# Comparison of MeshGraphNet Techniques for Subsurface Behavior Prediction During $CO_2$ Sequestration

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Science-informed Machine Learning to Accelerate Real Time (SMART) Decisions in Subsurface Applications

## ABSTRACT

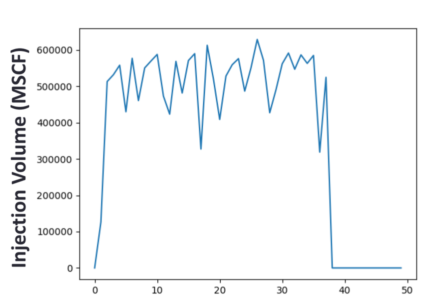
Carbon sequestration is a vital part of the effort to mitigate anthropogenic climate change. Previously, we have shown that Graph Neural Networks (GNNs) provide the ability to extract meaningful insights during prediction of subsurface behavior in carbon storage projects. However, these models have struggled with long-term prediction accuracy due to error accumulation caused by autoregressive prediction. This research leverages the Illinois Basin – Decatur Project (IBDP) dataset to examine strategies for minimizing loss over time in a MeshGraphNet GNN model to improve reliability of predictions while minimizing inferencing time.

## OBJECTIVES

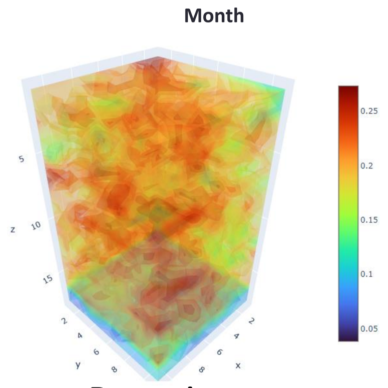
- Develop variations on the MeshGraphNet (MGN) model: MeshGraphNet + Multi-step Rollout (MGN-MR) and MeshGraphNet + Transformer (MGN-T)
- Compare previously developed MGN to variations to assess improvement of temporal prediction

## DATA – IBDP

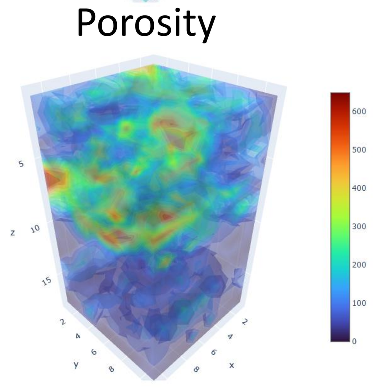
- Standardized data based on the IBDP
- 100 realizations (15,610 x 14,967 x 1,120 $m^3$)
- Full data shape: 126 x 125 x 110 (x, y, z)
- Experimental data shape: 11 x 11 x 18 (x, y, z)
- Single injector with a variable injection rate over 36 months and then monitored for another 12 months post-injection (1-month Δt) for a total of 50 timesteps




- Features of the data:
  - Static Features: Porosity, Permeability, Node Location
  - Calculated Features: Cell Volume (node-centric); Distance Between Nodes (Δx, Δy, Δz); Linear Distance Between Nodes (vector magnitude)
  - Dynamic Features: Pressure or Saturation, Injection Rate
  - Assigned Features: Node Types (injector, interior, edge, face, corner)



Porosity



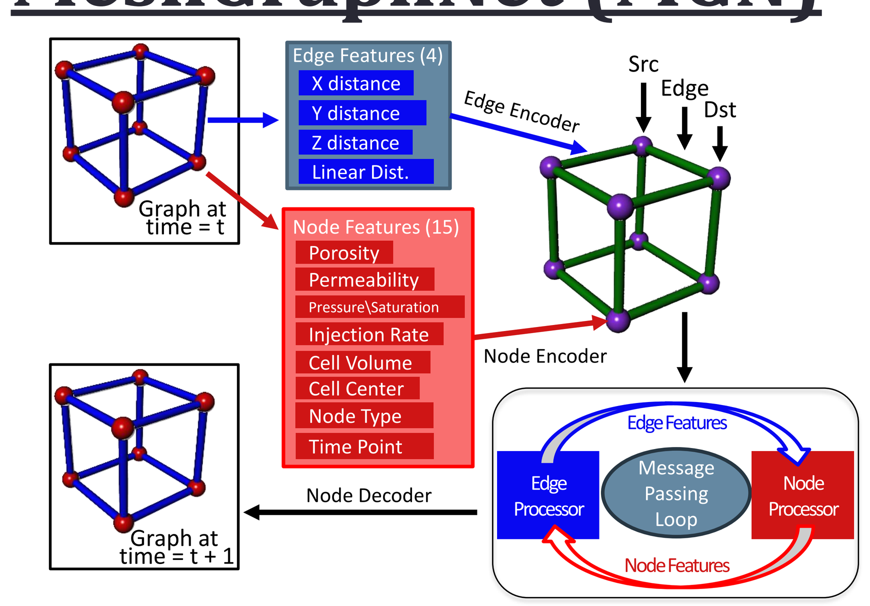
Permeability

## METHODS AND RESULTS

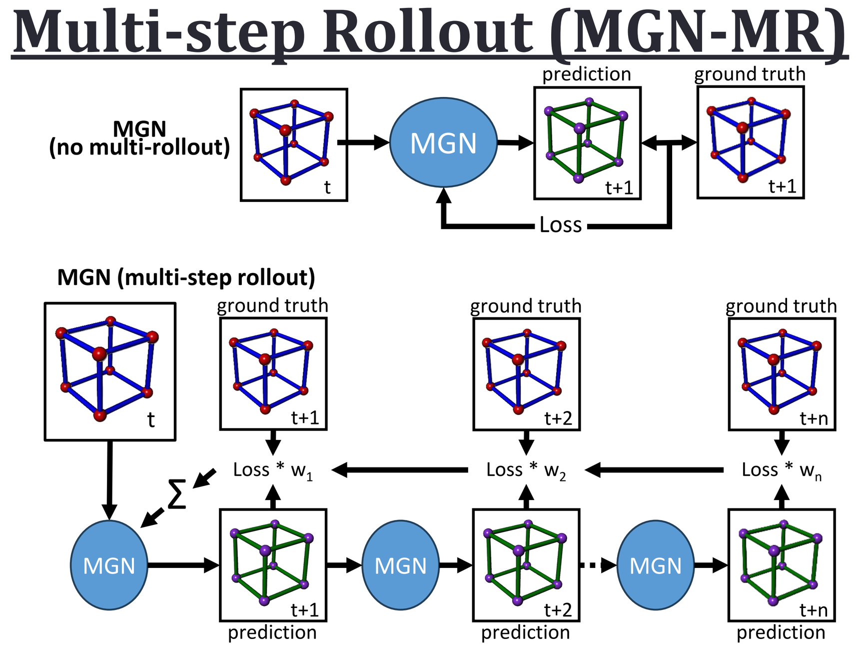
### EXECUTIVE SUMMARY

Graph neural networks (specifically the MeshGraphNets model) have been shown to accurately predict subsurface behavior in models with heterogeneous geological properties. However, predictions over time tend to accumulate errors. We show that implementing multi-step rollout during training can help stabilize prediction over time. Preliminary results using transformer methods suggest a further improvement in accuracy.

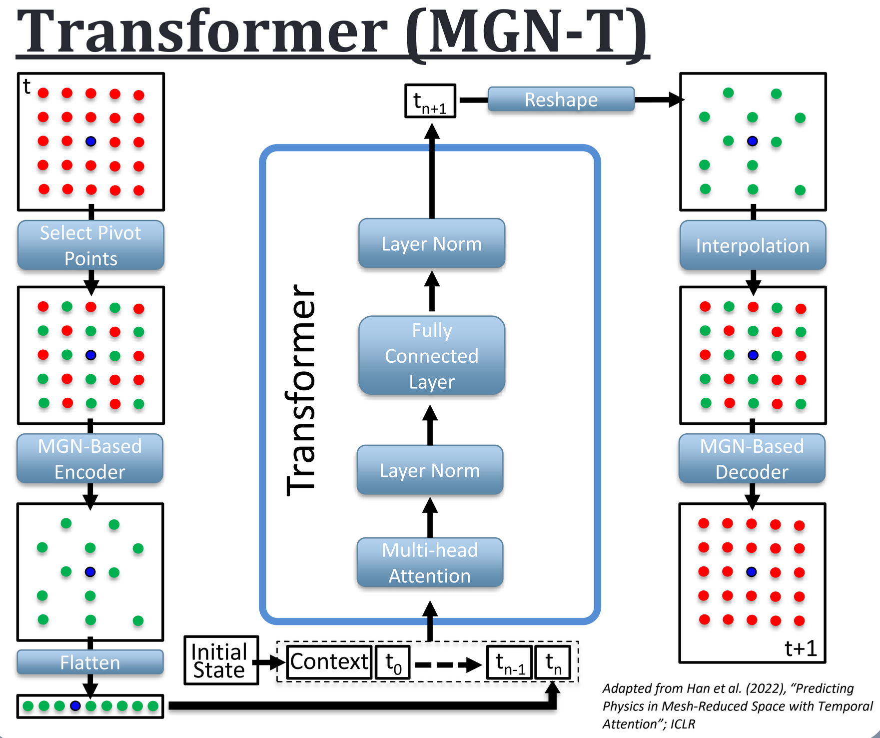
### MeshGraphNet (MGN)



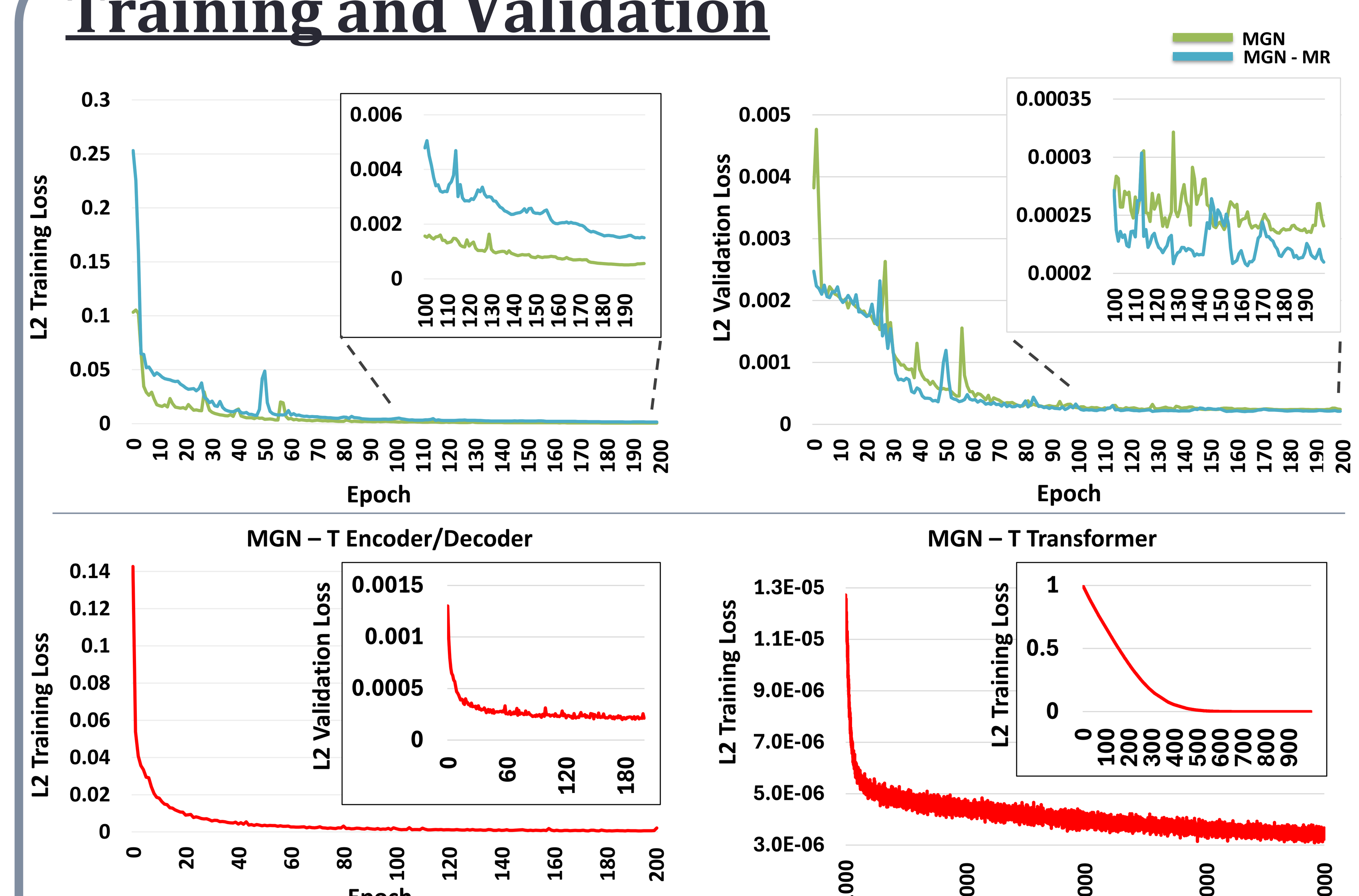

### Multi-step Rollout (MGN-MR)



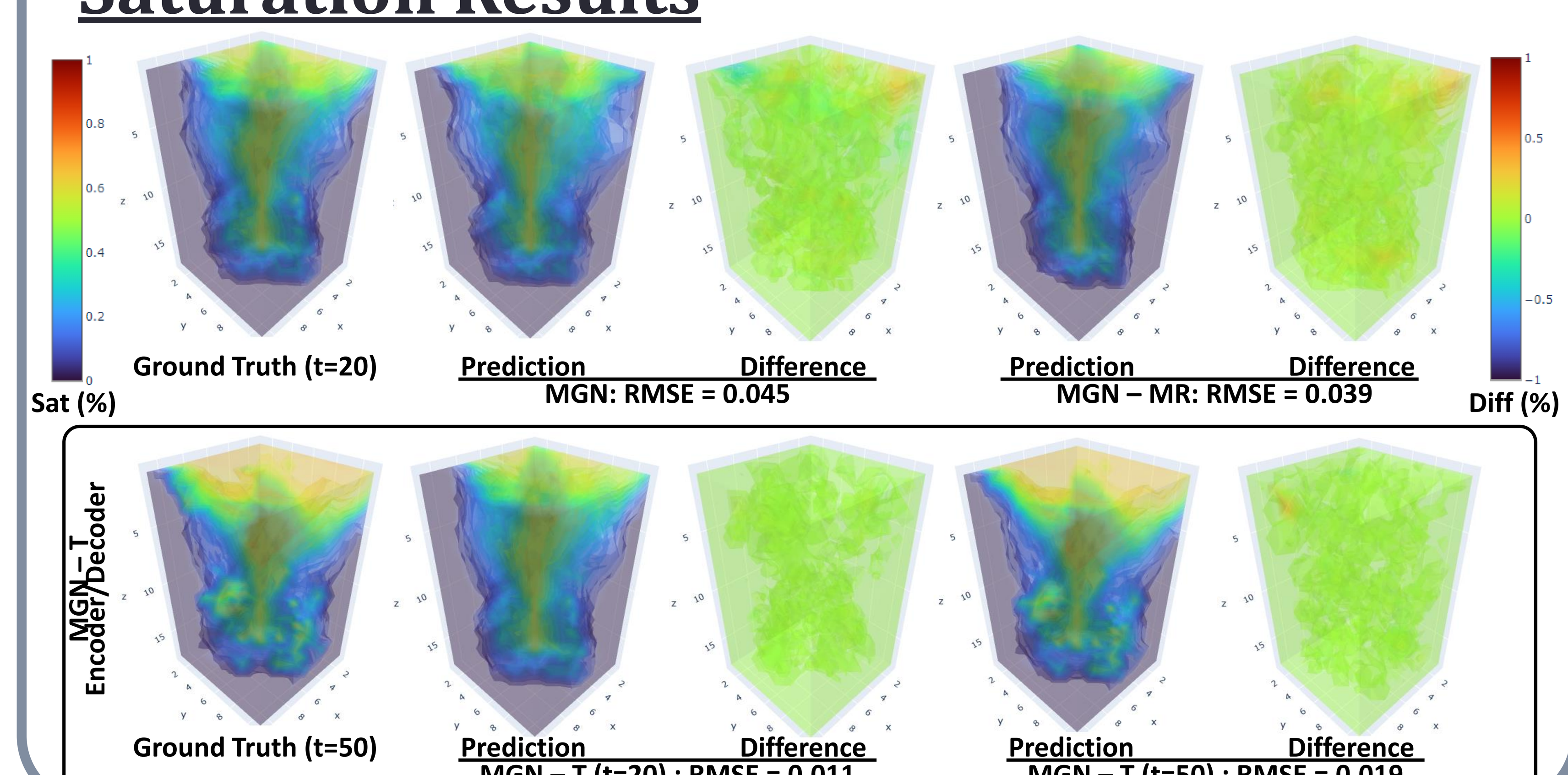

### Transformer (MGN-T)




### Training and Validation

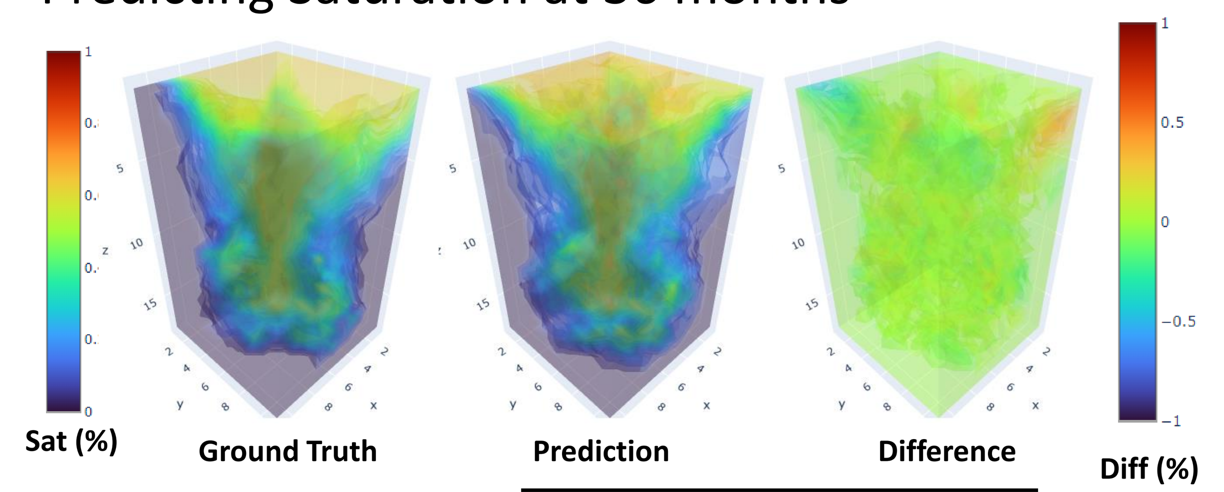


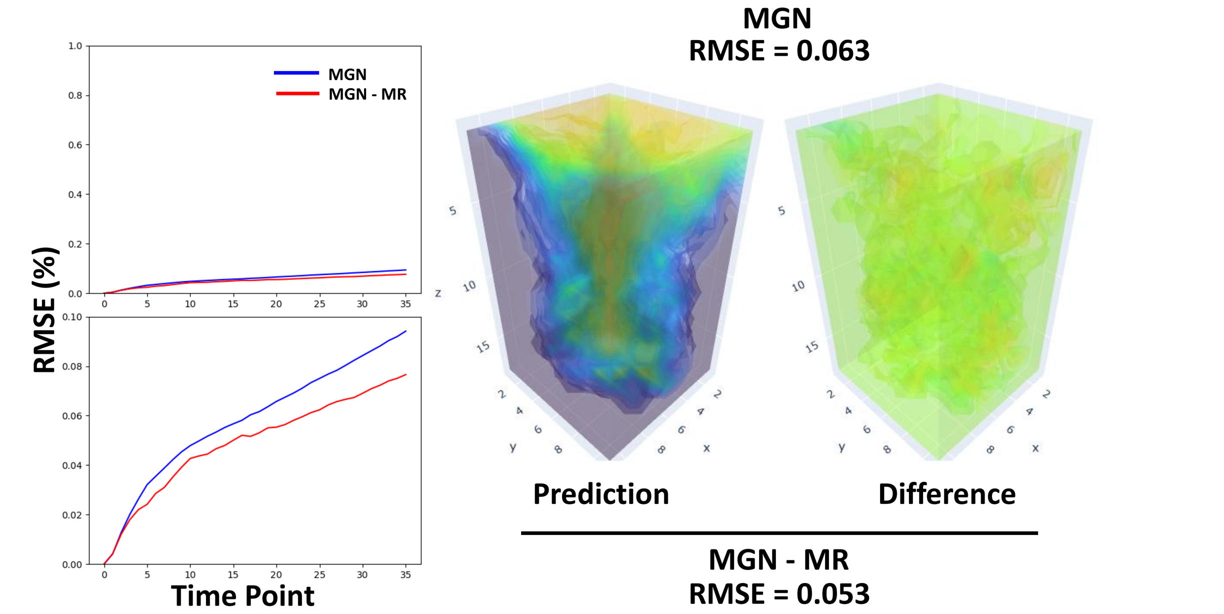

### Saturation Results




## FORWARD PREDICTION

Predicting Saturation at 36 months




## CONCLUSIONS

- Implemented multi-step rollout (MGN-MR) and transformer (MGN-T) improvements to the original MeshGraphNets model
- MGN-MR shows improvement of saturation prediction at both 20 months (during injection) and 36 months (end of injection)
- Preliminary MGN-T results show a high degree of accuracy in encoding and decoding graphs for transformer training
- Multi-step rollout helps stabilize prediction over time

## DISCLAIMER

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