Microsoft

Research Faculty Summit 2018

Systems | Fueling future disruptions

Microsoft

Infrastructure for Usable Machine Learning

Matei Zaharia
Stanford DAWN

It’s the Golden Age of ML*

Incredible advances in image recognition, natural language, planning, information retrieval

Society-scale impact: self-driving cars, real-time translation, personalized medicine

***for the best-funded, best-trained engineering teams**

Building ML Products is Too Hard

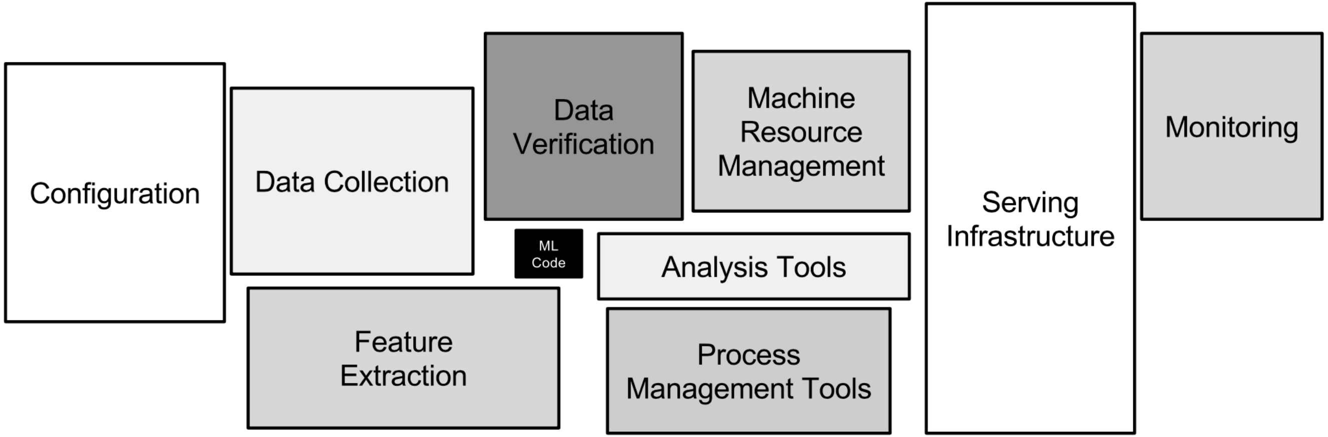
Major successes (e.g., Siri, Alexa, Autopilot) require hundreds to thousands of engineers

Most effort in data preparation, QA, debugging, productionization: not modeling!

Domain experts can’t easily build ML products

Hidden Technical Debt in Machine Learning Systems

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips
{dsculley,gholt,dgg,edavydov,toddphillips}@google.com
Google, Inc.



"Only a fraction of real-world ML systems is composed of ML code"

The Stanford DAWN Project

How can we enable any domain expert to build production-quality ML applications?

- Without a PhD in machine learning
- Without being an expert in systems
- Without understanding the latest hardware

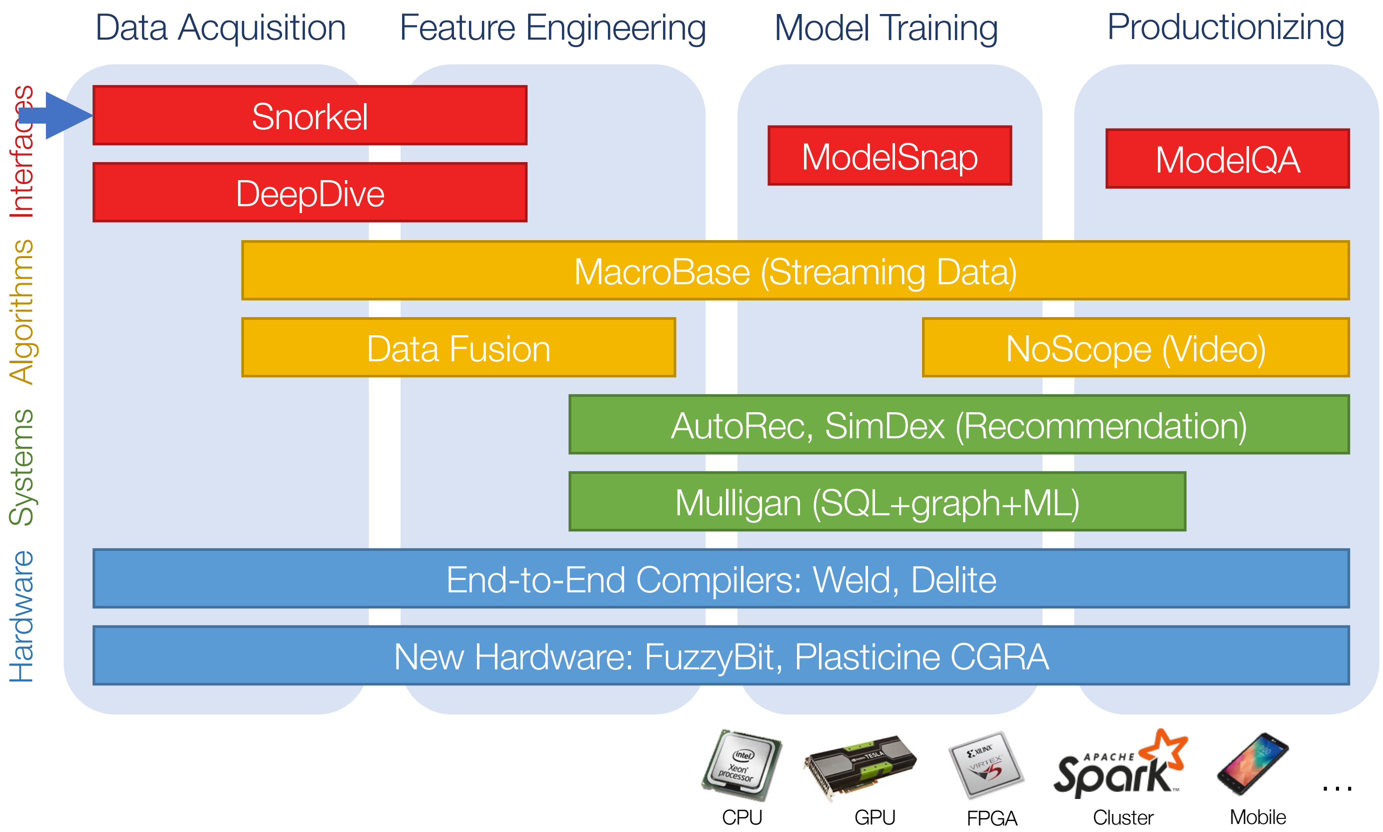

Peter Bailis


Chris Ré


Kunle Olukotun


Matei Zaharia

The DAWN Stack



Training Data is the Key to AI

Image search, speech, games: labeled training data is cheap & easy to obtain

Medicine, document understanding, fraud: labeled data requires expensive human experts!

How can we leverage data that's expensive to label at scale?

Snorkel Project (Chris Ré):
Labeling Functions, not Labels

snorkel

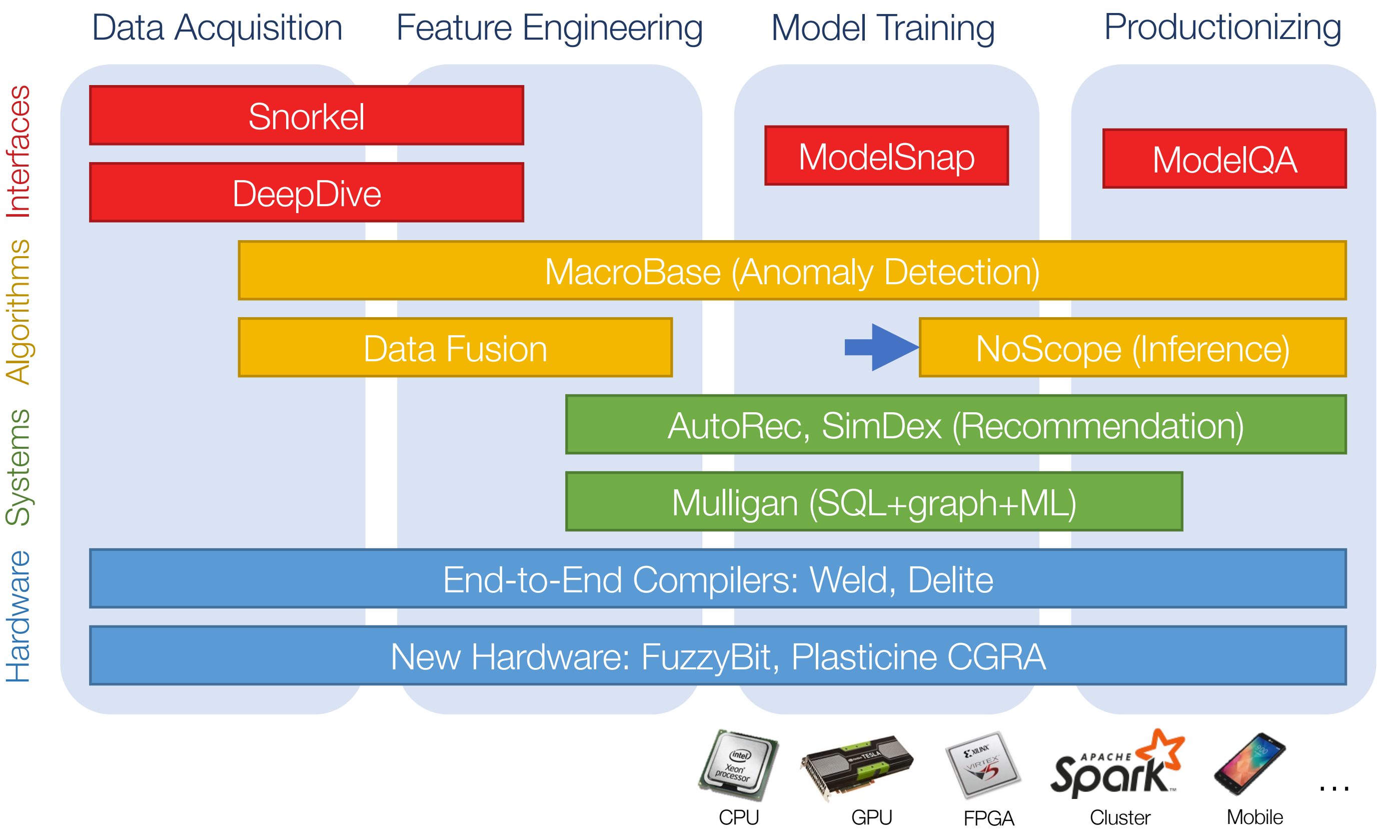
1) User writes *labeling functions*: short programs that may not always give right label
   - E.g. regex to search in text

2) Snorkel simultaneously learns *noise* in LFs and a *noise-aware* target model (e.g. LSTM)

System	NCBI Disease (F1)	CDR Disease (F1)	CDR Chem. (F1)
TaggerOne (Dogan, 2012)*	**81.5**	79.6	**88.4**
Snorkel: Logistic Regression	79.1	79.6	**88.4**
Snorkel: LSTM + Embeddings	79.2	**80.4**	88.2

NIPS '16, VLDB '18, github.com/HazyResearch/snorkel

The DAWN Stack

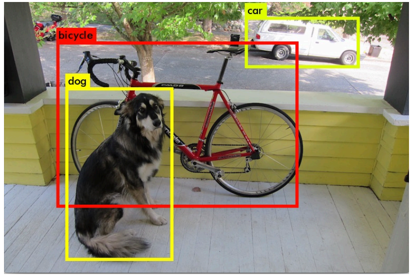


NoScope: Fast CNN-Based Queries on Video

Opportunity: CNNs allow more accurate queries on visual data than ever

Challenge: processing 1 video stream in real time requires a $1000 GPU

Result: 100-1000x faster with <1% loss in accuracy

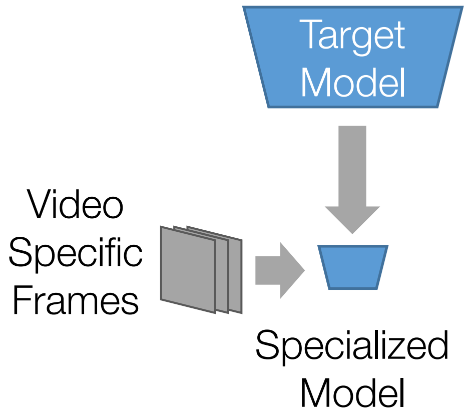


Key Idea: Model Specialization

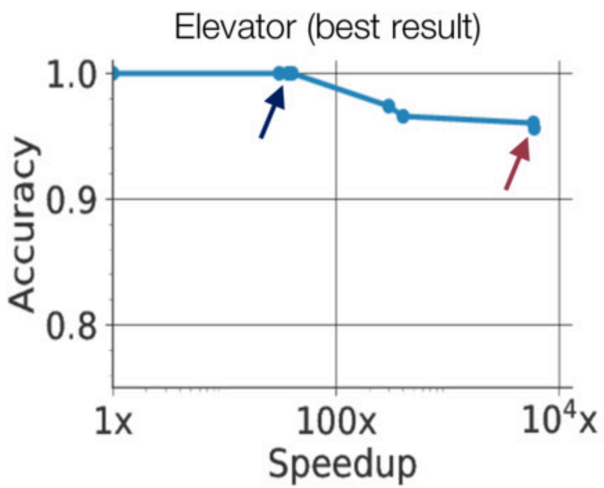
Given a target model and a query, train a much smaller *specialized model*

When this model is unsure, call original

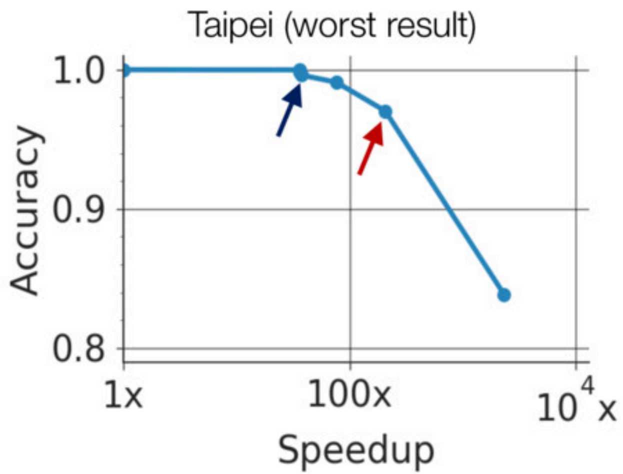
\+ Cost-based optimizer to select an efficient model cascade



NoScope Results



40x faster @ 99.9% accuracy
5858x faster @ 96% accuracy



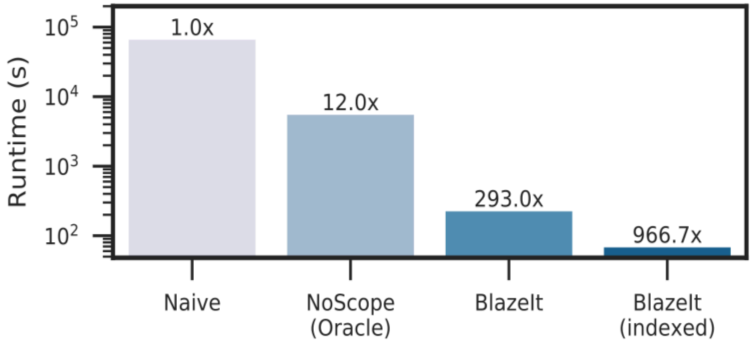
36.5x faster @ 99.9% accuracy
206x faster @ 96% accuracy

VLDB '17, github.com/stanford-futuredata/noscope

New Work: BlazeIt Query Engine

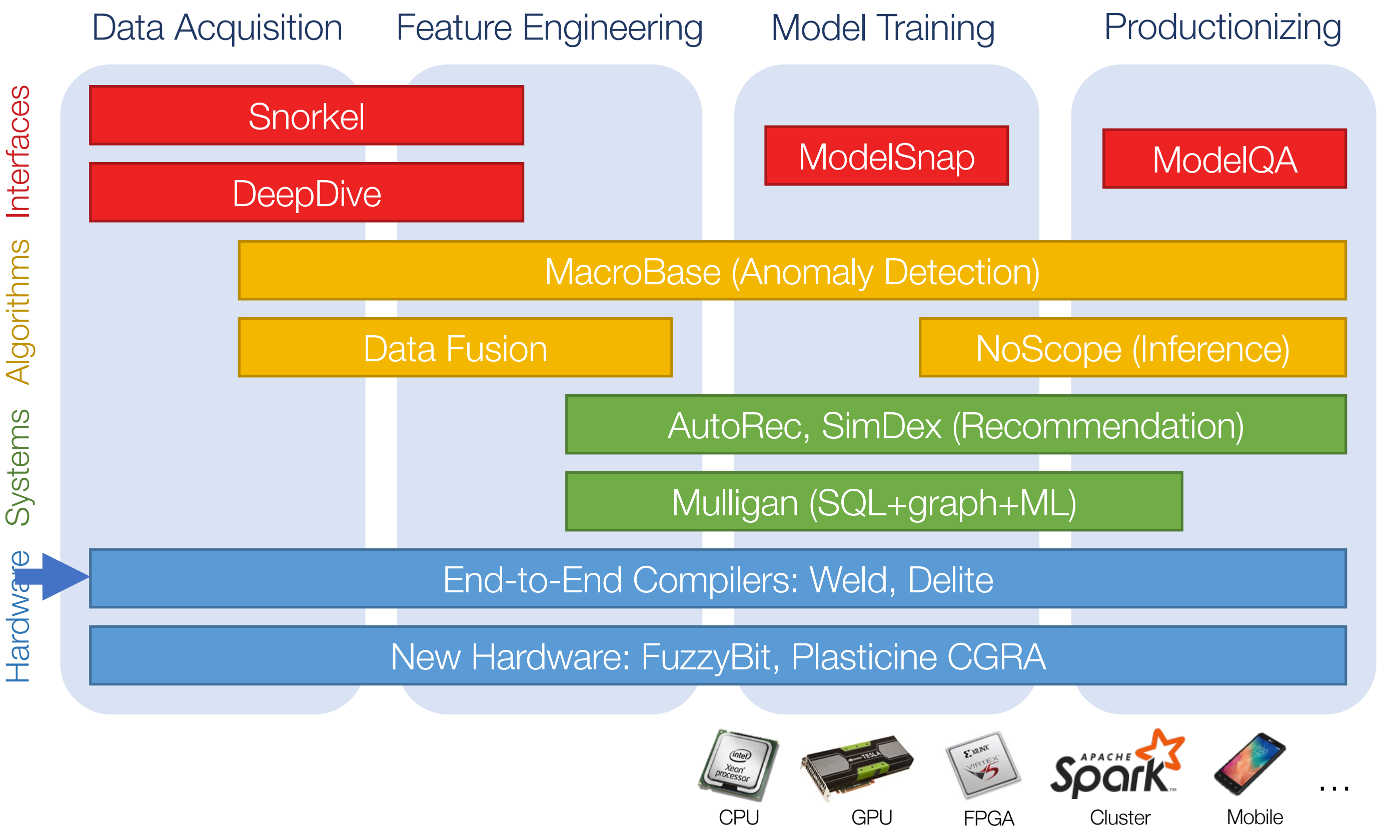
Accelerates complex, SQL-like queries using model specialization + statistical techniques

```
SELECT timestamp
FROM taipei
GROUP BY timestamp
HAVING SUM(class='bus')>=1
   AND SUM(class='car')>=5
LIMIT 10 GAP 300
```



https://arxiv.org/abs/1805.01046

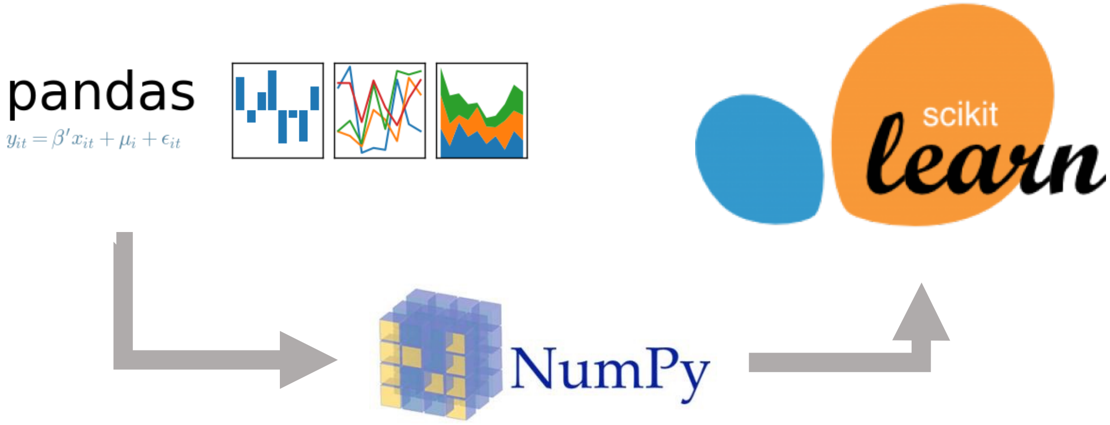
The DAWN Stack



Composition in Data Apps

ML app developers *compose* functions from dozens of high-level libraries

- Python packages, Spark packages, R, …

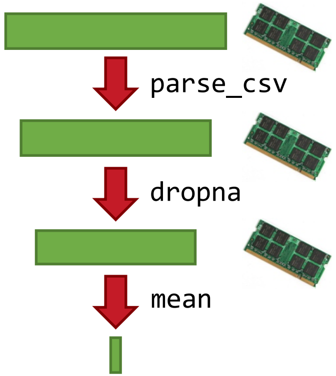


The Problem

Even if each individual function is well-optimized, the combined app may be highly inefficient

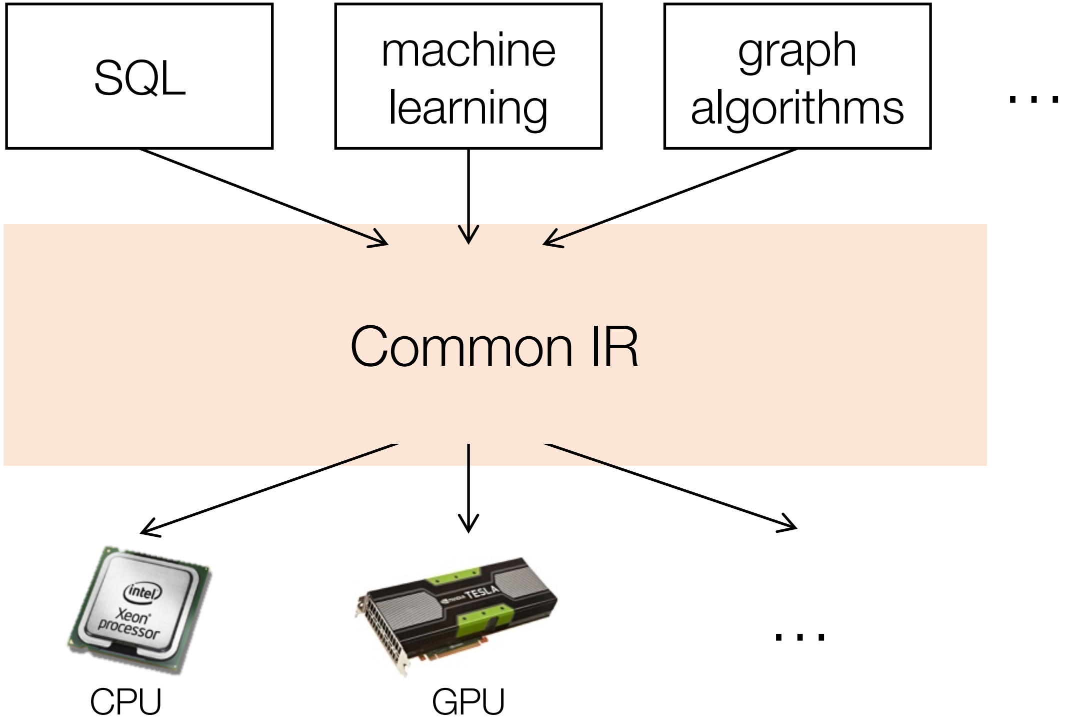
Traditional way to compose libraries: function calls that exchange data via buffers in memory

```
data = pandas.parse_csv(string)

filtered = pandas.dropna(data)

avg = numpy.mean(filtered)
```

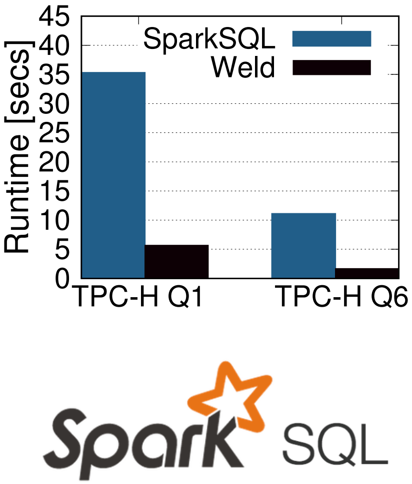


5-30x overheads in NumPy, Pandas, TensorFlow, etc

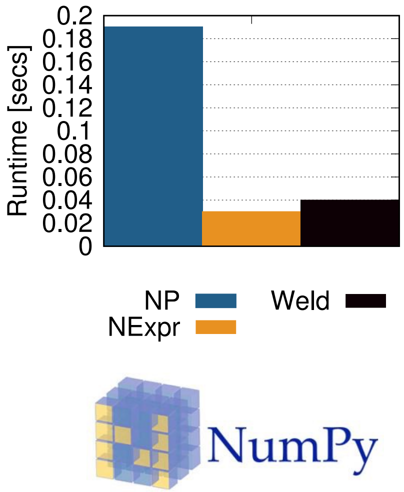
Weld’s Approach



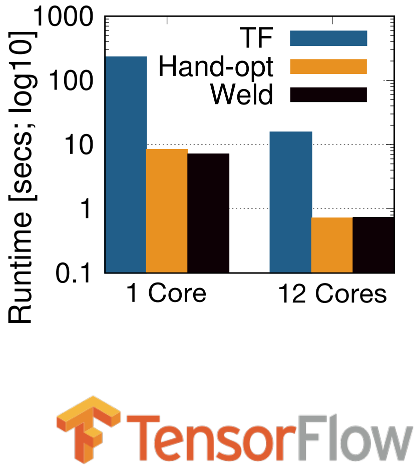
Results: Individual Libraries



TPC-H



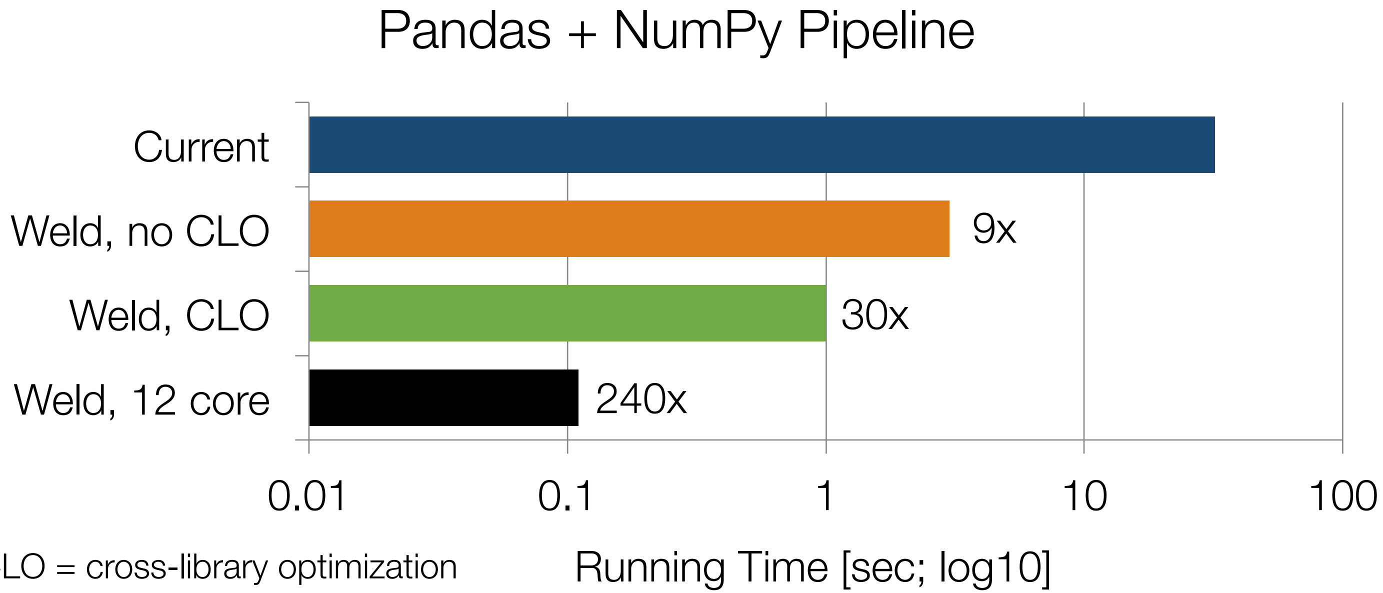
Vector Sum



Logistic Regression

Porting ~10 common functions per library

Results: Cross-Library



CLO = cross-library optimization

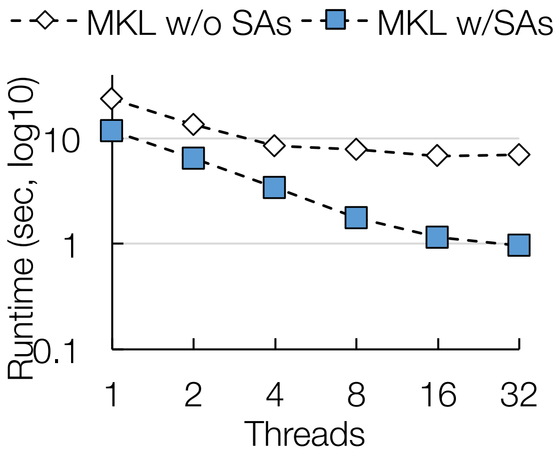
CIDR ’17, VLDB ‘18, https://weld.rs

“Weld without Weld”: Splittability Annotations

Data movement optimization and auto parallelization for **unmodified, black-box functions**

```
// @splittable
// (a: S, b: S, res: mut S)
void vdAdd(vec_t *a,
           vec_t *b,
           vec_t *res);
```

S: “split arrays the same way”



Competitive performance to Weld without rewriting libraries!

Machine Learning at Industrial Scale: ML Platforms

ML at Industrial Scale: ML Platforms

If you believe ML will be a key part of future products, *what should be the development process for it*?

Today, ML development is ad-hoc:

- Hard to track experiments: every data scientist has their own way
- Hard to reproduce results: won't happen by default
- Difficult to share & manage models

Need the equivalent of software dev platforms

ML Platforms

A new class of systems to manage the ML lifecycle

Pioneered by company-specific platforms: Facebook FBLearner, Uber Michelangelo, Google TFX, etc

+ Standardize the data prep / training / deploy loop: if you work with the platform, you get these!
– Limited to a few algorithms or frameworks
– Tied to one company's infrastructure

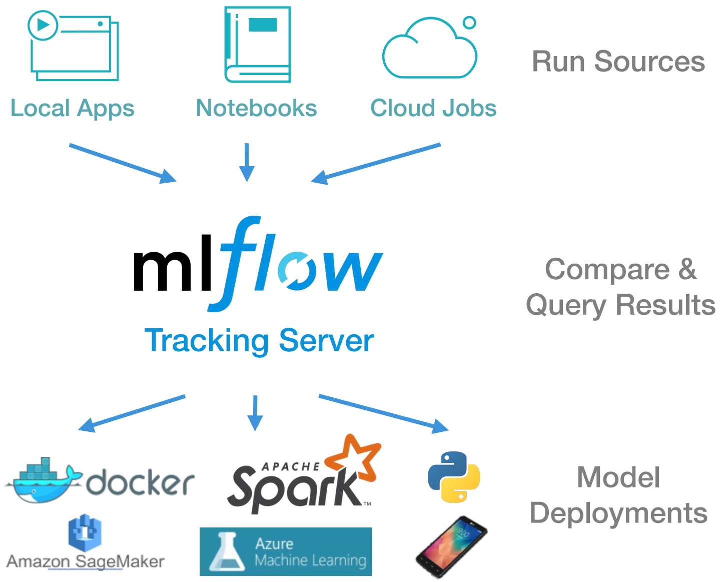
Databricks MLflow

Open source, open-interface ML platform (mlflow.org)

Projects: package code & data for reproducible runs

Experiment tracking: record code, params & metrics via a REST API

MLflow models: package models as functions to deploy to backends



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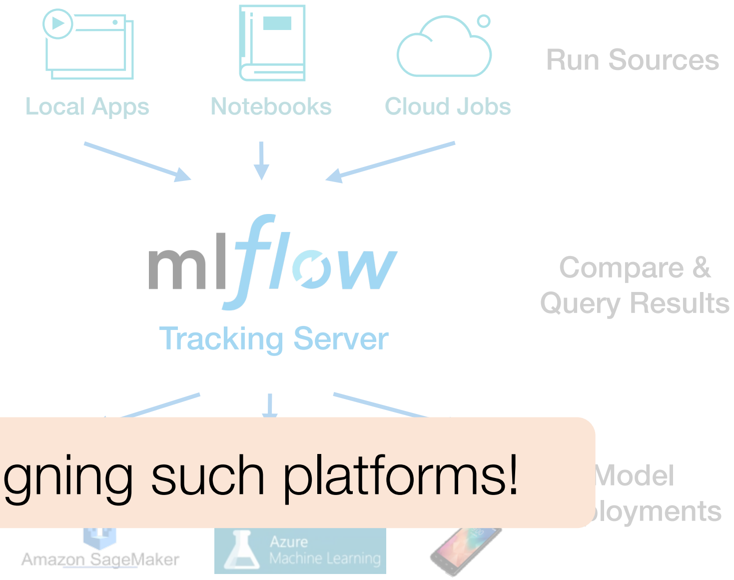

Many open questions left in designing such platforms!

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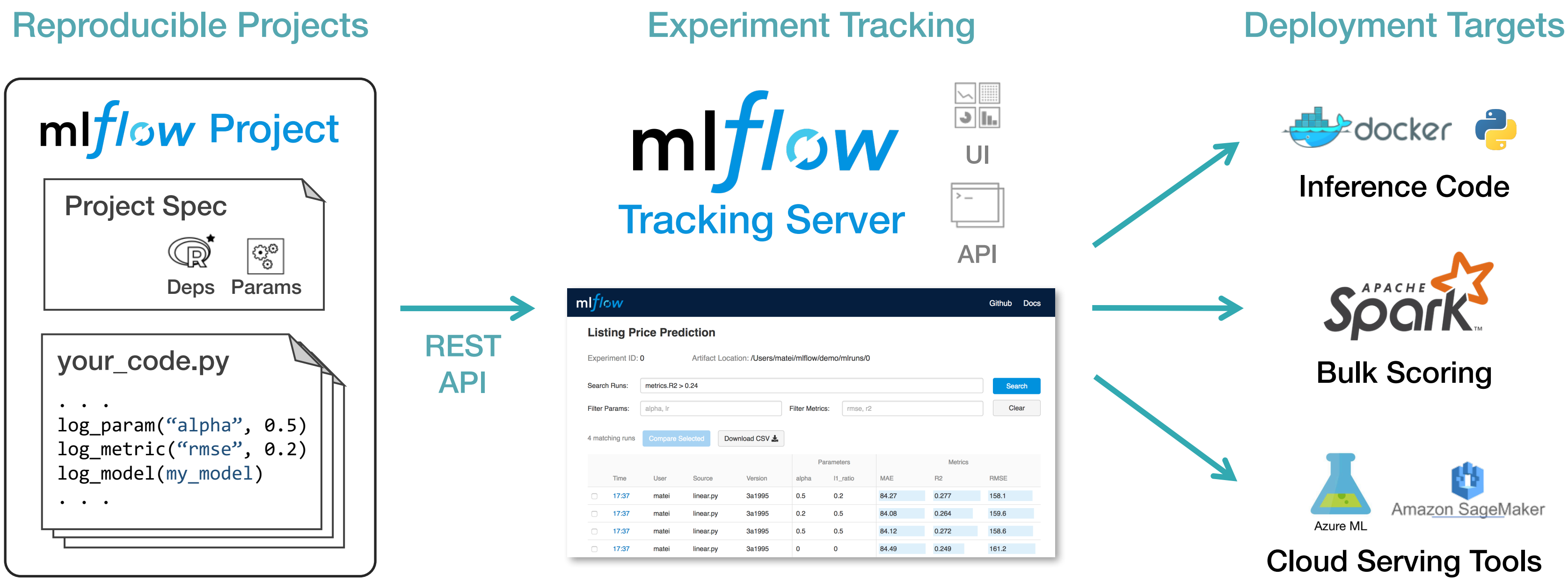

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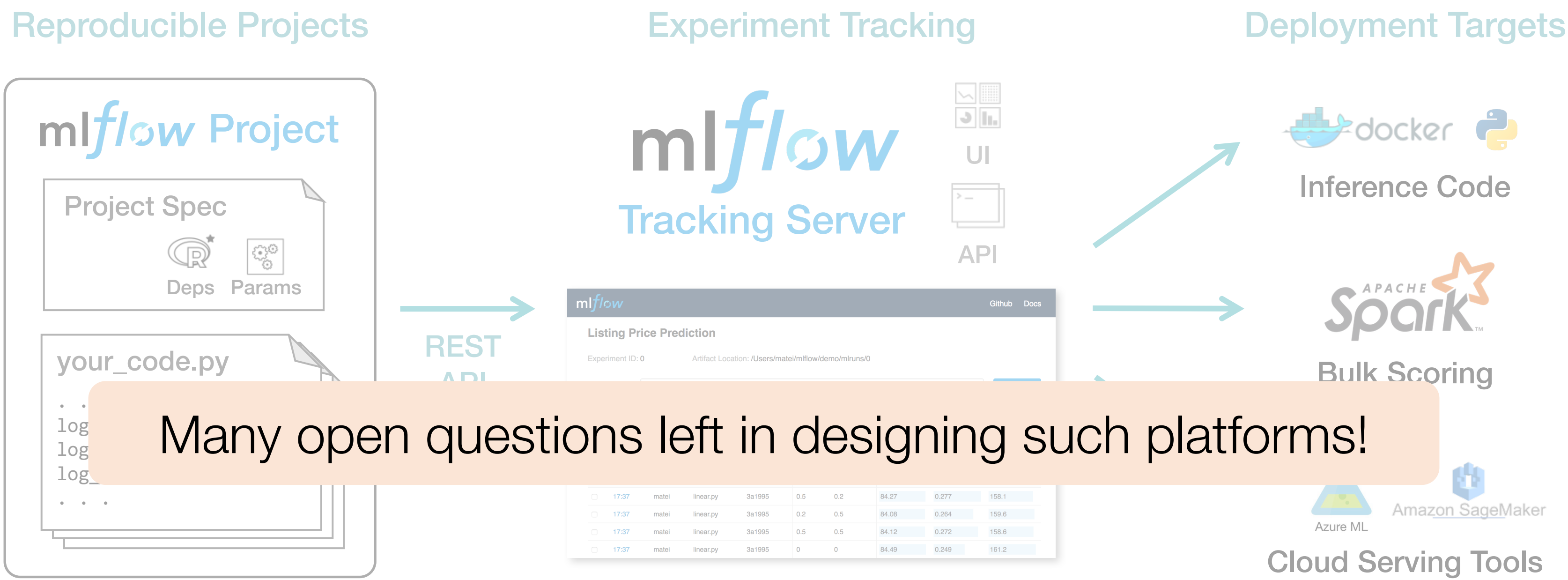

Many open questions left in designing such platforms!

Conclusion

The limiting factors for ML adoption are in dev and productionization tools, not training algorithms

Many of these are still very unexplored in research!

Follow DAWN for our research in this area: dawn.cs.stanford.edu

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Thank you!

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