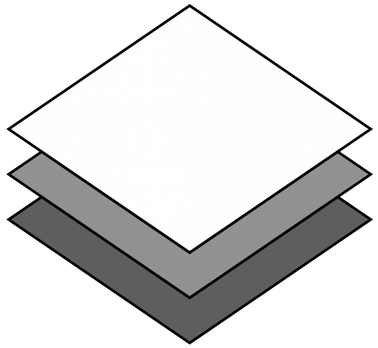


Data Management

Katherine Scott
@kscottz

One of the biggest failures I see in junior ML/CV engineers is a complete lack of interest in building data sets. While it is boring grunt work I think there is so much to be learned in putting together a dataset. It is like half the problem.

♡ 571 11:50 AM - Feb 1, 2019

mat kelcey
@mat_kelcey

for my last few ML projects the complexity hasn't been in the modelling or training; it's been in input preprocessing. find myself running out of CPU more than GPU & in one project i'm actually unsure how to optimise the python further (& am considering c++ for one piece)

♡ 130 2:01 PM - Feb 11, 2019

Vicki Boykis
@vboykis

Have been extremely curious about this for a while now, so I decided to create a poll.
"As someone titled 'data scientist' in 2019, I spend most of (60%+) my time:"
("Other") also welcome, add it in the replies.

♡ 189 8:17 AM - Jan 28, 2019

6% Picking features/models

67% Cleaning data/Moving data

4% Deploying models in prod

23% Analyzing/presenting data

2,116 votes • Final results

https://veekaybee.github.io/2019/02/13/data-science-is-different/

Data Sources → Training

- Images
- Text Corpus
- Logs
- DB records

Different for every project / company!

Local Filesystem

+

GPU

Data Sources

Training

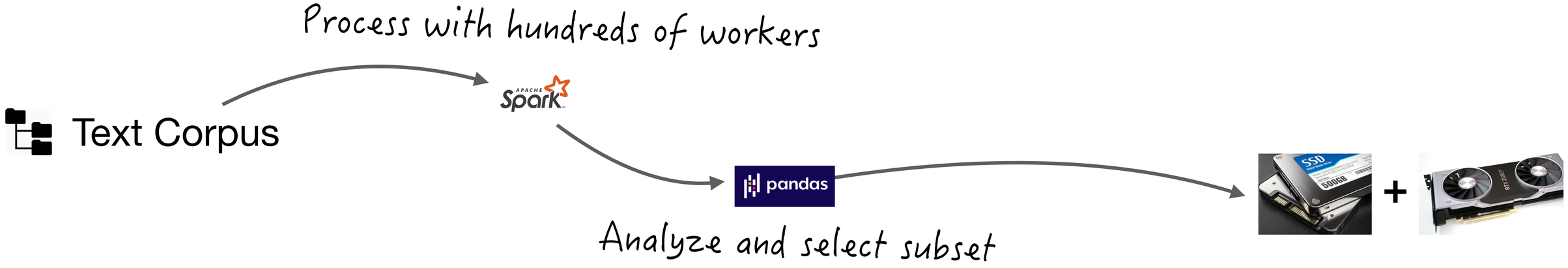
Images

Simply Download

+

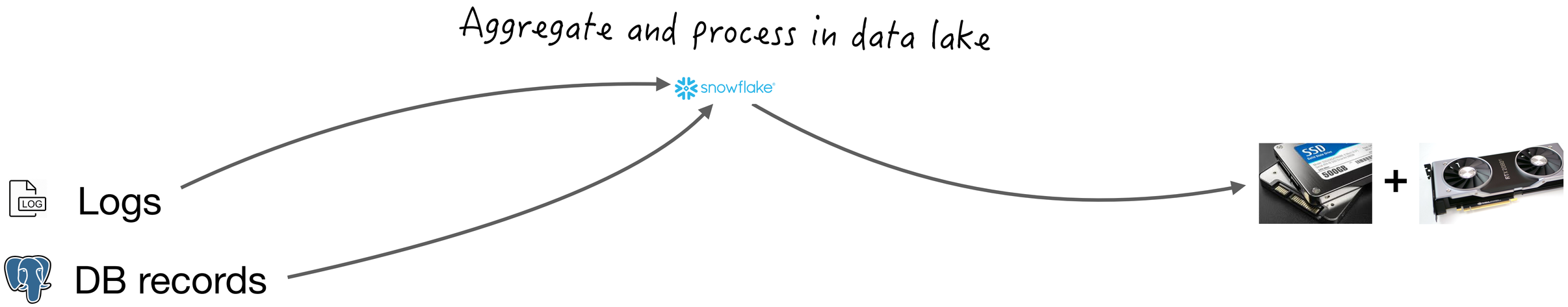
Data Sources

Training



Data Sources

Training



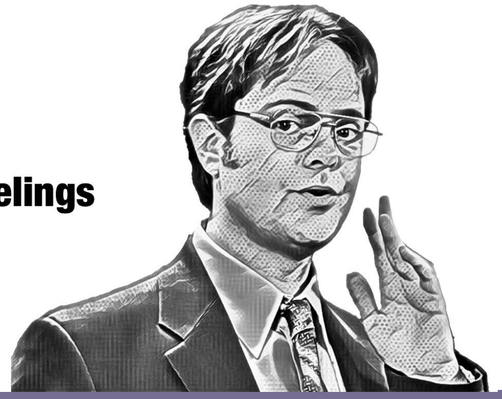
Countless possibilities

Key Points

- Spend 10x as much time exploring the data as you would like to
- Adding/augmenting data is the best way to improve performance
- KISS

Keep It Simple Stupid

“Great advice. Hurts my feelings every time.” - Dwight



Amazon SageMaker | gradient by Paperspace | FLOYD | DOMINO DATA LAB

"All-in-one"

Data

- Versioning: Pachyderm, DVC, LIQUIDATA
- Labeling: figure eight, scale, Label Studio, Aquarium
- Processing: Spark, DAGSTER, dbt
- Exploration: pandas, RAPIDS, DASK
- Data Lake / Warehouse: snowflake, databricks
- Sources: S3, LOG, Parquet

Training/Evaluation

- Frameworks & Distributed Training: fast.ai, PYTORCH, RAY, HOROVOD, K
- Hyperparameter Tuning: SIGOPT, Determined AI, Weights & Biases, tune
- Experiment Management: Weights & Biases, comet, TensorBoard, Neptune Machine Learning Lab, mlflow
- Resource Management: Determined AI, PY, slurm workload manager
- Software Engineering: jupyter, Streamlit, git
- Compute: CoreWeave, Lambda

Deployment

- Feature Store: tecton
- Monitoring: fiddler
- Edge: ML, OctoML, NVIDIA TensorRT, TensorFlow Lite, ONNX
- Web: ALGORITHMIA, SELDON
- CI / Testing: Buildkite, great_expectations

or | or

Amazon SageMaker · gradient by Paperspace · FLOYD · DOMINO DATA LAB

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- or · or

Sources

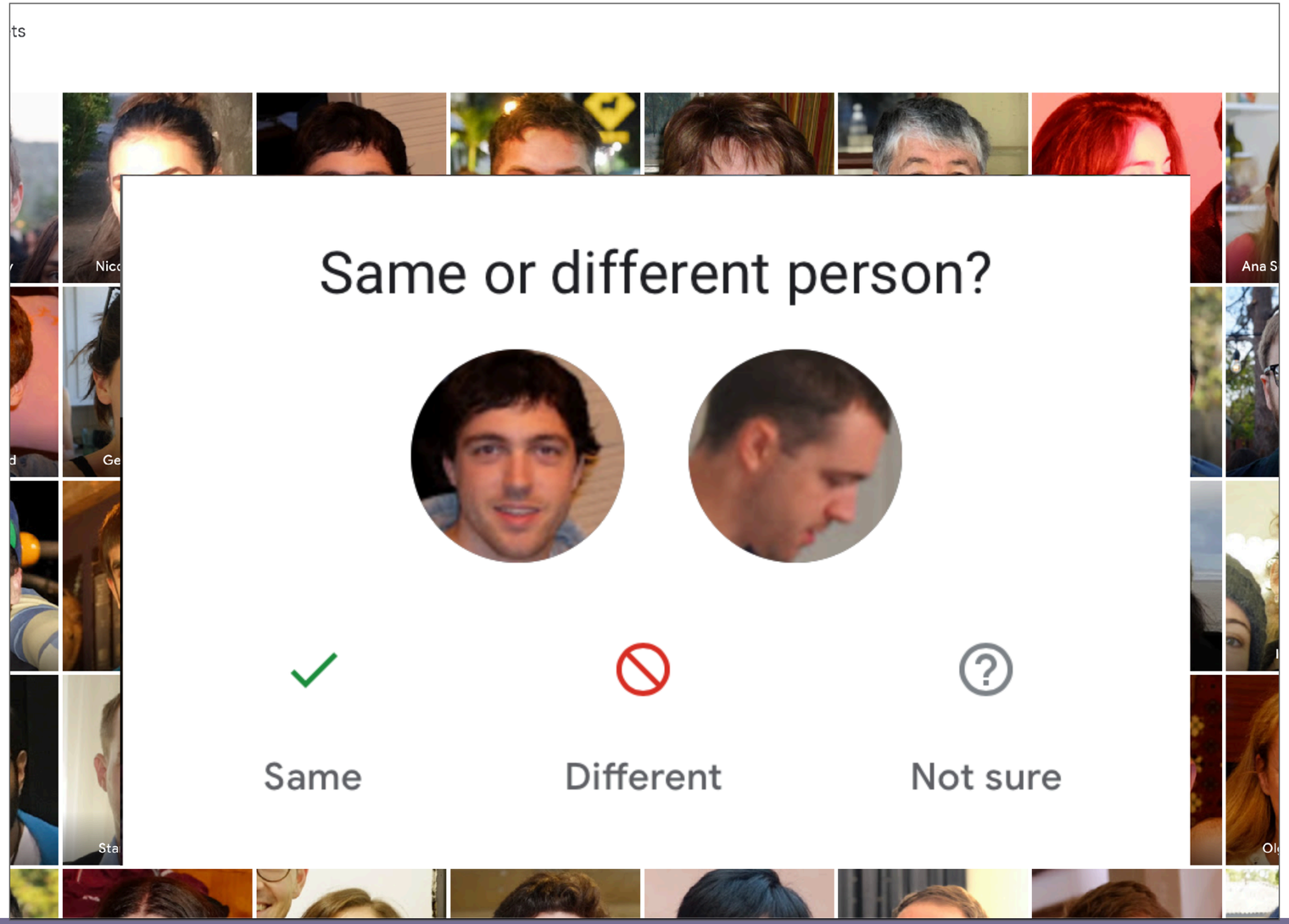
- Most DL applications require lots of proprietary data
  - Exceptions: RL, GANs, GPT-3
- Publicly available datasets = No competitive advantage
  - But can serve as starting point

Usually: spend $$$ and time to label own data

https://cdn-sv1.deepsense.ai/wp-content/uploads/2017/04/sample_image_from_the_training_set.jpg

Data flywheel

Enables rapid improvement with user labels



Semi-supervised learning

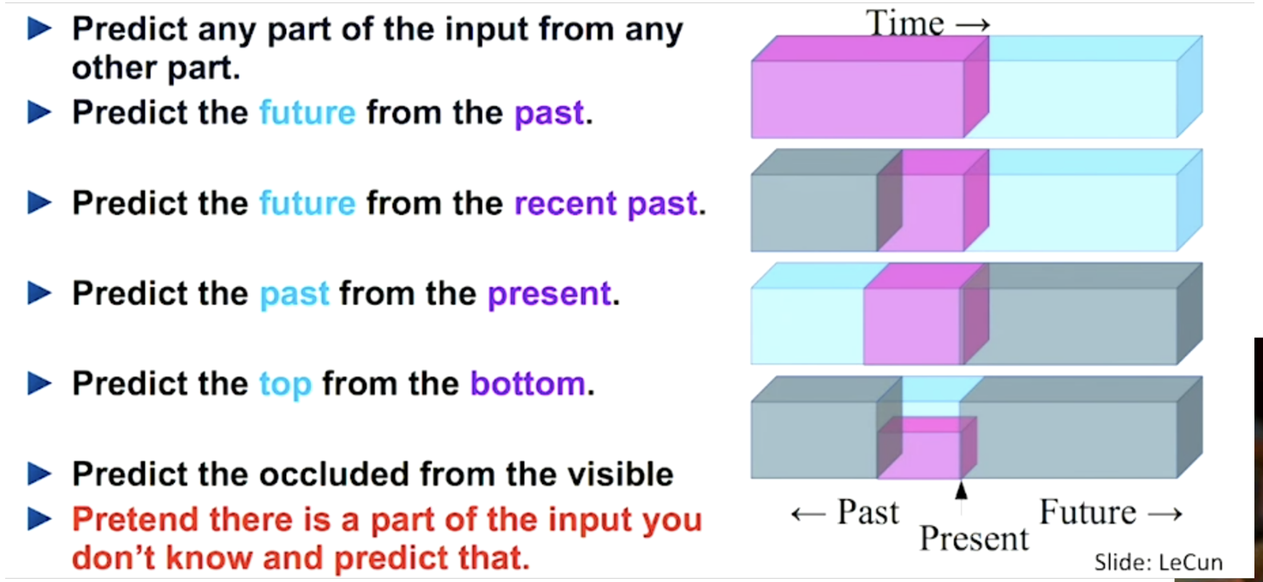


Fig. 1. A great summary of how self-supervised learning tasks can be constructed (Image source: LeCun's talk)

Use parts of data to label other parts

Very important idea!

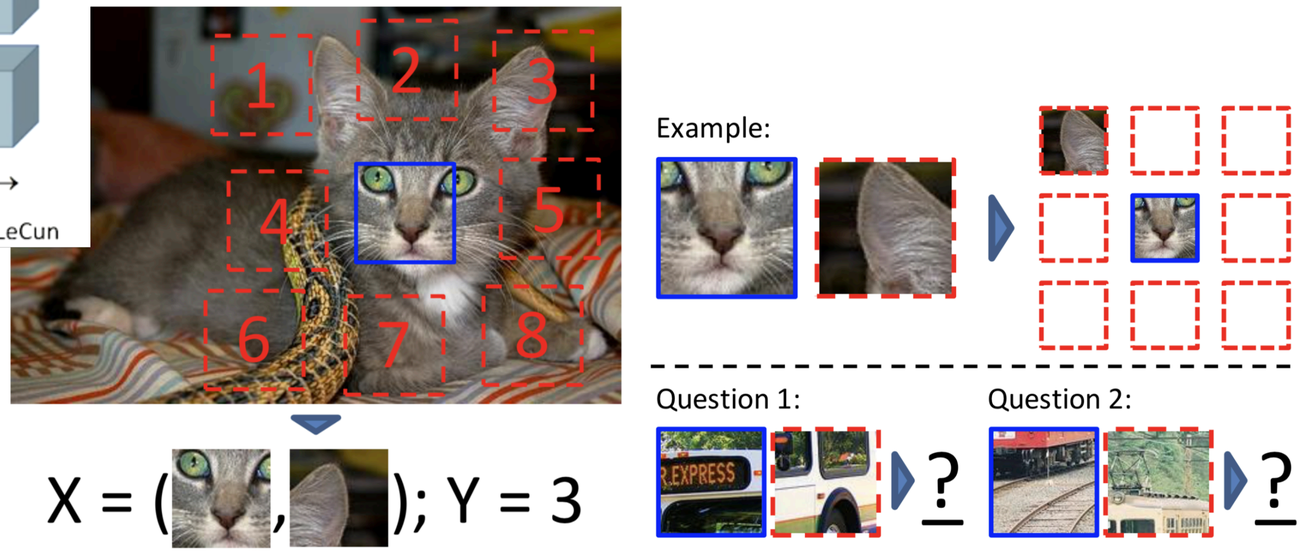


Fig. 4. Illustration of self-supervised learning by predicting the relative position of two random patches. (Image source: Doersch et al., 2015)

https://ai.facebook.com/blog/self-supervised-learning-the-dark-matter-of-intelligence

https://lilianweng.github.io/lil-log/2019/11/10/self-supervised-learning.html

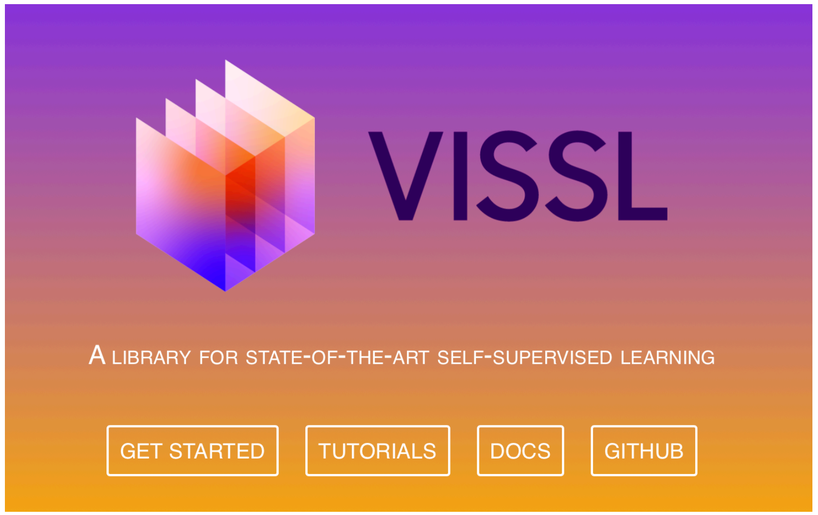
Semi-supervised learning

RESEARCH | COMPUTER VISION

SEER: The start of a more powerful, flexible, and accessible era for computer vision

March 4, 2021

- Trained on 1B random images
- Achieved SOTA accuracy on ImageNet top-1 prediction
- Open-source library



https://ai.facebook.com/blog/seer-the-start-of-a-more-powerful-flexible-and-accessible-era-for-computer-vision

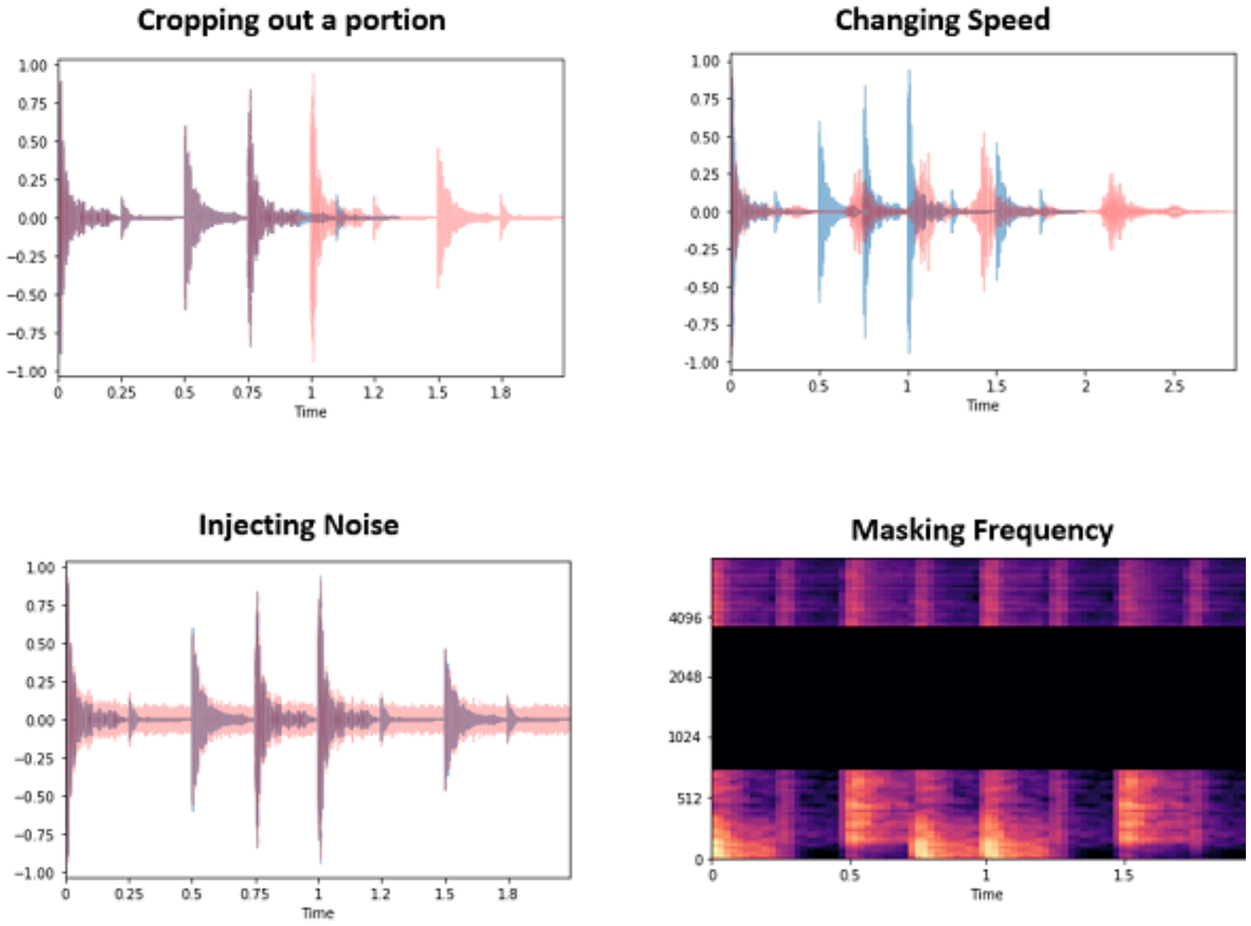
Image data augmentation

- **Must do** for training vision models
- Frameworks (e.g. torchvision) provide functions that do this
- Done in parallel to GPU training on the CPU

https://towardsdatascience.com/1000x-faster-data-augmentation-b91bafee896c

Other data augmentation

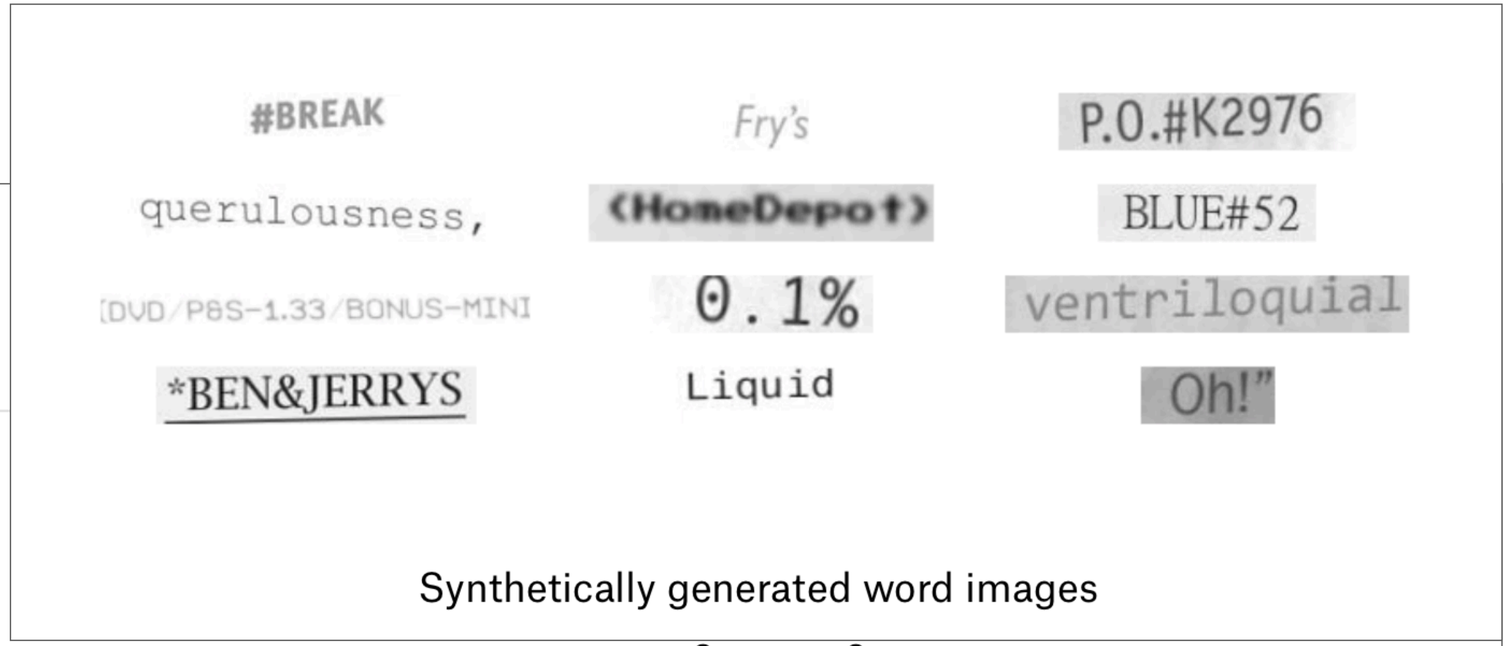
- Tabular
  - Delete some cells to simulate missing data
- Text
  - No well established techniques, but replace words with synonyms, change order of things.
- Speech/video
  - Change speed, inserts pauses, etc



https://github.com/makcedward/nlpaug

Synthetic data

Underrated idea that is often worth starting with



Synthetically generated word images

Dropbox

Creating a Modern OCR Pipeline Using Computer Vision and Deep Learning

Brad Neuberg | April 12, 2017

728 0

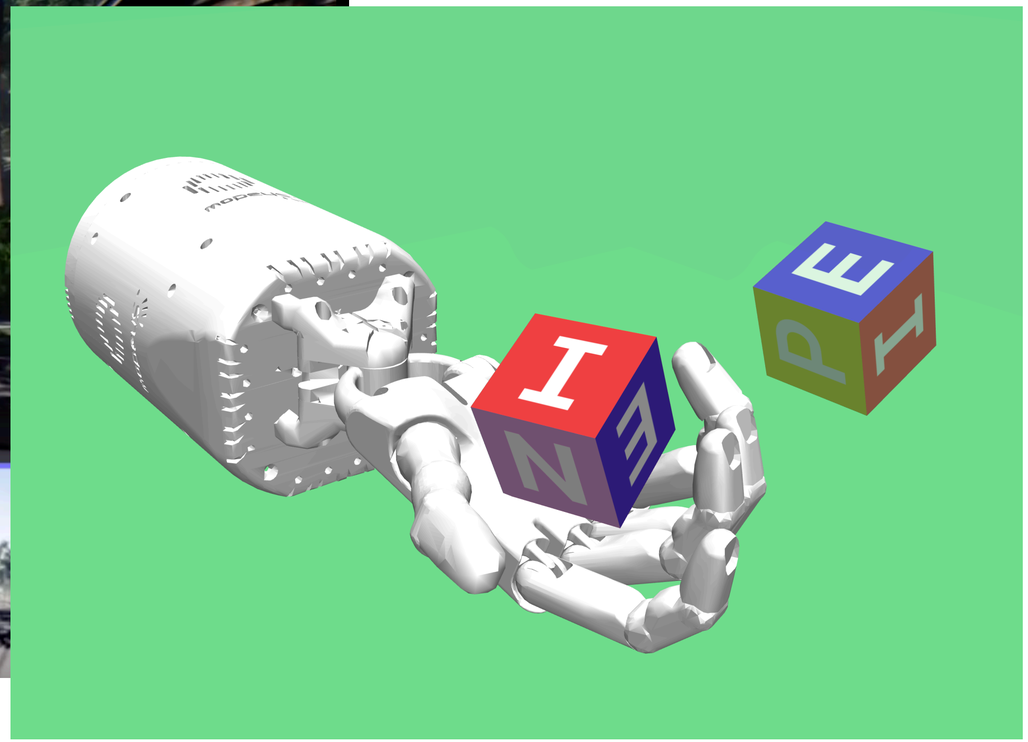
https://blogs.dropbox.com/tech/2017/04/creating-a-modern-ocr-pipeline-using-computer-vision-and-deep-learning/

This can get pretty deep!

- Receipt crinkliness
- Receipt curvature
- Receipt alignment with camera
- Receipt ink fadedness
- Receipt paper glossiness
- Table material
- Camera flash
- Camera location
- Camera direction
- Camera exposure
- Camera focal distance
- Camera aperature size
- Environment ambient brightness
- Primary light location

Andrew Moffat - https://github.com/amoffat/metabrite-receipt-tests

Especially for driving and robotics



https://microsoft.github.io/AirSim/

https://openai.com/blog/ingredients-for-robotics-research/

Questions?

Data Storage

1. Building blocks

    - Filesystem

    - Object Storage

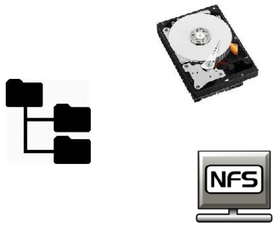
    - Database

    - Data Lake / Data Warehouse

2. What goes where

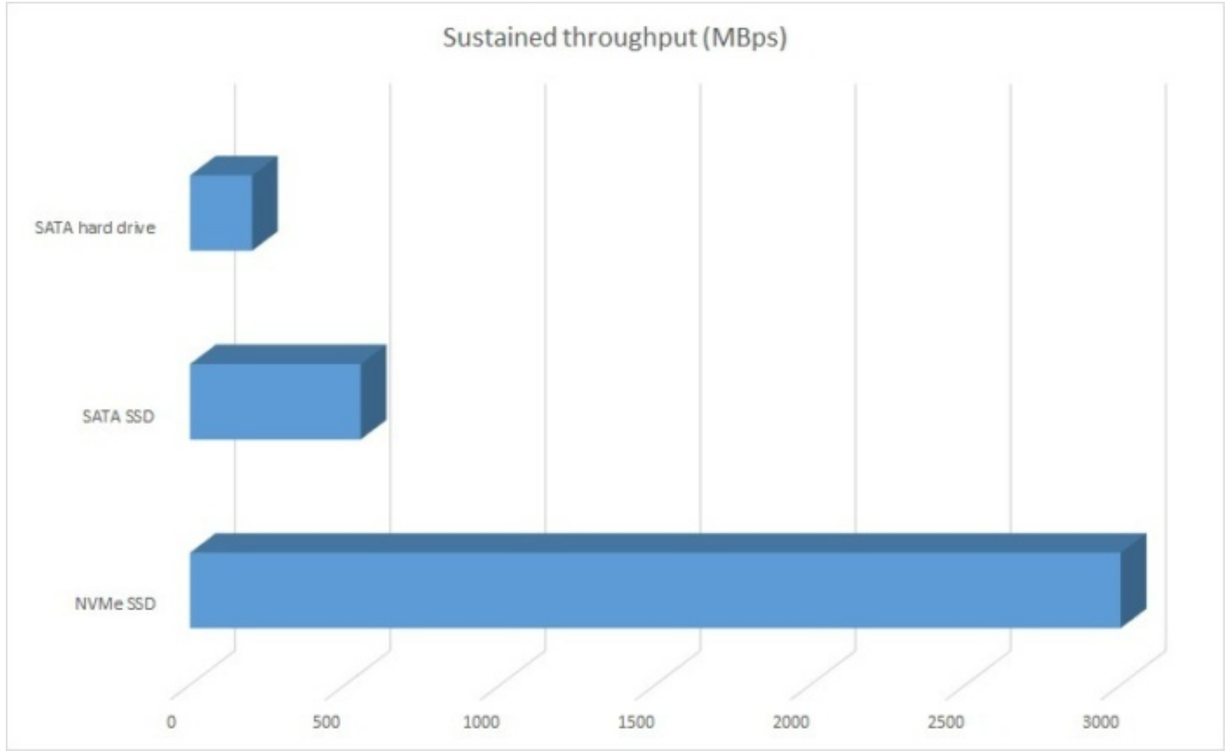
3. Where to learn more

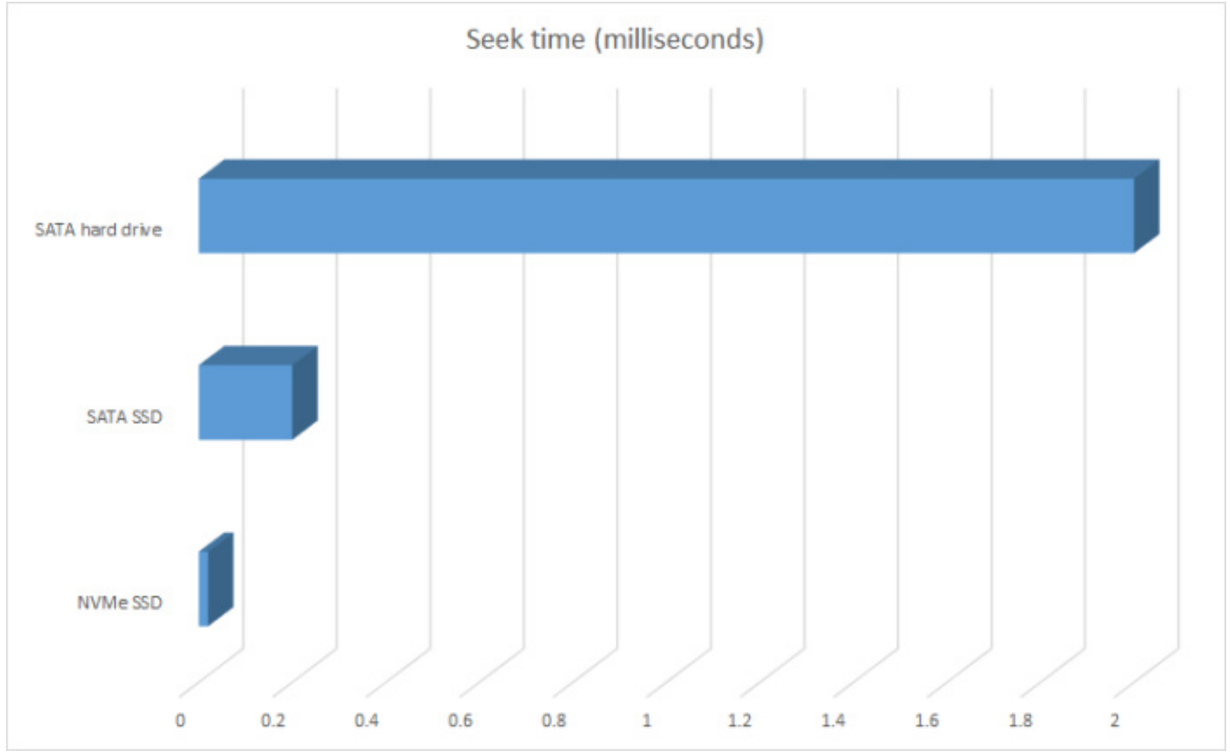
Filesystem



- Foundational layer of storage.
- Fundamental unit is a "file", which can be text or binary, is not versioned, and is easily overwritten.
- Can be as simple as a locally mounted disk containing all the files you need.
- Can be networked (e.g. NFS): accessible over network by multiple machines.
- Can be distributed (e.g. HDFS): stored and accessed over multiple machines
- Fastest option

Hard Drive Speeds





https://www.pcworld.com/article/2899351/everything-you-need-to-know-about-nvme.html

Local Data Format

- Binary data: just files
  - TFRecord batches files -- doesn't seem necessary with NVMe drives
- For large tabular / text data, have choices:
  - HDF5 is powerful, but bloated and declining
  - Parquet is widespread and recommended
  - Feather is powered by Apache Arrow, up-and-coming
- Try to use native Tensorflow and PyTorch dataset classes

Object Storage

- An API over the filesystem. GET, PUT, DELETE files to a service, without worrying where they are actually stored.
- Fundamental unit is an "object". Usually binary: image, sound file, etc.
- Versioning, redundancy can be built into the service.
- Not as fast as local, but fast enough within the cloud

	S3	HDFS	S3 vs HDFS
Elasticity	Yes	No	S3 is more elastic
Cost/TB/month	$23	$206	10X
Availability	99.99%	99.9% (estimated)	10X
Durability	99.999999999%	99.9999% (estimated)	10X+
Transactional writes	Yes with DBIO	Yes	Comparable

Database

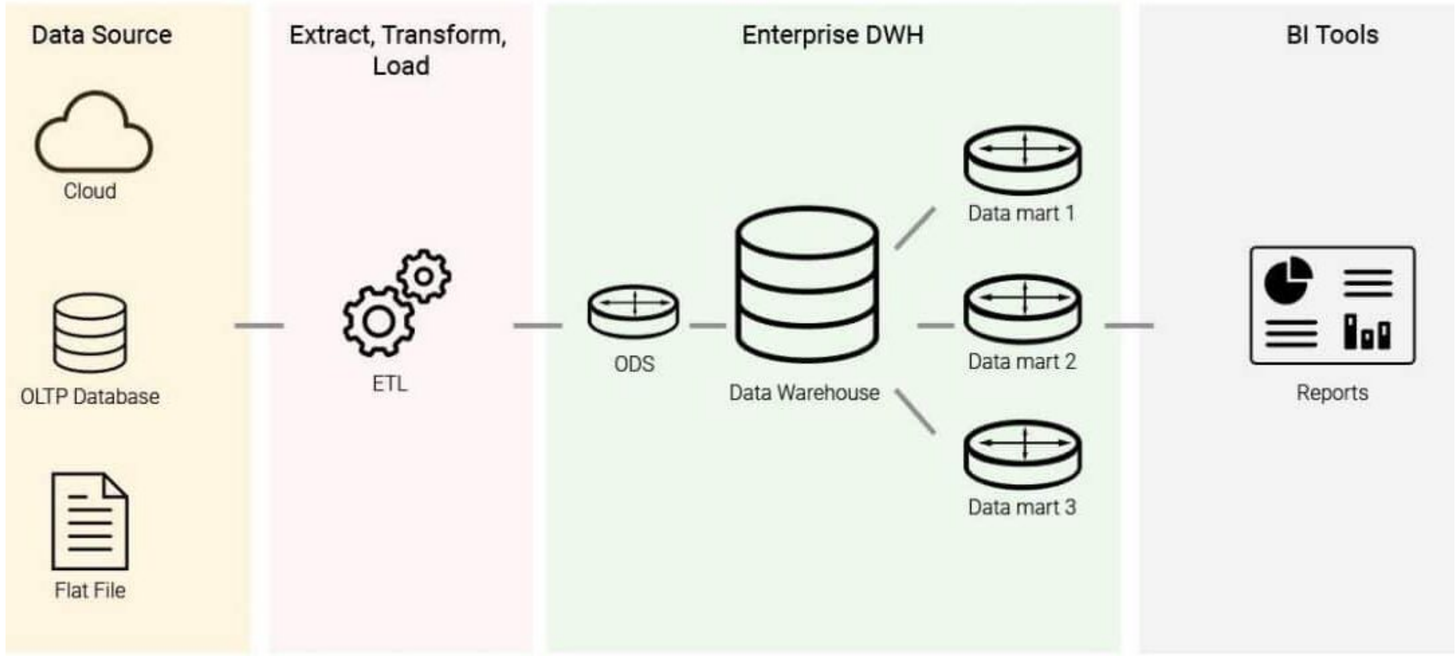


- Persistent, fast, scalable storage and retrieval of structured data that will be accessed repeatedly.
- AKA Online **Transaction** Processing (OLTP)
- Mental model: everything is actually in RAM, but software ensures that everything is logged to disk and never lost.
- Not for binary data! Store references instead.
- Postgres is the right choice most of the time. Supports unstructured JSON.
    - SQLite is perfectly good for small projects.
- "NoSQL" was a big craze in 2010's. Mostly avoid.
    - Redis is very useful when you need a simple key-value store.

Data Warehouse

- Structured aggregation of data for analysis
- AKA Online **Analytical** Processing (OLAP)
- Another acronym: ETL

Google Cloud BigQuery snowflake amazon REDSHIFT



https://addepto.com/implement-data-warehouse-business-intelligence/

SQL and DataFrames

- Most data solutions use SQL. Some, like Databricks, use DataFrames.
- SQL is the standard interface for structured data.
- Pandas is the main DataFrame in the Python ecosystem.
- Our advice: become fluent in both

In SQL, selection is done using a comma-separated list of columns you'd like to select (or a * to select all columns):

```
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With pandas, column selection is done by passing a list of column names to your DataFrame:

```
In [6]: tips[["total_bill", "tip", "smoker", "time"]].head(5)
Out[6]:
   total_bill   tip smoker    time
0       16.99  1.01     No  Dinner
1       10.34  1.66     No  Dinner
2       21.01  3.50     No  Dinner
3       23.68  3.31     No  Dinner
4       24.59  3.61     No  Dinner
```

Grouping by more than one column is done by passing a list of columns to the `groupby()` method.

```
SELECT smoker, day, COUNT(*), AVG(tip)
FROM tips
GROUP BY smoker, day;
/*
smoker day
No     Fri      4  2.812500
       Sat     45  3.102889
       Sun     57  3.167895
       Thur    45  2.673778
Yes    Fri     15  2.714000
       Sat     42  2.875476
       Sun     19  3.516842
       Thur    17  3.030000
*/
```

```
In [22]: tips.groupby(["smoker", "day"]).agg({"tip": [np.size, np.mean]})
Out[22]:
              tip
             size      mean
smoker day
No     Fri    4.0  2.812500
       Sat   45.0  3.102889
       Sun   57.0  3.167895
       Thur  45.0  2.673778
Yes    Fri   15.0  2.714000
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       Sun   19.0  3.516842
       Thur  17.0  3.030000
```
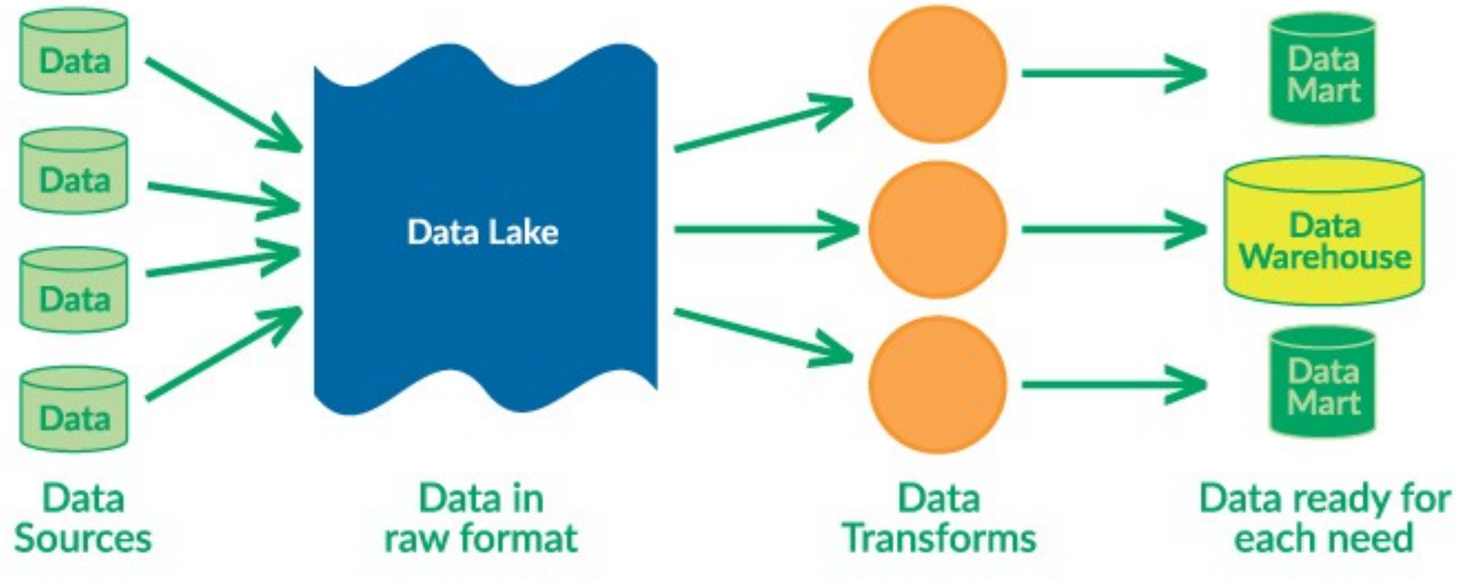

https://pandas.pydata.org/docs/getting_started/comparison/comparison_with_sql.html

Data Lake

- Unstructured aggregation of data from multiple sources, e.g. databases, logs, expensive data transformations.

- ELT: dump everything in, then transform for specific needs later.

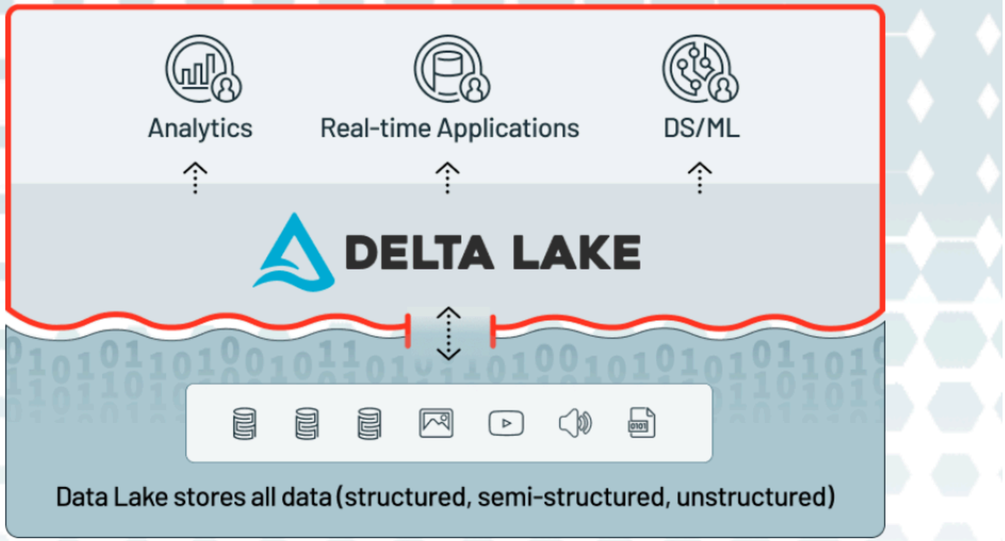


https://medium.com/data-ops/throw-your-data-in-a-lake-32cd21b6de02

Trend: Lake House

The Databricks Lakehouse Platform

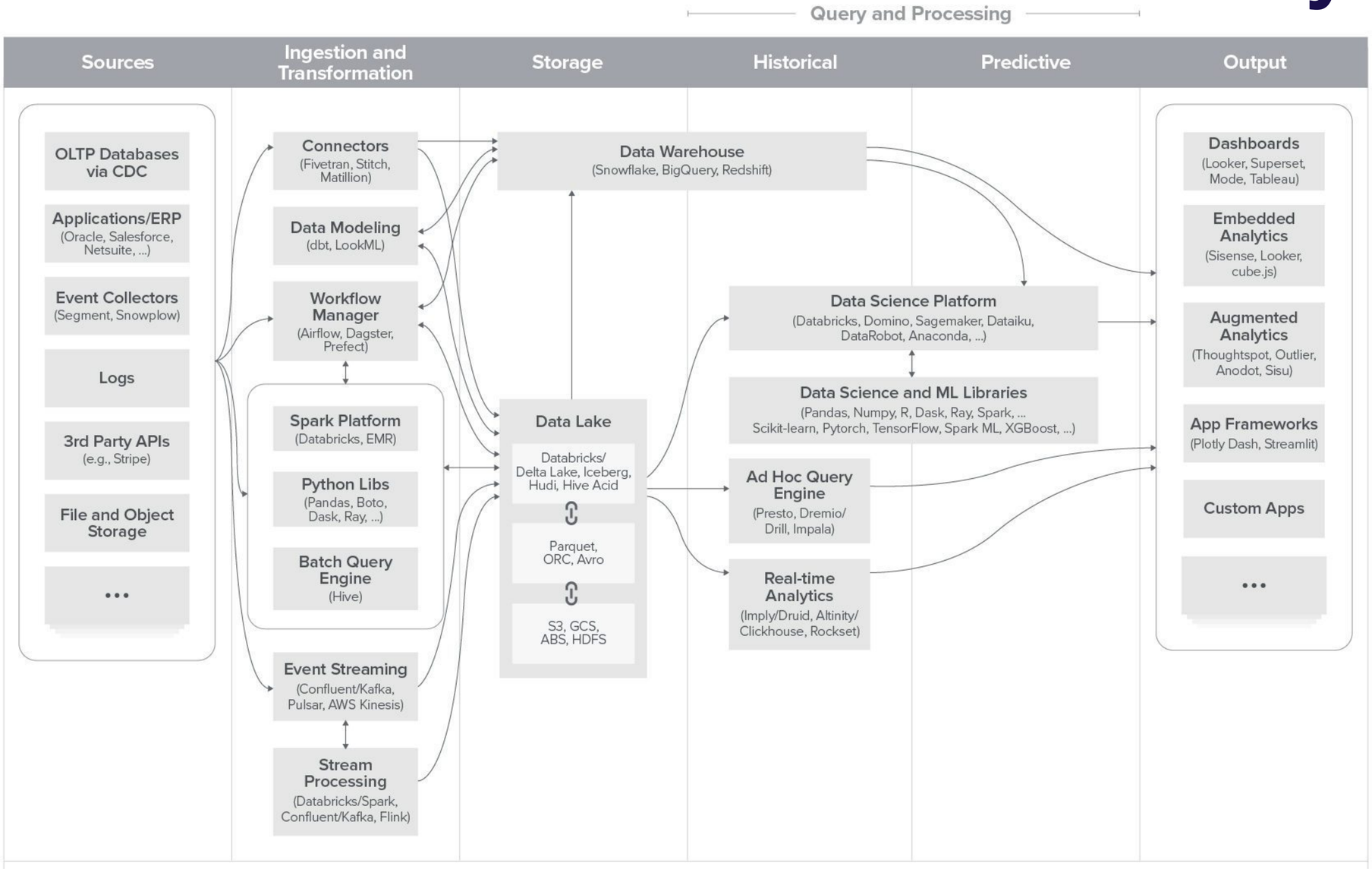
One open, simple platform to store and manage all of your data for all of your analytics workloads



For now

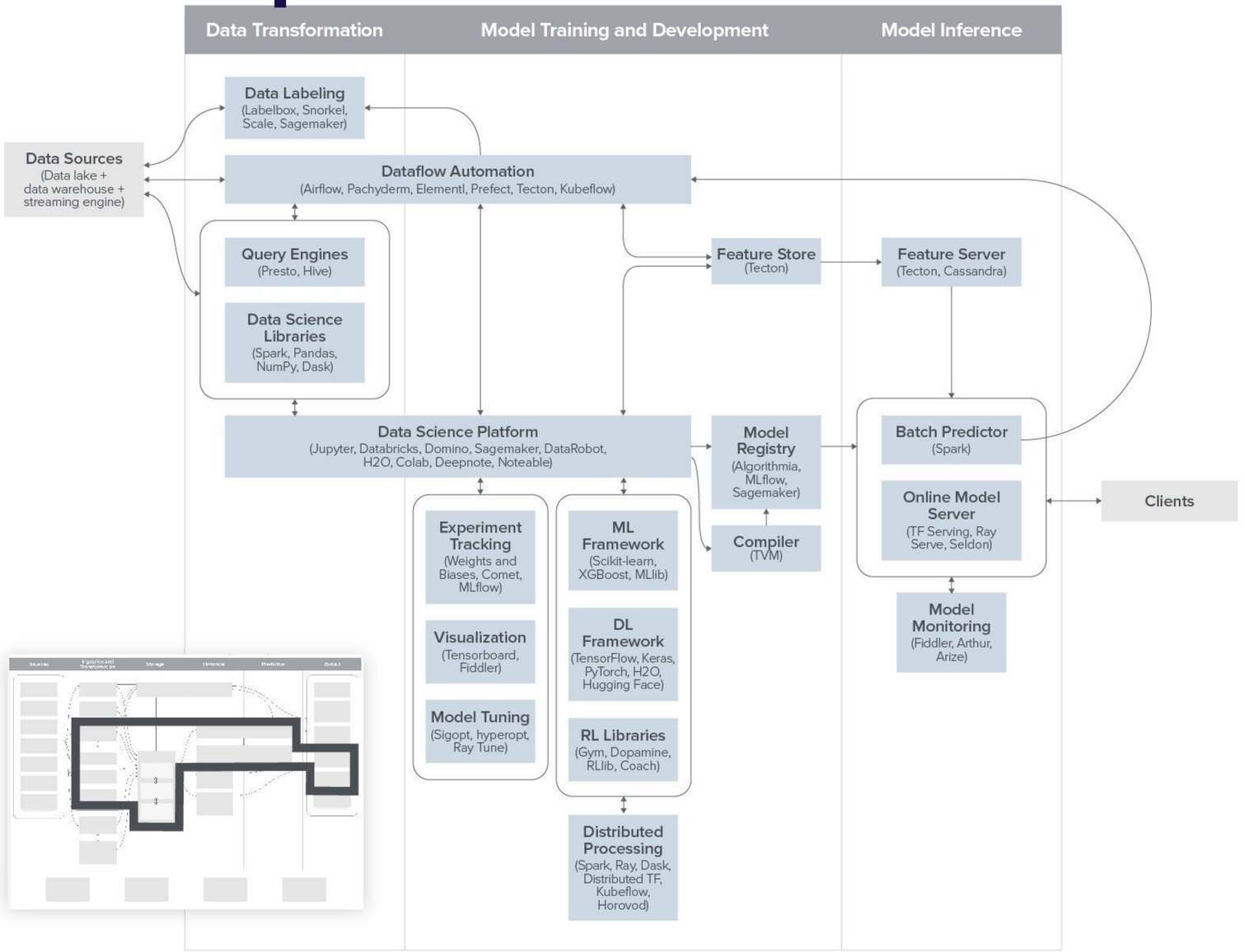
- **Binary data** (images, sound files, compressed texts) is stored as **objects**.
- **Metadata** (labels, user activity) is stored in **database**.
- If need features which are not obtainable from database (e.g logs), set up **data lake** and a process to aggregate needed data.
- At **training time**, copy the data that is needed to a **filesystem** on a fast drive.

There's a lot more to the story



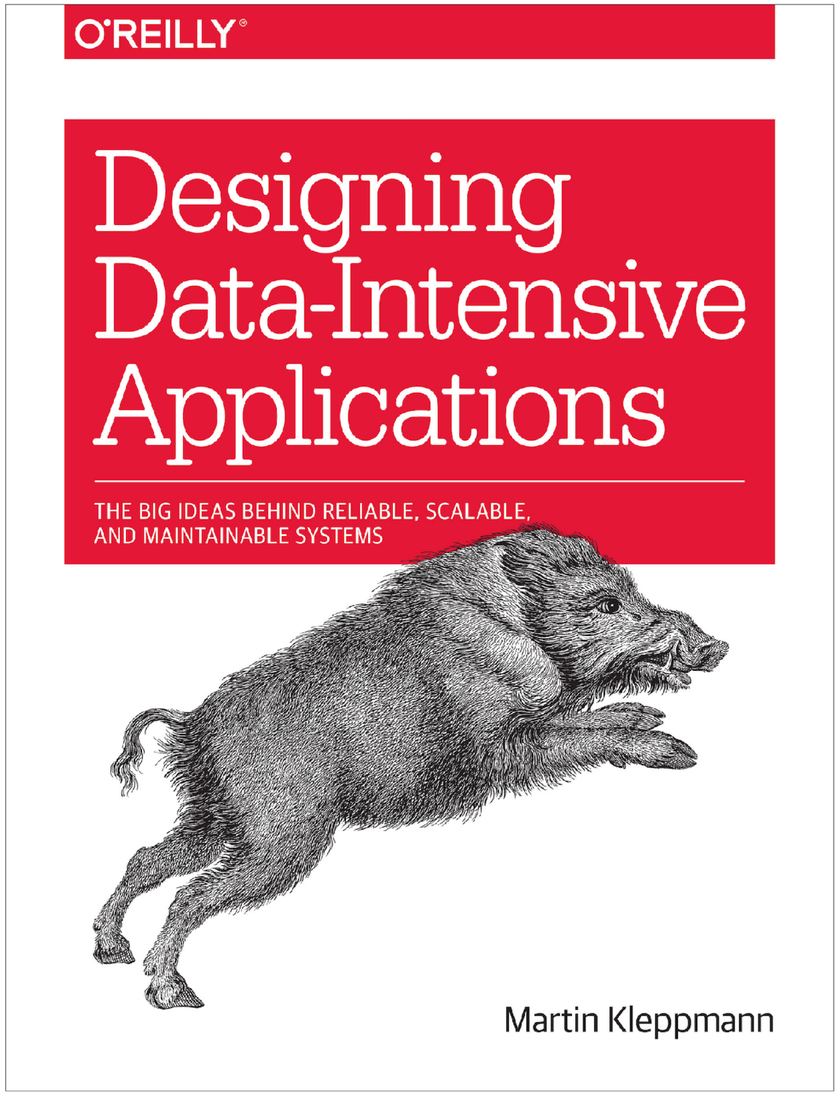
https://a16z.com/2020/10/15/the-emerging-architectures-for-modern-data-infrastructure/

Blueprint for AI and ML



https://a16z.com/2020/10/15/the-emerging-architectures-for-modern-data-infrastructure/

If you're truly interested



Don't just hack it together

NoSQL… Big Data… Scalability… CAP Theorem… Eventual Consistency… Sharding…

Nice buzzwords, but how does the stuff actually *work*?

https://dataintensive.net

Questions?

Amazon SageMaker · gradient by Paperspace · FLOYD · DOMINO DATA LAB

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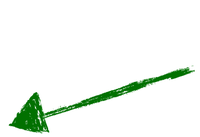
or or

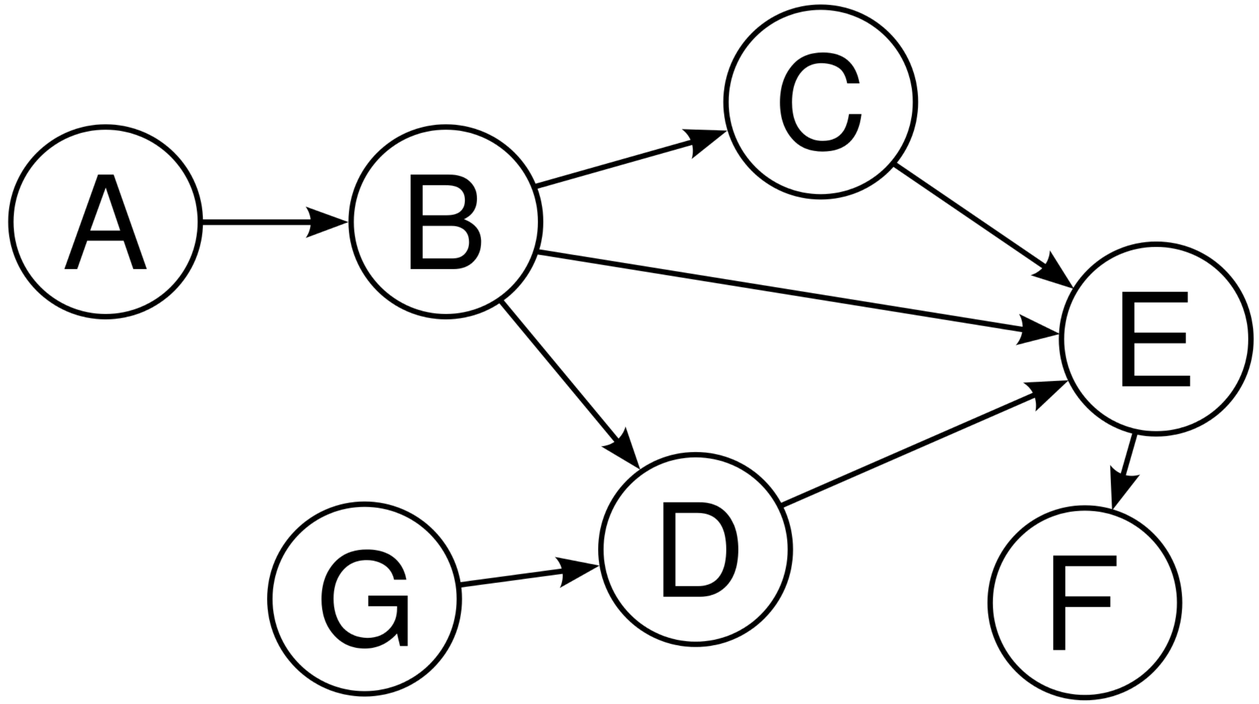
Motivational Example

- We have to train a photo popularity predictor every night.
- For each photo, training data must include:
  - Metadata such as posting time, title, location
  - Some features of the user, such as how many times they logged in today.
  - Outputs of photo classifiers (content, style)



Task Dependencies

- Some tasks can't be started until other tasks are finished.
- Finishing a task should "kick off" its dependencies

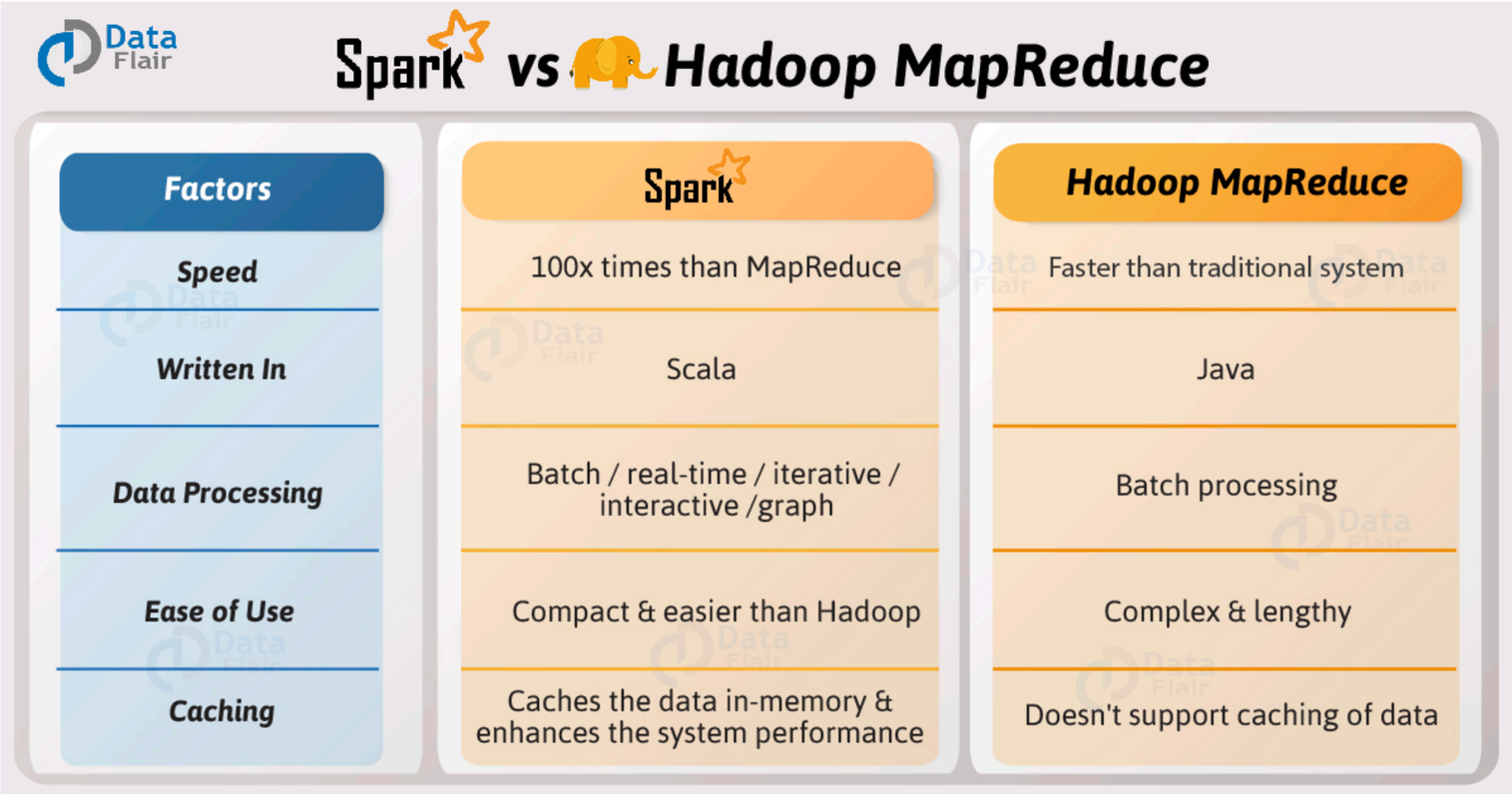


Desiderata

- Re-computation should depend on content
- Dependencies are not files, but programs and databases
- Work needs to be spread over many machines
- Many dependency graphs are executing all at once

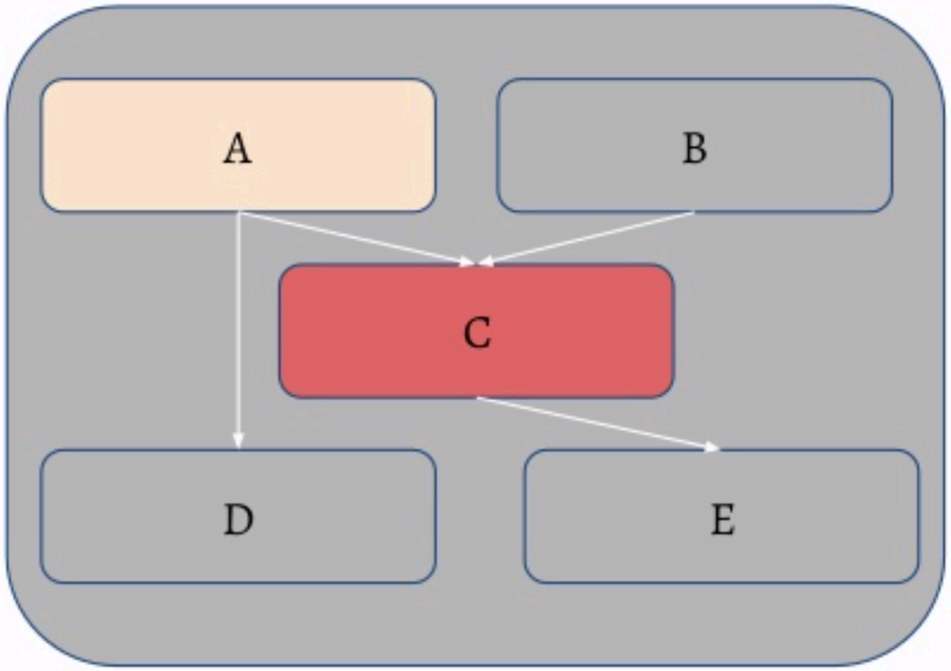
Hadoop/Spark

- Map/Reduce implementations
- Running data processing operations and simple ML on commodity hardware, with tricks to speed things up



https://data-flair.training/blogs/spark-vs-hadoop-mapreduce/

Airflow

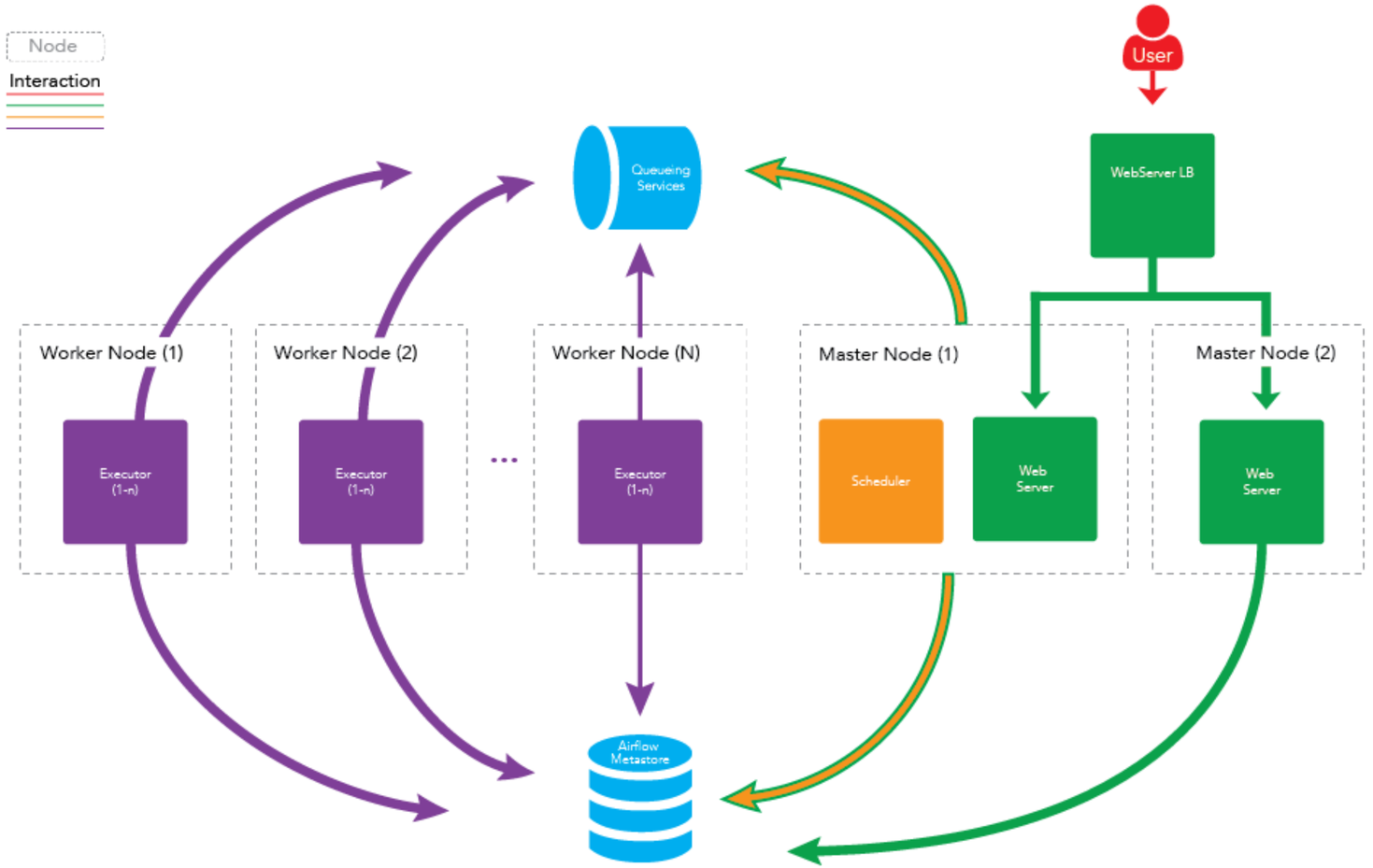



```
# Airflow
dag = DAG(schedule_interval=
              timedelta(days=1),
            start_date=
              datetime(2015,10,6))

a =  PythonOperator(
          task_id="A",
          python_callable=ClassA,
          dag=dag)
c =  MySQLOperator(
          task_id="B",
          sql="DROP TABLE hello",
          dag=dag)

c.set_upstream(a)
```

https://www.slideshare.net/PyData/how-i-learned-to-time-travel-or-data-pipelining-and-scheduling-with-airflow-67650418

Distributing work

- The workflow manager has a queue for the tasks, and manages workers that pull from it, restarting jobs if they fail.



http://site.clairvoyantsoft.com/making-apache-airflow-highly-available/

Tensorflow Datasets + Apache Beam

For example, the 7TB Colossal Clean Corpus

TensorFlow > Resources > Datasets > Guide

Generating big datasets with Apache Beam

Some datasets are too big to be processed on a single machine. `tfds` supports generating data across many machines by using Apache Beam.

This doc has two sections:

- For user who want to generate an existing Beam dataset
- For developers who want to create a new Beam dataset

Generating a Beam dataset

Below are different examples of generating a Beam dataset, both on the cloud or locally.

Warning: When generating the dataset with the **`tfds build`** CLI, make sure to specify the dataset config you want to generate or it will default to generate all existing configs. For example, for wikipedia, use **`tfds build wikipedia/20200301.en`** instead of **`tfds build wikipedia`**.

On Google Cloud Dataflow

To run the pipeline using Google Cloud Dataflow and take advantage of distributed computation, first follow the Quickstart instructions.

Once your environment is set up, you can run the `tfds build` CLI using a data directory on GCS and specifying the required options for the `--beam_pipeline_options` flag.

https://www.tensorflow.org/datasets/beam_datasets

Prefect

```python
from prefect import task, Flow

@task
def say_hello():
    print("Hello, world!")


with Flow("My First Flow") as flow:
    say_hello()


flow.run() # "Hello, world!"
```

PREFECTCORE

Focus on Your Code

Use a flexible Python framework to easily combine tasks into workflows, then deploy, schedule, and monitor their execution through the Prefect UI or API.

LEARN MORE | CORE DOCS

Execution in Your Cloud; Orchestration in Ours

STEP 01 – CORE

Build Your Flow

Design and test your workflow with our open-source Prefect Core framework.

STEP 02 – CLOUD

Register Your Flow

Send metadata (but never code!) to Prefect Cloud in order to register your flow for scheduling and execution.

STEP 03 – CORE

Run the Flow

Flow runs are executed on your private infrastructure, keeping data secure. State updates are sent to Cloud as metadata.

STEP 04 – CLOUD

Monitor and Manage

Use the Cloud UI to monitor all of your flows, no matter where or how often they run.

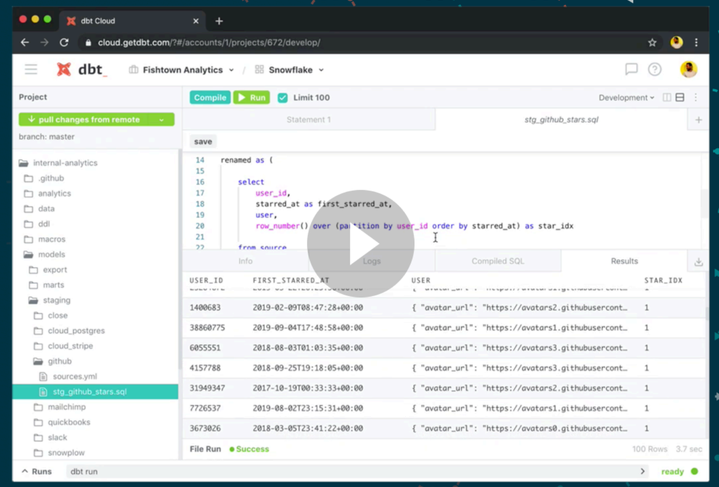
dbt

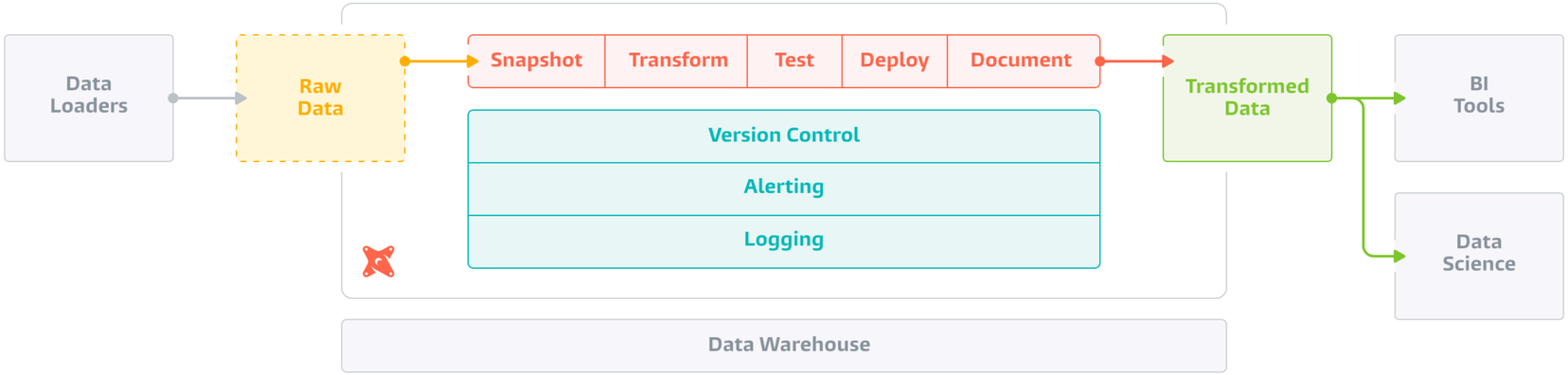
Your entire analytics engineering workflow

Analytics engineering is the data transformation work that happens between loading data into your warehouse and analyzing it. dbt allows anyone comfortable with SQL to own that workflow.

Sign Up

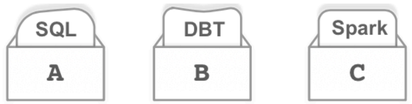
Learn More >





Dagster

Dagster is a data orchestrator for machine learning, analytics, and ETL



Implement components in any tool, such as Pandas, Spark, SQL, or DBT.

Define your pipelines in terms of the data flow between reusable, logical components.

Test locally and run anywhere with a unified view of data pipelines and assets.

Amazon SageMaker · gradient by Paperspace · FLOYD · DOMINO DATA LAB

"All-in-one"

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- Exploration: pandas, RAPIDS, DASK
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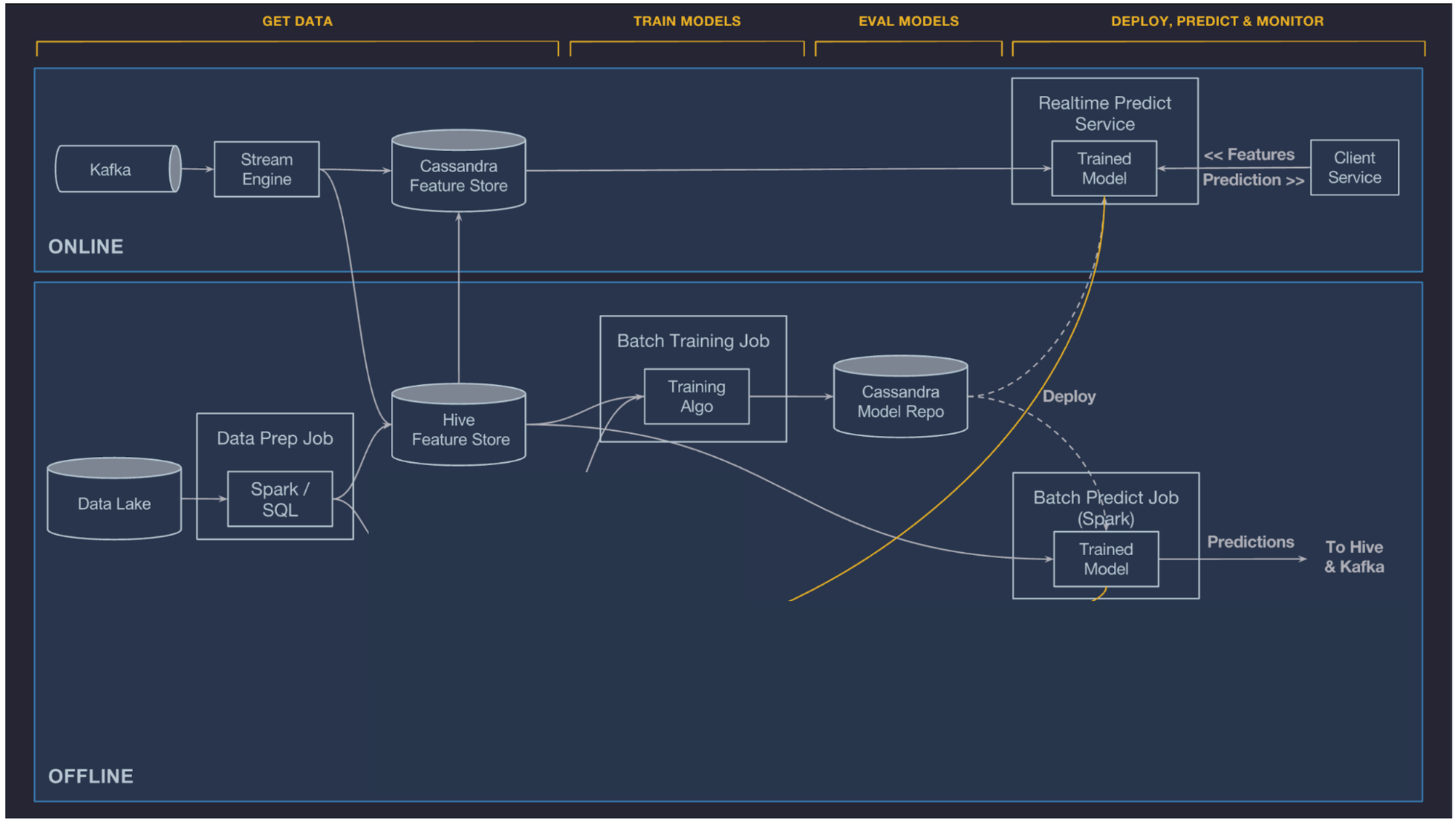
- Edge: OctoML, NVIDIA TensorRT, TensorFlow Lite, ONNX
- Web: ALGORITHMIA, SELDON
- CI / Testing: Buildkite, great_expectations

Meet Michelangelo: Uber's Machine Learning Platform

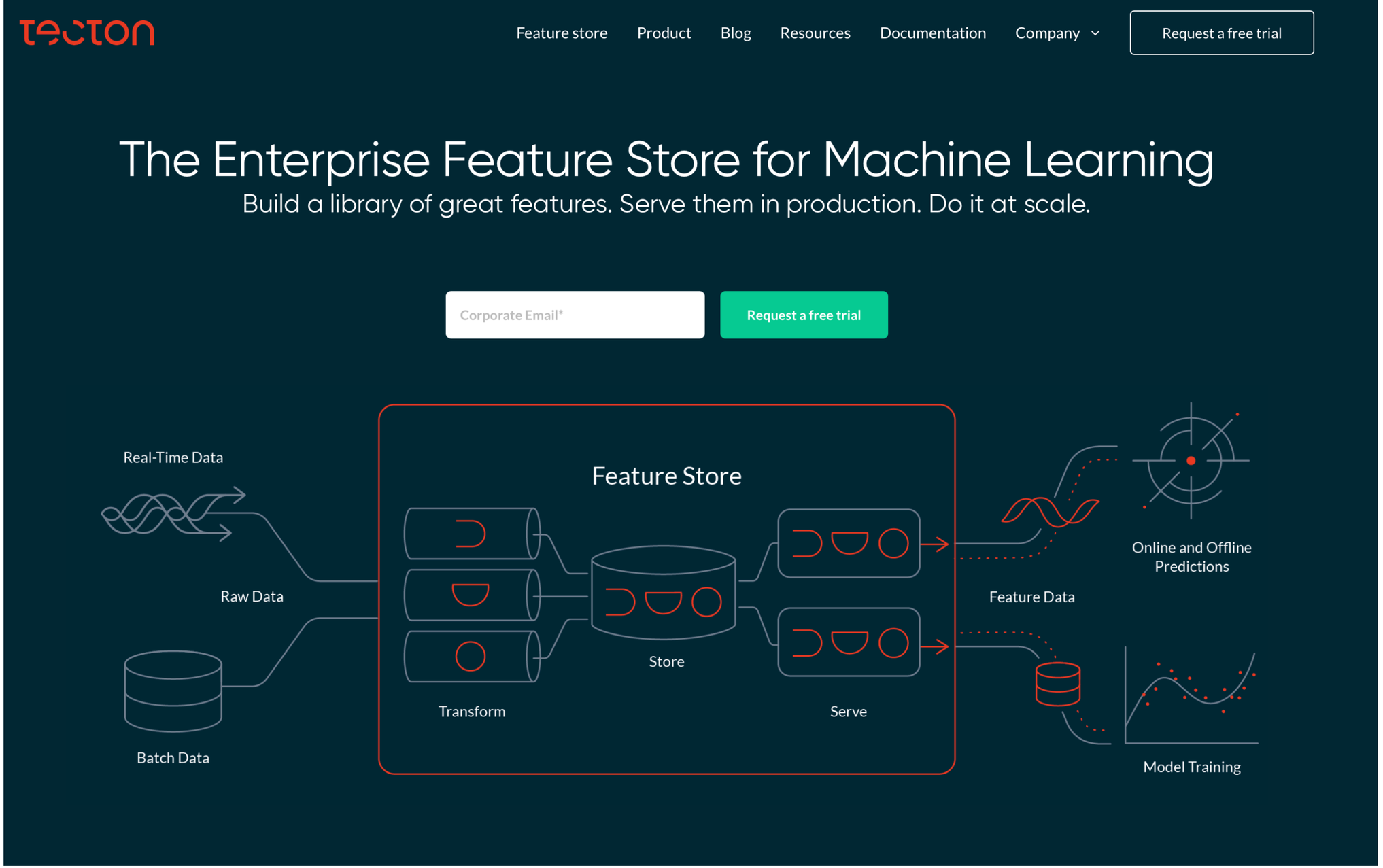
Jeremy Hermann and Mike Del Balso

September 5, 2017

Feature Store



https://eng.uber.com/michelangelo-machine-learning-platform/



https://www.tecton.ai

FEAST

Star Blog Docs

An open source feature store for machine learning

Feast is the bridge between your data and your machine learning models. It allows teams to register, ingest, serve, and monitor features in production.

Quickstart Learn More

```
customer_features = [
  'credit_score', 'balance', 'total_purchases', 'last_active'
]

# Fetch historical features
historical_features_df = fs.get_historical_features(customer_ids, customer_features)

# Train model
my_model = ml.fit(historical_features_df)

# Fetch online features
online_features = fs.get_online_features(customer_ids, customer_features)

# Predict using online features
prediction = my_model.predict(online_features)
```

Register

Feast provides a registry through which to explore, develop, collaborate on, and publish new feature definitions. The registry is the central interface for all interactions with the feature store.

Ingest

Easily ingest data from both batch and streaming sources into both online and offline feature stores, automating data management and making features available for serving.

Serve

A feature retrieval interface that provides a consistent view of features in stores. Feast provides a point-in-time correct interface for training data, and a low-latency API for online serving.

Monitor

Feast allows teams to confidently operate machine learning systems by publishing operational metrics, statistics, and logs to their existing production monitoring infrastructure.

Try to keep things simple

- Don't overengineer
- For example, UNIX has powerful parallelism, streaming, highly optimized tools

Command-line Tools can be 235x Faster than your Hadoop Cluster

January 18, 2014

26 minutes

in parallel

```
cat *.pgn | grep "Result" | sort | uniq -c
```

70 seconds

in parallel

18 seconds

```
find . -type f -name '*.pgn' -print0 \
  | xargs -0 -n4 -P4 mawk '/Result/ { split($0, a, "-"); res = substr(a[1], length(a[1]), 1); if (
    res == 1) white++; if (res == 0) black++; if (res == 2) draw++ } END { print white+black+draw,
    white, black, draw }' \
  | mawk '{games += $1; white += $2; black += $3; draw += $4; } END { print games, white, black,
    draw }'
```

https://adamdrake.com/command-line-tools-can-be-235x-faster-than-your-hadoop-cluster.html

Questions?

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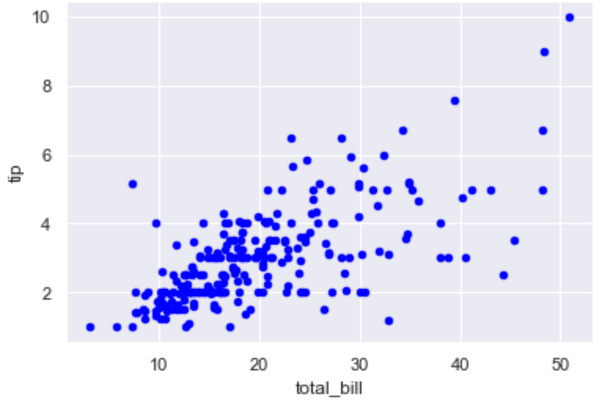
Pandas

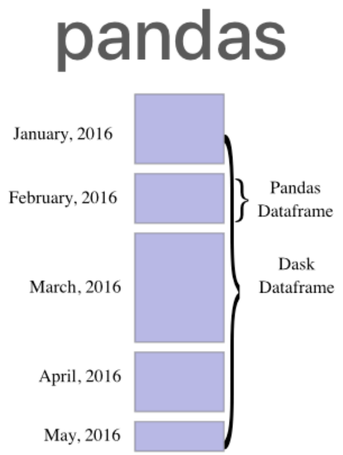
```
In [12]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt

         tips = pd.read_csv("tips.csv")
         tips.plot.scatter(x="total_bill", y="tip", c="Blue")

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xc5120b0>
```



- The workhorse of Python data science
- Definitely do a few projects using it if you haven't used it before

https://projectcodeed.blogspot.com/2019/08/setting-up-jupyter-notebooks-for-data.html

Dask



Dask dataframes scale pandas workflows, enabling applications in time series, business intelligence, and general data munging on big data.

RAPIDS

Open GPU Data Science

ACCELERATED DATA SCIENCE

The RAPIDS suite of open source software libraries gives you the freedom to execute end-to-end data science and analytics pipelines entirely on GPUs.

Learn about RAPIDS »

SCALE OUT ON GPUS

Seamlessly scale from GPU workstations to multi-GPU servers and multi-node clusters with Dask.

Learn about Dask »

PYTHON INTEGRATION

Accelerate your Python data science toolchain with minimal code changes and no new tools to learn.

Learn about our libraries »

GETTING STARTED

The RAPIDS data science framework is designed to have a familiar look and feel to data scientist working in Python. Here's a code snippet where we read in a CSV file and output some descriptive statistics:

```
import cudf

gdf = cudf.read_csv('path/to/file.csv')
for column in gdf.columns:
    print(gdf[column].mean())
```

Find more details on our **get started section »**

TRY NOW ONLINE

Jump right into a GPU powered RAPIDS notebook online.

Try with **BlazingSQL (RAPIDS 0.15+) »**

Or with **Colabratory (RAPIDS 0.14 only) »**

10 MINUTES TO CUDF

Modeled after 10 Minutes to Pandas, this is a short introduction to cuDF that is geared mainly for new users.

Go to guide »

MULTI-GPU WITH DASK-CUDF

A short introduction to multi-GPU solutions with a distributed DataFrame via Dask-cuDF.

Go to guide »

EXAMPLE NOTEBOOKS

A Github repository with our introductory examples of XGBoost, cuML demos, cuGraph demos, and more.

Go to repo »

EXAMPLE COMMUNITY NOTEBOOKS

A second Github repository with our extended collection of community contributed notebook examples.

Go to repo »

Amazon SageMaker · gradient by Paperspace · FLOYD · DOMINO DATA LAB

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or or

Data Labeling

1. User Interfaces

2. Sources of labor

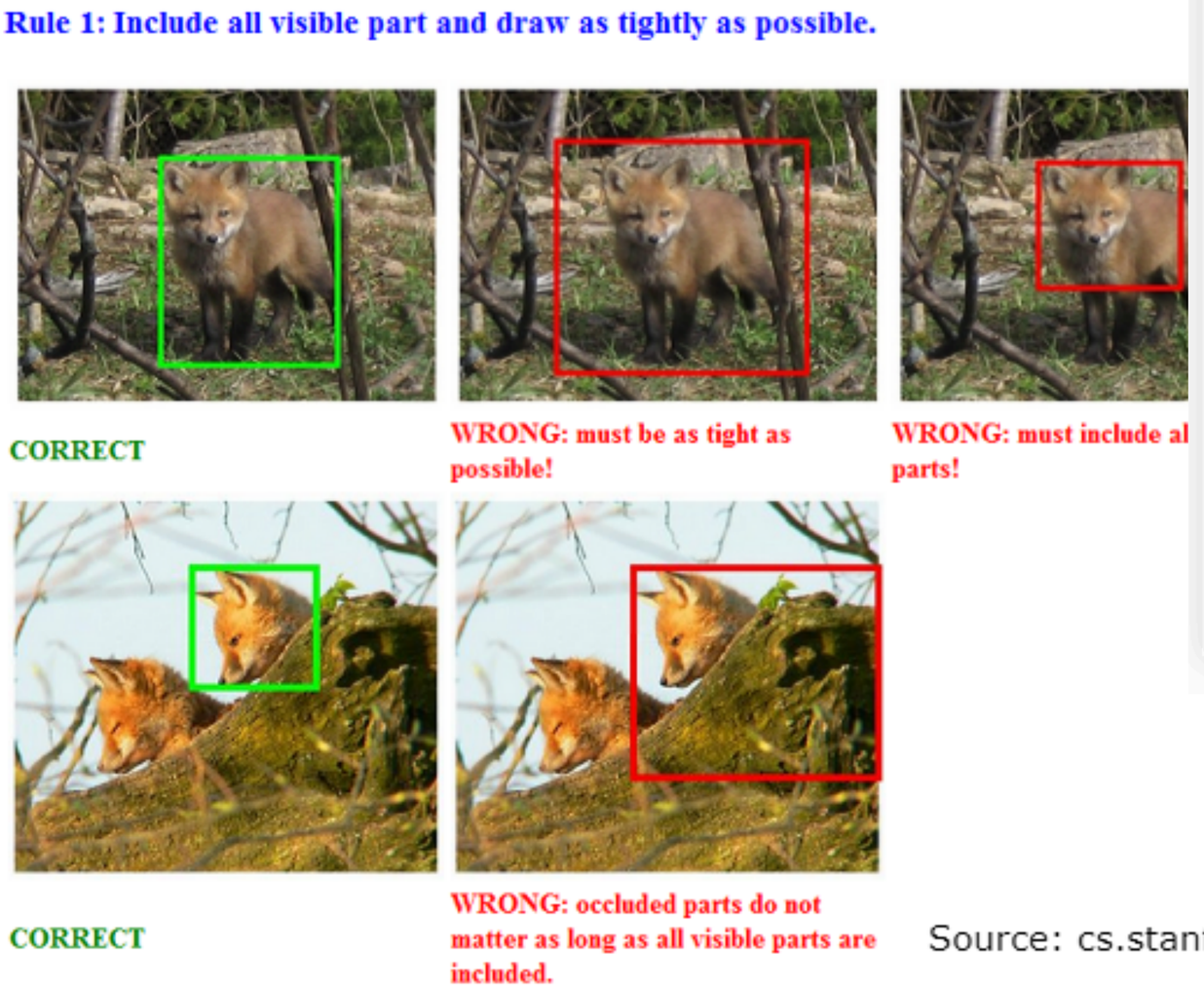
3. Service companies

Standard set of features:

- bounding boxes, segmentations, keypoints, cuboids

- set of applicable classes

Training the annotators is crucial



Source: cs.stanford.edu

Quality assurance is key

Sources of Labor

- Hire **own annotators**, promote best ones to quality control
  - Pros: secure, fast (once hired), less QC needed
  - Cons: expensive, slow to scale, admin overhead
- ...or, crowdsource (Mechanical Turk)
  - Pros: cheaper, more scalable
  - Cons: not secure, significant QC effort required
- ...or, full-service data labeling companies

Service Companies

- Data labeling requires separate software stack, temporary labor, and quality assurance. **Makes sense to outsource.**
- Dedicate several days to selecting the best one for you:
  - Label gold standard data yourself
  - Sales calls with several contenders, ask for work sample on same data
  - Ensure agreement with your gold standard, and evaluate on value

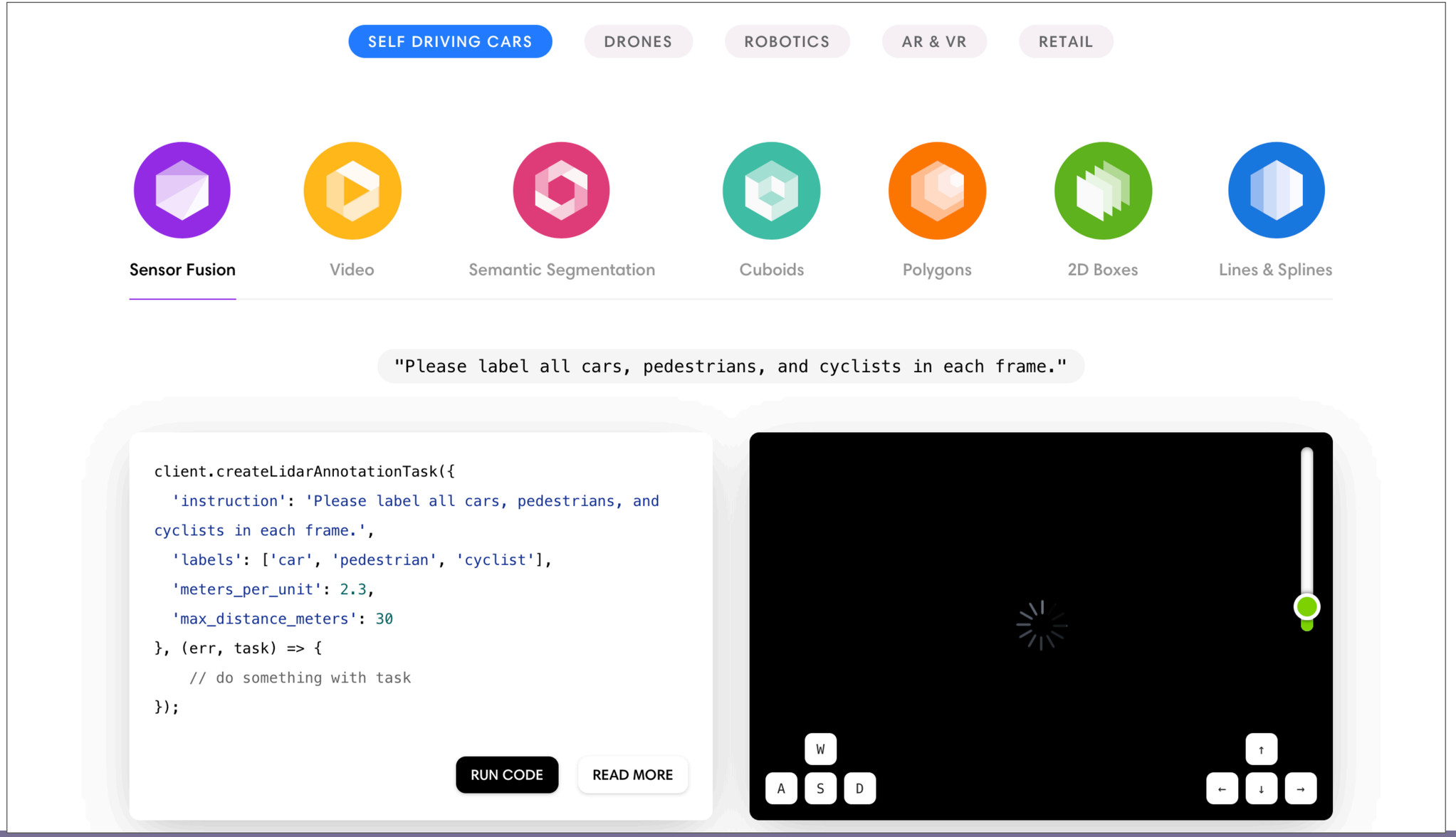
FigureEight is the original AI data labeling company

Over 100 million images labeled

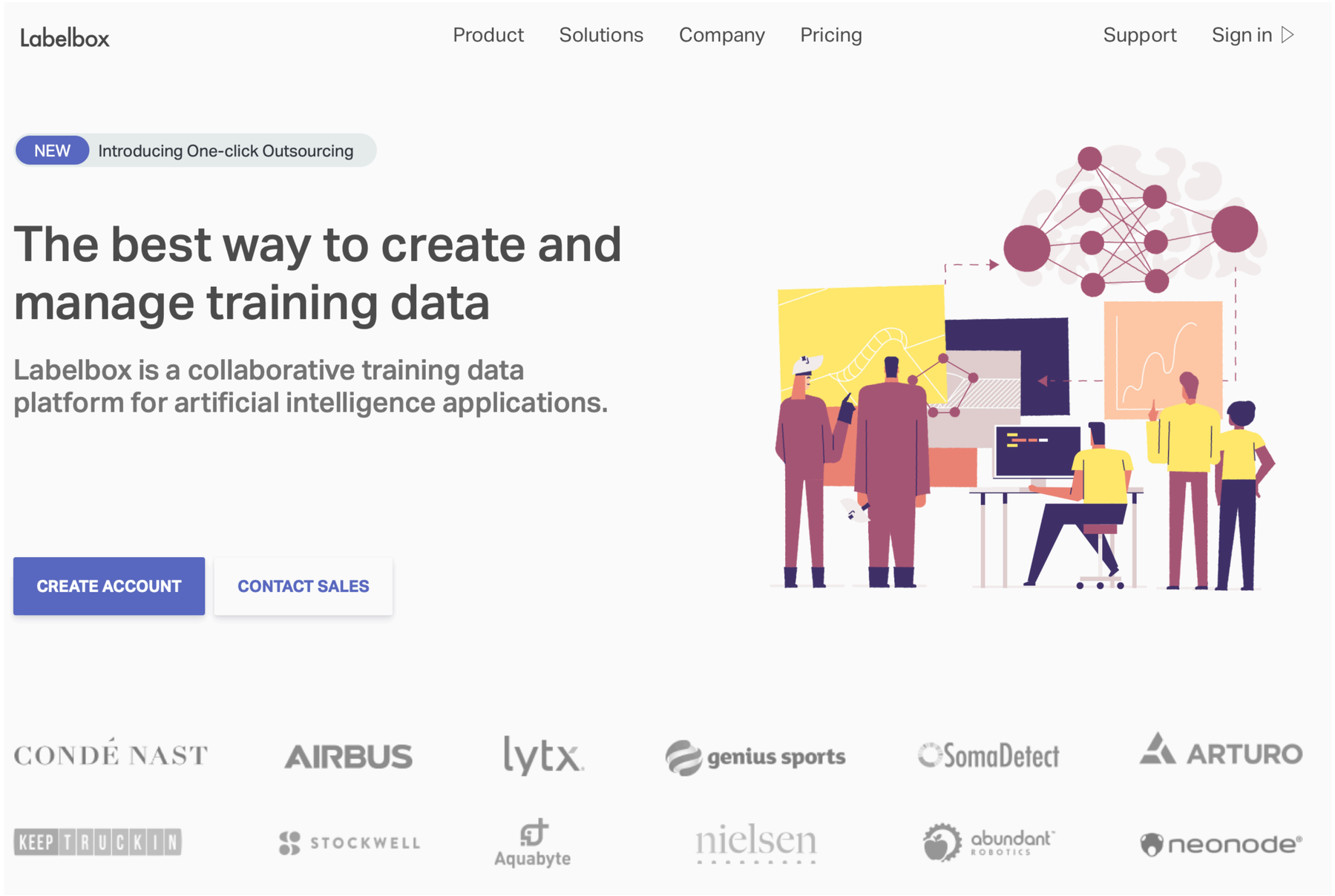
Over 1 billion human judgments in 2018

Over 10 years enabling AI projects

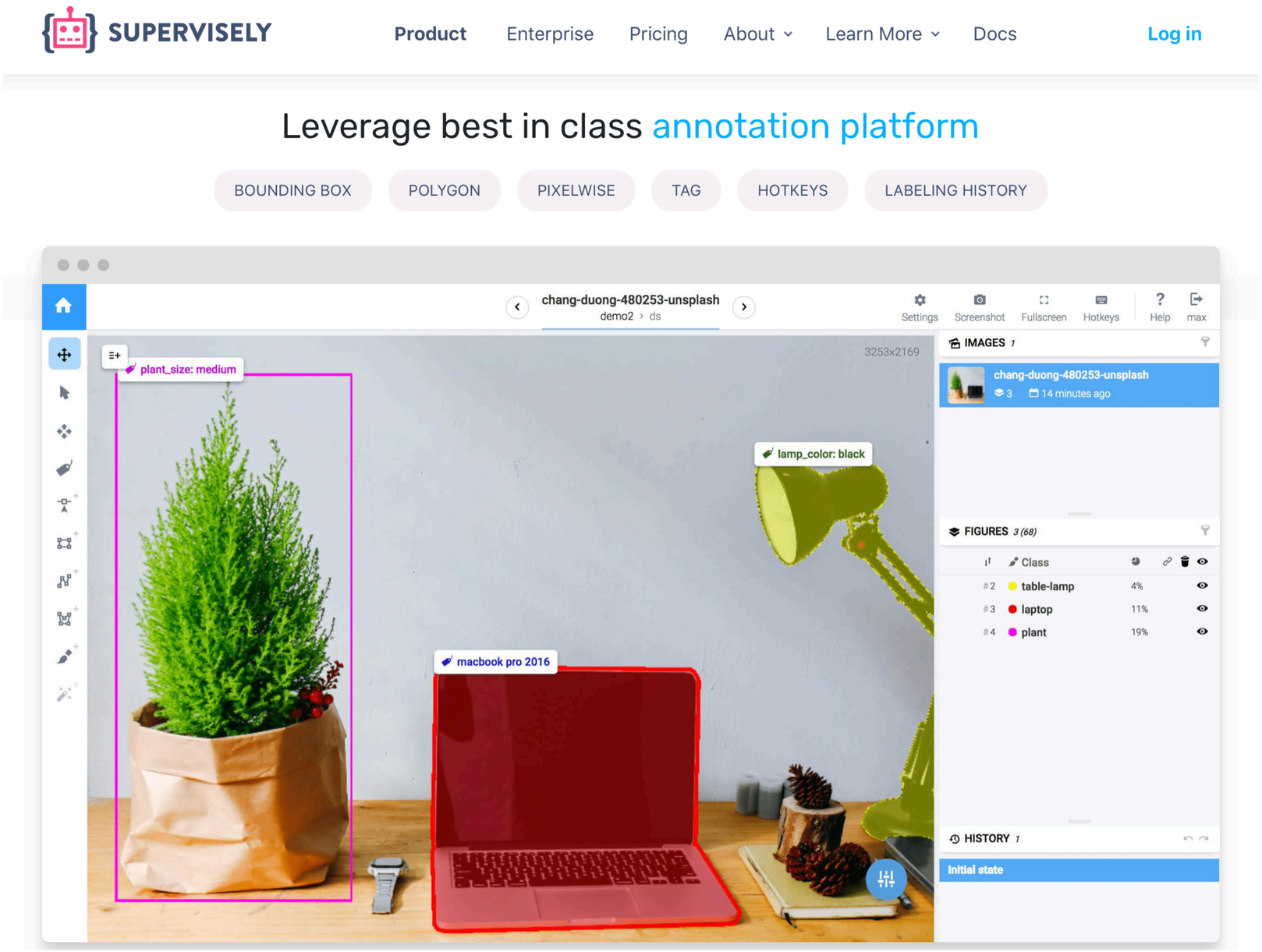
Scale.ai is a dominant up-and-comer



And there are a ton of others



And there are a ton of others



Software

- Full-service data labeling is always pricy
- But some companies offer their software without labor

Label Studio

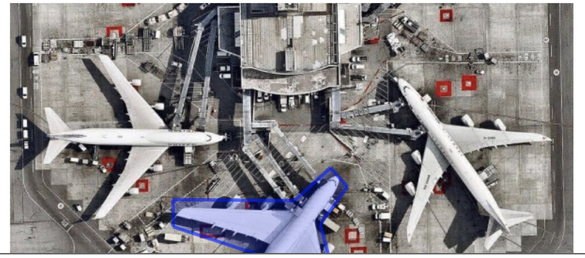
- Open-source edition to run yourself
- Enterprise edition for managed hosting
- Using in lab!

2. Edit Labeling config

```
<View>

  <!-- Image with Polygons -->
  <View style="padding: 25px;
               box-shadow: 2px 2px 8px #AAA">
    <Header value="Label the image with polygons"/>
    <Image name="img" value="$image"/>
    <Text name="text1"
          value="Select label, start to click on image"/>

    <PolygonLabels name="tag" toName="img">
      <Label value="Airbus" background="blue"/>
      <Label value="Boeing" background="red"/>
    </PolygonLabels>
  </View>

ulti-choices -->
gin-top: 20px; padding: 25px;
-shadow: 2px 2px 8px #AAA;">
"Classify the text"/>
```

3. Inspect Interface preview

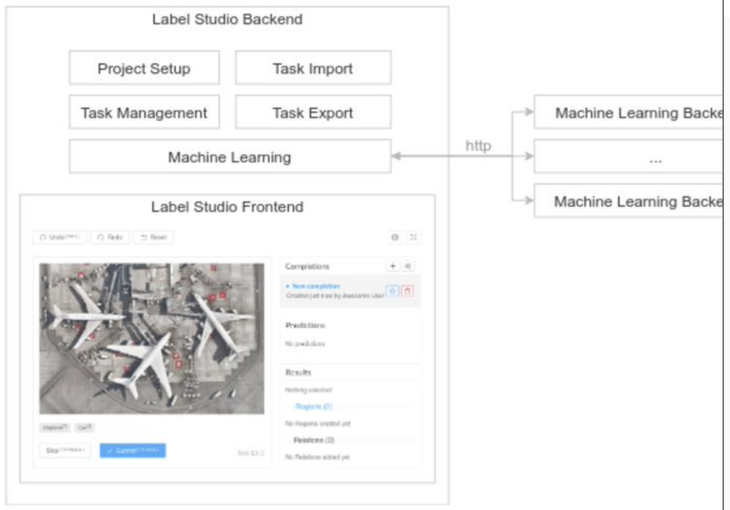
Label the image with polygons

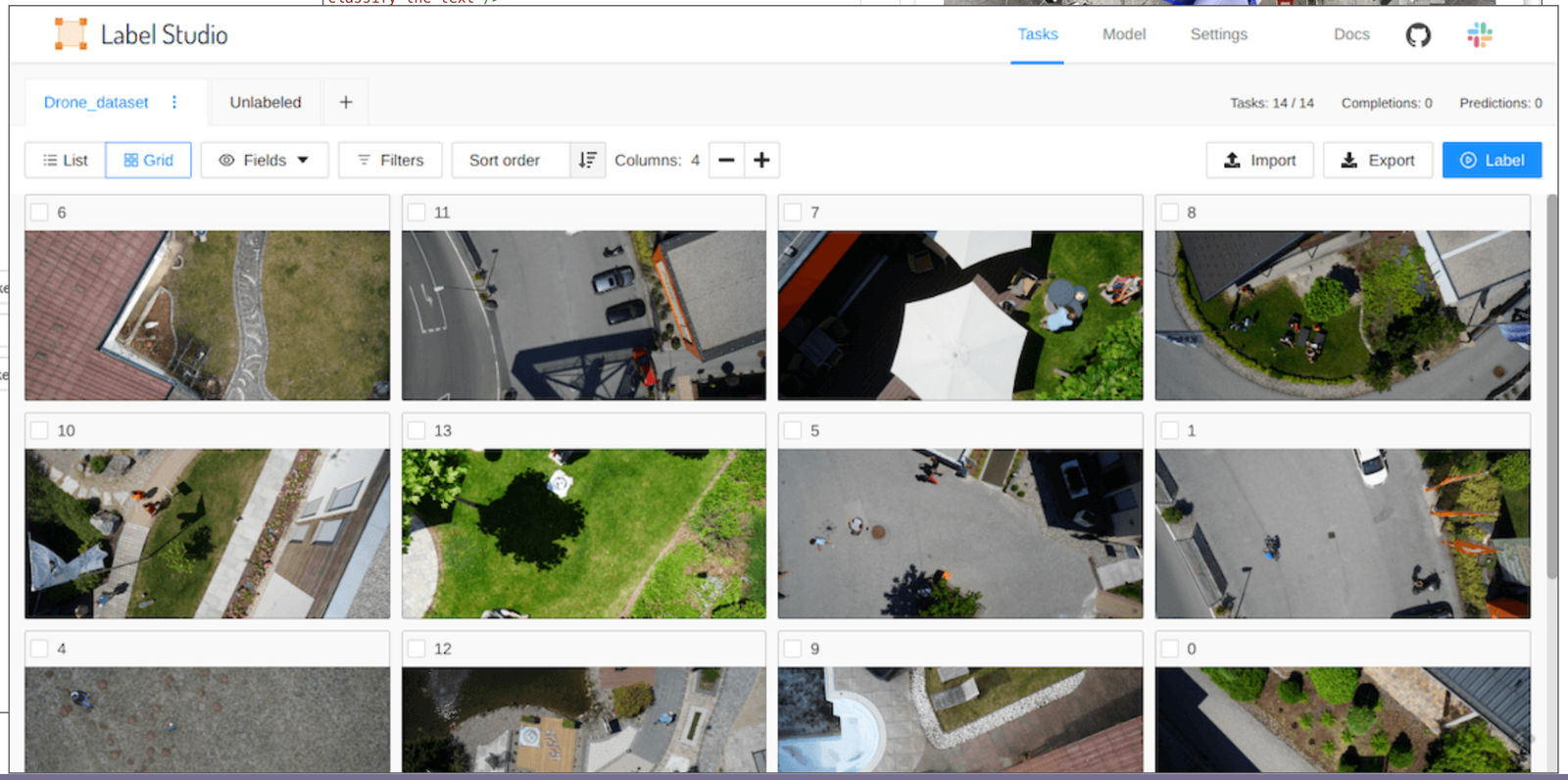


Main modules

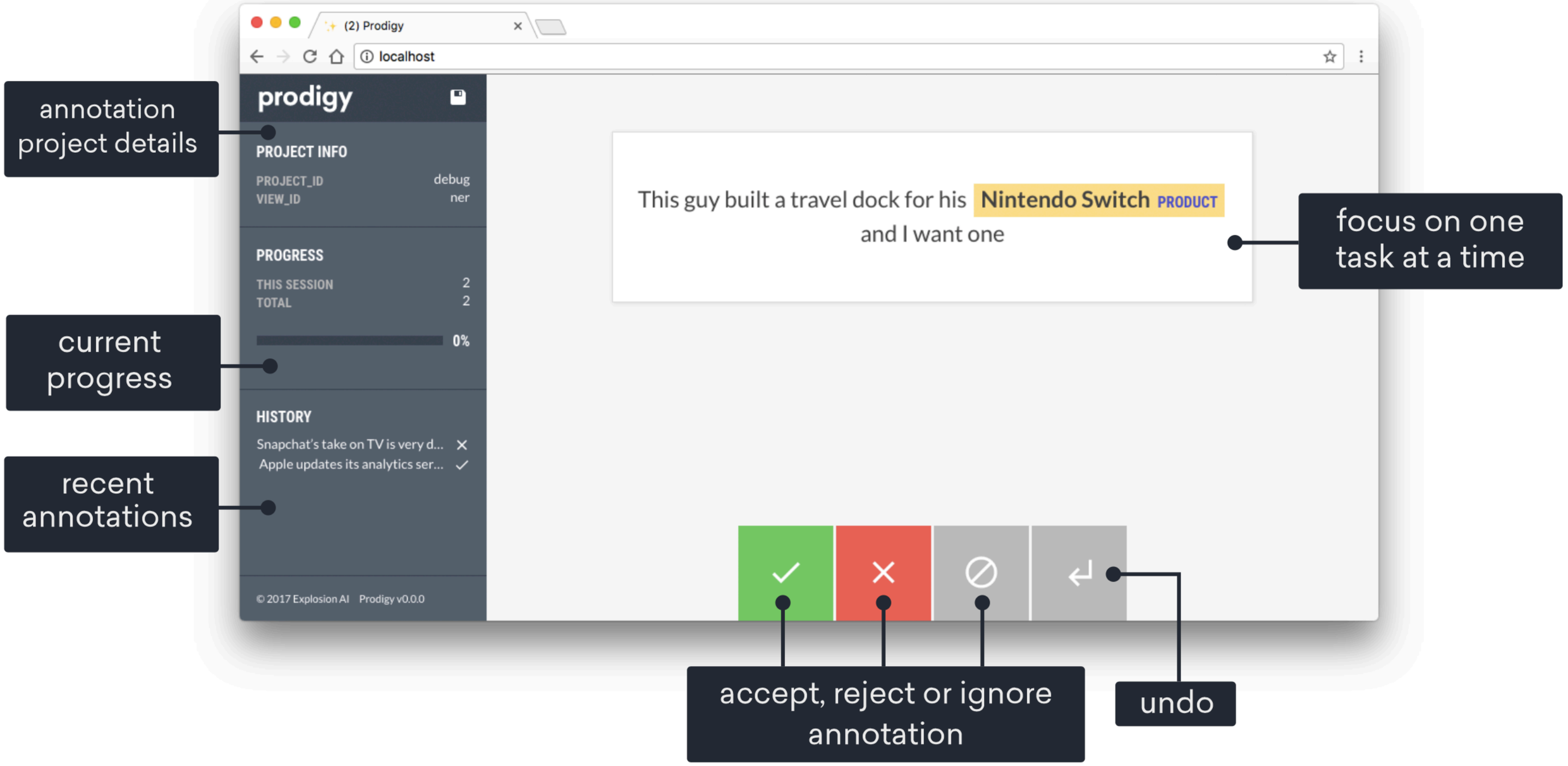
The main modules of LS are

- Label Studio Backend (LSB, main repository)
- Label Studio Frontend (LSF, editor)
- Machine Learning Backends (MLB)





Prodigy


annotation project details
current progress
recent annotations
(2) Prodigy
localhost
prodigy
PROJECT INFO
PROJECT_ID debug
VIEW_ID ner
PROGRESS
THIS SESSION 2
TOTAL 2
0%
HISTORY
Snapchat's take on TV is very d...
Apple updates its analytics ser...
© 2017 Explosion AI Prodigy v0.0.0
This guy built a travel dock for his Nintendo Switch PRODUCT
and I want one
focus on one task at a time
accept, reject or ignore annotation
undo

Aquarium

Better models through better data

Aquarium is an ML data management platform that helps you improve your models by improving your datasets.

Upload data

Aquarium's Python client API makes it easy to upload data, labels, and model inferences.

Explore your dataset

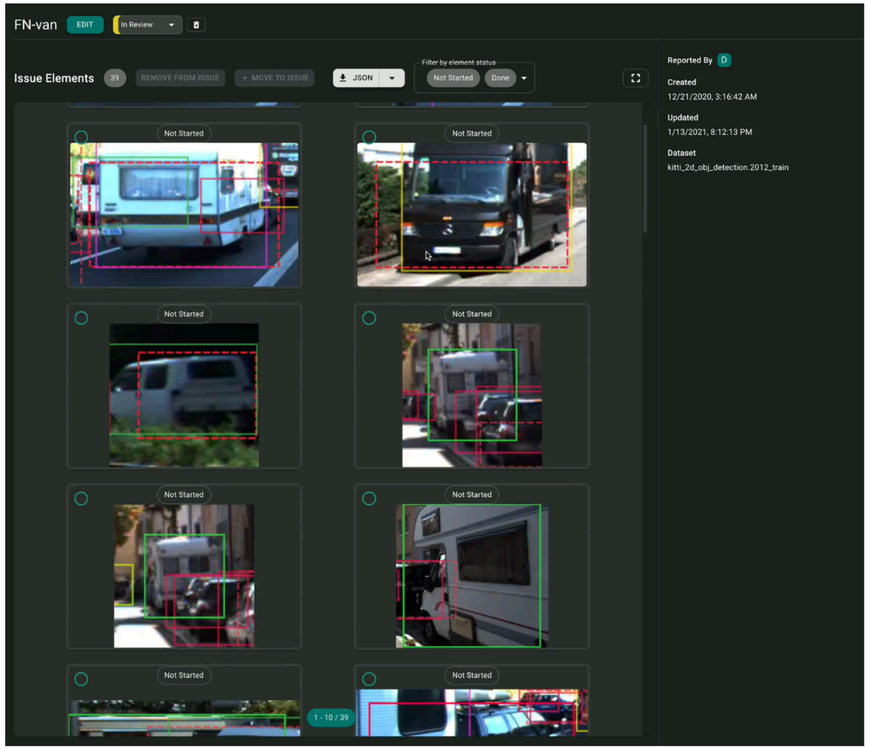
Visualize your dataset and model performance. Uncover corrupted data and difficult edge cases.

Curate data

Fix mislabeled examples and collect more examples of difficult edge cases. Aquarium's labeling service integrations lets you easily send data out for correction.

Model gets better!

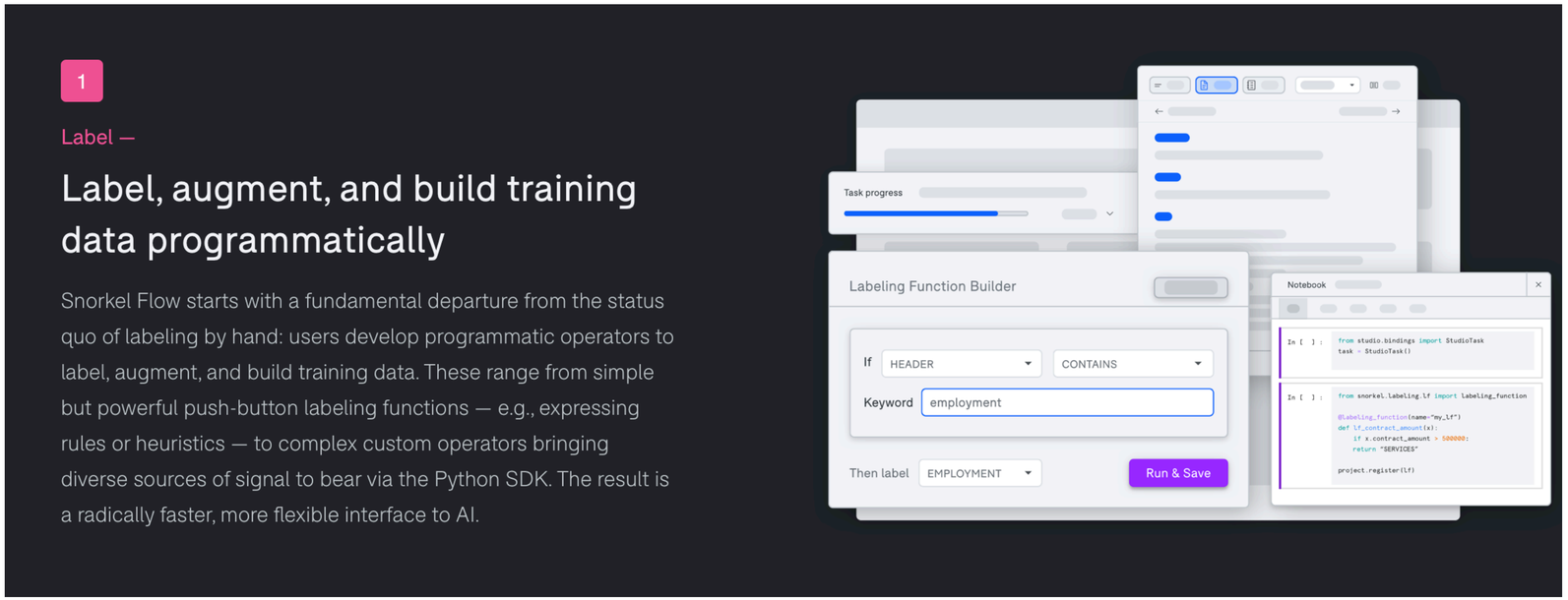
Retrain your model on the improved dataset. Use Aquarium to confirm that your new model is better. Success!



https://www.aquariumlearning.com

Weak supervision

- Snorkel
  - Open-source project snorkel.org
  - Commercial platform snorkel.ai




```python
from snorkel.labeling import labeling_function

@labeling_function()
def lf_contains_link(x):
    # Return a label of SPAM if "http" in comment text, otherwise ABSTAIN
    return SPAM if "http" in x.text.lower() else ABSTAIN
```

- Conclusions
  - outsource to full-service company if you can afford it
  - if not, then at least use existing software
  - hiring part-time makes more sense than trying to make crowdsourcing work

Questions?

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or or

Data Versioning

Level 0: unversioned

Level 1: versioned via snapshot at training time

Level 2: versioned as a mix of assets and code

Level 3: specialized data versioning solution

Level 0

- Data lives are on filesystem/S3 and database
- **Problem:** Deployments must be versioned. Deployed machine learning models are part code, part data. If data is not versioned, deployed models are not versioned.
- Problem you **will** face: inability to get back to a previous level of performance

Level 1

- Data is versioned by storing a snapshot of everything at training time
- This allows you to version deployed models, and to get back to past performance, but is super hacky.
- Would be far better to be able to version data just as easily as code.

Level 2

- Data is versioned as a mix of assets and code.
- Heavy files stored in S3, with unique ids. Training data is stored as JSON or similar, referring to these ids and include relevant metadata (labels, user activity, etc).
- JSON files can get big, but using git-lfs lets us store them just as easily as code
    - Can improve further with "lazydata": only syncing files that are needed.
- The git signature + of the raw data file defines the version of the dataset
    - Often helpful to add timestamp

Level 3

- Specialized solutions for versioning data.
- Avoid these until you can fully explain how they will improve your project.
- Leading solutions are DVC, Pachyderm, Quill.

Data Versioning Solutions

	Open Source	Data Format Agnostic	Cloud/Storage Agnostic* (Supports most common cloud and storage types)	Simple to Use	Easy Support for BIG Data
DVC	✅ (Apache 2.0)	✅	✅	✅	❌
DELTA LAKE	✅ (Apache 2.0)	❌	✅	❌	✅
Git Large File Storage	✅ (MIT)	✅	❌	✅	❌
Pachyderm	✅⚠️ (Non-standard license)	✅	✅	❌	✅
DOLT	✅ (Apache 2.0)	❌	❌	❌	❌
lakeFS	✅ (Apache 2.0)	✅	❌	❌	✅
DAGsHub					

https://dagshub.com/blog/data-version-control-tools/

DVC

Open-source
Version Control System
for Machine Learning Projects

1

```
$ dvc add data.xml
```

DVC stores information about your data file in a special `.dvc` file, that has a human-readable description and can be committed to Git to track versions of your file:

```
$ git add .gitignore data.xml.dvc
$ git commit -m "add source data to DVC"
```

2

```
$ dvc run \
    -d prepare.py -d data.xml \
    -o data.tsv -o data-test.tsv \
    python prepare.py data.xml
```

3

The first stage, feature extraction:

```
$ dvc run -d featurization.py -d data.tsv \
          -o matrix.pkl \
          python featurization.py data.tsv matrix.pkl
```

The second stage, training:

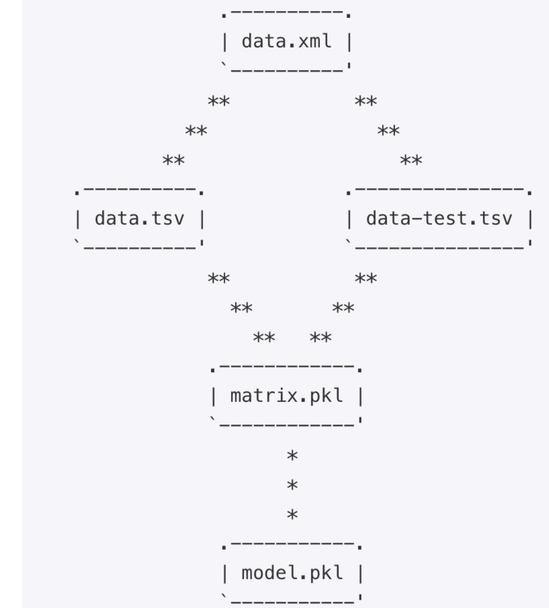
```
$ dvc run -d train.py -d matrix.pkl \
          -o model.pkl \
          python train.py matrix.pkl model.pkl
```

Let's commit meta-files that describe our pipeline:

```
$ git add .gitignore matrix.pkl.dvc model.pkl.dvc
$ git commit -m "add featurization and train steps to the pipe
```

4

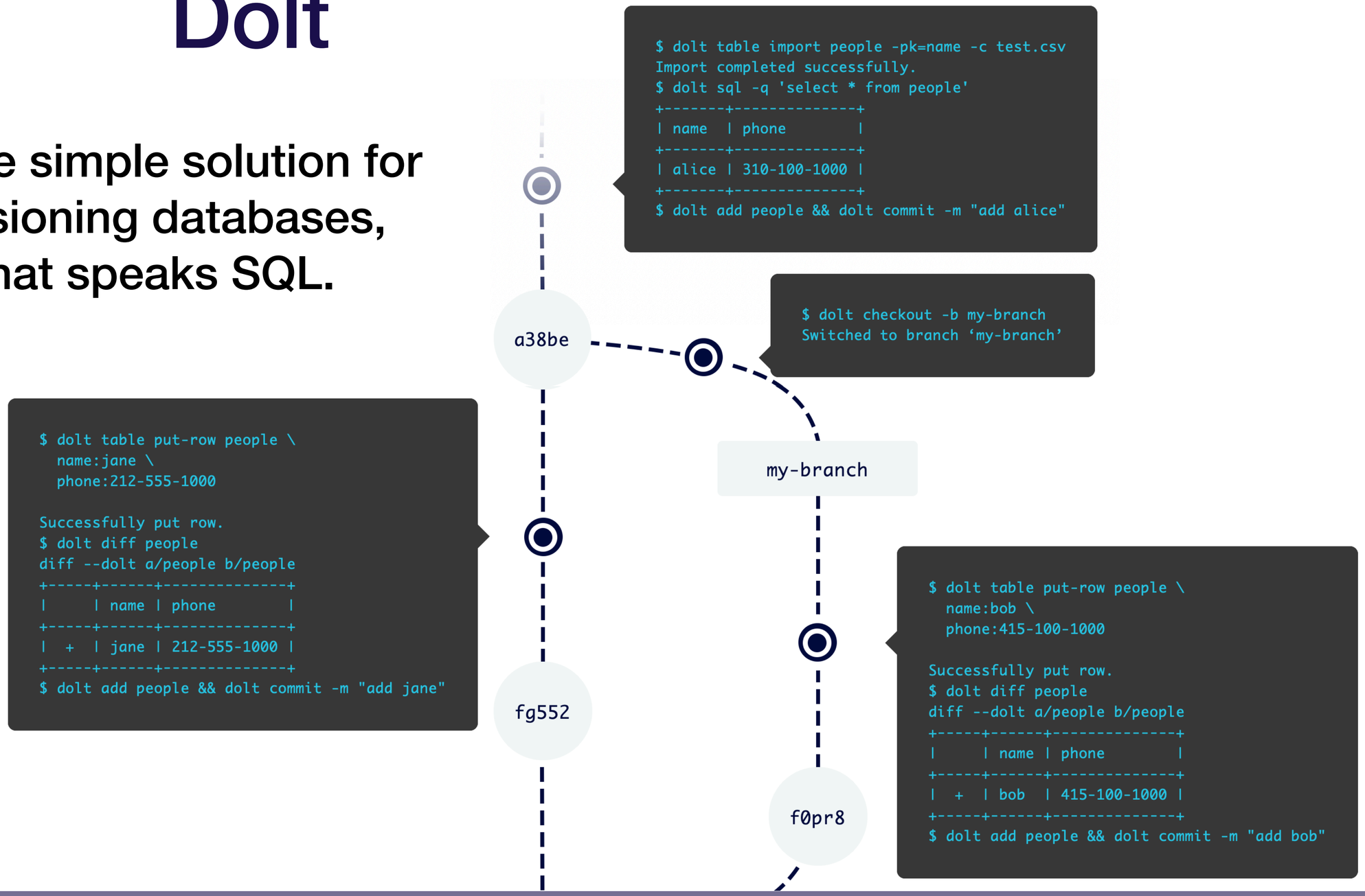
```
$ dvc pipeline show --ascii model.pkl.dvc --outs
```



LIQUIDATA

Dolt

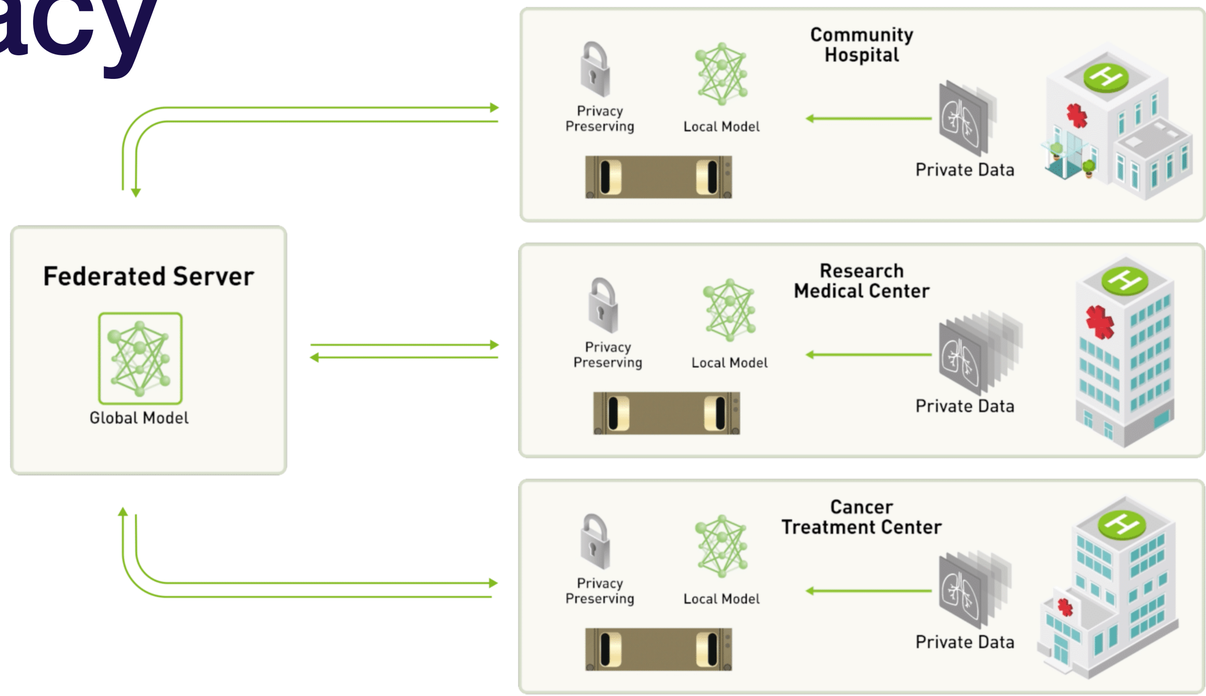
A nice simple solution for versioning databases, that speaks SQL.



Questions?

Privacy

- Federated Learning: training a global model from data on local devices, without ever having access to the data
- Differential privacy: aggregating data such that individual points cannot be identified
- Another topic: Learning on encrypted data
- Let us know about the best resources!



Expensive Communication

Systems Heterogeneity

Statistical Heterogeneity

Privacy Concerns

https://blog.ml.cmu.edu/2019/11/12/federated-learning-challenges-methods-and-future-directions/

https://blogs.nvidia.com/blog/2019/10/13/what-is-federated-learning/

Thank you!