



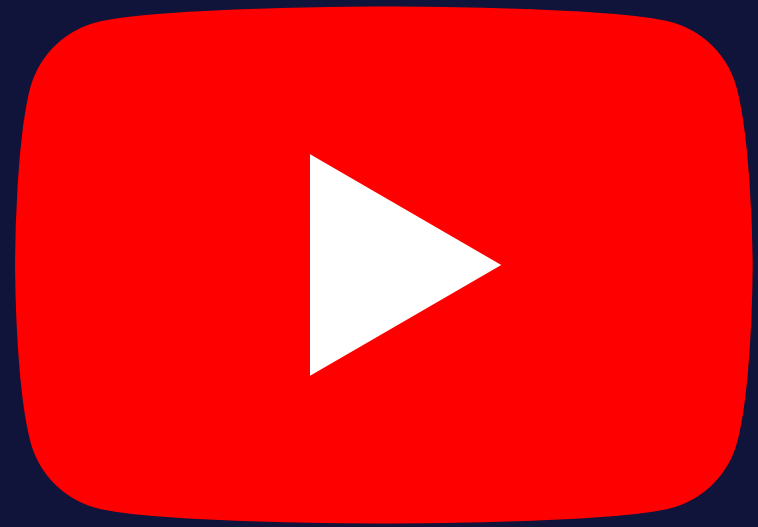
# A Ascensão de MLOps

Mar 2021

Felipe C Penha

#DataScienceBits

# Data Science Bits



<https://linktr.ee/felipepenha>

# Análítico Vs Operacional

## ANALYTICAL ML

Human-Driven Decisions

- Non time-sensitive
- Low production requirements
- Low scale
- Little regulation
- 1-person team

### ML ENVIRONMENT

ML-Powered Analysis/BI

*e.g. Sales Forecast, Demand Forecast, Customer LTV Estimation*



Internal User/  
Employee

## OPERATIONAL ML

Machine-Made Decisions

- Time sensitive
- Real-time input data
- Production service level agreement and scale
- Direct connection to business impact
- Regulations and compliance
- Large cross functional team

### ML ENVIRONMENT

ML-Powered Product

*e.g. Real-time fraud detection, Real-time pricing, Personalization, Chat Bots*



Customer

**MLOps:** "conjunto padrão de práticas para Operações de Machine Learning em grande escala"

2021 TECHNOLOGY SPOTLIGHT  
The Emergence of MLOps

2021

 DeepLearning.AI

**A CHAT WITH ANDREW**

## MLOps: From Model-centric to Data-centric AI

 **Wed, MARCH 24**

 **10 to 11am PT**

 **RSVP: [mlops0324.eventbrite.com](https://mlops0324.eventbrite.com)**

**ANDREW NG**  
Founder  
DeepLearning.AI



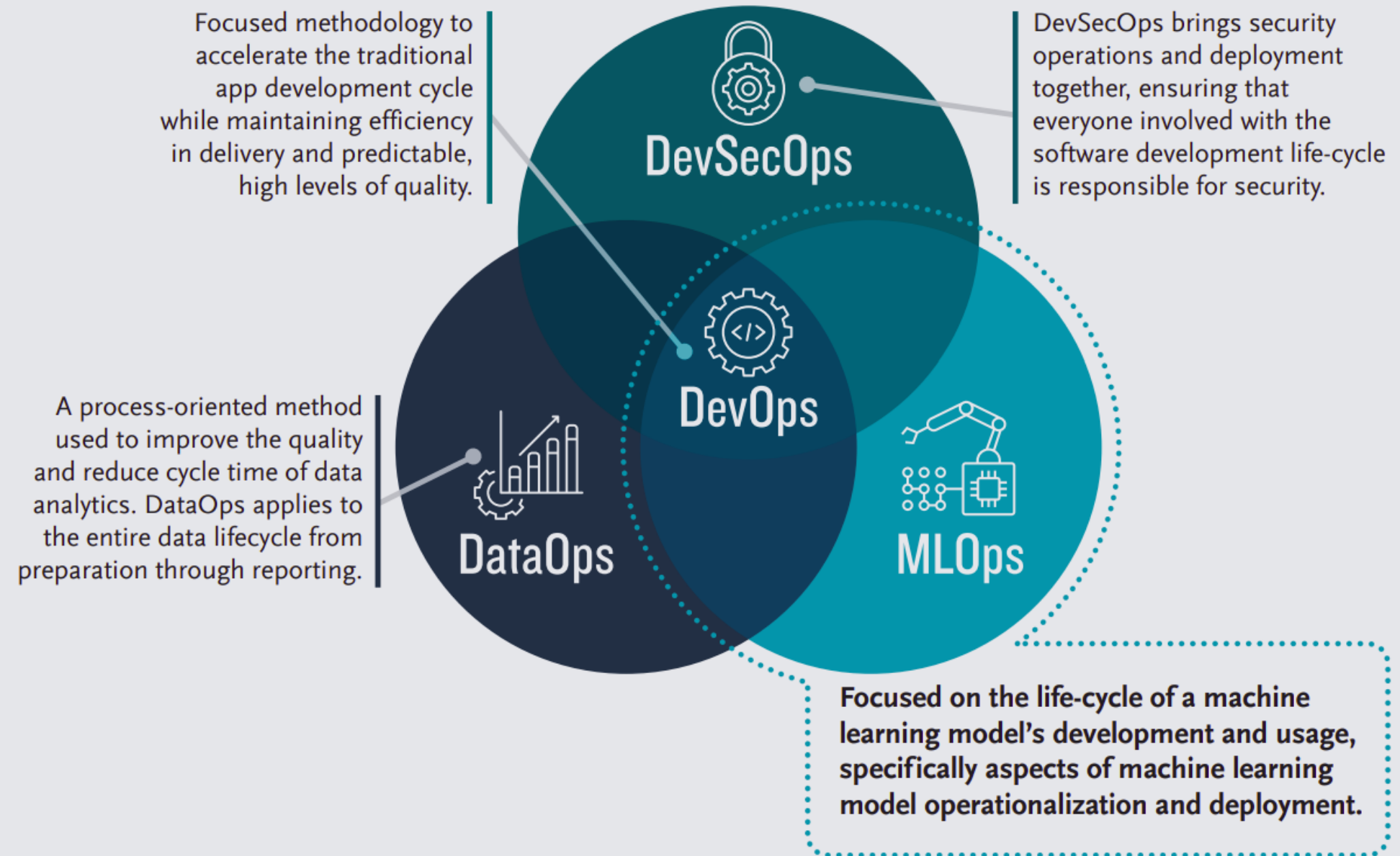
MLOps ~ DataOps ?  
ML Eng. ~ Data Eng. ?



2021 TECHNOLOGY SPOTLIGHT

## The Emergence of MLOps

Figure 1—MLOps focuses on intricacies of the ML lifecycle often neglected in the DevOps framework



"Focado no ciclo de vida do desenvolvimento e uso de modelos, especificamente aspectos de operacionalização e deployment"



2021 TECHNOLOGY SPOTLIGHT

## The Emergence of MLOps

### COMMON GOALS OF OPERATIONAL ML

Most MLOps solutions often share common goals born from the problems encountered in Analytical ML solutions. These include the need for auditability, performance across a variety of environments, transparency into the functioning of a model, technology that enables the AI solution to scale, automation for model updates, and solving the common issue of model drift.



**Auditability:** A given model will have multiple versions, a specific set of training data, and finely tuned hyperparameters. Each must be carefully tracked for versioning and testing purposes



**Different Environments:** Different environments for data preparation, training, and model deployment reduce speed and scalability of model deployment



**Model Transparency:** Individual models are difficult to understand and/or explain to others



**Scalability:** Models created from scratch for individual problems reduce deployment speed because of the inability to reuse and recycle code



**Model Drift:** Models may lessen in accuracy over time as the statistical properties the model tries to predict change in the real world



## Reproducible

Reproducibility and productivity are inextricably linked. It's difficult to be productive when different team members can't reproduce each others' work. This is harder in ML than in software because test & training data and metrics need to be versioned alongside the code and environment.



## Accountable

Models that are deployed without full provenance, a record of all the steps taken to create the models, can fail to be compliant, and are hard to debug. Maintaining this provenance record manually slows you down and is error-prone, so automated tooling is needed.



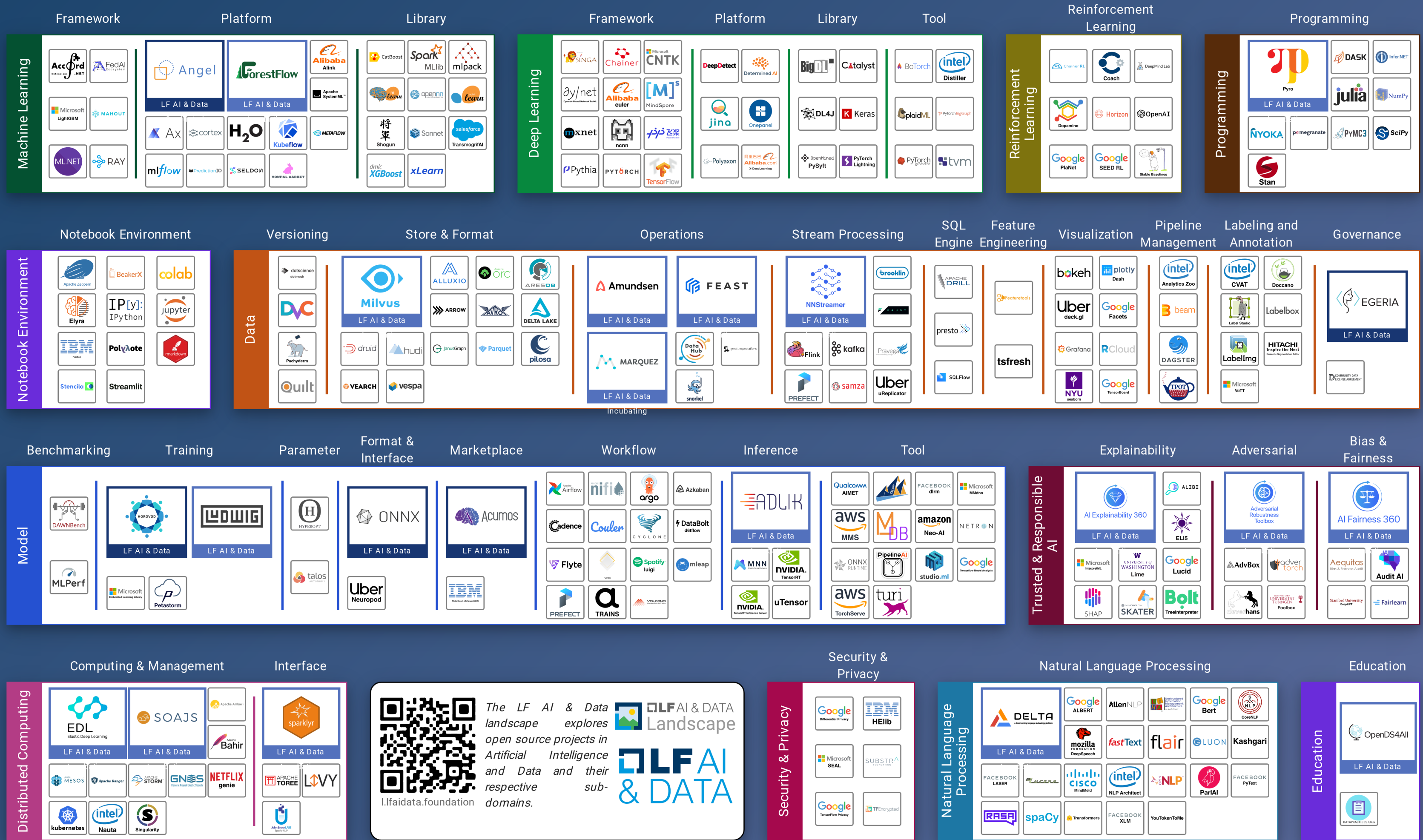
## Collaborative

Concurrent collaboration – that is, collaboration without treading on each others' toes – is essential. In ML this is harder than in normal software engineering, because collaboration applies to notebooks, data, models and metrics as well as code.



## Continuous

You're not done when you ship. In order to continue delivering value to the business, models must be retrained and statistically monitored to compensate for model drift due to constant changes in your business environment.



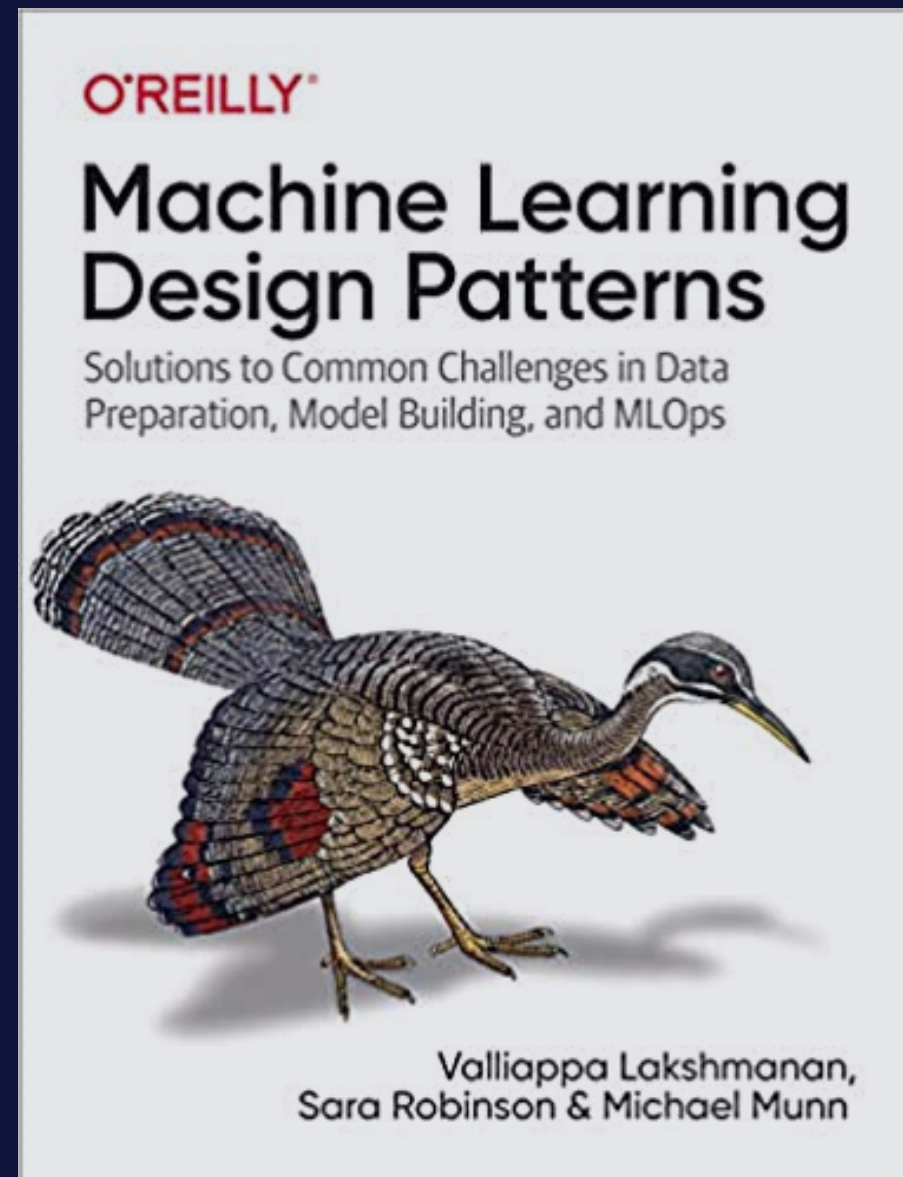
The LF AI & Data landscape explores open source projects in Artificial Intelligence and Data and their respective domains.

[l.faidata.foundation](https://l.faidata.foundation)

**LF AI & DATA Landscape**

**LF AI & DATA**

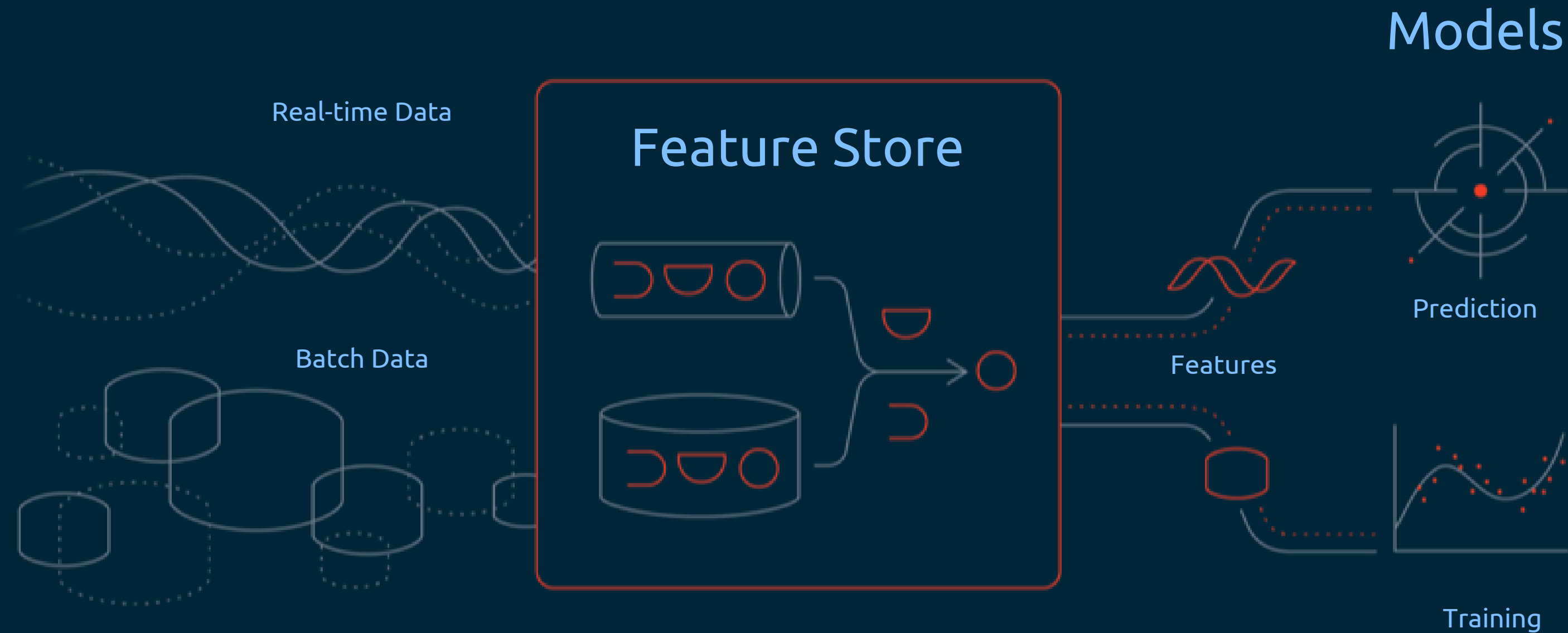




# Design Patterns 1-30

- Problema
- Solução
- Por que funciona
- Prós, contras e alternativas

# Design Pattern 26

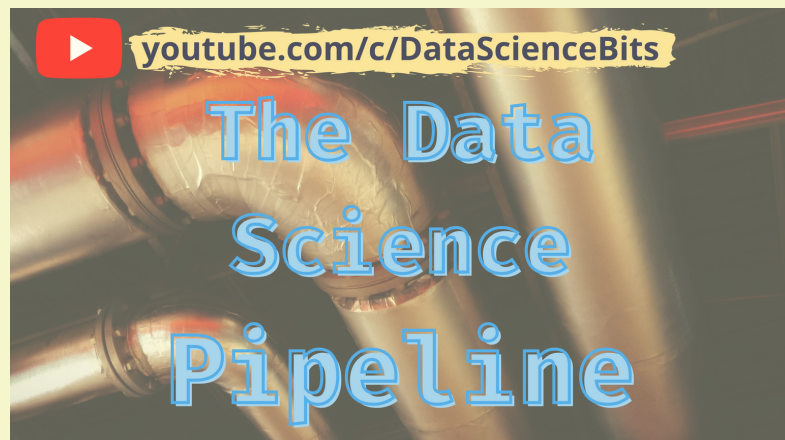
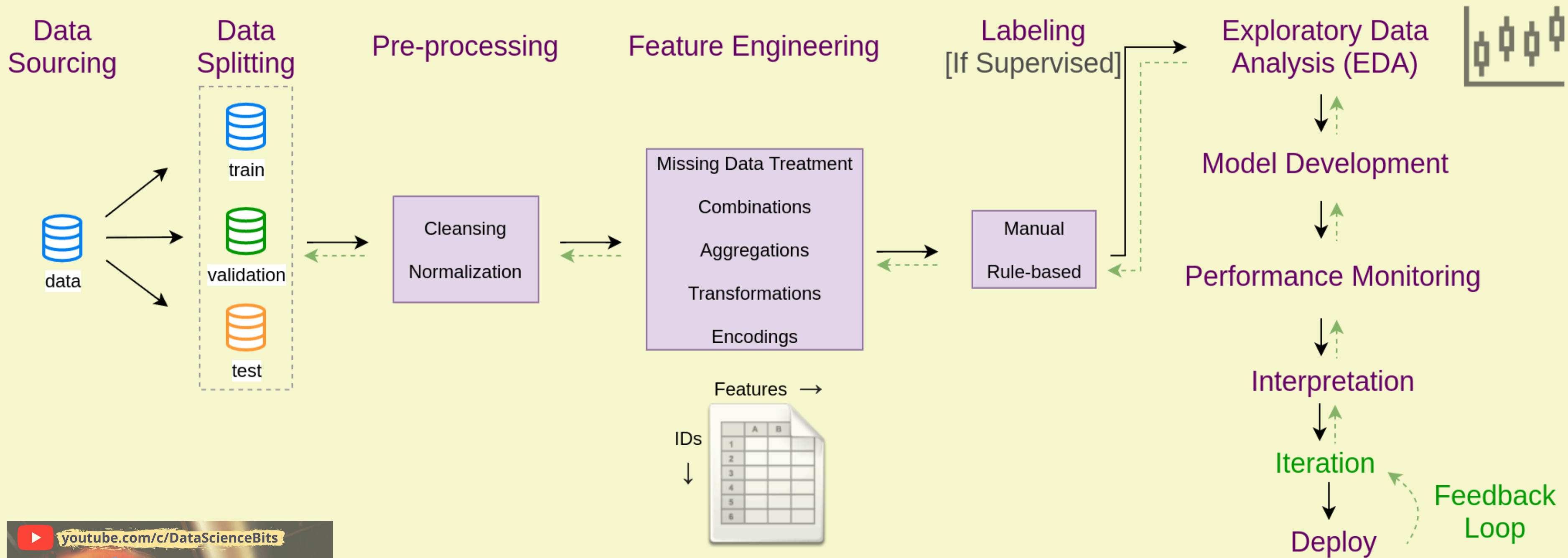


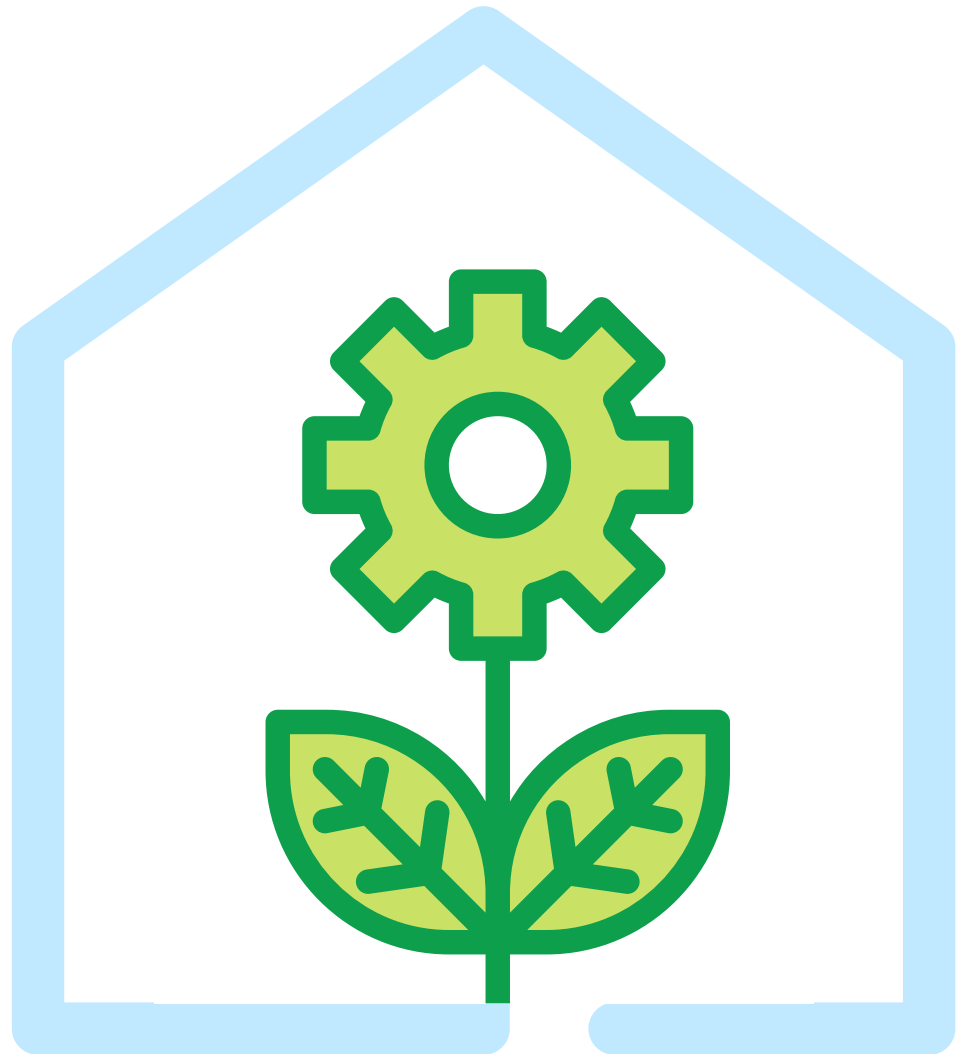
Features →

IDs ↓

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6		

# Design Pattern 25

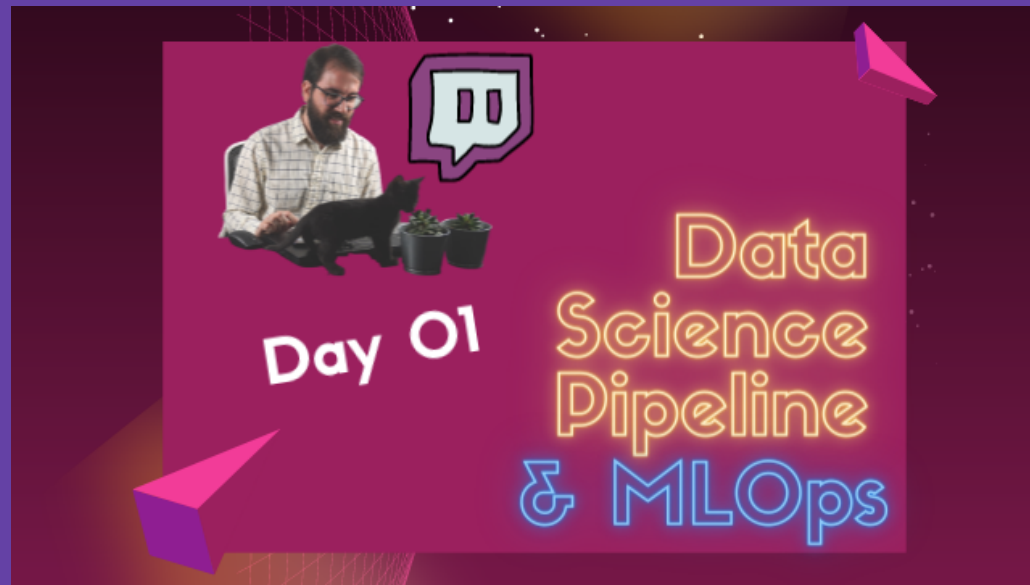




# GREENHOUSE

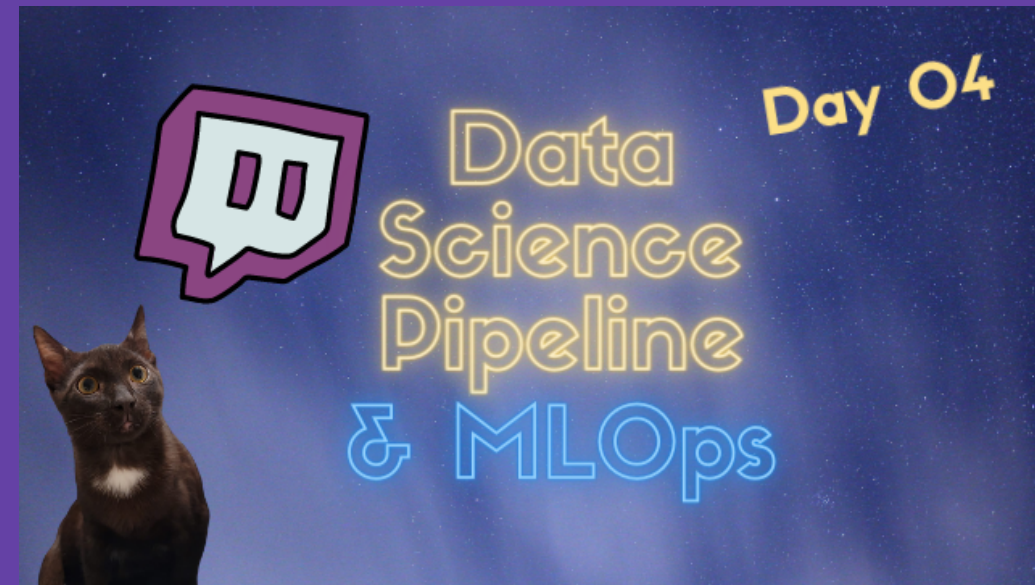
A CONTAINERIZED FRAMEWORK  
FOR BETTER DATA X

[github.com/felipepenha/py-greenhouse](https://github.com/felipepenha/py-greenhouse)



Day 01

Data Science Pipeline & MLOps



Day 04

Data Science Pipeline & MLOps

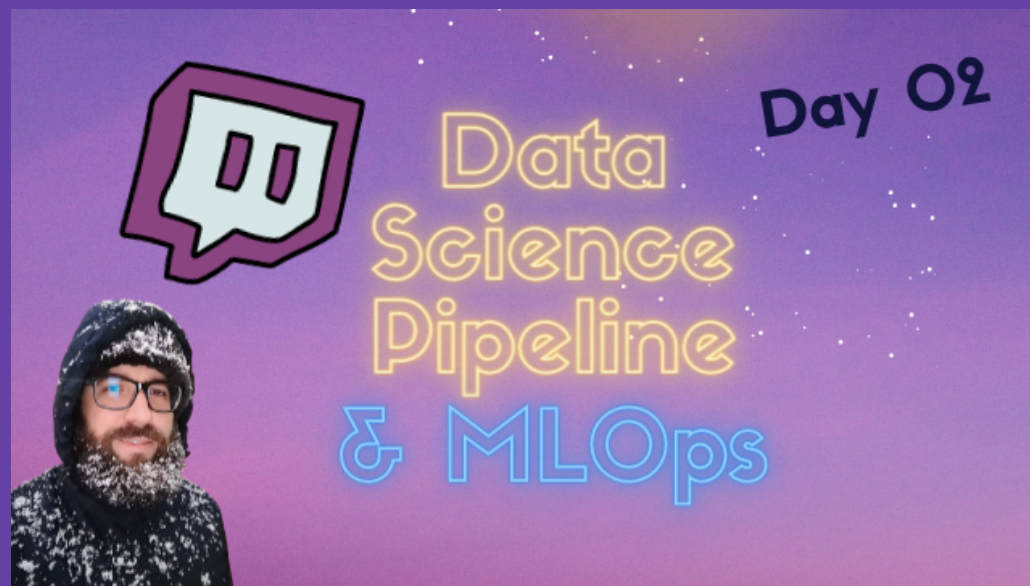


twitch.tv/DataScienceBits

Day 07

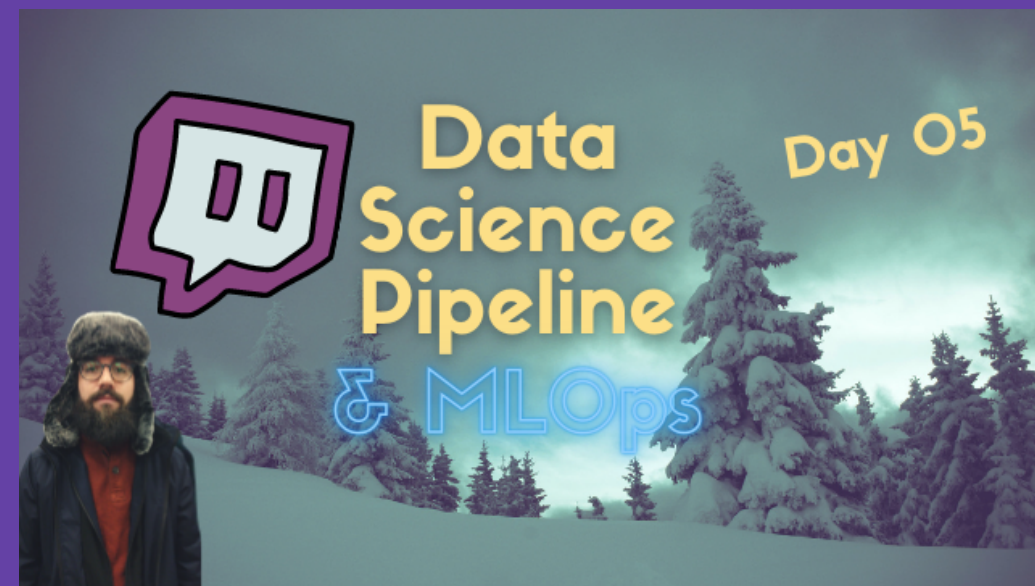
Segunda 08/03  
17:30 - 19:30 BRT

MLOps



Day 02

Data Science Pipeline & MLOps



Day 05

Data Science Pipeline & MLOps

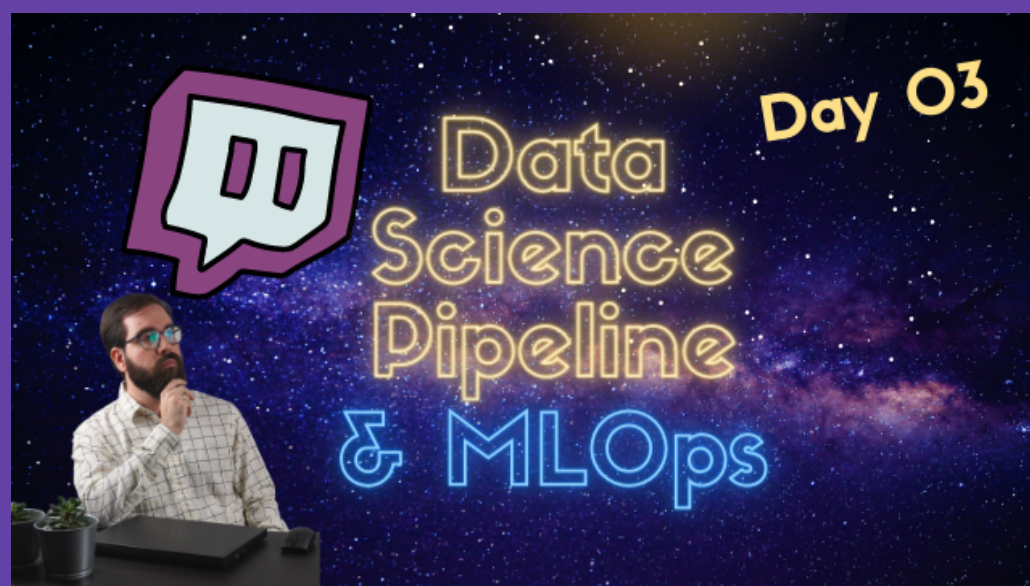


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Day 08

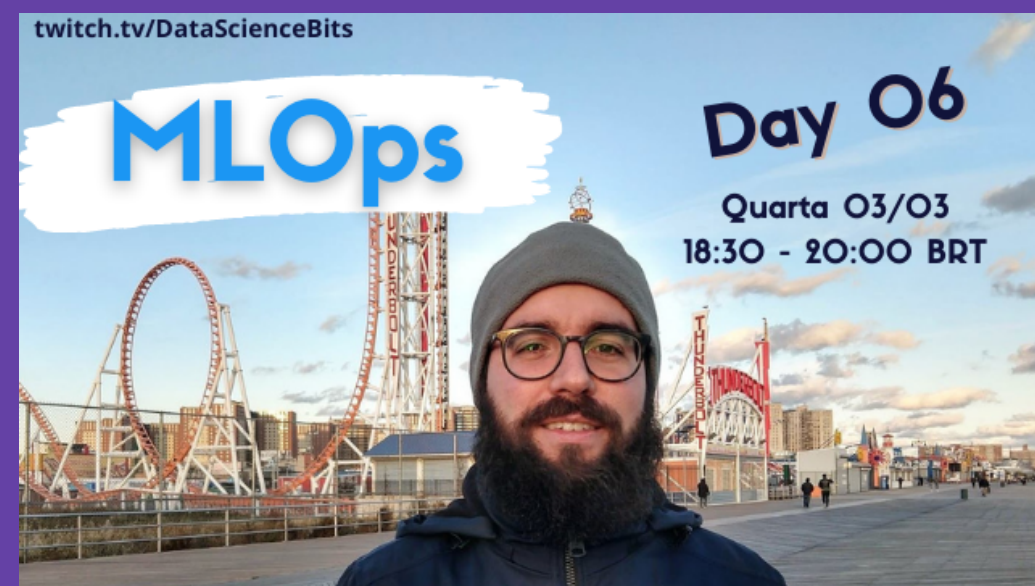
Terça 09/03  
18:00 - 19:30 BRT

MLOps



Day 03

Data Science Pipeline & MLOps



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MLOps

Day 06

Quarta 03/03  
18:30 - 20:00 BRT

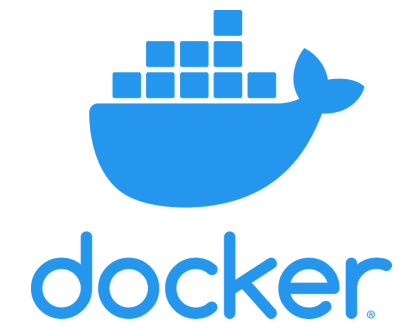


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Day 09

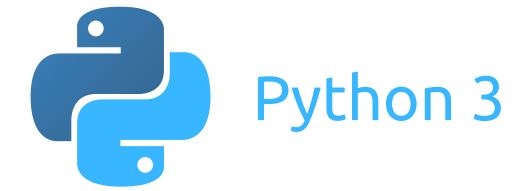
Quarta 10/03  
18:00 - 19:30 BRT

MLOps



docker compose

bash  
python3  
jupyter



pip3 requirements



volumes



pre-commit  
git hooks

test

pytest



Visual Studio Code



Server + extensions

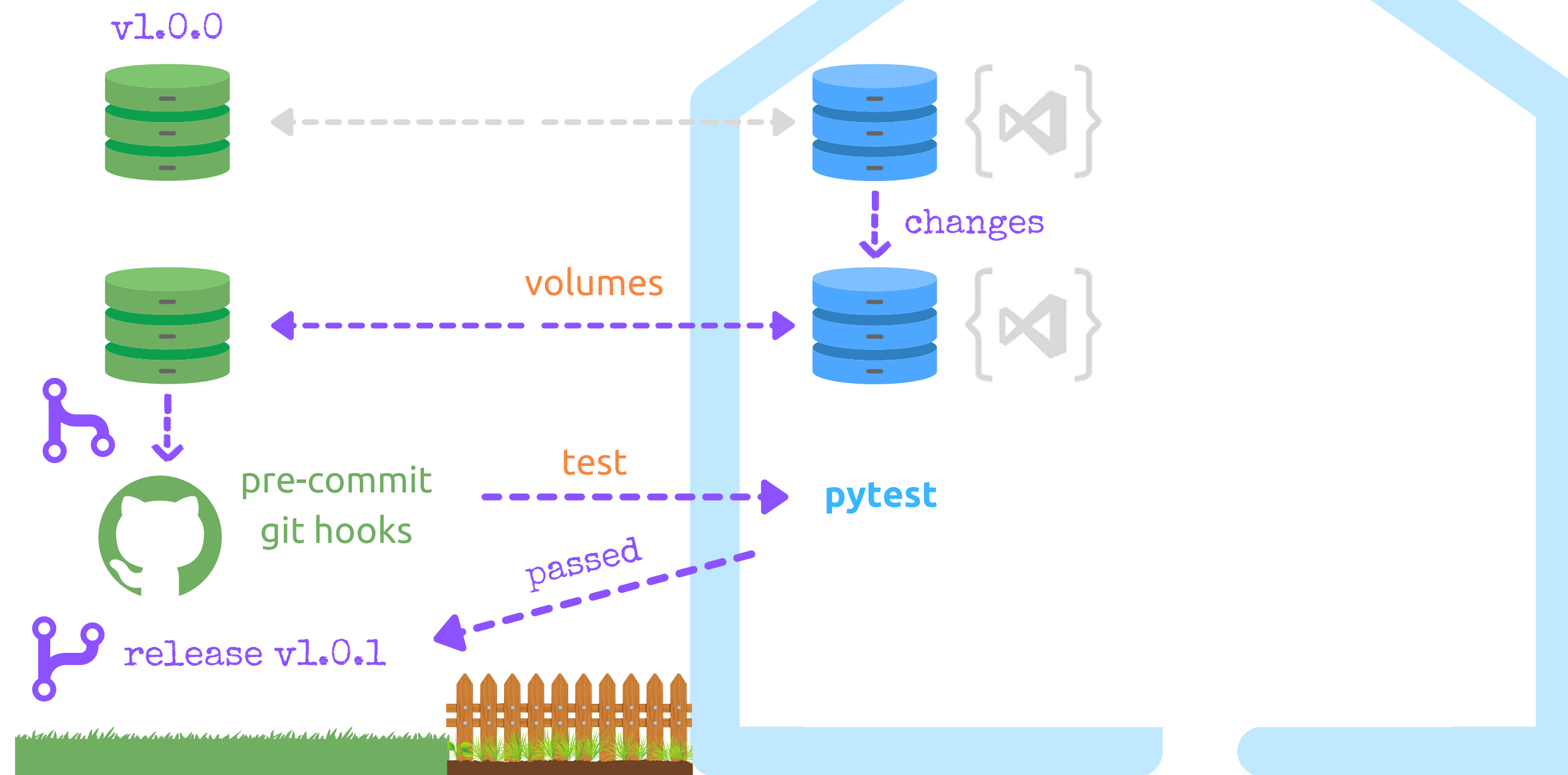
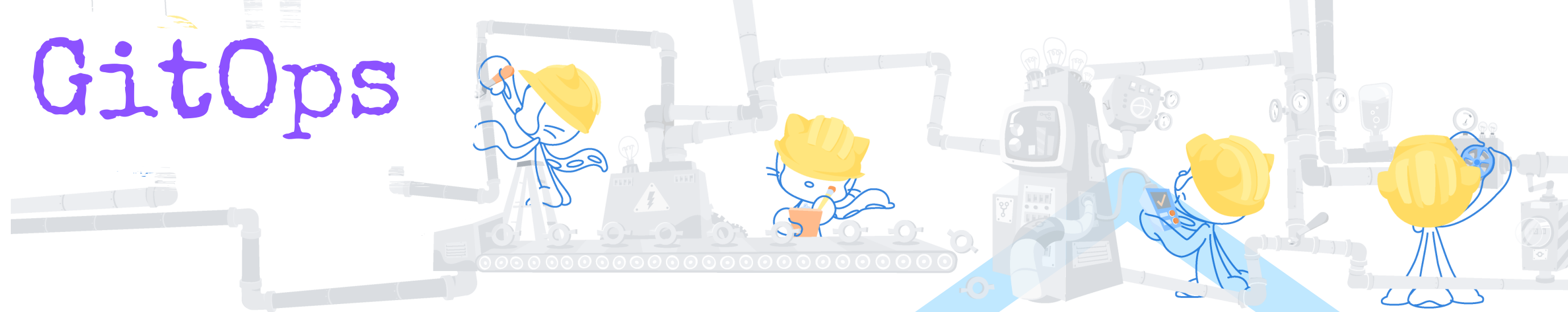


Local OS

Services

Container

# GitOps



Local OS

Services

Container

<https://linktr.ee/felipepenha>

Muito Obrigado!

**Fique Ligadx!**

**12 de Maio**

**Participação no Podcast**

**MLOps.community**

**A place to discuss MLOps**

An open community where all are welcome

**Slack com 2.5k+ usuários**