MSDS 603 – Machine Learning Operations

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What if we were asked to build a Smart Transportation System?

- The SFMTA wants to implement a smart transportation management system to optimize traffic flow, reduce congestion, and lower emissions. Using data from traffic cameras, vehicle sensors, public transit GPS, mobile apps, weather services, and scheduled events, the system would predict traffic patterns and adjust traffic light timings, suggest route alternatives, and manage MUNI schedules. The system should be able to adjust to unexpected events, such as collisions, and ensure equitable service across neighborhoods. It should be live 24/7 and demonstrate measurable improvements in commute times and air quality.

We will come back to this!

MLOps

- In this course you will learn about MLOps
  - Sometimes called ModelOps.

- Most important aspects of the end-to-end ML pipeline will be covered
  - Introduce open source tools to get some hands-on practice.
  - Note: some steps require more *theory* than others (e.g. concept drift).
  - Note: some aspects & tools covered in previous courses (e.g. version control with git; docker; orchestration with airflow).
  - Note: different companies use different stacks – we can't learn every tool available!

In This Course…

We will be talking about:

- Requirements gathering and system design
- Experiment tracking
- Registering artifacts
- Data versioning and quality
- Orchestration
- Infrastructure as code
- CI/CD/CT
- Model serving
- Model and operational monitoring

We won’t be talking about:

- How to train ML models
- Data storage/warehouses
- Model re-training
- Ethics/Responsible AI
- Compliance
- Experimentation (in the A/B testing sense)
- ALL of the tools and steps of MLOps

How We Will Learn

- Lecture and Discussion
  - Bring your Practicum/previous job experiences to class
- In-class Demos and Labs
- Homework Assignments

- Grade is based on:
  - Participation (**5%**)
  - Quizzes (**5%**)
  - Homeworks (**20%**)
  - Labs (**35%**)
  - Final Project (**35%**)

Disclaimer: MLOps is a software engineering-heavy field
I am not a software engineer

Discussion Participation (5%)

- Some days we will break up into groups to discuss a problem
- Write answer in **#2025-msds-603-discussion** Slack channel
- Tag everybody in your group to get credit

Mini-quizzes (5%)

- Once per week on Canvas during class
- Open book/note, no talking or sharing answers
- Covers material from previous week
- Can retake it once

Homework Assignments (20%)

- 2 assignments

- Assignment 1 is a two-part assignment
  - First half done in class
  - Second half done at home

- Done ***individually***

Labs (35%)

- Labs assigned once or twice per week
- Due following Monday 11:59PM
- Practice with using open source tools locally and in GCP
- Working together encouraged

Final Project (35%)

Project

- Group project
- Identical to our previous Data Science Entrepreneurship project
- 5-minute demo presentation during last class session
- More details, with rubric, will be in Canvas

Final Project Milestones

- 4 milestones will be due throughout module
- Included as part of final project grade
- Details in Canvas

Course Resources

- Office Hours: T/Th 9:00-10:00 in Room 605, or by appt
- Canvas: for sharing lectures, demos and labs
- Two Slack channels:
  - **#2025-msds-603-discussion** for discussion question participation
  - **#2025-msds-603-general** for general course Q&A and announcements
- GCP Credits ($50) will be provided for labs and project

Path of Least Resistance

- Let's not get bogged down by technology – plenty of time for spinning your wheels when you start working at a company.

- We will use simple, easy to set up, tools (for the most part).

- Meant to be a fun interactive class – if you want to explore other tools, or playing more with GCP, you are free to do so, but is not always required.

Resources for Learning

- Slides and demo notebooks
- Two books in our library related to MLOps:
  - Effective Data Science Infrastructure *by Ville Tuulos*
  - Designing Machine Learning Systems *by Chip Huyen*
- Other resources I will give you during each lecture

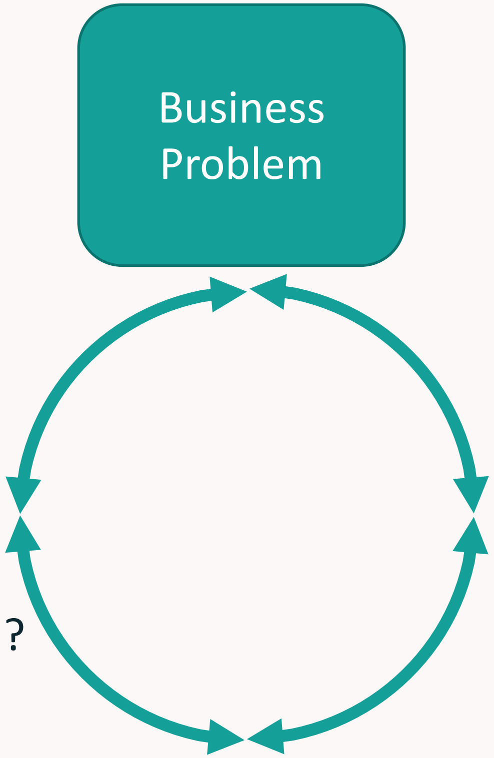
What is MLOps?

What is MLOps?

- Develop, deploy and maintain ML applications - https://madewithml.com/#mlops
- Set of best practices for putting machine learning models into production - https://github.com/DataTalksClub/mlops-zoomcamp
- DevOps (software apps) and MLOps (ML apps) are both about streamlining processes
    - MLOps is more complex than DevOps, though.

The MLOps Pipeline/Lifecycle

always begins with the question: do we even need to use ML?



What is our goal?

What does the customer really need?

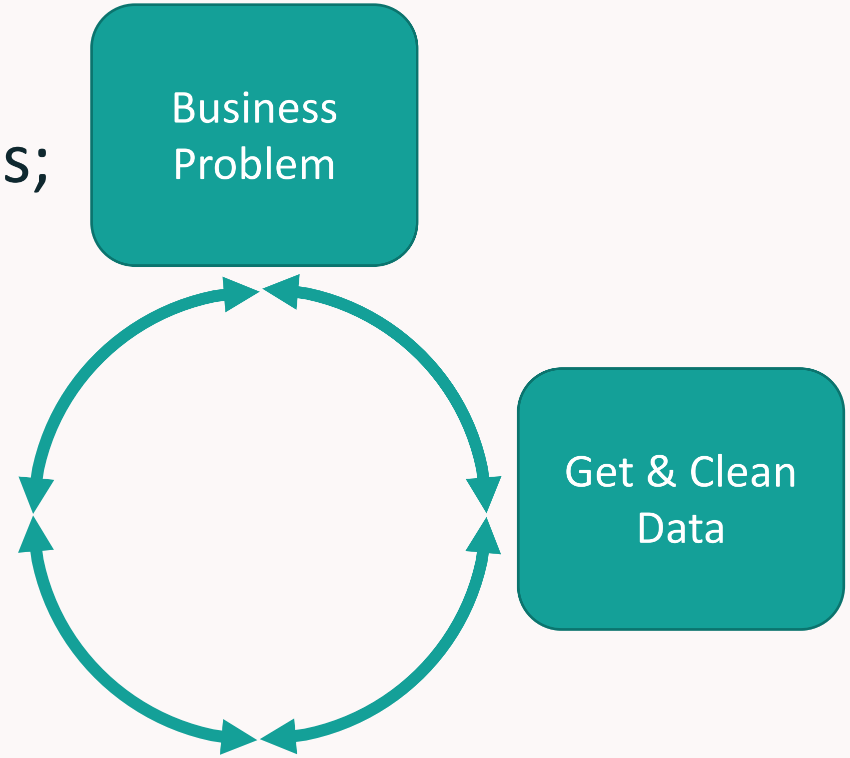
Is there at least some chance of success?

Is there tangible value?

Is there a non-ML solution that will work?

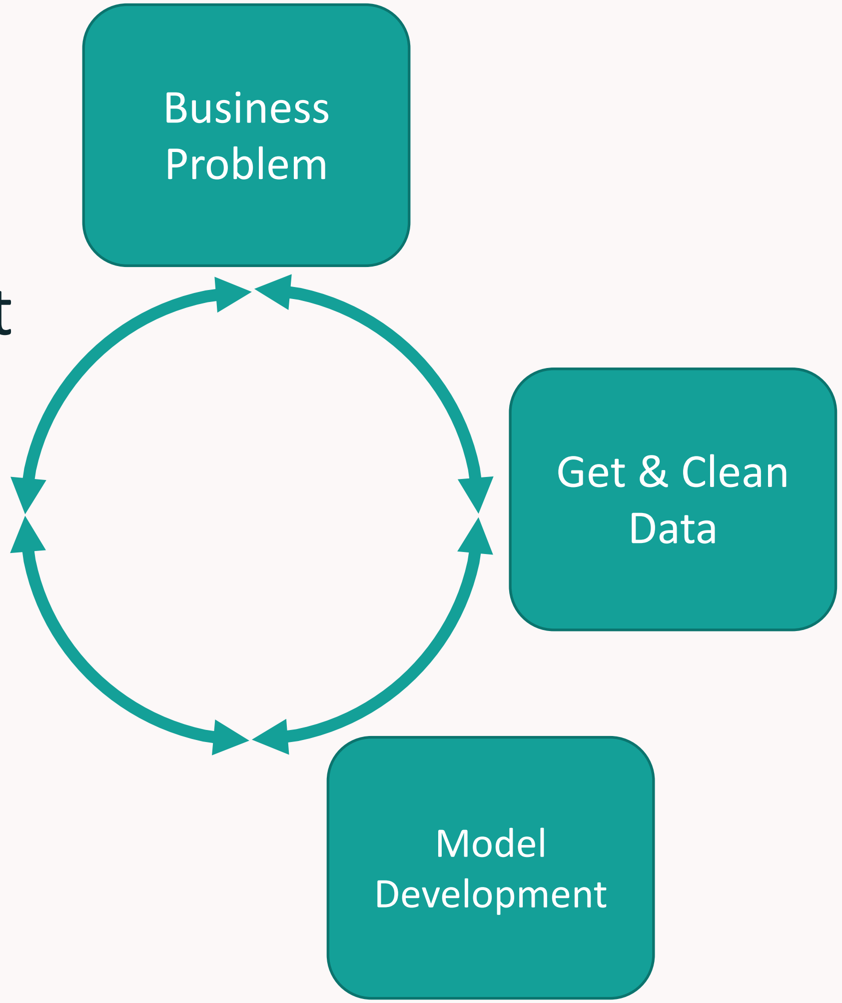
The MLOps Pipeline/Lifecycle

- Do we have data?
- Where is the data: flat files; database; datalake; lakehouse?
- Is it labeled?
- How clean/accurate is it?



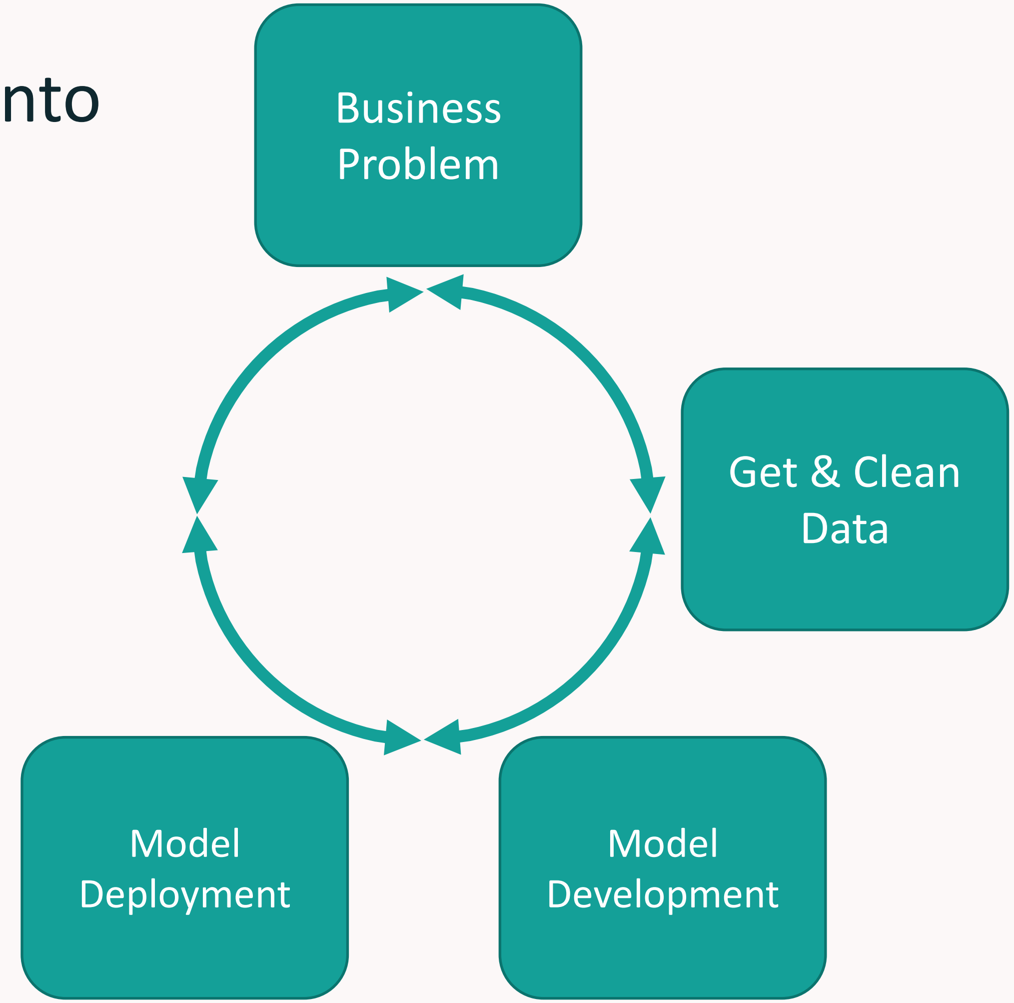
The MLOps Pipeline/Lifecycle

- Do we have infra to train models?
- Do we have development environment?
- Can we keep track of our experiments?



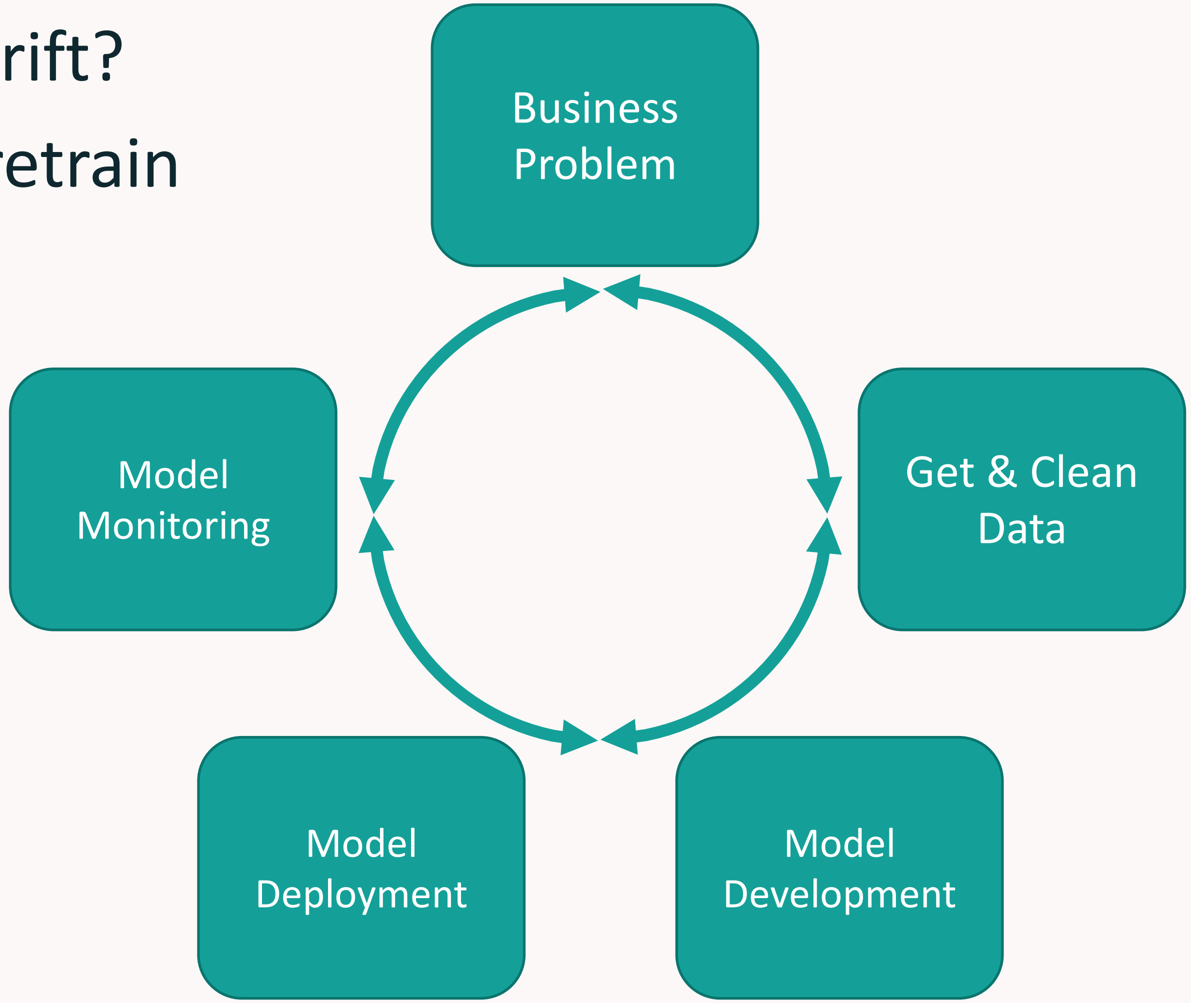
The MLOps Pipeline/Lifecycle

- Can we put model into production?
- Is it scalable?
- Is it secure?
- Is it fault tolerant?



The MLOps Pipeline/Lifecycle

- Does our data drift?
- Do we need to retrain or redevelop?
- Can we explain the predictions?



Infrastructure

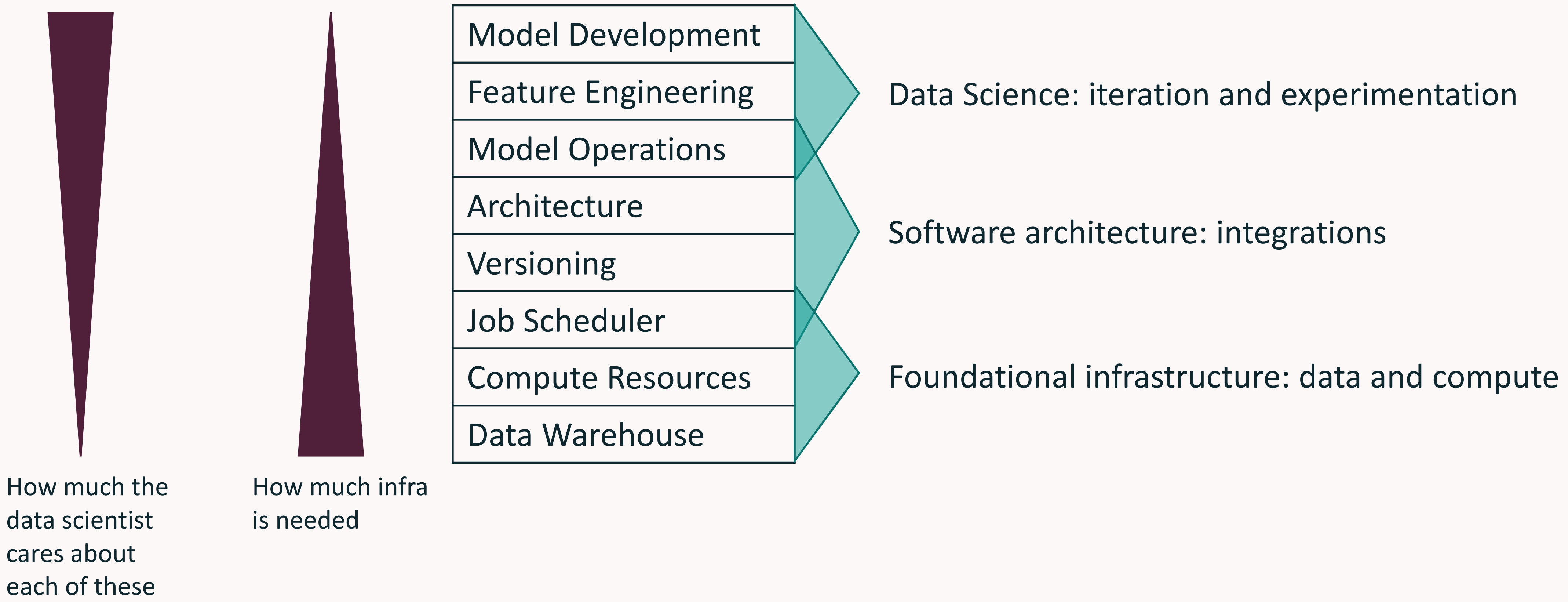


Image reproduced from Effective Data Science Infrastructure

A Side Note about Titles

- Data Scientist – develops and prototypes models/solutions, looks for insights (analytics). A sometimes all-encompassing title for some below roles.
- ML Eng – implements the model in a scalable, production-ready way
- Data Eng – sets up data pipelines for input/output data
- DevOps Eng – deploys applications in prod and maintains them
- Infra/Platform Eng – provide general pieces of infra (data warehouse, compute platforms) for many applications to use
- Product/Program/Portfolio/Project managers, business owners, etc.

Current Trends

- ML development is getting easier:
  - CV and NLP has tons of pre-trained (**foundation**) models ready for use
    - Huggingface being the most popular example
  - Azure, GCP, AWS offer ml-as-a-service (MLaaS)
    - Though these tend to also be NLP and CV-based, there are some that do time series forecasting and anomaly detection
  - AutoML can do a lot of the tedious work for you
- MLOps has some notable toolkit offerings, some of which we'll be exploring in this course

Back to our example!

What if we were asked to build a Smart Transportation System?

- The SFMTA wants to implement a smart transportation management system to optimize traffic flow, reduce congestion, and lower emissions. Using data from traffic cameras, vehicle sensors, public transit GPS, mobile apps, weather services, and scheduled events, the system would predict traffic patterns and adjust traffic light timings, suggest route alternatives, and manage MUNI schedules. The system should be able to adjust to unexpected events, such as collisions, and ensure equitable service across neighborhoods. It should be live 24/7 and demonstrate measurable improvements in commute times and air quality.

Get in groups and discuss the following:

Discuss three potential issues when designing and implementing the Smart Transportation System? Think of one issue for each of these categories:

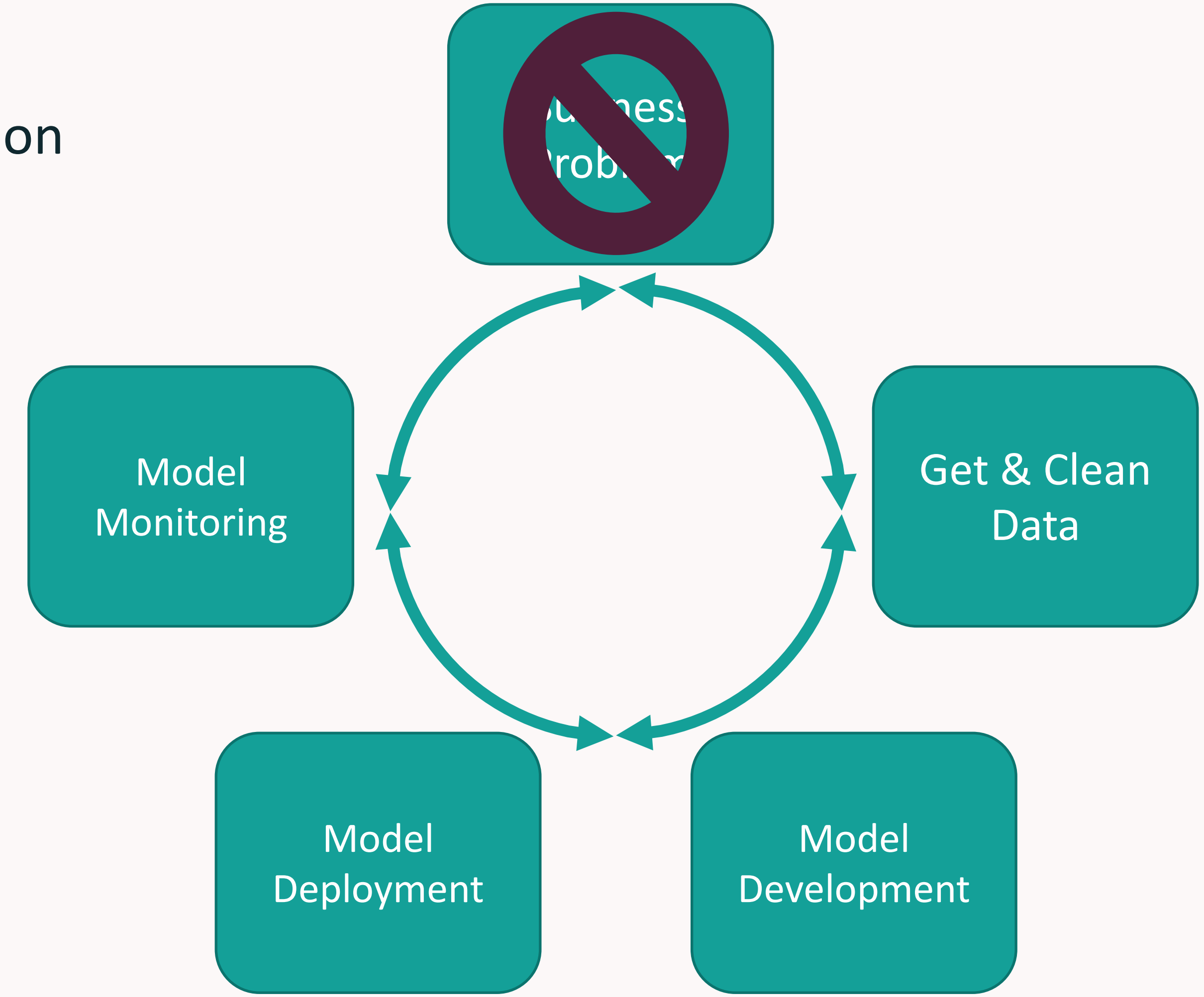
- Technical: the ML/AI model
- Technical: the development of the system
- Non-technical: anything related to safety, personnel, operations, politics, sociological, etc..

Write your answers as three bullets, and tag your group members, in **2025-msds-603-discussion**

Tools

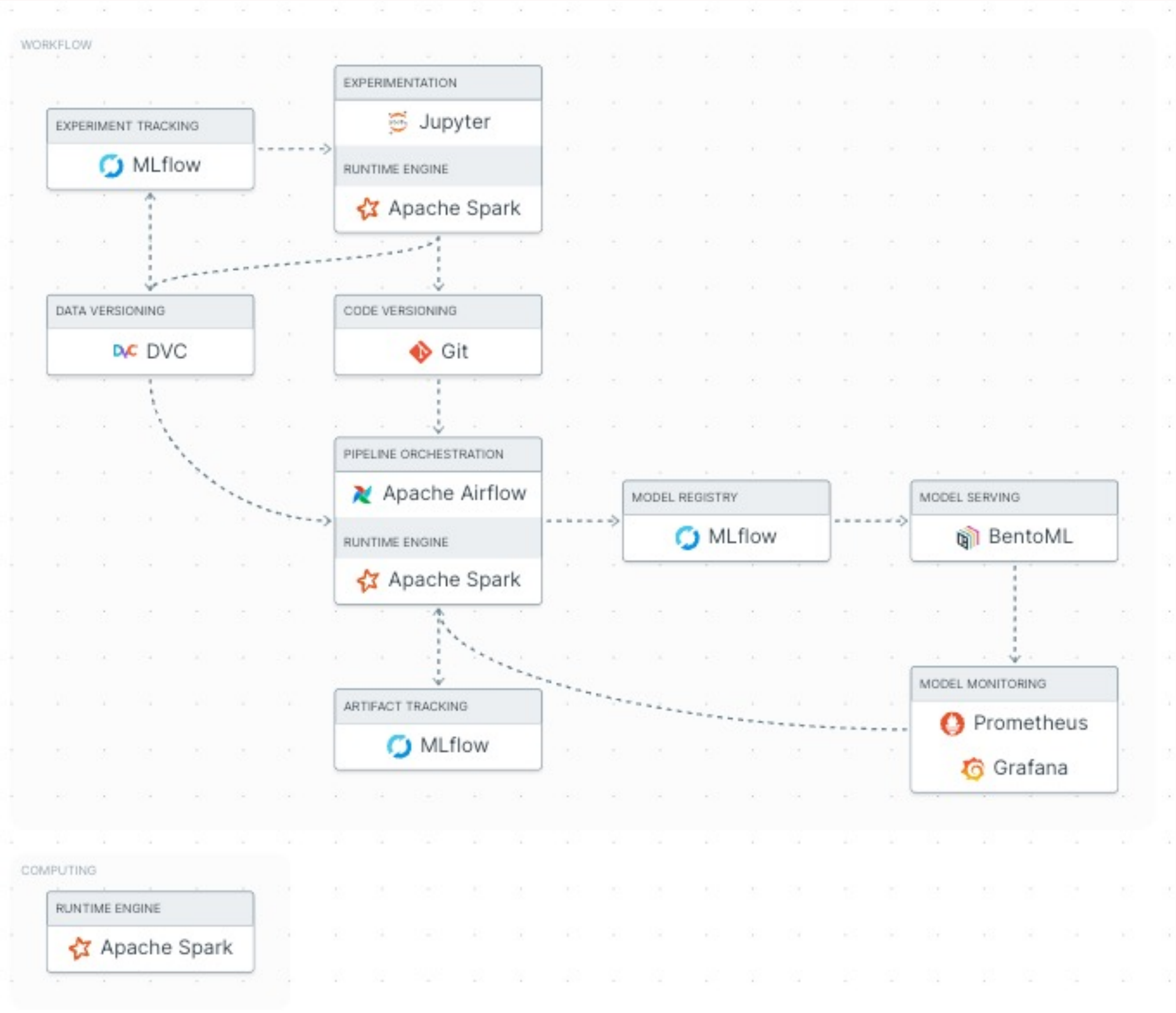
MLOps Pipeline Revisited

1. Experiment tracking
2. Artifact/model tracking & registration
3. Code versioning
4. Data versioning
5. Data quality
6. Data & Feature stores*
7. ML Orchestration
8. Orchestration & Scaling
9. CI/CD/CT
10. Model serving
11. Model monitoring
12. Model explainability/fairness*



*Limited coverage in this class

The MLOps Stack



MLOps Pipeline Tools

1. Model development – python (local and GCP/Colab)
2. Experiment tracking – MLFlow (local and GCP)
3. Artifact/model tracking & registration – MLFlow (local and GCP)
4. Code versioning - Github
5. Data versioning – DVC (local)
6. Data quality – Great Expectations (local)
7. Data & Feature stores* - dbt (not included)
8. ML Orchestration – Metaflow (local and GCP)
9. Orchestration & Scaling – Docker, K8s (GKE), Google Cloud Run, Terraform, Argo
10. CI/CD/CT – Github Actions
11. Model serving – FastAPI + Streamlit (local and GCP)
12. Model monitoring – Evidently (local)
13. Model explainability/fairness*

*Limited coverage in this class

So. Many. Tools

The MLOps tool that we choose isn’t important,
it’s the *why* we use it that matters.

Model Development Environment

Environments

DEV

- Dev data & storage
  - Exploration
- Mirror of prod data
- Mix of formats
  - Flat files; S3; SQL/NoSQL; Hive; etc.

- Use dev branch
- Use dev cluster (compute)

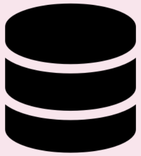
Sandbox environment. Go crazy!

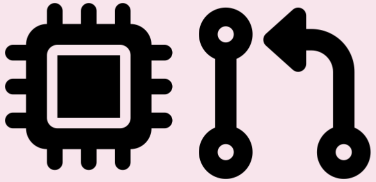
- Develop models
- EDA
- Track experiments

Environments

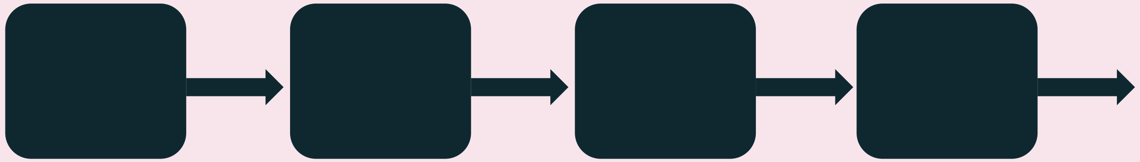
STAGE

- Stage data & storage
  - Test ML pipeline
- Mirror of prod data





- Merge with staging branch
  - Or alternatively, pull request
- Use stg cluster (compute)

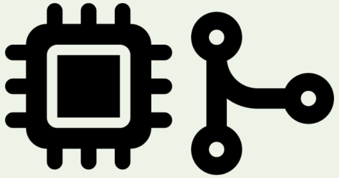


- Trigger ”build”
- Trigger unit/regression/integration tests

Environments

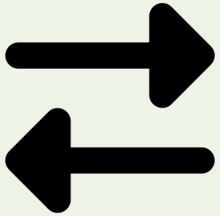
PROD

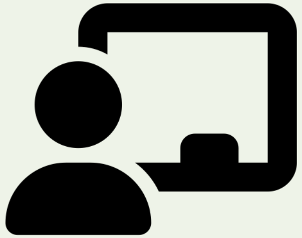
- Prod data & storage
    - “Live” data
- Feature store



- Merge with main/release branch
- Use prod cluster (compute)

- Deploy model
    - Batch, streaming, on-demand





- Monitor
    - Input data
    - Output data
    - Model performance
    - Resources

Optimal Development Environment

- Optimizes for two things:
  - Rapid prototyping of models
  - Interaction with the production environment

- Laptop vs Cloud
  - Cloud can be an on-prem ”cloud” or true cloud instance (AWS, GCP, Azure, etc.)
  - Laptops are not: secure; scalable; like the production environment; easy to monitor and support

IDEs and Notebooks

- No shortage of options
- Jupyterlab
- **VS Code**, pycharm
- Amazon Sagemaker
- Databricks

Virtual Environments

Virtual Environments

requirements.txt

python libraries and versions

setup.py or pyproject.toml

Project metadata and instructions for setting up environment

Project Organization

- data
  - raw
  - processed
- src
  - data.py; main.py, etc.
- config
- notebooks
  - eda.ipynb
  - experiments.ipynb

Do what feels comfortable for you, I am not going to be prescriptive.

Project Documentation

Be explicit

```python
def get_random_ingredients(kind: array=None) -> array:
"""
Return a list of random ingredients as strings.

:param kind: Optional "kind" of ingredients.
:type kind: list[str] or None
:raise lumache.InvalidKindError: If the kind is invalid.
:return: The ingredients list.
:rtype: list[str]
"""
        return ["shells", "gorgonzola", "parsley"]
```

Use descriptive doc strings
(use [sphinx] or mkdocs/mkdocstrings to
generate a [readthedocs style site]).
OR
Create a dedicated site for your project
with all the bells and whistles.

Dev Environment Demo and Lab