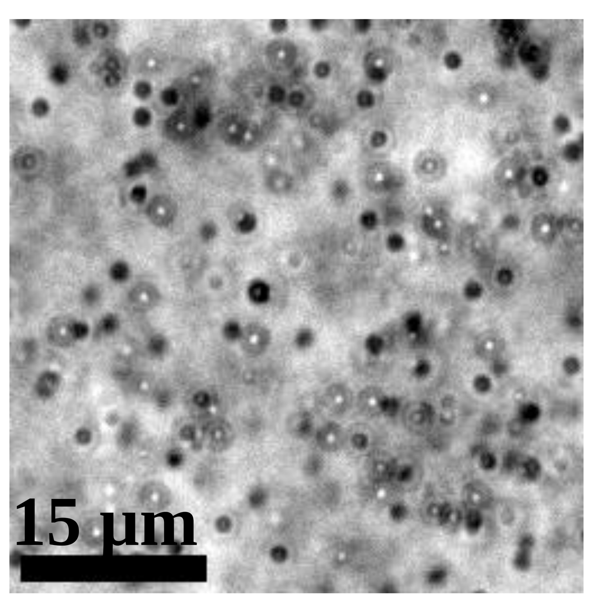
Differential Dynamic Microscopy Enhanced with Convolutional Neural Networks

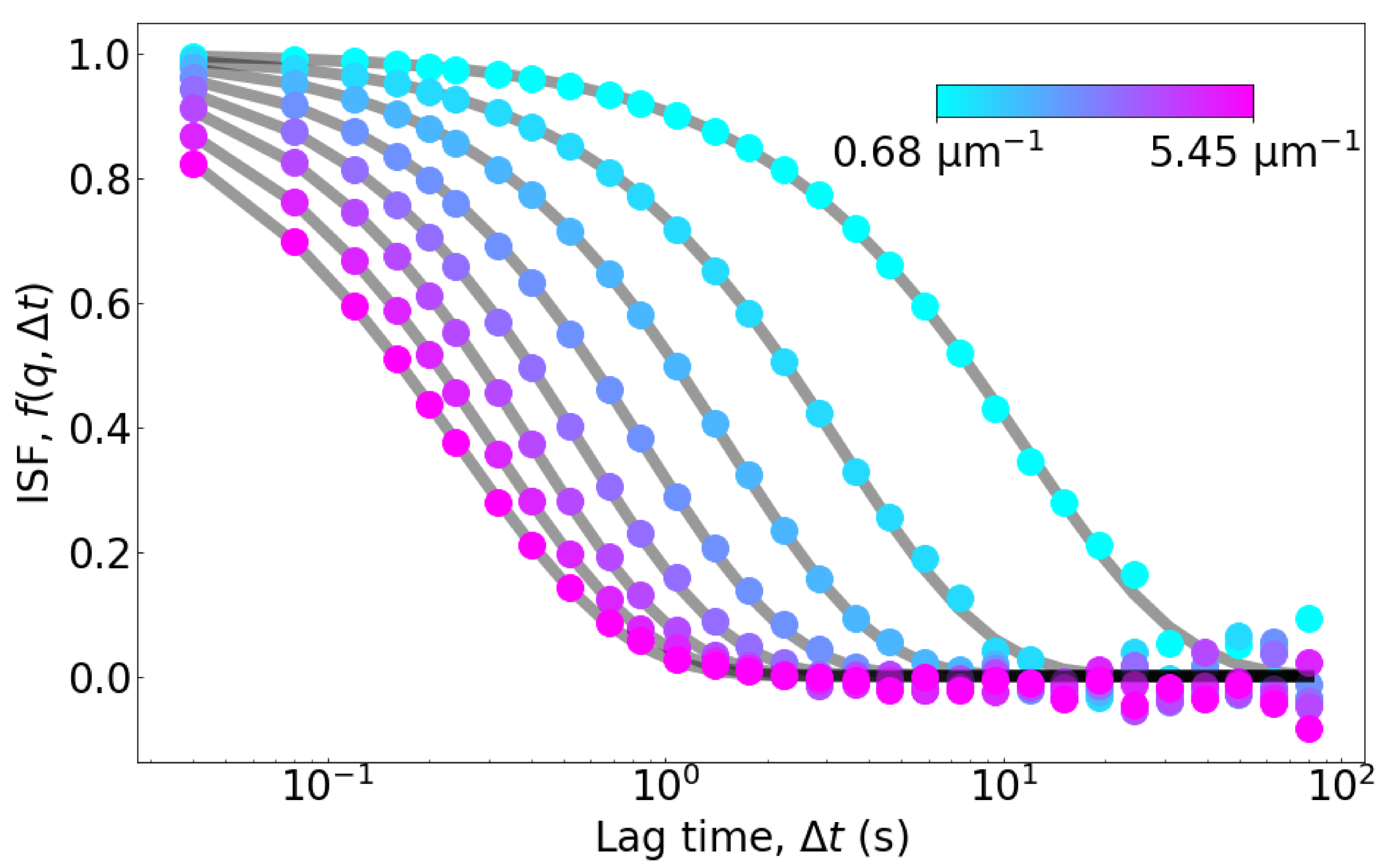
Justin Siu, Ruilin You, Philip Neill, Steven Dang, and Ryan McGorty
University of San Diego, Department of Physics and Biophysics

Differential Dynamic Microscopy (DDM) has been widely used to analyze the dynamics of bacteria, colloidal particles, gels, and other soft matter systems. One limitation of DDM is that a large number of images, typically 100s to 1000s, are needed to quantify dynamics. When fewer images are used for DDM analysis, the output can be too noisy to accurately quantify the dynamics. Here, we employ a Convolutional Neural Network (CNN) to denoise DDM data. With this machine learning approach, we can obtain accurate values for the characteristic decay time of density fluctuations in colloidal suspensions using only 10s of frames. The ability to accurately perform DDM with short durations of imaging data enables the study of samples in which the dynamics are quickly changing.



With DDM, we determine the **diffusion coefficient** of micron-sized colloidal particles in solution.

We record images with a 40× objective. Though the **particle density is too great for particle tracking**, we can **accurately measure the dynamics using DDM**.

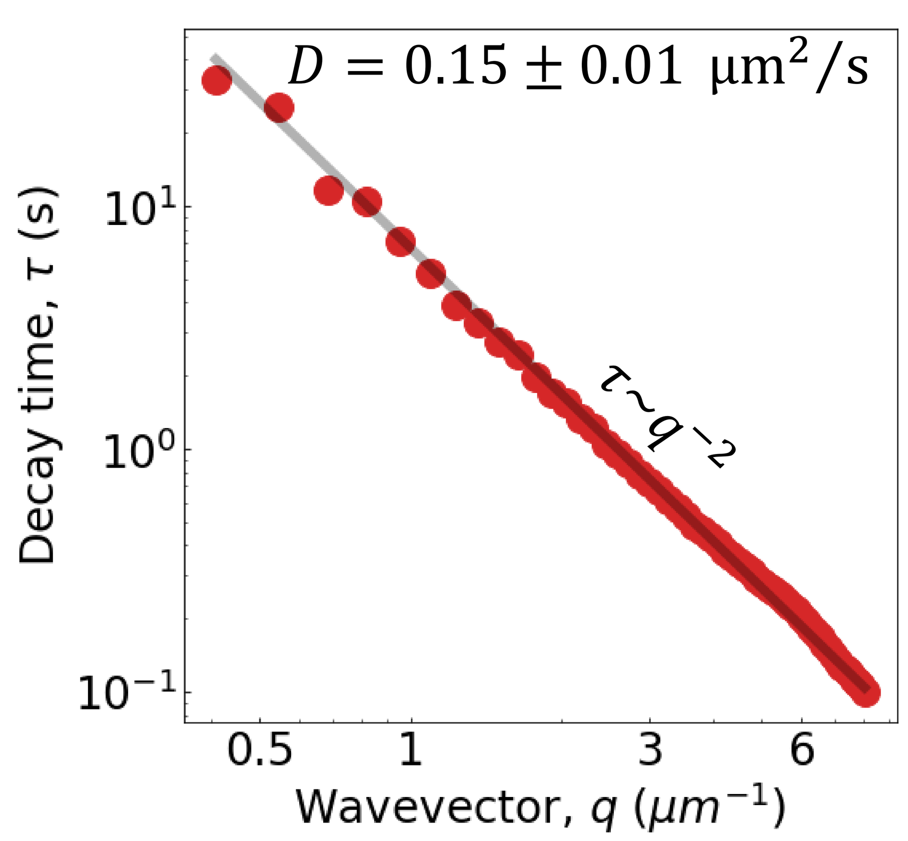


From 8000 images, we calculate the **intermediate scattering function (ISF)** and fit that to

$$f(q,\Delta t) = \exp(-\Delta t/\tau(q))$$

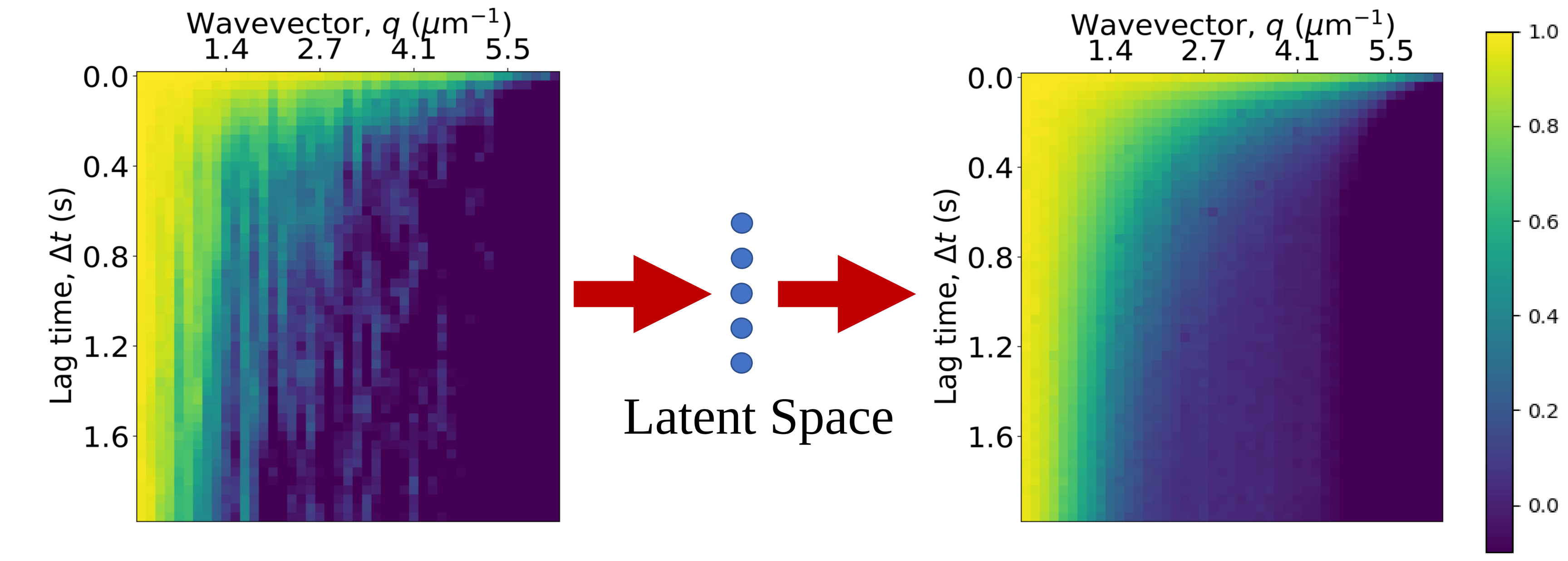
The dynamics can be determined from how the decay time, τ, depends on the wavevector, q. For **diffusive** motion:

$$\tau = 1/Dq^2$$



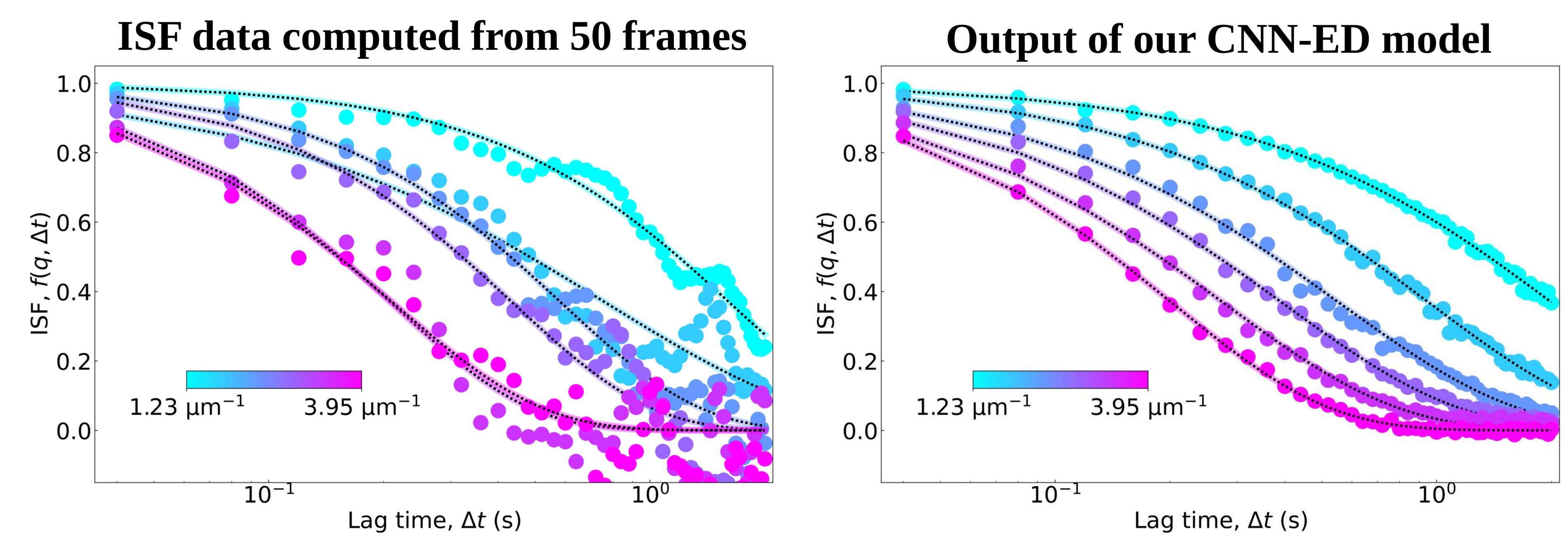
Convolutional Neural Network (CNN) used to denoise DDM data

We can represent our ISF data as a 2D function of the wavevector, q, and lag time, Δt. If we compute this ISF from a collection of only 50 frames, then the limited statistics and high noise makes extracting characteristic decay times from the ISFs difficult. Therefore, we use a CNN-based encoder-decoder (CNN-ED) model to remove noise.



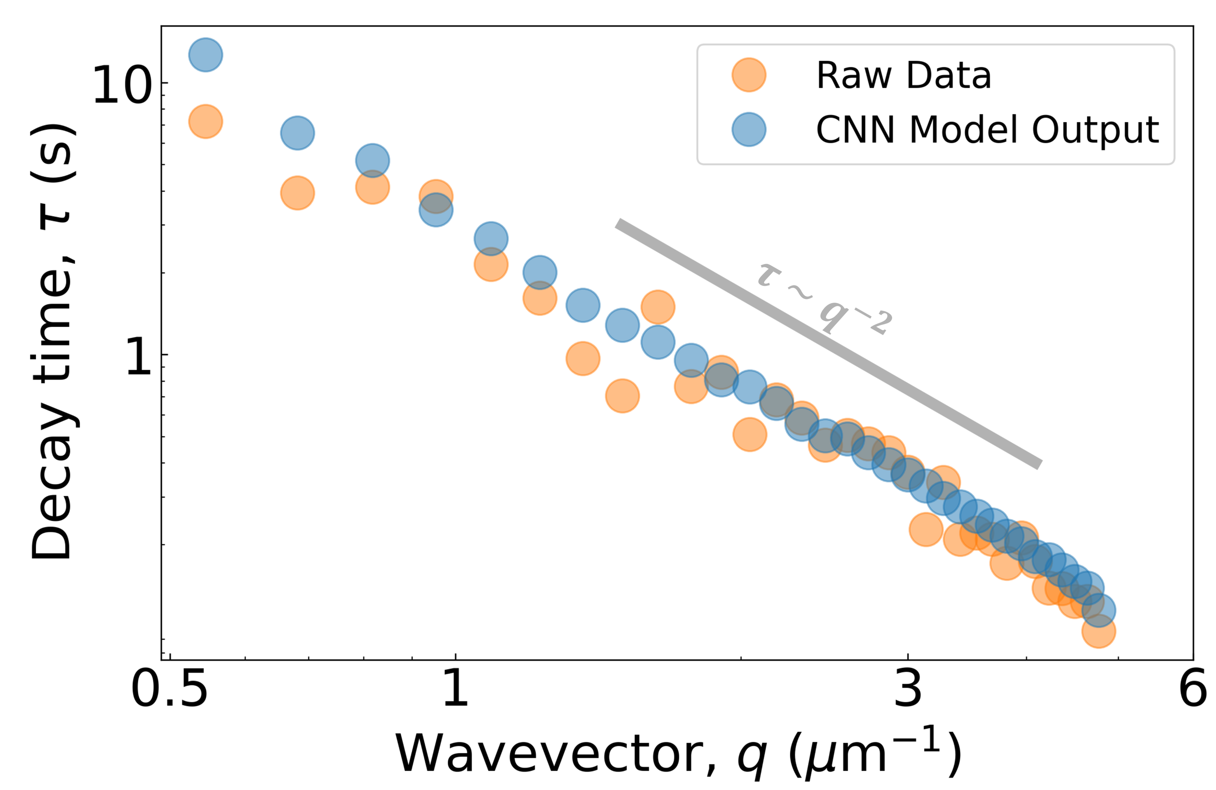
By applying a trained CNN-ED model on our ISF data, $f(q,\Delta t)$, we can more accurately fit slices of this ISF at particular wavevectors to determine characteristic decay times, $\tau(q)$.

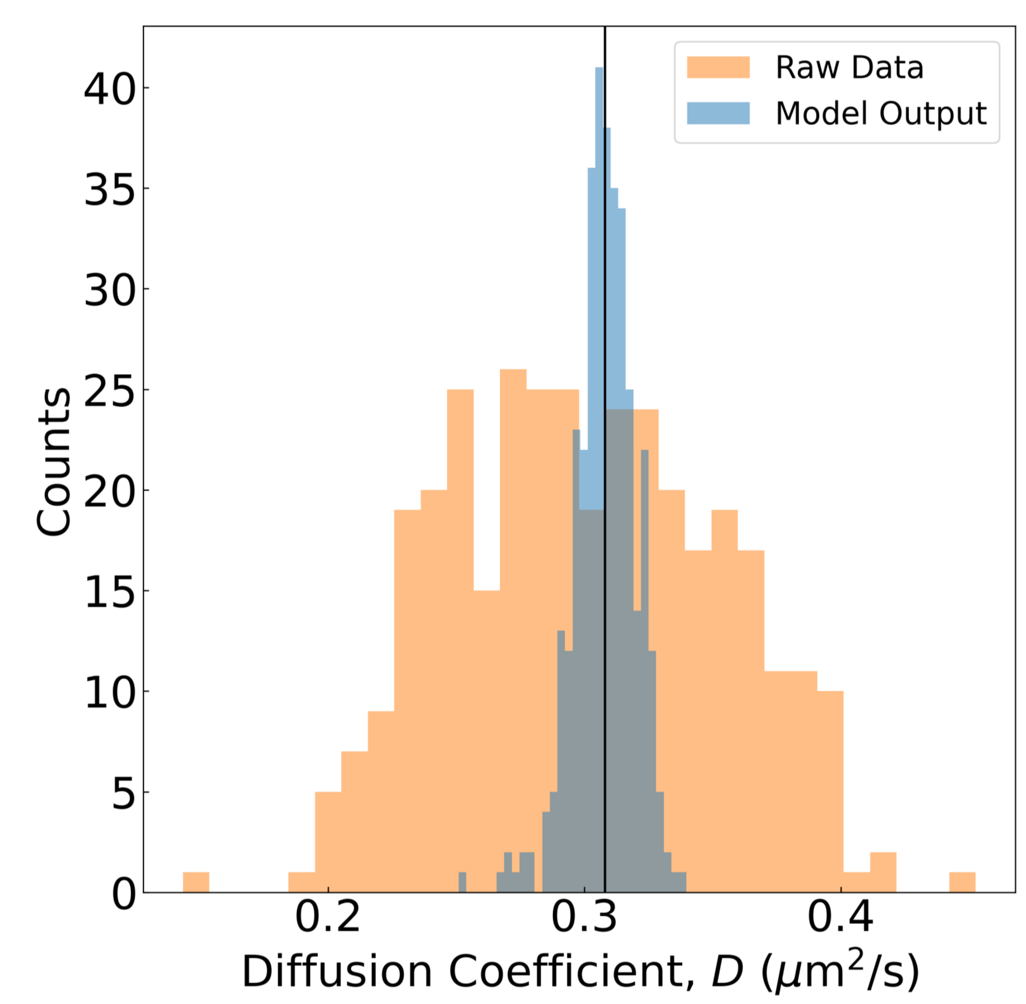
This allows us to employ DDM on short videos (10s of frames) rather than the typical 100s or 1000s of frames needed.



Accurately measuring the diffusion coefficient from short videos with DDM-CNN

After determining the characteristic decay time, τ, for a range of wavevectors, q, we then determine the diffusion coefficient, $D = 1/\tau q^2$.

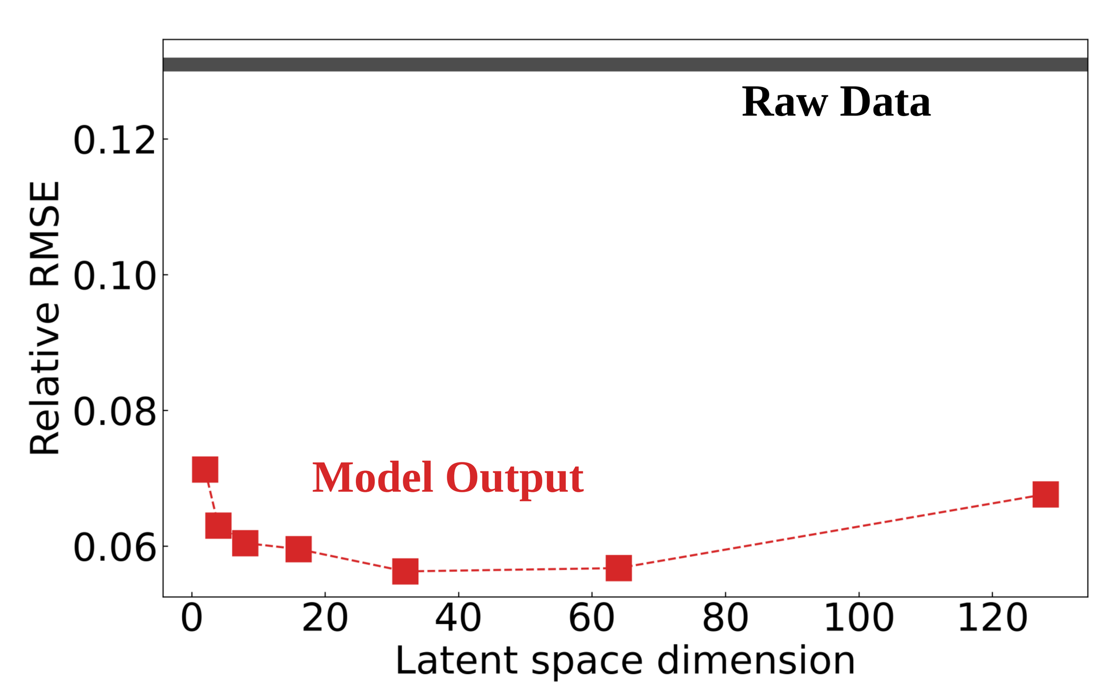




From hundreds of 50-frame videos we find the diffusion coefficient using either the raw ISF data or the data processed through our CNN-ED model. Our determination of D is much more precise after using our model.

$$D_{raw} = 0.30 \pm 0.05 \ \mu\text{m}^2/s$$

$$D_{CNN\ output} = 0.31 \pm 0.01 \ \mu\text{m}^2/s$$



We have computed the root-mean-squared-error in the diffusion coefficient for multiple sets of 50-frame videos. Without our CNN-ED model, our relative RMSE is ~13%. Our model performed best with a latent space of 32 where we had a relative RMSE of just under 6%.

Conclusion: Using a CNN-ED model to denoise DDM data results in more accurate determinations of diffusion coefficients when using short videos (e.g., only 50 frames). We plan to use this method to perform high-throughput characterization of non-equilibrium dynamics.

We acknowledge support from the Research Corporation for Science Advancement through the Cottrell Scholars program.