



# Machine Learning in Production Versioning, Provenance, and Reproducability

# More Foundational Technology for Responsible Engineering

## Fundamentals of Engineering AI-Enabled Systems

**Holistic system view:** AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

### Requirements:

System and model goals  
User requirements  
Environment assumptions  
Quality beyond accuracy  
Measurement  
Risk analysis  
Planning for mistakes

### Architecture + design:

Modeling tradeoffs  
Deployment architecture  
Data science pipelines  
Telemetry, monitoring  
Anticipating evolution  
Big data processing  
Human-AI design

### Quality assurance:

Model testing  
Data quality  
QA automation  
Testing in production  
Infrastructure quality  
Debugging

### Operations:

Continuous deployment  
Contin. experimentation  
Configuration mgmt.  
Monitoring  
Versioning  
Big data  
DevOps, MLOps

**Teams and process:** Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

## Responsible AI Engineering

Provenance,  
versioning,  
reproducibility

Safety

Security and  
privacy

Fairness

Interpretability  
and explainability

Transparency  
and trust

Ethics, governance, regulation, compliance, organizational culture

# Readings

## Required readings

- Hulten, Geoff. "[Building Intelligent Systems: A Guide to Machine Learning Engineering.](#)" Apress, 2018, Chapter 21 (Organizing Intelligence).
- 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 on Management of Data, pp. 795-806. ACM, 2016.

# 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



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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



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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...



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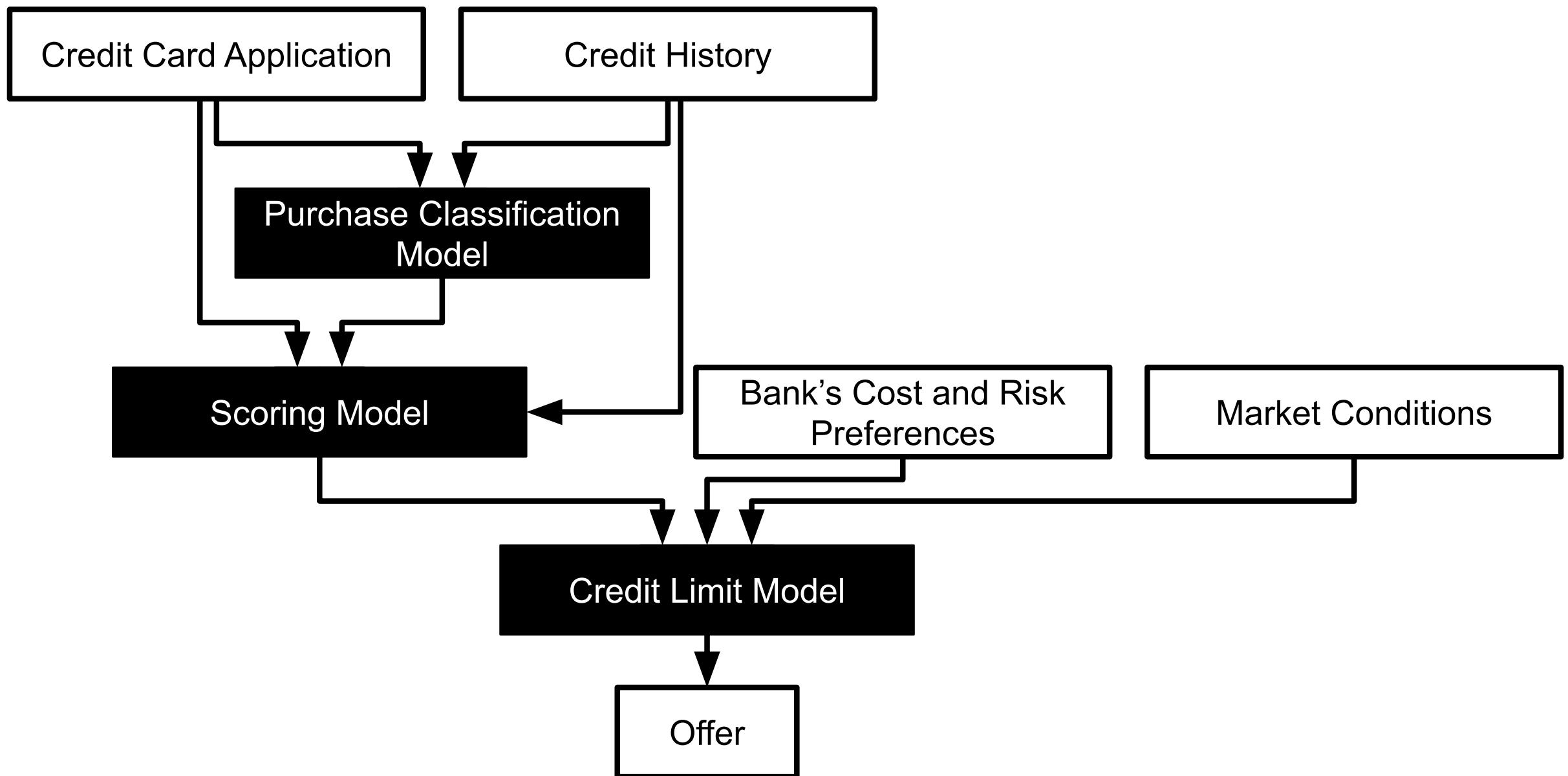
She spoke to two Apple reps. Both very nice, courteous people representing an utterly broken and reprehensible system. The first person was like "I don't know why, but I swear we're not discriminating, IT'S JUST THE ALGORITHM". I shit you not. "IT'S JUST THE ALGORITHM!".

11:20 PM · Nov 8, 2019



4.3K Reply Copy link

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# 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 pipeline code was the model trained with?
- Where does the data come from? How was it processed/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?

# Model Chaining: Automatic meme generator



*Version all models involved!*

# Complex Model Composition: ML Models for Feature Extraction

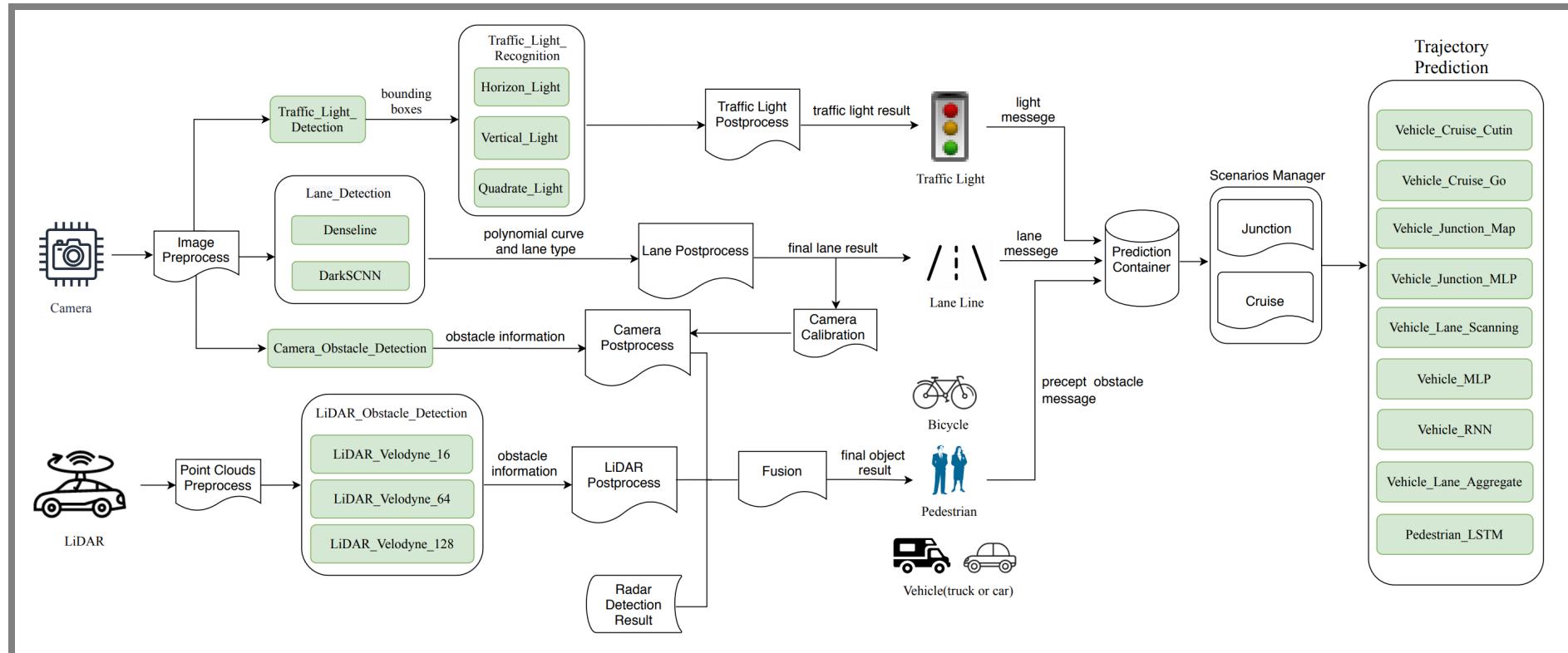


Image: Peng, Zi, Jinqiu Yang, Tse-Hsun Chen, and Lei Ma. "A first look at the integration of machine learning models in complex autonomous driving systems: a case study on Apollo." In Proc. FSE. 2020.

## Speaker notes

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



# Breakout Discussion: Movie Predictions

*Assume you are receiving complains that a child gets many recommendations about R-rated movies*

In a group, discuss how you could address this in your own system and post to #lecture, tagging team members:

- How could you identify the problematic recommendation(s)?
- How could you identify the model that caused the prediction?
- How could you identify the training code and data that learned the model?
- How could you identify what training data or infrastructure code "caused" the recommendations?

K.G Orphanides. [Children's YouTube is still churning out blood, suicide and cannibalism](#). Wired UK, 2018; Kristie Bertucci. [16 NSFW Movies Streaming on Netflix](#). Gadget Reviews, 2020

# Provenance Tracking

*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 driven from many sources through many steps, including other models



# Excursion: Provenance Tracking in Databases

Whenever value is changed, record:

- who changed it
- time of change
- history of previous values
- possibly also justification of why

Embedded as feature in some databases or implemented in business logic

Possibly signing with cryptographic methods



# Tracking Data Lineage

Document all data sources

Identify all model dependencies and flows

Ideally model all data and processing code

Avoid "visibility debt"

(Advanced: Use infrastructure to automatically capture/infer dependencies and flows as in [Goods](#))

# Feature Provenance

How are features extracted from raw data?

- during training
- during inference

Has feature extraction changed since the model was trained?

Recommendation: Modularize and version feature extraction code

Example?

# Advanced Practice: Feature Store

Stores feature extraction code as functions, versioned

Catalog features to encourage reuse

Compute and cache features centrally

Use same feature used in training and inference code

Advanced: Immutable features -- never change existing features, just add new ones (e.g., creditscore, creditscore2, creditscore3)

# Model Provenance

How was the model trained?

What data? What library? What hyperparameter? What code?

Ensemble of multiple models?



# In Real Systems: Tracking Provenance Across Multiple Models



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

# Complex Model Composition: ML Models for Feature Extraction

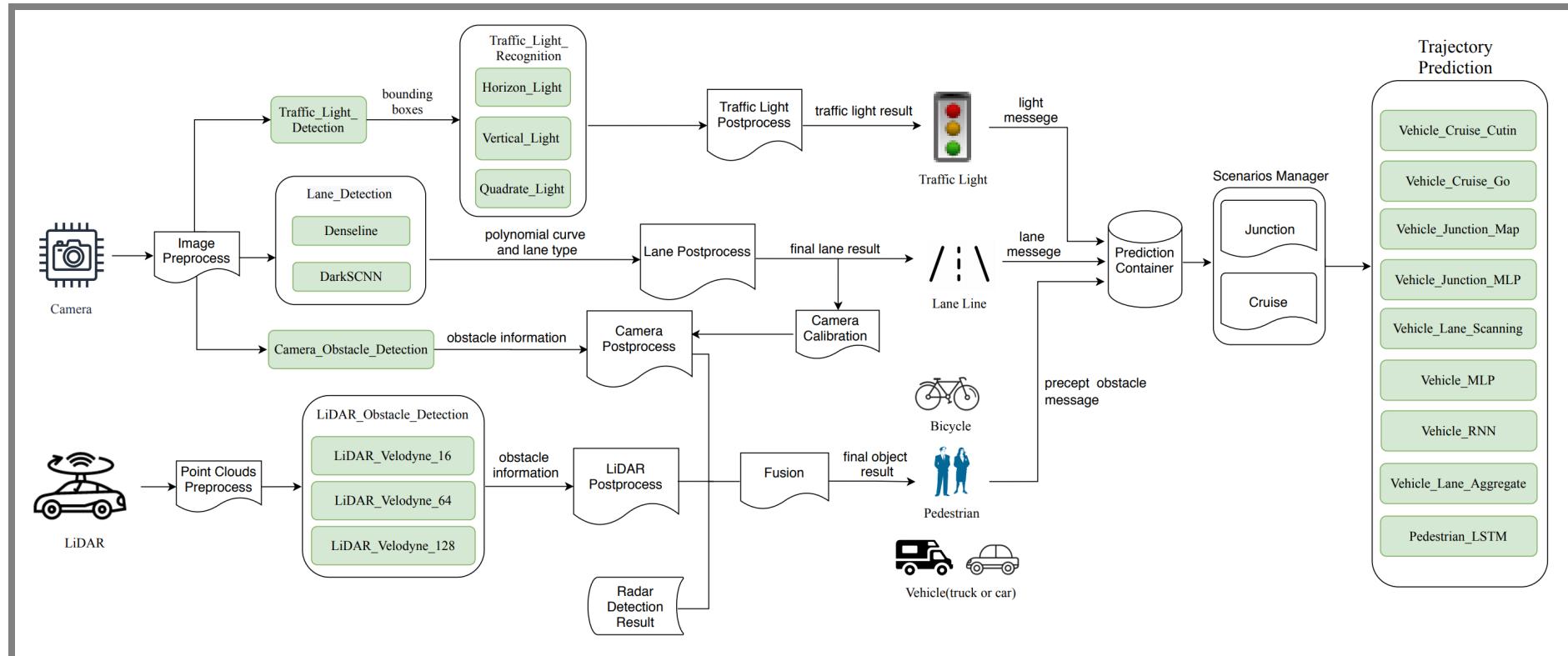


Image: Peng, Zi, Jinqiu Yang, Tse-Hsun Chen, and Lei Ma. "A first look at the integration of machine learning models in complex autonomous driving systems: a case study on Apollo." In Proc. FSE. 2020.

# Summary: Provenance

Data provenance

Feature provenance

Model provenance

# Practical Data and Model Versioning

# How to Version Large Datasets?



(movie ratings, movie metadata, user data?)

# 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 Strategies for Datasets

1. Store copies of entire datasets (like Git), identify by checksum
2. Store deltas between datasets (like Mercurial)
3. Offsets in append-only database (like Kafka), identify by offset
4. 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
5. Version pipeline to recreate derived datasets ("views", different formats)
  - e.g. version data before or after cleaning?

# Aside: Git Internals



# Versioning Models



# Versioning Models

Usually no meaningful delta/compression, version as binary objects

Any system to track versions of blobs

# Versioning Pipelines



Associate model version with pipeline code version, data version, and hyperparameters!

# Versioning Dependencies

Pipelines depend on many frameworks and libraries

Ensure reproducible builds

- Declare versioned dependencies from stable repository (e.g. requirements.txt + pip)
- Avoid floating versions
- Optionally: commit all dependencies to repository ("vendorizing")

Optionally: Version entire environment (e.g. Docker container)

Test build/pipeline on independent machine (container, CI server, ...)

# ML Versioning Tools (MLOps)

Tracking data, pipeline, and model versions

Modeling pipelines: inputs and outputs and their versions

- automatically 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/>

# DVC Example

```
stages:  
  features:  
    cmd: jupyter nbconvert --execute featurize.ipynb  
    deps:  
      - data/clean  
    params:  
      - levels.no  
  outs:  
    - features  
metrics:  
  - performance.json
```

# Experiment Tracking

Log information within pipelines: hyperparameters used, evaluation results, and model files

The screenshot shows the MLflow interface for a "Listing Price Prediction" experiment. At the top, it displays "Experiment ID: 0" and "Artifact Location: /Users/matei/mlflow/demo/mlruns/0". Below this are search and filter controls: "Search Runs: metrics.R2 > 0.24" with a "Search" button, and "Filter Params: alpha, lr" and "Filter Metrics: rmse, r2" with a "Clear" button. A message indicates "4 matching runs". Below these are two buttons: "Compare Selected" and "Download CSV". The main area is a table with the following data:

Time	User	Source	Version	Parameters		Metrics		
				alpha	l1_ratio	MAE	R2	RMSE
17:37	matei	linear.py	3a1995	0.5	0.2	84.27	0.277	158.1
17:37	matei	linear.py	3a1995	0.2	0.5	84.08	0.264	159.6
17:37	matei	linear.py	3a1995	0.5	0.5	84.12	0.272	158.6
17:37	matei	linear.py	3a1995	0	0	84.49	0.249	161.2

Many tools: MLflow, ModelDB, Neptune, TensorBoard, Weights & Biases, Comet.ml, ...

## Speaker notes

Image from Matei Zaharia. [Introducing MLflow: an Open Source Machine Learning Platform](#), 2018

# ModelDB Example

```
from verta import Client
client = Client("http://localhost:3000")

proj = client.set_project("My first ModelDB project")
expt = client.set_experiment("Default Experiment")

# log the first run
run = client.set_experiment_run("First Run")
run.log_hyperparameters({"regularization": 0.5})
run.log_dataset_version("training_and_testing_data", dataset_v
model1 = # ... model training code goes here
```

# Google's Goods

Automatically derive data dependencies from system log files

Track metadata for each table

No manual tracking/dependency declarations needed

Requires homogeneous infrastructure

Similar systems for tracking inside databases, MapReduce, Sparts, etc.

# From Model Versioning to Deployment

Decide which model version to run where

- automated deployment and rollback (cf. canary releases)
- Kubernetes, Cortex, BentoML, ...

Track which prediction has been performed with which model version  
(logging)

# Logging and Audit Traces

**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?

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

```
<date>,<model>,<model version>,<feature inputs>,<output>
<date>,<model>,<model version>,<feature inputs>,<output>
<date>,<model>,<model version>,<feature inputs>,<output>
```

# Logging for Composed Models

*Ensure all predictions are logged*



# Breakout Discussion: Movie Predictions (Revisited)

*Assume you are receiving complains that a child gets mostly recommendations about R-rated movies*

Discuss again, updating the previous post in #lecture:

- How would you identify the model that caused the prediction?
- How would you identify the code and dependencies that trained the model?
- How would you identify the training data used for that model?

# Reproducability

# On Terminology



**Replicability:** ability to reproduce results exactly

- Ensures everything is clear and documented
- All data, infrastructure shared; requires determinism

**Reproducibility:** the ability of an experiment to be repeated with minor differences, achieving a consistent expected result

- In science, reproducing important to gain confidence
- many different forms distinguished: conceptual, close, direct, exact, independent, literal, nonexperimental, partial, retest, ...

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

# "Reproducibility" of Notebooks

2019 Study of 1.4M notebooks on GitHub:

- 21% had unexecuted cells
- 36% executed cells out of order
- 14% declare dependencies
- success rate for installing dependencies <40% (version issues, missing files)
- notebook execution failed with exception in >40% (often ImportError, NameError, FileNotFoundError)
- only 24% finished execution without problem, of those 75% produced different results

2020 Study of 936 executable notebooks:

- 40% produce different results due to nondeterminism (randomness without seed)
- 12% due to time and date
- 51% due to plots (different library version, API misuse)
- 2% external inputs (e.g. Weather API)
- 27% execution environment (e.g., Python package versions)



Pimentel, João Felipe, et al. "A large-scale study about quality and reproducibility of jupyter notebooks." In Proc. MSR, 2019. and Wang, Jiawei, K. U. O. Tzu-Yang, Li Li, and Andreas Zeller.

# Practical Reproducibility

Ability to generate the same research results or predictions

Recreate model from data

Requires versioning of data and pipeline (incl. hyperparameters and dependencies)

# Nondeterminism

- Model inference almost always deterministic for a given model
- Many machine learning algorithms are nondeterministic
  - Nondeterminism in neural networks initialized from random initial weights
  - Nondeterminism from distributed computing, random forests
  - Determinism in linear regression and decision trees
- Many notebooks and pipelines contain nondeterminism
  - Depend on time or snapshot of online data (e.g., stream)
  - Initialize random seed
  - Different memory addresses for figures
- Different library versions installed on the machine

# 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

# Further Readings

- Sugimura, Peter, and Florian Hartl. “Building a Reproducible Machine Learning Pipeline.” *arXiv preprint arXiv:1810.04570* (2018).
- Chattopadhyay, Souti, Ishita Prasad, Austin Z. Henley, Anita Sarma, and Titus Barik. “[What’s Wrong with Computational Notebooks? Pain Points, Needs, and Design Opportunities.](#)” In Proceedings of the CHI Conference on Human Factors in Computing Systems, 2020.
- Sculley, D, et al. “[Hidden technical debt in machine learning systems.](#)” In Advances in neural information processing systems, pp. 2503–2511. 2015.

# Bonus: Debugging and Fixing Models

See also Hulten. Building Intelligent Systems. Chapter 21

See also Nushi, Besmira, Ece Kamar, Eric Horvitz, and Donald Kossman. "[On human intellect and machine failures: troubleshooting integrative machine learning systems.](#)" In *Proceedings of the Thirty-first AAAI Conference on Artificial Intelligence*, pp. 1017-1025. 2017.

# Recall: Composing Models: Ensemble and metamodels

**Ensemble**



**Metamodel / model stacking**



Legend: machine-learned model, non-ML aggregation function, prediction

# Recall: Composing Models: Decomposing the problem, sequential



# Recall: Composing Models: Cascade/two-phase prediction



# Decomposing the Image Captioning Problem?



## Speaker notes

Using insights of how humans reason: Captions contain important objects in the image and their relations. Captions follow typical language/grammatical structure



# State of the Art Decomposition (in 2015)



Example and image from: Nushi, Besmira, Ece Kamar, Eric Horvitz, and Donald Kossmann. "[On human intellect and machine failures: troubleshooting integrative machine learning systems.](#)" In Proc. AAAI. 2017.

# Blame assignment?

		Visual Detector	Language Model	Caption Reranker
1.	teddy	0.92	1. A teddy bear.	1. A <b>blender</b> sitting on top of a cake.
2.	on	0.92	2. A stuffed bear.	2. A teddy bear <b>in front of</b> a birthday cake.
3.	cake	0.90	...	3. A cake sitting on top of a <b>blender</b> .
4.	bear	0.87		
5.	stuffed	0.85		
...			...	
15.	<b>blender</b>	0.57	108. A <b>blender</b> sitting on top of a cake.	

Example and image from: Nushi, Besmira, Ece Kamar, Eric Horvitz, and Donald Kossmann. "[On human intellect and machine failures: troubleshooting integrative machine learning systems.](#)" In Proc. AAAI. 2017.

# Nonmonotonic errors



## Visual Detector

teddy	0.92
computer	0.91
bear	0.90
wearing	0.87
keyboard	0.84
glasses	0.63

1. A teddy bear  
sitting on top  
of a computer.

## Fixed Visual Detector

teddy	1.0
bear	1.0
wearing	1.0
keyboard	1.0
glasses	1.0

1. a person wearing  
glasses and holding  
a teddy bear sitting  
on top of a keyboard.

Example and image from: Nushi, Besmira, Ece Kamar, Eric Horvitz, and Donald Kossmann. "[On human intellect and machine failures: troubleshooting integrative machine learning systems.](#)" In Proc. AAAI. 2017.

# 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



# Ideas?



