MLOps – ⚙ of life

Sumit Tyagi

All About Today

- Talk about MLOPs
  - Motivation
  - Design
  - Lifecycle
  - Levels
- Do MLOps
  - Build Model
  - API based deployment
  - Containerise using Docker
  - Scale-up using Kubernetes

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Talk about MLOPs

- Motivation
- Design
- Lifecycle
- Levels

Do MLOps

infogain
Engineering Business Outcomes

MLOPS

Motivation

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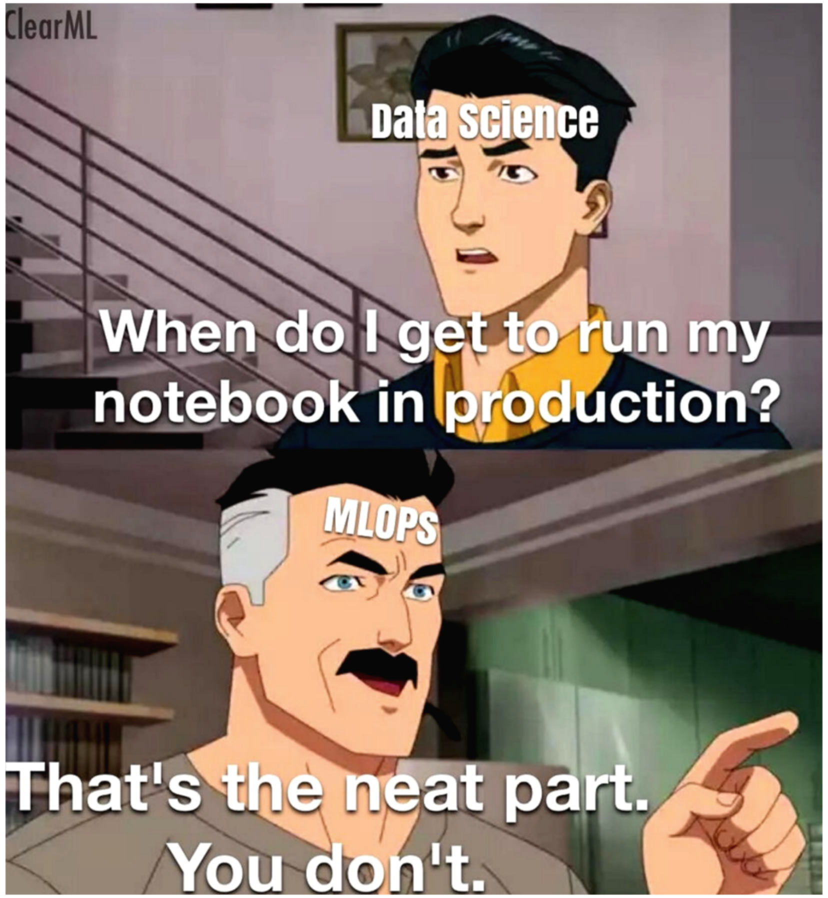
What is MLOps?	
For all my analyst/ consultant friends	
	

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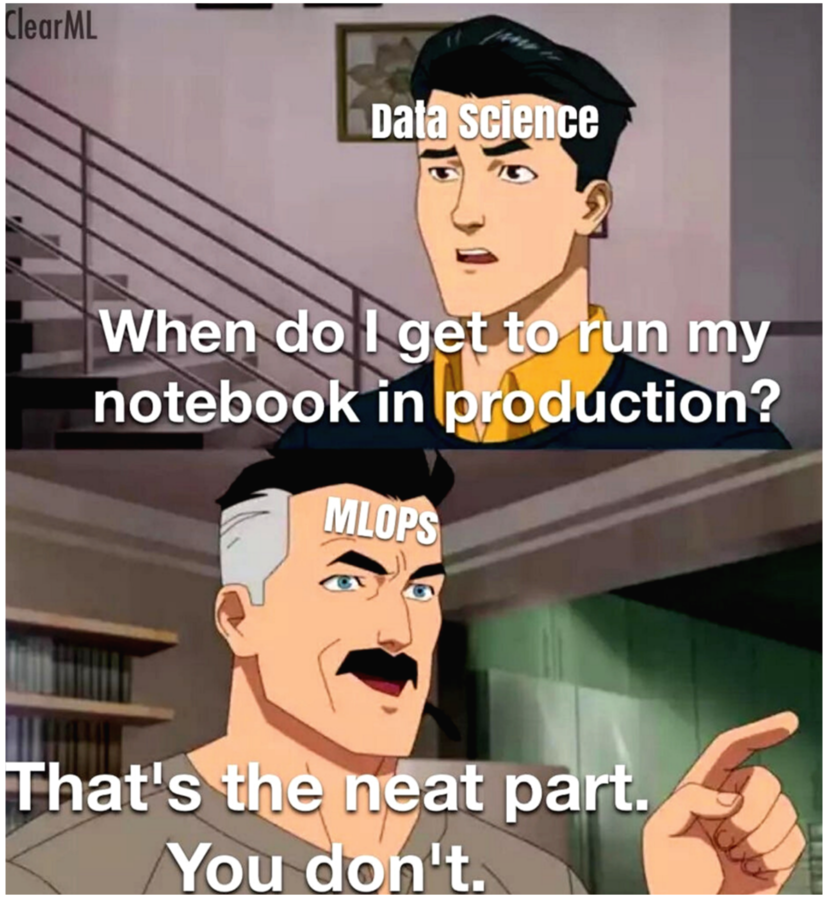
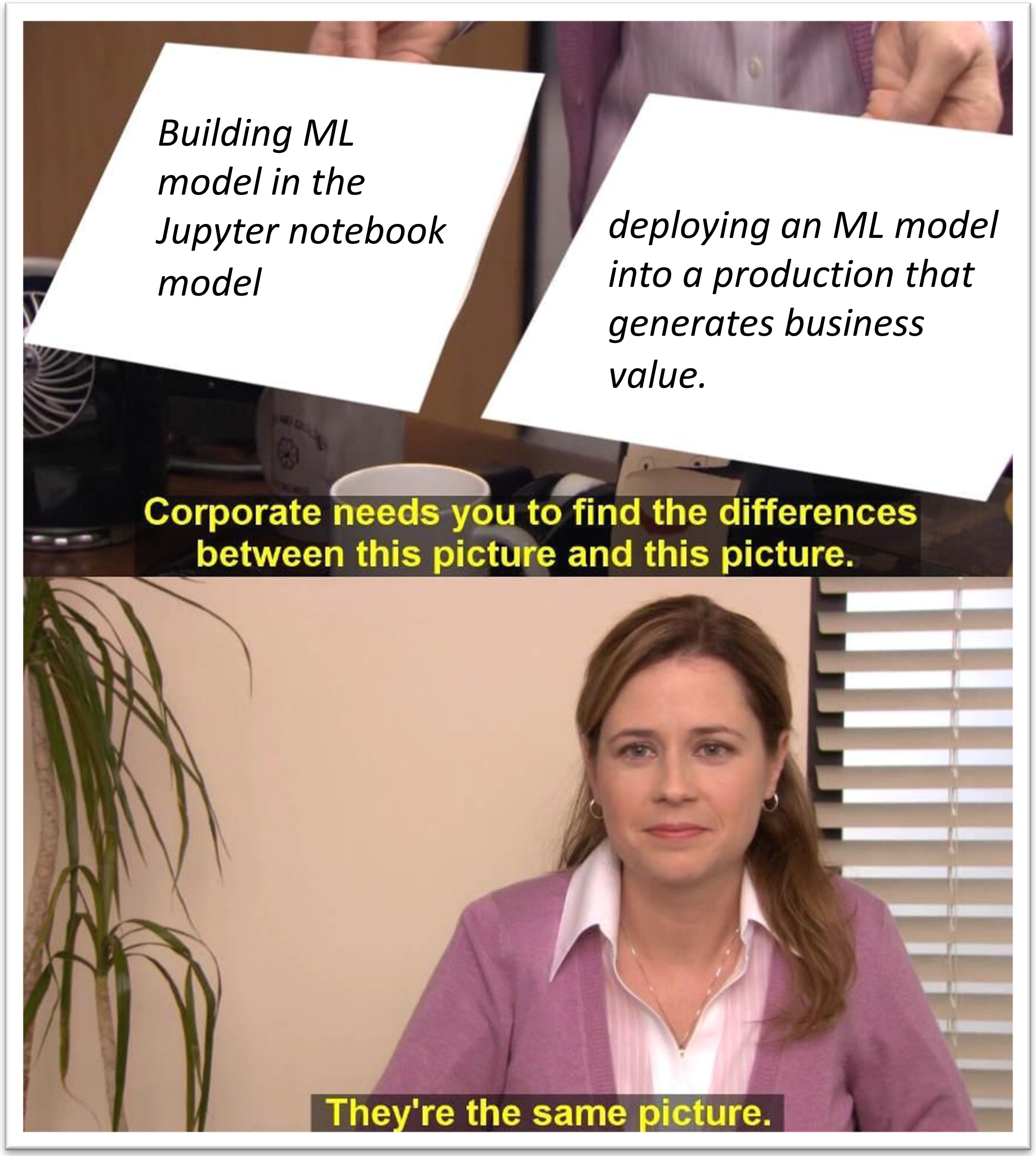


For all my PM friends

Motivation

Deployment Gap:

- Although AI budgets are on the rise, only 22 percent of companies that use machine learning have successfully deployed an ML model into production.



Motivation

Deployment Gap:

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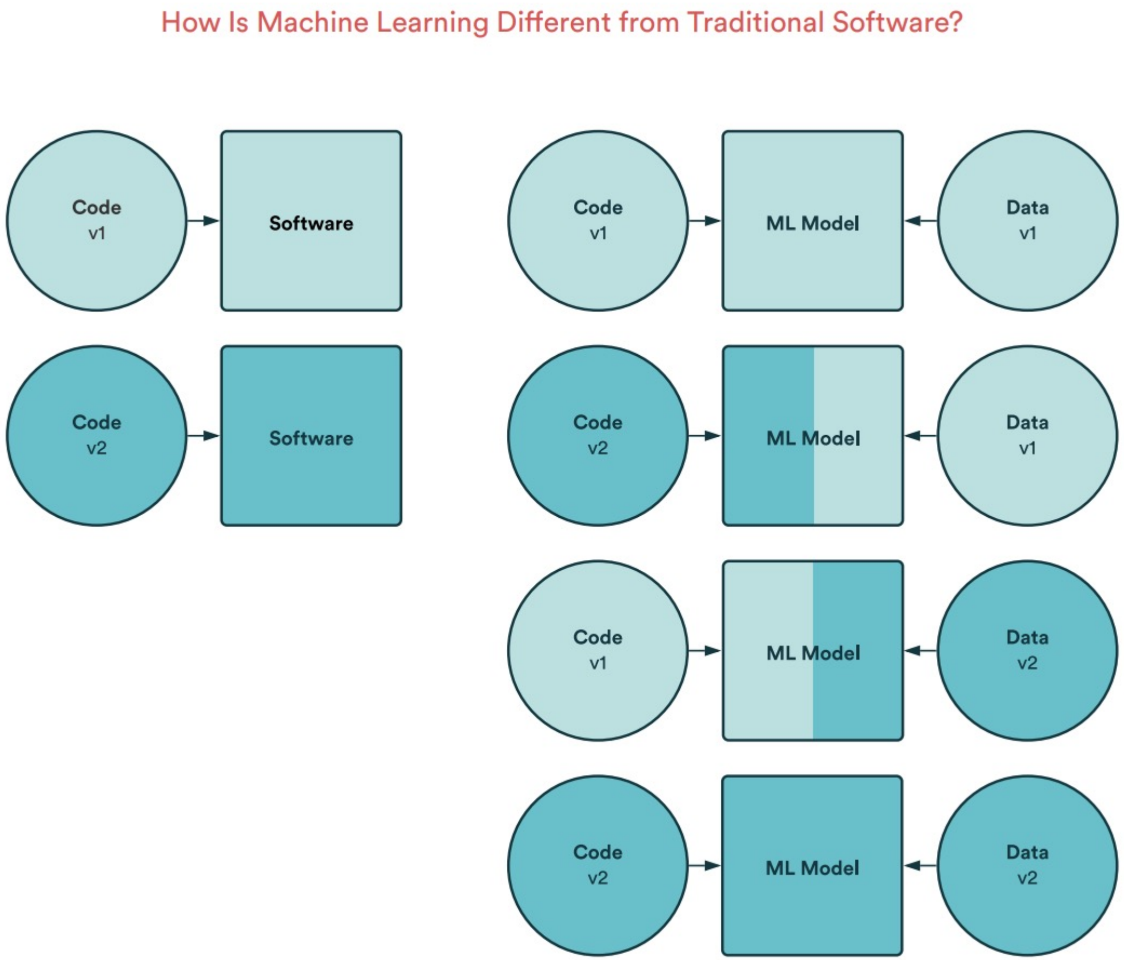
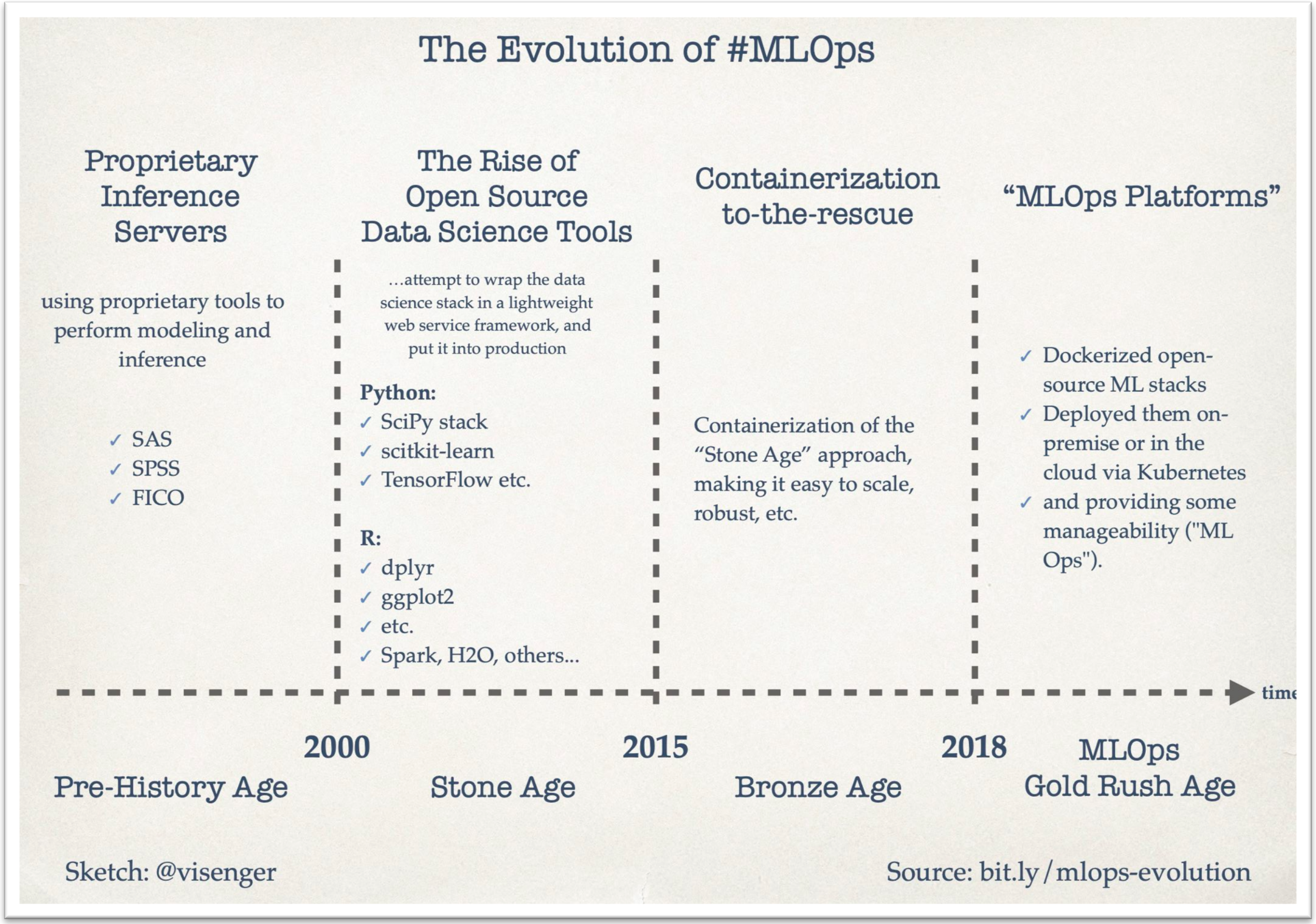
Scenarios that needs to be managed

- In machine learning-based systems, the trigger for a build might be the combination of a code change, data change, or model change.



Motivation



The Evolution of #MLOps
Proprietary Inference Servers
using proprietary tools to perform modeling and inference
✓ SAS
✓ SPSS
✓ FICO
The Rise of Open Source Data Science Tools
…attempt to wrap the data science stack in a lightweight web service framework, and put it into production
Python:
✓ SciPy stack
✓ scitkit-learn
✓ TensorFlow etc.
R:
✓ dplyr
✓ ggplot2
✓ etc.
✓ Spark, H2O, others...
Containerization to-the-rescue
Containerization of the "Stone Age" approach, making it easy to scale, robust, etc.
"MLOps Platforms"
✓ Dockerized open-source ML stacks
✓ Deployed them on-premise or in the cloud via Kubernetes
✓ and providing some manageability ("ML Ops").
time
2000
2015
2018
Pre-History Age
Stone Age
Bronze Age
MLOps Gold Rush Age
Sketch: @visenger
Source: bit.ly/mlops-evolution

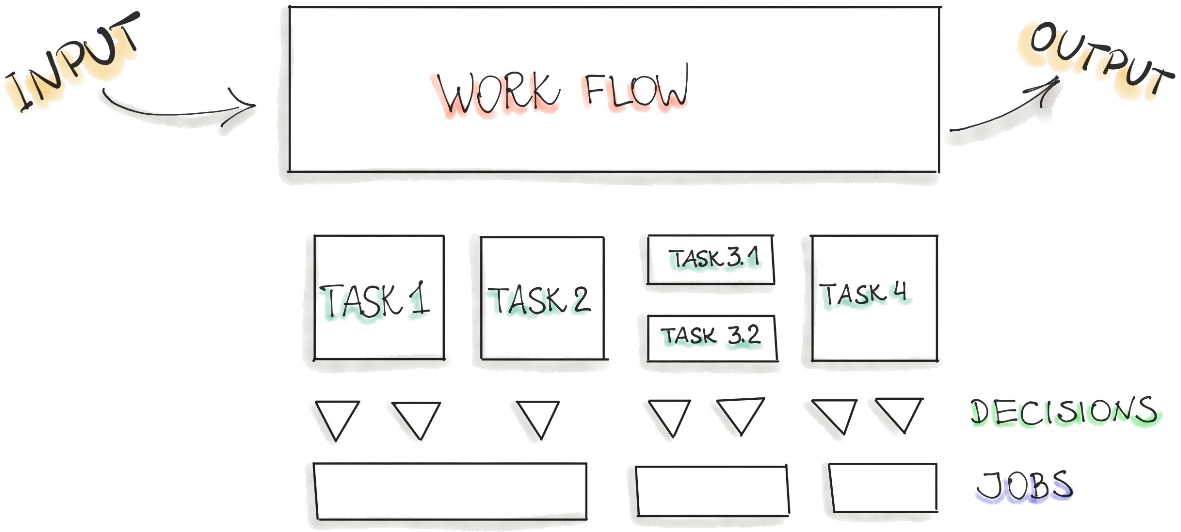
MLOPS

Design

Design a ML-powered software

To answer the question *“how to implement AI/ML”*, we follow the next steps:

1. Identify the concrete ***process*** that might be powered by AI/ML.
2. Decompose that process into a directed graph of ***tasks***.
3. Identify where humans can be removed from the task, meaning, what task can be replaced by a prediction element such as ML model?
4. Estimate the ROI for implementing an AI/ML tool to perform each task.
5. Rank-order the AI/ML implementation for each ***task*** in terms of ROI.
6. Start from the top of the list and structure the AI/ML implementation by *Machine Learning Canvas*.



MLOPS

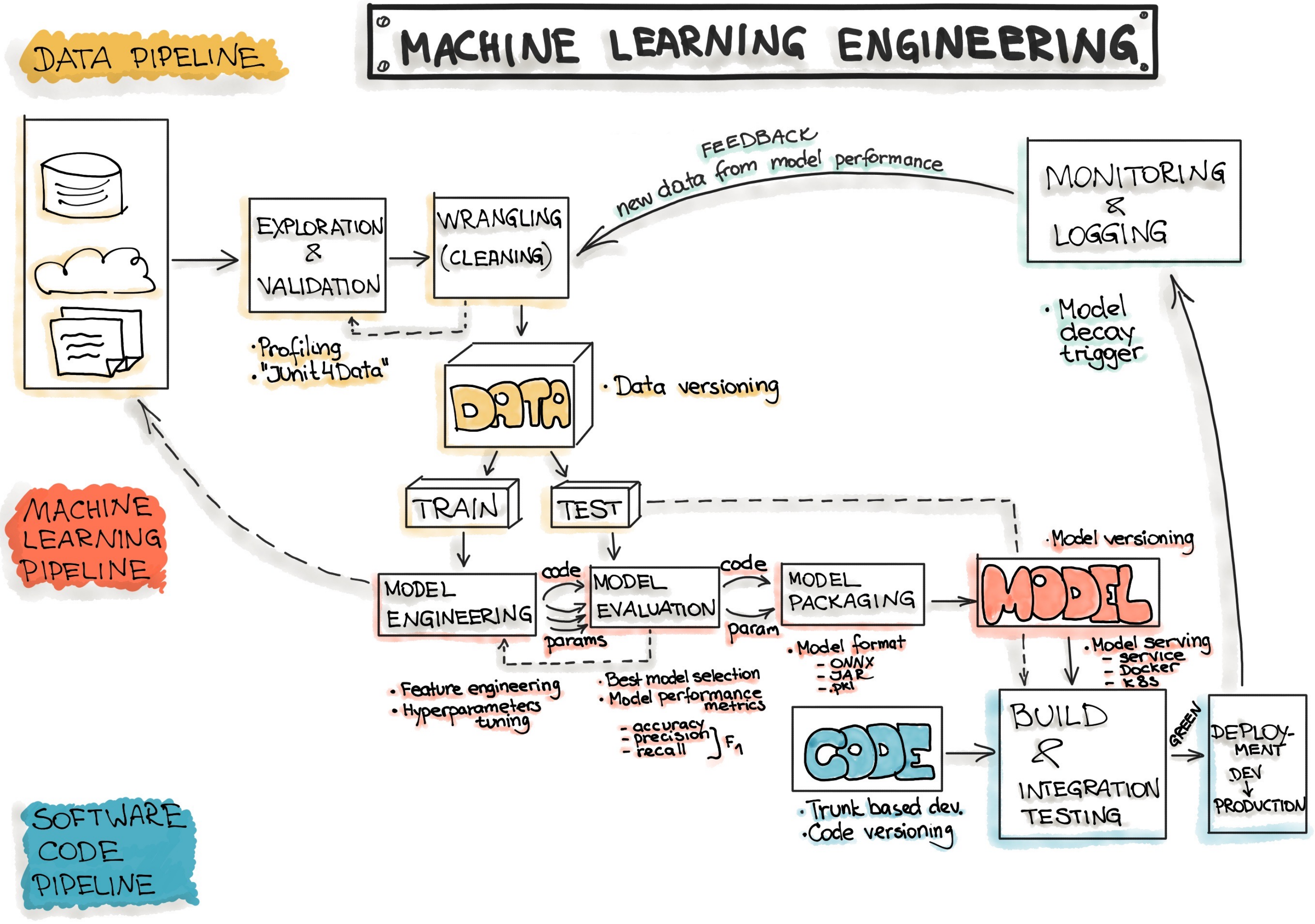
Life Cycle

Lifecycle

The Figure below shows the core steps involved in a typical ML workflow.

Based of three artifacts Data, ML Model, and Code, we have three ML workflows:

- **Data Engineering**: data acquisition & data preparation,
- **ML Model Engineering**: ML model training & serving, and
- **Code Engineering** : Integrating ML model into the final product.



MLOPS

Levels

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- Data Engineering Pipelines – this is something you already now
- ML Pipelines and ML workflows
- Model Serving Patterns and Deployment Strategies

– Let’s talk about this

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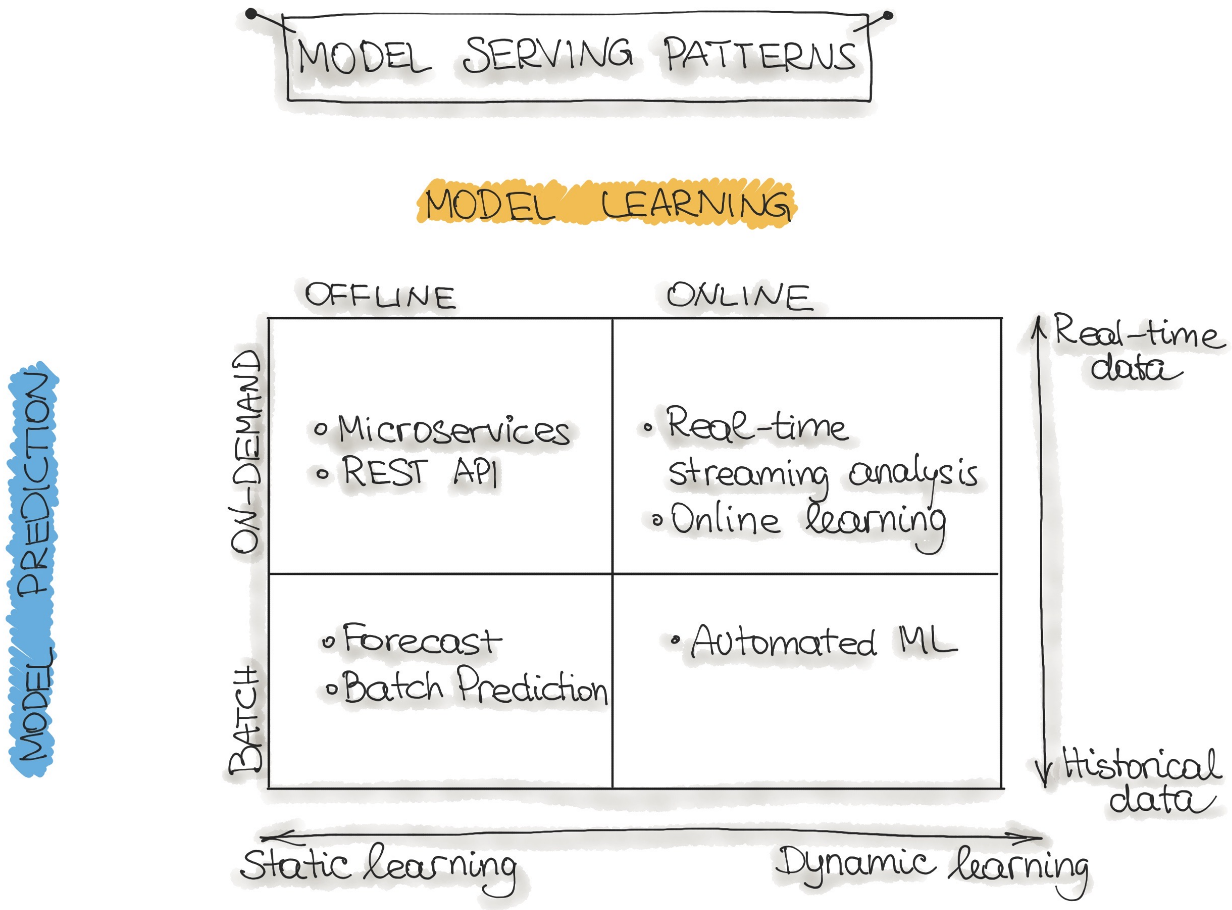

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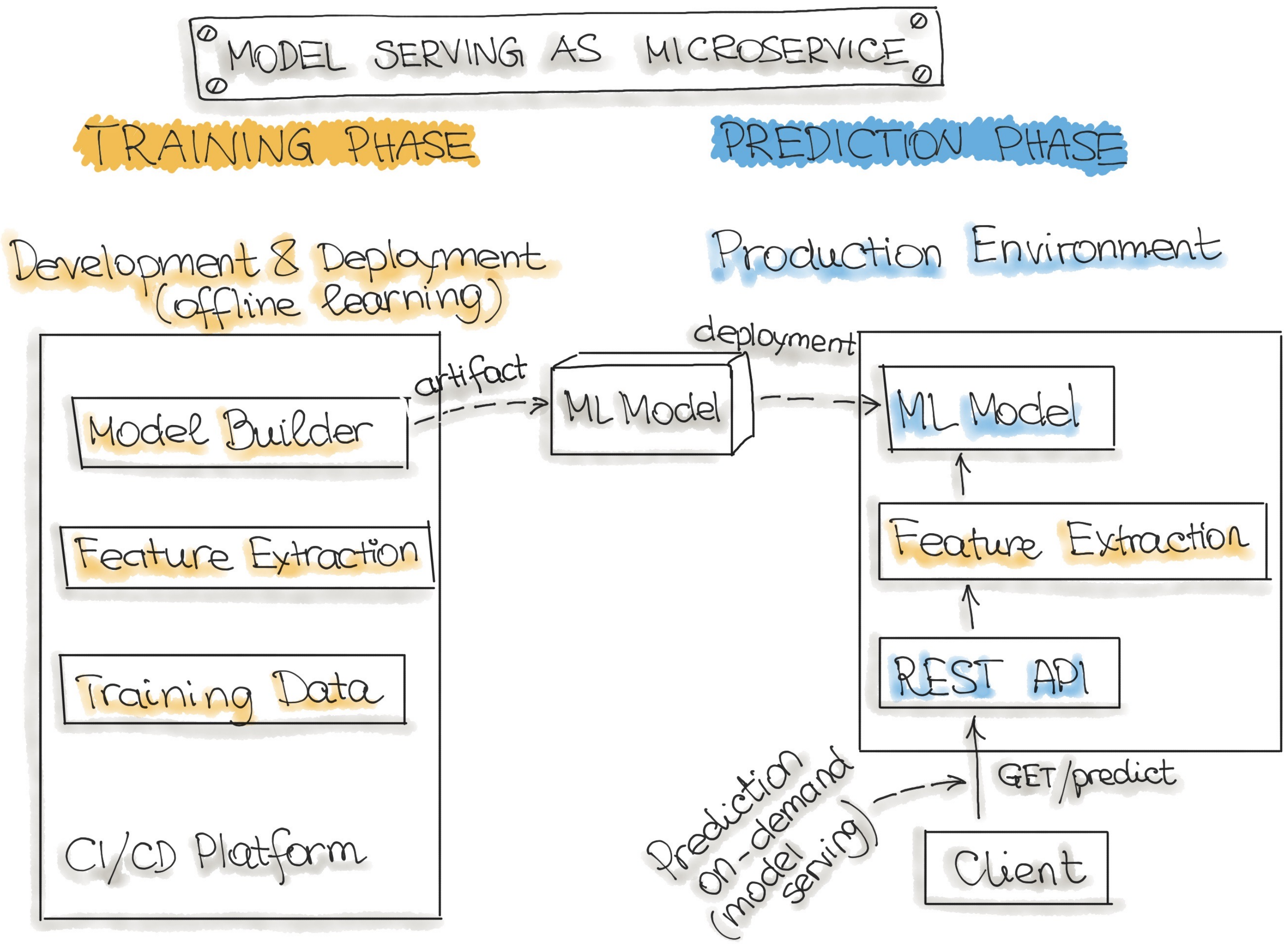

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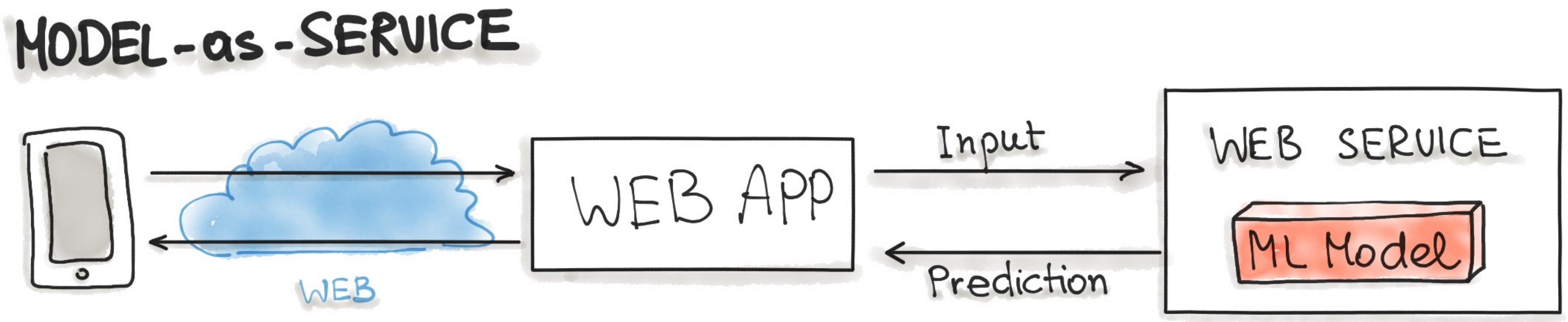

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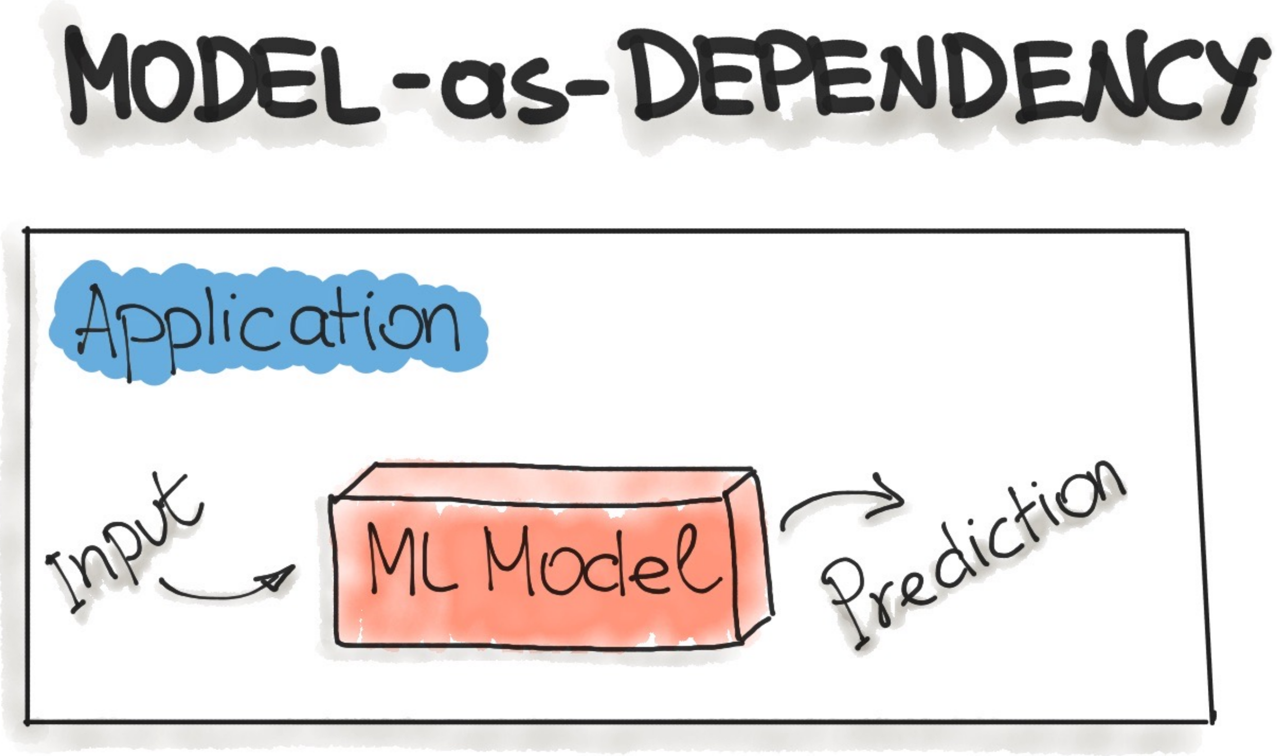

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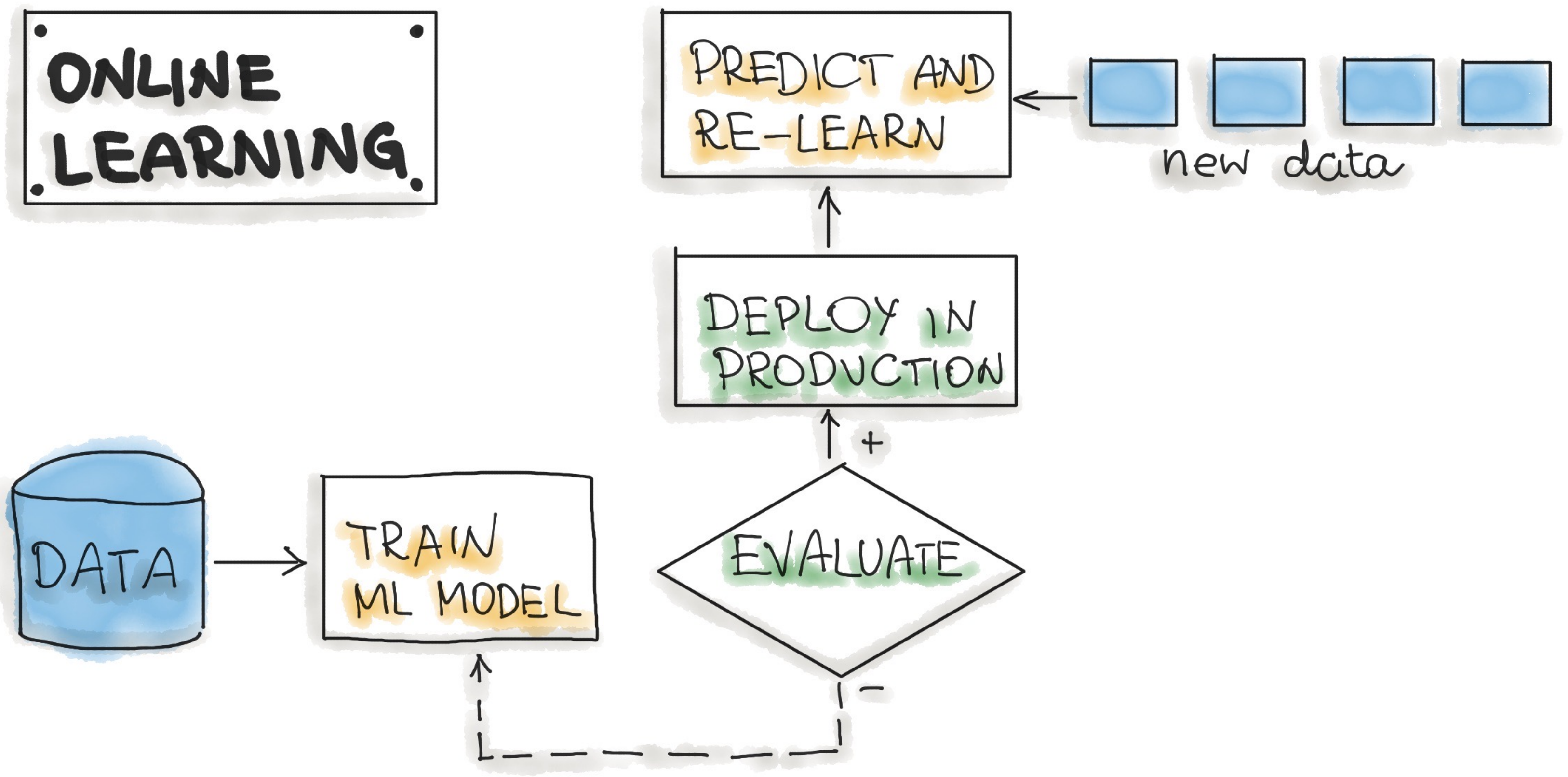

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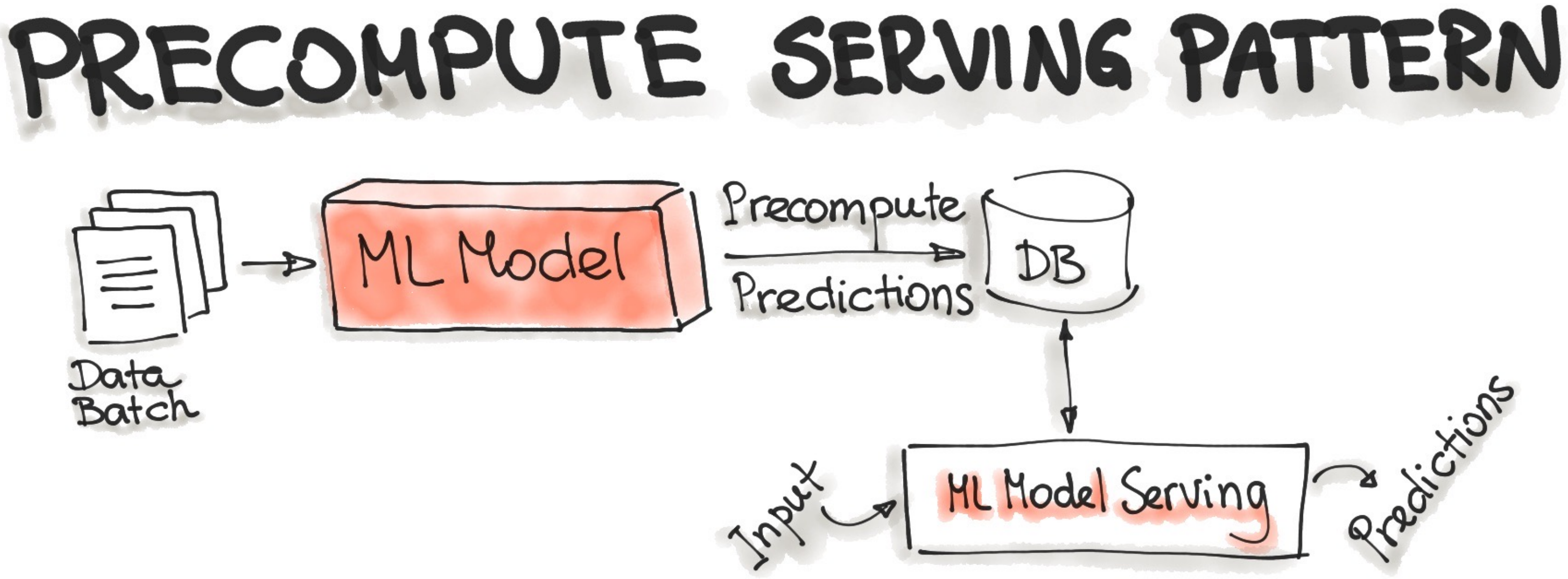

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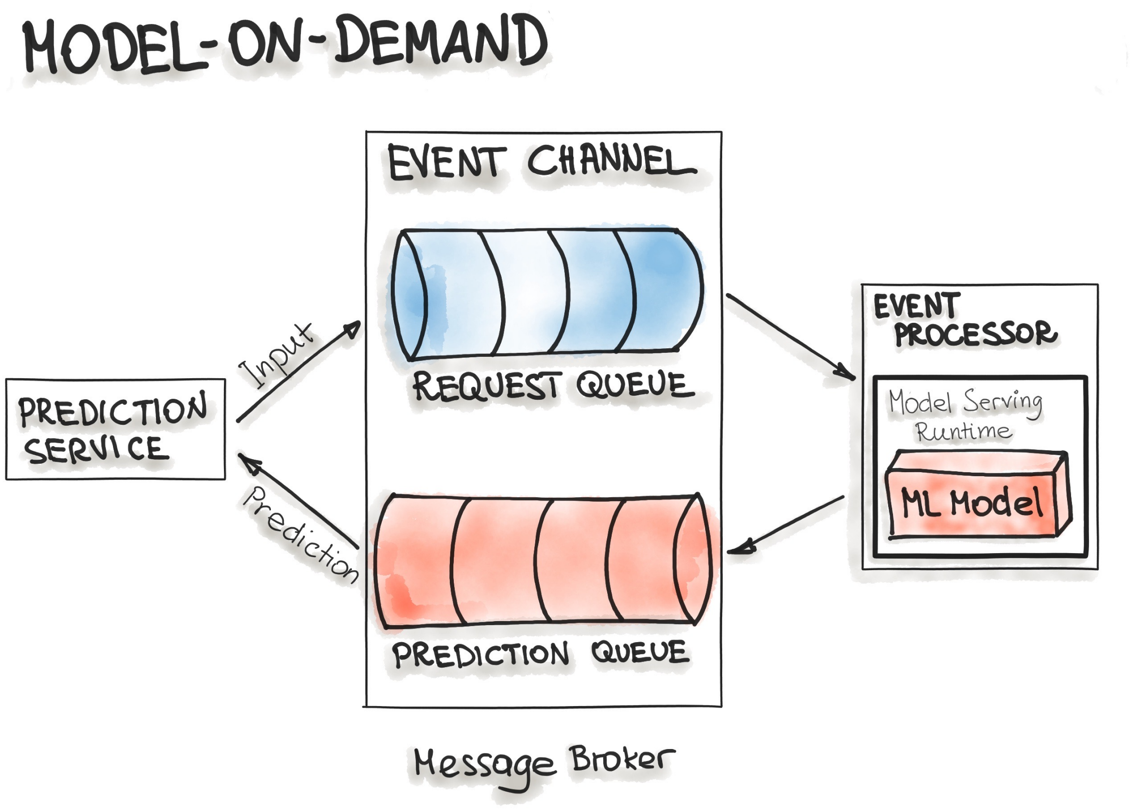

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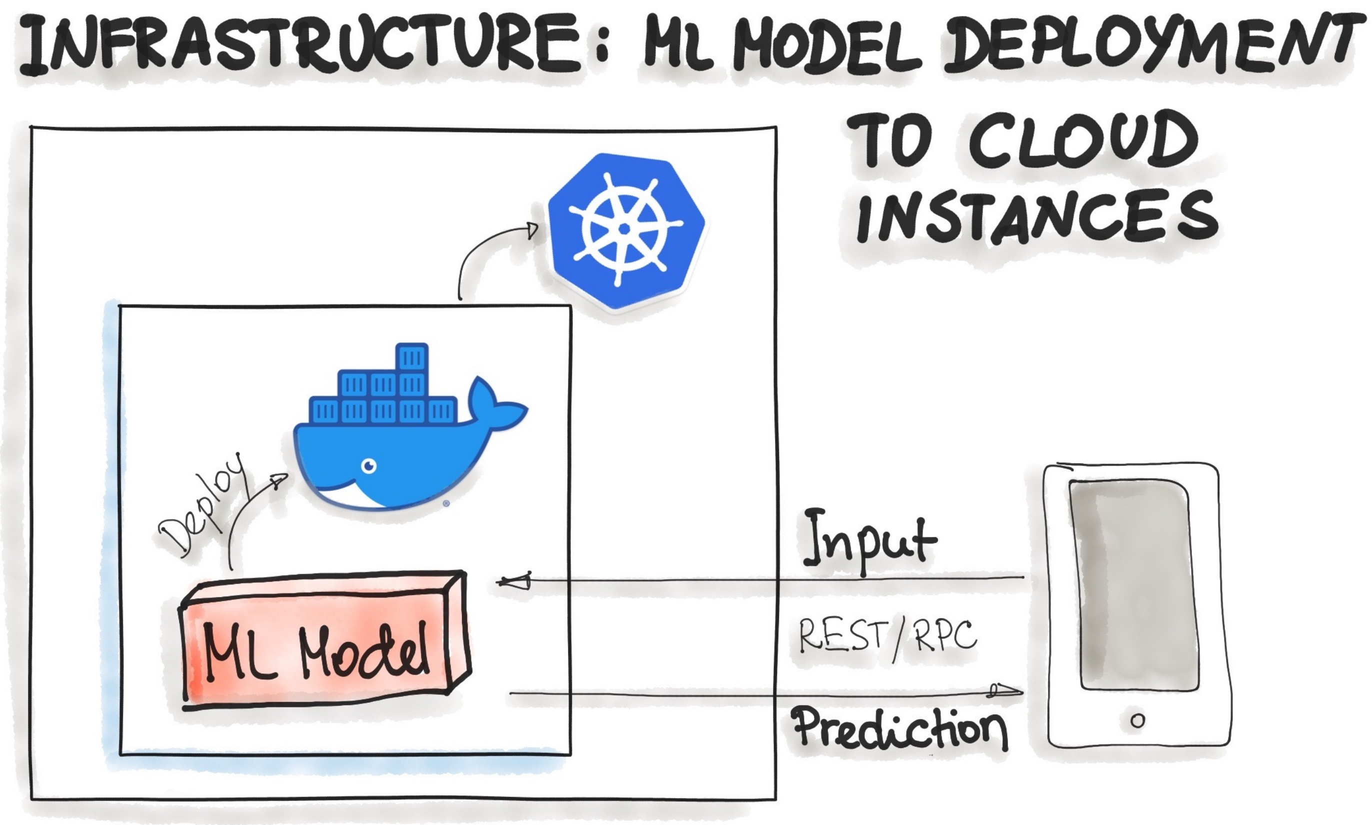

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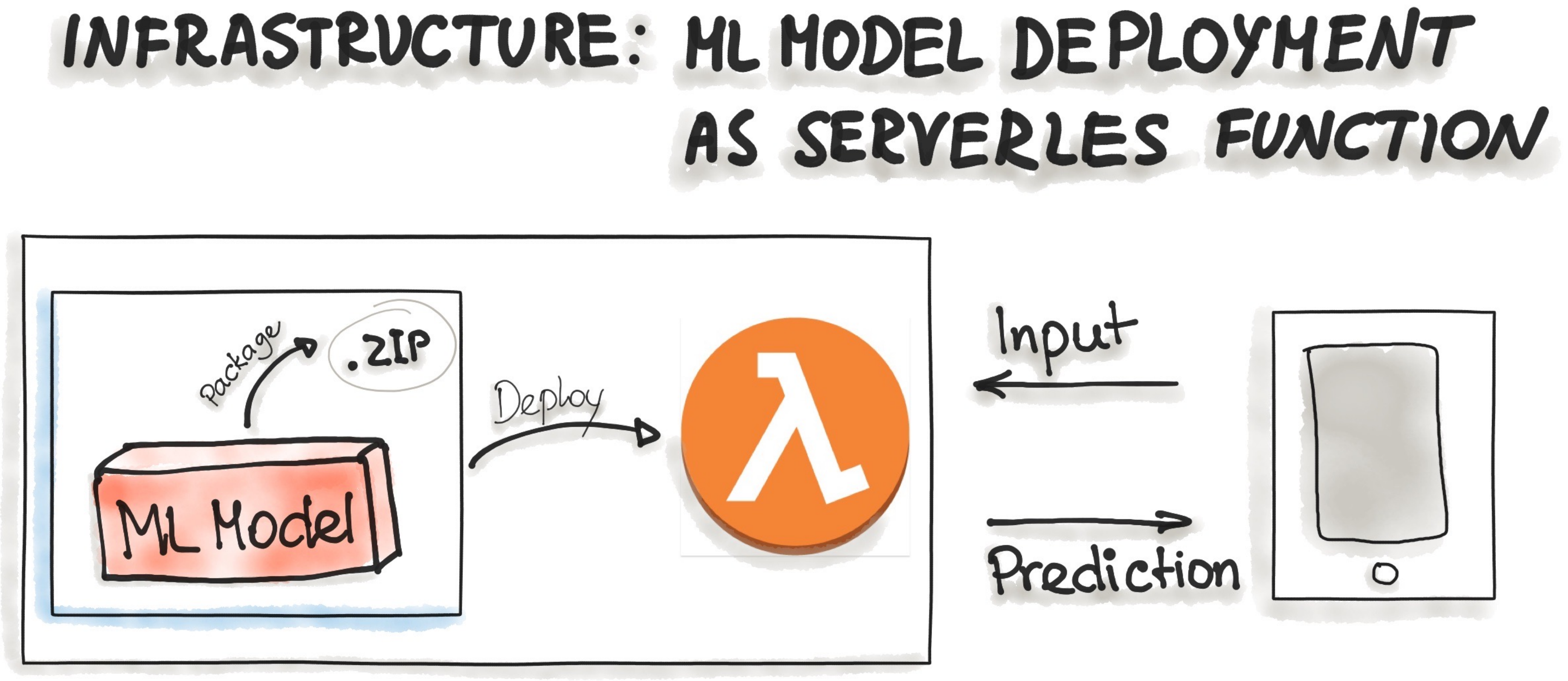

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Thank You