

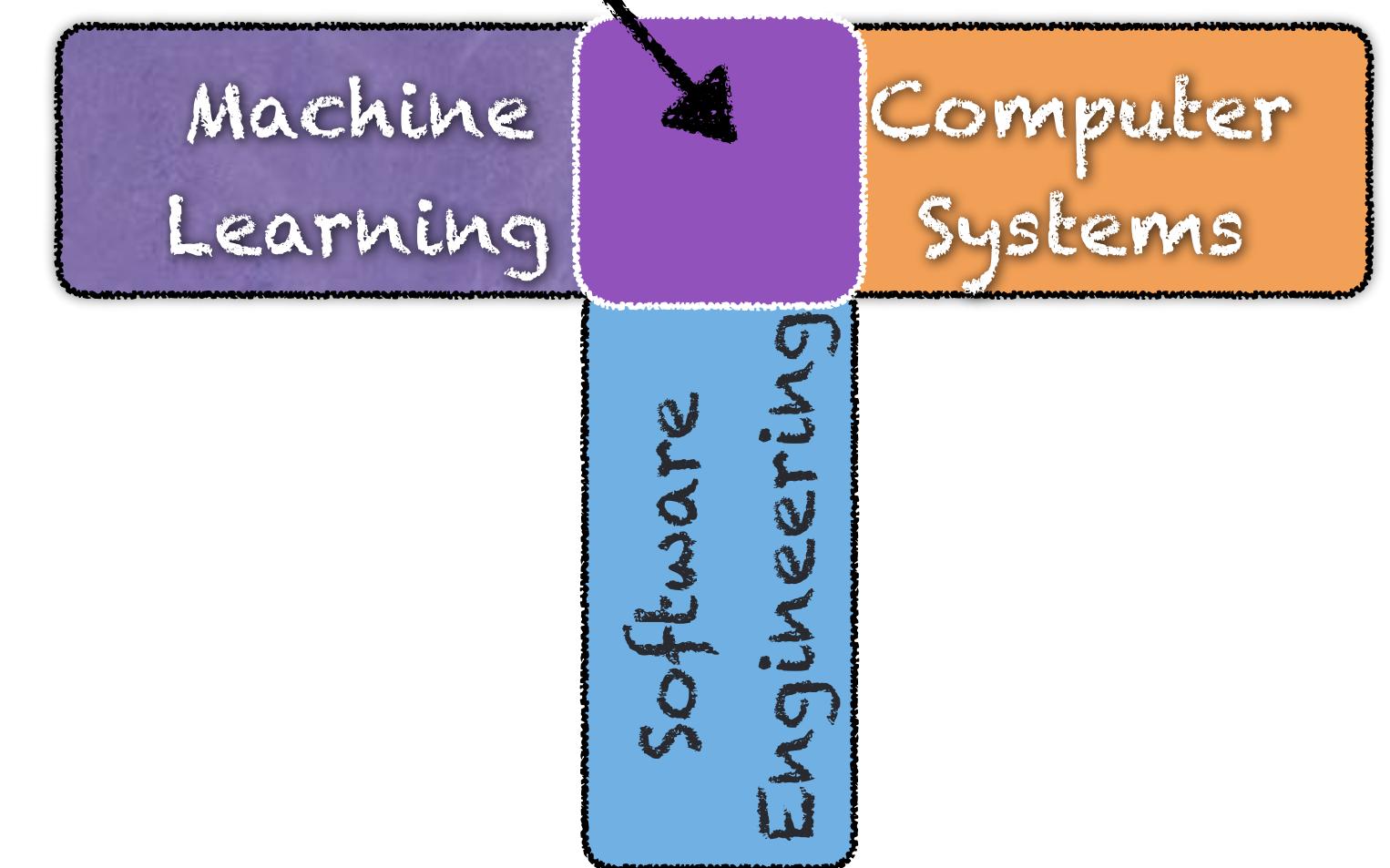
Designing Computer Systems for Machine Learning

CSCE 585: Machine Learning Systems



Pooyan Jamshidi
UofSC

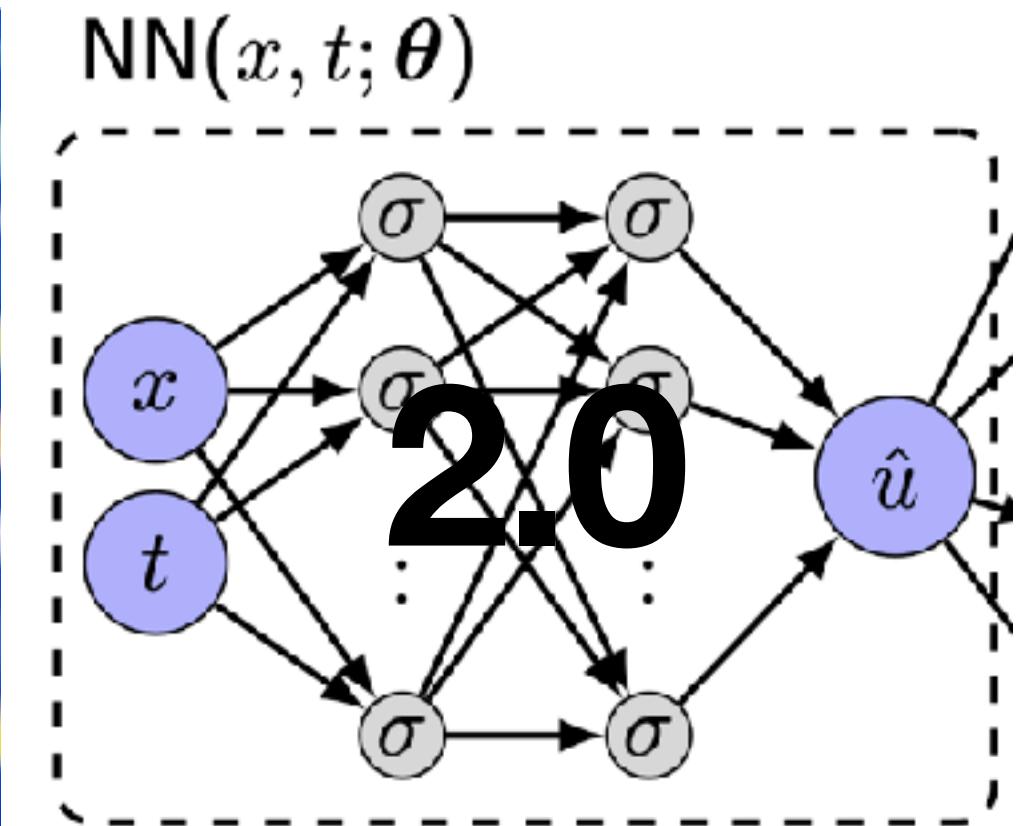
ML Systems



Software 1.0 vs Software 2.0

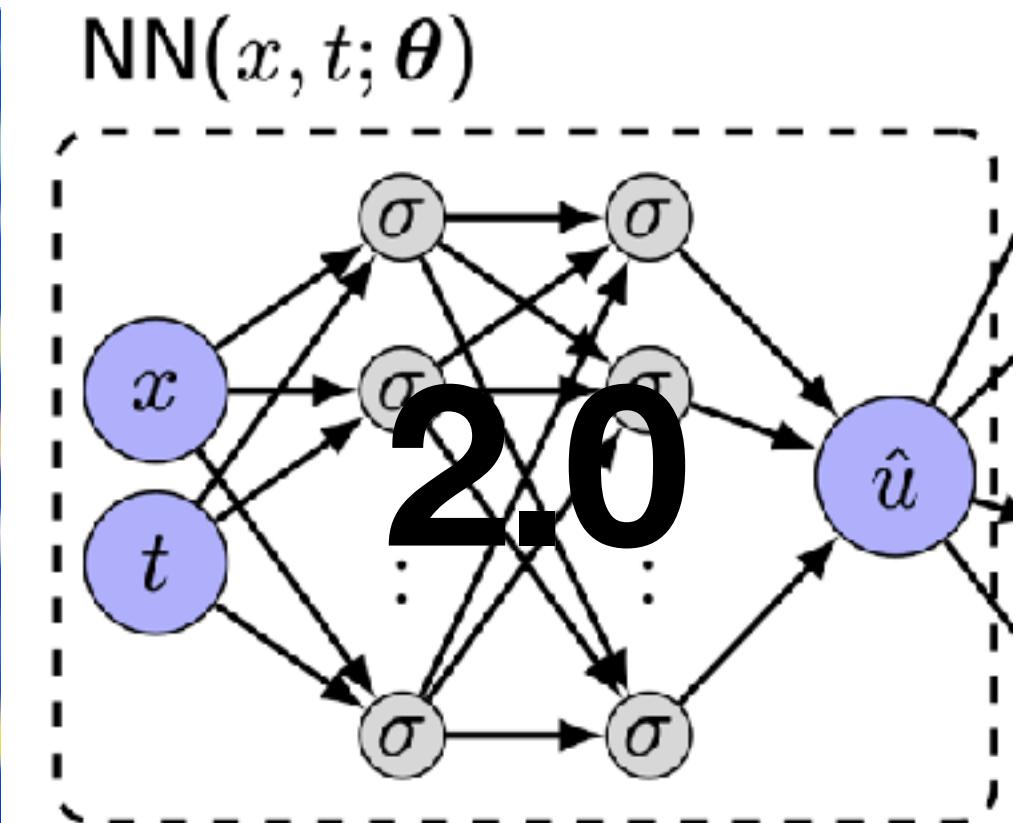


- Written in code (C++, ...)
- Requires domain expertise
 - 1. Decompose the problem
 - 2. Design algorithms
 - 3. Compose into a system



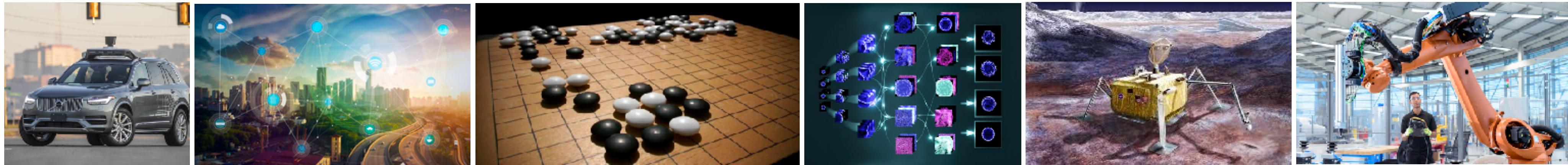
- Written in terms of a neural network model with
 - A model architecture
 - Weights that are determined using optimization

Software 1.0 vs Software 2.0



- **Input:** Algorithms in code
- **Compiled to:** Machine instructions
- **Input:** Training data
- **Compiled to:** Learned parameters

Software 1.0 vs Software 2.0



- **Easier to build and deploy**
 - Build products faster
 - Predictable runtimes and memory use: easier qualification
- **A wide range of applications** from self-driving cars, to game, healthcare, robotics, space, and social good.
- **1000x Productivity:** Google shrinks language translation code from 500k LoC to 500

<https://jack-clark.net/2017/10/09/import-ai-63-google-shrinks-language-translation-code-from-500000-to-500-lines-with-ai-only-25-of-surveyed-people-believe-automationbetter-jobs/>

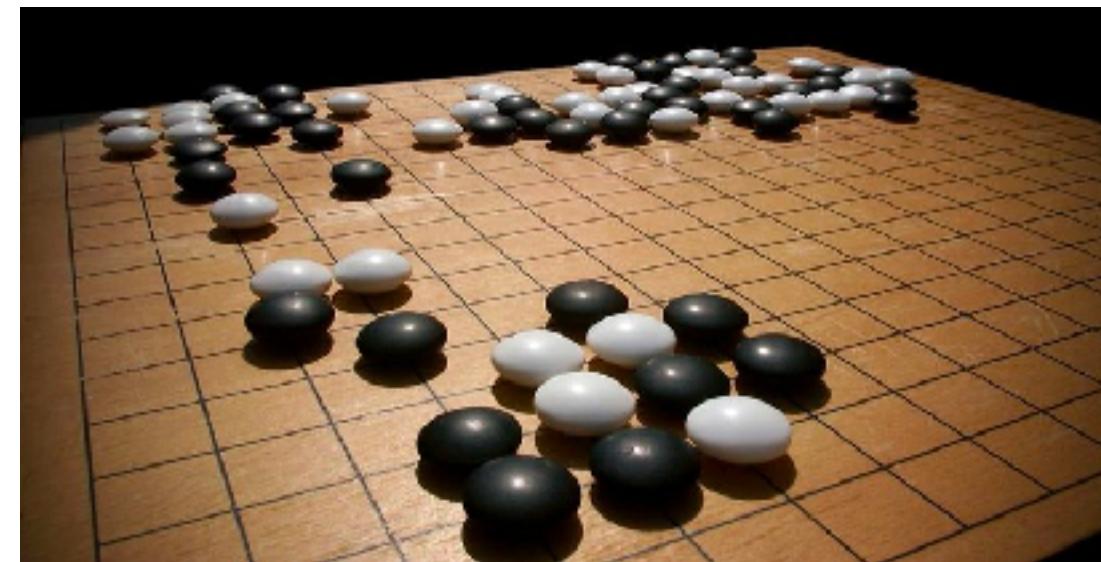
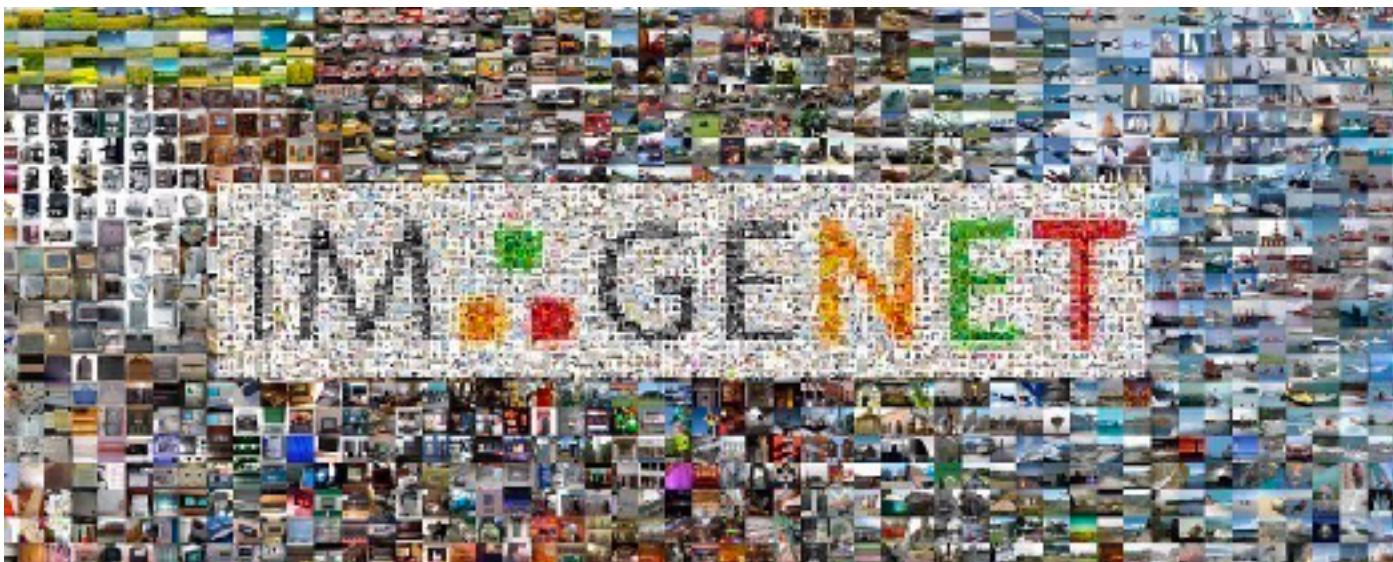
<https://ai.google/social-good/>

What is going on in this mad era of AI/ML!

It's incredible, isn't it?

Incredible advances in:

1. Image Recognition (ImageNet + Deep Learning)
2. Reinforcement Learning (DeepMind AlphaGo Zero)
3. Natural Language Processing (GPT-3)



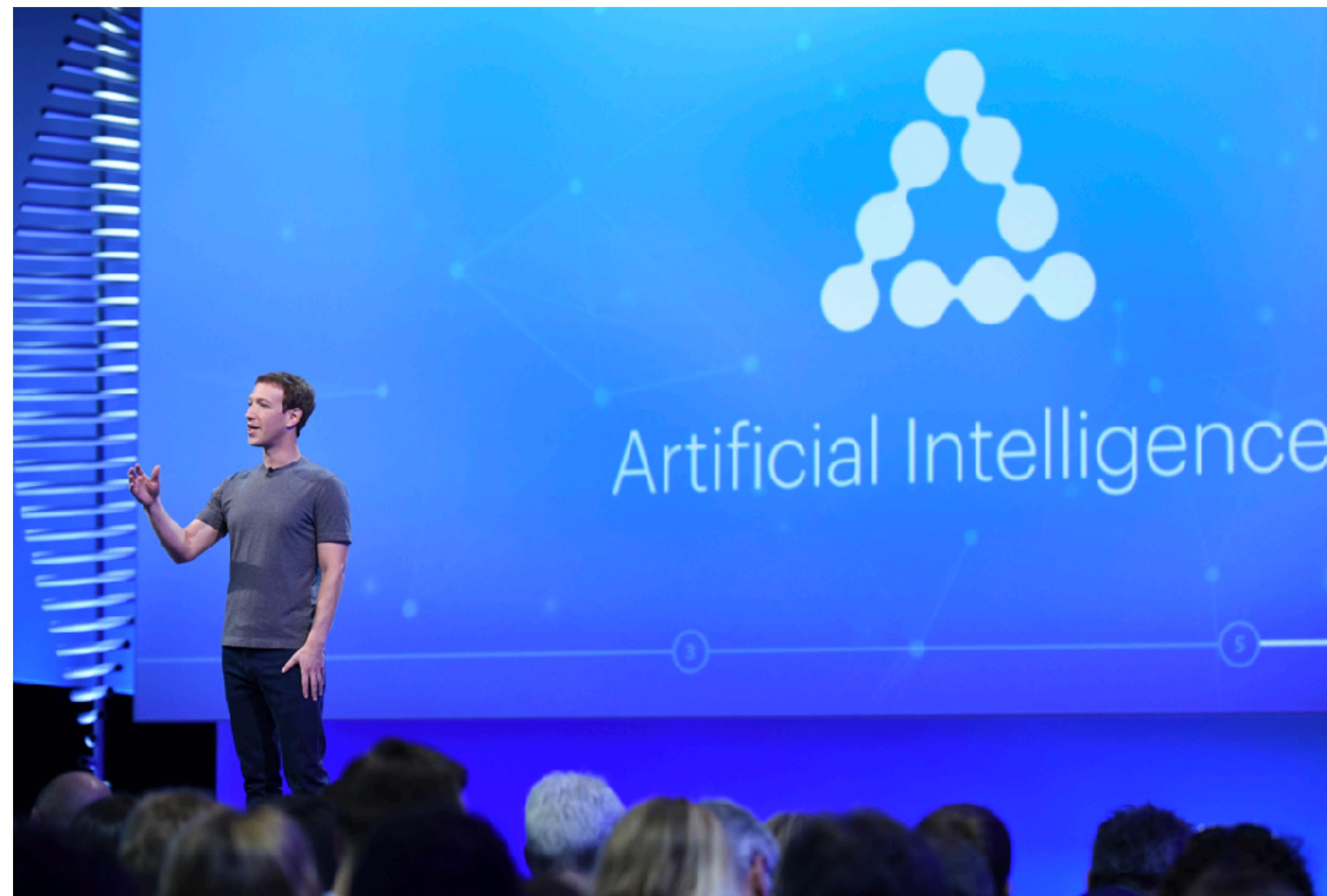
What is going on in this mad era of AI/ML!

They are taking over our society too!



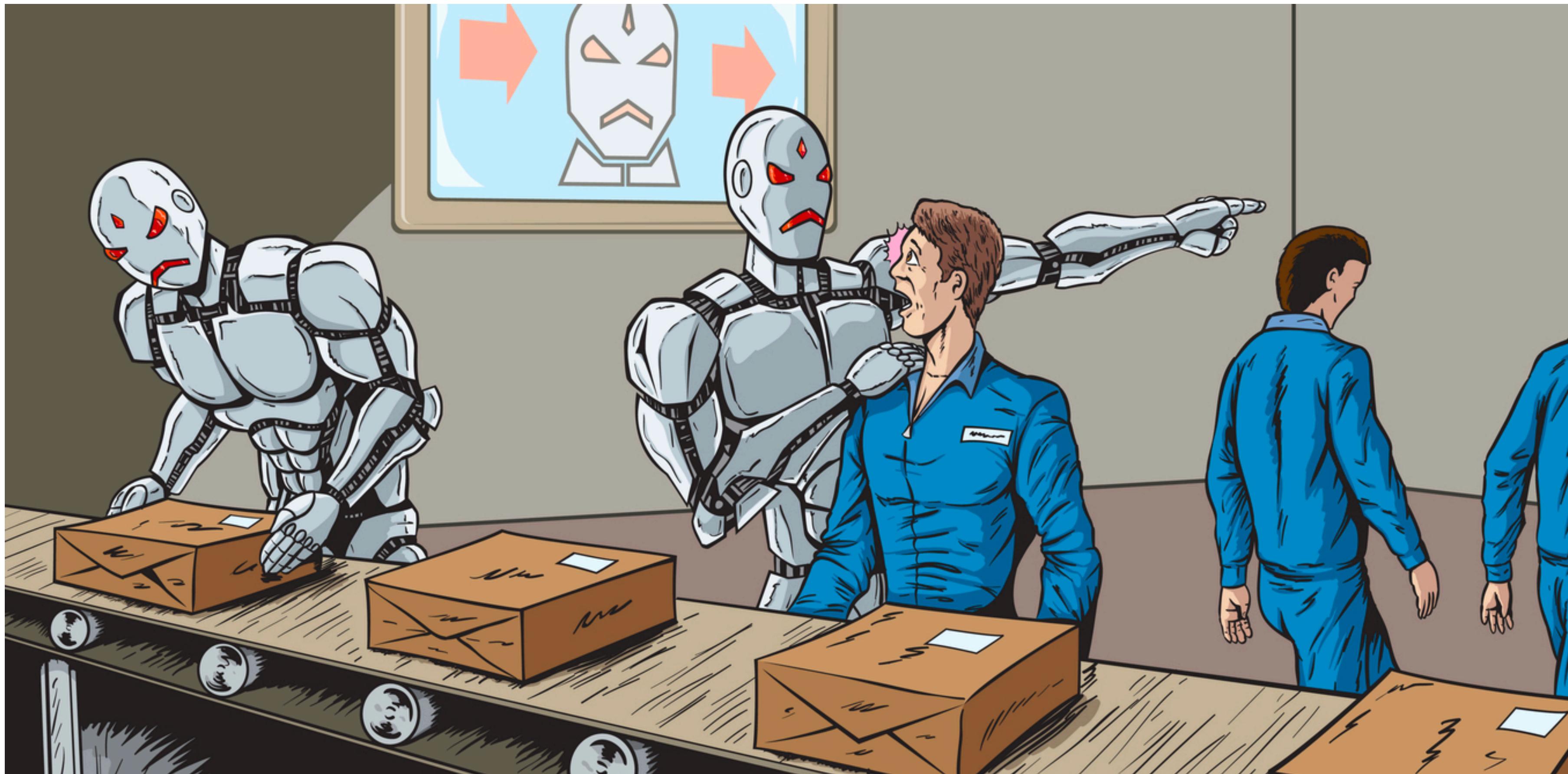
AI is becoming the integral part of our everyday life

Should we be worried?



AI is becoming the integral part of our everyday life

Should we be worried?



AI could be racist

Algorithmic bias

NEWS · 24 OCTOBER 2019 · UPDATE 26 OCTOBER 2019

Millions of black people affected by racial bias in health-care algorithms

Study reveals rampant racism in decision-making software used by US hospitals – and highlights ways to correct it.

Heidi Ledford



Black people with complex medical needs were less likely than equally ill white people to be referred to programmes that provide more personalized care. Credit: Ed Kashi/VII/Redux/eyevine

An algorithm widely used in US hospitals to allocate health care to patients has been systematically discriminating against black people, a sweeping analysis has found.

PDF version

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A fairer way forward for AI in health care



Bias detectives: the researchers striving to make algorithms fair

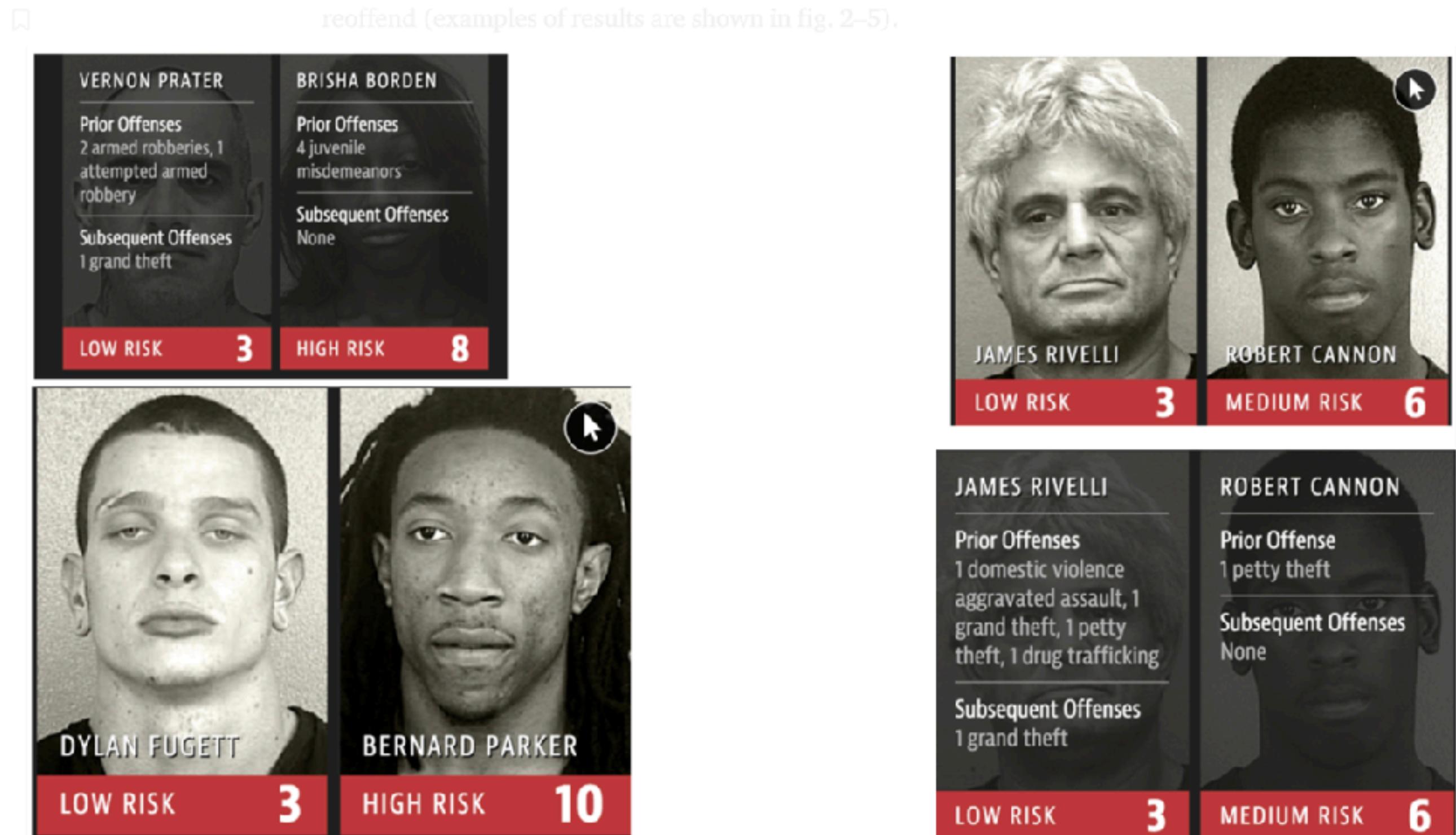


Can we open the black box of AI?

SUBJECTS

Computer science Health care Policy

Society



Despite this discovery, the research study by ProPublica were dictated by a

AI could be racist

Algorithmic bias

Google search results for "woman".

The search interface shows the Google logo, a search bar with "woman", and a "Images" tab selected. Below the search bar are filters for "All", "Images", "Videos", "News", "Shopping", "More", "Settings", and "Tools". A "Collections" and "SafeSearch" button is also present.

Top search results include:

- Trump Has Affected American Women - time.com
- Woman hit by harasser in Paris talks to ... - euronews.com
- Woman Mentally Rifles Through Friend's ... - local.theonion.com
- Selective Service System > - ssa.gov
- Closeup Photo of Woman With Bro... - pexels.com
- I don't feel like a woman. I am a ... - lifeisnews.com
- 'Wonder Woman 2' Will Be Rela... - forward.com
- prosthetic nose - news.com.au
- Seriously ill women wrong... - independent.ie
- The Pitfalls Of Dating A Married Woman ... - askmen.com
- How To Order Flowers for a Woman - ... - florists.com
- Walgreens Pharmacist De... - walgreens.com
- Why you should vote for a woman in 2... - thefeministproject.org
- Cartoon' Woman Underwent Over ... - cartoonwoman.com
- Best Vitamins Every Woman Should ... - healthline.com

Google search results for "girl".

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Top search results include:

- Hammock Killed After Tree Falls on He... - nbowashington.com
- Galway Girl - Ed Sheeran - YouTube - youtube.com
- Who Is The Girl In Shawn ... - capitalfm.com
- girl missing in Western Isles ... - bbc.com
- Girl Images - Pexels - Free Stock... - pixele.com
- Missing Wisconsin Girl Foun... - nytimes.com
- KZN girl diagnosed with deadly illnes... - news24.com
- Hair style street fashion beautiful ... - freepik.com
- Trolls used disabled girl's photo to ... - cnn.com
- Girl Road Long - Free phot... - pixabay.com
- EVO - evomagazine.com
- Halle Berry - Most Girls - YouTube - youtube.com
- named the most beautiful girl ... - us.hola.com
- meet the girl Im in love with... - youtube.com
- girl who died after eating a Pret... - telegraph.co.uk
- Greenwich Girl - Home | F... - facebook.com

AI could be also gender biased

Algorithmic bias

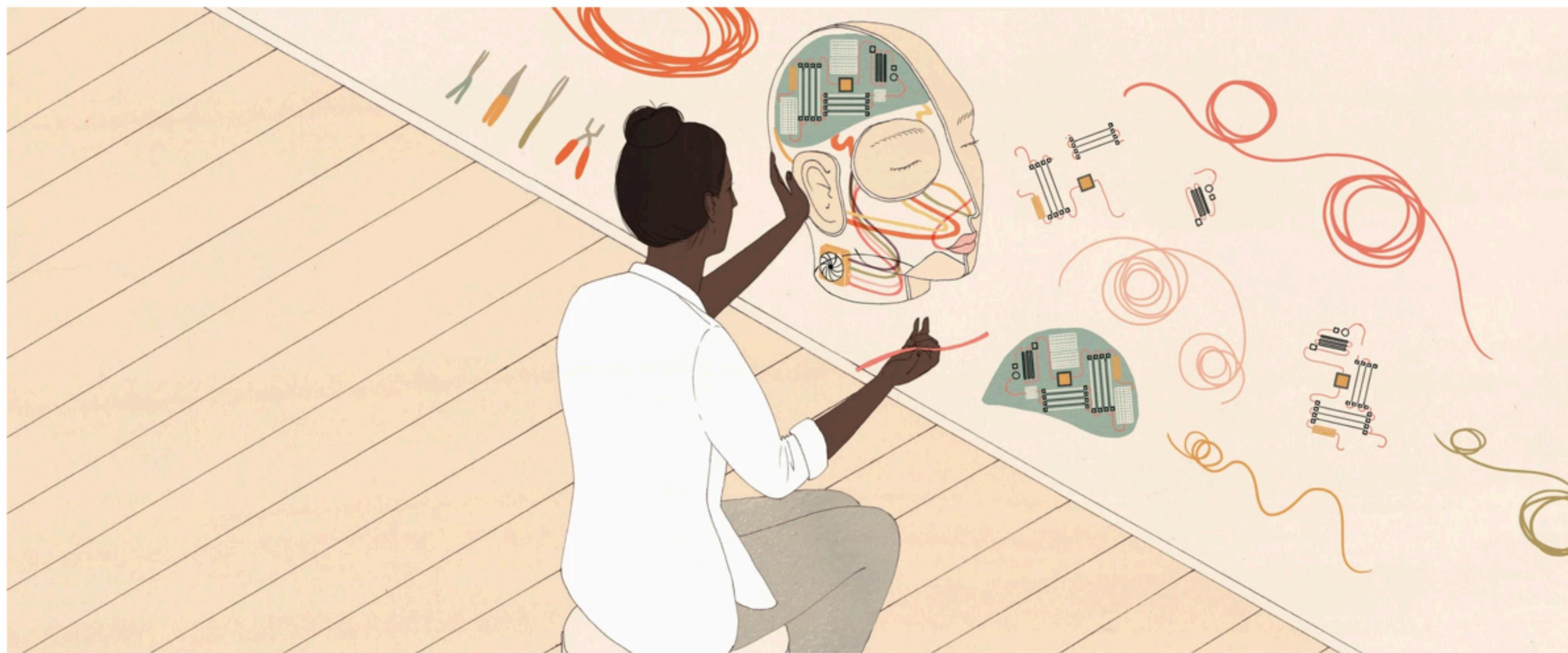


AI could be also gender biased

Algorithmic bias

Dealing With Bias in Artificial Intelligence

Three women with extensive experience in A.I. spoke on the topic and how to confront it.



Harriet Lee-Merrion

What is the source of the problem?

Data or Algorithms or Both?

ALGORITHMIC JUSTICE LEAGUE AJL

Revisiting Benchmarks

Data is Destiny

Does your data reflect the world?

BENCHMARK SKEWS
80% PALE 75% MALE

Category	Percentage
Darker Female (NIST)	22.4%
Darker Female (NIST)	22.1%
Darker Female (NIST)	24.8%
Darker Female (NIST)	4.4%
Darker Male (NIST)	30.4%
Darker Male (NIST)	20.2%
Darker Male (NIST)	16%



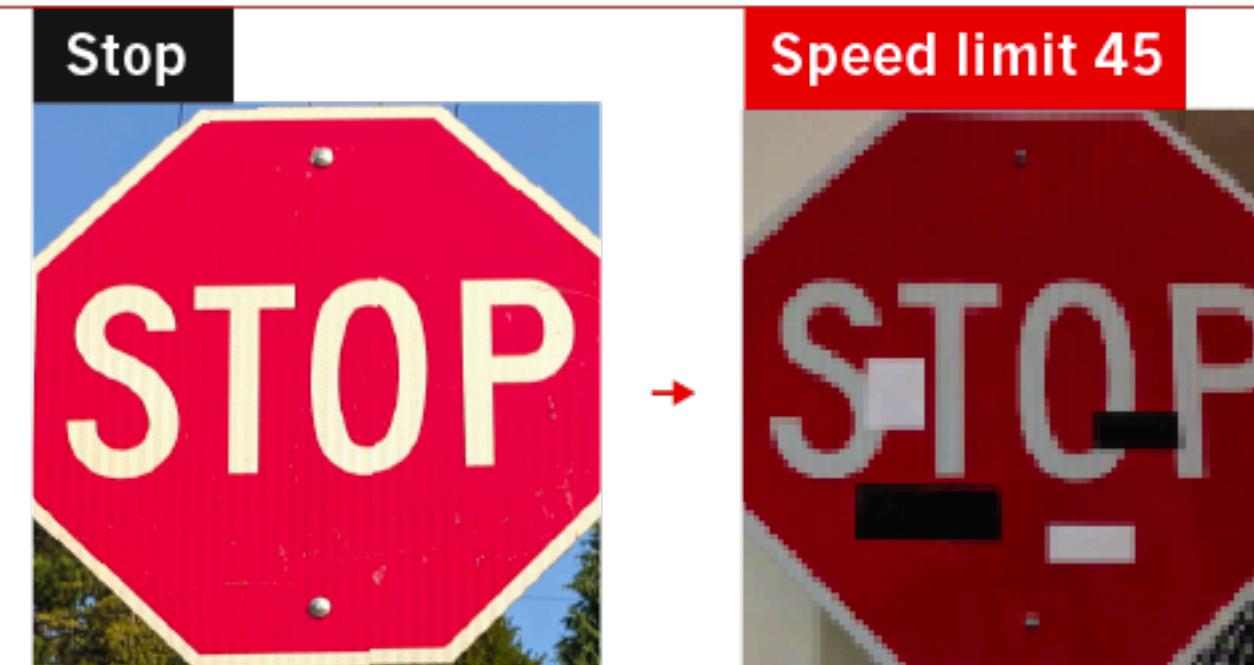
AI/ML Systems can be easily fooled!

What? Yes, it is true, and the implications could be massive!

FOOLING THE AI

Deep neural networks (DNNs) are brilliant at image recognition — but they can be easily hacked.

These stickers made an artificial-intelligence system read this stop sign as 'speed limit 45'.



Scientists have evolved images that look like abstract patterns — but which DNNs see as familiar objects.

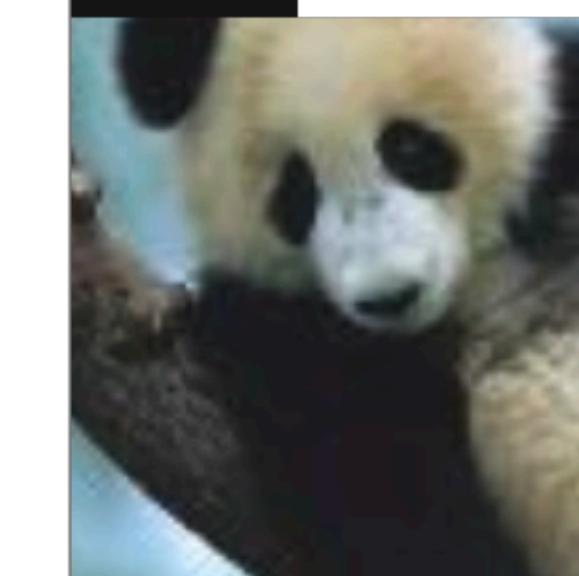


©nature

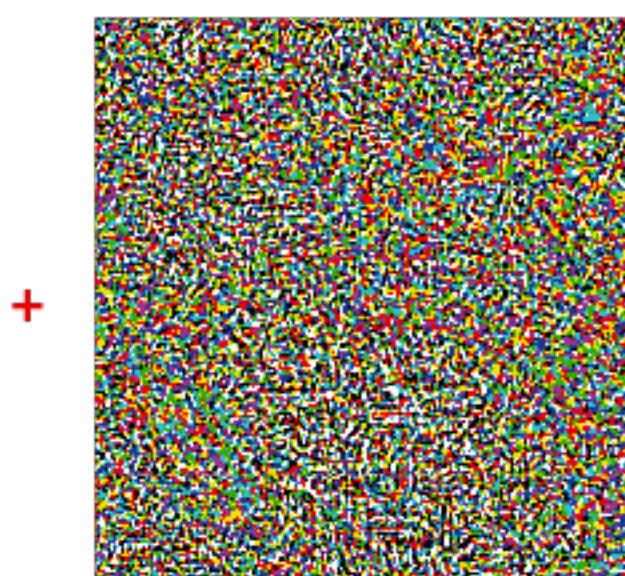
PERCEPTION PROBLEMS

Adding carefully crafted noise to a picture can create a new image that people would see as identical, but which a DNN sees as utterly different.

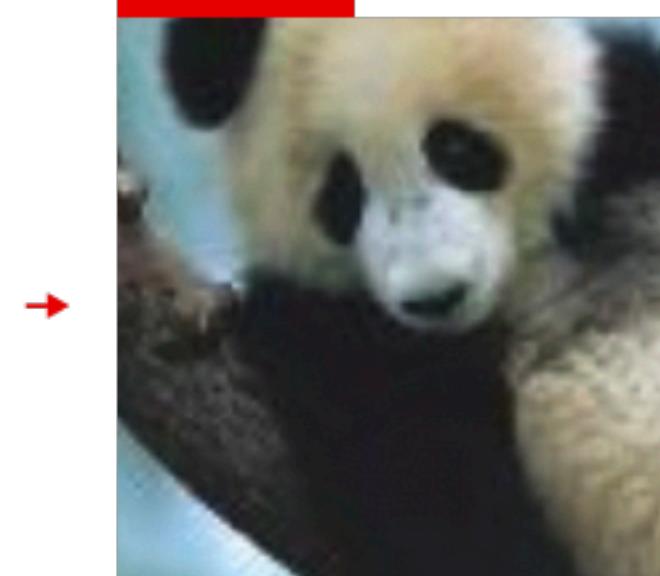
Panda



+

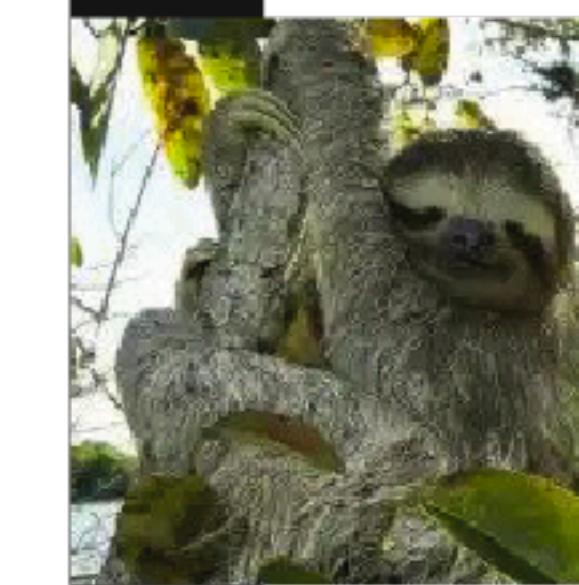


Gibbon



In this way, any starting image can be tweaked so a DNN misclassifies it as any target image a researcher chooses.

Sloth



+



Target image: race car

Race car



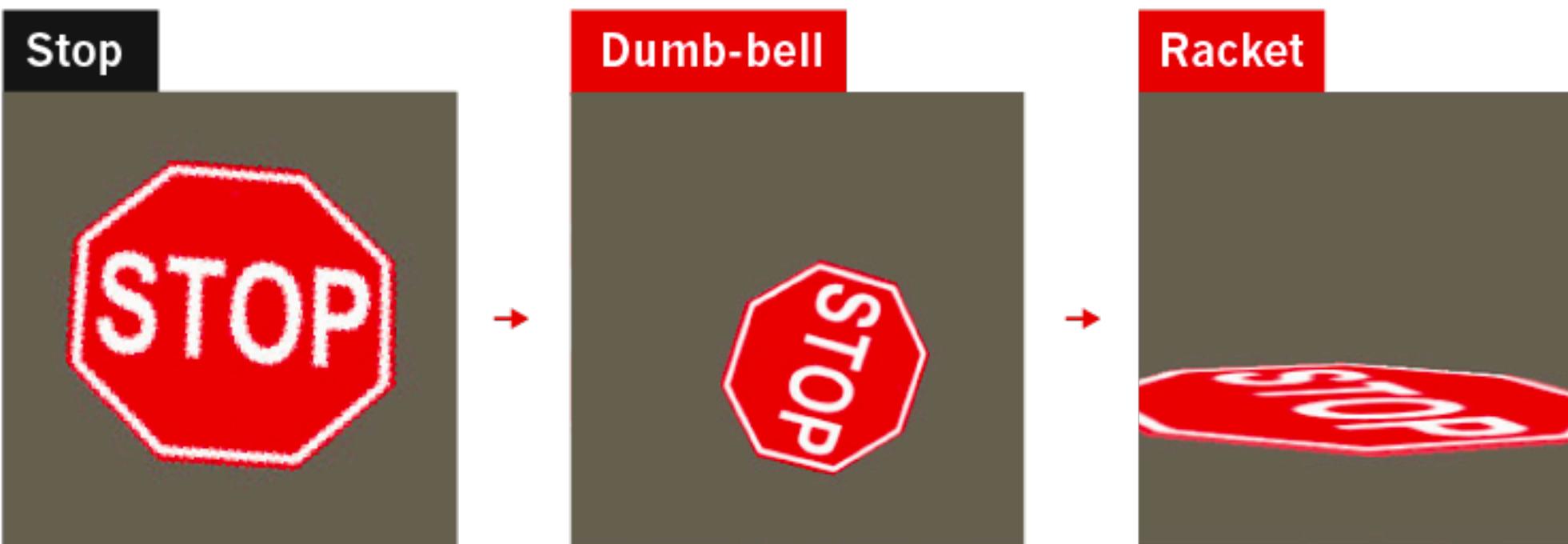
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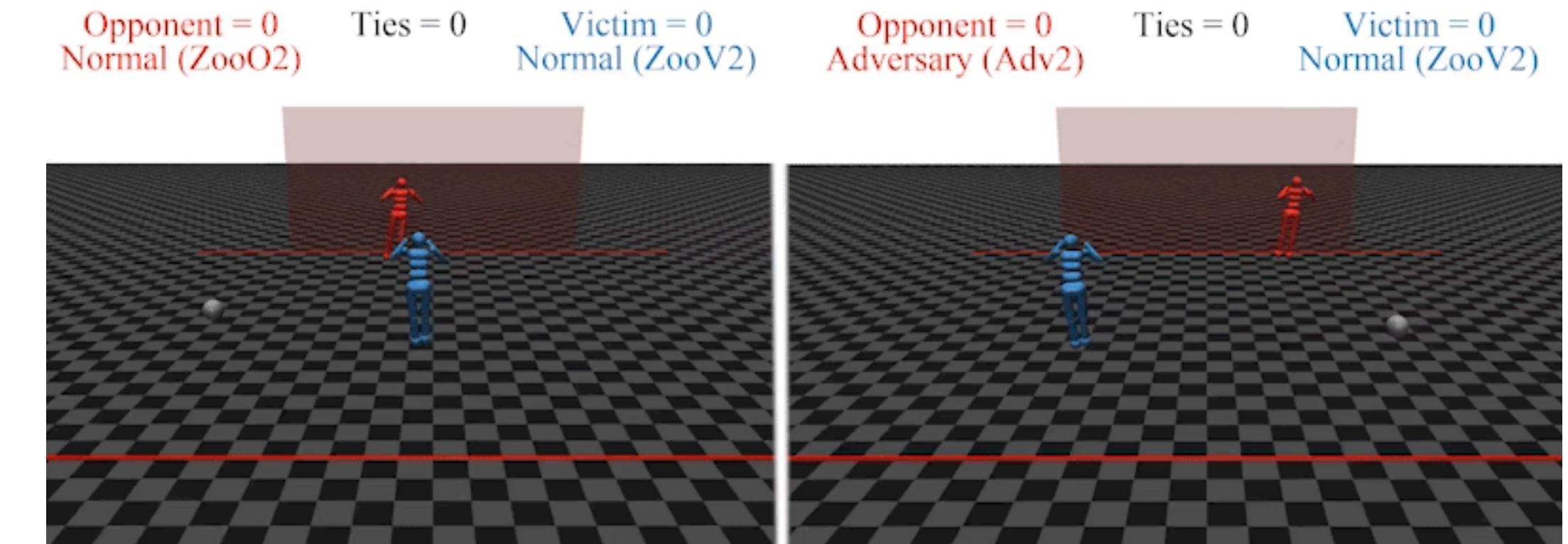
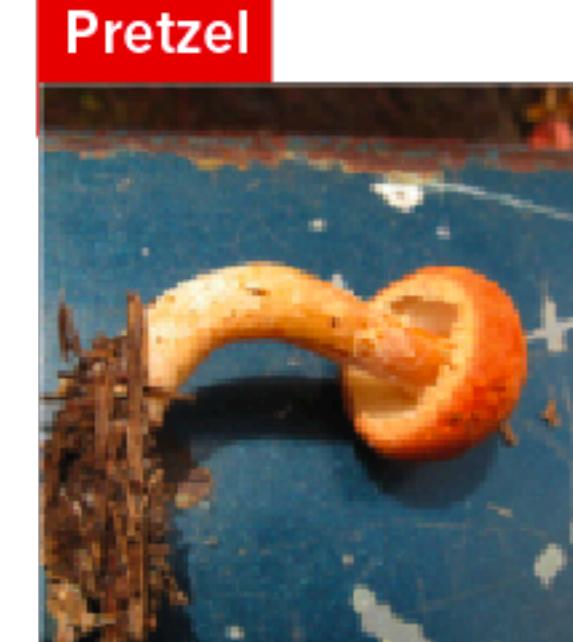
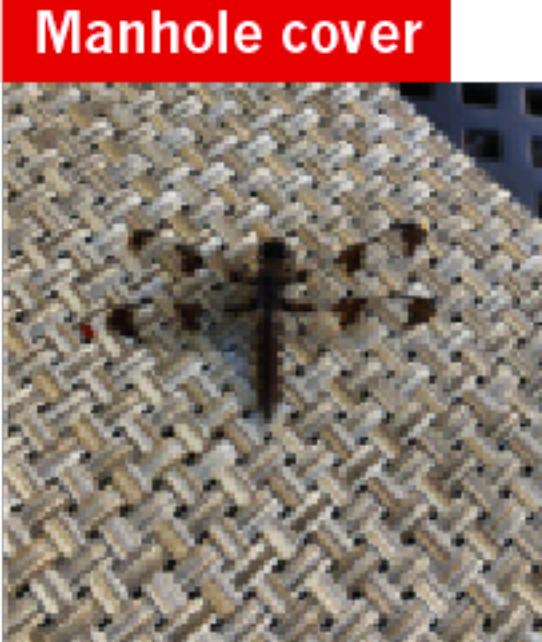
What? Yes, it is true, and the implications could be massive!

LATEST TRICKS

Rotating objects in an image confuses DNNs, probably because they are too different from the types of image used to train the network.

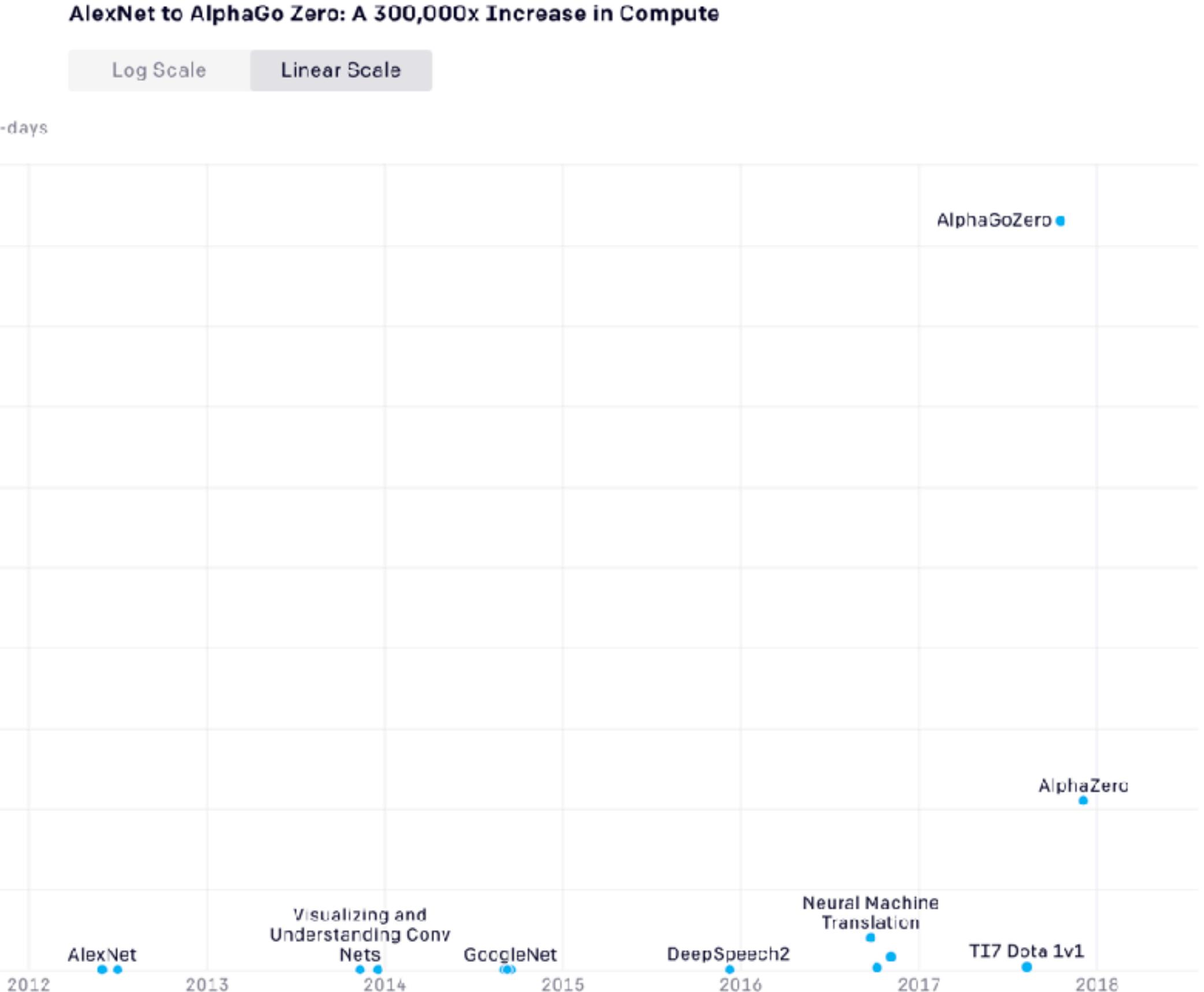
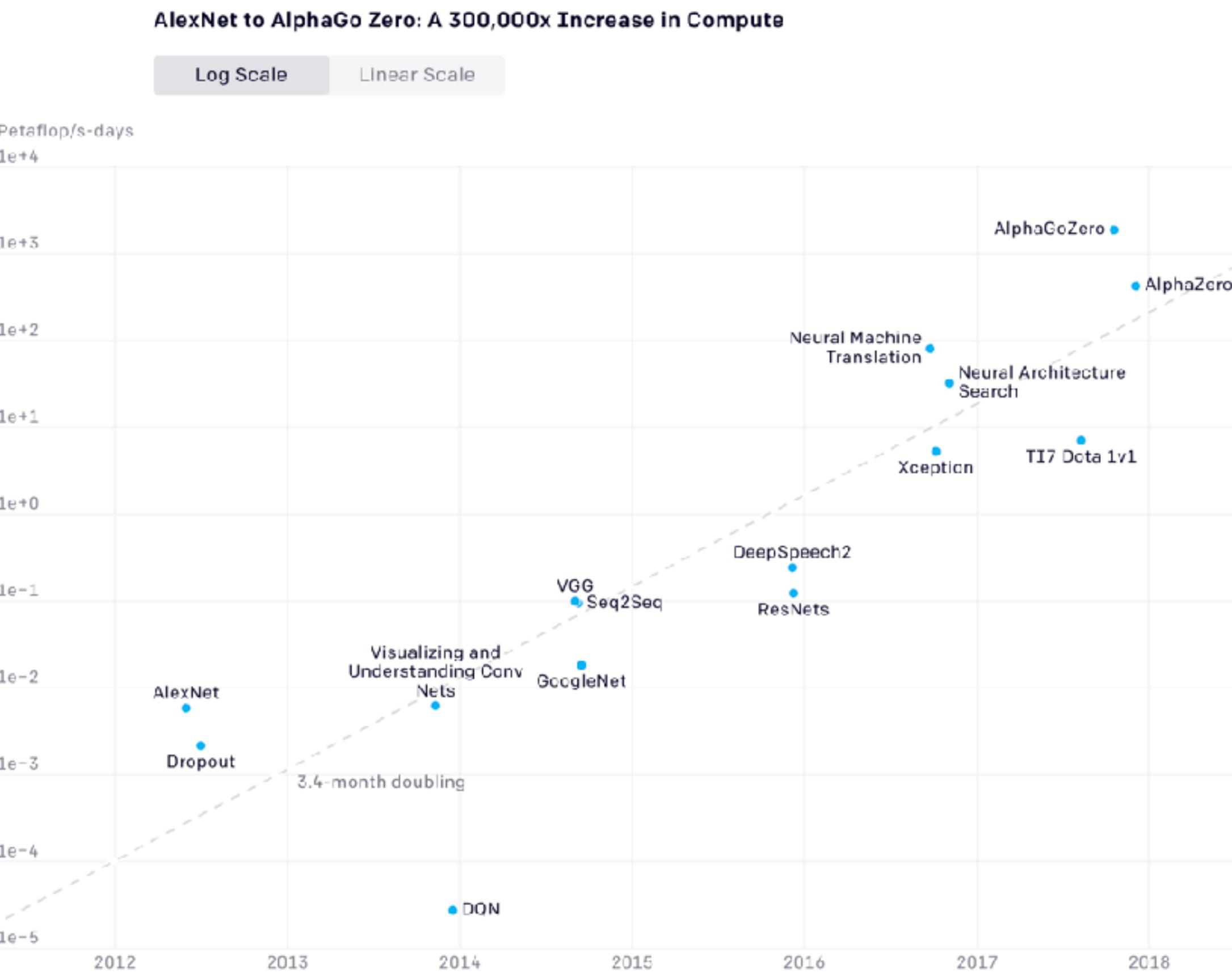


Even natural images can fool a DNN, because it might focus on the picture's colour, texture or background rather than picking out the salient features a human would recognize.



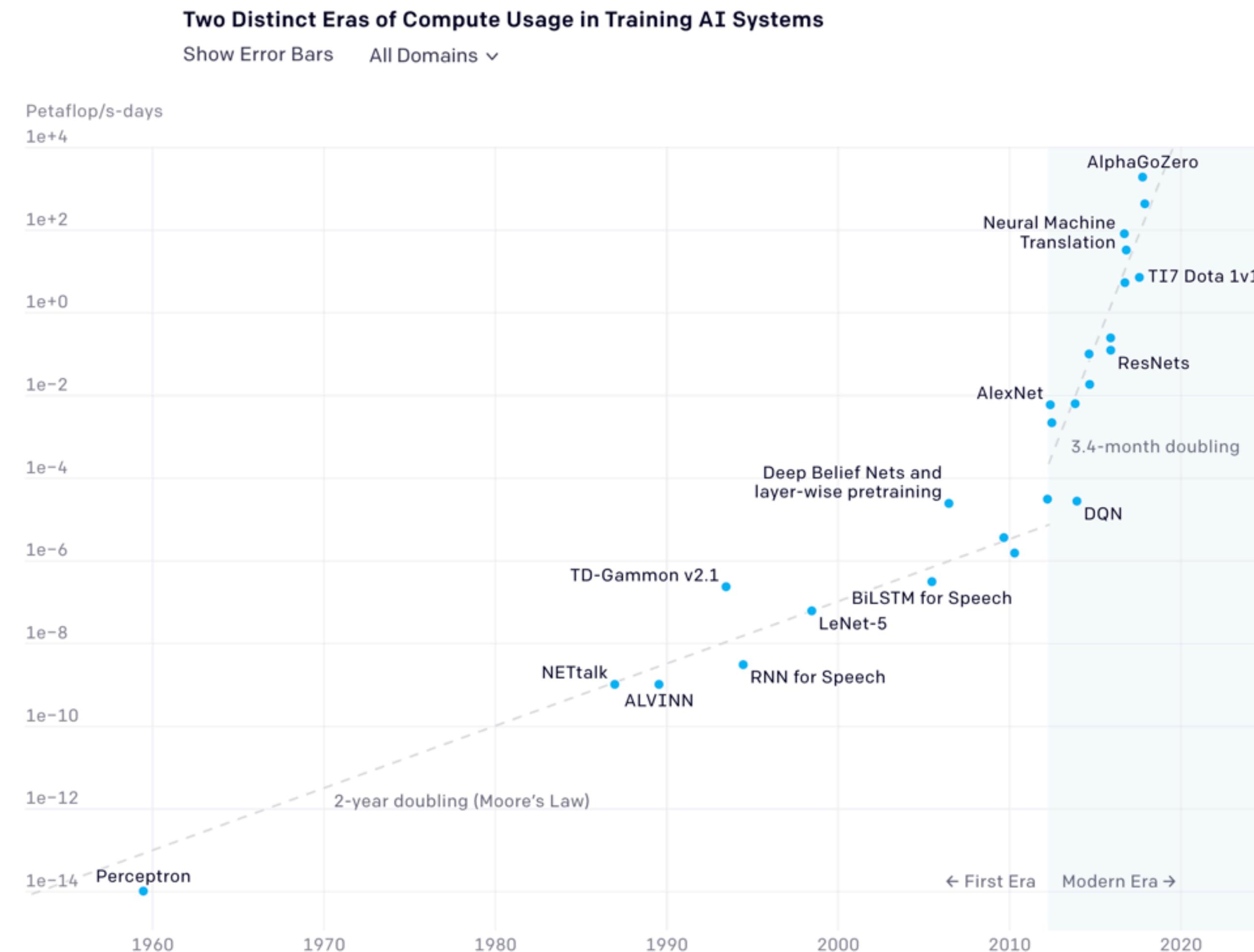
AI and Compute

The amount of compute used in the largest AI training runs has been increasing exponentially with a 3.4-month doubling time (by comparison, Moore's Law had a 2-year doubling period).



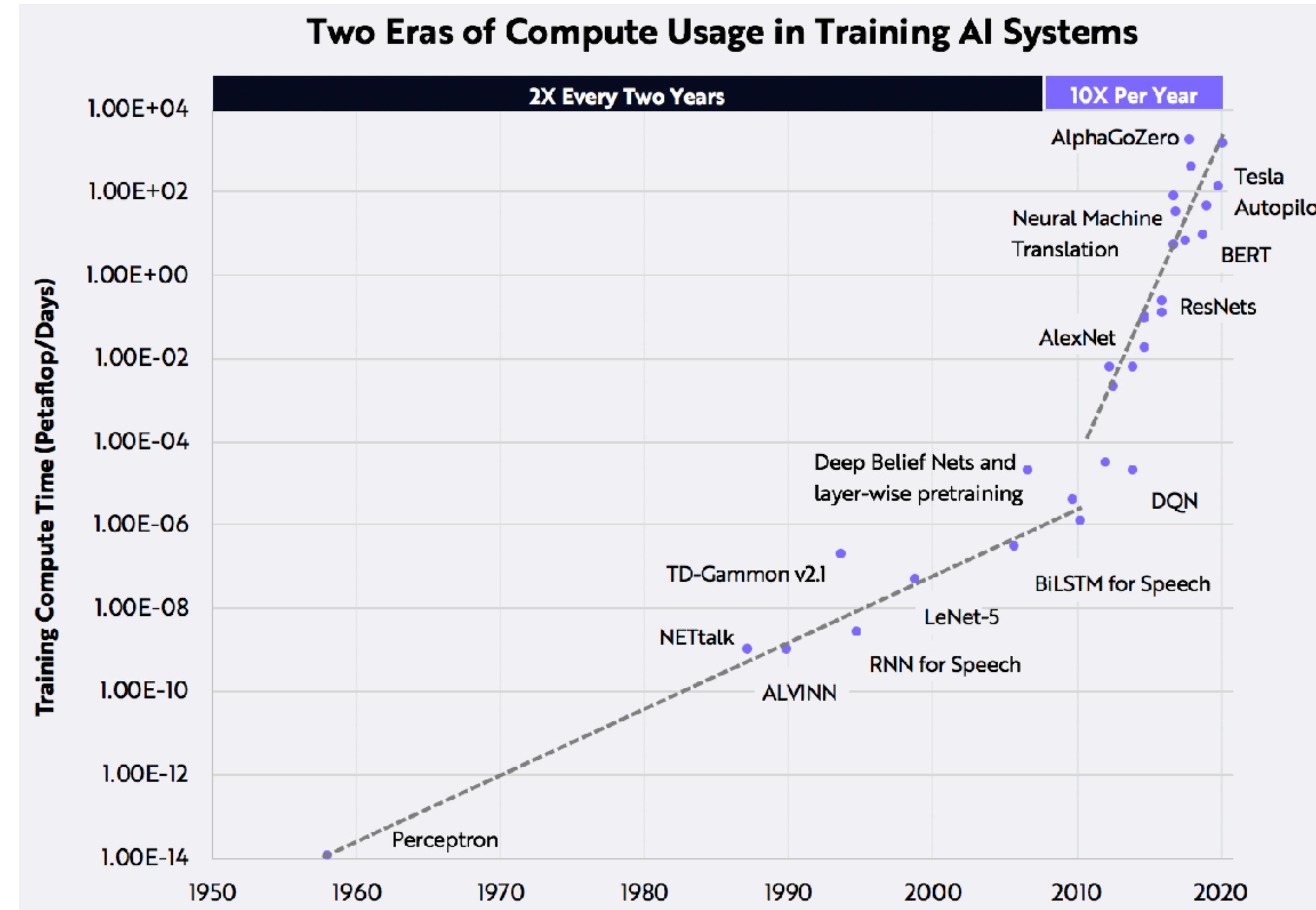
AI and Compute

Two Distinct Eras of Compute Usage in Training AI Systems



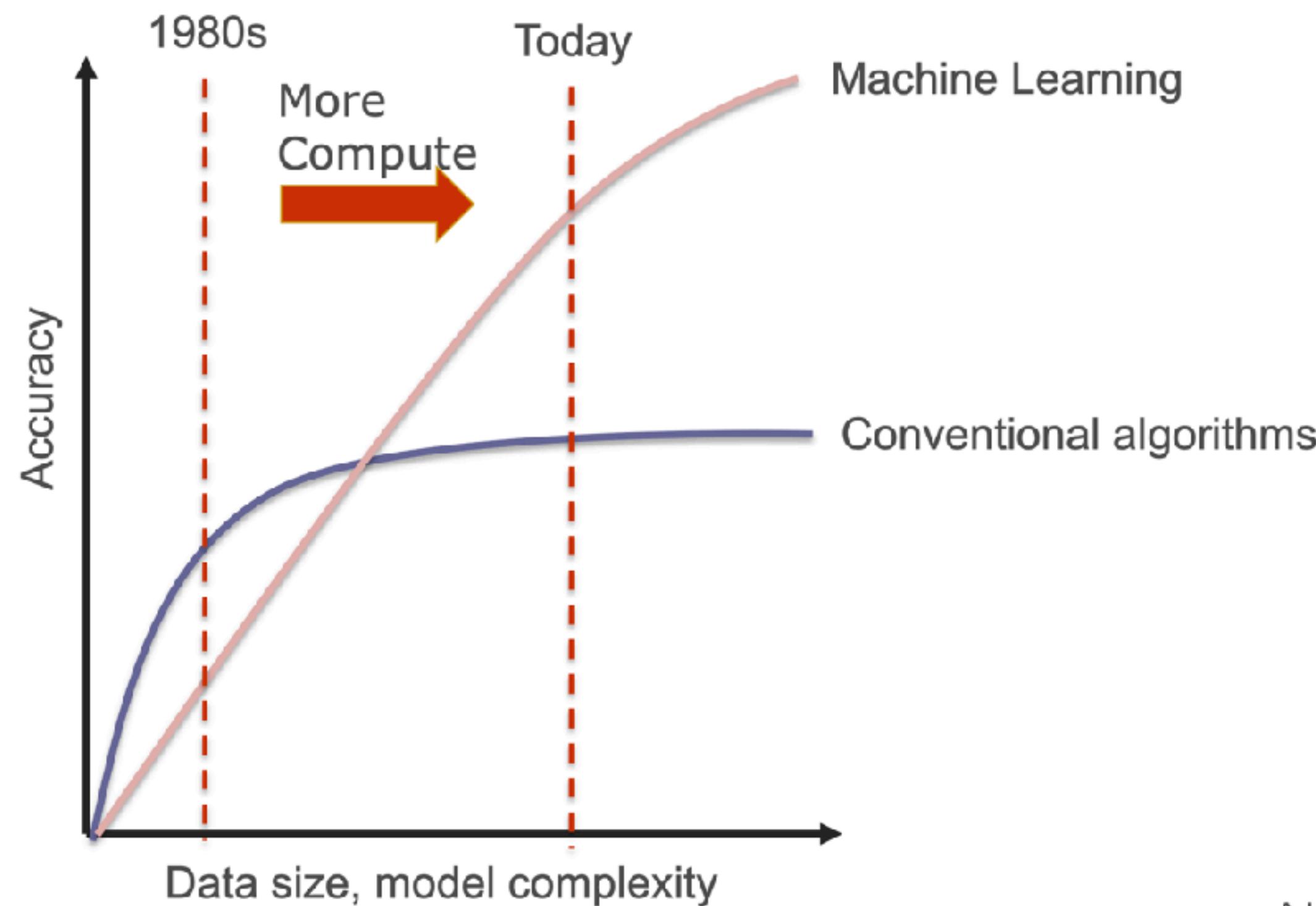
AI and Compute

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AI and Compute

Two Distinct Eras of Compute Usage in Training AI Systems



Adapted from Jeff Dean
HotChips 2017

Machine Learning Systems

Algorithmic Bias

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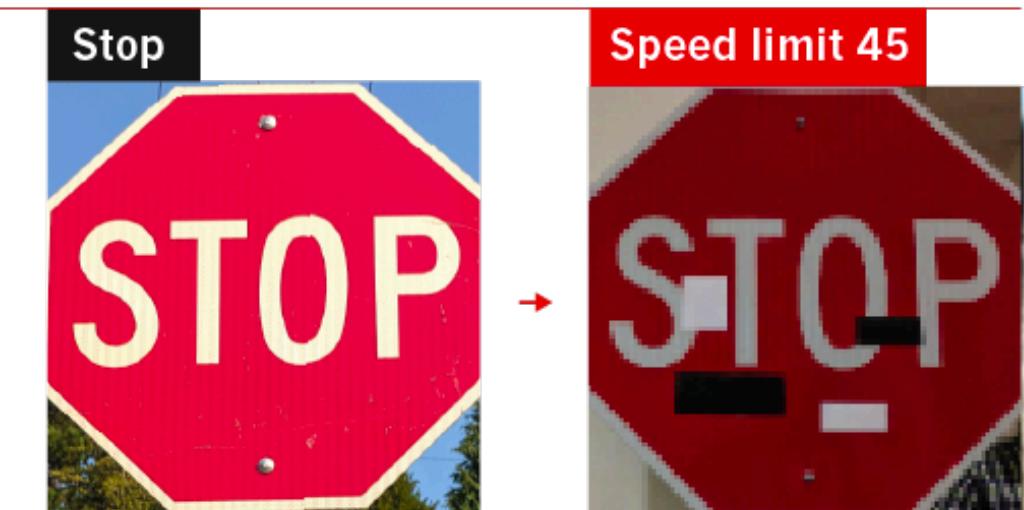
Computer science · Health care · Policy

Society

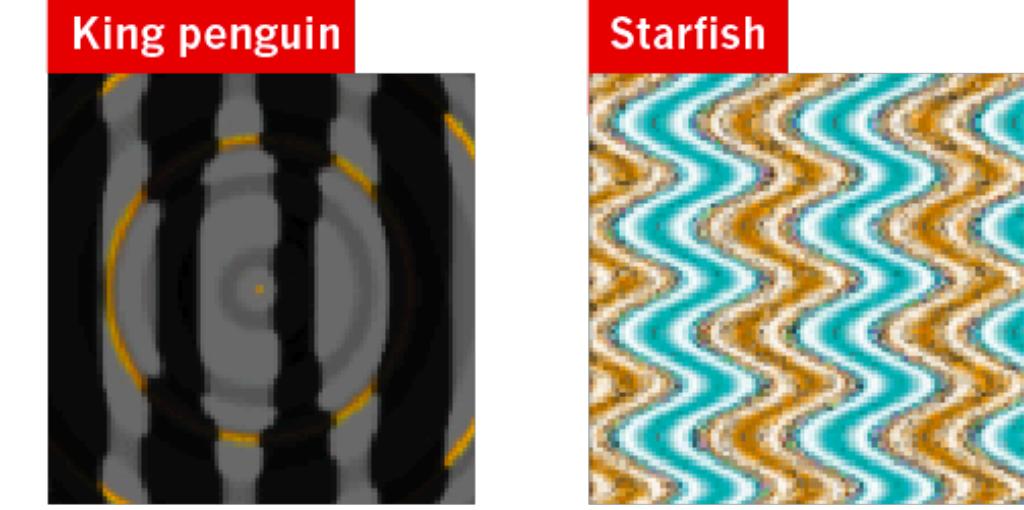
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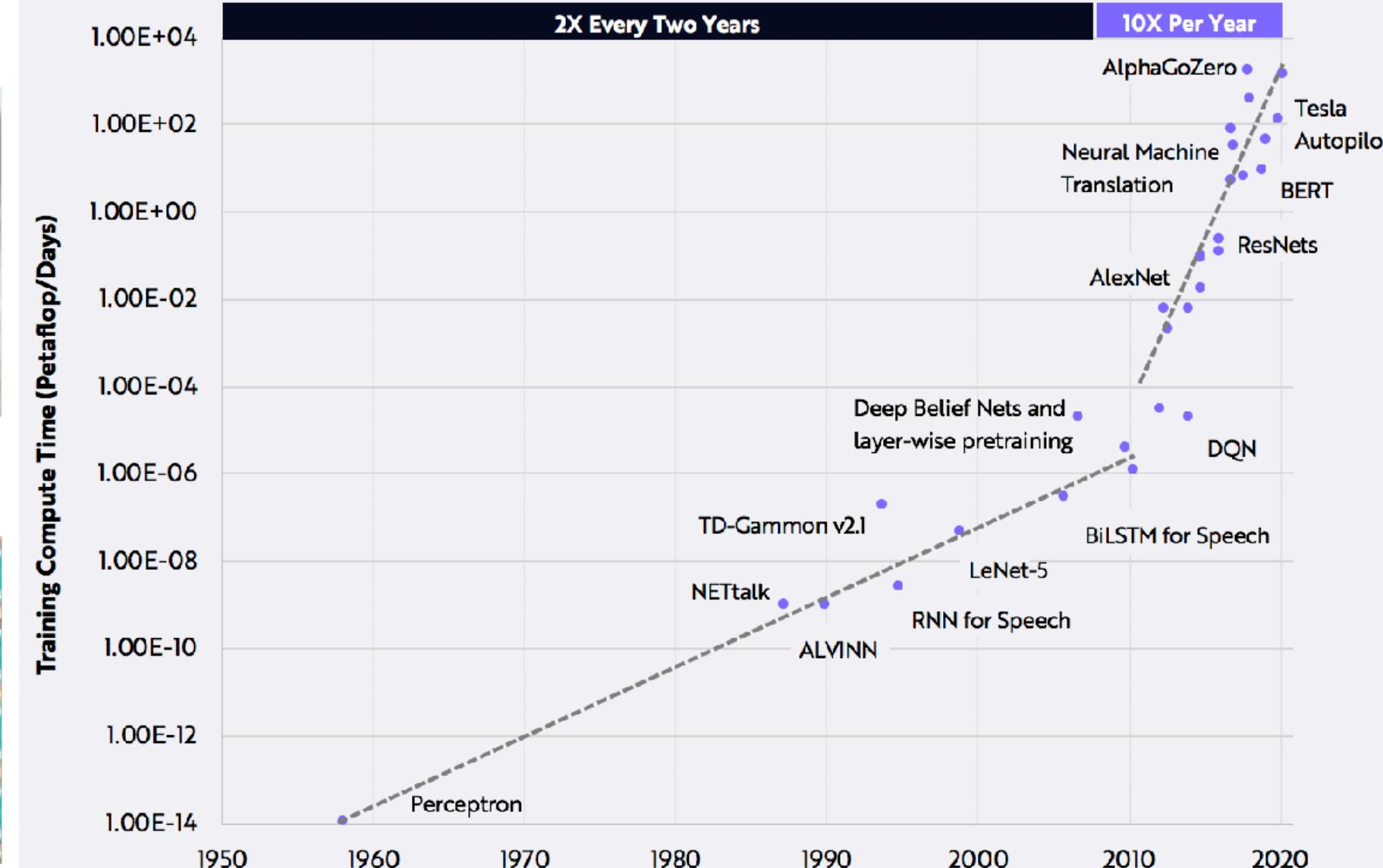


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Fooling AI Systems

AI and Compute

Two Eras of Compute Usage in Training AI Systems



Design a Machine Learning System



What is missing?

The gap between ML Research and Production

Chip Huyen @chipro · Jul 19, 2019
Replying to @chipro

Most candidates told me the hardest questions for them are the machine learning system design questions. They don't know what a good answer to these questions looks like. Interviewers: any tips?

18 replies 11 retweets 132 likes

Ravi Ganti @gmravi2003 · Jul 19, 2019

When I ask such questions, what I am looking for is the following. 1. Can the candidate break down the open ended problem into simple components (building blocks) 2. Can the candidate identify which blocks require ML and which do not.

9 replies

What is missing?

The gap between ML Research and Production



Dmitry Kislyuk @dkislyuk · Jul 19, 2019

Replies to [@lishali88](#) and [@chipro](#)

Most candidates know the model classes (linear, decision trees, lstms, convnets) and memorize the relevant info, so for me the interesting bits in ML systems interviews are data cleaning, data prep, logging, eval metrics, scalable inference, feature stores (recommenders/rankers)



What is missing?

The gap between ML Research and Production



Illia Polosukhin @ilblackdragon · Jul 20, 2019

I think this is the most important question. Can person define problem, identify relevant metrics, ideate on data sources and possible important features, understands deeply what ML can do. ML methods change every year, solving problems stays the same.



In ML Systems, only a small fraction is comprised of actual ML code

Hidden Technical Debt in Machine Learning Systems

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips

{dsculley, gholt, dg, edavydov, toddphillips}@google.com
Google, Inc.

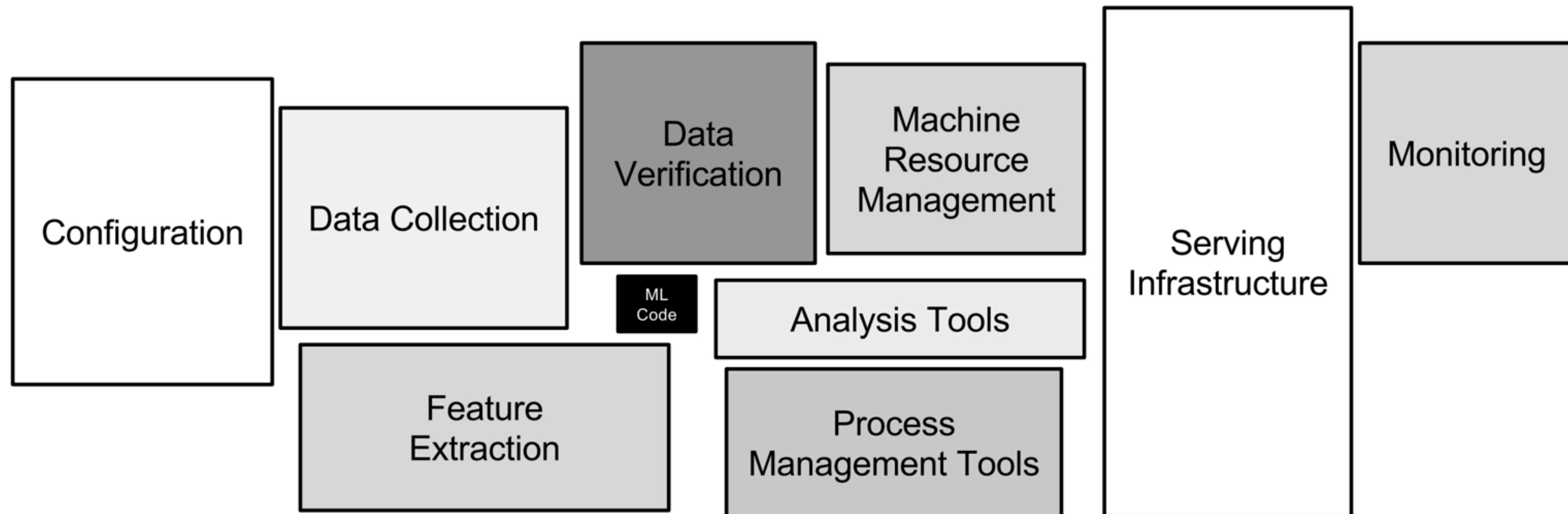
Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-François Crespo, Dan Dennison

{ebner, vchaudhary, mwyoung, jfcrespo, dennison}@google.com
Google, Inc.

Abstract

Machine learning offers a fantastically powerful toolkit for building useful complex prediction systems quickly. This paper argues it is dangerous to think of these quick wins as coming for free. Using the software engineering framework of *technical debt*, we find it is common to incur massive ongoing maintenance costs in real-world ML systems. We explore several ML-specific risk factors to account for in system design. These include boundary erosion, entanglement, hidden feedback loops, undeclared consumers, data dependencies, configuration issues, changes in the external world, and a variety of system-level anti-patterns.

A vast array of surrounding infrastructure and processes is needed to support evolution of ML systems



Technical debt that can accumulate in ML systems

- Data dependencies
- Model complexity
- Reproducibility
- Testing
- Monitoring
- Configuration issues
- External changes

Systems issues in ML Systems

Understanding the Nature of System-Related Issues in Machine Learning Frameworks: An Exploratory Study

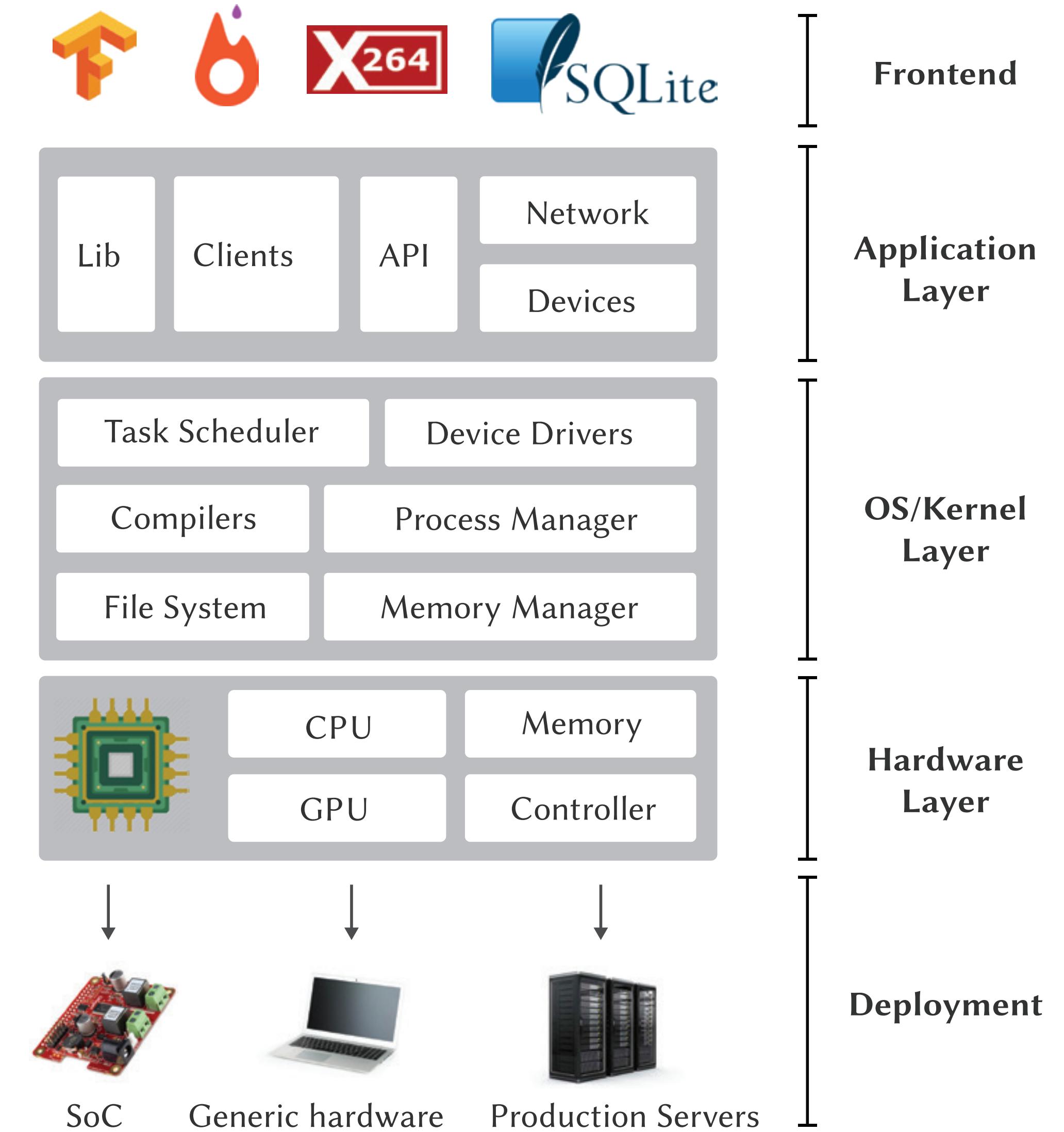
Yang Ren
University of South Carolina
USA

Gregory Gay
Chalmers and the University of Gutenberg
Sweden

Christian Kästner
Carnegie Mellon University
USA

Pooyan Jamshidi
University of South Carolina
USA

System = Software + Middleware + Hardware

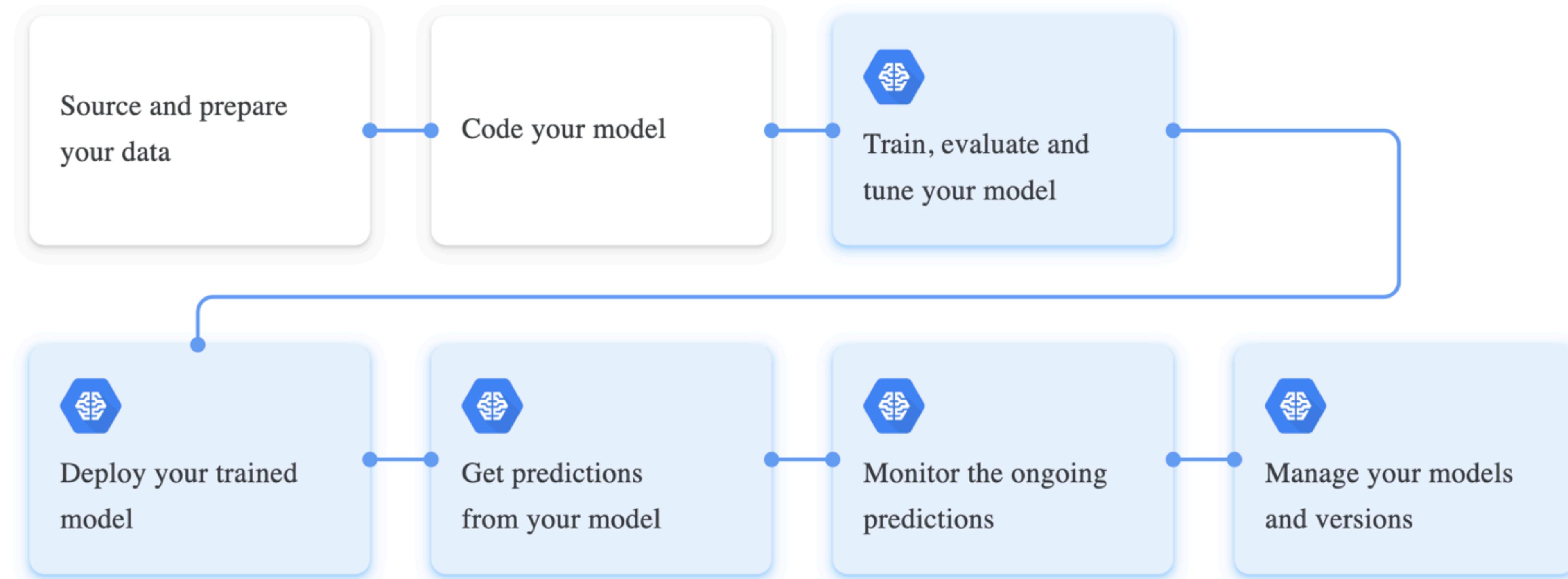


Systems issues in ML Systems

Category (Short Title)	Definition
API Mismatch (API)	Change to API version or mixed usage of APIs leading to performance degradation.
Compilation Error (Compl)	Failure to compile the source code.
Configuration Error (Config)	Configuration settings lead to performance degradation or error.
Connection Error (Conn)	Unexpected or wrongly-formatted connection request leads to error.
Data Race (Race)	Two or more threads access the same memory location concurrently.
Execution Error (Exec)	Unexpected error leads to the execution process crashing.
Hardware-Architecture Mismatch (HA)	Unfit hardware architecture leads to performance degradation or compilation error.
Memory Allocation (MA)	Memory allocation leads to performance degradation.
I/O Slowdown (I/O)	Issues with I/O processes lead to performance degradation.
Memory Leak (ML)	A failure in a program to release memory.
Model Conversion (Conv)	Performance degradation due to type conversion/cast.
Multi-Threading Error (MT)	Performance degradation due to thread interaction.
Performance Regression (PR)	Performance degradation after a change to the system.
Slow Synchronization (SYNC)	Synchronization between components leads to performance degradation.
Unexpected Resource Usage (RU)	Unusual system resource usage or requests leading to error or performance degradation.

ML in Research vs ML Systems in Production

The fundamental differences between machine learning in an academic setting and machine learning in production



A Machine Learning System is more than just a model

Change in ML Systems



Data

Schema

Sampling over Time

Volume



Model

Algorithms

More Training

Experiments



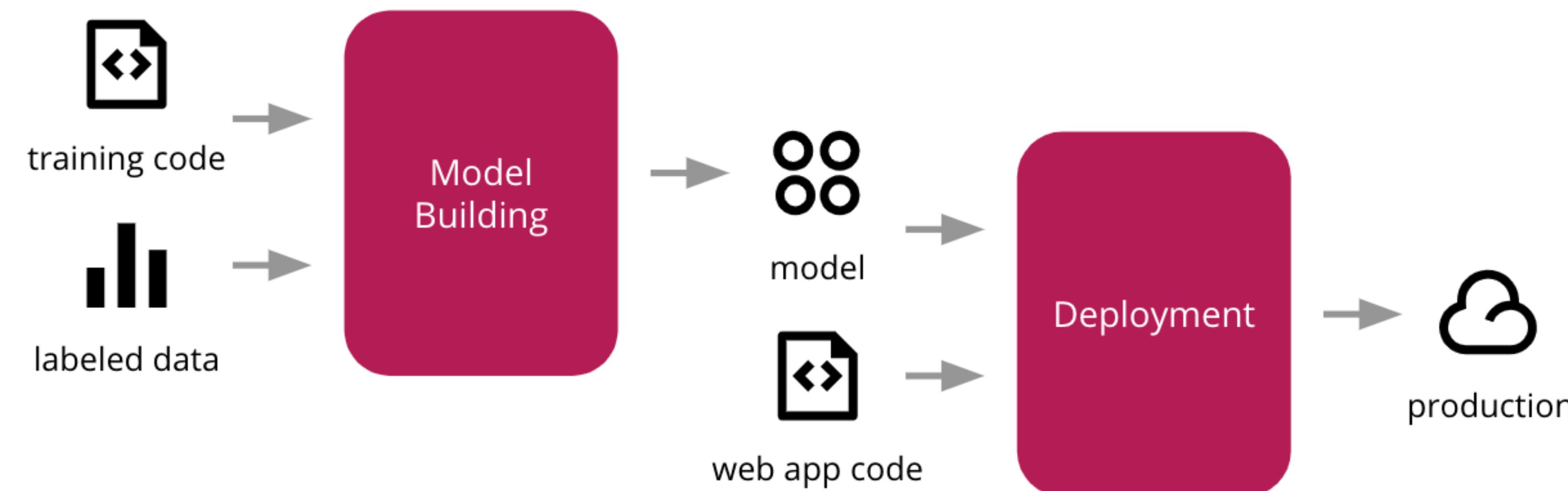
Code

Business Needs

Bug Fixes

Configuration

Train ML model, integrate it with an application, and deploy into production



ML model behind a web application

A screenshot of a web browser window displaying a "Sales forecast" application. The browser's address bar shows "localhost:5005". The main content area has a title "Sales forecast". Below it are two input fields: "Date" with a placeholder "YYYY-MM-DD" and "Product" with a dropdown menu currently showing "Milk". A blue "Submit" button is positioned below these fields. At the bottom, there is a long, empty rectangular input field with the label "Prediction:".

← → ⌂ ⓘ localhost:5005

Sales forecast

Date YYYY-MM-DD

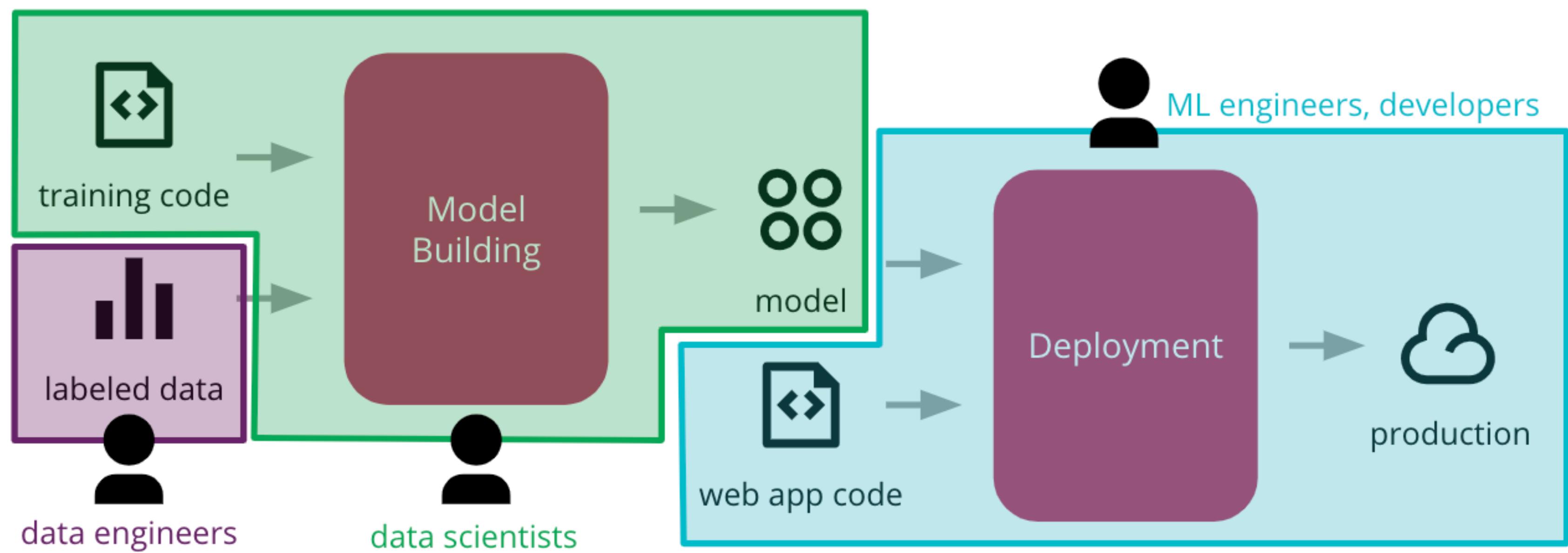
Product Milk ▾

Submit

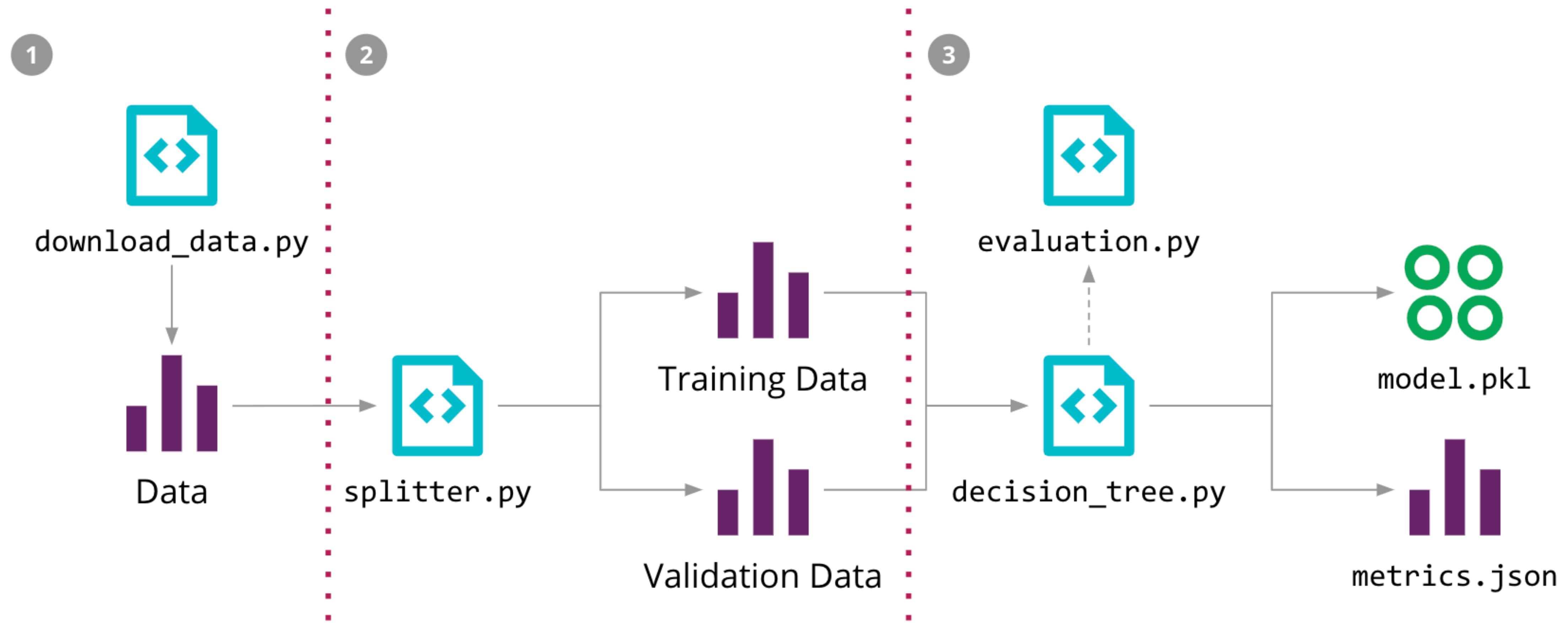
Prediction:

Challenges

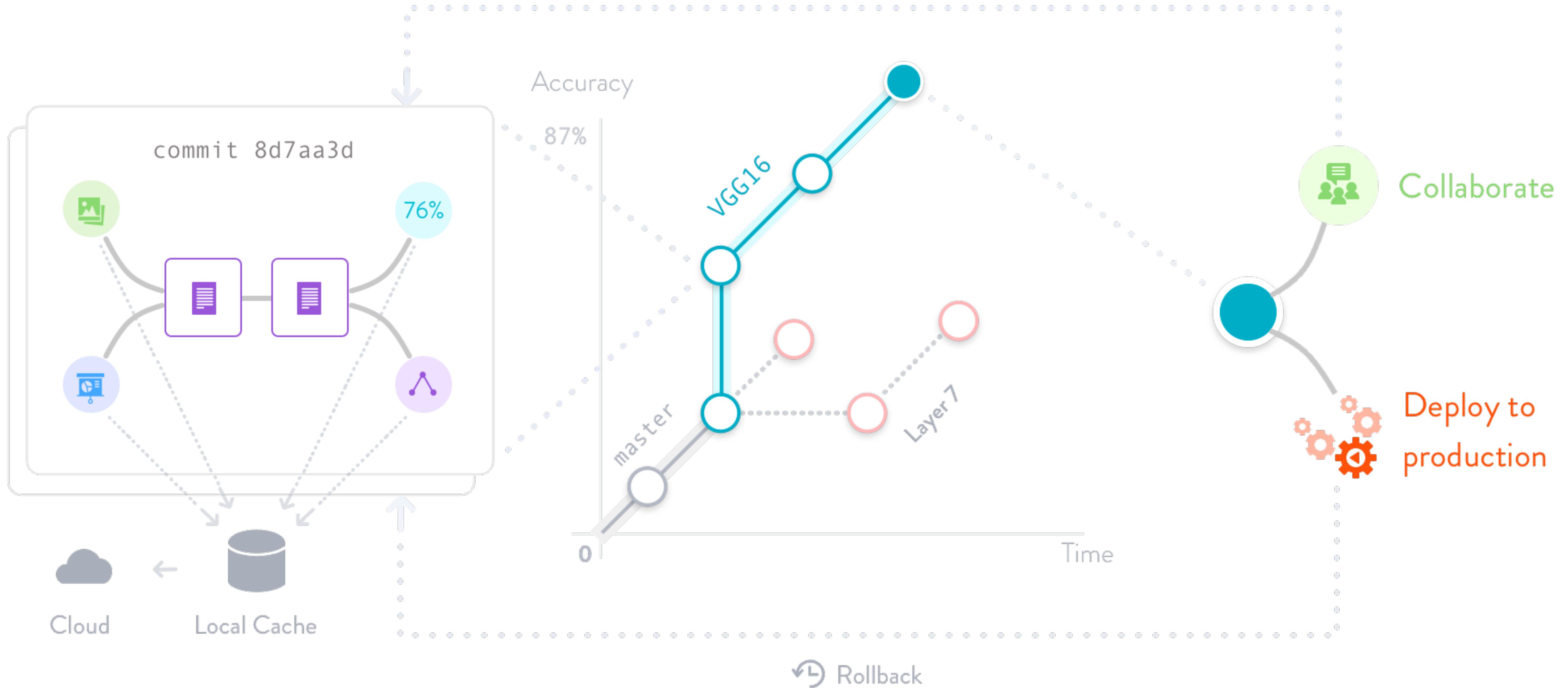
- Throw over the wall
- Models that only work in a lab environment
- Even if make it to production, they become stale and hard to update
- Reproducible and auditable



ML pipeline



Configure ML pipeline: DVC tracks ML models and data sets



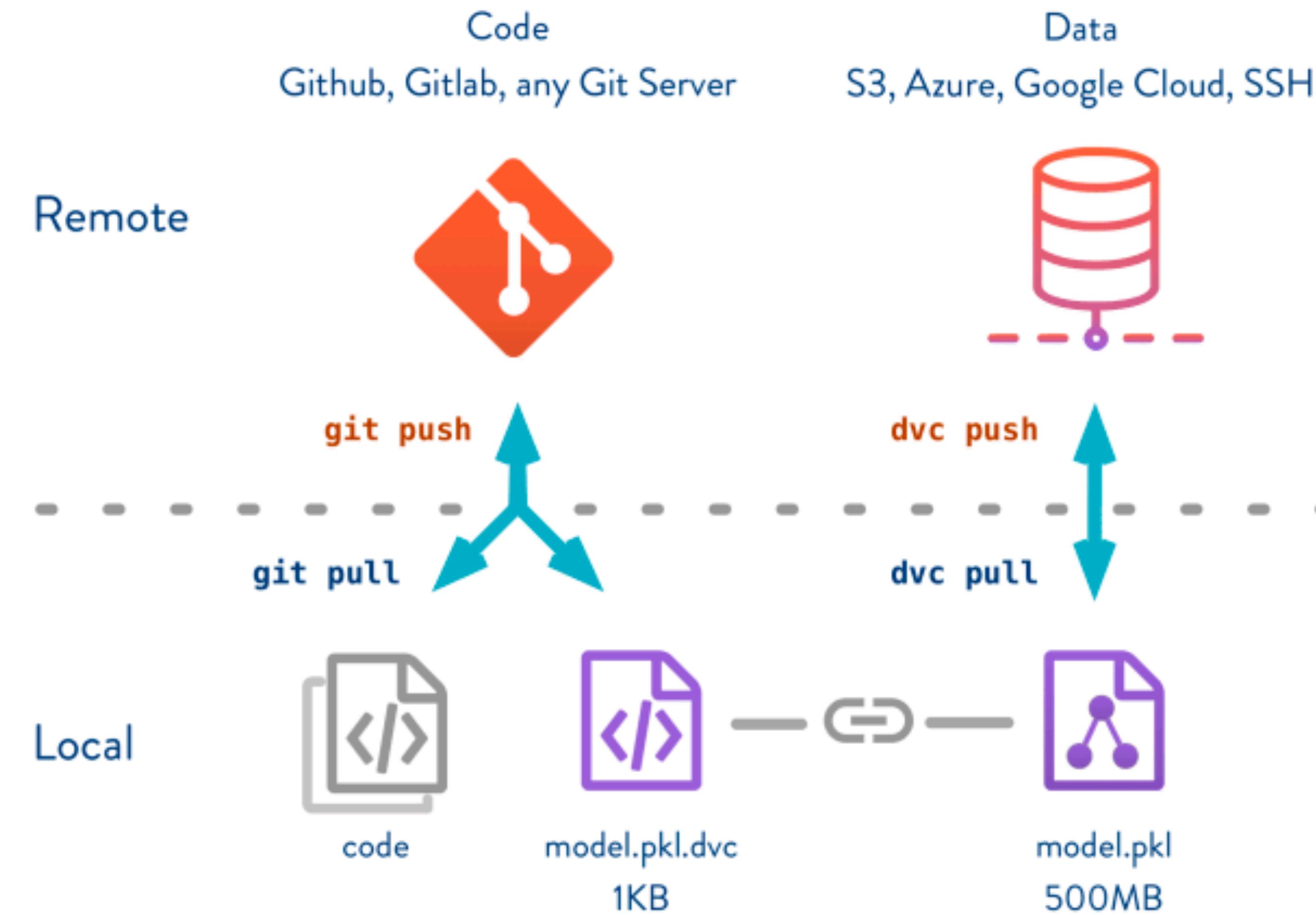
Configure ML pipeline: DVC tracks ML models and data sets

```
dvc run -f input.dvc \ ①
  -d src/download_data.py -o data/raw/store47-2016.csv python src/download_data.py
dvc run -f split.dvc \ ②
  -d data/raw/store47-2016.csv -d src/splitter.py \
  -o data/splitter/train.csv -o data/splitter/validation.csv python src/splitter.py
dvc run ③
  -d data/splitter/train.csv -d data/splitter/validation.csv -d src/decision_tree.py \
  -o data/decision_tree/model.pkl -M results/metrics.json python src/decision_tree.py
```

Configure ML pipeline: DVC tracks ML models and data sets

- Each run will create a file, that can be committed to version control
- DVC allows other people to reproduce the entire ML pipeline, by executing the *dvc repro* command.
- Once we find a suitable model, we will treat it as an artifact that needs to be *versioned* and *deployed* to production.
- With DVC, we can use the *dvc push* and *dvc pull* commands to publish and fetch it from *external storage*.

Configure ML pipeline: DVC tracks ML models and data sets

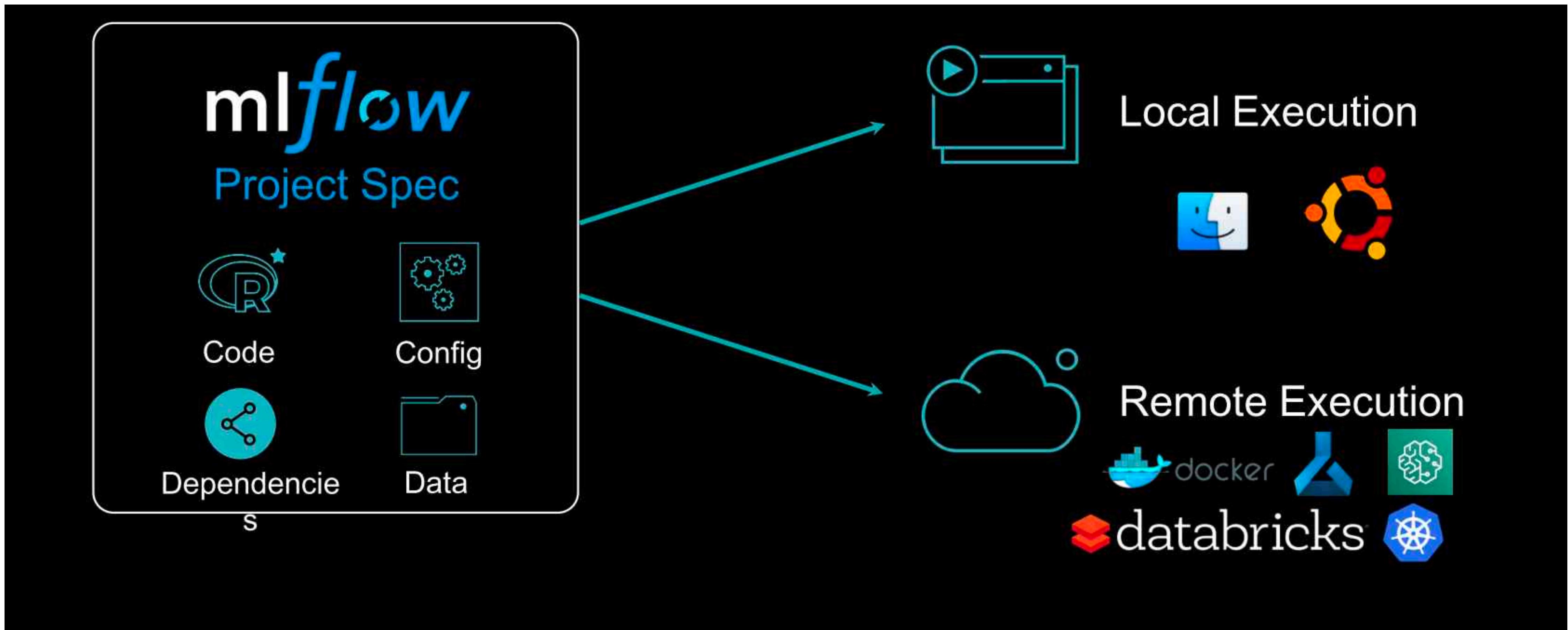


There are other open source tools for versioning

Pachyderm

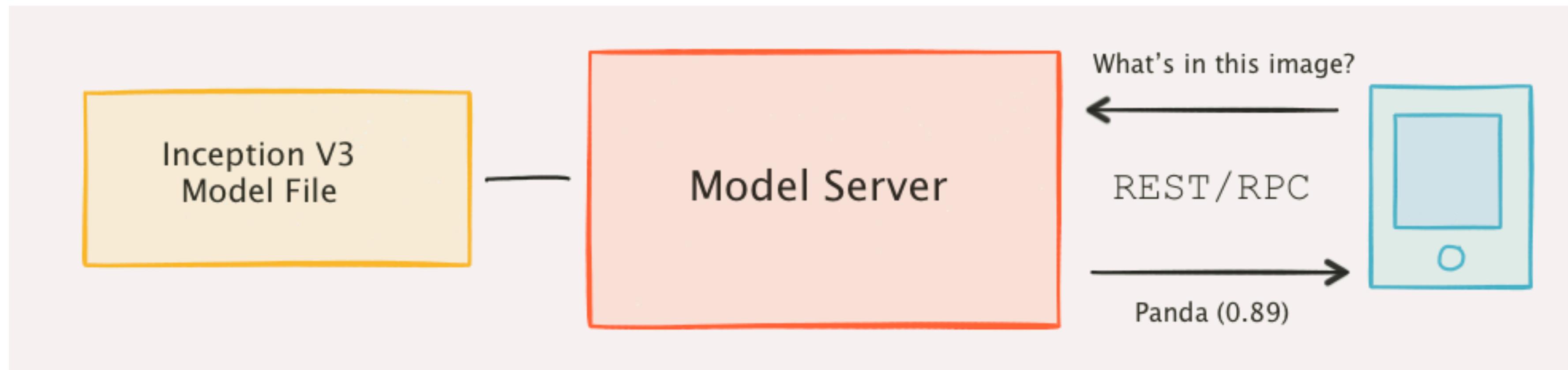


There are other open source tools for versioning MLflow



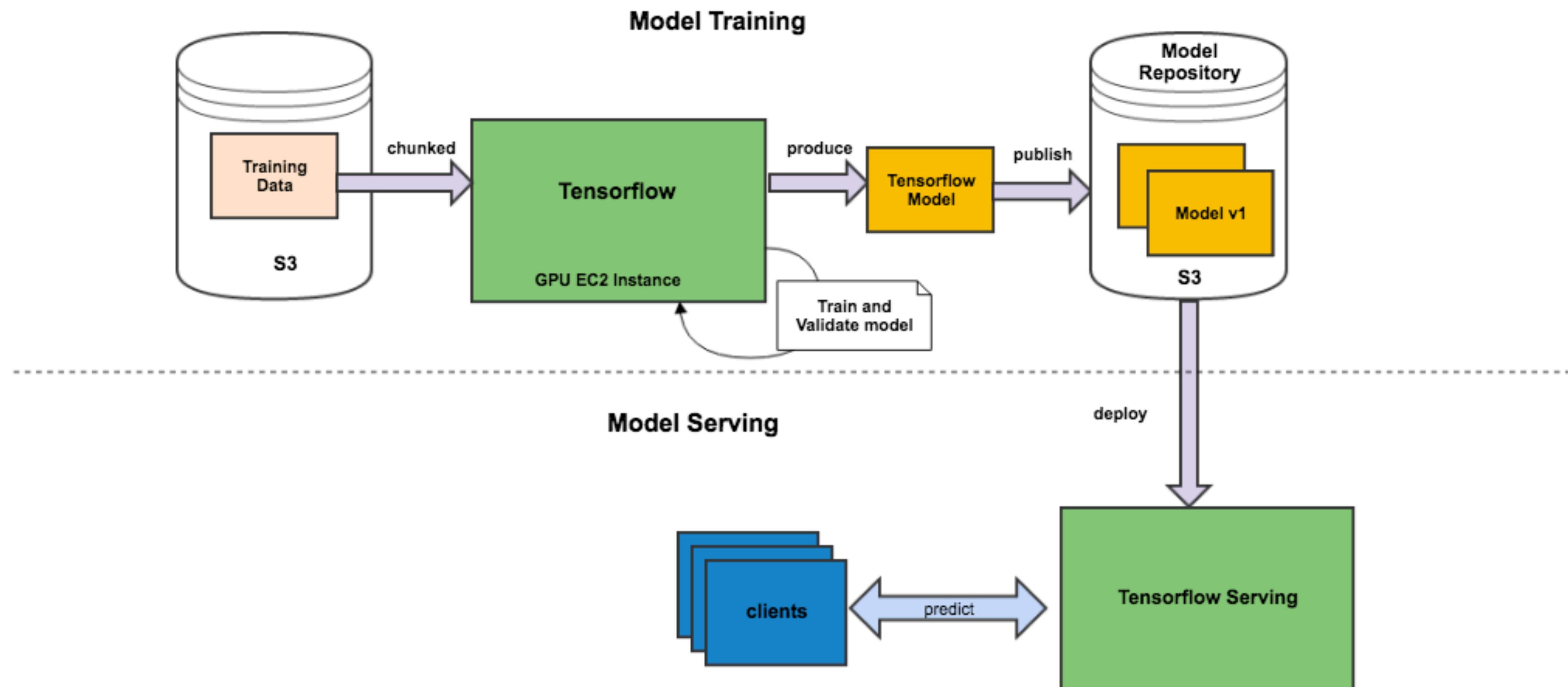
Model Serving

Abstract level



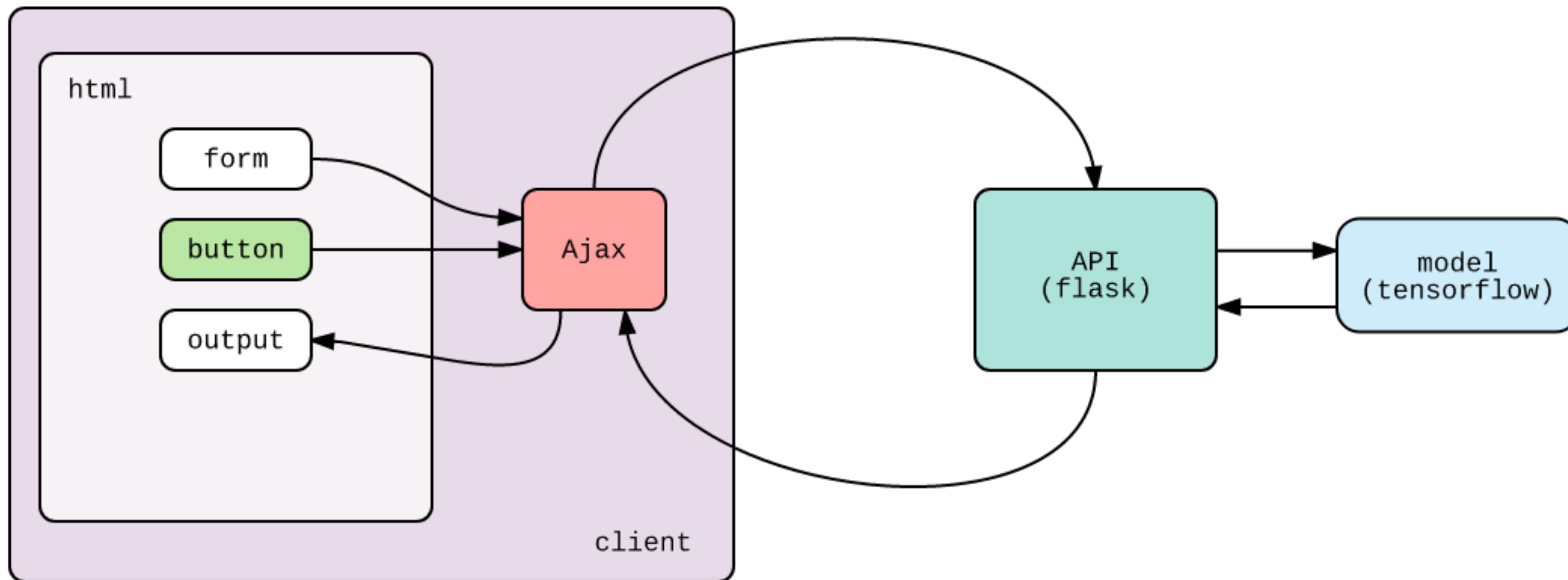
Model Serving

TF Serving



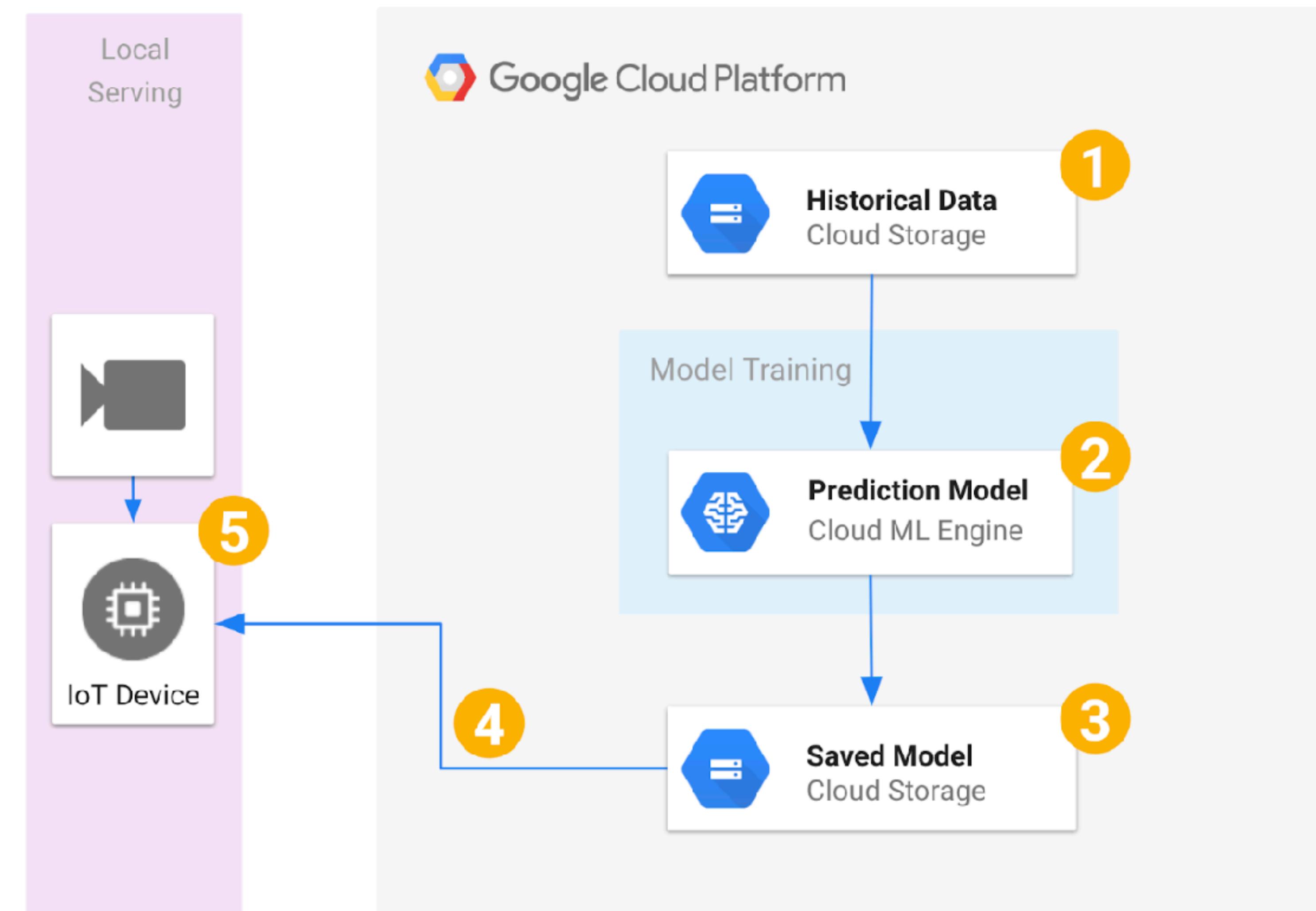
Model Serving

Web app

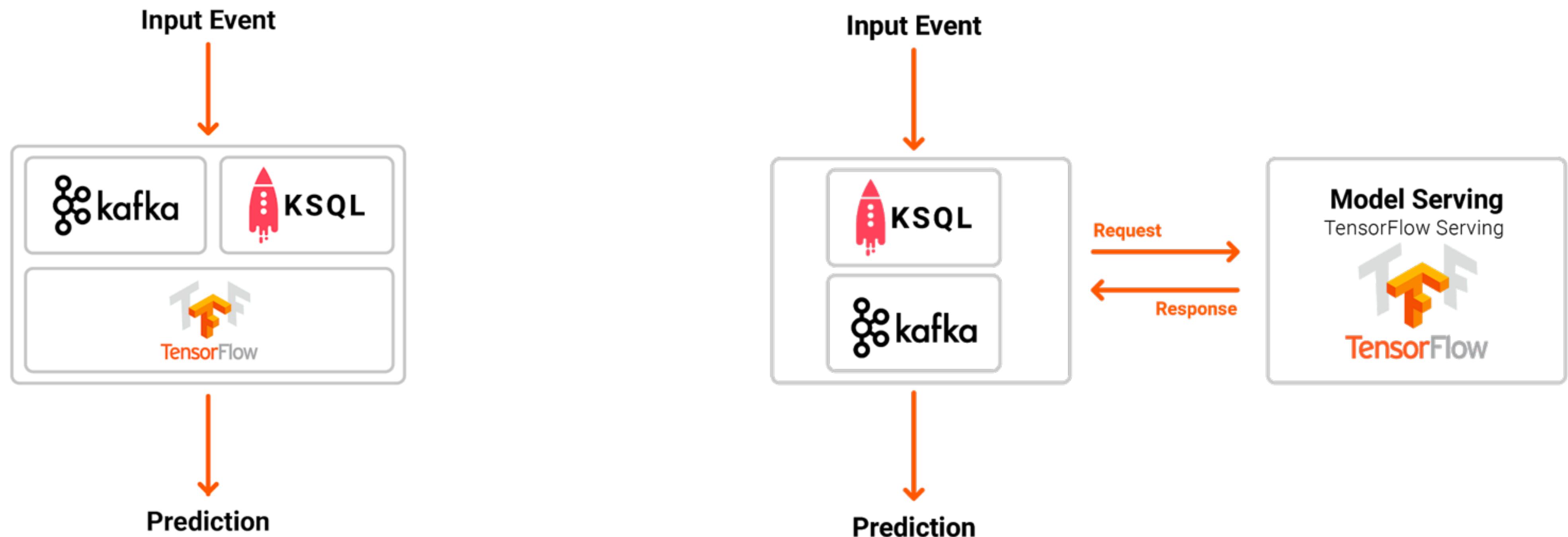


Model Serving

Internet of Thing



Model Serving Stream Processing System



Model Serving

Embedded model

- Simple approach
- You treat the model artifact as a dependency that is built and packaged within the consuming application.
- You can treat the application artifact and version as being a combination of the application code and the chosen model.

Model Serving

Model deployed as a separate service

- The model is wrapped in a service that can be deployed independently of the consuming applications.
- This allows updates to the model to be released independently, but it can also introduce latency at inference time
- There will be some sort of remote invocation required for each prediction.

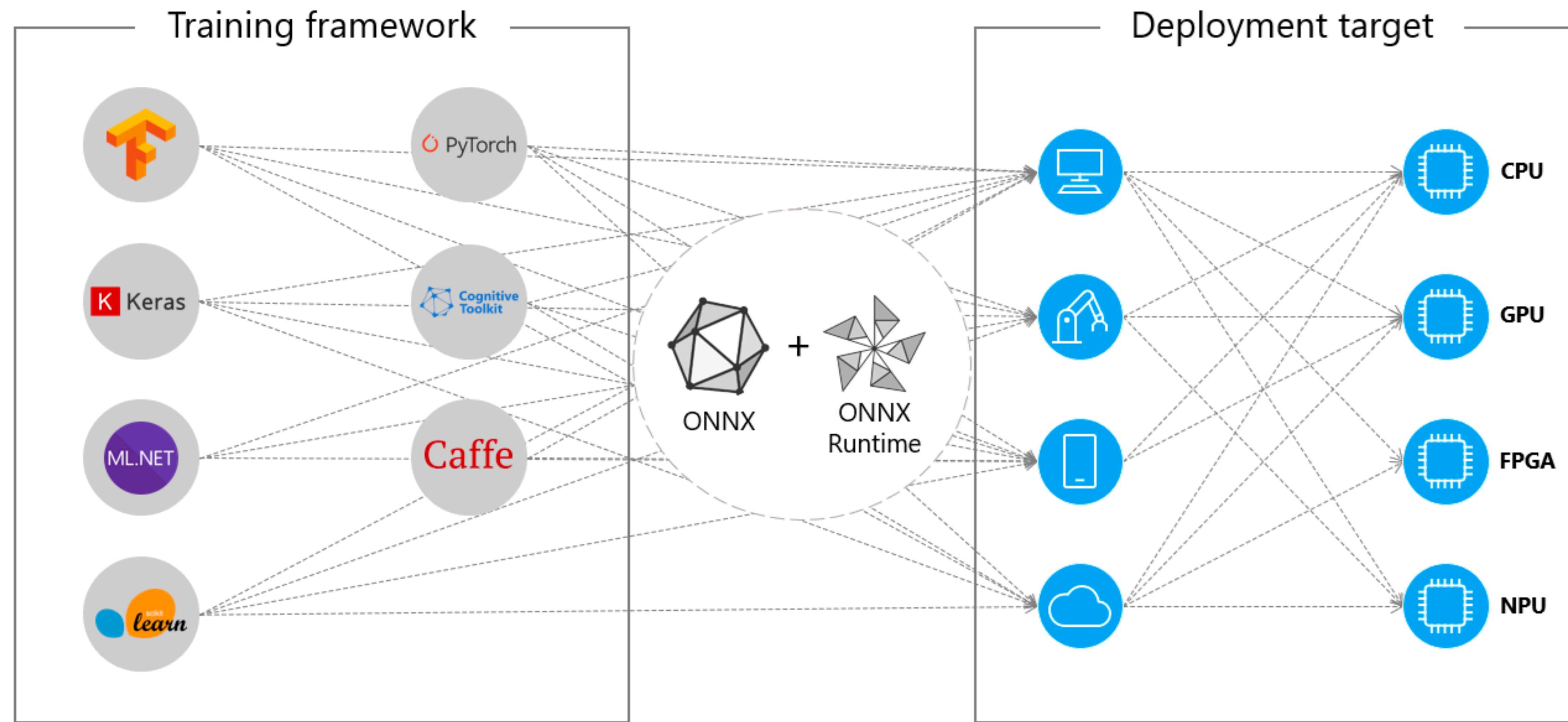
Model Serving

Model published as data

- The model is also treated and published independently,
- But the consuming application will ingest it as data at runtime.
- We have seen this used in streaming/real-time scenarios where the application can subscribe to events that are published whenever a new model version is released, and ingest them into memory while continuing to predict using the previous version.
- Software release patterns such as Canary Releases can also be applied in this scenario.

Export ML models to production environment

Open Neural Network Exchange



Testing and Quality in Machine Learning

- Regardless of which pattern you decide to use, there is always an implicit contract between the model and its consumers.
- The model will usually expect input data in a certain shape, and if Data Scientists change that contract to require new input or add new features, you can cause integration issues and break the applications using it.
- So testing becomes important.

Testing Machine Learning Systems

Validating data

- Tests to **validate input data** against the expected schema, or to validate our **assumptions** about its valid values:
 - Values fall within expected ranges
 - Values are not null
- Unit tests to check **features** are calculated correctly:
 - Numeric features are scaled or normalized,
 - One-hot encoded vectors contain all zeroes and a single 1
 - Missing values are replaced appropriately

Testing Machine Learning Systems

Validating component integration

- Test the **integration** between different services:
 - Contract Tests to validate that the expected model interface is compatible with the consuming application.
- Test that the **exported model** still produces the same results:
 - Running the original and the productionized models against the same validation dataset, and comparing the results are the same.

Testing Machine Learning Systems

Validating the model quality

- ML **model performance** is non-deterministic.
- Collect and monitor **metrics** to evaluate a model's performance,
 - Error rates, accuracy
 - Precision, recall
 - AUC, ROC, confusion matrix
- **Threshold Tests** in our pipeline, to ensure that new models don't degrade against a known performance baseline.

Testing Machine Learning Systems

Validating model bias and fairness

- Check how the model performs against **baselines** for specific **data slices**:
 - Inherent bias in the training data where there are many more data points for a given value of a feature (e.g. race, gender, or region) compared to the actual distribution in the real world.
 - A tool like **Facets** can help you visualize those slices and the distribution of values across the features in your datasets.

Testing Machine Learning Systems

Integration Test

- When models are **distributed or exported** to be used by a different application,
- The engineered features are **calculated differently** between training and serving time.
- Distribute a **holdout dataset** along with the model artifact, and allow the consuming application team to reassess the model's performance against the holdout dataset after it is integrated.
- This would be the equivalent of a broad **Integration Test** in traditional software development.

Governance process for ML Systems

Experiments Tracking

- To capture and display information that will allow humans to decide if and which model should be promoted to production.
- It is common that you will have multiple experiments being tried in parallel, and many of them might not ever make it to production.
- The code for many of these experiments will be thrown away, and only a few of them will be deemed worthy of making it to production.
- Different Git branches to track the different experiments in source control.
- Tools such as DVC can fetch and display metrics from experiments running in different branches or tags, making it easy to navigate between them.

Governance process for ML Systems

MLflow Tracking web UI

The screenshot shows the MLflow Tracking web UI interface. At the top, there is a dark header bar with the 'mlflow' logo on the left and 'GitHub Docs' on the right. Below the header, the page title is 'Experiments' with a back arrow and the text 'user1'. On the left, there is a sidebar with user names: 'user2' (disabled), 'user1' (selected), and another 'user2' (disabled). The main content area displays experiment details for 'user1': 'Experiment ID: 1' and 'Artifact Location: gs://cd4ml-mlflow-tracking/1'. It includes search filters: 'Search Runs: metrics.rmse < 1 and params.model = "tree"', 'State: Active', and a 'Search' button. There are also 'Filter Params: alpha, lr' and 'Filter Metrics: rmse, r2' fields with a 'Clear' button. Below these filters, there is a message '1 matching run' followed by buttons for 'Compare', 'Delete', 'Download CSV', and two icons. A table then lists the single matching run with columns: Date, User, Run Name, Source, Version, Parameters, and Metrics. The run details are: Date 2019-04-28 00:03:29, User go, Run Name 5, Source decision_tree.py, Version b24402, Parameters model: RANDOM_FOREST, n_estimators: 10, Metrics: nwrmsle: 0.743, r2_score: 0.109.

Date	User	Run Name	Source	Version	Parameters	Metrics
2019-04-28 00:03:29	go	5	decision_tree.py	b24402	model: RANDOM_FOREST, n_estimators: 10	nwrmsle: 0.743, r2_score: 0.109

Model Deployment

Multiple models

- More than one model performing the same task.
 - Train a model to predict demand for each product.
 - Deploying the models as a separate service might be better for consuming applications to get predictions with a single API call.
 - You can later evolve how many models are needed behind that Published Interface.

Model Deployment

Shadow models

- Deploy the new model side-by-side with the current one, as a shadow model
- Send the same production traffic to gather data on how the shadow model performs before promoting it into the production.

Model Deployment

Competing models

- Multiple versions of the model in production – like an A/B test
 - Infrastructure and routing rules required to ensure the traffic is being redirected to the right models.
 - To gather enough data to make statistically significant decisions, which can take some time.
- Evaluating multiple competing models is Multi-Armed Bandits,
 - To define a way to calculate and monitor the reward associated with using each model.

Model Supervisor

No one
Likes dogs

French
Bulldog

French
Bulldog

French
Bulldog



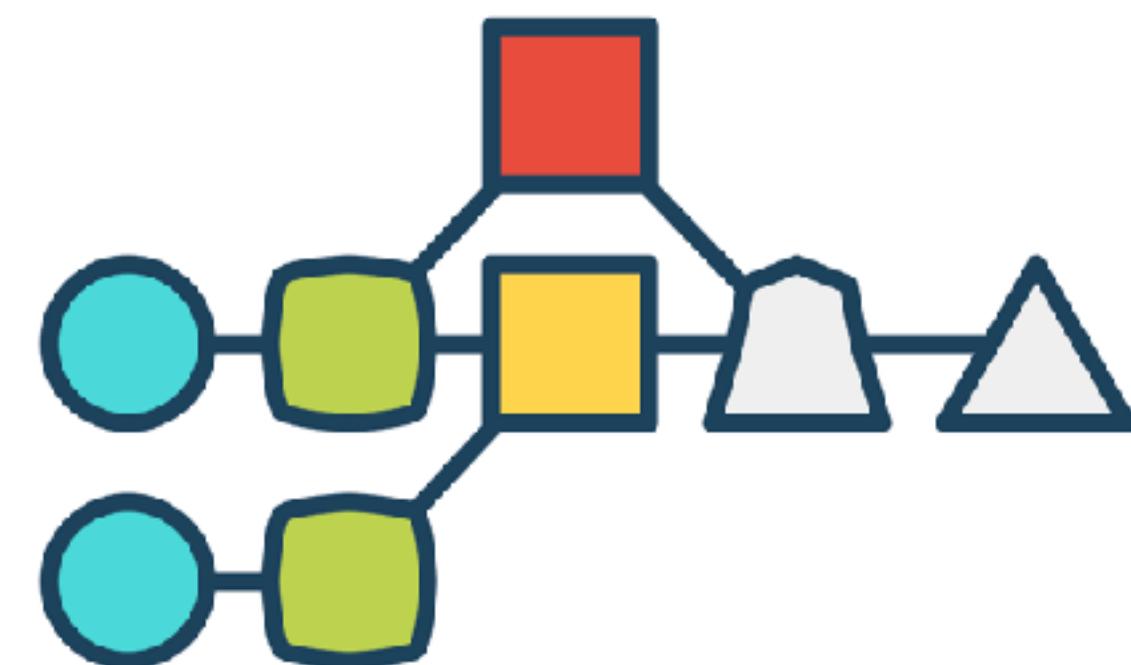
Model Deployment

Online learning models

- To use algorithms and techniques that can continuously improve its performance with the arrival of new data.
- Constantly learning in production.
- Extra complexities, as versioning the model as a static artifact won't yield the same results if it is not fed the same data.
- You will need to version not only the training data, but also the production data that will impact the model's performance.

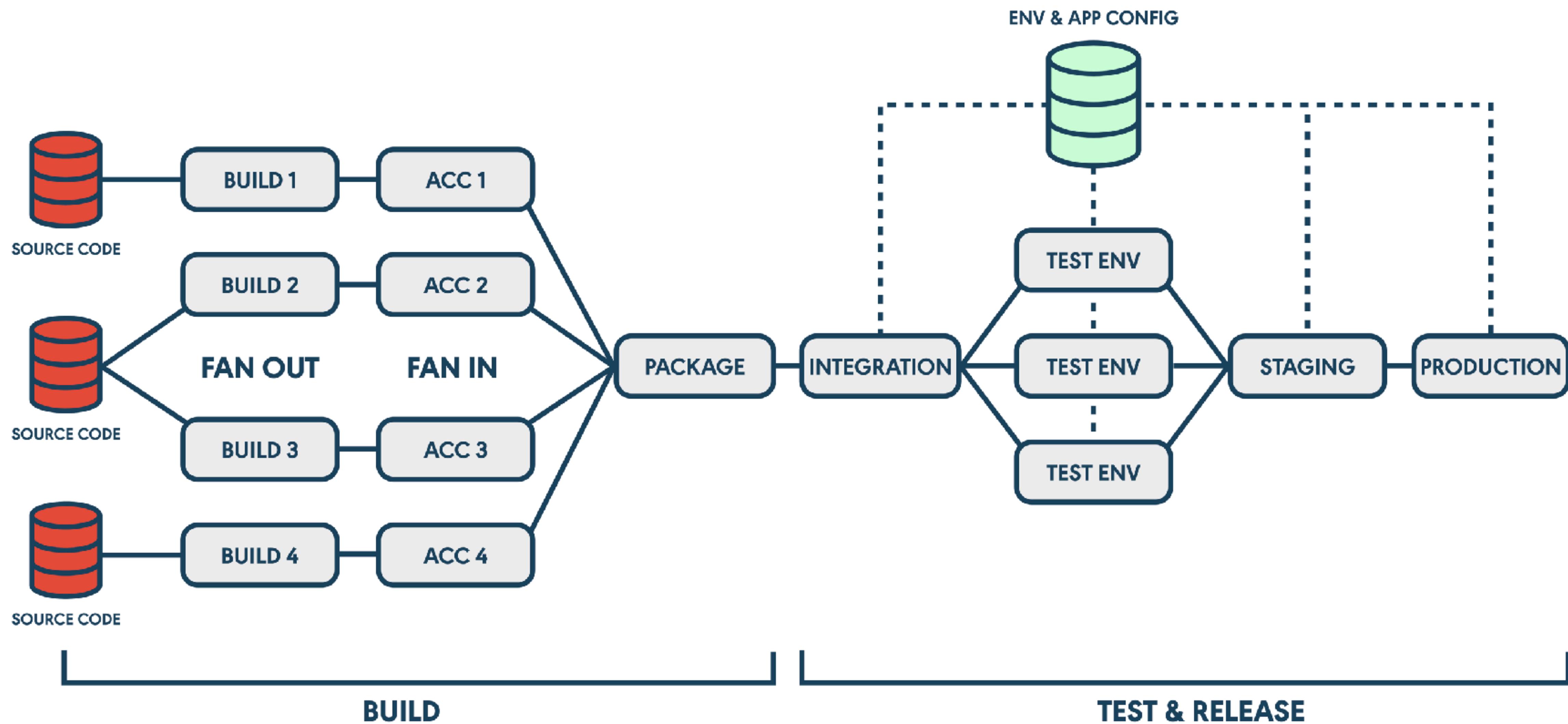
Orchestration in ML Pipelines

- Provisioning of infrastructure and the execution of the ML Pipelines to train and capture metrics from multiple model experiments
- Building, testing, and deploying Data Pipelines
- Testing and validation to decide which models to promote
- Provisioning of infrastructure and deployment of models to production



Continuous Integration and Delivery

GoCD



A Continuous Delivery Scenario for ML

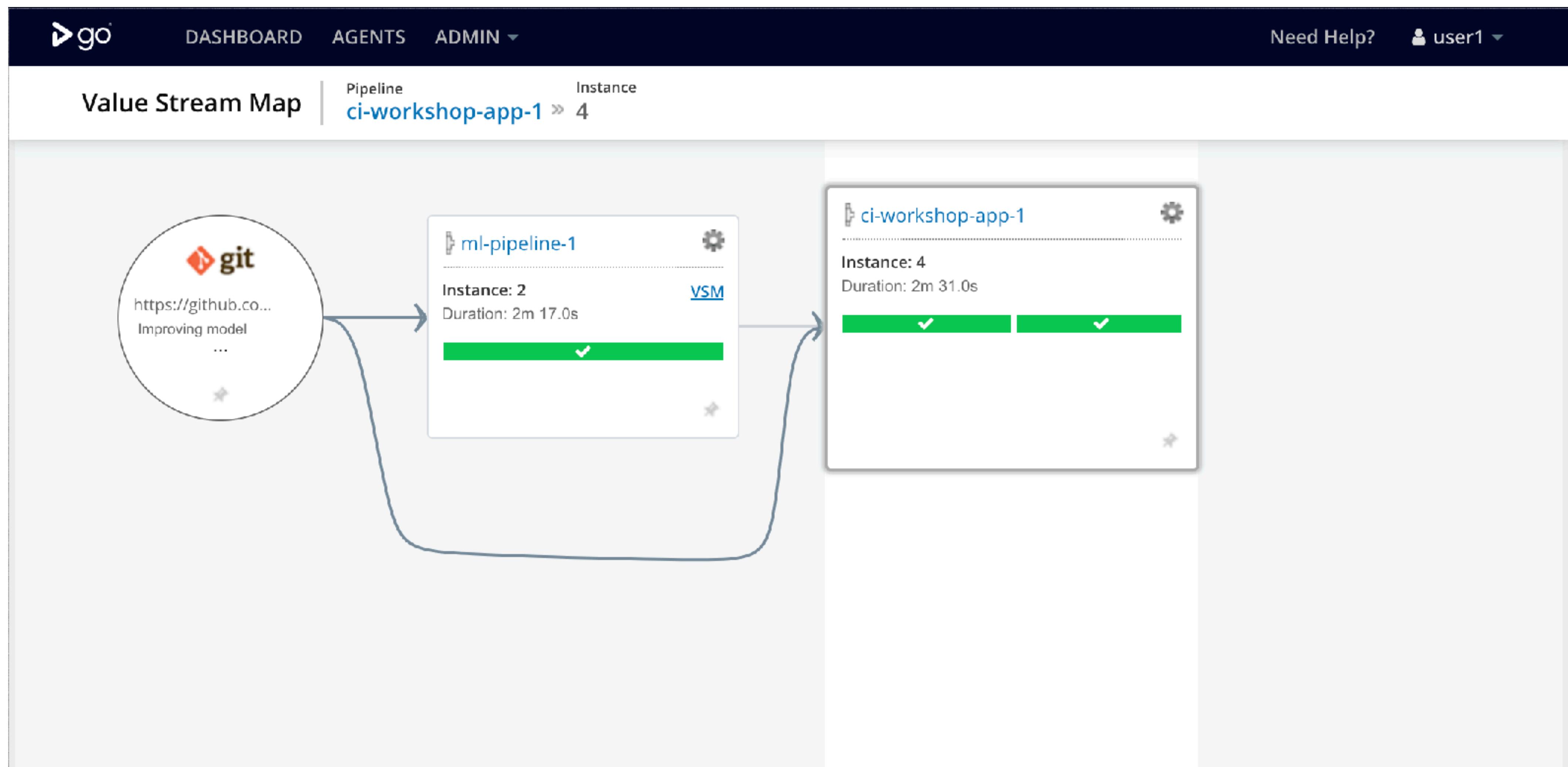
1. Machine Learning Pipeline:

- To train and evaluate ML models
- To execute threshold test to decide if the model can be promoted or not
- *dvc push* to publish it as an artifact

2. Application Deployment Pipeline:

- To build and test the application code
- To fetch the promoted model from the upstream pipeline using *dvc pull*
- To package a new combined artifact that contains the model and the application as a Docker image
- To deploy them to a production cluster

Combining Machine Learning Pipeline and Application Deployment Pipeline



ML Model Monitoring

How models perform in production and rollback mechanisms

- **Model inputs:**
 - What data is being fed to the models, identifying training-serving skew.
- **Model outputs:**
 - What predictions and recommendations are the models making from these inputs, to understand how the model is performing with real data.

ML Model Monitoring

How models perform in production and rollback mechanisms

- **Model interpretability outputs:**

- Metrics such as model coefficients, ELI5, or LIME outputs that allow further investigation to understand how the models are making predictions to identify potential overfit or bias that was not found during training.



hi there, i am here looking for some help. my friend is a interie
graphics software on pc. any suggestion on which software to
sophisticated software(the more features it has,the better)

y=0 (probability 0.000) top features			y=1 (probability 0.100) top features			y=2 (probability 0.900) top features		
Contribution?	Feature	Value	Contribution?	Feature	Value	Contribution?	Feature	Value
+0.301	<BIAS>	1.000	+0.427	<BIAS>	1.000	+0.289	hue	0.670
+0.064	color_intensity	8.500	+0.033	proline	630.000	+0.272	<BIAS>	1.000
+0.004	malic_acid	4.600	+0.022	od280/od315_of_diluted_wines	1.920	+0.095	color_intensity	8.500
-0.018	alcalinity_of_ash	25.000	+0.009	alcalinity_of_ash	25.000	+0.083	flavanoids	0.960
-0.044	total_phenols	1.980	+0.006	total_phenols	1.980	+0.067	proline	630.000
-0.055	flavanoids	0.960	-0.003	proanthocyanins	1.110	+0.056	malic_acid	4.600
-0.100	proline	630.000	-0.010	alcohol	13.400	+0.038	total_phenols	1.980
-0.153	hue	0.670	-0.028	flavanoids	0.960	+0.010	alcohol	13.400
			-0.060	malic_acid	4.600	+0.009	alcalinity_of_ash	25.000
			-0.137	hue	0.670	+0.003	proanthocyanins	1.110
			-0.160	color_intensity	8.500	-0.022	od280/od315_of_diluted_wines	1.920

“Why Should I Trust You?”

Explaining the Predictions of Any Classifier

Example #3 of 6 True Class:  Atheism Instructions Previous Next

Algorithm 1

Words that A1 considers important:

GOD	
mean	
anyone	
this	
Koresh	
through	

Predicted:  Atheism

Prediction correct: 

Document

From: pauld@verdix.com (Paul Durbin)
Subject: Re: DAVID CORESH IS! GOD!
Nntp-Posting-Host: sarge.hq.verdix.com
Organization: Verdix Corp
Lines: 8

Algorithm 2

Words that A2 considers important:

Posting	
Host	
Re	
by	
in	
Nntp	

Predicted:  Atheism

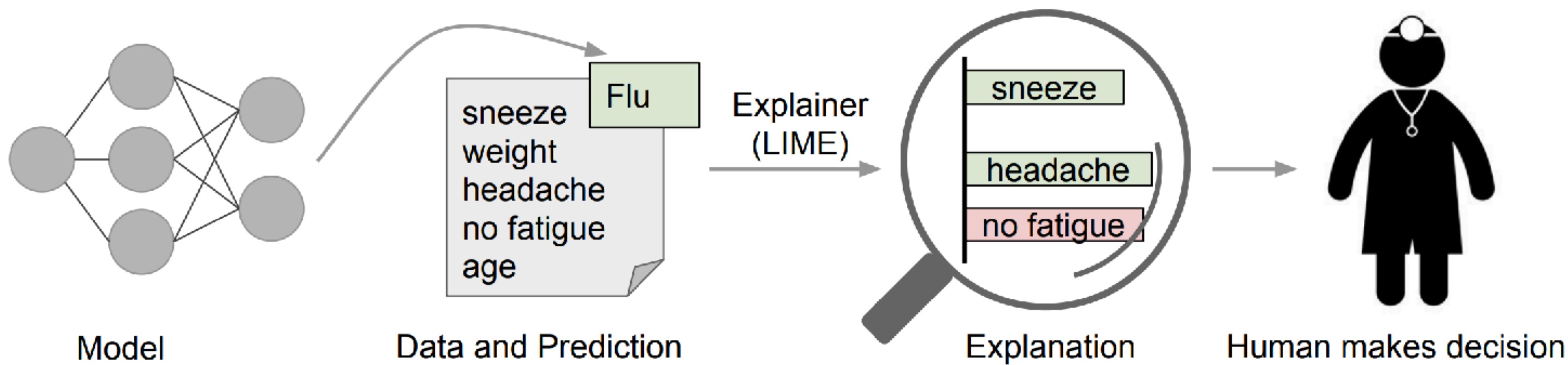
Prediction correct: 

Document

From: pauld@verdix.com (Paul Durbin)
Subject: Re: DAVID CORESH IS! GOD!
Nntp-Posting-Host: sarge.hq.verdix.com
Organization: Verdix Corp
Lines: 8

Explaining individual predictions

A model predicts that a patient has the flu, and LIME highlights the symptoms in the patient's history that led to the prediction



ML Model Monitoring

How models perform in production and rollback mechanisms

- **Model outputs and decisions:**

- What predictions our models are making given the production input data, and also which decisions are being made with those predictions.
- Sometimes the application might choose to ignore the model and make a decision based on pre-defined rules (or to avoid future bias).

ML Model Monitoring

How models perform in production and rollback mechanisms

- **User action and rewards:**
 - Based on further user action, we can capture reward metrics to understand if the model is having the desired effect.
 - For example, if we display product recommendations, we can track when the user decides to purchase the recommended product as a reward.

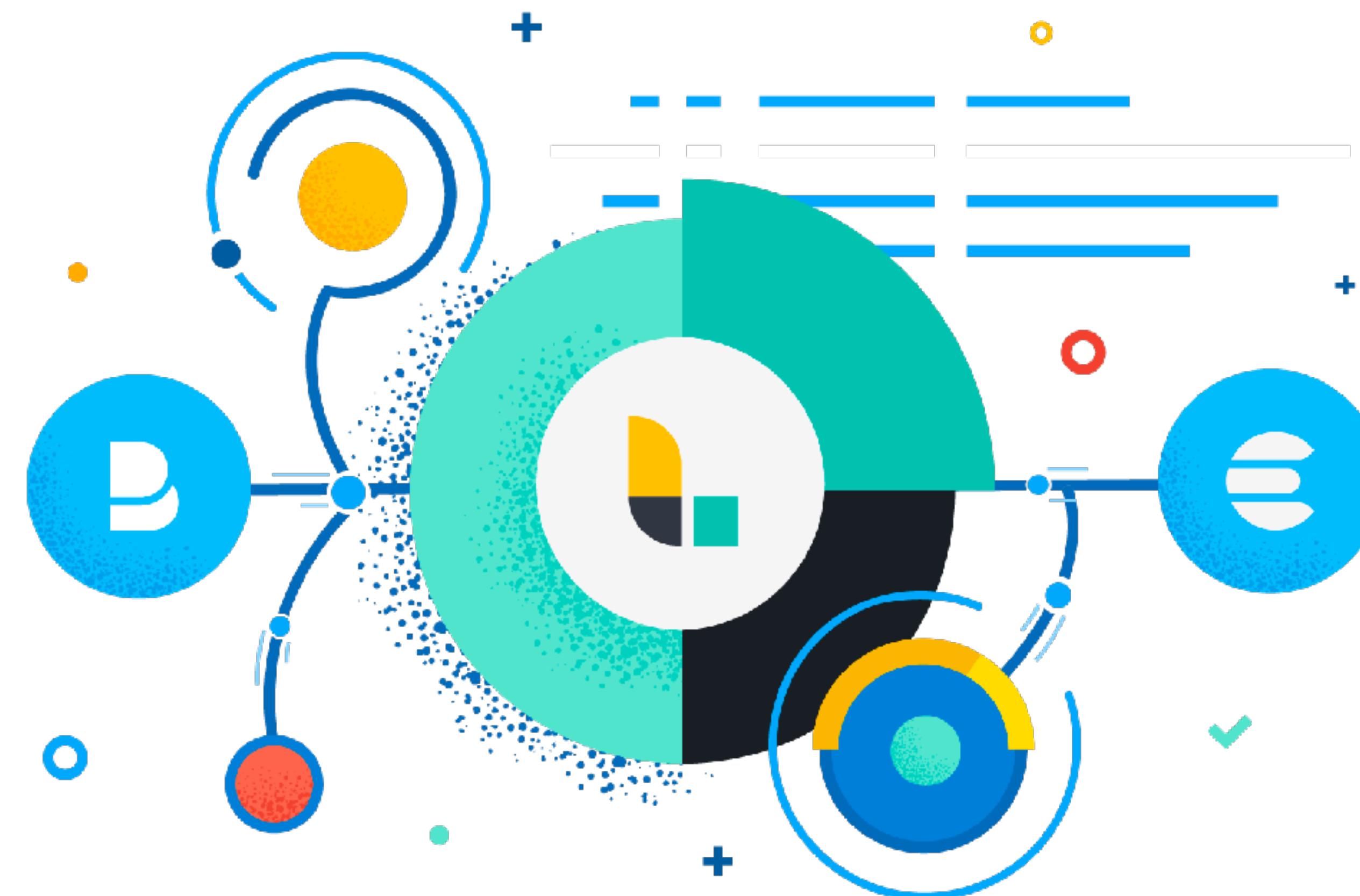
A pipeline for model monitoring

ELK

- **Elasticsearch**: an open source *search* engine.
- **Logstash**: an open source data collector for unified *logging* layer.
- **Kibana**: an open source web UI that makes it easy to explore and *visualize* the data indexed by Elasticsearch.

A pipeline for model monitoring

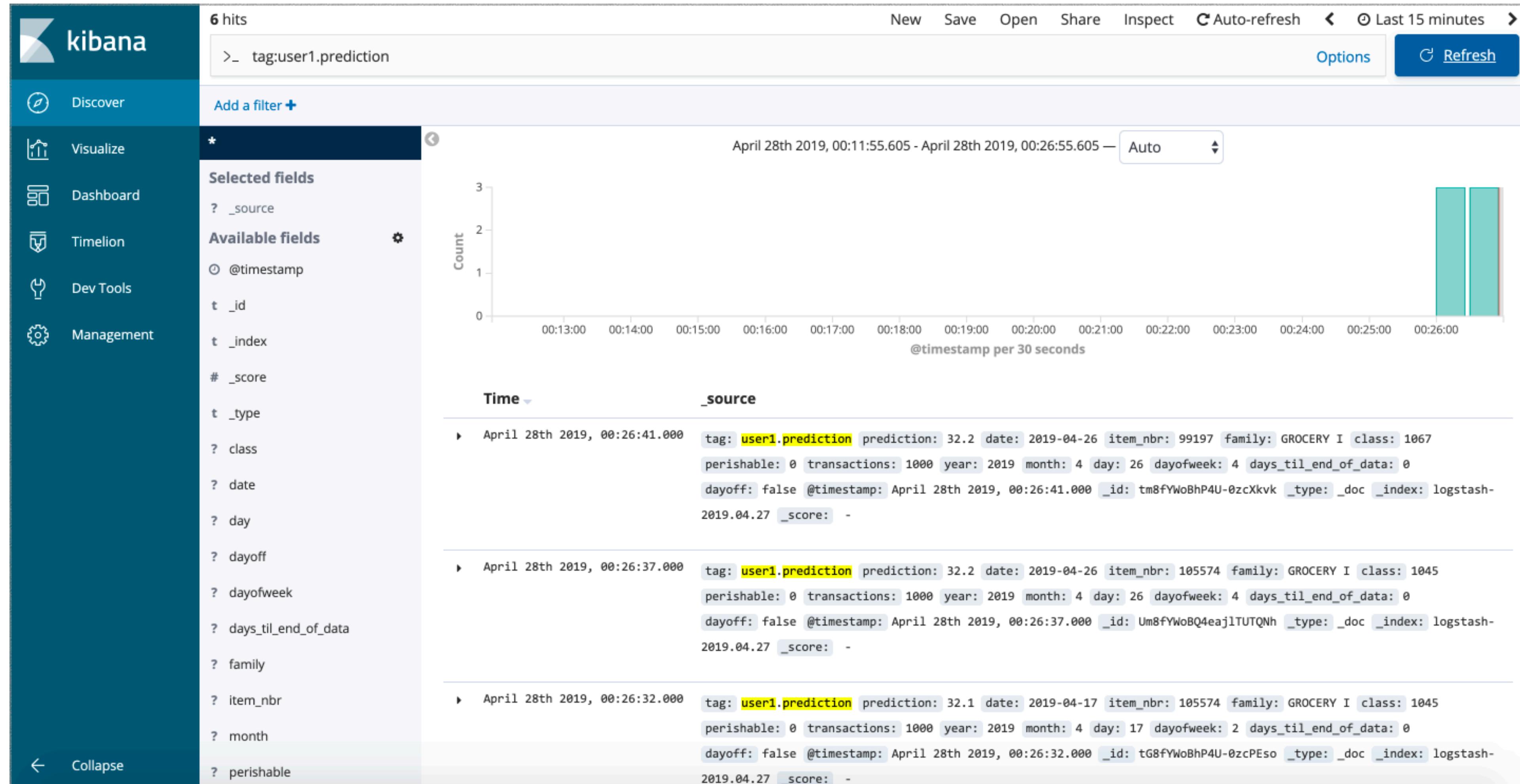
ELK



Logging

```
predict_with_logging.py...
df = pd.DataFrame(data=data, index=['row1'])
df = decision_tree.encode_categorical_columns(df)
pred = model.predict(df)
logger = sender.FluentSender(TENANT, host=FLUENTD_HOST, port=int(FLUENTD_PORT))
log_payload = {'prediction': pred[0], **data}
logger.emit('prediction', log_payload)
```

A pipeline for model monitoring



An End-to-End ML Building Process

