Relating Initial Distribution to Beam Loss on the Front End of a Heavy-Ion Linac Using Machine Learning

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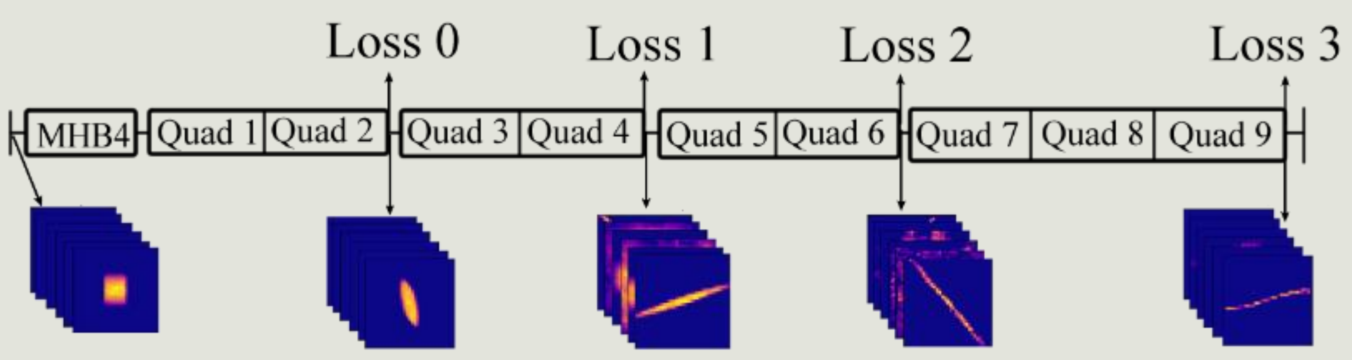

Figure 1: Cartoon of accelerator and beam measurements. The image shows where each beam measurement was collected from.

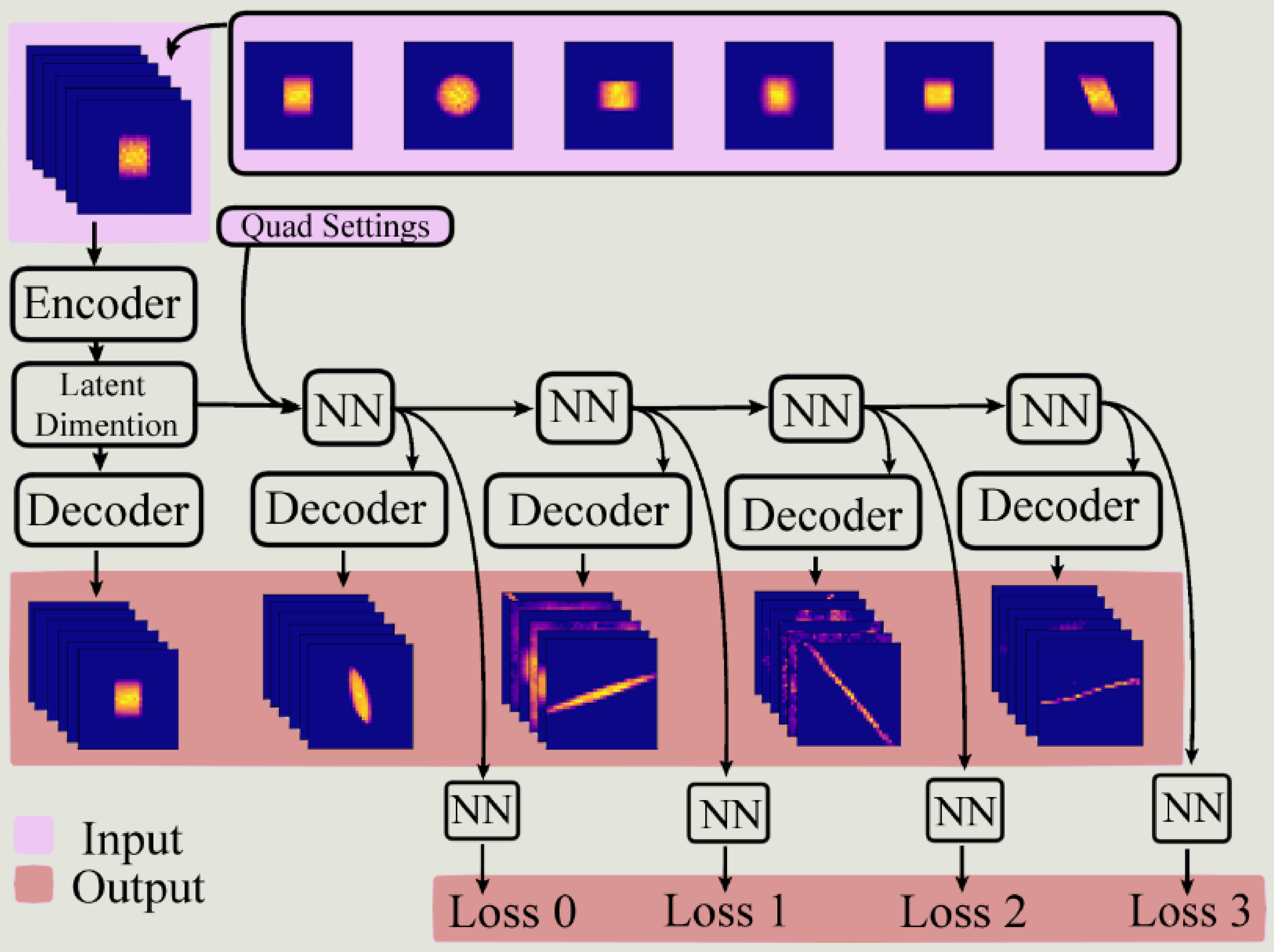

Figure 2: Cartoon of architecture. During training, the model takes all the 2D projections and loss value as input into the training. During testing, only the initial 2D projections were given and the model predicts the loss values and 2D projections in addition.

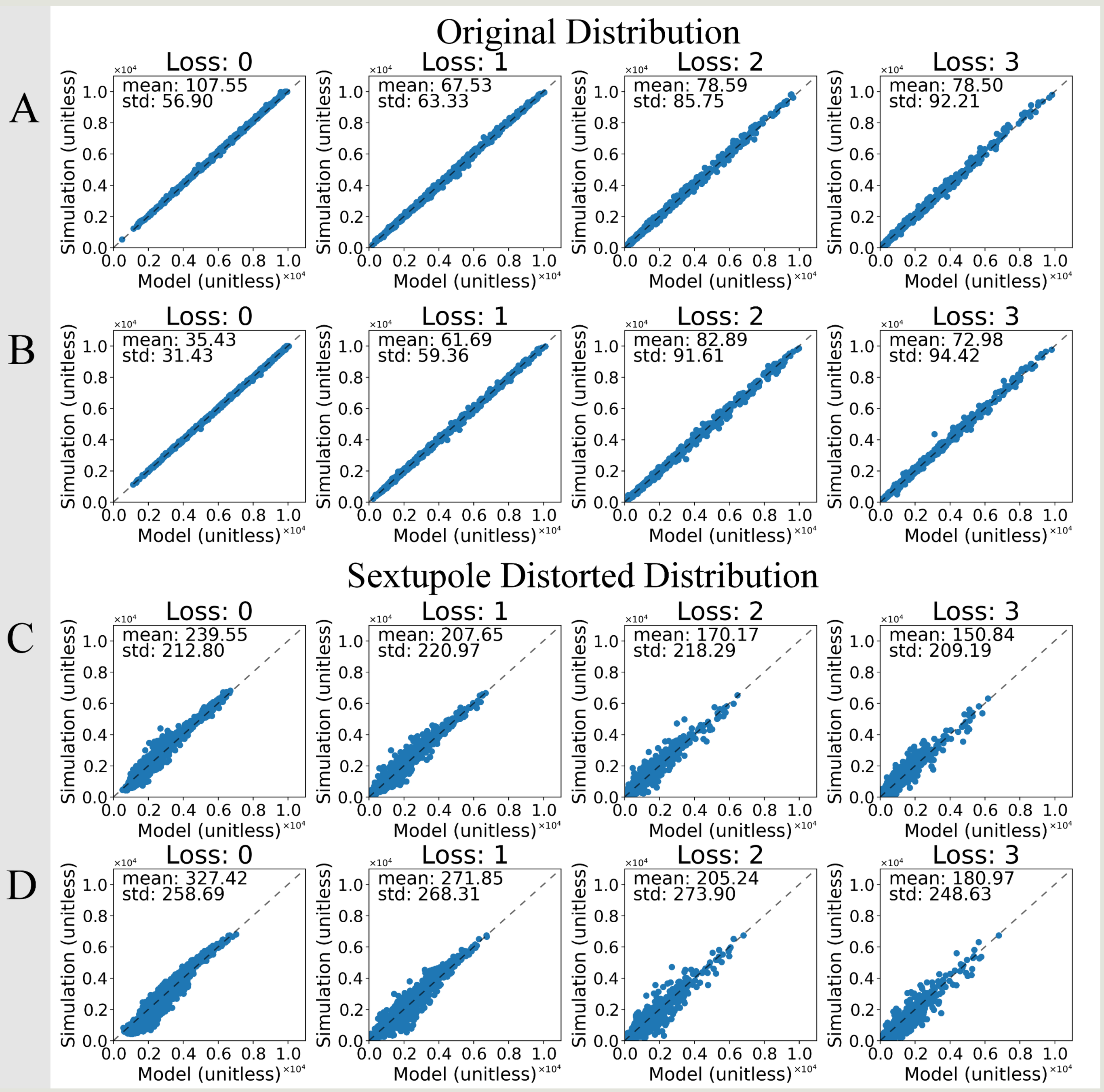

Figure 3: (A) Histogram of original data set using six projections, **(B)** and same model but using three projections. **(C)** Histogram of original data set using six projections, **(D)** and same model but using three projections.

Motivations

Understanding and minimizing uncontrolled beam loss, an unexpected loss to the beam within the beamline, is a challenging problem in obtaining high beam power in hadron linacs such as ATLAS, SNS, and FRIB.
The loss depends on many factors such as the optics settings, beam aperture, and beam distribution.
Machine learning allows us to obtain hidden correlations from high dimensional data and can be use to predict the beam loss given the initial distribution.

Approach using Convolutional Autoencoders

TRACK simulation of the ATLAS LEBT created 430,000 data points to serve as our training set. The data taken were the number of particles lost at four different locations and six projections of the 4D phase space onto a 33x33 pixel grid, as seen in Fig. 1.
Figure 2 shows a neural network model using convolutional autoencoders that trained the model.
Convolutional Autoencoders reduce high dimensional projections into a small latent dimension. If the original projections can be recreated from this, then that latent dimension contains the core information of the beam phase space.
The frozen layer technique was used to train the model. This was done first by having the network learn to model the phase space evolution, then learn to predict the beam transmission.
This was done with the first 6 projections, then using 3 projections.
The initial distribution was distorted using a sextuple and trained using also 6 and 3 projections. This is to gauge the robustness of the model is when it receives data it has never seen before.

Results

A test dataset was generated and the results are shown in Figure 3. This is a correlation graph so a straight line would be a perfect result.
Looking at the original distributions, the model worked well since the lines are mostly straight. Using only 3 projections resulted in an error of around 3%.
When using a sextuple distorted distribution, the model performed worst, which was expected, but it was still able to predict beam loss fairly well.
A transfer learning study would be beneficial here to see if similar accuracy can be achieved and if the knowledge learned can be conserved.

Conclusion

The results show that if given only three projections of the 4D phase space, the projections can be reduced into smaller latent dimensions that contain the core information.
This information can then be used to predict the beam transmission downstream.
The latent dimension was verified to have contained the core information through a decoder that correctly reconstructed the encoded images.
Finally, this method generalizes fairly well to initial beam distributions with non-linear perturbations, showing robustness and the potential to model the real machine.

Acknowledgements

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