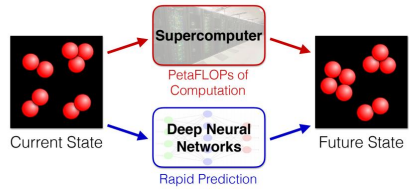


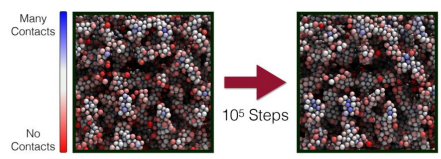
### Motivation

- Scientists utilize molecular dynamics (MD) and Brownian dynamics (BD) to study dynamic or non-equilibrium properties of materials.<sup>1</sup>
- The principle challenge of MD/BD simulations is the prohibitive computational cost to simulate phenomena that occur at long time scales.
- The goal is to predict the future states of simulations using deep neural networks and bypass explicit computation of every time step:



### Data & Features

- 14,400 simulation trajectories — list of particle positions (x,y,z) at a given time step — generated using the LAMMPS Molecular Dynamics Simulator.<sup>2</sup>
- Simulation undergoes slow arrested phase separation with different system parameters (volume fraction and interparticle attraction strength).<sup>3</sup>

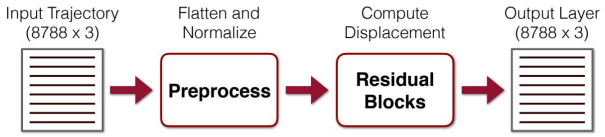


Images rendered from simulation snapshots undergoing slow phase separation, separated by  $10^5$  time steps. Particle colors indicate number of contacts

- Each input and output snapshot contains (x, y, z) positions of 8,788 particles: i.e. 26,364 floating point numbers.
- Particle motion is mildly stochastic and largely deterministic; particles with few contacts are free to diffuse while particles with many contacts move less.

### Model

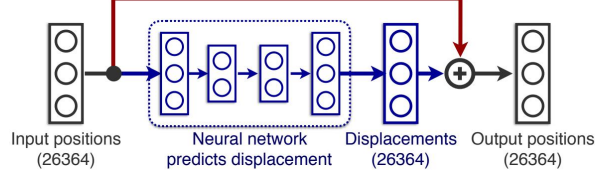
#### Model Architecture



- Mean-squared error (MSE) for loss function.
- Use Adam optimizer with L2 regularization.
- Scan over architectures and hyperparameters.

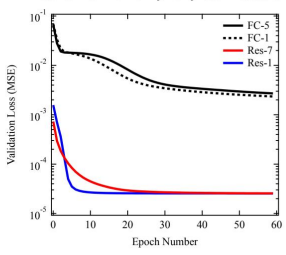
#### Residual Block<sup>4</sup>

Transfer input positions via residual connection



### Results

- Our model accurately predicts particle positions with small MSE.
- Residual networks result in significantly smaller loss compared to simple plain networks with only fully connected layers.



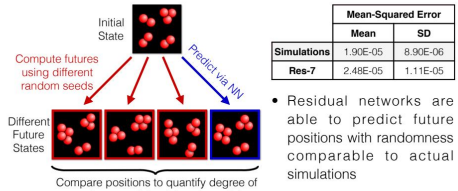
	Mean-Squared Error		
	Training	Validation	Test
<b>FC-1</b>	2.41E-03	2.35E-03	2.34E-03
<b>FC-5</b>	2.81E-03	2.71E-03	2.74E-03
<b>Res-1</b>	2.61E-05	2.55E-05	2.48E-05
<b>Res-3</b>	2.60E-05	2.55E-05	2.48E-05
<b>Res-5</b>	2.60E-05	2.56E-05	2.49E-05
<b>Res-7</b>	2.60E-05	2.55E-05	2.48E-05

Plain (fully connected) Nets: FC-(# of Layers)  
 Residual Nets: Res-(# of Residual Blocks)

### Discussion and Conclusions

#### Bayes Error Quantification

- Different random seeds in simulations result in different realizations of future states.
- Mean-squared difference of particle positions are compared across simulation and predicted outcomes.



Simulations	Mean-Squared Error	
	Mean	SD
<b>Res-7</b>	1.90E-05	8.90E-06
<b>Res-7</b>	2.48E-05	1.11E-05

- Residual networks are able to predict future positions with randomness comparable to actual simulations

- L2 regularization ( $\lambda = 0.0001$ ) suppresses overfitting.
- Learning rate  $\alpha = 0.00005$ , achieves slow training but small loss.
- Batch size 512 achieves a balance of speed and performance.
- Residual block size with 3 fully-connected hidden layers each with  $O(1000)$  neurons provide accurate displacement predictions.

#### Conclusions and Future Work

- Successfully developed a deep neural network for predicting future states in Brownian Dynamics simulations.
- Utilizing a residual network structure to focus on displacement significantly improves performance.
- Future work should visualize and interpret what and how each residual block is computing displacements.
- Future work should extend current architecture for variable number of particles.

### Acknowledgements and References

- The author would like to thank Ahmad Momeni and the CS 230 teaching staff for helpful discussion and guidance.
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