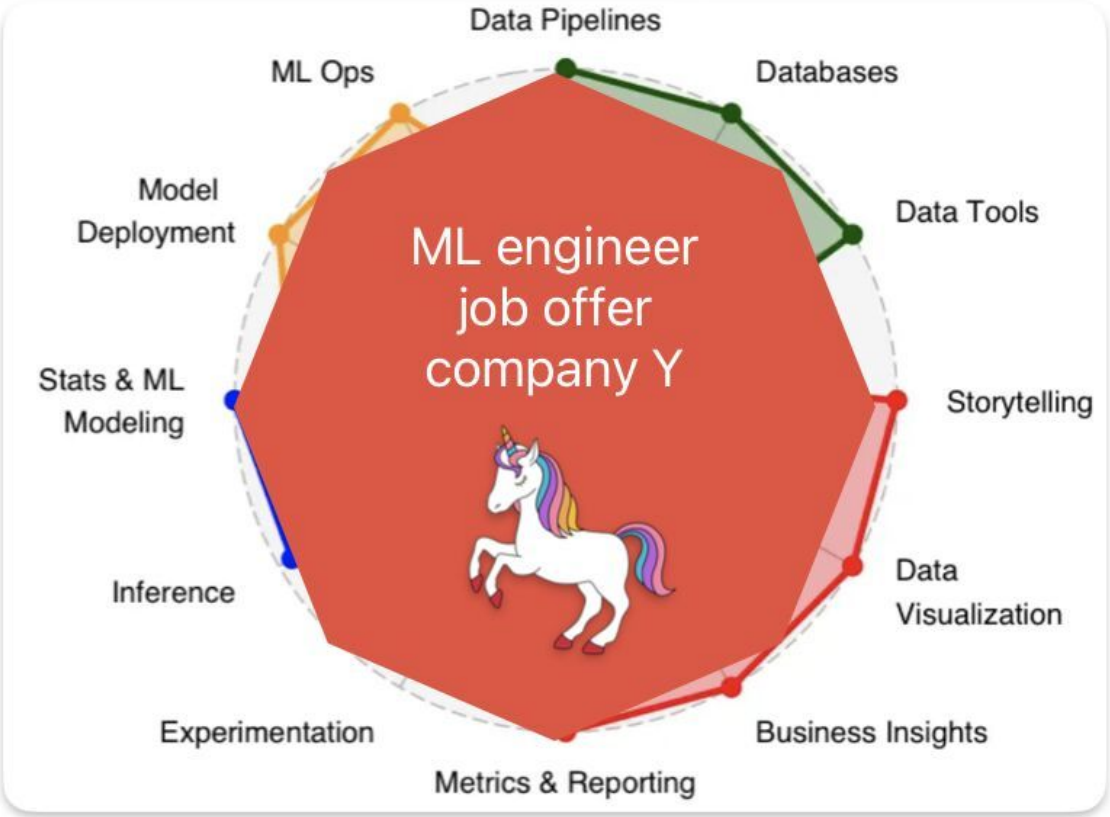

https://www.linkedin.com/posts/maria-vechtomova_data-ai-mlops-activity-7125095266403143680-9X-U/

ML Engineering skills are in high demand

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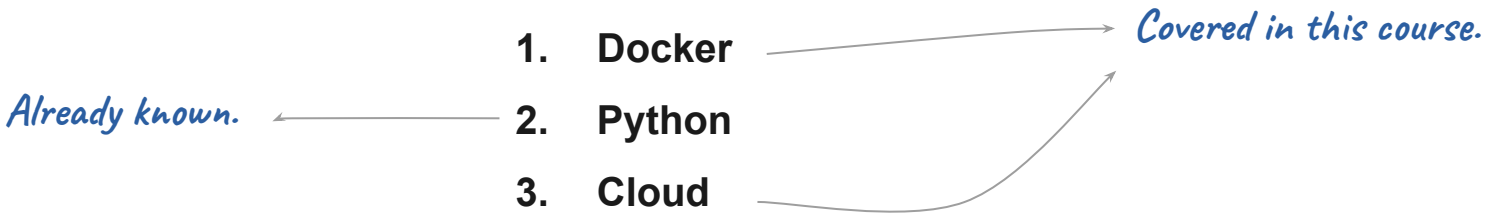
Study on demanded skills for MLOps engineers.

Looking at 310 job offers on MLOps/ML Engineering

Top 3 highest demanded skills:



https://marvelousmlops.substack.com/p/what-do-teams-really-want-from-an?utm_source=profile&utm_medium=reader2 (Q4 2023)

Project definition framework

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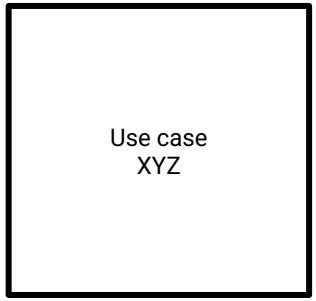
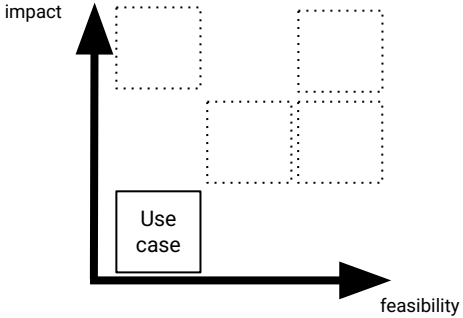
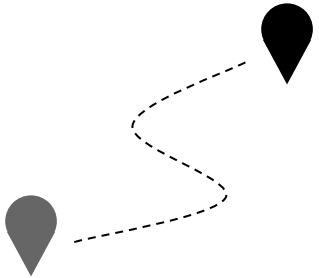
A process for ideating new AI project.







1 **Identify** AI opportunities

2 **Refine** selected use cases and their feasibility

3 **Prioritize** the use cases, select the one(s) to be implemented.

4 **Scope** the project. Build a technical design and implementation roadmap.

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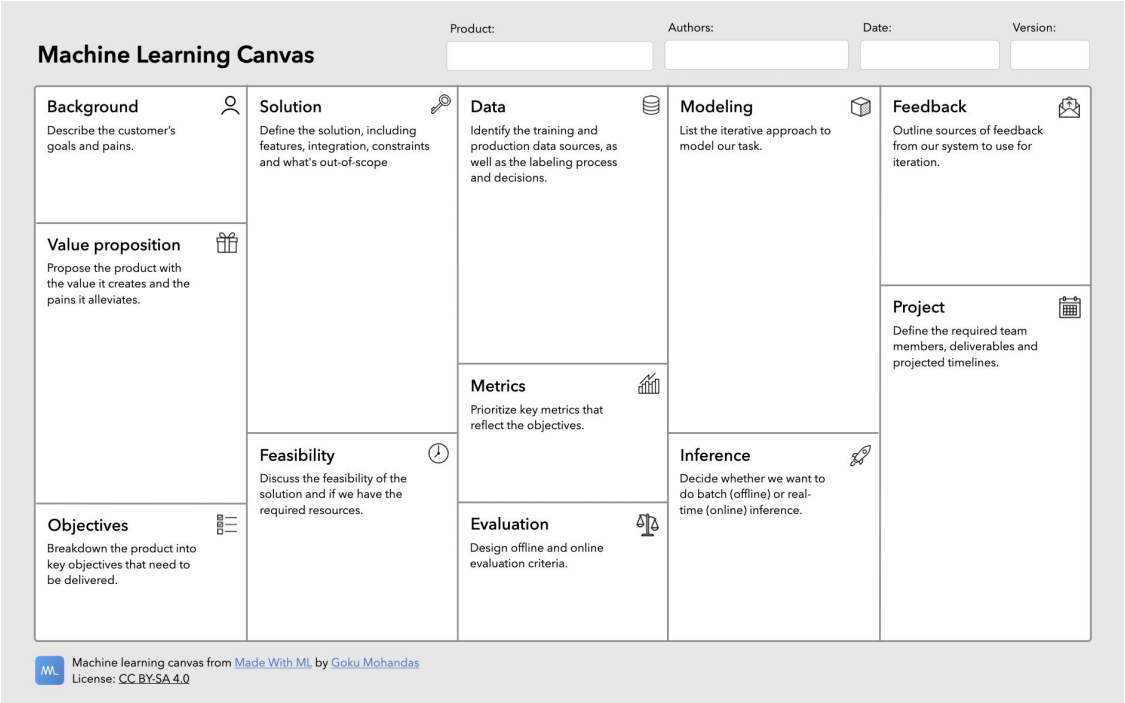
Define and scope your project.

Product design template



https://madewithml.com/courses/mlops/product-design/

Build different stages of your solution

Proof of Concept

Use easily available data to show that your model or solution can work.
Low efforts.
Prove the feasibility and value.
Iterate fast.

Minimum Viable Product

Just enough features for a small set of users to start using it.
Gather feedback and make sure that it is designed in an optimal way.

Productionisation / scaling

Build the infrastructure to finally deploy your solution and let users use it.
Gradual roll-out to more and more users in more and more markets.
Deploy better models, attract more users, go to new markets, maintain the solution, …

Maintenance

Keep the solution up and running.
Monitor resources and performance.
Update packages and dependencies (software around solution change).
Security and up-time.

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Build different stages of your solution

Use eas
to show
or solut
Low eff
Prove t
value.
Iterate

POC

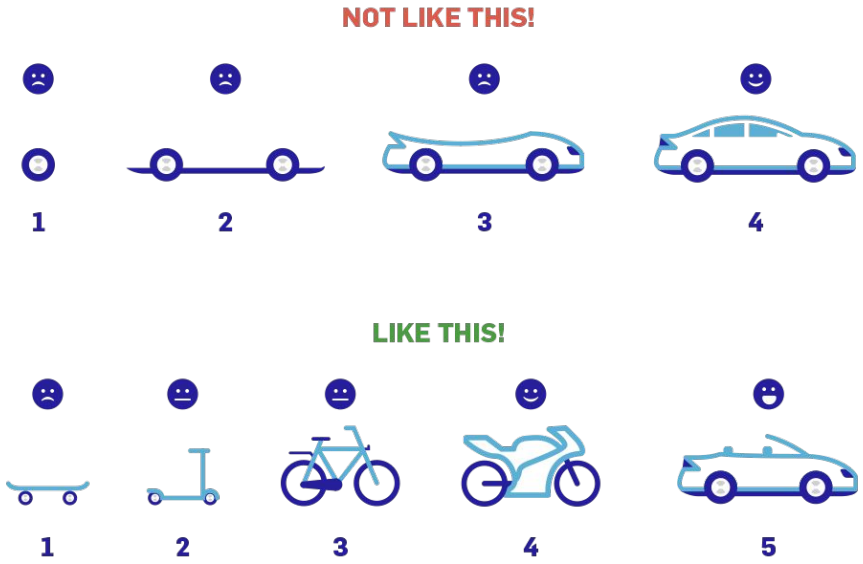
2 weeks

tenance

...

it's up...

At each stage, your product should be usable



Data science projects are challenging to bring to production

Breaking the myth

Forbes

VentureBeat

*"**87%** of data science projects never make it into production…"*

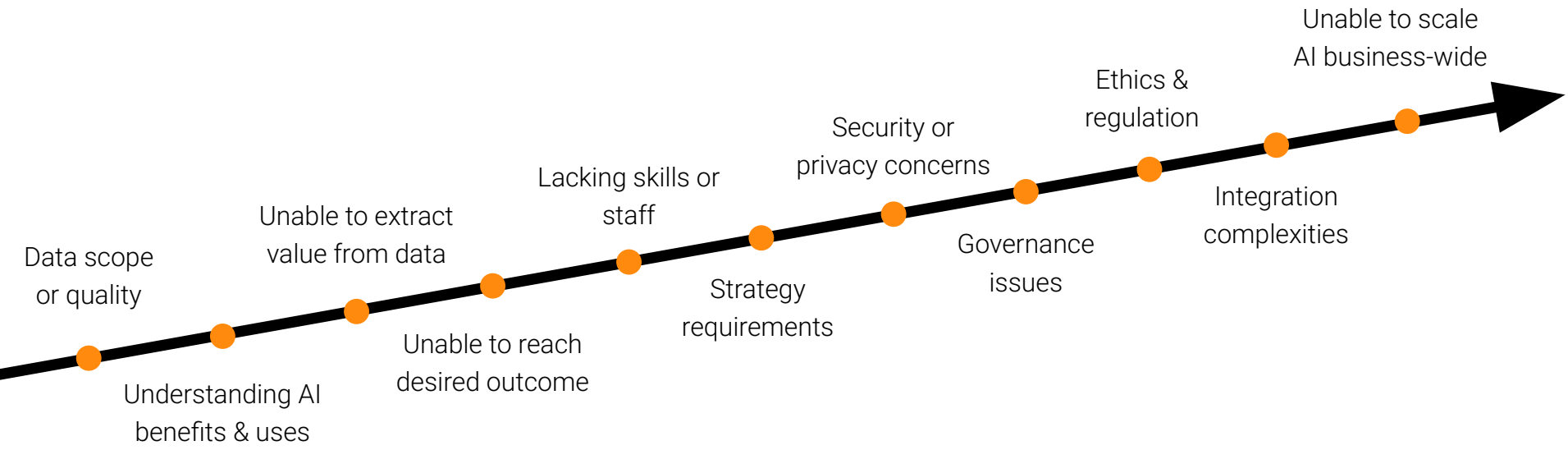
(Might not be a factual number...)

But data science project are still challenging to actually roll-out to the real world!

https://mtszkw.medium.com/why-do-87-of-data-science-projects-fail-and-are-we-sure-that-it-is-true-fe8b5ba1404c

AI Journey Challenges.

While AI is an enabler for strategic priorities, it doesn't come without its challenges.



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When not to use Machine Learning?

It’s not always the right solution...

- Clear specifications are available
- Simple heuristics are good enough
- Cost of building and maintaining the ML system outweighs its benefits
- Correctness is of utmost importance
- ML is used only for the hype (e.g., to attract funding)

Examples of these?

(Really) accurate predictions might not even be that important

The over-optimizing paradox

- "Good enough" may be good enough
- Prediction critical for system success or just an gimmick?
- Better predictions may come at excessive costs
  - Data is often the bottleneck
  - Cost of producing more data (labeling, infra, collection, …)
- Better user interface ("experience") may mitigate many problems
  - Explain decisions to users with Explainable AI (XAI)
- Use only high-confidence predictions?

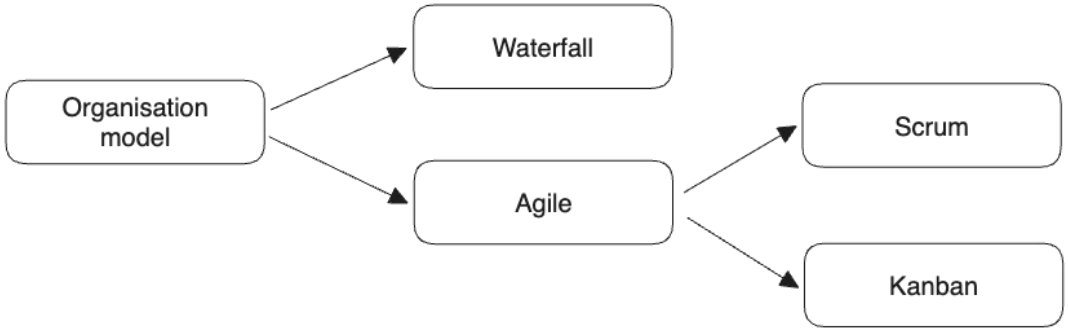
Critical thinking when doing the project definition

Ask the right questions - make sure you have a solid use case before you start building anything.

- **Baseline**: What is the performance of an alternative to ML? How do simple heuristics or human guess-predictions perform?
- **Probabilistic**: ML is by definition not deterministic. Are probabilities/ranges fine for this use case? E.g. for demand forecasting the model can make errors, for self-driving cars not…
- **Precision / recall**: Are both important? If not, can I make it a success by sacrificing one? E.g. for fraud detection we can raise a warning on false positive, but cannot have false negative…
- **Interpretability**: Do we need to explain why the model makes specific decisions? If yes, can we?
- **Do not reinvent the wheel:** Are there existing open source or 3rd party solutions? Did anybody in my organisation work on something like this?

Working “Agile”

Different models for organising an IT project



Waterfall model

Models for organising IT projects and teams

Organise a project as a **waterfall**, flowing down **sequentially** through 5 phases. It is **rigid**, **structured** and **linear** (it is not Agile).

Decision maker team sets a detailed plan for the whole project implementation, with limited flexibility.

Waterfall methodology

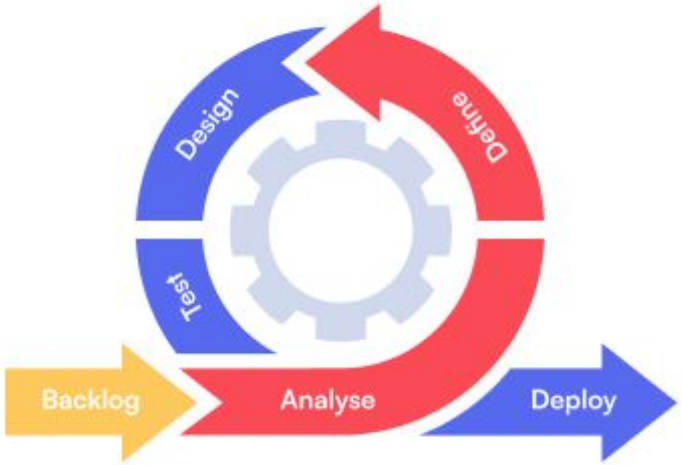
Agile model

Models for organising IT projects and teams

Iterative approach to delivering a project, which focuses on **continuous releases** that incorporate **customer feedback**.

Ability to **adjust** during each iteration promotes **velocity** and **adaptability**.

This approach is different from a linear, waterfall project management approach, which follows a set path with limited deviation.



Agile methodology

Agile:
Scrum vs Kanban

Kanban methodology

In Japanese, kanban literally translates to "visual signal."

- Originally comes from *lean manufacturing* in Japan (at Toyota)
- Simple and clean application of Agile
- Matches the amount of Work in Progress (WIP) to the team's capacity - *Just In Time (JIT)*
- Minimal set of rules - easy to pick up for new software engineering teams

Advantages

+ Planning flexibility
  - Once done with an item, pick up the next on the backlog
  - Product owner can update the backlog without disrupting the team
+ Short time cycles
  - Time for a unit of work to cycle through the whole process
+ Fewer bottlenecks
+ Visual metrics, transparency

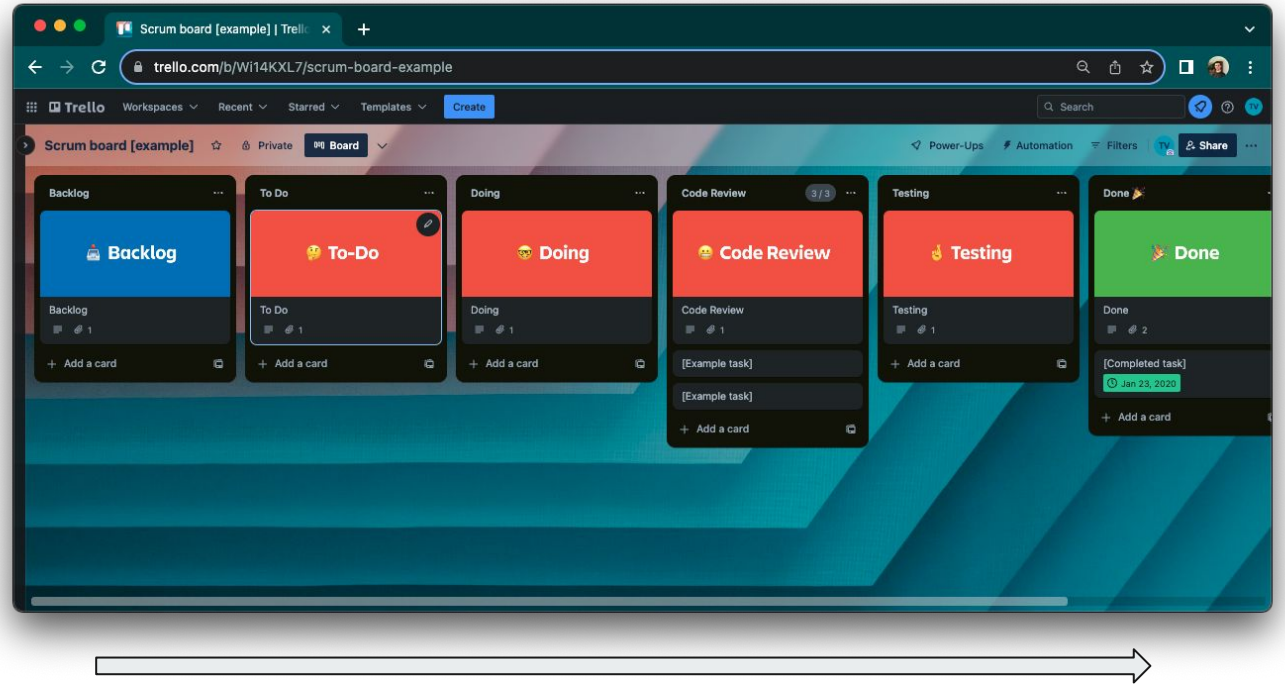
https://www.atlassian.com/agile/kanban

Kanban board

The kanban board is filled with kanban cards (aka tickets or tasks).

New tasks are added to the backlog.

They are then gradually moved along the board.



https://trello.com/

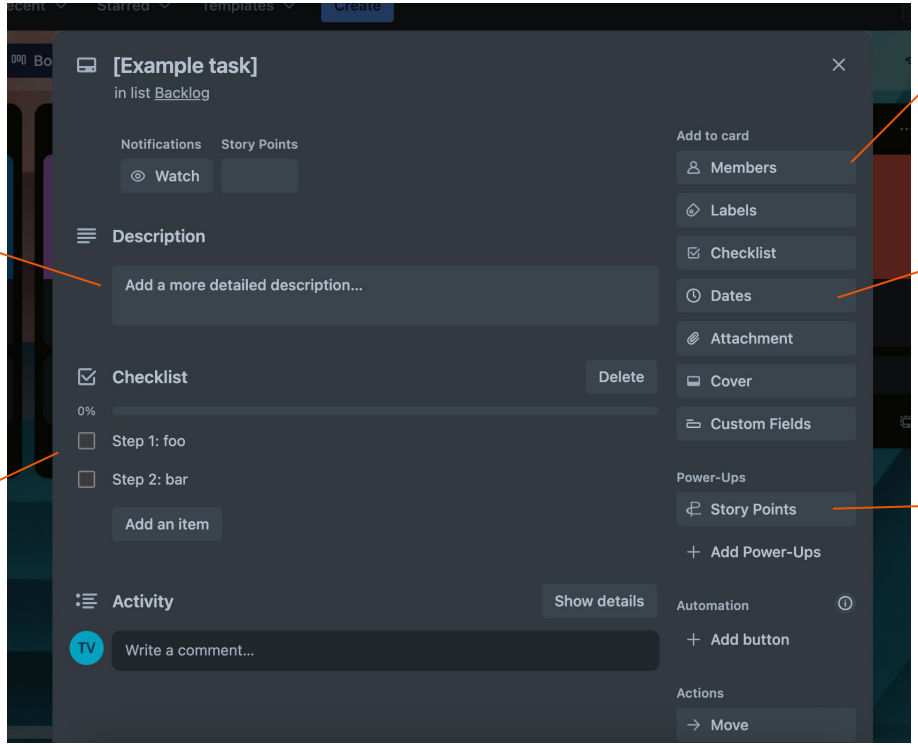
Kanban card

A detailed description of what should be done and how ensures quality of delivery and alignment in the team.

Define task

Include definition of done!

Break up tasks into steps



Assign task

Ideally timebox (not always)

Define efforts...

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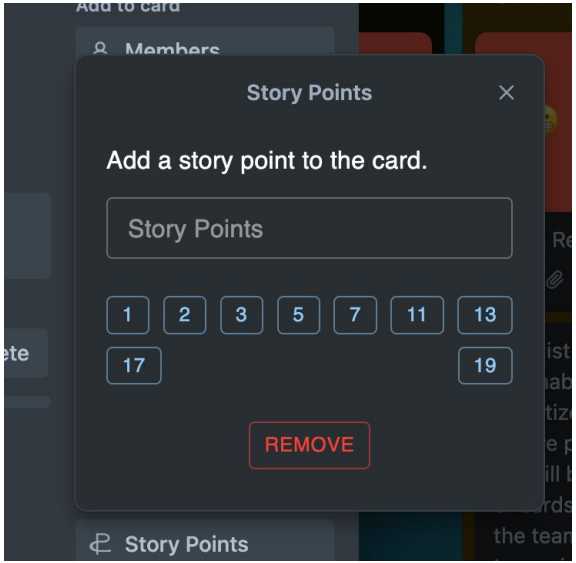
Kanban card



Story points are a measure of *effort* and *complexity* of a task.

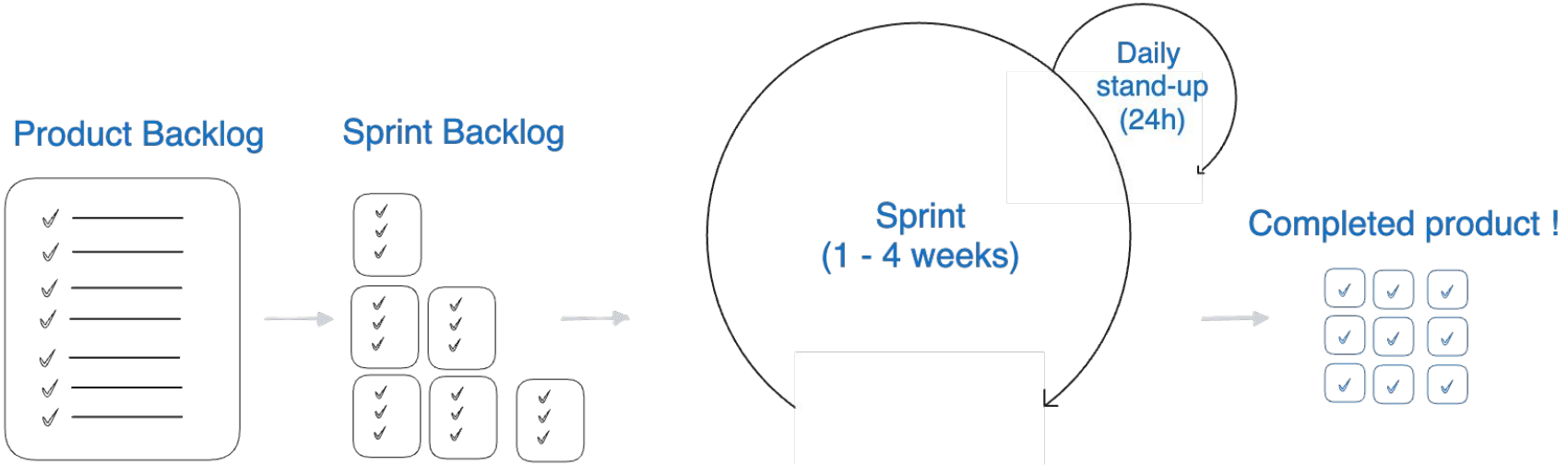
Follows the fibonacci scale.

Sometimes voted on
(e.g. https://www.pointingpoker.com/)

If you want more information…

https://www.youtube.com/watch?v=CD0y-aU1sXo

Scrum methodology

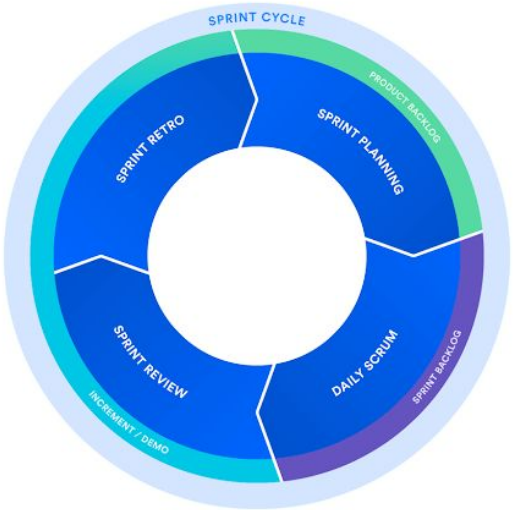


Scrum methodology

Sprint organisation

Each **sprint cycle** will include (1-4 weeks per sprint cycle):

- **Sprint planning**: Before each sprint, plan and add tasks from the product backlog to the sprint backlog.
- **Refinement session**: The technical team refines each ticket into a concrete implementation plan (approach, dependencies, definition of done, …).
- **Daily stand-up** (aka daily scrum): During the sprint, have dailies to update the scrum board, similar to kanban board.
  Everyone state what they have done the day before, what they will do today and any blockers they might have.
- **Sprint review**: Casually present the work that was done in the last sprint to the rest of the team (definition, celebration and transparency).
- **Sprint retrospective**: Feedback on what went well and what can be improved regarding last sprint.



https://www.atlassian.com/agile/scrum

Why are “daily stand-up” meetings called that way?

Why are “daily stand-up” meetings called that way?

Goal is to make the meeting efficient.

All team members have to answer a fixed set of questions such as:

- What did you do yesterday?
- What did you do today?
- What, if anything, is blocking your progress?

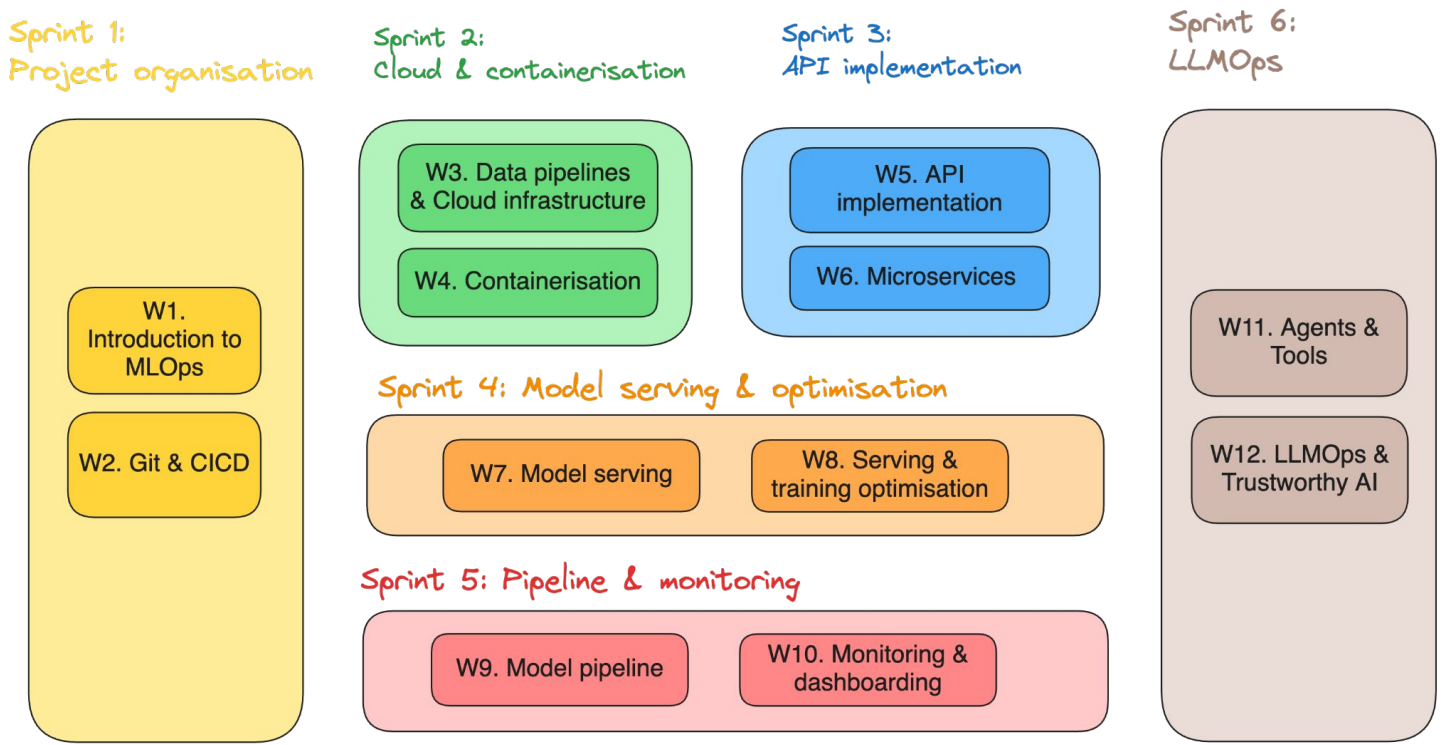
The scrum team

Roles & responsibilities

- **Product Owner**: Represents stakeholders' interests. Selects what is relevant to work on considering product objectives. Define user stories, priorities backlog and decide on product's direction.
- **Scrum Master**: Coach for the team. Ensures the best following of the scrum framework. Maintains the scrum board and backlog, facilitates and leads meetings and addresses obstacles.
- **Scrum Development Team**: Cross-functional developer team (data scientists, ML Engineers, data engineers, DevOps, front-end engineers, …). Delivers a quality product.

https://www.atlassian.com/agile/project-management/scrum-board

This course follows sprints!



MLSD Course structure

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Objective for this course.

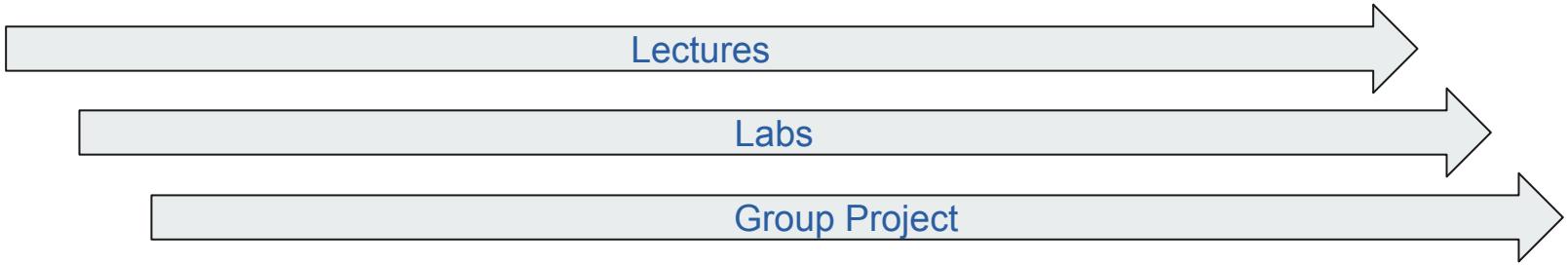
This course will provide you with concepts, tools and practical skill enabling you to design and build fully operational ML application 🛠️

The tools covered in this course are selected based on usability, performance, popularity and accessibility.

Goal is to provide:

- Theoretical concepts
- Technical tools & skills
- Practical real world practices

Structure of the course



Relevant

Focused on core concepts of building ML applications. Tailored choice of current best practices.

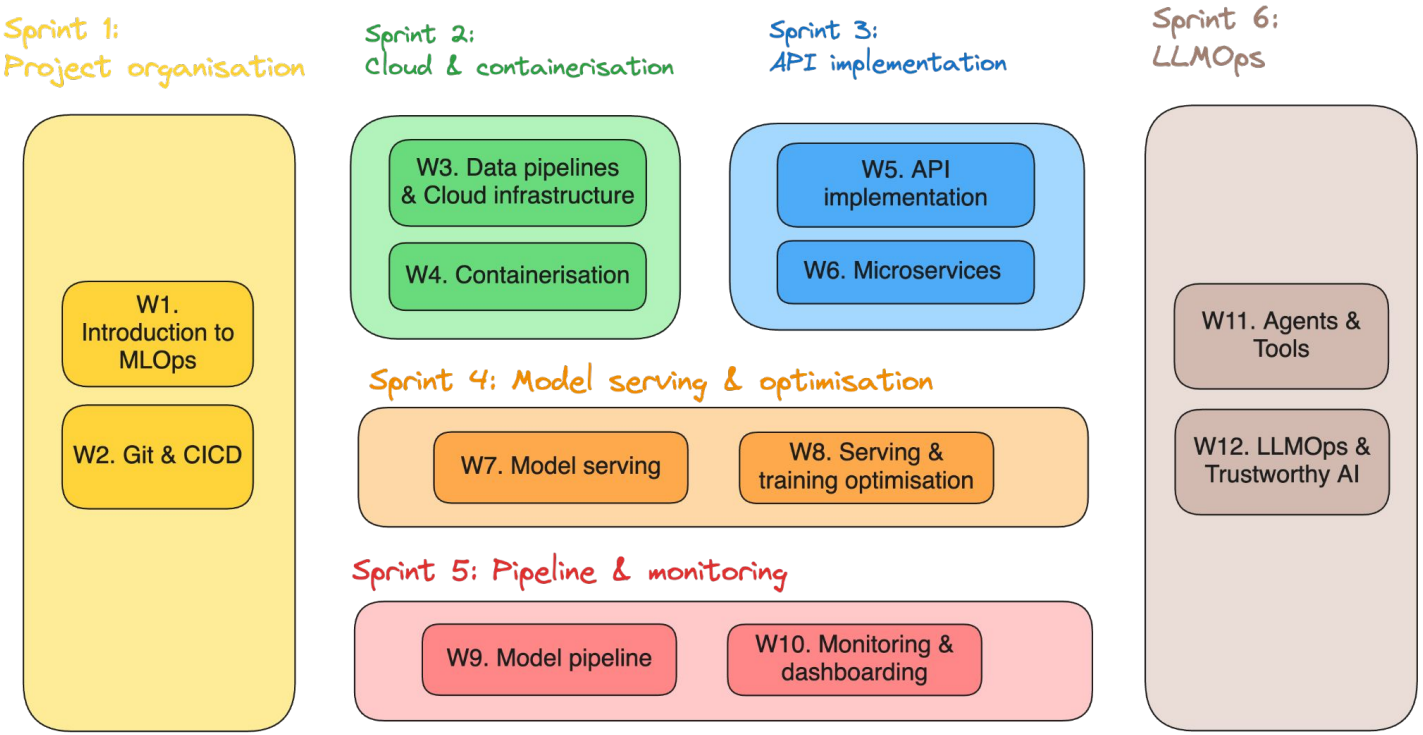
Practical

Concrete Labs, resources, real life examples, time to experiment, support line, …

Engaging

Interactive class session.
Healthy tempo (break out exercises, QA, …).

Course outline

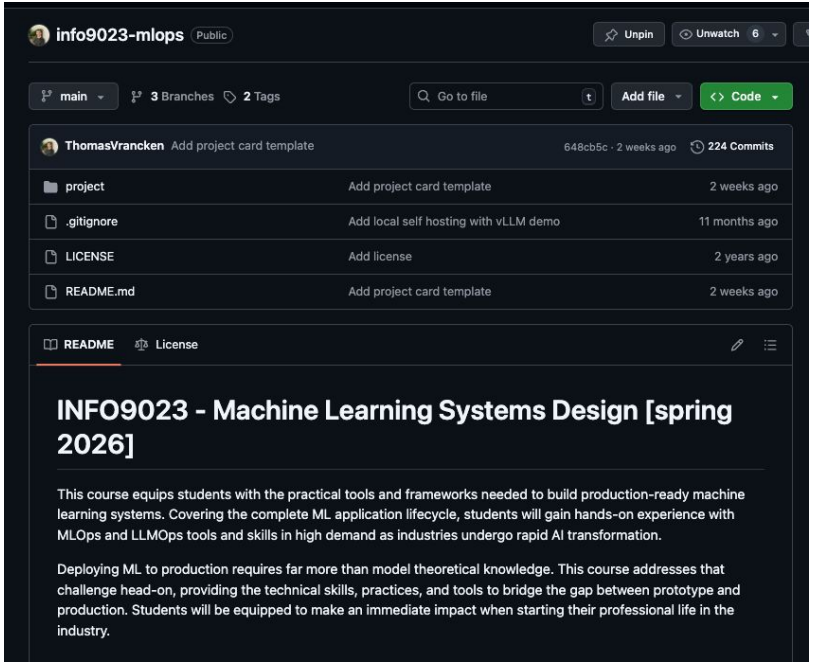


Course material

Everything is on Github!

- Project info
- Lecture & labs (before the class)
- Directed work
- Practice exam (before the exams)

https://github.com/ThomasVrancken/info9023-mlops



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Practicals & communication

Class practicals

- We meet every Monday from **9:00** to **12:30**
- ~2h30 of lecture/directed work (& break). Remaining of the time can be spent working on your project.

Communication

- Discord: https://discord.gg/5gucJ9CV
- Open office hours on **Monday afternoons** (office Number I 77 B in Montefiore)

Type of work & grade

Your final grade is divided in:

- **Exam (40%)**: Oral exam on the topics covered during the lectures
- **Directed work (10%)**: Pass/fail on practical exercises given at the end of the courses. Each TD is worth an equal proportion of the total 20%.
- **Group project (50%)**: One large group project, see next slides.

Directed work

- You are given an **assignment** to do at the end of the course, in class.
- The teaching staff is there to **support** 🧑‍🤝‍🧑
- You need to upload your results to **Gradescope**
- In most cases **by the end of the day** (we will confirm the deadlines)
- You will get a **pass/fail** grades

Project

Project information is also on Github:

Organisation

Build one ML system throughout the course. The application is picked by yourself.

- **Teams:** 2 - 3 students
  - Form group by next week!
  - Let the teaching staff know if you don't have a group and you'll be assigned one
- **Structure**
  - The building blocks to be implemented in the project follow the course's **6 sprints**.
- **You're in the driving seat!**
  - Many building blocks are optional. You are free to choose the overall design and tools used for your project. Experiment and ask questions if you have any.

Project

Handovers

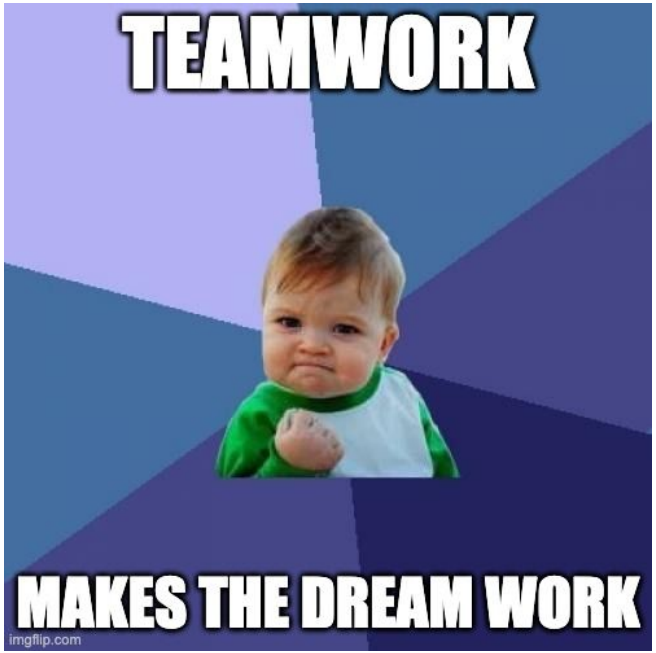
1. There will be **3 milestone meetings** where you can present your results
2. You must **submit the codes** for your implementation **at each milestone**:
   - You do so by creating a Pull Request (PR) from develop → main
     - ⚠️ You must follow Gitflow principles: Work on *feature* branches based on *develop*. Once per “release” (aka Milestone), you merge *develop* into *main*.
   - Send a link to that PR by email to the teaching staff before the milestone meeting! We will not accept late PRs
   - Make sure to document your codes:
     - Include Markdown files explaining key components in the `docs/` directory (`e.g. docs/DEPLOYMENT.md`)
     - Write a clear description of your PR when creating it
     - Write readable, structured and well documented code → Points are deducted if we cannot easily verify how something works
   - We will ask you questions about your codebase during the milestone meeting. If you cannot answer detailed question we will assume it was writen by an AI and will deduct some points.

Project

Grading & collaboration

We want to foster **teamwork**!

To incentivise every team member to contribute, we will give **individual grades**.



Project

Grading & collaboration

$$Individual\_grade = project\_grade * individual\_contribution$$

$$Individual\_grade \in [0, 20]$$
$$project\_grade \in [0, 20]$$
$$Individual\_contribution \in [0, 1]$$

Project

Grading & collaboration

$$Individual\_grade = project\_grade * individual\_contribution$$

$$Individual\_grade \in [0, 20]$$
$$project\_grade \in [0, 20]$$
$$Individual\_contribution \in [0, 1]$$

Project grade will take into account

- The implementation and maturity of each of the work packages (see grid of “work packages” per sprint)
- The quality of your codes and documentatin
- Your presentations

Project

Grading & collaboration

$$Individual\_grade = project\_grade * individual\_contribution$$

$$Individual\_grade \in [0, 20]$$
$$project\_grade \in [0, 20]$$
$$Individual\_contribution \in [0, 1]$$

Individual contribution is calculated based on

- Participation in milestone **presentations** (make sure to spread talking time to represent what you each did)
- Ability to answer **questions**
- Contribution to **code implementation** in github
- A question **form** sent to the team at key moment(s)

Of course, for a healthy project with an even work distribution, all students can get an individual contribution of 1

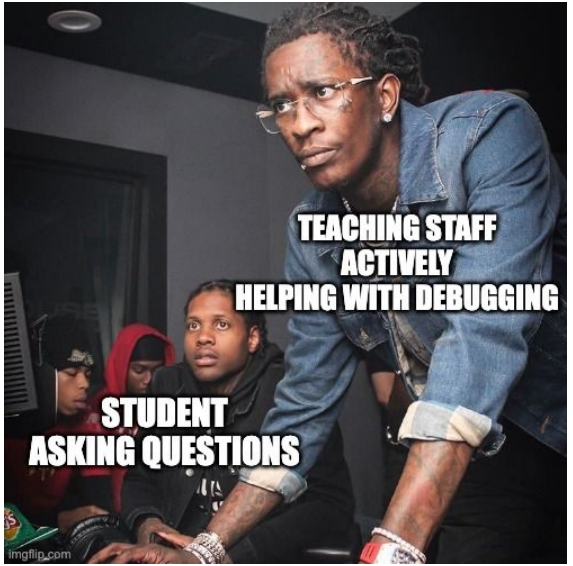
Project

Support

- You will learn new tools!
- At first, some of those tools might be less straightforward to debug
  - Running things in the cloud means that your logs are not directly on your computer
  - There will be new dimensions such as access rights, connections, …

That is why…

- The teaching staff is there to support!
- We will stay after each lesson to help with any issue, question, bug… you might have!
- **Make sure to attend the class and actively ask questions about the direction of your project, choices you make and any issue/bug you might have!**
  - If you implement everything at the last minute there will be less opportunities to ask us questions



Project

Guiding principles

- Learn, learn and learn!
- Find an interesting project to work on → with a real world usage
- Come up with your own design and toolstack
- Focus on relevant parts of your specific system
- Motivate your choices

- … And pick a cool name for it ✨🚀

Project

Examples from last year

- Hessian: https://github.com/alexandre-eymael/HESSIAN
- ClipMorph: https://github.com/iSach/clipmorph
- Triple-P: https://github.com/lambi702/MLOps-TripleP
- …

We strive at improving this course!

Help us help you 🫵

- Quick feedback cycles
- Open communication
- Enthusiasm for trying new things 🧪
- Active support from teaching staff
- Students in the classroom

Project objective for sprint 1

Project guidelines on github!

#	Week	Work package
1.1	W01	Pick a **team** ● Try to mix skills and experience ● If you didn't find one let one of the teachers know and we'll allocate you to one
1.2	W01	Select a **use case** Source options ● Previous course ● Kaggle Datasets ● … Make sure to pick a use case where **data is available**. A requirement for this project is to train and deploy your own ML model. It is **not** an option to work with LLMs, as there is too much overhead in training and serving those. Note that the ML modeling itself won't be a big part of the course. You can pick data from one of your previous projects if it is available. Ideally pick something with interesting data and a real world application.
1.3	W01	Find a **cool name** for your project ✨
1.4	W01	Fill in the project card template (docx version is in this course's github repository, under "project/project_card_template.docx") and send it via email to the teaching staff. The teaching staff needs to **approve and provide feedback on your project** - if the project is deemed not feasible then we will ask you to come up with a new one.

Deliverable: Submit all of your projects by sending in a filled in project card template by email before next week's lesson! We'll give you some feedback

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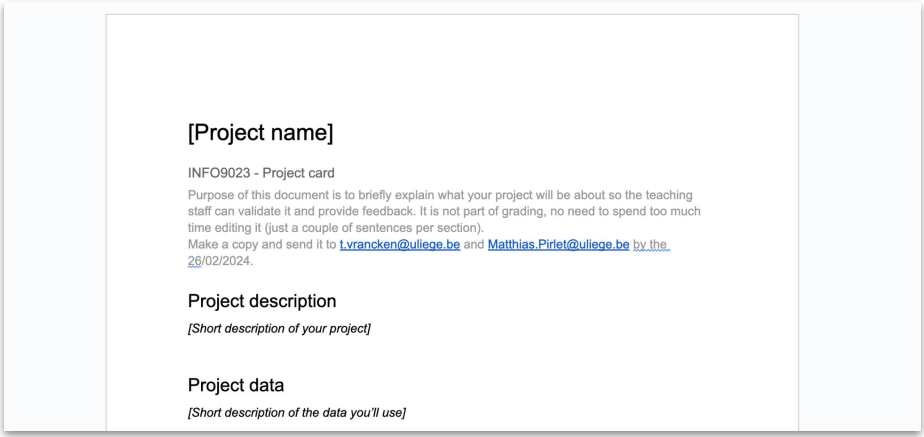
Project deliverable for next week!

Submit your **team** and **project** by filling in the **project card template** and sending it to the teaching staff.

- The template is on github: https://github.com/ThomasVrancken/info9023-mlops/blob/main/project/project_card_template.docx
- You can download the docx file, fill it in and send it back by email to the teaching staff:
  - t.vrancken@uliege.be
  - Matthias.Pirlet@uliege.be

The teaching staff needs to approve and provide feedback on your project - if the project is deemed not feasible then we will ask you to come up with a new one.

⚠️ **Send it by email by to the teaching staff by Thursday 5th of February at 23:59**



[Project name]

INFO9023 - Project card

Purpose of this document is to briefly explain what your project will be about so the teaching staff can validate it and provide feedback. It is not part of grading, no need to spend too much time editing it (just a couple of sentences per section).
Make a copy and send it to t.vrancken@uliege.be and Matthias.Pirlet@uliege.be by the 26/02/2024.

Project description

[Short description of your project]

Project data

[Short description of the data you'll use]

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That’s it for today!

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