Neural Network Hyperparameter Optimization

Chris Ouyang (CUHK Mathematics)

Daniel McBride (UTK Mathematics)

2019 JICS RECSEM REU. Coordinator: Kwai Wong

Presentation Outline

- **Introduction**

- **Part I:** An Early Stopping Algorithm Based on Learning Curve Matching
  Chris Ouyang

- **Part II:** Population Based Training with MagmaDNN and OpenDIEL
  Daniel McBride

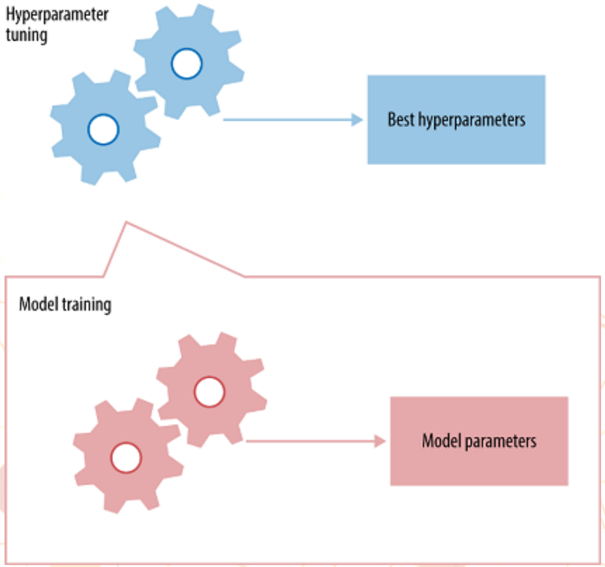
Introduction

- **What is a hyperparameter?**

  They are neural network “presets” like network architecture, learning rate, batch size, and more.

- **Why do we need to optimize the hyperparameters?**

  A poor choice of hyperparameters can cause a network’s accuracy to converge slowly or not at all.



Introduction

- **What are some obstacles to optimizing hyperparameters?**
  - The Curse of Dimensionality
  - Highly irregular (nonconvex, nondifferentiable) search spaces

- **What are some standard hyperparameter optimization techniques?**
  - Classic Approaches: Grid Search, Random Search
  - Modern Approaches: Early Stopping, Evolutionary Algorithms

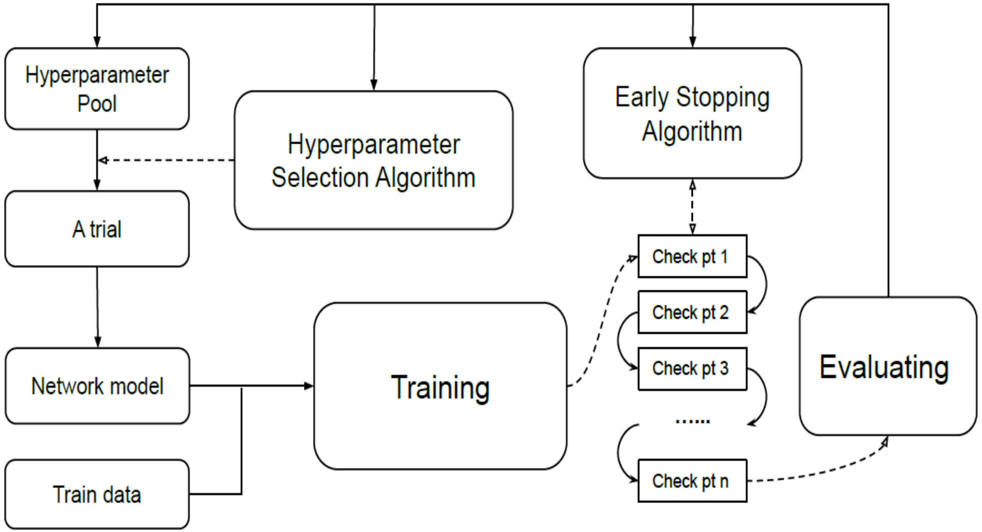
Part I

An Early Stopping Algorithm Based on Learning Curve Matching

Chris Ouyang

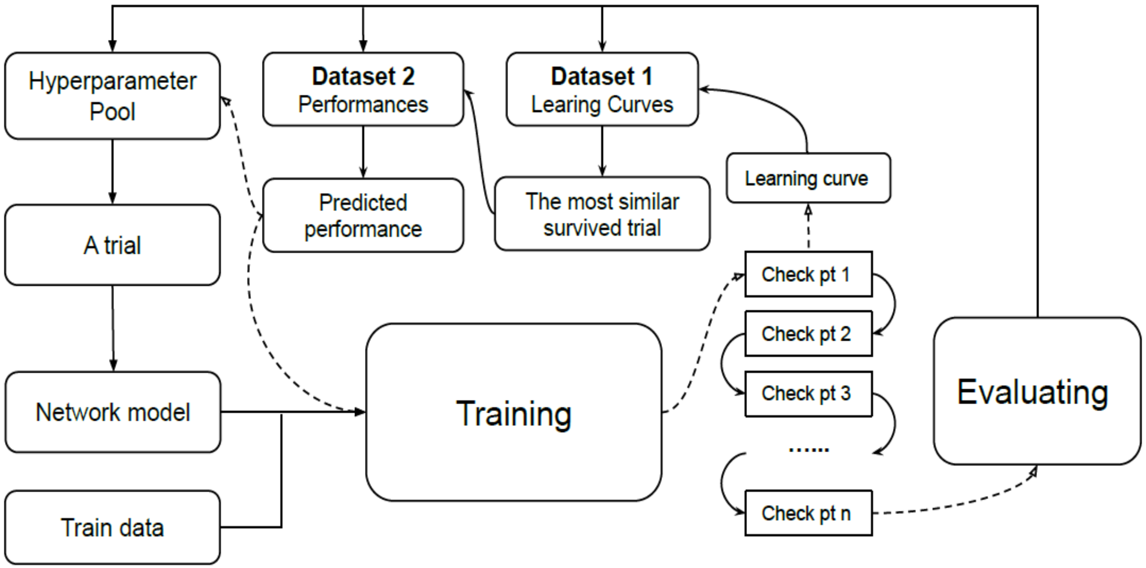
Hyperparameter Algorithms

- **Hyperparameter Selection**: Random search, grid search and Bayesian optimization
- **Early stopping**: Successive Halving Algorithm (SHA) and Hyperband
- **Advanced Algorithm**: Evolutionary Algorithm, such as population based training (PBT) and swarm optimization.



LCM Algorithm: Flow Chart and Terms

- ***Trials***: Sets contain a single sample for every hyperparameter.
- ***Learning Curves***: arrays of the numerical values of loss function in some certain stages during a single training.
- ***Check Points***: points where apply LCM to decide whether abort the training



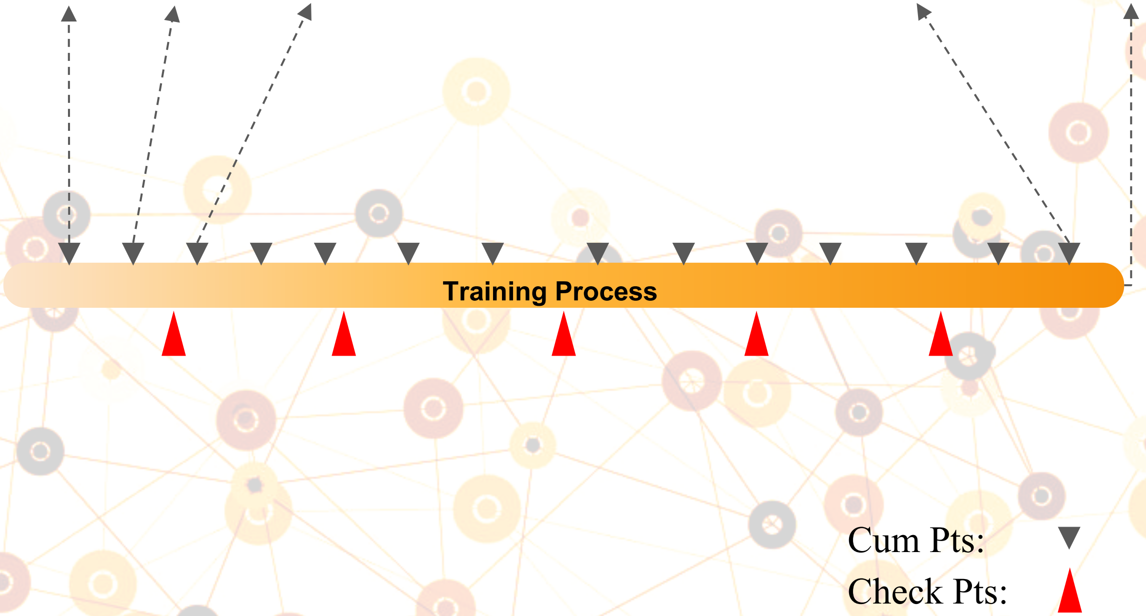
LCM Algorithm: Cumulation Stage

Learning Curve with performance

[Loss_1, Loss_2, Loss_3, Loss_4, Loss_5, …… , Loss_n, Performance]

Data Set:

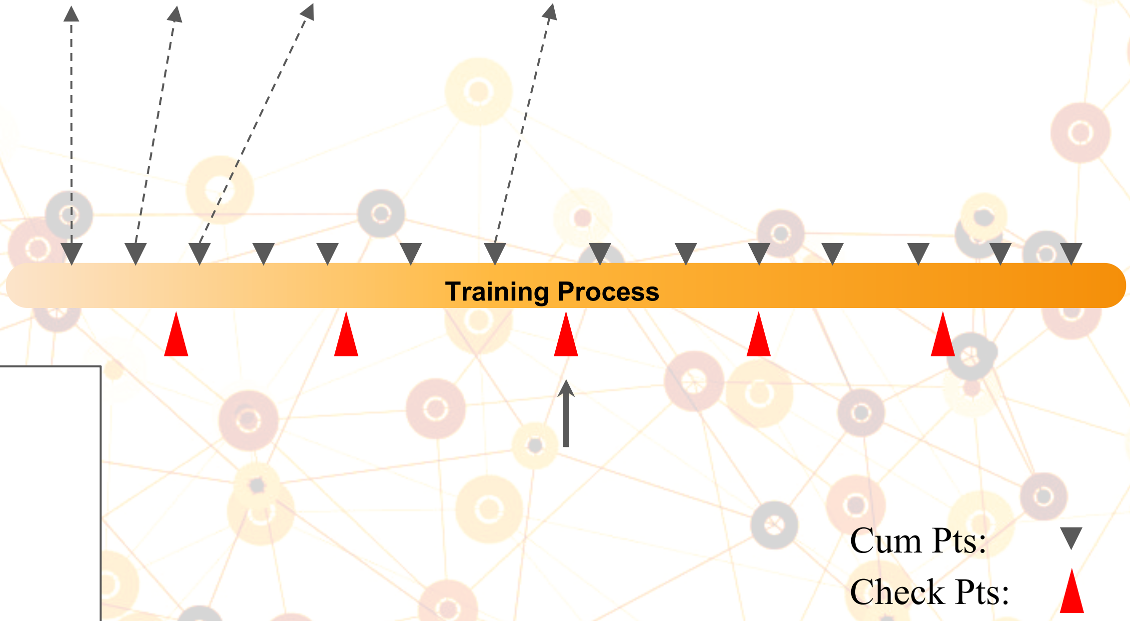
[LC_1, Performance_1],
[LC_2, Performance_2],
[LC_3, Performance_3],
[LC_4, Performance_4],
……
[LC_m, Performance_m]



LCM Algorithm: Checking Stage

Data Set:
[L11, L12, L13, ..., L1k],
[L21, L22, L23, … , L2k],
[L31, L32, L33, … , L3k],
[L41, L42, L43, … , L4k],
……
[Lm1, Lm2, Lm3, … , Lmk]

Learning Curve
[Loss_1, Loss_2, Loss_3, …… , Loss_k]



Data Set:
[L11, L12, L13, ..., L1n Performance_1],
[L21, L22, L23, … , L2n Performance_2],
[L31, L32, L33, … , L3n Performance_3],
[L41, L42, L43, … , L4n Performance_4],
……
[Lm1, Lm2, Lm3, … , Lmn, Performance_m]

LCM Algorithm: Checking Stage

Distance Function F
(such as L1, L2, L∞)

Learning Curve
[L_1, L_2, L_3, …… , L_k]

Data Set:
[L11, L12, L13, ..., L1k],
[L21, L22, L23, … , L2k],
[L31, L32, L33, … , L3k],
[L41, L42, L43, … , L4k],
……
[Lm1, Lm2, Lm3, … , Lmk]

Distance List:
[Distance_1,
Distance_2,
Distance_3,
Distance_4
…
Distance_m]

The nearest neighbor j := argmin(Distance list)

Data Set:
[Performance_1,
Performance_2,
Performance_3,
Performance_4,
…
Performance_m]

Predicted Performance:
Performance_j

The **rank** of it: rank_j

The **rank percentage**:
Percentage_j

If Per_j < **keep_rate**:
Stop training;
Otherwise, continue training.

LCM Algorithm: Comparisons

- **Network**: Only one dense layer
- **Dataset**: MNIST
- **Optimizer:** stochastic gradient descent
- **Hyperparameter**: Epochs, batch sizes, learning rate, momentum and decay
- **Benchmark**: Random search
- **Times**: 9

	Trials	Computer Time (S)	Best Performance (%)
LCM	100	778.50	97.10
Random	100	3657.75	97.41
Remark: In 5 of 9 experiments, two algorithms got the same optimal hyperparameters.			

LCM Algorithm: Comparisons

- **Network**: Only one dense layer
- **Dataset**: MNIST
- **Optimizer:** stochastic gradient descent
- **Hyperparameter**: Epochs, batch sizes, learning rate, momentum and decay
- **Benchmark**: Random search
- **Times**: 6

	Trials	Computer Time (S)	Best Performance (%)
LCM	37.67	4800	97.82
Random	67.33	4800	97.69
Remark: In 4 of 6 experiments, two algorithms got the same optimal hyperparameters.			

LCM Algorithm: Comparisons

- **Network**: Four CNN layers and several dense layers
- **Dataset**: CIFAR10
- **Optimizer:** Adam
- **Hyperparameter**: More than 10 hyperparameters
- **Benchmark**: Random search
- **Times**: 12

	Trials	Computer Time (S)	Best Performance (%)
LCM	100	8069.08	67.05
Random	100	26498.00	67.26
Remark: in 7 of 12 experiments, two algorithms got the same optimal hyperparameters.			

Part II

Population Based Training with MagmaDNN and OpenDIEL

Daniel McBride

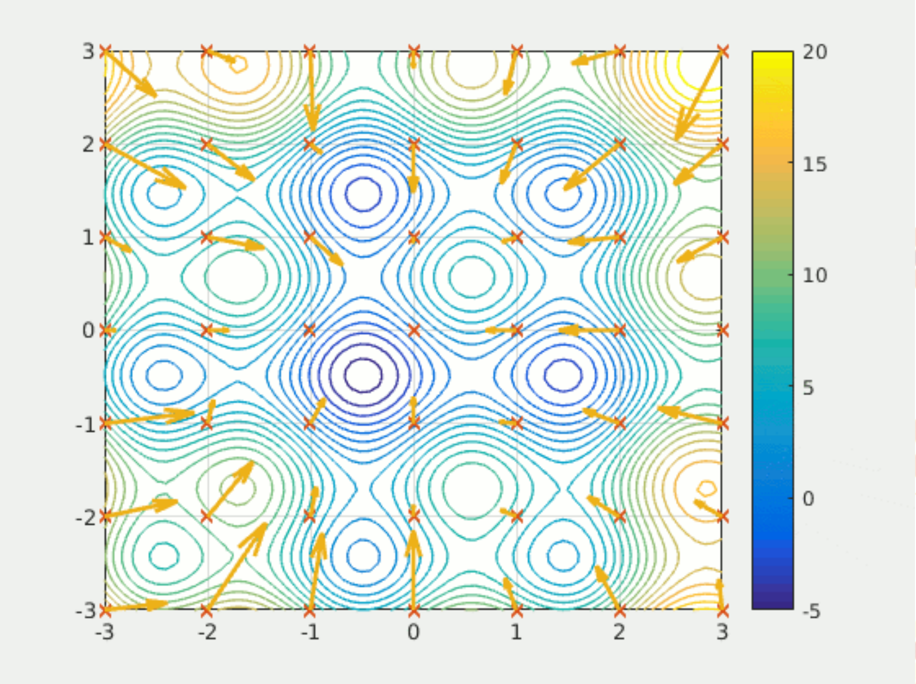
PBT: Background

- **What is Population Based Training (PBT)?**

  PBT is an evolutionary hyperparameter optimization algorithm.

- **Evolutionary optimization algorithms** use natural models to inspire a particular approach to traversing a search space. One classic case is the Particle Swarm Optimization algorithm, inspired by the swarming behavior of bees.

Particle Swarm Optimization



PBT: Background

- **What are the benefits of PBT?**

  PBT outperforms the standard hyperparameter tuning benchmarks. These benchmark algorithms, **Grid Search and Random Search**, each have their own limitations, which PBT overcomes.

- **Why should we implement it on MagmaDNN and OpenDIEL?**
  - MagmaDNN and OpenDIEL are engineered for supercomputers.
  - The current standard implementation (Ray-Tune: shared memory model) has a scalability bottleneck.

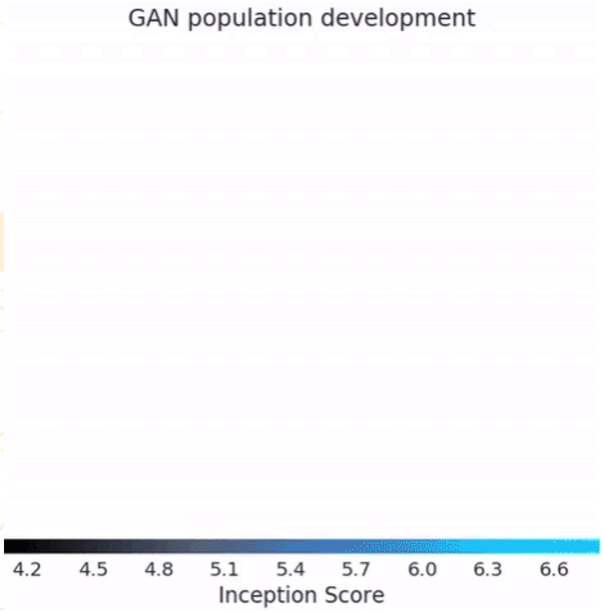
PBT: Algorithm

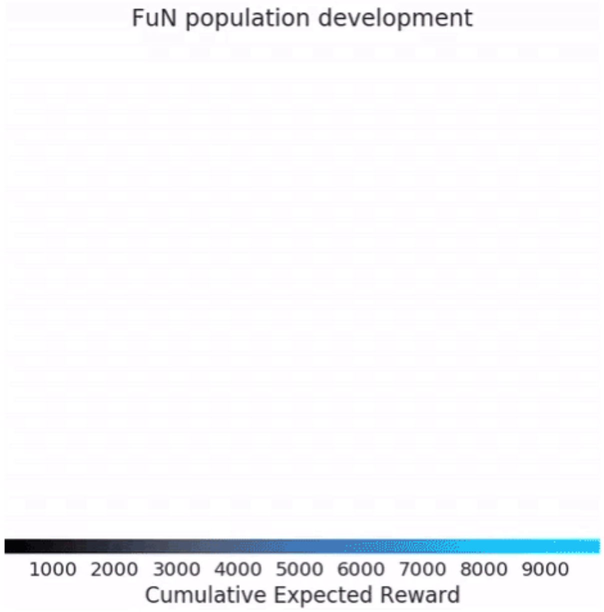
How does the PBT Algorithm work?

- Population Model
- Stochasticity
- Explore / Exploit
- Early Stopping
- Evolution
- Adaptive Hyperparameter Scheduling

PBT: Algorithm

How does the PBT Algorithm work?





PBT: Algorithm

Does PBT's functionality improve on the benchmark algorithms?

	Grid Search	Random Search	PBT
Parallelizability	✔	✔	✔
Stochasticity	✗	✔	✔
Early Stopping	✗	✗	✔
Adaptive Hyperparameters	✗	✗	✔

PBT: Analysis - Dynamic Learning Rate

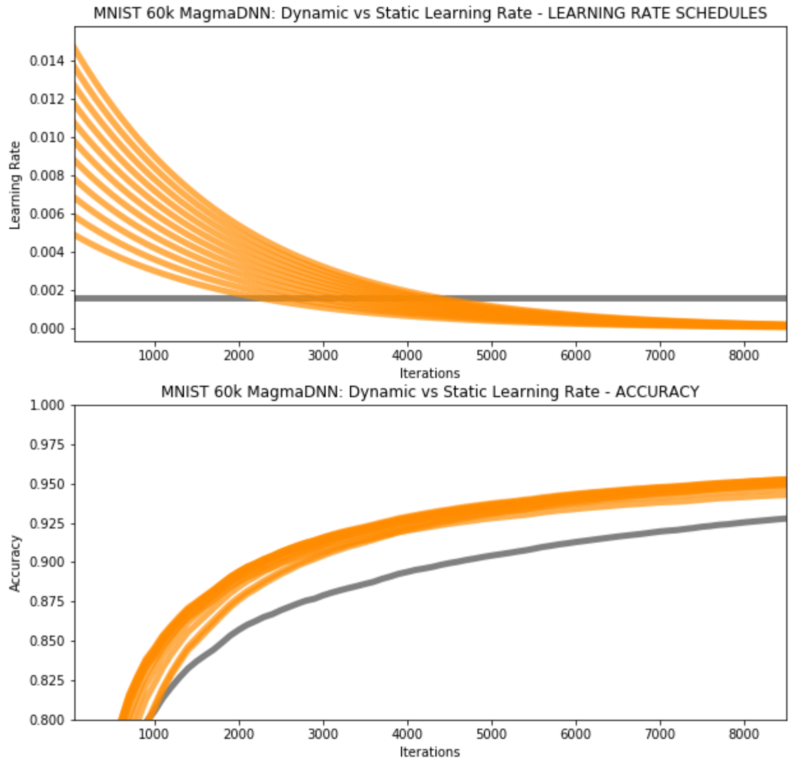
- **Data: MNIST**
  - **60k images of handwritten digits 0-9**
  - **256 greyscale pixels per image**
  - **10 categories (0-9)**

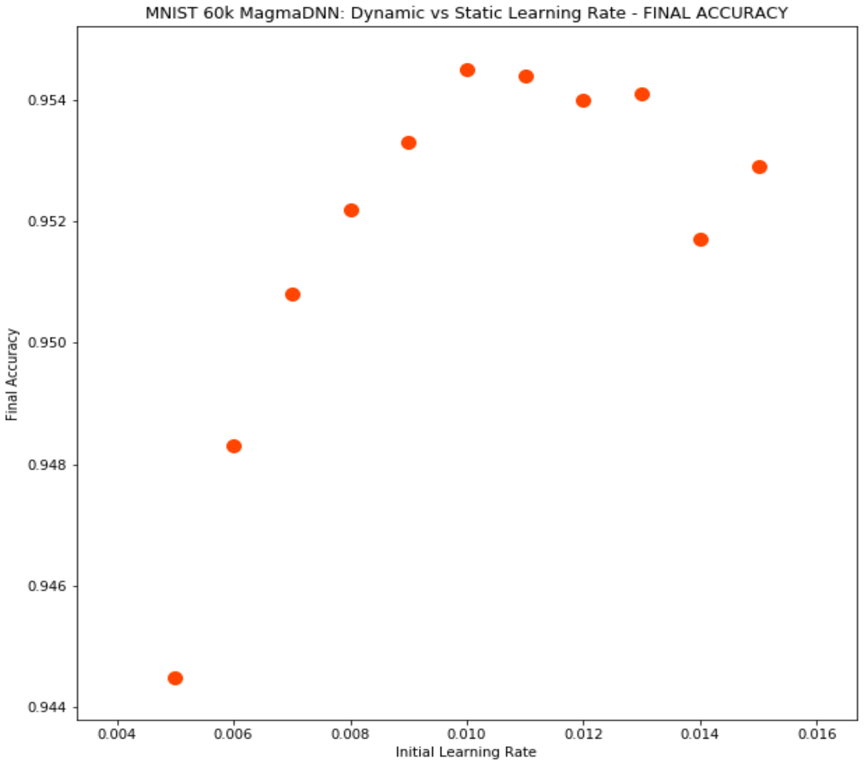
- **Network: MagmaDNN**
  - **Network Structure: In -> FCB -> Sig -> FCB -> Sig -> FCB -> Out**
  - **Weight Optimizer: Stochastic Gradient Descent**
  - **Number of Epochs = 5**
  - **Batch Size = 32**

- **Benchmark:** constant learning rate = .0016
- **Experiments:** dynamic learning rate schedules with variable initial values

*FCB := Fully Connected Layer with Bias
*Sig := Sigmoid

PBT: Analysis - Dynamic Learning Rate





Population Based Training with MagmaDNN and OpenDIEL - Daniel McBride

PBT: Goals

- Extend the OpenDIEL Grid Search Application to have PBT functionality, i.e. stochasticity and evolution.
- Program more custom MagmaDNN classes to explore the effect of tuning Convolutional Neural Network hyperparameters.
- Implement PBT on MagmaDNN and OpenDIEL with a distributed Worker, and overcome the Ray-Tune bottleneck.

Thanks for listening!

-The Hyperparameter Team