LCD and LArIAT Datasets And CaloDNN and LArTPCDNN

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LCD Calo Dataset made by M. Pierini (CMS/CERN) + JR Vlimant (CMS/Caltech)
LArIAT Dataset made by S. Shahsavarani (Neutrinos/UTA) + AF

Intro

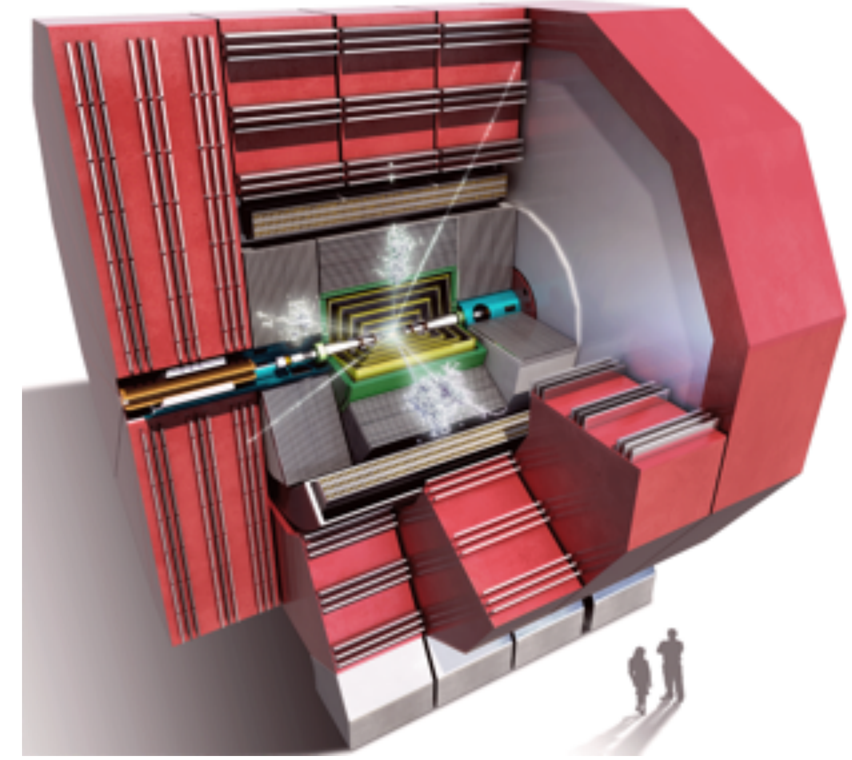
- Reconstruction level DL requires realistic detector simulation… not as easy as 4-vectors or parameterized detectors.
- Experiments are understandably strict about their data. Prohibits:
    - Cross experiment or HEP/ML collaboration
    - Rapid publication of DL R&D (no physics).
- Imaging detectors (Granular Calorimeters, TPCs, Cherenkov, …) ideally suited for Deep Learning.
- We generated the LCD and LArIAT Datasets to avoid these issues.
    - Dataset and code very similar, so I'll talk about both.
    - Weekly LCD meetings to organize work. Should do for LArIAT.
- Data Science @ LHC (Nov 2015 @ CERN) -> DS@HEP.
    - Experts workshop (July 2015): these datasets were introduced in prim. Goal was to make them public for NIPS… btut we didn't get a workshop and got busy.
    - Goal is to reveal datasets at next workshop. May 8-12 @ FNAL. https://indico.fnal.gov/conferenceDisplay.py?confId=13497

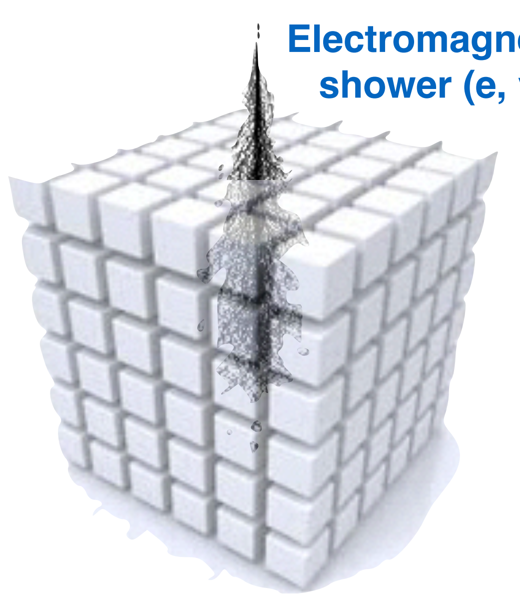
Message

- Everyone is busy, so help is appreciated:
  - Contribute to finalizing data and Nature Scientific Data paper.
  - Collaborate on research.
  - We ask that Dataset paper would be the first, and all work done before DS@HEP WS be collaborative.
- These are large datasets (LCD = 20 GB so far, LArIAT = 20 TB)
  - Distribution and processing require extra thought
  - Code to efficiently read the data should be provided.
- Not clear if we should distribute full running examples… or even collaborative code used for papers.
  - I'll present my packages… open to input and suggestions.
- I feel like I'm often working in a corner may make mistakes.
  - I have lots of questions I have no one to ask.
  - I hope this forum could be a place to share experiences and give advice…

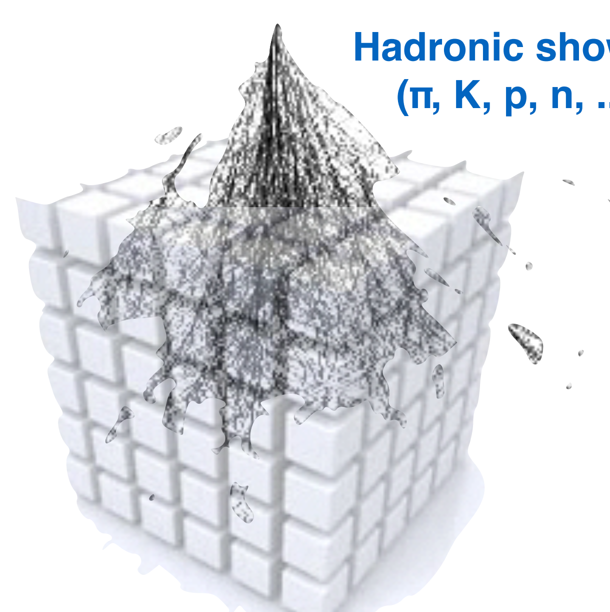
LCD Calorimeter

- CLIC is a proposed CERN project for a linear accelerator of electrons and positrons to TeV energies (~ LHC for protons)
    - Not a real experiment yet, so we) can simulate data and make it public.
    - Simpler geometry than ATLAS…
- The LCD calorimeter is an array of absorber material and silicon sensors comprising the most granular calorimeter design available
    - Data is essentially a 3D image
    - So far several million Pi0, Elec, ChPi, Gamma. 10 to 510 GeV. Low energy and Jet samples planned.
    - ECAL (25x25x25) / HCAL (5x5x60) “window”. Aux info: Energy, …
- First studies, π^0 vs γ classification with various DNNs by summer students.
    - Code/results not collected… but should be easy to redo.
    - New version of dataset.
    - Some visualization code exists… Full running example in CaloDNN.
- Many interesting problems: PID Classification, Energy Regression, Shower generative models.

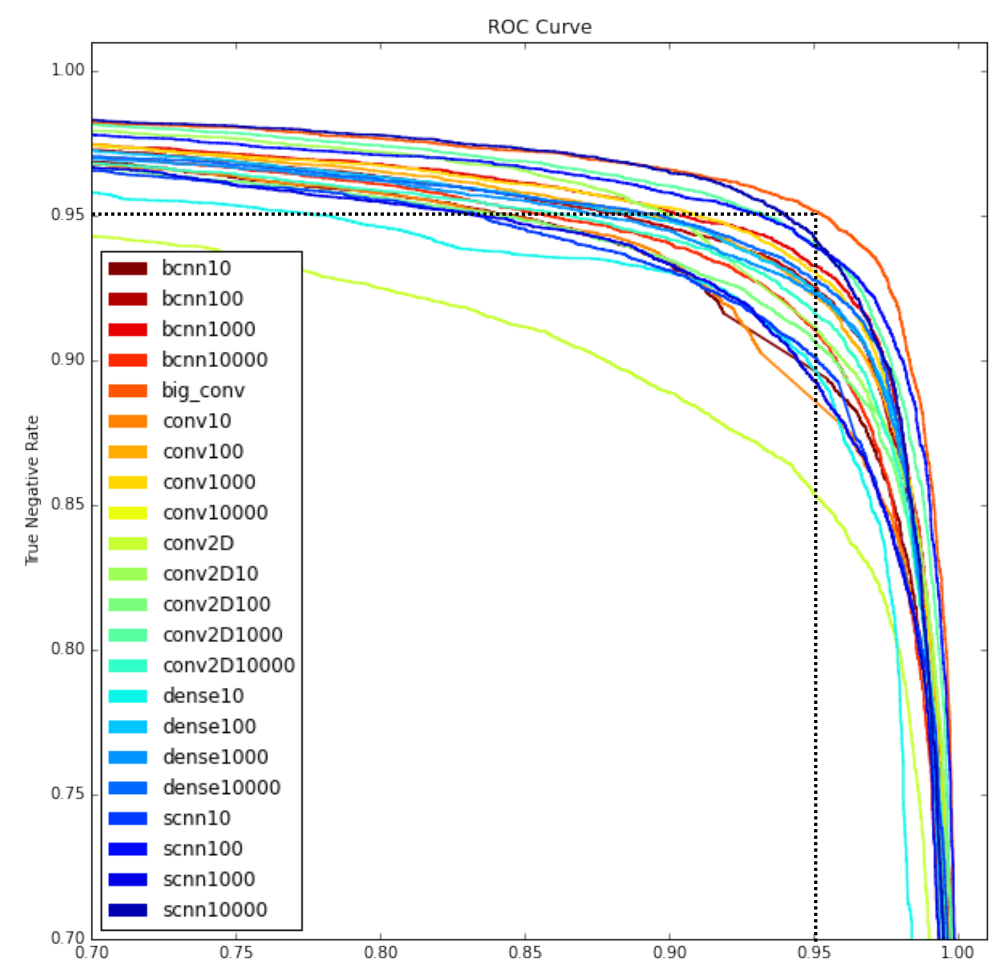




Electromagnetic shower (e, γ)



Hadronic shower (π, K, p, n, ..)



Join the fun….

Imaging calorimeter data for Machine Learning applications in HEP

Josh Bendavid[a] **Kaustuv Datta**[a,b] **Amir Farbin**[c] **Nikolaus Howe**[d,e] **Jayesh Mahapatra**[d] **Maurizio Pierini**[d] **Maria Spiropulu**[a] **Jean-Roch Vlimant**[a]

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[c] *University of Texas at Arlington*
[d] *CERN*
[e] *Williams College*

Photon identifiction and energy measurement with a highly granular calorimeter through Deep Learning

Josh Bendavid[a] **Kaustuv Datta**[a,b] **Amir Farbin**[c] **Nikolaus Howe**[d,e] **Jayesh Mahapatra**[d] **Maurizio Pierini**[d] **Maria Spiropulu**[a] **Jean-Roch Vlimant**[a]

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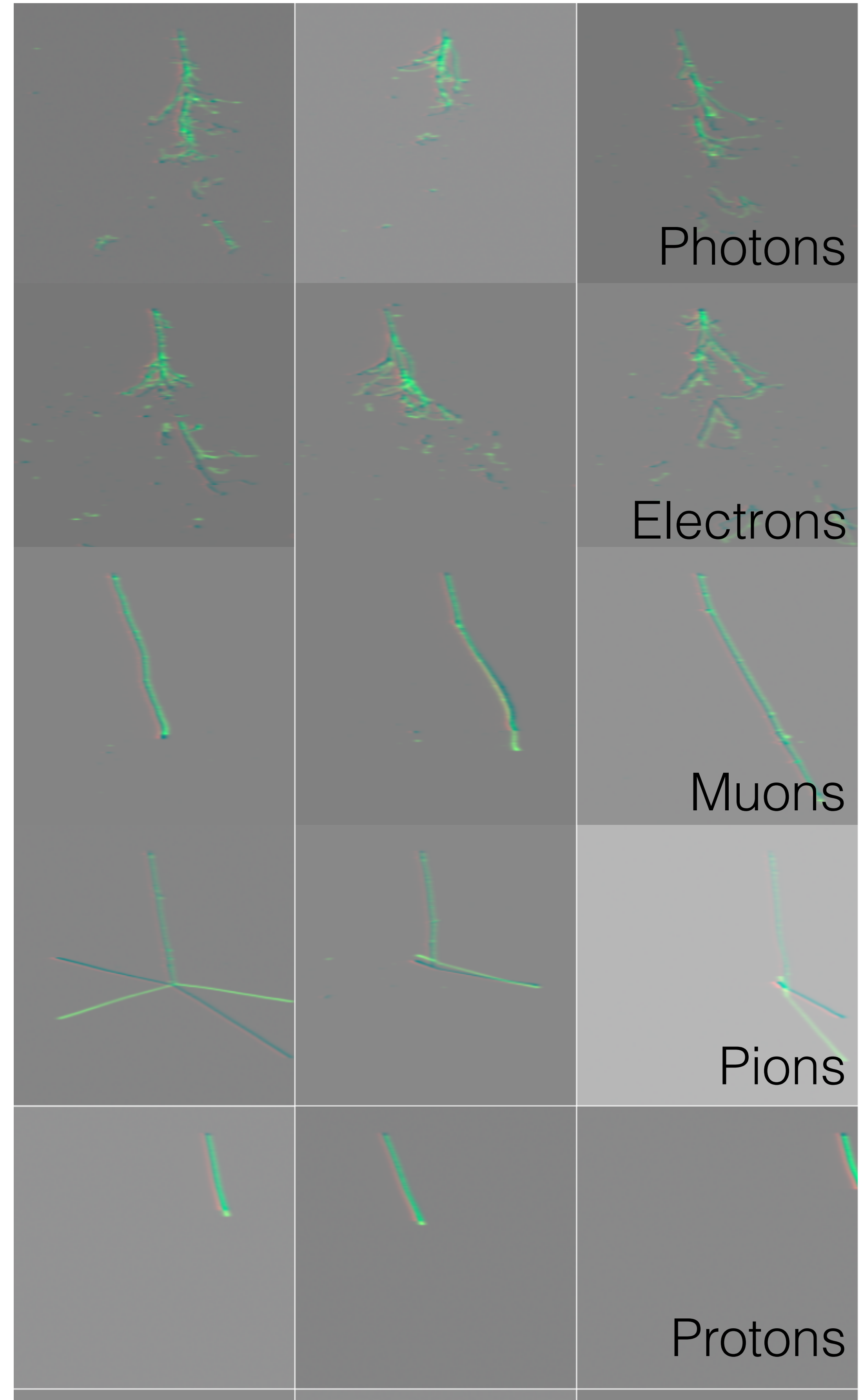
LArIAT Data

- LArIAT is a small LArTPC detector: 2 wire places with 240 wires each, 4096 samples.
- 1 M each of: antielectron, kaonPlus, nue_CC, nutaubar_CC pionMinus, antimuon, nue_NC, nutaubar_NC, pionPlus, antiproton, muon, numubar_CC, nutau_CC, electron, numubar_NC nutau_NC, proton, nuebar_CC, numu_CC, photon, kaonMinus, nuebar_NC, numu_NC, pion_0
- Data: Sim done.
    - Raw ADC readout: 2 x 4096 x 240 (essentially no noise)
    - Geant4 charge deposits. SparseTensor allows creating 3D images of any resolution. (Needs reprocessing of data-prep steps)
    - Aux info: type of interaction, energy, …
- Studies:
    - Preliminary studies very promising.
    - Subsequent work (P. Sadowski + ?) showed impressive classification performance using siamese inception model trained for 1 week.
    - A bit of work on energy regression… not as straightforward.
    - Progress stalled…
- Interesting problems: PID classification, Energy Regression, Compression/ Noise suppression, 2x 2D -> 3D (DNN tomography)

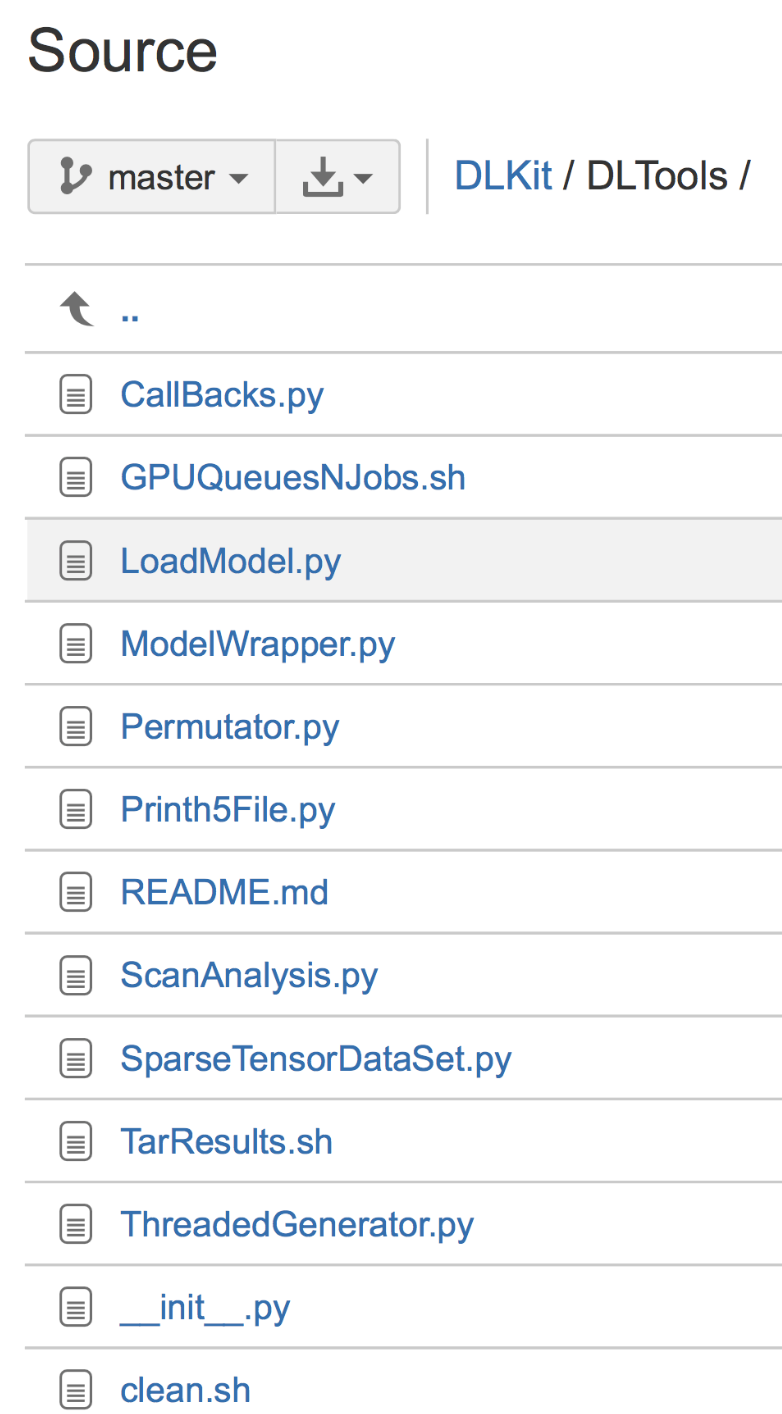


Technical Challenges

- Data comes as many h5 files, each containing O(1000) events, organized into directories by particle type.
- Needs to be read, mixed, “labeled”, and normalized…. can be time consuming.
- Doesn’t fit in memory…
- Very difficult to keep the GPU fed with data. GPU utilization often < 10%, rarely > 50%.
- Keras python generator mechanism:
    - Allows reading on the fly and parallel read
    - Found 2 problems: (Am I crazy?)
        - Multiprocessing requires the generators to be thread_safe, which means putting in a locking mechanism which only allows one process to read the data at a time. So > 2 processes not useful.
        - Easy to mess up and have parallel generator instances deliver overlapping data.
    - LCD data is ~ x10 slower with naive Keras generator vs preloading in memory.
- I wrote a standalone parallel generator: DLKit/ThreadedGenerator:
    - Python Global Interpreter Lock (GIL) allows only one thread to run at a time… so must use multiprocessing.
    - Current implementation: Filler process sends requests (file/block) via multiprocessing queues to workers processes that deliver data to corresponding threads via pipes that feed the generator via thread queues.
    - Bottle neck is the process to thread pipe… data needs to be serialized. Working on share memory solution…
    - Data can be premixed. Premix: ~2x slower than data in memory. Mix as you go: ~4x slower than data in memory.
    - System resources become problem when running many trainings in same system. Working on framework upgrade to simultaneously train several models with same data.

DLKit

- Thin layer on top of Keras.
- My personal DNN framework. I imagine many of you would write something similar…
- Handles book keeping for comparing large number of training sessions (e.g. for hyper parameter scan or optimization)
- Tools necessary to setup HEP problems.
- I have several HEP problems setup using this package:
  - EventClassificationDNN, MEDNN, CaloDNN, LArTPCDNN, …
- Hyperas or Spearmint integration demonstrated, but needs work.
- Keras / MPI Integration also in the works.
- Already ran on BlueWaters and Titan.
- https://bitbucket.org/anomalousai/dlkit/src



CaloDNN/LArTPCDNN

- Instantiates generators for efficiently reading or premixing data.
- Provides out-of-the-box running realistic (not toy) models.
- Orchestrates running large HP scans.
    - Makes tables…
    - Jupyter notebook analysis in works.
- Generates standard plots.
- https://github.com/UTA-HEP-Computing/CaloDNN
- Polishing up package for public…
- Gearing up for a big BlueWaters run…
    - Large HP Scan (not optimization)
    - “Regularization”: training time.

Analysis.py
ClassificationArguments.py
ClassificationExperiment.py
ClassificationScanConfig.py
LCDData.py
Models.py
README.md
ScanJob.py
ScanJob.sh
SubmitMerge.sh
__init__.py
requirements.txt

afarbin — ssh -YX orodruin.uta.edu — 111×29

```
Last login: Tue Feb 28 08:47:35 2017 from 192.168.1.13
afarbin@thecount:~$ cd LCD/DLKit/
afarbin@thecount:~/LCD/DLKit$ source setup.sh
(Keras) afarbin@thecount:~/LCD/DLKit$ python -m CaloDNN.ClassificationExperiment --help
usage: ClassificationExperiment.py [-h] [-C CONFIG] [-L LOADMODEL]
                                   [--gpu GPUID] [--cpu] [--NoTrain]
                                   [--NoAnalysis] [--Test] [-s HYPERPARAMSET]
                                   [--nopremix] [--preload] [-r RUNNINGTIME]

optional arguments:
  -h, --help            show this help message and exit
  -C CONFIG, --config CONFIG
                        Use specified configuration file.
  -L LOADMODEL, --LoadModel LOADMODEL
                        Loads a model from specified directory.
  --gpu GPUID           Use specified GPU.
  --cpu                 Use CPU.
  --NoTrain             Do not run training.
  --NoAnalysis          Do not run analysis.
  --Test                Run in test mode (reduced examples and epochs).
  -s HYPERPARAMSET, --hyperparamset HYPERPARAMSET
                        Use specificed (by index) hyperparameter set.
  --nopremix            Do not use the premixed inputfile. Mix on the fly.
  --preload             Preload the data into memory. Caution: requires lots
                        of memory.
  -r RUNNINGTIME, --runningtime RUNNINGTIME
                        End training after specified number of seconds.
(Keras) afarbin@thecount:~/LCD/DLKit$
```

ScanConfig.py

```
# Input for Premixed Generator
InputFile="/data/afarbin/LCD/LCD-Merged-All.h5"
# Input for Mixing Generator
FileSearch="/data/afarbin/LCD/*/*.h5"

# Generation Model
Config={
    "GenerationModel":"'Load'",
    "MaxEvents":int(3.e6),
    "NTestSamples":100000,
    "NClasses":4,

    "Epochs":1000,
    "BatchSize":1024,

    # Configures the parallel data generator that read the input.
    # These have been optimized by hand. Your system may have
    # more optimal configuration.
    "n_threads":4,  # Number of workers
    "multiplier":2, # Read N batches worth of data in each worker

    # How weights are initialized
    "WeightInitialization":"'normal'",

    # Normalization determined by hand.
    "ECAL":True,
    "ECALNorm":150.,

    # Normalization needs to be determined by hand.
    "HCAL":True,
    "HCALNorm":150.,
```

```
    # Set the ECAL/HCAL Width/Depth for the Dense model.
    # Note that ECAL/HCAL Width/Depth are changed to "Width" and "Depth",
    # if these parameters are set.
    "HCALWidth":32,
    "HCALDepth":2,
    "ECALWidth":32,
    "ECALDepth":2,

    # No specific reason to pick these. Needs study.
    # Note that the optimizer name should be the class name (https://keras.io/optimizers/)
    "loss":"'categorical_crossentropy'",

    # Specify the optimizer class name as True (see: https://keras.io/optimizers/)
    # and parameters (using constructor keywords as parameter name).
    # Note if parameter is not specified, default values are used.
    "optimizer":"'SGD'",
    #"lr":0.01,
    #"decay":0.001,

    # Parameter monitored by Callbacks
    "monitor":"'val_loss'",

    # Active Callbacks
    # Specify the CallBack class name as True (see: https://keras.io/callbacks/)
    # and parameters (using constructor keywords as parameter name,
    # with classname added).
    "ModelCheckpoint":True,
    "Model_Chekpoint_save_best_only":False,

    # Configure Running time callback
    # Set RunningTime to a value to stop training after N seconds.
    "RunningTime": 3600,
}
```

```

# Parameters to scan and their scan points.
Params={ "Width":[32,64,128,256,512],
         "Depth":range(1,5),
         "lr":[0.1,0.01,0.001],
         "decay":[0.1,0.01,0.001],
          }

```