Lecture 5: Docker Workflows

AC215

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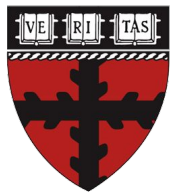

Logistics/Reminders

- Approx. 70% of class has project partners - if you have formed group make sure to update this group info spreadsheet
- We highly encourage you to find project partners based on your mutual interests or goals (rather than us assigning later on)
- Even if you don’t have partners, you must submit fill the form so we know you are active.
- Class video recordings are available on Canvas -> Panopto

Outline

1. Recap: Review of Previous Material
2. Working with Containers Workflow
3. Data Pipelines
4. Data Labeling

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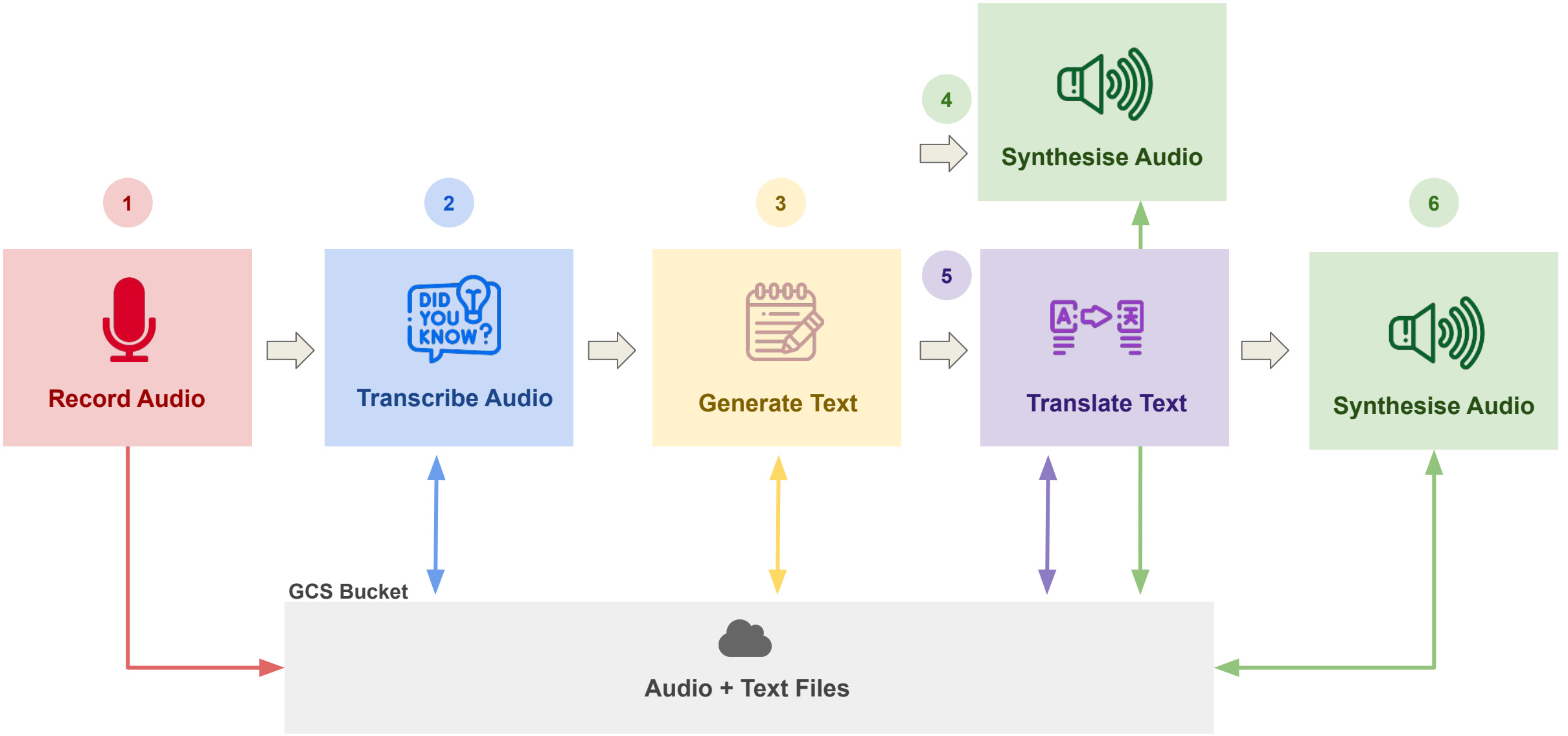
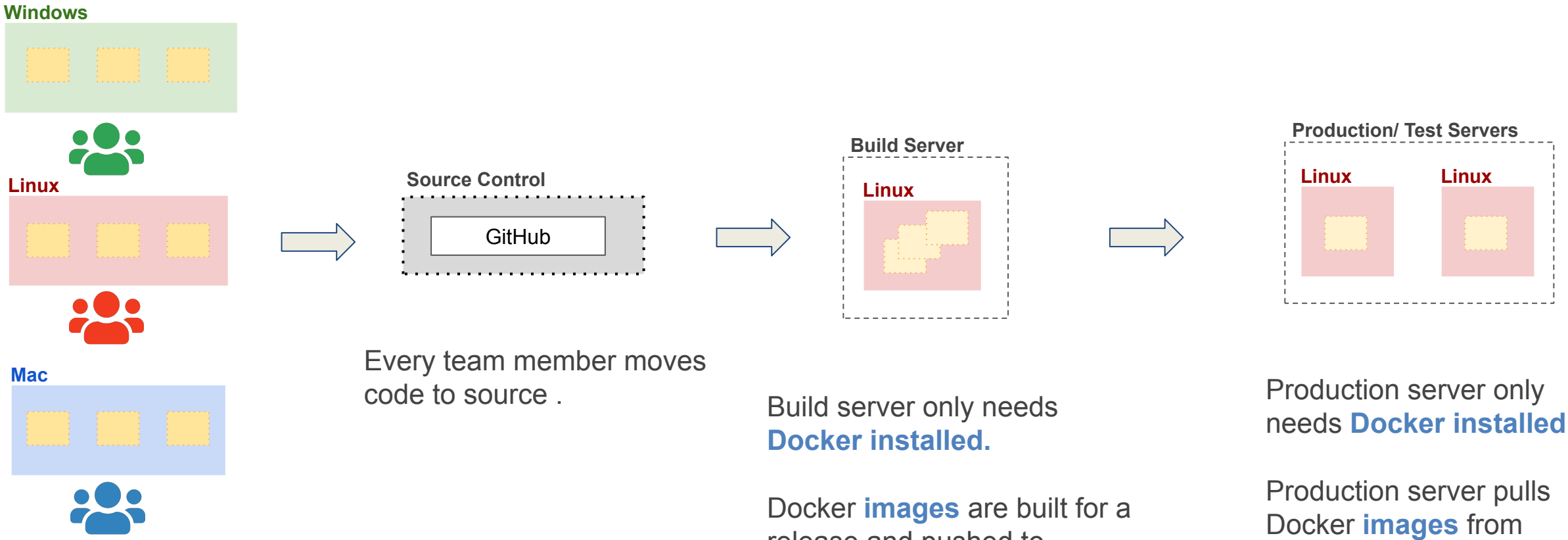
Tutorial (T5) - Building the Mega Pipeline App



Software Development Workflow (with Docker)



Development machines only needs **Docker installed.**

Containers need to be setup only once.

Every team member moves code to source .

Build server only needs **Docker installed.**

Docker **images** are built for a release and pushed to **container registry.**

Production server only needs **Docker installed.**

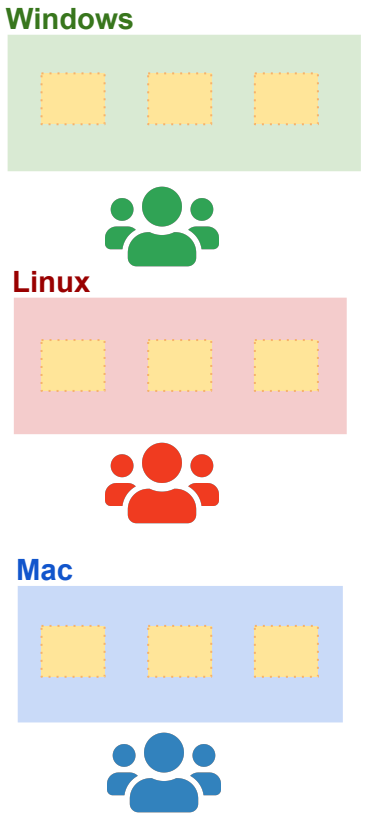
Production server pulls Docker **images** from **container registry** and runs them.

Software Development Workflow (with Docker)

Who creates the Dockerfile, and where is it stored? Do we use pre-built images or does each developer build them? Who is in charge of managing this? Also, what's the process for handling the Pipfile and Pipfile.lock?

This seems like a lot.

Software Development Workflow (with Docker)

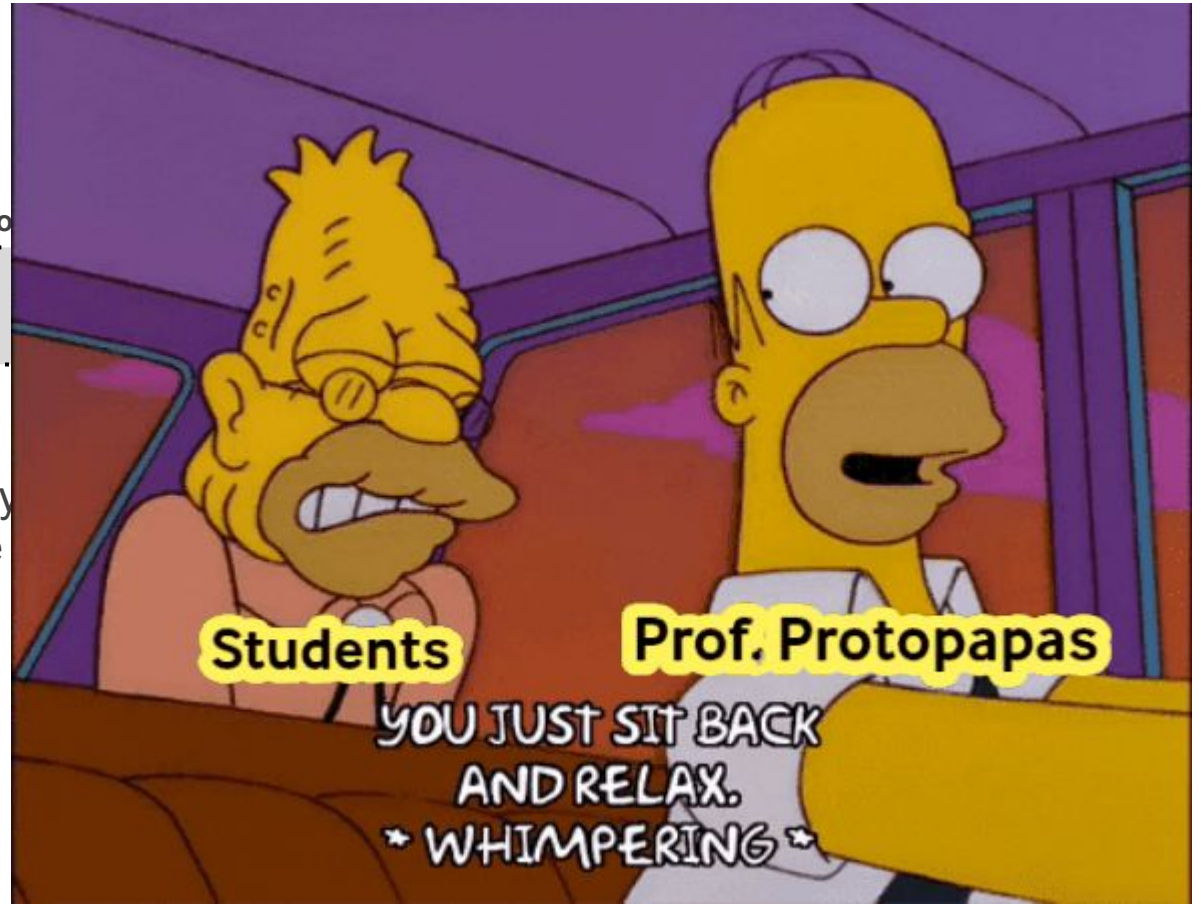


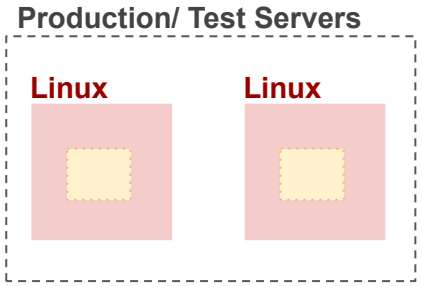
Development machines only needs **Docker installed.**

Containers need to be setup only once.

So

Every
code





Production server only needs **Docker installed.**

Production server pulls Docker **images** from **container registry** and runs them.

Software Development Workflow (with Docker)

At this stage, creating multiple Dockerfiles along with their corresponding Pipfiles and secrets has become repetitive.

Is there any way to optimize the process?

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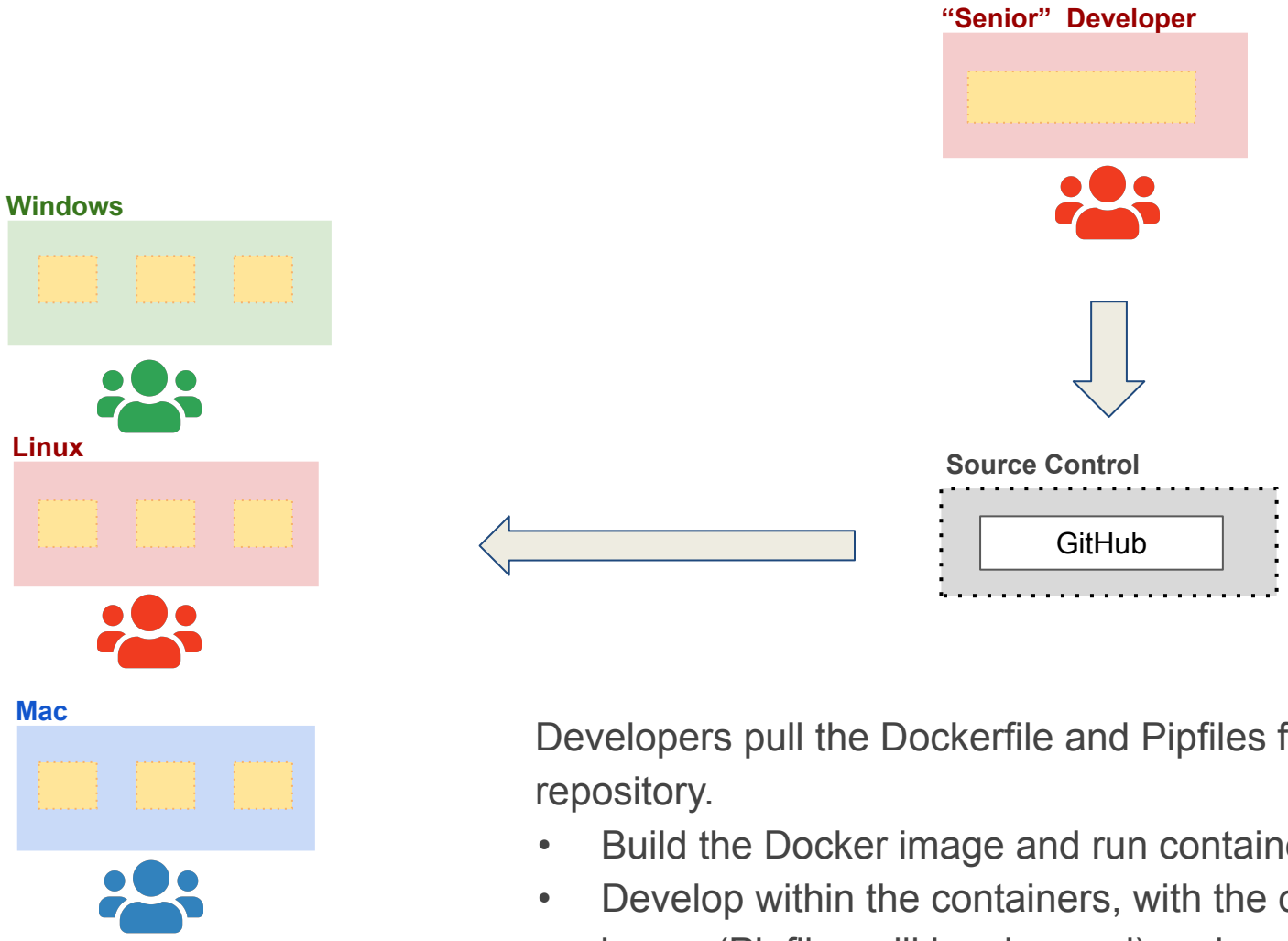
Workflow with Docker: Scenario 1 (early stages of development)



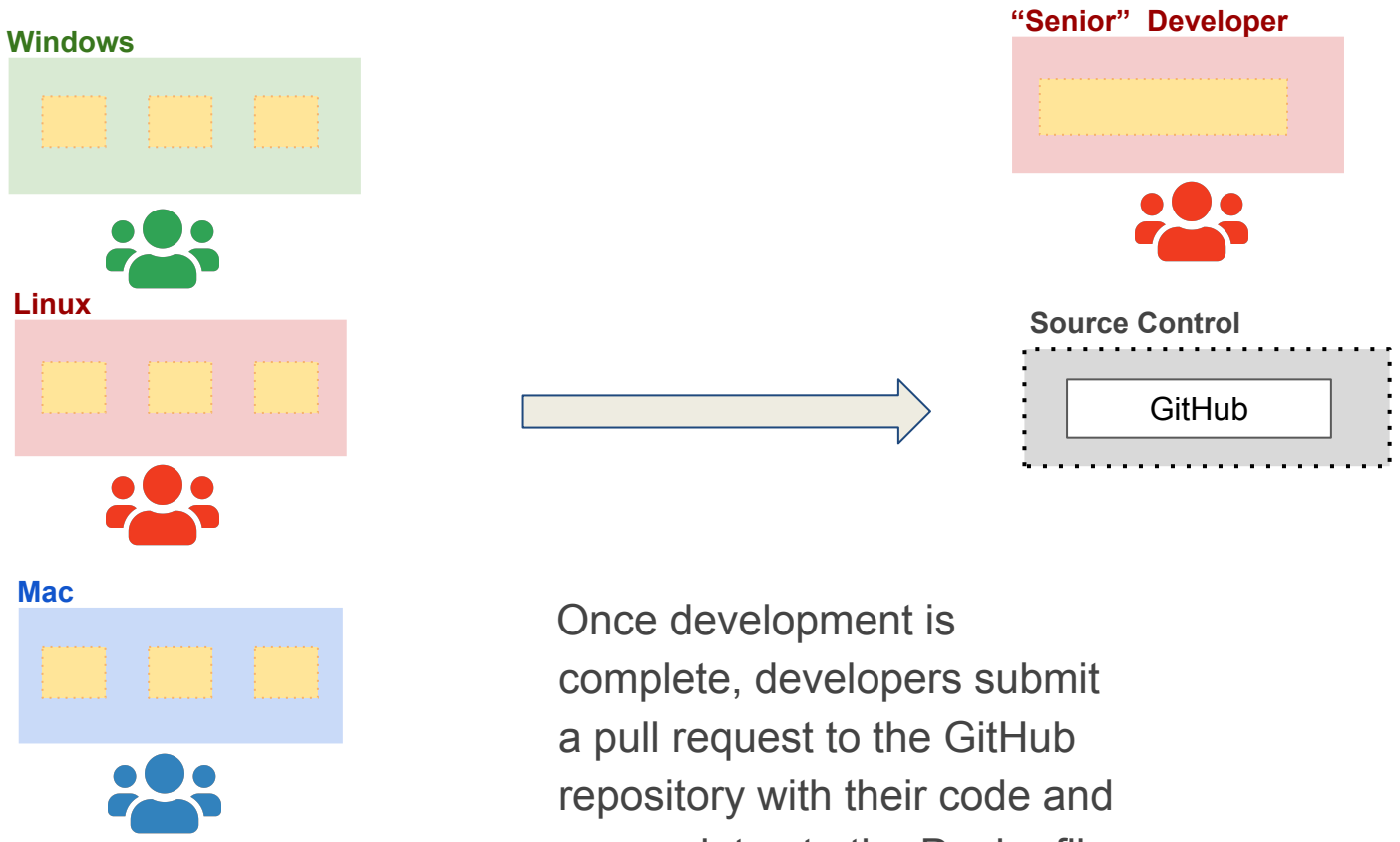
A senior developer is responsible for creating the Dockerfile, along with the initial Pipfile and Pipfile.lock.

Push Dockerfile and Pipfiles to the GitHub repository

Developers pull the Dockerfile and Pipfiles from the GitHub repository.

- Build the Docker image and run containers.
- Develop within the containers, with the option to install packages (Pipfiles will be changed) and modify the Dockerfile if needed, then rebuild.

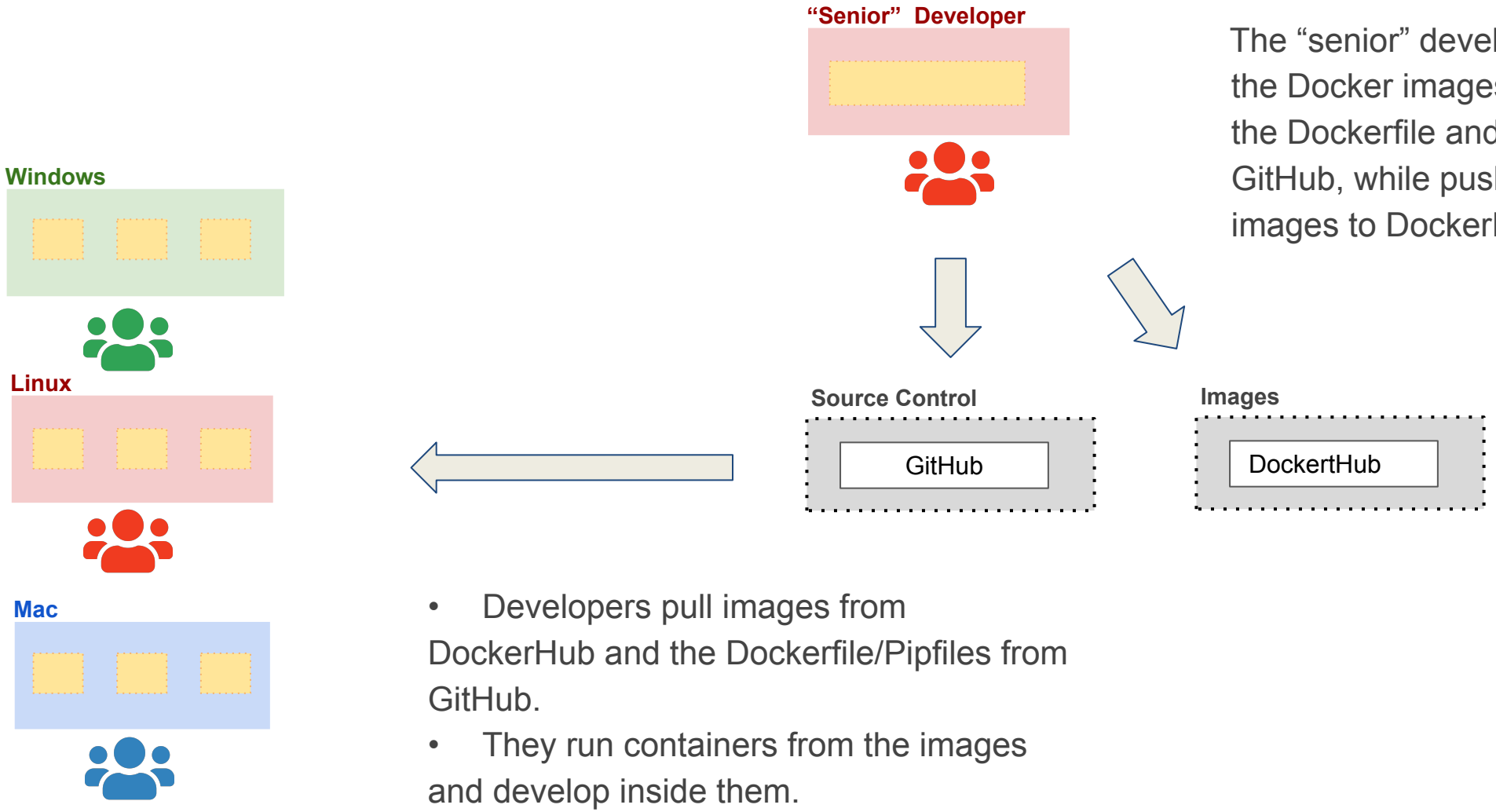
Workflow with Docker: Scenario 1 (early stages of development)



Once development is complete, developers submit a pull request to the GitHub repository with their code and any updates to the Dockerfile or Pipfiles.

The senior developer reviews and merges all pull requests, then consolidates the updates into a new Dockerfile and Pipfiles.

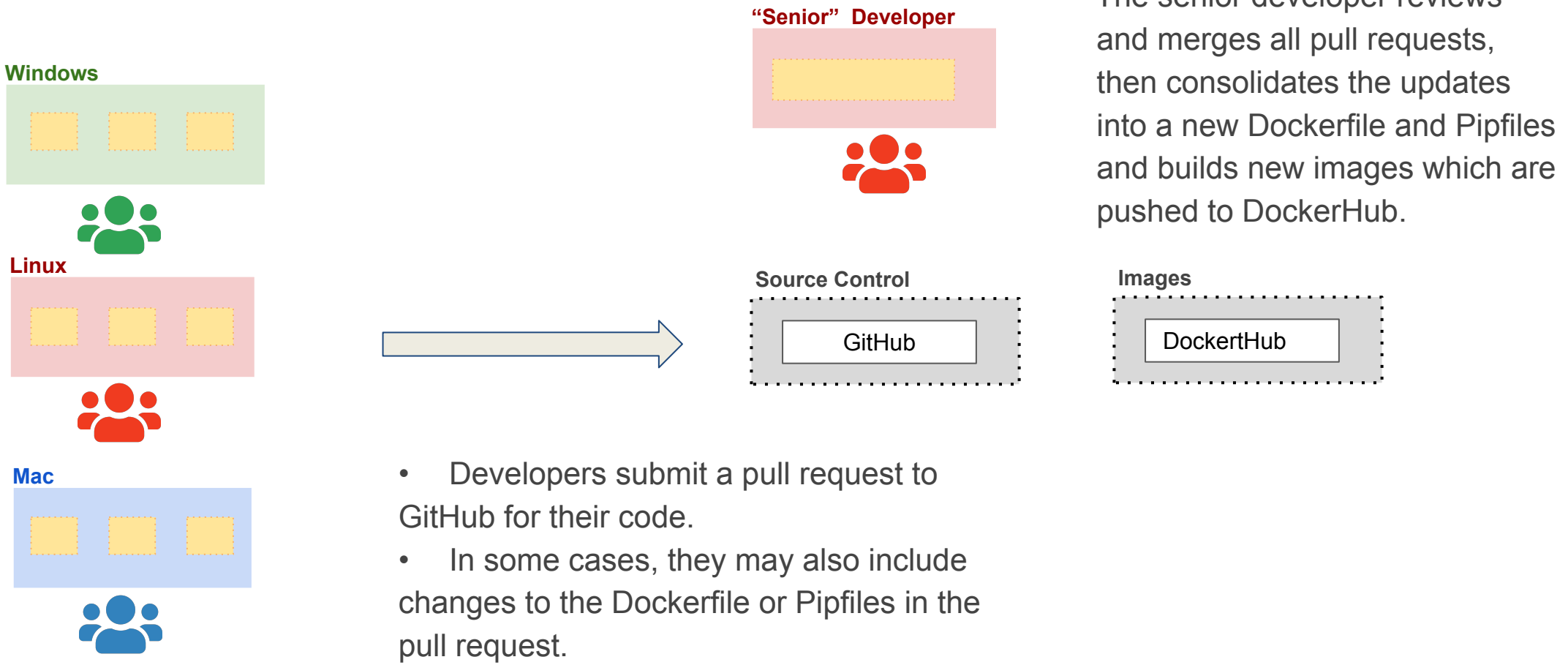
Workflow with Docker: Scenario 2 (later stages of development)



The "senior" developer creates the Docker images and pushes the Dockerfile and Pipfiles to GitHub, while pushing the images to DockerHub.

- Developers pull images from DockerHub and the Dockerfile/Pipfiles from GitHub.
- They run containers from the images and develop inside them.
- Rebuilding the images is only needed on rare occasions.

Workflow with Docker: Scenario 2 (later stages of development)



The senior developer reviews and merges all pull requests, then consolidates the updates into a new Dockerfile and Pipfiles and builds new images which are pushed to DockerHub.

- Developers submit a pull request to GitHub for their code.
- In some cases, they may also include changes to the Dockerfile or Pipfiles in the pull request.

Workflow with Docker: A Flexible Approach

Is there a “perfect” workflow?

No

So, how do we decide what to do?

Clear communication and rules are essential. Each team can have its own workflow, based on the project and team needs.

Tutorial (T5B) - Building the Mega Pipeline App with a structured workflow

In this tutorial we will build the Mega Pipeline App (again).

Unlike what we did in T5, this time we will follow a more structured workflow.

- The Dockerfiles and Pipfiles will be provided; you won't need to create them.
- You can either build the images yourself or run them directly from DockerHub.
- Secrets should be stored in a folder outside the app directories, which will not be part of the repository.
- A `docker-shell.sh` script is provided to handle all Docker-related tasks, including building, setting environments, and running containers.

- App: https://ac215-mega-pipeline.dlops.io/
- Instructions: https://github.com/dlops-io/mega-pipeline/tree/flexible-workflow

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1. Recap: Review of Previous Material
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3. **Data Pipelines**
4. Data Labeling

Motivation

The 3 components for better Deep Learning

More Data

- Extraction
- Transformation
- Labeling
- Versioning
- Storage

- Processing
- Input to Training

Better/Faster Models

- SOTA Models
- Transfer Learning
- Distillation
- Compression

Faster Hardware

- Scaling data processing
- GPU, TPU
- Multi GPU Server Training

Motivation

The 3 components for better Deep Learning

More Data

- Extraction
- Transformation
- Labeling
- Versioning
- Storage

- Processing
- Input to Training

The narrative of the data challenges

- When collecting cheese images or text, we might source them from web searches or user uploads, but the quality and format of these images or text can vary over time.
- Also images may not always be in the correct format, and we need to address issues with duplicates or poor-quality images.
- Additionally, cheese text needs to be chunked for Retrieval-Augmented Generation (RAG) applications and converted into a suitable format for fine-tuning large language models (LLMs).
- Managing this data involves labeling new images from both users and web searches, keeping track of different versions of cheese data, and ensuring that the images we acquire are of high quality.

Challenges

Extraction

- **Varied Sources/Formats**: Data comes in different shapes, sizes, and formats.
- **Timelines of Updates**: Data can change over time, affecting model performance.

Transformation

- **Labeling**: Manual annotation is often labor-intensive.
- **Versions**: Multiple versions can cause inconsistency.
- **Quality**: Poorly processed data can lead to poor models.

Management

- **Labeling**: Consistency and quality are paramount.
- **Versions**: Ensuring data traceability and reproducibility.
- **Quality**: Ensuring the data is clean, relevant, and well-documented.

Solution

Containerize Data Tasks

- **Benefits**: Consistent environment, easy to scale, and improves reproducibility.

Using Prebuilt Containers for Data Tasks

- **Benefits**: Saves time, ensures quality, and utilizes community-verified methods.

Manage Tasks Using Pipeline Management Tools

- **Examples**: Apache Airflow, Kubeflow Pipelines.
- **Benefits**: Streamlines data workflows, manages dependencies, and allows for easy monitoring.

Tools

Pipeline Management [FUTURE LECTURE]

- **Kubeflow** End-to-end orchestration of machine learning pipelines

Data Labeling [TODAY]

- **Label Studio**
  - Annotation of text, images, audio, and more.
  - Customizable templates, multi-format support.
  - Teams needing flexibility in data labeling tasks.

Data Versioning [NEXT LECTURE]

- **DVC (Data Version Control)**
  - Version control for datasets and machine learning models.
  - Git-like commands, storage optimization.
  - Teams that want to maintain version history of data and models.

Components (artifacts) of an AI Application

What are the components of an AI App?

- **Data**: The backbone of any AI application, needed for training and validation.
- **Model**: The trained AI algorithm
- **Source Code:** Includes the model implementation, front end, back end, and Dockerfiles
- **Container Images:** Encapsulated environments that ensure the application runs consistently across different systems.

How do we manage all of these?

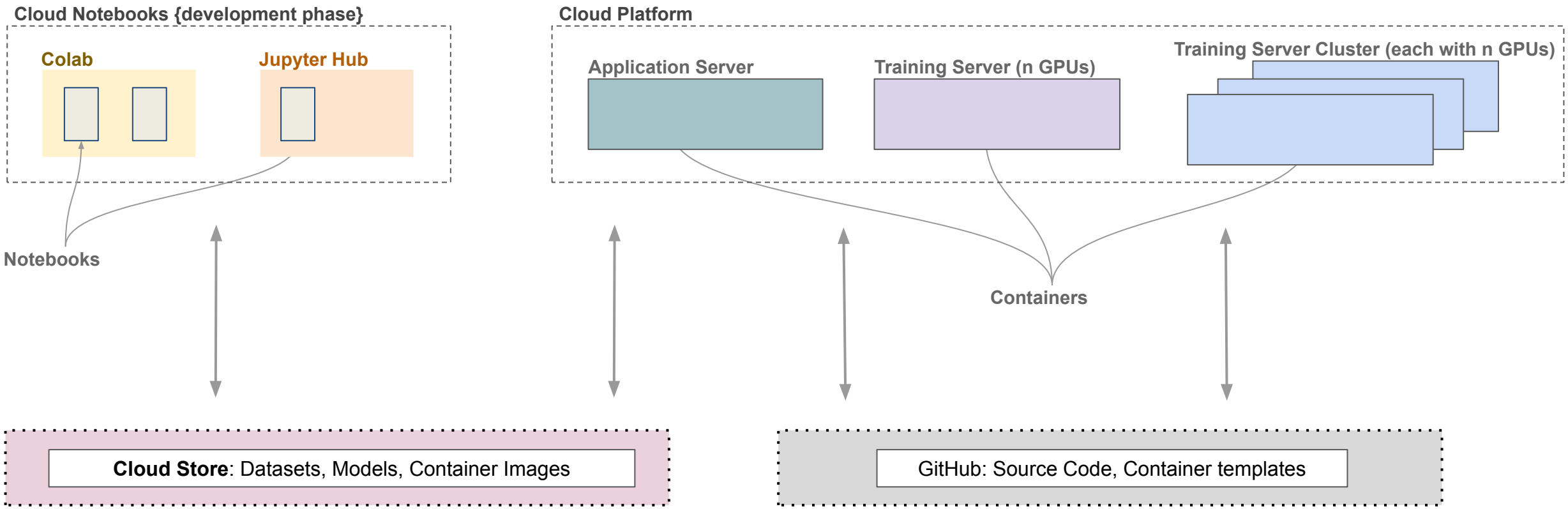
Components (artifacts) of an AI Application

Management Strategies

- **Data:** Implement storage, versioning, and backup.
- **Model**: Track versions and performance; update as needed.
- **Source Code**: Use version control and maintain documentation.
- **Containers**: Use orchestration tools for deployment and scaling.

What are Pipelines

Example components of an AI App:



Streamline with Tools

- **Manual Methods:** Scripts and manual tasks can work, but they’re often slow and prone to mistakes.
- **Automated Tools:** For better efficiency and fewer errors, use tools that simplify and automate these processes.

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Wish List

We want a system with these features:

- Version control code, data, and models
- Easy access of data and models from external tools
- Automate data and model tasks

Pipelines

And a few more things like:

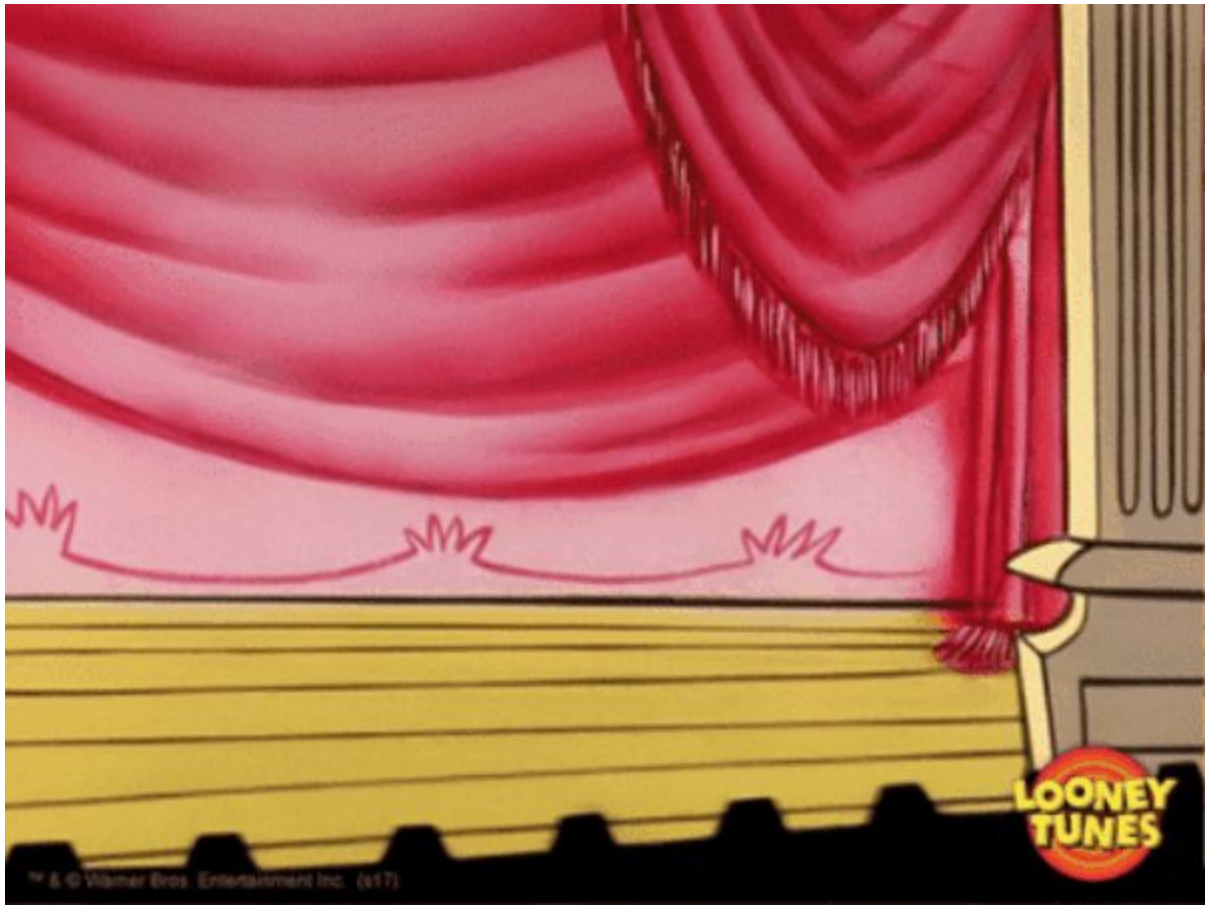
- Real-Time Monitoring of Models (data monitoring, future lecture)
- Auto-Scaling Resources (Kubernetes, future lecture)
- Automated Testing Frameworks (Continuous Integration, future lecture)
- Easy Rollback and Rollforward Mechanisms (Continuous Deployment, future lecture)
- Built-in Security Measures (AIP, GCP secrets)

What are Data Pipelines

Various data tasks in a Machine/Deep Learning project:

- Extraction
- Transformation
- Pre-processing
- Train, validate, test split
- Pre-process step during model inference


Delete! Delete! Delete!



THANK YOU