



Installing CANDLE In Other Environments CANDLE NIH Workshop February 2018

George Zaki [C]

BIDS, FNLCR

February 22nd 2018



Agenda

- **Introduction to containers**
- **Example of hyper-parameter optimization on HPC clusters**
- **Using CANDLER on Biowulf**



Agenda

- **Introduction to containers**
- Example of hyper-parameter optimization on HPC clusters
- Using CANDLE on Biowulf

Why containers? Why singularity?

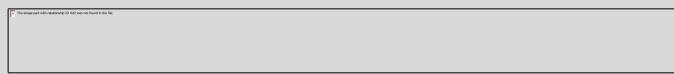


Containers

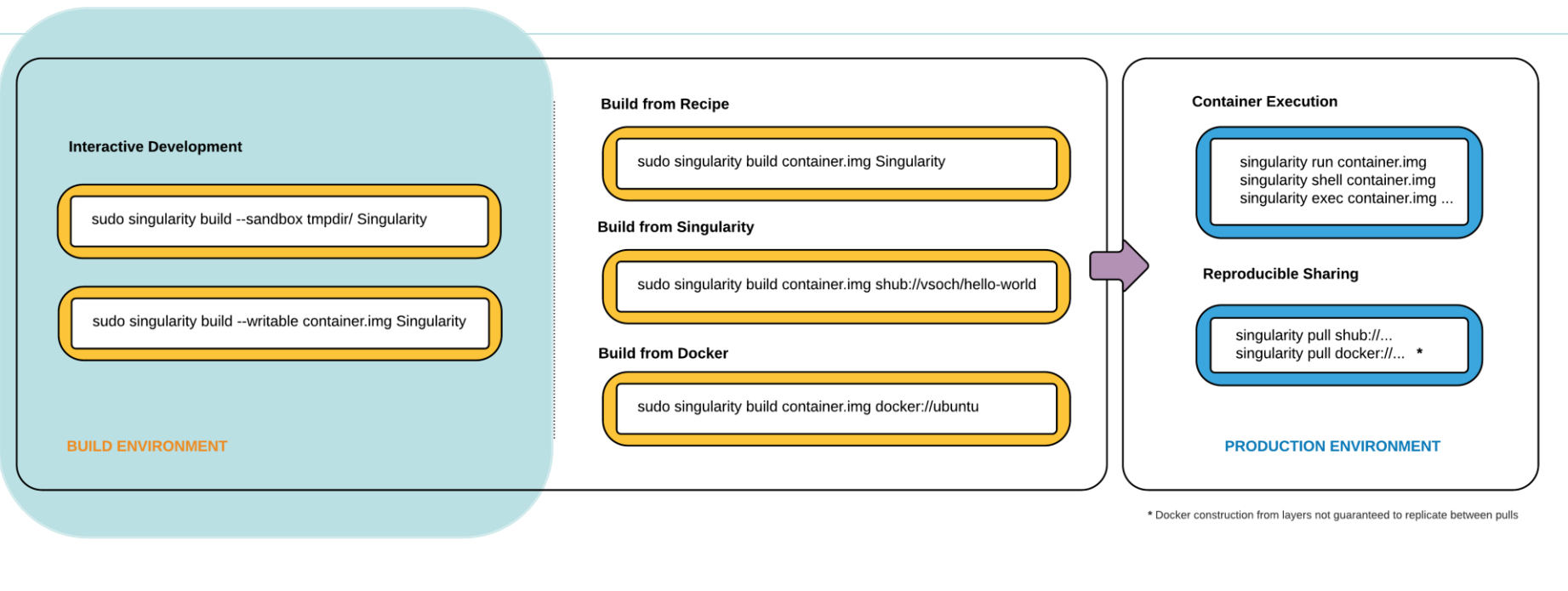
- Light weight OS virtualization (i.e., user your preferred OS)
- Package entire scientific workflow, and share your code
- No need to for system admin to install software
- Be in control of versioning and updates

Singularity

- Adopted by most HPC systems including Biowulf.
- Can run your MPI jobs
- Support from Biowulf system admins
- Very active user group



Singularity cycle



- 1- Build your singularity image (one file) from a recipe, or a Docker on your local sandbox.
- 2- Copy the singularity image to the HPC cluster / Cloud cluster.
- 3- Run on production environment.

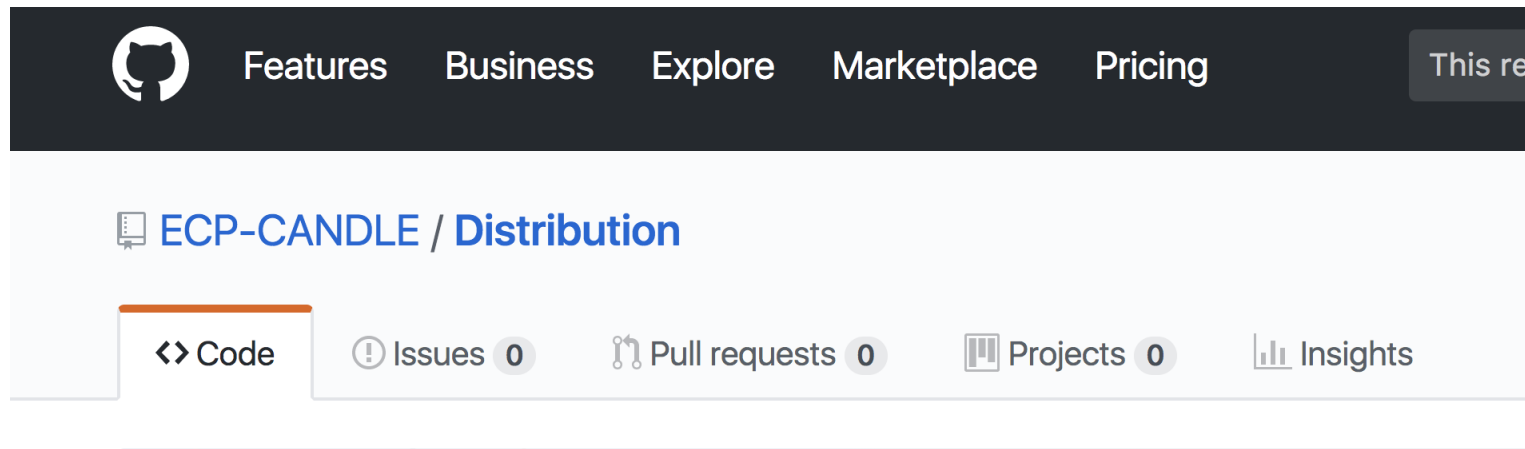
singularity.lbl.gov

Frederick National Laboratory for Cancer Research

Building CANDLE Using Singularity



- A singularity recipe that encapsulates all CANDLE dependencies is shared on GitHub.
- Navigate to the Distribution and follow the README.



- All you need is to install singularity and mpi on your laptop, cluster, cloud, etc.



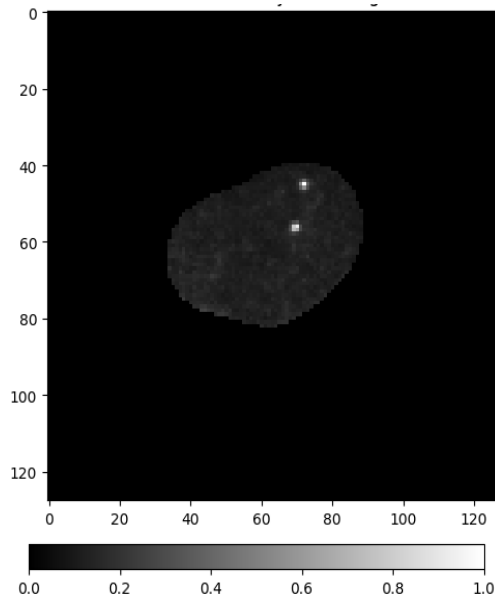
Agenda

- Introduction to containers
- **Example of hyper-parameter optimization on HPC clusters**
- Using CANDLE on Biowulf

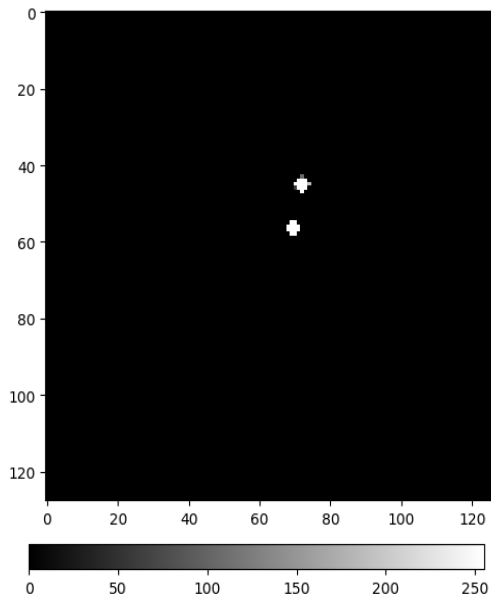
The Problem: Pixel based segmentation for RNA activities



Input

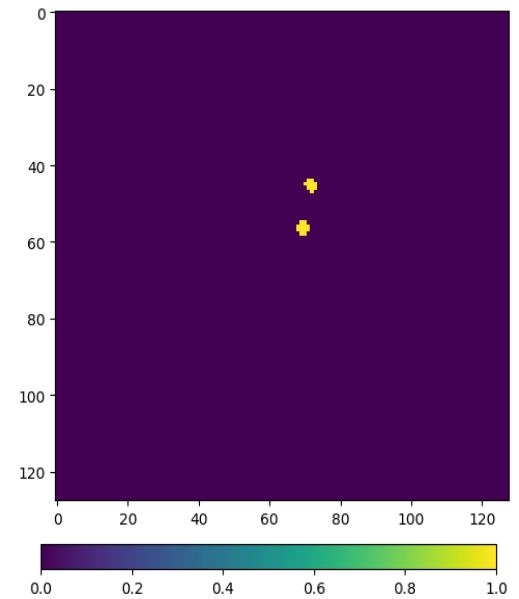


Test FISH Image



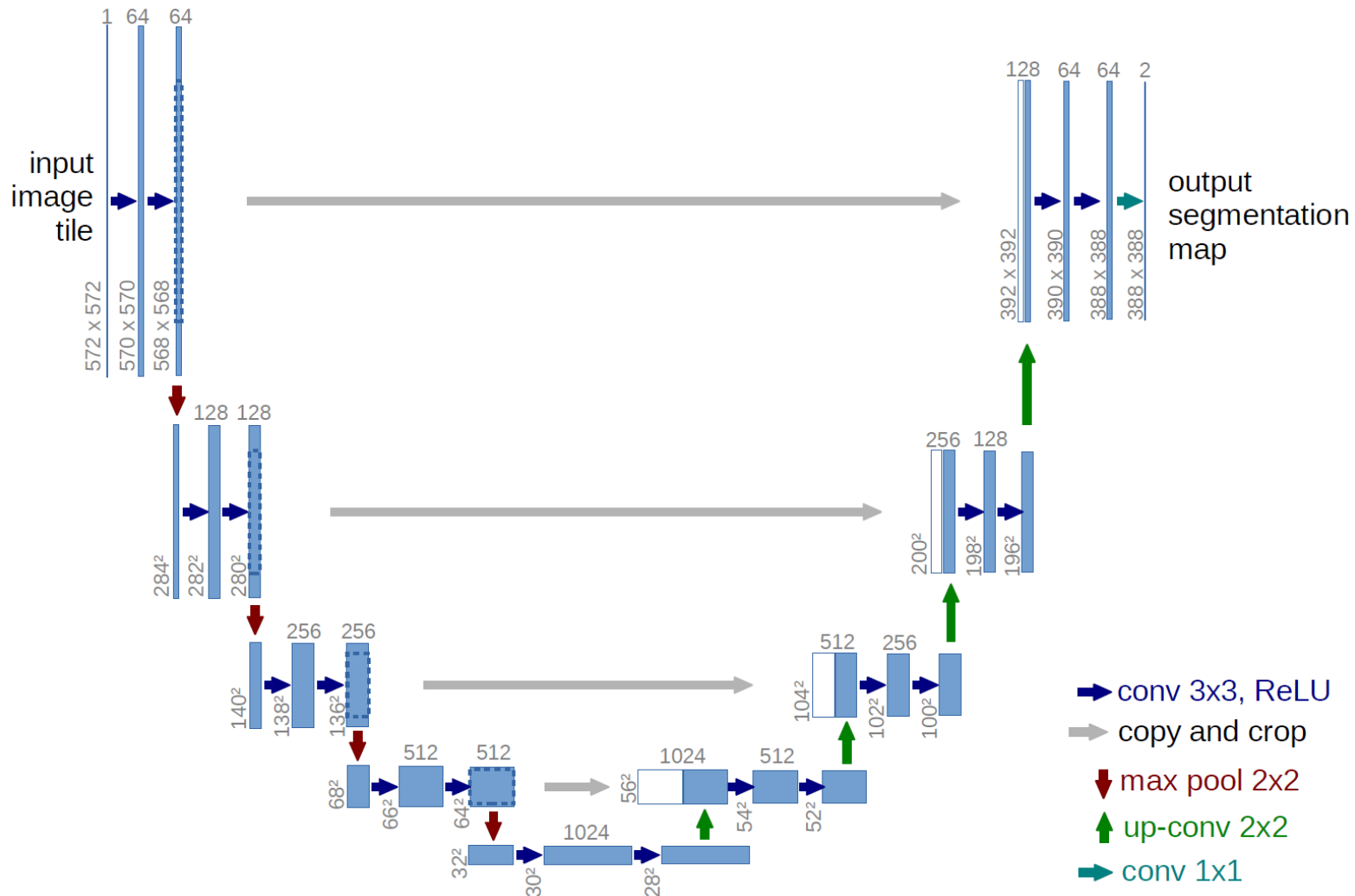
Ground Truth

Output

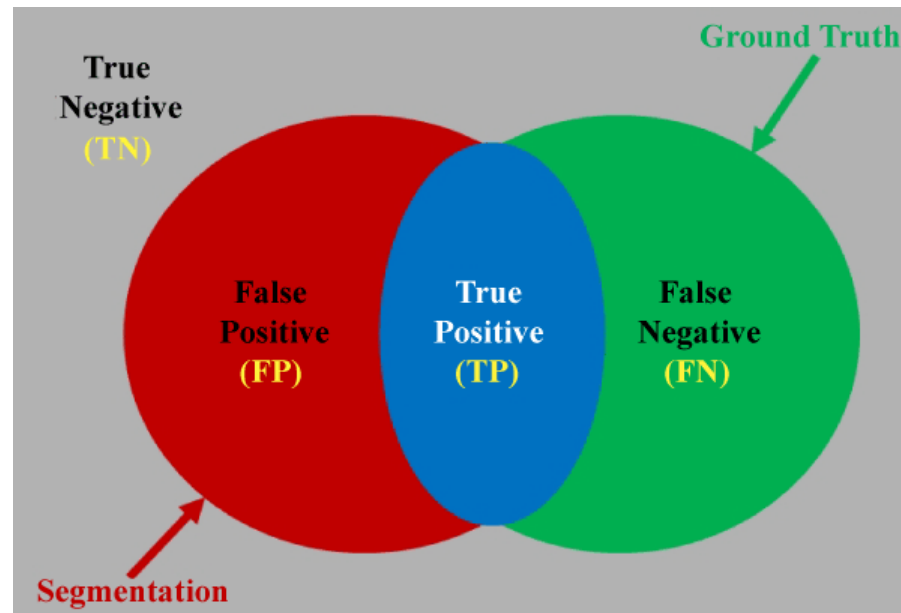


Prediction

UNet – A Fully Convolution Neural Network For Pixel-Based Segmentation

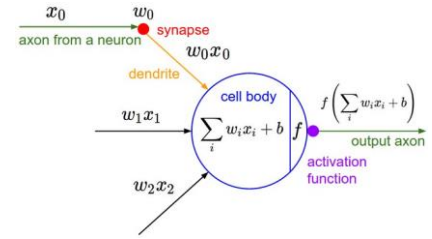
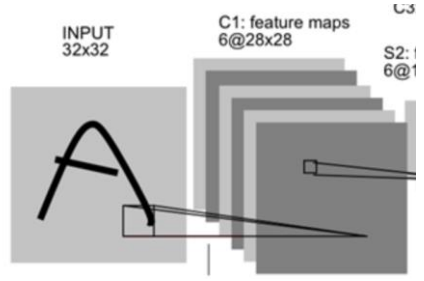
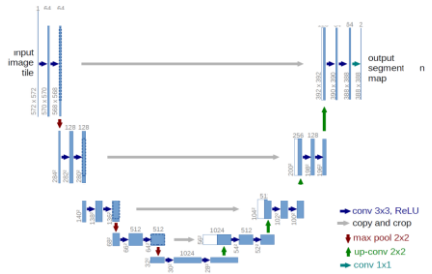


UNet objective function: Dice Coefficient



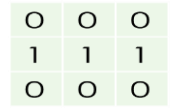
$$\text{Dice Coefficient} = \frac{(2*TP)+1.0}{(FP+TP+FN)+1.0} \in [0,1]$$

Unet Hyper parameters: (288 possible values)



ONLY 2 Levels of Max-Pooling

$N_layers = \{2,3,4,5\}$



Size of conv filter?

$Filter_size = \{3x3, 5x5\}$

How many convolution filters?

$Num_filters = \{16,32,64\}$

Drop out some results to avoid overfitting?

$Drop_out = \{0, 0.2, 0.4, 0.6, 0.8\}$

What is the activation function?

$Activation = \{relu, softmax, tanh\}$

Experiment on Biowulf:

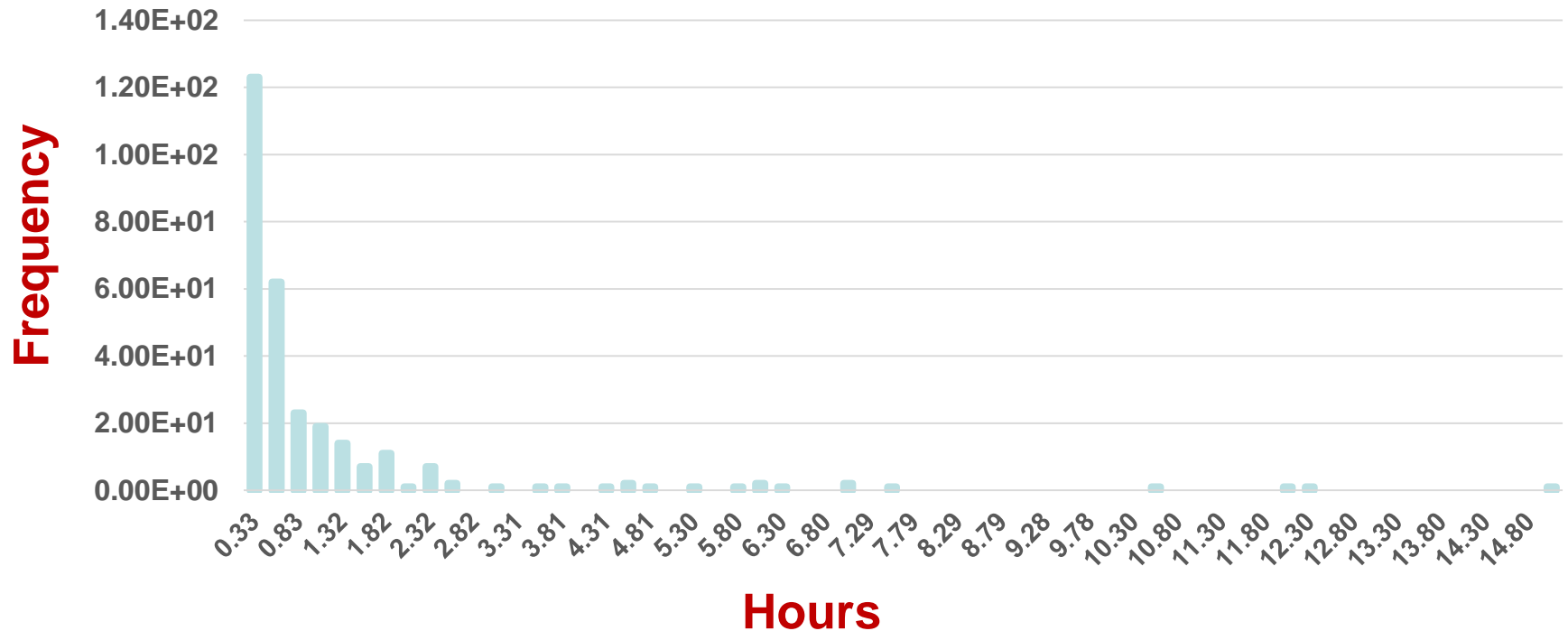


- local swit-t installation
- 16 **K80 GPU** nodes
- 30 hours
- 10GB memory per task

The need for ADLB



Runtime Histogram



Total runtime = 17.5 hours, experiment runtime = 30 hours.

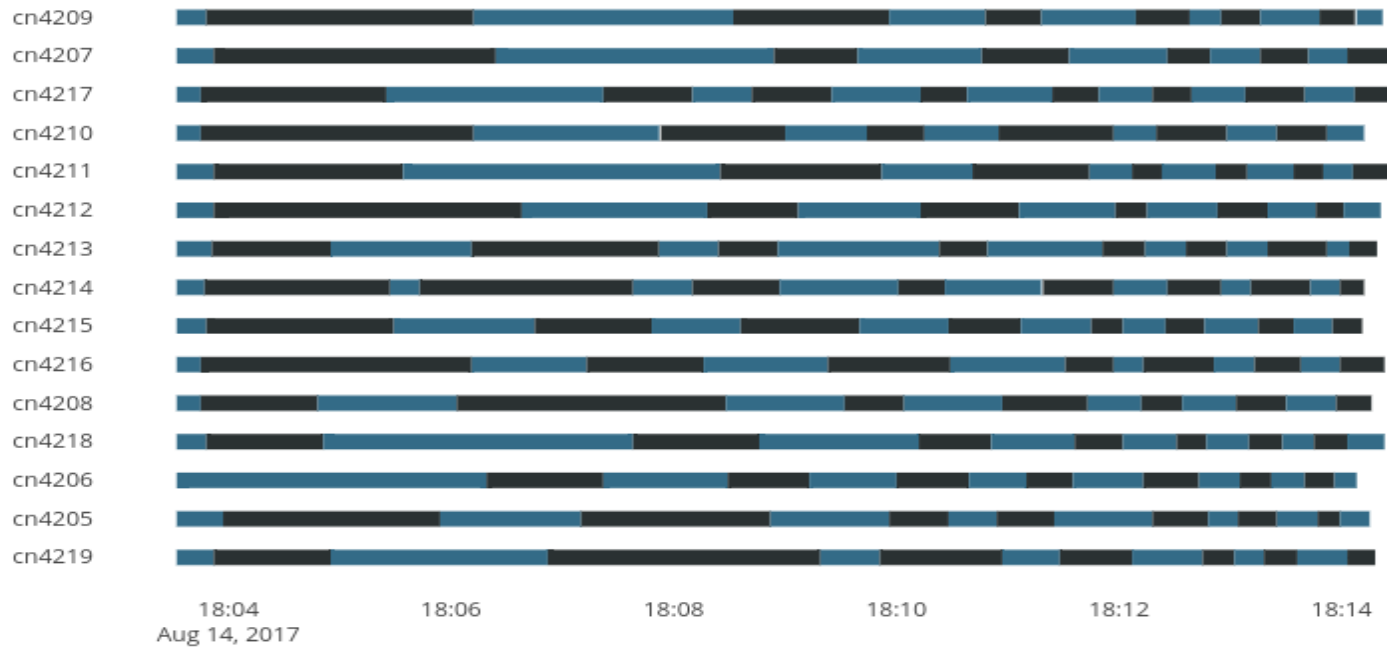
Can be multiple threads are using the same GPU. Need further investigation.

Smoke test on 14 GPUs.



Image segmentation sweep, total time=657 secs

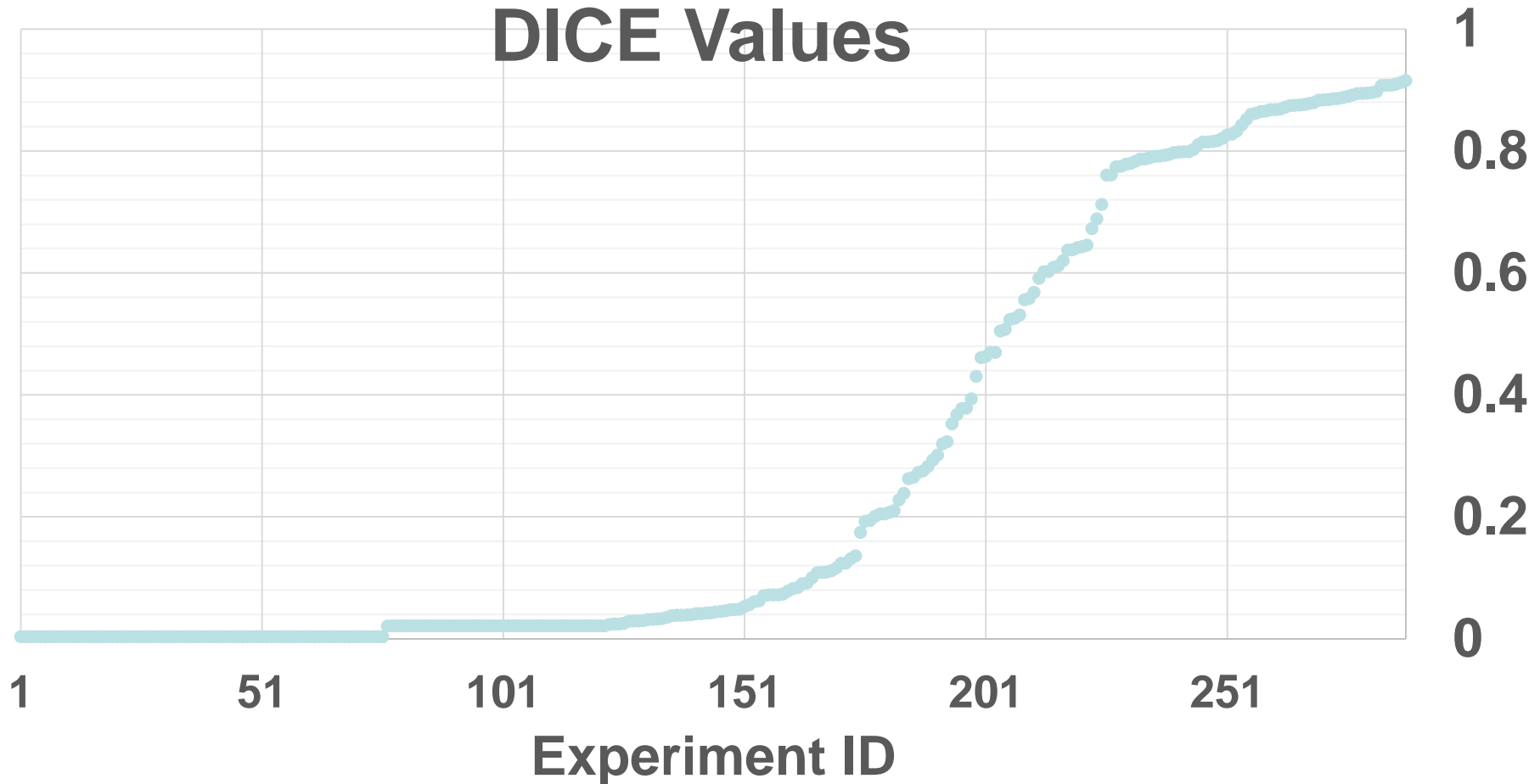
1w 1m 6m YTD 1y all



Hyper parameters sweep



DICE Values



Can we do better than sweeping all parameters?



Agenda

- Introduction to containers
- Example of hyper-parameter optimization on HPC clusters
- **Using CANDLE on Biowulf**

Hyper-parameter optimization using mlrMBO



- **Objective:** Optimize a black box function using Bayesian optimization
 $P(\text{score}/\text{configuration})$ using a History of $(\text{score}, \text{configuration})$ pairs.
- **Arguments:**
 - Budget (number of evaluations)
 - Initial design, to create the history.
 - Number of iterations
- Swift/T workflow is integrated with the mlrMBO R package.
- Users have to define the parameters space and the simulation arguments. mlrMBO will suggest multiple points in every iterations

Parameter space example



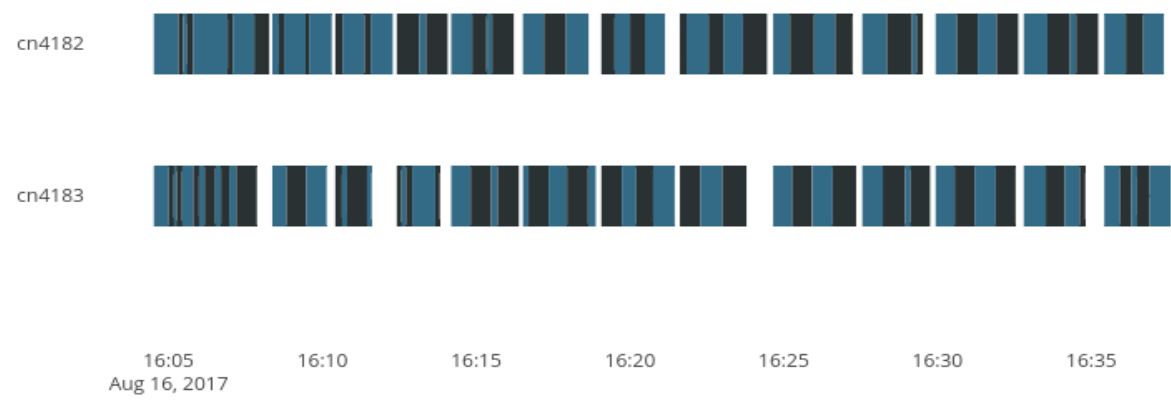
```
param.set <- makeParamSet(  
  makeNumericParam("learning_rate", lower= 0.00001, upper= 0.1 ),  
  makeNumericParam("dropout", lower= 0, upper= 0.9 ),  
  makeDiscreteParam("activation",  
    values= c( "softmax","elu","softplus","softsign",  
              "relu", "tanh","sigmoid","hard_sigmoid",  
              "linear" ) ),  
  makeDiscreteParam("optimizer",  
    values = c("adam", "sgd", "rmsprop","adagrad",  
              "adadelat")),  
  makeDiscreteParam("shared_nnet_spec",  
    values= c( "400", "500", "600", "700"  
              #"800", "900", "1000", "1100", "1200",  
              #"400,400", "500,500", "600,600", "700,700",  
              #"800,800", "900,900", "1000,1000", "1100,1100",  
              #"1200,1200"  
              ) ),  
  makeDiscreteParam("ind_nnet_spec",  
    values= c( "400:400:400", "600:600:600"  
              #"800:800:800", "1000:1000:1000",  
              #"1200:1200:1200",  
              #"400,400:400,400:400,400", "600,600:600,600:600,600",  
              #"800,800:800,800:800,800", "1000,1000:1000,1000:1000,1000",  
              #"1200,1200:1200,1200:1200,1200",  
              #"800,400:800,400:800,400",  
              #"1200,400:1200,400:1200,400",  
              #"1200,800,400:1200,800,400:1200,800,400"  
              ) ),  
  makeDiscreteParam("batch_size", values = c(16,32,64,128,256)),  
  makeIntegerParam("epochs", lower = 5, upper = 50)  
)
```



Biowulf run: Budget = 110, initial design = 20 2 working GPUs

p3b1mlrmbo-4-gpus, total time=1984 secs

1w 1m 6m YTD 1y all

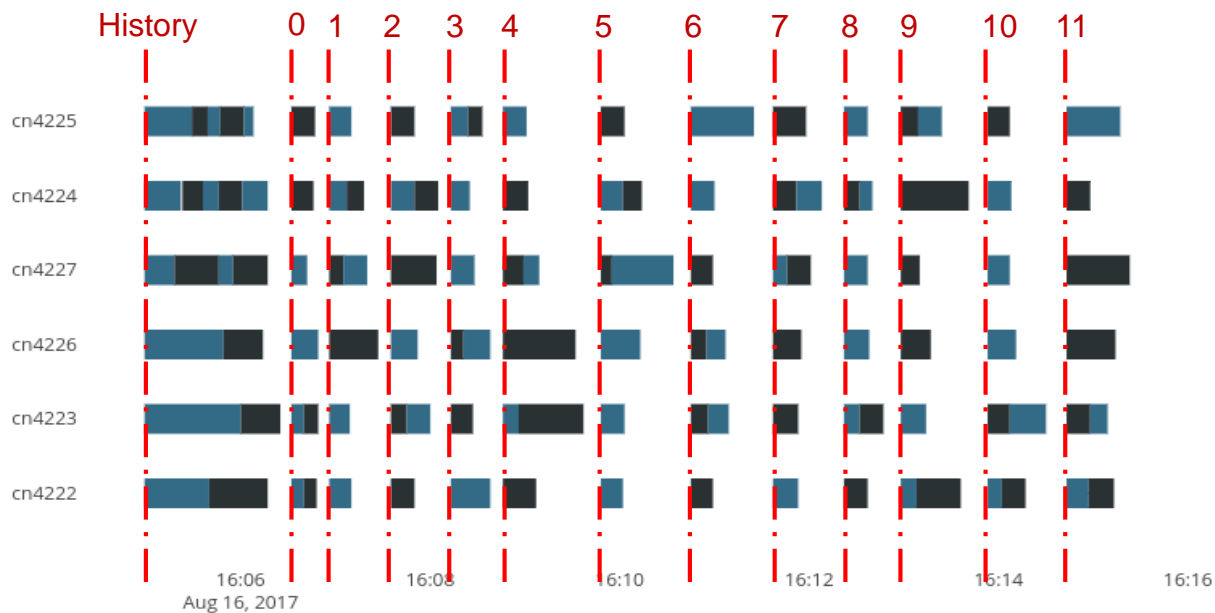


Biowulf run: Budget = 110, initial design = 20 6 working GPUs



p3b1mlrmob-8-gpus, total time=624 secs

1w 1m 6m YTD 1y all



Can I use mlrMBO with Swift/T today?



- **Yes!**
 - A Swift/T project template exists on Biowulf under **`/data/classes/candle/mlrmob-template`**
 - Follow the readme files
- **Arguments:**
 - Define the function
 - Define the Arguments
 - Set the Budget (number of iterations)
 - Allocate resources (up to 32 K80 GPUs on Biowulf)
- **Dependencies:**
 - Singularity to run the container. Already installed on Biowulf!

Quick Demo



- singularity **shell** <singularity-image>
- singularity **exec** <singularity-image> <your-command>

- Running CANDLER using singularity on Biowulf.

CANDLE status on Biowulf



- Hyper parameter optimization is integrated with mlrMBO and hyperopt packages.
- Configuration of the GPU ID per training instance is available. Allocate 4 GPUs per node and let every GPU train a different model.
- Data parallelism is supported on single node by assigning every MPI job on a node.
- Next release should support data parallelism on multiple nodes.

Conclusions / Take Aways



- The blue print (definition file) for the singularity image is available on GitHub under **ECP-CANDLE/Distribution**
- The art of hyper-parameter optimization can be automated using Bayesian models.
- A template is available on **Biowulf** to make use of mlrMBO optimization package with Swift/T load balancer.
- Data parallelism can be controlled on 1 node in Biowulf today!