# Bootcamp
# Bringing ML Models into Production

## Lesson 1: Intro

Alyona Galyeva

# Agenda

- About us
- Bootcamp Setup
- MLOps
- Home assignment

# ABOUT US

# PyLadies Amsterdam Team

# Where to find us?

Website
https://amsterdam.pyladies.com

Materials
https://github.com/pyladiesams
https://www.youtube.com/pyladiesamsterdam

Events
https://www.meetup.com/PyLadiesAMS

Updates
https://www.linkedin.com/company/pyladies-amsterdam
https://twitter.com/PyLadiesAMS

# Bootcamp Setup

DEXTER

# FORECASTING ENERGY USING AI.

# Dexter-PyLadies energy case

July 2021


| cluster | imba/h [€/MWh] | imba irr. [€/MWh] | imba/pte [€/MWh] | imba/pte [GWh] | total abs load [GWh] | NMAE [%] | total cost [€] |
|---|---|---|---|---|---|---|---|
| B2C solar | 2.613 | 0.721 | 2.016 | 0.034 | 0.069 | 49.45 | 180 |
| wind | 1.197 | 0.483 | 0.949 | 0.072 | 0.391 | 18.34 | 468 |
| B2B solar | 2.566 | 0.558 | 2.110 | 0.077 | 0.448 | 17.18 | 1,150 |
| profile | 0.817 | 0.239 | 0.638 | 0.058 | 0.866 | 6.64 | 708 |
| telemetry | -0.100 | 0.078 | -0.139 | 0.047 | 0.954 | 4.89 | -95 |
| total | 0.858 | 0.265 | 0.658 | 0.167 | 2.729 | 6.14 | 2,342 |

# Impact of Dexter

Forecast renewable energy to:

- Make renewable energy more profitable and push fossil fuel energy out of the market
- Balance the demand and generation of electricity to prevent strongly polluting emergency solutions

# About Dexter

- Founded in 2016, based in Amsterdam
- Focused on short-term power trading optimisation
- Team:
  22 FTE - Energy market experts |
  Computer & Data Scientists |
  Weather model experts
- Countries:
  Benelux, Germany, Austria & UK

# Working at Dexter

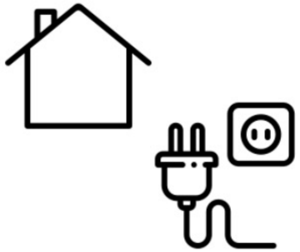
- Dynamic and young start-up
- Challenging software development & data science
- Contributing to the transition to renewable energy
- Fun team

Website: [https://dexterenergy.ai/](https://dexterenergy.ai/)
Feel free to contact us with any questions

# Dexter - PyLadies case

## OLD APPROACH

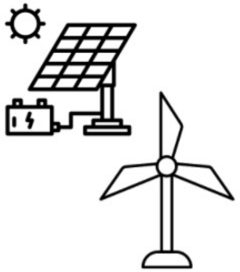
Determine
energy consumption



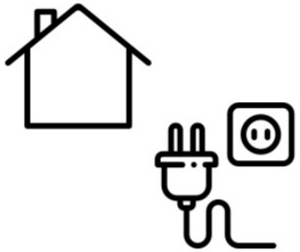
Adjust
energy generation

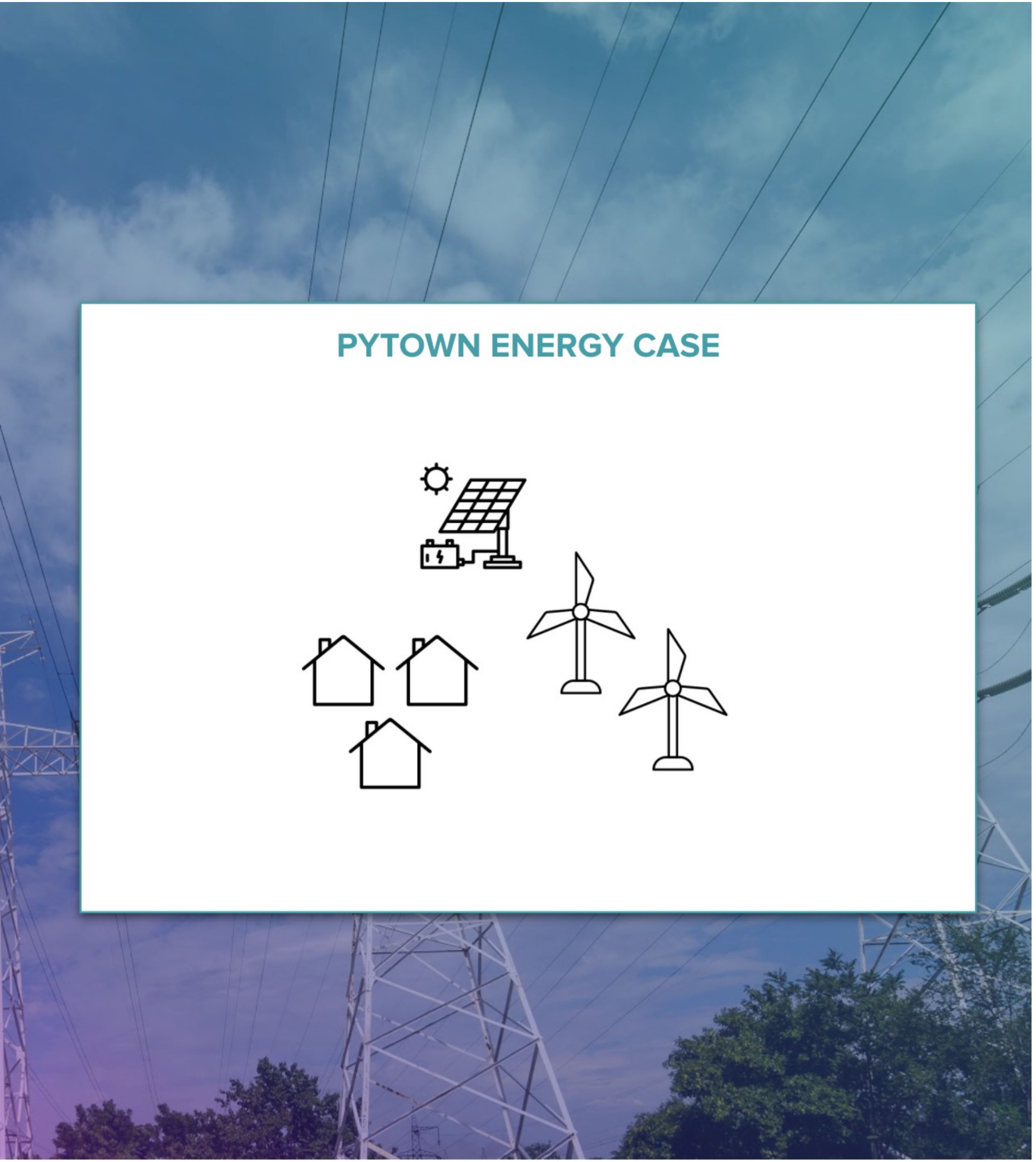
## NEW APPROACH

Determine
energy generation



Adjust
energy consumption






# Dexter-Pyladies energy case

Pytown is a village in the North of the Netherlands that wants to become fully self-sufficient with 100% renewable energy.

✓ The village has built sufficient solar panels & wind turbines to produce their own energy demand.

X The timing of the energy generation does not match the timing of demand. This raises a lot of problems for Pytown. Frequent blackouts are the order of the day. Can you help Pytown to adjust their demand to the energy generation?

# Alyona Galyeva

- AI & Data Engineering Lead at **LINKIT**
- **PyLadies Amsterdam** Organizer
- AI Mentor at **WAI Accelerate**
- Microsoft **AI MVP**

# Bootcamp

- Schedule and Learning materials
- Slack
- Mentor support
- Capstone

MLOps = ML + DEV + OPS


# MLOps

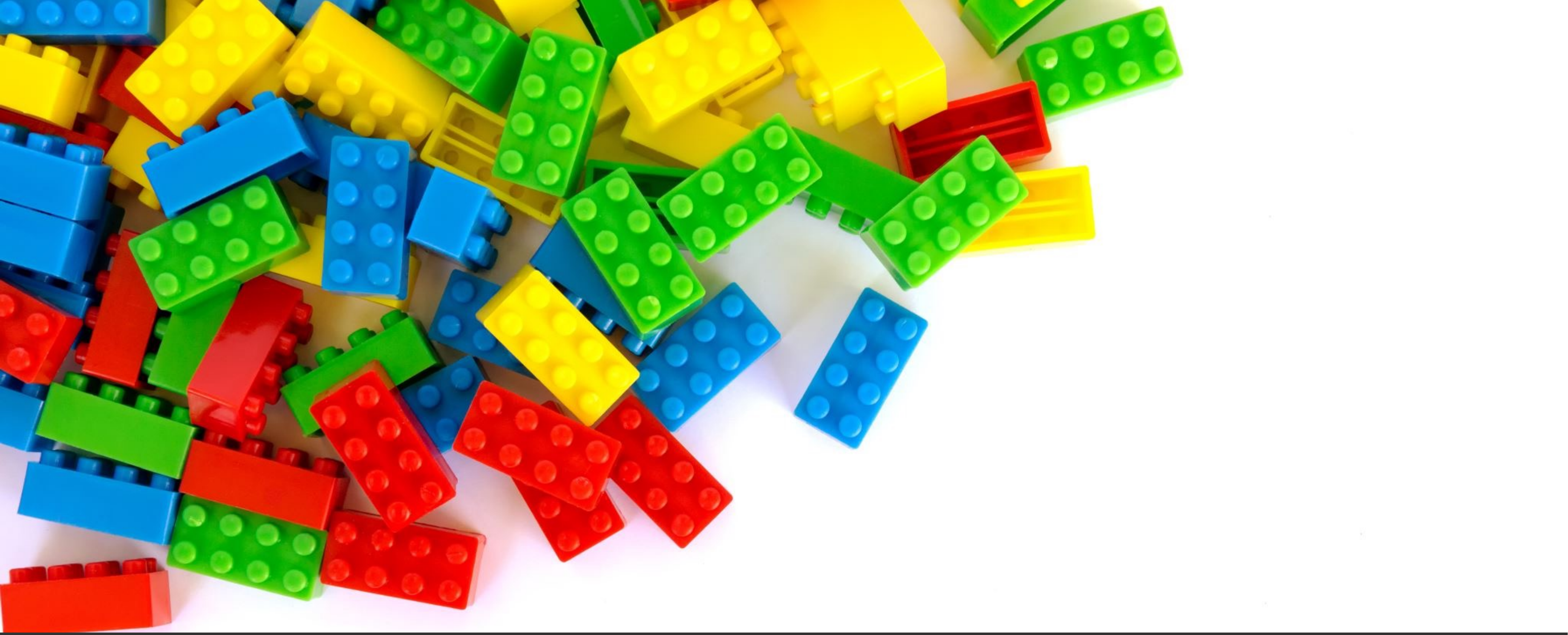
# MLOps

MLOps is the standardization and streamlining of machine learning life cycle management.

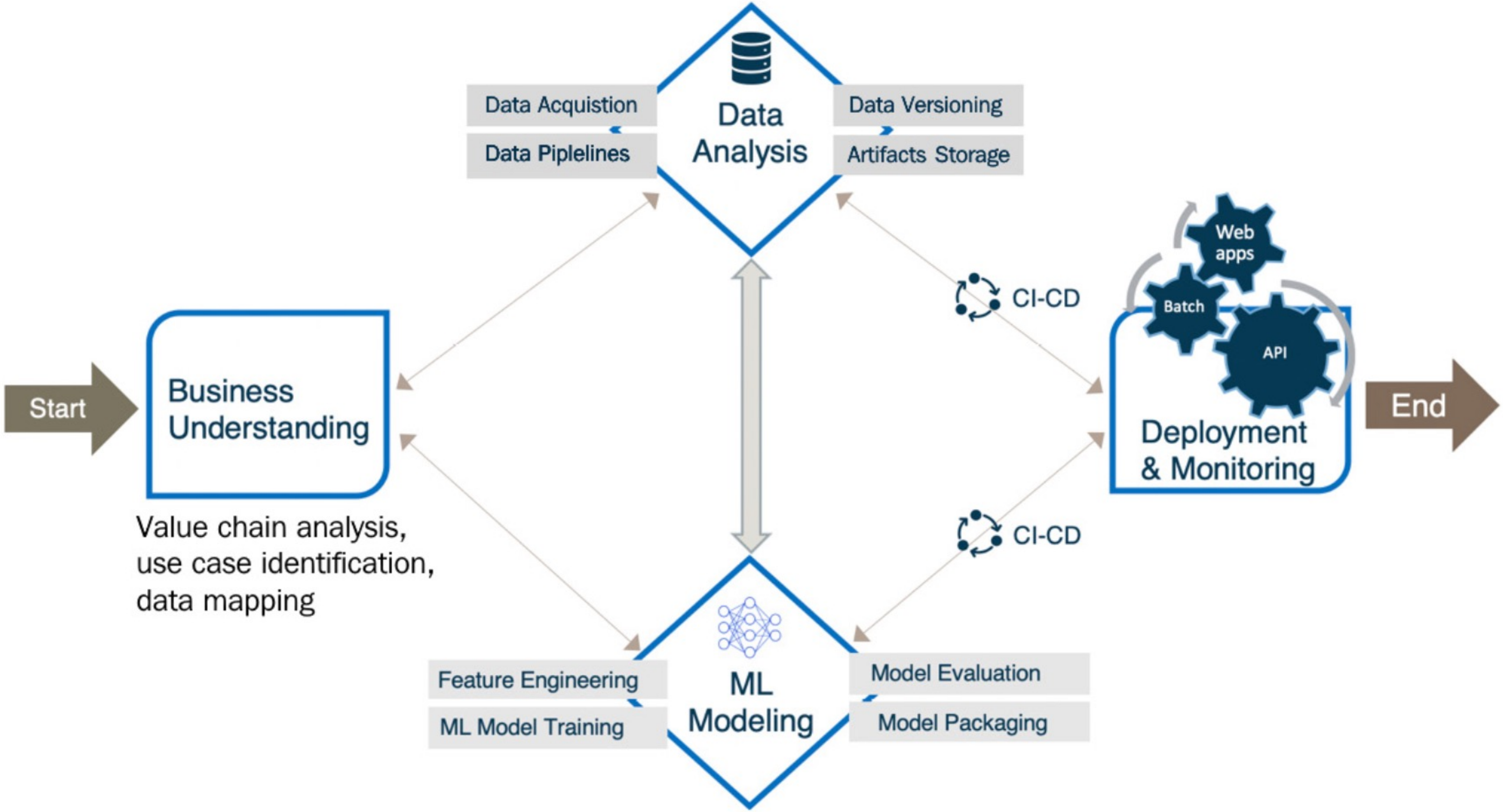
There are three key reasons that managing machine learning life cycles at scale is challenging:

- There are many dependencies
- Not everyone speaks the same language
- Lack of software engineers with ML knowledge

Source: Du Phan and others. Introducing MLOps. Chapter 1.



# ML lifecycle building blocks




Source: Emmanuel Raj. Engineering MLOps. Chapter 2. Figure 2.1 – ML solution development process

# Common ML challenges

- Data quality – “garbage in, garbage out” (accuracy, completeness, consistency, timeliness)
- Reproducibility – inherent element of randomness
- Data and Model Drift – data and target relationships change over time
- Scale – infrastructure needs per each step
- Multiple Objectives – balanced optimizations


# ML model deployment scenarios

| | Research | Production |
|---|---|---|
| Data | Static | Dynamic (constantly changing) |
| Fairness | Recommended | Necessary |
| Interpretability | Recommended | Necessary |
| Performance | State of the art | Better than simpler models |
| Priority | Fast training | Fast inference |

Source: Emmanuel Raj. Engineering MLOps. Chapter 6. Table 6.1 – ML in research and production

# ML model deployment scenarios

The right approach depends on your needs, such as latency requirements, hardware, network and privacy concerns, and inference costs.

Server-Side Deployment:

- streaming workflow
- batch workflow

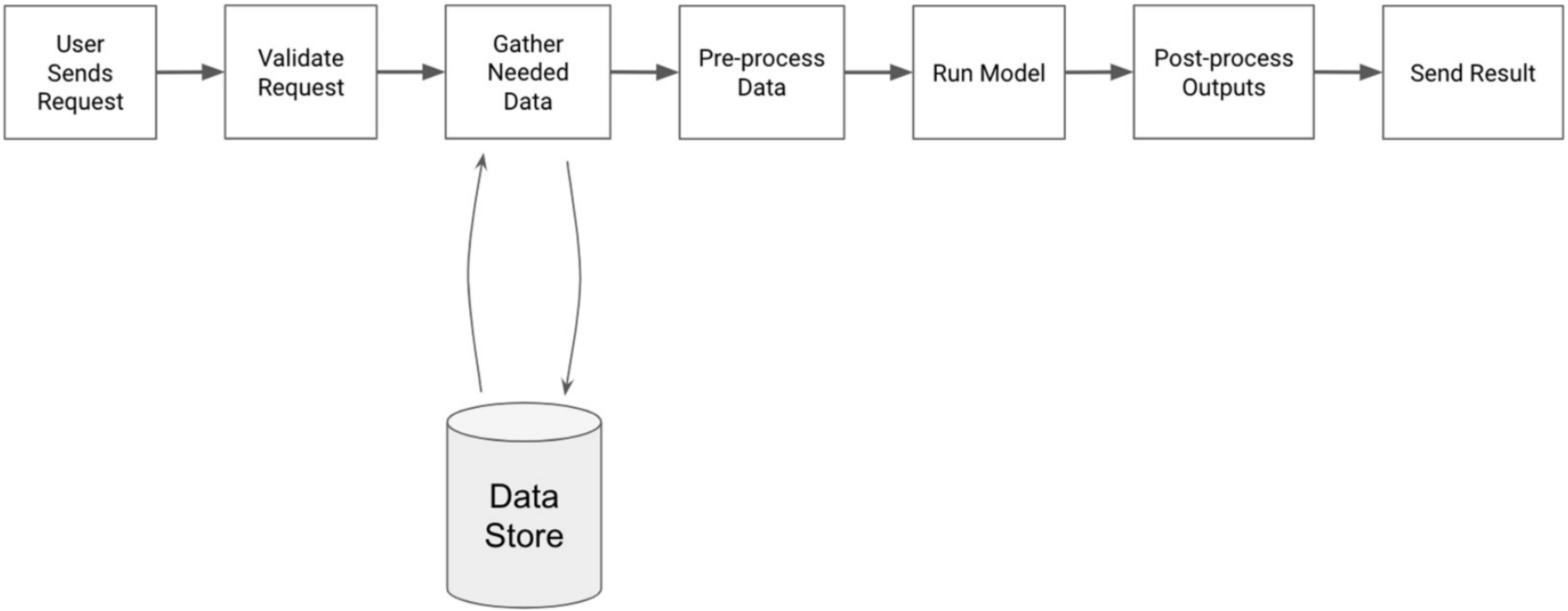
Client-Side Deployment:

- on device
- browser side

Federated Learning (A Hybrid Approach)

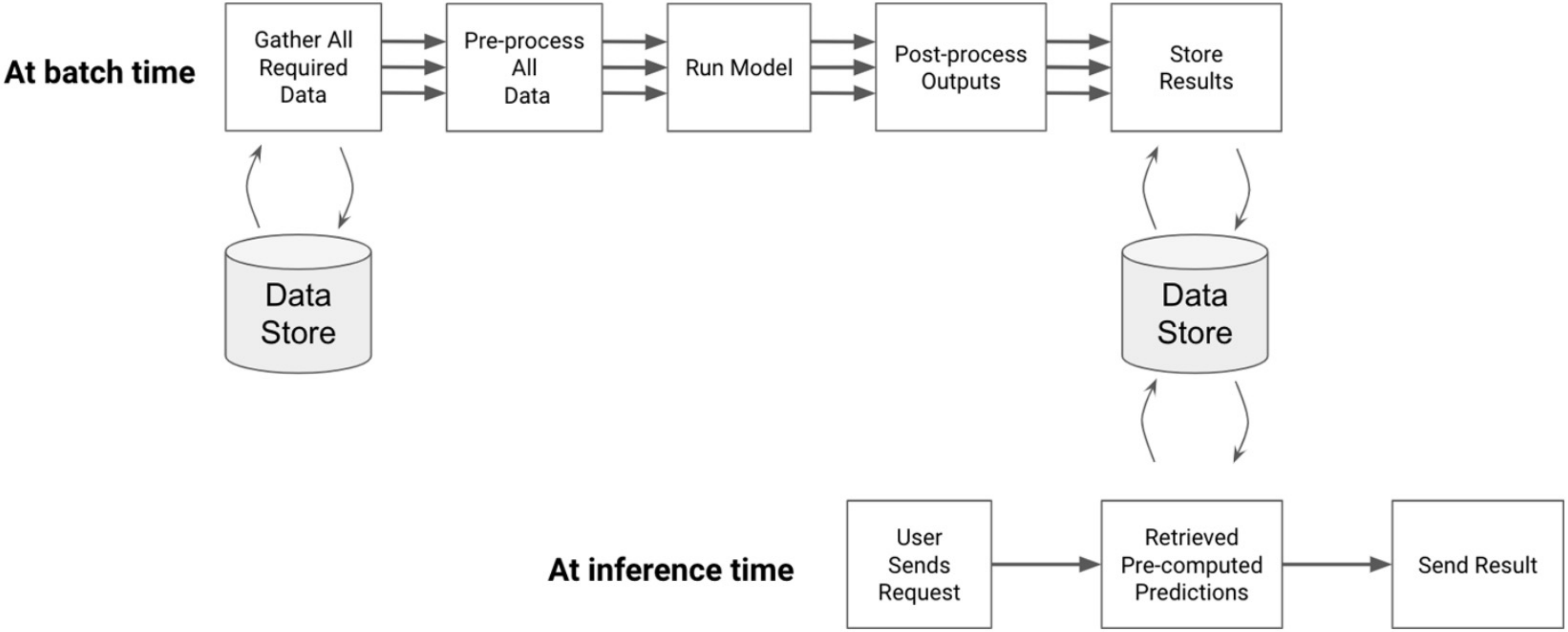
Source: Emmanuel Ameisen. Building Machine Learning Powered Applications. Chapter 9.

# Streaming API Workflow

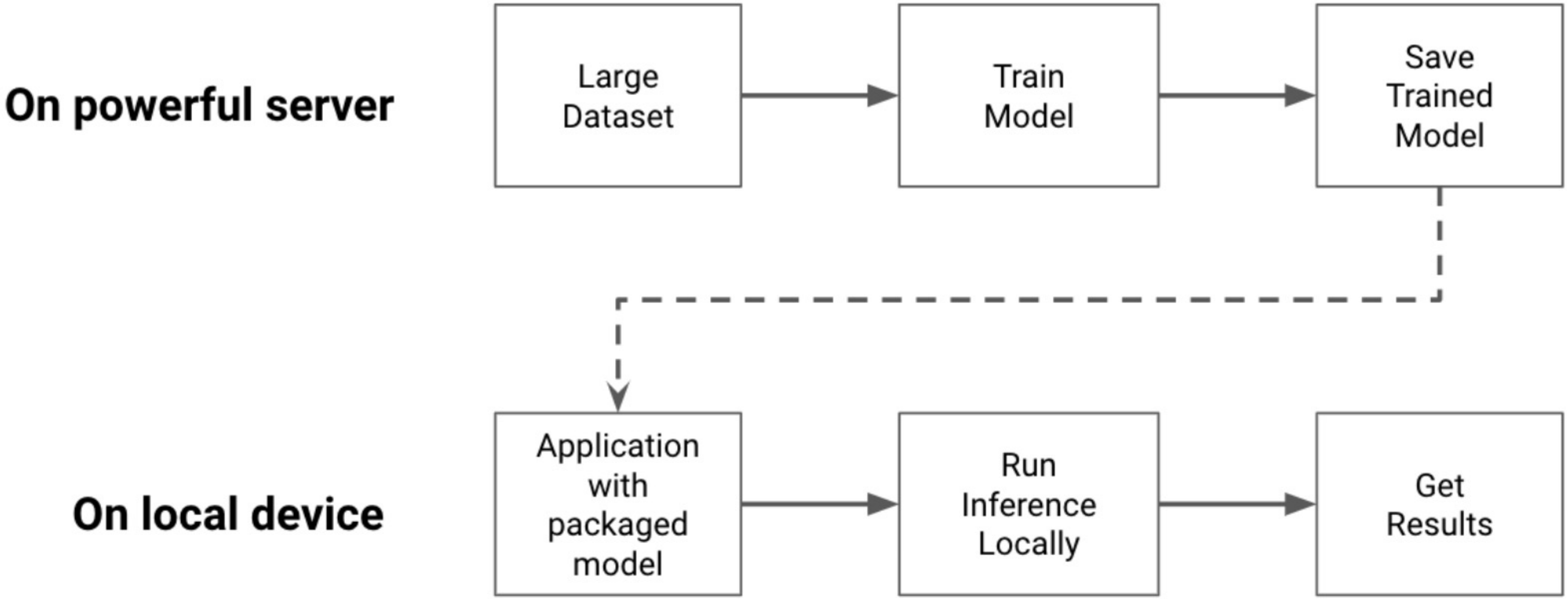



Source: Emmanuel Ameisen. Building Machine Learning Powered Applications. Chapter 9. Figure 9-1. Streaming API workflow

# Batch Workflow

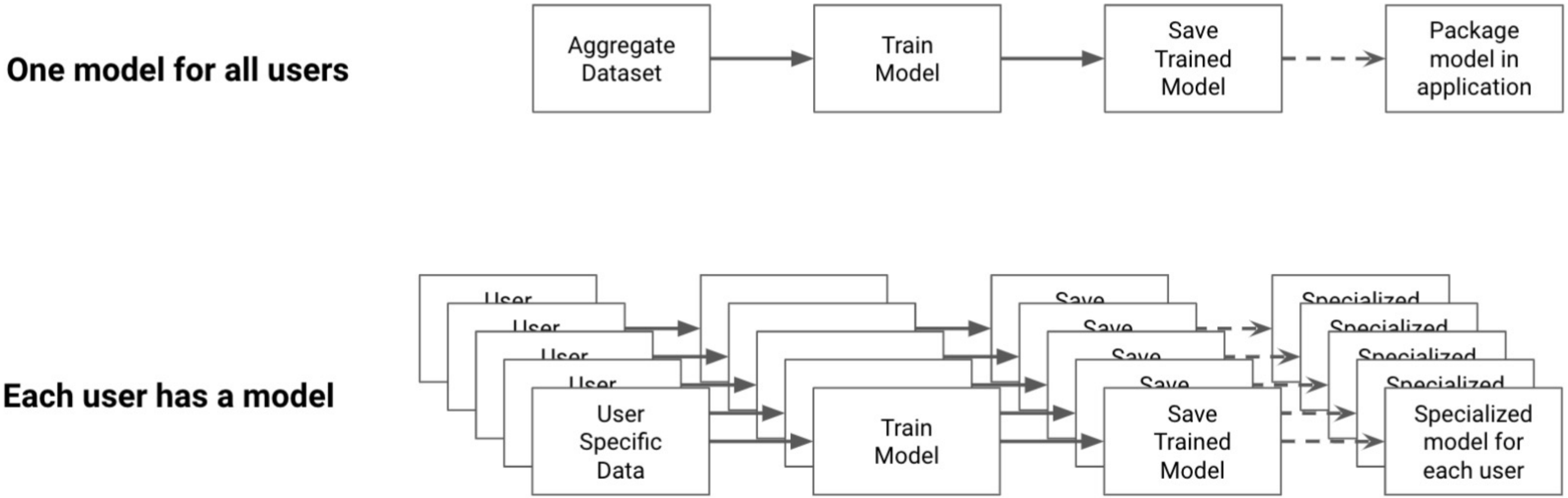


# Device workflow




Source: Emmanuel Ameisen. Building Machine Learning Powered Applications. Chapter 9. Figure 9-4. A model running inference on device

# Federated Learning




Source: Emmanuel Ameisen. Building Machine Learning Powered Applications. Chapter 9. Figure 9-6. One big model or many individual ones

# Steps to prepare model for deployment

Phase 1

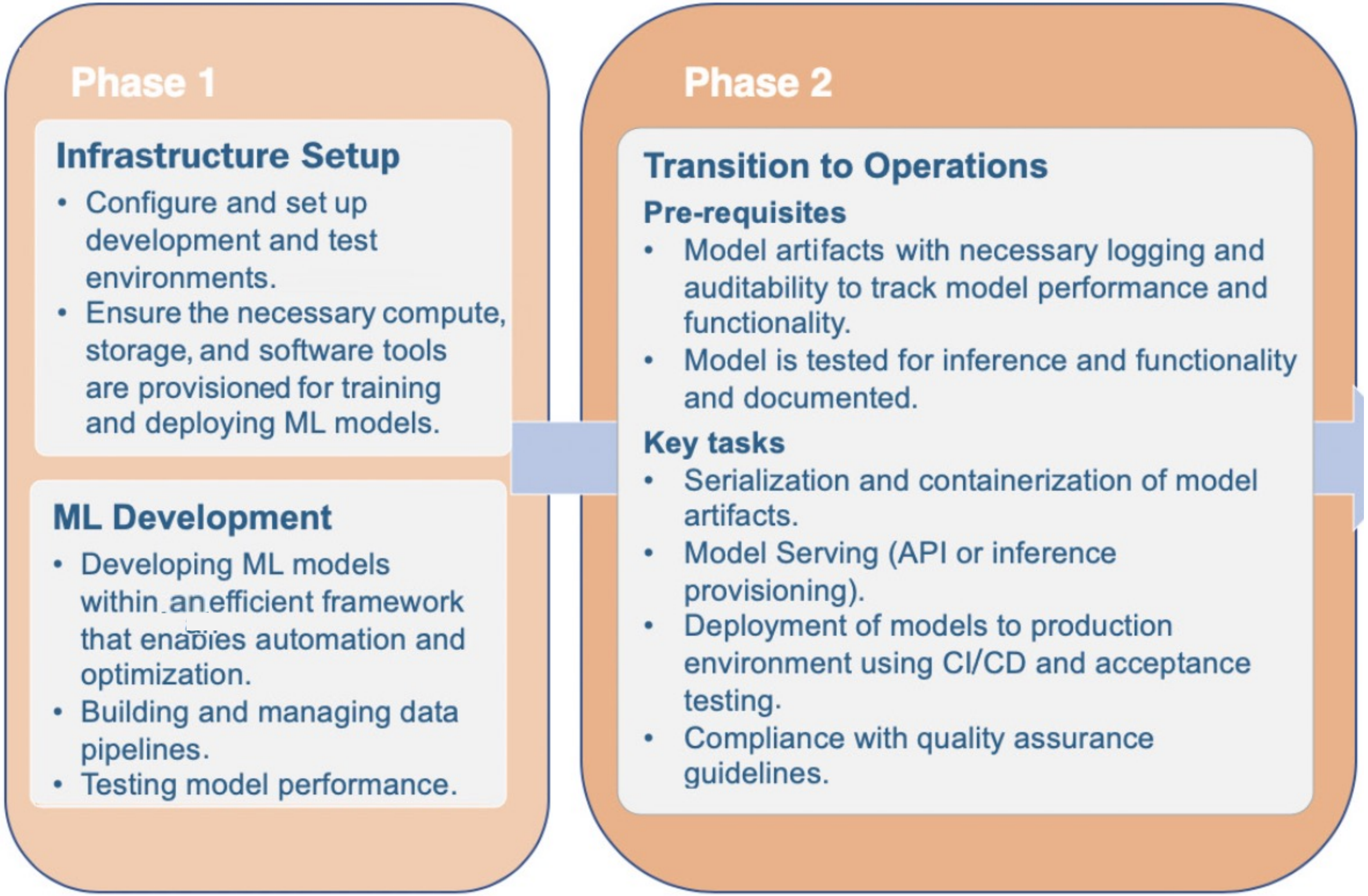
**Infrastructure Setup**

- Configure and set up development and test environments.
- Ensure the necessary compute, storage, and software tools are provisioned for training and deploying ML models.

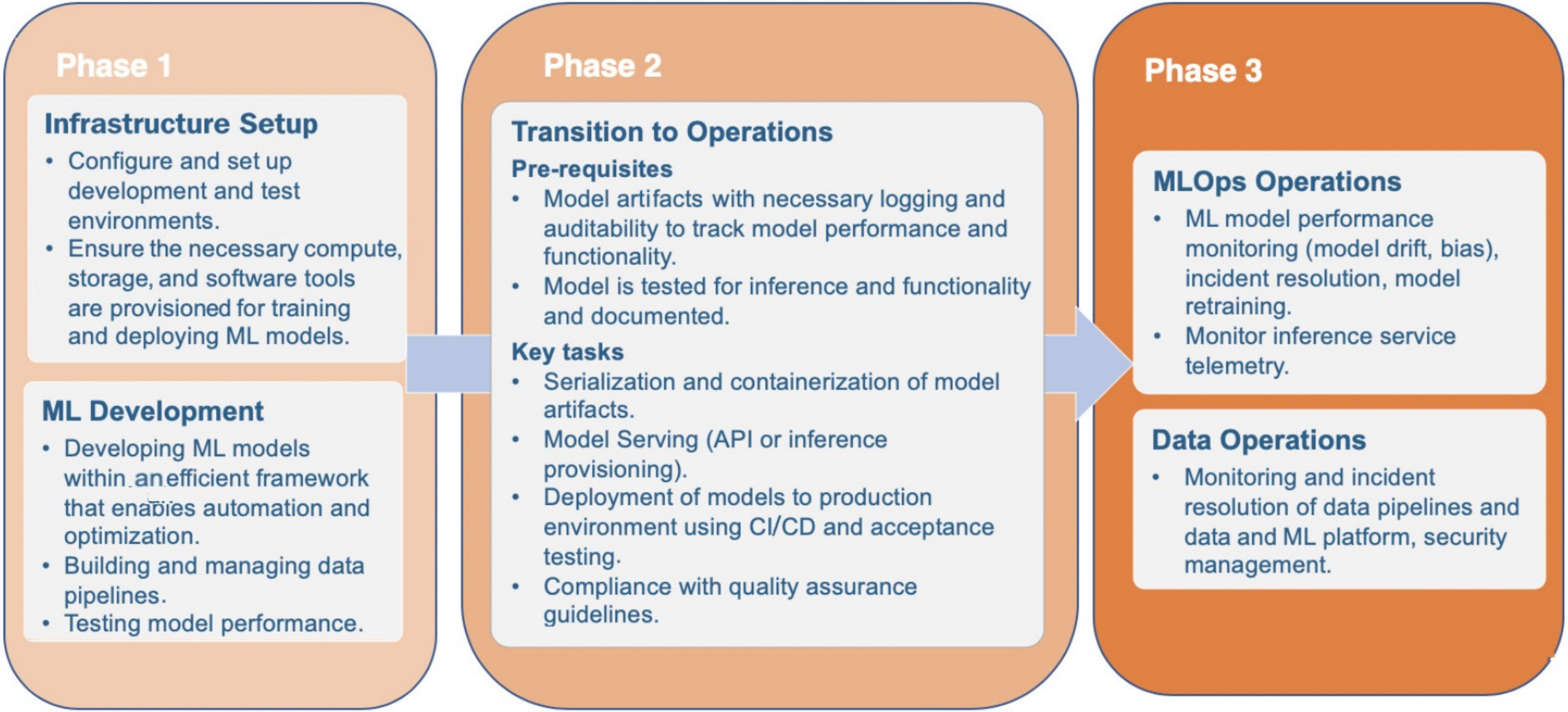
**ML Development**

- Developing ML models within an efficient framework that enables automation and optimization.
- Building and managing data pipelines.
- Testing model performance.

Source: Emmanuel Raj. Engineering MLOps. Chapter 2. Figure 2.10 – Implementation roadmap for an MLOps-based solution




Source: Emmanuel Raj. Engineering MLOps. Chapter 2. Figure 2.10 – Implementation roadmap for an MLOps-based solution




Source: Emmanuel Raj. Engineering MLOps. Chapter 2. Figure 2.10 – Implementation roadmap for an MLOps-based solution

# Home assignment

# Home assignment – Lesson 1

https://github.com/pyladiesams/bootcamp-bringing-ML-models-into-production-intermediary-jun-aug2021/blob/master/bootcamp/lesson1/lesson1_tasks.md

```
print(f"{user_name} thanks for watching")
```