DATA ANALYSIS IN HIGH-ENERGY PHYSICS USING MACHINE LEARNING METHODS

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CFNS-SURGE Summer Workshop on the Physics of the Electron-Ion Collider

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- Therefore, we aim to **break the cost** established by MC simulations by proposing the use of generative **Machine Learning (ML)** models for **synthetic data generation**.
- We seek to optimize the performance and statistics of standard analyses of high-energy physics by synthesizing secondary decay particles.

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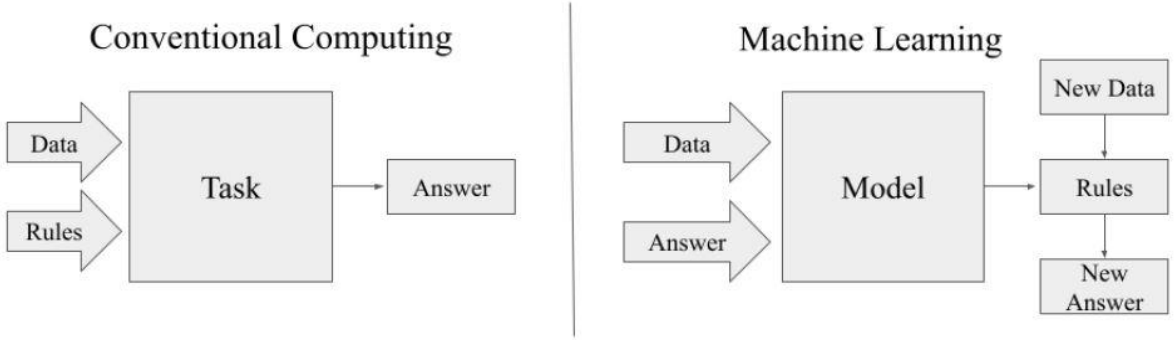

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What can we do with ML?

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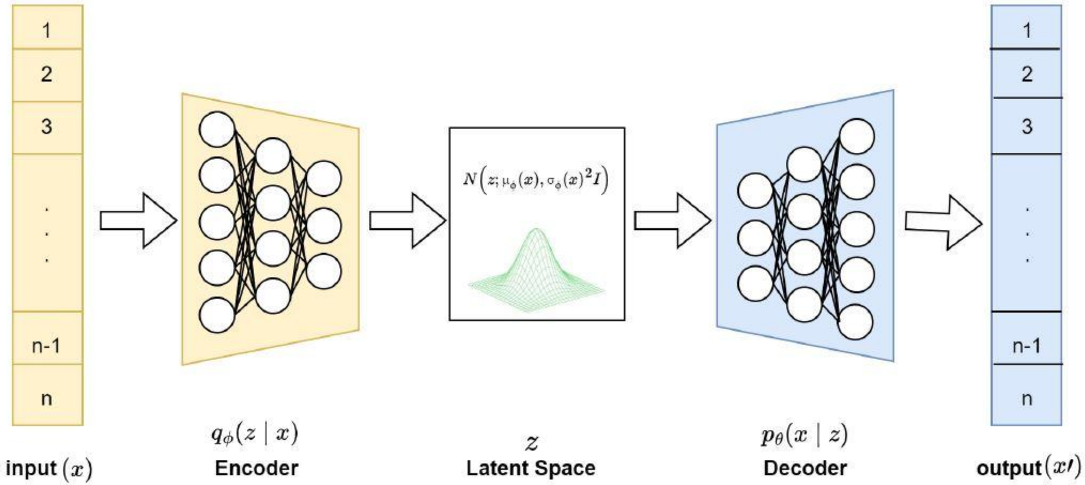
- Variational Autoencoders (Vae):



AMMARA, D.; DING, J.; TUTSCHKU, T. "*Synthetic Data Generation in Cybersecurity: A Comparative Analysis*". 2024. arXiv: 2410.16326 [cs.CR].

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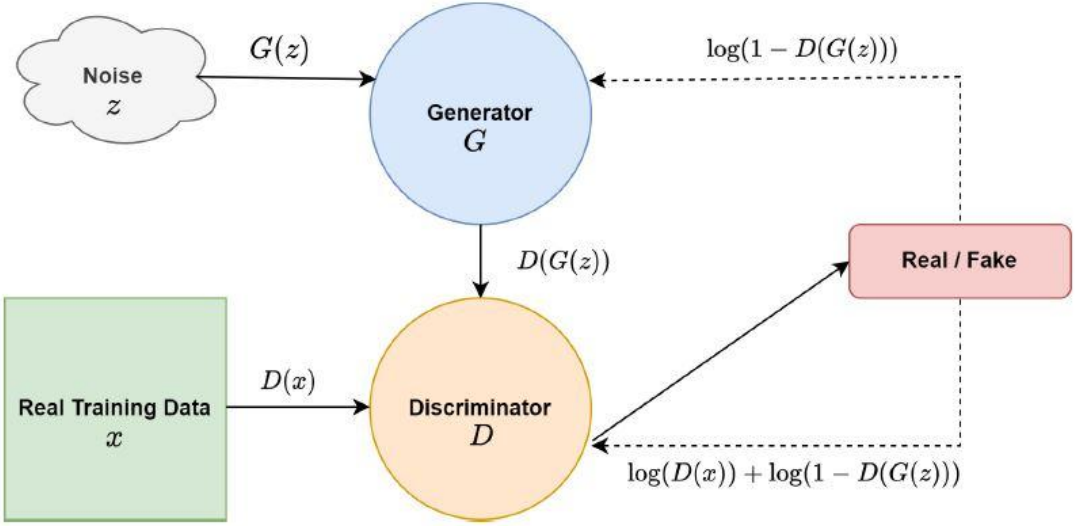
- Conditional Tabular Generative Adversarial Network (Ctgan):



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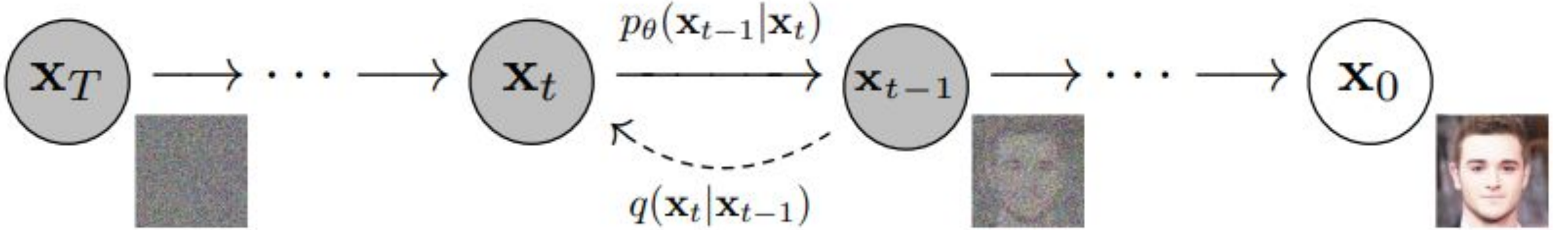
- Tabular Denoising Diffusion Probabilistic Model (TabDDPM):



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- The TabDDPM model employed 6 layers with 1024 neurons each. A cosine noise scheduler was applied with the number of diffusion timesteps to 1000 and a learning rate of 0,003. The remaining parameters followed the original implementation.

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- The Vae model architecture was optimized using the Optuna Python library for efficient hyperparameter tuning.

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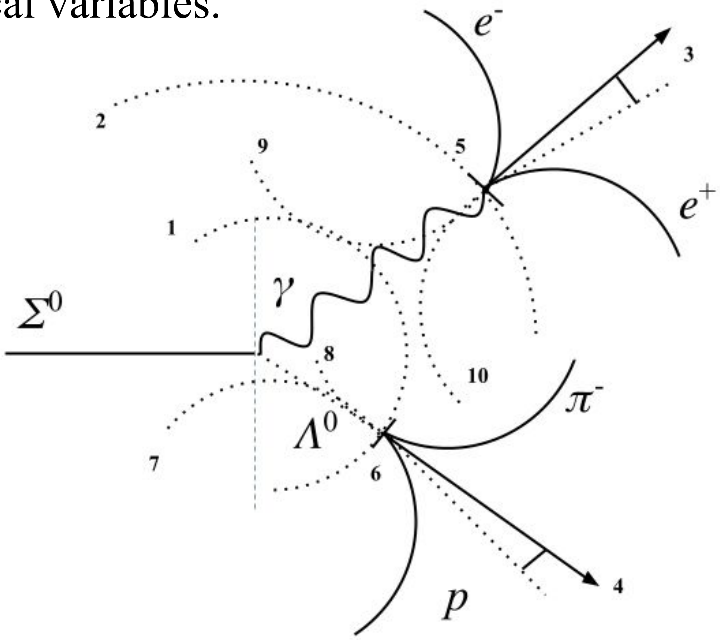

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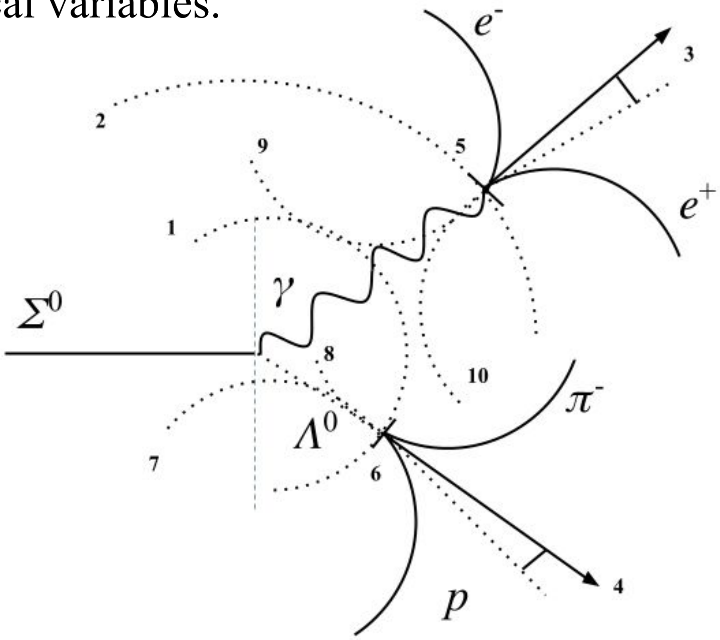

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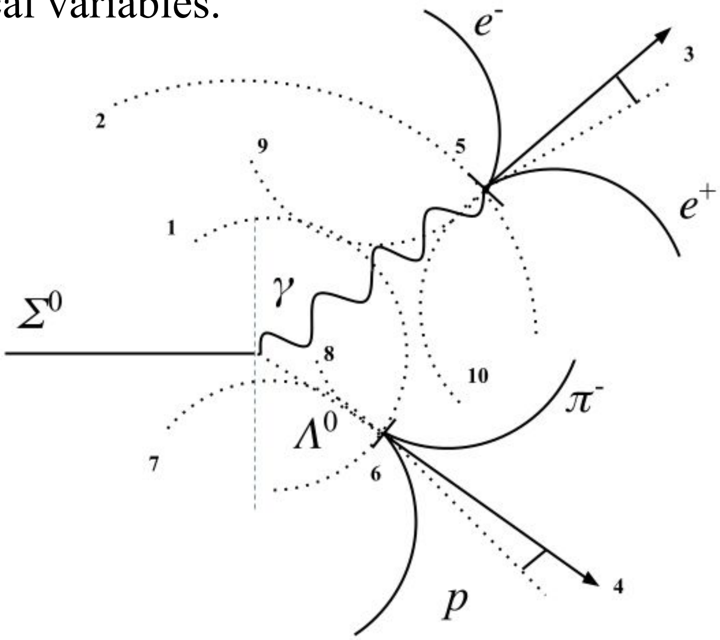

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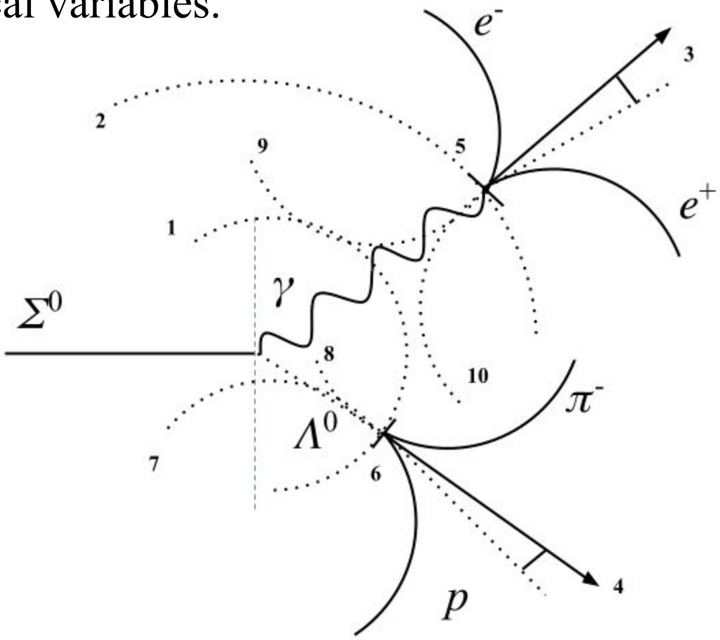

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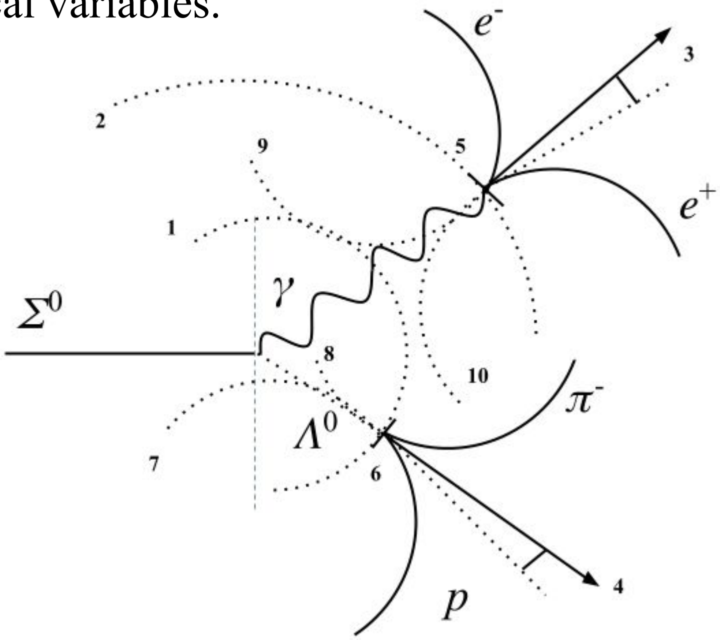

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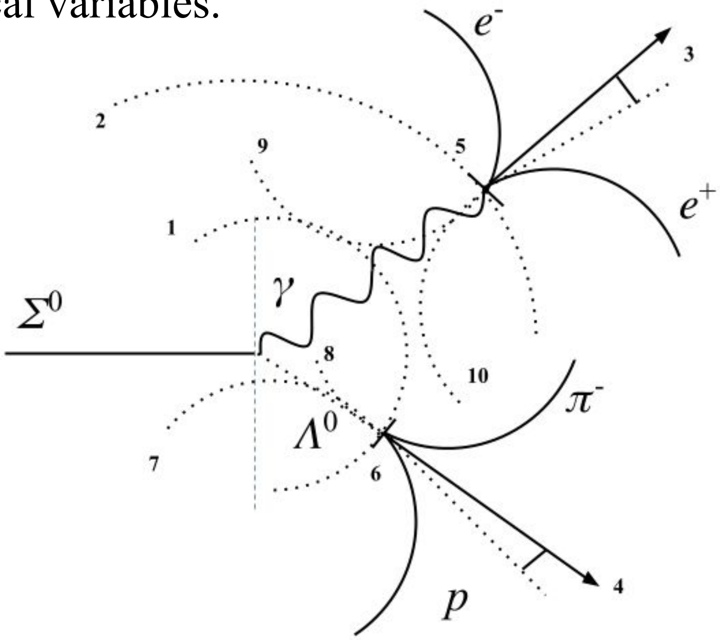
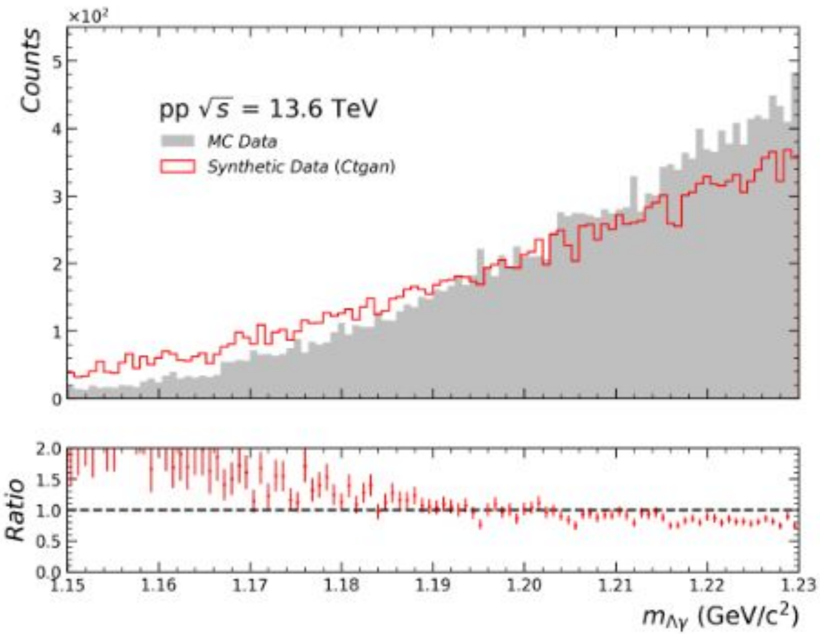
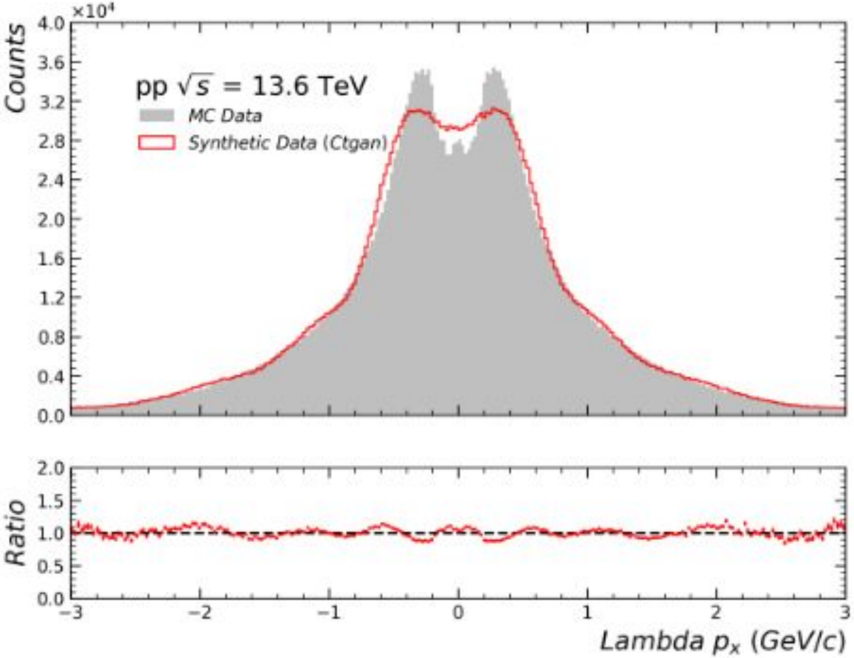
- Train your model.
- Evaluate the results.

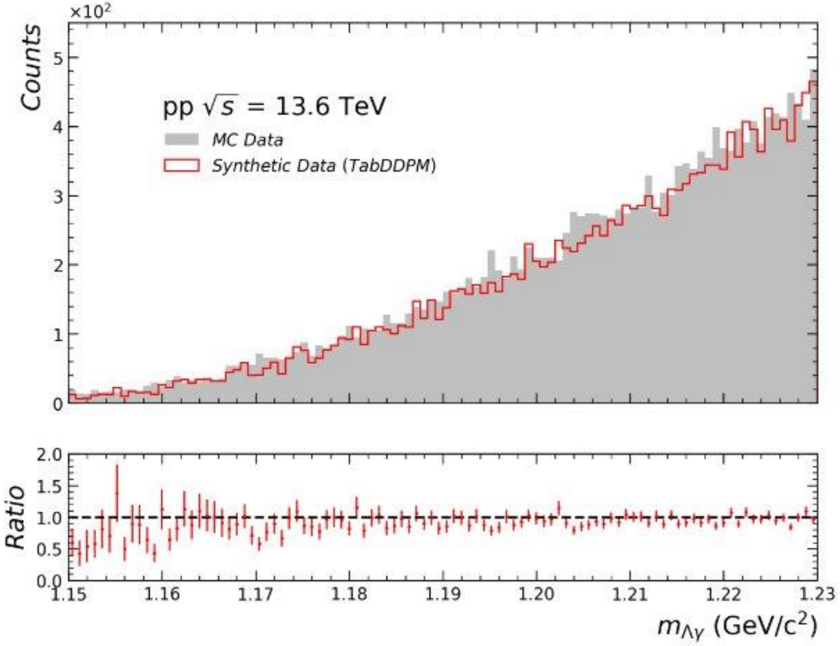


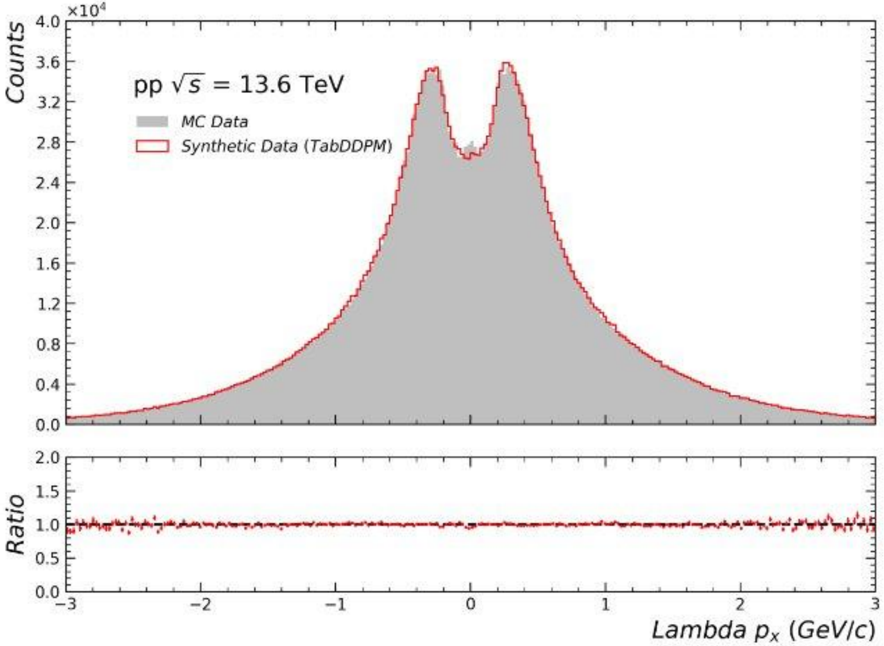
Results - Ctgan Model





Results - TabDDPM Model





- **Early results! Only momentum coordinates of particles were used in training process!**

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- We have explored and implemented generative models, including Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs) and Diffusion Models.
- We have shown the ability of most of these models to learn complex, unstructured data while preserving first-order correlations and feature distributions.
- Therefore, we have demonstrated that CTGAN and TabDDPM can successfully generate millions of synthetic data points within seconds, thereby reducing generation time from hours to even days.

Next Steps

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- Engage in a PhD project.

THANK YOU!

ACKNOWLEDGMENTS