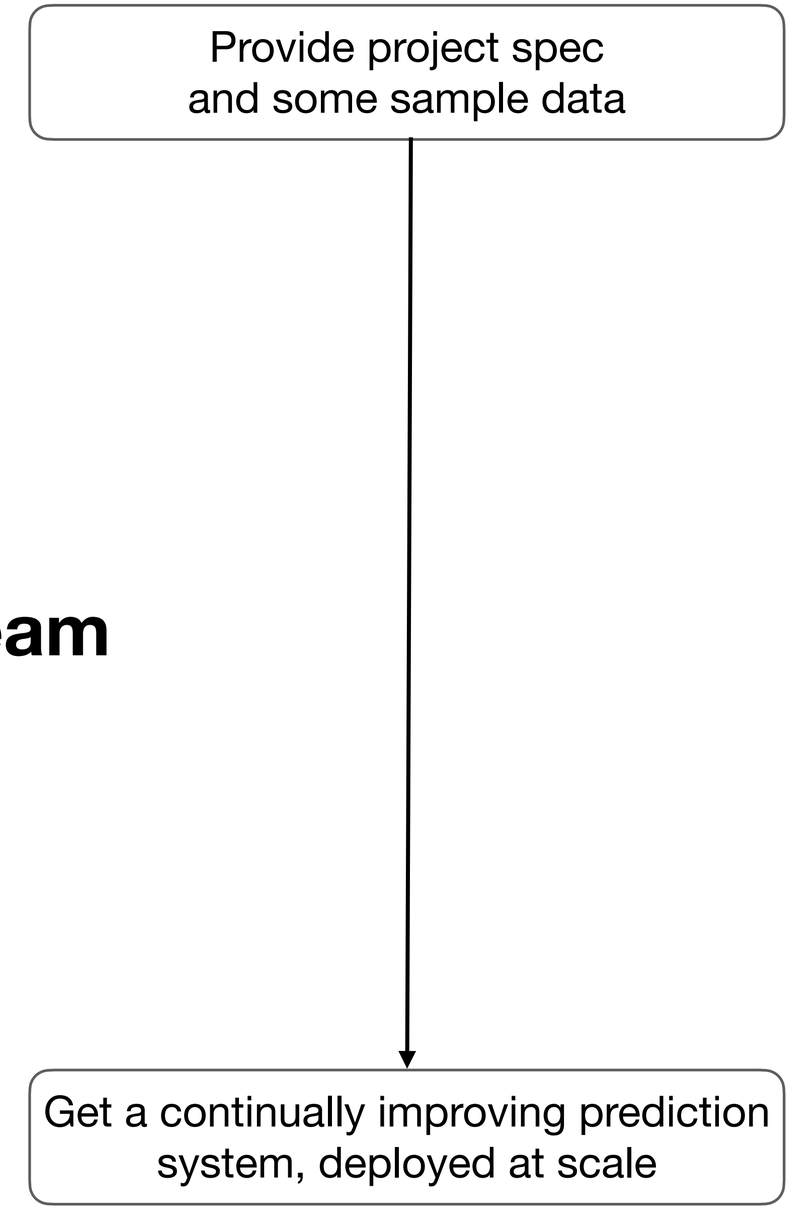
FSDL 2022

Development Infrastructure & Tooling

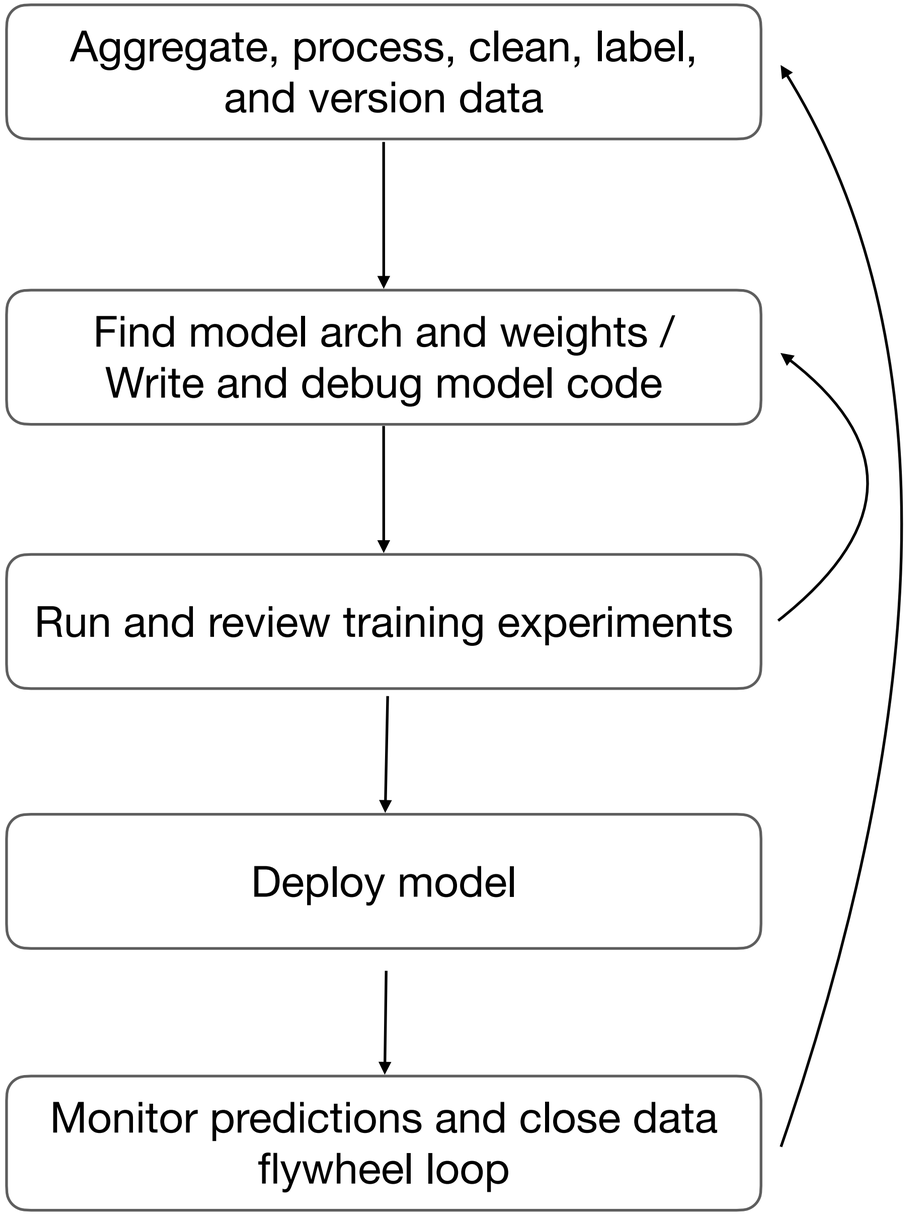
Sergey Karayev

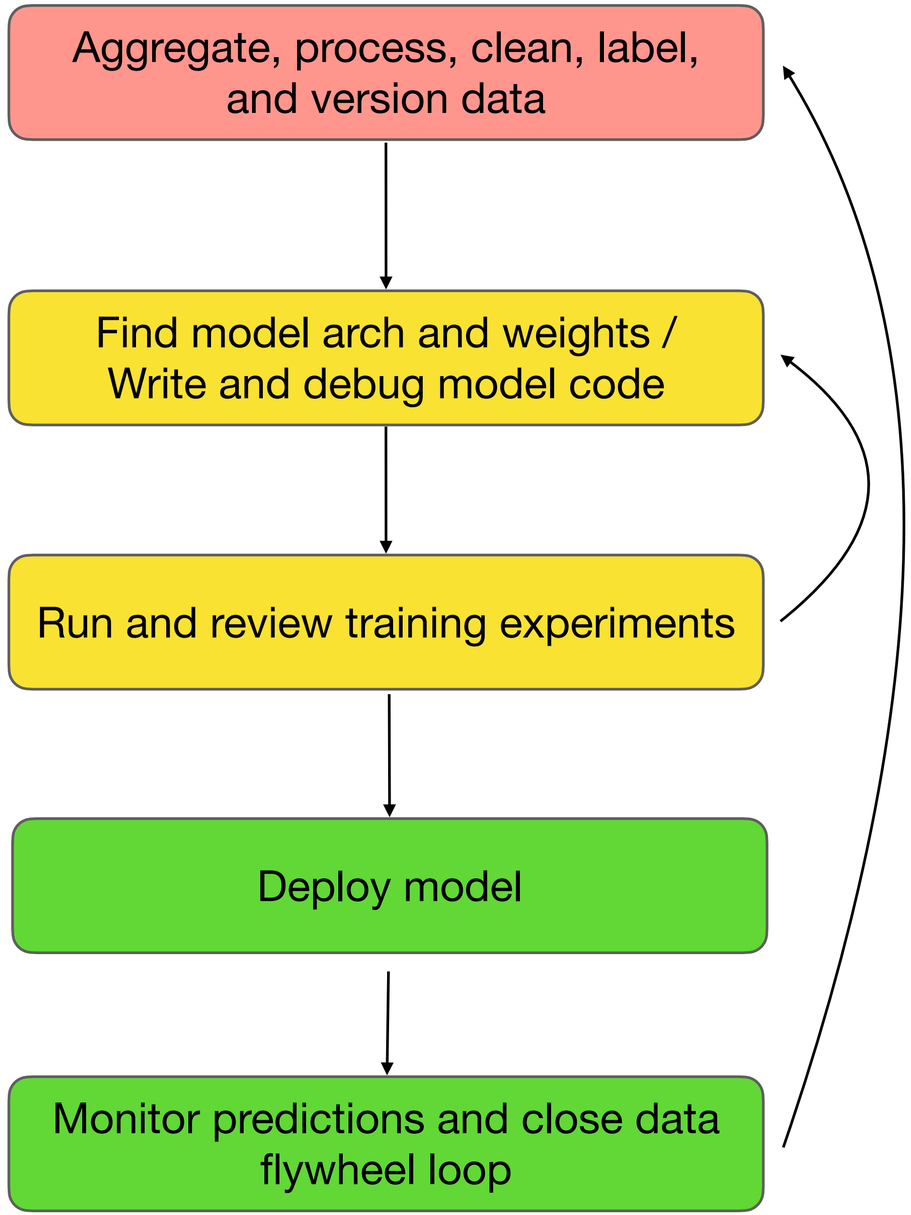
August 15, 2022

Dream



Reality




Aggregate, process, clean, label, and version data
Find model arch and weights / Write and debug model code
Run and review training experiments
Deploy model
Monitor predictions and close data flywheel loop

“All-in-one”

Amazon SageMaker

gradient by Paperspace

DOMINO DATA LAB

Data

Versioning: Pachyderm, DVC, LIQUIDATA

Labeling: Label Studio, scale, prodigy

Processing: Spark, DAGSTER

Exploration: pandas, RAPIDS, dbt

Data Lake / Warehouse: snowflake, databricks

Sources: S3, LOG, Parquet

Development

Frameworks & Distributed Training: PyTorch, fast.ai, DeepSpeed, FairScale

Experiment and Model Management: comet, Weights & Biases, TensorBoard, mlflow, neptune.ai

Resource Management: Determined AI, PY, slurm

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Compute: CoreWeave, Lambda

Deployment

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Web: ALGORITHMIA, SELDON

CI / Testing: Buildkite, great_expectations

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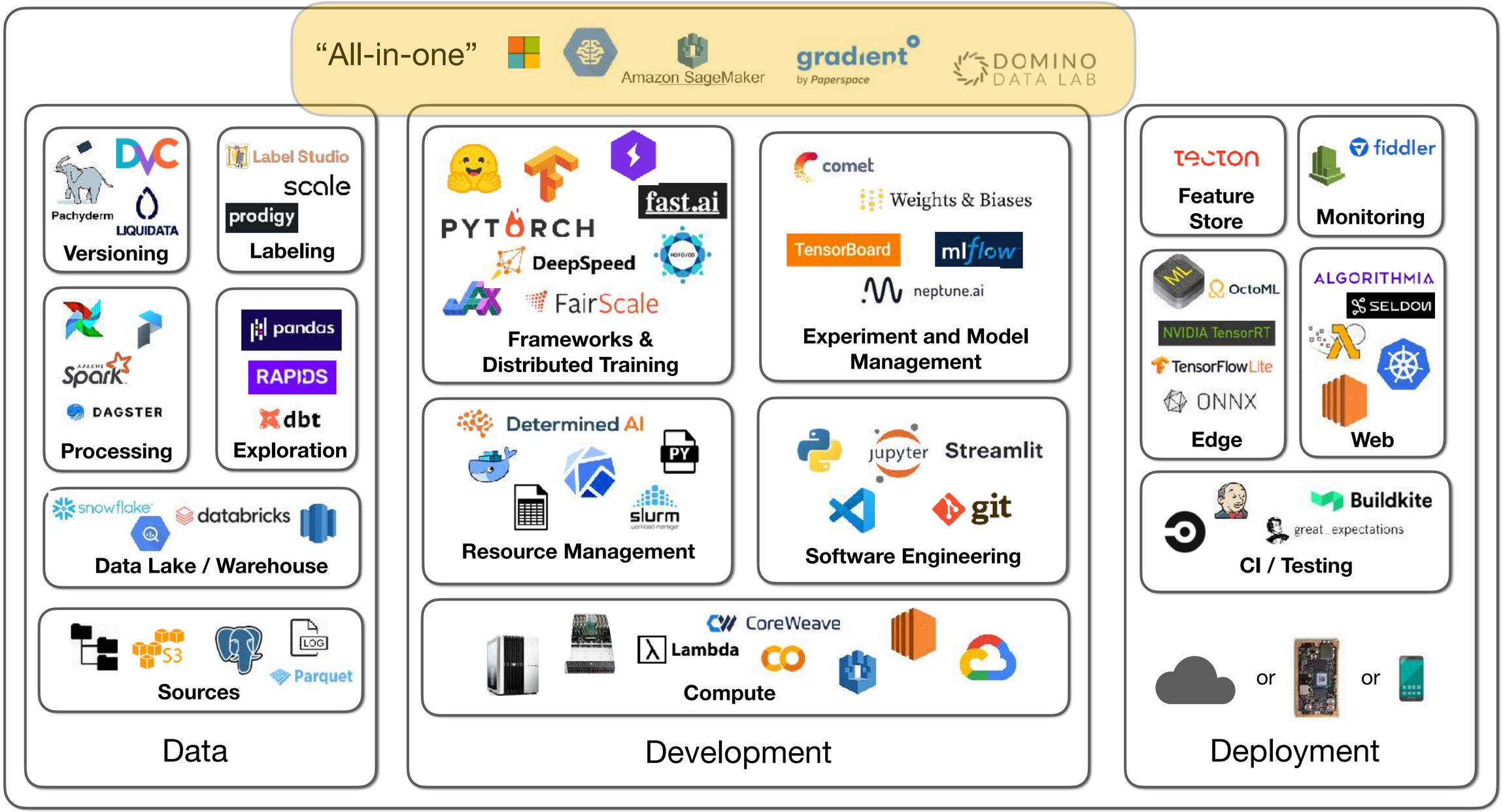
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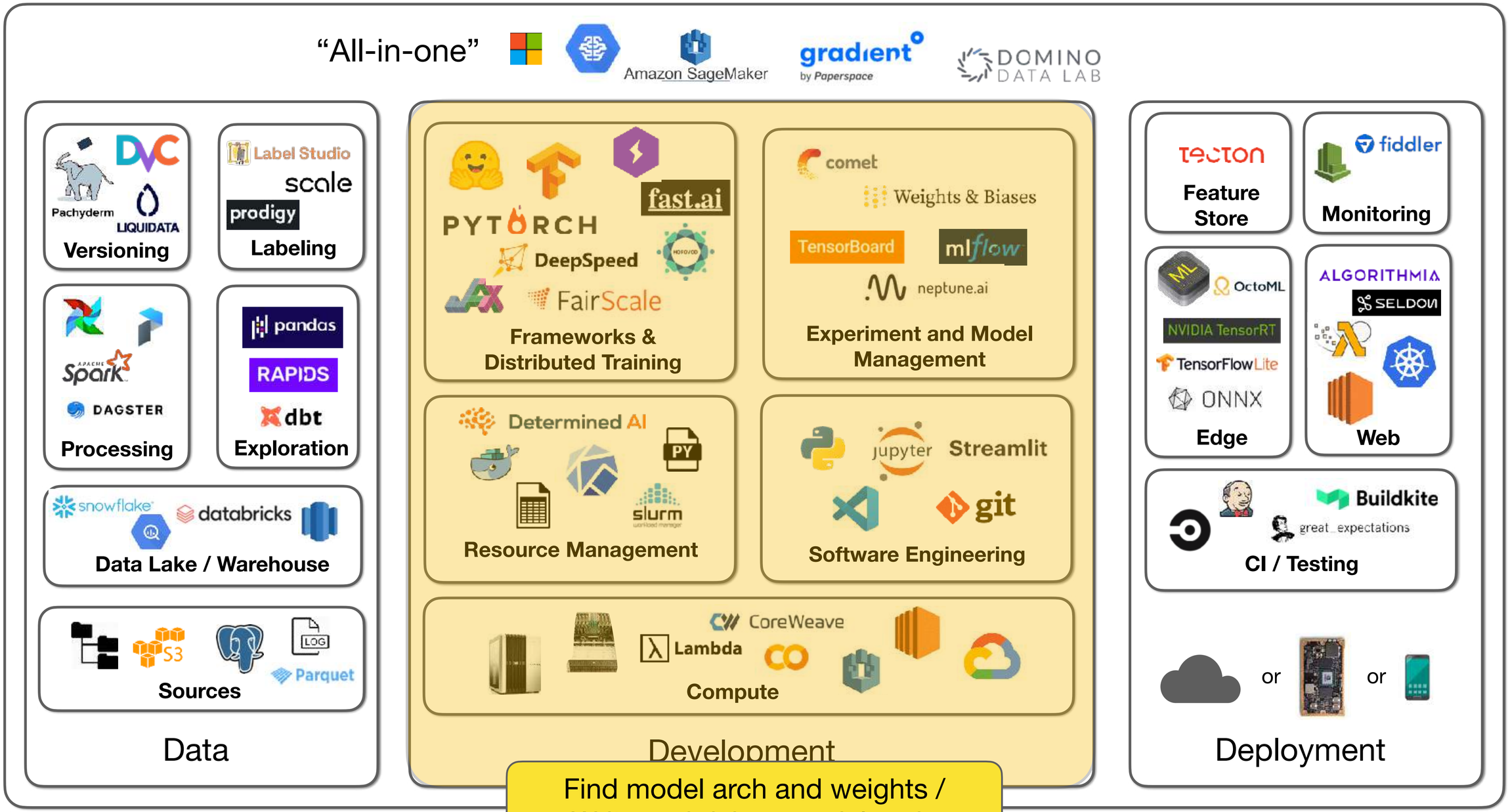
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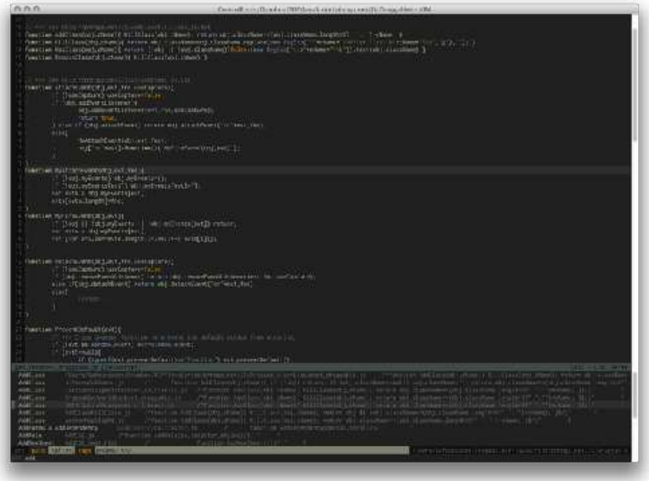
or or

Software Engineering

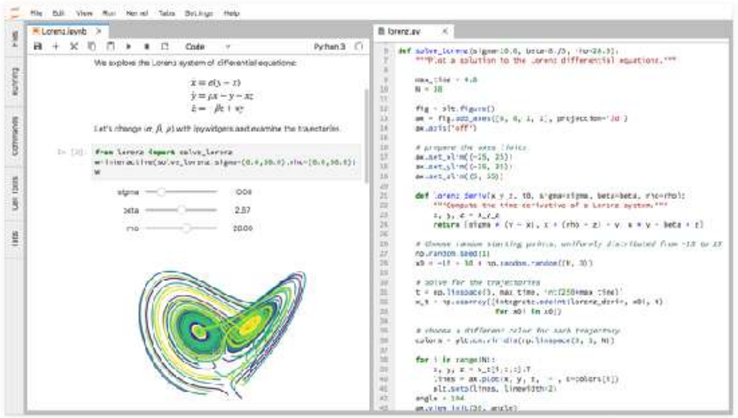
Programming Language

- Python, because of the libraries
  - Clear winner in scientific and data computing
- Contenders:
  - Julia (**Ju**pyter!)
  - C/C++

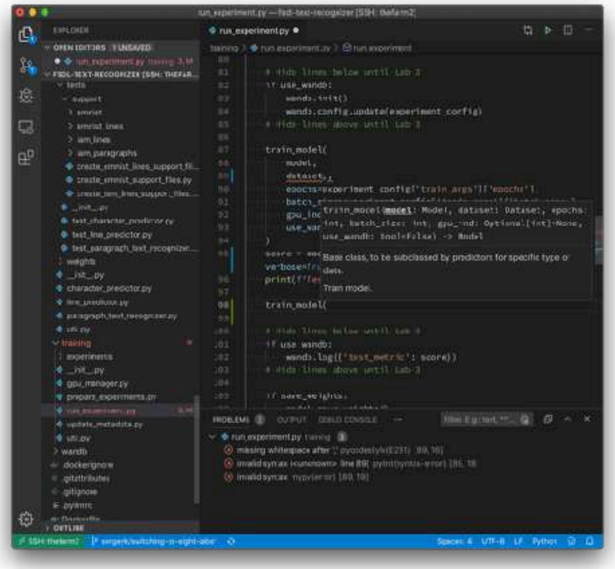
Editors



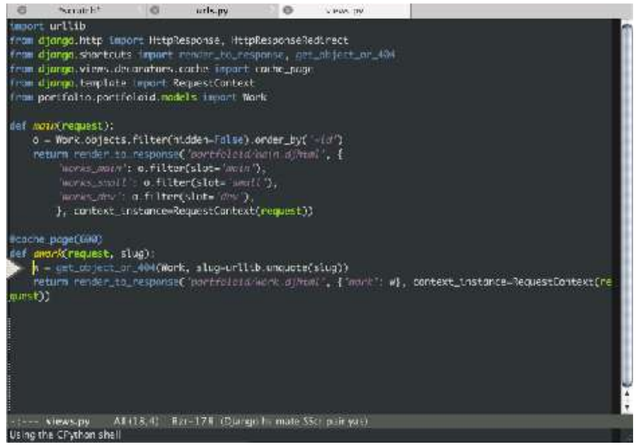
Vim



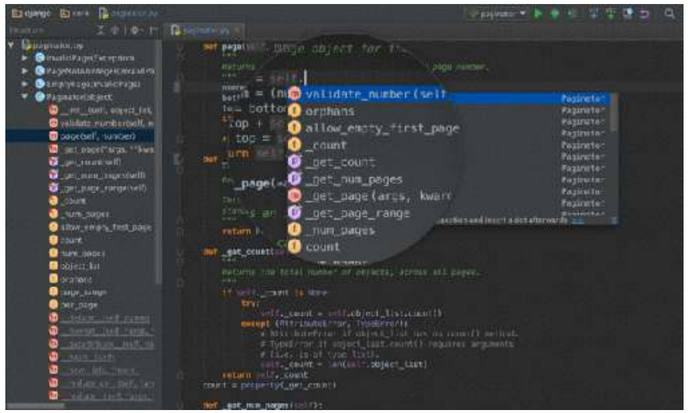
Jupyter



VS Code



Emacs



PyCharm

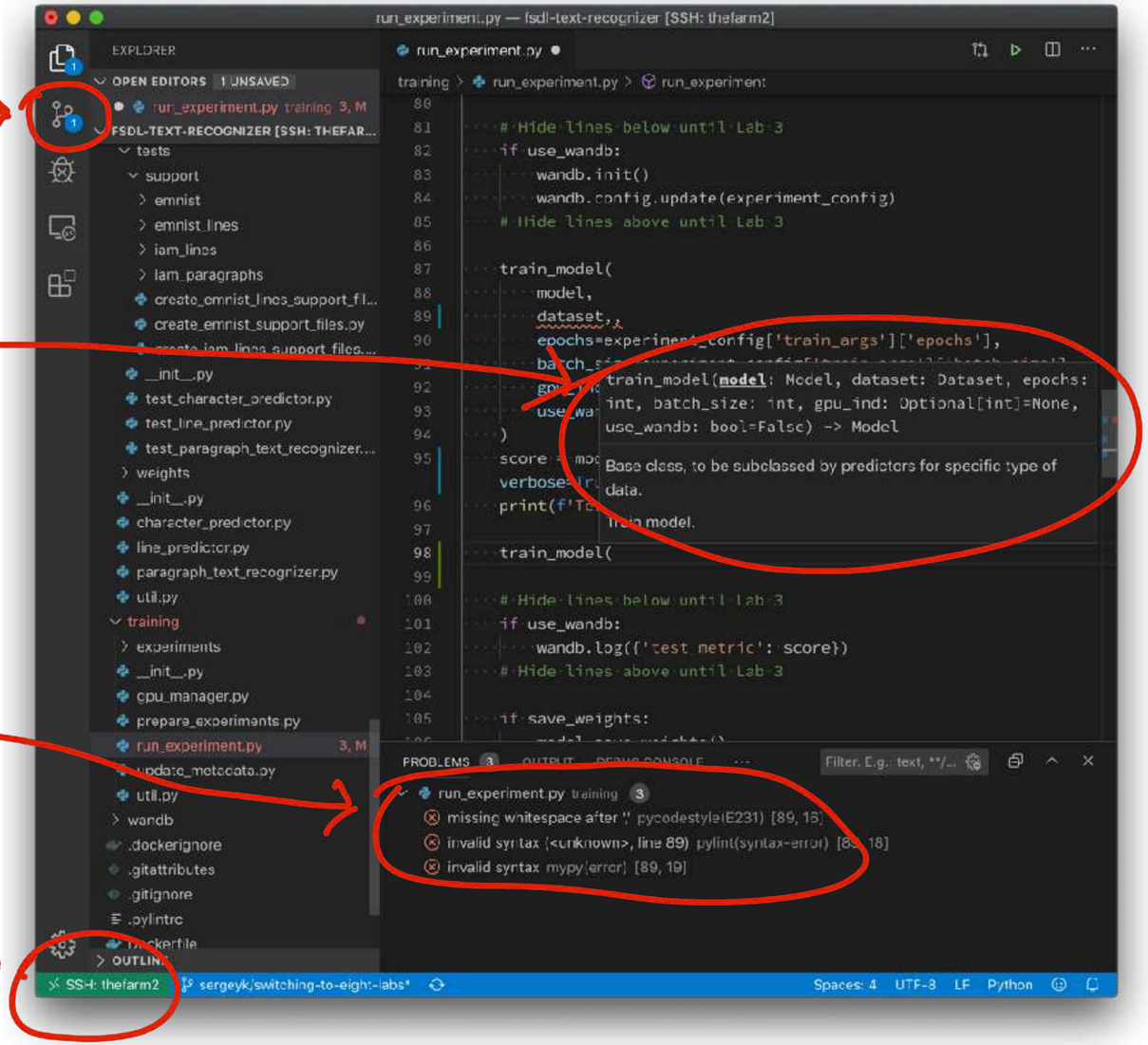
VS Code

Built-in git staging and diffing

Peek documentation

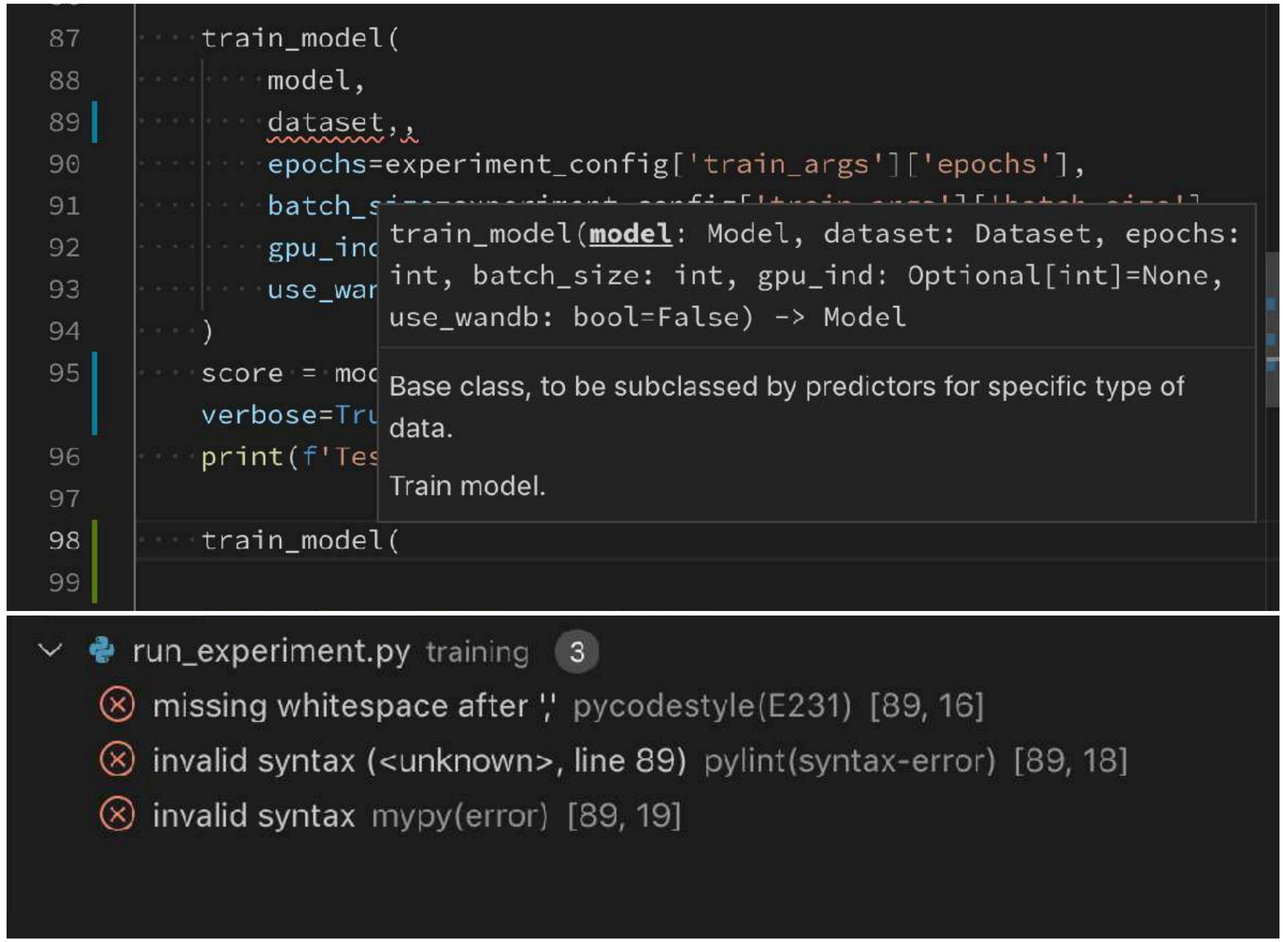
Lint code as your write

Open whole projects remotely



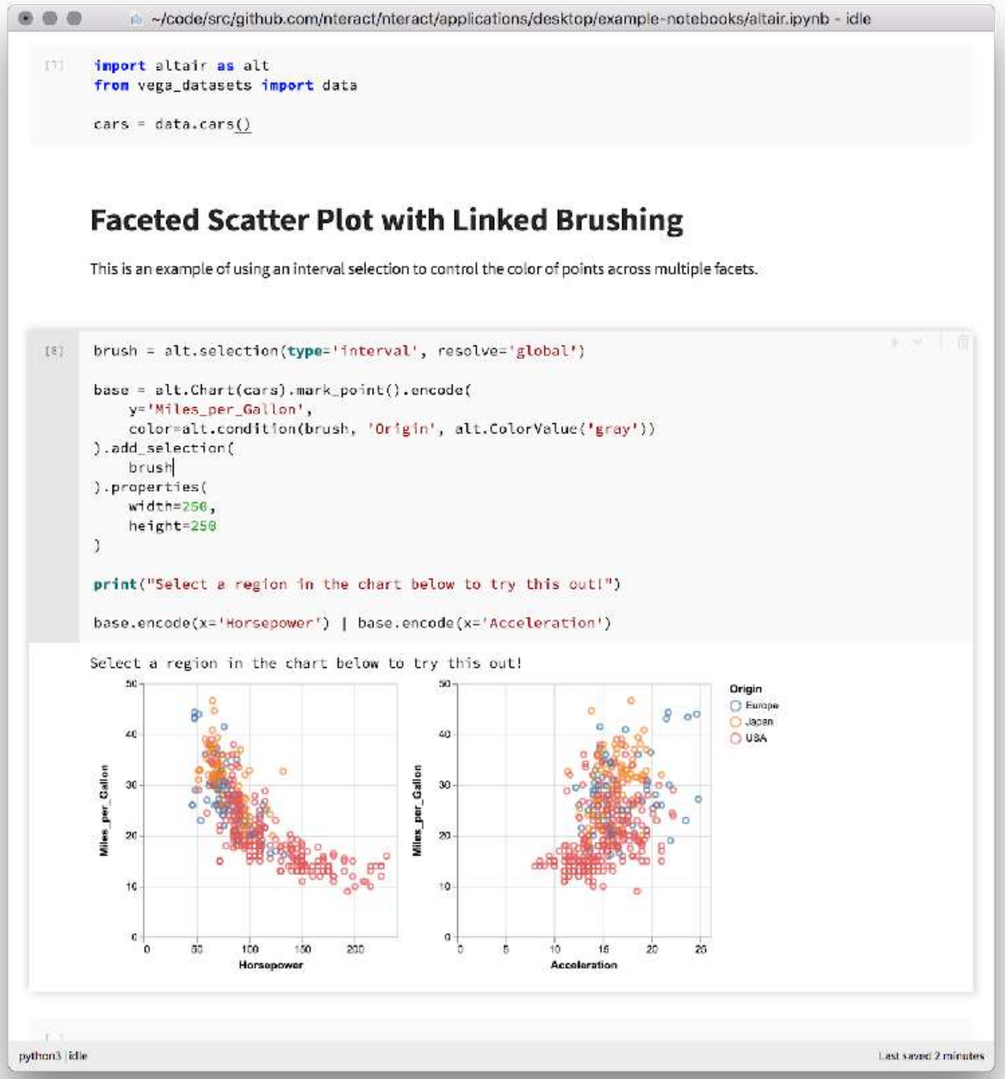
Linters and Type Hints

- Whatever code style rules can be codified, should be
- Static analysis can catch some bugs
- Static type checking both documents code and catches bugs



Jupyter Notebooks

- Notebooks have become fundamental to data science
  - Great as the "first draft" of a project
  - Jeremy Howard great to learn from (course.fast.ai videos)

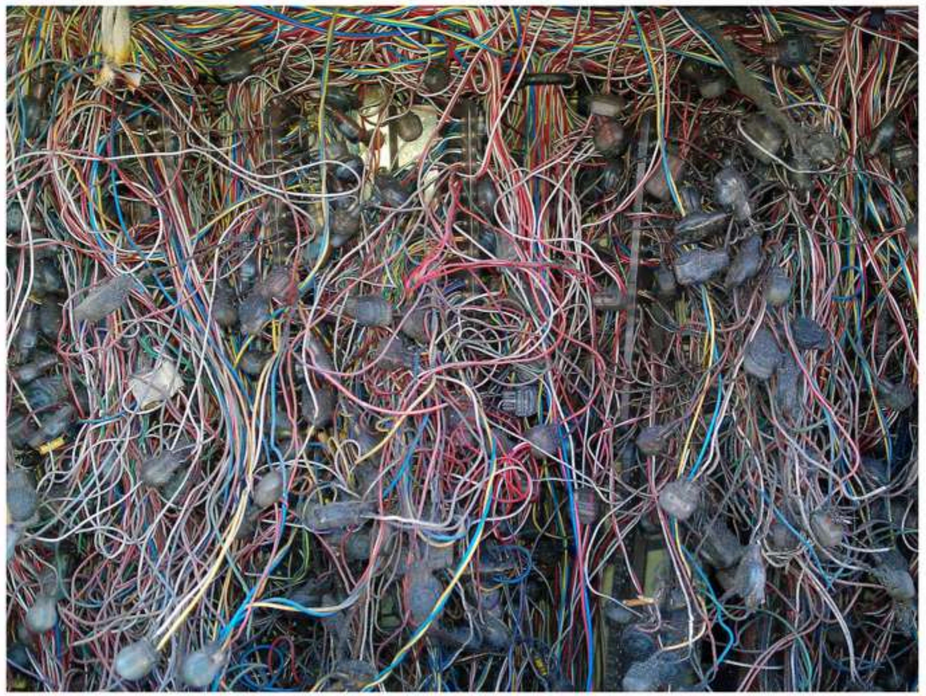


Problems with notebooks

- Notebook editor is primitive
- Out-of-order execution artifacts
- Hard to version
- Hard to test

5 reasons why jupyter notebooks suck

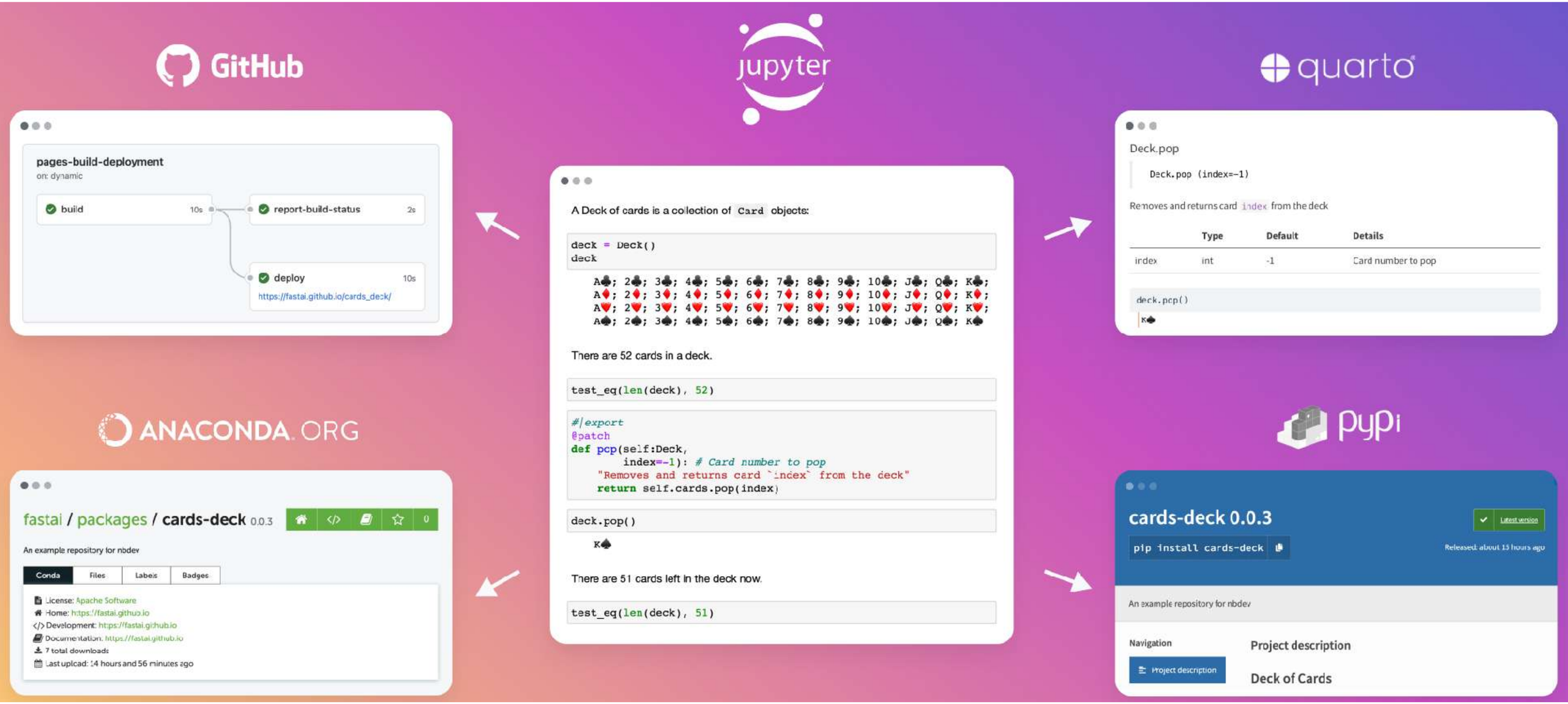
Alexander Mueller Follow
Mar 24, 2018 · 3 min read ★



How it feels like managing jupyter notebooks (Complexity © https://www.flickr.com/photos/bitterjug/7670055210)

https://towardsdatascience.com/5-reasons-why-jupyter-notebooks-suck-4dc201e27086

Counterpoint: nbdev

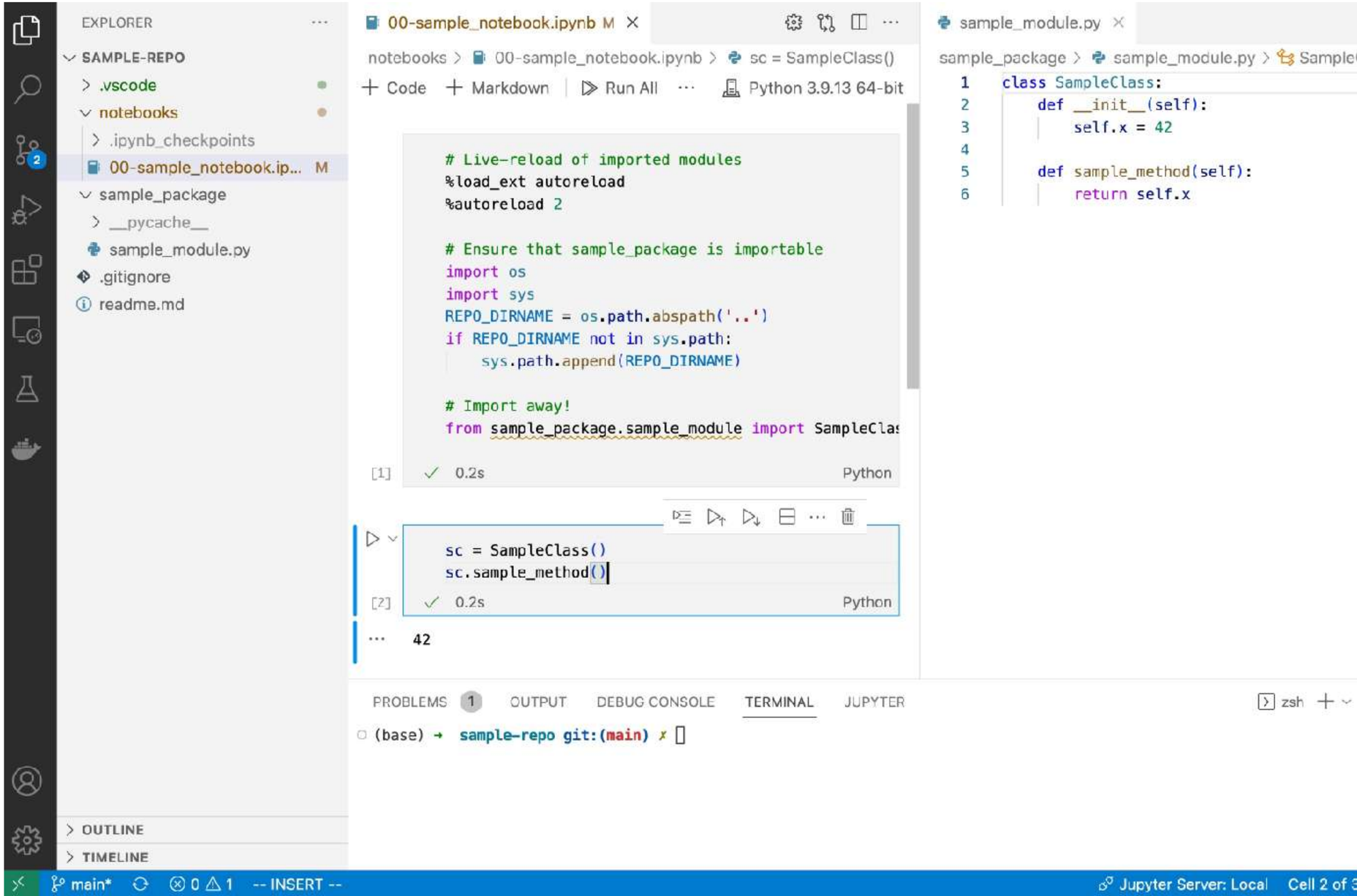


https://nbdev.fast.ai

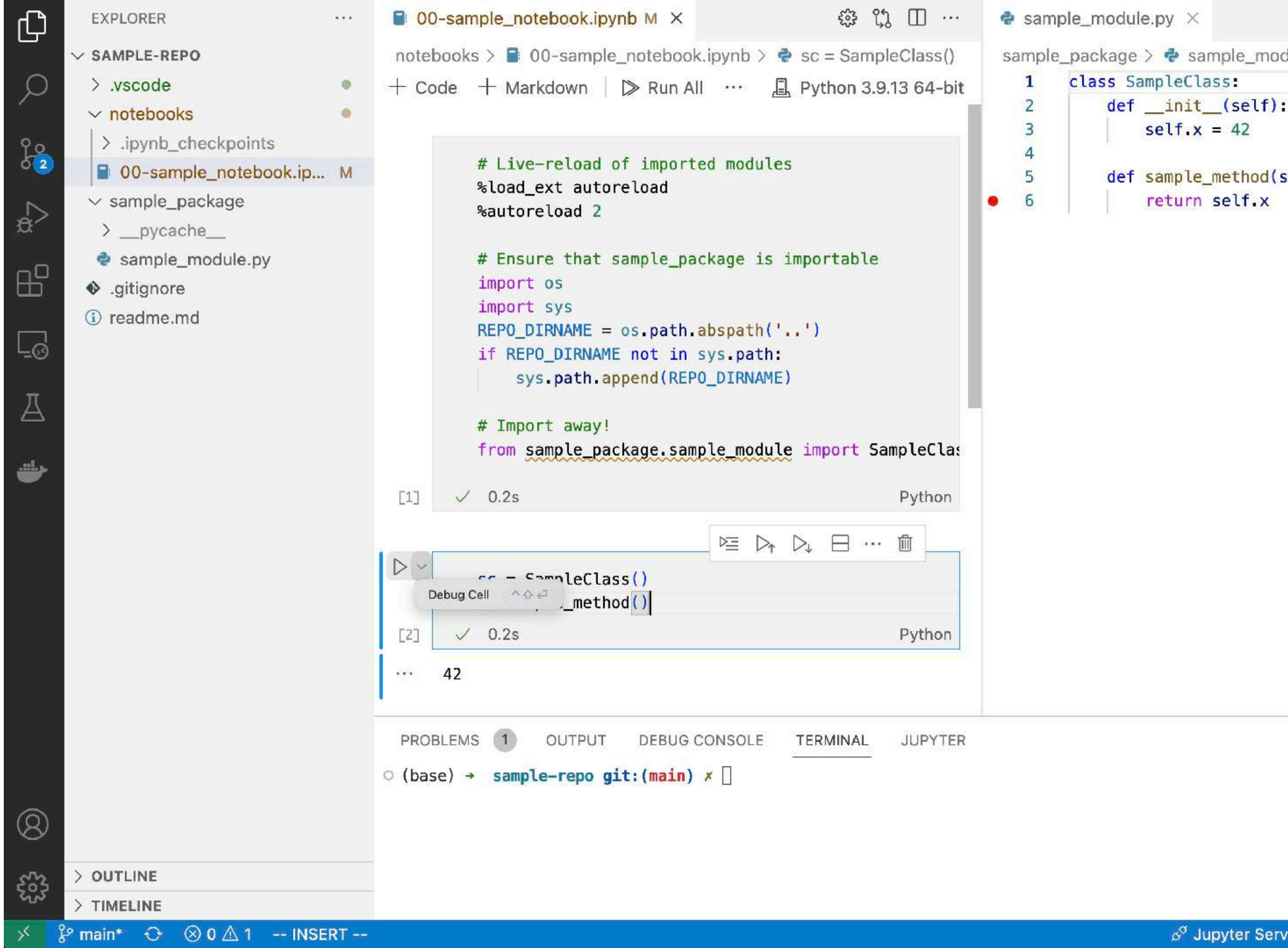
FSDL Recommendation

https://github.com/full-stack-deep-learning/sample-repo

- Write code in modules imported into notebooks



- Enables awesome debugging



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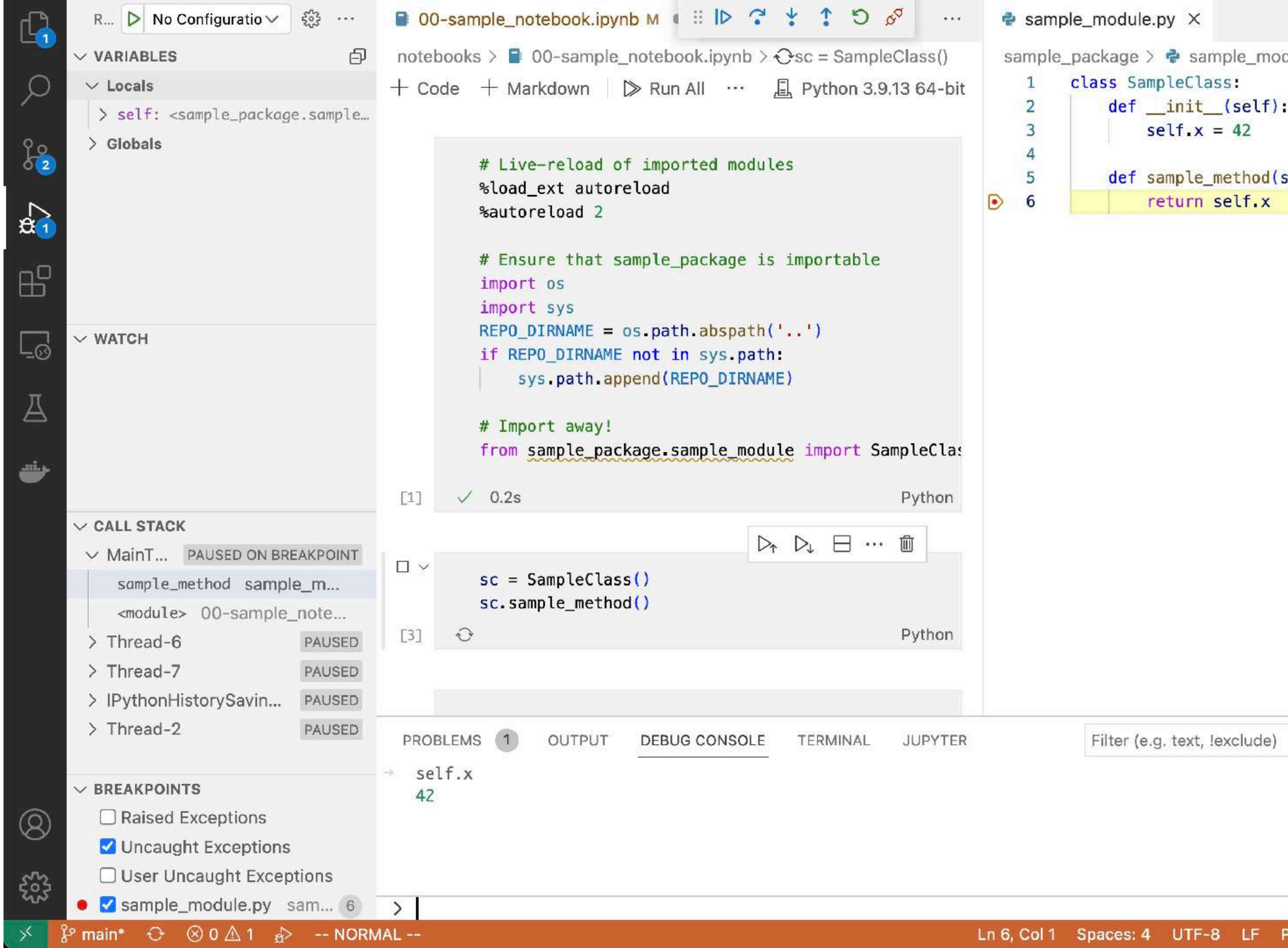


Streamlit

- Decorate Python code
- Get interactive applets
- Publish to the web

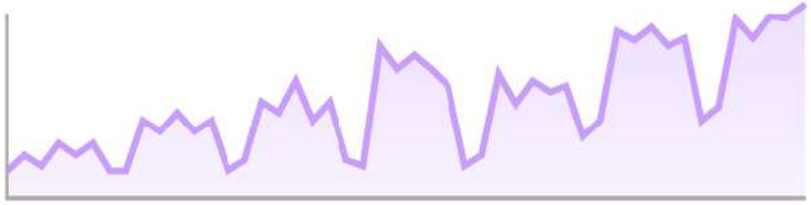
MyApp.py

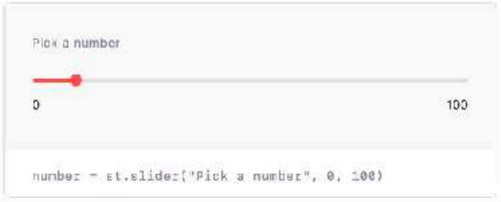
```
import streamlit as st
import pandas as pd

st.write("""
# My first app
Hello *world!*
""")

df = pd.read_csv("my_data.csv")
st.line_chart(df)
```

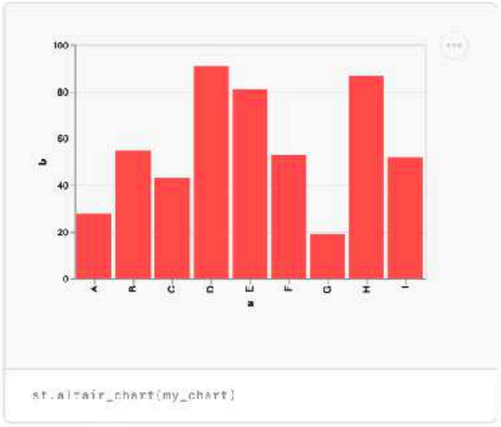
My App • Streamlit

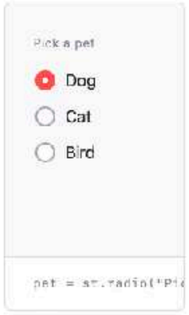
My first app

Hello *world!*









https://streamlit.io

Environment

Our goals:

- Easily specify the exact Python, CUDA, CUDNN environment
- Humans should specify minimal constraints (`torch >= 1.7` and `numpy`), computer should figure out exact, mutually compatible versions (`torch==1.7.1; numpy==1.19.5`)
- Separate production (`torch`) from development (`black`) dependencies

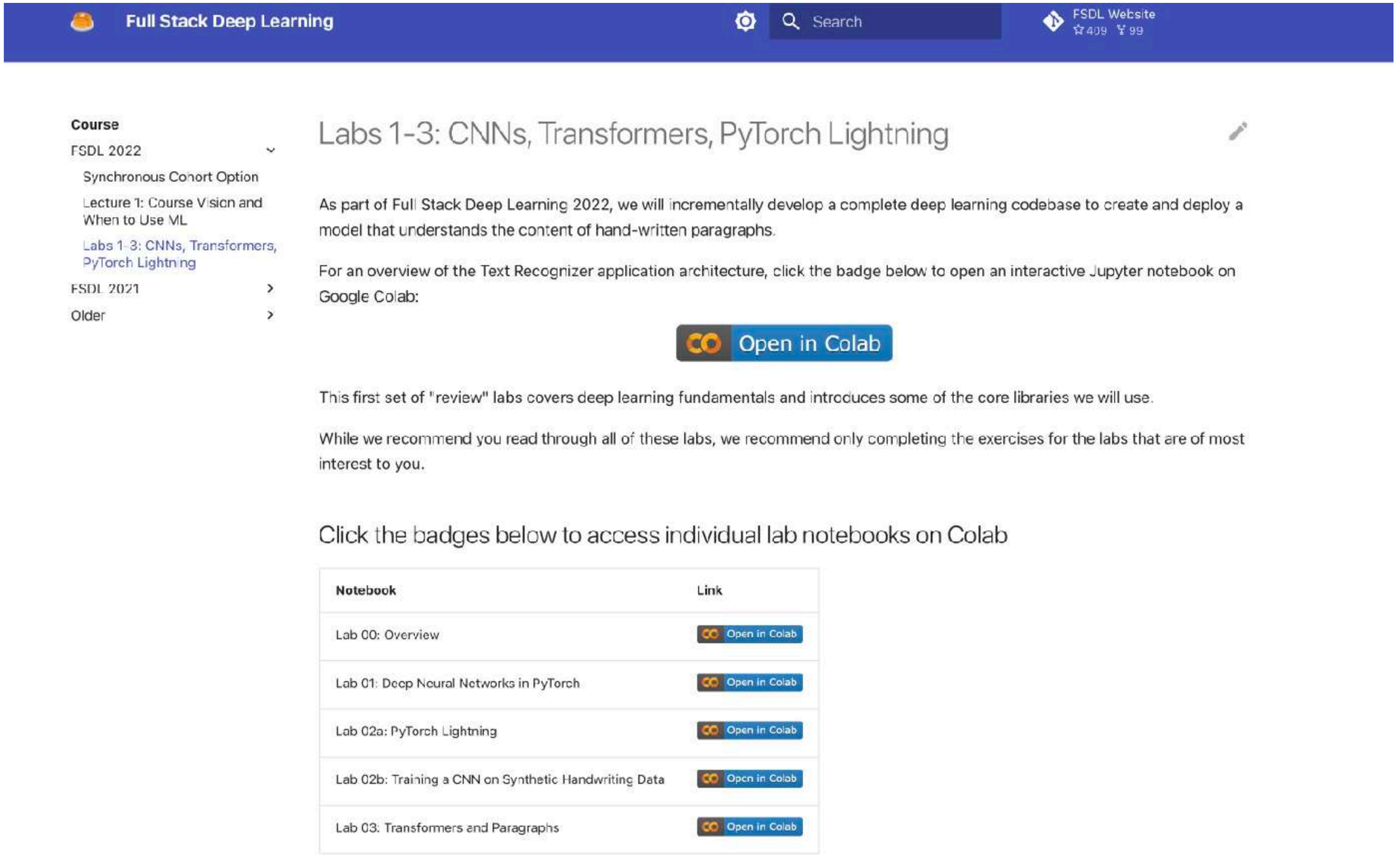
We achieve this by:

- We specify our Python and CUDA versions in `environment.yml`
- We use the `conda` package manager to create our environment from this file
- We specify our requirements in `requirements/prod.in` and `requirements/dev.in`
- We use `pip-tools` to lock in mutually compatbile versions of all requirements
- We add a `Makefile` so we can simply run `make` to update everything

(How we do it in lab)

https://github.com/full-stack-deep-learning/conda-piptools

Go through Labs 1-3!



https://fullstackdeeplearning.com/course/2022/labs-1-3-cnns-transformers-pytorch-lightning/

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Deep Learning Frameworks

Why do we need frameworks?

- Deep Learning is not lot of code with a matrix math library (Numpy)
- BUT: auto-differentiation and CUDA are a lot of work
- ...Also all the layer types, optimizers, data interfaces, etc.

```python
class Linear:
  def __init__(self, input_dim: int, num_hidden: int = 1):
    self.weights = np.random.randn(input_dim, num_hidden) * np.sqrt(2. / input_dim)
    self.bias = np.zeros(num_hidden)

  def __call__(self, x):
    self.x = x
    output = x @ self.weights + self.bias
    return output

  def backward(self, gradient):
    self.weights_gradient = self.x.T @ gradient
    self.bias_gradient = gradient.sum(axis=0)
    self.x_gradient = gradient @ self.weights.T
    return self.x_gradient

  def update(self, lr):
    self.weights = self.weights - lr * self.weights_gradient
    self.bias = self.bias - lr * self.bias_gradient
```

Which to use?

Josh Tobin
@josh_tobin_

Why do people always ask what ML framework to use?
It's easy:

- jax is for researchers
- pytorch is for engineers
- tensorflow is for boomers

6:24 PM · Mar 11, 2021 · Twitter Web App

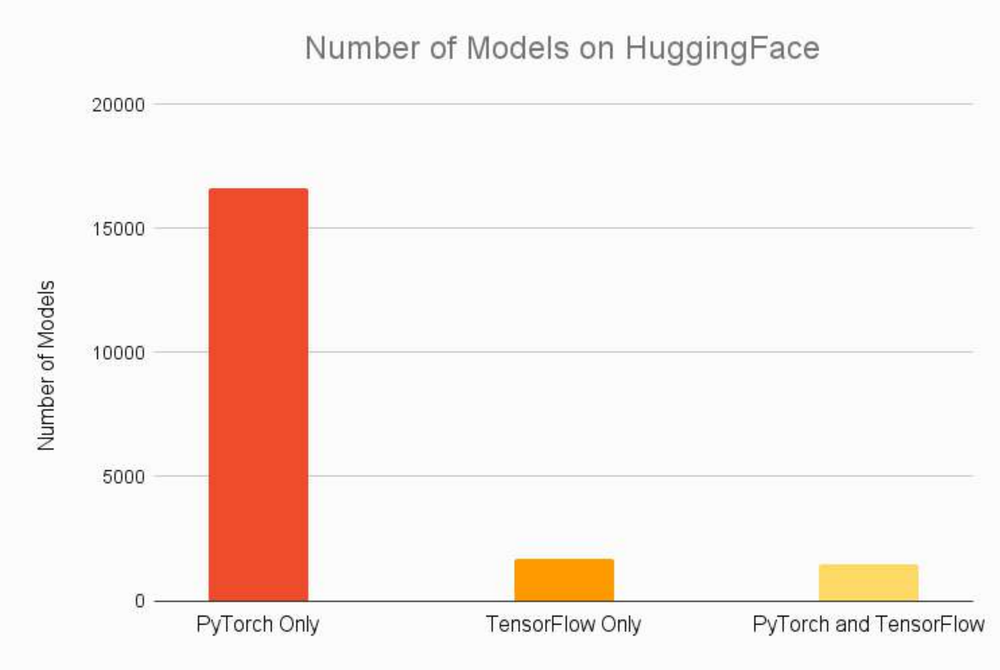
263 Retweets **65** Quote Tweets **2,884** Likes

But seriously

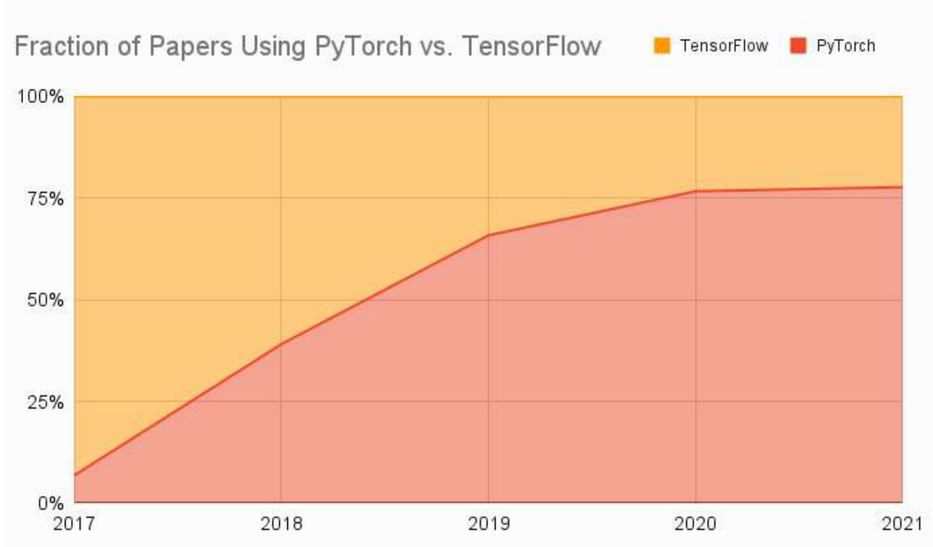
- PyTorch / Tensorflow / Jax
  - Define model by running Python code
  - Optimized execution graph for CPU, GPU, TPU, mobile
- PyTorch
  - 😃 Absolutely dominant (by # models, # papers, # competition winners)
- Tensorflow
  - 😊 Tensorflow.js and Keras are pretty cool
- Jax
  - 😢 Need a meta-framework for deep learning

77% of 2021 ML competition winners used PyTorch

https://blog.mlcontests.com/p/winning-at-competitive-ml-in-2022?s=w



https://www.assemblyai.com/blog/pytorch-vs-tensorflow-in-2022/



https://horace.io/pytorch-vs-tensorflow/

PyTorch

- Excellent dev experience
- Production-ready as is, and even faster with TorchScript
- Great distributed training ecosystem
- Libraries for vision, audio, etc
- Mobile deployment

```
training_data = datasets.FashionMNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor()
)

train_dataloader = DataLoader(training_data, batch_size=64)
test_dataloader = DataLoader(test_data, batch_size=64)

class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__init__()
        self.flatten = nn.Flatten()
        self.linear_relu_stack = nn.Sequential(
            nn.Linear(28*28, 512),
            nn.ReLU(),
            nn.Linear(512, 512),
            nn.ReLU(),
            nn.Linear(512, 10),
        )

    def forward(self, x):
        x = self.flatten(x)
        logits = self.linear_relu_stack(x)
        return logits

model = NeuralNetwork()
```

+ PyTorch Lightning

- Run your code on any hardware
- Performance & bottleneck profiler
- Model checkpointing
- 16-bit precision
- Run distributed training

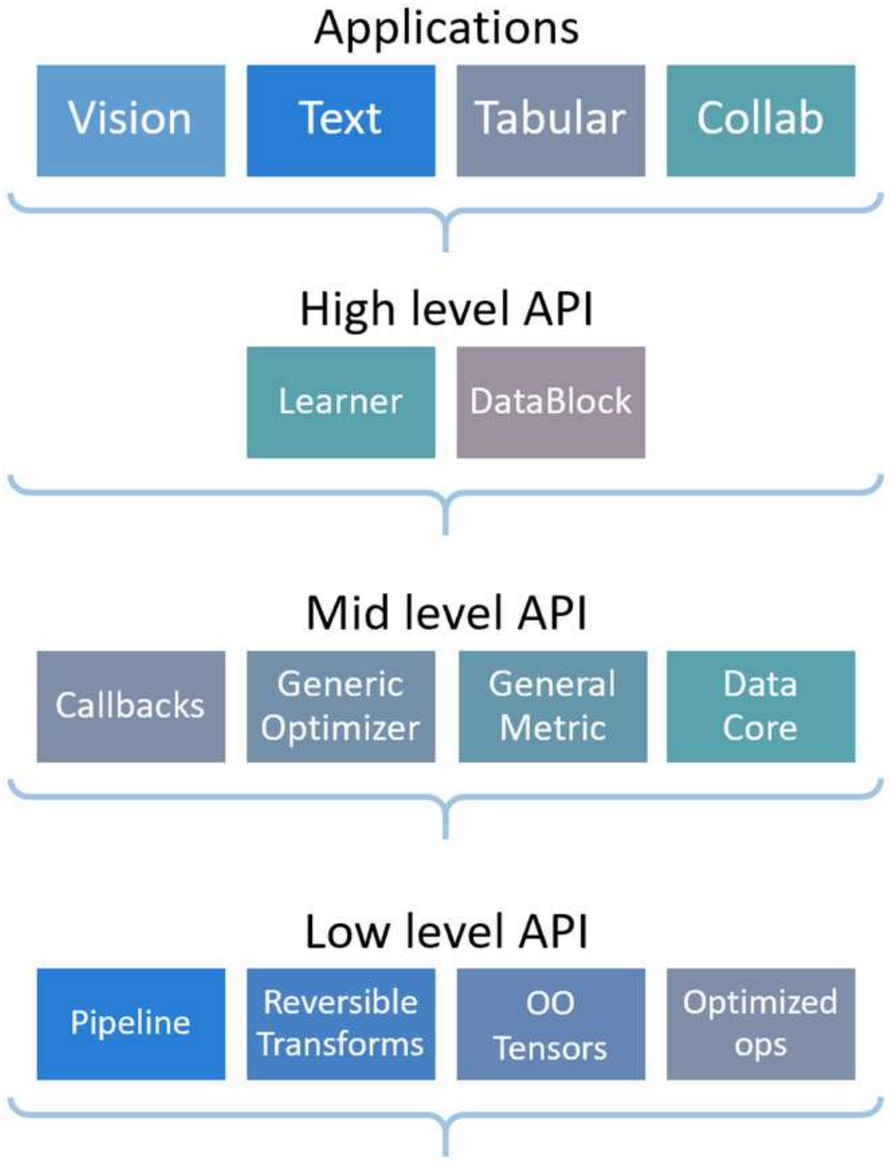
```python
class LitAutoEncoder(pl.LightningModule):
    def __init__(self):
        super().__init__()
        self.encoder = nn.Sequential(
            nn.Linear(28 * 28, 64),
            nn.ReLU(),
            nn.Linear(64, 3))
        self.decoder = nn.Sequential(
            nn.Linear(3, 64),
            nn.ReLU(),
            nn.Linear(64, 28 * 28))

    def forward(self, x):
        embedding = self.encoder(x)
        return embedding

    def configure_optimizers(self):
        optimizer = torch.optim.Adam(self.parameters(), lr=1e-3)
        return optimizer

    def training_step(self, train_batch, batch_idx):
        x, y = train_batch
        x = x.view(x.size(0), -1)
        z = self.encoder(x)
        x_hat = self.decoder(z)
        loss = F.mse_loss(x_hat, x)
        self.log('train_loss', loss)
        return loss
```

```python
# data
dataset = MNIST('', train=True, download=True,
transform=transforms.ToTensor())
mnist_train, mnist_val = random_split(dataset, [55000, 5000])

train_loader = DataLoader(mnist_train, batch_size=32)
val_loader = DataLoader(mnist_val, batch_size=32)

# model
model = LitAutoEncoder()

# training
trainer = pl.Trainer(gpus=4, precision=16, limit_train_batches=0.5)
trainer.fit(model, train_loader, val_loader)
```

What we use in labs!

Another possibility: FastAI

- Software developed alongside the fast.ai course
- Provides many advanced tricks (data augmentations, better initializations, learning rate scheduling)
- Code style is quite different from mainstream Python



https://docs.fast.ai

TensorFlow

- FSDL prefers PyTorch, as the ecosystem is now unquestionably stronger.
- But if you have a specific reason to prefer TensorFlow, could still make sense.

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(128, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

Jax

- General vectorization, auto-differentiation, and compilation to GPU/TPU code
- Need separate framework for deep learning (Flax or Haiku)
- FSDL says: only use if you have a specific need

Meta-frameworks and model zoos

PYTORCH HUB

Discover and publish models to a pre-trained model repository designed for research exploration.
Check out the models for Researchers, or learn How It Works.

Contribute Models

**This is a beta release - we will be collecting feedback and improving the PyTorch Hub over the coming months.*

FOR RESEARCHERS —

EXPLORE AND EXTEND MODELS FROM THE LATEST CUTTING EDGE RESEARCH

All | Audio | Generative | Nlp | Scriptable | Vision

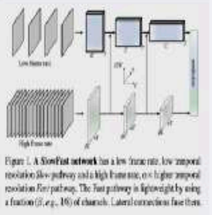
Sort

HybridNets 296

HybridNets - End2End Perception Network

3D ResNet 2.6k

Resnet Style Video classification networks pretrained on the Kinetics 400 dataset

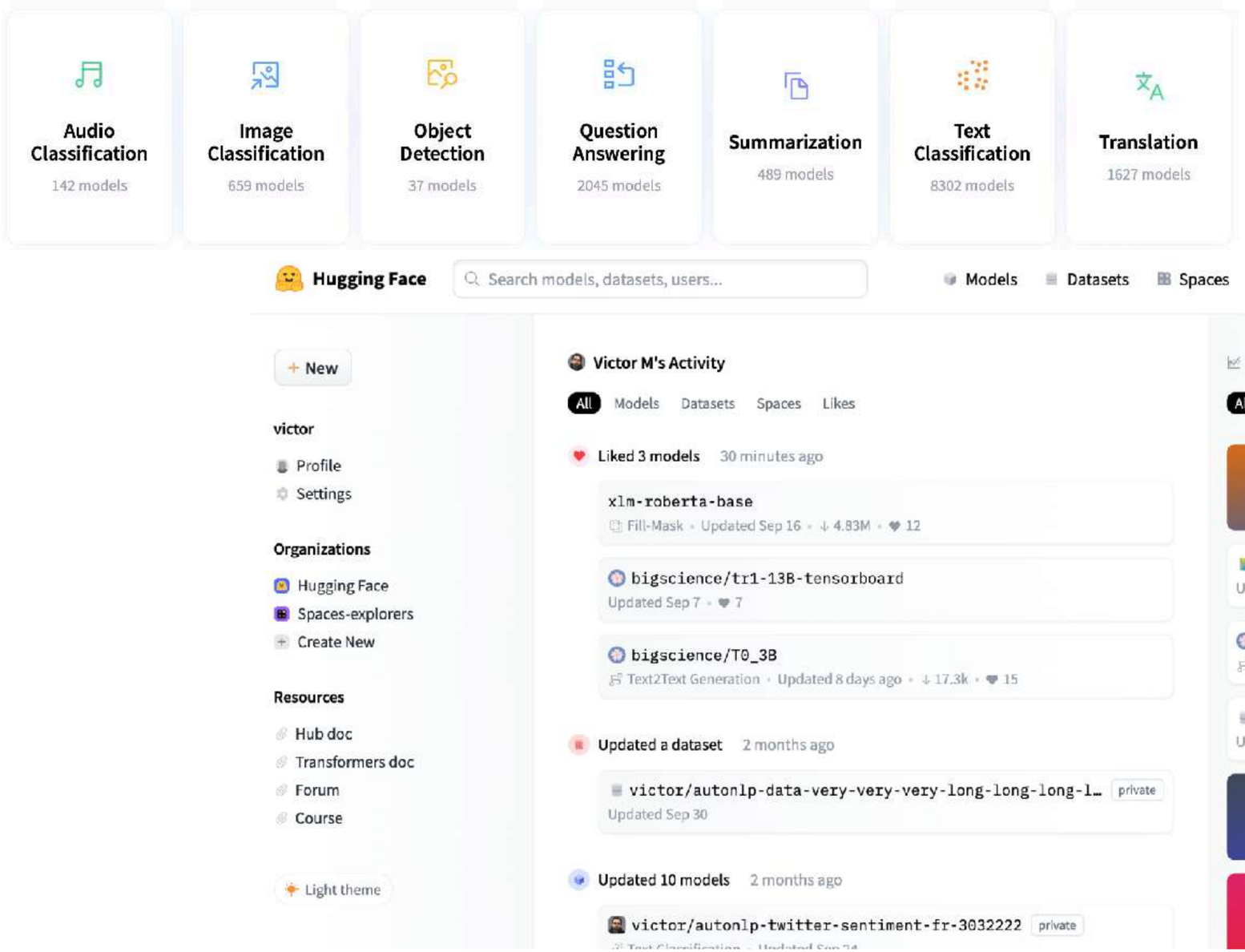


Interoperability ONNX

- Open standard for **saving** deep learning models
- Can convert PyTorch -> TF, etc.
- Can work well, but can run into edge cases…

Hugging Face

- The most popular Model Zoo: 60K pre-trained models
- Transformers library that works with PyTorch, TF, Jax
- And 7.5K Datasets
- Plus Spaces, hosted Inference, and more



TIMM

- Collection of SOTA computer vision models + related code
- By Ross Wightman

Model	Acc@1 (Err)	Acc@5 (Err)	Param # (M)	Interpolation	Image Size
efficientnet_b3a	82.242 (17.758)	96.114 (3.886)	12.23	bicubic	320 (1.0 crop)
efficientnet_b3	82.076 (17.924)	96.020 (3.980)	12.23	bicubic	300
regnet_32	82.002 (17.998)	95.906 (4.094)	19.44	bicubic	224
skresnext50d_32x4d	81.278 (18.722)	95.366 (4.634)	27.5	bicubic	288 (1.0 crop)
seresnext50d_32x4d	81.266 (18.734)	95.620 (4.380)	27.6	bicubic	224
efficientnet_b2a	80.608 (19.392)	95.310 (4.690)	9.11	bicubic	288 (1.0 crop)
resnet50d	80.530 (19.470)	95.160 (4.840)	25.6	bicubic	224
mixnet_xl	80.478 (19.522)	94.932 (5.068)	11.90	bicubic	224
efficientnet_b2	80.402 (19.598)	95.076 (4.924)	9.11	bicubic	260
	80.274 (19.726)	95.070 (4.930)	28.1	bicubic	224
	80.156 (19.844)	94.642 (5.358)	27.5	bicubic	224
	80.058 (19.942)	95.084 (4.916)	27.6	bicubic	256

```
import timm
import torch

model = timm.create_model('resnet34', num_classes=10)
x     = torch.randn(1, 3, 224, 224)
model(x).shape
```

```
torch.Size([1, 10])
```

Distributed Training

Scenarios

- Multiple machines, with multiple GPUs
- **Data batch** may:
  - Fit on a single GPU
  - Or not
- **Model parameters** may:
  - Fit on a single GPU
  - Or not

Scenarios

- Multiple machines, with multiple GPUs
- **Data batch** may:
  - Fit on a single GPU
  - Or not
- **Model parameters** may:
  - Fit on a single GPU
  - OR not

Trivial Parallelism

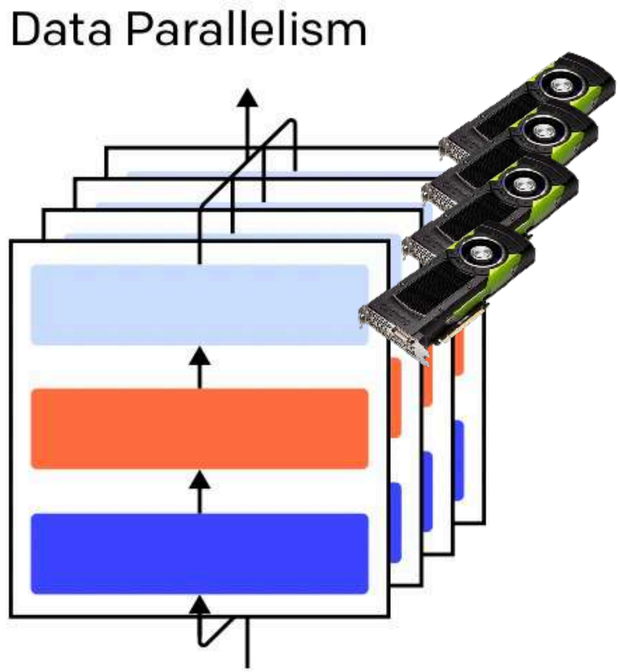
- Either launch more independent experiments on other GPUs and/or machines
- Or increase batch size until it no longer fits on one GPU...

Scenarios

- Multiple machines, with multiple GPUs
- **Data batch** may:
  - Fit on a single GPU
  - Or not
- **Model parameters** may:
  - Fit on a single GPU
  - Or not

Data Parallelism

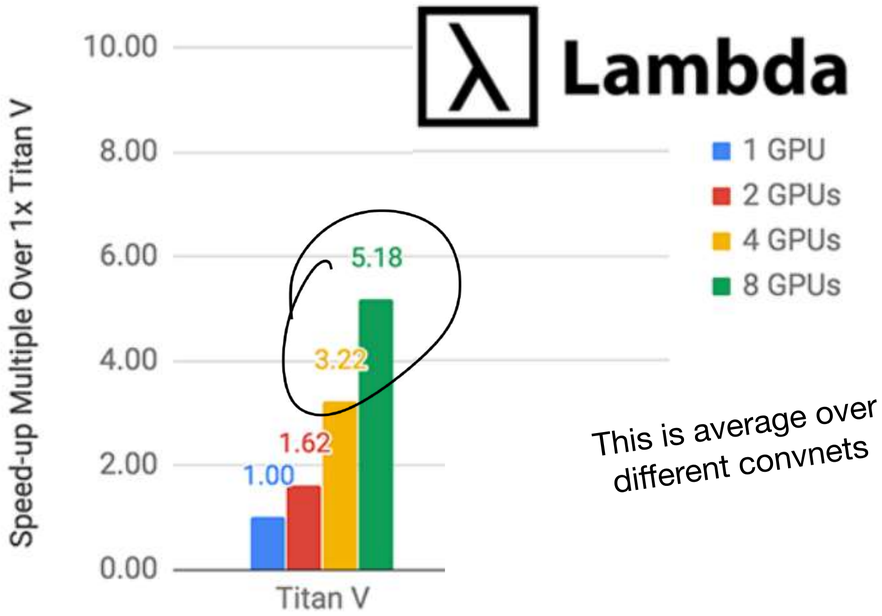
- Distribute a single batch of data across GPUs, then average gradients across them
- Extra work is cross-GPU, so make sure that GPUs have fast interconnects (NVLink, etc)



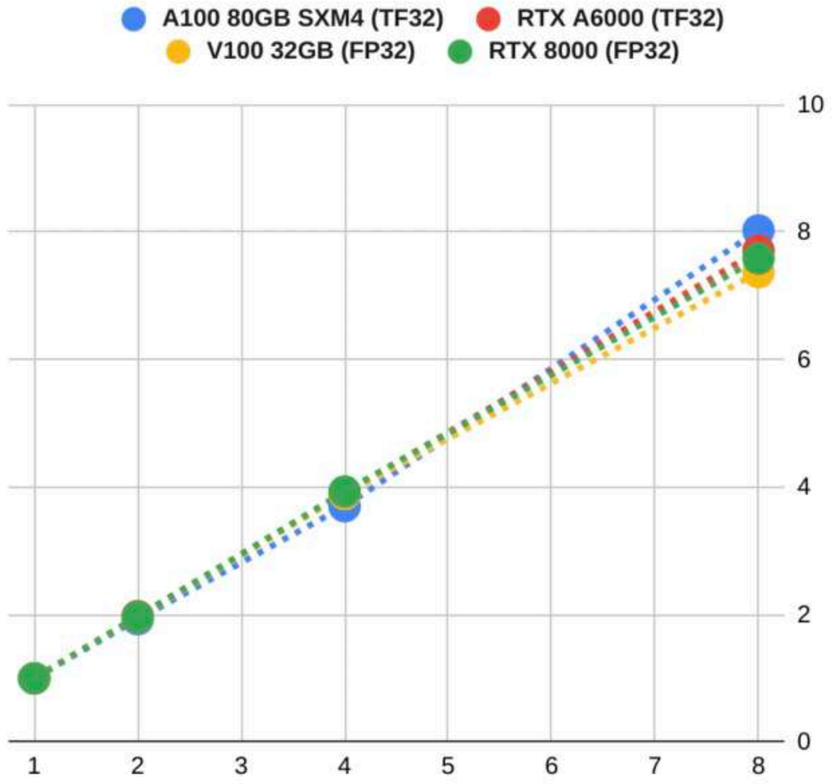
https://openai.com/blog/techniques-for-training-large-neural-networks/

Speedup

- Expect a linear speedup for server cards
- But a sublinear speedup for consumer cards (2-3x for 4 GPUs)



https://lambdalabs.com/blog/titan-v-deep-learning-benchmarks/



https://lambdalabs.com/blog/best-gpu-2022-sofar/

Data Parallelism

- PyTorch has a robust DistributedDataParallel library
- Horovod is a third-party library for the same (and more)
- Lightning makes either one dead-simple to use
- Speedup seems to be the same


```python
# train on 8 GPUs (same machine (ie: node))
trainer = Trainer(accelerator="gpu", devices=8, strategy="ddp")

# train on 32 GPUs (4 nodes)
trainer = Trainer(accelerator="gpu", devices=8, strategy="ddp", num_nodes=4)
```

```python
# train Horovod on GPU (number of GPUs / machines provided on command-line)
trainer = Trainer(strategy="horovod", accelerator="gpu", devices=1)

# run training with 4 GPUs on a single machine
horovodrun -np 4 python train.py

# run training with 8 GPUs on two machines (4 GPUs each)
horovodrun -np 8 -H hostname1:4,hostname2:4 python train.py
```

Train Mode	V100x1	V100x4	V100x8
Vanilla	32m 58s	-	-
DistributedDataParallel	-	11m 16s	9m 8s
Horovod	-	10m 23s	7m 50s

https://www.reddit.com/r/MachineLearning/comments/hmgr9g/d_pytorch_distributeddataparallel_and_horovod/

Scenarios

- Multiple machines, with multiple GPUs
- **Data batch** may:
  - Fit on a single GPU
  - Or not
- **Model parameters** may:
  - Fit on a single GPU
  - Or not

Going beyond simple data-parallel

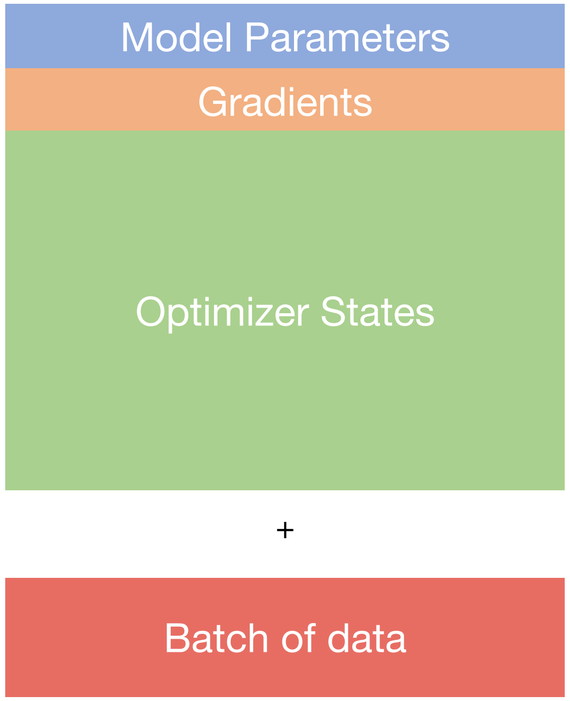
- If model does not fit on one GPU, there are three main solutions:
  - Sharded data-parallelism
  - Pipelined model-parallelism
  - Tensor-parallelism

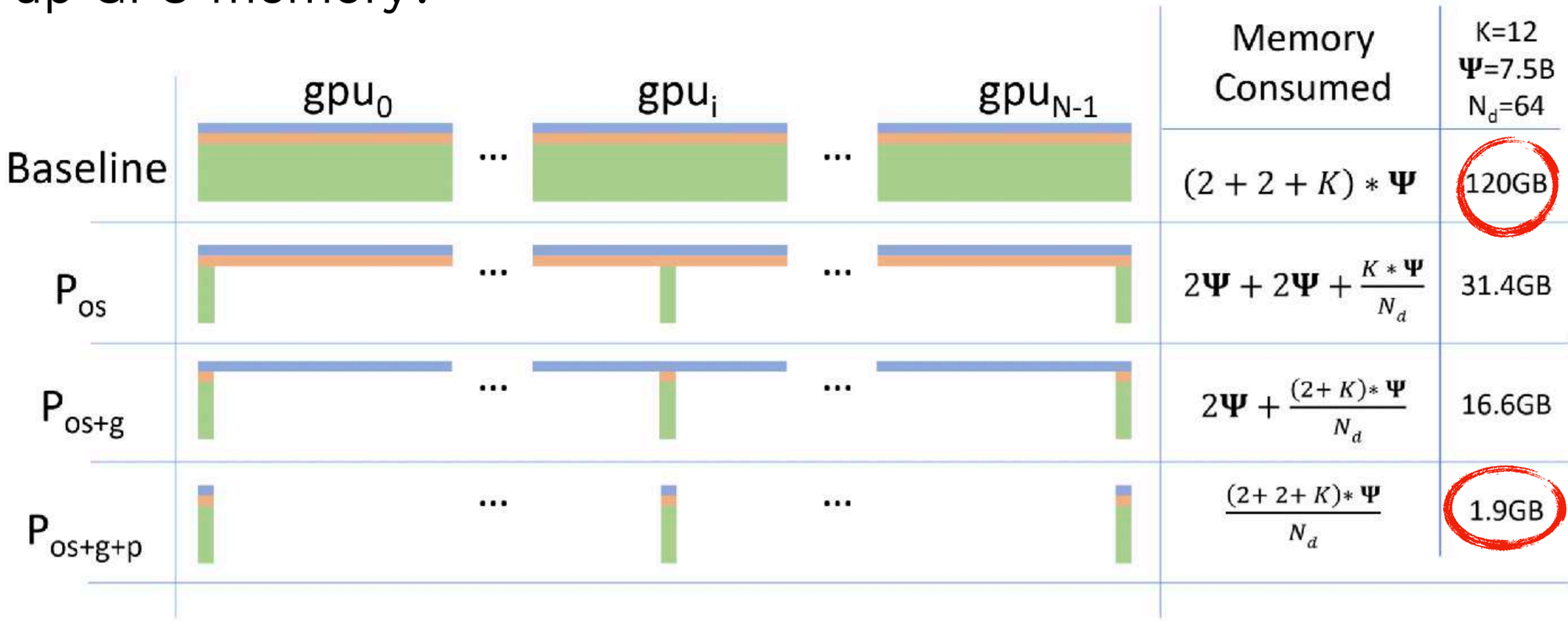
Going beyond simple data-parallel

- If model does not fit on one GPU, there are three main solutions:
  - **Sharded data-parallelism**
  - Pipelined model-parallelism
  - Tensor-parallelism

Sharded Data-Parallelism

What exactly takes up GPU memory?





	Memory Consumed	K=12 Ψ=7.5B N_d=64
Baseline	$(2+2+K)*\Psi$	120GB
P_{os}	$2\Psi+2\Psi+\frac{K*\Psi}{N_d}$	31.4GB
P_{os+g}	$2\Psi+\frac{(2+K)*\Psi}{N_d}$	16.6GB
P_{os+g+p}	$\frac{(2+2+K)*\Psi}{N_d}$	1.9GB

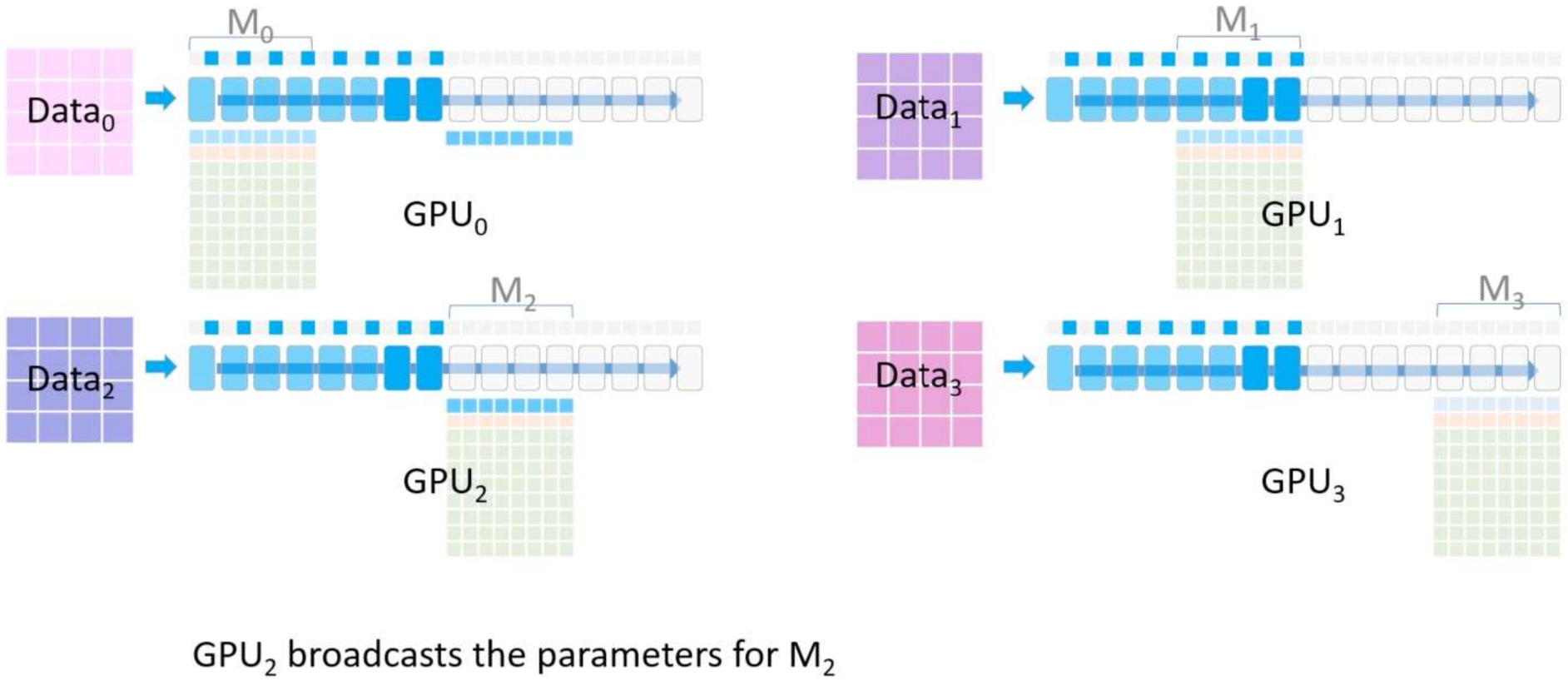
ZeRO-3: 10x reduction in memory use!

ZeRO: Memory Optimizations Toward Training Trillion Parameter Models

Samyam Rajbhandari*, Jeff Rasley*, Olatunji Ruwase, Yuxiong He
{samyamr, jerasley, olruwase, yuxhe}@microsoft.com

https://arxiv.org/pdf/1910.02054.pdf

Sharded Data-Parallelism



Literally pass around model params between GPUs as computation is proceeding!

Helpful video:

https://www.microsoft.com/en-us/research/blog/zero-deepspeed-new-system-optimizations-enable-training-models-with-over-100-billion-parameters/

Sharded Data-Parallel

- Implemented by Deepspeed library from Microsoft, as well as Fairscale library from Facebook. And recently, natively by PyTorch.
  - ZeRO-3 is called Fully-sharded DataParallel by Fairscale and PyTorch.
- Try for a massive memory reduction without changing model code!

```
# train using Sharded DDP
trainer = Trainer(strategy="ddp_sharded")
```

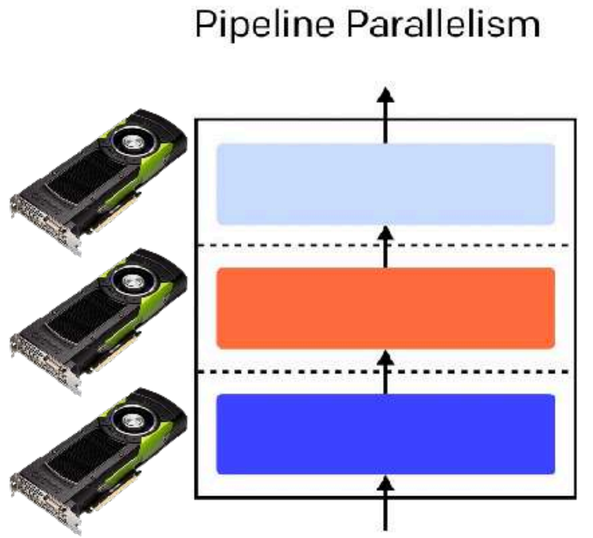
ZeRO-Offload

- ZeRO-3 principle: only send the GPU the params it needs in the moment
- Same principle can be applied to a single GPU
- Can train a 13B-param model on a single V100 (32GB) GPU!
- (Fairscale calls this CPU-offloading)

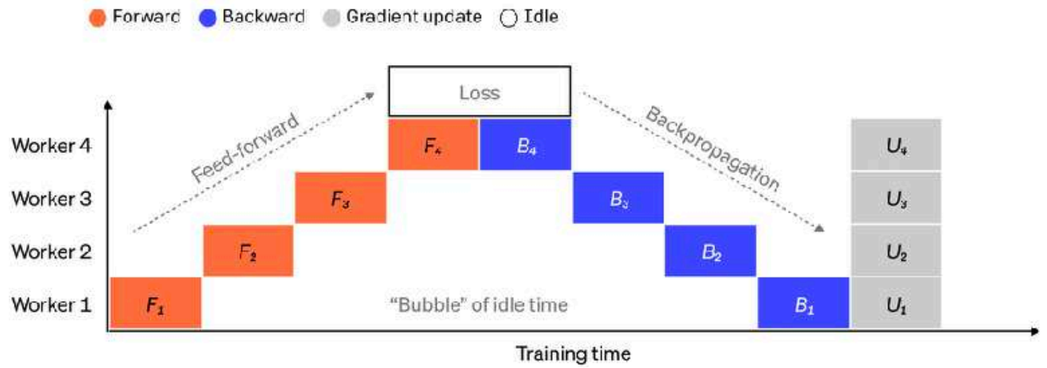
Going beyond simple data-parallel

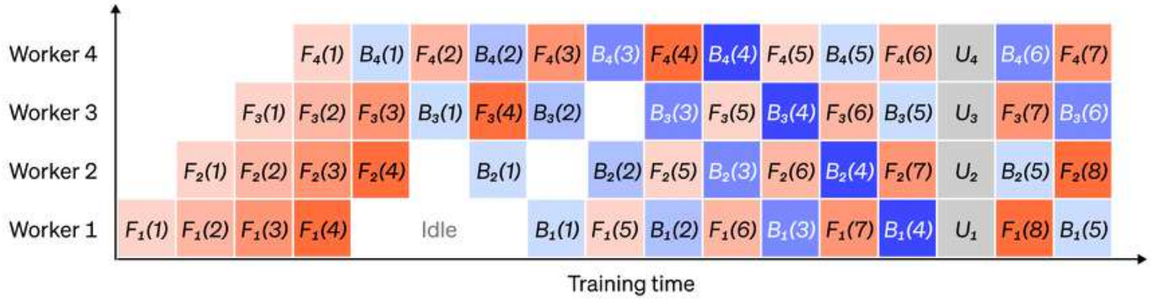
- If model does not fit on one GPU, there are three main solutions:
  - Sharded data-parallelism
  - **Pipelined model-parallelism**
  - Tensor-parallelism

Pipelined Model-Parallelism



- Trivial to implement naively, but results in only one GPU being active at a time
- Libraries like DeepSpeed and FairScale (and native PyTorch) make it better.
- But need to tune amount of pipelining.





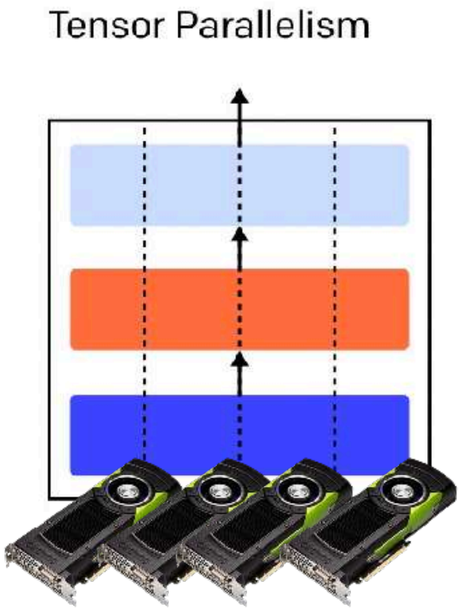
https://openai.com/blog/techniques-for-training-large-neural-networks/

Going beyond simple data-parallel

- If model does not fit on one GPU, there are three main solutions:
  - Sharded data-parallelism
  - Pipelined model-parallelism
  - **Tensor-parallelism**

Tensor Parallelism

- Matrix multiplication itself can be distributed over GPUs
- NVIDIA published Megatron-LM repo which does this for the Transformer



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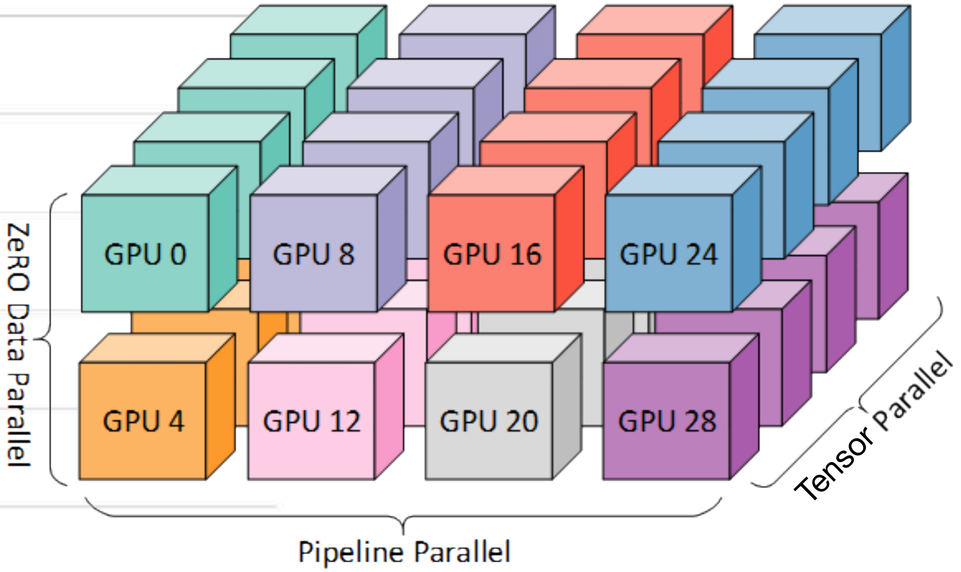
Going beyond simple data-parallel

- If model does not fit on one GPU, there are three main solutions:
  - **Sharded data-parallelism**
  - **Pipelined model-parallelism**
  - **Tensor-parallelism**

3d-parallelism: can use all three!

BLOOM (GPT-3 sized LM)

Component	DeepSpeed	Megatron-LM
ZeRO Data Parallelism	V	
Tensor Parallelism		V
Pipeline Parallelism	V	
BF16Optimizer	V	
Fused CUDA Kernels		V
DataLoader		V



BUT:

ZeRO stage 3 can also be used to train models at this scale, however, it requires more communication than the DeepSpeed 3D parallel implementation. After careful evaluation in our environment which happened a year ago we found Megatron-DeepSpeed 3D parallelism performed best. Since then ZeRO stage 3 performance has dramatically improved and if we were to evaluate it today perhaps we would have chosen stage 3 instead.

July 2022

https://huggingface.co/blog/bloom-megatron-deepspeed

Conclusion

- If model+data fits on one GPU, great.
- If not, or you want to speed up training, try DistributedDataParallel.
- If model still doesn't fit, try ZeRO-3 / Fully-Sharded Data Parallel.

Other ways to speed up

- DeepSpeed and Fairscale (and Lightning) provide other tricks...

DeepSpeed

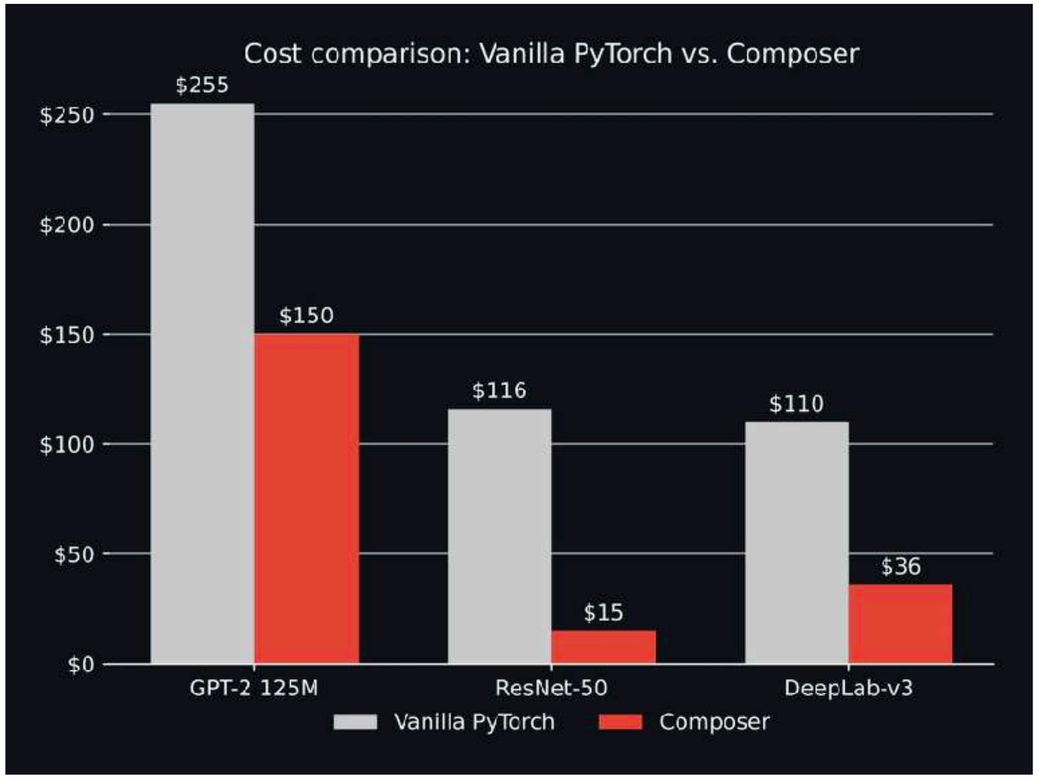
- Distributed Training with Mixed Precision
  - 16-bit mixed precision
  - Single-GPU/Multi-GPU/Multi-Node
- Ultra-fast dense transformer kernels
- Sparse attention
  - Memory- and compute-efficient sparse kernels
  - Support 10x long sequences than dense
  - Flexible support to different sparse structures
- 1-bit Adam, 0/1 Adam and 1-bit LAMB
  - Custom communication collective
  - Up to 26x communication volume saving
- Additional Memory and Bandwidth Optimizations
  - Smart Gradient Accumulation
  - Communication/Computation Overlap

https://www.deepspeed.ai/training/

Even More Training Tricks

- There are things that can improve convergence speed
- For NLP, can use Alibi instead of position encoding and train on shorter sequences, and use sequence length warmup.
- For vision, can use image size warmup, smooth labels, use special optimizer, and more.

MosaicML Composer




```python
import composer.functional as cf
from torchvision import models

my_model = models.resnet18()

# add blurpool and squeeze excite layers
my_model = cf.apply_blurpool(my_model)
my_model = cf.apply_squeeze_excite(my_model)

# your own training code starts here
```

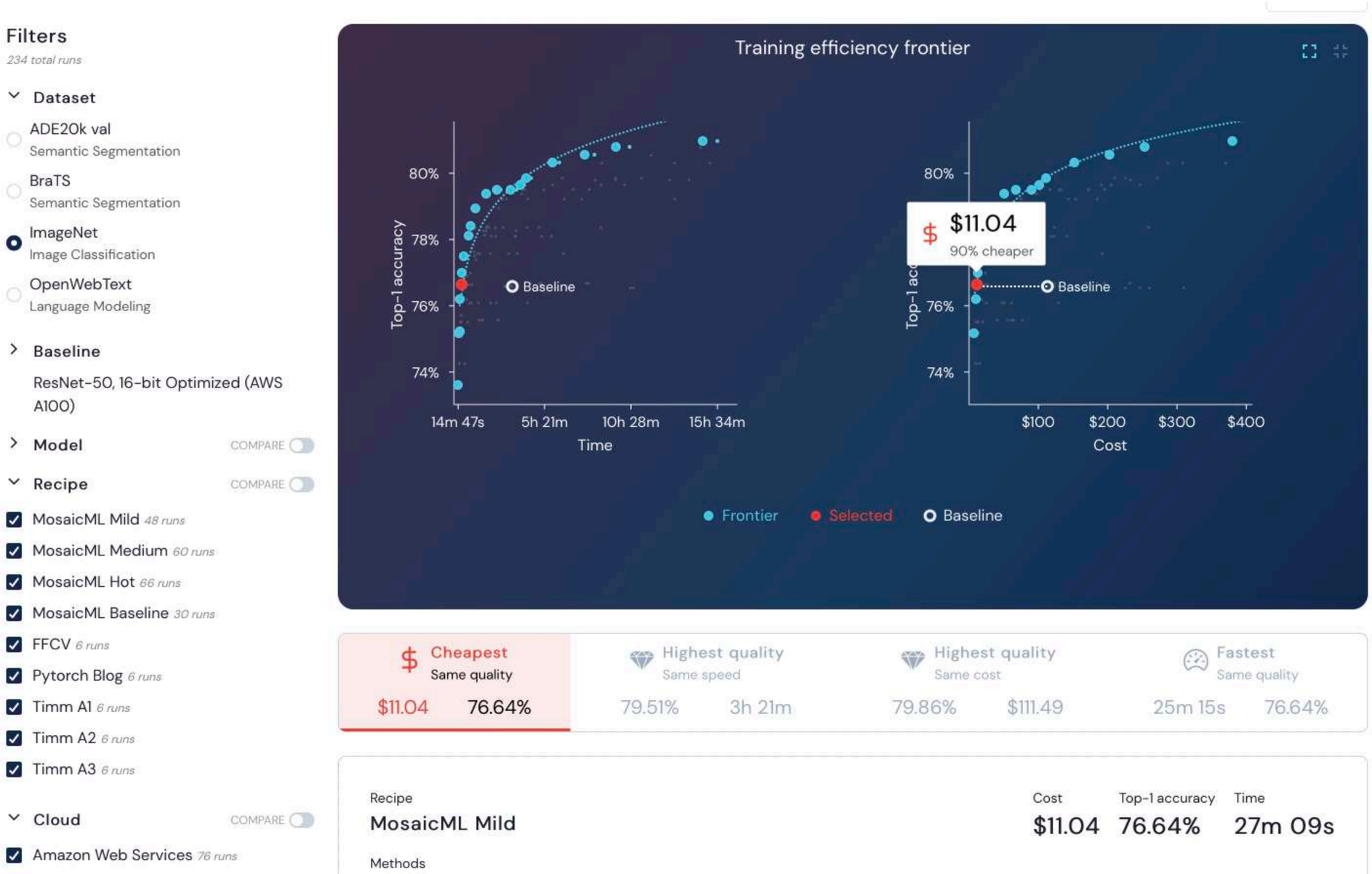
Name	Attribution	tl;dr	Example Benchmark	Speed Up*
Alibi	Press et al, 2021	Replace attention with AliBi.	GPT-2	1.5x
BlurPool	Zhang, 2019	Applies an anti-aliasing filter before every downsampling operation.	ResNet-101	1.2x
ChannelsLast	PyTorch	Uses channels last memory format (NHWC).	ResNet-101	1.5x
CutOut	DeVries et al, 2017	Randomly erases rectangular blocks from the image.	ResNet-101	1.2x
LabelSmoothing	Szegedy et al, 2015	Smooths the labels with a uniform prior	ResNet-101	1.5x
MixUp	Zhang et al, 2017	Blends pairs of examples and labels.	ResNet-101	1.5x
RandAugment	Cubuk et al, 2020	Applies a series of random augmentations to each image.	ResNet-101	1.3x
SAM	Foret et al, 2021	An optimization strategy that seeks flatter minima.	ResNet-101	1.4x
SeqLengthWarmup	Li et al, 2021	Progressively increase sequence length.	GPT-2	1.2x
Stochastic Depth	Huang et al, 2016	Replaces a specified layer with a stochastic version that randomly drops the layer or samples during training	ResNet-101	1.1x

* = time-to-train to the same quality as the baseline.

https://www.mosaicml.com

MosaicML Explorer

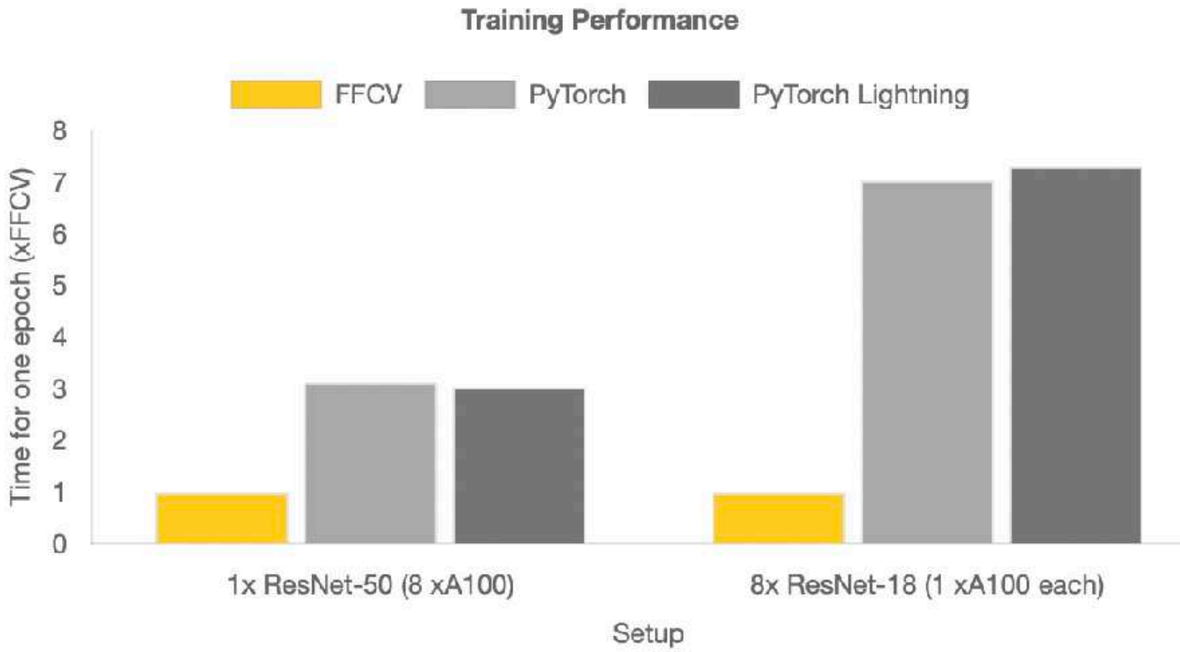
https://explorer.mosaicml.com



FFCV

```
train_loader = Loader('/pth/to/data.beton', batch_size=512,
    num_workers=8, order=OrderOption.RANDOM,
    pipelines={'image': [
            RandomResizedCropRGBImageDecoder((224, 224)),
            ToTensor(),
            # Move to GPU asynchronously as uint8:
            ToDevice(ch.device('cuda:0')),
            # Automatically channels-last:
            ToTorchImage(),
            Convert(ch.float16),
            # Standard torchvision transforms still work!
            tv.transforms.Normalize(MEAN, STDEV)
        ]})

# Prefetching, caching, move to GPU, all handled!
for ims, labs in train_loader:
    # Model training (FAST!)
```



https://ffcv.io

“All-in-one”

Amazon SageMaker

gradient by Paperspace

DOMINO DATA LAB

Data

Versioning: Pachyderm, DVC, LIQUIDATA

Labeling: Label Studio, scale, prodigy

Processing: Spark, DAGSTER

Exploration: pandas, RAPIDS, dbt

Data Lake / Warehouse: snowflake, databricks

Sources: S3, LOG, Parquet

Development

Frameworks & Distributed Training: PYTORCH, fast.ai, DeepSpeed, HOROVOD, FairScale

Experiment and Model Management: comet, Weights & Biases, TensorBoard, mlflow, neptune.ai

Resource Management: Determined AI, PY, slurm

Software Engineering: jupyter, Streamlit, git

Compute: CoreWeave, Lambda, CO

Deployment

Feature Store: tecton

Monitoring: fiddler

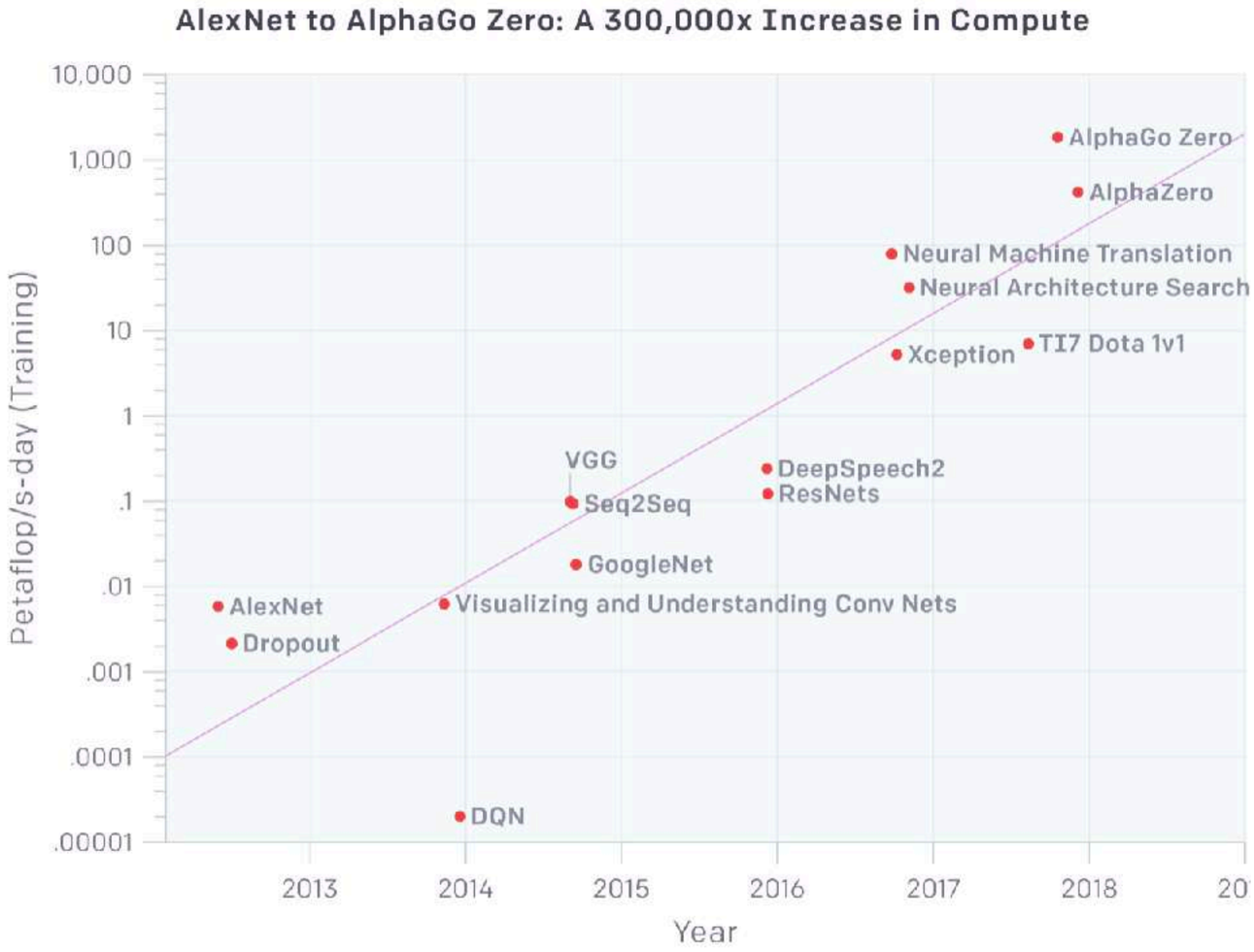
Edge: ML, OctoML, NVIDIA TensorRT, TensorFlowLite, ONNX

Web: ALGORITHMIA, SELDON

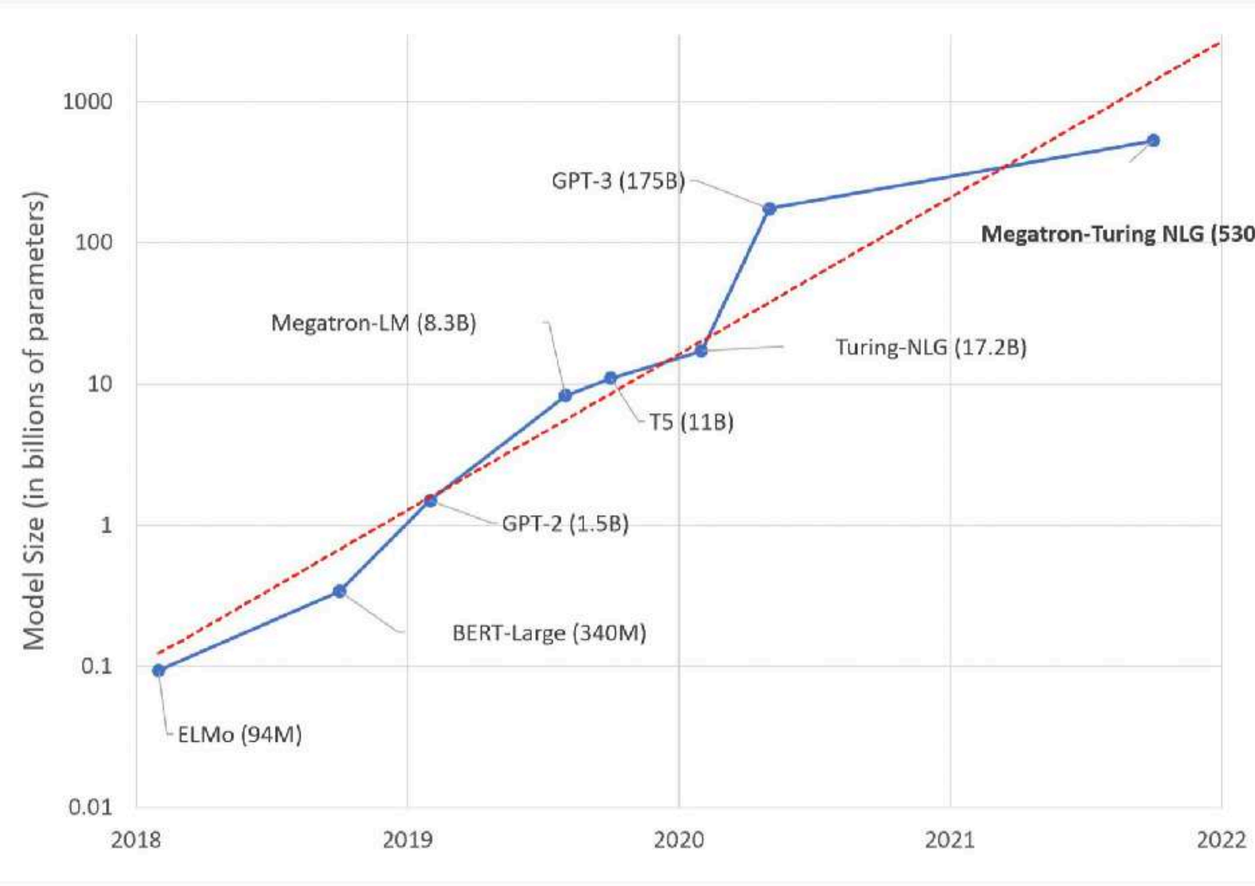
CI / Testing: Buildkite, great_expectations

or or

Why compute matters



https://openai.com/blog/ai-and-compute/



https://huggingface.co/blog/large-language-models

GPU Basics

- NVIDIA has been the only choice for a while
- Google TPUs are also very nice (only in the GCP cloud)
- Three main factors:
  - Amount of data that fits on the GPU
  - Speed of crunching through data on GPU (different speeds for 32bit data and 16bit data)
  - Speed of communicating between CPU and GPU, and between GPUs

GPU Comparison

Card	Release	Arch	Use-case	RAM (Gb)	32bit TFlops	Tensor TFlops	16bit
K80	2014	Kepler	Server	24	5	N/A	No
P100	2016	Pascal	Server	16	10	N/A	Yes
V100	2017	Volta	Server	16 or 32	14	120	Yes
RTX 2080 Ti	2018	Turing	PC	11	13	107	Yes
RTX 3090	2021	Ampere	PC	24	35	285	Yes
A100	2020	Ampere	Server	40 or 80	19.5	312	Yes
A6000	2022	Ampere	Server	48	38	?	Yes

GPU Comparison

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A100	2020	Ampere	Server	40 or 80	19.5	312	Yes
A6000	2022	Ampere	Server	48	38	?	Yes

- New NVIDIA architecture every year
  (Kepler —> Pascal —> Volta -> Turing -> Ampere)
- For business, only supposed to use server cards.

GPU Comparison

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K80	2014	Kepler	Server	24	5	N/A	No
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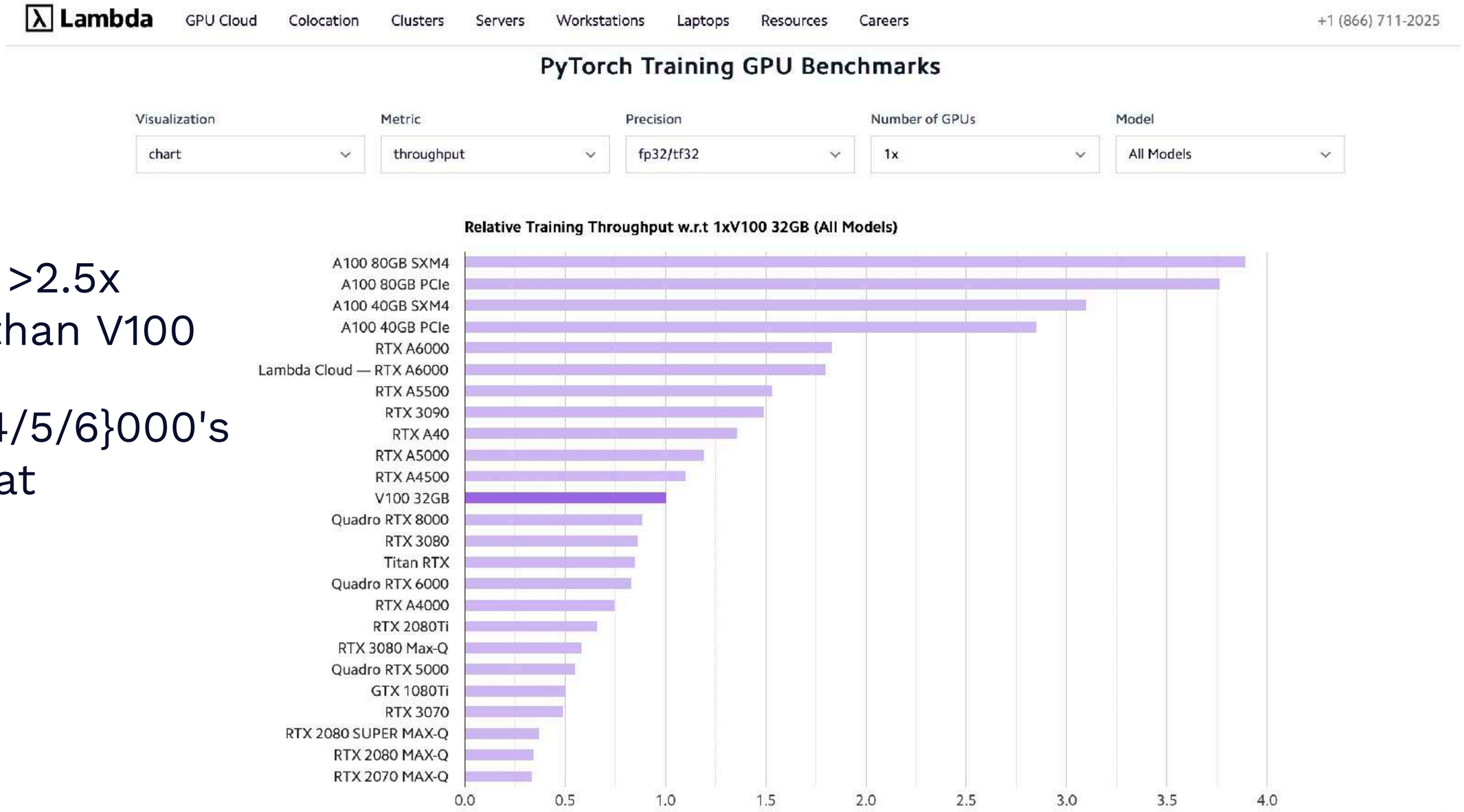
A100	2020	Ampere	Server	40 or 80	19.5	312	Yes
A6000	2022	Ampere	Server	48	38	?	Yes

- **RAM**: should fit your model + meaningful batch of data
- **32bit vs Tensor TFlops**
  - Tensor Cores are specifically for deep learning operations (mixed precision)
- **16bit** ~doubles your effective RAM capacity

Benchmarks

https://lambdalabs.com/gpu-benchmarks



- A100 is >2.5x faster than V100
- RTX A{4/5/6}000's are great

Benchmarks

- Time for ResNet-50 to go through 1.4M images
- 4xA100 vs 4xV100:
  - 3x faster in fp32
  - 1.5x faster in fp16

AIME

Configuration	float 32 training	float 16 training
CPU(32 cores)	27 hours	27 hours
Single RTX 2080 TI	69 minutes	29 minutes
Single RTX 3080	53 minutes	22 minutes
Single RTX 3080 TI	45 minutes	21 minutes
Single RTX 3090	41 minutes	18 minutes
Single RTX A6000	41 minutes	16 minutes
Single NVIDIA A100	23 minutes	8.5 minutes
4 x RTX 2080TI	19 minutes	8 minutes
4 x Tesla V100	15 minutes	4,5 minutes
4 x RTX 3090	11.5 minutes	5 minutes
4 x NVIDIA A100	6.5 minutes	3 minutes

https://www.aime.info/en/blog/deep-learning-gpu-benchmarks-2021/

Cloud Providers

- Amazon Web Services, Google Cloud Platform, Microsoft Azure are the heavyweights.
  - GCP is special because it also has TPU's
- Startups are Lambda Labs, Paperspace, Coreweave, and others

TPUs

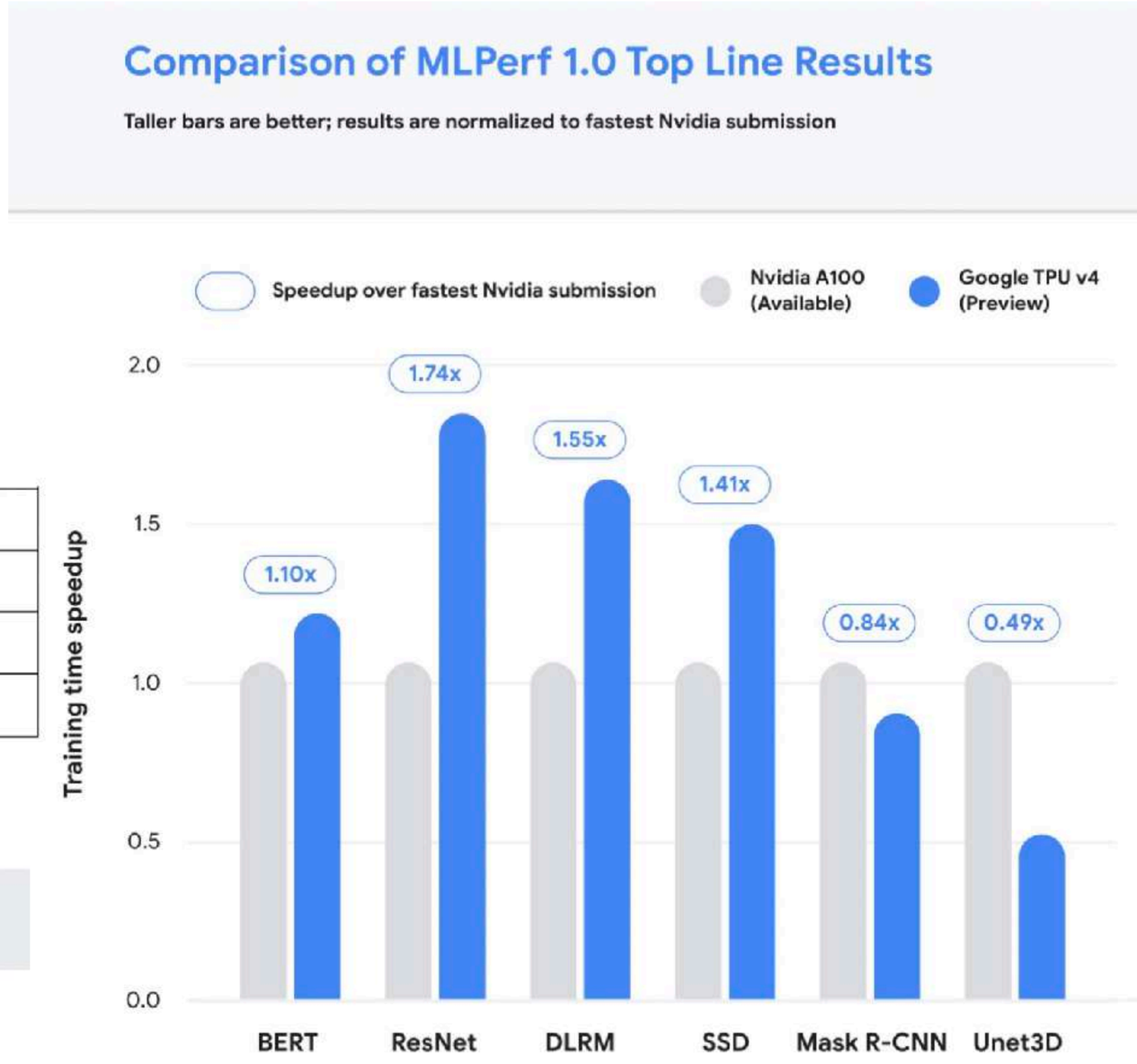
- TPU v4 are fastest, but not quite in GA yet
- TPU v3 are quite fast and excel at scaling (fast interconnect)

	TFLOPS (bf16)	Cost (Google Cloud)	TFLOPS / $
A100 + a2-1g instance	312	$2.90 + $1.01	79.8
TPU v2 - 8 cores	180*	$4.50	40.0
TPU v3 - 8 cores	420*	$8.00	52.5

https://eng.snap.com/training-models-with-tpus

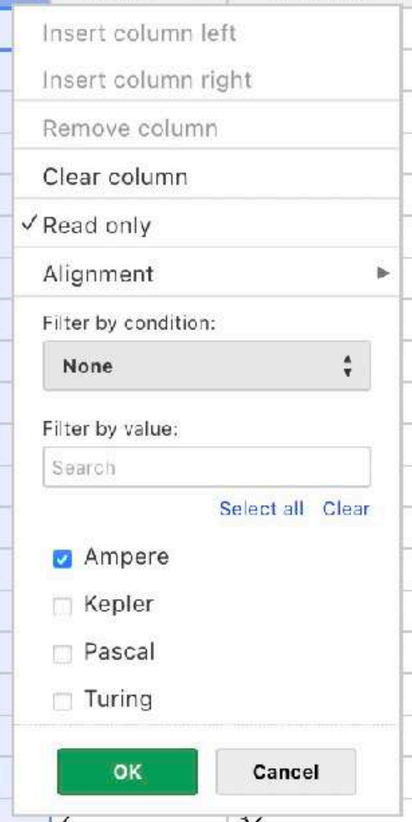
TPU type (v3)	TPU v3 cores	Total TPU memory
v3-8	8	128 GiB

https://cloud.google.com/tpu/docs/tpus



FSDL GPU Cloud Comparison

Cloud	GPU Type	GPU Arch	GPUs	GPU RAM	vCPUs	RAM	On-demand	Per-GPU	Spot	Name
AWS	A100 (80 GB)	Ampere			96	1152	$40.97	$5.12		p4de.24xlarge
AWS	A100 (40 GB)	Ampere			96	1152	$32.77	$4.10	$9.83	p4d.24xlarge
AWS	V100 (16 GB)	Volta			8	61	$3.06	$3.06	$0.92	p3.2xlarge
AWS	V100 (16 GB)	Volta			32	244	$12.24	$3.06	$3.67	p3.8xlarge
AWS	V100 (16 GB)	Volta			64	488	$24.48	$3.06	$7.34	p3.16xlarge
AWS	V100 (32 GB)	Volta			96	768	$31.21	$3.90	$9.36	p3dn.24xlarge
AWS	A10G (24 GB)	Ampere			16	64	$1.62	$1.62	$0.49	g5.4xlarge
AWS	A10G (24 GB)	Ampere			48	192	$5.67	$1.42	$1.74	g5.12xlarge
AWS	A10G (24 GB)	Ampere			192	768	$16.29	$2.04	$4.89	g5.48xlarge
AWS	T4 (16 GB)	Turing			16	64	$1.20	$1.20	$0.36	g4dn.4xlarge
AWS	K80 (12 GB)	Kepler			4	61	$0.90	$0.90	$0.27	p2.xlarge
AWS	K80 (12 GB)	Kepler			32	488	$7.20	$0.90	$2.16	p2.8xlarge
AWS	K80 (12 GB)	Kepler			64	732	$14.40	$0.90	$4.32	p2.16xlarge
GCP	A100 (40 GB)	Ampere			12	85	$3.67	$3.67	$1.10	a2-highgpu-1g
GCP	A100 (40 GB)	Ampere			24	170	$7.34	$3.67	$2.20	a2-highgpu-2g
GCP	A100 (40 GB)	Ampere			48	340	$14.68	$3.67	$4.41	a2-highgpu-4g
GCP	A100 (40 GB)	Ampere			96	680	$29.36	$3.67	$8.81	a2-highgpu-8g
GCP	A100 (40 GB)	Ampere			96	1360	$55.68	$3.48	$16.72	a2-megagpu-16g
GCP	V100 (16 GB)	Volta			8	52	$2.95	$2.95	$0.84	n1-highmem-8
GCP	V100 (16 GB)	Volta	2	32	16	104	$5.91	$2.95	$1.68	n1-highmem-16
GCP	V100 (16 GB)	Volta	4	64	32	208	$11.81	$2.95	$3.36	n1-highmem-32
GCP	V100 (16 GB)	Volta	8	128	64	416	$23.63	$2.95	$6.72	n1-highmem-64
GCP	P100 (16 GB)	Pascal	1	16	8	52	$1.93	$1.93	$0.53	n1-highmem-8
GCP	P100 (16 GB)	Pascal	2	32	16	104	$3.87	$1.93	$1.06	n1-highmem-16
GCP	P100 (16 GB)	Pascal	4	64	32	208	$7.73	$1.93	$2.12	n1-highmem-32
GCP	K80 (12 GB)	Kepler	1	12	8	52	$0.92	$0.92	$0.14	n1-highmem-8

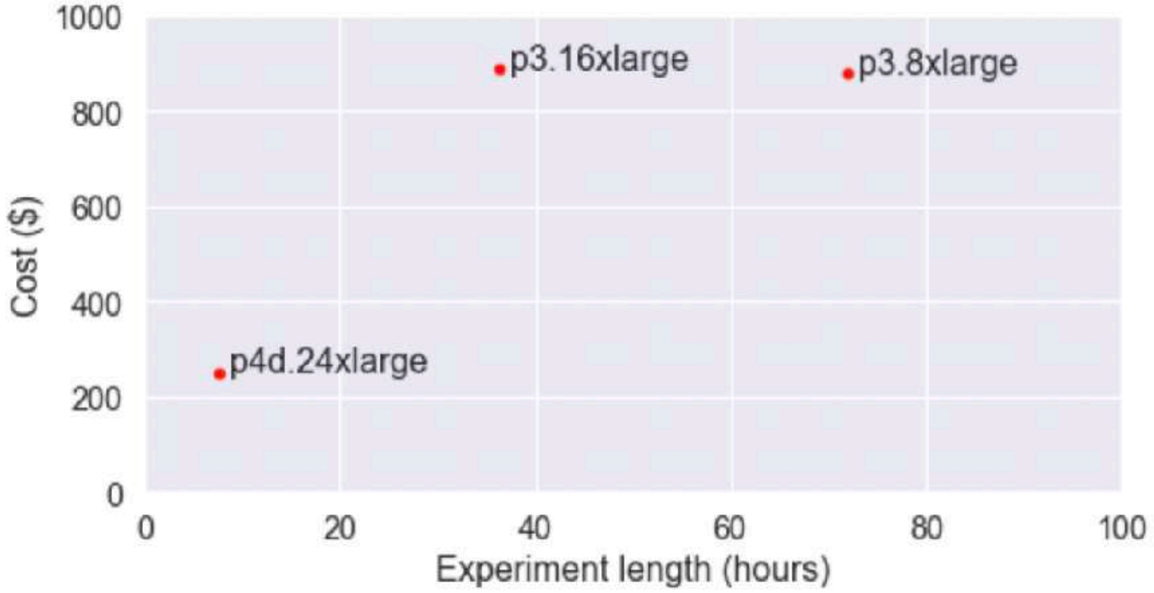


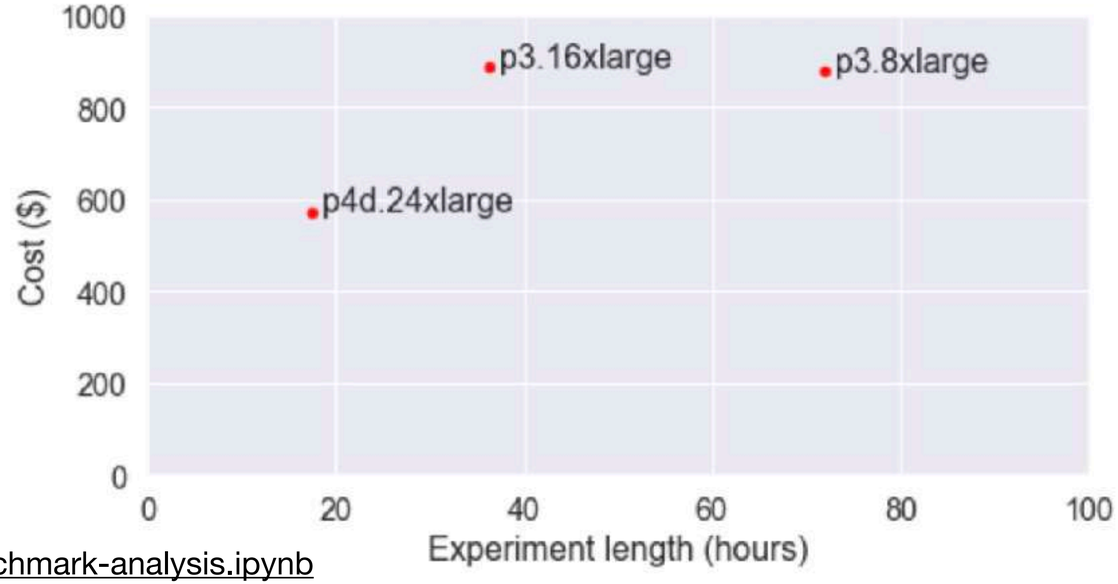
https://fullstackdeeplearning.com/cloud-gpus/

Let's combine cost with benchmark data

Expensive per-hour ≠ Expensive per-experiment

- A Transformers experiment that takes 72 hours on 4xV100 (p3.8xlarge) will cost $1750 to run.
- **But it will take only 8 hours and cost only $250 on 8xA100 (p4d.24xlarge)!**
- Similar story for CNN's.



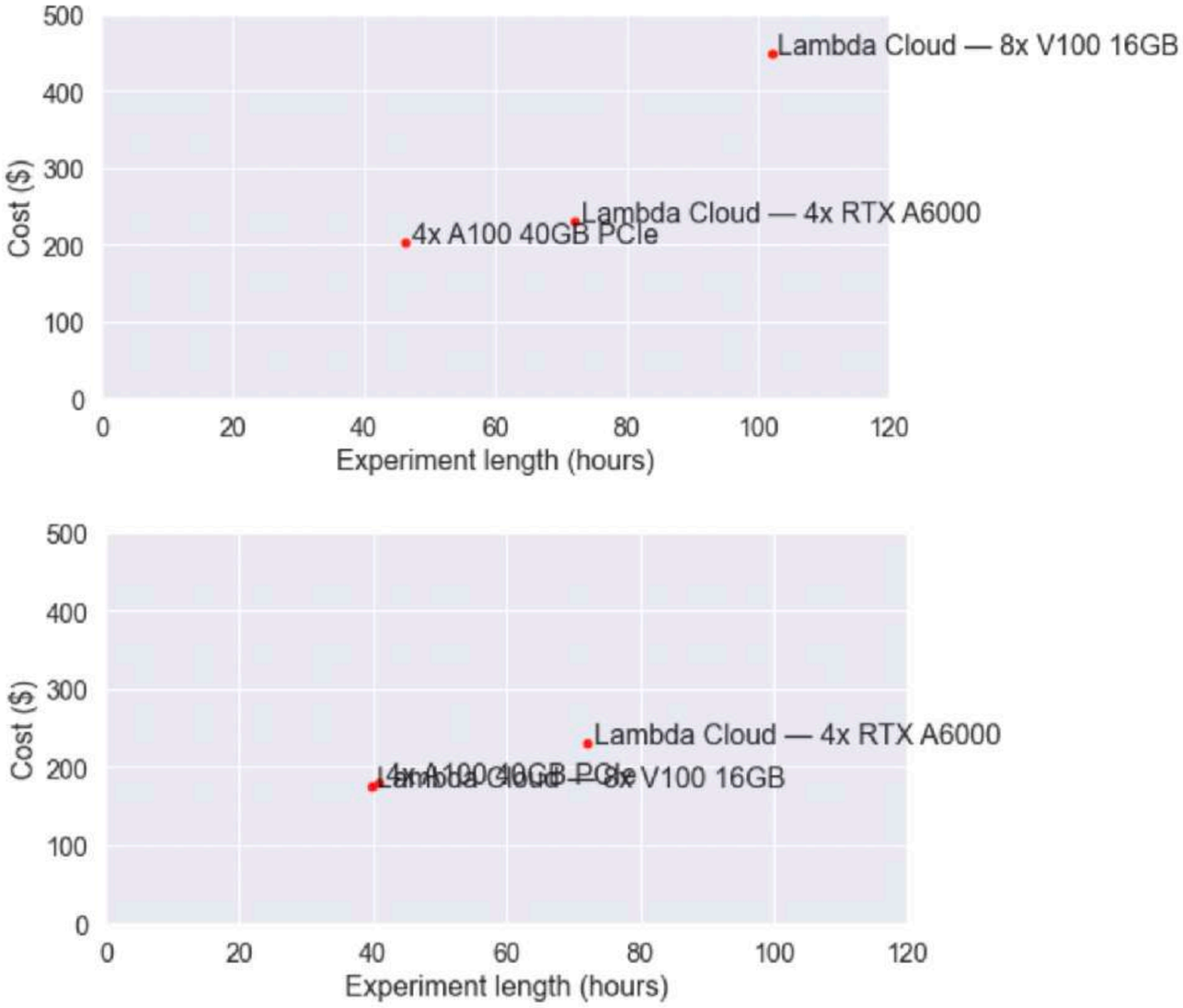


Lambda Benchmark Data

https://github.com/full-stack-deep-learning/website/blob/main/docs/cloud-gpus/benchmark-analysis.ipynb

Expensive per-hour ≠ Expensive per-experiment

- On Lambda Labs cloud, story is similar
- 8xV100 takes **2x** longer and is **2x** more expensive (Transformers)
- Similar story for CNN's.



Lambda Benchmark Data

https://github.com/full-stack-deep-learning/website/blob/main/docs/cloud-gpus/benchmark-analysis.ipynb

Expensive per-hour ≠ Expensive per-experiment

- MosaicML benchmarking ResNet-50
- 8xA100 is **1.5x** faster and **15%** cheaper than 8xV100

Recipe	Cost	Top-1 accuracy	Time
MosaicML Baseline	$113.09	76.59%	3h 27m

Model	Cloud	Instance	Scale Schedule Ratio
ResNet-50	Amazon Web Services	p4d.24xlarge	1.00

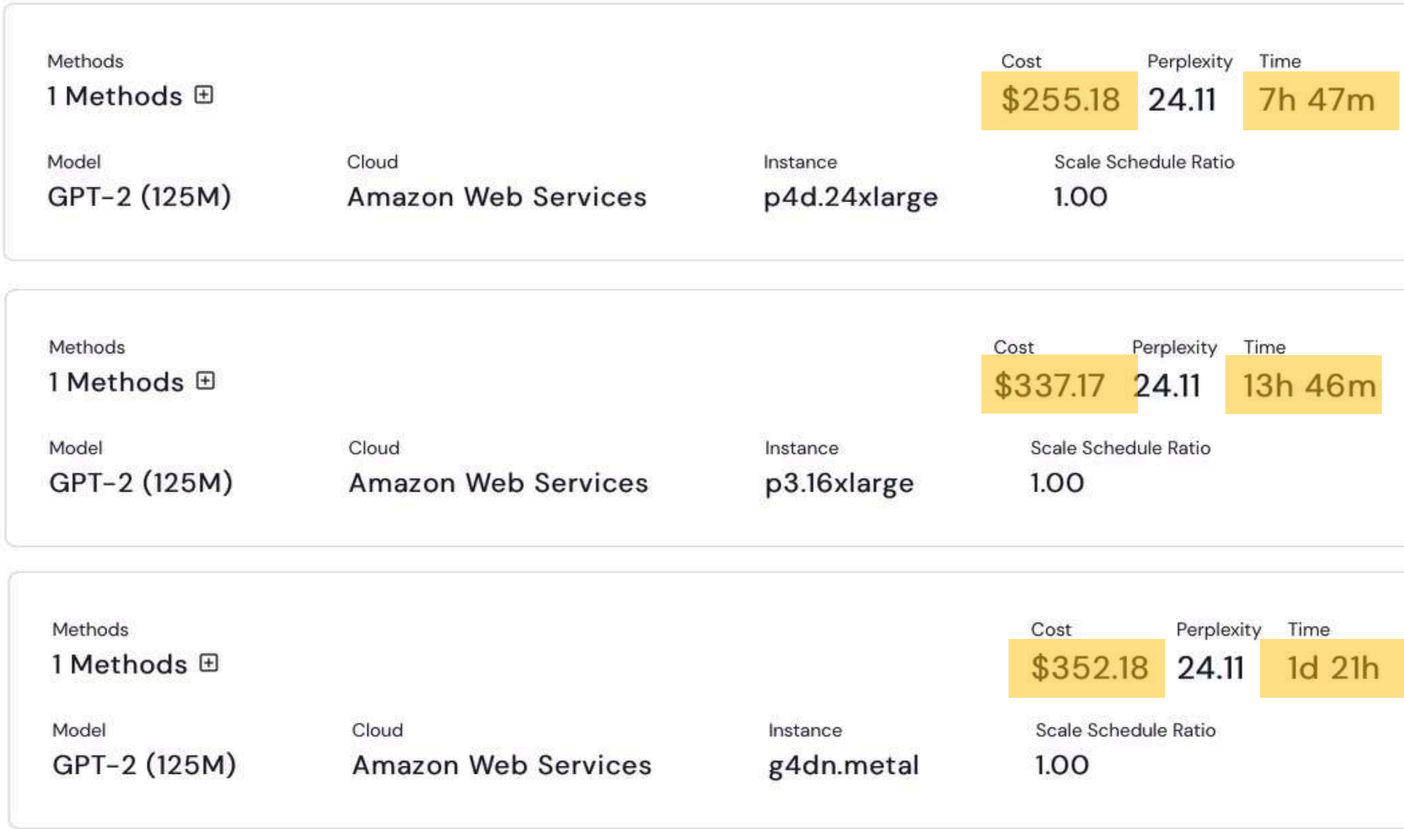
Recipe	Cost	Top-1 accuracy	Time
MosaicML Baseline	$130.29	76.59%	5h 19m

Model	Cloud	Instance	Scale Schedule Ratio
ResNet-50	Amazon Web Services	p3.16xlarge	1.00

https://explorer.mosaicml.com

Expensive per-hour ≠ Expensive per-experiment

- MosaicML benchmarking GPT-2 (125M)
- 8xA100 is **~2x** faster and **25%** cheaper than 8xV100
  - And **~3x** faster and **30%** cheaper than 8xT4



https://explorer.mosaicml.com

Conclusions

- Good heuristic: use the most expensive per-hour GPUs (4x or 8x A100's) in the least-expensive cloud
- The startups are **much** cheaper than the big boys

Cloud	GPU Type	GPU Arch	GPUs	GPU RAM	vCPUs	RAM	On-demand	Per-GPU ↑	Spot	Name
Lambda	A100 (40 GB)	Ampere	4	160	120	800	4.40	1.10		
Jarvislabs	A100 (40 GB)	Ampere	4	160	28	128	4.4	1.1	2.76	
Jarvislabs	A100 (40 GB)	Ampere	8	320	56	256	8.8	1.1	5.52	
Datacrunch	A100 (80 GB)	Ampere	4	320	88	480	9.00	2.25		4A100.88V
Datacrunch	A100 (80 GB)	Ampere	8	640	176	960	18.00	2.25		8A100.176V
Paperspace	A100 (40 GB)	Ampere	4	160	48	360	12.36	3.09		
Paperspace	A100 (40 GB)	Ampere	8	320	96	720	24.72	3.09		
Paperspace	A100 (80 GB)	Ampere	4	320	48	360	12.72	3.18		
Paperspace	A100 (80 GB)	Ampere	8	640	96	720	25.44	3.18		
Azure	A100 (80 GB)	Ampere	4	320	96	880	14.69	3.67	5.88	NC96ads A100 v4
GCP	A100 (40 GB)	Ampere	4	160	48	340	14.68	3.67	4.41	a2-highgpu-4g
GCP	A100 (40 GB)	Ampere	8	320	96	680	29.36	3.67	8.81	a2-highgpu-8g
AWS	A100 (40 GB)	Ampere	8	320	96	1152	32.77	4.10	9.83	p4d.24xlarge
Azure	A100 (80 GB)	Ampere	8	640	96	1900	37.18	4.64		ND96amsr A100 v4
AWS	A100 (80 GB)	Ampere	8	640	96	1152	40.97	5.12		p4de.24xlarge

https://fullstackdeeplearning.com/cloud-gpus/

On-prem Options

- Build your own
  - Up to 4 Turing or 2 Ampere GPUs is easy
- Buy pre-built
  - Lambda Labs, NVIDIA, and builders like Supermicro, Cirrascale, etc.

Building your own

- Decently quiet PC with 128GB RAM and 2x RTX 3090's: ~$7000
  - One day to build and set up
  - Rite of passage?
- Going beyond 4 2000-series or 2 3000-series can be painful

Pre-built: Lambda Labs

Lambda

Go back

Ubuntu 20.04
Lambda Stack pre-installed

Threadripper Pro 3955WX
16 cores, 3.90 GHz

2x RTX A5000
NVLinked, 24 GB VRAM each

128 GB
System memory

1 TB NVMe
OS Drive

0 TB
Extra storage

2x RTX 3080	- $4,347
2x RTX 3080 Ti	- $1,909
2x RTX 3090	- $1,909
2x RTX A4000	- $4,022
2x RTX A4500 with NVLink	- $2,112
2x RTX A5000 with NVLink	
2x RTX A5500 with NVLink	- $3,738
2x RTX A6000 with NVLink	- $6,663
3x RTX 3080	- $2,762
3x RTX 3090 with NVLink	- $1,178
3x RTX A4000	- $2,640
3x RTX A4500 with NVLink	+ $447
3x RTX A5000 with NVLink	- $3,616
3x RTX A5500 with NVLink	- $9,222
3x RTX A6000 with NVLink	+ $13,610
4x RTX A4000	- $893

$12,034.00
Apply for a discount

Download quote | Add to cart

Pre-built: Lambda Labs

Lambda

Go back

Ubuntu 20.04
Lambda Stack pre-installed

2x AMD EPYC 7513
32 cores, 2.60 GHz

8x NVIDIA RTX A6000
NVLinked, 48 GB VRAM per GPU

512 GB
Memory

1.92 TB SSD (NVMe)
OS Drive

0 TB
Extra storage

GPUs

4x NVIDIA RTX A4500 20 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$38,290
8x NVIDIA RTX A4500 20 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$30,240
4x NVIDIA RTX A5000 24 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$34,650
8x NVIDIA RTX A5000 24 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$22,960
4x NVIDIA RTX A5500 24 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$28,210
8x NVIDIA RTX A5500 24 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$10,080
4x NVIDIA RTX A6000 48 GB of VRAM per GPU, NVLinked, PCIe 4.0	-$23,170
8x NVIDIA RTX A6000 48 GB of VRAM per GPU, NVLinked, PCIe 4.0	
4x NVIDIA A40 48 GB of VRAM per GPU, NVLinked, PCIe 4.0, passive cooling	-$20,510
8x NVIDIA A40 48 GB of VRAM per GPU, NVLinked, PCIe 4.0, passive cooling	$5,320
4x NVIDIA A30 24 GB of VRAM per GPU, NVLinked, PCIe 4.0, passive cooling	-$22,330

3

$61,121.00
Apply for a discount

Download quote

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Actionable advice for selecting a GPU machine

Best GPU for Deep Learning in 2022 (so far)

February 28, 2022

GPU recommendation

So, which GPUs to choose if you need an upgrade in early 2022 for Deep Learning? We feel there are two yes/no questions that help you choose between `A100`, `A6000`, and `3090`. These three together probably cover most of the use cases in training Deep Learning models:

- **Do you need multi-node distributed training?** If the answer is yes, go for `A100 80GB` / `40GB SXM4` because they are the only GPUs that support `Infiniband`. Without `Infiniband`, your distributed training simply would not scale. If the answer is no, see the next question.
- **How big is your model?** That helps you to choose between `A100 PCIe` (`80GB`), `A6000` (`48GB`), and `3090` (`24GB`). A couple of `3090`s are adequate for mainstream academic research. Choose `A6000` if you work with a large image/language model and need multi-GPU training to scale efficiently. An `A6000` system should cover most of the use cases in the context of a single node. Only choose `A100 PCIe 80GB` when working on extremely large models

Lambda

https://lambdalabs.com/blog/best-gpu-2022-sofar/

More information about GPU machines

Which GPU(s) to Get for Deep Learning: My Experience and Advice for Using GPUs in Deep Learning

2020-09-07 by Tim Dettmers — 1,618 Comments

TL;DR advice

Best GPU overall: RTX 3080 and RTX 3090.

GPUs to avoid (as an individual): Any Tesla card; any Quadro card; any Founders Edition card; Titan RTX, Titan V, Titan XP.

But beware: the article is missing many Ampere cards like A5000, etc.

https://timdettmers.com/2020/09/07/which-gpu-for-deep-learning/

Analyzing cloud vs on-prem

- Basically, if utilization is high, on-prem is cheaper

We surveyed three performance levels - low, mid, and high - based on GPU model.[4]

We also considered two utilization assumptions: low (10%) and high (100%).

	Low End Performance, 10% Utilization	Low End Performance, 100% Utilization	Mid Tier Performance, 10% Utilization	Mid Tier Performance, 100% Utilization	High End Performance, 10% Utilization	High End Performance, 100% Utilization
AWS	$1.80	$0.92	N/A	N/A	$3.06	$1.13
GCP	$1.42	$0.99	$1.98	$1.08	$3.00	$1.58
Paperspace	$0.78	$0.63	$1.10	$0.88	$2.30	$1.84
Pre-Built DL Server	$1.56	$0.16	$1.67	$0.17	$3.42	$0.34
Built-from-scratch DL Ser	$1.17	$0.12	$1.26	$0.13	$2.57	$0.26

Table 2: Cost Per Hour of Cloud and On-Prem Options

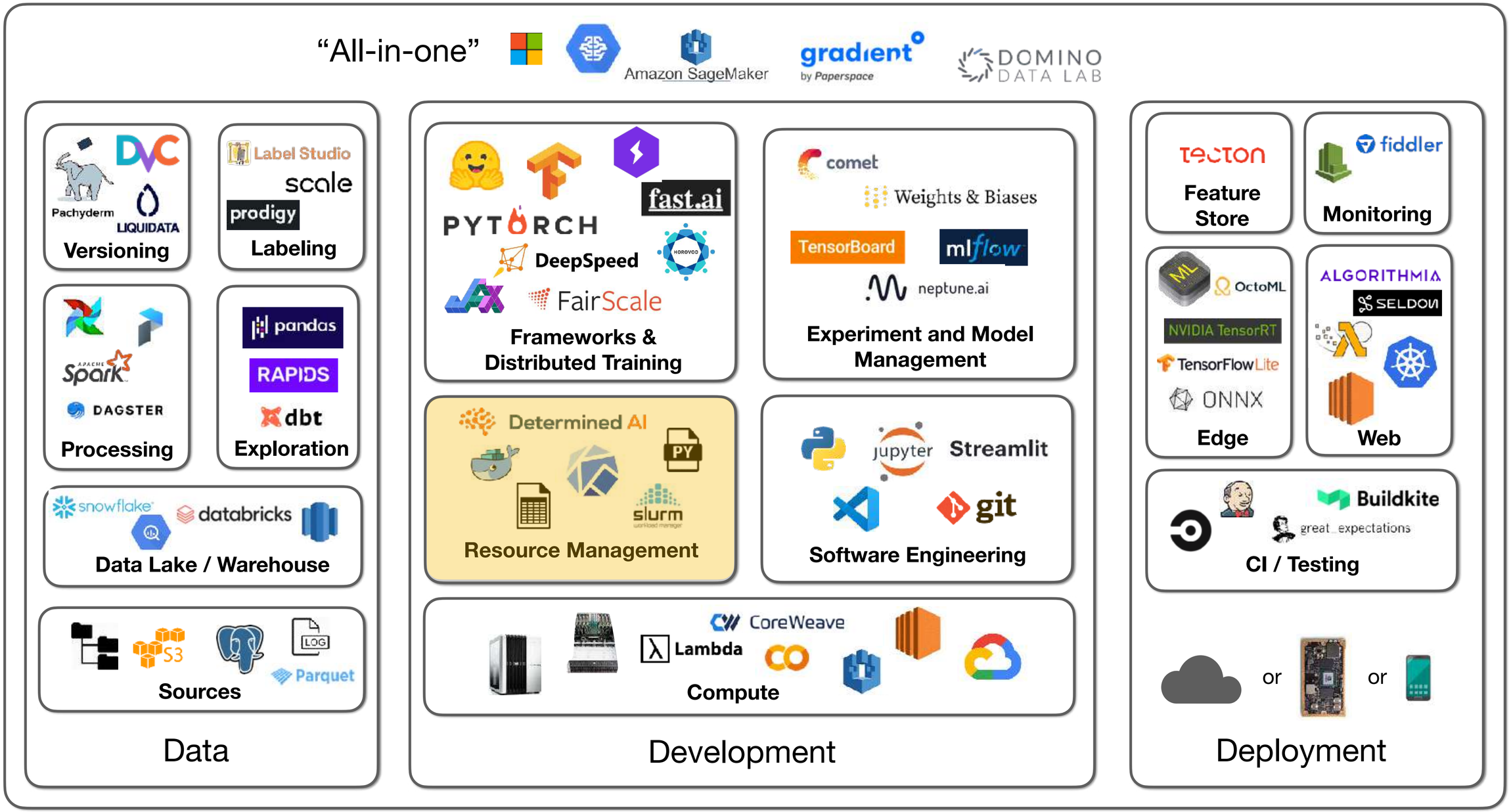
Pre-Ampere!

Determined AI

https://www.determined.ai/blog/cloud-v-onprem

Recommendations

- Your own GPU machine is worth it just for the mindset shift of maximizing utility vs minimizing cost.
- To scale out experiments, use the most expensive per-hour machines in the least expensive cloud.
  - TPUs are worth experimenting with for large-scale training
- Lambda Labs is a sponsor of the FSDL projects this year, and an excellent choice for both!


"All-in-one"
Amazon SageMaker
gradient by Paperspace
DOMINO DATA LAB
Pachyderm
LIQUIDATA
Versioning
Label Studio
scale
prodigy
Labeling
Spark
DAGSTER
Processing
pandas
RAPIDS
dbt
Exploration
snowflake
databricks
Data Lake / Warehouse
S3
LOG
Parquet
Sources
Data
PYTORCH
fast.ai
DeepSpeed
HOROVOD
FairScale
Frameworks & Distributed Training
Determined AI
PY
slurm
Resource Management
comet
Weights & Biases
TensorBoard
mlflow
neptune.ai
Experiment and Model Management
jupyter
Streamlit
git
Software Engineering
CoreWeave
Lambda
Compute
Development
tecton
Feature Store
fiddler
Monitoring
ML
OctoML
NVIDIA TensorRT
TensorFlowLite
ONNX
Edge
ALGORITHMIA
SELDON
Web
Buildkite
great_expectations
CI / Testing
or
or
Deployment

Resource Management

- We want to launch an experiment or set of experiments
- Each experiment needs
  - Machine(s) + GPU(s)
  - Setup (Python+CUDA version, Python requirements)
  - Data
- Solutions
  - Manual
  - SLURM
  - Docker + Kubernetes
  - Software specialized for ML use cases

Manual

- Follow best practices for specifying dependencies (e.g. conda + pip-tools)
- Log in to machine, launch experiment
- This works just fine for one machine

Slurm

- What if you have a **cluster** of machines?
- Slurm is an old-school solution to *workload management* that is still widely used
- A job defines necessary resources, gets queued
- FSDL 🙂

master ▾ bigscience / train / tr11-176B-ml / **tr11-176B-ml.slurm**

 **stas00** auto-sync flag was renamed

4 contributors    

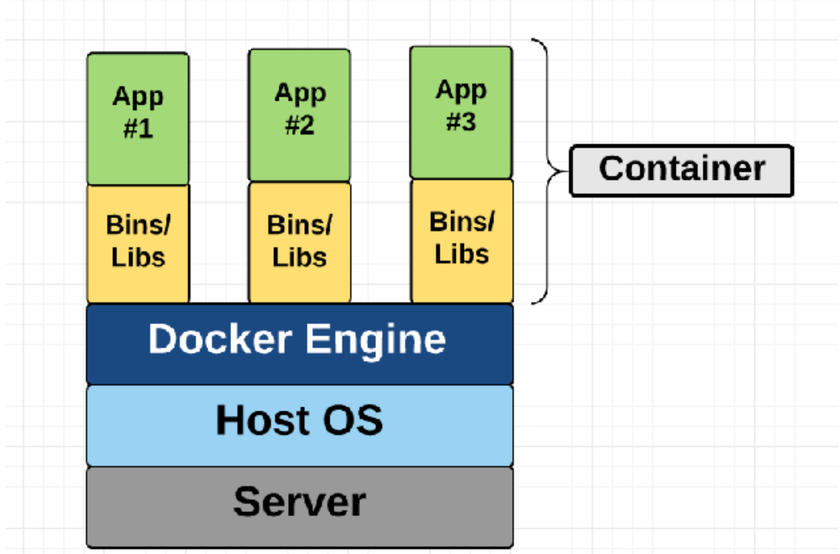
221 lines (184 sloc) | 6.87 KB

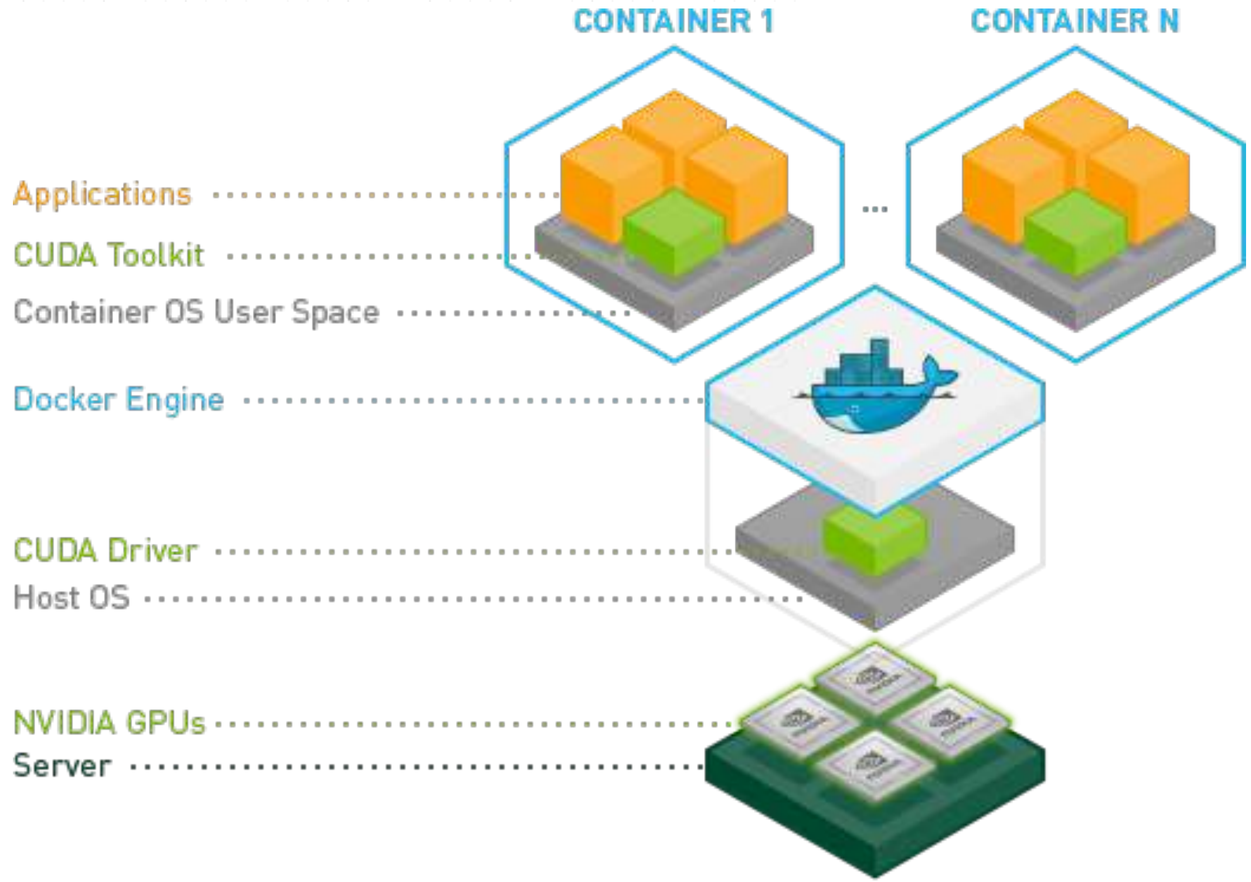
```
1  #!/bin/bash
2  #SBATCH --job-name=tr11-176B-ml
3  #SBATCH --partition=gpu_p5
4  #SBATCH --constraint=a100
5  #SBATCH --reservation=hug
6  #SBATCH --qos=qos_gpu-gc              # up to 100h
7  #SBATCH --nodes=24
8  #SBATCH --ntasks-per-node=1           # crucial - only 1 task per dist per node
9  #SBATCH --cpus-per-task=64            # number of cores per tasks
10 #SBATCH --hint=nomultithread         # we get physical cores not logical
11 #SBATCH --gres=gpu:8                 # number of gpus
12 #SBATCH --time 100:00:00             # maximum execution time (HH:MM:SS)
13 #SBATCH --output=%x-%j.out           # output file name
14 #SBATCH --account=six@a100
15
16 set -x -e
17
18 #source $six_ALL_CCFRWORK/start-py38-pt110
19 #source $six_ALL_CCFRWORK/start-py38-pt111
20 source $six_ALL_CCFRWORK/code/tr11-176B-ml/bigscience/train/tr11-176B-ml/start
21
22 echo "START TIME: $(date)"
```

https://github.com/bigscience-workshop/bigscience/blob/master/train/tr11-176B-ml/tr11-176B-ml.slurm

Docker

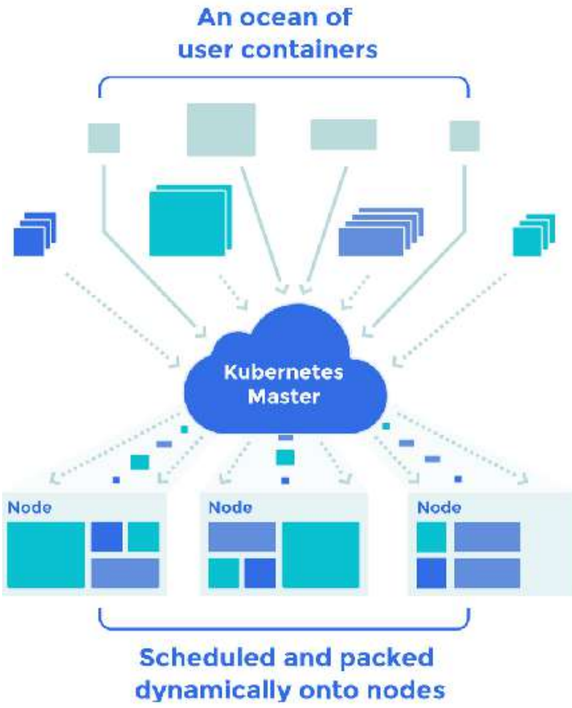
- Docker is a way to package up an entire dependency stack in a lighter-than-a-VM package
- NVIDIA Docker is required for GPUs
- We will talk more about Docker in the Deployment lecture, and use it in lab

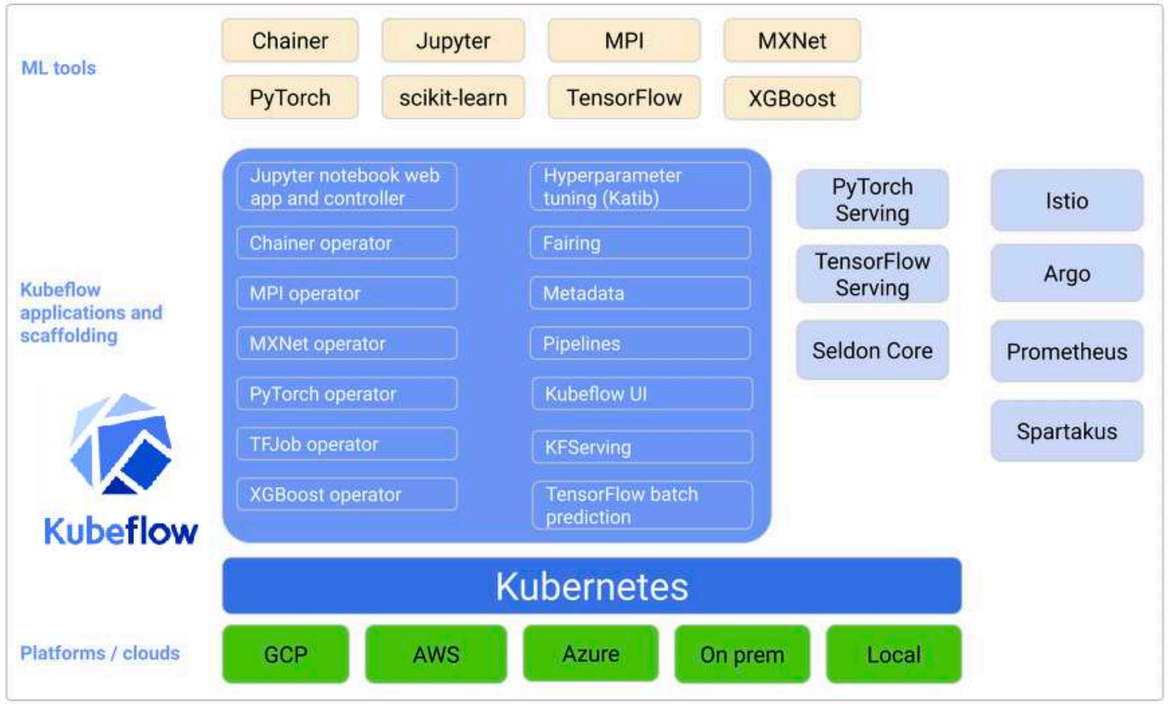




Kubernetes + Kubeflow

- Kubernetes is a way to run many Docker containers on top of a cluster
- Kubeflow is an open source project from Google
- Spawn and manage Jupyter notebooks, and manage multi-step ML workflows
- FSDL 😑





What about the cloud?

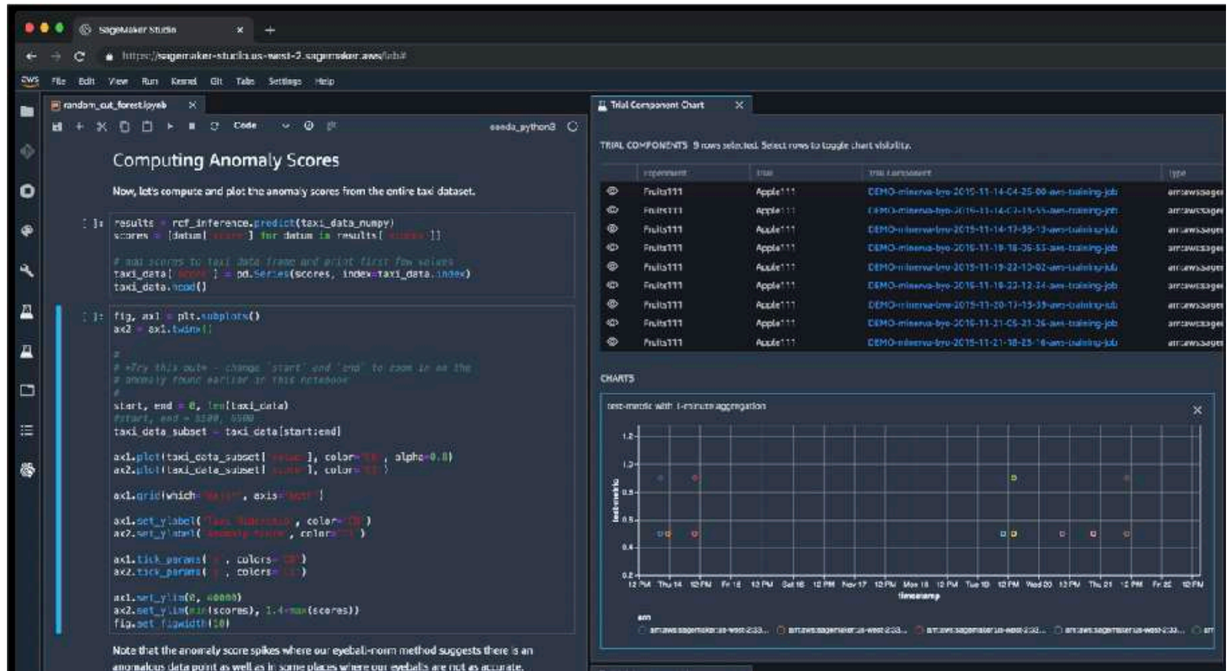
- Slurm or Kubeflow make sense if you already have a cluster up and running.
- But how do we get it up and running in the cloud in the first place?

Before we proceed...

I prefer not to mention SaaS that does not show pricing

AWS SageMaker

- Set of ML-focused solutions from AWS
- Notebooks are a key feature
- Could make sense to adopt if already using AWS for everything



Typical SageMaker workflow

1. Label data

Set up and manage labeling jobs for highly accurate training datasets within Amazon SageMaker, using active learning and human labeling.

2. Build

Connect to other AWS services and transform data in Amazon SageMaker notebooks.

3. Train

Use Amazon SageMaker's algorithms and frameworks, or bring your own, for distributed training.

4. Tune

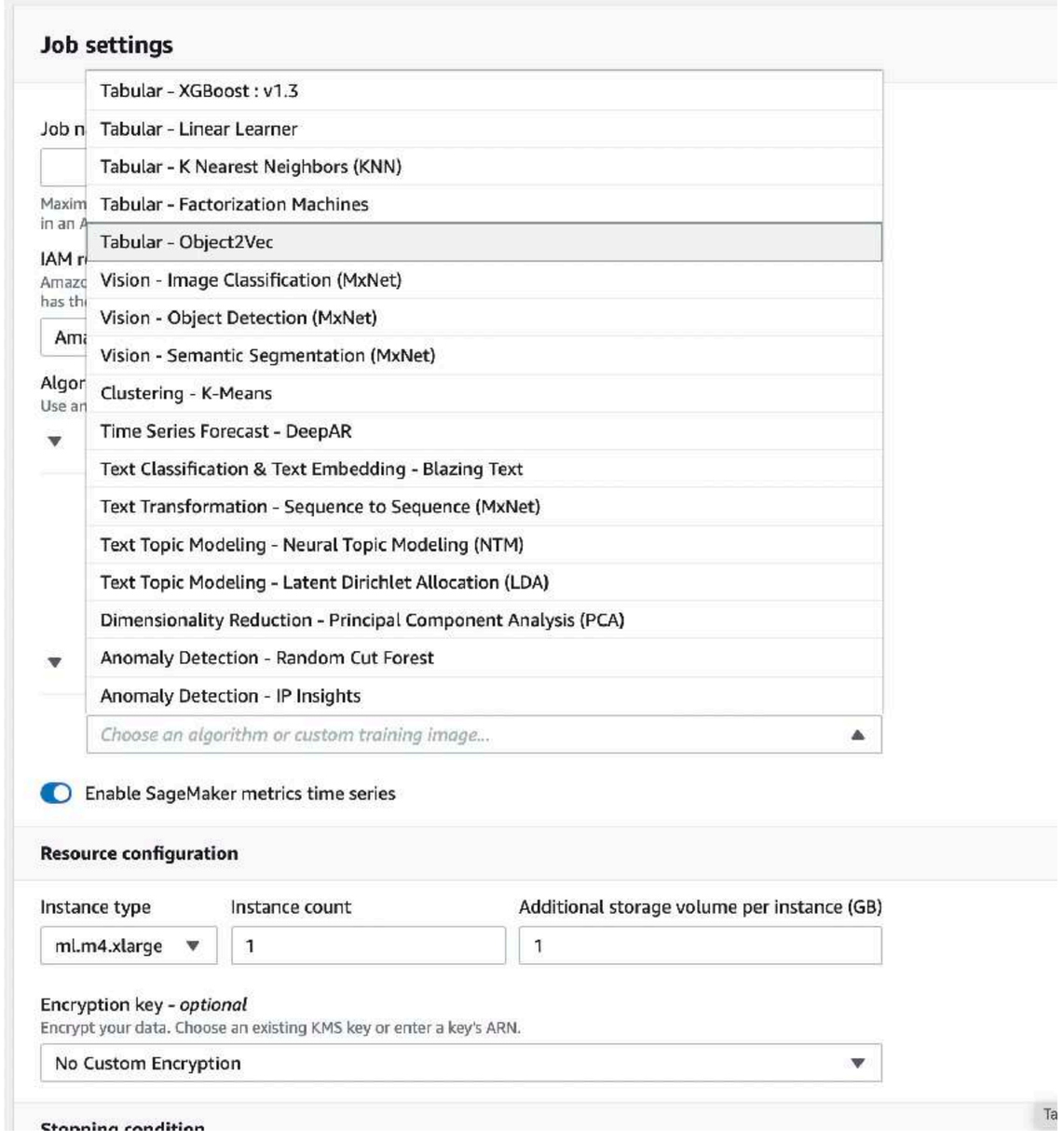
Amazon SageMaker automatically tunes your model by adjusting multiple combinations of algorithm parameters.

5. Deploy

After training is completed, models can be deployed to Amazon SageMaker endpoints, for real-time predictions.

AWS SageMaker for Training

- Intended use cases are more old-school
- And you may perhaps get overwhelmed by all the AWS-specific configurations...



AWS SageMaker for Training

- But increasing support for PyTorch
- Support for using cheap spot instances (see link at bottom)

```
[ ]: from sagemaker.pytorch import PyTorch

estimator = PyTorch(
    base_job_name="pytorch-smdataparallel-mnist",
    source_dir="code",
    entry_point="train_pytorch_smdataparallel_mnist.py",
    role=role,
    framework_version="1.11.0",
    py_version="py38",
    # For training with multinode distributed training, set this count. Example: 2
    instance_count=1,
    # For training with p3dn instance use - ml.p3dn.24xlarge, with p4dn instance use - ml.p
    instance_type="ml.p4d.24xlarge",
    sagemaker_session=sagemaker_session,
    # Training using SMDataParallel Distributed Training Framework
    distribution={"smdistributed": {"dataparallel": {"enabled": True}}},
    debugger_hook_config=False,
)
```

```
[ ]: estimator.fit()
```

https://sagemaker-examples.readthedocs.io/en/latest/training/distributed_training/pytorch/data_parallel/mnist/pytorch_smdataparallel_mnist_demo.html

15-20% markup vs basic EC2!

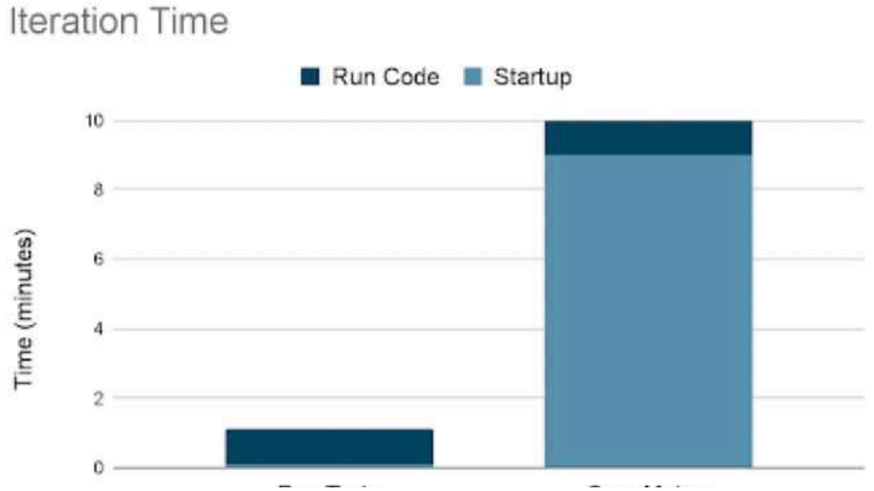
ml.p3.8xlarge	32	244 GiB	$14.688	12.24
ml.p3.16xlarge	64	488 GiB	$28.152	24.48
ml.p3dn.24xlarge	96	768 GiB	$35.894	31.21

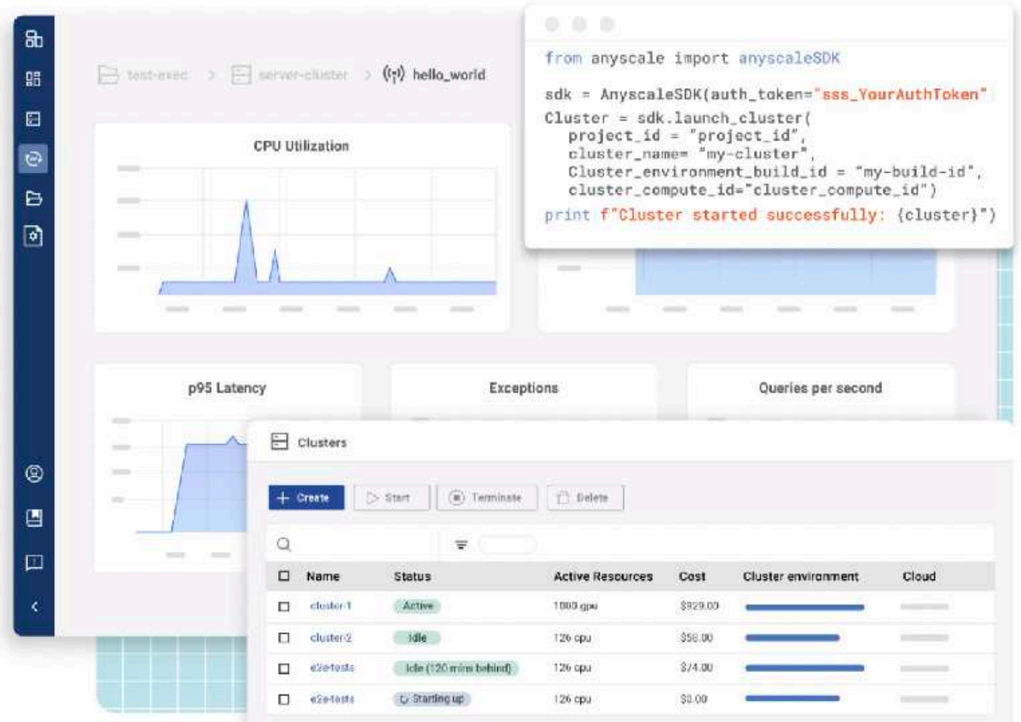
https://github.com/aws-samples/amazon-sagemaker-managed-spot-training/blob/main/pytorch_managed_spot_training_checkpointing/pytorch_managed_spot_training_checkpointing.ipynb

Anyscale (makers of Ray, from Berkeley)

```
trainer = Trainer(backend="torch", num_workers=100, use_gpu=True)
```

- Ray Train is a new project from Ray
  - Faster than SageMaker
  - Intelligent spot instance support
- Anyscale makes it super simple to provision compute (at a **significant** markup to AWS)





https://docs.ray.io/en/latest/train/train.html

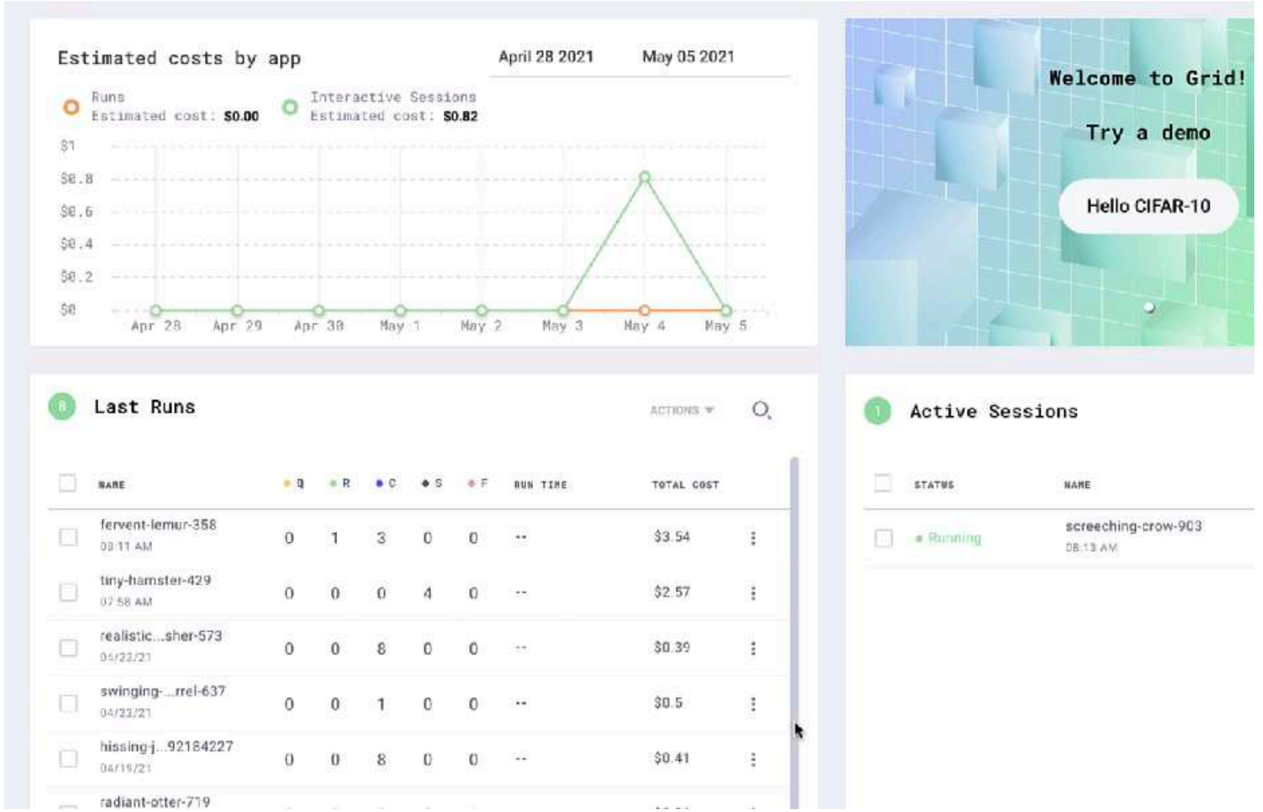
Grid.ai

From the makers of PyTorch Lightning

```
(flash) ➜  dcgan git:(master) ✗ grid run --g_instance_type 4_v100_16gb --g_gpus 2 --g_use_spot mai
n.py --dataset cifar10 --lr 0.0002 --dataroot . --ngpu 2 --cuda
```

SEAMLESSLY TRAIN 100s OF MACHINE LEARNING MODELS ON THE CLOUD FROM YOUR LAPTOP

With zero code changes



Not sure about long-term viability of this (grid.ai vs lightning.ai)

https://docs.grid.ai

Non-ML specific solutions

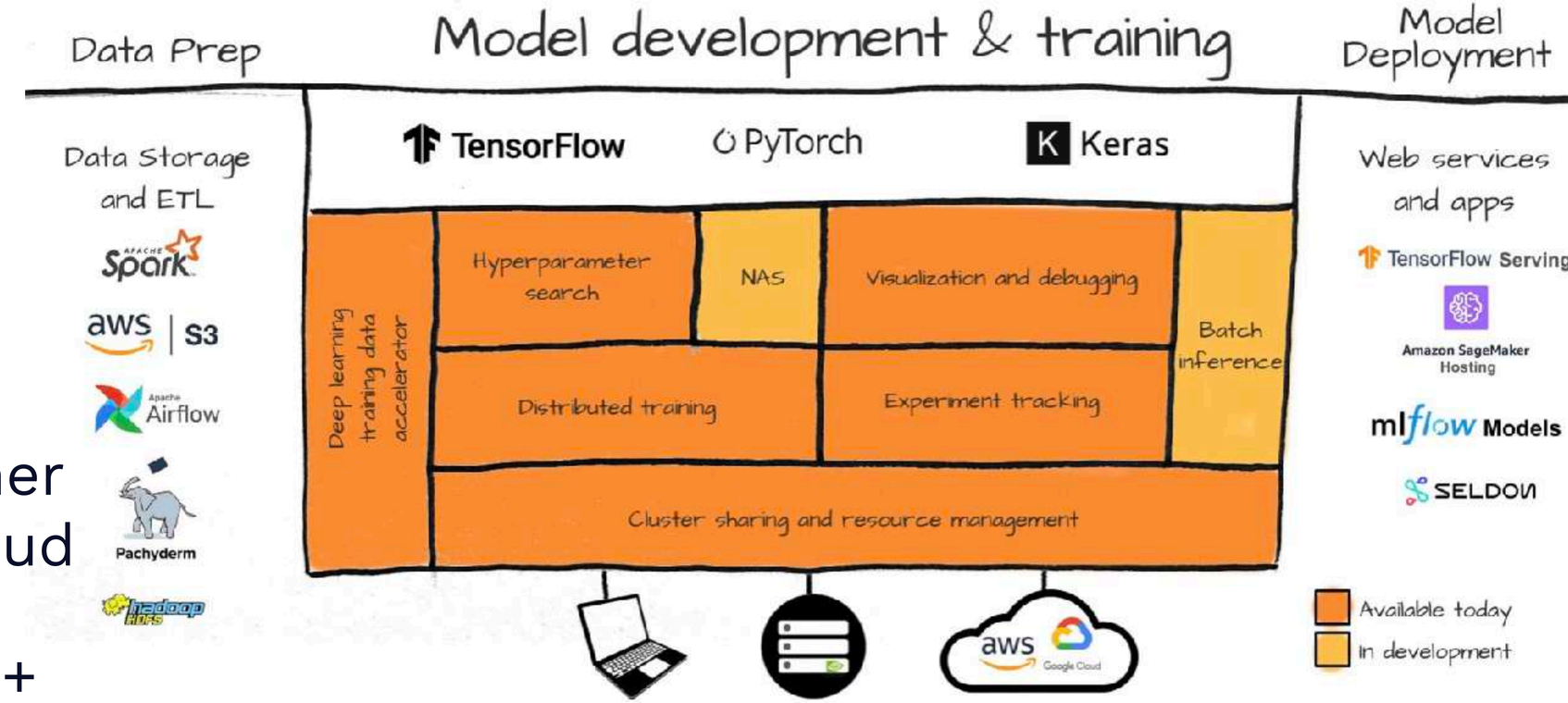
- You don't **need** SageMaker to provision training job compute on AWS
- Can write your own scripts, or use some libraries
- (But nothing we can recommend)

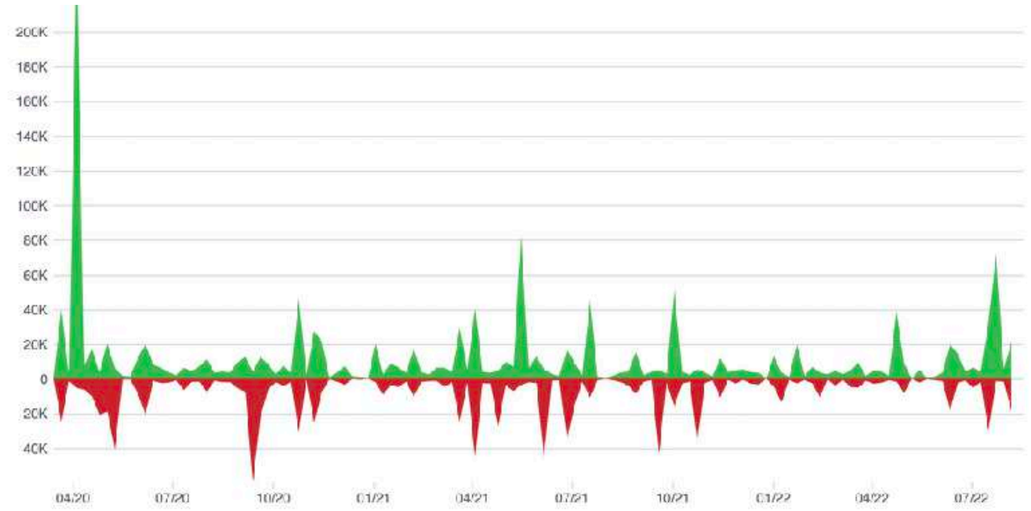
Spotty drastically simplifies training of deep learning models on AWS and GCP:

https://github.com/spotty-cloud/spotty

Determined.ai

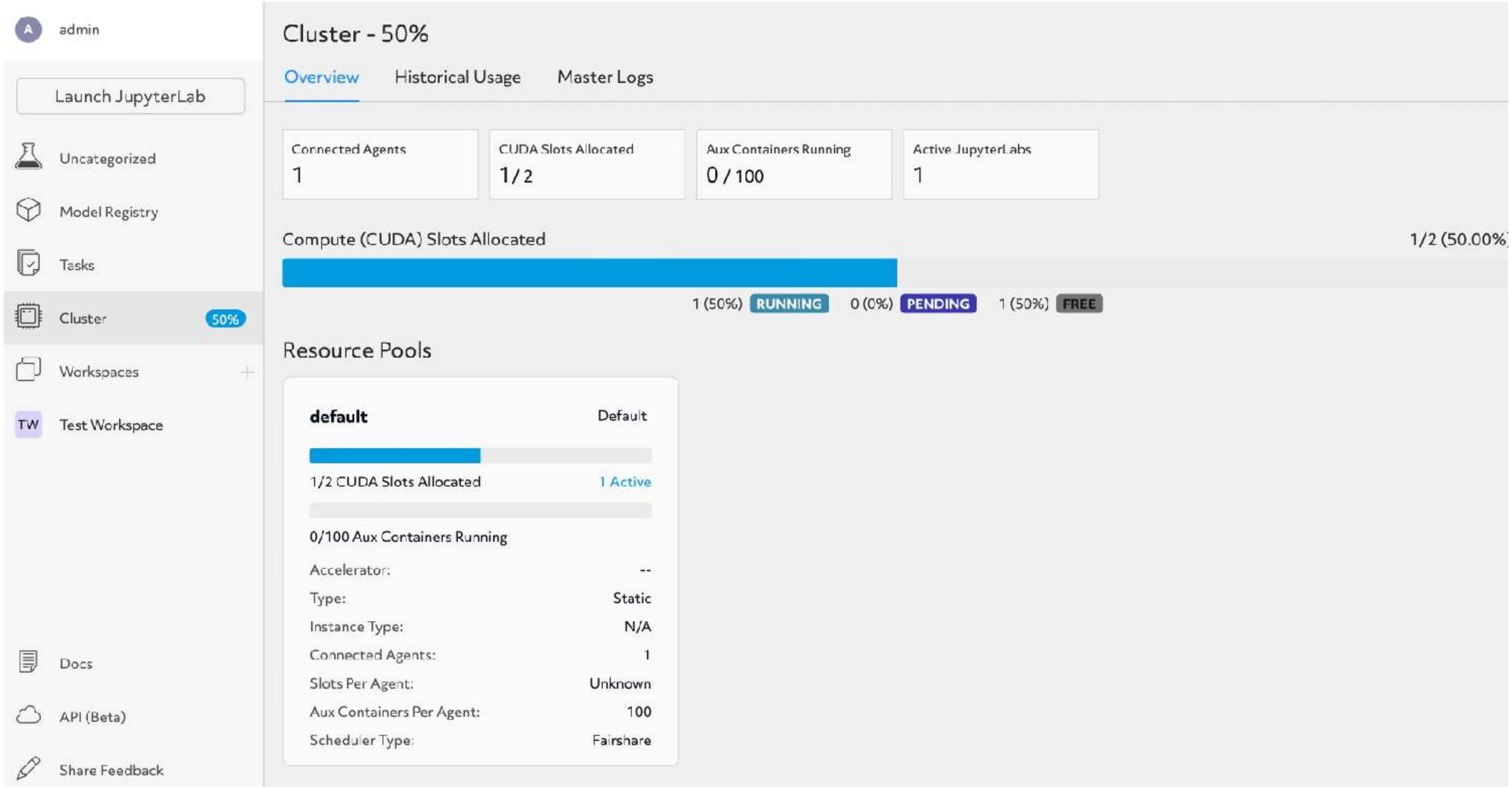
- Great open-source solution that lets you manage a cluster either on-prem or in the cloud
- Cluster management + distributed training + extra stuff
- Acquired by HP, but still in active development





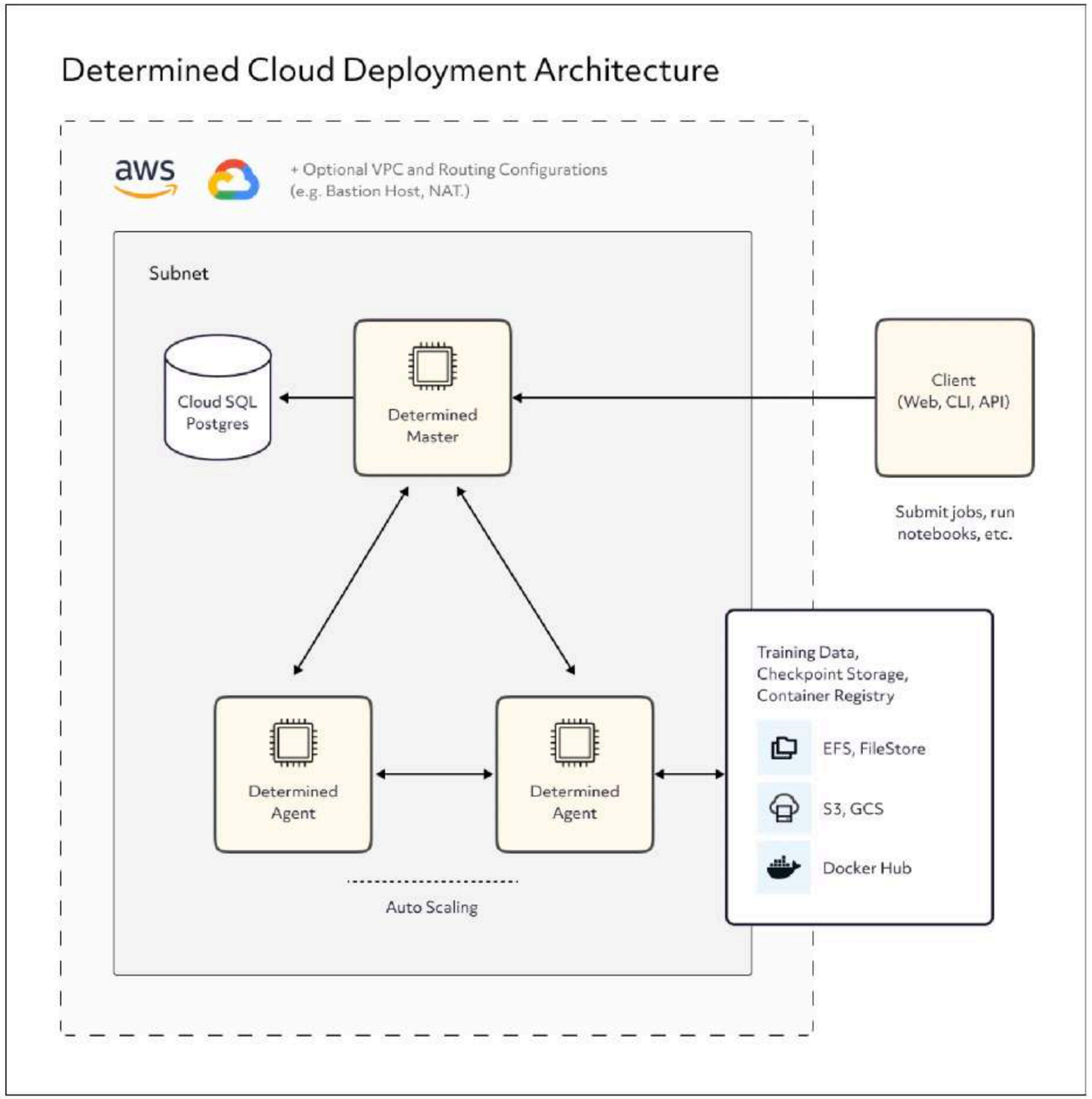
Determined.ai

```
# To start a cluster with GPUs, remove `no-gpu` flag.
det deploy local cluster-up --no-gpu
# Access web UI at localhost:8080. By default, "determined" user accepts a blank password.
```

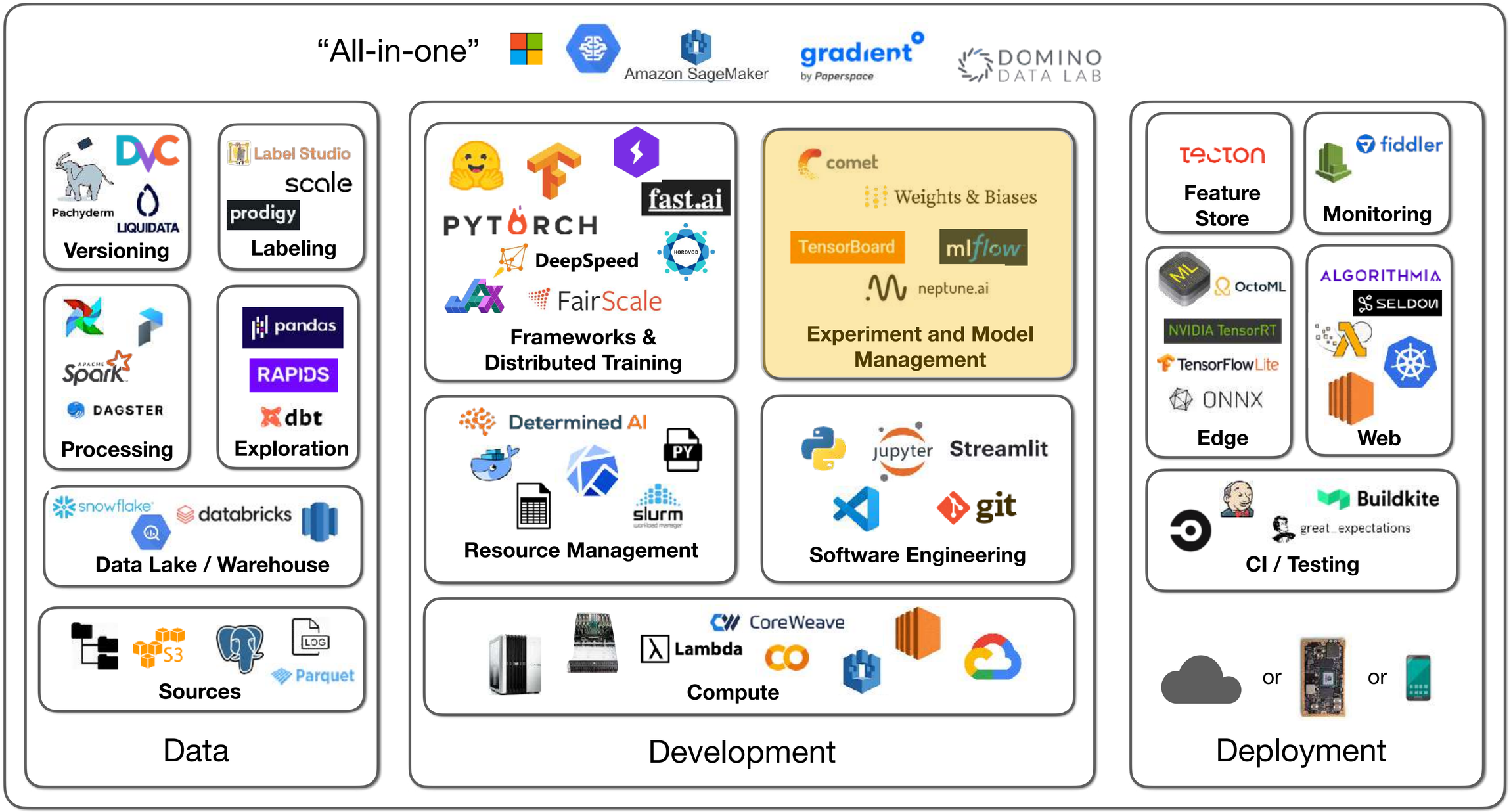


Determined.ai

- Support for both AWS and GCP (and anything else you can run Kubernetes on)



I feel that a truly simple solution to launching training on many cloud instances still does not exist


"All-in-one"
Amazon SageMaker
gradient by Paperspace
DOMINO DATA LAB
Pachyderm
LIQUIDATA
Versioning
Label Studio
scale
prodigy
Labeling
Processing
DAGSTER
pandas
RAPIDS
dbt
Exploration
snowflake
databricks
Data Lake / Warehouse
S3
LOG
Parquet
Sources
Data
PYTORCH
fast.ai
DeepSpeed
HOROVOD
FairScale
Frameworks & Distributed Training
comet
Weights & Biases
TensorBoard
mlflow
neptune.ai
Experiment and Model Management
Determined AI
PY
slurm
Resource Management
jupyter
Streamlit
git
Software Engineering
CoreWeave
Lambda
Compute
Development
tecton
Feature Store
fiddler
Monitoring
OctoML
NVIDIA TensorRT
TensorFlowLite
ONNX
Edge
ALGORITHMIA
SELDON
Web
Buildkite
great_expectations
CI / Testing
or
or
Deployment

Experiment Management

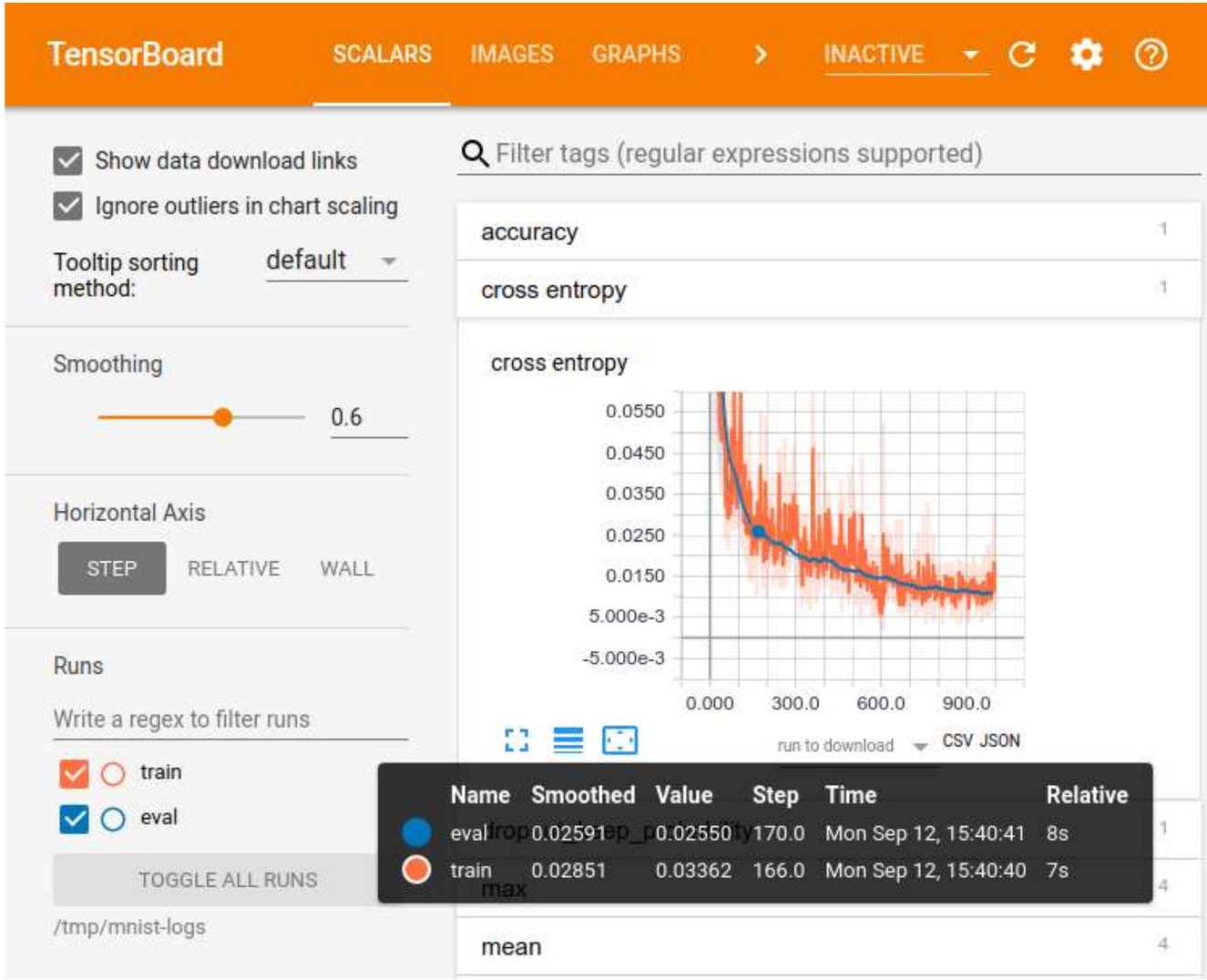
- Even running one experiment at a time, can lose track of which code, parameters, and dataset generated which trained model.
- When running multiple experiments, problem is much worse.

11	Dataset	Split (trian/dev/test)	0.7/0.2/0.1	0.7/0.2/0.1	0.7/0.2/0.1	0.7/0.15/0.15	0.7/0.15/0.15
12		Class ratio (train/dev/test)	0.42/0.42/0.42	0.42/0.42/0.42	0.42/0.42/0.42	/0.3/0.3	/0.3/0.3
13		train/dev/test size	4871/1392/696	4871/1392/696	5315/1518/760	5315/1139/1139	5315/1139/1139
14	Training hyperparameters	Learning rate	1.00E-05	1.00E-05	1.00E-05	1.00E-05	1.00E-05
15		epoch	3	2	1	5	6
16		batch size	32	32	32	32	32
17	Results	accuracy	0.88304595	0.8650862069	0.8687747	0.86997364	0.65
18		f1	0.82495437	0.8108753316	0.82383946	0.81827954	0.44
19		precision	0.878865	0.7848381601	0.8407407	0.8556561	0.56
20		recall	0.7780239	0.8389705882	0.8076923	0.78442625	0.36
21		tp	1398	1402	1460	1334	1130
22		tn	1692	1663	1707	1543	1504
23		fp	1113	1142	1161	1108	1148
24		fn	1189	1185	1190	1154	1357
25		loss	0.59637538	0.594134	0.594134	0.6037084	0.594134
26	Test results	accuracy	0.90747	0.90747	0.88026	0.88314	0.75847
27		f1	0.85636	0.85636	0.83108	0.83469	0.5915
28		precision	0.90934	0.90934	0.86689	0.87027	0.77626
29		recall	0.8099	0.8099	0.79846	0.80226	0.48604
30							

https://towardsdatascience.com/tracking-ml-experiments-using-mlflow-7910197091bb

Tensorboard

- From Google, but not exclusive to Tensorflow
- A fine solution for single experiments
- Gets unwieldy to manage many experiments, and to properly store past work



MLFlow tracking

- Open-source solution for experiment and model management
- Need to host yourself

/Shared/experiments/cryptocurrency/analysis-forecasting-1

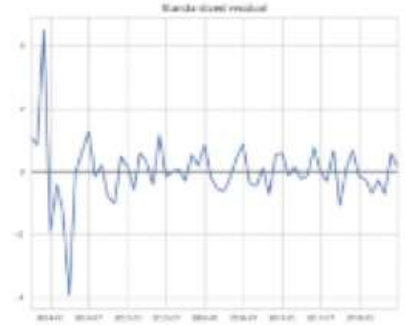
Experiment ID: 450992 Artifact Location: dbfs:/databricks/mlflow/450992

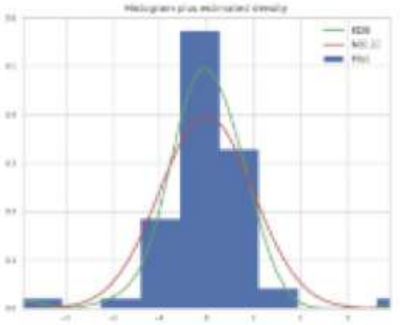
Search Expression: metrics.rmse < 1 and params.model = "tree" State: Active Search Clear

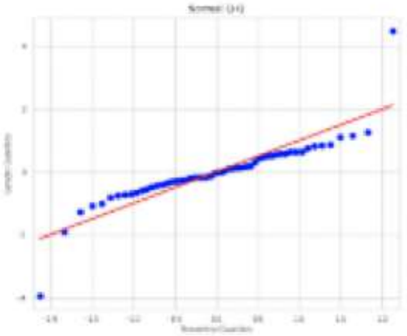
Params: alpha, lr Metrics: rmse, r2

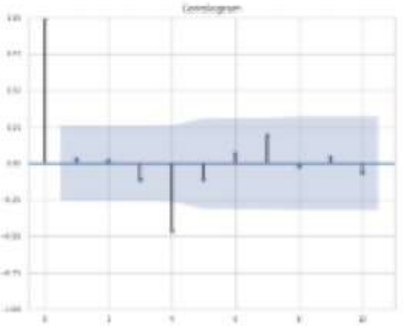
8 matching runs Compare Delete Download CSV

	Date	User	Run Name	Source	Version	Tags	Parameters		Metrics
							param-ps	param-qs	metric
	2019-07-13 08:20:35	hafidzz	arima_param	cryptocurrency-price-forecasting-after			2	2	-219.8
	2019-07-13 08:20:34	hafidzz	arima_param	cryptocurrency-price-forecasting-after			1	2	-221.7
	2019-07-13 08:20:33	hafidzz	arima_param	cryptocurrency-price-forecasting-after			0	2	-223.2
	2019-07-13 08:20:32	hafidzz	arima_param	cryptocurrency-price-forecasting-after			2	1	-221.2
	2019-07-13 08:20:32	hafidzz	arima_param	cryptocurrency-price-forecasting-after			1	1	-223.2
	2019-07-13 08:20:31	hafidzz	arima_param	cryptocurrency-price-forecasting-after			0	1	-225.1
	2019-07-13 08:20:30	hafidzz	arima_param	cryptocurrency-price-forecasting-after			2	0	-222.9
	2019-07-13 08:20:30	hafidzz	arima_param	cryptocurrency-price-forecasting-after			1	0	-224.7





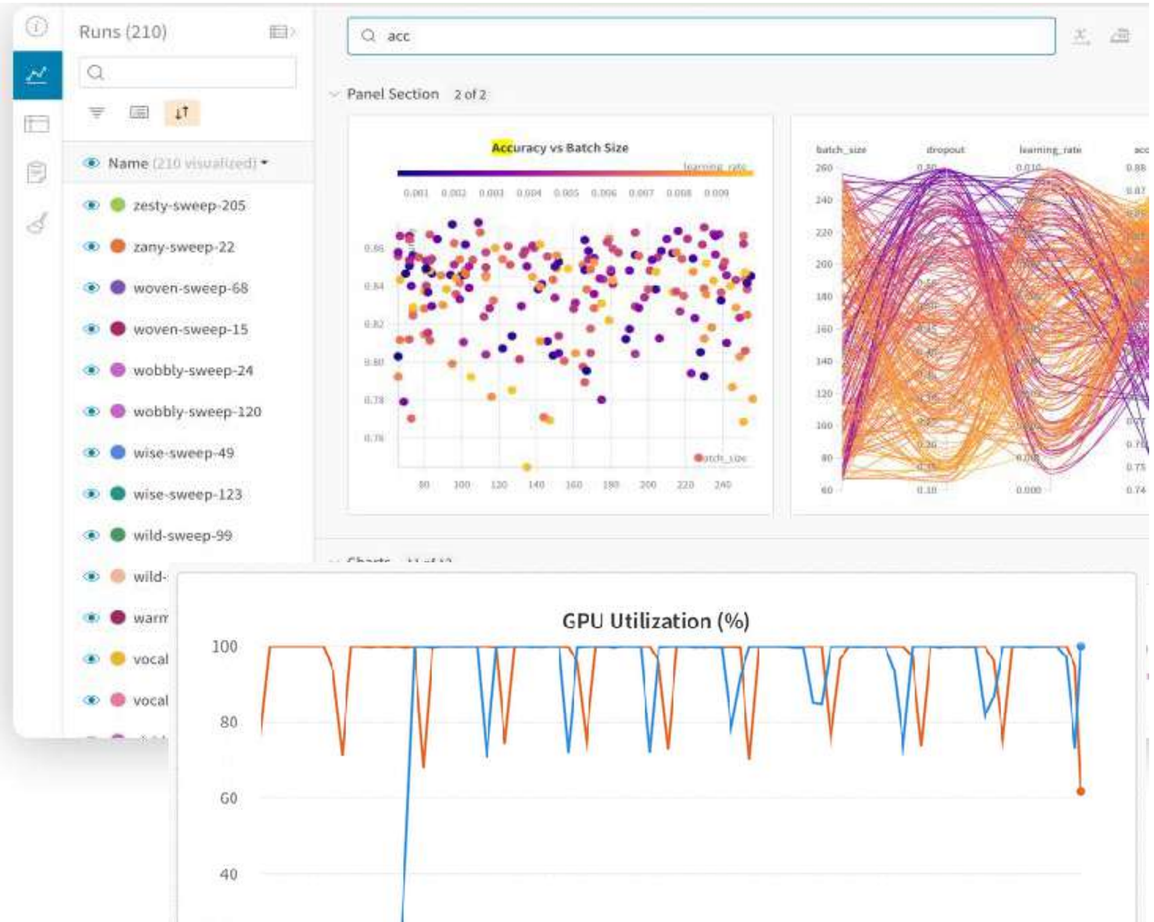


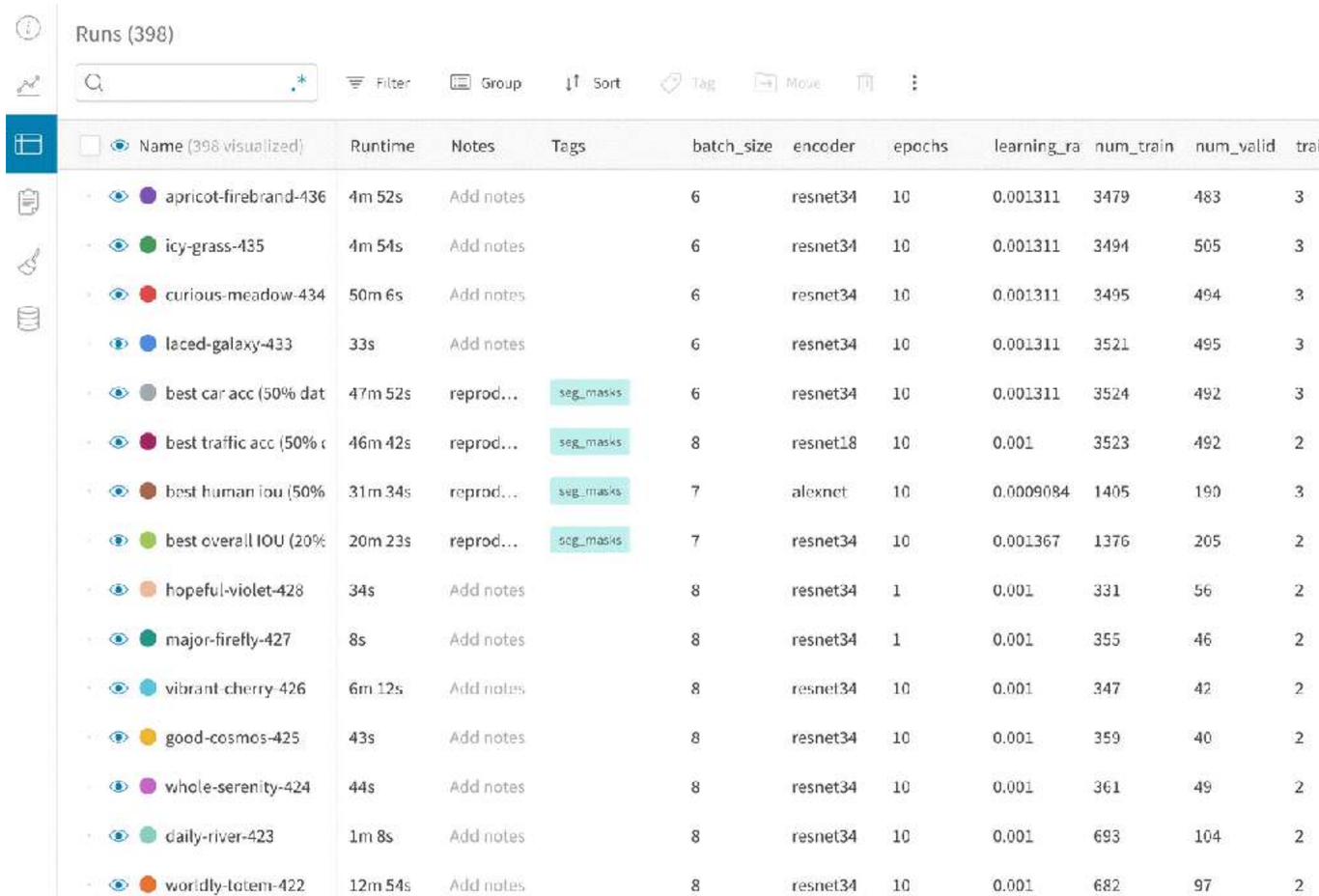


https://towardsdatascience.com/tracking-ml-experiments-using-mlflow-7910197091bb

Weights & Biases

- Really popular, super easy-to-use solution
- Hosted free for public projects





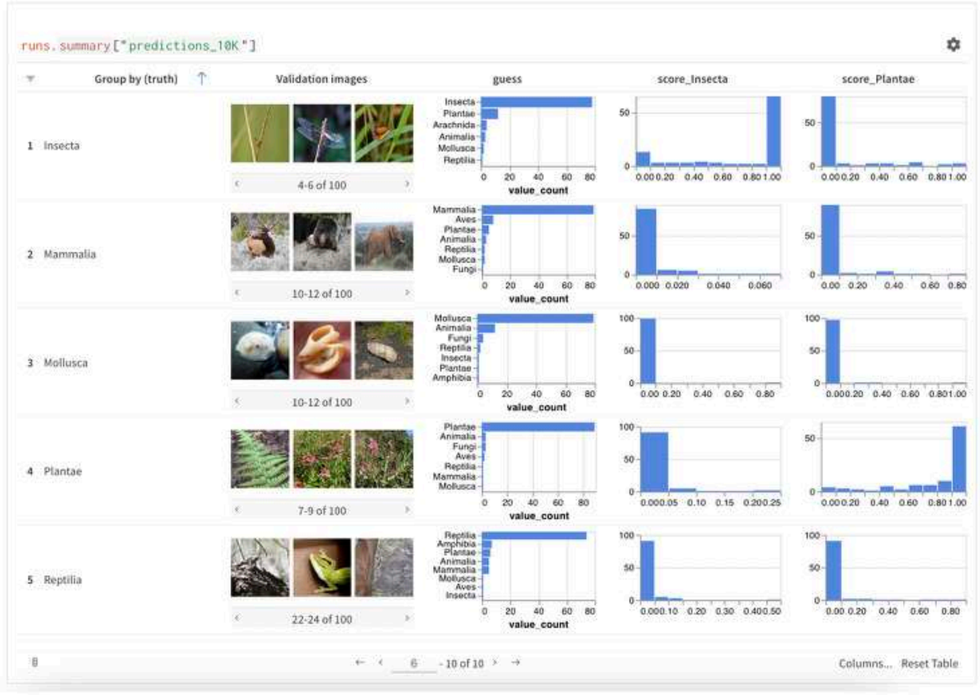
Weights & Biases

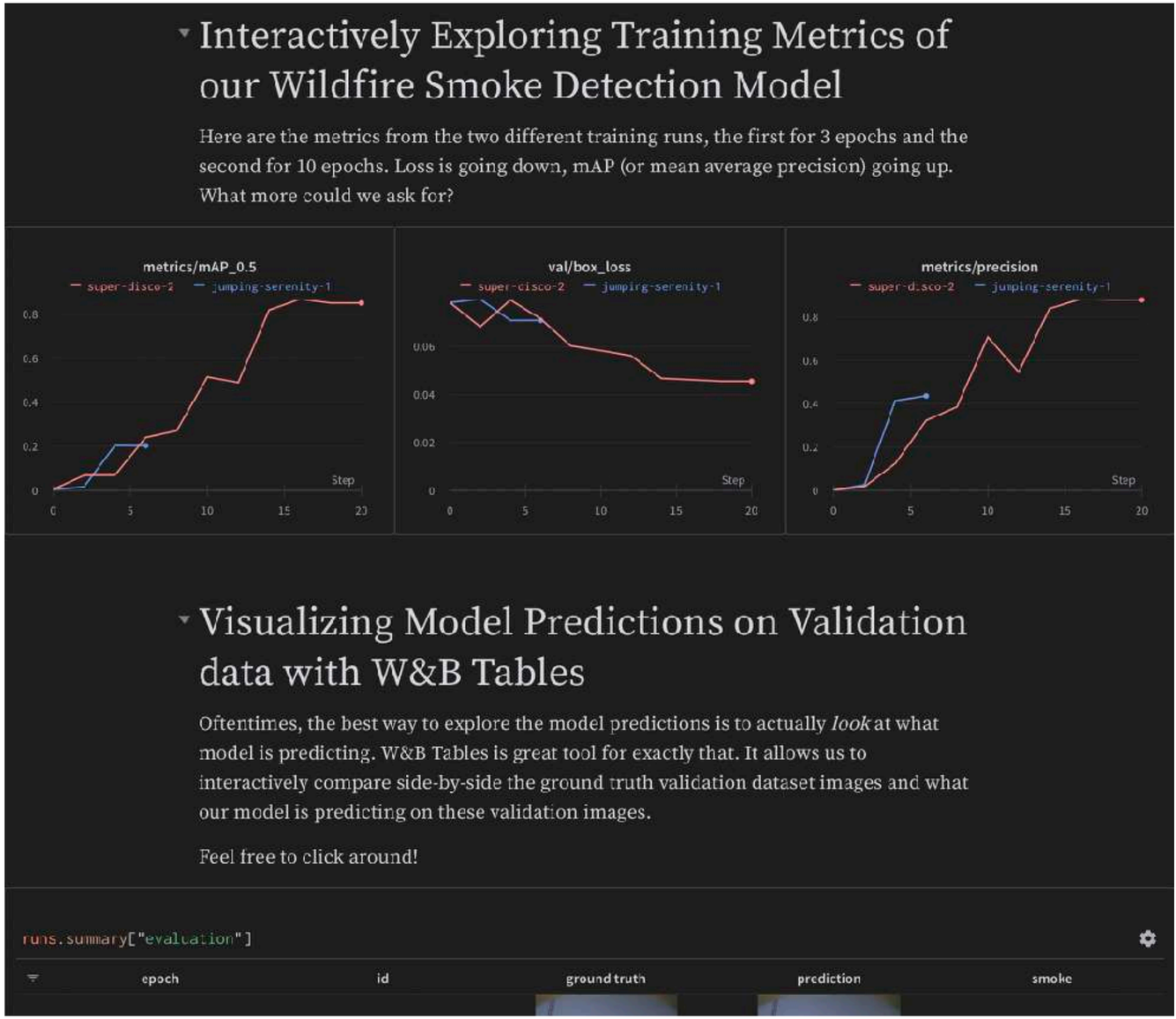
- Simply init with experiment config (automatic for PyTorch-Lightning), and then log anything you want, including images
- We will use this in Lab 4 this week

```
# Flexible integration for any Python script
import wandb

# 1. Start a W&B run
wandb.init(project='gpt3')

# 2. Save model inputs and hyperparameters
config = wandb.config
config.learning_rate = 0.01

# Model training here

# 3. Log metrics over time to visualize performance
wandb.log({"loss": loss})
```

Weights & Biases Reports and Tables

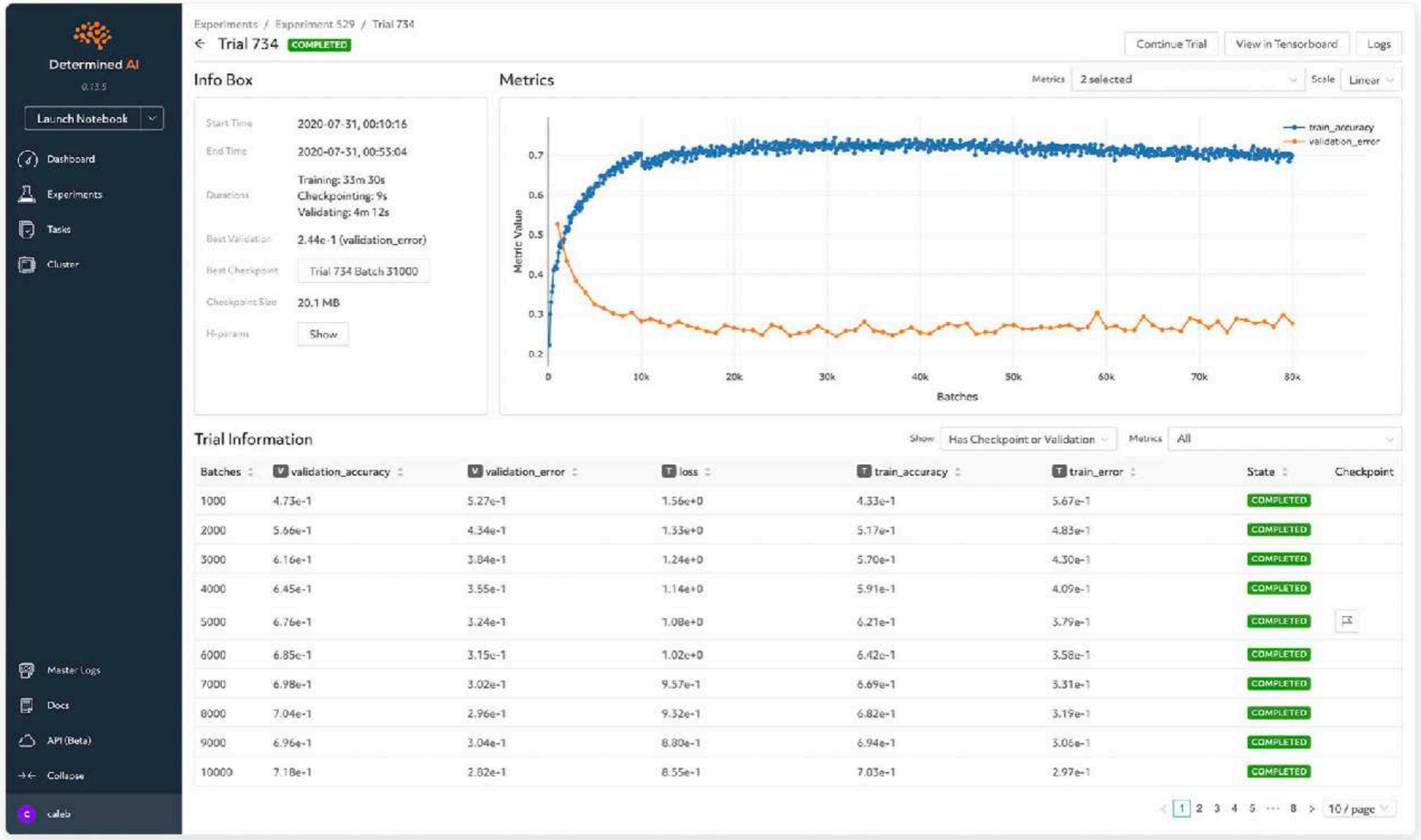
- Share results of your project
- Explore data/predictions



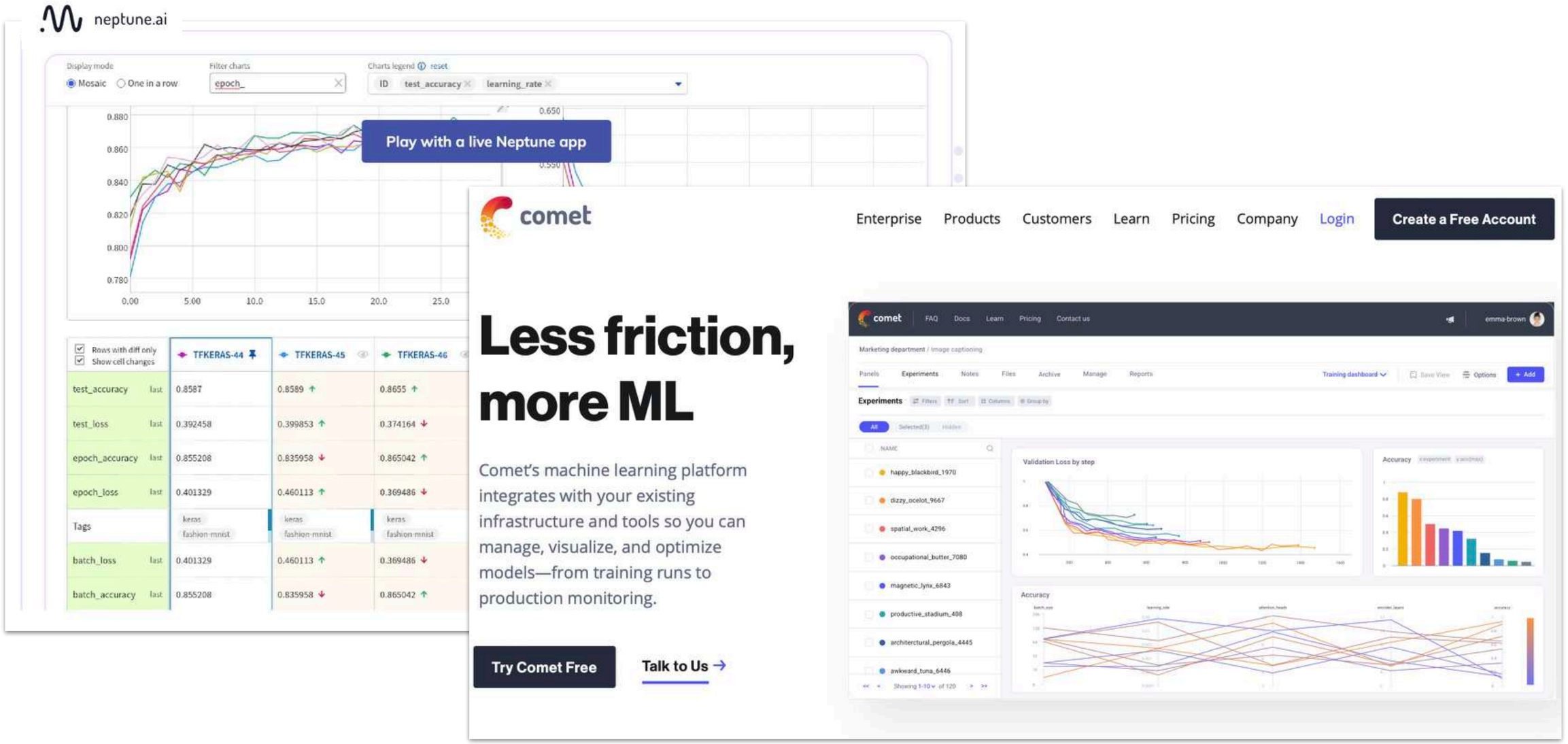


Determined.ai

- Determined.ai also has experiment tracking



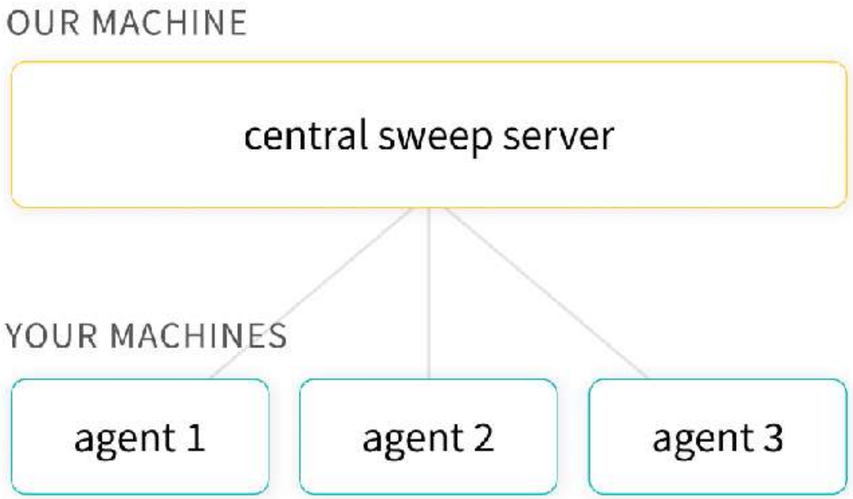
Other solutions



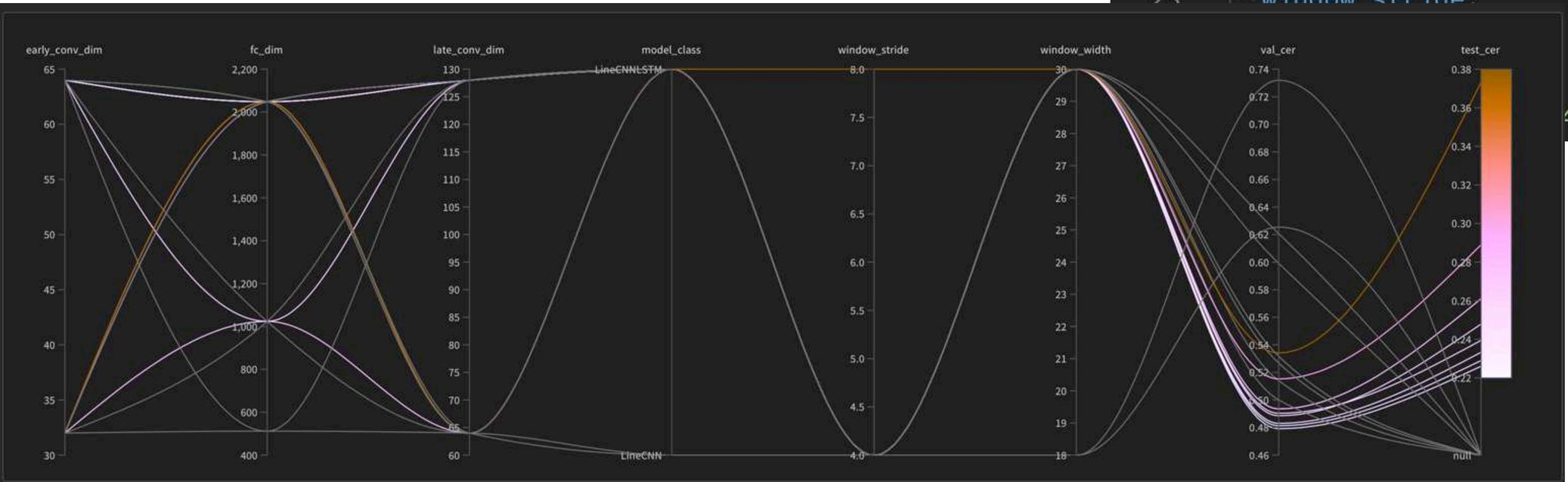
Hyperparameter Optimization

- Useful to have software that helps you search over hyper parameter settings.
- Could be as simple as being able to provide `—lr=(0.0001, 0.1) --num_layers=[128, 256, 512]` to training script
- Would be even better if settings were selected intelligently, and underperforming runs stopped early.

W&B Sweeps




```yaml
program: training/run_experiment.py
method: bayes
metric:
  goal: minimize
  name: val_cer
early_terminate:
  type: hyperband
  min_iter: 20
parameters:
  early_conv_dim:
    values: [32, 64]
  late_conv_dim:
    values: [64, 128]
  window_width:
    values: [18, 24, 30]
  window_stride:
```



Other solutions

- Also provided by SageMaker, Determined.ai, Ray, etc
- Usually not worth using anything specialized

"All-in-one" Amazon SageMaker gradient by Paperspace DOMINO DATA LAB

Versioning: Pachyderm, DVC, LIQUIDATA

Labeling: Label Studio, scale, prodigy

Processing: Spark, DAGSTER

Exploration: pandas, RAPIDS, dbt

Data Lake / Warehouse: snowflake, databricks

Sources: S3, LOG, Parquet

Data

Frameworks & Distributed Training: PYTORCH, fast.ai, DeepSpeed, HOROVOD, FairScale

Experiment and Model Management: comet, Weights & Biases, TensorBoard, mlflow, neptune.ai

Resource Management: Determined AI, PY, slurm

Software Engineering: jupyter, Streamlit, git

Compute: CoreWeave, Lambda

Development

Feature Store: tecton

Monitoring: fiddler

Edge: ML, OctoML, NVIDIA TensorRT, TensorFlowLite, ONNX

Web: ALGORITHMIA, SELDON

CI / Testing: Buildkite, great_expectations

or or

Deployment

All-in-one Solutions

- Single system for everything
  - development (hosted notebook)
  - scaling experiments to many machines (sometimes even provisioning)
  - tracking experiments and versioning models
  - deploying models
  - monitoring performance

Amazon SageMaker

Prepare →

SageMaker Ground Truth
Label training data for machine learning

SageMaker Data Wrangler NEW
Aggregate and prepare data for machine learning

SageMaker Processing
Built-in Python, BYO R/Spark

SageMaker Feature Store NEW
Store, update, retrieve, and share features

SageMaker Clarify NEW
Detect bias and understand model predictions

Build →

SageMaker Studio Notebooks
Jupyter notebooks with elastic compute and sharing

Built-in and Bring-your-own Algorithms
Dozens of optimized algorithms or bring your own

Local Mode
Test and prototype on your local machine

SageMaker Autopilot
Automatically create machine learning models with full visibility

SageMaker JumpStart NEW
Pre-built solutions for common use cases

Train & tune →

One-click Training
Distributed infrastructure management

SageMaker Experiments
Capture, organize, and compare every step

Automatic Model Tuning
Hyperparameter optimization

Distributed Training Libraries NEW
Training for large datasets and models

SageMaker Debugger NEW
Debug and profile training runs

Managed Spot Training
Reduce training cost by 90%

Deploy & manage →

One-click Deployment
Fully managed, ultra low latency, high throughput

Kubernetes & Kubeflow Integration
Simplify Kubernetes-based machine learning

Multi-Model Endpoints
Reduce cost by hosting multiple models per instance

SageMaker Model Monitor
Maintain accuracy of deployed models

SageMaker Edge Manager NEW
Manage and monitor models on edge devices

SageMaker Pipelines NEW
Workflow orchestration and automation

SageMaker Studio

Integrated development environment (IDE) for ML

gradient
by Paperspace

DEVELOP, TRAIN, & DEPLOY

Notebooks
1-Click Jupyter Notebooks

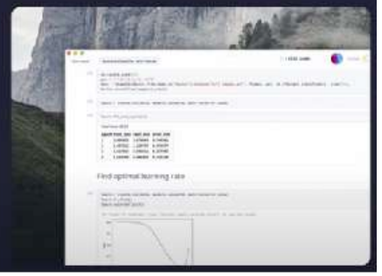
Experiments
Develop, train, and track results

Datasets
Connect, version, and track data

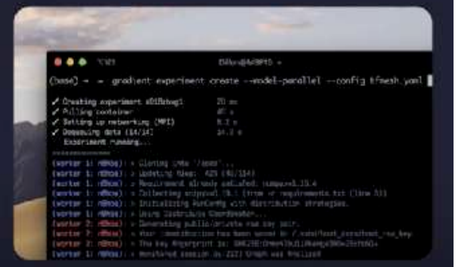
Models
Store, analyze and version models

Inference
Deploy models as API endpoints

01
Develop
1-click Jupyter Notebooks with free GPUs and zero management



02
Train
Run single experiments to large-scale distributed training



Run anywhere
Gradient runs in the public cloud or on your private servers

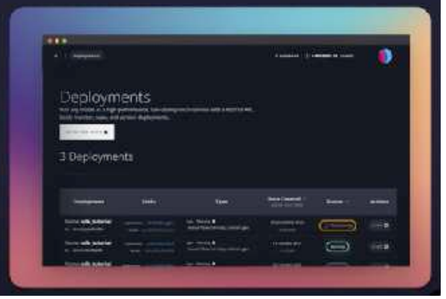
Azure aws Google Cloud Platform NVIDIA DGX

01
Interface

02
CLI

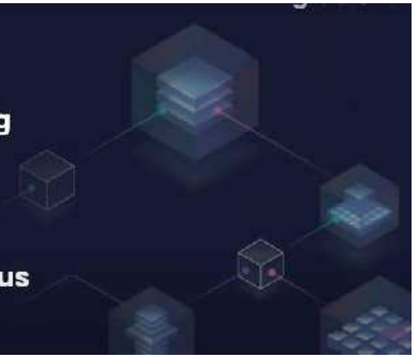
03
GitHub

03
Deploy
Model Serving with scalable API endpoints



04
Scale
Advanced Features & Pipelines

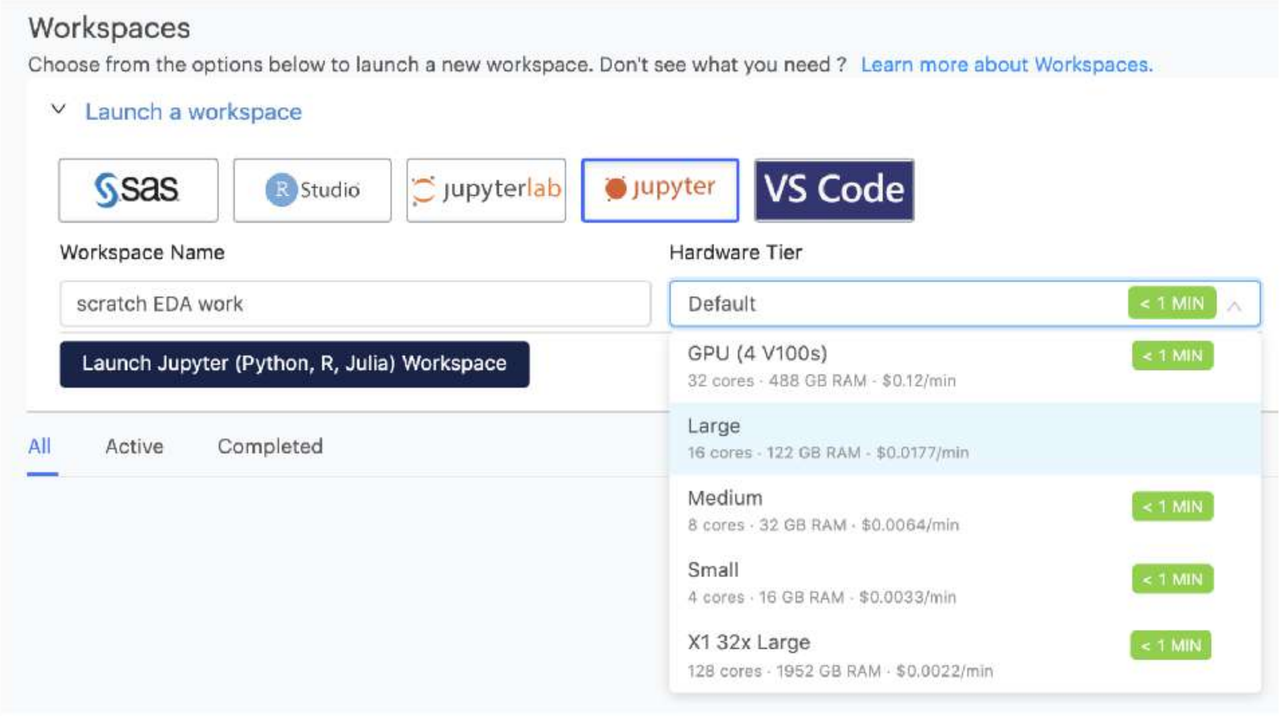
Auto-scaling
Monitoring
Versioning
Continuous



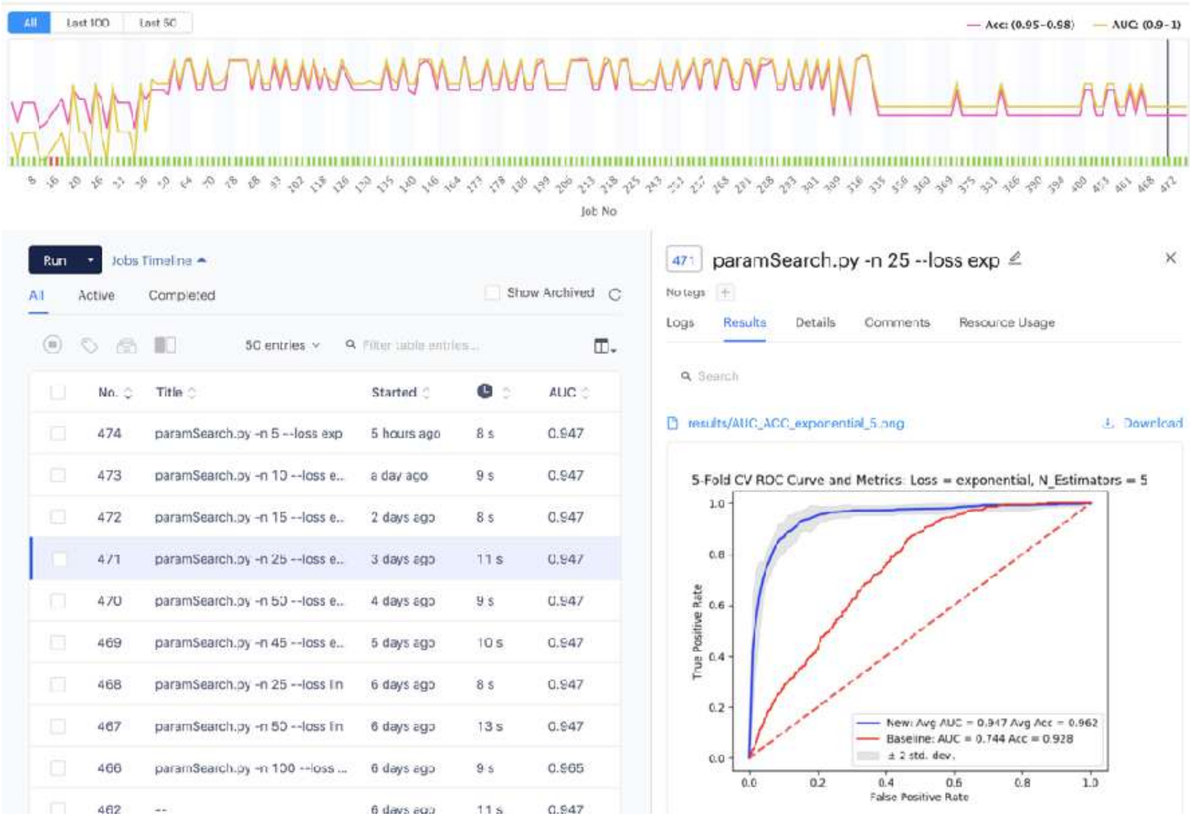
DOMINO

One place for your data science tools, apps, results, models, and knowledge.

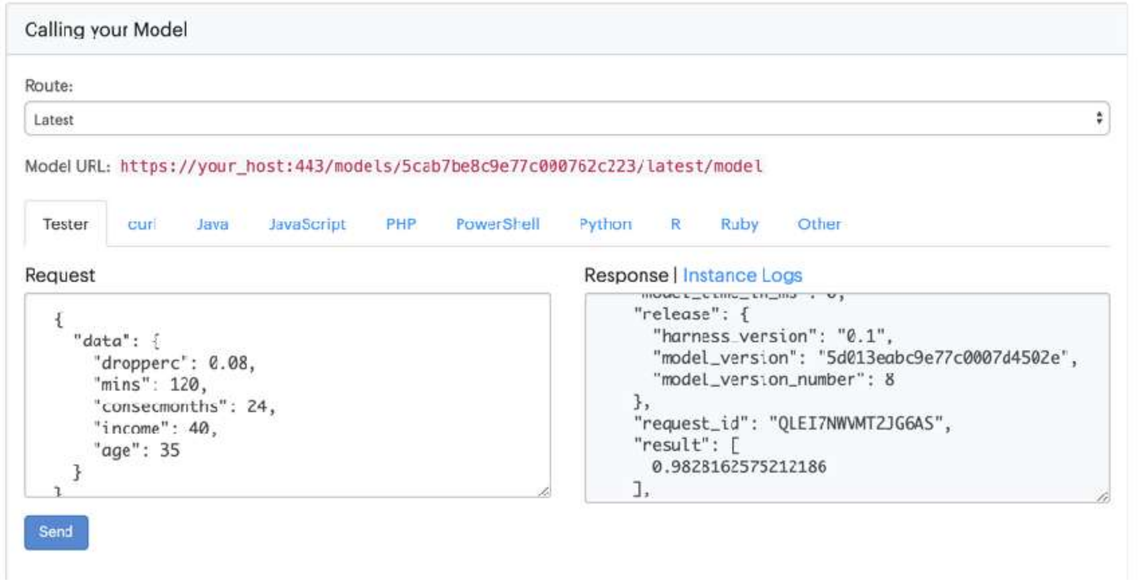
Provision compute



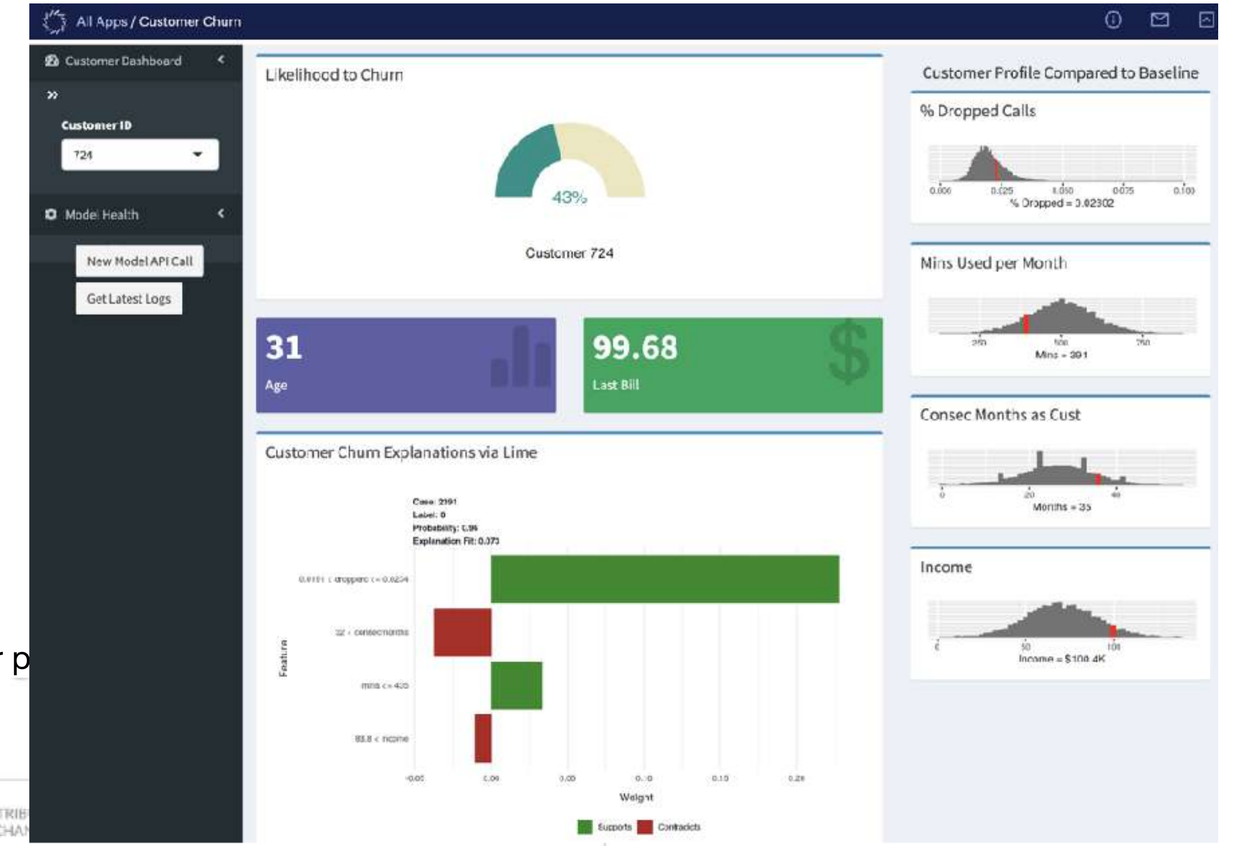
Track experiments



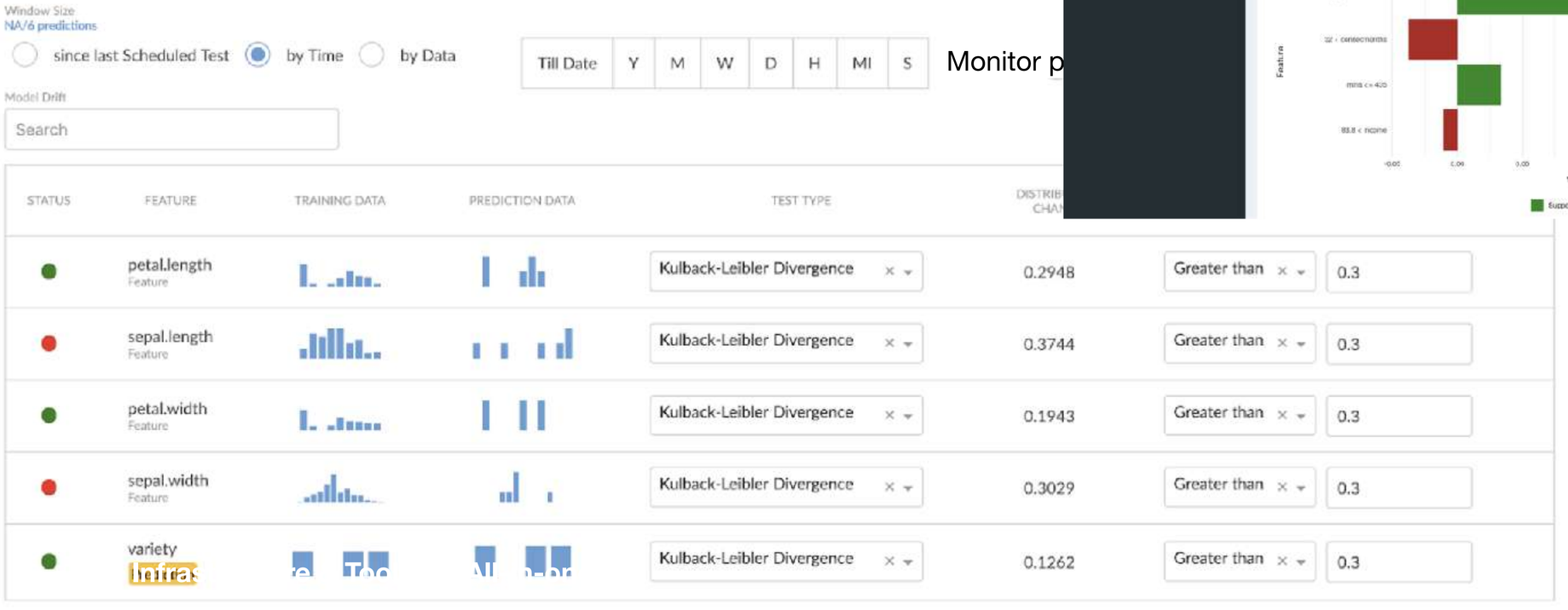
Deploy REST API

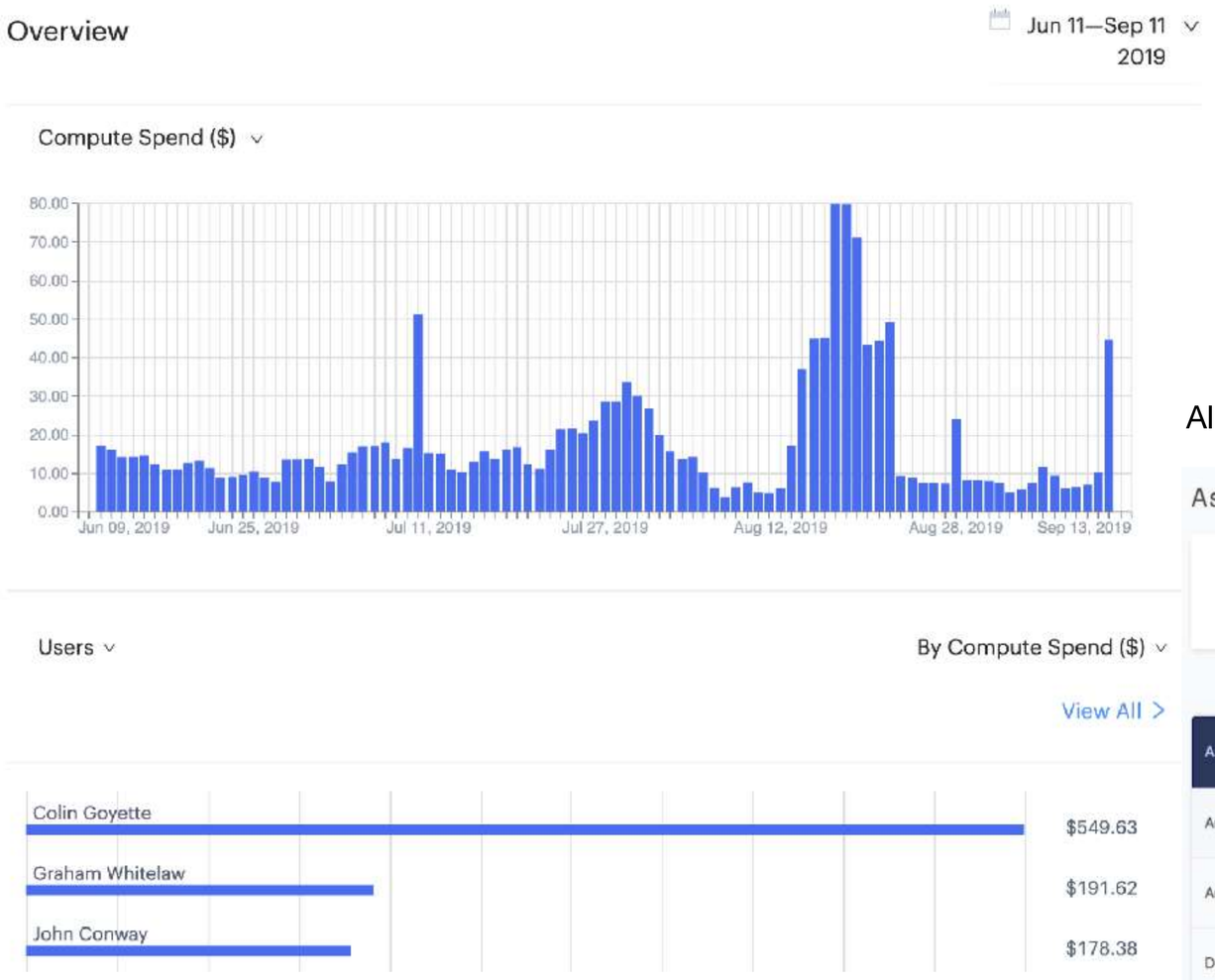


Publish applets

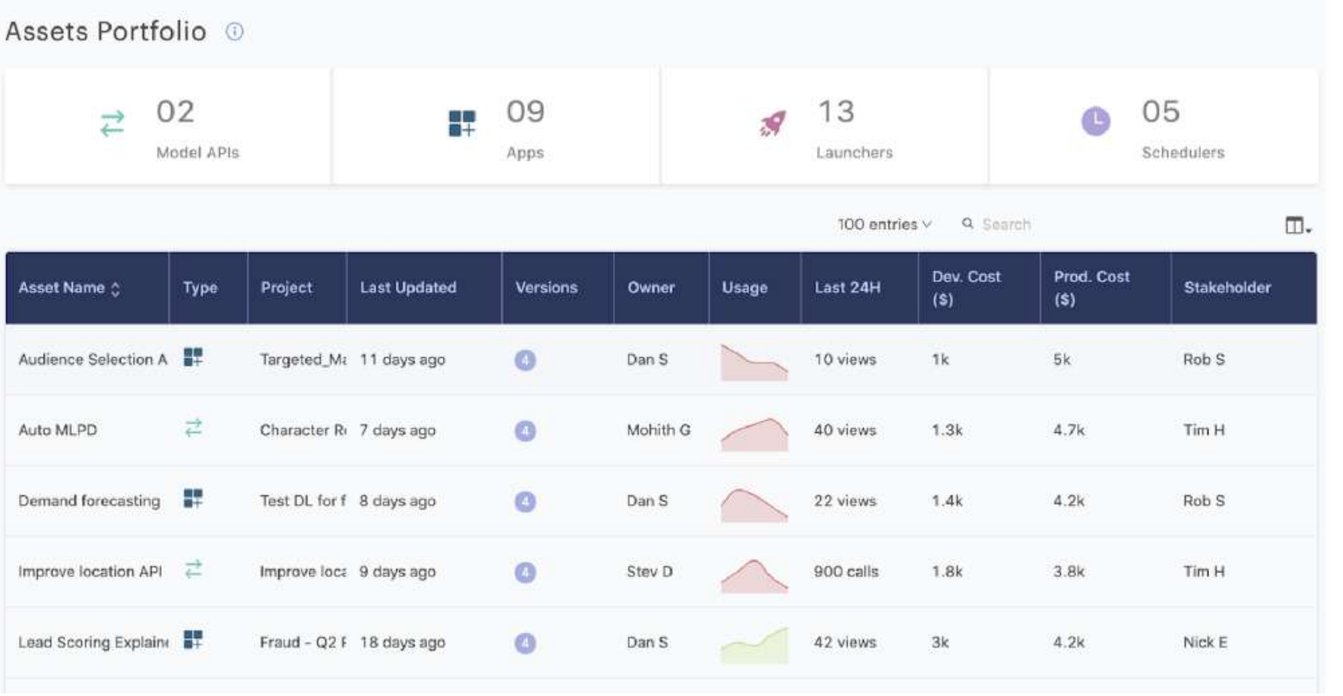


Monitor p



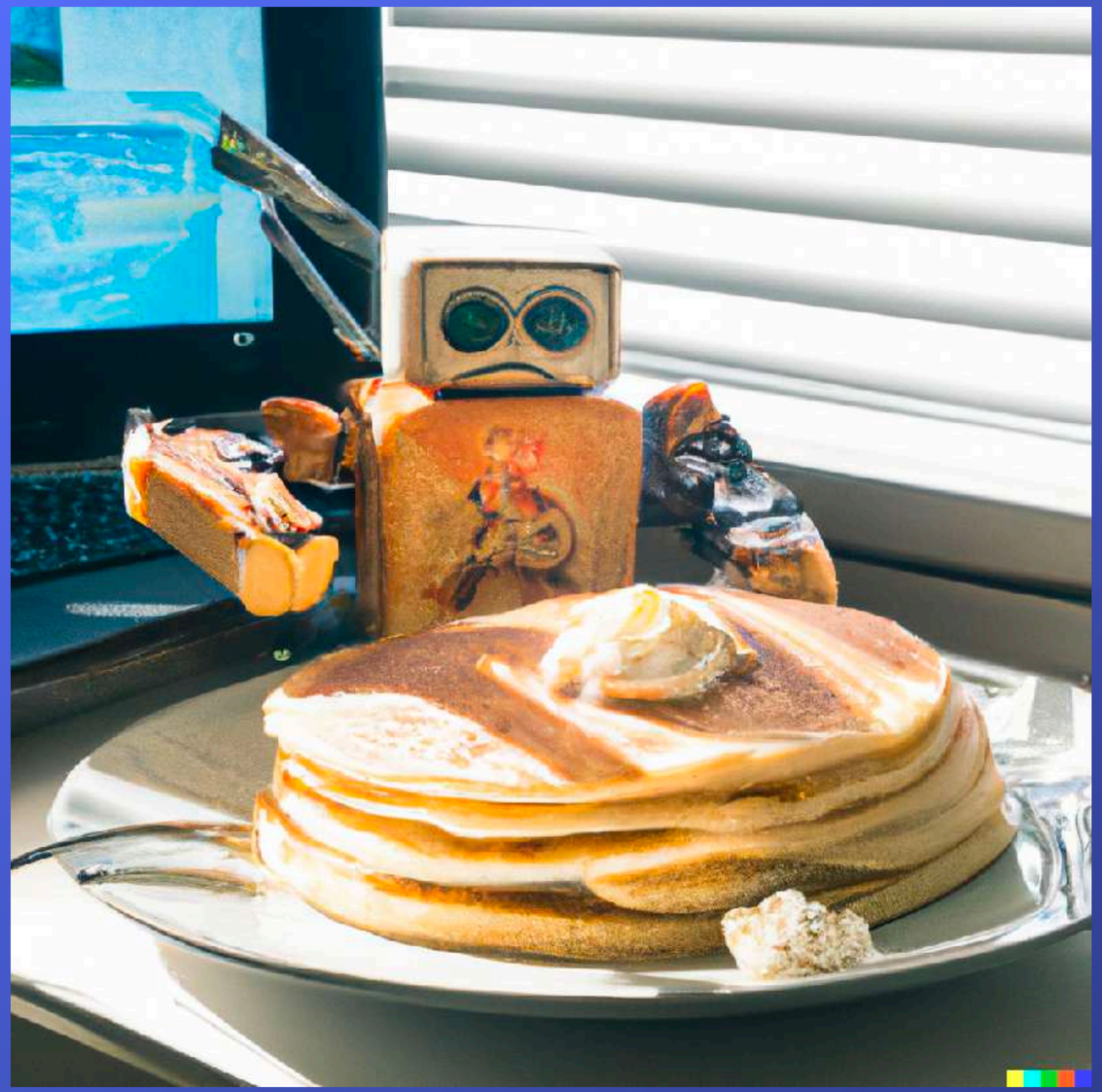


All projects in one place



These could be good!

But let's wait to learn more about Data Management and Deployment in the weeks ahead.



Thank you!