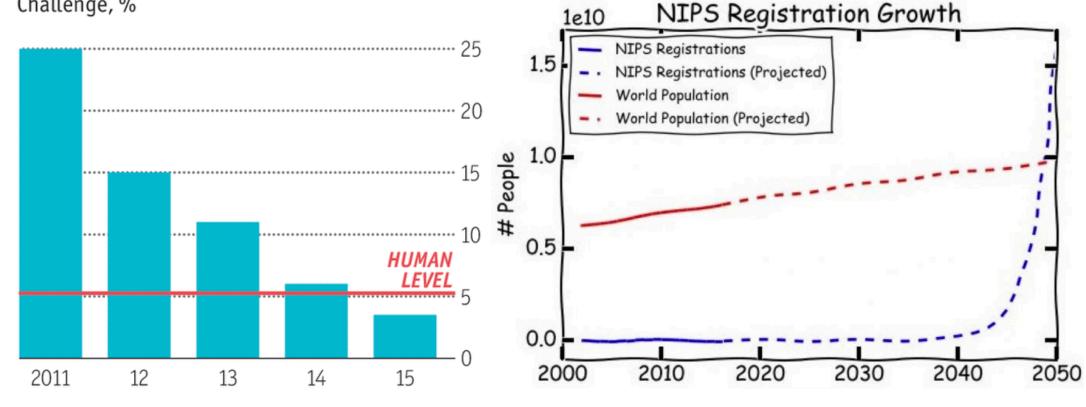
Golden Age for Al, Dark Ages for Al Infrastructure

Neil Conway Co-Founder and CTO, Determined Al April 28, 2019



The Golden Age of Al



Error rates on ImageNet Visual Recognition Challenge, %

Technology

Coming This Fall to Carnegie Mellon: America's First Al Degree

TECHNOLOGY

Stanford's Top Major Is Now Computer Science







Al ready for widespread adoption?





The Dark Age of Al Infrastructure

Forcing users to wait for **days** to recover from faults.

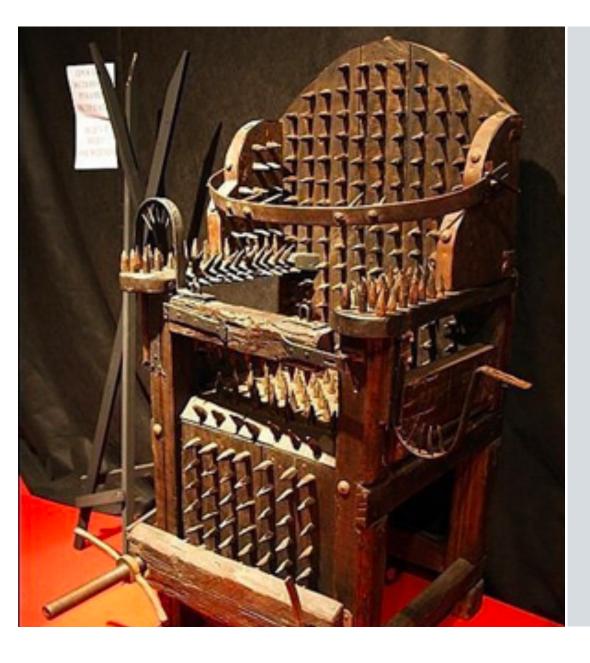
Reproducing existing models is **death by a thousand cuts:** data ordering, software versions, hyperparmeters, random seeds, model weights.



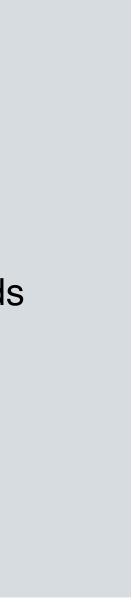






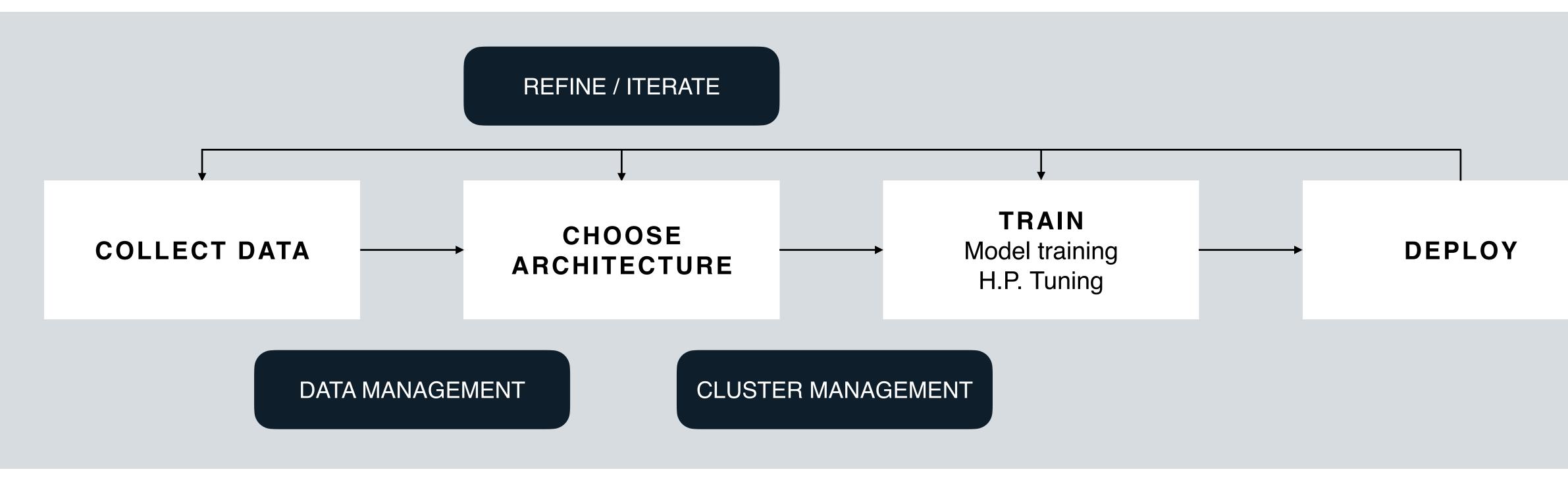


Hand-implemented, **impossibly slow** methods to find good models.





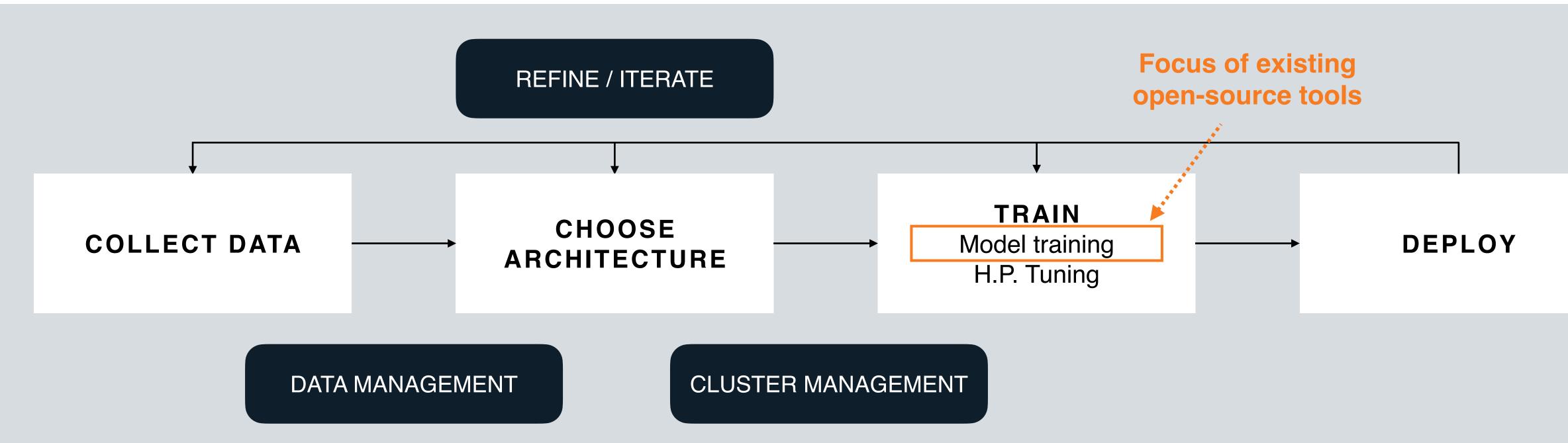
Deep Learning Today (For Everyone Else)







Deep Learning Today (For Everyone Else)



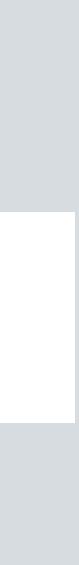
Existing Tools (e.g., TensorFlow):

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



Limited Support For:

- Teams of researchers, clusters of GPUs, many models
- Deployment, ops, and collaboration
- Data management or cluster management





Most existing tools fall into one of two buckets:

Too Generic (e.g., Spark, Sun Grid Engine)



Technical Point Solutions (e.g., TensorFlow, Horovod)



Specialized for Deep Learning

DL is both <u>different</u> and <u>extremely important</u>



We need Al Infrastructure that is:

Holistic & Integrated

Orders of magnitude wins in performance and usability!



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The Dark Age of Al Infrastructure

Forcing users to wait for **days** to recover from faults.

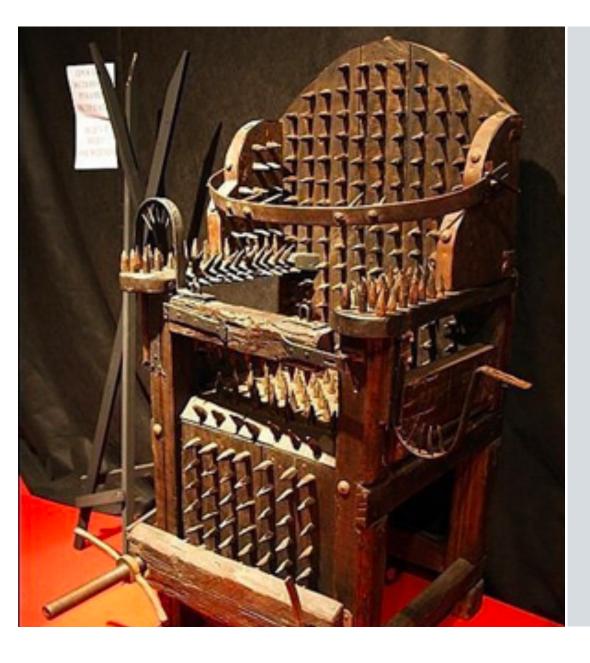
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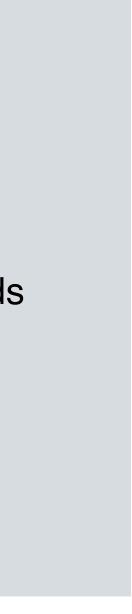








Hand-implemented, **impossibly slow** methods to find good models.

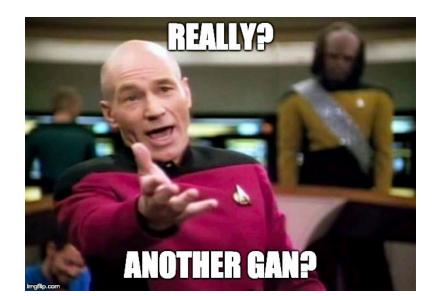




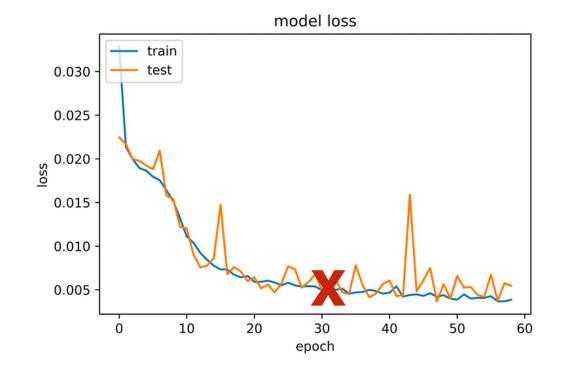
Dave's got a problem.

- Dave's a super smart DL engineer.
- He's got a brilliant model for style transfer that automatically makes every picture a dank meme.
- It takes two days for his model to converge on a couple of DGX-1s.
- Every time his model crashes he loses (on average) a day of work and 400 GPU-hours of compute time.
- This makes Dave sad.







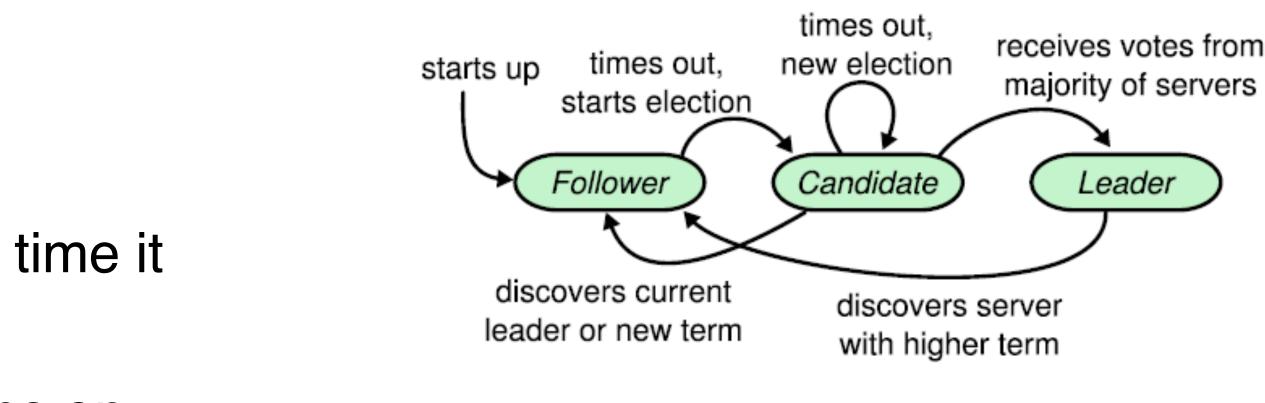


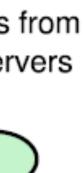


Dave's got a solution!

- Dave wants to make sure he doesn't lose work.
- In general, this is a "hard problem."
- In Deep Learning this isn't so bad. Enter tf.saved model.simple save.
- So, Dave instruments his code, and the next time it crashes he loads his model using tf.saved model.loader.load and keeps on training.







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Only, he doesn't.

- TensorFlow only saves:
 - Weights, optimizer state.
- Dave also needs
 - Input read position, random seeds, model definition, dependencies.
- Eventually, Dave writes a pile of code to save all this stuff.



eds, model definition, dependencies. Ficade to save all this stuff.

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And Dave's life still sucks

- Learns the hard way that checkpoints are really big and runs out of disk space.
- Teaches himself PagerDuty so that he can find out when his models crash and ssh back into the cluster to kick the models off.
- Loses his place in the queue.
- Dave writes a pile of cron jobs to make sure his work is being done.





What if Dave had <u>holistic</u> but <u>specialized</u> Al infrastructure?

- Fault tolerance would be taken care of (the right way) out of the box.
- The infrastructure would automatically take checkpoints.
- The **infrastructure** would monitor and retry failed jobs from latest checkpoint automatically.
- The infrastructure would manage its own checkpoint storage according to sane rules ("keep checkpoints with the best n validation errors").
- The infrastructure could leverage checkpoints in other, surprising ways: to enable reproducibility, as a unit of scheduling/job migration, and to enable distributed training.
- All of this would be **transparent** to Dave.







The Dark Age of Al Infrastructure

Forcing users to wait for **days** to recover from faults.

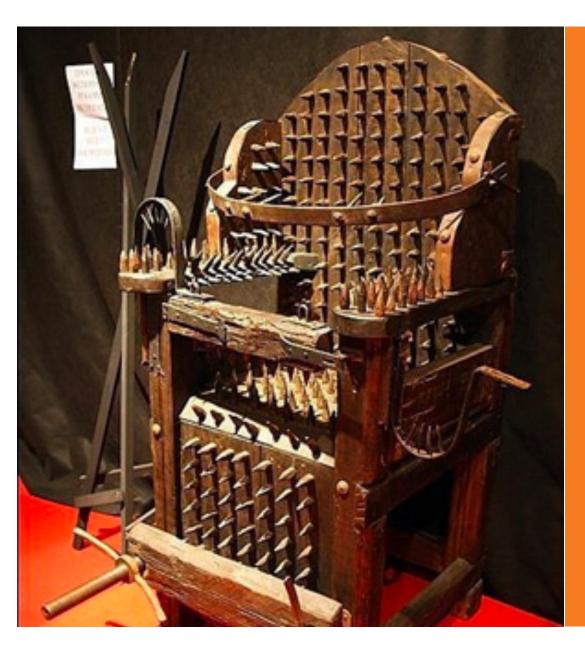
Reproducing existing models is **death by a thousand cuts:** data ordering, software versions, hyperparameters, random seeds, model weights.











Hand-implemented, **impossibly slow** methods to find good models.



14

Dave trains his model

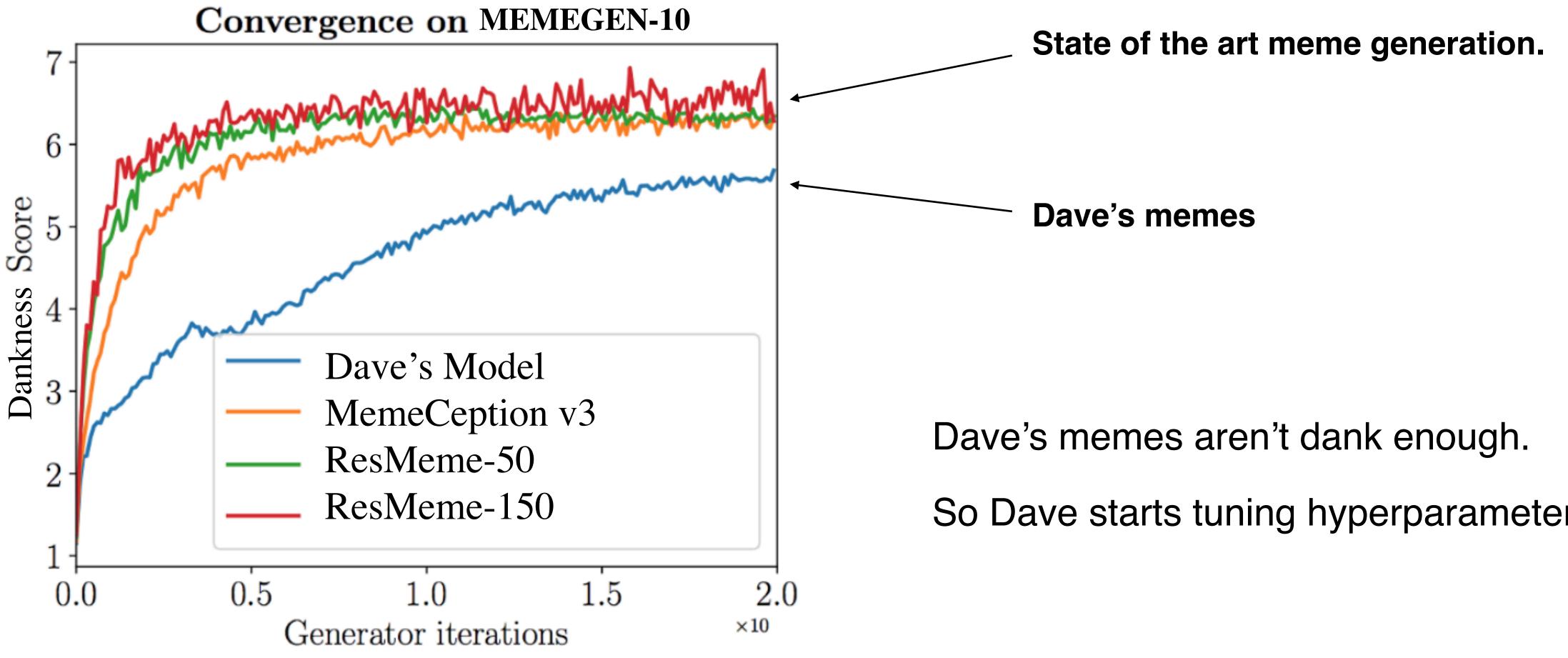
[freshpond:DLRox sparks\$ python train_script.py --learning_rate=0.1 --dropout=0.5 > logs/result-0.1-0.5.log [freshpond:DLRox sparks\$ ls logs result-0.1-0.5.log







Dave's got a quality problem

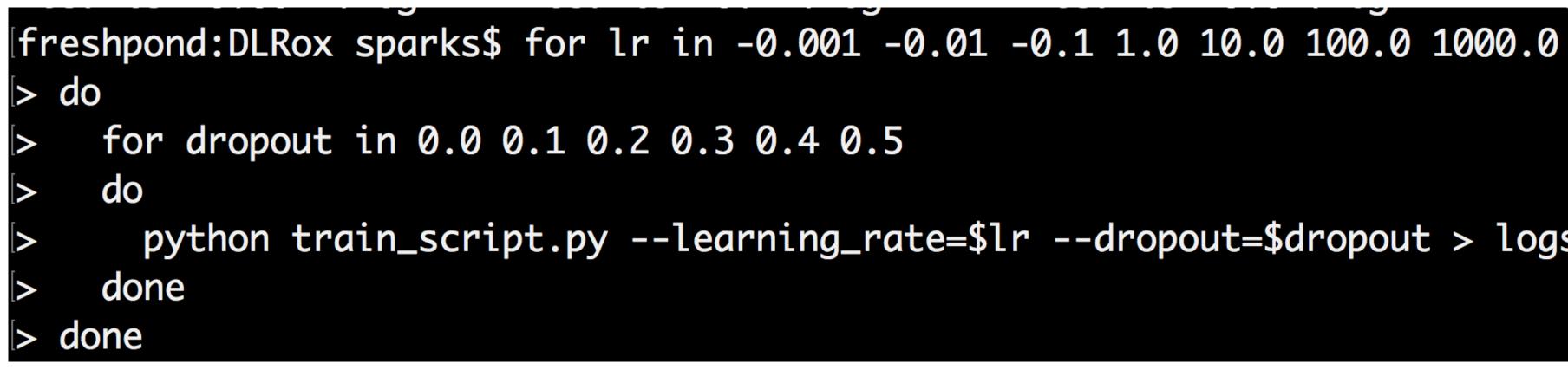




So Dave starts tuning hyperparameters.



Dave Discovers Grid Search



Nested for loops FTW



python train_script.py --learning_rate=\$lr --dropout=\$dropout > logs/results-\$lr-\$dropout.log





Dave Discovers Grid Search

[freshpond:DLRox sparks\$ ls logs result-0.1-0.5.log results--0.001-.log results--0.001-0.0.log results--0.001-0.1.log results--0.001-0.2.log results--0.001-0.3.log results--0.001-0.4.log results--0.001-0.5.log results--0.01-.log results--0.01-0.0.log results--0.01-0.1.log results--0.01-0.2.log results--0.01-0.3.log

results--0.01-0.4.log results--0.01-0.5.log results--0.1-.log results--0.1-0.0.log results--0.1-0.1.log results--0.1-0.2.log results--0.1-0.3.log results--0.1-0.4.log results--0.1-0.5.log results-1.0-.log results-1.0-0.0.log results-1.0-0.1.log results-1.0-0.2.log



The results are in.. (kinda)

results-1.0-0.3.log results-1.0-0.4.log results-1.0-0.5.log results-10.0-.log results-10.0-0.0.log results-10.0-0.1.log results-10.0-0.2.log results-10.0-0.3.log results-10.0-0.4.log results-10.0-0.5.log results-100.0-.log results-100.0-0.0.log results-100.0-0.1.log

results-100.0-0.2.log results-100.0-0.3.log results-100.0-0.4.log results-100.0-0.5.log results-1000.0-.log results-1000.0-0.0.log results-1000.0-0.1.log results-1000.0-0.2.log results-1000.0-0.3.log results-1000.0-0.4.log results-1000.0-0.5.log





results--0.00001-0.2.log results--0.00001-0.25.log Dave Discovers Grid Sear (results--0.00001-0.35.10 results--0.00001-0.35.10 results--0.00001-0.35.10 results--0.00001-0.45.log

That's slow, let's

results--0.001-0.5.log [freshpond:DLRox sparks\$ for 1r in -0.0000 results-0.01-.log results--0.01-0.05.log for dropout in 0.0 0.05 0.1 0.15 0.2 results--0.01-0.1.log results--0.01-0.1.log do results--0.01-0.2.log earning_rate=\$lr --dropout=\$dropout > log: results-0.01-0.25.log results--0.01-0.35.log



RCE_MANAGER

 $1.0 \ 10.0 \ 100.0 \ 1000.0 \ 10000.0 \ 100000.0$; qsub python train_script.py --1 do done; done

results-100.0-0.0.log

freshpond:DLRox sparks\$ ls logs

01-0.35.log

0001-0.4.log

result-0.1-0.5.log

results--0.00001-0.0.log

results--0.00001-0.05.log

results--0.00001-0.1.log

results--0.00001-0.15.log

results--0.00001-0.5.log

results--0.0001-0.0.log

results--0.0001-0.05.log

results--0.0001-0.1.log

results--0.0001-0.15.log

results--0.0001-0.2.log

esults--0.0001-0.25.log

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results--0.0001-0.35.log

results--0.0001-0.4.log

results--0.0001-0.45.log

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esults--0.001-0.0.log

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esults--0.001-0.15.log

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results--0.001-0.4.log

esults--0.01-0.4.log

esults--0.01-0.45.log

esults--0.01-0.5.log

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results-1.0-0.5.log

results-10.0-0.0.log

results-10.0-0.05.log

results-10.0-0.1.log

results-10.0-0.15.log

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results-10.0-0.4.log

results-10.0-0.45.log

results-10.0-0.5.log

results-10.0-.log

esults-1.0-0.25.log

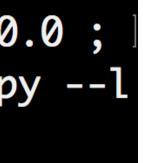
results--0.1-0.2.log

results--0.001-0.45.log

sults--0.001-0.25.log

esults--0.001-.log

results2--0.01-0.3.log results2--0.01-0.35.log results2--0.01-0.4.log results2--0.01-0.45.log results2--0.01-0.5.log results2--0.1-0.0.log results2--0.1-0.05.log results2--0.1-0.1.log results2--0.1-0.15.log results2--0.1-0.2.log results2--0.1-0.25.log results2--0.1-0.3.log results2--0.1-0.35.log results2--0.1-0.4.log results2--0.1-0.45.log results2--0.1-0.5.log results2-1.0-0.0.log results2-1.0-0.05.log results2-1.0-0.1.log results2-1.0-0.15.log results2-1.0-0.2.log results2-1.0-0.25.log results2-1.0-0.3.log results2-1.0-0.35.log results2-1.0-0.4.log results2-1.0-0.45.log results2-1.0-0.5.log results2-10.0-0.0.log results2-10.0-0.05.log results2-10.0-0.1.log results2-10.0-0.15.log results2-10.0-0.2.log results2-10.0-0.25.log results2-10.0-0.3.log results2-10.0-0.35.log results2-10.0-0.4.log results2-10.0-0.45.log results2-10.0-0.5.log results2-100.0-0.0.log results2-100.0-0.05.log results2-100.0-0.1.log results2-100.0-0.15.log results2-100.0-0.2.log results2-100.0-0.25.log results2-100.0-0.3.log results2-100.0-0.35.log results2-100.0-0.4.log results2-100.0-0.45.log results2-100.0-0.5.log results2-1000.0-0.0.log results2-1000.0-0.05.log results2-1000.0-0.1.log results2-1000.0-0.15.log results2-1000.0-0.2.log results2-1000.0-0.25.log results2-1000.0-0.3.log results2-1000.0-0.35.lc results2-1000.0-0.4.log results2-1000.0-0.45.log results2-1000.0-0.5.lo results2-10000.0-0.0.lo results2-10000.0-0.05.lo results2-10000.0-0.1.loc results2-10000.0-0.15.log results2-10000.0-0.2.log results2-10000.0-0.25.lo results2-10000.0-0.3.lo results2-10000.0-0.35.log results2-10000.0-0.4.log results2-10000.0-0.45. results2-10000.0-0.5.log results2-100000.0-0.0.log results2-100000.0-0.05.log results2-100000.0-0.1.log results2-100000.0-0.15.log results2-100000.0-0.2.log results2-100000.0-0.25.log results2-100000.0-0.3.log results2-100000.0-0.35.log results2-100000.0-0.4.log results2-100000.0-0.45.log results2-100000.0-0.5.log





Now Dave Has Two Problems

(1) Poor Infrastructure Support

- No fault tolerance
- No experiment tracking
- No metadata storage
- Missed optimization opportunities



(2) Dumb Search Strategy

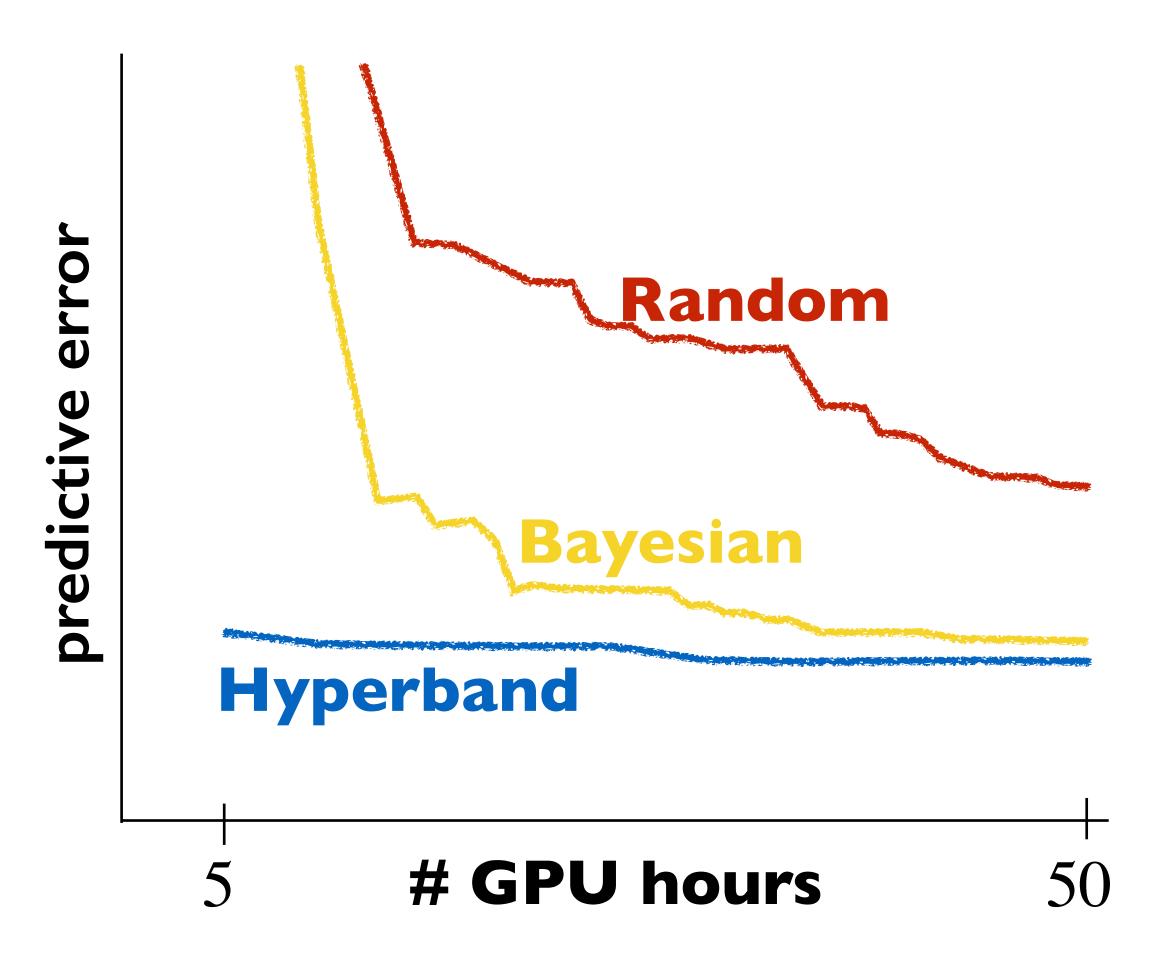
Dave is wasting > 99% of his time!



Hyperparameter Optimization

4 layer CNN 8 Hyperparameters Image recognition CIFAR10





Hyperband: Massively Parallel HPO [ICLR 2017]

Intuition:

- •Examine **many** hyperparameter configurations at once
- **Prune** the configurations that are doing poorly ("early stopping")
- •Adaptively allocate more training resources to the configurations that are doing well



Speedups

>50x over Random

10x over Bayesian

Lower final error

✓ Lower variance



Unfortunately, Dave can't Hyperband



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Dave's Infrastructure Dilemma

Cluster Manager:

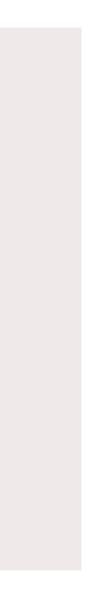
Doesn't understand the semantics of deep learning workloads

> What's missing is holistic but specialized infrastructure to provide the glue between these two



DL Frameworks:

Built to train a **single model** for a single user on a single machine



24

The Dark Age of Al Infrastructure

Forcing users to wait for **days** to recover from faults.

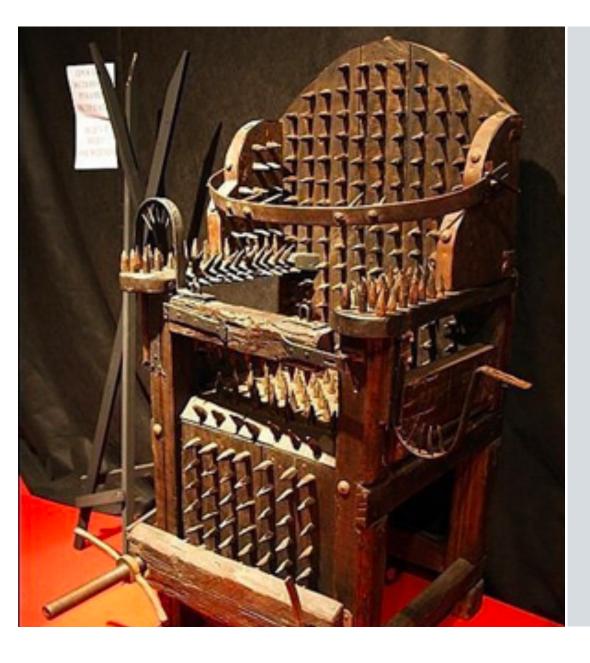
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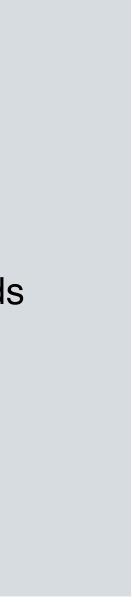








Hand-implemented, **impossibly slow** methods to find good models.





Dave is taking over for Leslie

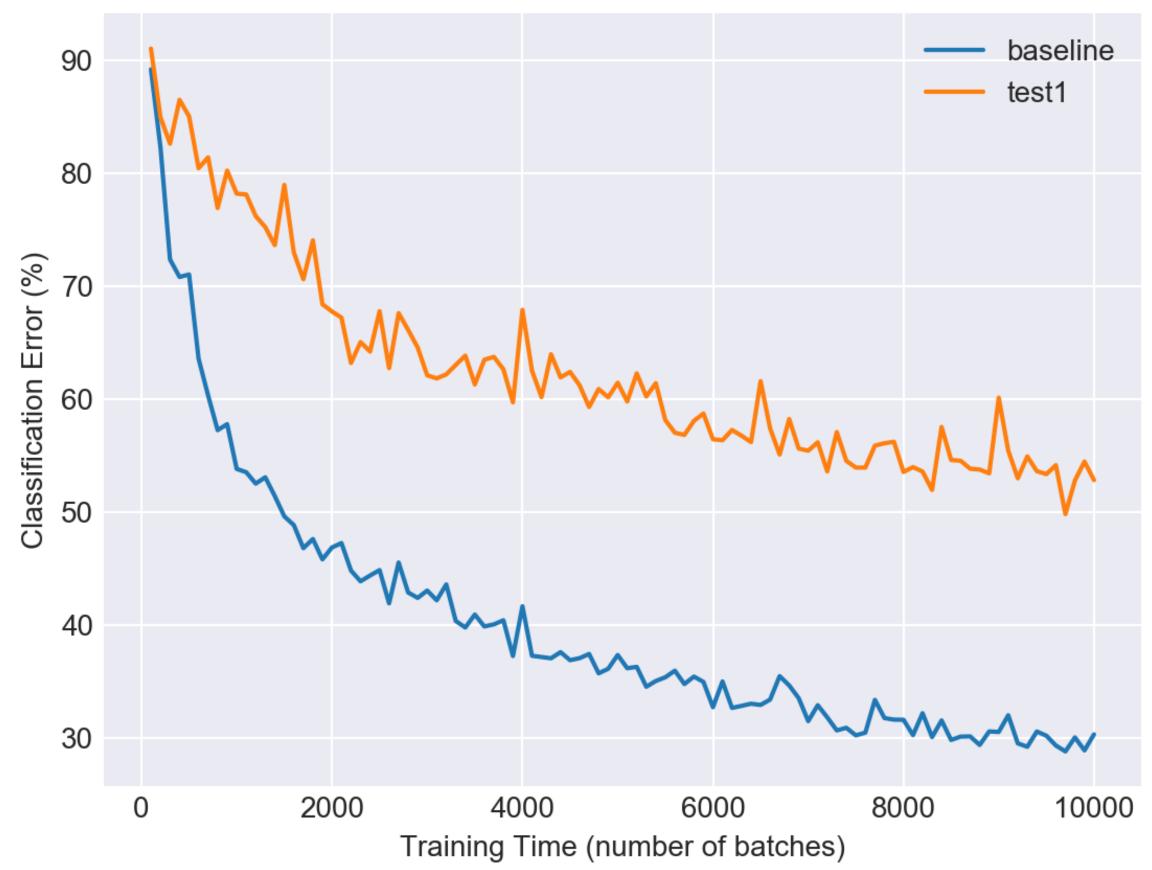
Dave is assigned to a new project. A former colleague, Leslie, trained a production model six months ago. Dave wants to explore new modeling techniques to see if he can improve the model's performance.

He re-runs Leslie's training script but get drastically higher error

Time to debug...



Model Error





What does Dave discover?

Training data: New samples recently added to Leslie's directory Hyperparameters: Leslie didn't use default values, and instead specified batch size and learning rate at runtime





Validation Error	Difference from Baseline	
30.3%	0.0%	
52.8%	22.5%	
37.3%	7%	





Ugh...Debug...

Randomness is an intrinsic part of training





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

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



Ugh...Debug...

Variation across specialized software

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



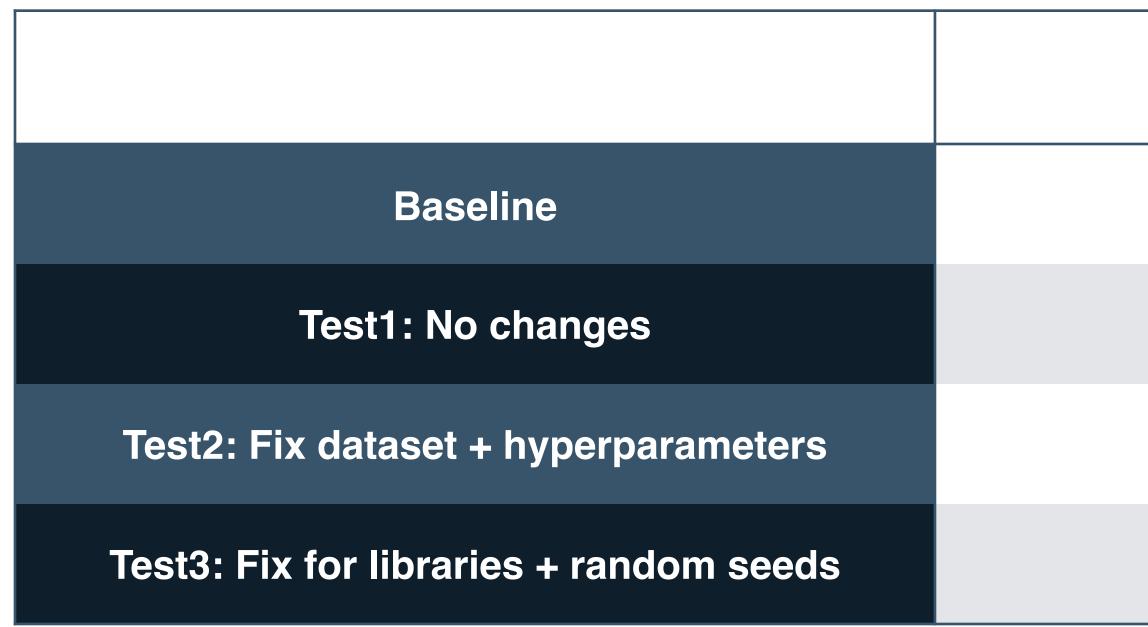
Requires non-trivial engineering infrastructure







Ugh...Debug...



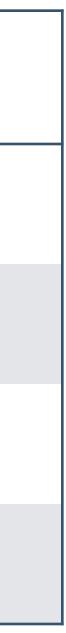
UGH!!!

Inherent System/Hardware Level Randomness

- non-deterministic GPU operations
- CPU multi-threading

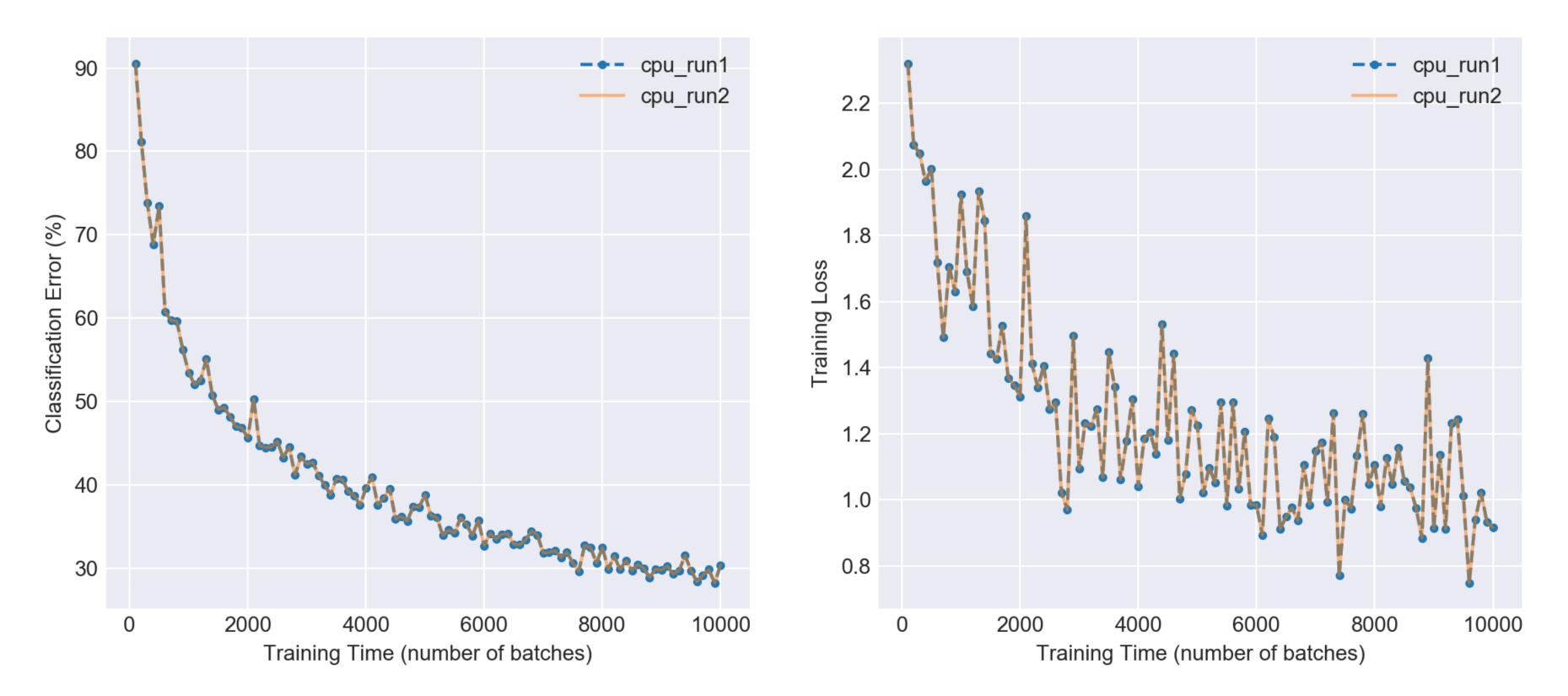


Validation Error	Difference from Baseline	
30.3%	0.0%	
52.8%	22.5%	
37.3%	7.0%	
29.2%	-1.1%	





Fixing this, at last, we have perfect reproducibility





Model Results with Full Reproducibility Enabled (CPU-only training)

But it requires **CPU-only** training with multi-threading disabled...**SLOW**!



What would an <u>holistic</u> but <u>specialized</u> DL reproducibility solution include?

Feature	
Version control for model definitions	Track change
Metadata capture and storage	
Dependency management	Ensure M
Experiment seed management	
Hardware resource flexibility	Allow



Purpose

es in model architecture, optimization algorithm, data preprocessing pipeline

Record training + validation metrics, training logs, model hyperparameters

AL framework and all dependencies are consistent between runs

Generate the same pseudo-random values every run

w users to disable multi-threading and GPU usage, if desired





Conclusion

- 1. Dave's life sucks because today's DL Infrastructure tools are bad.
- 2. Existing tools: overly generic or narrow technical point solutions
- 3. What we need: tools that are **specialized**
- for DL and support DL workflows in a
- holistic, end-to-end way.







Our platform gives AI teams the tools they need to train and deploy DL models dramatically more quickly.

Best-in-class AutoML capabilities

Automated GPU resource optimization

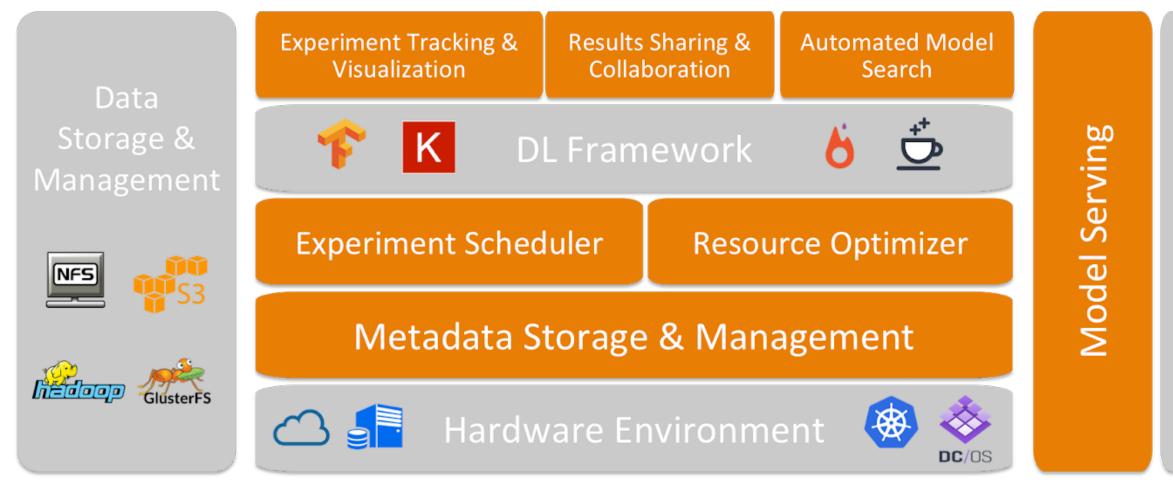
Reproducibility and experiment tracking

Supports cloud, on-premise, hybrid usage

Works with TensorFlow, PyTorch, and Keras







= Provided by PEDL

= Integrates with PEDL



Thank you!

neil@determined.ai

https://determined.ai

