Determined AI

Deep learning at scale

Tools and techniques

Schedule

Part I: How DL training scales

1:30-2:20

- Introduction
- Challenges when scaling
- Components to a codebase
- CLI install

Part II: Topic deep dives

2:20-3:00 Reproducibility

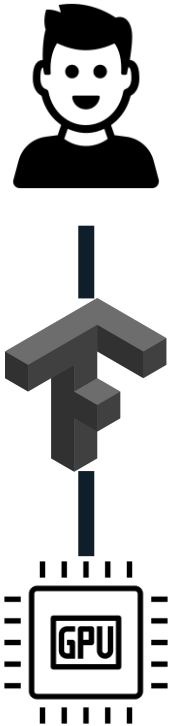
3:00-3:30 Conference Tea Break (30 mins)

3:30-4:10 Hyperparameter Tuning

4:10-4:20 Break (10 mins)

4:20-5:00 Model Serving

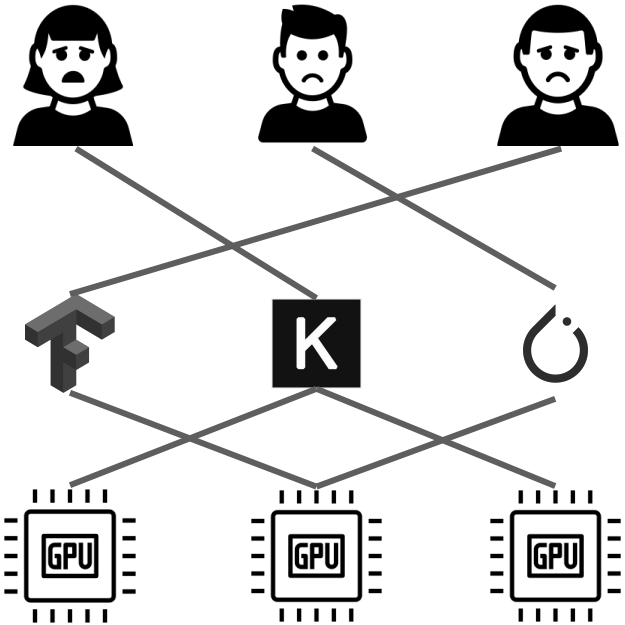
Team of one



- Relatively small experiments on single machine
- No need to share resources or productionize results
- Relatively simple infrastructure to manage
- Simple experiment tracking is sufficient:

```
results/lstm.dataset.batchsize-16.epochs-500.opt-adam.log
```

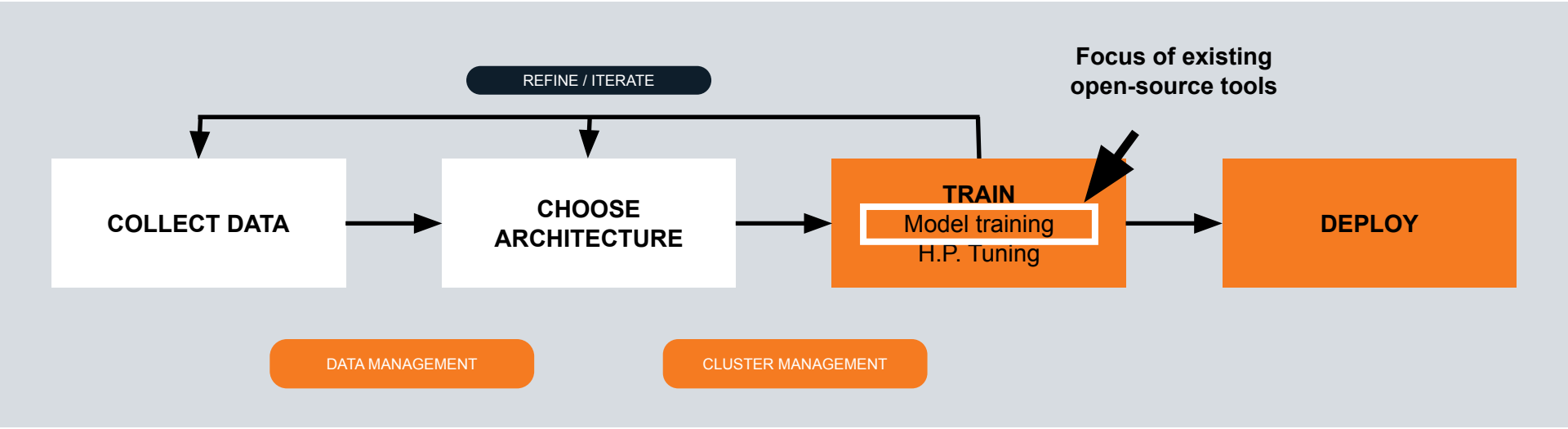
As scalability kicks in



Challenges surface:

- Resource/GPU sharing and infrastructure management
- Repetitive and time-consuming work in training, e.g. hyperparameter search
- Experiment tracking for reproducibility and collaboration
- Model deployment in production

Deep Learning Today (For Everyone Else)



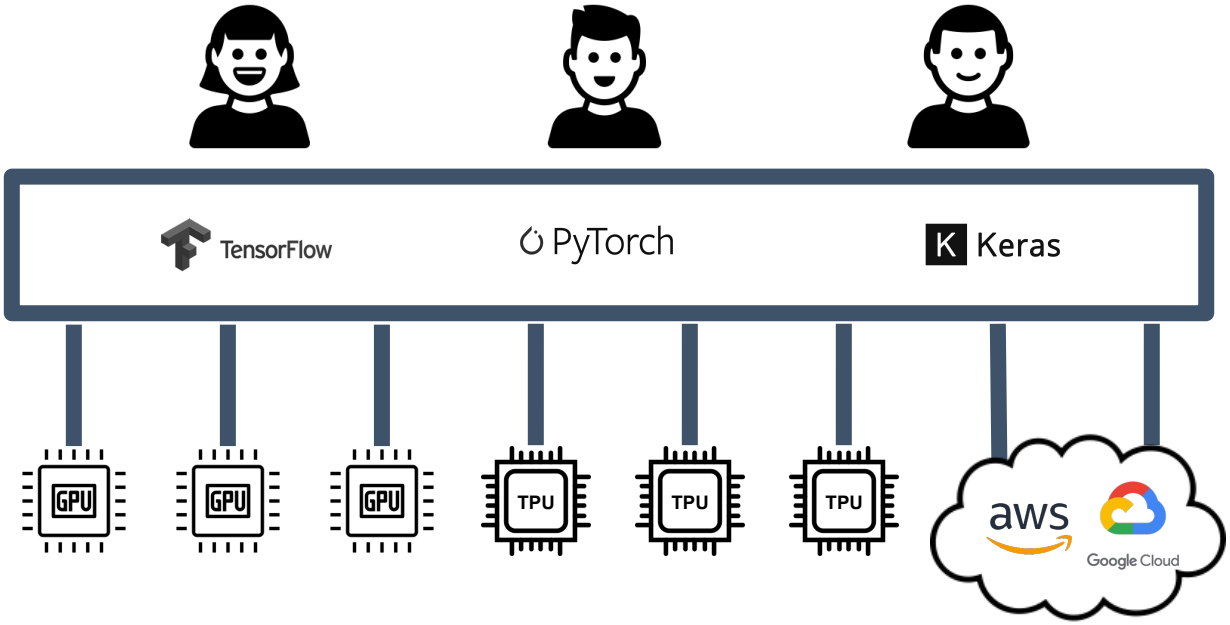
Existing Tools (e.g., TensorFlow):

- Mostly focused on 1 researcher training 1 model on 1 GPU

Minimal Support For:

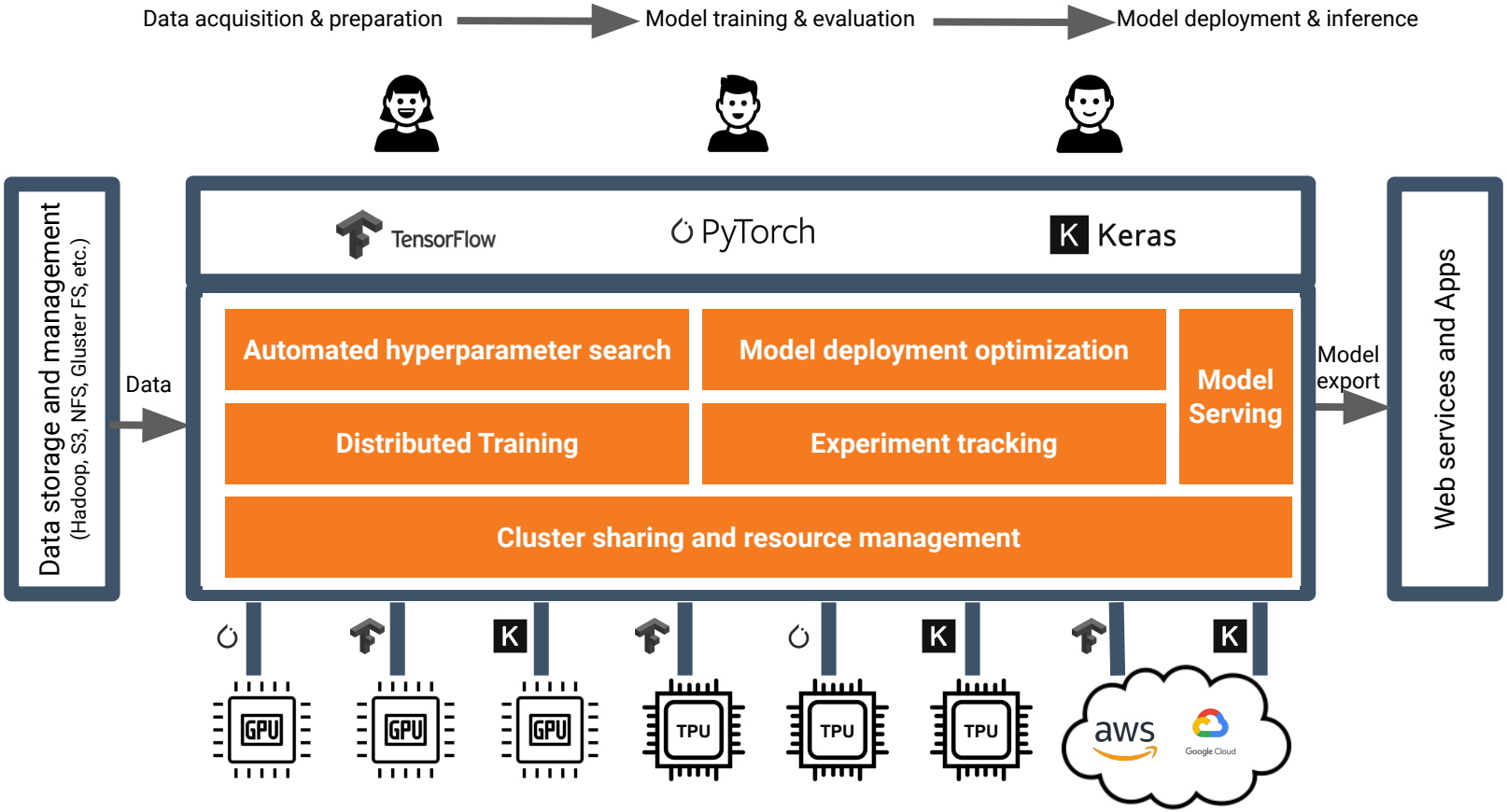
- Teams of researchers, clusters of GPUs, many models
- Deployment, ops, and collaboration

What kind of AI infrastructure is needed to address scalability?

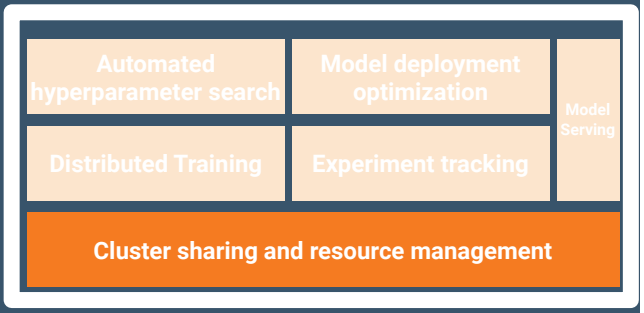


We need **holistic** and **specialized**
AI-native software infrastructure.

Determined AI offers holistic and specialized AI-native infrastructure



Cluster sharing and resource management



DIY

Static allocation

Calendar-based system

Queuing with jobs starving

GPU

GPUs under-utilized

Point Solutions

Kubernetes

Mesos

State of the Art

Dynamic flexible sharing

Fault tolerance

Simultaneous progress

Priority and quota

Automated hyperparameter search

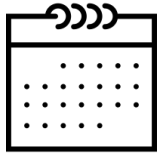
Automated hyperparameter search	Model deployment optimization	Model Serving
Distributed Training	Experiment tracking	
Cluster sharing and resource management		

DIY

Grid search

Long delay to market

$$$



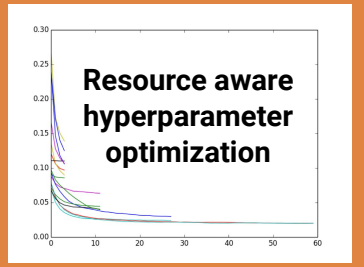
Point Solution

Bayesian optimization

Marginally better model performance

$$$

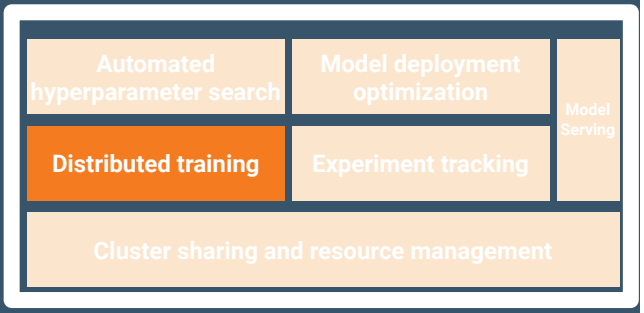
State of the Art

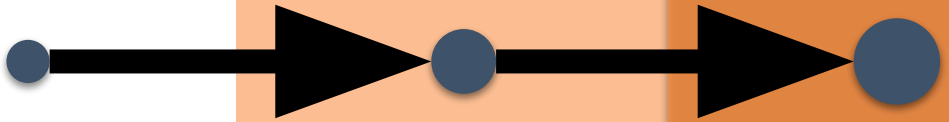


5x-50x faster

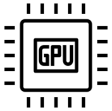
$

Parallel and distributed training





DIY



Single node training

tf.distribute torch.distributed

Framework dependency

Manual configuration
No fault tolerance

Point Solution

Horovod

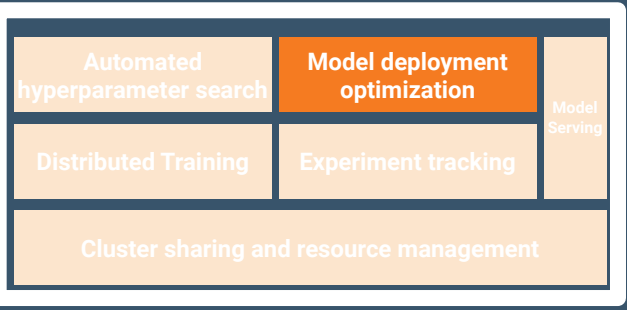
Configure MPI/Gloo
Change Model Code

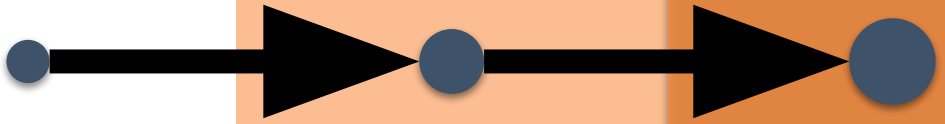
State of the Art

Simple distributed toggle
(model code unchanged)

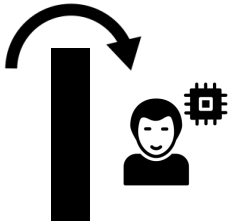
Efficient Scaling

Model deployment optimization





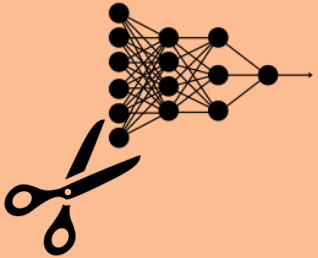
DIY



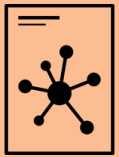
Rewrite model for production usage

Manual optimization

Point Solution



Hand-implemented pruning strategies

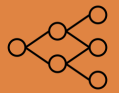


Use experimental technique from research

State of the Art

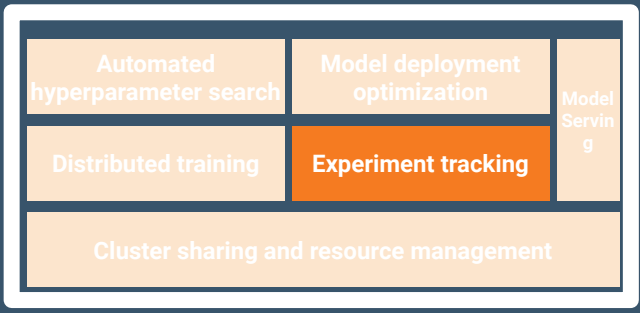
Full automation

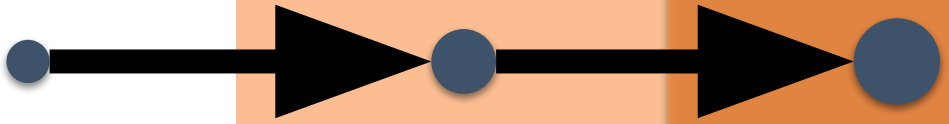
Deployment constraints at design time



System-assisted navigation of Accuracy vs. Performance tradeoff space

Experiment tracking





DIY

lstm.dataset.try3.log

Disorganized metadata

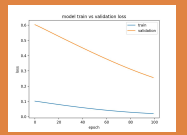
Point Solution

Experiment run logging

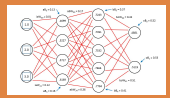
State of the Art

Containerized execution

Complete tracking of training environment



Automatic metrics capture



DL-specific reproducibility

Query-able checkpoint database

Fostering collaboration

What does holistic AI-native software infrastructure look like?

Pre-existing Keras implementation

Checkpoints

Logs

Visualizations

Horovod

Validation Metrics

Datasets

Training Loss Curves

Code

Hyperparameters

Library Version(s)

Components to a Keras codebase

Data Loading

Preprocessing

Model Architecture

keras.layer

Experiment Config

Specifies crucial metadata

Experiment Configuration

- data setup
- package versioning
- train time resources (distributed vs parallel)
- other plumbing

```yaml
description: cifar10_keras_adaptive
data:
  url: https://s3-us-west-2.amazonaws.com/determined-ai-datasets/cifar10/cifar-10-python.tar.gz
environment:
  tensorflow: 1.14.0
hyperparameters:
  learning_rate:
    type: log
    minval: -5.0
    maxval: 1.0
    base: 10.0
  learning_rate_decay: 1e-6
  layer1_dropout:
    type: double
    minval: 0.2
    maxval: 0.5
  layer2_dropout:
    type: double
    minval: 0.2
    maxval: 0.5
  layer3_dropout:
    type: double
    minval: 0.2
    maxval: 0.5
  batch_size:
    type: int
    minval: 16
    maxval: 64
  width_shift_range:
    type: double
    minval: 0.0
    maxval: 0.2
  height_shift_range:
    type: double
    minval: 0.0
    maxval: 0.2
  horizontal_flip:
    type: categorical
    vals:
      - True
      - False
searcher:
  name: adaptive
  mode: aggressive
  metric: validation_error
  target_trial_steps: 800
  step_budget: 4800
checkpoint_storage:
  type: s3
  bucket: determined-ai-examples
```

Model Code

```
class CIFARTrial(TFKerasTrial):
    def __init__(self, *args: Any, **kwargs: Any):
        super().__init__(*args, **kwargs)

        self._base_learning_rate = self._hparams["learning_rate"]  # type: float
        self._learning_rate_decay = self._hparams["learning_rate_decay"]  # type: float
        self._layer1_dropout = self._hparams["layer1_dropout"]  # type: float
        self._layer2_dropout = self._hparams["layer2_dropout"]  # type: float
        self._layer3_dropout = self._hparams["layer3_dropout"]  # type: float
        self._batch_size = self._hparams["batch_size"]  # type: int

    def session_config(self, hparams: Dict[str, Any]) -> tf.ConfigProto:
        if hparams.get("disable_CPU_parallelism", False):
            return tf.ConfigProto(intra_op_parallelism_threads=1, inter_op_parallelism_threads=1)
        else:
            return tf.ConfigProto()

    def build_model(self, hparams: Dict[str, Any]) -> Sequential:
        model = Sequential()
        model.add(
            Conv2D(32, (3, 3), padding="same", input_shape=[IMAGE_SIZE, IMAGE_SIZE, NUM_CHANNELS])
        )
        model.add(Activation("relu"))
        model.add(Conv2D(32, (3, 3)))
        model.add(Activation("relu"))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Dropout(self._layer1_dropout))

        model.add(Conv2D(64, (3, 3), padding="same"))
        model.add(Activation("relu"))
        model.add(Conv2D(64, (3, 3)))
        model.add(Activation("relu"))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Dropout(self._layer2_dropout))

        model.add(Flatten())
        model.add(Dense(512))
        model.add(Activation("relu"))
        model.add(Dropout(self._layer3_dropout))
        model.add(Dense(NUM_CLASSES))
        model.add(Activation("softmax"))

        return model
```

Data loading

```python
def make_data_loaders(
    experiment_config: Dict[str, Any], hparams: Dict[str, Any]
) -> Tuple[Sequence, Sequence]:
    """Provides training and validation data for model training.

    This example demonstrates how you could configure PEDL to help you optimize your data loading.

    In this example we added some fields of note under the `data` field in the YAML experiment
    configuration: the `acceleration` field. Under this field, you can configure multithreading by
    setting `use_multiprocessing` to `False`, or set it to `True` for multiprocessing. You can also
    configure the number of workers (processes or threads depending on `use_multiprocessing`).

    Another thing of note are the data augmentation fields in hyperparameters. The fields here get
    passed through to Keras' `ImageDataGenerator` for real-time data augmentation.
    """

    acceleration = experiment_config["data"].get("acceleration")
    url = experiment_config["data"]["url"]
    width_shift_range = hparams.get("width_shift_range", 0.0)
    height_shift_range = hparams.get("height_shift_range", 0.0)
    horizontal_flip = hparams.get("horizontal_flip", False)
    batch_size = hparams["batch_size"]

    (train_data, train_labels), (test_data, test_labels) = get_data(url)

    # Setup training data loader.
    data_augmentation = {
        "width_shift_range": width_shift_range,
        "height_shift_range": height_shift_range,
        "horizontal_flip": horizontal_flip,
    }
    train = augment_data(train_data, train_labels, batch_size, data_augmentation)

    if acceleration:
        workers = acceleration.get("workers", 1)
        use_multiprocessing = acceleration.get("use_multiprocessing", False)
        train = KerasDataAdapter(train, workers=workers, use_multiprocessing=use_multiprocessing)

    # Setup validation data loader.
    test = CIFARSequence(test_data, test_labels, batch_size)

    return train, test
```

Example: RCNN with Inception V2 on COCO

http://52.38.76.131:8080/

Schedule

Part I: how DL training scales

1:30-2:20 Introduction

Challenges when scaling

Components to a codebase

CLI install

Part II: topic deep dives

2:20-3:00 Reproducibility

Conference Tea Break (30 min)

3:30-4:10 Hyperparameter Tuning

Break (10 min)

4:20-5:00 Model Serving

Reproducibility

Death by a thousand cuts: data ordering, software versions, hyperparameters, random seeds, model weights

Why should we care?

Scientific Progress

Collaboration

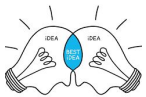
Accountability

Reproducibility is a fundamental tenet of scientific progress

Hidden sources of randomness can lead to erroneous conclusions

Why should we care?

Scientific Progress



Collaboration

Accountability

Enable sharing & encourages experimentation

Easily ramp-up new hires

Reduce dependency on individual team member

Why should we care?

Scientific Progress

Collaboration

Accountability

Avoid lossy translation between training and deployment

Easily roll back in case of system crash or poor performance

Wait…isn't this a solved problem?

Traditional Software Engineering

compile(code, deps) → binary

Deep Learning Engineering

optimize(
    architecture, deps, data, init state
) → ML model

Additional inputs + noisy optimizer = **ML reproducibility is hard!**

We’re taking over for Leslie

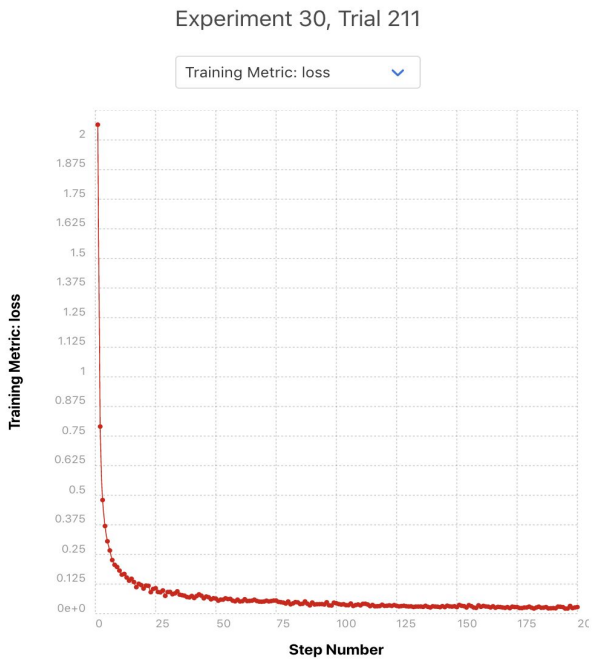
to improve on the model she trained then deployed

Artifacts from Leslie

```python
class MultiTaskMNistTrial(KerasTrial):
    def __init__(self, hparams: Dict[str, Any]):
        super().__init__(hparams)
        self._dropout = hparams.get("dropout", 0.5)

    def build_model(self, hparams: Dict[str, Any]):
        model = Sequential()
        model.add(Conv2D(32, kernel_size=(3,3), activation="relu",
        model.add(Conv2D(64, (3, 3), activation="relu"))
        model.add(MaxPooling2D(pool_size=(2, 2)))
        model.add(Dropout(self._dropout))
        model.add(Flatten())
        model.add(Dense(128, activation="relu"))
        model.add(Dropout(0.5))
        model.add(Dense(NUM_CLASSES, activation="softmax"))
        return model

    def batch_size(self) -> int:
        return BATCH_SIZE

    def optimizer(self) -> keras.optimizers.Optimizer:
        return SGD(lr=0.001)

    def loss(self) -> dict:
        return categorical_crossentropy

    def training_metrics(self) -> dict:
        return { "accuracy": categorical_accuracy }

    def validation_metrics(self) -> dict:
        return { "accuracy": categorical_accuracy }
```

files @ OReilly/reproducibility

Exp 30 @ <cluster_ip>:8080



Let's retrain to get a baseline!

In PEDL, for simplicity:

Leslie's artifacts: Experiment 30 at <cluster_ip>:8080

Let's rerun her script:

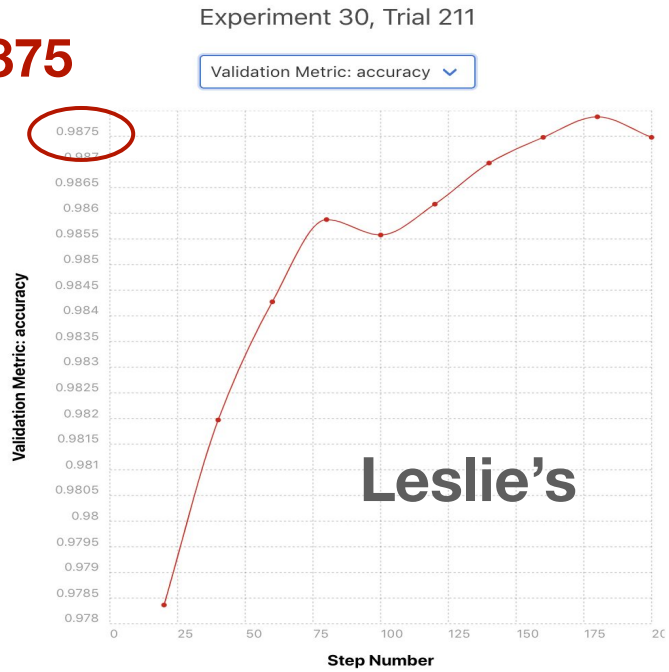
```
pedl e create leslie.yaml .
```

from **`OReilly/reproducibility/model_code`**

Reminder, to set up you need to:
1) Clone https://github.com/determined-ai/OReilly
2) Install PEDL CLI
3) Point PEDL CLI to cluster address: **`export PEDL_MASTER=<cluster_ip>`**

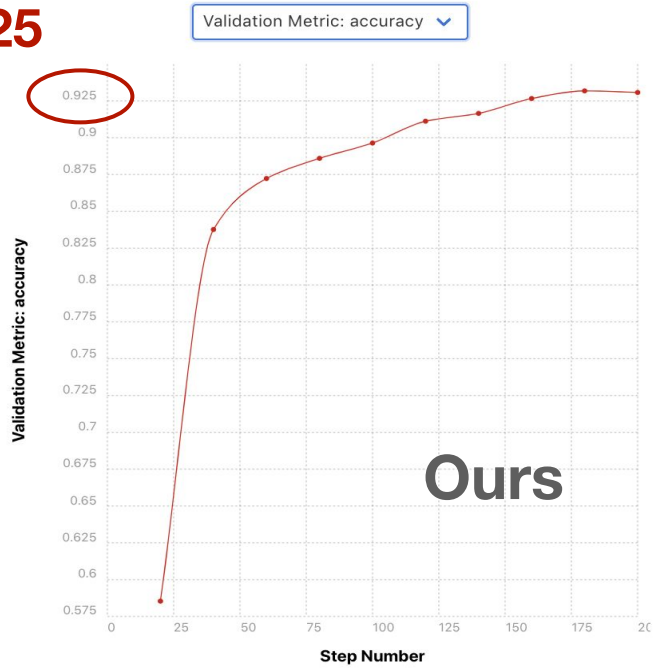
Results…

.9875



Leslie's

.925



What could've gone wrong?

After digging, we find out…

Training data: 30K data points were added to her data directory recently, so she had actually trained on a subset of the data.

Hyperparameters: Leslie didn't use default values, but specified hyperparameters:

- batch size = 64
- dropout = 0.6684
- learning rate = 0.00362
- momentum = 0.953

Can we fix this?

model_leslie.py
in OReilly/reproducibility/model_code

Fixes so far

Training data: Trained on correct subset of data

Hyperparameters: Specified the same hyperparameters at runtime as Leslie

	Validation Accuracy	Difference from Baseline
Baseline	98.75%	0.00%
Test1: code as is	93.50%	5.25%
Test2: data, hp fixes	98.90%	**-0.15%**

Why is this happening?

Ugh…Debug…Randomness

Randomness is an intrinsic part of training

- e.g., weight initialization, shuffling and augmentation of datasets, noisy hidden layers (e.g. dropout)

Fix random seeds!

- There are lots of them!
- ML framework dependent
- Must be recorded for reuse

Can we fix this?

Ugh…Debug…Randomness

Fix random seeds!

- There are lots of them!
- ML framework dependent
- Must be recorded for reuse

Can we fix this?

Setting random seed handled by PEDL

docs.determined.ai -> reference -> experiment configuration

```
reproducibility:
  experiment_seed: 999
```

in `leslie.yaml`

Ugh…Debug…Versioning

Variation across specialized software

- Within versions and across ML frameworks (TF, Keras, PyTorch)
- Underlying libraries (NumPy, cuDNN, CUDA, MKL)

Leverage the power of containerization!

Requires non-trivial engineering infrastructure

Already fixed!

Ugh…Debug…Hardware

	Validation Error	Difference from Baseline
Baseline	98.75%	0.00%
Test1: code as is	93.50%	5.25%
Test2: data, hp fixes	98.90%	-0.15%
Test3: +library, random seeds fixes	98.80%	-0.05%

UGH!!!

Inherent System/Hardware Level Randomness

- non-deterministic GPU operations
- CPU multi-threading

Taming hardware non-determinism

Fundamental issue: floating point computations in underlying hardware operations

gathering partial computations from separate threads

PyTorch

- torch manual seed
- CuDNN backend flags

```
cudnn.deterministic
cudnn.benchmark
```

Reproducibility not guaranteed if functions directly call CUDA ops

Tensorflow

- NGC Tensorflow containers 19.06, 19.07

```
TF_DETERMINISTIC_OPS=1
```

- Or, with TF 1.14

```
TF_CUDNN_DETERMINISM=1
```

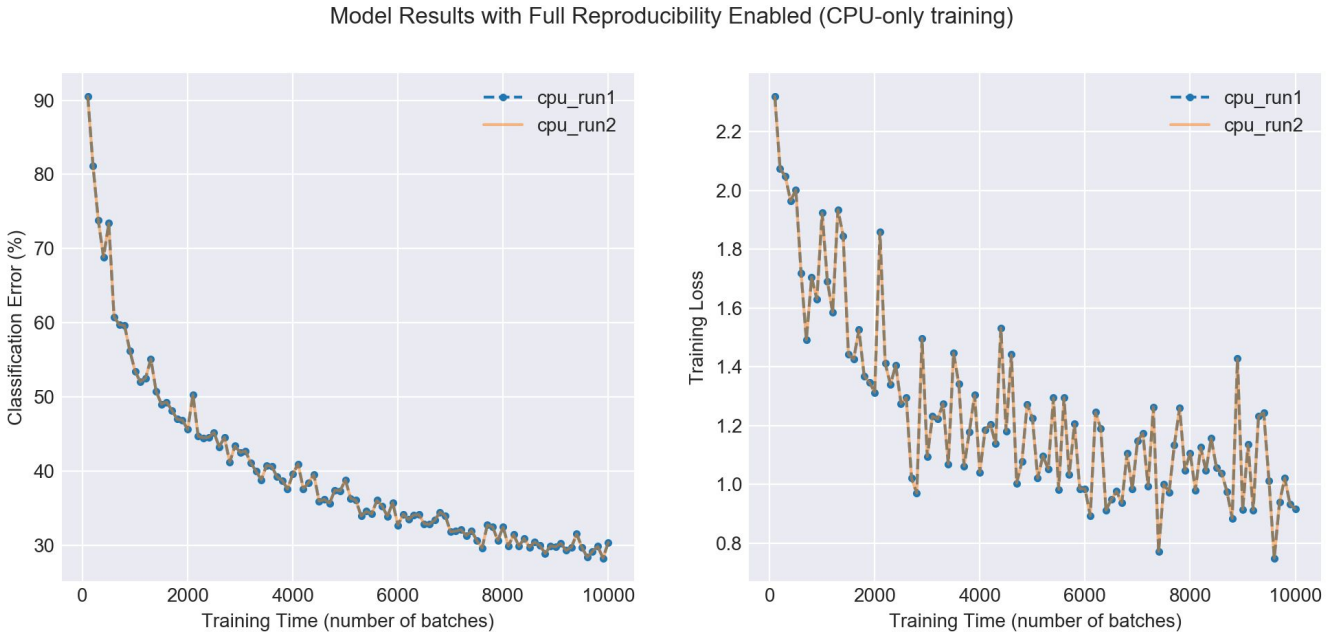
and `tfdeterminism` patch

Imperfect determinism

Feature Request: Support for configuring deterministic options of cudNN Conv routines #18096

Open **yoavz** opened this issue on Mar 29, 2018 · 13 comments

At last...we *could* achieve perfect reproducibility!



Requires **CPU-only** training with multi-threading disabled… **SLOW**

What is needed for perfect reproducibility?

Feature	Purpose
Version control for model definitions	Track changes in model architecture, optimization algorithm, data preprocessing pipeline
Metadata capture and storage	Record training + validation metrics, training logs, model hyperparameters
Dependency management	Ensure ML framework and all dependencies are consistent between runs
Experiment seed management	Generate the same pseudo-random values every run
Hardware resource flexibility	Allow users to disable multi-threading and GPU usage, if desired

Schedule

Part I: how DL training scales

1:30-2:20 Introduction

Challenges when scaling

Components to a codebase

CLI install

Part II: topic deep dives

2:20-3:00 Reproducibility

Conference Tea Break (30 min)

3:30-4:10 Hyperparameter Tuning

Break (10 min)

4:20-5:00 Model Serving

Determined AI

Hyperparameter Tuning

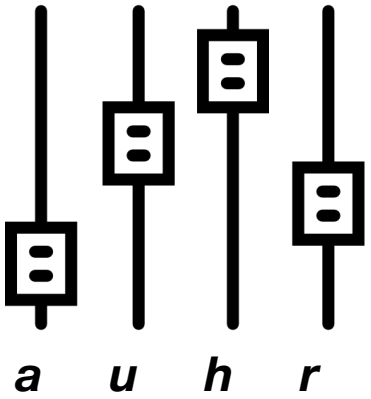
Table of content

- What is hyperparameter search?
- Hyperparameter search algorithms
  - Random Search
  - Bayesian Methods
  - Successive Halving Algorithm and Hyperband

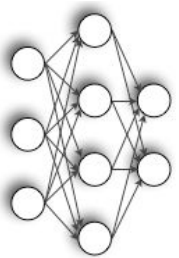
What are hyperparameters?

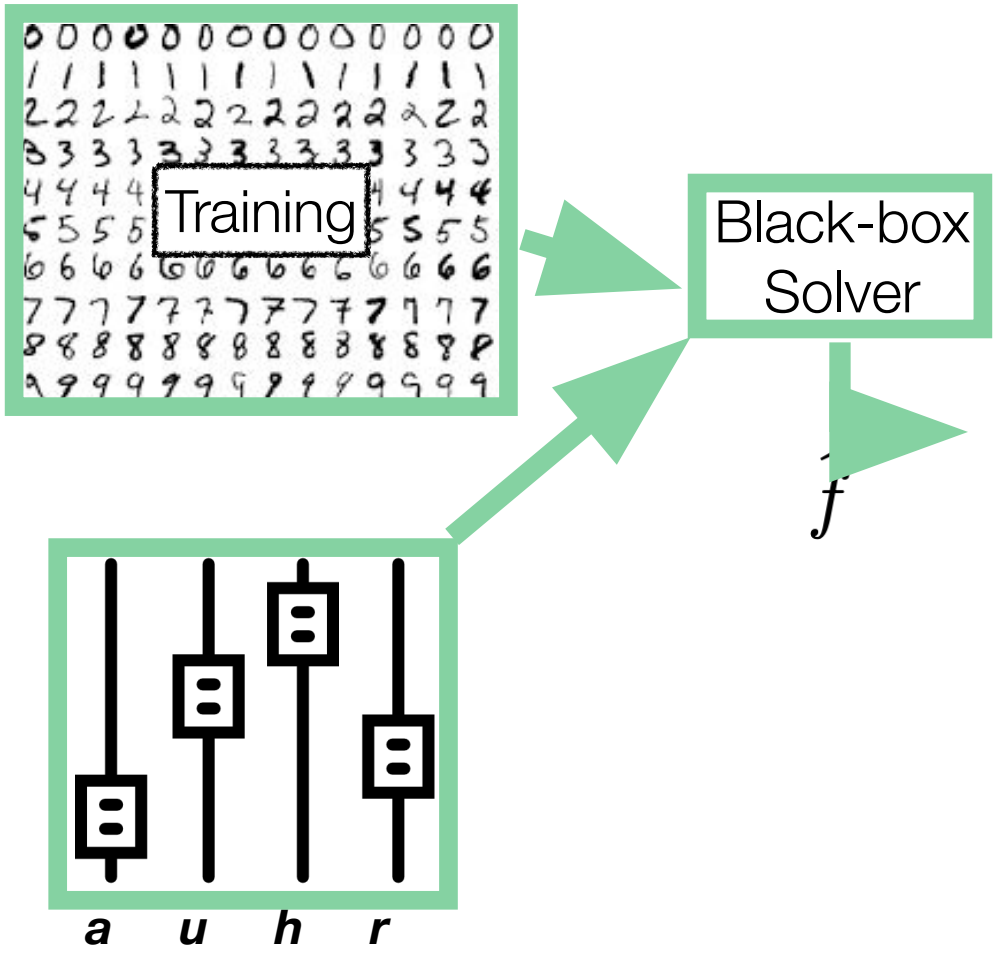
Model space defined by

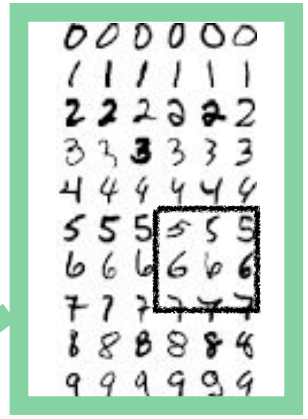
‘hyperparameters’



- activation function (***a***)
- # units per layer (***u***)
- # hidden layers (***h***)
- regularization (***r***)



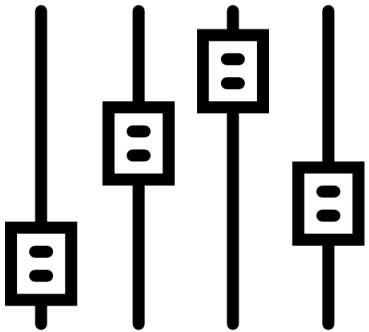

Training
Black-box
Solver
f
a
u
h
r



$\widehat{f}$

Predictive Error

0.058



a ***u*** ***h*** ***r***

Everything is a hyperparameter!

- *activation function (**a**)*
- *# units per layer (**u**)*
- *# hidden layers (**h**)*
- *regularization (**r**)*
- The subset of input features you decide to include in the model.
- How you decide to preprocess your data (e.g. adding random augmentation)
- The seed you are using to shuffle input data.
- The optimization procedure you decide to use.
- The total size of your training data.
- What type of early stopping procedure you decide to use, if any.

Exercise 1: Train a model with fixed hyperparameters

```
$ open single.yaml
```
rameter_tuning folder:

```
$ cd hyperparameter_tuning
```

Edit single.yaml to change the fixed hyperparameters:

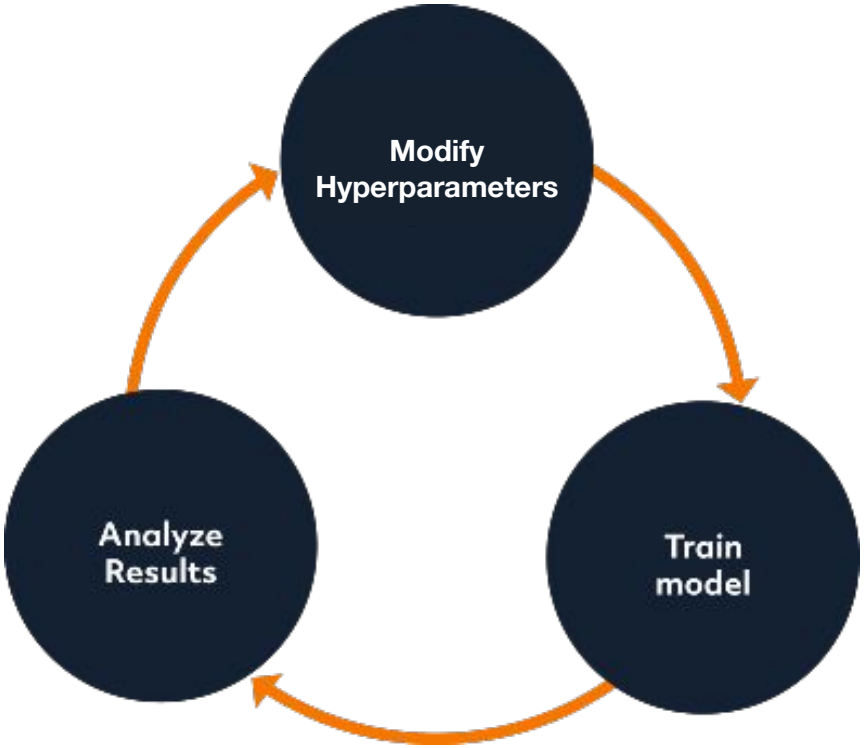
```yaml
hyperparameters:
  batch_size: 64
  dropout: 0.5
  learning_rate: 1e-3
  activation: "relu"
  kernel_size: 3
```

Kick off a single model training job:

```
$ pedl experiment create single.yaml .
```

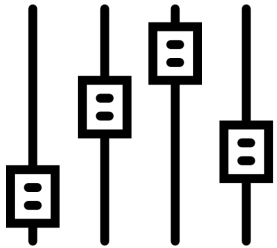
Repeat!

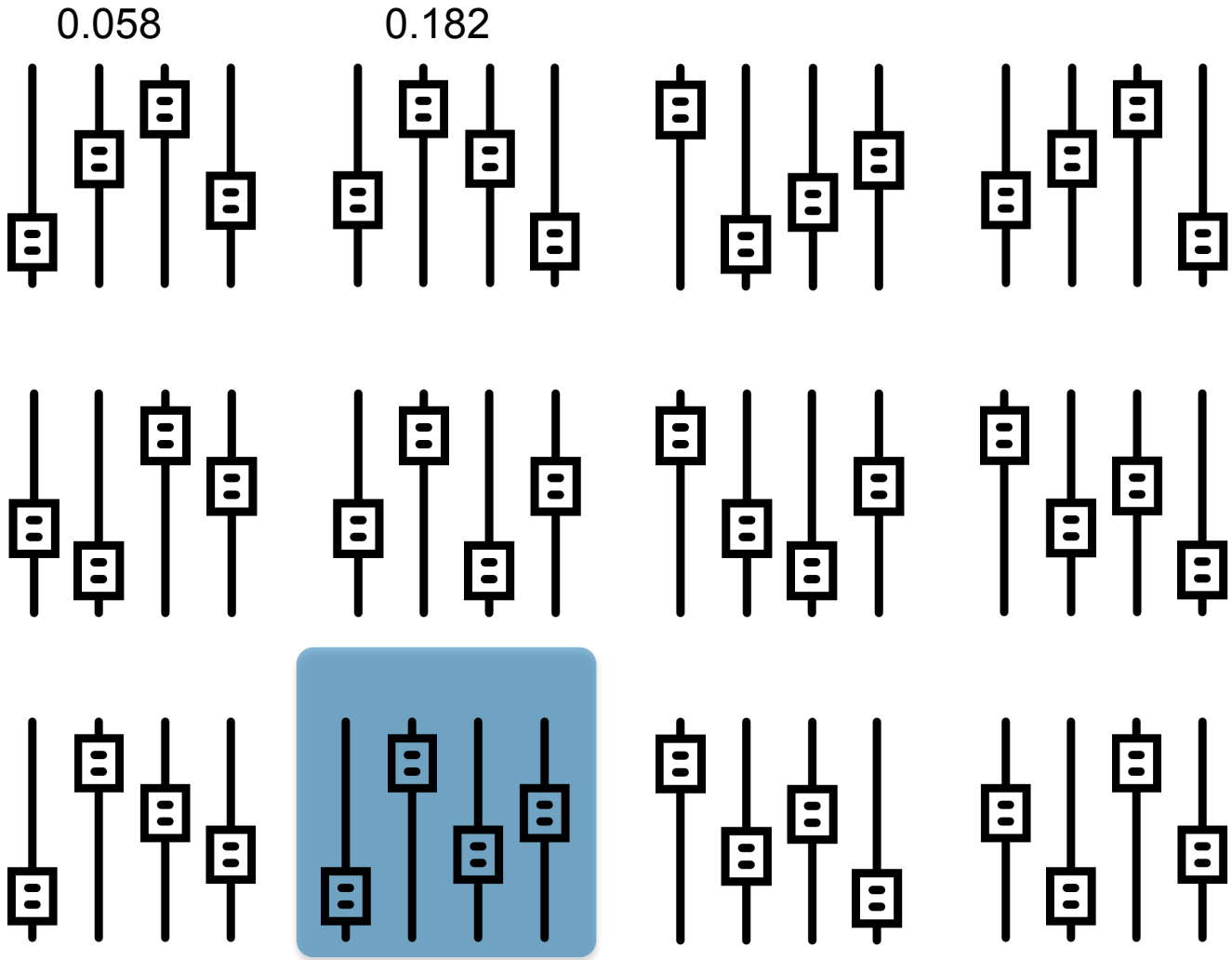
Iterative Model Development



What is hyperparameter search?

0.058




0.058
0.182

How can we efficiently identify high-quality hyperparameters?

Efficiency ⇔ resources consumed

Quality ⇔ predictive error

Training and Tuning Models is Expensive and Time Consuming

"One major drawback of current architectures is that they are expensive to train, typically requiring ***days to weeks of GPU time***"

"We report results … corresponding to over ***250,000 GPU hours*** on the standard WMT English to German translation task"

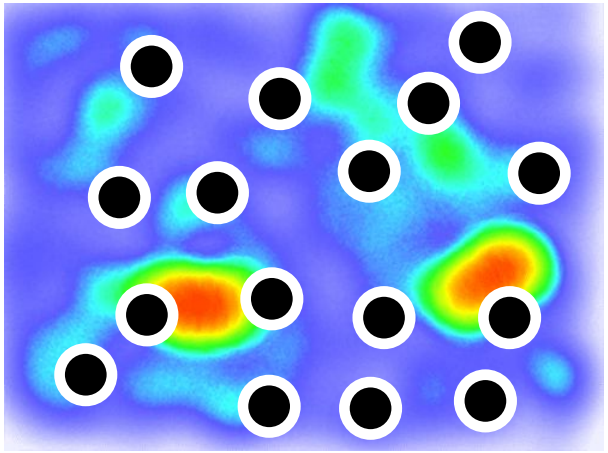
"Massive Exploration of Neural Machine Translation Architectures" (Britz et. al., 2017)

10K Train Models, 29 Compute Years, $200K

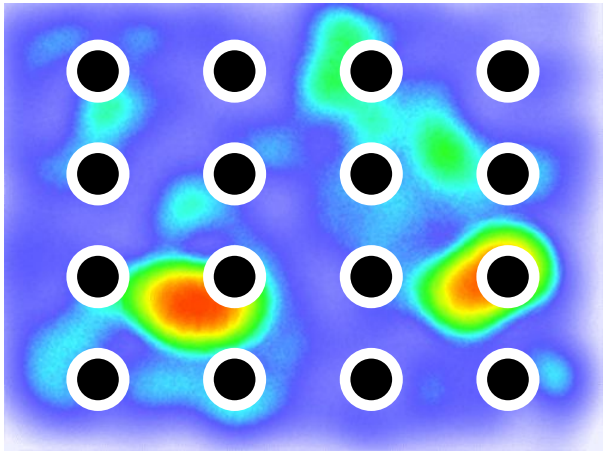
Search Methods: Random / Grid

Classic Methods

Random



Grid



Pros: Simple

Cons: Curse of dimensionality for large search spaces

Exercise 2: Random hyperparameter search

```
$ open random.yaml
```
rameter_tuning folder:

```
$ cd hyperparameter_tuning
```

Edit random.yaml to your desired search space:

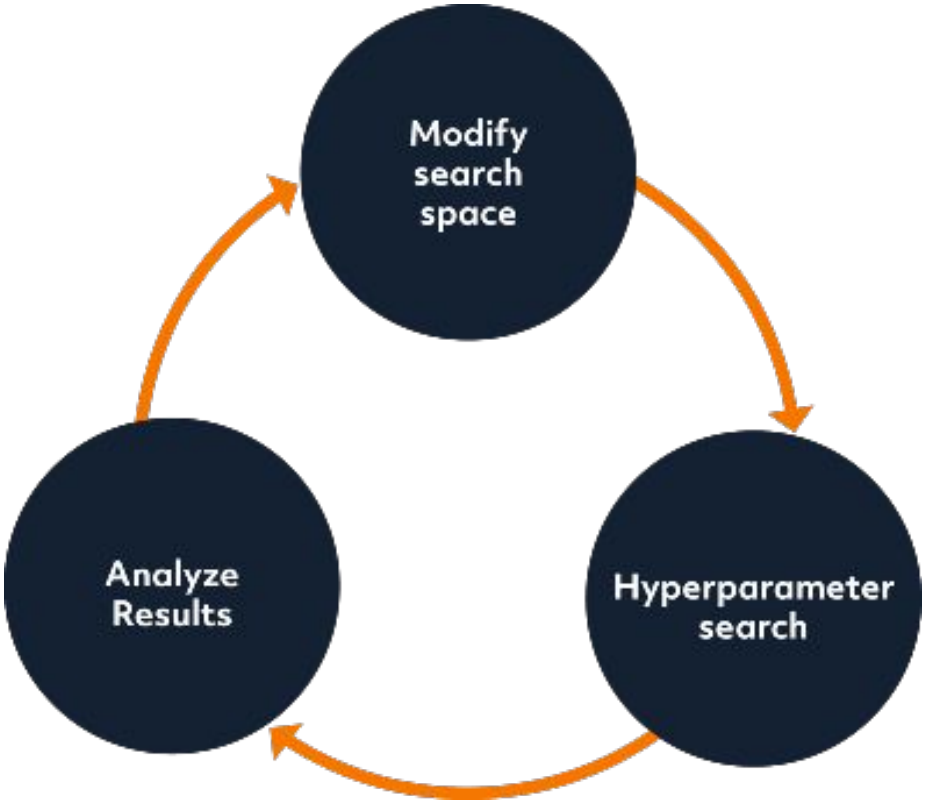
Kick off a random hyperparameter search job:

```
$ pedl experiment create random.yaml .
```

Repeat!

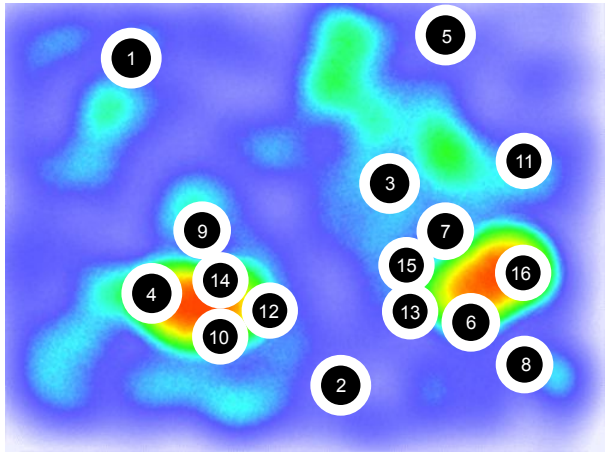
```yaml
hyperparameters:
  batch_size:
    type: int
    minval: 32
    maxval: 64
  dropout:
    type: double
    minval: 0.1
    maxval: 0.5
  learning_rate:
    type: log
    minval: -5.0
    maxval: -1.0
    base: 10
  kernel_size: 3
  activation:
    type: categorical
    vals: ["relu", "sigmoid"]
```

Search Driven Model Development



Configuration Selection Methods

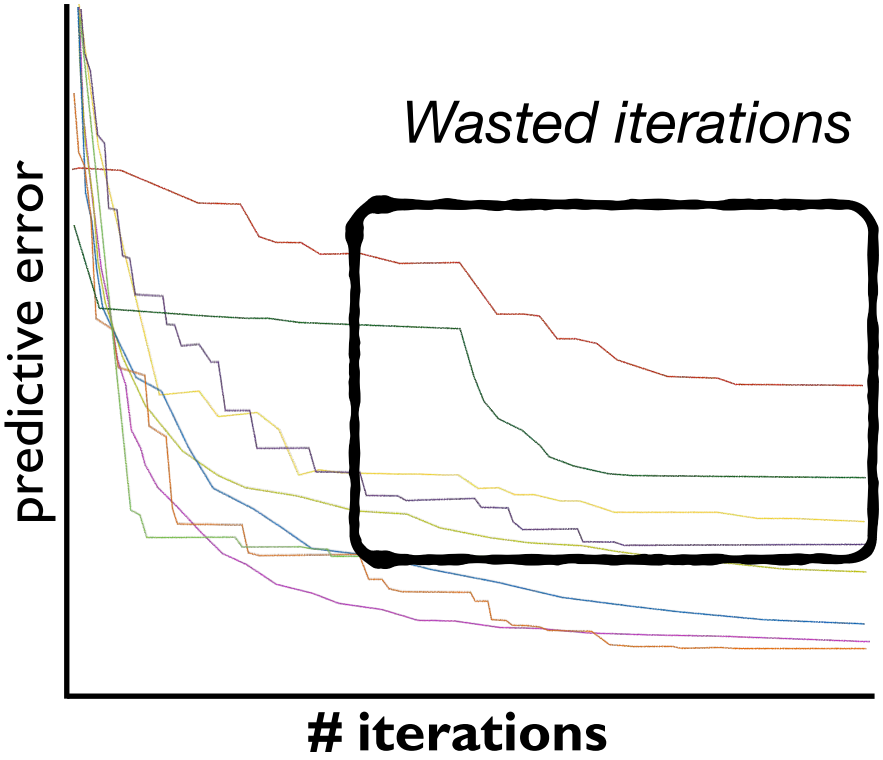
e.g., Bayesian Optimization



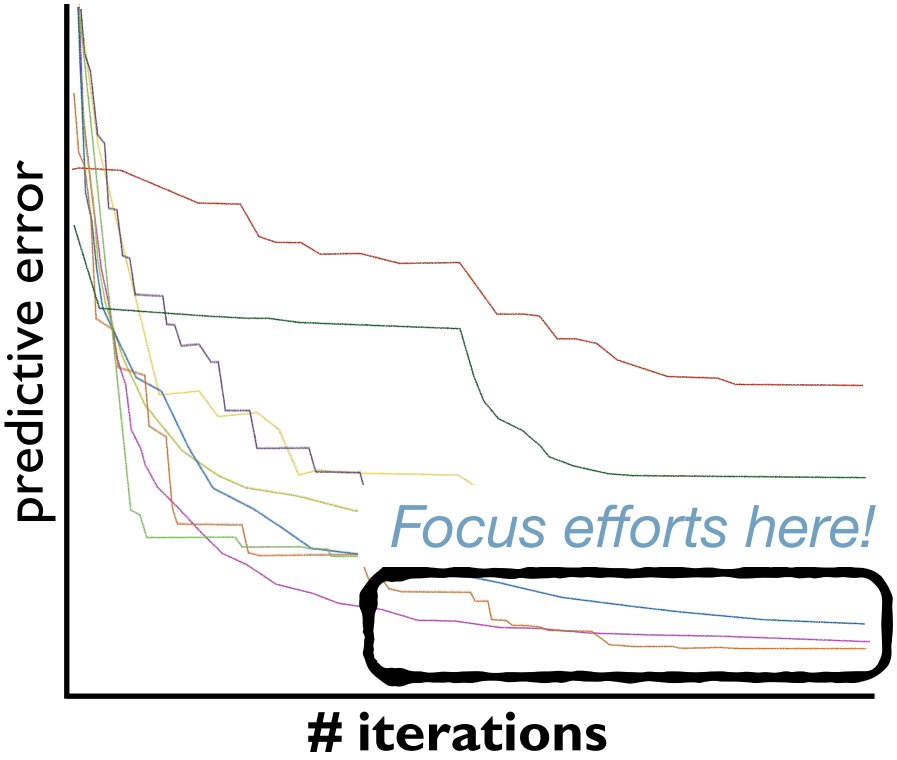
Pros: Better than classical methods in low-dimensional spaces
Cons: Curse of dimensionality for large search spaces
Difficult to parallelize

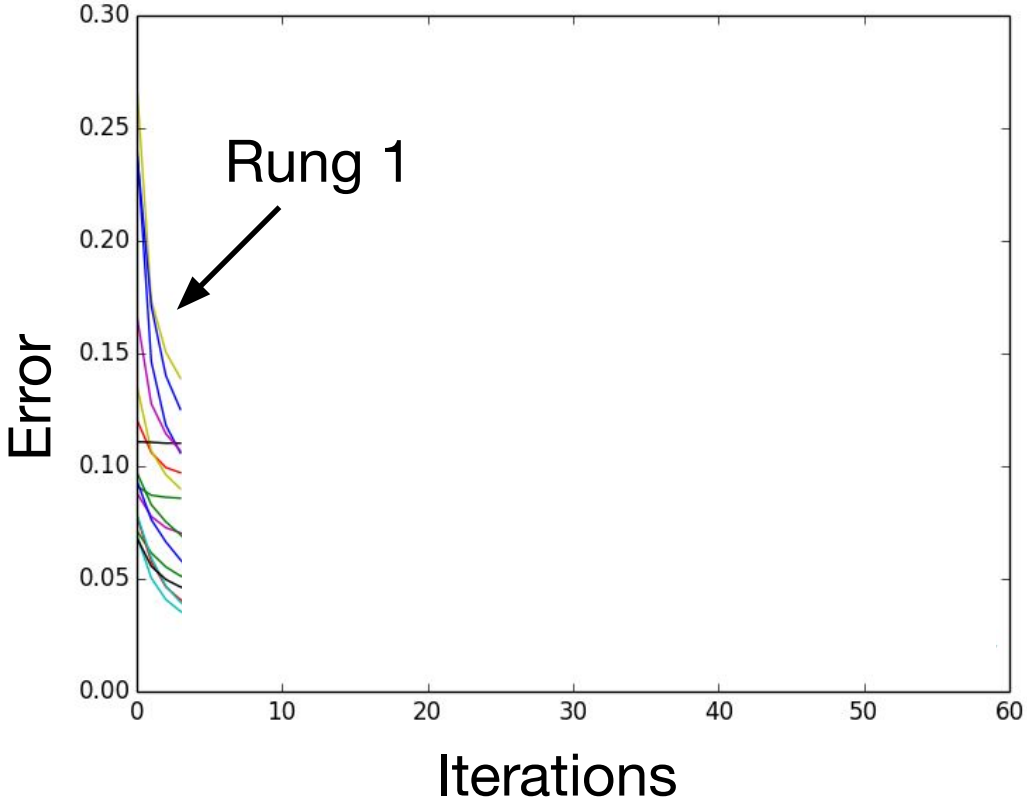
Search Methods: Successive Halving and Hyperband

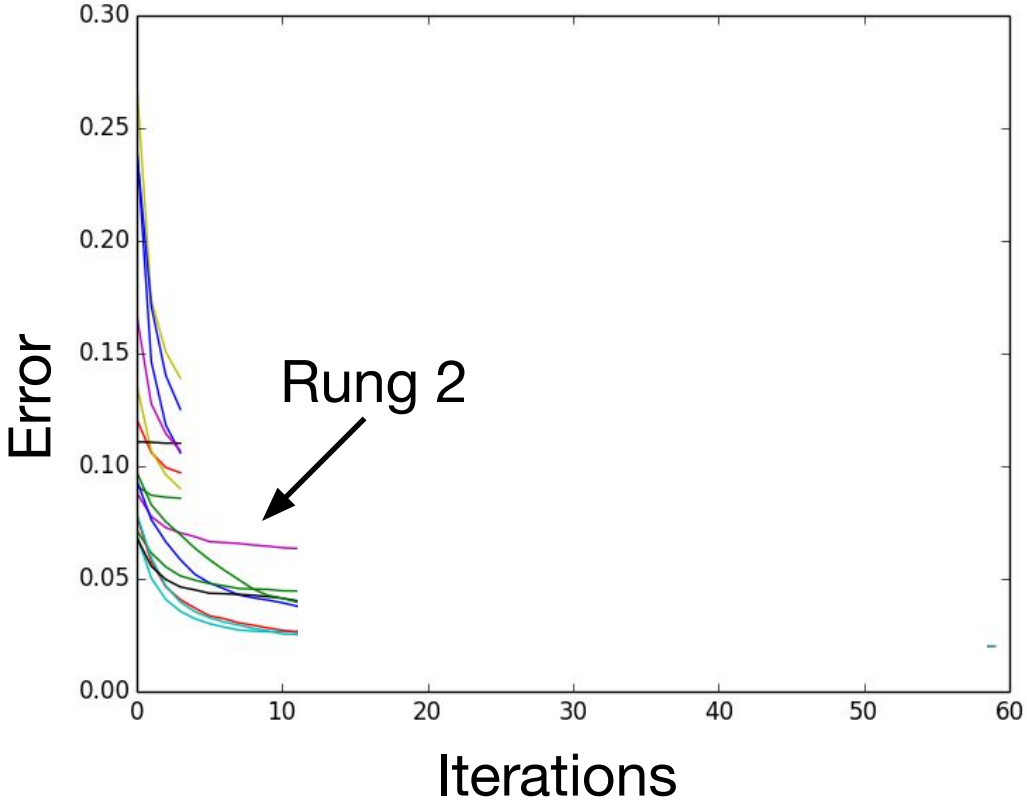
Downsampling Iterations

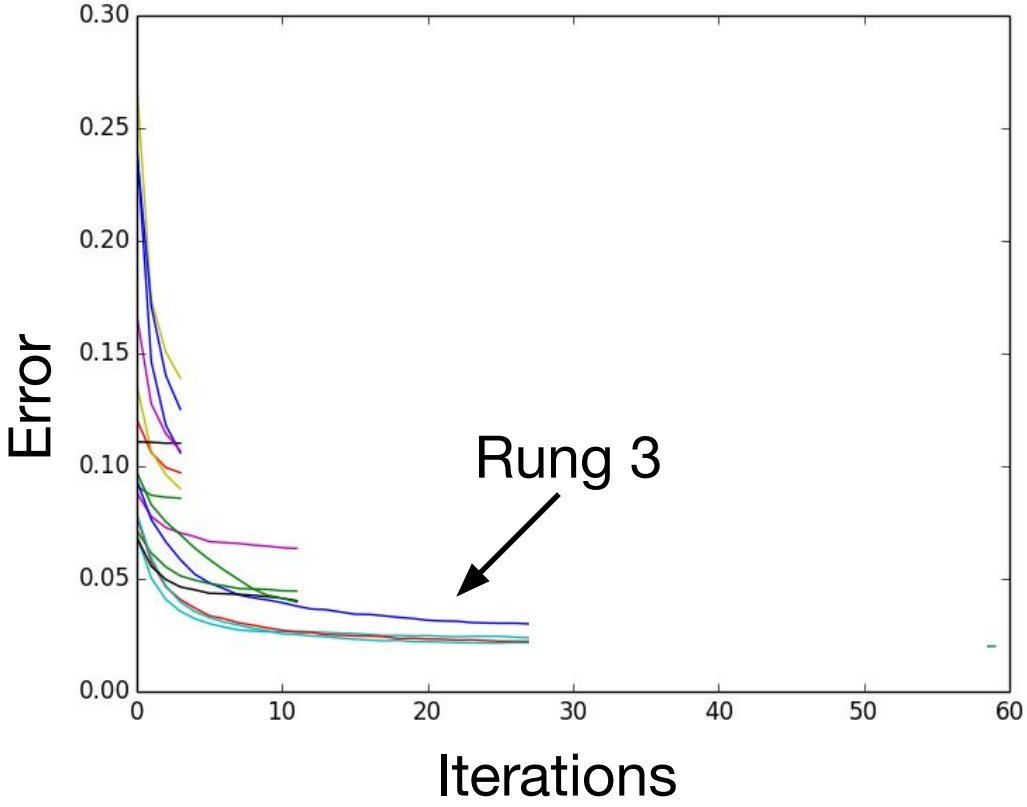


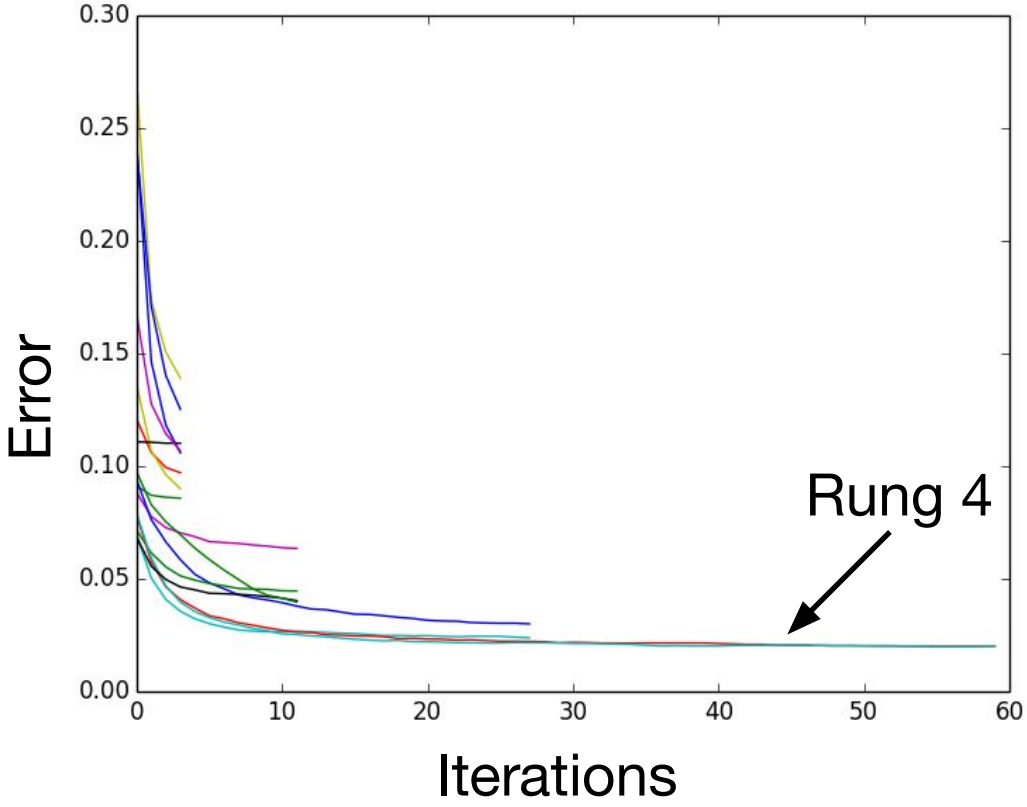
Downsampling Iterations



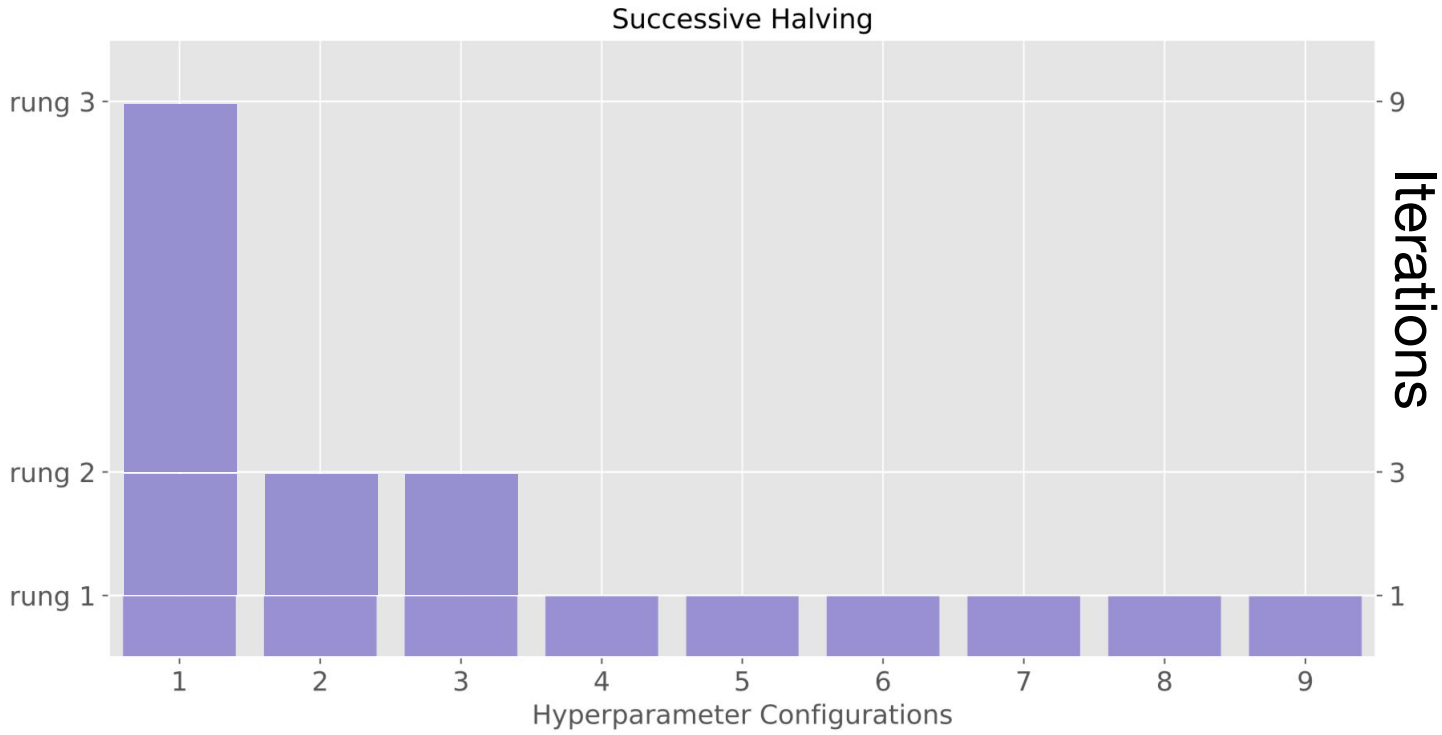

Rung 1
Error
Iterations
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
50
60


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Error
Rung 2
0
10
20
30
40
50
60
Iterations


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Error
0
10
20
30
40
50
60
Iterations
Rung 3


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Error
0
10
20
30
40
50
60
Iterations
Rung 4

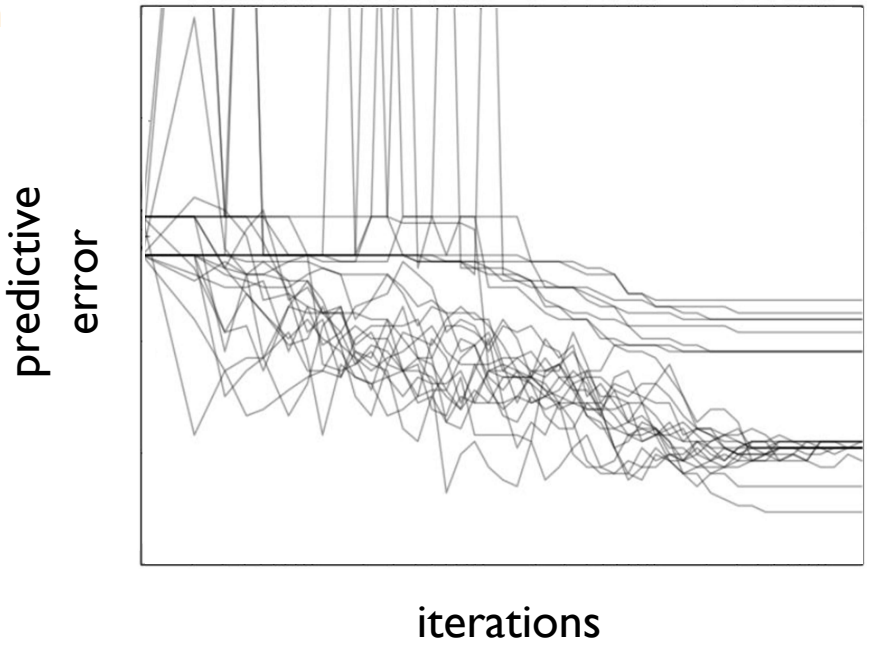
Successive Halving Algorithm



What could go wrong?

Sequences can be **non-monotonic**, **non-smooth**

How can we “safely” discard a configuration?



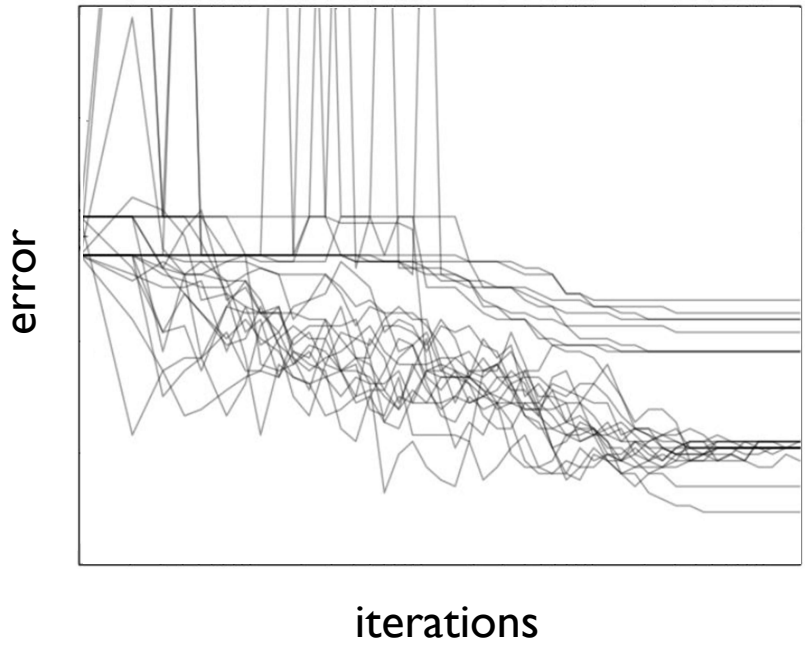
What could go wrong?

Hyperband: Novel **downsampling** approach

[AISTATS16, ICLR17, JMLR18]

✔ **State-of-the-art** empirical performance

✔ **Provably correct**



Massively Parallel Hyperparameter Optimization

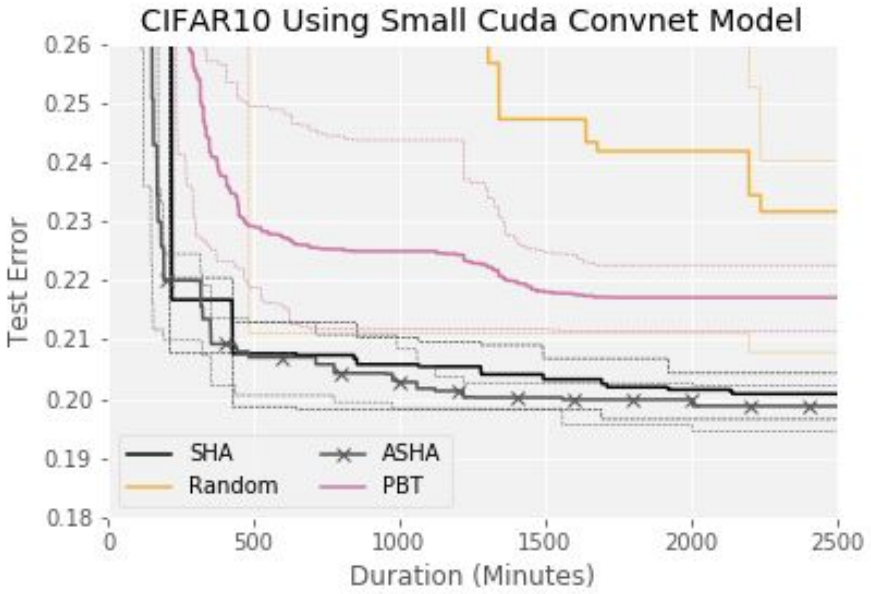
Speedups

>50x over Random

10x over PBT

✓ **Lower final error**

✓ **Lower variance**




Microsoft


Preferred
Networks


OPTUNA


facebook


Neural Network Intelligence


TensorFlow


Katib


PYTORCH


scikit
learn


DASK


Determined AI


K Keras


RAY


mxnet


Polyaxon


Caffe2


Oríon


R


HyperSearch


IBM

Exercise 3: Hyperband Search

```
$ open adaptive.yaml
```
meter_tuning folder:

```
$ cd hyperparameter_tuning
```

Edit adaptive.yaml to your desired search space:

Kick off an adaptive hyperparameter search job:

```
$ pedl experiment create adaptive.yaml
```

Repeat!

Schedule

Part I: How DL training scales

1:30-2:20

Introduction

Challenges when scaling

Components to a codebase

CLI install

Part II: Topic deep dives

2:20-3:00 Reproducibility

3:00-3:30 Conference Tea Break (30 mins)

3:30-4:10 Hyperparameter Tuning

4:10-4:20 Break (10 mins)

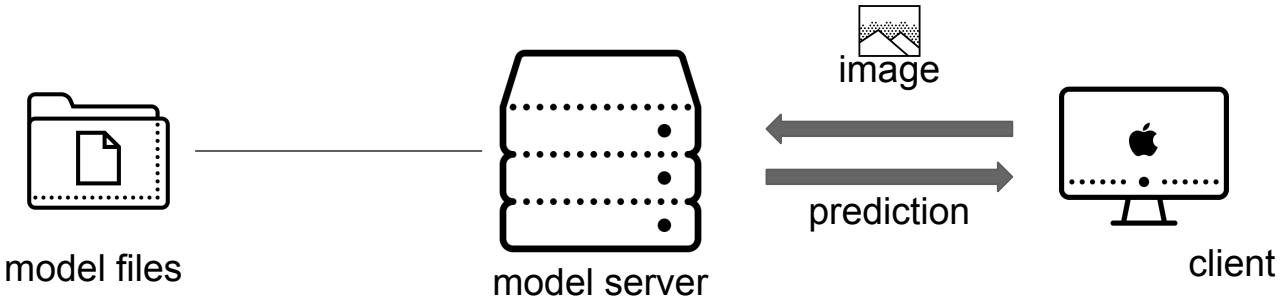
4:20-5:00 Model Serving

Determined AI

Model Serving and Optimization

What is model serving?

Model Serving Architecture



Goals In Production Serving

Low Latency Online Inference

Experimentation

Rollout and Rollback

Dynamic Scaling

Monitoring

Goals In Production Serving

Low Latency Online Inference

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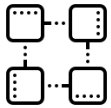


Dynamic Scaling

Monitoring

Goals In Production Serving

Low Latency Online Inference

Experimentation

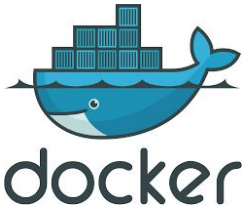
Rollout and Rollback

Dynamic Scaling

Monitoring

How can we accomplish these goals?

Model Serving Tools



Some Model Deployment Challenges

- Model Size
- Deployment Constraints
- Adaptive Batching

How can we optimize our models for production?

The model you want to train

is **not**

the model you want to use for inference

Optimization Methods

General Methods

- Distillation
- Pruning
- Folding Batch Normalization
- Quantization

For TensorFlow Models Specifically

- Freezing
- Constant Folding

Optimization Methods

General Methods

- Distillation
- **Pruning**
- **Folding Batch Normalization**
- **Quantization**

For TensorFlow Models Specifically

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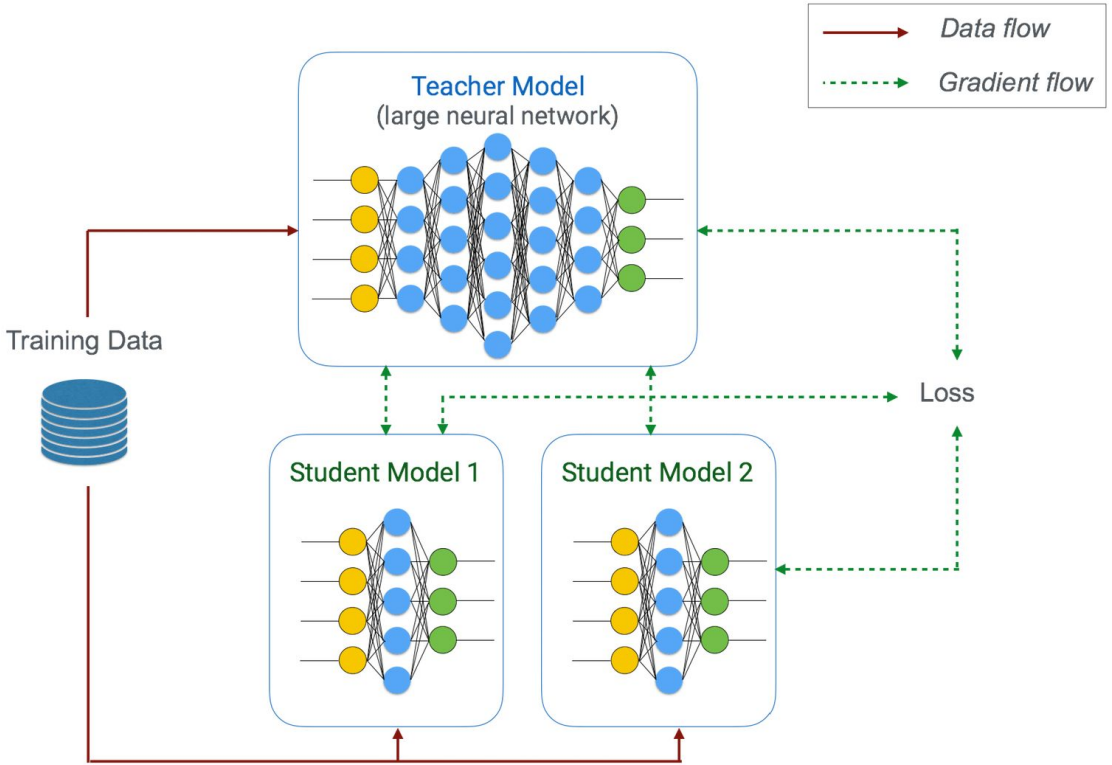
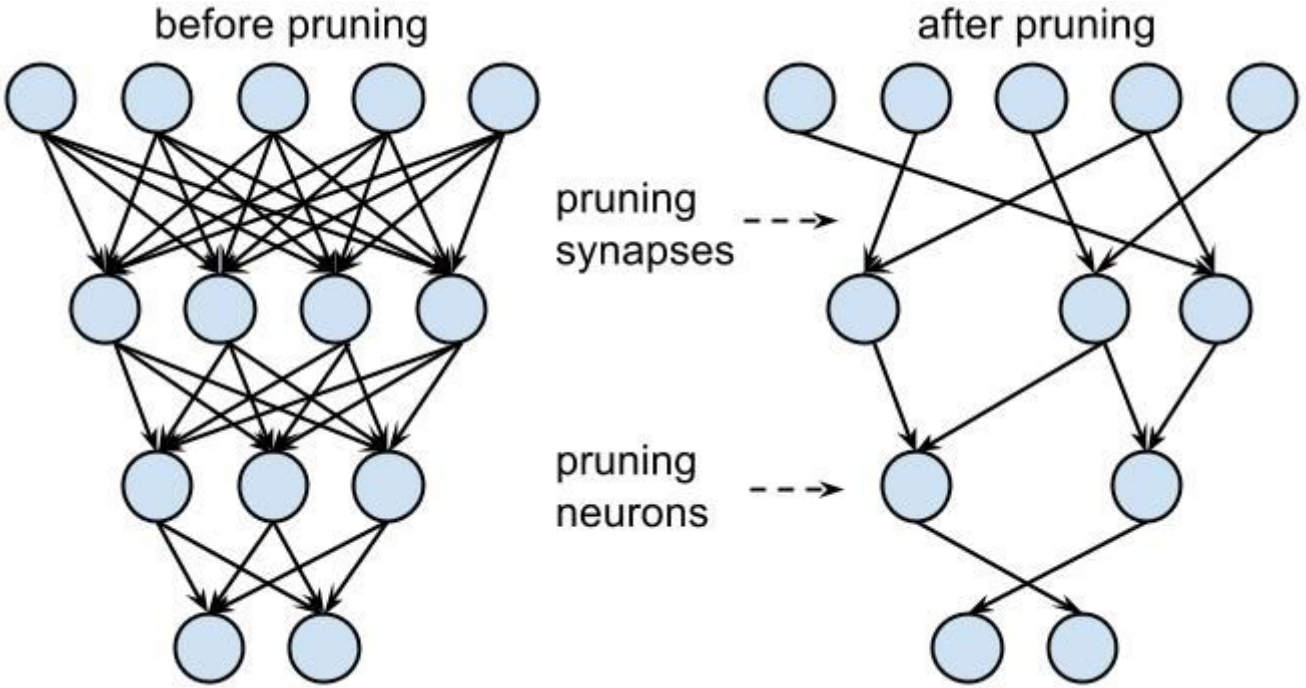
- **Constant Folding**

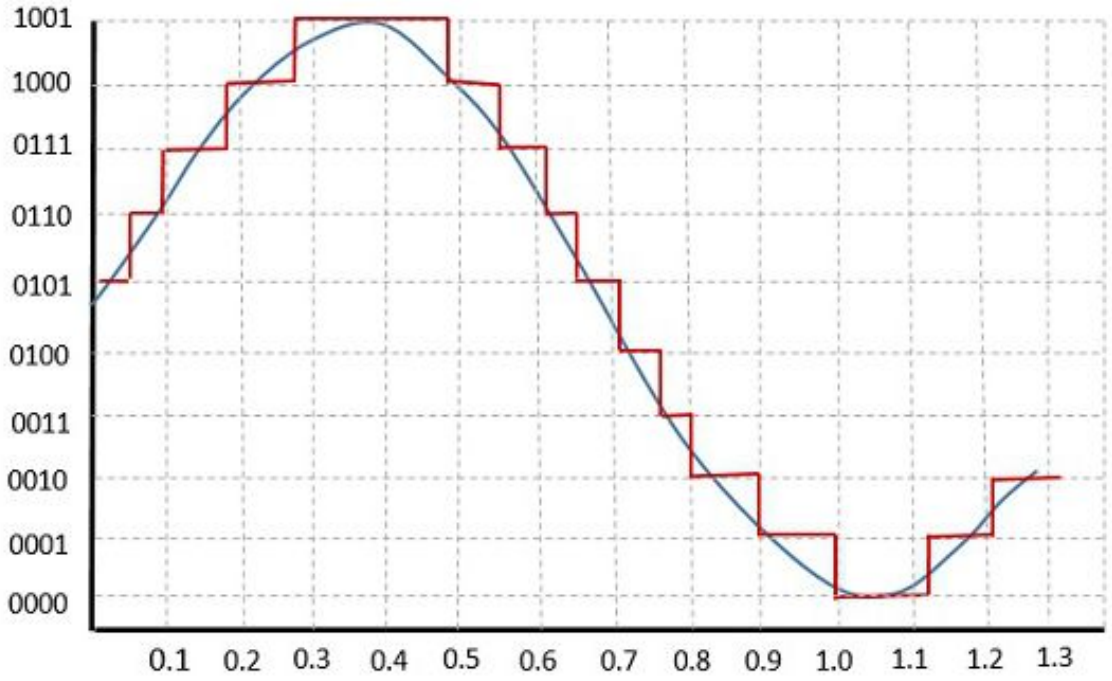
Model Distillation



Model Pruning



Quantization



Optimization Methods

General Methods

- Distillation
- Pruning
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For TensorFlow Models Specifically

- **Freezing**
- Constant Folding

Optimization Methods

General Methods

- Distillation
- Pruning
- Folding Batch Normalization
- Quantization

For TensorFlow Models Specifically

- Freezing
- **Constant Folding**

Hands On - Train, Deploy, Optimize

In this exercise we will:

1. Train a model on MNIST
2. Convert our model into a servable artifact
3. Serve the model artifact
4. Optimize our artifacts to reduce size and latency
5. Redeploy our newly optimized models

pedl notebook start --config-file model_serving/config.yaml

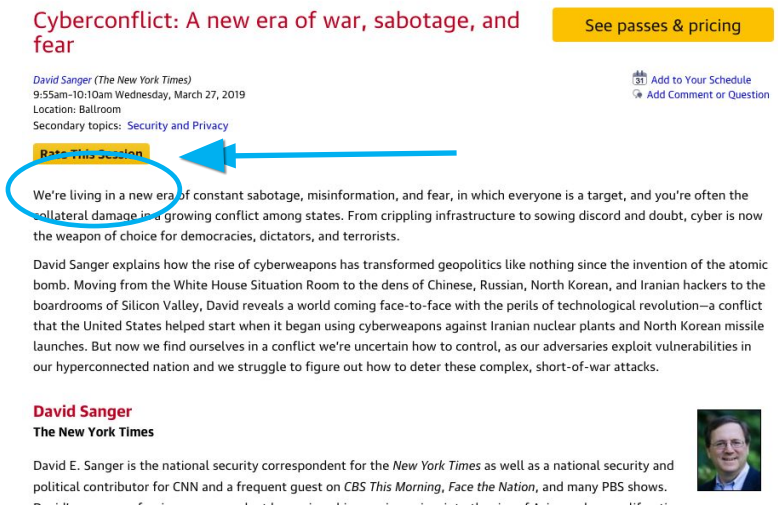
Navigate to **model-optimization.ipynb**

Feedback

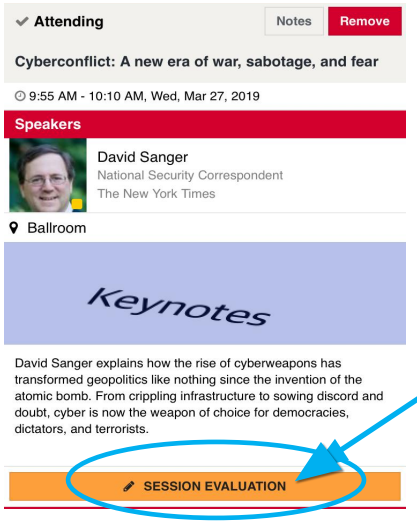
How did we do?

Link at the bottom of github page
https://forms.gle/PBxr9YmtXbDCmt1s9

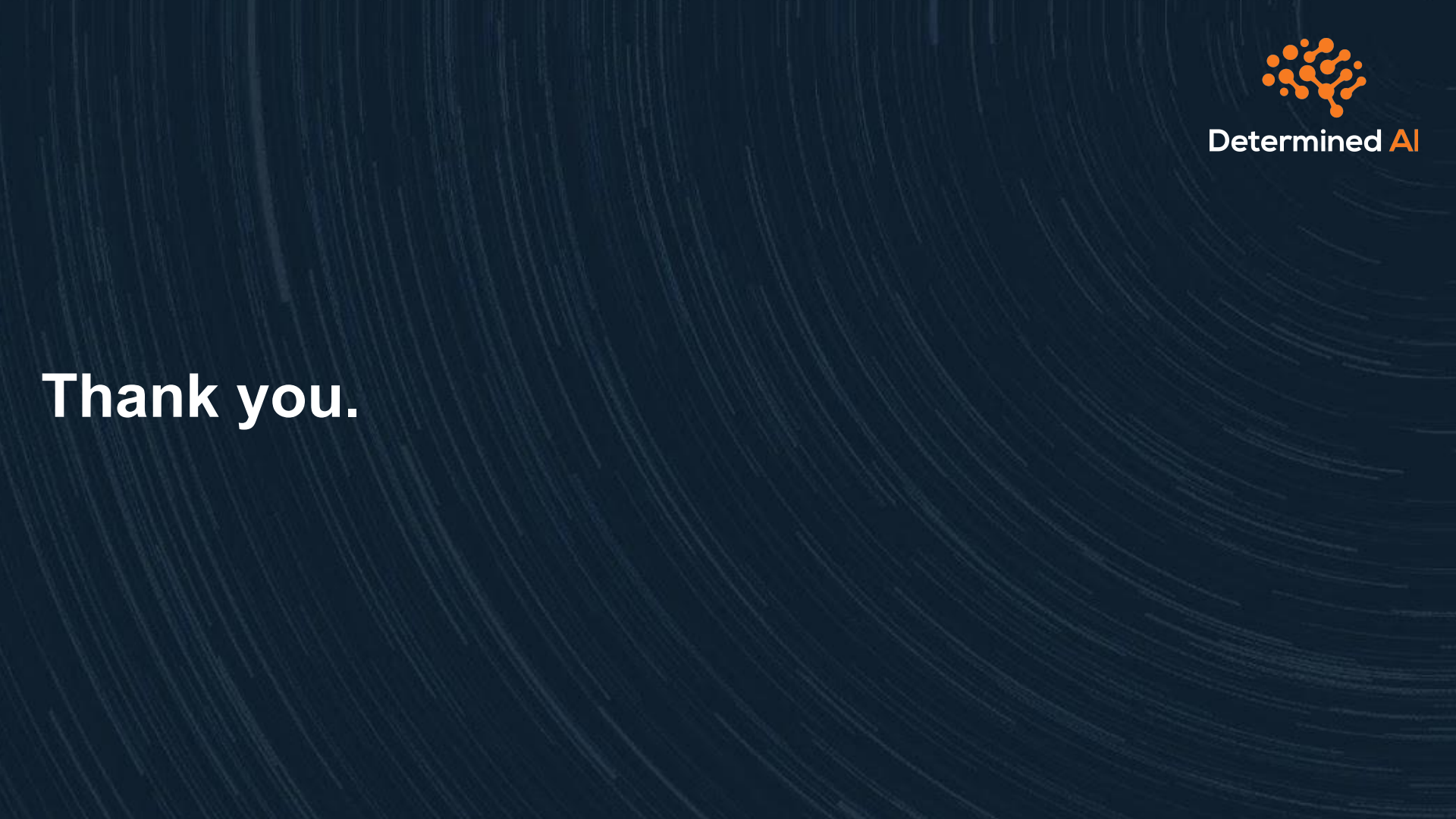
Rate today's session



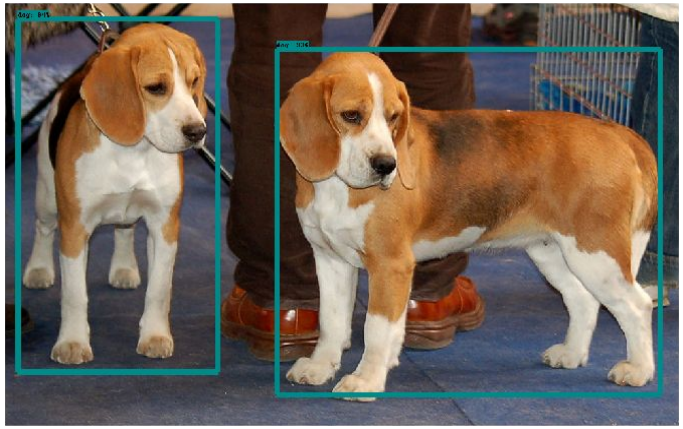
Session page on conference website



O'Reilly Events App


Determined AI
Thank you.

Bonus: Object Detection



pedl notebook start --config-file model_serving/config.yaml

Navigate to **object-detection.ipynb**