

Full Detector Simulation of Pair Monitor and Machine Learning

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December 6, 2019

Overview

- 1 Pair Monitor
- 2 DNN
 - CNN
- 3 Try out with MNIST data
- 4 My data with 4×4 classes
- 5 My data with 5×5 classes
- 6 To Do List

Pair Monitor: Principle

- Many low energy e^+e^- pairs are created during Beam Crossing due to $\gamma\gamma \rightarrow e^+e^-$, $e^\pm \rightarrow e^\pm e^+e^-$ and $e^+e^- \rightarrow e^+e^-e^+e^-$ processes.
- particles with same charge as that of the beam are deflected at a larger angle
- Beam size can be measured using the deflection pattern
- In the current study, incoherent pair particles were simulated by CAIN

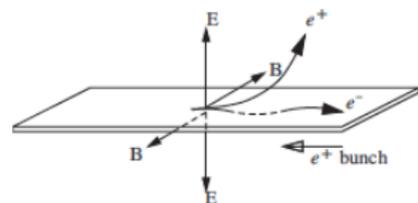


Figure 1: e^+e^- pair creation and deflection of the "same" charged particle^[1]

Pair Monitor at ILD

- Pair Monitor has not been implemented inside the ILD framework
- The first layer of BeamCal can fully mimic the Pair Monitor signals
- The midpoint of the first two positions of energy contribution step inside the first layer of BeamCal has been taken to be the signal.
- Detector simulation has been carried out by using DD4HEP package using ILD-I05-v05 configuration

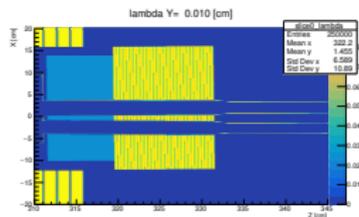


Figure 2: BeamCal view from Y perpendicular region

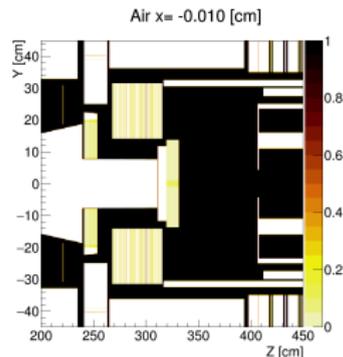
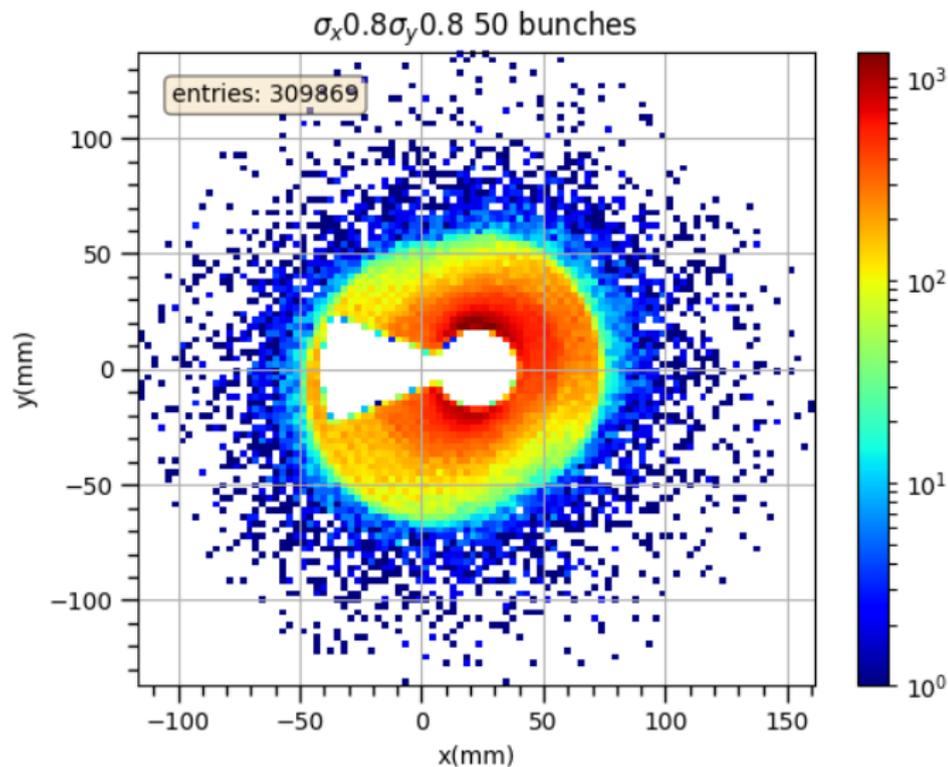


Figure 3: FCal region in ILD framework [2]

Position Distribution of the energy contribution

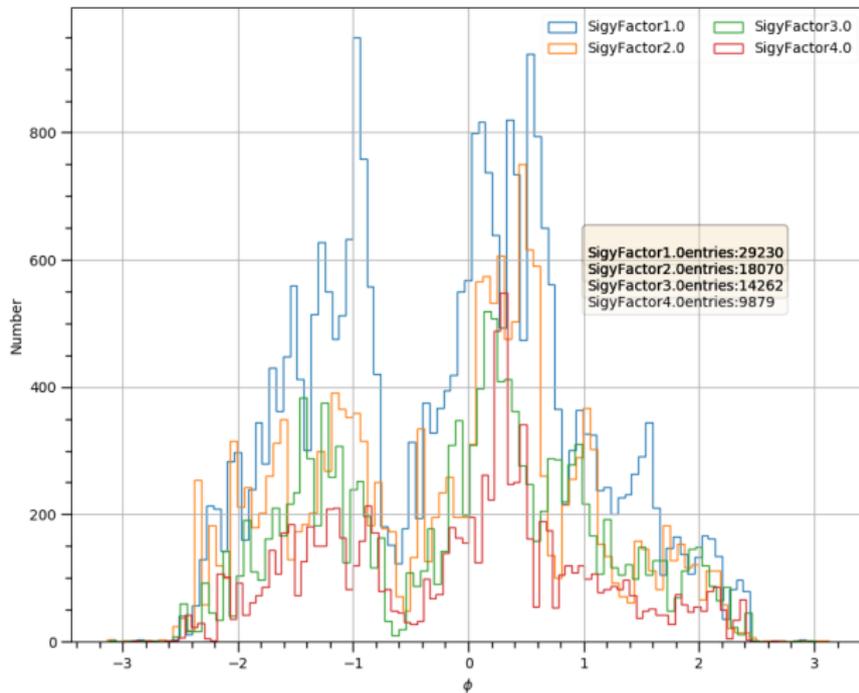


Parameters Used

- Simulation has been carried out for two sets of parameters
- set 1: 4×4 values of σ_x, σ_y : 1,2,3,4
- set 2: 5×5 values of σ_x, σ_y : 0.8, ..., 1.6 with a step of 0.2

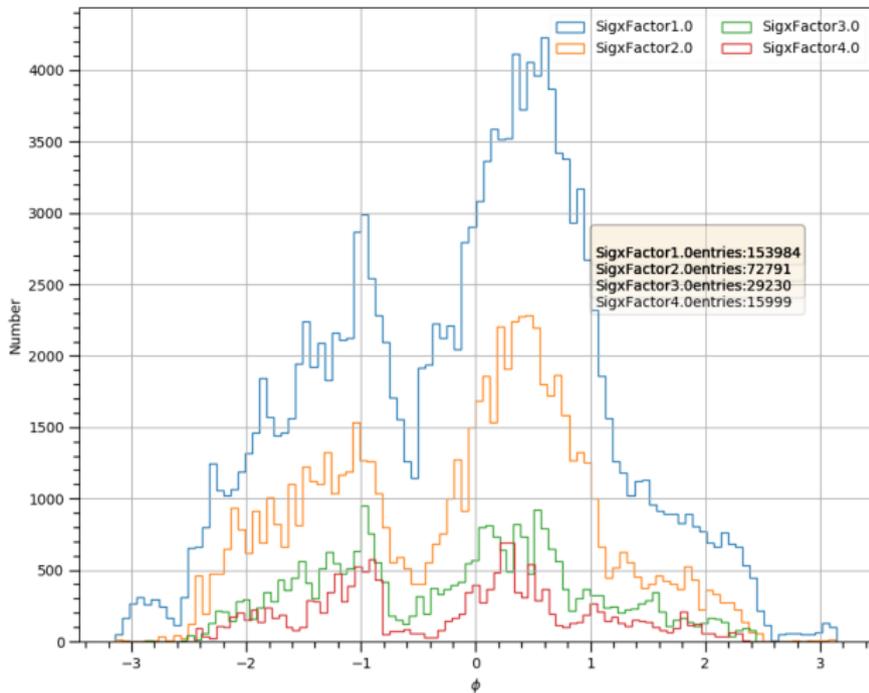
Set 1: ϕ plots for constant σ_x (factor 1.0)

ϕ Plots BeamCal_z>0 Positron 50 bunches



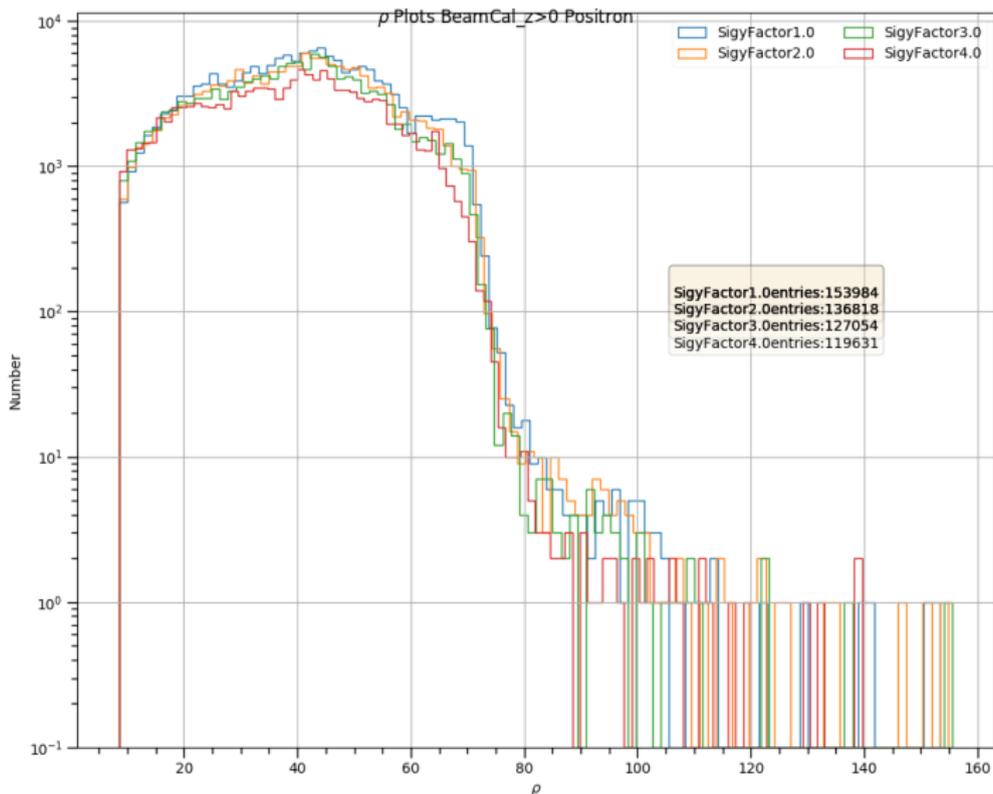
Set 1: ϕ plots for constant σ_y (factor 1.0)

ϕ Plots BeamCal_z>0 Positron 50 bunches

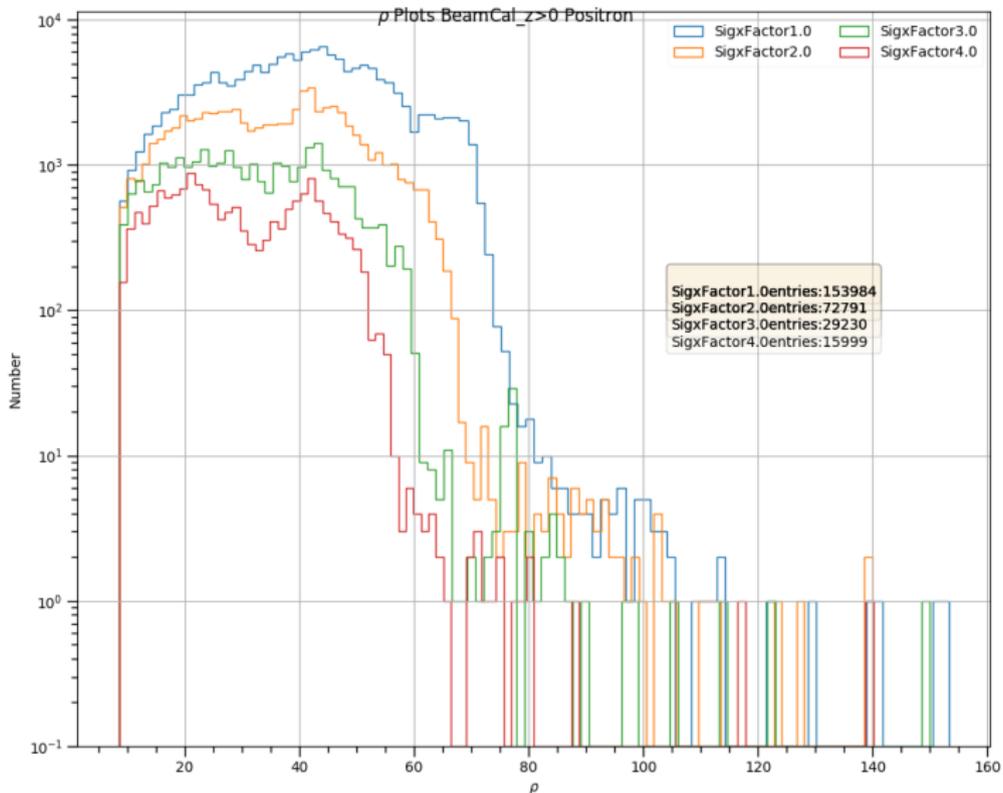


Set 1: ρ plots for constant σ_x (factor 1.0)

$$\rho = \sqrt{x^2 + y^2}$$

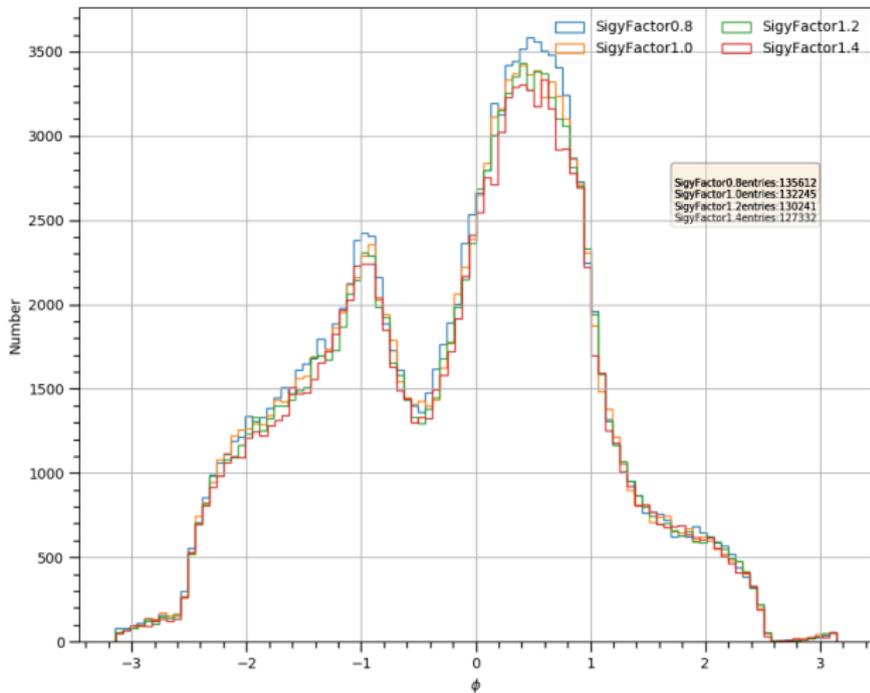


Set 1: ρ plots for constant σ_y (factor 1.0)



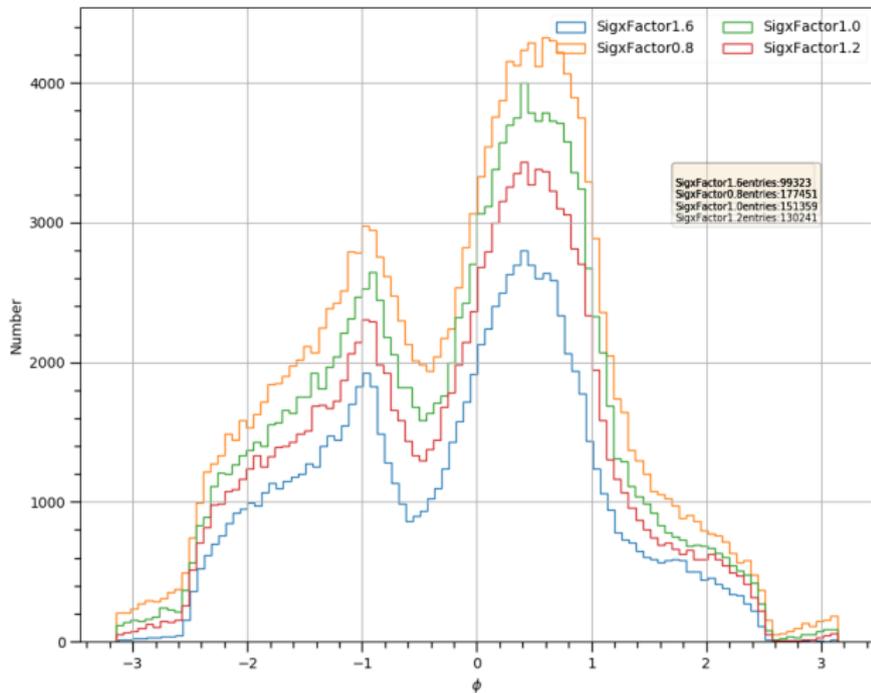
Set 2: ϕ plots for constant σ_x (factor 1.0)

ϕ Plots BeamCal_z>0 Positron 50 bunches



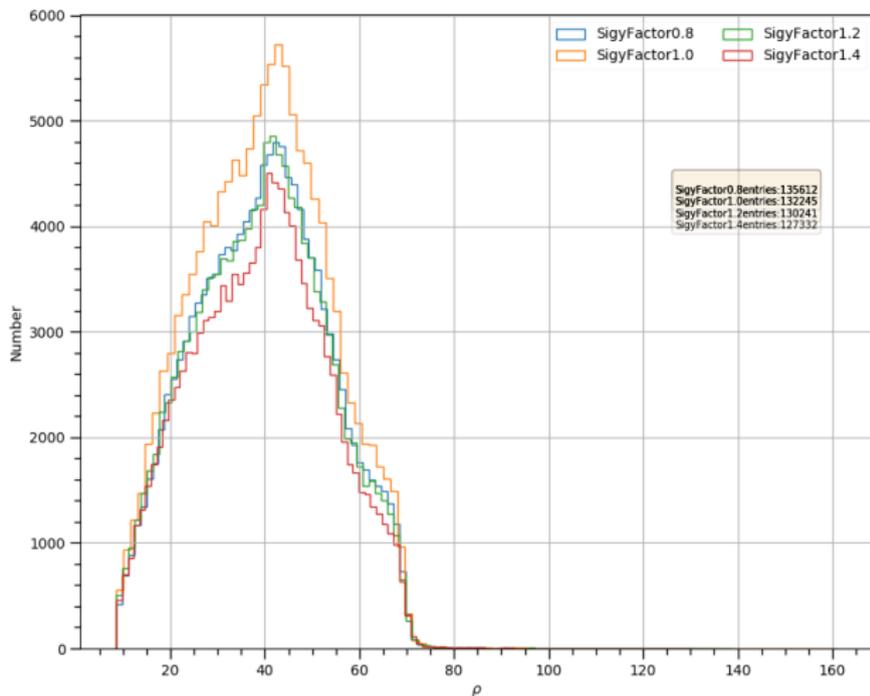
Set 2: ϕ plots for constant σ_y (factor 1.0)

ϕ Plots BeamCal_z>0 Positron 50 bunches



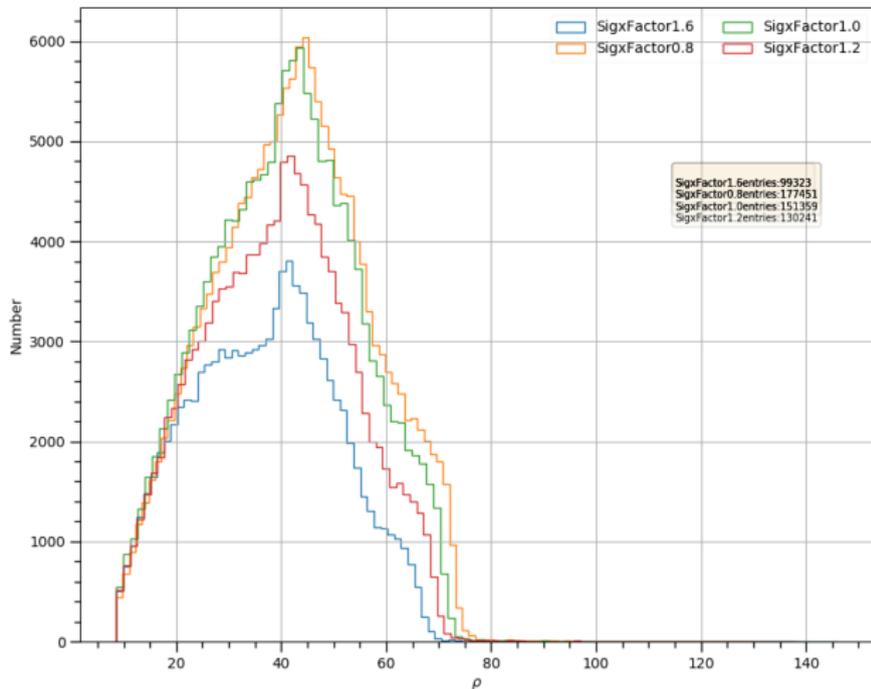
Set 2: ρ plots for constant σ_x (factor 1.0)

ρ Plots BeamCal_z>0 Positron 50 bunches



Set 2: ρ plots for constant σ_y (factor 1.0)

ρ Plots BeamCal_z>0 Positron 50 bunches



CNN Architecture

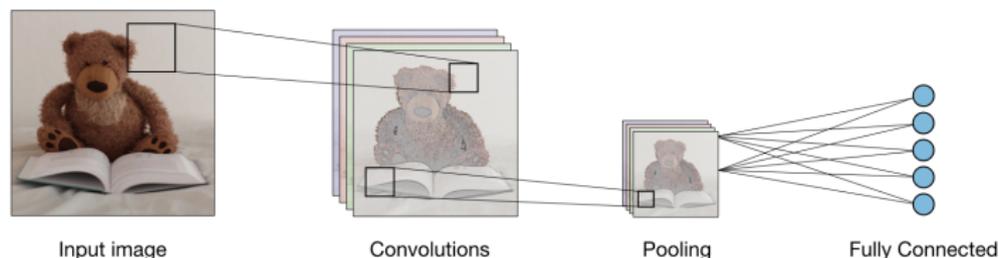


Figure 4: CNN architecture^[2]

Types of layers:

- Conv Layer: uses filters that perform convolution operations as it is scanning the input I with respect to its dimensions. Hyper parameters: Filter size F and Stride S
- Max Pooling: Maximum value within a filter is collected
- Fully connected (FC): operates on a flattened input where each input is connected to all neurons

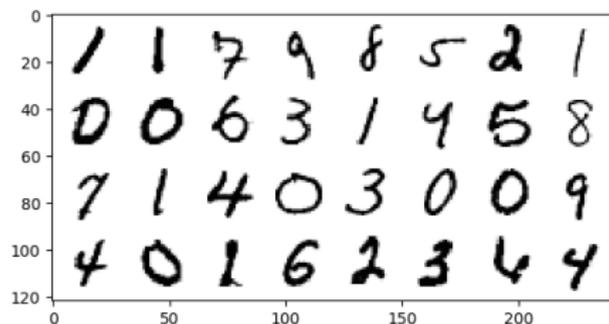
- Activation Function: ReLU (Rectified Linear Unit), defined by $g(z) = \max(0, z)$ non-linearity has been applied after every Conv and FC layers.
- Softmax: takes as input a vector of scores $x \in \mathbb{R}^n$ and outputs a vector of output probability $p \in \mathbb{R}^n$ $p = (p_1 \dots p_n)$ where $p_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$
- Softmax Cross Entropy: $CE = -\sum_i^C t_i \log(f(s_i))$ where t_i is the true label and $f(s_i)$ is the softmax output. For two classes:
$$CE = -\sum_{i=1}^{C=2} t_i \log(f(s_i)) = -t_1 \log(f(s_1)) - (1 - t_1) \log(1 - f(s_1))$$
- Each sample can belong to ONE of C classes. The CNN will have C output neurons that can be gathered in a vector s (Scores). The target (ground truth) vector t will be a one-hot vector with a positive class and $C - 1$ negative classes.

- PyTorch is a deep learning framework designed by Facebook AI
- CNN has been carried out using pytorch
- Some tools from SkLearn has been used for visualization and data division

The logo for PyTorch, featuring the word "PYTORCH" in a bold, black, sans-serif font. The letter "O" is replaced by a stylized orange flame icon with a small purple dot at its tip.

Testing by MNIST data

- MNIST data are handwritten digits and have 10 labels
- They are used as standards to make sure code is running properly



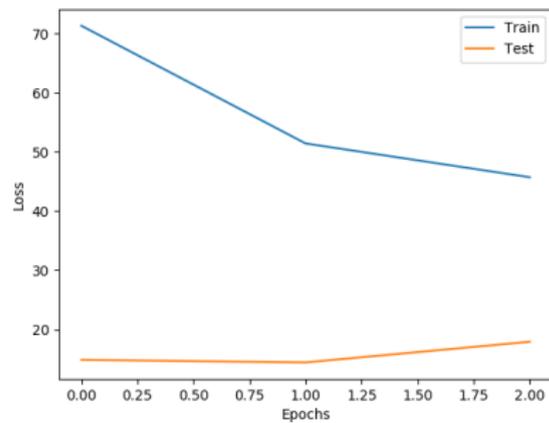
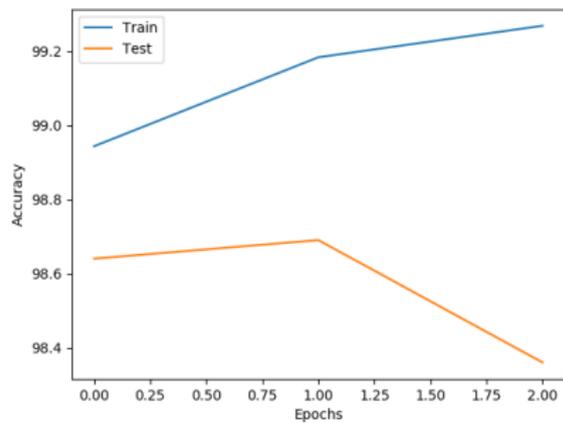
Architecture used

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 28, 28]	640
ReLU-2	[-1, 64, 28, 28]	0
Conv2d-3	[-1, 64, 28, 28]	36,928
ReLU-4	[-1, 64, 28, 28]	0
MaxPool2d-5	[-1, 64, 14, 14]	0
Linear-6	[-1, 1024]	12,846,080
ReLU-7	[-1, 1024]	0
Linear-8	[-1, 512]	524,800
ReLU-9	[-1, 512]	0
Linear-10	[-1, 10]	5,130

=====
Total params: 13,413,578
Trainable params: 13,413,578
Non-trainable params: 0
=====

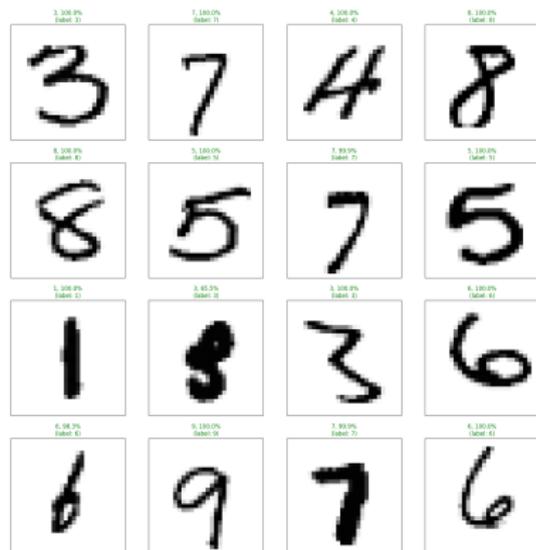
Input size (MB): 0.00
Forward/backward pass size (MB): 1.65
Params size (MB): 51.17
Estimated Total Size (MB): 52.82
=====

Loss Accuracy

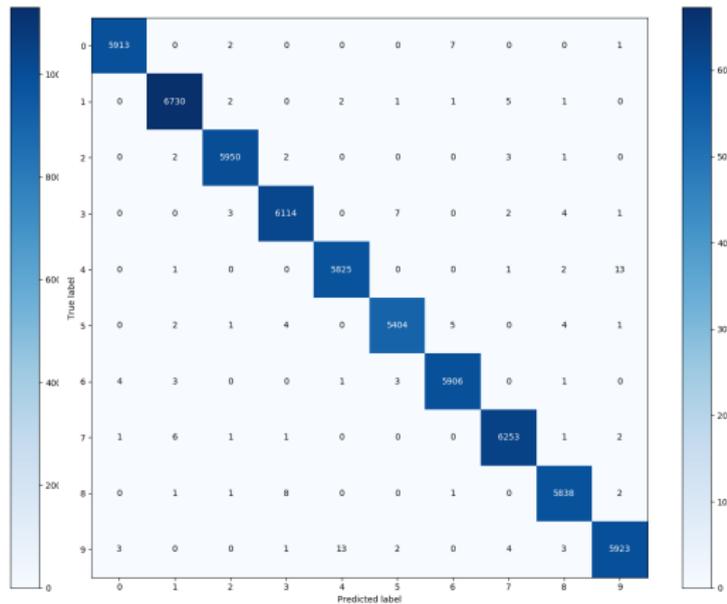
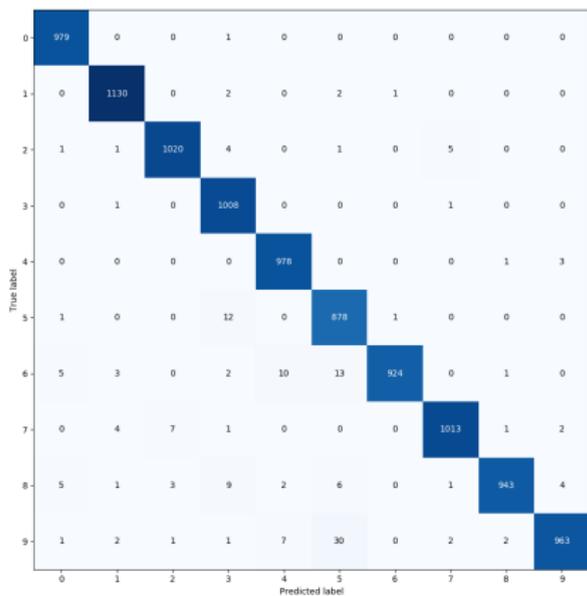


Viewing predictions on random batches

- MNIST data are handwritten digits and have 10 labels
- They are used as standards to make sure code is running properly
- The figure shows the labeled and predicted images from random batches

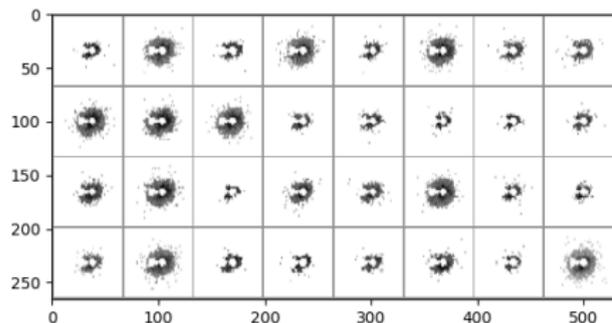


Confusion Matrix: Test and Train



Testing by Set1 data

- Several images from different classes are shown in grid
- Set 1 data which contains 16 labels have strong signals



Architecture used

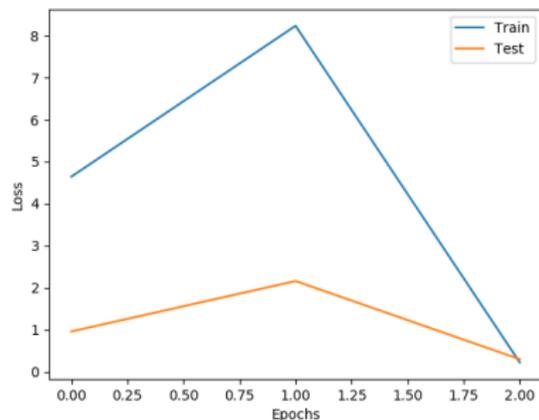
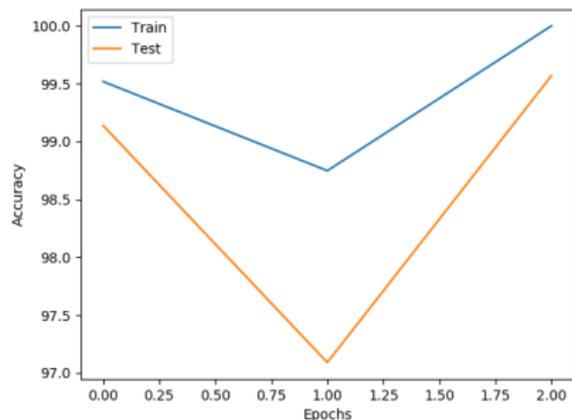
Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 64, 64]	640
ReLU-2	[-1, 64, 64, 64]	0
Conv2d-3	[-1, 64, 64, 64]	36,928
ReLU-4	[-1, 64, 64, 64]	0
MaxPool2d-5	[-1, 64, 32, 32]	0
Linear-6	[-1, 1024]	67,109,888
ReLU-7	[-1, 1024]	0
Linear-8	[-1, 512]	524,800
ReLU-9	[-1, 512]	0
Linear-10	[-1, 16]	8,208

=====
Total params: 67,680,464
Trainable params: 67,680,464
Non-trainable params: 0
=====

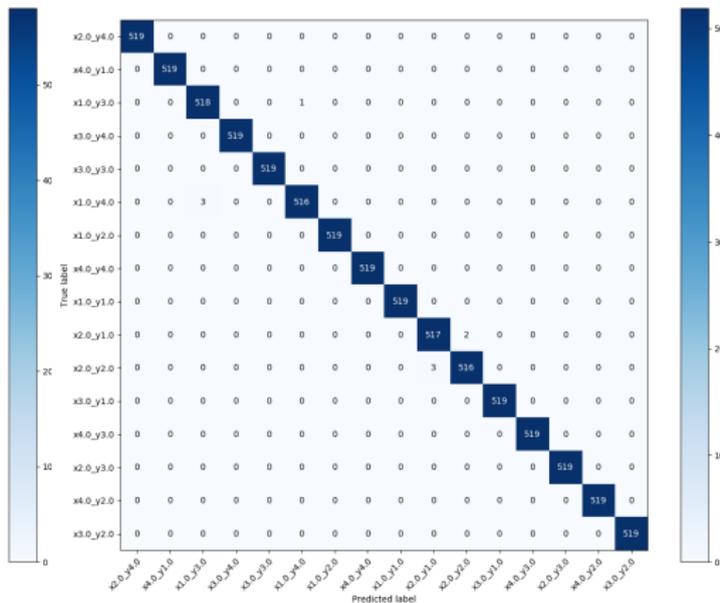
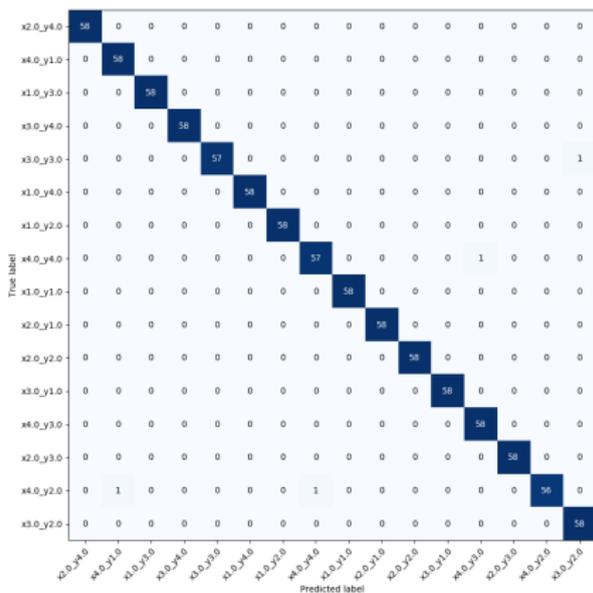
Input size (MB): 0.02
Forward/backward pass size (MB): 8.52
Params size (MB): 258.18
Estimated Total Size (MB): 266.72
=====

Loss Accuracy

- Set 1 data have very strong signals
- High accuracy in just 2 epochs

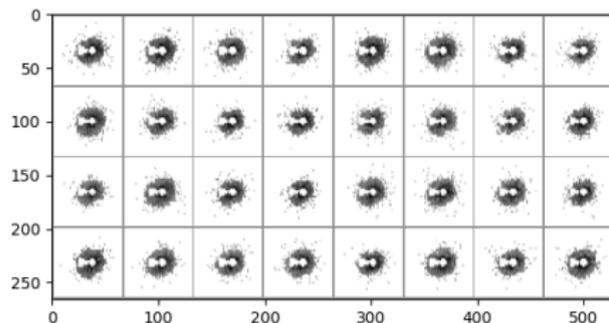


Confusion Matrix: Test and Train



Set 2 data

- The images are not very discriminatory
- Signals are not as strong
- Batch Normalization has been included after every conv layer



Architecture used

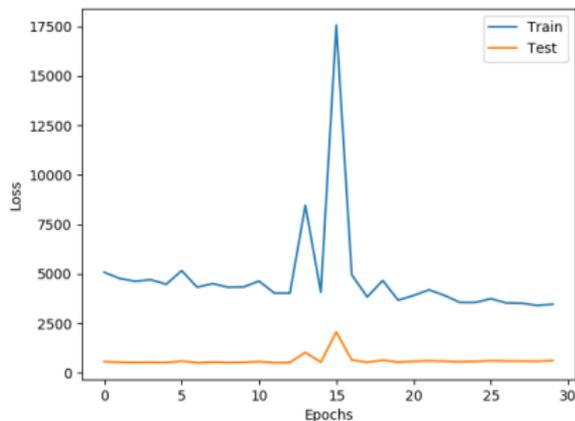
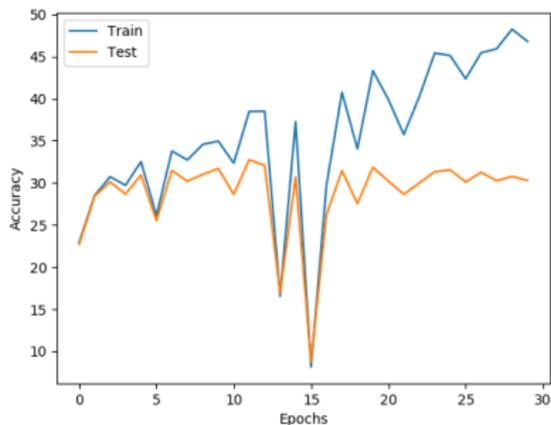
Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 64, 64, 64]	640
BatchNorm2d-2	[-1, 64, 64, 64]	128
ReLU-3	[-1, 64, 64, 64]	0
Conv2d-4	[-1, 64, 64, 64]	36,928
BatchNorm2d-5	[-1, 64, 64, 64]	128
ReLU-6	[-1, 64, 64, 64]	0
MaxPool2d-7	[-1, 64, 32, 32]	0
Linear-8	[-1, 1024]	67,109,888
ReLU-9	[-1, 1024]	0
Linear-10	[-1, 512]	524,800
ReLU-11	[-1, 512]	0
Linear-12	[-1, 25]	12,825

Total params: 67,685,337
Trainable params: 67,685,337
Non-trainable params: 0

Input size (MB): 0.02
Forward/backward pass size (MB): 12.52
Params size (MB): 258.20
Estimated Total Size (MB): 270.74

Loss Accuracy

- Loss displayed are running losses; Should have plotted loss per dataset length
- Overfitting occurs after 15 epochs
- The one entry hits with high ρ values might be a reason because they increase sample noise: proper augmentation method would be necessary



Viewing predictions on random batches



Number of entries vs ρ_{mean}

- Different colors have been used to visualize different classes
- It will be easier to classify by means of simple machine learning algorithms such as SVM or multilayer perceptron

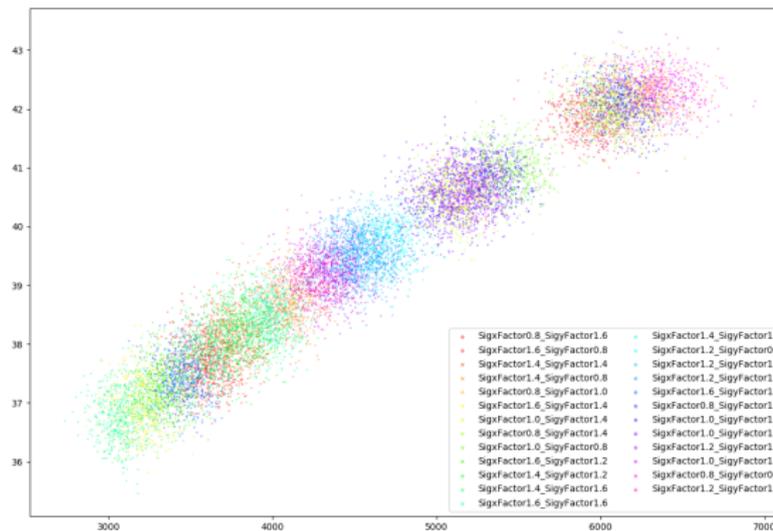


Figure 5: Number of entries: horizontal vs ρ_{mean} vertical

The End