Roto-translated Local Coordinate Frames For Interacting Dynamical Systems

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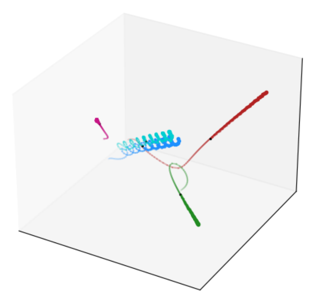
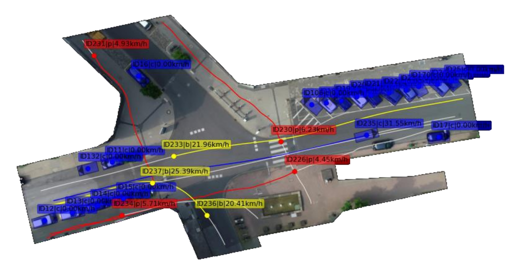
Neural Information Processing Systems

Interacting systems are everywhere

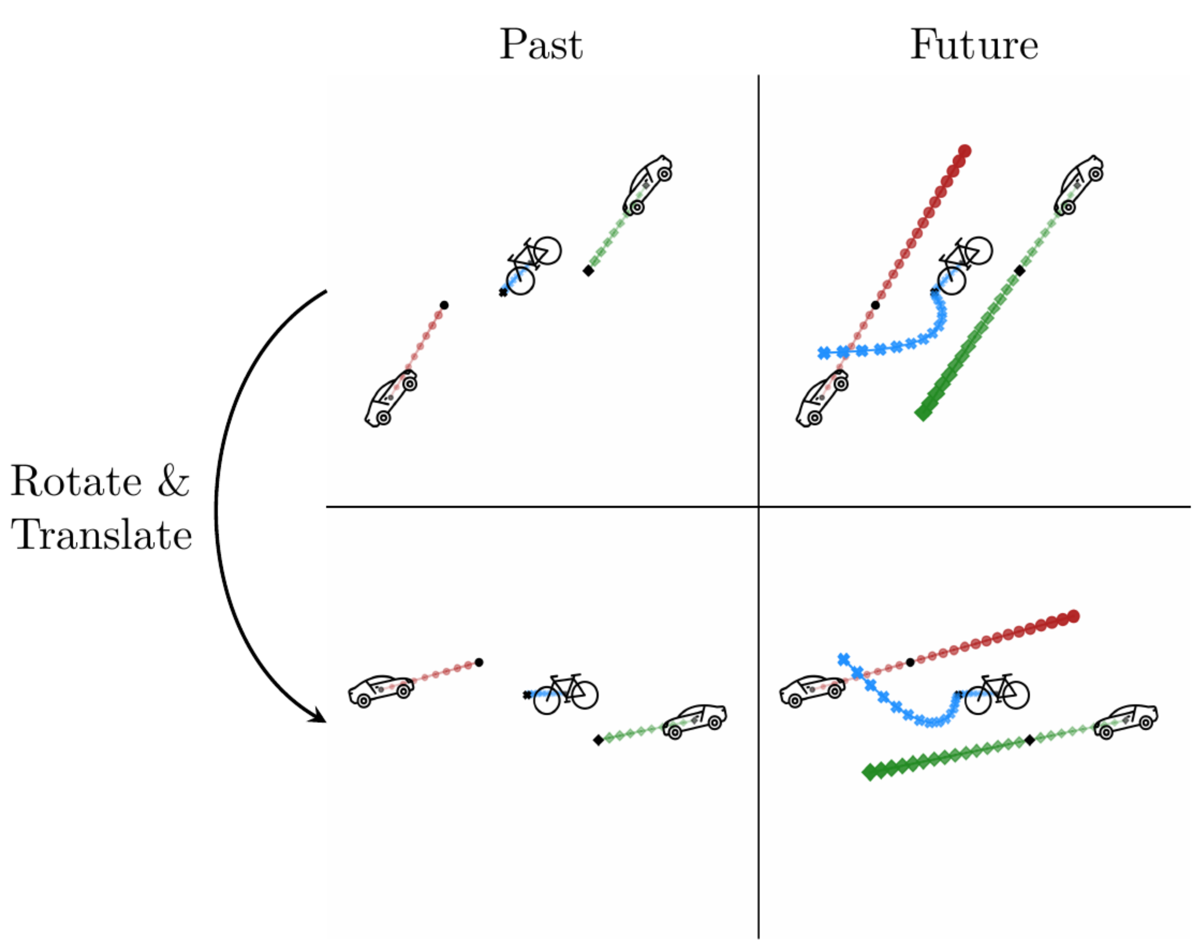
- Colliding particles
- N-body systems
- Molecules
- Motion capture
- Traffic scenes





Motivation - Roto-translation equivariance

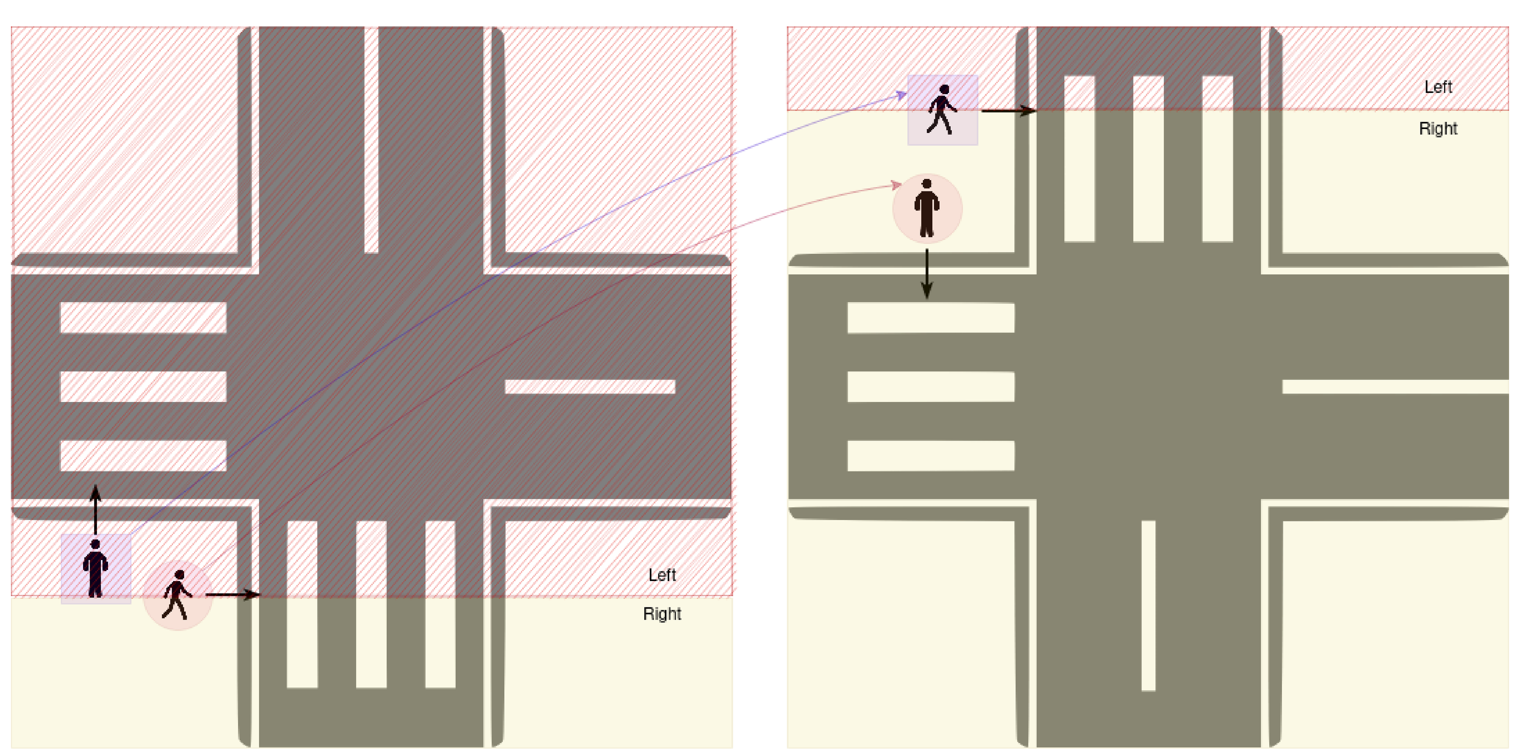
Dynamics do not change under rotations and translations.



Most works do not have this property and address it approximately using data augmentation techniques.

Motivation - Ego-centric perspective

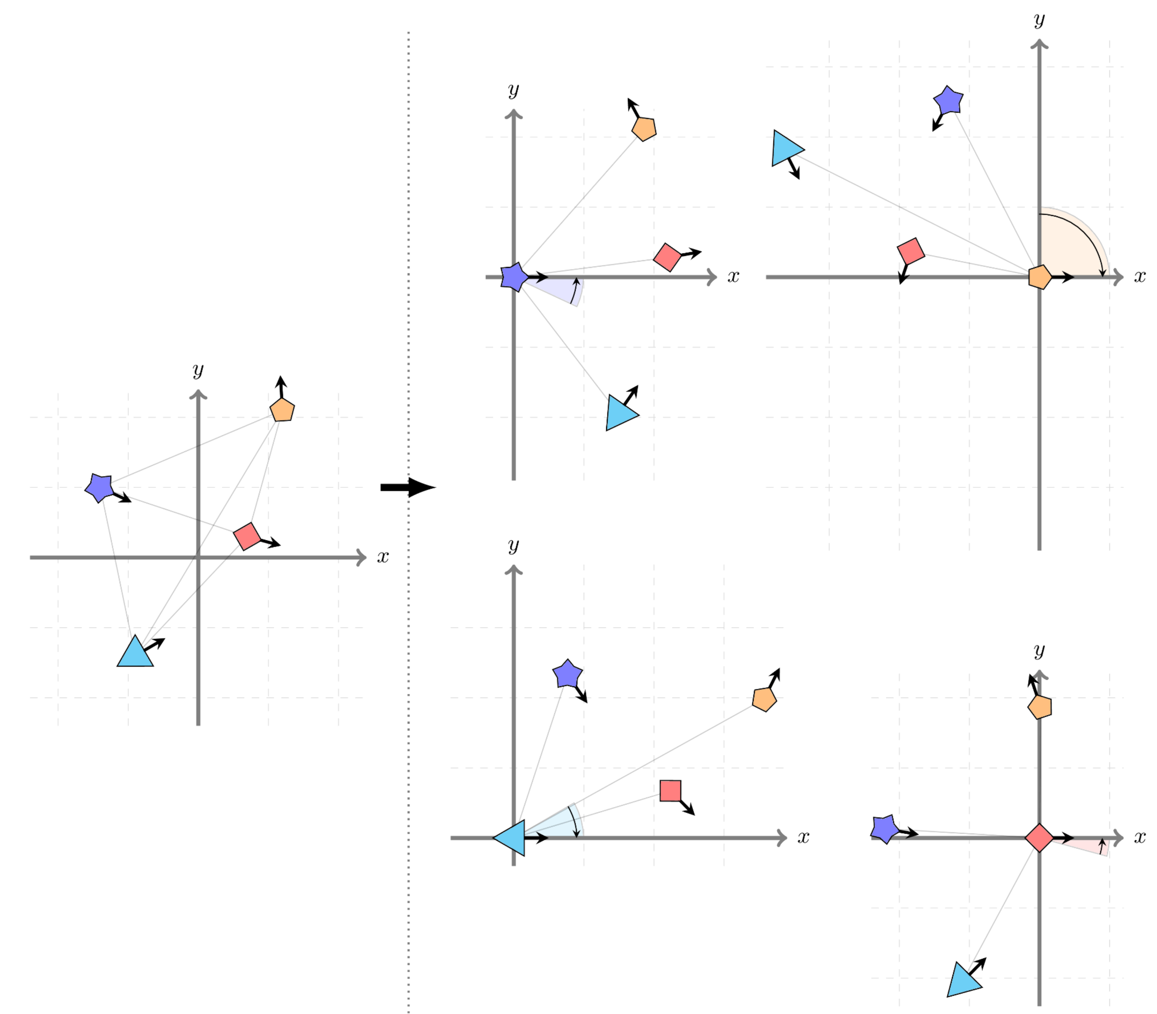
Objects often operate in ego-centric and asymmetric views of the world.



However, graph are often embedded in arbitrary global coordinate frames.

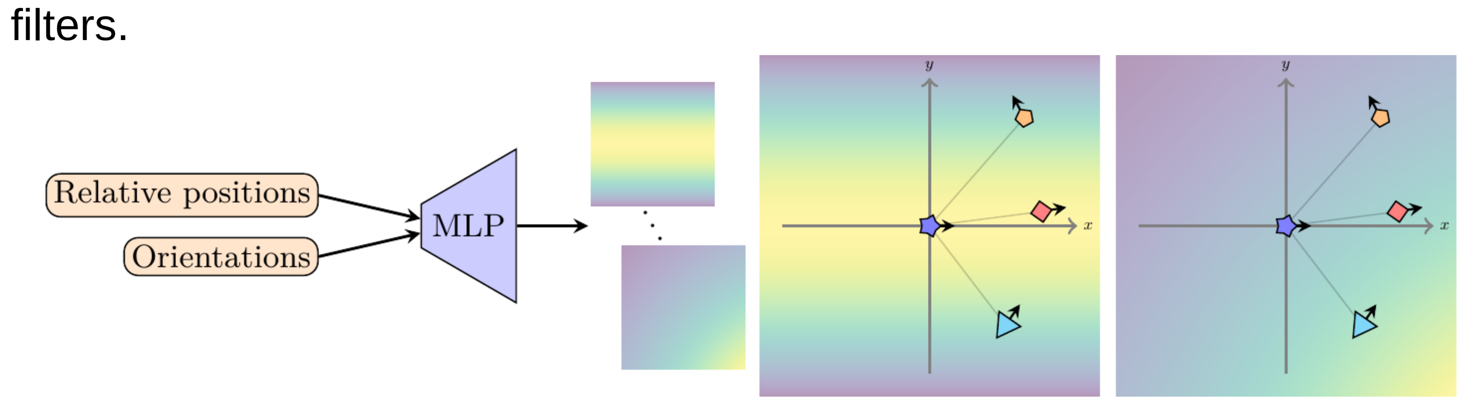
Roto-translated Local Coordinate Frames

We propose local coordinate frames for all objects in an interacting dynamical system. Each local coordinate frame is translated to match the target object's position and rotated to match its orientation/velocity.



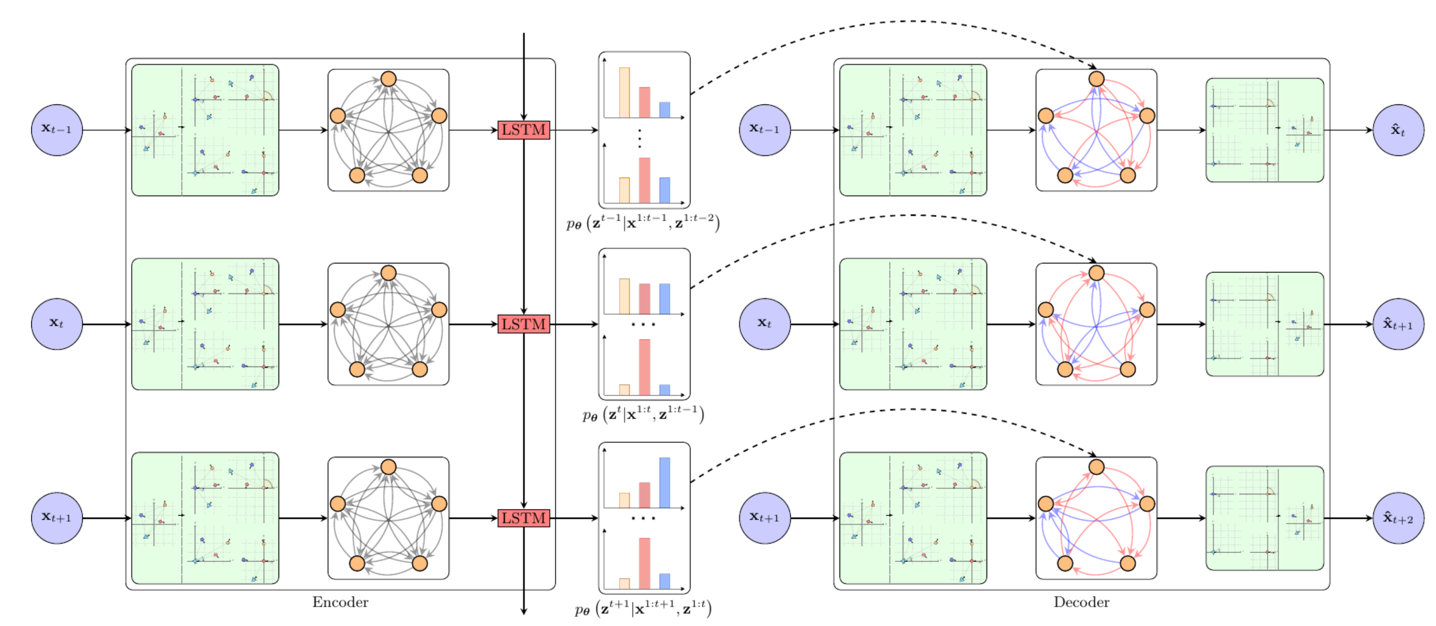
Anisotropic Continuous Filtering

Directionality in local coordinate frames allows for anisotropic continuous filters.



Neural Relational Inference Backbone

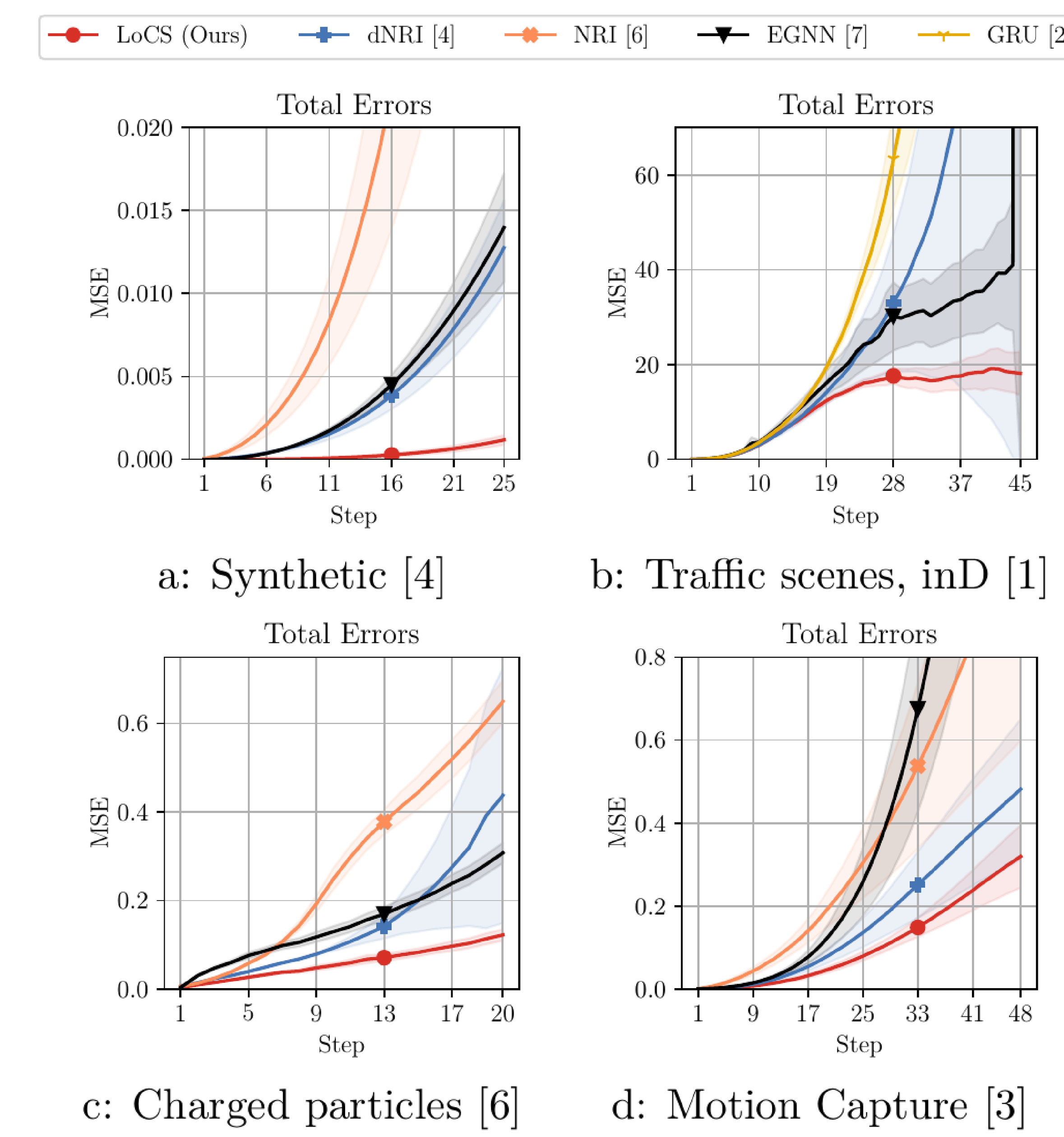
We formulate our model as a VAE [5] with latent edge types, using Dynamic Neural Relational Inference [4] as a backbone.



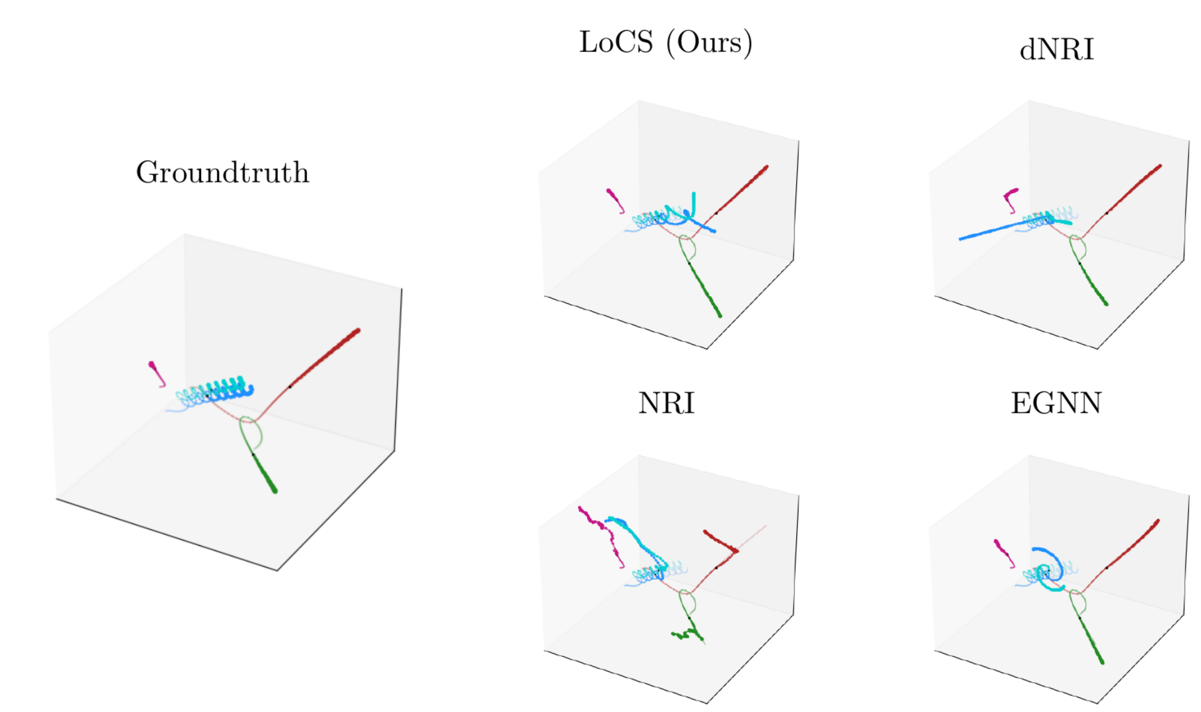
In principle, our method is agnostic to the choice of backbone architecture and can be integrated to any graph network that operates on spatially positioned nodes evolving through time.

Results

Experiments on 2D/3D settings show the effectiveness of our method.



Qualitative Results – Charged Particles



References

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[2] Cho, K. et al. "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation". In: EMNLP 2014.
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[6] Kipf, T. & Fetaya, E. et al. "Neural Relational Inference for Interacting Systems". In: ICML 2018.
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https://github.com/mkofinas/locs