Reconstruction of particle tracks using Deep Neural Networks and estimation of reconstruction errors

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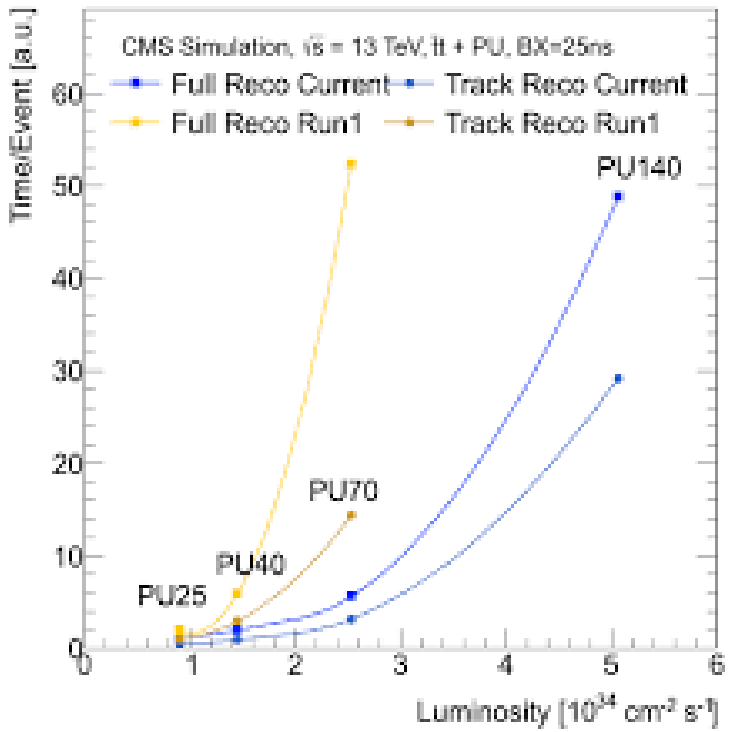
PPSS Programme, IFJ

August 2, 2019

Motivation

- For currently used algorithms tracking time needed to process one event grows quickly (worse than $O(n^2)$) with luminosity.



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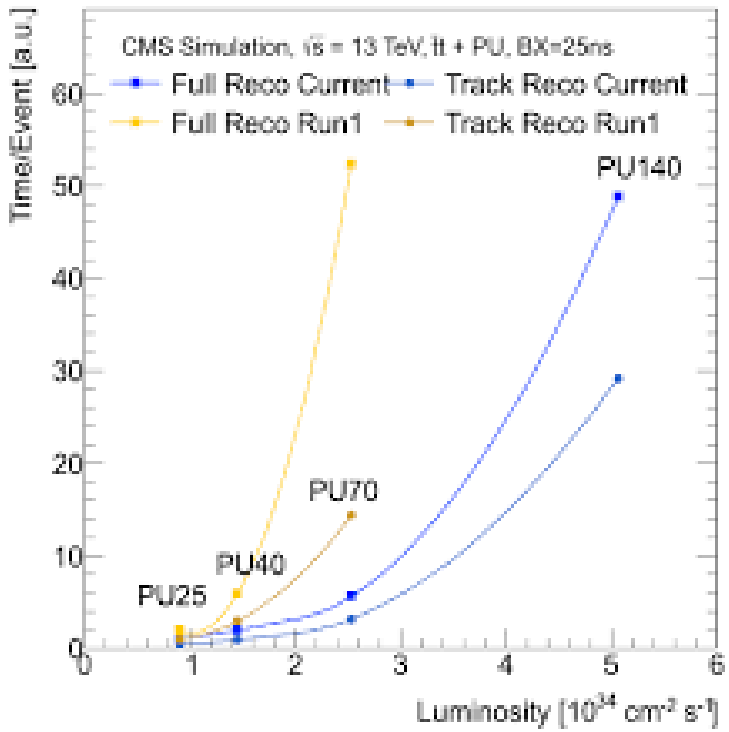

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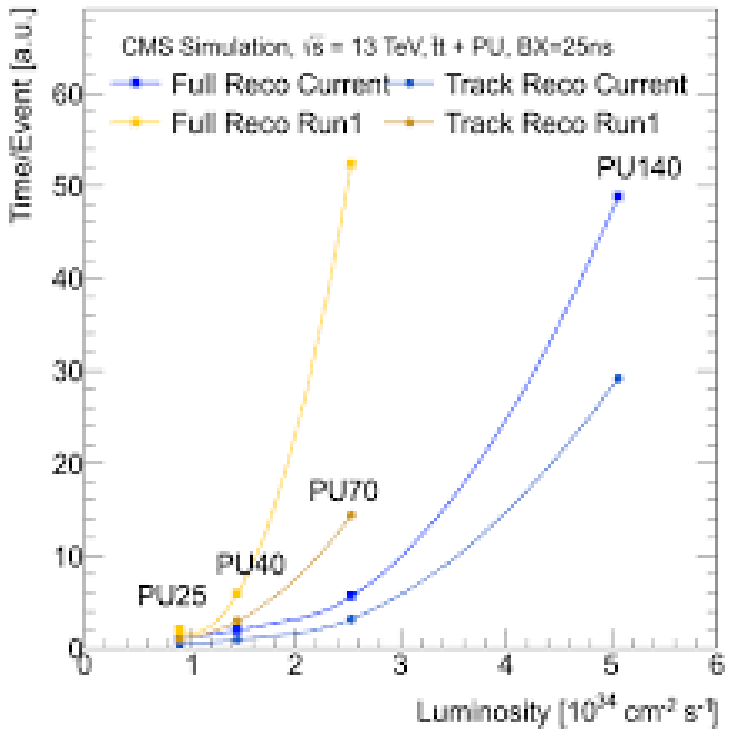

- Training neural networks can also be long, but can be parallelized.
- Once trained, neural networks work much faster.

Classical Approach - Convolutional Neural Network

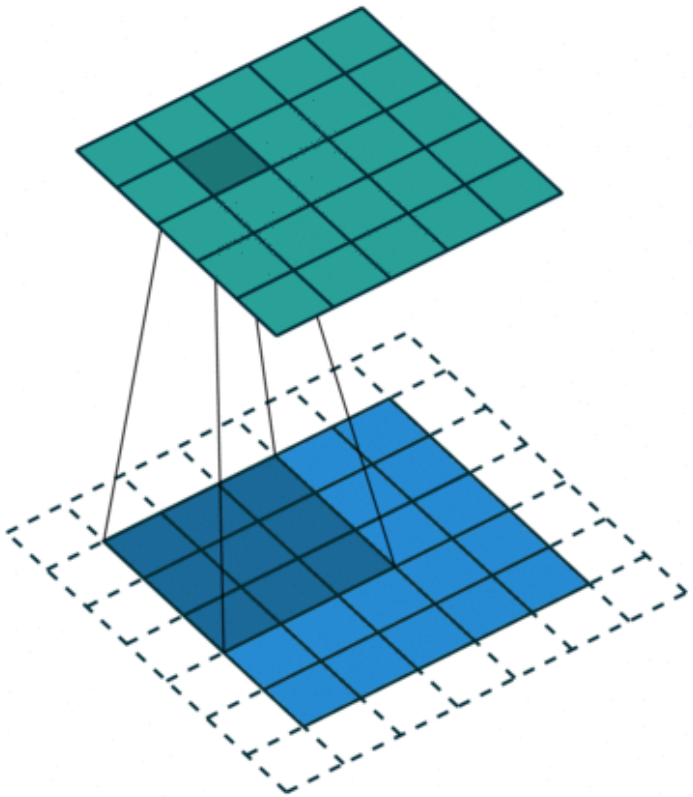

Fig. 1: Convolutional Layer [1]

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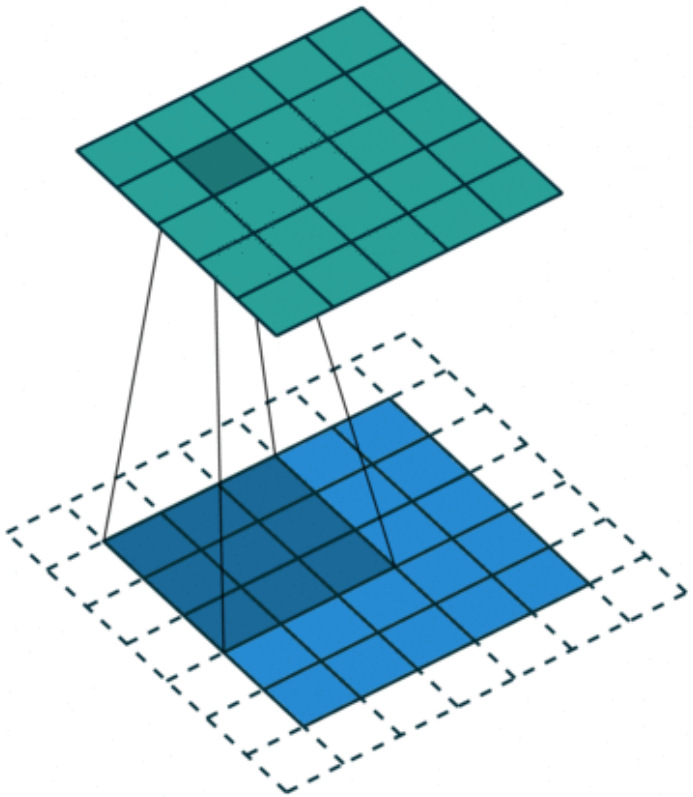

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CNN returns only a single value $\rightarrow$ no error estimation!

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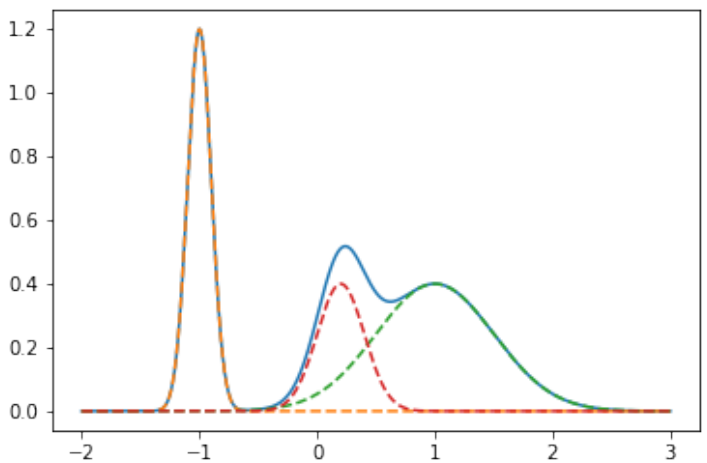
$$\rho(y) = \sum_{i=1}^{M} w_i \mathcal{N}_i(\mu_i, \sigma_i^2, y)$$



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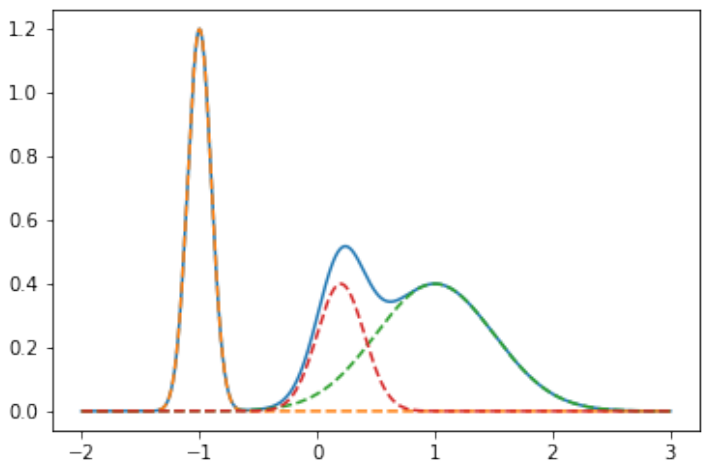

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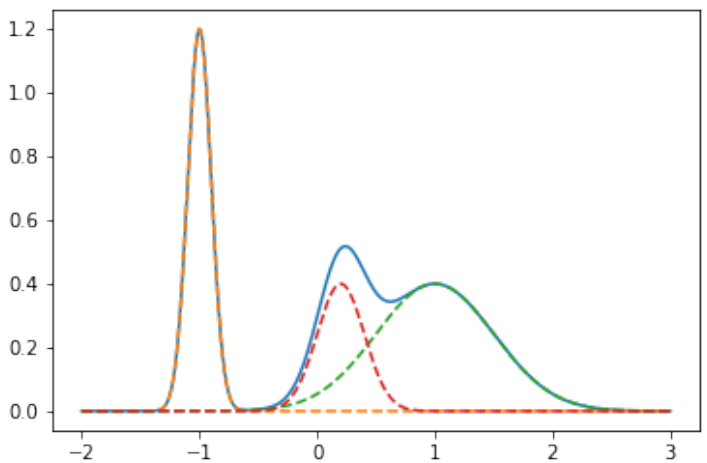
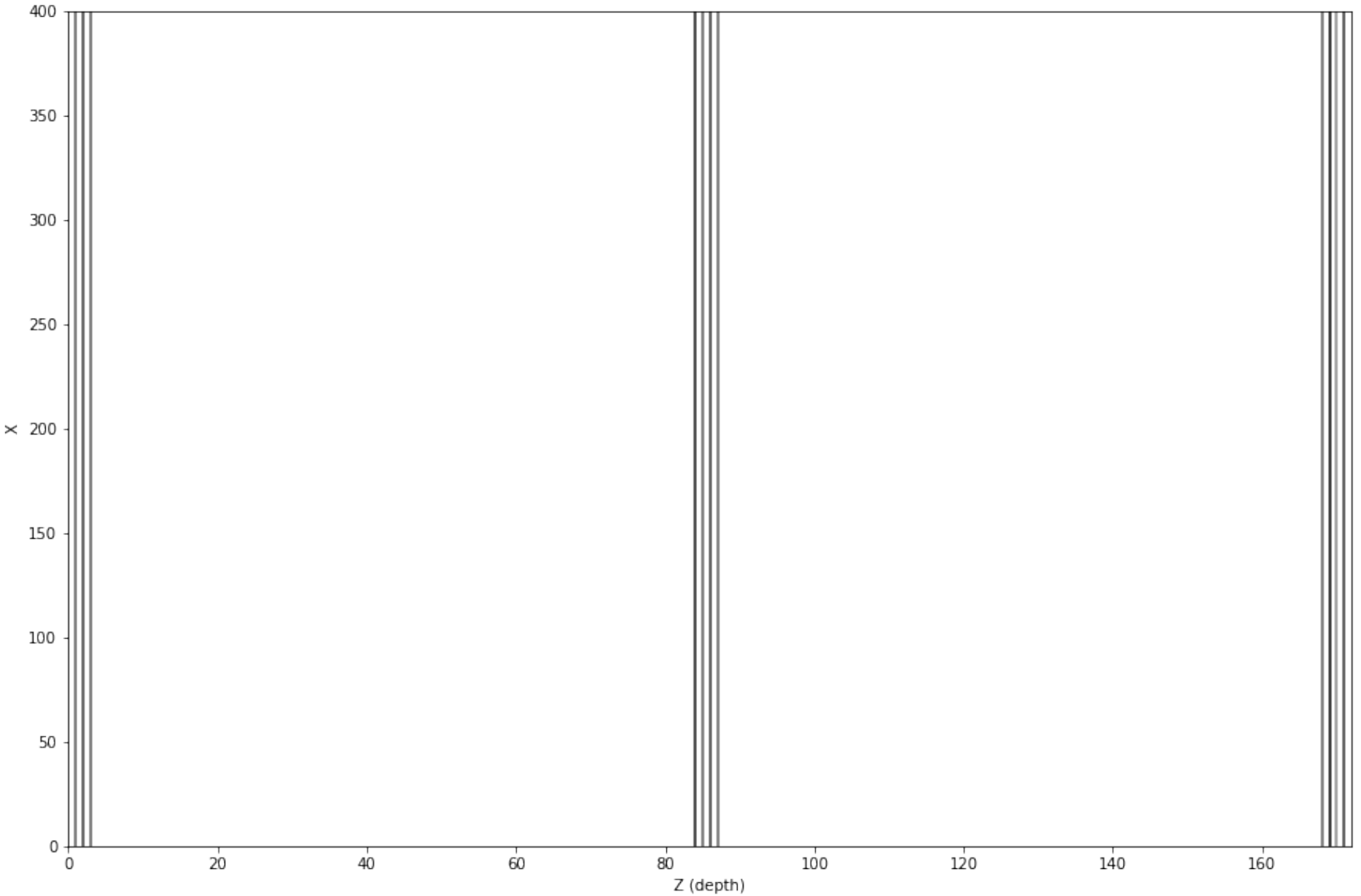


- Only one track parameters are given to the network during training
- Works well with variable output size (number of tracks may differ)

Goal - reconstruction of particle tracks



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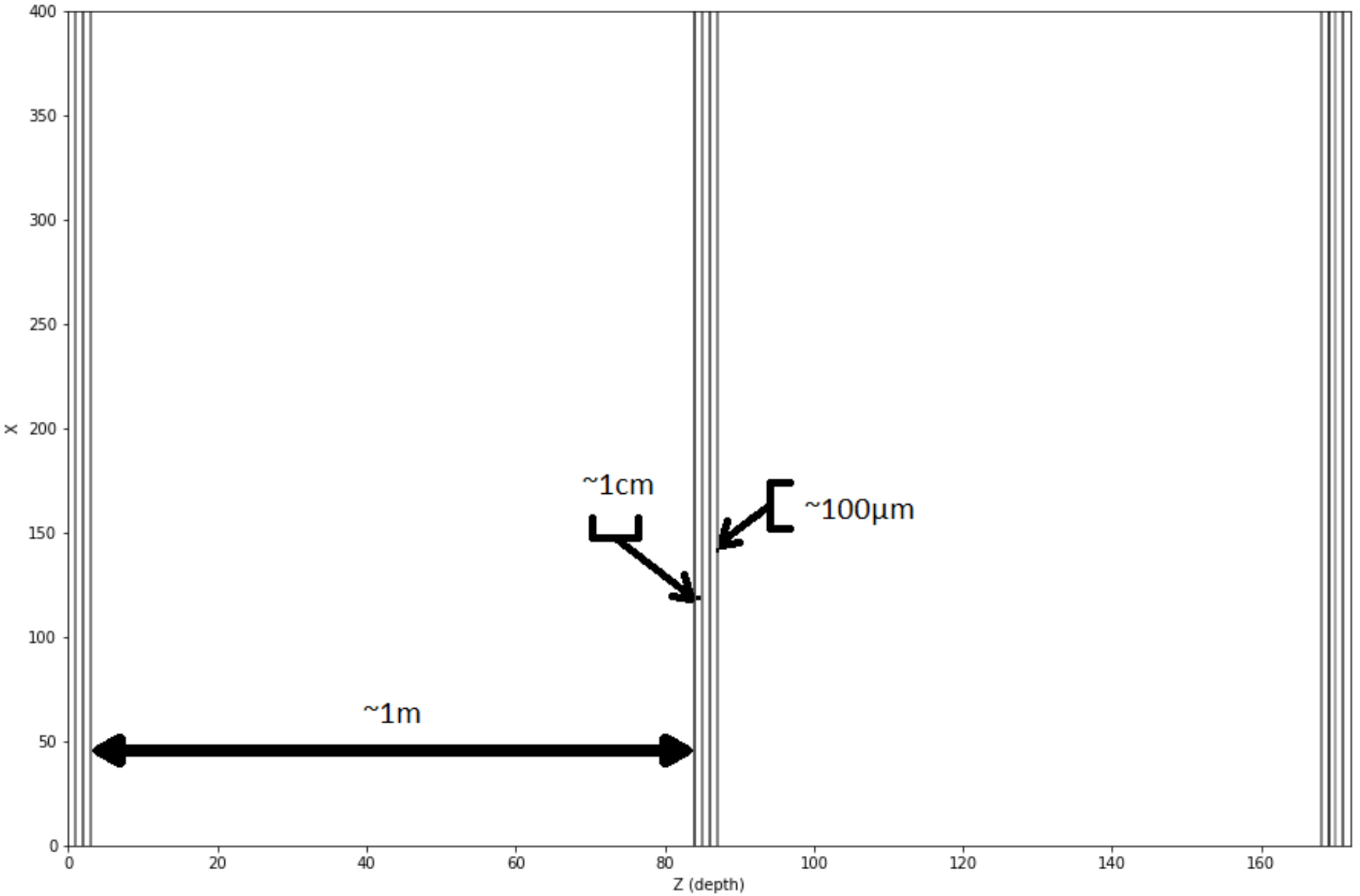

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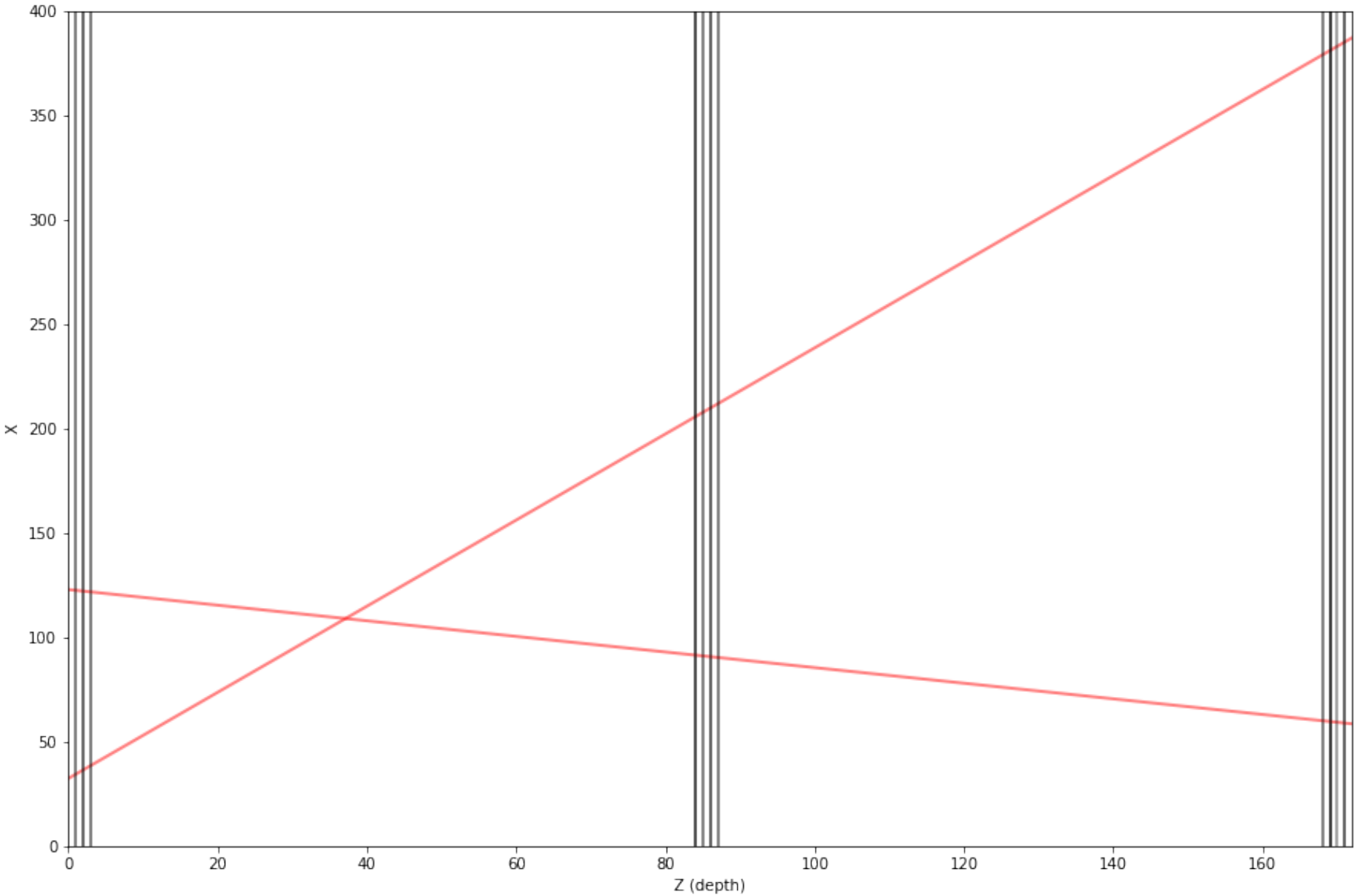

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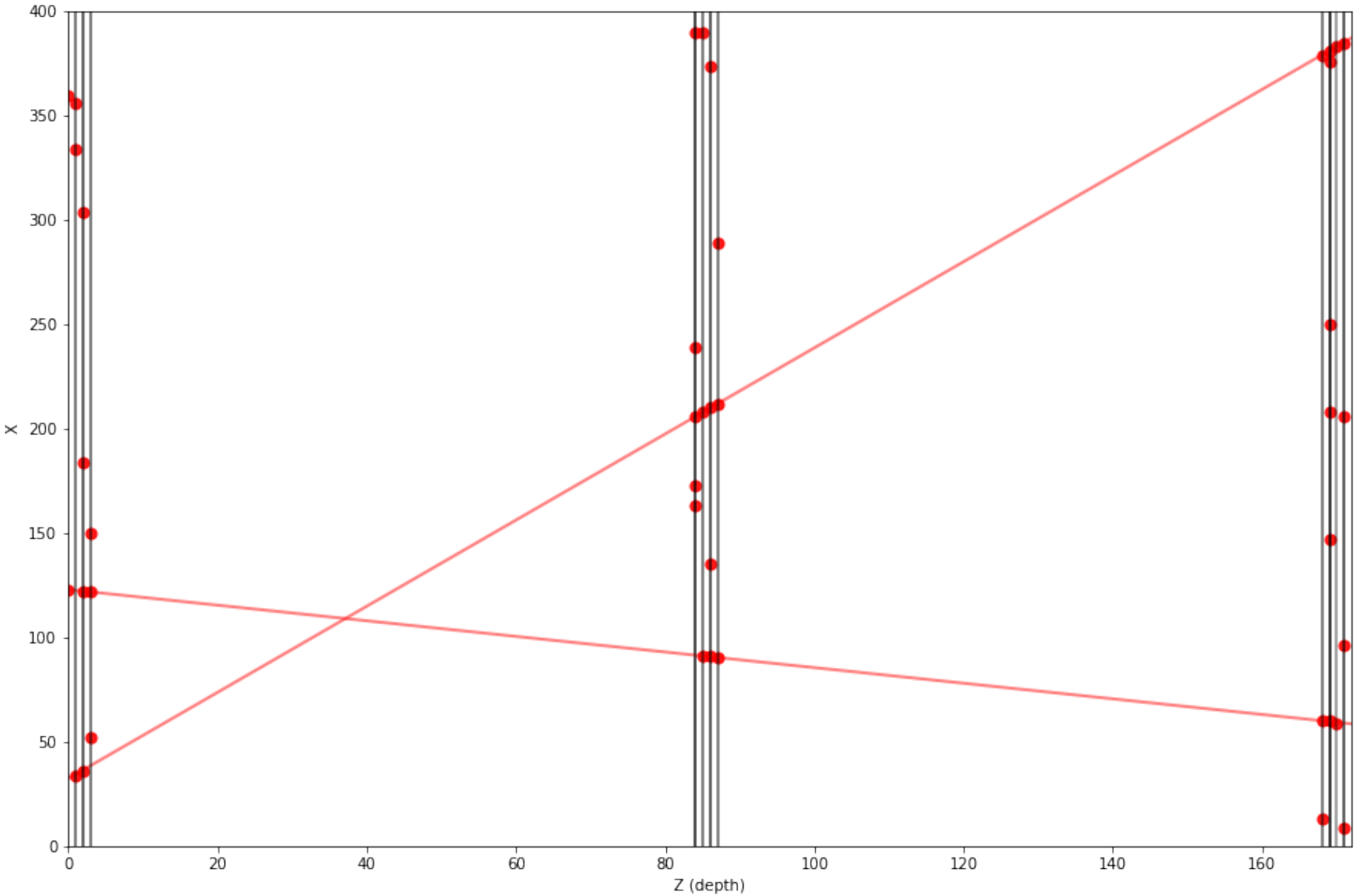

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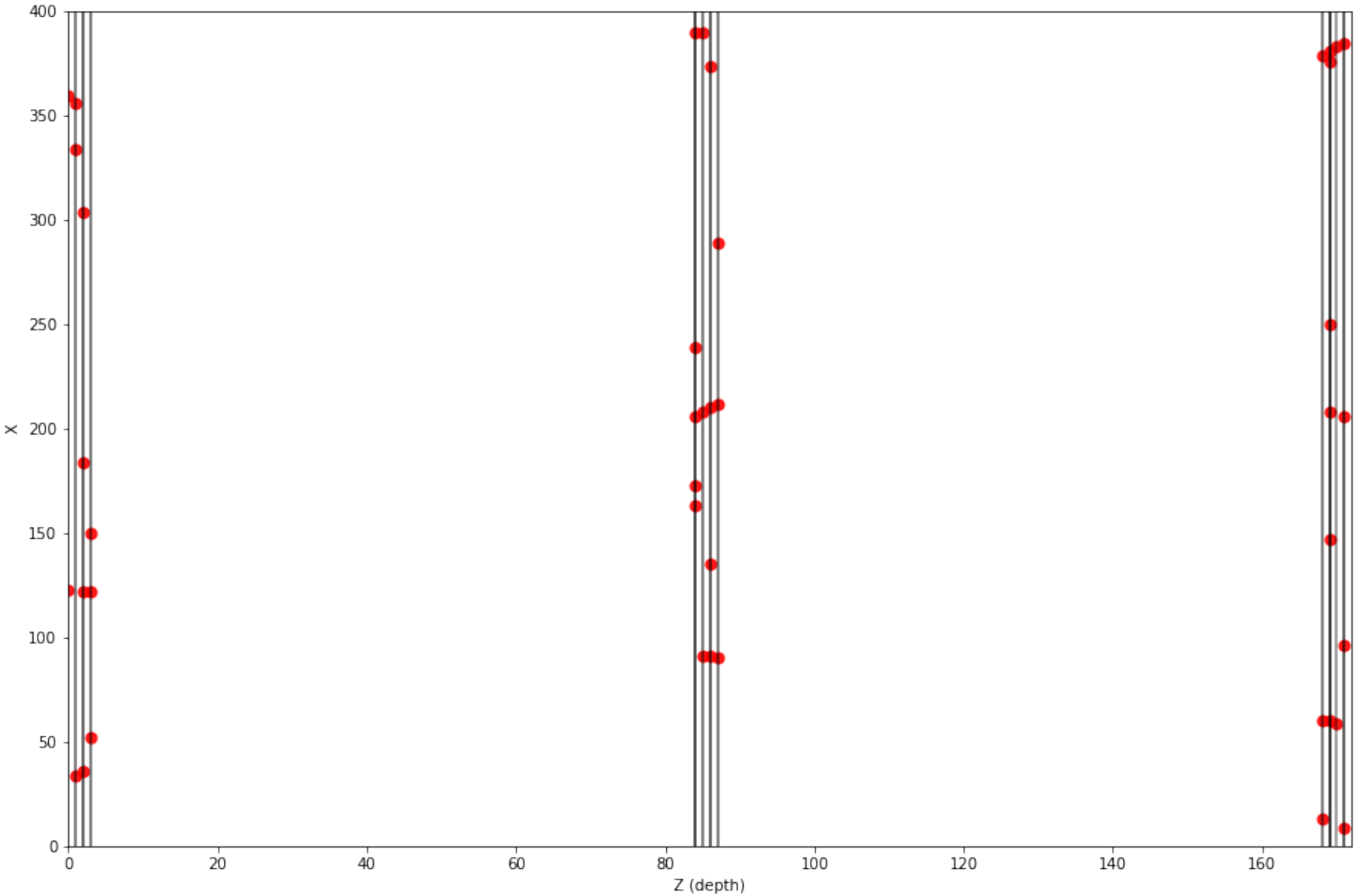

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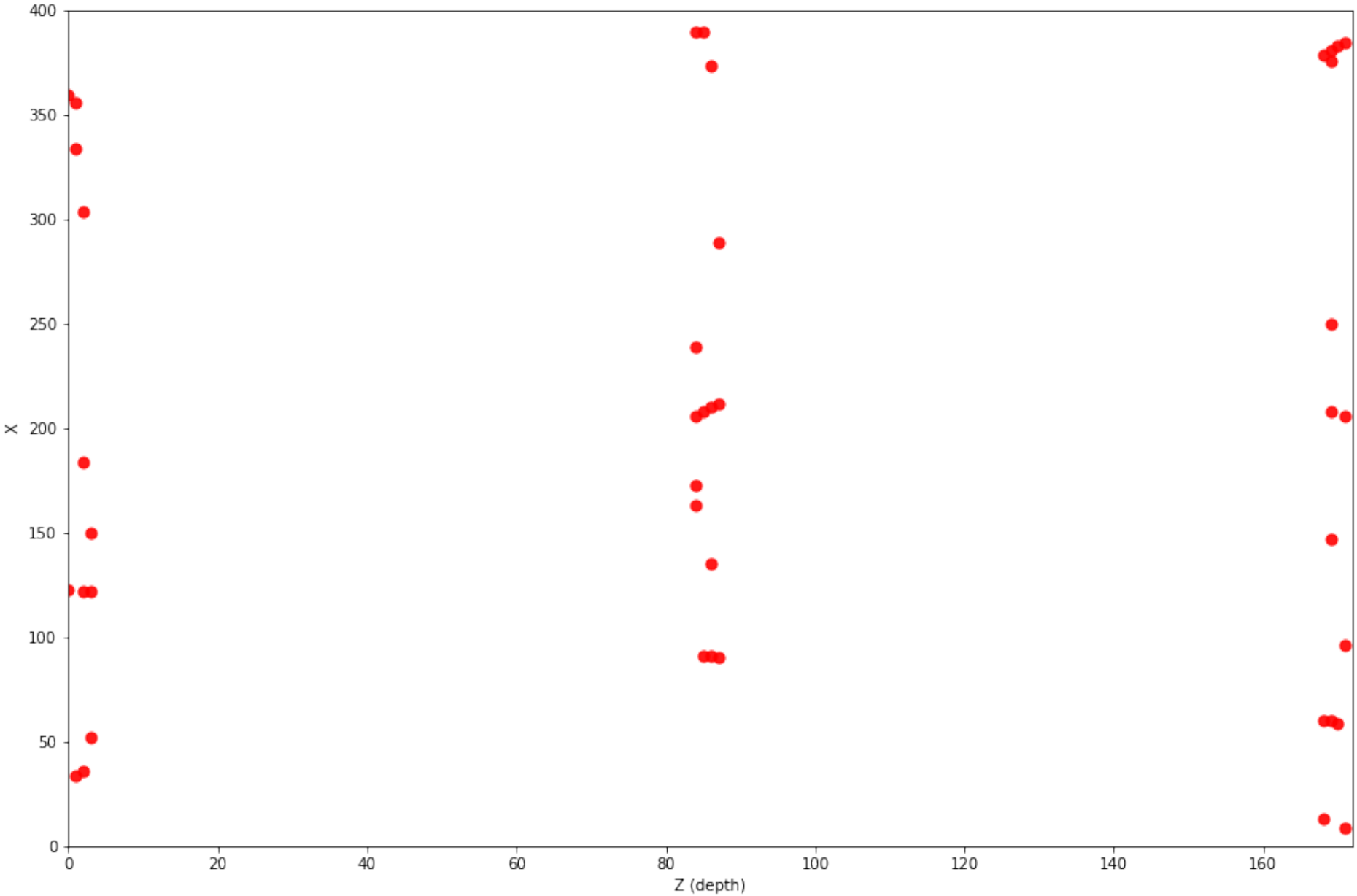

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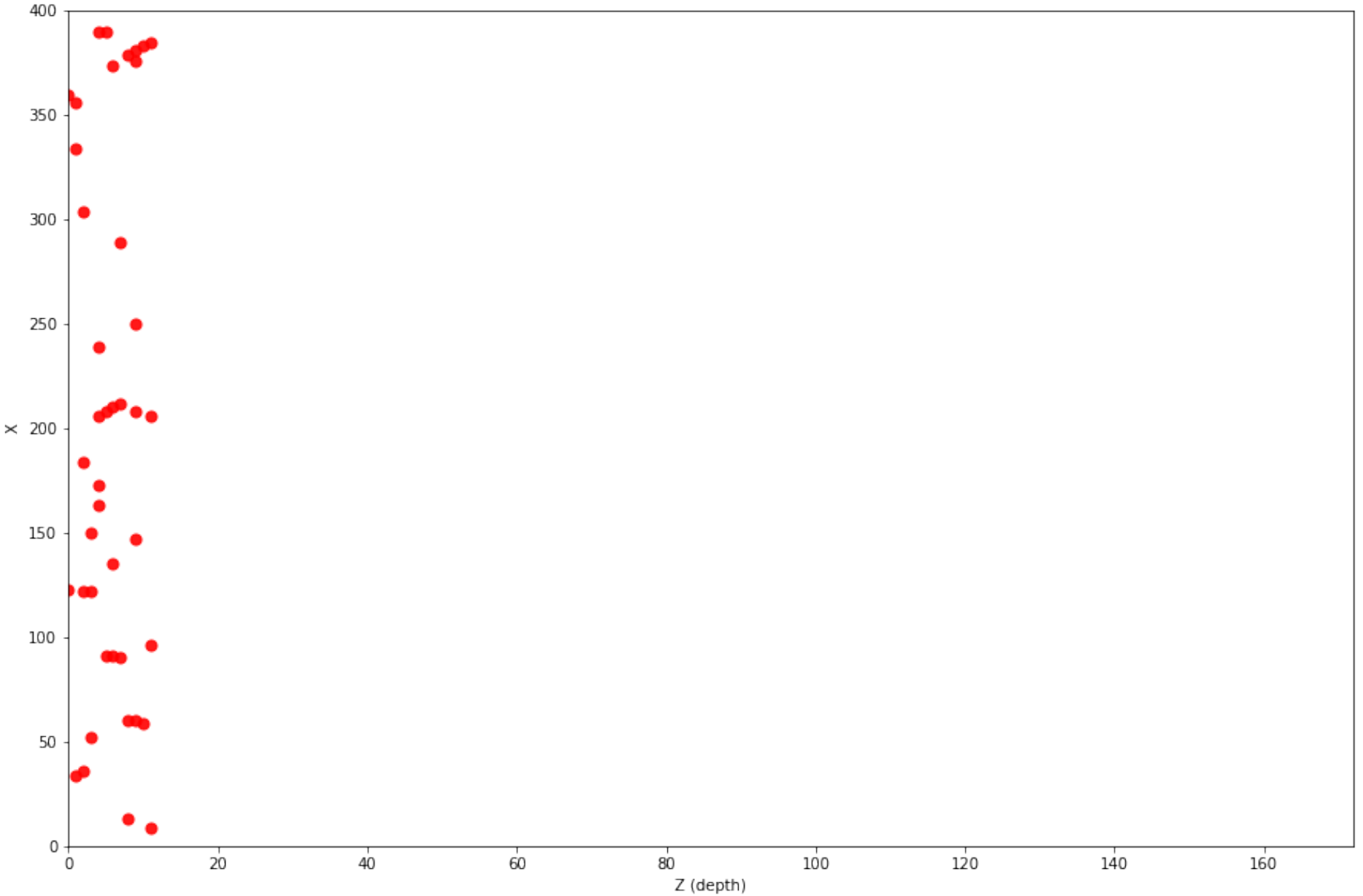
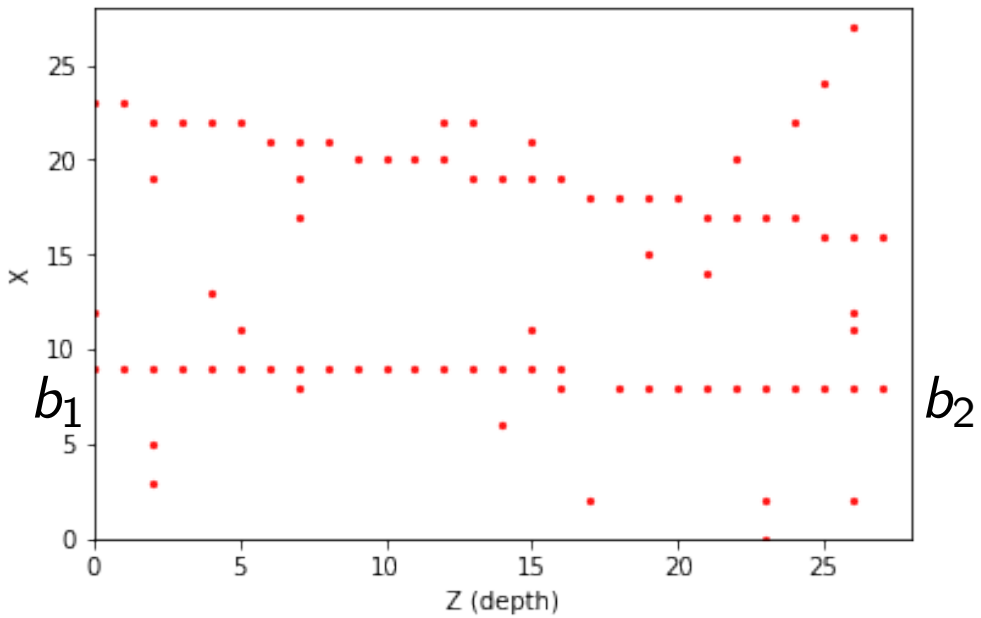


Toy Problem - Generating Data

- Generating images of size 28x28 pixels with straight lines and some random noise (matrix of 0s and 1s)



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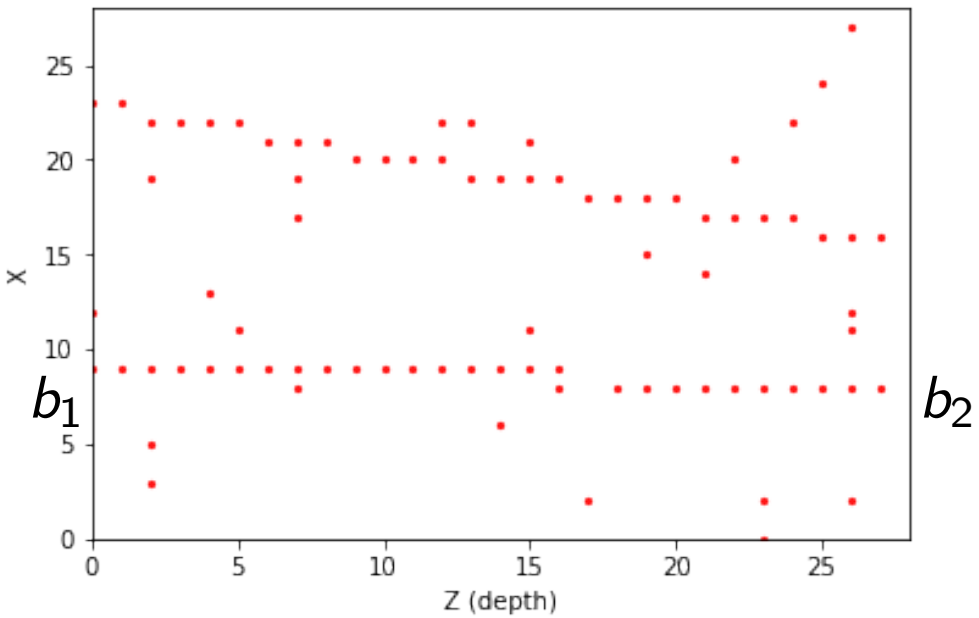

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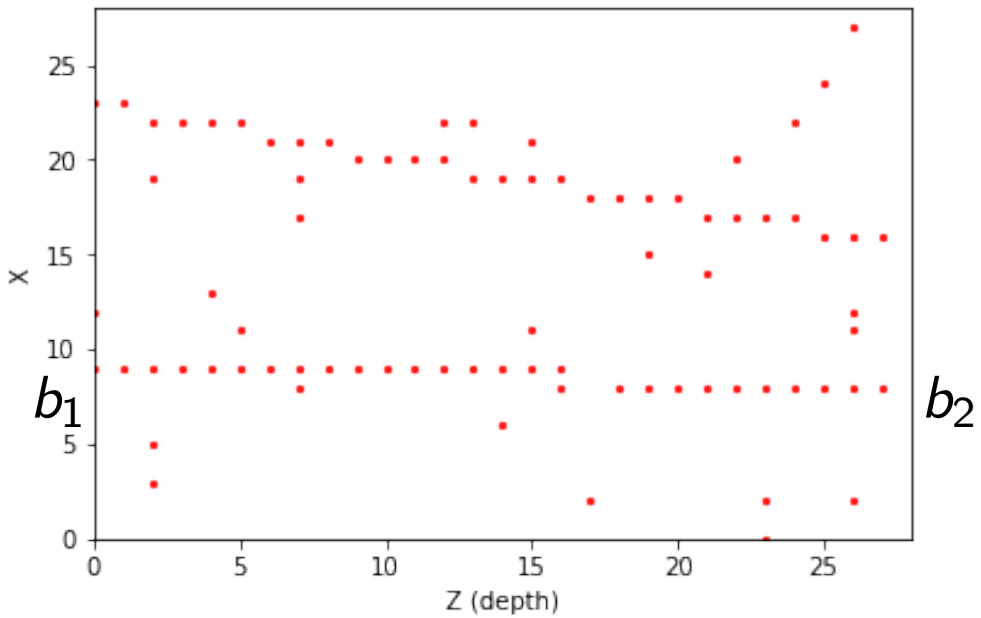
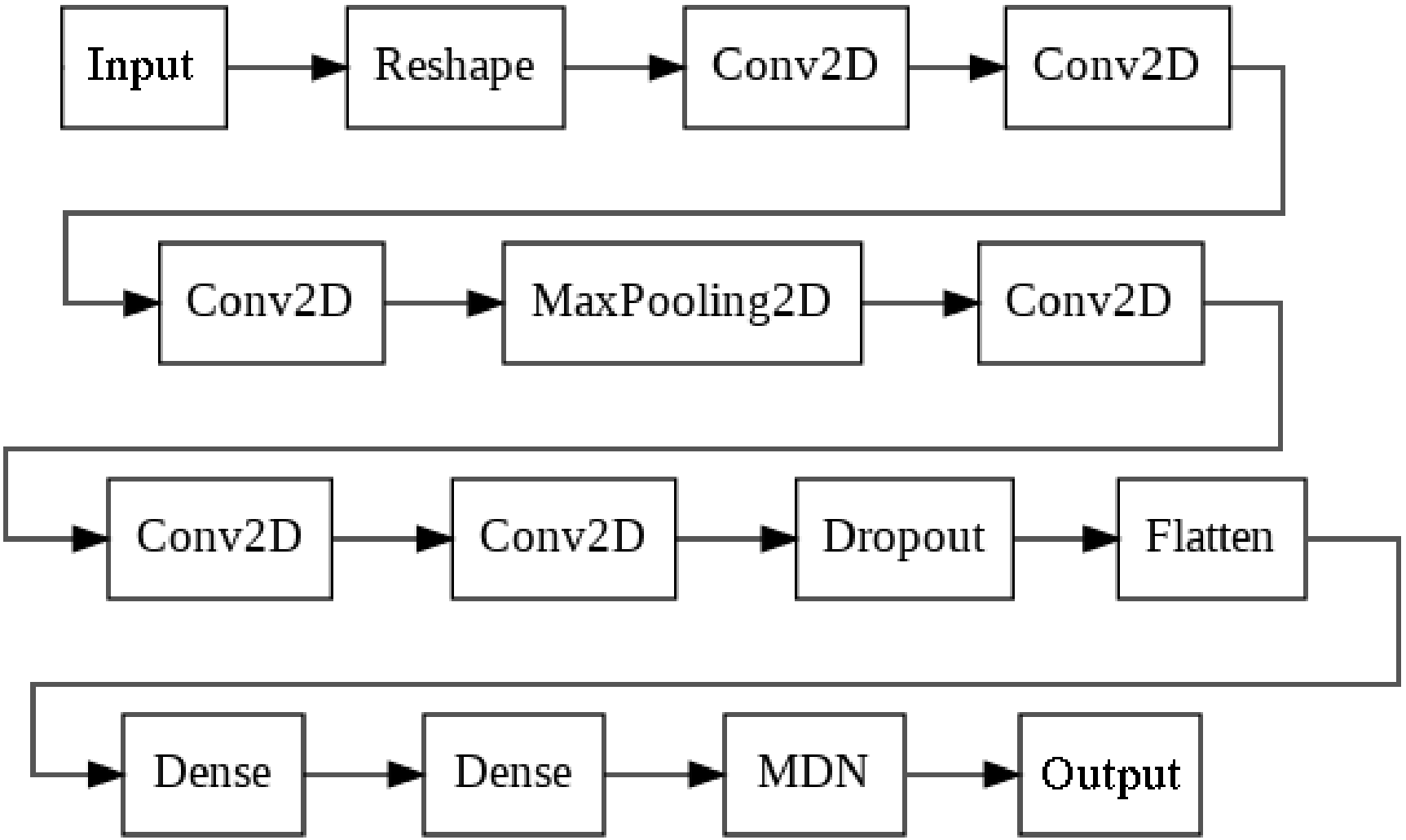
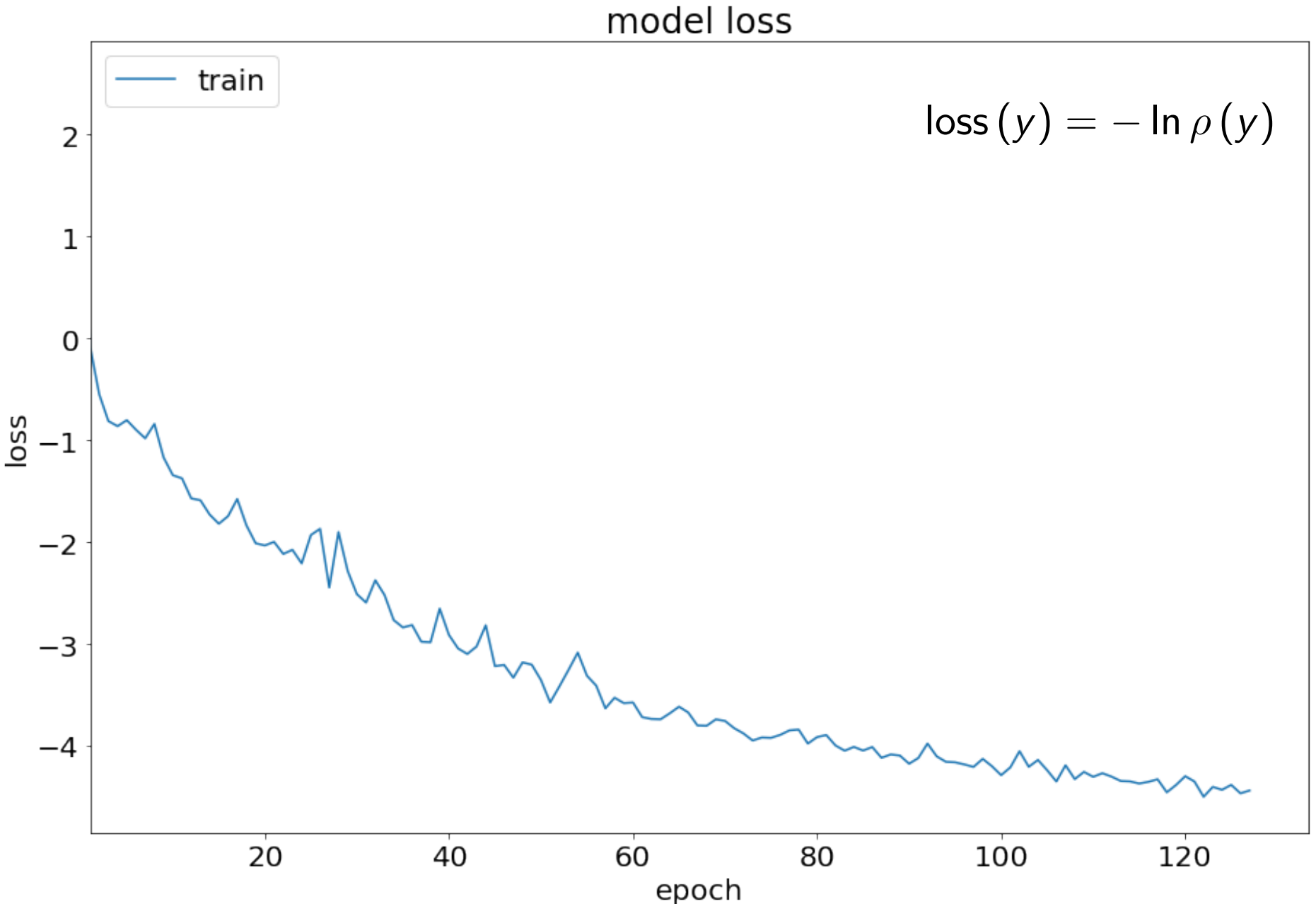


- Training vector (single track): $[b_1, b_2]$
- Prediction vector (3 mixtures):
  $\left[b_1^1, b_2^1, b_1^2, b_2^2, b_1^3, b_2^3, \sigma_1^1, \sigma_2^1, \sigma_1^2, \sigma_2^2, \sigma_1^3, \sigma_2^3, w^1, w^2, w^3\right]$

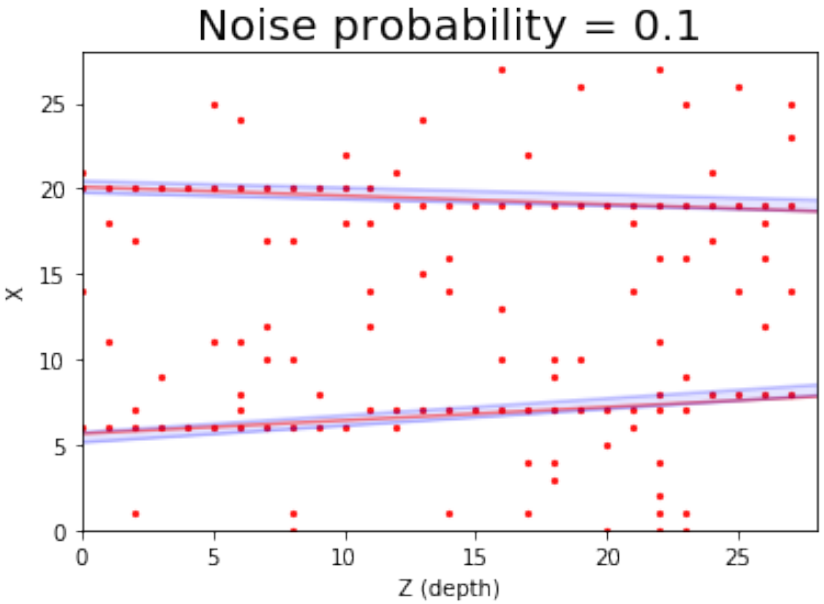
Neural Network used

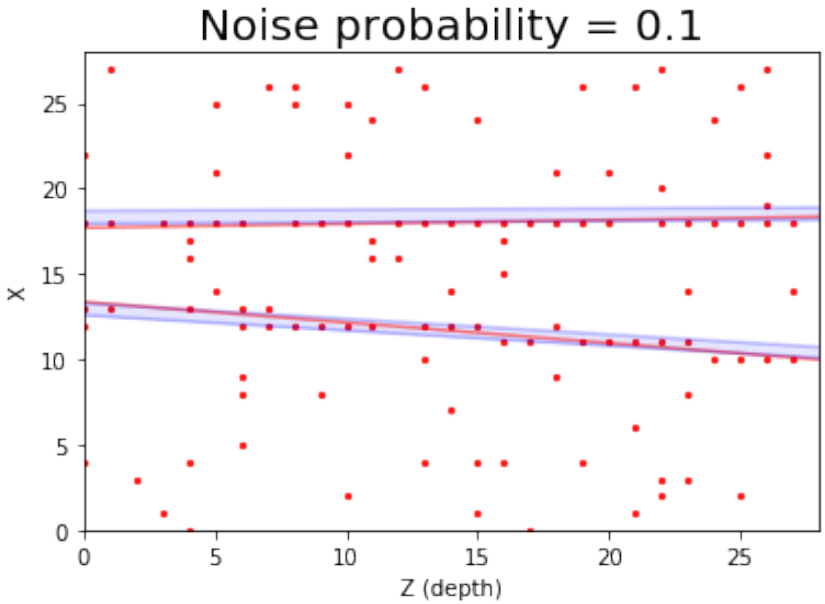


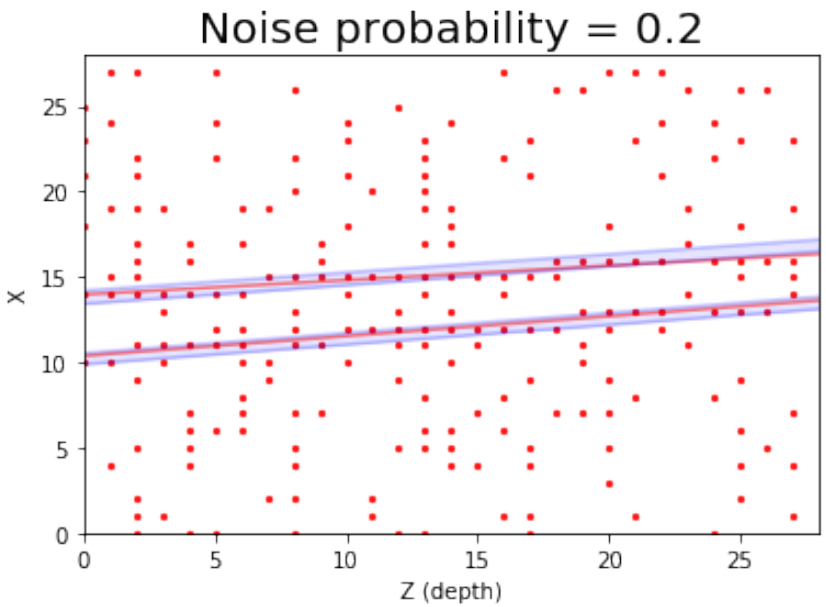
Learning process

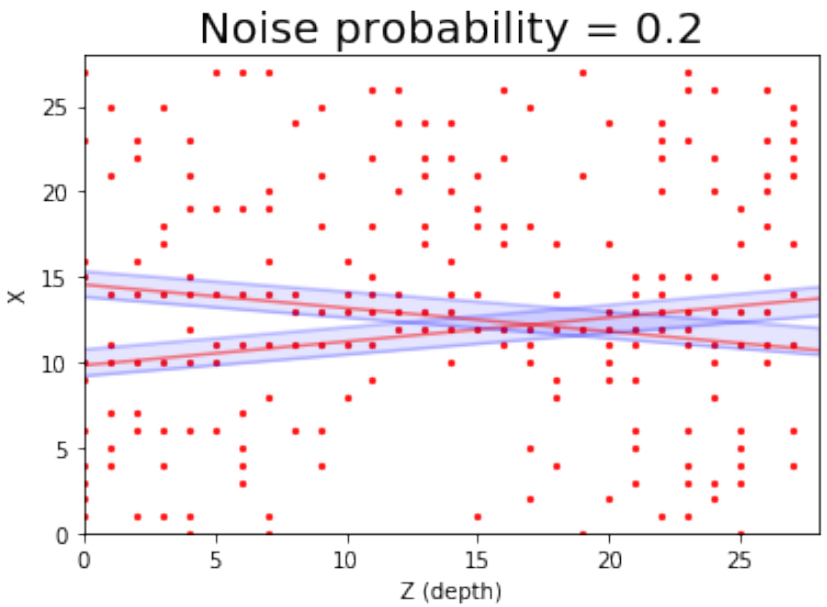


Toy Problem - Results

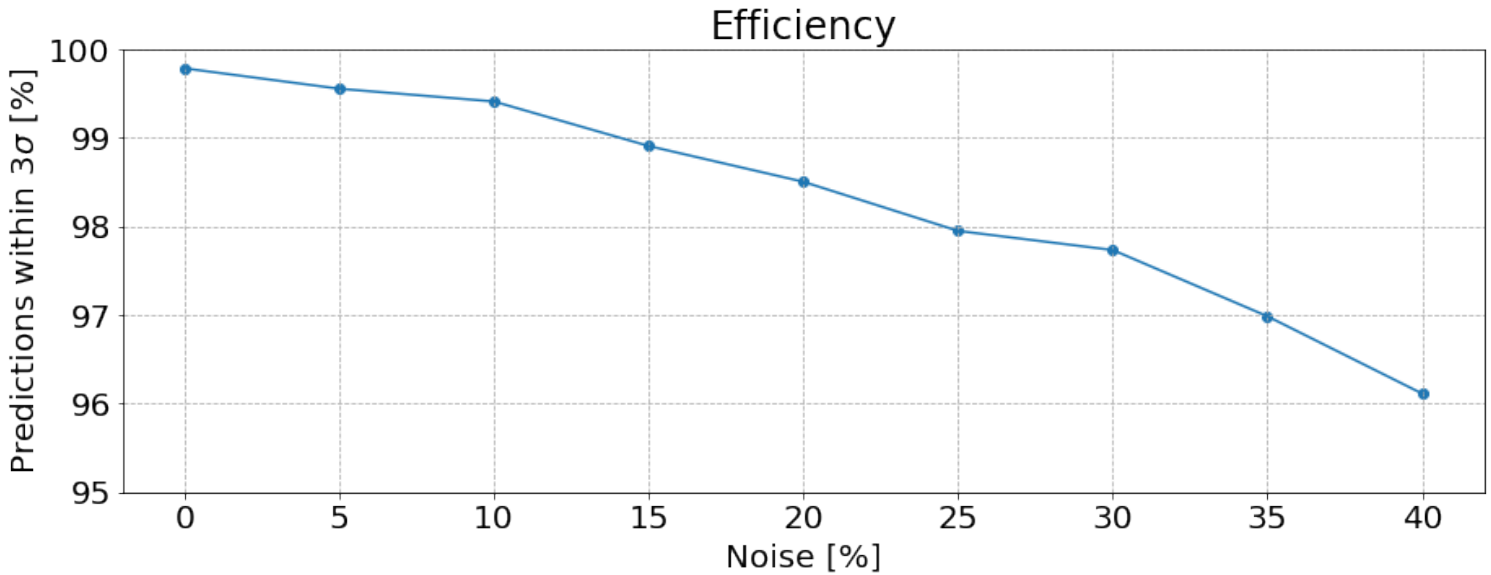








How does random noise affect prediction ability?



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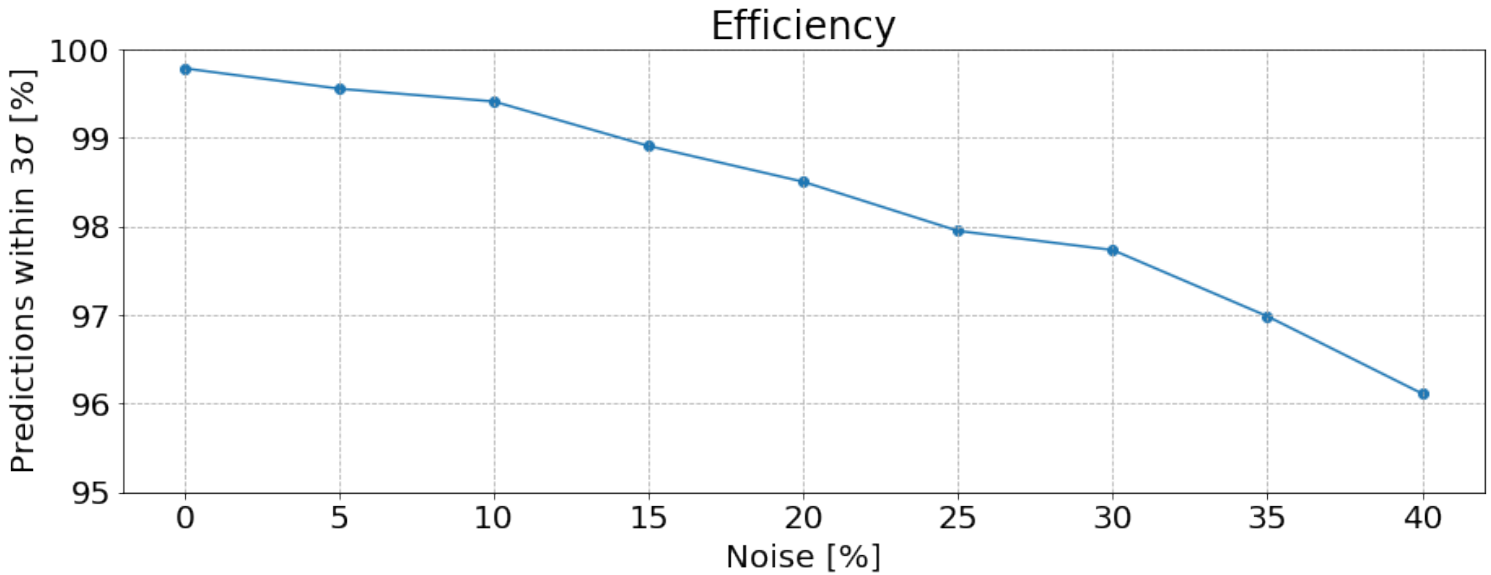
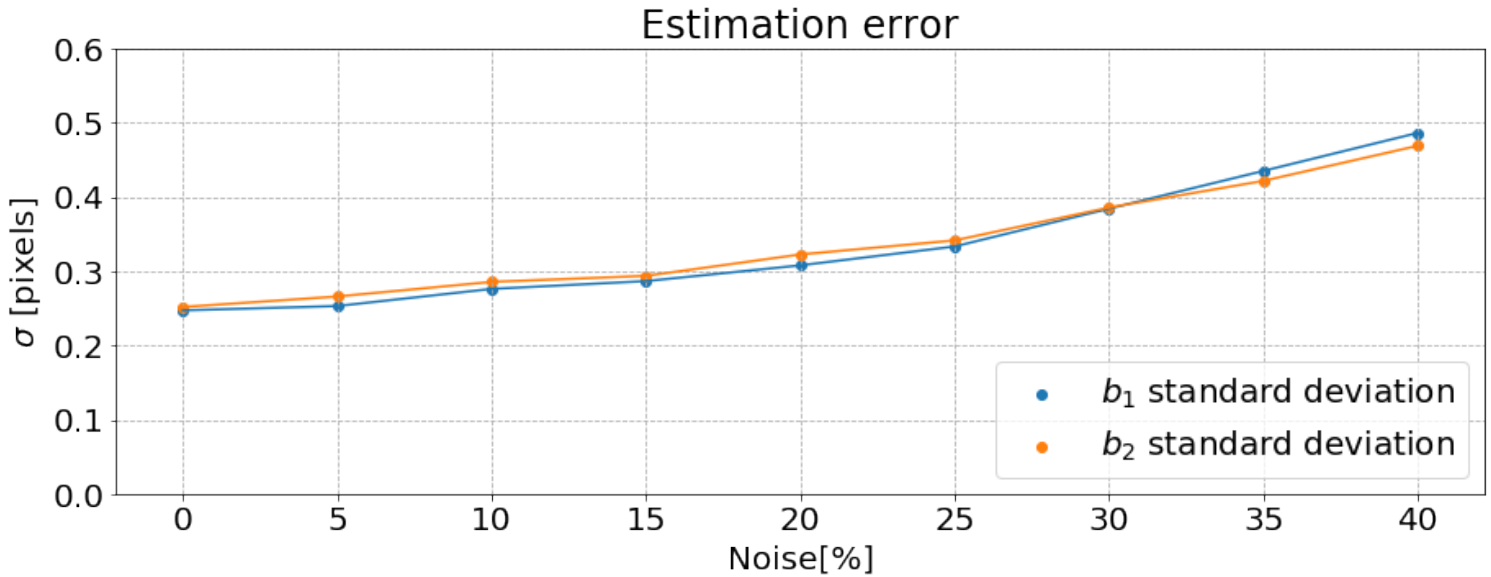
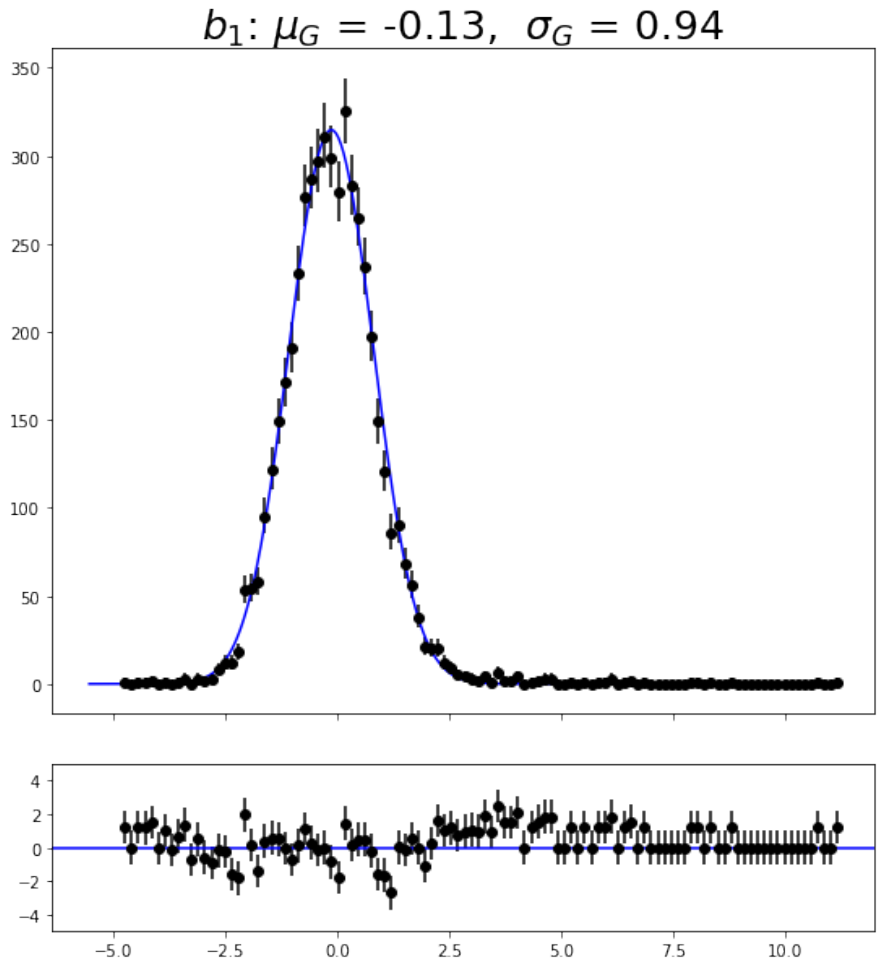
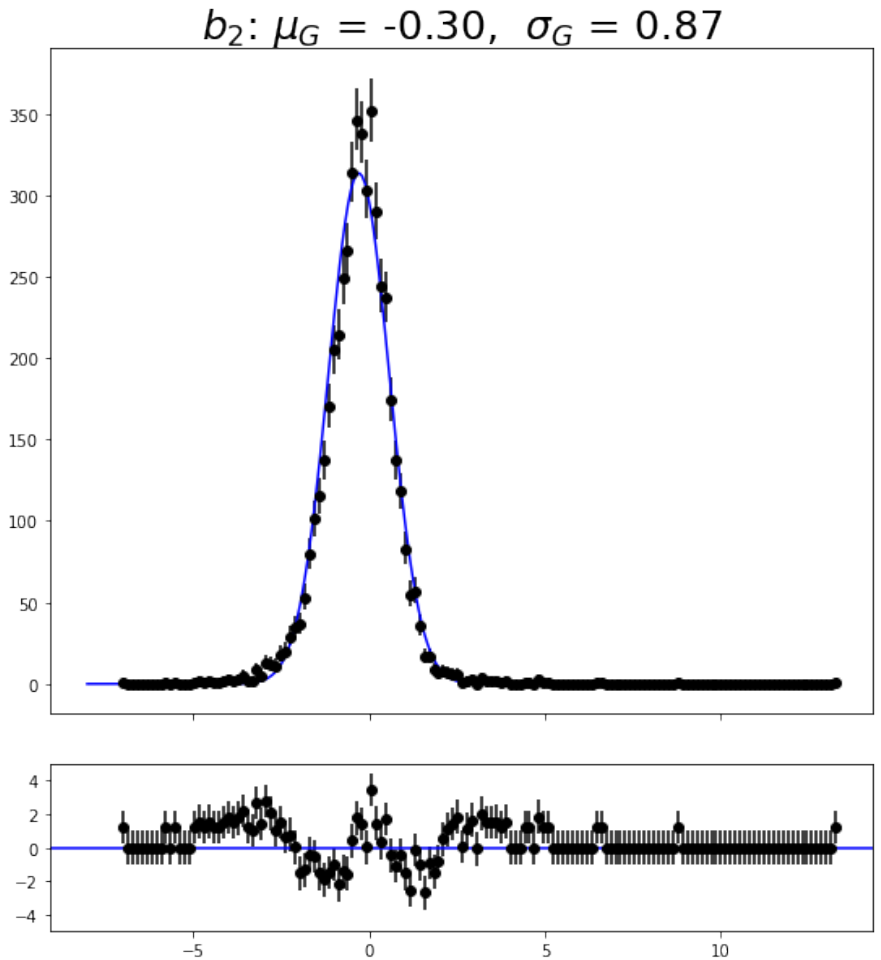




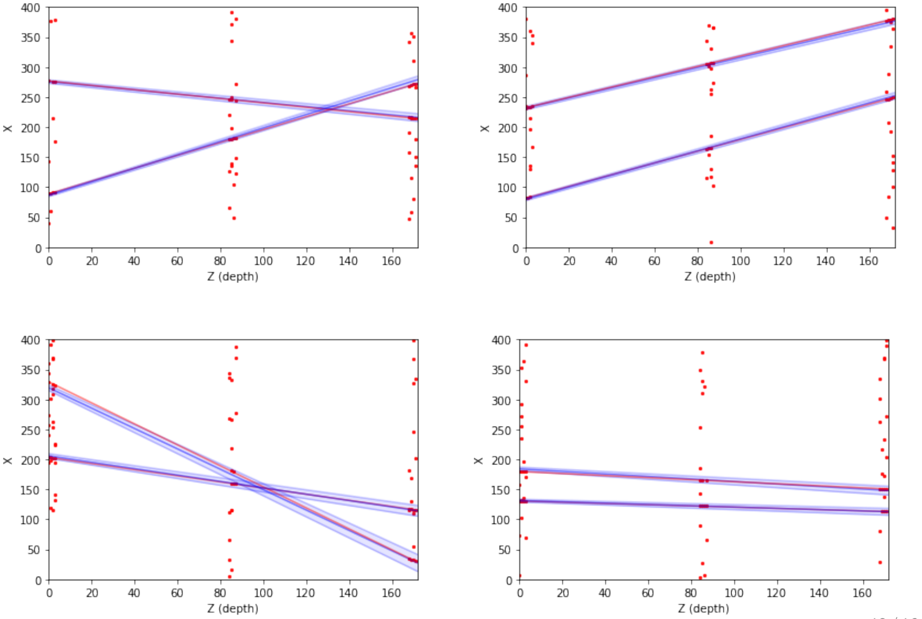
Pull plots - error estimation



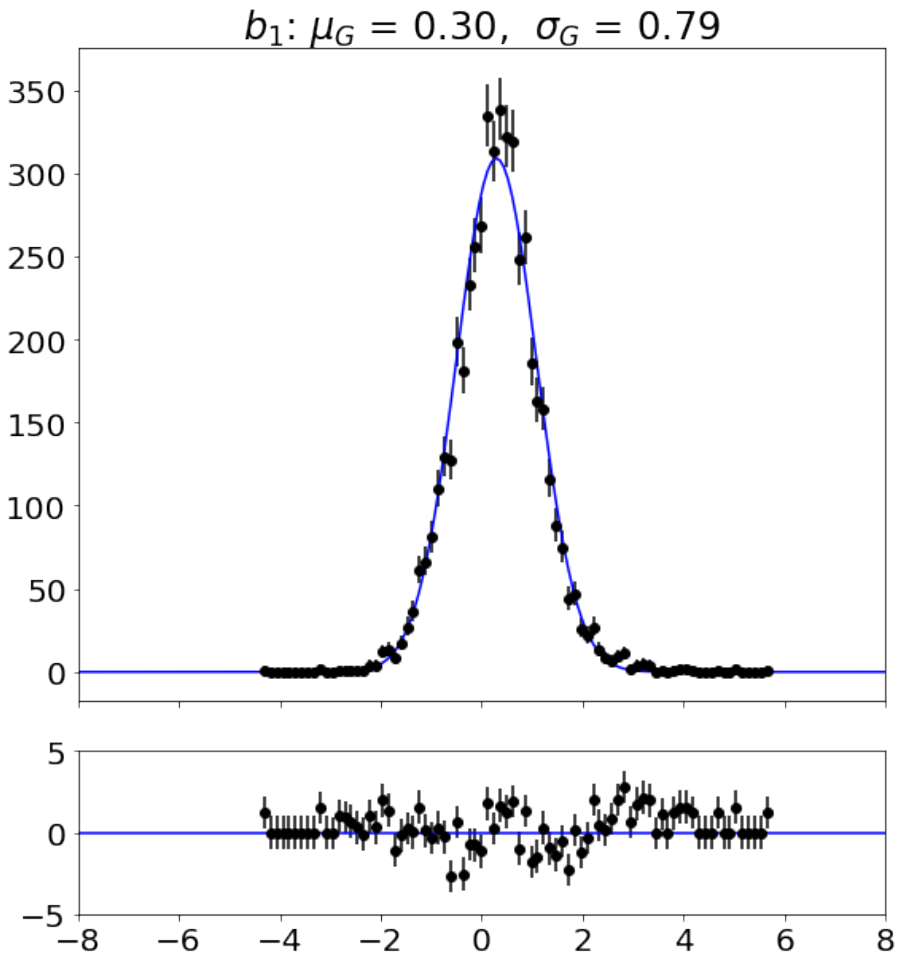


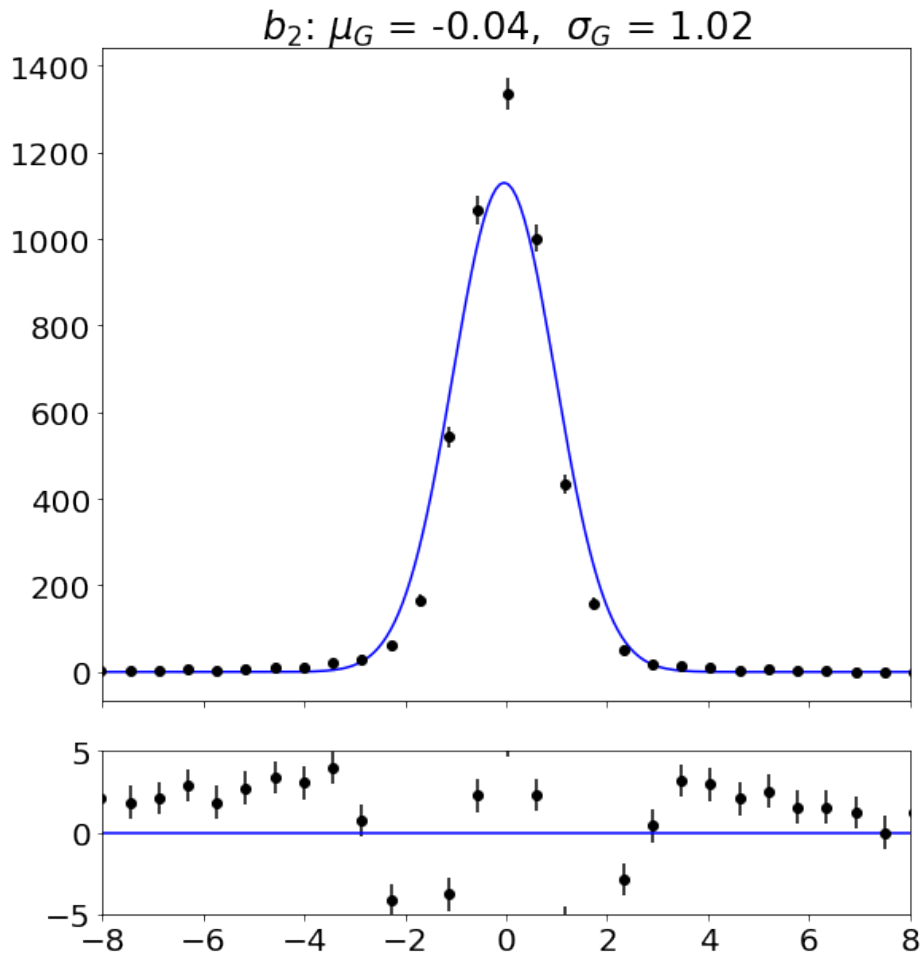
$$\frac{y_{true} - \mu}{\sigma}$$

Results - Realistic Data



Pull plots - realistic case





Potential future use

- There are plans to use neural network tracking in MuonE experiment operating at the SPS accelerator at CERN

Fig. 2: MUonE experiment logo[2]

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- Including magnetic fields $\rightarrow$ more layers
- Extending the model to 3D

Technologies used

Keras

TensorFlow

python™

colab

Link to PPSS-Particle-Tracking Repository:
https://github.com/Matek1731/PPSS-Particle-Tracking

Questions?

Bibliography


Convolution arithmetic tutorial.


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Backup

Loss - 400x12