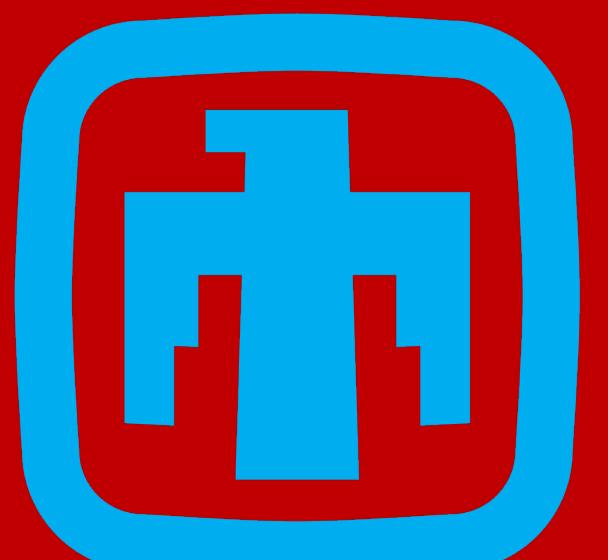


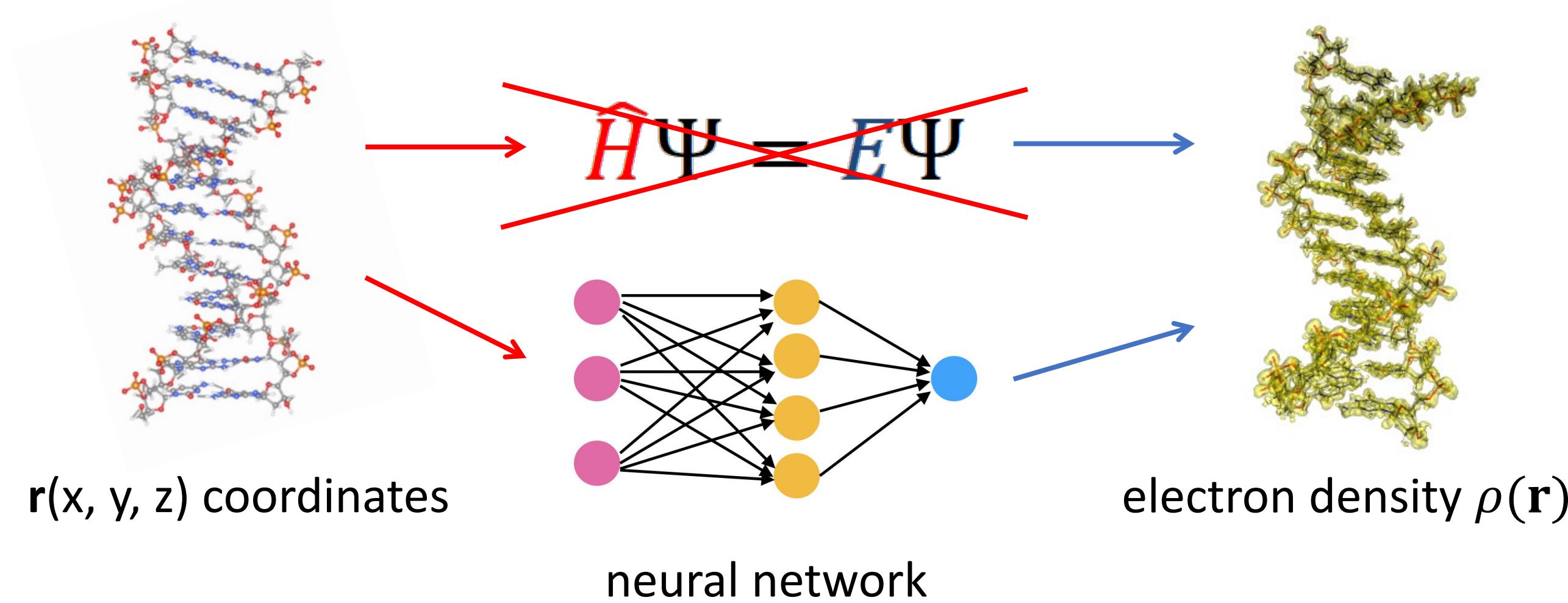
# Predicting accurate *ab initio* DNA electron densities with equivariant neural networks

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 Sandia  
National  
Laboratories

## MOTIVATION

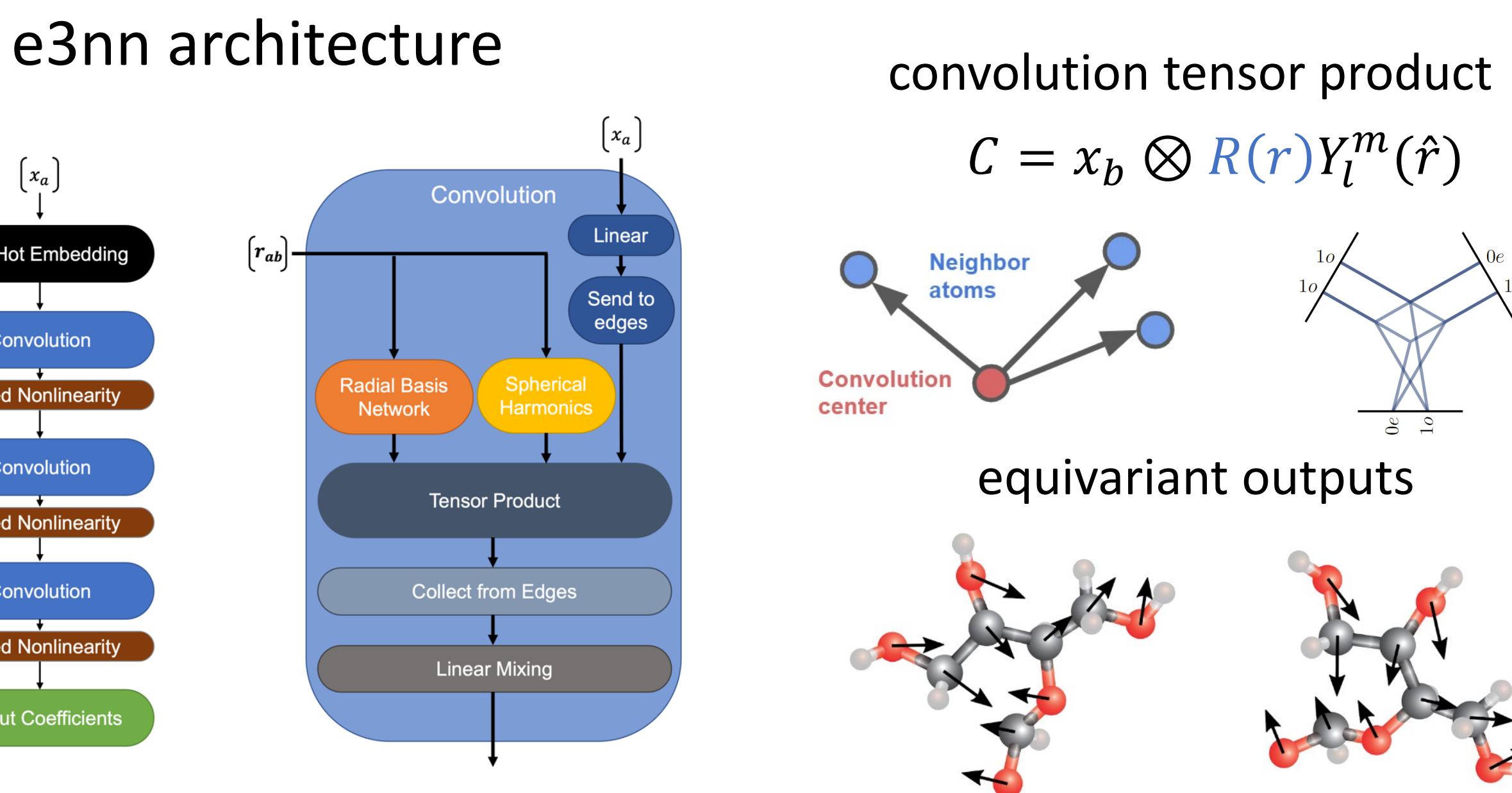
Quantum molecular modeling can predict a system's properties from **first principles** but is limited by **computational scaling**.



Machine learning **breaks traditional scaling barriers** and opens up the study of large biological macromolecules like DNA.

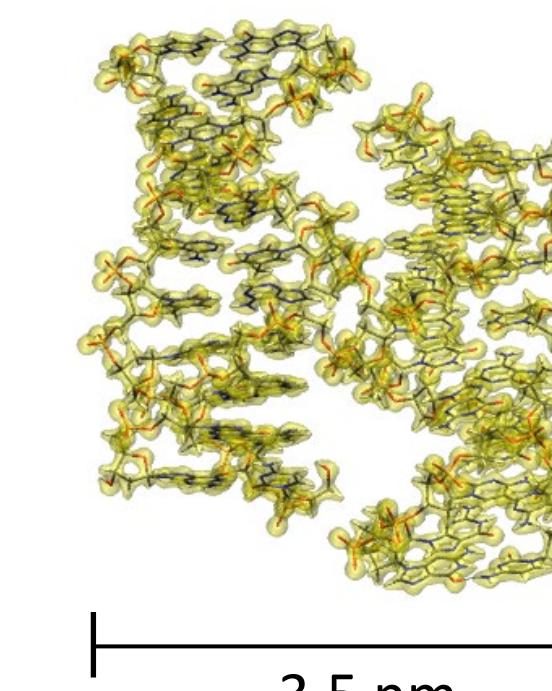
## NEURAL NETWORK (e3nn)

e3nn is a type of **graph convolutional neural network** that is **equivariant** to translations, rotations, and reflections.

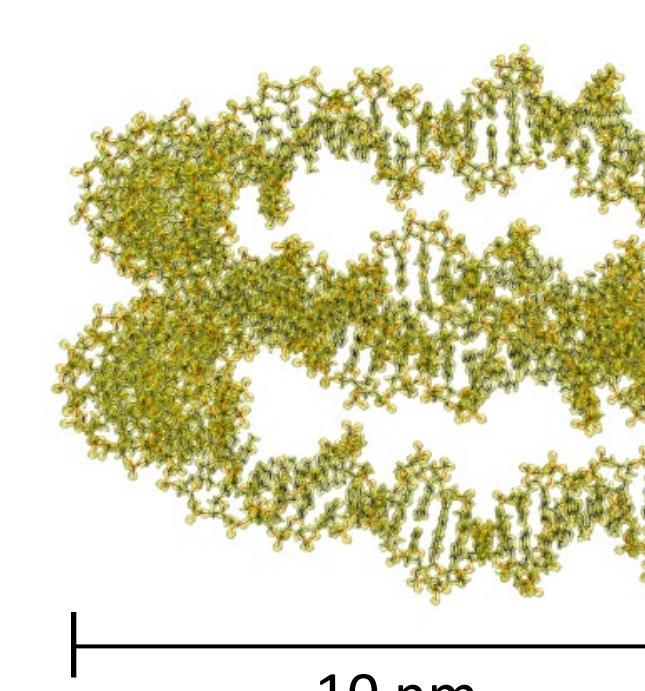


## RESULTS: LARGE DNA STRUCTURES

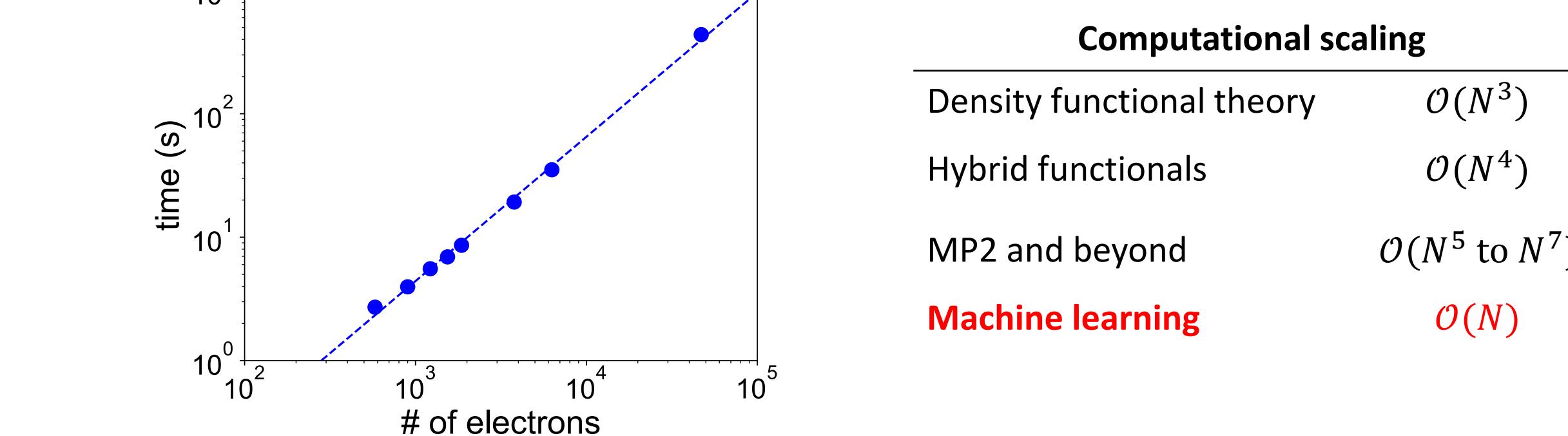
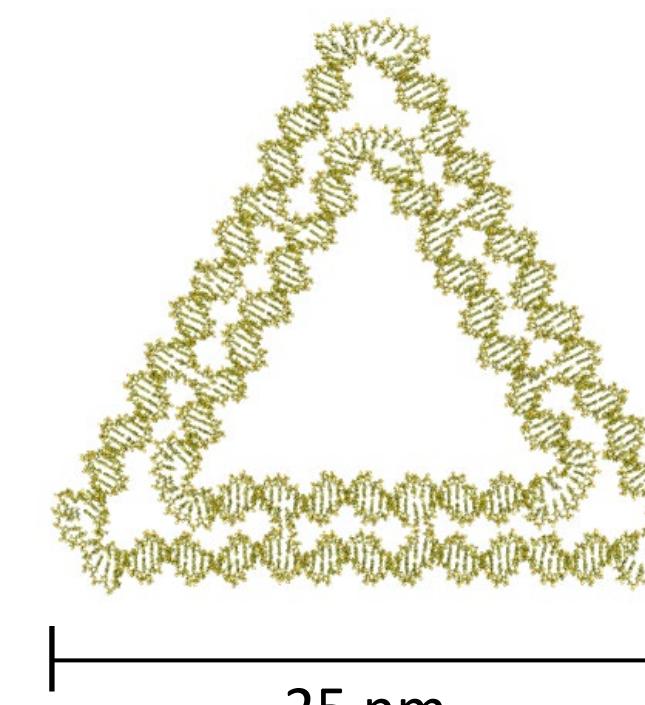
Stacked 4-way junction  
1260 atoms, 6280 electrons  
(PDB: 1dcw)



Nucleosome core particle  
9346 atoms, 46980 electrons  
(PDB: 1kx5)

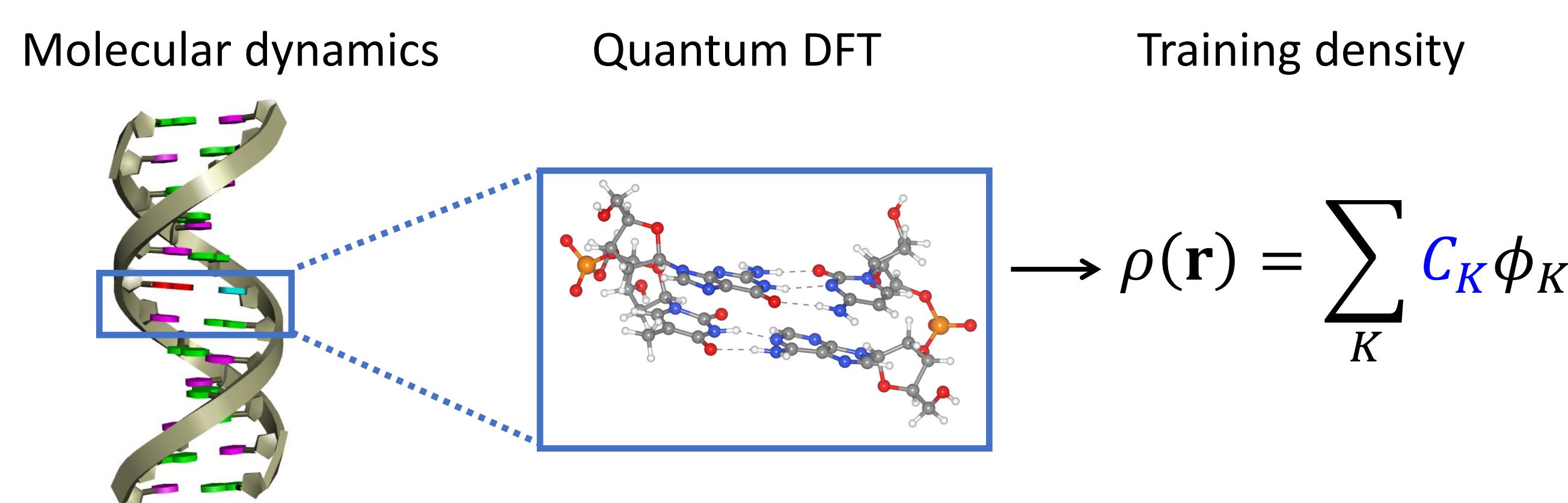


DNA origami structure  
21658 atoms, 108654 electrons

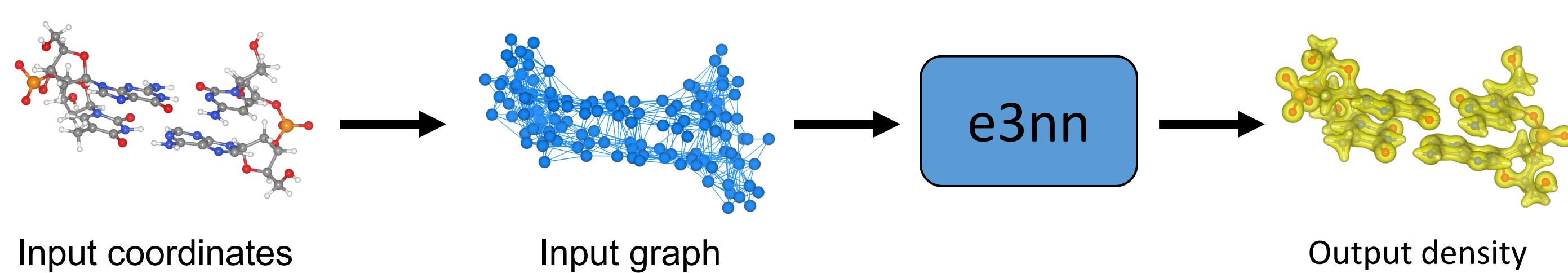


## TRAINING THE MODEL

- Configurations sampled from molecular dynamics
- Smallest meaningful unit – **base pair step**
- Machine learning target is the **electron density  $\rho(\mathbf{r})$**



During training, the model learns geometric features such as bonding interactions about its environment.

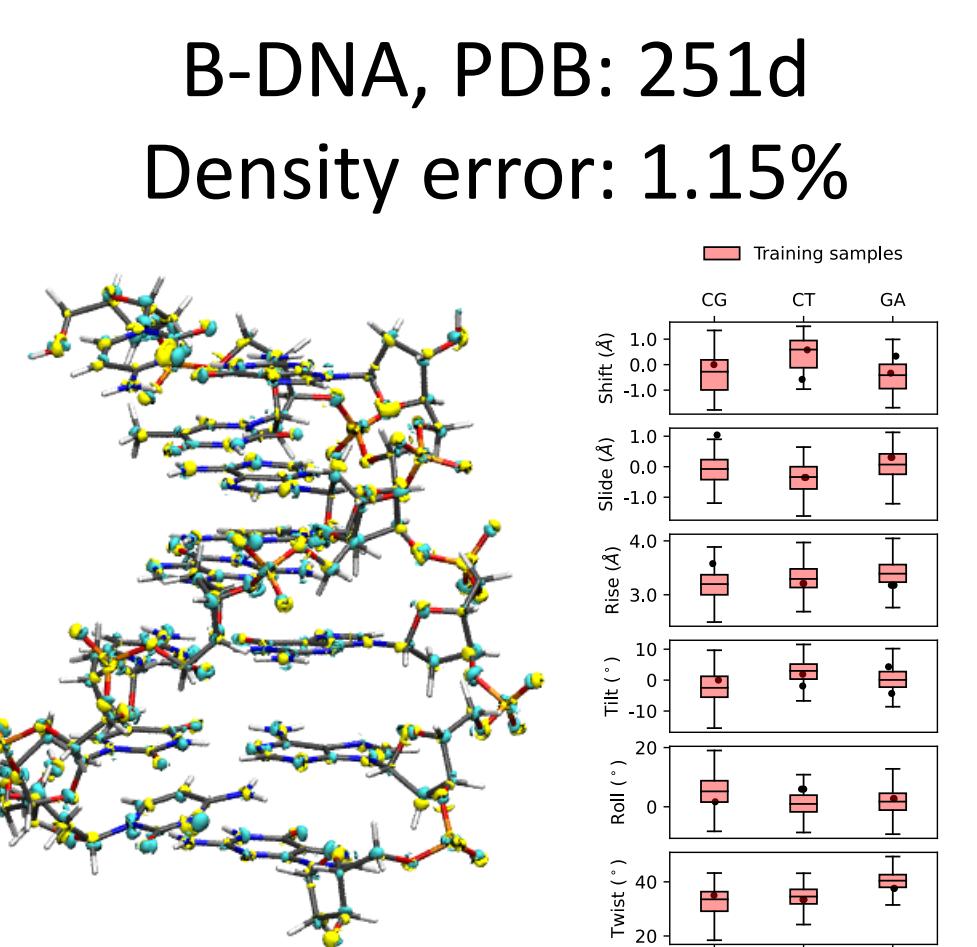


## RESULTS: PREDICTION ACCURACY

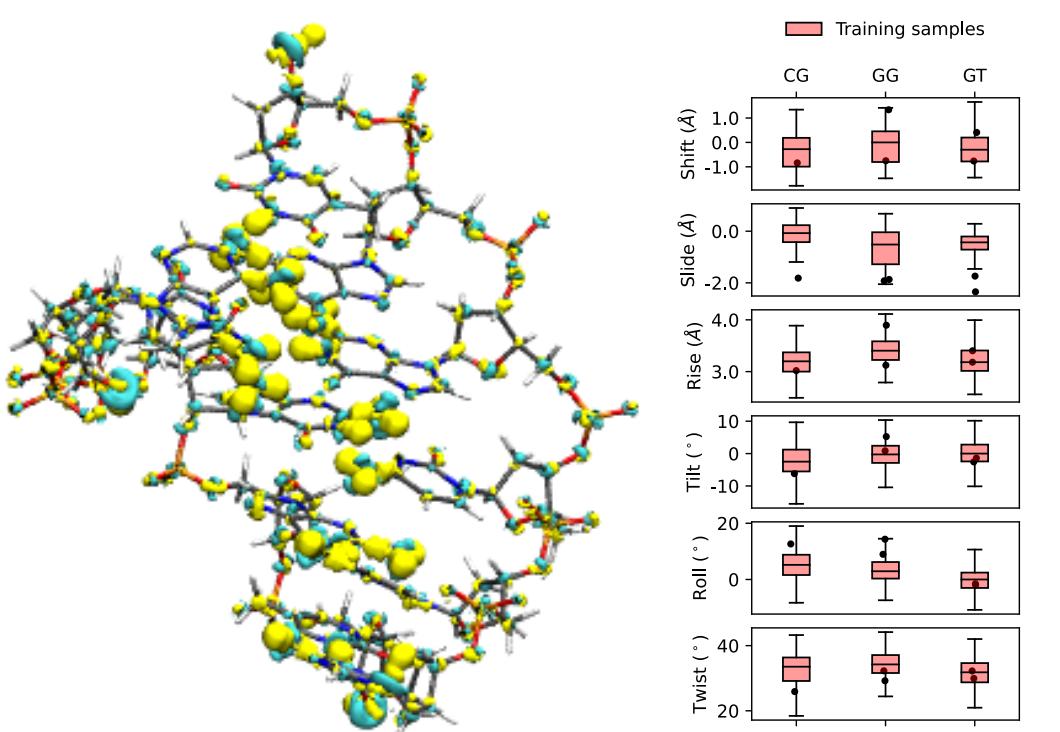
- Density prediction errors (%) for a model **trained only on B-DNA**

(L) Charge density difference plots  
(R) Base step structure parameters

B-DNA, PDB: 251d  
Density error: 1.15%



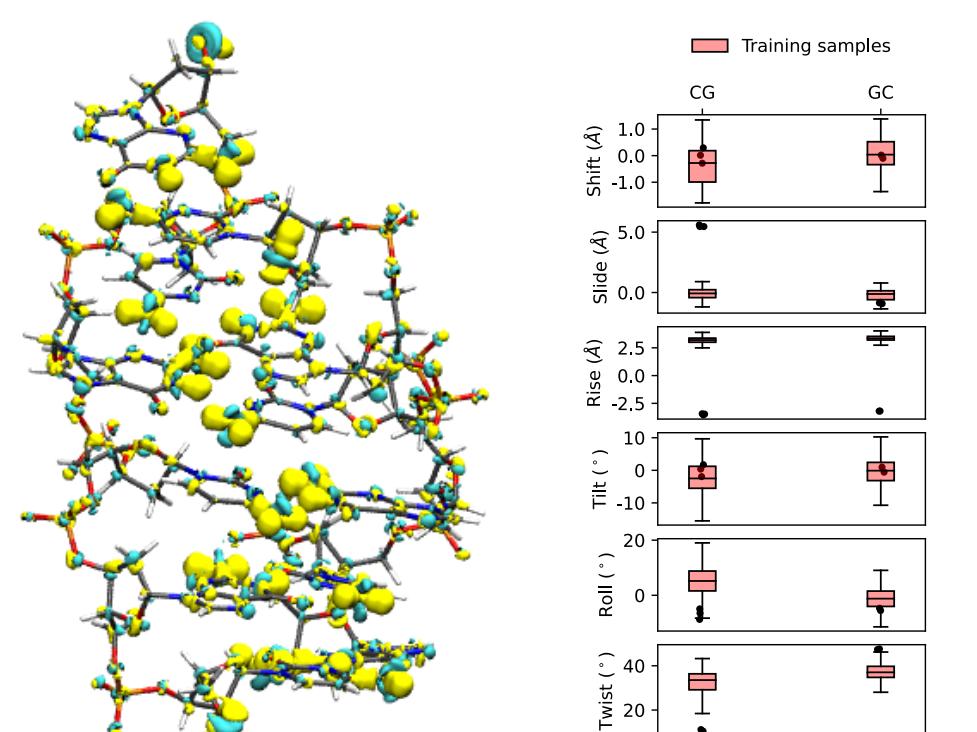
A-DNA, PDB: 1zf8  
Density error: 1.69%



Preprint available on chemRxiv

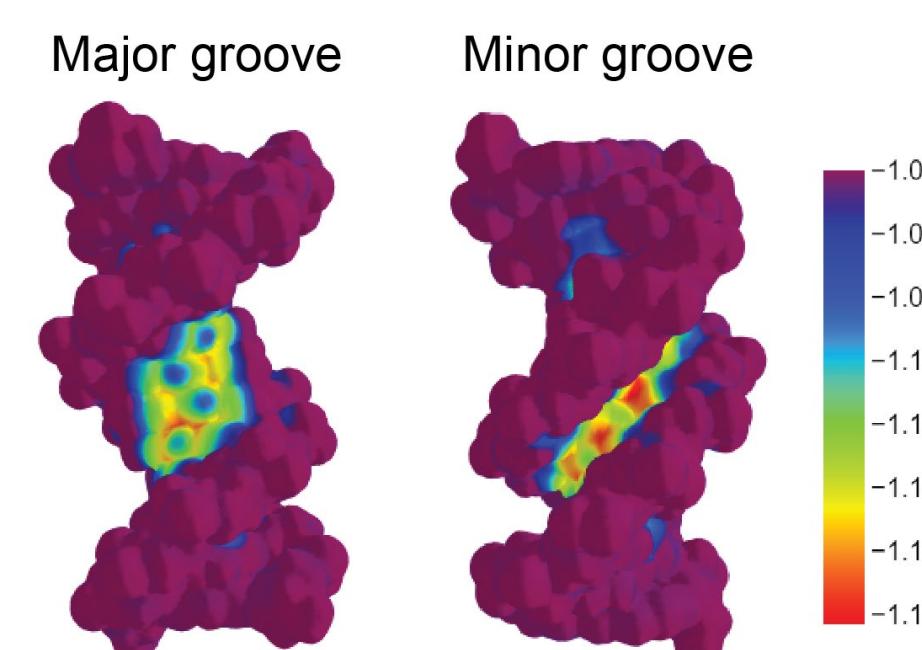
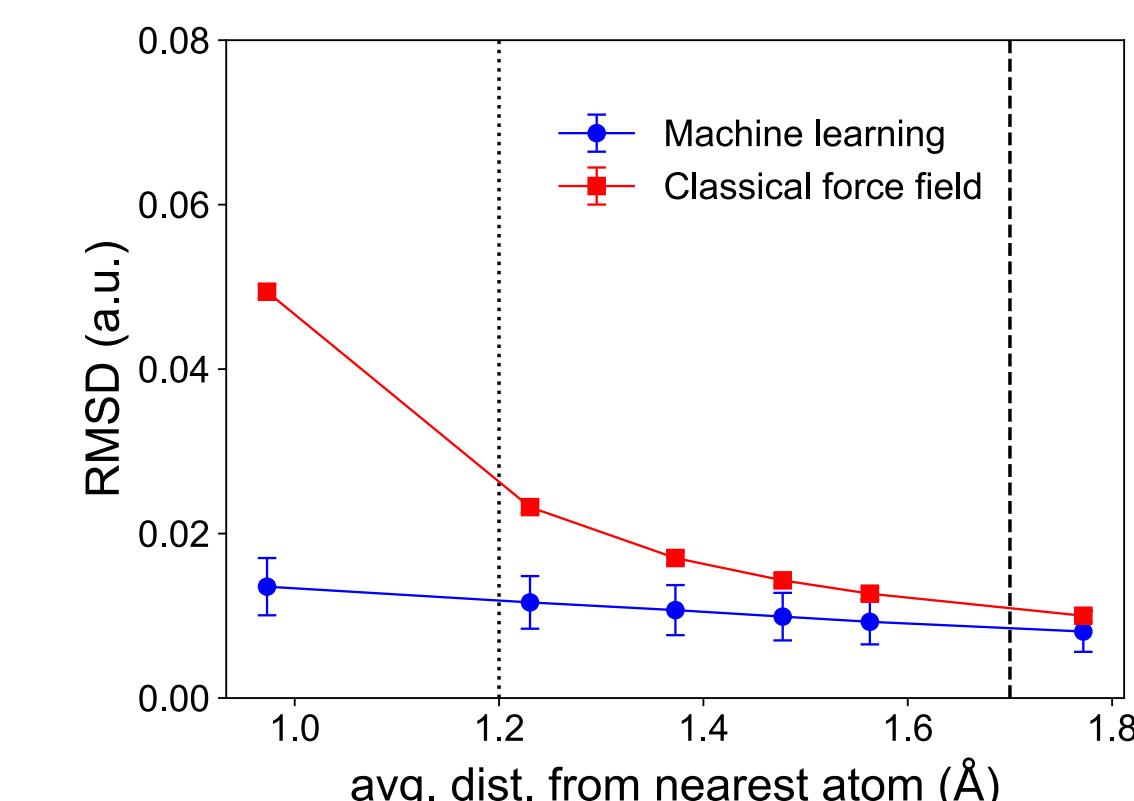
DOI: [10.26434/chemrxiv-2022-pmrg8](https://doi.org/10.26434/chemrxiv-2022-pmrg8)

Z-DNA, PDB: 4fs5  
Density error: 1.77%

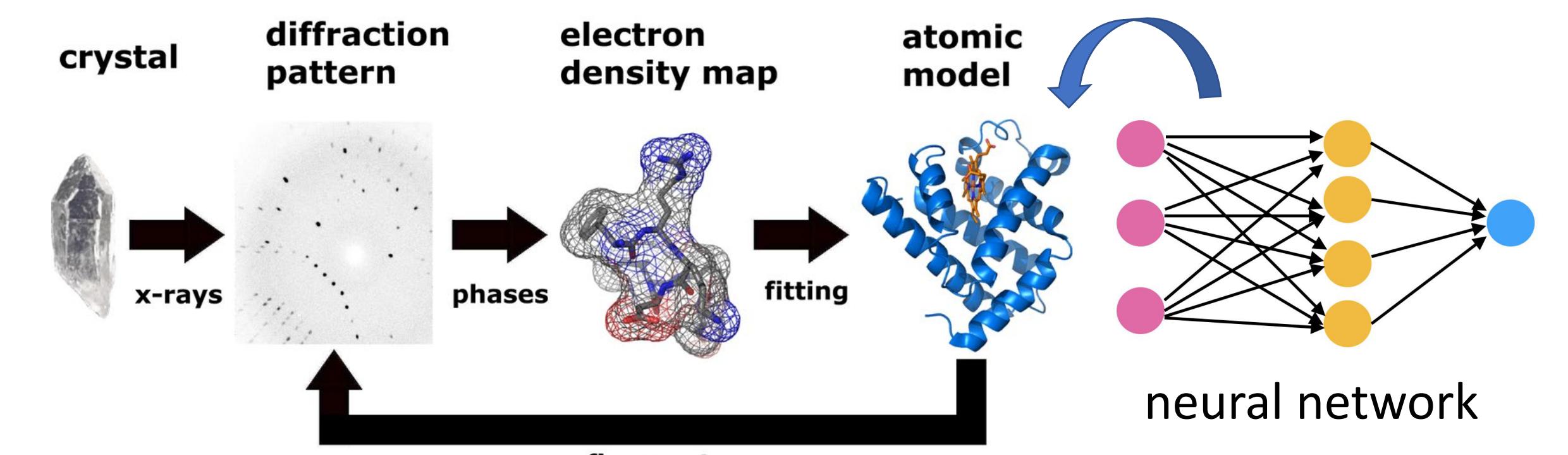


## FUTURE APPLICATIONS

- Machine-learning derived electrostatic potentials



- High-resolution X-ray crystal structure refinement



- Hellman-Feynman forces for *ab initio* molecular dynamics

$$\vec{F} = - \left\langle \psi_R \left| \frac{d\hat{H}_R}{dR} \right| \psi_R \right\rangle$$

Only needs density predicted by ML