OSS Stack for ML

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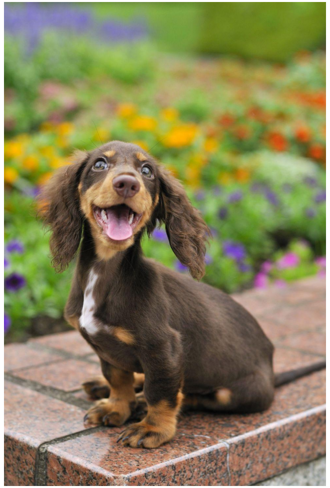
Agenda

What should an OSS Stack to build ML look like?

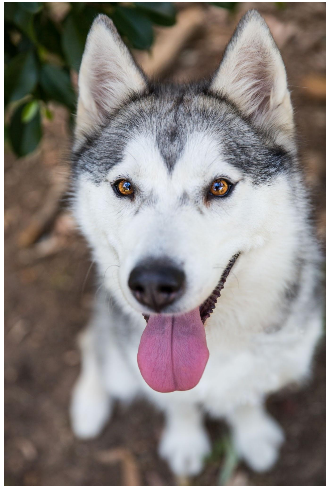
Part-0: Framing MLOps
Part-1: OSS for ML Engineering
Part-2: OSS for ML Science
Part-3: OSS model for ML Development

Stakeholder Expectations

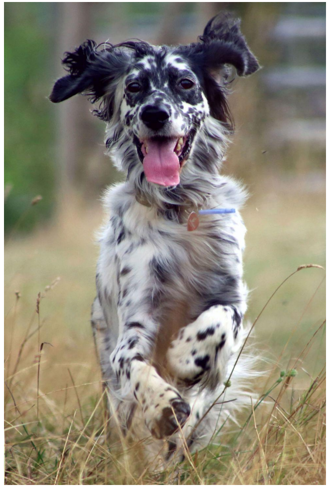
ML team
highest accuracy



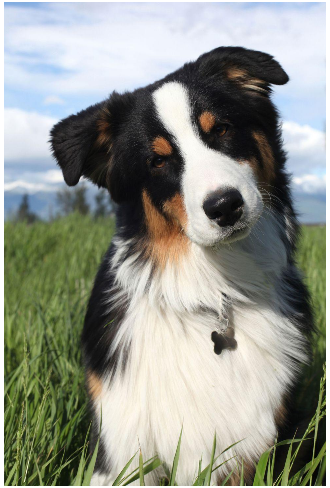
Sales
sells more ads



Product
fastest inference



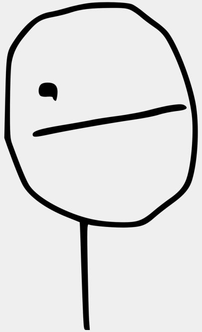
Manager
maximizes profit
= laying off ML teams



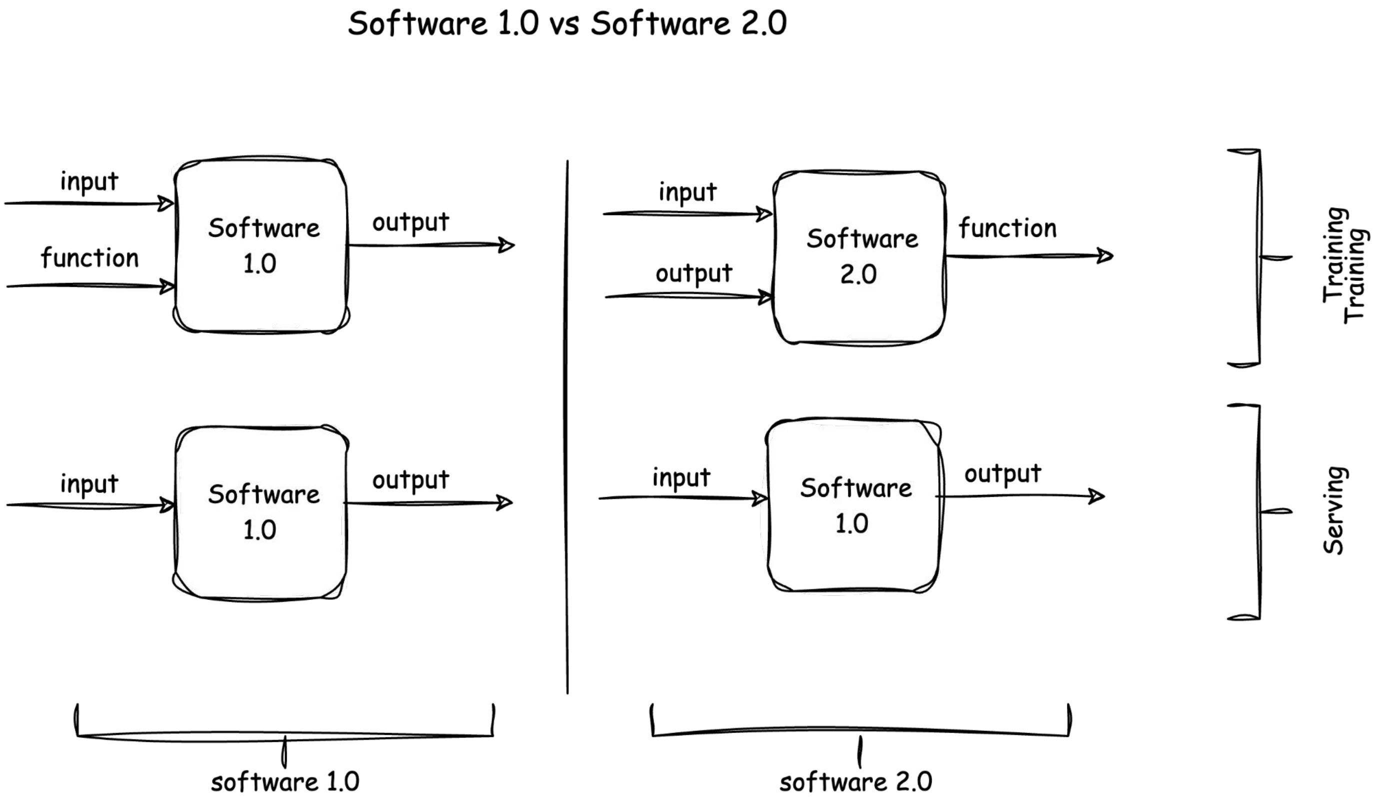
source: [CS329S @ Stanford]

Expectation

Reality



But why?



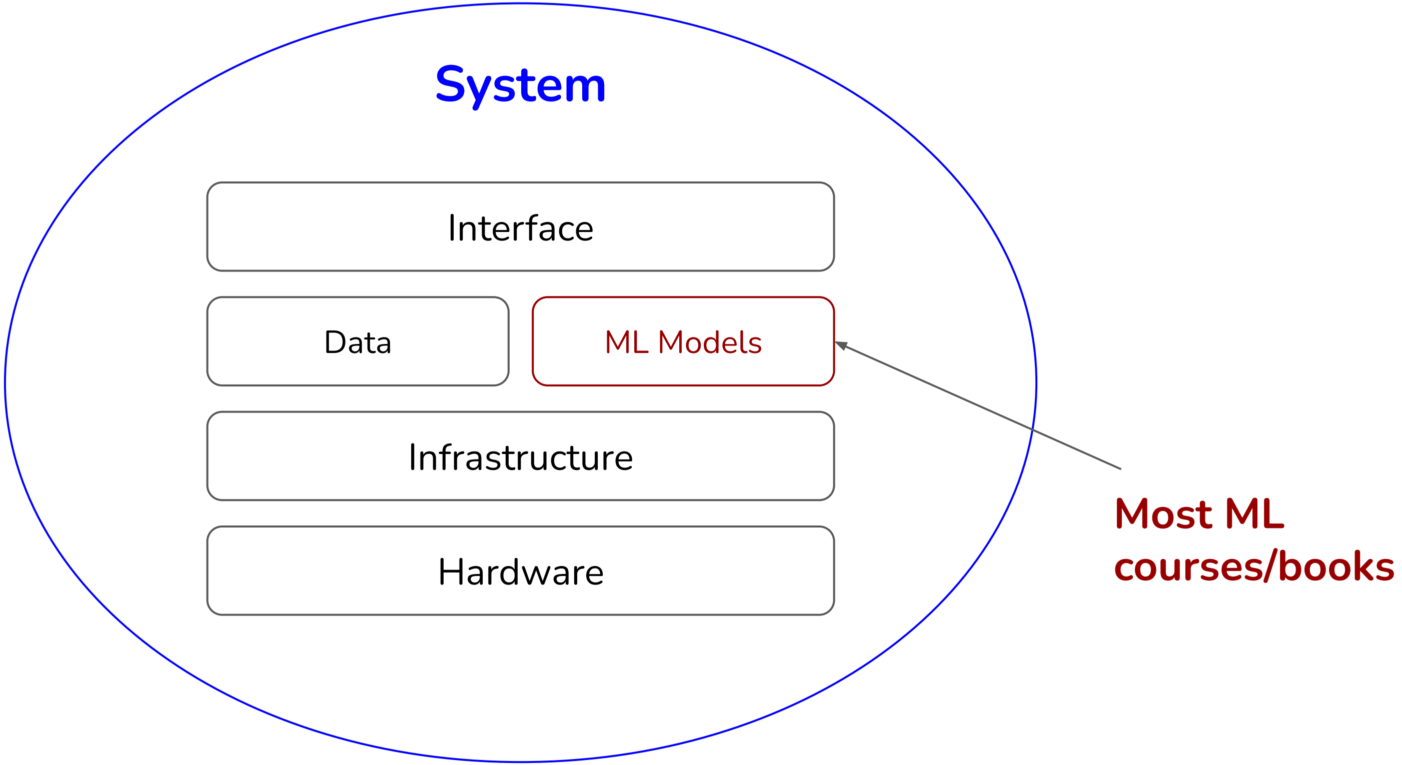
ML as a software is a *fundamentally* different beast.

But why?

	Software 1.0	Software 2.0
Codified in	Formal Language	Weights & Biases (parameters)
Developed by	Programming	Training
Specification	PRD/SRD	Data
Behaviour	Deterministic	Stochastic
	Provably correct	Provably wrong
	Debuggable	Hard to Debug
	Verifiable	Hard to verify
	Explainable	Hard to explain
	Fixable	Hard to fix
	Idempotent	Hard to reproduce

Determinism and Control (of the build process and products) - we take them for granted. But no longer.

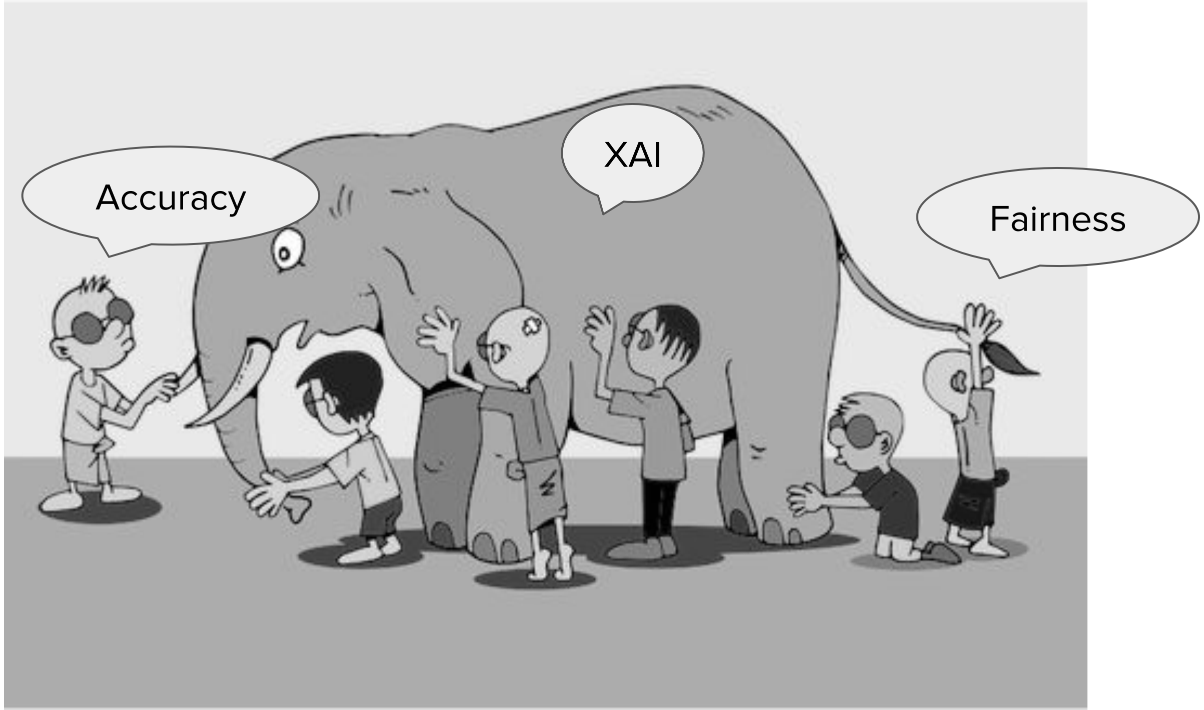
But why?



Think systems, not models. Think modeling, not models.
Combating this intellectual inertia is hard.

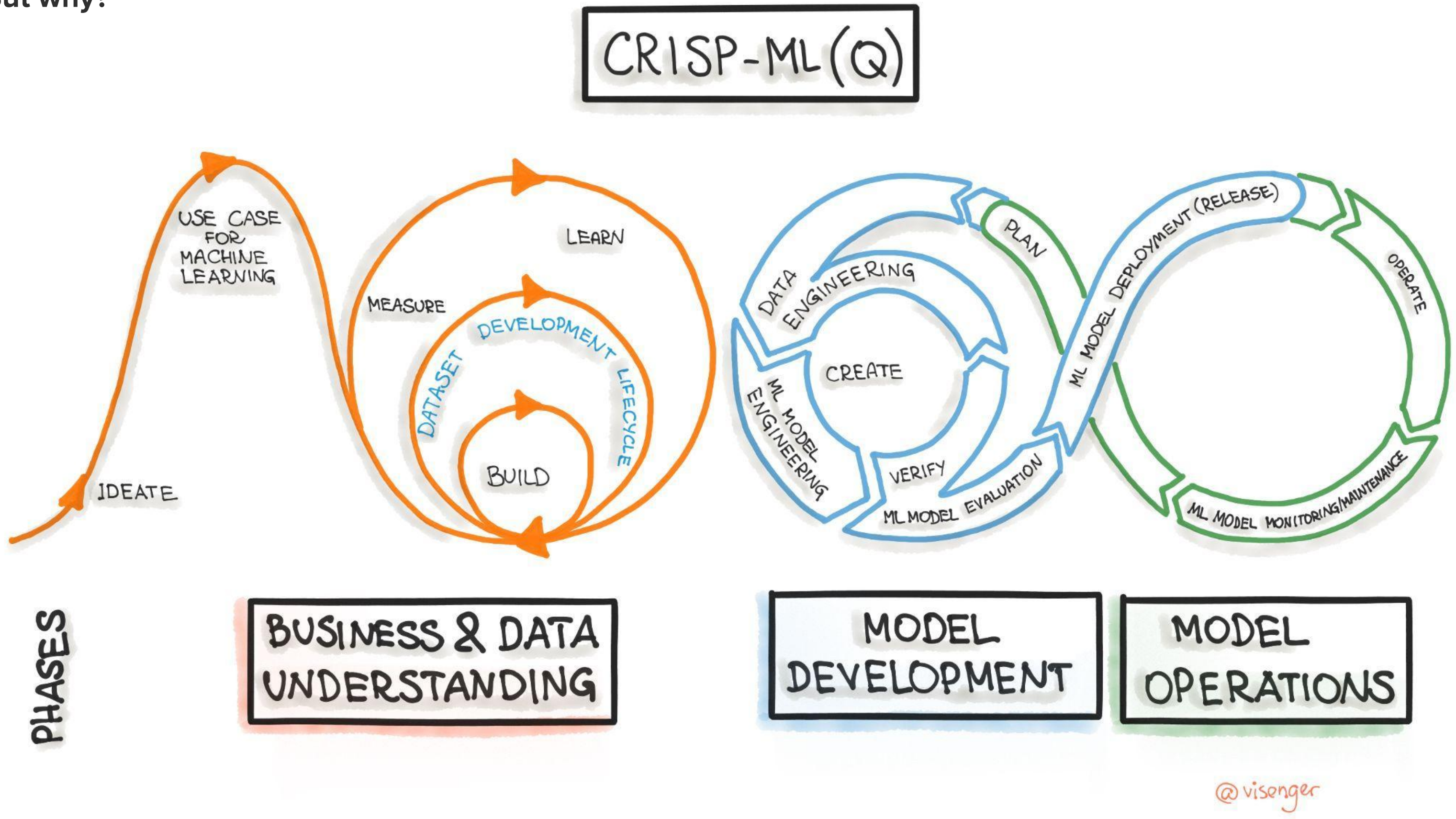
source: [CS329S @ Stanford]

But why?



Semi-orthogonal sub-fields.

But why?



anything changes > everything changes
modeling is highly iterative and nonlinear

source: [ml-ops.org](ml-ops.org)

Non-deterministic systems
Build must be agile and address ambiguity

Design must address “reliability” in the presence of “uncertainty”

IF

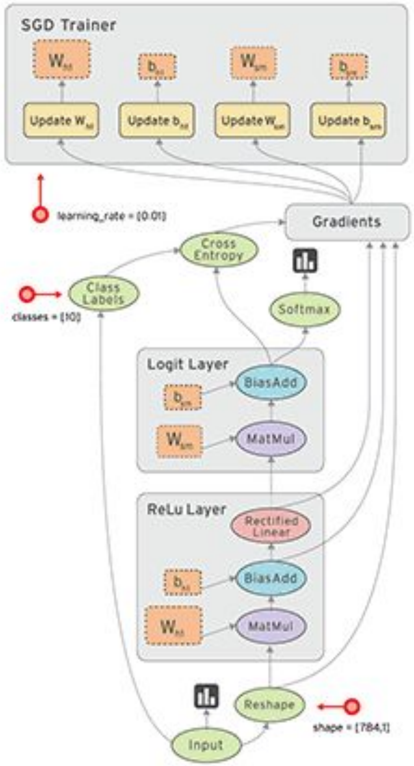
$$CS = DS + A$$

THEN

$$ML = ?$$

need an abstraction for Models and Modeling

“ML modeling” is a DAG



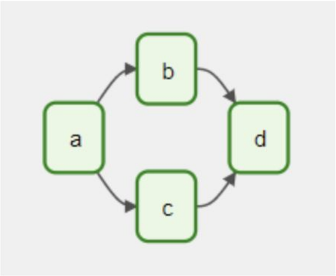
TensorFlow: Data Flow Model to writing programs

Home /Concepts / DAGs

DAGs

A *DAG* (Directed Acyclic Graph) is the core concept of Airflow, collecting Tasks together, organized with dependencies and relationships to say how they should run.

Here's a basic example DAG:

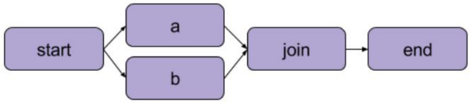


AirFlow: Build ETL pipelines

source: airflow.apache.org

Branch

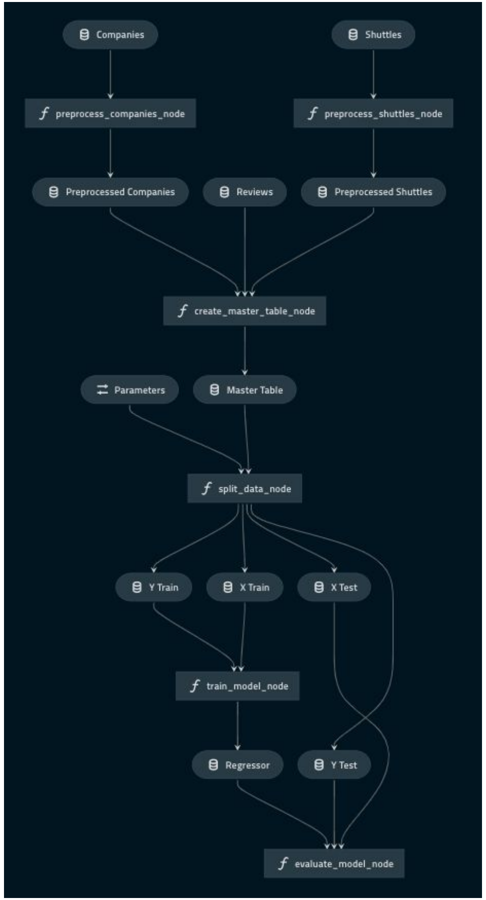
You can express parallel steps with **a branch**. In the figure below, `start` transitions to two parallel steps, `a` and `b`. Any number of parallel steps are allowed. A benefit of a branch like this is performance: Metaflow can execute `a` and `b` over multiple CPU cores or over multiple instances in the cloud.




```python
from metaflow import FlowSpec, step

class BranchFlow(FlowSpec):

    @step
    def start(self):
        self.next(self.a, self.b)

    @step
    def a(self):
        self.x = 1
        self.next(self.join)

    @step
    def b(self):
        self.x = 2
        self.next(self.join)

    @step
    def join(self, inputs):
        print('a is %s' % inputs.a.x)
        print('b is %s' % inputs.b.x)
        print('total is %d' % sum(input.x for input in inputs))
        self.next(self.end)

    @step
    def end(self):
        pass

if __name__ == '__main__':
    BranchFlow()
```

MetaFlow: develop locally, deploy and scale via (just) python decorators

source: metaflow.org



Kedro is a toolbox for production-ready data science. It uses software engineering best practices to help you create data engineering and data science pipelines that are reproducible, maintainable, and modular. You can find out more at kedro.org.

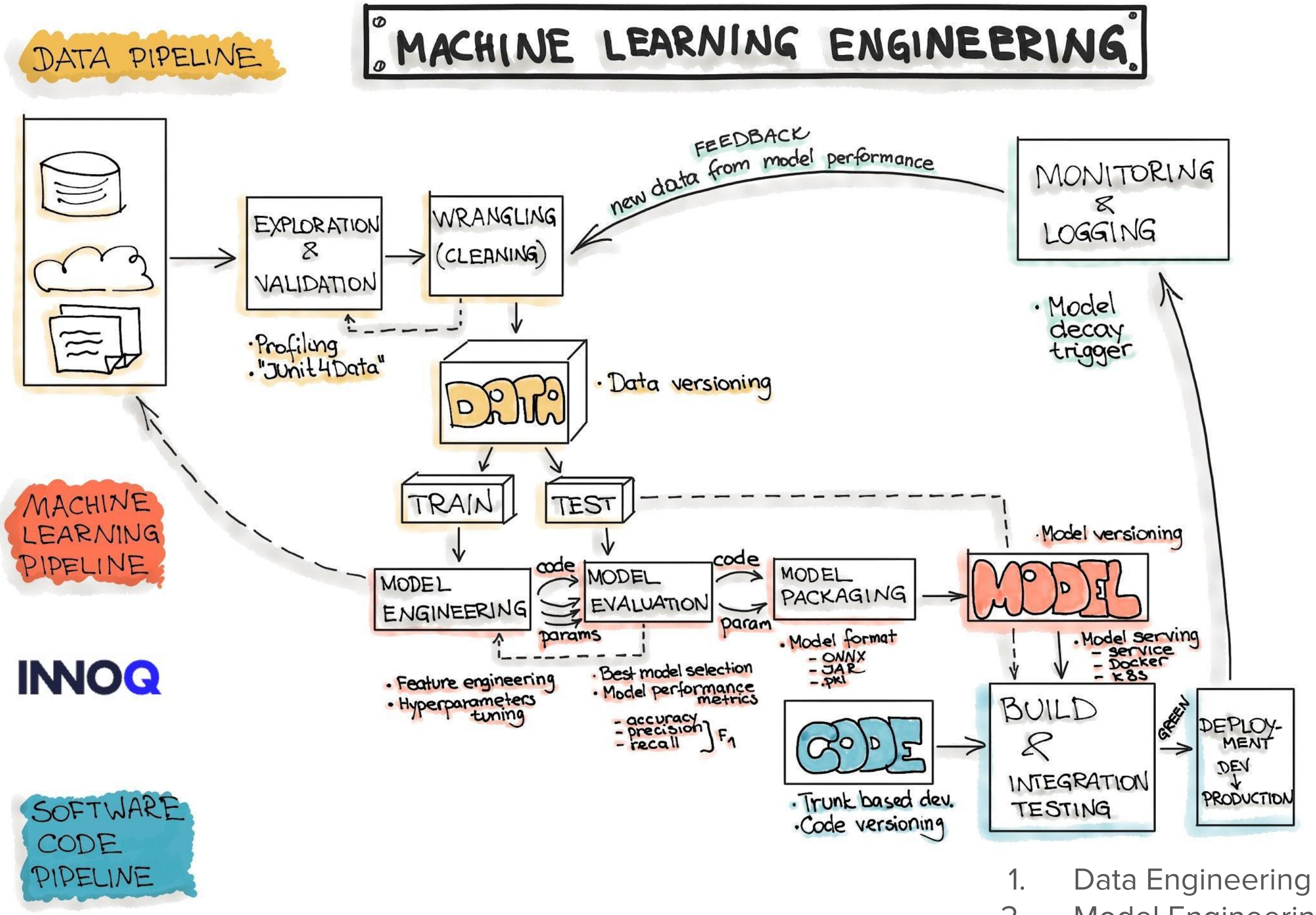
Kedro is an open-source Python framework hosted by the LF AI & Data Foundation.

Kedro: build ML with best software engineering practices

source: kedro

OSS for
ML Engineering

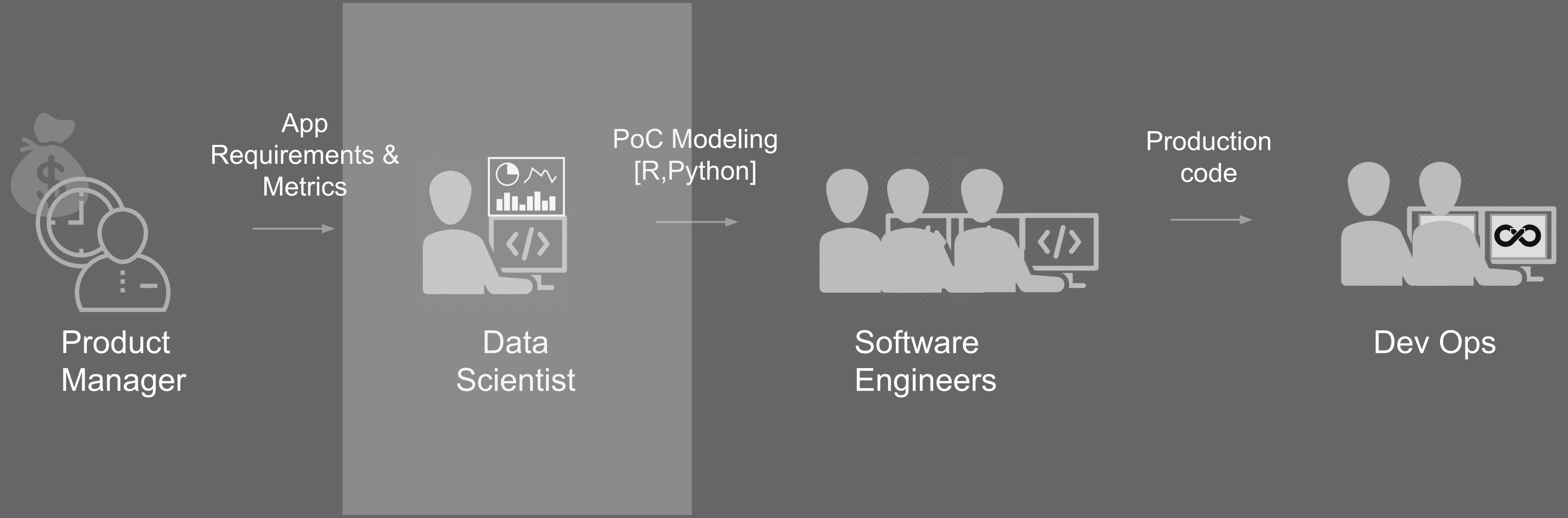
But why?



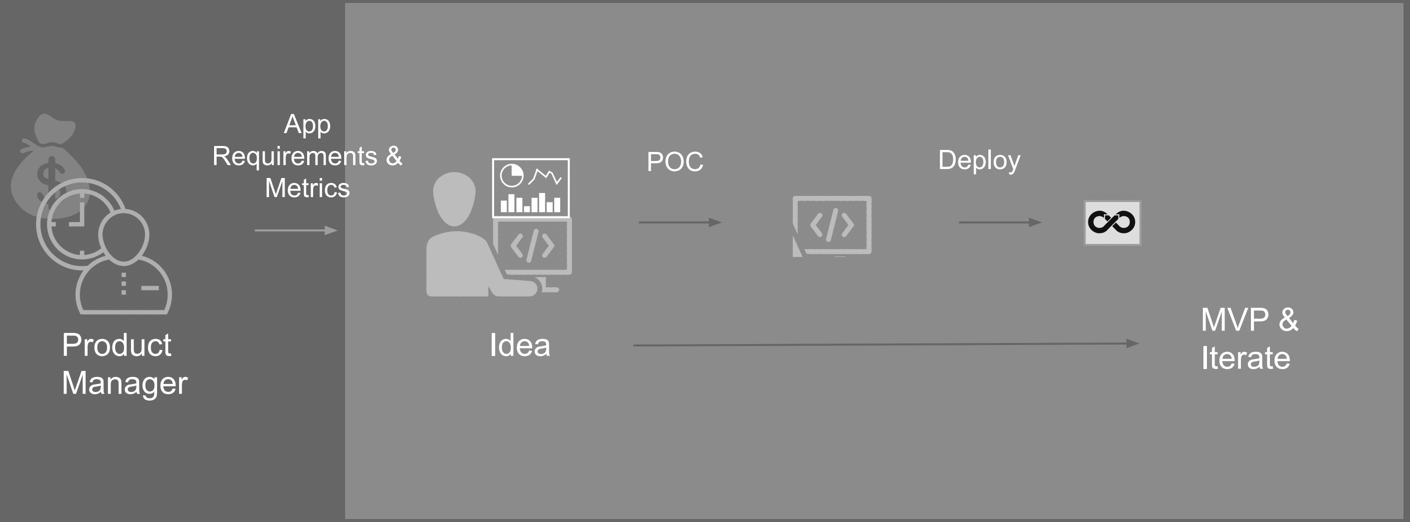
INNOQ

1. Data Engineering
2. Model Engineering
3. Model Deployment

(Lot of) Hidden Tech Debt



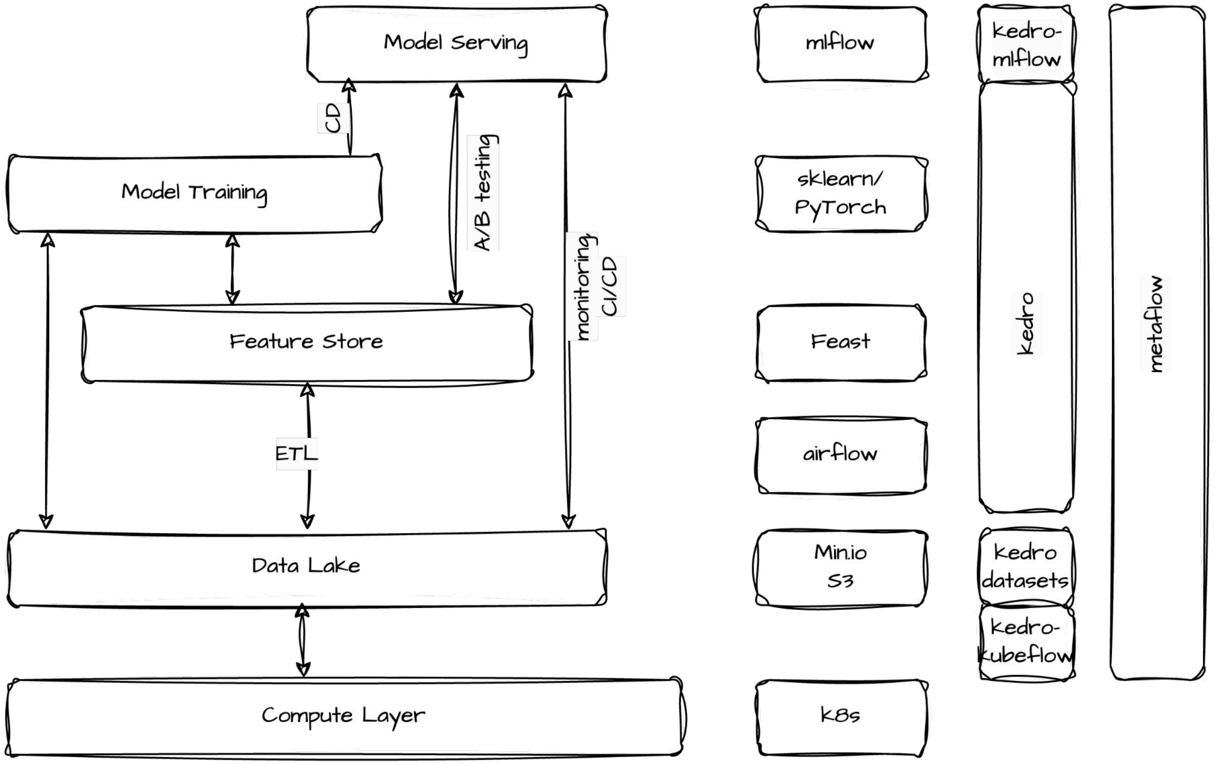
- Tech stacks could be different.
- Dev and Prod env could be different.
- Scalability could be an issue!
- Most importantly, skill sets could be different



Automate and Delegate the responsibility to Tools

Layer	Promise	Task	Tool
Solution	Reproducibility	Versioning - Data, Code, Model	DVC, Kedro,mlflow, MetaFlow
	Observibility	Logging | Monitoring | Tracking	Kedro/mlflow, MetaFlow | evidently | WandB
	Agility	EDA | Experiment Tracking	Notebook environment (Kedro, MetaFlow) | mlflow, Weights and Biases
	CI/CD	Integrate | Deploy | Serve	git-actions | docker/ Kedro/ mlflow | FastAPI
Docs	Truthful/ Up to date	Code | Data | Solution	quarto/ sphinx
Code	Testability| Readability	Linting | Testing | Documentation	ruff/ black | pytest | quarto/ sphinx
Data	Veracity	Drift Detection and Schema Validation	pymfe/ pydantic/ evidently/ greatexpectations
		ETL | Feature Stores	airflow | feast
	Agility | Auditability	Data Lake	minio/ s3 + athena | Kedro Data Catalogues
Compute	Scalability	Elastic Compute	k8s

Quite a number of OSS tools available to address specific gaps, with overlaps

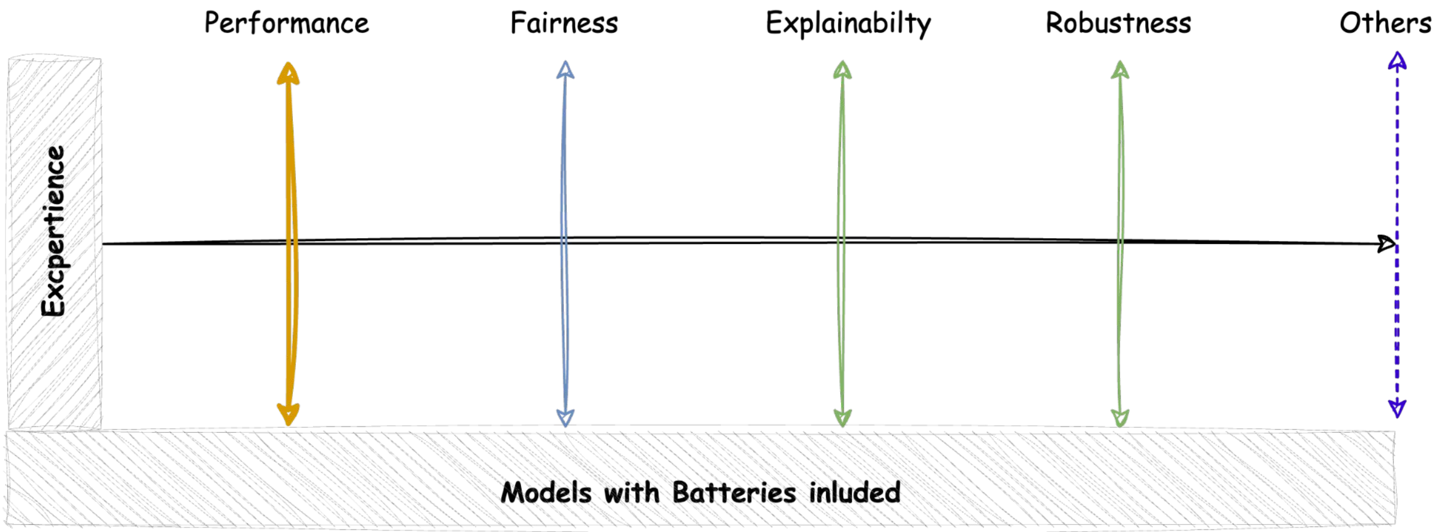


ML POD: ML Engineering

An (opinionated) **git template** with integrations enabled

OSS for
ML Science

Performance-centric ML developement



But what is an enabling technology that addresses these sub-orthogonal fields?

inputs

Text
Speech
Image
Numerical

Fixed
Variable

Single
Many

layers

Dense
Conv
GRU
Attention

Merge

LDA/QDA

DT
FM

Kernels

losses

CE
MSE
MAE
..

CheckLoss
Hinge
Ordinal

optimizers

Adam
RMSProp
NeverGrad
...

PSO

runtime

cpu
gpu
tpu

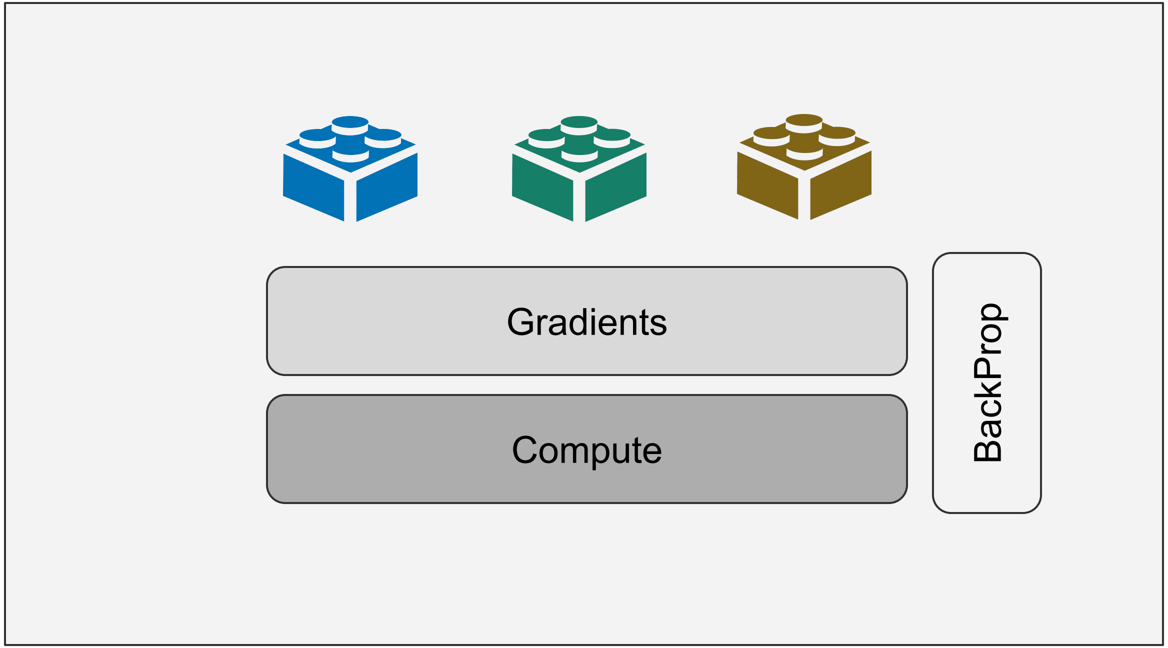
outputs

Text
Speech
Image
Numerical

Fixed
Variable

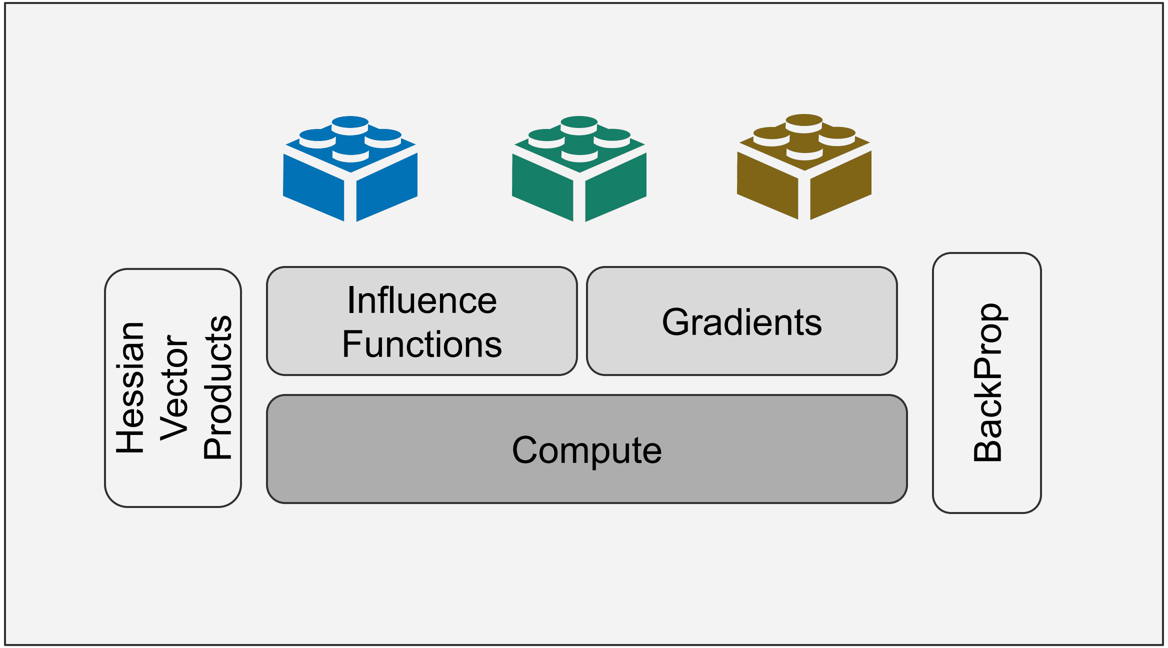
Single
Many

Deep Learning as a technology breaks monolithic scientific computing paradigm.
It is OOPs for scientific computing at large.



ML Engineering Backbone

Scalable computation of gradients is at the heart of modern Deep Learning Engineering



ML Science Backbone

Perhaps, the answer is in IHVP

IVHF: pyDVF
IFs: influentiate:
For more see: AI-839@IIIT-B

[ML²] SQUARE

for more see: [Project DEEL]

Promise	Methods	Tool
Statistical Reliability	Conformal Prediction Techniques Learn-Then-Test Framework	torchcp, mapie, puncc
OOD	RMD, Entropy, Clustering	pytorch-ood, oodeel
Security	Adversarial Attacks	foolbox
Explainability	Integrated Gradients SHAPLEY values, LIME, Decision Sets, Influence Functions Counterfactuals	shap, xplique, dice
Bias and Fairness	Metrics (for detection) and Methods (to mitigate) Influence Functions	AI Fairness 360, influentiate
Robustness	Adversarial Training Robust Losses Regulaization	All of above

OOD, Robustness, Security, XIA, Bias & Fairness – share common principles!

Expectation

Reality

Make ML great again :)