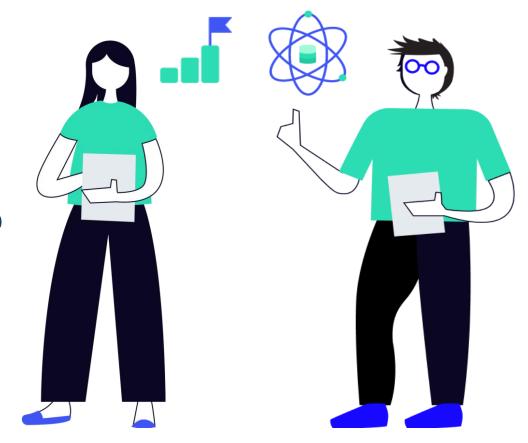
Dilemma in ML development



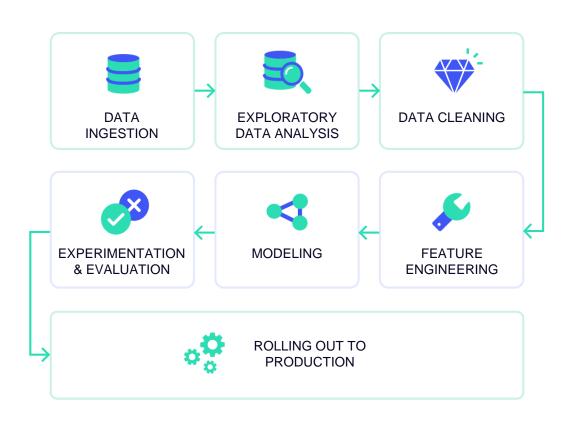
Building everything **manually** from scratch vs. using a **tool to support** the development phase (from collecting data to deploying on the edge).





Standard ML workflow









ML pipeline in practice

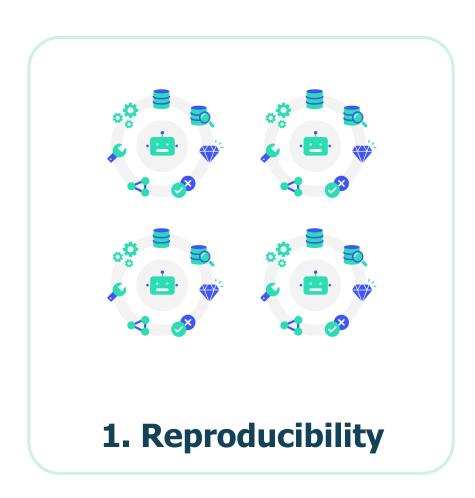




model model_1 features **EDA** model_1_2 data features copy EDA₂ model_prefinal data v2 features 2 EDA_3 model_data_v2 features 3 model_2_2 model final

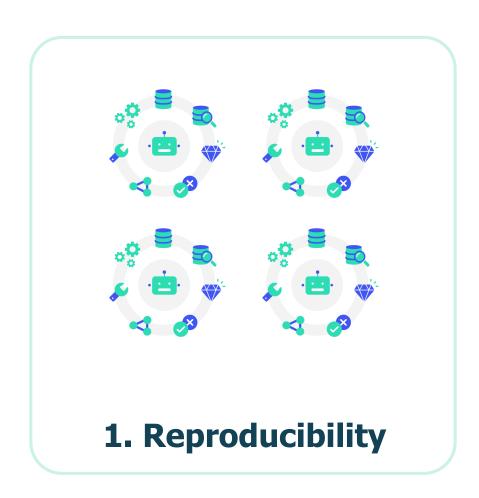
*EDA = Exploratory data analysis





- Teamwork
- Usually ad-hoc processes
- Productivity bottleneck
- Challenges
 - Changes in data
 - Hyperparams inconsistency
 - Randomness
 - Manual and ad-hoc execution of experiments







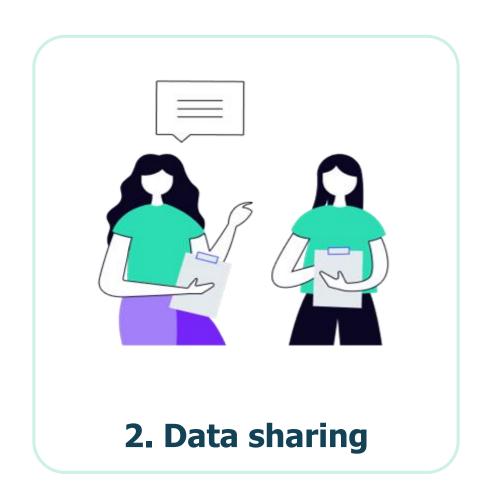
"Changes are uploaded, please run all the notebook again."

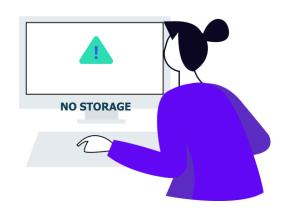




- Complex READMEs on how to gather data from remote storage
- Security and data privacy risks
- Manual versioning of dataset changes







"I wish I could automate this process..."





- Experiments setup traceability challenges
- Inefficient results comparison & evaluation
- Manual process:
 - Spreadsheet
 - Github (metadata files)
 - Tracking tools (big learning curve)

Ideal development experience





Structured pipeline composed by interdependent steps



Easily adding files or directories to a remote repository

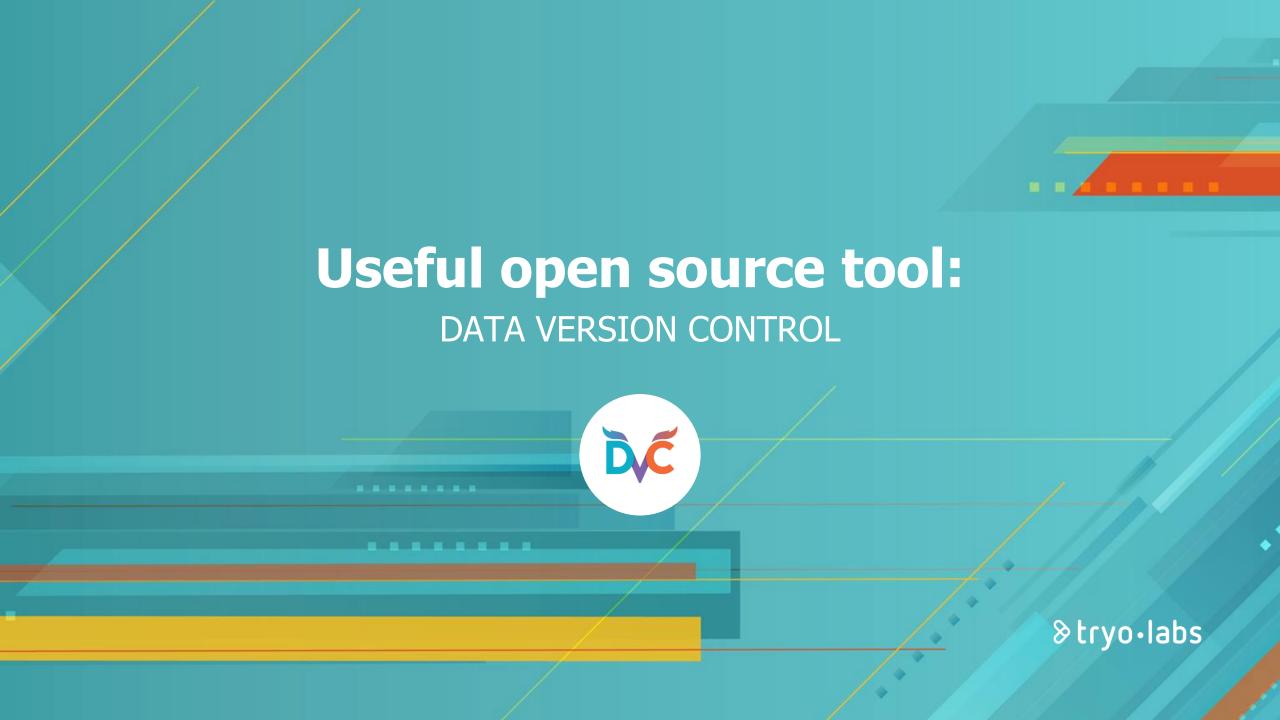


Sharing
experiments,
models, and results
in a simple way



Stop worrying about source code and data association





DVC high-level overview

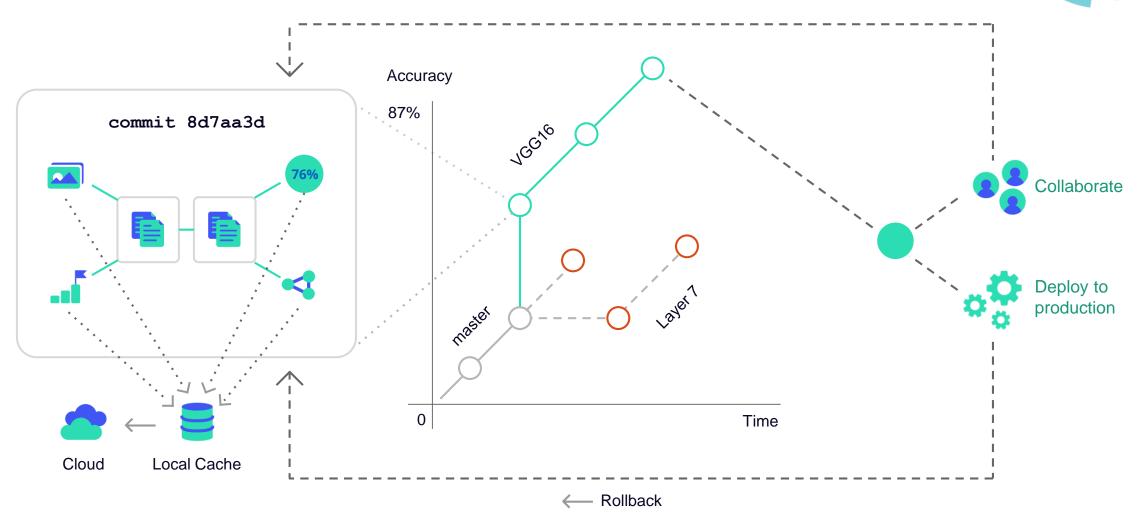


data data features features model model 7fe5fc5 d512ef1 23811e0 e7eb61f 020c55f **Update features** Add the new **Update dataset** Adjusting input Adjusting input and input parameters dataset and parameters features parameters data data data features features features model model model



DVC high-level overview







Main features



- Git-compatible
- Storage agnostic
- Reproducible
- Low friction branching

- ML pipeline framework
- Language & framework agnostic
- Track failures
- Experiments & metrics tracking

Pipelines



- Pipelines composed by interdependent steps
 - Dependencies
 - Code to execute
 - Outputs

Additional pipeline
 visualization command
 dvc dag

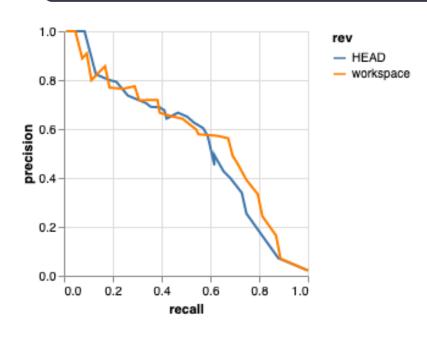
```
$ dvc dag
          featurize
 train
          evaluate
```

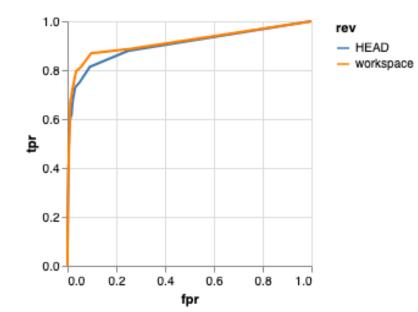
```
stages:
  build:
    cmd: python train.py
    deps:
      - features.csv
    outs:
      - model.pt
    metrics:
      - accuracy.txt:
          cache: false
    plots:
      - auc.json:
          cache: false
```

Metrics differences



Smooth comparison process: **numeric** and **graphic** visualization

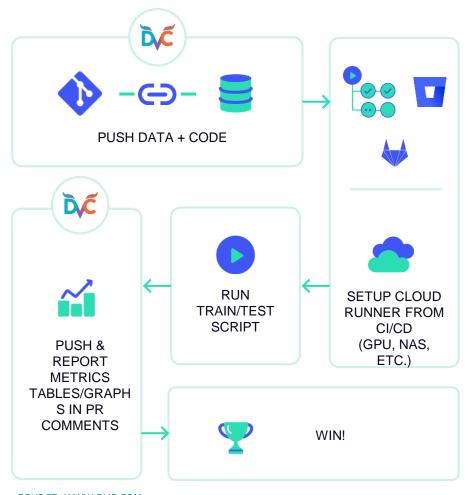




Continuous integration



- Automatically check data version
- Benchmark new model against previously deployed models
- Metrics diff & interactive plots in Pull Requests
- Re-train & refine in the cloud



SOURCE: WWW.DVC.COM

Experiments batch execution



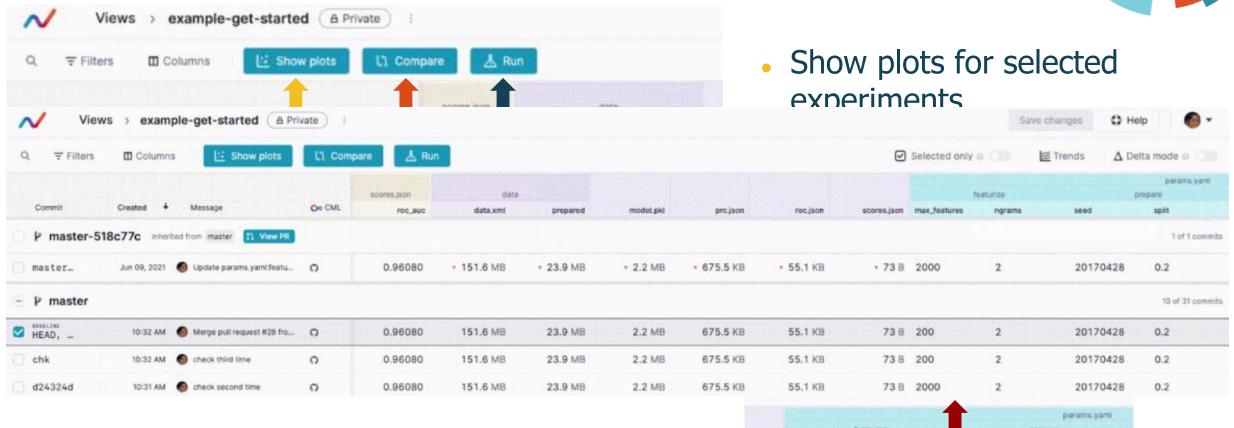
Experiment	Created	train	test	model.n_estimators	model.max_depth	model.min_samples_split	model.min_samples_leaf	model.max_leaf_nodes	model.random_state
workspace dvc	03:49 PM	96.257 96.257 76.946 68.263	70.404 74.439 71.749	100 100 100 100	20 - 20 5 1 2	2 2 2 2 2 2	1 1 1 1 1		42 42 42 42 42 42 42

"I can't believe the number of hours saved by queuing and executing experiments in parallel."



UI does not have to be built from scratch





Generate trend charts





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