Proposal

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"Using Diffusion Probabilistic Models for Denoising Tracks from AT-TPC Detector"

General idea:

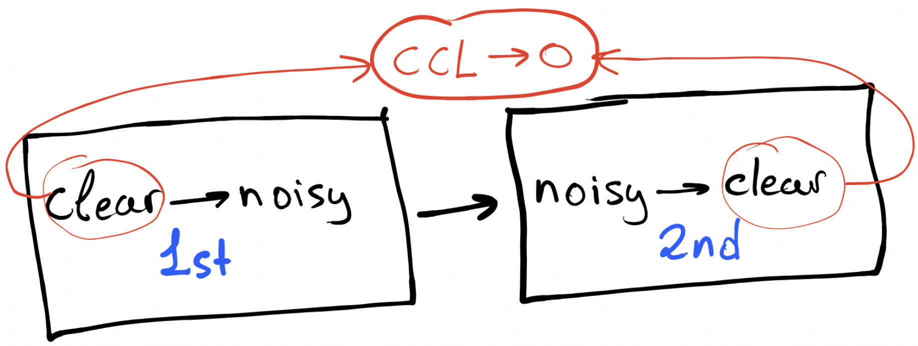
Preliminary work in Dr. Kuchera's group investigated using diffusion probabilistic models (dpm) [6] as a surrogate simulator for generating point clouds from the AT-TPC detector. I propose to continue this idea, but in order to denoise and clean charged particle tracks recorded by the AT-TPC detector. We plan to model the problem as unpaired, event-to-event domain translation. One domain would comprise AT-TPC events generated via simulation; the other would comprise events recorded during actual experiments with the detector. We expect the trained model to be able to remove noise from tracks.

Steps to complete the task:

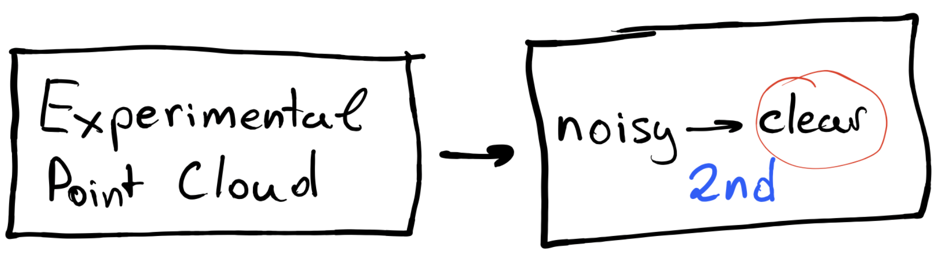
1.**Data preparation:** To train the model, we will use simulated data for the AT-TPC detector, as well as data from experimental runs. The former will be devoid of any noise, while the latter will include detector effects and noise from other sources.

2.**Diffusion Model Implementation:** We will implement DM using existing software libraries, such as [6], and by developing our own code. Existing dpm models for point clouds assume three-dimensional points in Euclidean space, ATTPC data is 4-dimensional, which requires modifications. A dpm will be trained to recreate noiseless tracks from a noisy point cloud, which will be created by gradually adding noise to our "clean" data. We train this in an end-to-end fashion using a cycle consistency loss (i.e., the distance between the original event and the final event in that chain should be close to 0, because you've just completed a cycle)

3.**Validation and testing on new data**: As we don't have a paired experimental dataset, meaning that we have a noisy experimental point cloud, but at the same time we don't have the same experimental point cloud that is free from noise. This makes the validation issue less trivial. Our suggestion is to use Cycle Consistency Loss. To understand the principle, we need to delve a little into the details of how Diffusion Models work. We have two models, the first of which converts a pure point cloud to a noisy point cloud. The second model performs the reverse operation, recreating a pure point cloud from a noisy point cloud.



What is specifically of practical interest is to remove the first model, the purpose of which is to make the image noisy, and instead, under the guise of an already noisy image, feed our experimental data to the second model. And it is planned to evaluate the accuracy of recreating a noise-free point cloud using simulated data



Software Deliverables: Trained pyTorch model, training and validation code, and simplified toy dataset

TimeLine:

Duration	***Task***
2 weeks	*Become familiar with Diffusion Models and cycle-GAN. Learn more about prior ML-based noise reduction attempts in the AT-TPC detector.*
4 weeks	*Modify a DM to condition on simulated data. Find parameters that allow us to achieve maximum accuracy. Use different metrics to compare results*
4 weeks	*Combine two diffusion models and add cycle consistency to train both models together.* *Explore the limits of the model (i.e. the degree of noisiness of the point cloud, which allows you to recreate a noise-free point cloud).*
2 weeks	*Final implementation and preparation for distribution.*

References

[1] J. Bradt, D. Bazin, F. Abu-Nimeh, T. Ahn, Y. Ayyad, S.B. Novo, L. Carpenter, M. Cortesi, M. Kuchera, W. Lynch, W. Mittig, S. Rost, N. Watwood, J. Yurkon, Commissioning of the active-target time projection chamber, Nucl. Instrum. Methods Phys. Res. A 875 (2017) 65–79

[2] - Machine learning methods for track classification in the AT-TPC M.P. Kuchera a,∗ , R. Ramanujan b , J.Z. Taylor a , R.R. Strauss b , D. Bazin c , J. Bradt c , Ruiming Chen; Nuclear Inst. and Methods in Physics Research, A940 (2019) 156-167

[3] - Unsupervised learning for identifying events in active target experiments R. Solli a,b,∗ , D. Bazin c , M. Hjorth-Jensen c,d , M.P. Kuchera e , R.R. Straussf; Nuclear Inst. and Methods in Physics Research, A 1010 (2021) 165461

[4] - PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation Charles R. Qi Hao Su* Kaichun Mo Leonidas J. Guibas Stanford University (2017)*

[5] - PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space Charles R. Qi Li Yi Hao Su Leonidas J. Guibas Stanford University (2017)

[6] - *Diffusion Probabilistic Models for 3D Point Cloud Generation Shitong Luo, Wei Hu * Wangxuan Institute of Computer Technology Peking University*