



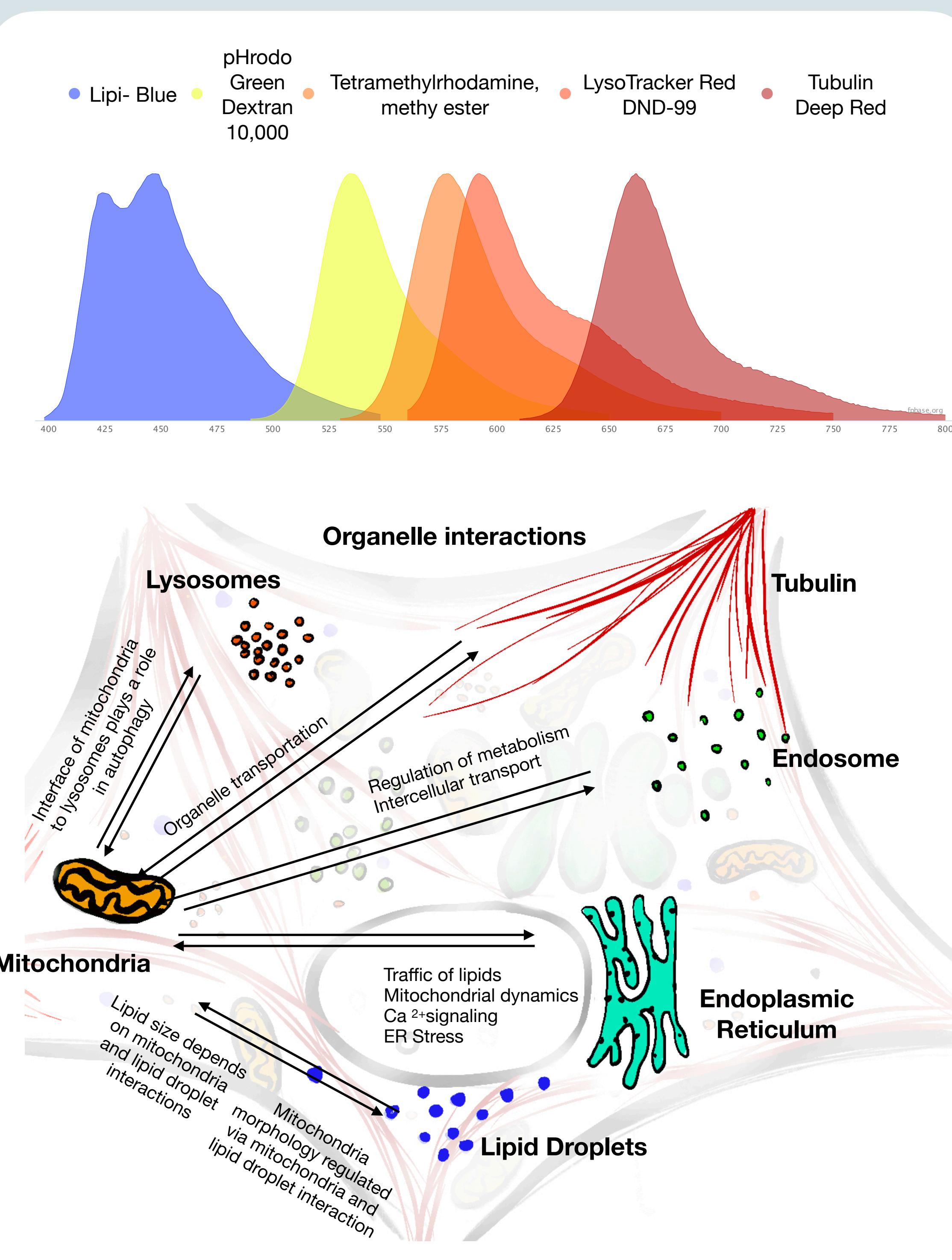
# Learning From Live Cell Hyper Spectral Fluorescence Imaging Data via Stochastic Physics-informed Equivariant Autoencoders

**UCI** Center for Complex Biological Systems

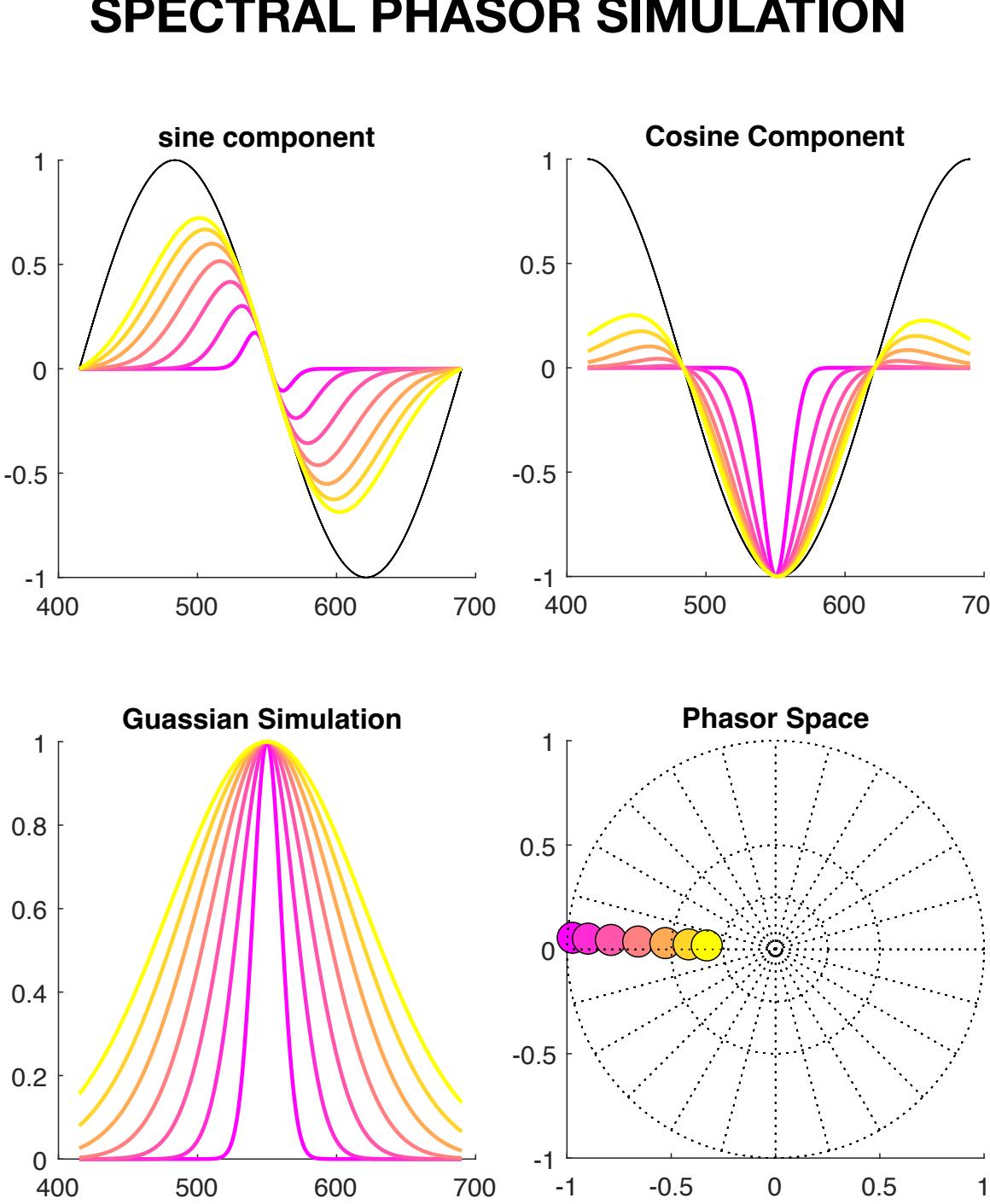
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## ABSTRACT

The adage that a picture is worth a thousand words suggests that a video—composed of thousands of frames—conveys exponentially more information. This concept is particularly relevant in live-cell hyperspectral fluorescence microscopy, where recent technological advances have dramatically improved data fidelity and resolution. Nevertheless, the analysis of such high-dimensional data remains challenging, necessitating the extraction of meaningful latent representations for efficient interpretation and prediction. Traditional generative AI models have been applied to this problem, yet they often underperform due to their limited grasp of physical dynamics and inability to accurately model pixel-level variations. To address these issues, we propose a Graph Attention-based Variational Autoencoder (GAT-VAE) tailored for next-frame prediction in time-lapse hyperspectral imaging. In parallel, we develop a soft-spring model of cellular movement, which not only serves as a benchmark but also lays the groundwork for integrating physical priors into the learning process. By fusing our GAT-VAE with physics-informed modeling, we aim to construct atemporally structured latent space that faithfully captures the dynamics of cellular behavior. This hybrid approach not only enhances prediction accuracy but also provides deeper insights into the underlying physical processes governing cell movement.

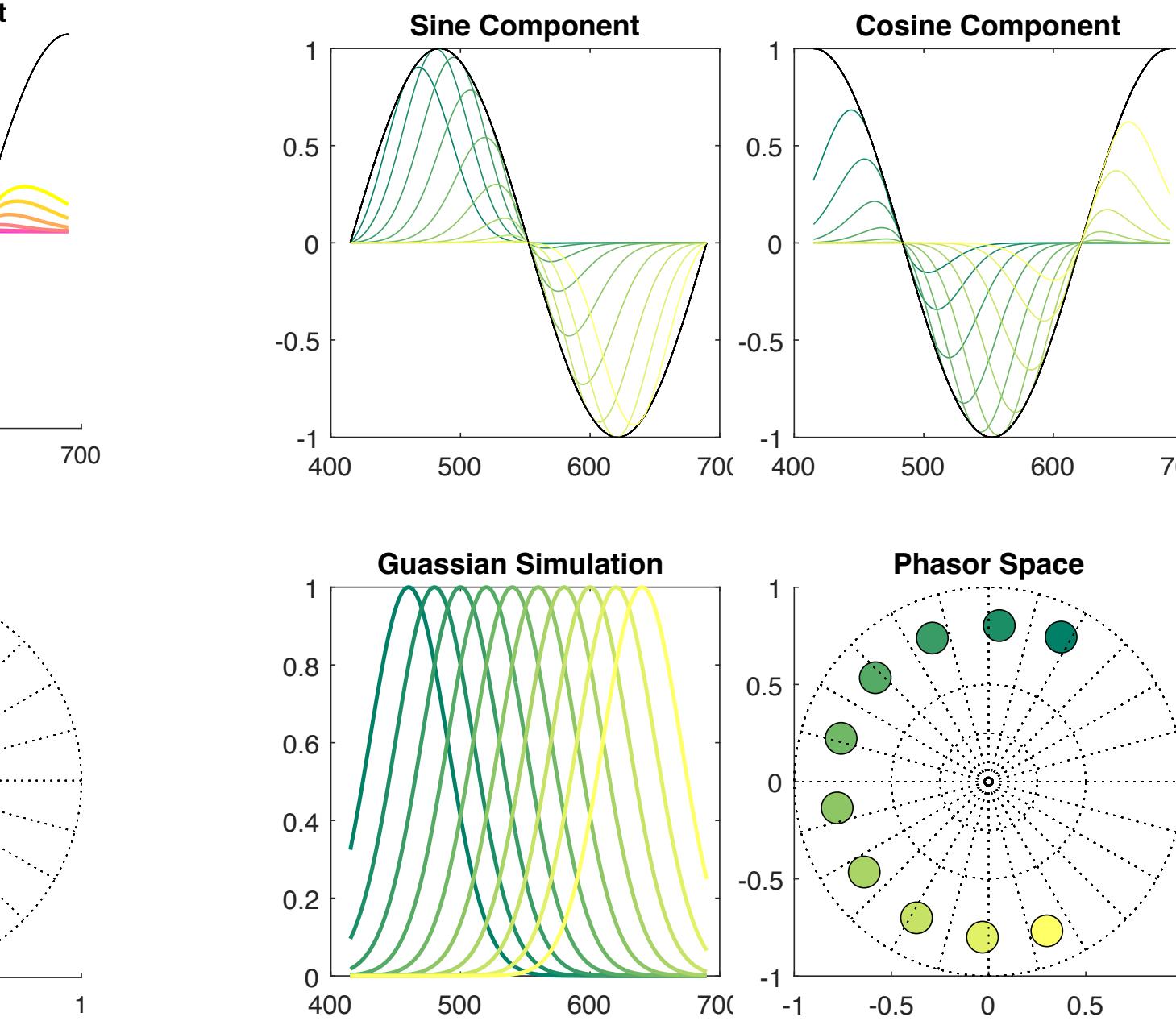


## SPECTRAL PHASOR SIMULATION

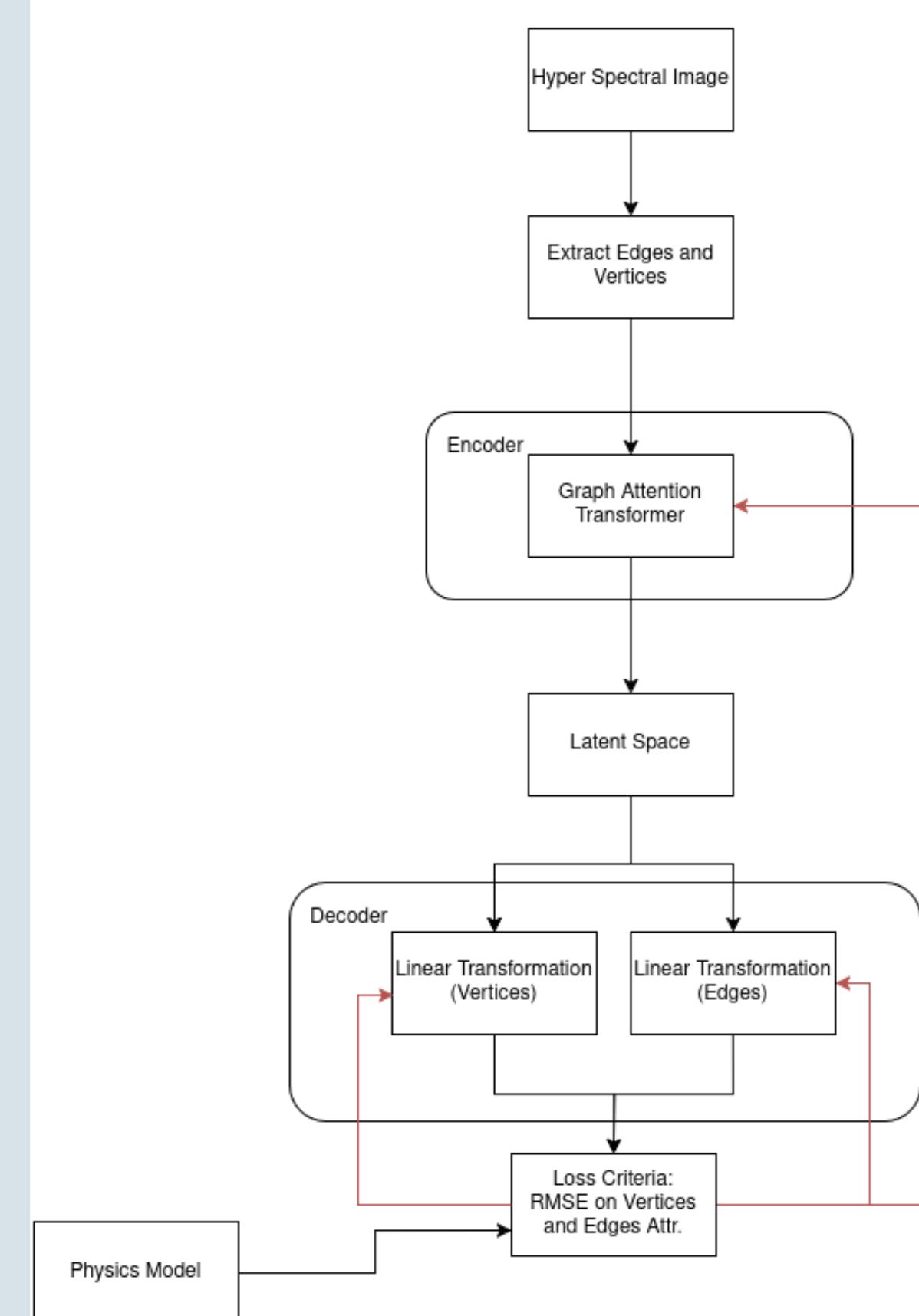


## RESULTS

$$g_n(\omega) = \frac{\int_0^T I(t)\cos(n\omega dt)}{\int_0^T I(t)dt} \quad S_n(\omega) = \frac{\int_0^T I(t)\sin(n\omega dt)}{\int_0^T I(t)dt}$$



## GAT-VAE



$$e_{ij} = a(\vec{W_h}_i, \vec{W_h}_j)$$

$$\vec{h}'_i = \sigma \left( \frac{1}{K} \sum_{k=1}^K \sum_{j \in \mathcal{N}_i} \alpha_{ik}^k \vec{W}^k \vec{h}_j \right)$$

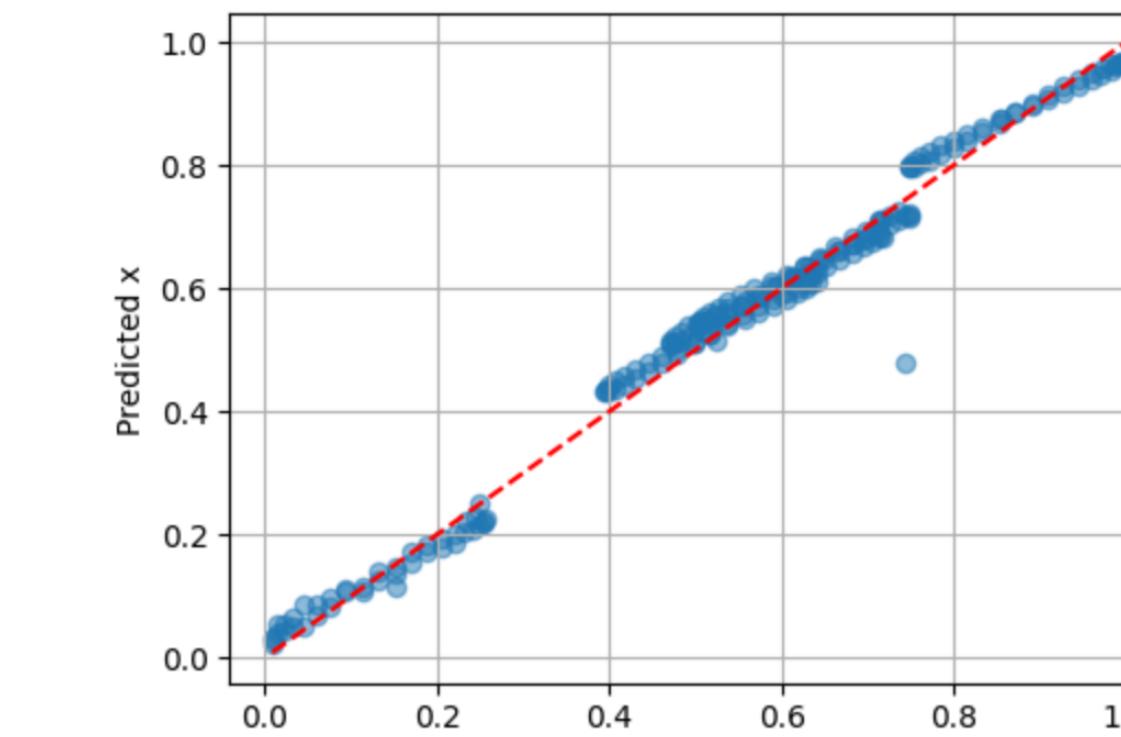
$$a_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}_i} \exp(e_{ik})}$$

## Model Architecture and Graph Representation of A Single Cell

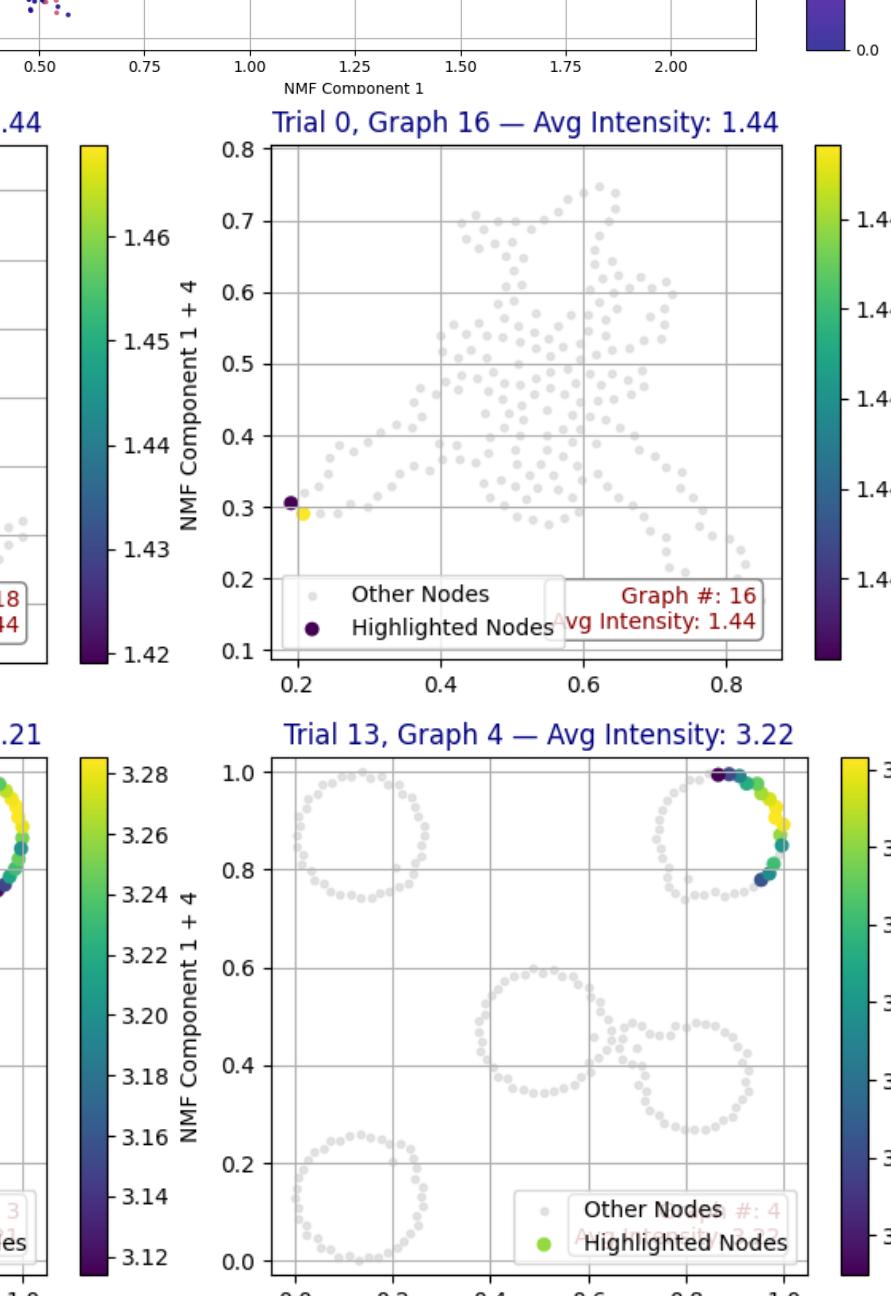
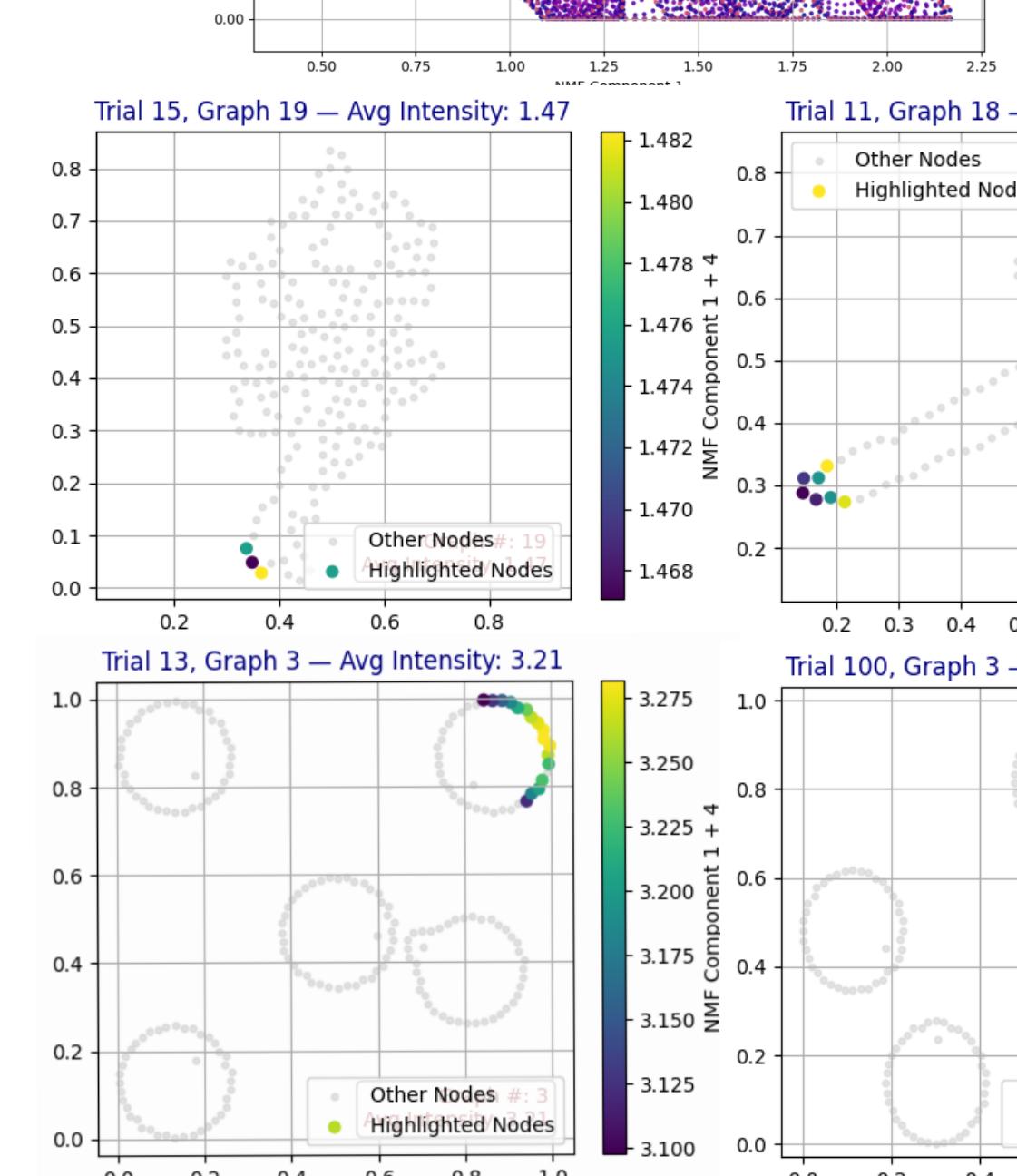
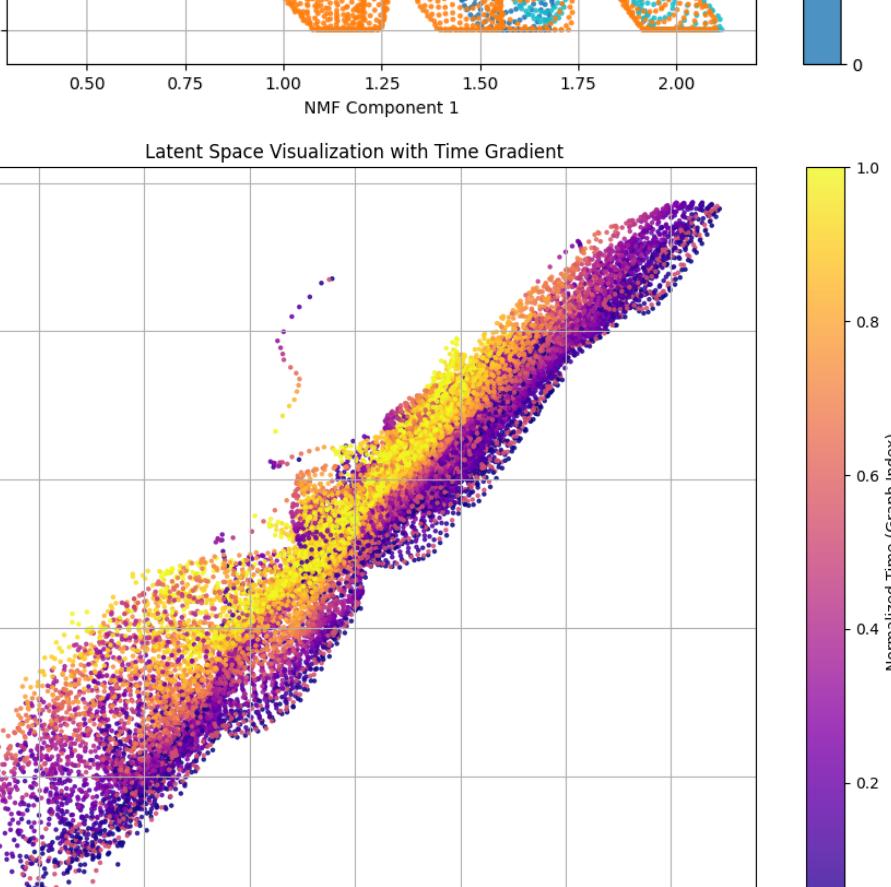
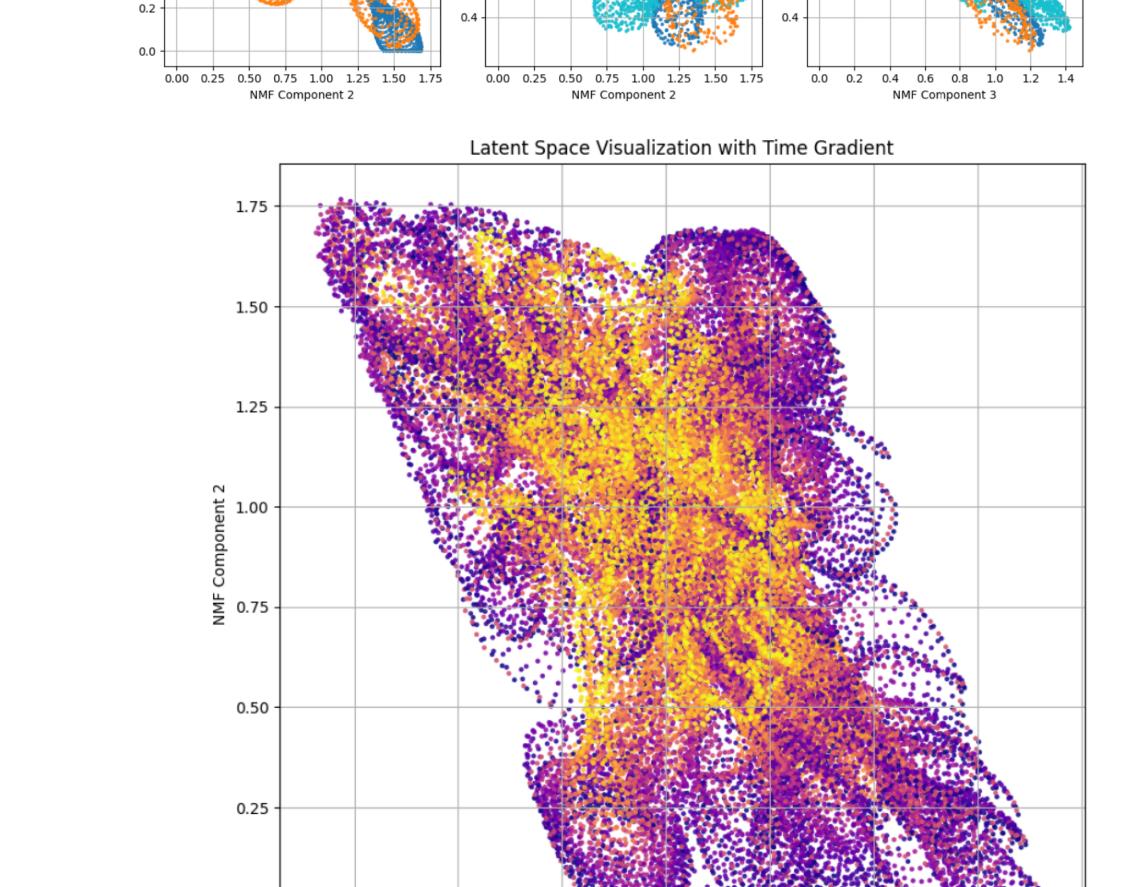
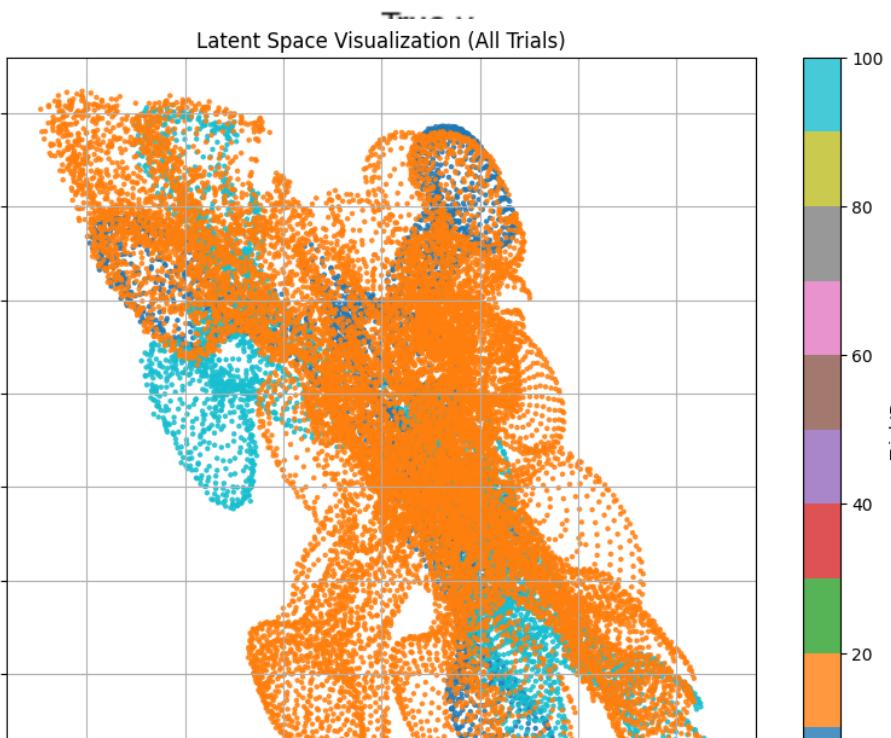
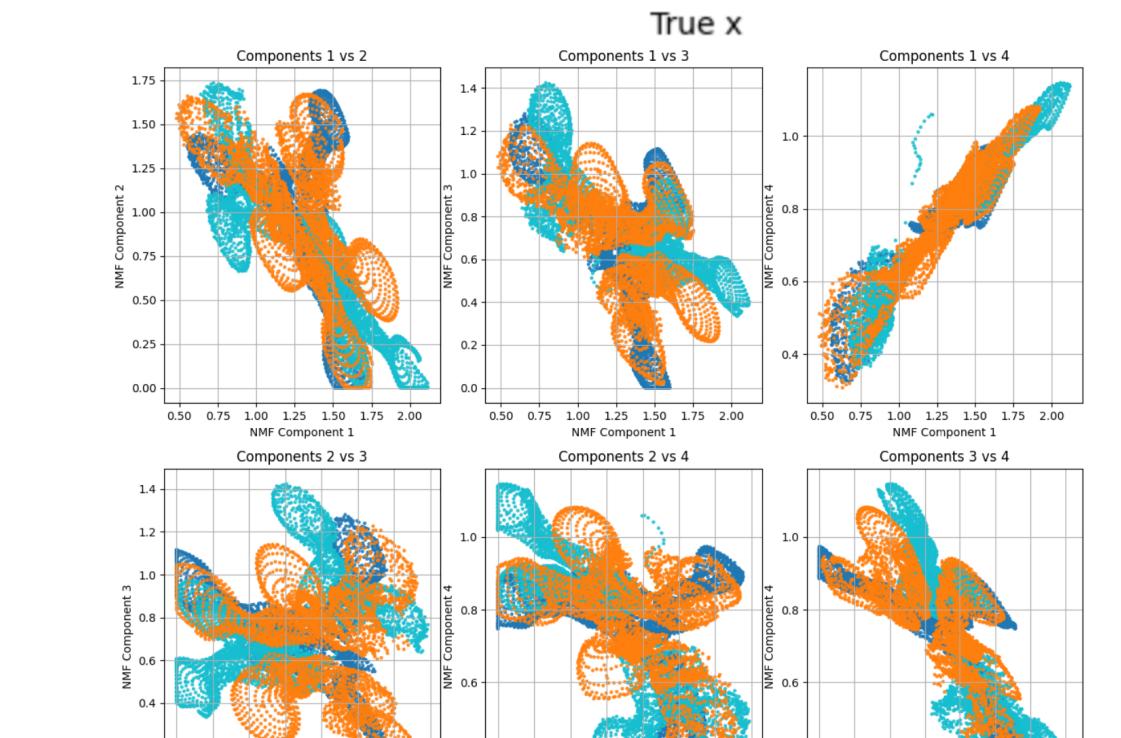
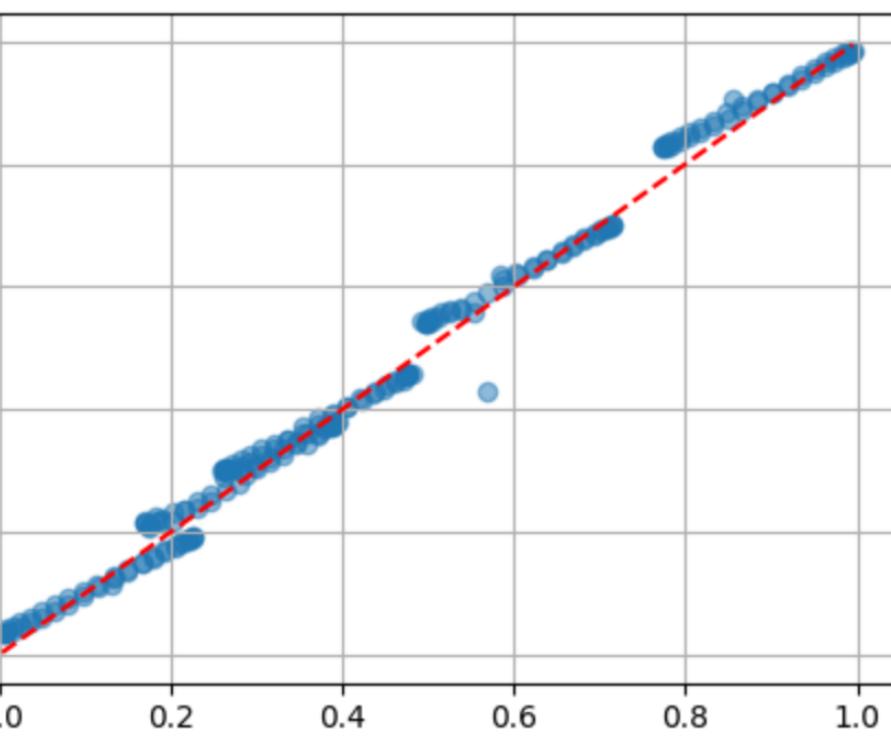
In our model we are looking to take hyper spectral image data and extract edges and vertices along with their associated features such as position, displacement over time, and channel intensity. In the above graph, each vertex represents a corresponding meaningful vertex in the image such as a cellular membrane or the center of the cell. Moreover, each vertex and edge contains features such as position, displacement and eventually intensity. These graphs are then fed to our graph attention transformer to be condensed into a latent space. This latent space is created by using a linear projection from the encoding step. Similarly, in the decoding steps we do a linear transformation back to recreate the next time step. This decoder is essentially learning how to predict the next time step from the new features given in the latent space. In the above diagram, the red arrows represent propagating the loss and the forward arrows input.

## RESULTS

Feature 0: Prediction vs Ground Truth



Feature 1: Prediction vs Ground Truth



Trial 13, Graph 3 — Avg Intensity: 3.21

Trial 0, Graph 16 — Avg Intensity: 1.44

Trial 100, Graph 3 — Avg Intensity: 3.21

Trial 13, Graph 4 — Avg Intensity: 3.22

Trial 13, Graph 3 — Avg Intensity: 3.21

Trial 13, Graph 4 — Avg Intensity: 3.22

## CONCLUSION & ACKNOWLEDGEMENT

Overall, we have seen the potential of our model to learn on our simulated model of the system. We can see that the latent representation allows us to probe interesting questions about our system and learn its dynamics. In our real data that we have collected this can represent cellular migration and dynamics as it responds to the environment. In future work we plan on incorporating this physics model into our loss function while also training on real data. This would involve expanding and fitting our physics model to match our collected data. The final goal is to create a pipeline that can incorporate hyper-spectral-temporal data to understand cellular dynamics under different conditions.

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