VERSIONING, PROVENANCE, AND REPRODUCABILITY

Christian Kaestner

Required reading: 🕮 Halevy, Alon, Flip Korn, Natalya F. Noy, Christopher Olston, Neoklis Polyzotis, Sudip Roy, and Steven Euijong Whang. Goods: Organizing google's datasets. In Proceedings of the 2016 International Conference

LEARNING GOALS

- Judge the importance of data provenance, reproducibility and explainability for a given system
- Create documentation for data dependencies and provenance in a given system
- Propose versioning strategies for data and models
- Design and test systems for reproducibility

CASE STUDY: CREDIT SCORING

DHH
@dhh

The @AppleCard is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple’s black box algorithm thinks I deserve 20x the credit limit she does. No appeals work.

8:34 PM · Nov 7, 2019

28.5K   10.6K people are Tweeting about this

DHH @dhh · Nov 8, 2019

Replying to @dhh

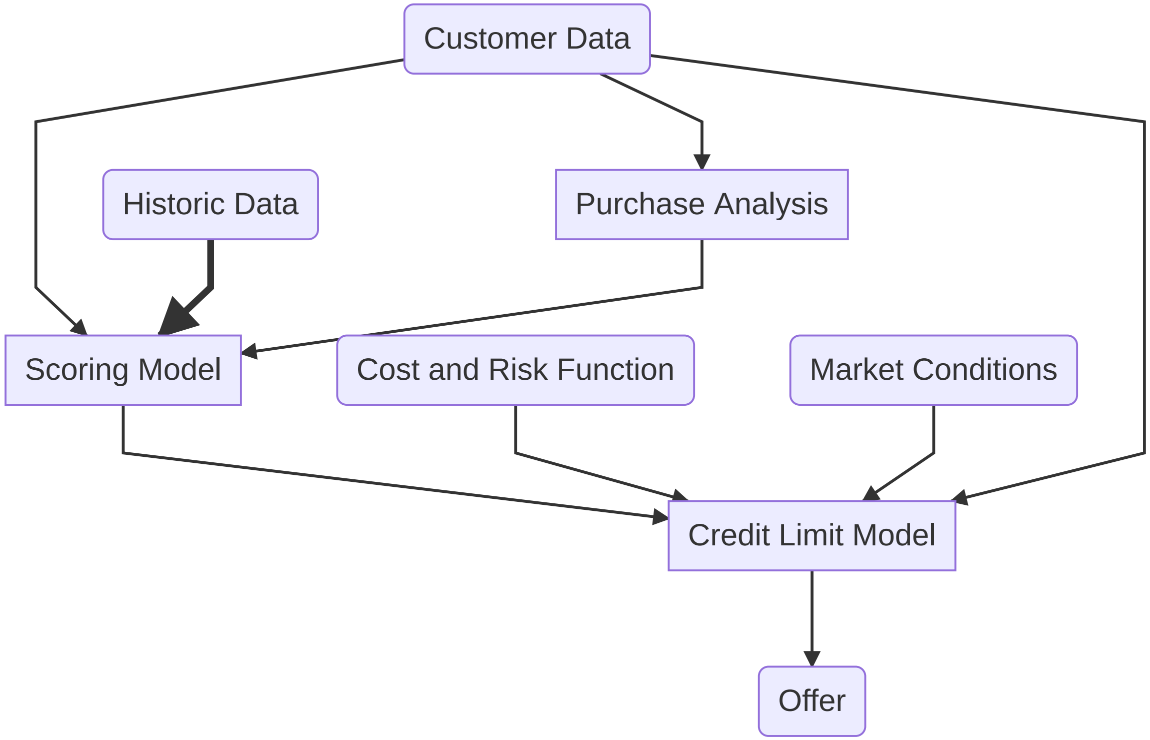
I wasn’t even pessimistic to expect this outcome, but here we are: @AppleCard just gave my wife the VIP bump to match my credit limit, but continued to be an utter fucking failure of a customer service experience. Let me explain...

DHH
@dhh

She spoke to two Apple reps. Both very nice, courteous people representing an utterly broken and reprehensible system. The first person was like “I don’t know why, but I swear we’re not discriminating, IT’S JUST THE ALGORITHM”. I shit you not. “IT’S JUST THE ALGORITHM!”.

11:20 PM · Nov 8, 2019

4.8K   625 people are Tweeting about this



Customer Data
Historic Data
Purchase Analysis
Scoring Model
Cost and Risk Function
Market Conditions
Credit Limit Model
Offer

DEBUGGING?

What went wrong? Where? How to fix?

DEBUGGING QUESTIONS BEYOND INTERPRETABILITY

- Can we reproduce the problem?
- What were the inputs to the model?
- Which exact model version was used?
- What data was the model trained with?
- What learning code (cleaning, feature extraction, ML algorithm) was the model trained with?
- Where does the data come from? How was it processed and extracted?
- Were other models involved? Which version? Based on which data?
- What parts of the input are responsible for the (wrong) answer? How can we fix the model?

DATA PROVENANCE

Historical record of data and its origin

DATA PROVENANCE

- Track origin of all data
  - Collected where?
  - Modified by whom, when, why?
  - Extracted from what other data or model or algorithm?
- ML models often based on data drived from many sources through many steps, including other models

TRACKING DATA

- Document all data sources
- Model dependencies and flows
- Ideally model all data and processing code
- Avoid "visibility debt"

- Advanced: Use infrastructure to automatically capture/infer dependencies and flows (e.g., Goods paper)

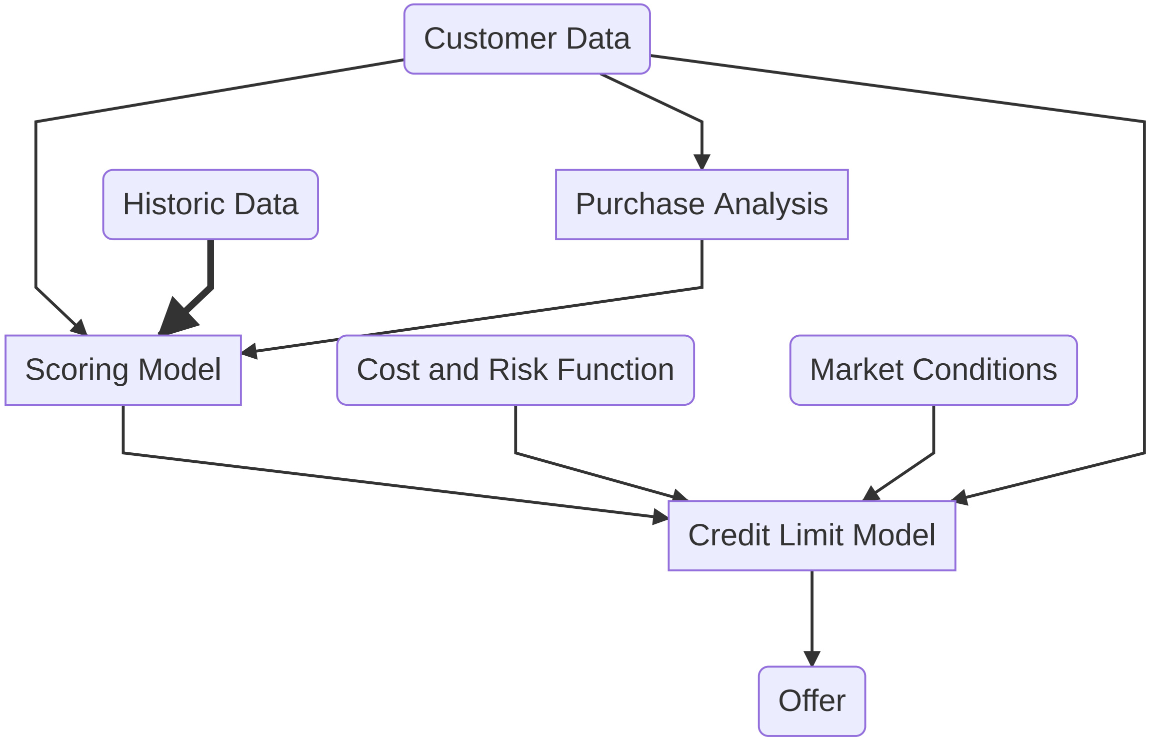
FEATURE PROVENANCE

- How are features extracted from raw data
    - during training
    - during inference
- Has feature extraction changed since the model was trained?

Example?

MODEL PROVENANCE

- How was the model trained?
- What data? What library? What hyperparameter? What code?
- Ensemble of multiple models?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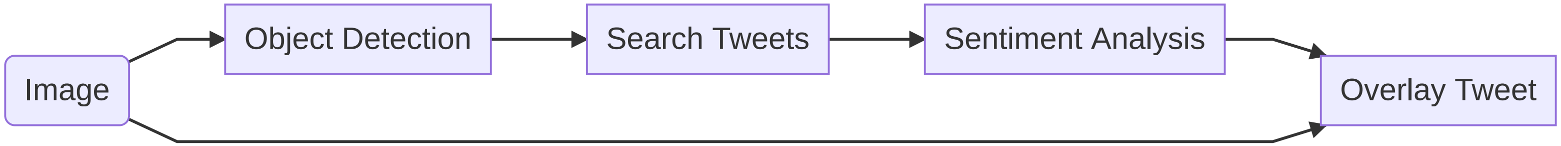
RECALL: MODEL CHAINING

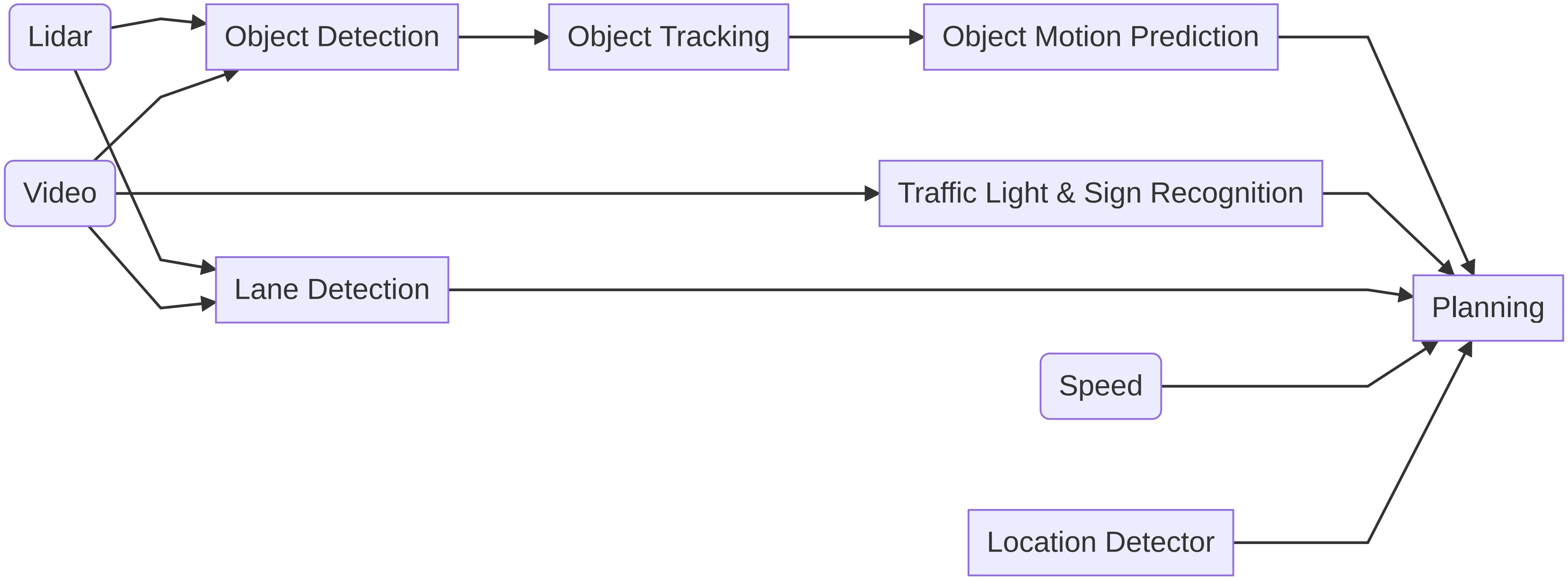
automatic meme generator



Example adapted from Jon Peck. [Chaining machine learning models in production with Algorithmia](). Algorithmia blog, 2019

RECALL: ML MODELS FOR FEATURE EXTRACTION

self driving car



Example: Zong, W., Zhang, C., Wang, Z., Zhu, J., & Chen, Q. (2018). [Architecture design and implementation of an autonomous vehicle](). IEEE access, 6, 21956-21970.

SUMMARY: PROVENANCE

- Data provenance
- Feature provenance
- Model provenance

PRACTICAL DATA AND MODEL VERSIONING

HOW TO VERSION LARGE DATASETS?

RECALL: EVENT SOURCING

- Append only databases
- Record edit events, never mutate data
- Compute current state from all past events, can reconstruct old state
- For efficiency, take state snapshots
- Similar to traditional database logs

```
createUser(id=5, name="Christian", dpt="SCS")
updateUser(id=5, dpt="ISR")
deleteUser(id=5)
```

VERSIONING DATASETS

- Store copies of entire datasets (like Git)
- Store deltas between datasets (like Mercurial)
- Offsets in append-only database (like Kafka offset)
- History of individual database records (e.g. S3 bucket versions)
  - some databases specifically track provenance (who has changed what entry when and how)
  - specialized data science tools eg Hangar for tensor data
- Version pipeline to recreate derived datasets ("views", different formats)
  - e.g. version data before or after cleaning?

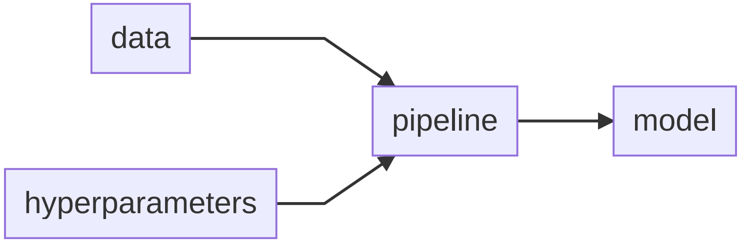
- Often in cloud storage, distributed
- Checksums often used to uniquely identify versions
- Version also metadata

VERSIONING MODELS

VERSIONING MODELS

- Usually no meaningful delta, versioning as binary objects
- Any system to track versions of blobs

VERSIONING PIPELINES



VERSIONING DEPENDENCIES

- Pipelines depend on many frameworks and libraries
- Ensure reproducable builds
    - Declare versioned dependencies from stable repository (e.g. requirements.txt + pip)
    - Optionally: commit all dependencies to repository ("vendoring")
- Optionally: Version entire environment (e.g. Docker container)
- Avoid floating versions
- Test build/pipeline on independent machine (container, CI server, ...)

ML VERSIONING TOOLS (SEE MLOPS)

- Tracking data, pipeline, and model versions
- Modeling pipelines: inputs and outputs and their versions
    - explicitly tracks how data is used and transformed
- Often tracking also metadata about versions
    - Accuracy
    - Training time
    - ...

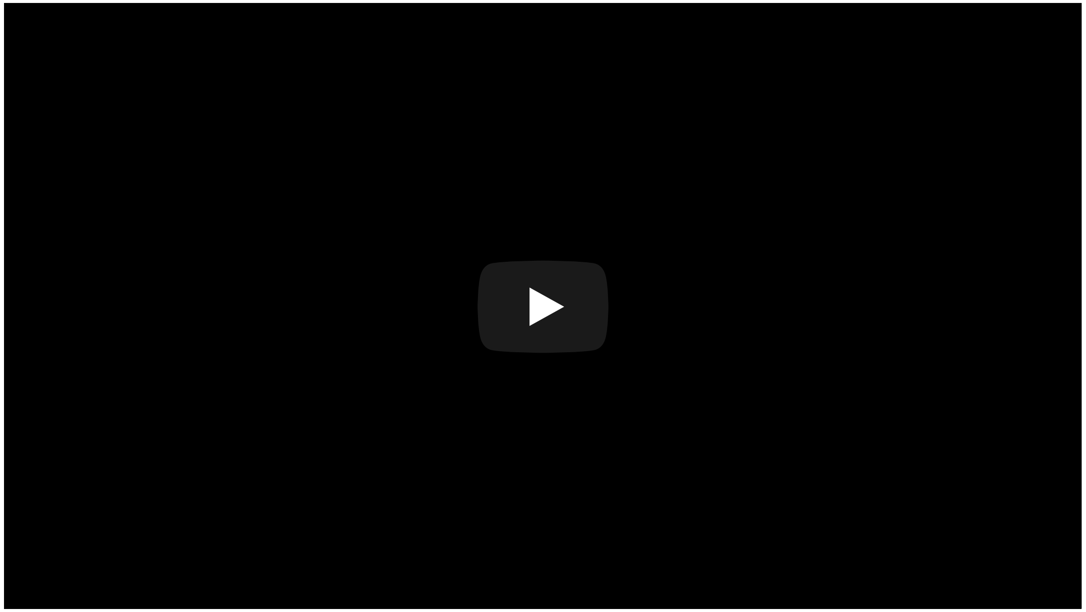
EXAMPLE: DVC

```
dvc add images
dvc run -d images -o model.p cnn.py
dvc remote add myrepo s3://mybucket
dvc push
```

- Tracks models and datasets, built on Git
- Splits learning into steps, incrementalization
- Orchestrates learning in cloud resources

https://dvc.org/

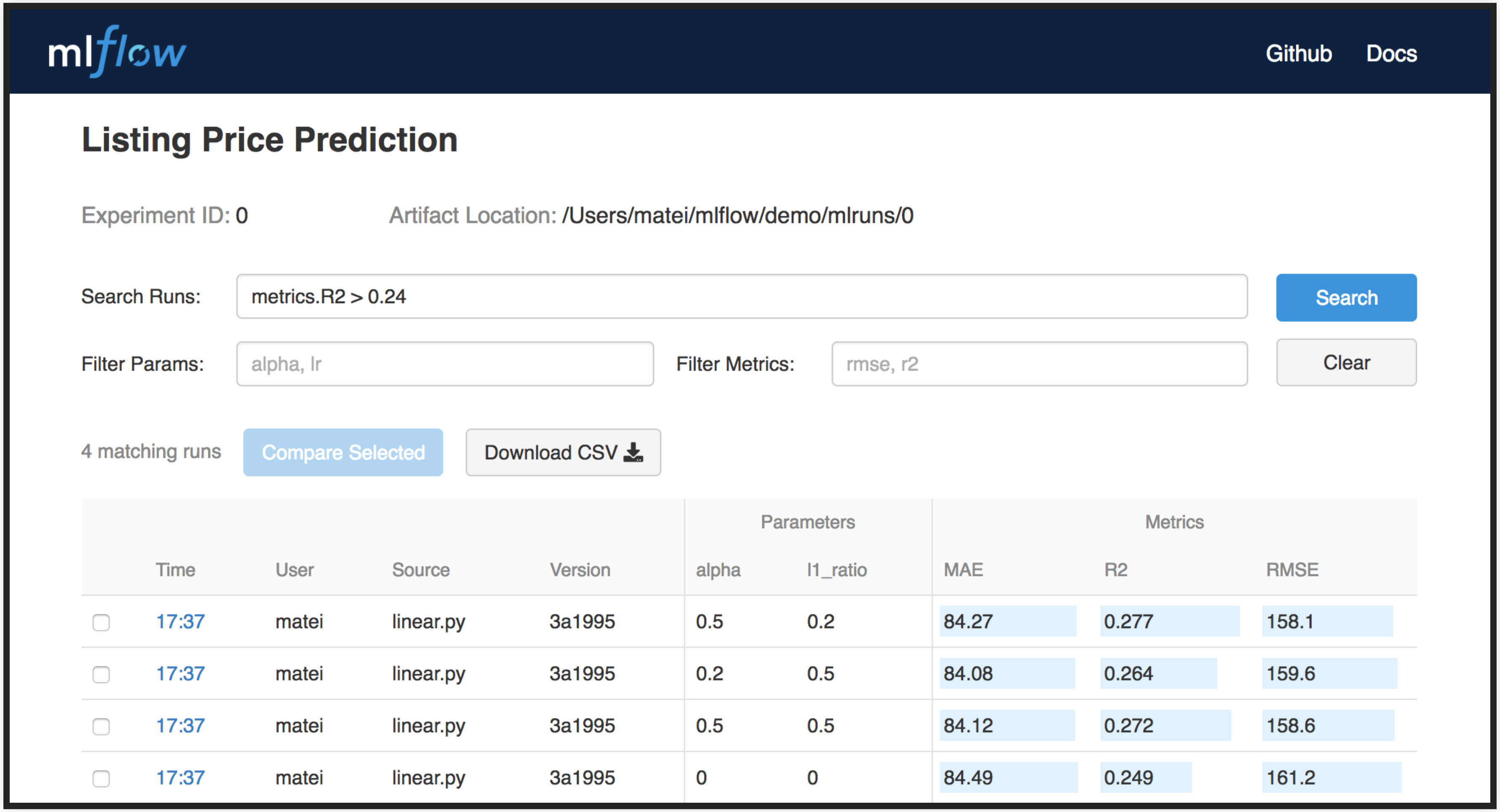
EXAMPLE: MODELDB



https://github.com/mitdbg/modeldb

EXAMPLE: MLFLOW

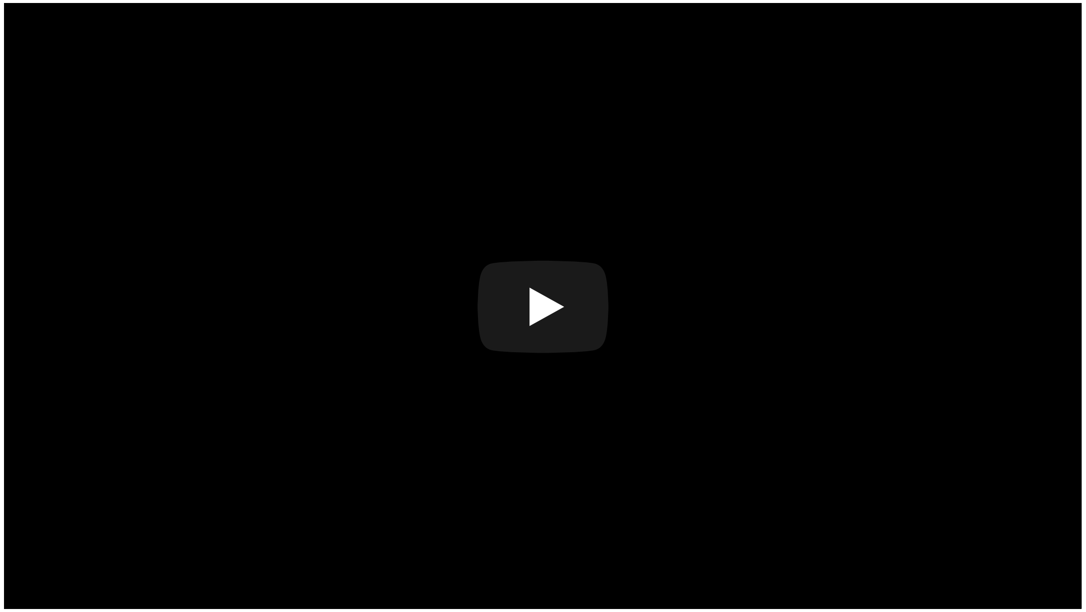
- Instrument pipeline with *logging* statements
- Track individual runs, hyperparameters used, evaluation results, and model files



Matei Zaharia. Introducing MLflow: an Open Source Machine Learning Platform, 2018

ASIDE: VERSIONING IN NOTEBOOKS WITH VERDANT

- Data scientists usually do not version notebooks frequently
- Exploratory workflow, copy paste, regular cleaning



Further reading: Kery, M. B., John, B. E., O'Flaherty, P., Horvath, A., & Myers, B. A. (2019, May). Towards effective foraging by data scientists to find past analysis choices. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1-13).

FROM MODEL VERSIONING TO DEPLOYMENT

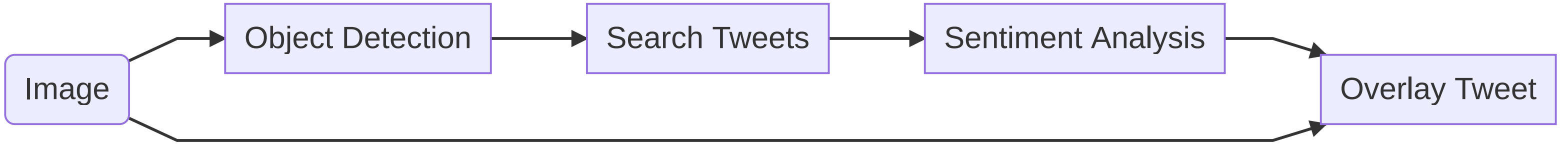
- Decide which model version to run where
  - automated deployment and rollback (cf. canary releases)
  - Kubernetis, Cortex, BentoML, ...
- Track which prediction has been performed with which model version (logging)

LOGGING AND AUDIT TRACES

- Version everything
- Record every model evaluation with model version
- Append only, backed up

Key goal: If a customer complains about an interaction, can we reproduce the prediction with the right model? Can we debug the model's pipeline and data? Can we reproduce the model?

LOGGING FOR COMPOSED MODELS



Ensure all predictions are logged

DISCUSSION

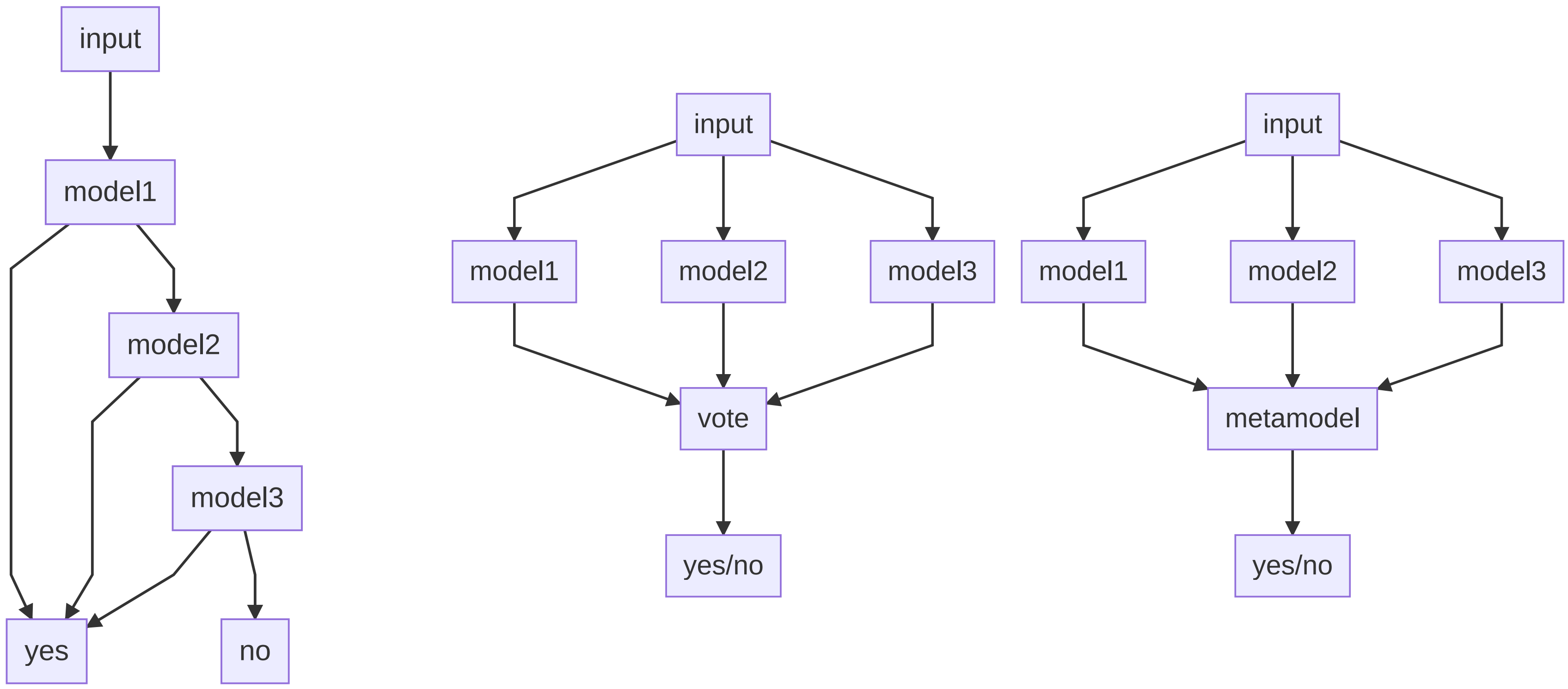
What to do in movie recommendation and popularity prediction scenarios? And how?

FIXING MODELS

See also Hulten. Building Intelligent Systems. Chapter 21

ORCHESTRATING MULTIPLE MODELS

- Try different modeling approaches in parallel
- Pick one, voting, sequencing, metamodel, or responding with worst-case prediction

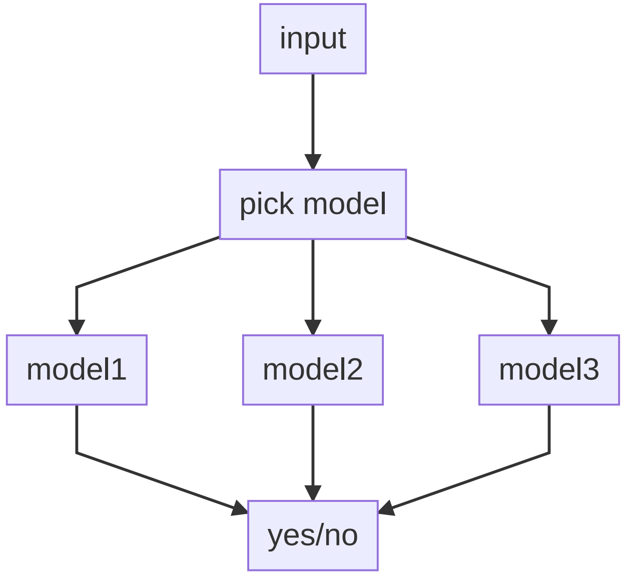


CHASING BUGS

- Update, clean, add, remove data
- Change modeling parameters
- Add regression tests
- Fixing one problem may lead to others, recognizable only later

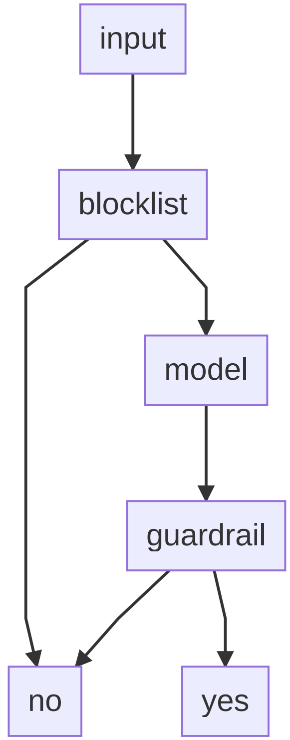
PARTITIONING CONTEXTS

- Separate models for different subpopulations
- Potentially used to address fairness issues
- ML approaches typically partition internally already



OVERRIDES

- Hardcoded heuristics (usually created and maintained by humans) for special cases
- Blocklists, guardrails
- Potential neverending attempt to fix special cases



REPRODUCABILITY

DEFINITIONS

- **Reproducibility:** the ability of an experiment to be repeated with minor differences from the original experiment, while achieving the same qualitative result
- **Replicability:** ability to reproduce results exactly, achieving the same quantitative result; requires determinism

- In science, reproducing results under different conditions are valuable to gain confidence
  - "conceptual replication": evaluate same hypothesis with different experimental procedure or population
  - many different forms distinguished "... replication" (e.g. close, direct, exact, independent, literal, nonexperiemental, partial, retest, sequential, statistical, varied, virtual)

Juristo, Natalia, and Omar S. Gómez. "Replication of software engineering experiments." In Empirical software engineering and verification, pp. 60-88. Springer, Berlin, Heidelberg, 2010.

PRACTICAL REPRODUCABILITY

- Ability to generate the same research results or predictions
- Recreate model from data
- Requires versioning of data and pipeline (incl. hyperparameters and dependencies)

NONDETERMINISM

- Some machine learning algorithms are nondeterministic
    - Recall: Neural networks initialized with random weights
    - Recall: Distributed learning
- Many notebooks and pipelines contain nondeterminism
    - Depend on snapshot of online data (e.g., stream)
    - Depend on current time
    - Initialize random seed
- Different library versions installed on the machine may affect results
- (Inference for a given model is usually deterministic)

RECOMMENDATIONS FOR REPRODUCIBILITY

- Version pipeline and data (see above)
- Document each step
    - document intention and assumptions of the process (not just results)
    - e.g., document why data is cleaned a certain way
    - e.g., document why certain parameters chosen
- Ensure determinism of pipeline steps (-> test)
- Modularize and test the pipeline
- Containerize infrastructure -- see MLOps

SUMMARY

- Provenance is important for debugging and accountability
- Data provenance, feature provenance, model provenance
- Reproducibility vs replicability
- Version everything
    - Strategies for data versioning at scale
    - Version the entire pipeline and dependencies
    - Adopt a pipeline view, modularize, automate
    - Containers and MLOps, many tools
- Strategies to fix models