Data Version Control (DVC):
Tutorial 2: Iris Demo Project

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2019

DVC core concepts

- Experiment
- State (experiment state)
- Reproducibility
- Pipeline
- Workflow
- Data files
- Data cache
- Cloud storage

Source:
https://dvc.org/doc/understanding-dvc/what-is-dvc

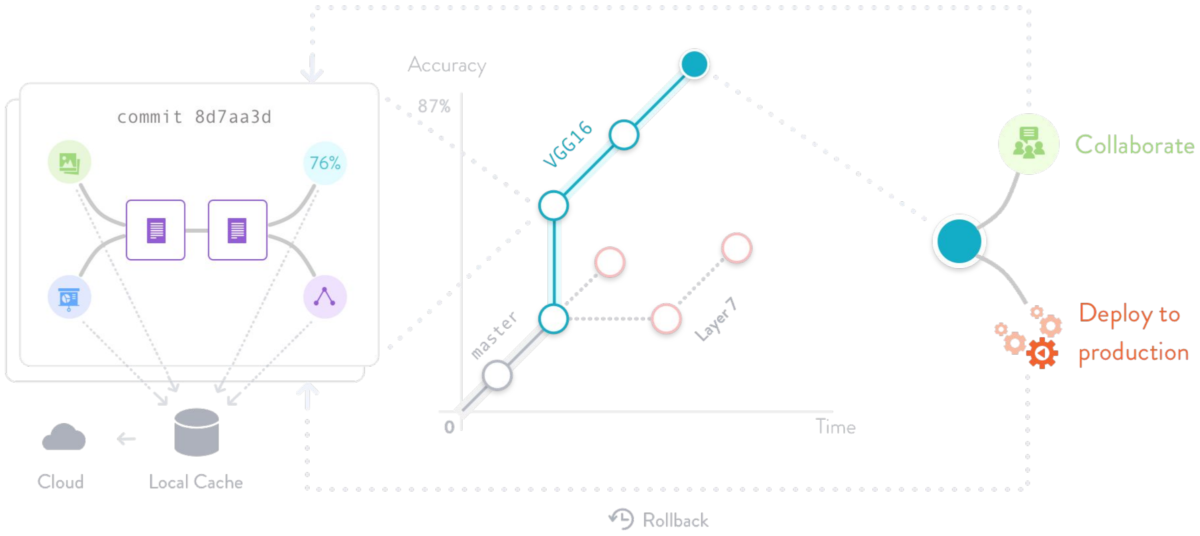

Image source: https://dvc.org/doc/tutorial

Experimentation methodology

DVC core concepts

- Experiment
- State (experiment state)
- Reproducibility
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DVC tracks ML models and data sets

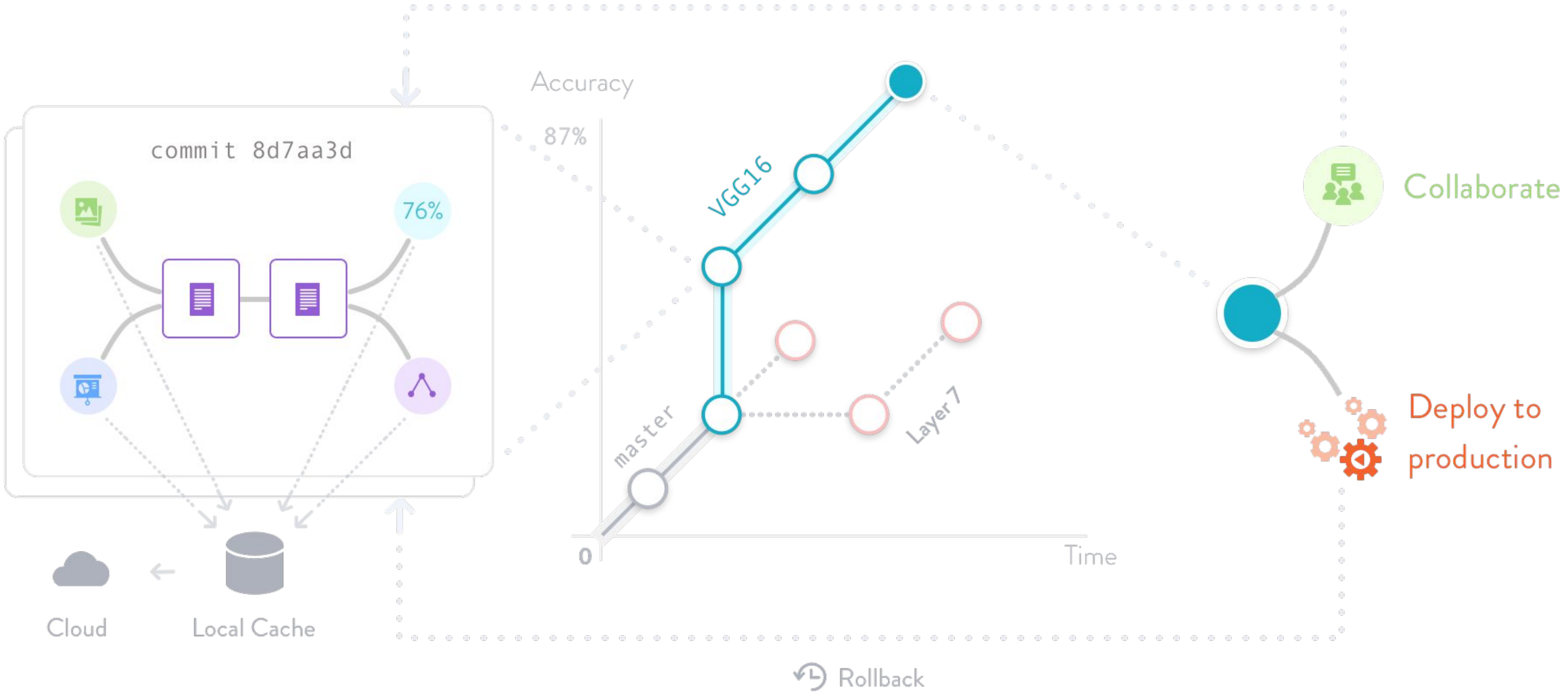
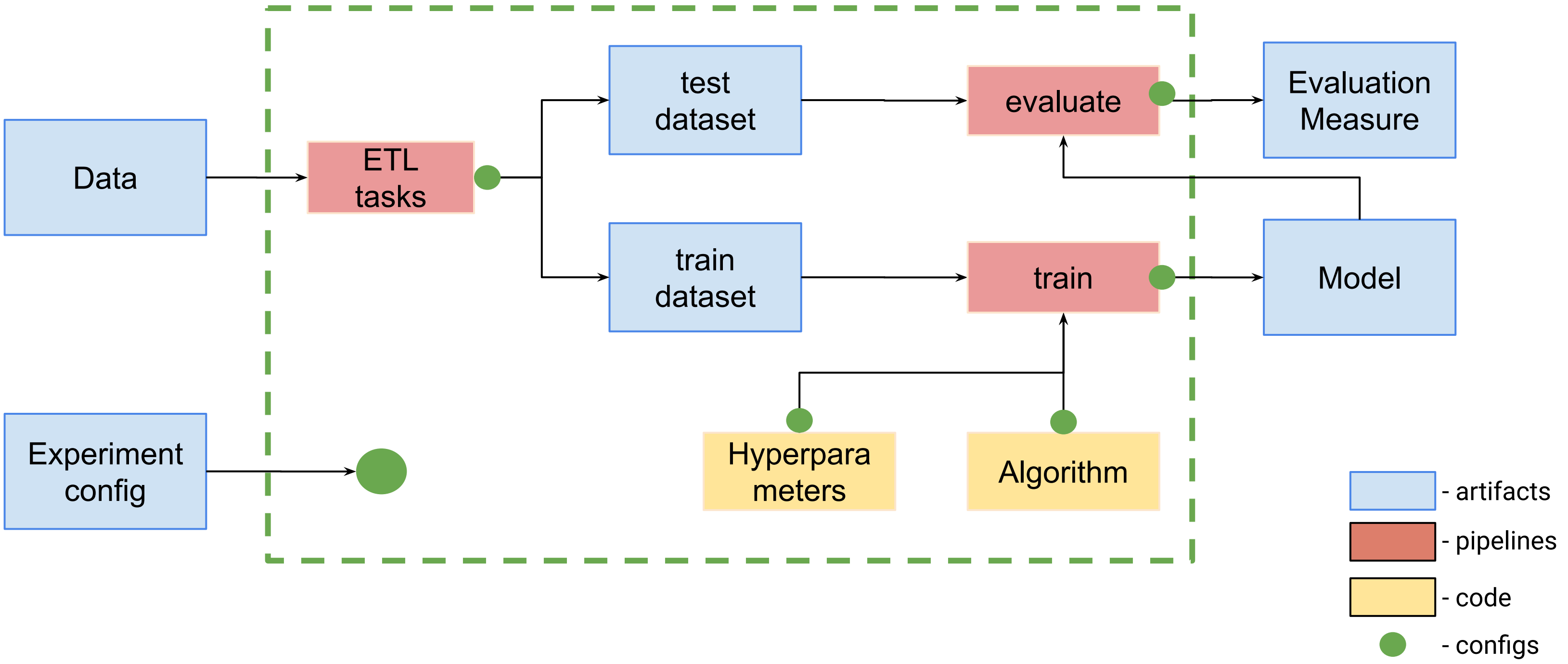


Image source: https://dvc.org/doc/tutorial

Experiment: pipelines, configs and artifacts



Use Case:

Iris Flowers Classification

- Task: classify Iris flowers
- Dataset: Iris dataset
- Metrics: F1

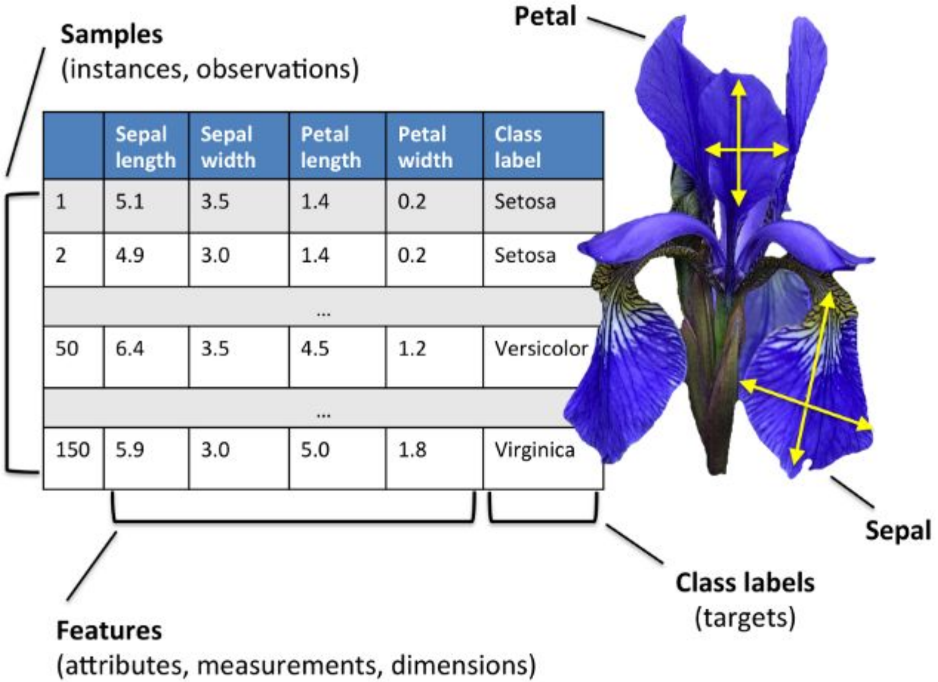
References:

- https://en.wikipedia.org/wiki/Iris_flower_data_set
- https://scikit-learn.org/stable/tutorial/statistical_inference/supervised_learning.html

Image source:
https://medium.com/@jebaseelanravi96/machine-learning-iris-classification-33aa18a4a983

Use Case:

Iris Flowers Classification



	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

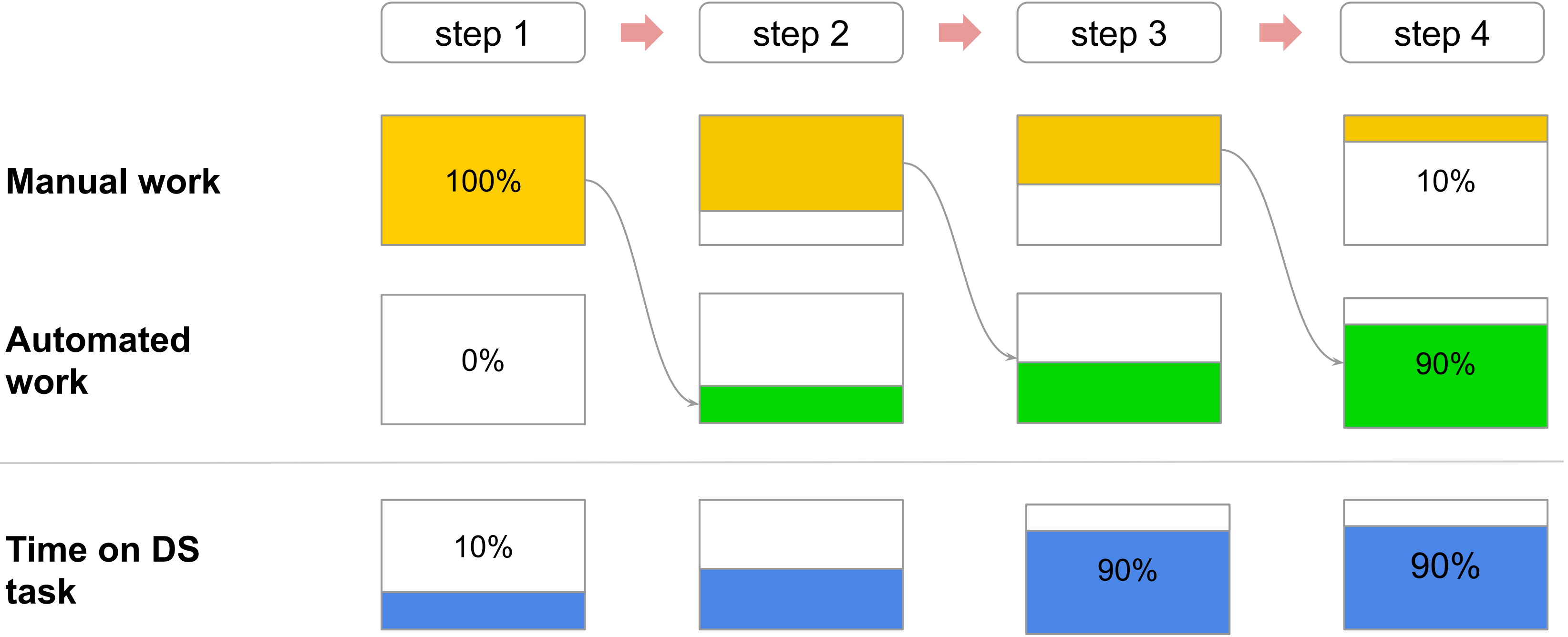
Image source:
https://medium.com/@jebaseelanravi96/machine-learning-iris-classification-33aa18a4a983

ML Reproducibility checklist

1. Automated pipelines
2. Control run params
3. Control execution DAG
4. Code version control
5. Artifacts version control (models, datasets, etc.)
6. Use shared/cloud storage for artifacts
7. Environment dependencies control

How to start?

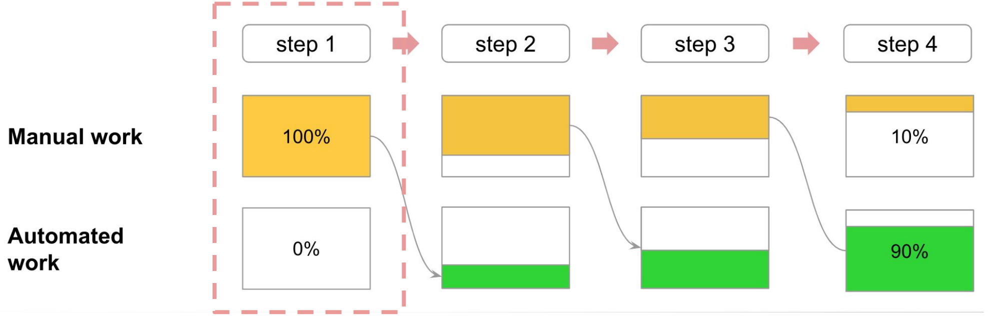

HELP!


step 1
step 2
step 3
step 4
Manual work
100%
10%
Automated work
0%
90%
Time on DS task
10%
90%
90%

Step 1:

Jupyter Notebook

- code in Jupyter Notebook
- everything in Docker



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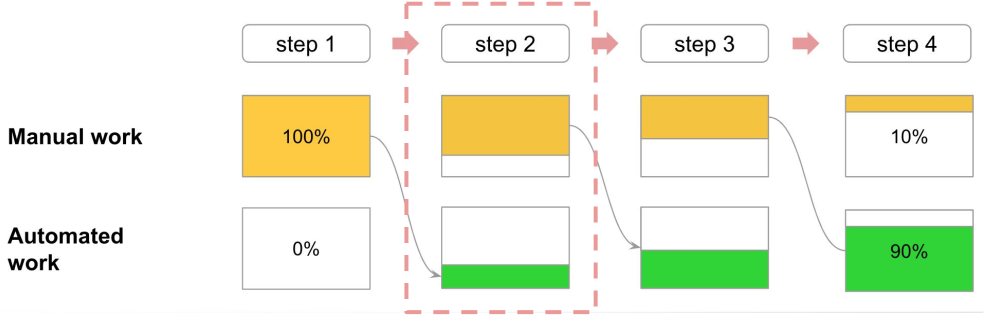
Step 2:
Build pipelines

- move common code into .py modules
- build pipelines
- everything in Docker
- run experiments in terminal or Jupyter Notebook

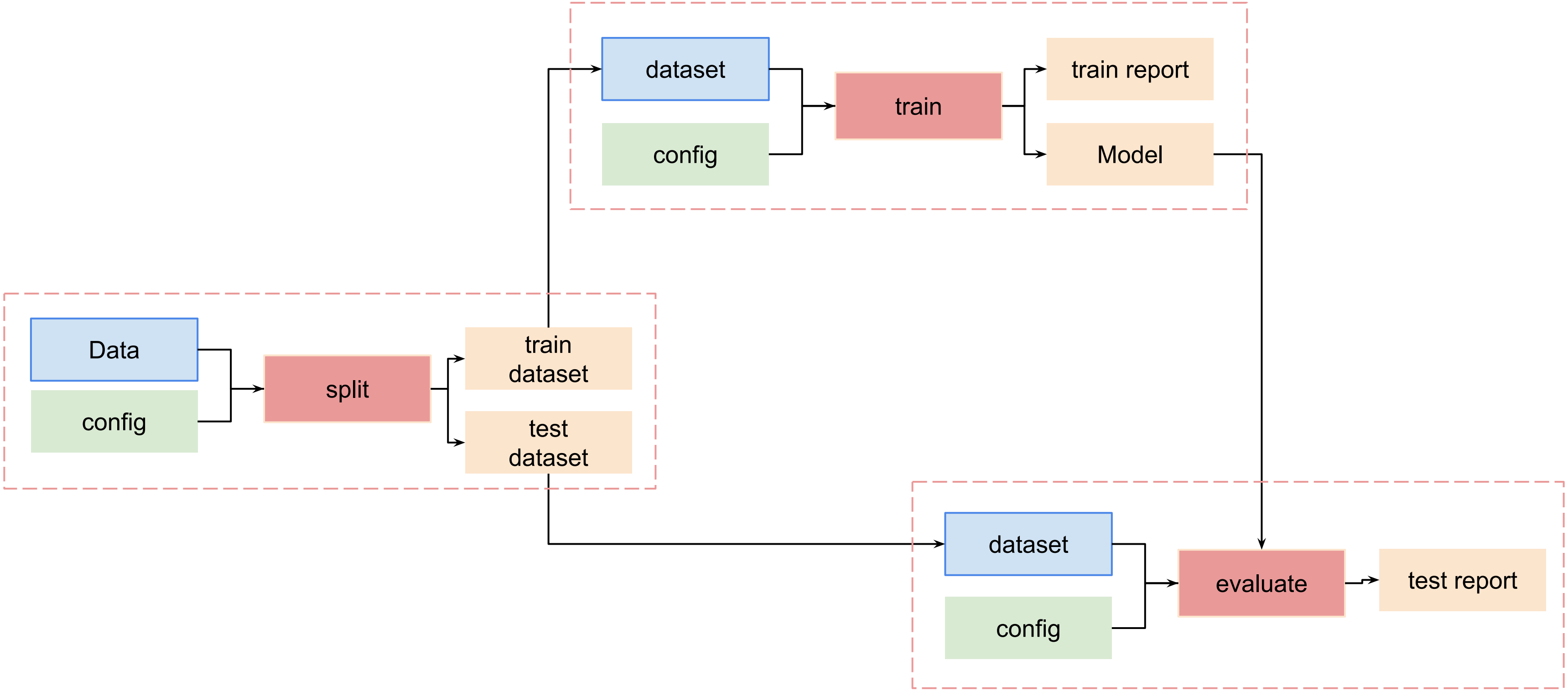


Project structure

```
.
├── README.md
├── config  <- any configuration files
├── data
│      ├── external <- external data
│      ├── interim <- data in intermediate processing stage
│      ├── processed <- data after all preprocessing has been done
│      └── raw <- original unmodified data acting as source of truth and provenance
├── docker <- docker image(s) for running project inside container(s)
├── docs  <- usage documentation or reference papers
├── models  <- compiled model .pkl or HDFS or .pb format
├── notebooks <- jupyter notebooks for exploratory analysis and explanation
└── src
      ├── data <- data prepare and/or preprocess
      ├── evaluate <- evaluating model stage code
      ├── features <- code to compute features
      ├── pipelines <- scripts of pipelines
      ├── report <- visualization (used in notebooks)
      ├── train <- train model stage code
      ├── transforms <- transformations data code (e.g., augmentation)
      └── utils.py <- auxiliary functions and classes
```

not sync with GIT

Setup pipelines



ML Reproducibility checklist

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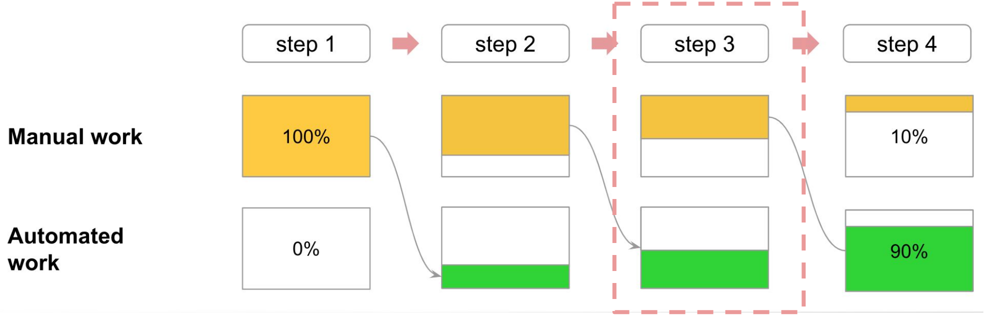
Step 3:

Pipelines automation

- add pipelines dependencies under DVC control
- add models/data/configs under DVC control
- models/data/congis under DVC control
- same code in .py modules
- same pipelines
- everything in Docker
- run experiments in terminal or Jupyter Notebook



ML Reproducibility checklist

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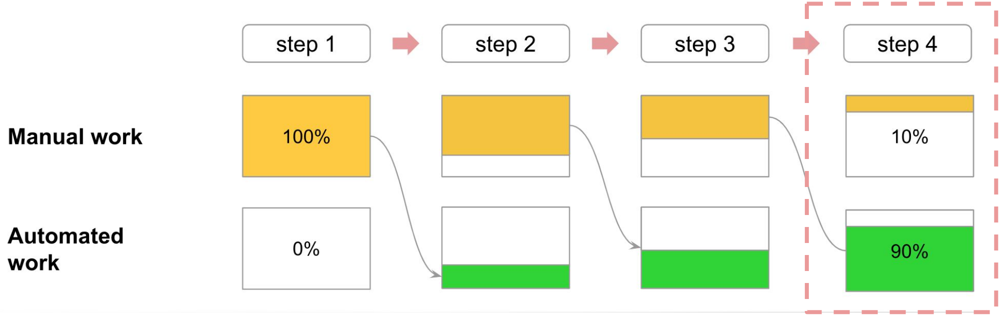
Step 4:

Experiments management

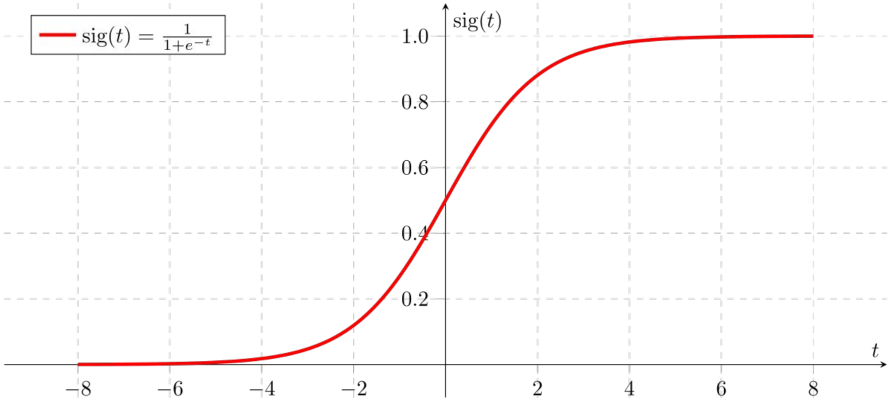
- add metrics tracking
- add experiments benchmark (DVC)
- pipelines dependencies under DVC control
- models/data/congis under DVC control
- same code in .py modules
- same pipelines
- everything in Docker
- run experiments in terminal or Jupyter Notebook



Experiment 1:

Tune Logistic Regression

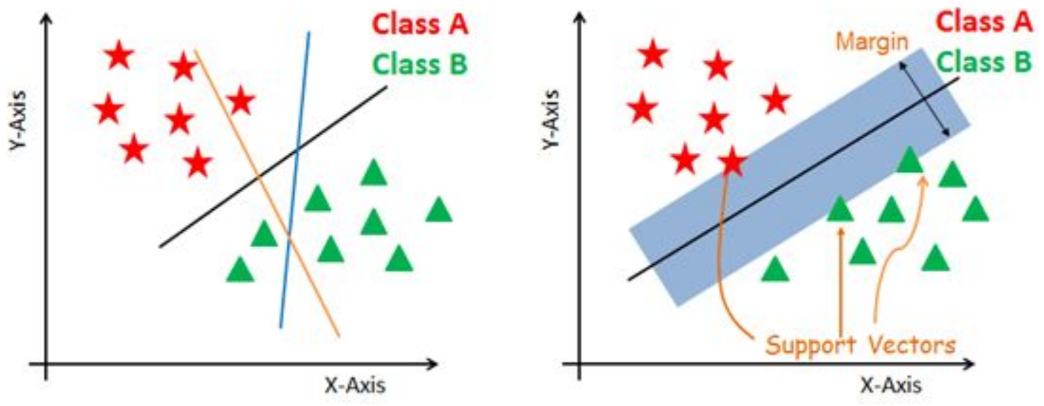
- hyperparameters tuning



Experiment 2:

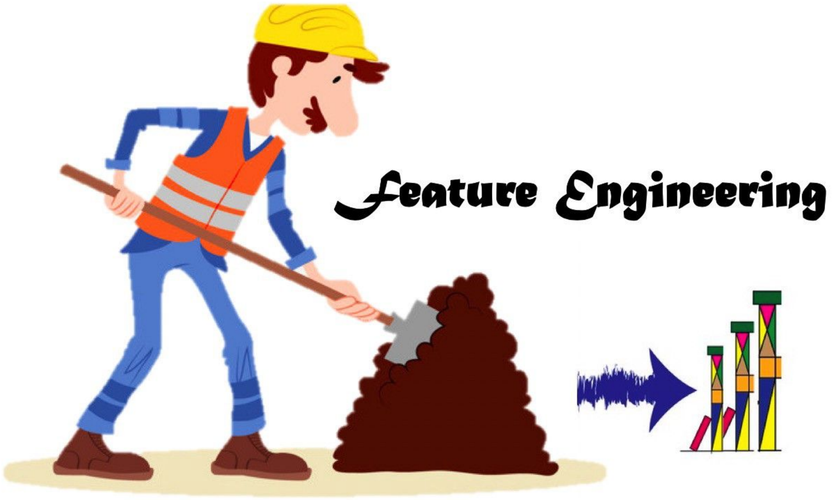
Use SVM

- use SVM estimator
- hyperparameters tuning



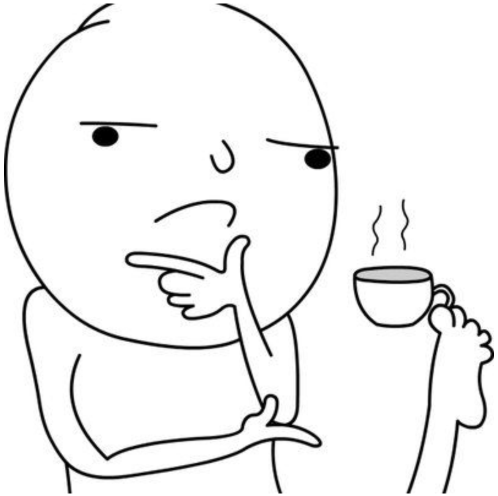
Experiment 3:
Add new features

- add squared features



Compare experiments

- **dvc metrics show**
- **dvc metrics show** -a
- **dvc metrics show** -t json -x f1_score -a
- **dvc metrics show** -T



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Conclusions

1. pipelines - not difficult
2. start where you detect a “copy-paste” pattern
3. artifacts version control - MUST
4. discipline in a team is important
5. more benefits for high complexity and large team projects

Contact me

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