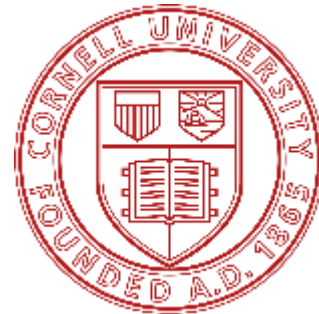


Dual-Readout Calorimetry Signal Analysis with Neural Networks

Murali Saravanan



Overview

- Dual-Readout Calorimetry Recap
- Current Results
 - Part I: Monte Carlo Simulations
 - Part II: Real Data
 - Part III: hls4ml
- Future Steps

The LHC and Calorimetry

- Calorimeters are responsible for energy measurement in ATLAS, CMS, and various particle detectors
- **Hadronic** and Electromagnetic Calorimetry
 - ↳ protons, pions, and fragmenting quarks and gluons

Hadronic Calorimetry

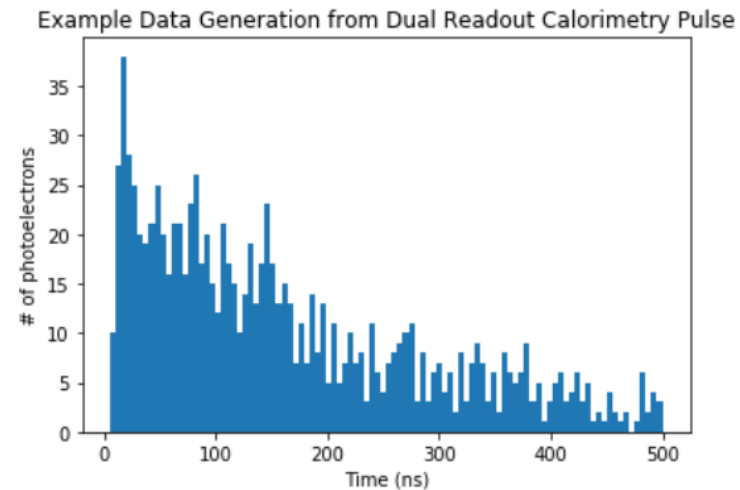
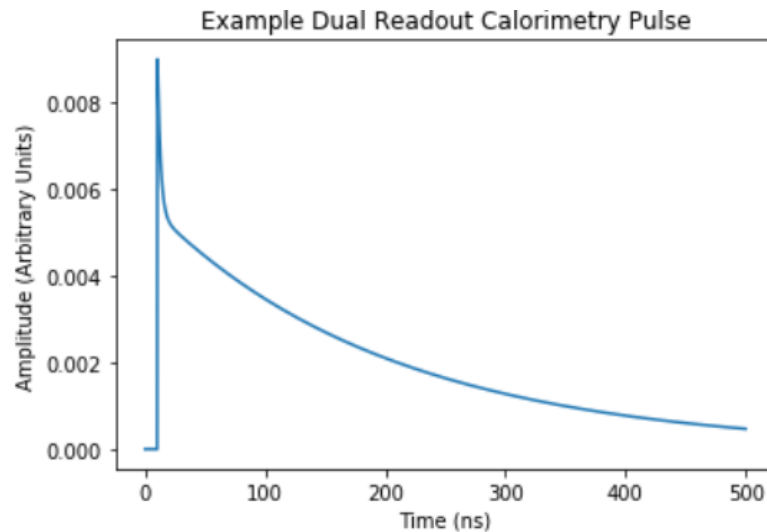
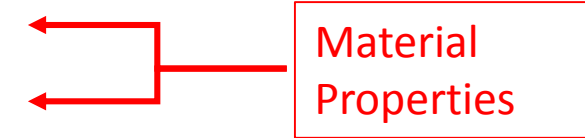
- Measure em and non-em components
 - Huge fluctuations in em component (up to 40%) on event-by-event basis
- Different calorimeter materials respond to em and non-em differently. Use response curves but this works on average

Dual Readout Calorimetry Recap

- Measure both Cerenkov and Scintillation radiation to achieve em energy resolution on event-by-event basis
 - Amount of Cerenkov/Scint light can be tweaked by materials and geometry of physical calorimeter
- Huge improvement for hadronic energy resolution, would be useful in future colliders (FCC, ILC, CLIC)

Single Channel Readout?

- Single Channel saves overhead
- Four parameters vary
 1. Ratio of Cerenkov/Scintillation Radiation (Area)
 2. Scintillation Decay Rate
 3. Photoelectron Count
 4. Digitizer Freq/Bin Number



Using NN

- NN is constant time
- Predict two parameters
 1. Cerenkov pulse area
 2. Scintillation pulse area

Layer (type)	Output Shape	Param #
dense_5 (Dense)	(None, 10)	1010
dense_6 (Dense)	(None, 2)	22

=====
Total params: 1,032
Trainable params: 1,032
Non-trainable params: 0
=====
None

Part 1: Monte Carlo Simulated Data

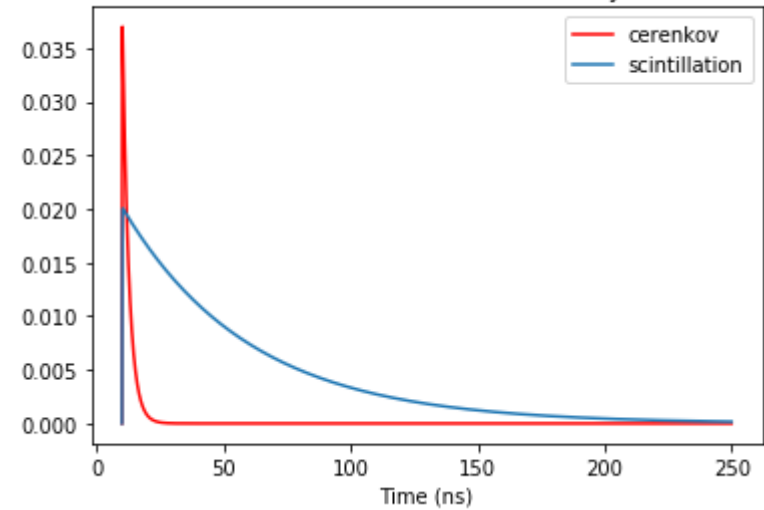
Monte-Carlo Generation of Data

- Modify:
 - Ratio
 - 10-> 10x more area of Cerenkov than Scintillation
 - -10-> 10x more area of Scintillation than Cerenkov
 - Scintillation Decay
 - Photoelectron Count
 - Binning
- Generate a library of histograms, varying the above parameters to create different experiments
- Create many events per experiment to create needed random fluctuations

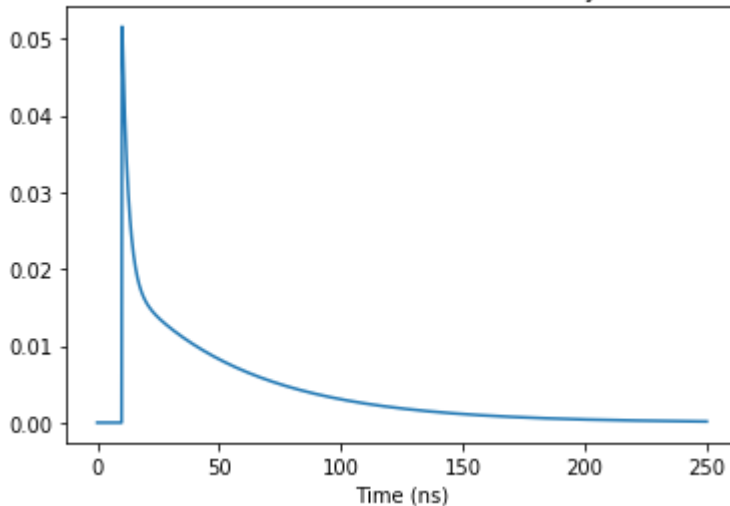
Example Pulse

- Vary Ratio between -25 and 25
- Vary Scint Decay from 15ns to 50ns
- 1k-5k photoelectrons
- 30, 100, 300 bins

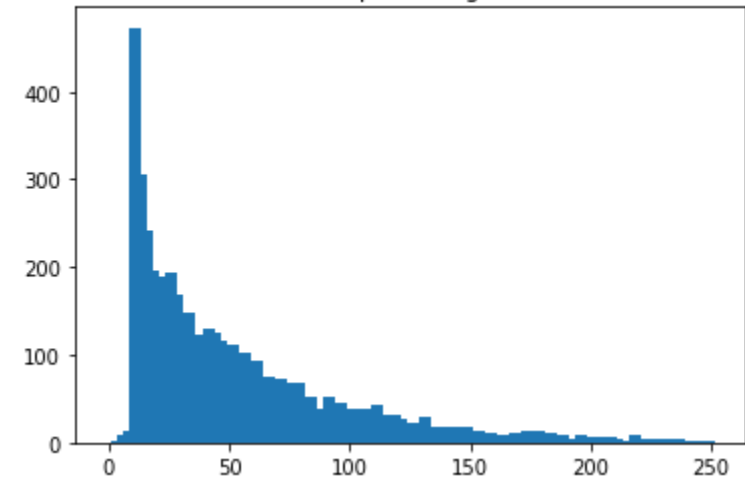
Pulse with ratio 0.1 and scint decay 50

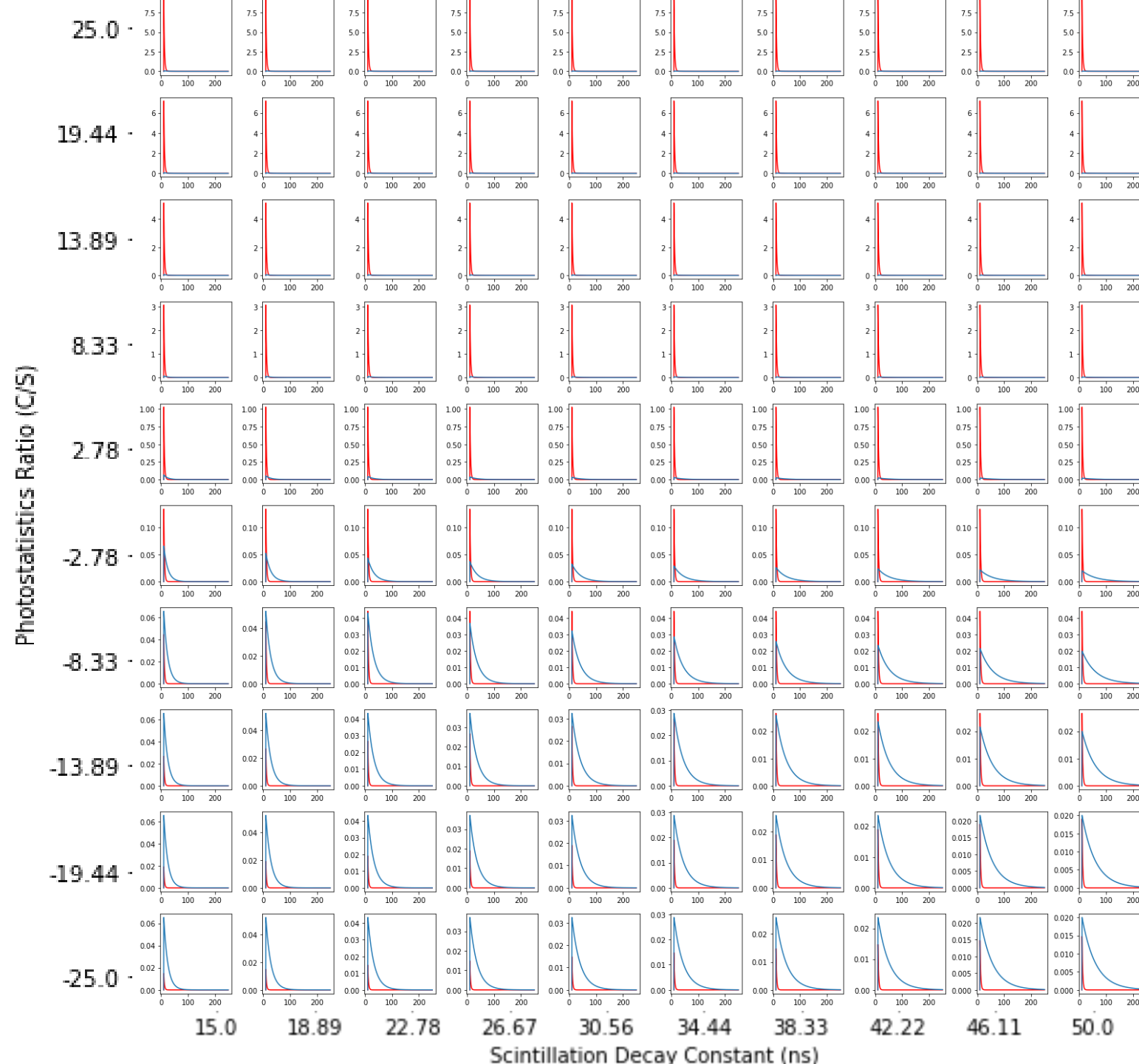


Pulse with ratio 0.1 and scint decay 50

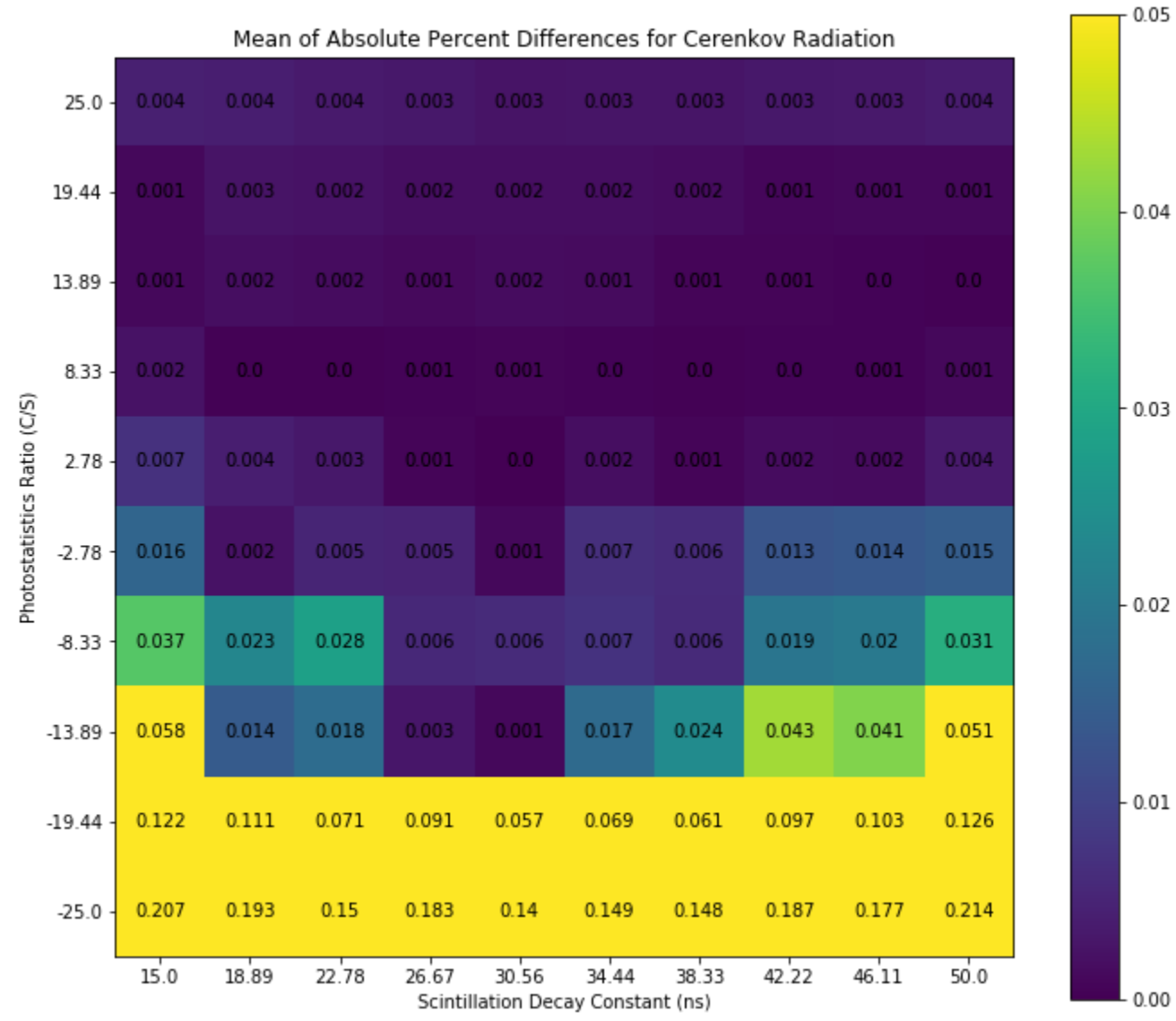
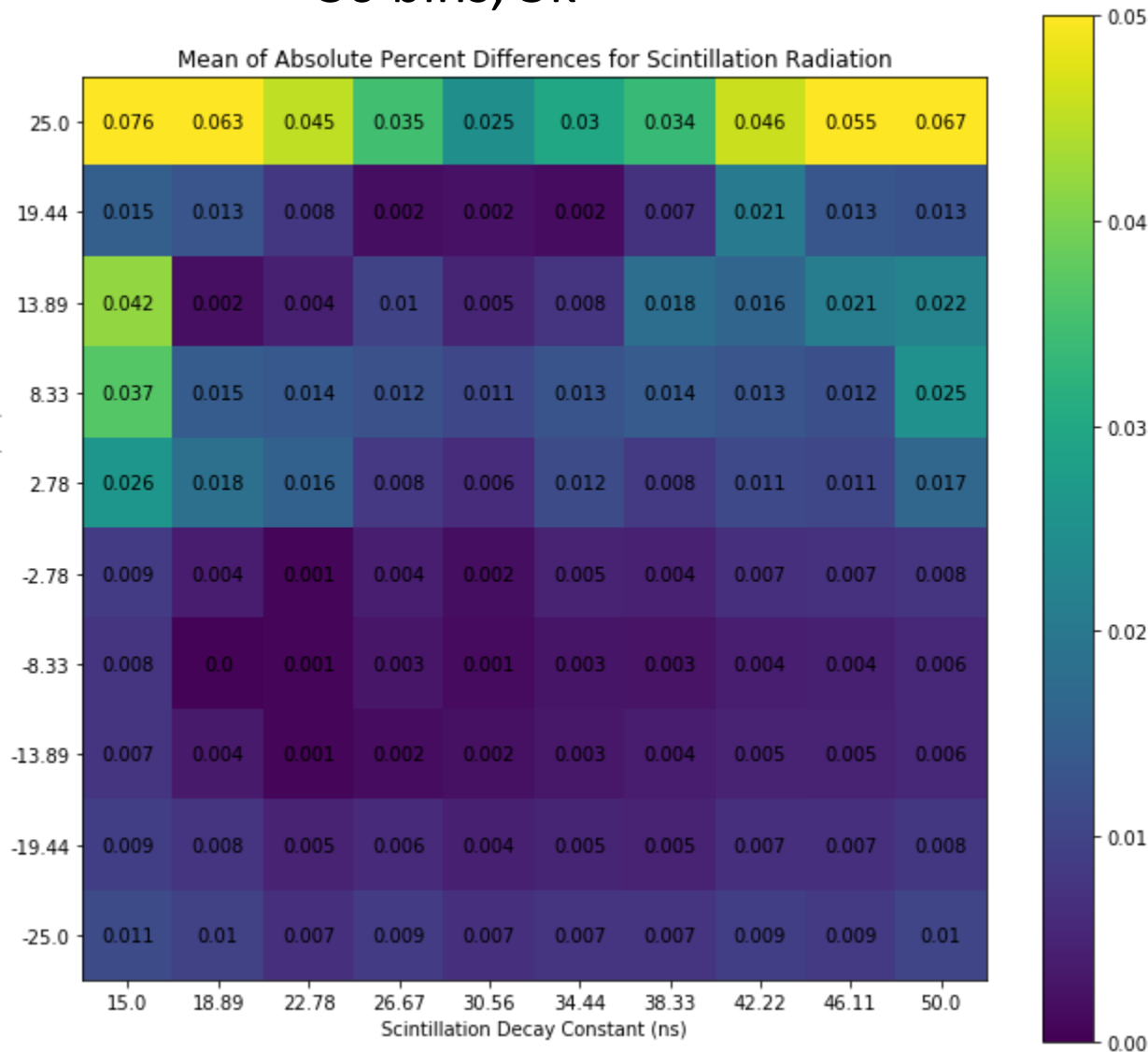


Example Histogram





- Vary digitizer freq and photostatistics
- 30 bins, 5k



Part I Conclusions

- Major dependence is on ratio and not scintillation decay time
- Higher photoelectron count gives better results
 - Gradual change over 1k-5k photoelectrons range (no tipping point)
- Higher digitizer freq \neq better prediction
 - Low freq hides the effects of fluctuations
- Scintillation prediction is much more stable than Cerenkov prediction

Part 2: Real Data

Dual Cherenkov and Scintillation Response to High-Energy Electrons of Rare-Earth-Doped Silica Fibers

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Real Data

- response of Ce-doped silica fibers exposed to electrons in the 20–200-GeV
- What does a realistic pulse look like? What is the actual ratio of C/S? Expected photoelectron count?

Average Pulse

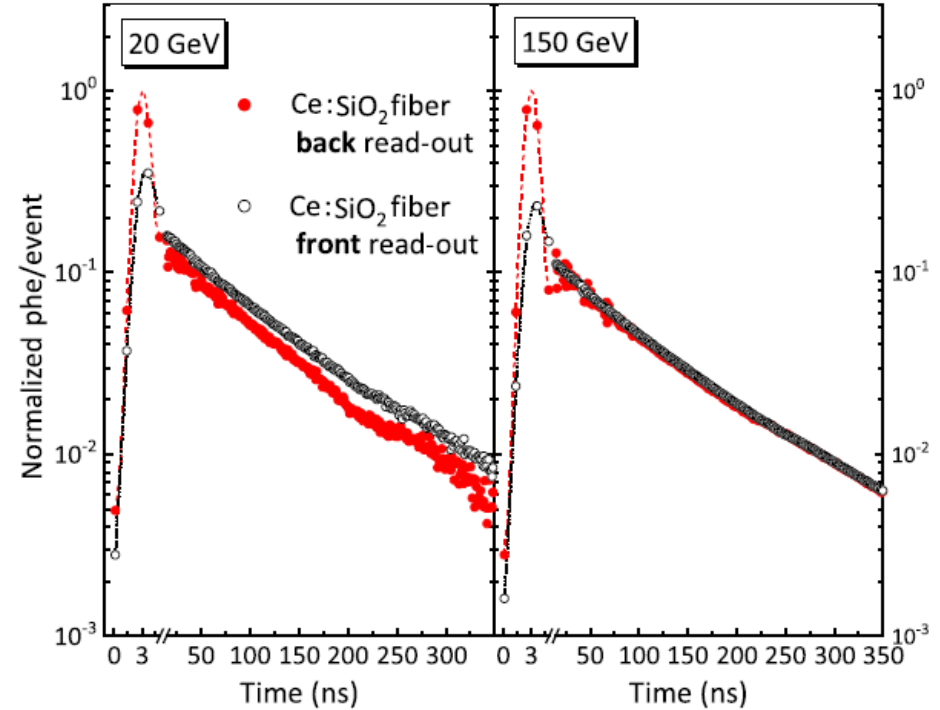
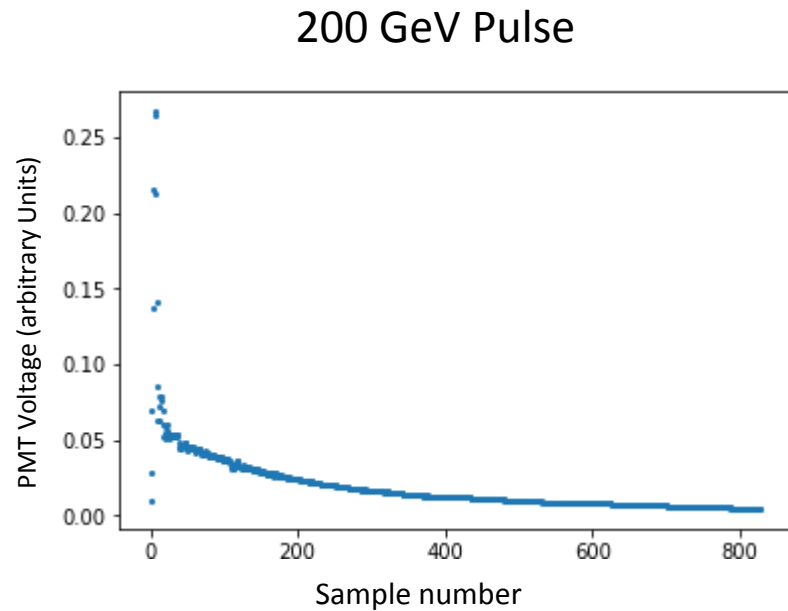
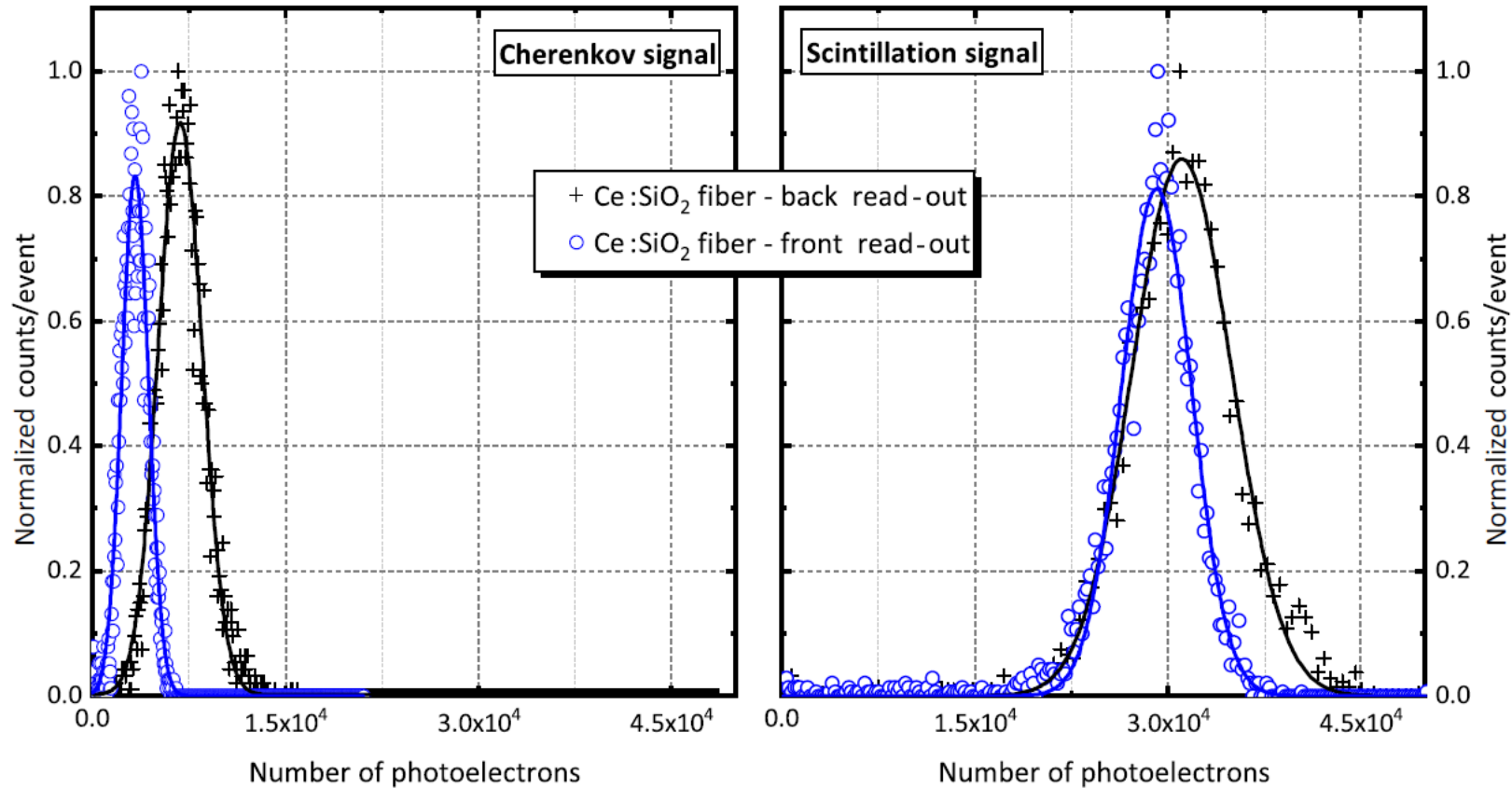
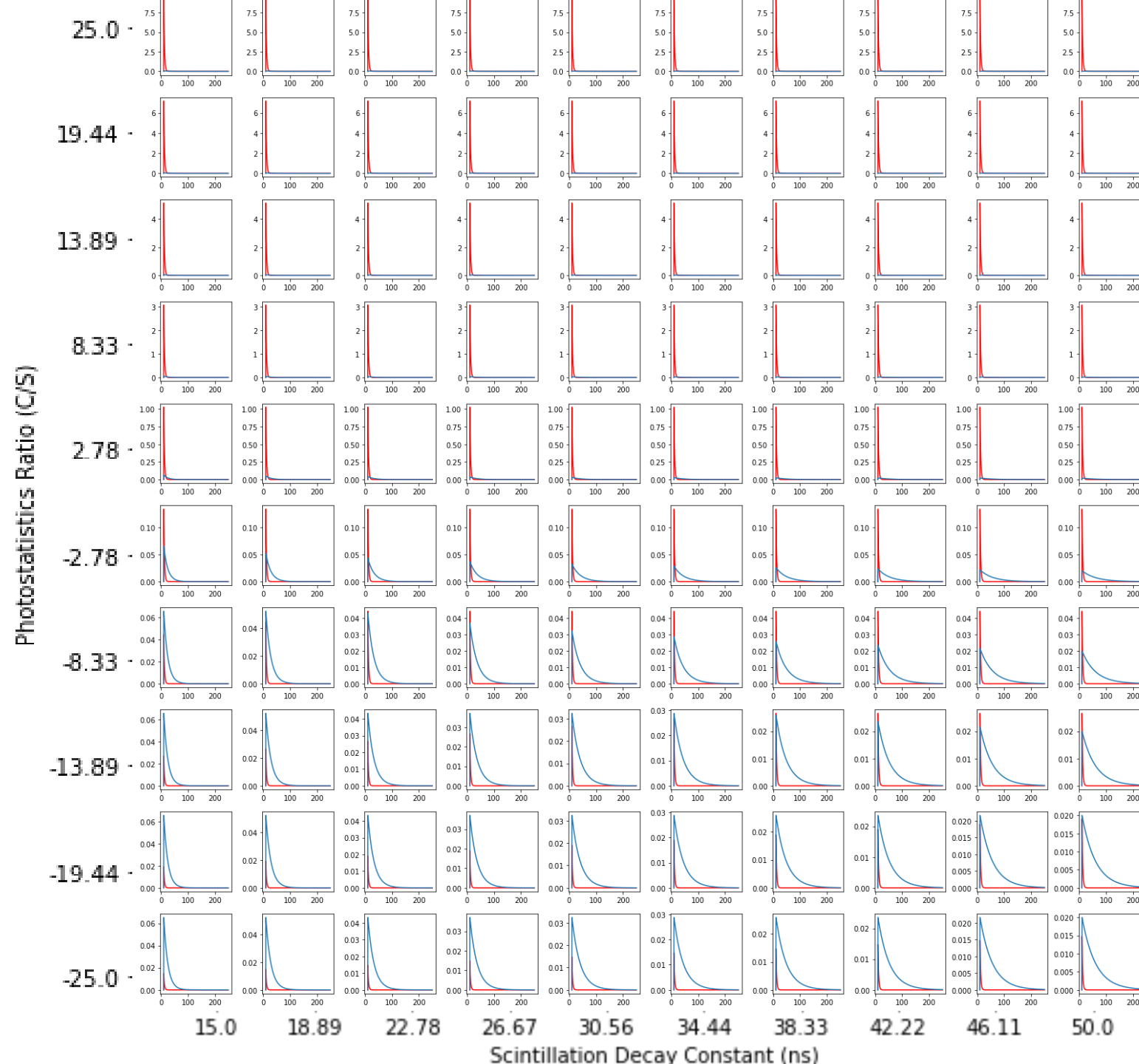


FIG. 6. Average pulse shape normalized to the number of events for Ce:SiO₂ fibers for a 20-GeV electron beam (left panel) and a 150-GeV electron beam (right panel). Back and front read-out are compared. The dashed lines are guides for the eye. phe, photoelectrons.

Photoelectron Count

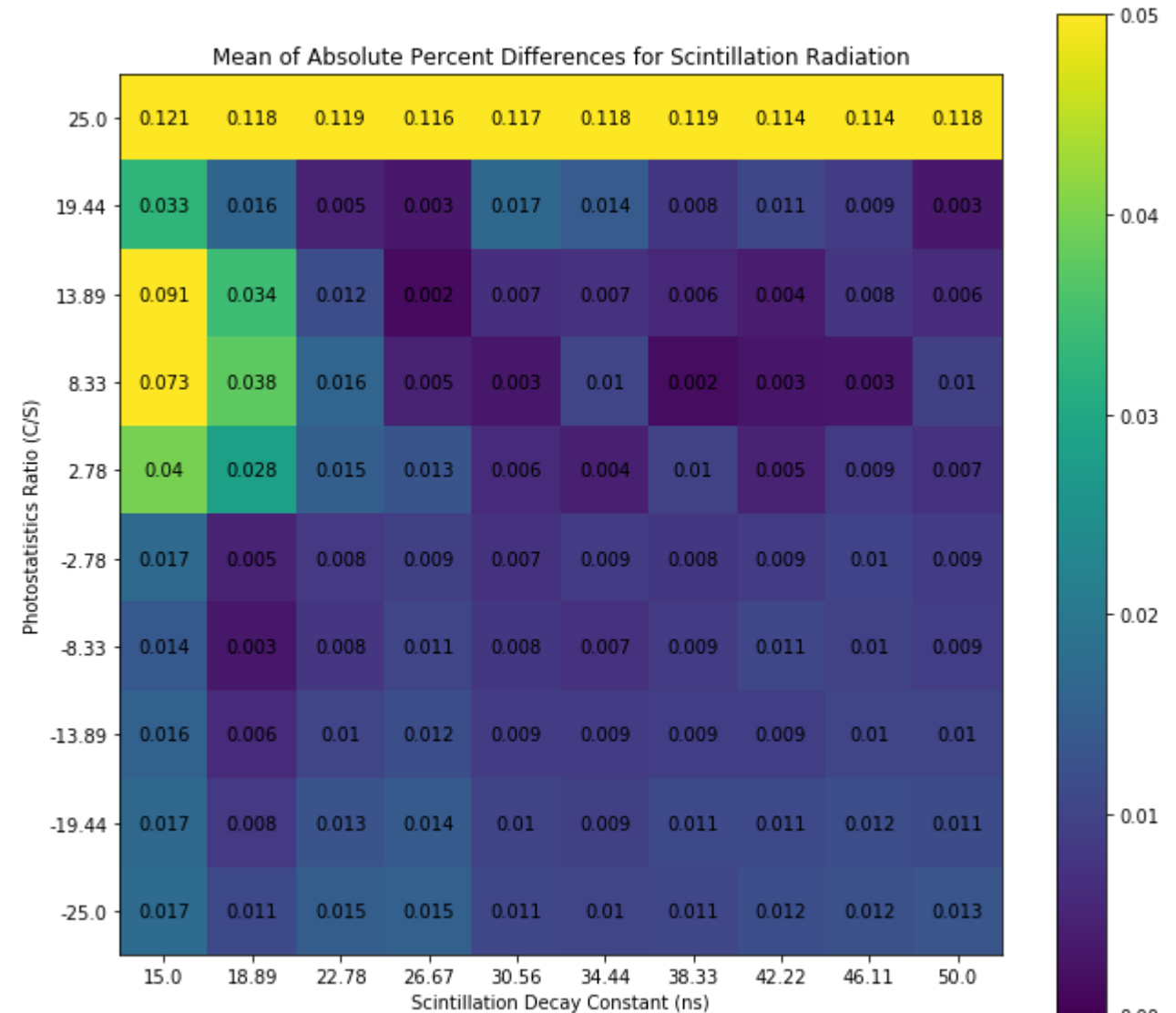
- 7.5k for Cerenkov, 30k for Scintillation (ratio=-4)





Monte Carlo results in this area

- With 5,000 photoelectrons and 100 bins, possibility of less than 1% error



Real Data NN

- In progress!
- Need to consistently clean data

Part 3: Implementation on FPGAs

Intro to FPGAs

- Multiplier Units
 - Does arithmetic
- Flip Flops
 - Short term memory registers
- Wire algorithms into board
- High Level Synthesis (HLS) is the language that Xilinx FPGAs use

hls4ml

- Takes NN and creates HLS implantation that provides resource usage estimates
- Up to 6,000 parallel operations=# of multiplication units=max # of nodes and weights in NN if we aim for one clock cycle per analysis
- Can trade latency for lower resource usage

Preliminary Results

- 100 bin Model with 5ns goal

Synthesis Report for 'testModel'

General Information

Date: Tue Apr 9 15:50:37 2019
Version: 2017.2 (Build 1909853 on Thu Jun 15 18:55:24 MDT 2017)
Project: testModel_prj
Solution: solution1
Product family: kintexu
Target device: xcku115-flvb2104-2-i

Performance Estimates

Timing (ns)

Summary

Clock	Target	Estimated	Uncertainty
ap_clk	5.00	4.37	0.63

Latency (clock cycles)

Summary

Latency		Interval		Type
min	max	min	max	
4	4	1	1	function

Detail

Instance

Loop

Utilization Estimates

Preliminary Results

- hls4ml in general provides an overestimate of resource usage

Utilization Estimates

▣ **Summary**

Name	BRAM_18K	DSP48E	FF	LUT
DSP	-	-	-	-
Expression	-	-	0	6
FIFO	-	-	-	-
Instance	-	718	19902	16648
Memory	-	-	-	-
Multiplexer	-	-	-	36
Register	-	-	1766	-
Total	0	718	21668	16690
Available	4320	5520	1326720	663360
Available SLR	2160	2760	663360	331680
Utilization (%)	0	13	1	2
Utilization SLR (%)	0	26	3	5

- Can prune unnecessary nodes from intermediate layer to decrease resource usage

Project Conclusions

- Dual Readout Calorimetry is promising for improving resolution of em-portion of hadronic energy on an event-by-event basis
- Neural Networks can be implemented into FPGAs for low latency inference in **single channel** dual readout calo
 - Small networks are adequate
- Simulated performance of NNs can be used to inform the geometry/construction of the calorimeters and the associated hardware

Project Conclusions

**Single Channel Dual Readout Calorimetry can work
thanks to Neural Networks**

Future Steps

- Produce NN results on real data
- Look at implementation on real FPGA

Questions?