iterative

Practices and tools for collaboration

in ML projects

Lesson 2

DVC Tools for Data Scientists & Analysts

2021

Course lessons

Lesson 1. Course Introduction

Lesson 2. Practices and Tools for Efficient Collaboration in ML projects

Lesson 3. Pipelines Automation and Configuration Management

Lesson 4. Versioning Data and Models

Lesson 5. Visualize Metrics & Compare Experiments with DVC and Studio

Lesson 6. Experiment Management and Collaboration

Lesson 7. Tools for Deep Learning Scenarios

Lesson 8. Review Advanced Topics and Use Cases

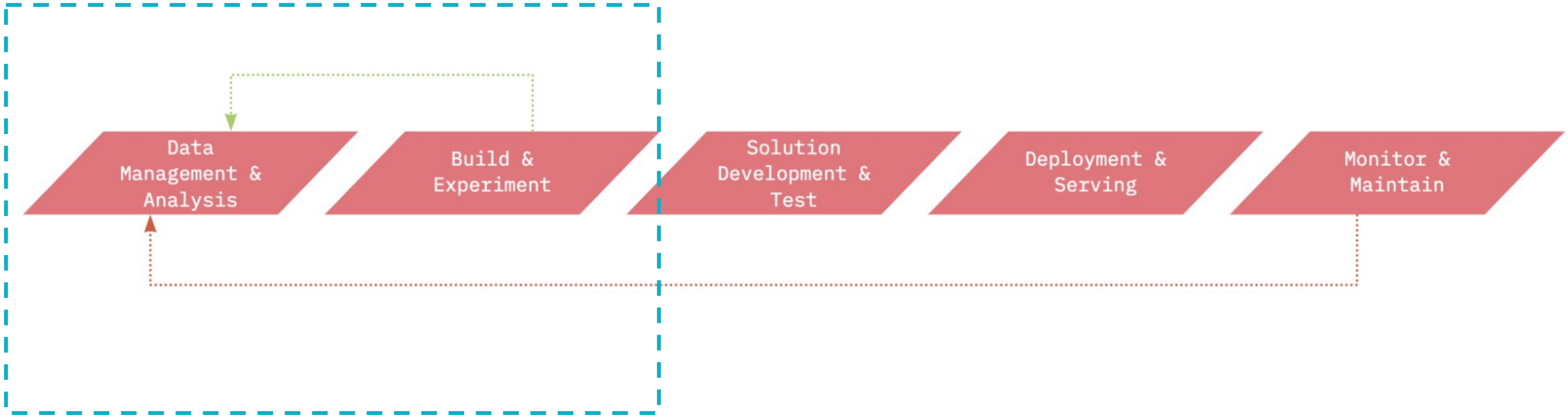
Lesson Outline

- ML development workflow & collaboration
- Git
- Project repository structure & dev environment
- Coding (software development)
- Documentation & task tracking
- ML pipelines & experiments

ML development workflow

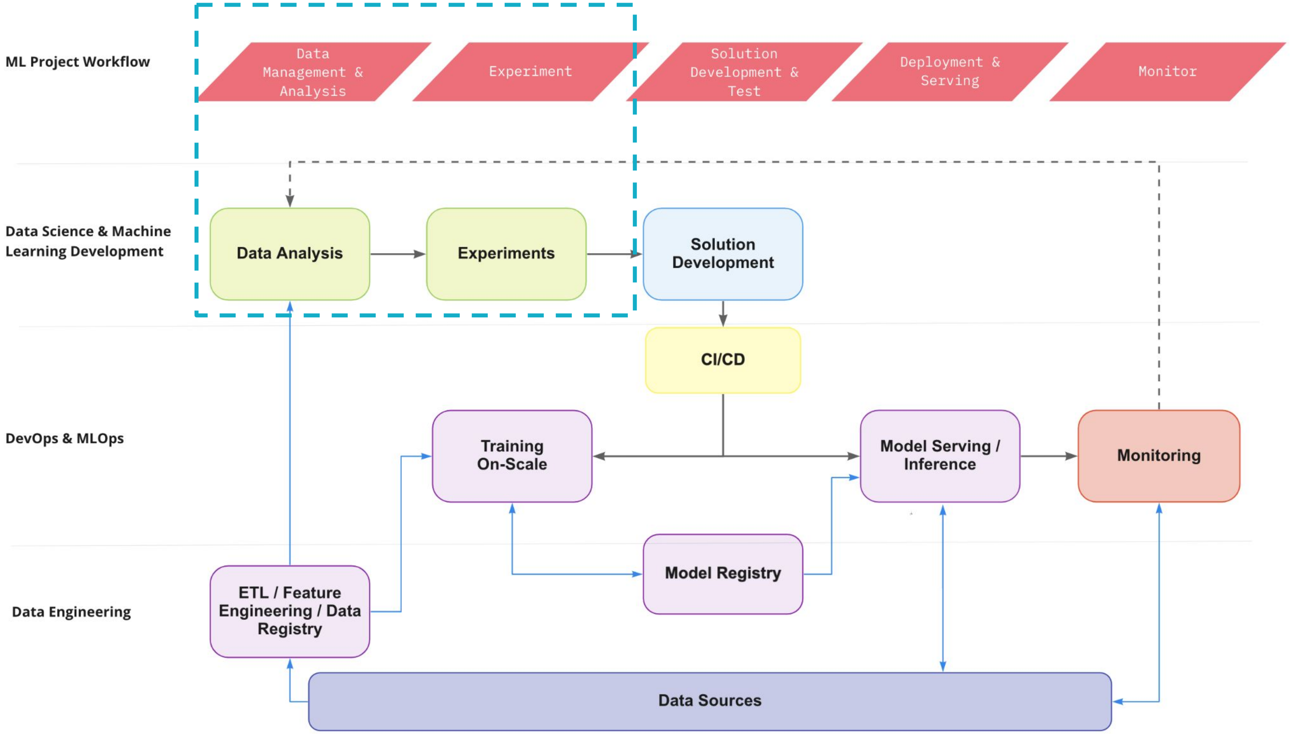
Machine Learning Workflow

This course focuses on ML experiments and data management



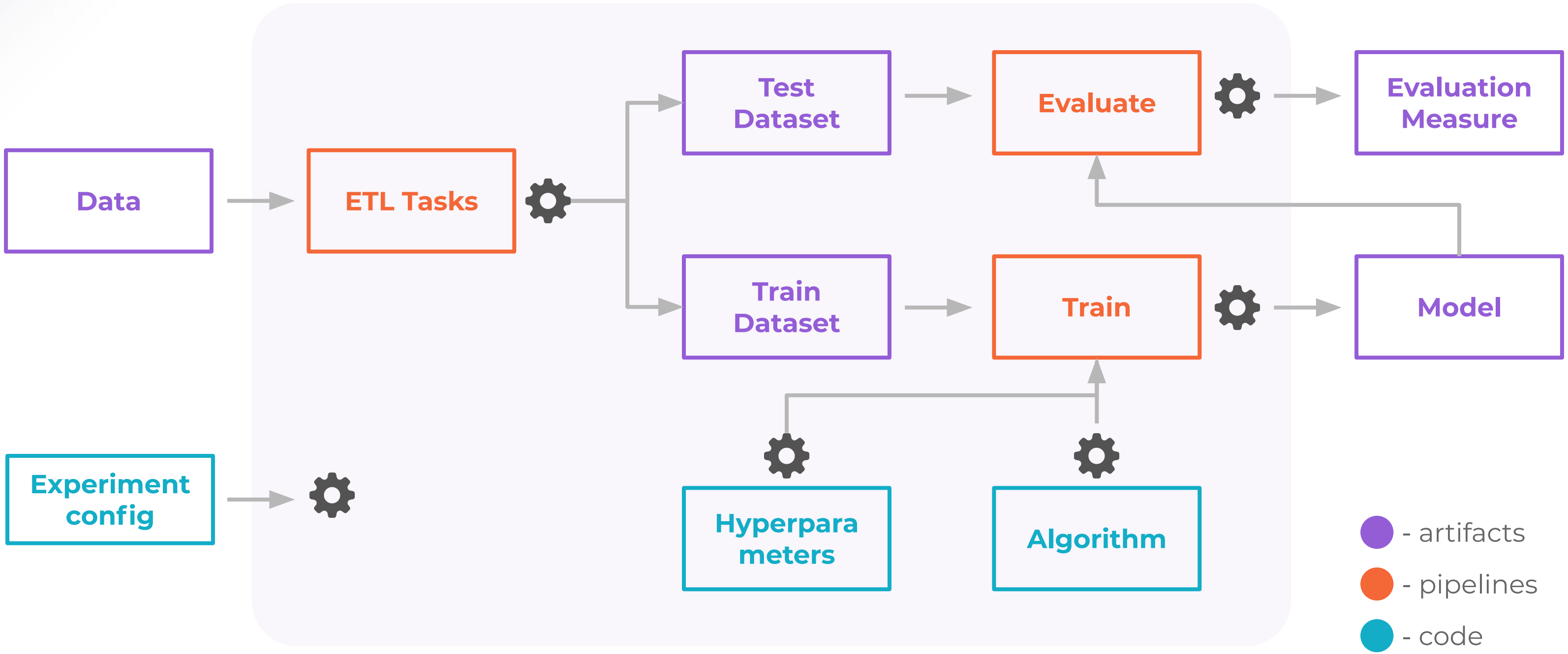
Machine Learning Workflow

This course focuses on ML experiments and data management



ML Experiments

take long time and produce mess of metrics and artifacts



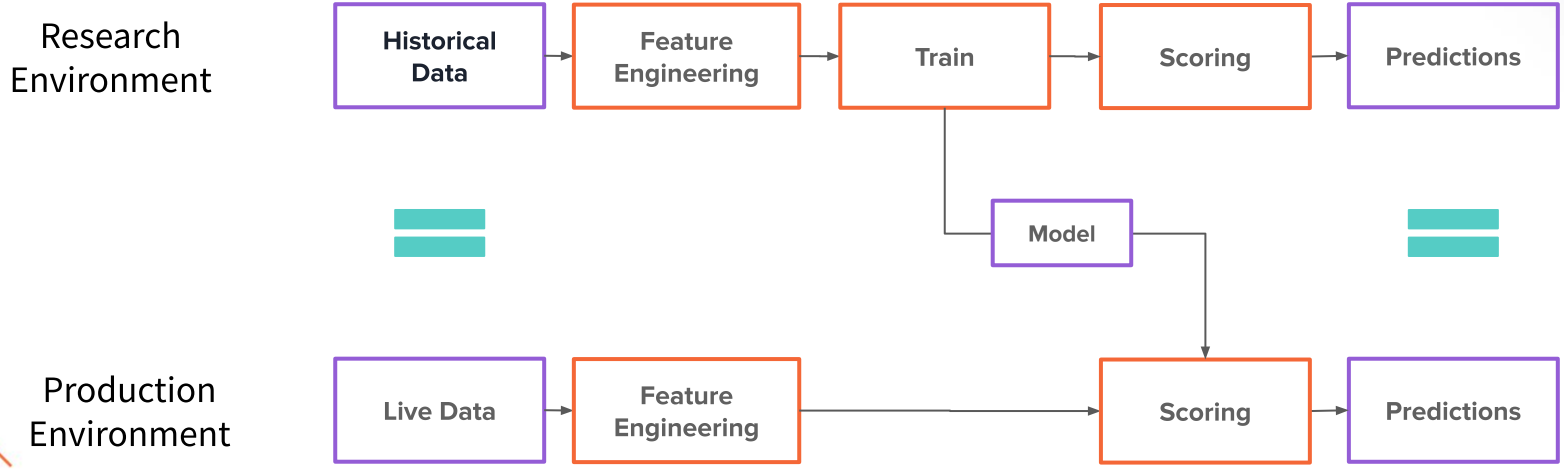
EXPERIMENT = CODE + DATASET + OUTPUTS

Collaboration in ML projects

Common DS/ML Challenges

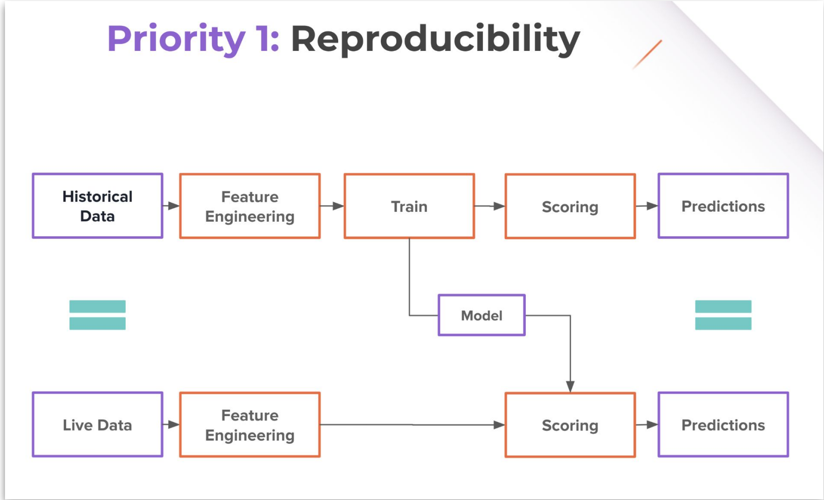
- Difficult sharing & collaboration
- Inefficiency & work duplication
- Slow updates
- Pipelines not reliable or not reproducible
- Data quality issues
- Model metrics tracking

Priority 1: Reproducibility



ML Reproducibility checklist

1. Environment dependency control
2. Code version control
3. Control run params
4. Automated pipelines
5. Artifact version control
6. Experiment results tracking
7. Automated CI/CD and MLOps



Good practices for ML projects

1. **Coding (Software Development)**
   - Clean Code
   - Code version control (Git)
   - Testing

2. **Project structure & dev environment**
   - Organize a project repository
   - Environment dependencies control

3. **Documentation & task tracking**
   - Document your code, experiments and findings
   - Task tracking

4. **ML pipelines development & experiments**
   - Automated pipelines
   - Control run params
   - Model and artifact version control
   - Experiment results tracking
   - Reproducible experiments

Coding (software development)

Coding (Software Development)

- Organize code into clean reusable units (functions, classes, modules)
- Use Git for code version control
- Follow style-guides (i.t. PEP8 in case of Python)
  a. Write comments, docstrings and type annotations
  b. Give functions and variables meaningful names
- Make dependencies and requirements explicit
  a. Add requirements.txt and Dockerfile to a project repository
- Testing

```python
def headline(text: str, align: bool = True):
    if align:
        return f"{text.title()}\n{'-' * len(text)}"
    else:
        return f" {text.title()} ".center(50, "o")

print(headline("python type checking"))
print(headline("use pycharm", "center"))
```

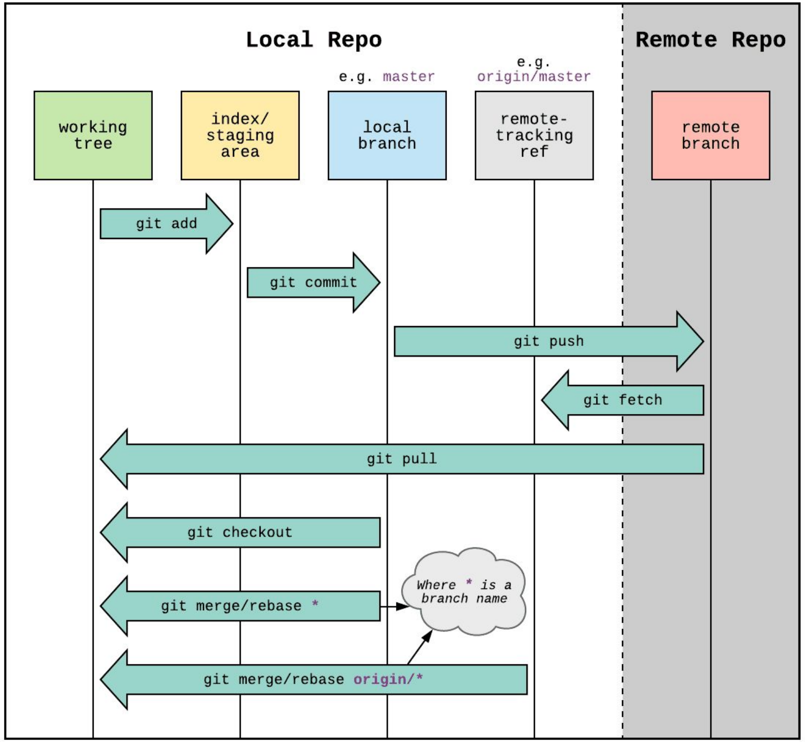
Expected type 'bool', got 'str' instead more... (Ctrl+F1)

Source: https://dev.to/dev0928/what-is-a-python-virtual-environment-2hkn

Git basics for machine learning development

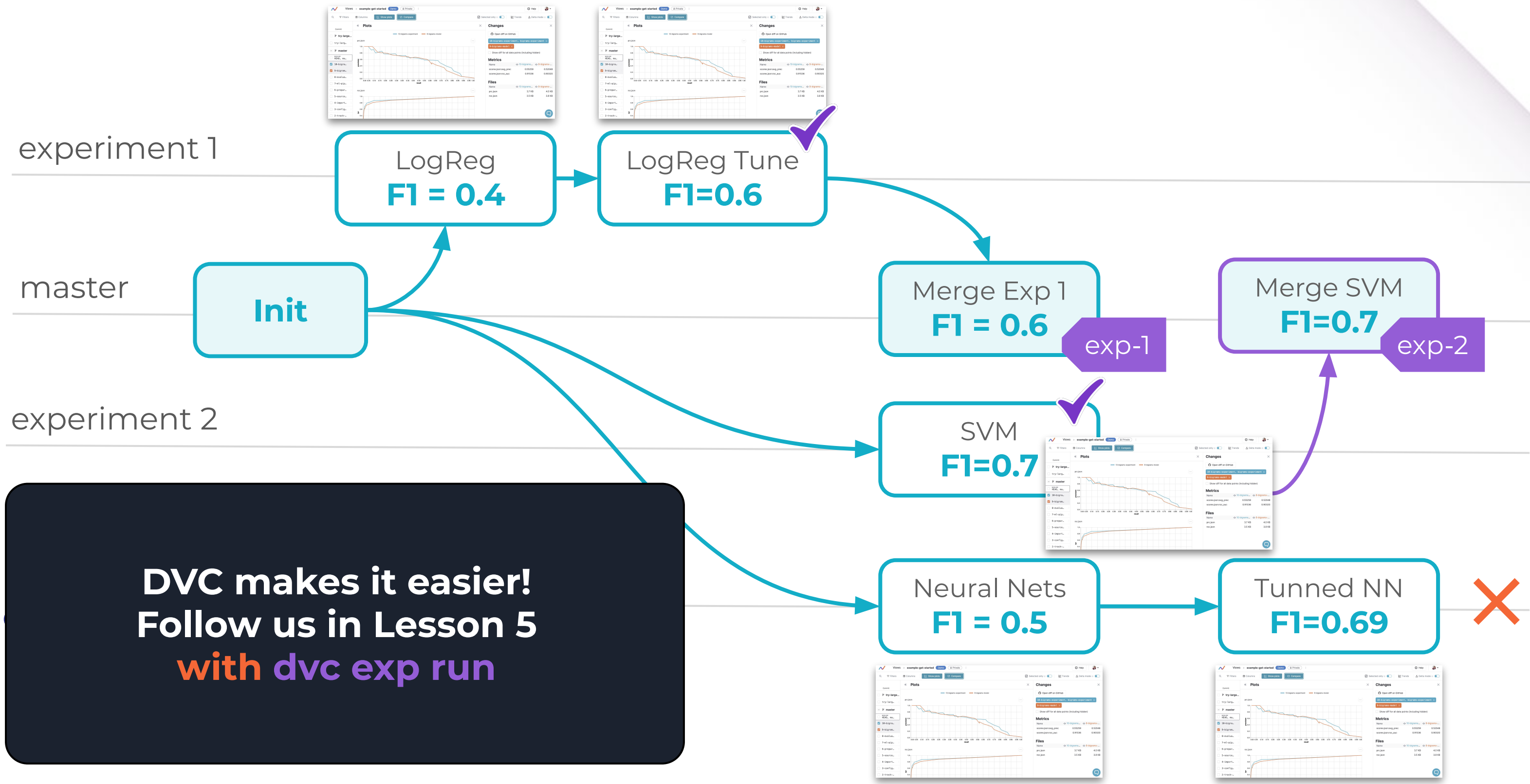
Git workflow

- git add
- git commit
- git push
- git fetch
- git pull
- git checkout
- git merge / rebase



Source: https://www.reddit.com/r/git/comments/99ul9f/git_workflow_diagram_showcasing_the_role_of/

Apply Git based workflows to ML development



DVC makes it easier!
Follow us in Lesson 5
with dvc exp run

Live code example

Git basics

Project repository structure

Cookiecutter DS Project structure

```
...
├── README.md     <- The top-level README for developers using this project.
├── data
│   ├── external      <- Data from third party sources.
│   ├── interim       <- Intermediate data that has been transformed.
│   ├── processed     <- The final, canonical data sets for modeling.
│   └── raw           <- The original, immutable data dump.
├── docs              <-  A default Sphinx project (sphinx-doc.org)  (optional: Text documents associated with the project)
│
├── models            <- Trained and serialized models, model predictions, or model summaries
│
├── notebooks         <- Jupyter notebooks. Naming convention is a number (for ordering),
│                        the creator's initials, and a short `-` delimited description, e.g.
│                        `1.0-jqp-initial-data-exploration`.
...
├── reports           <- Generated analysis as HTML, PDF, LaTeX, etc.
│   └── figures       <- Generated graphics and figures to be used in reporting
│
├── requirements.txt  <- The requirements file for reproducing the analysis environment, e.g.
│                        generated with `pip freeze > requirements.txt`
... (part 2)
```

Source: https://drivendata.github.io/cookiecutter-data-science/#requirements

Cookiecutter DS Project structure

...(part 1)

```
│
├── src                    <- Source code for use in this project.
│   ├── __init__.py    <- Makes src a Python module
│   │
│   ├── data               <- Scripts to download or generate data
│   │   └── make_dataset.py
│   │
│   ├── features       <- Scripts to turn raw data into features for modeling
│   │   └── build_features.py
│   │
│   ├── models         <- Scripts to train models and then use trained models to make  predictions
│   │   ├── predict_model.py
│   │   └── train_model.py
│   │
│   └── visualization  <- Scripts to create exploratory and results oriented visualizations
│       └── visualize.py
│
└── tox.ini                <- tox file with settings for running tox; see tox.readthedocs.i
```

Source: https://drivendata.github.io/cookiecutter-data-science/#requirements

Custom template_repo

```
├── README.md
├── config/
├── data/
├── models/
├── notebooks/
├── reports/
└── src/
    ├── data/         <- data prepare and/or preprocess
    ├── evaluate/  <- code for model quality evaluation and metrics
    ├── features/  <- code to compute features
    ├── stages/    <- DVC stages code
    ├── report/       <- code for visualization and plots
    └── train/        <- code for training and hyper-parameters tuning
```

Custom structure

- simple
- flexible
- easy to share & collaborate

Live code example

Project repository structure

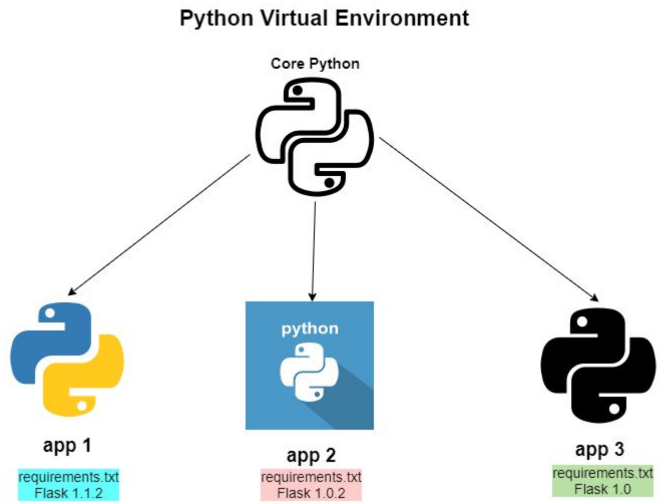
Python Virtual Environments

Virtual Environments

- a simple solution for reproduce development environment
- isolates the project-related libraries
- controls Python version

Example packages:

- venv & virtualenv
- conda
- pipenv
- poetry
- ...



Source: https://dev.to/dev0928/what-is-a-python-virtual-environment-2hkn

Virtual Environments with venv

```
# create virtual environment
python -m venv dvc-venv

# activate a virtual environment
source dvc-venv /bin/activate

# exit the virtual environment
deactivate
```

- venv a subset of virtualenv project, integrated into the standard library
- *Changed in version 3.5:* The use of venv is now recommended for creating virtual environments

Source: https://docs.python.org/3/library/venv.html#module-venv

Specify Python dependencies: requirements.txt

- Environment documentation
  a. Add requirements.txt to the project repository

- Install dependencies from requirements.txt

```
# create virtual environment
pip install -r requirements.txt
```

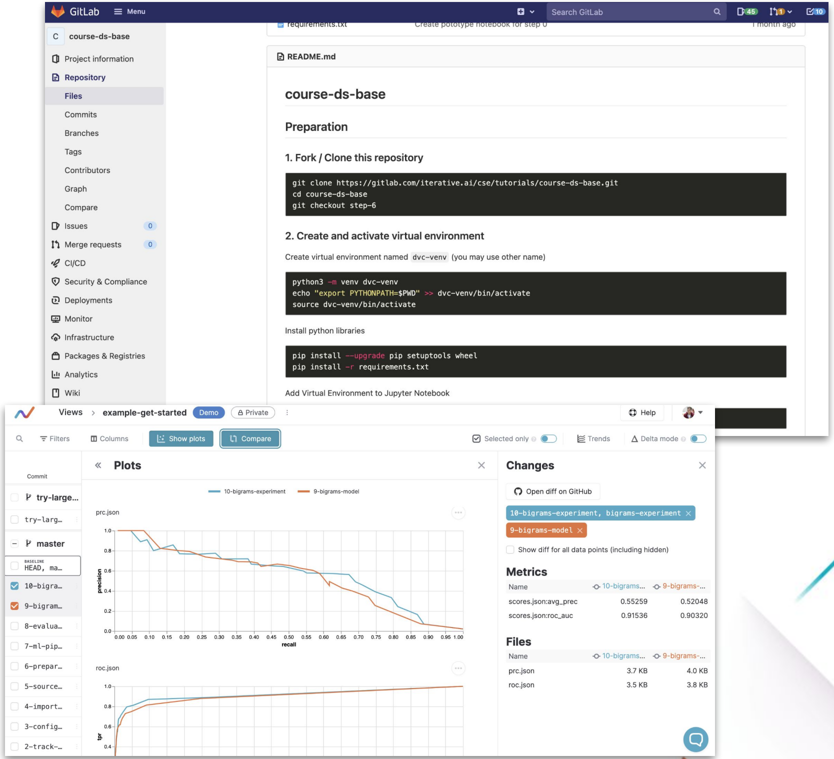
Live code example

Python Virtual Environments

Documentation & task tracking

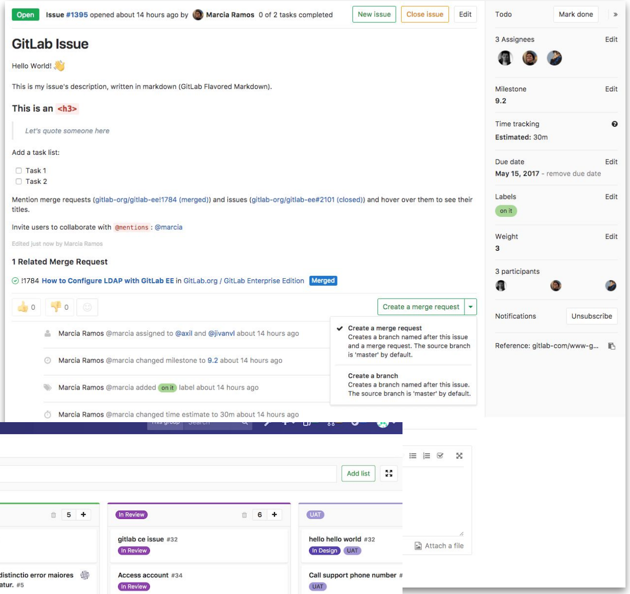
Good practices: Documentation

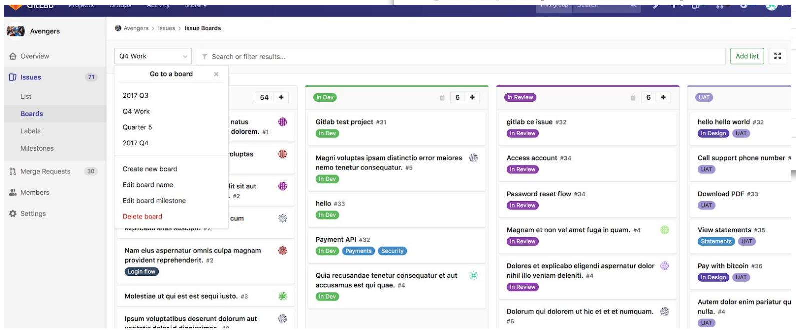
- Project repository documentation
  a. README
     - info about the project
     - how to install and run instructions
     - contacts and author(s) details
  b. docs/
  c. License
- Project documentation (problem statement, methods, data, findings)
- Experiment metrics and reports



Good practices: Task Tracking

- Create a shared "to-do" list (task tracking)
- Keep changes small
- Share changes frequently
- Create tasks (issues) for each changes in task tracking systems (i.e. GitLab/GitHub/Bic)
- Link tasks to Git branches





Live code example

Documentation & task tracking

What have we learned?

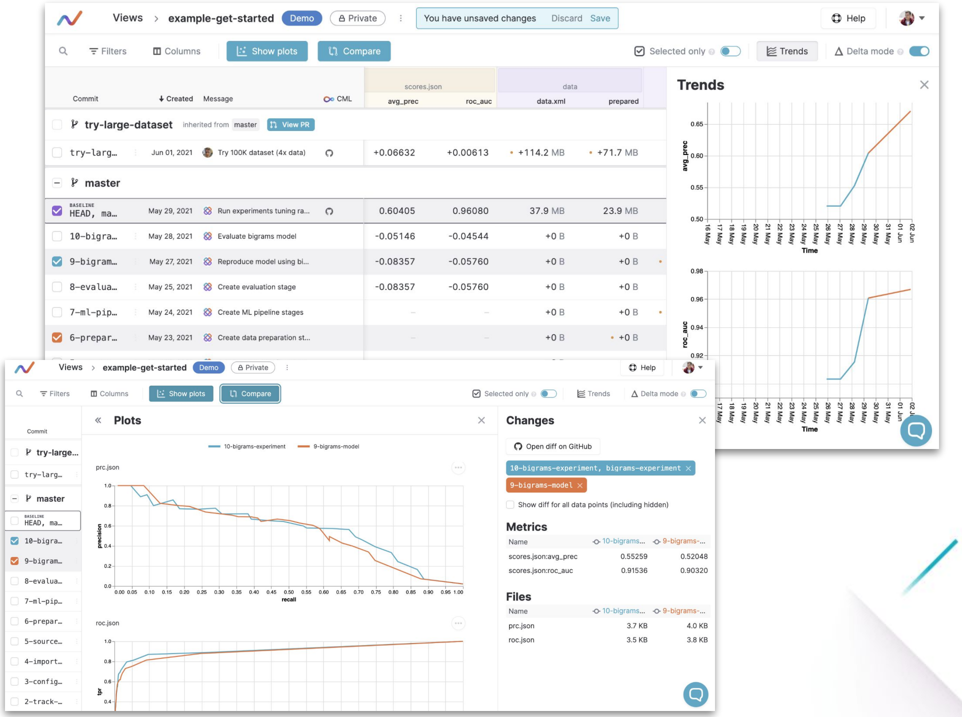
What have we learned?

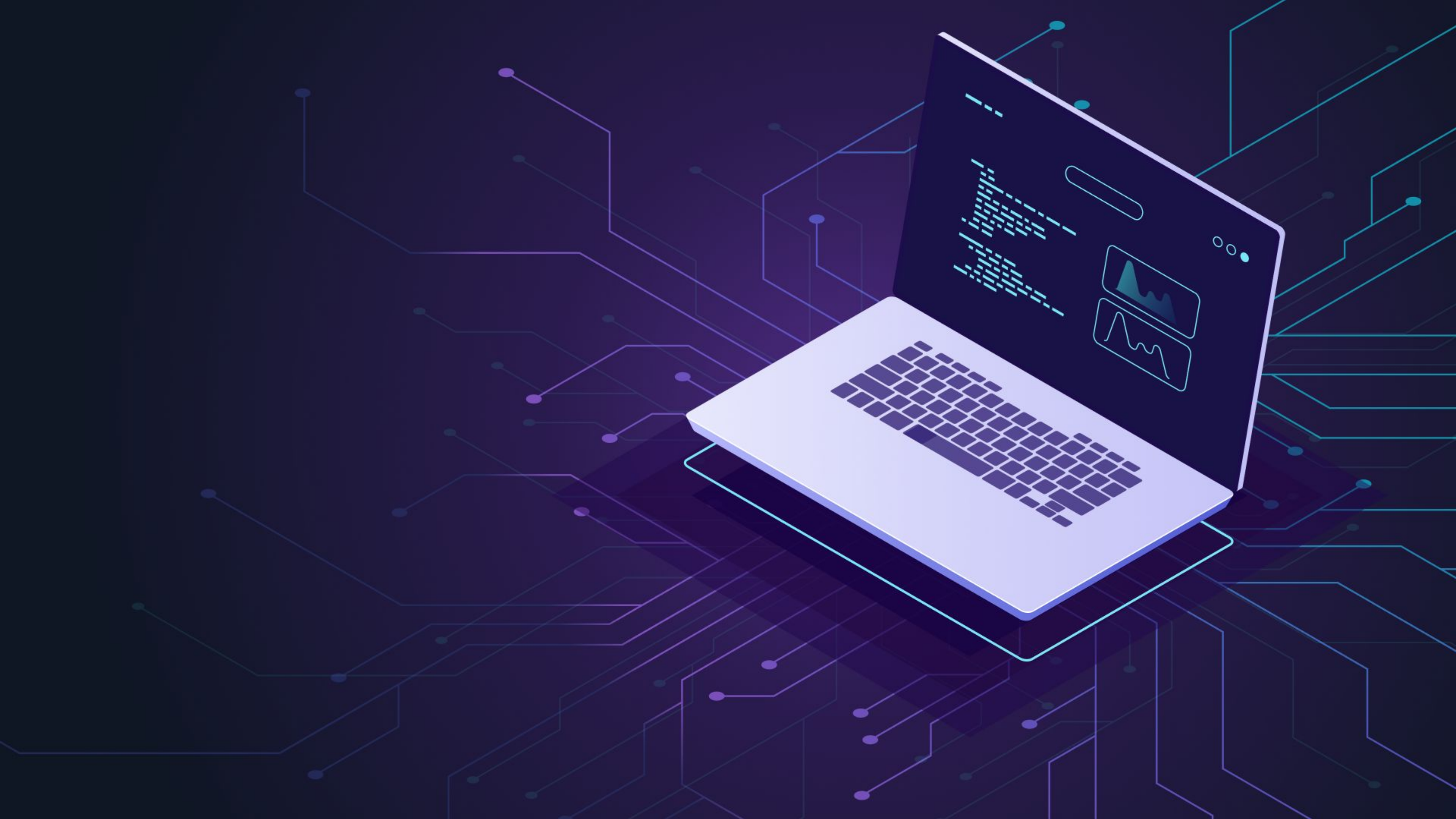
1. Requirements for successful collaboration
2. How to structure your repository
3. Good practices for coding and collaboration
4. Good practices for documentation and task tracking

Good practices: ML pipelines & experiments

- Automated pipelines
- Control run params
- Models and artifacts version control
- Experiments results tracking
- Reproducible experiments

Follow the next lessons...





Links

- Data Science blueprint
  https://data-science-blueprint.readthedocs.io/en/latest/presentation/schema.html