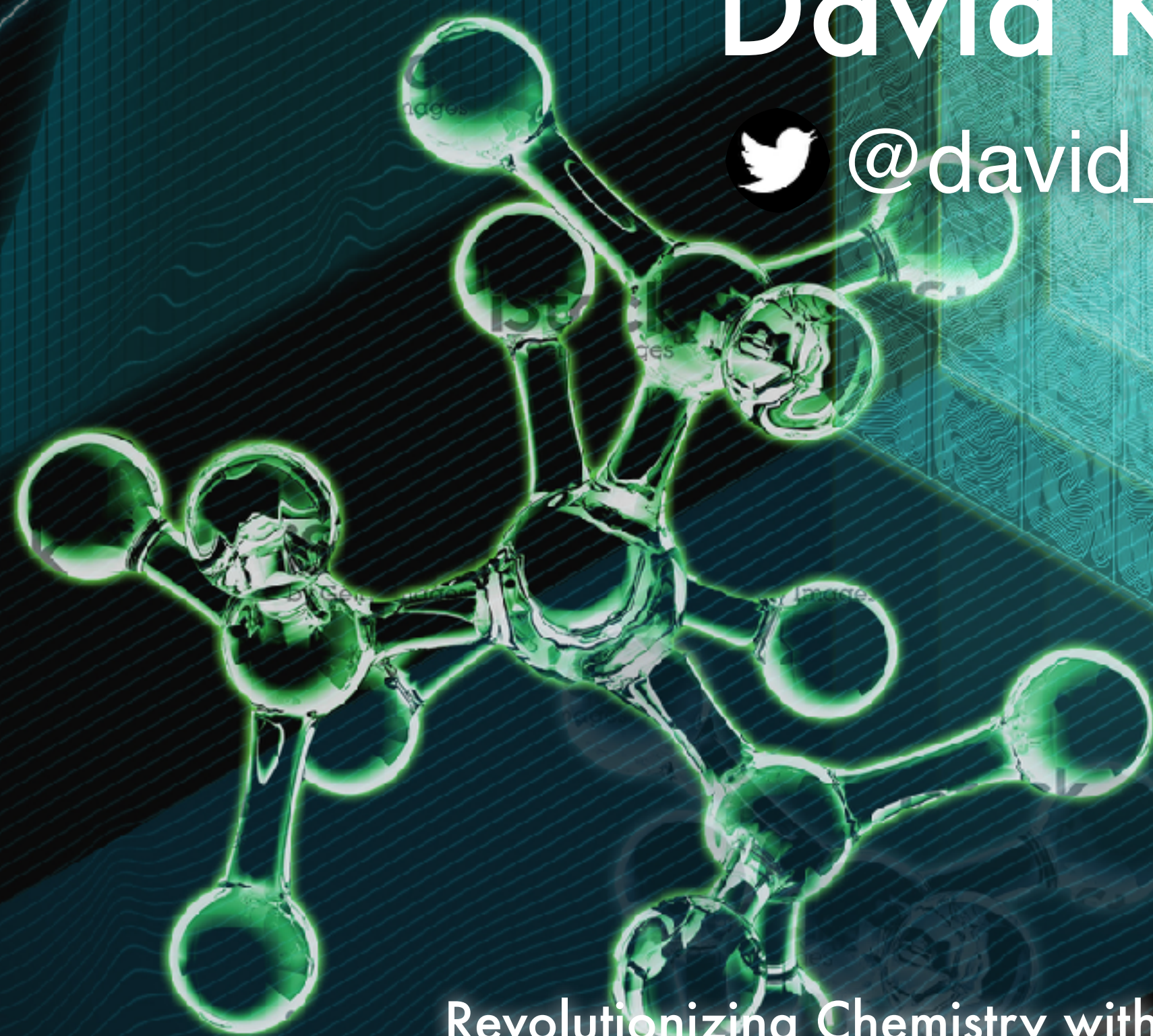


Generative models for structure-based drug design

David Koes



@david_koes



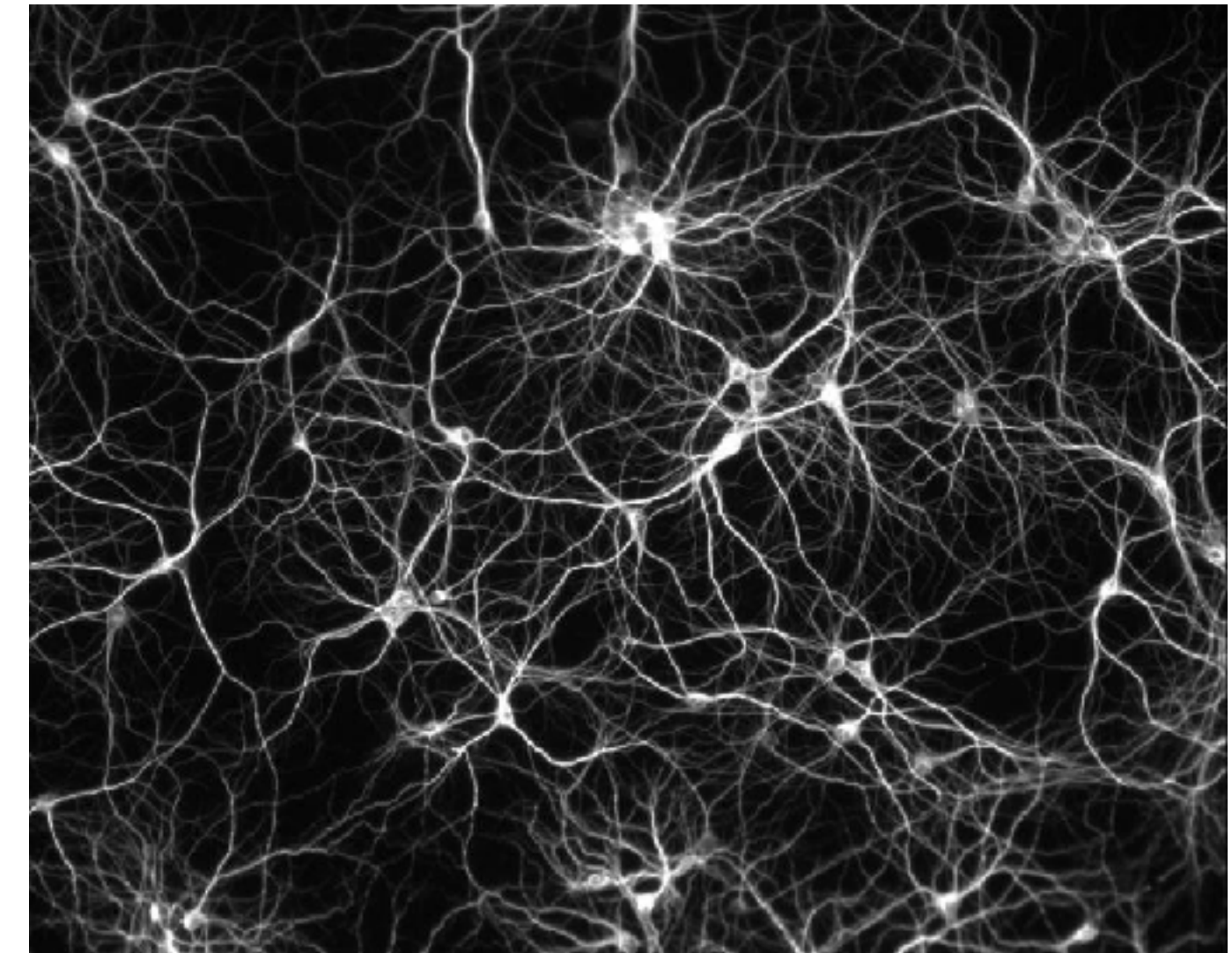
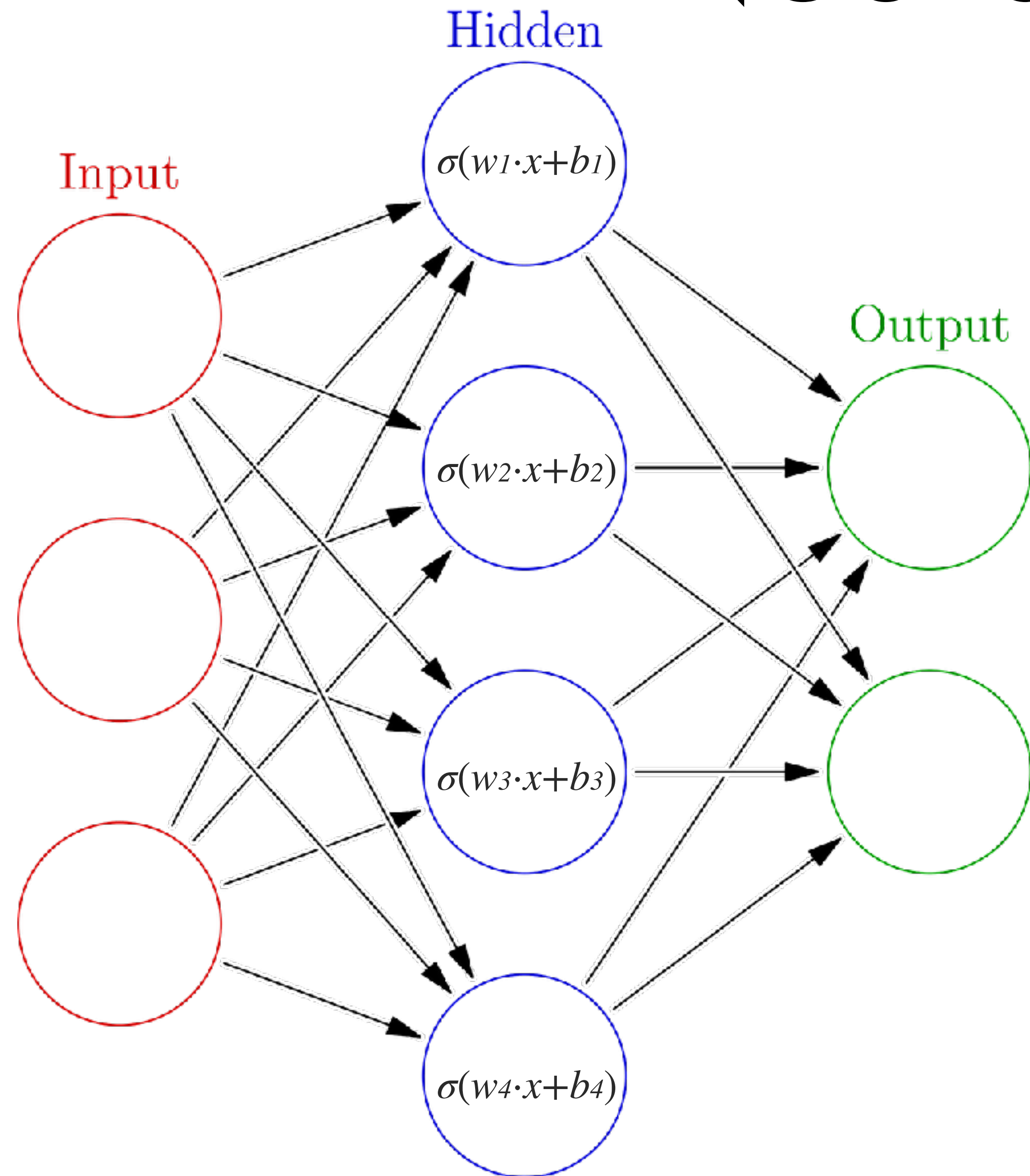
Revolutionizing Chemistry with Artificial Intelligence
American Chemical Society
Boston, MA
August 20, 2018



Machine Learning

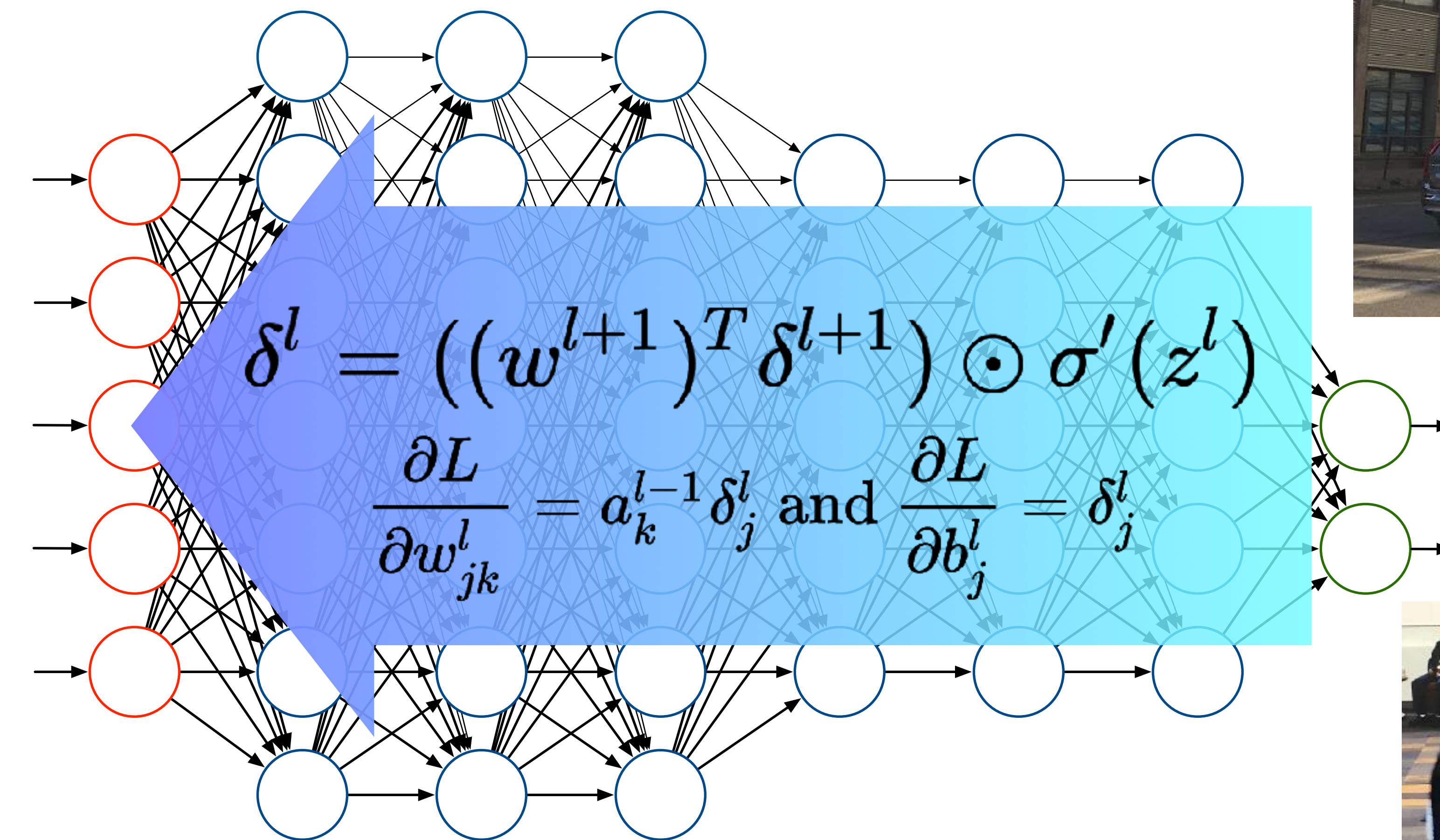


Neural Networks



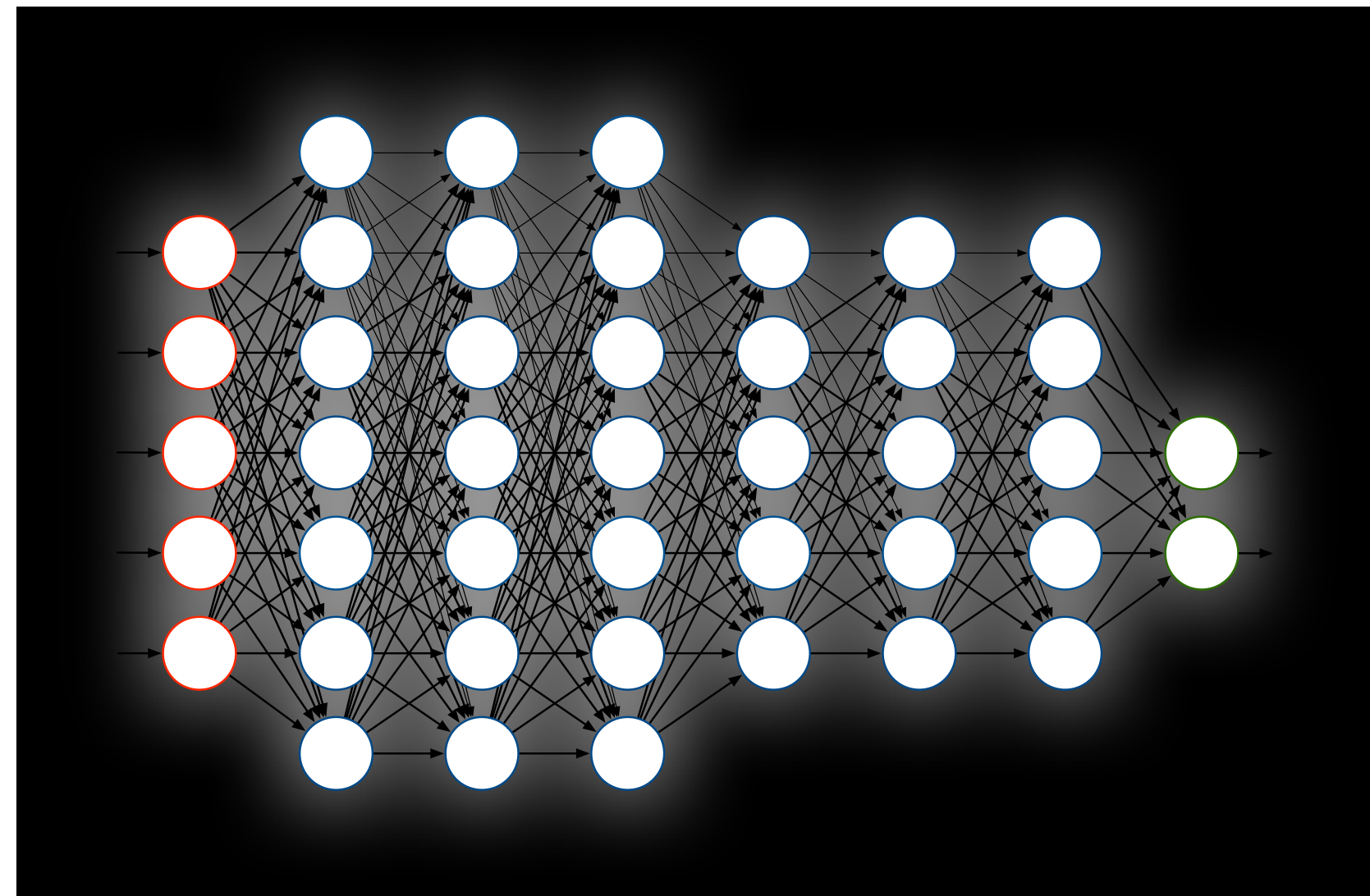
The **universal approximation theorem** states that, under reasonable assumptions, a feedforward **neural network** with a finite number of nodes **can approximate any continuous** function to within a given error over a bounded input domain.

Deep Learning



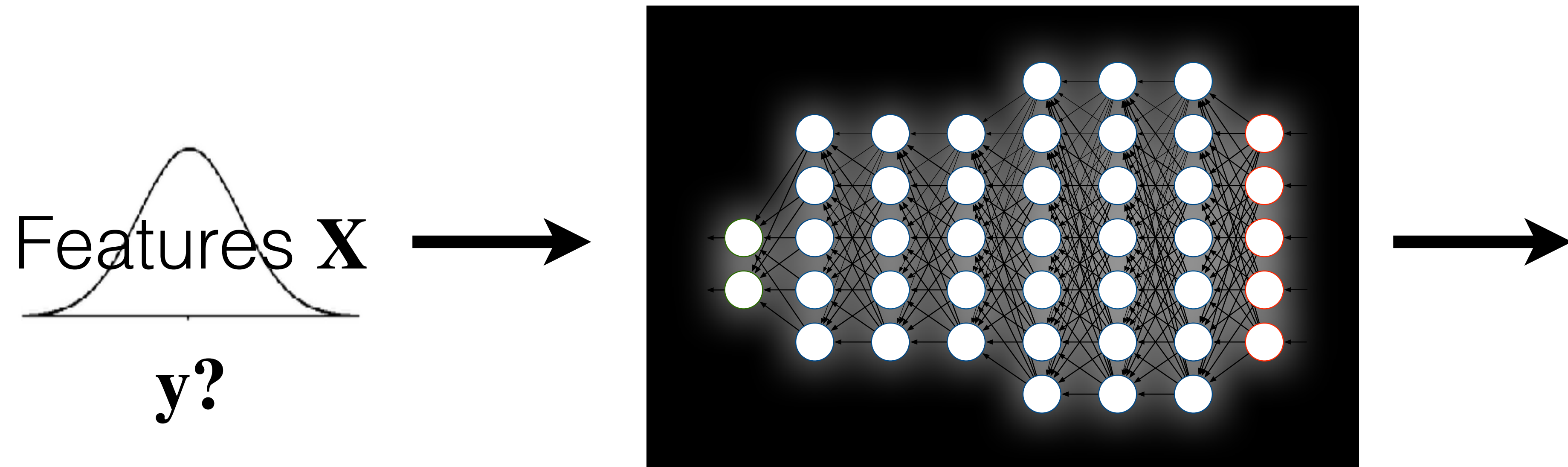
Discriminative Model

Features \mathbf{X}

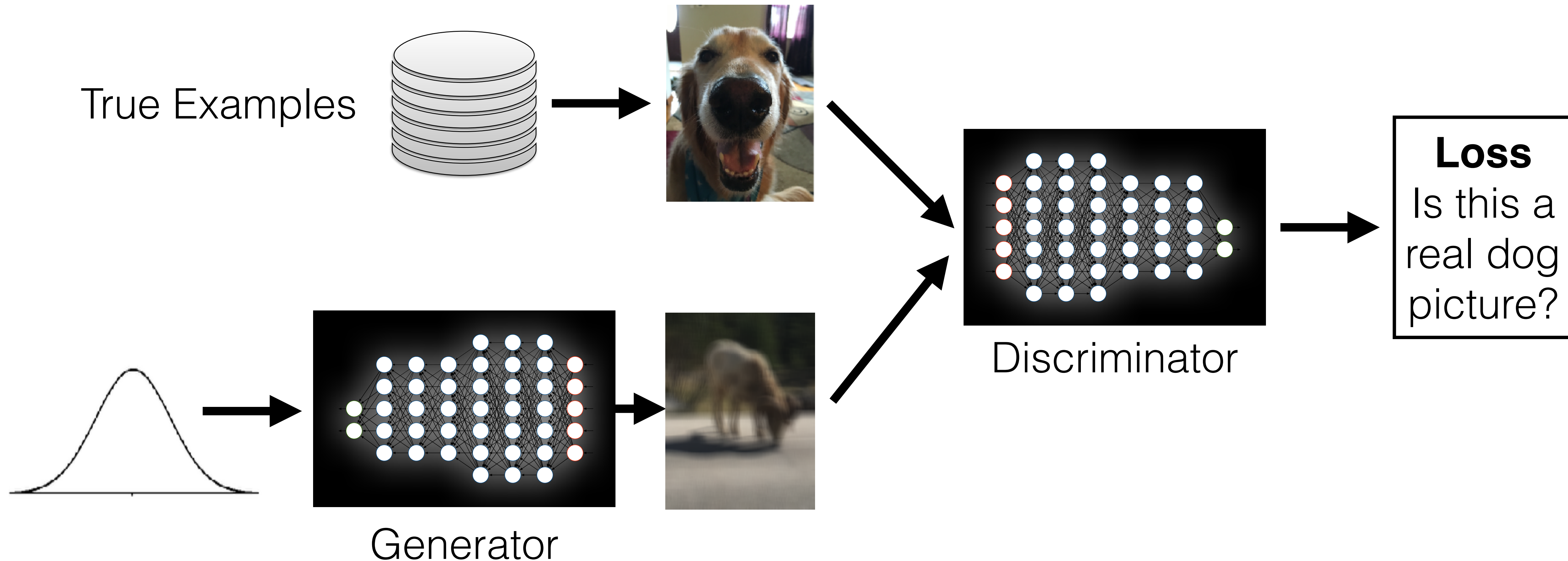


Prediction \mathbf{y}

Generative Model



Generative Adversarial Networks



Generative Adversarial Networks



Generative Adversarial Networks

<https://arxiv.org> › stat ▼

by IJ Goodfellow - 2014 - Cited by 4339 - Related articles

Jun 10, 2014 - Submission history. From: Ian **Goodfellow** [view email] [v1] Tue, 10 Jun 2014 18:58:17

GMT (1257kb,D). Which authors of this paper are ...



<http://torch.ch/blog/2015/11/13/gan.html>

PROGRESSIVE GROWING OF GANs FOR IMPROVED QUALITY, STABILITY, AND VARIATION

Tero Karras
NVIDIA

Timo Aila
NVIDIA

Samuli Laine
NVIDIA

Jaakko Lehtinen
NVIDIA
Aalto University



<https://youtu.be/G06dEcZ-QTg>

Generative models for structure-based drug design

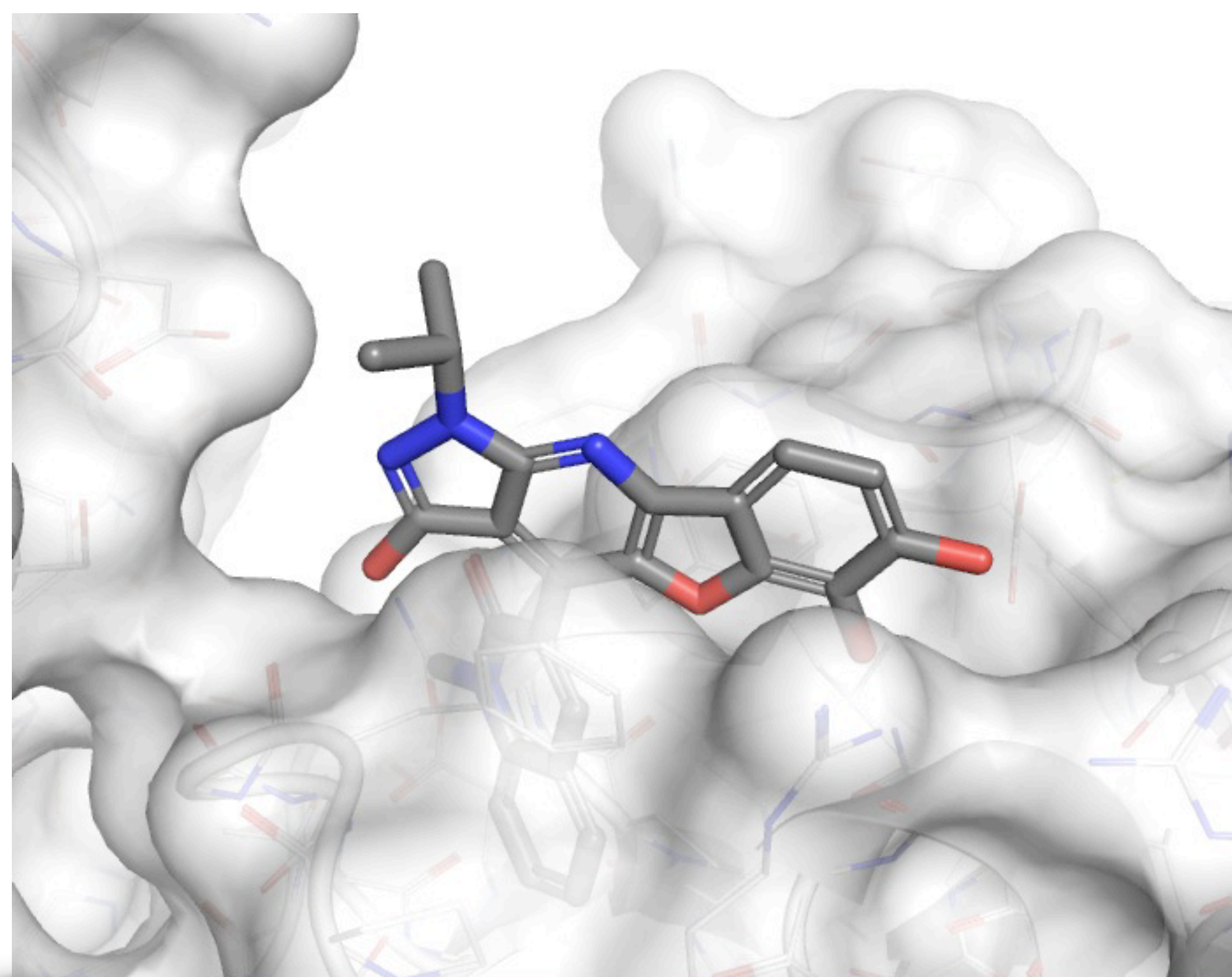


Structure Based Drug Design

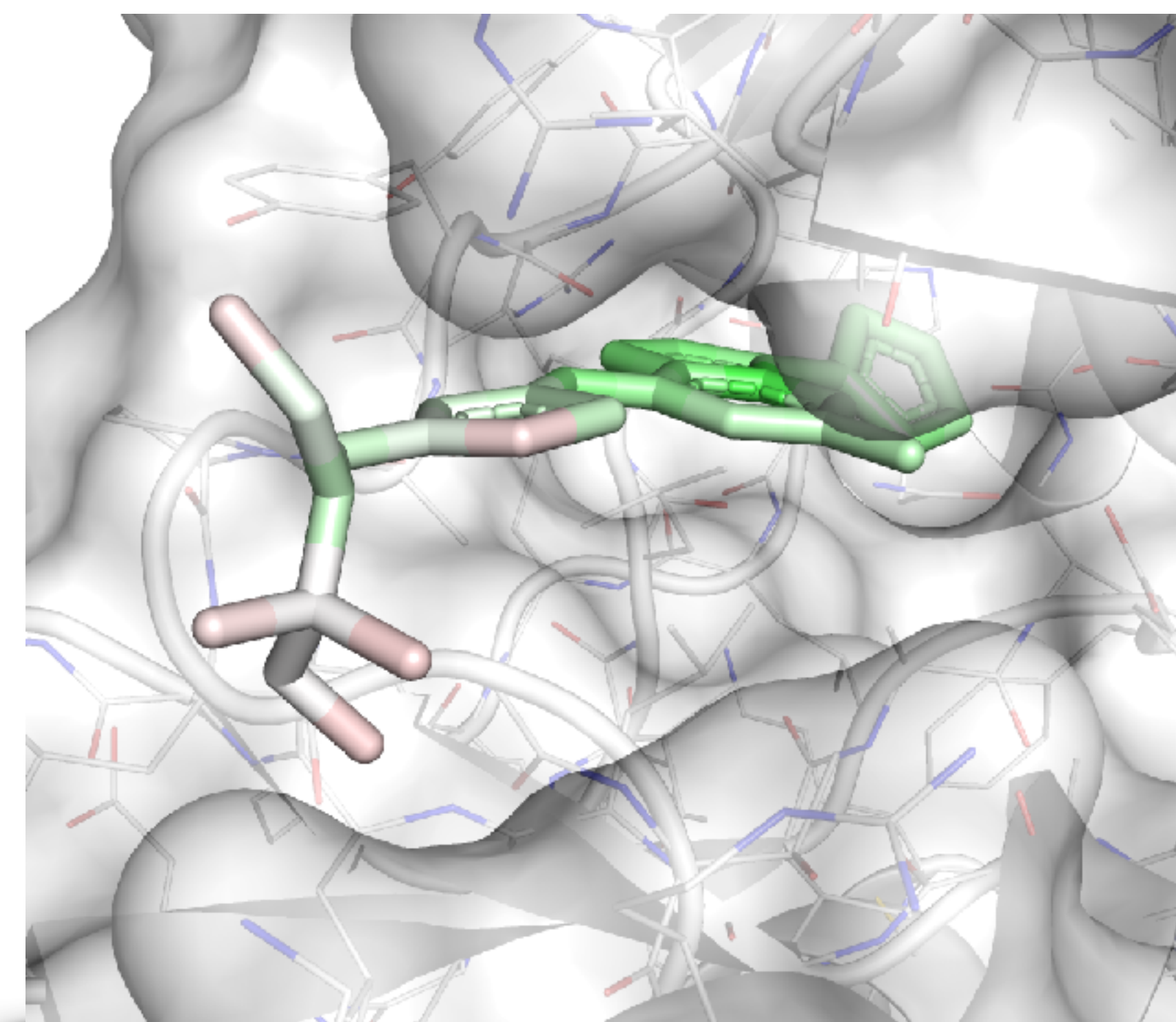
Pose Prediction

Binding Discrimination

Affinity Prediction

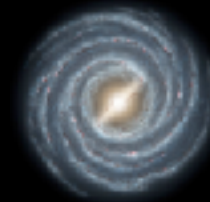


Virtual Screening



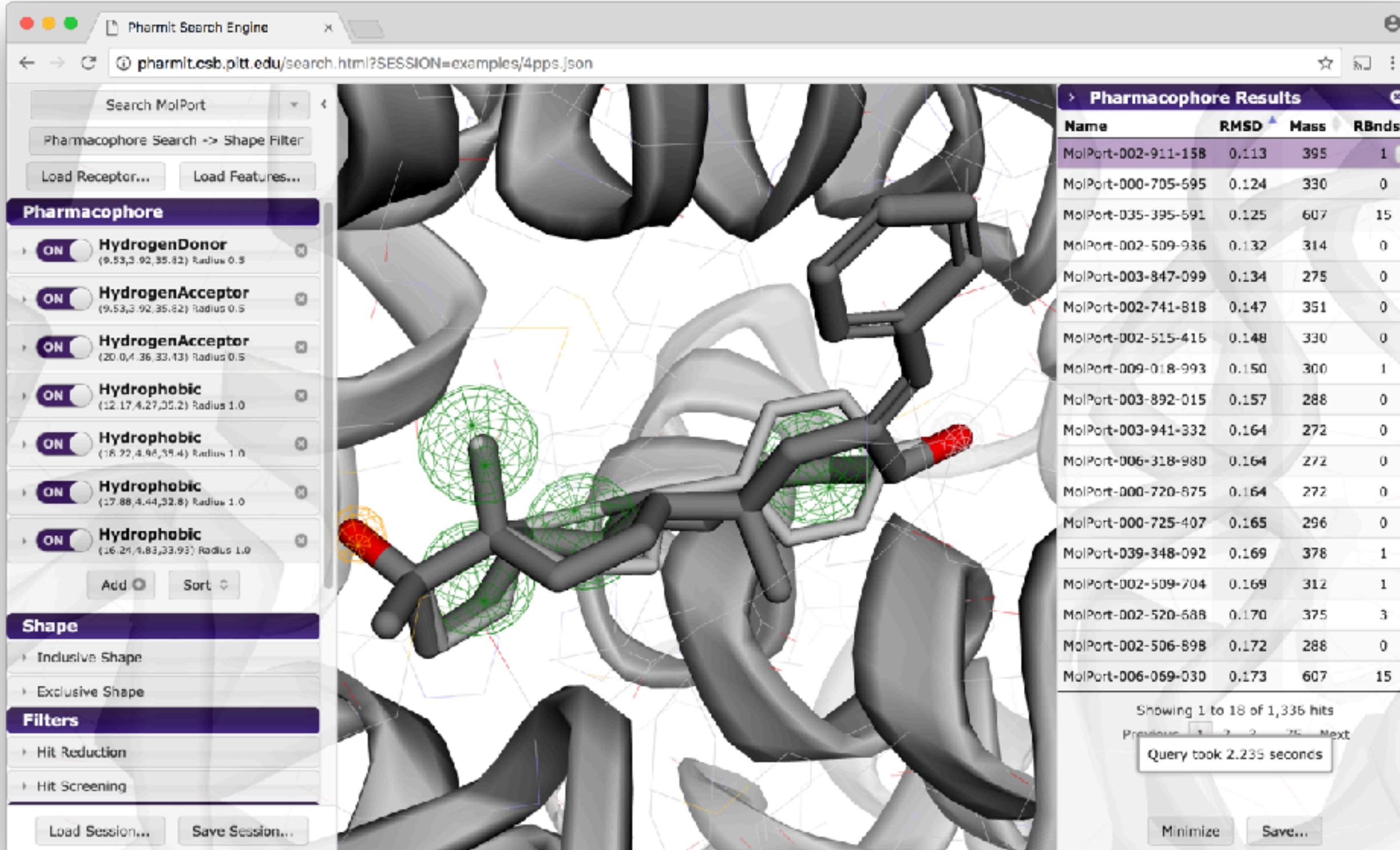
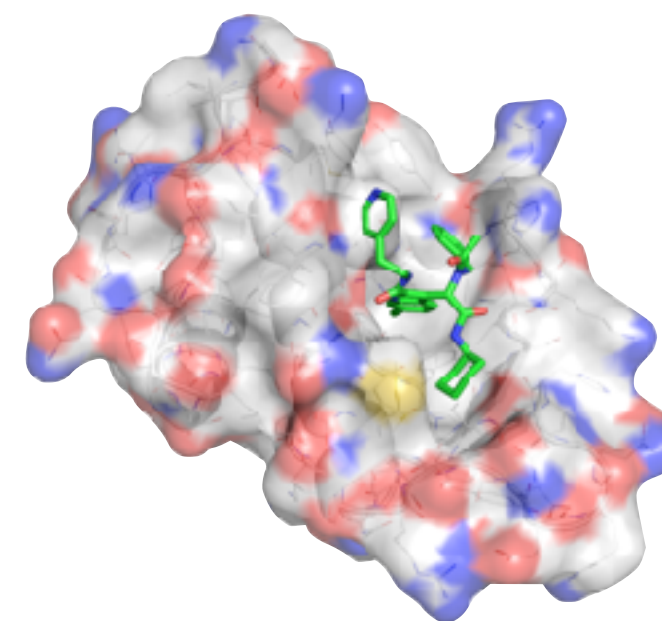
Lead Optimization

Purchasable



Accessible

Drug Discovery Funnel

**Matching****Scoring****Dynamics**

Pharmit Search Engine

Search MolPort

Pharmacophore Search -> Shape Filter

Load Receptor... Load Features...

Pharmacophore

- ☒ **HydrogenDonor** (9.53,3.92,35.82) Radius 0.5
- ☒ **HydrogenAcceptor** (9.53,3.92,35.82) Radius 0.5
- ☒ **HydrogenAcceptor** (20.0,4.36,33.13) Radius 0.5
- ☒ **Hydrophobic** (12.17,4.27,35.2) Radius 1.0
- ☒ **Hydrophobic** (18.72,4.46,35.4) Radius 1.0
- ☒ **Hydrophobic** (17.88,4.44,32.8) Radius 1.0
- ☒ **Hydrophobic** (16.24,4.83,33.93) Radius 1.0

Add Sort

Shape

- ☐ Inclusive Shape
- ☐ Exclusive Shape

Filters

- ☐ Hit Reduction
- ☐ Hit Screening

Load Session... Save Session...

Pharmacophore Results

Name	RMSD	Mass	RBnds
MolPort-002-911-158	0.113	395	1
MolPort-000-705-595	0.124	330	0
MolPort-035-395-591	0.125	607	15
MolPort-002-509-936	0.132	314	0
MolPort-003-847-099	0.134	275	0
MolPort-002-741-818	0.147	351	0
MolPort-002-515-416	0.148	330	0
MolPort-009-018-993	0.150	300	1
MolPort-003-892-015	0.157	288	0
MolPort-003-941-332	0.164	272	0
MolPort-006-318-980	0.164	272	0
MolPort-000-720-875	0.164	272	0
MolPort-000-725-407	0.165	296	0
MolPort-039-348-092	0.169	378	1
MolPort-002-509-704	0.169	312	1
MolPort-002-520-688	0.170	375	3
MolPort-002-506-898	0.172	288	0
MolPort-006-069-030	0.173	607	15

Showing 1 to 18 of 1,335 hits

Query took 2.235 seconds

Minimize Save...

<http://pharmit.csb.pitt.edu>

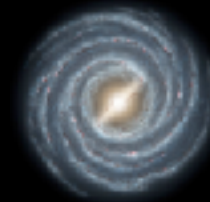


COMP 528: Structure-based searching of chemical space with Pharmit

Thursday, Aug 23 9:20 AM

Douglass, Westin Boston Waterfront

Purchasable



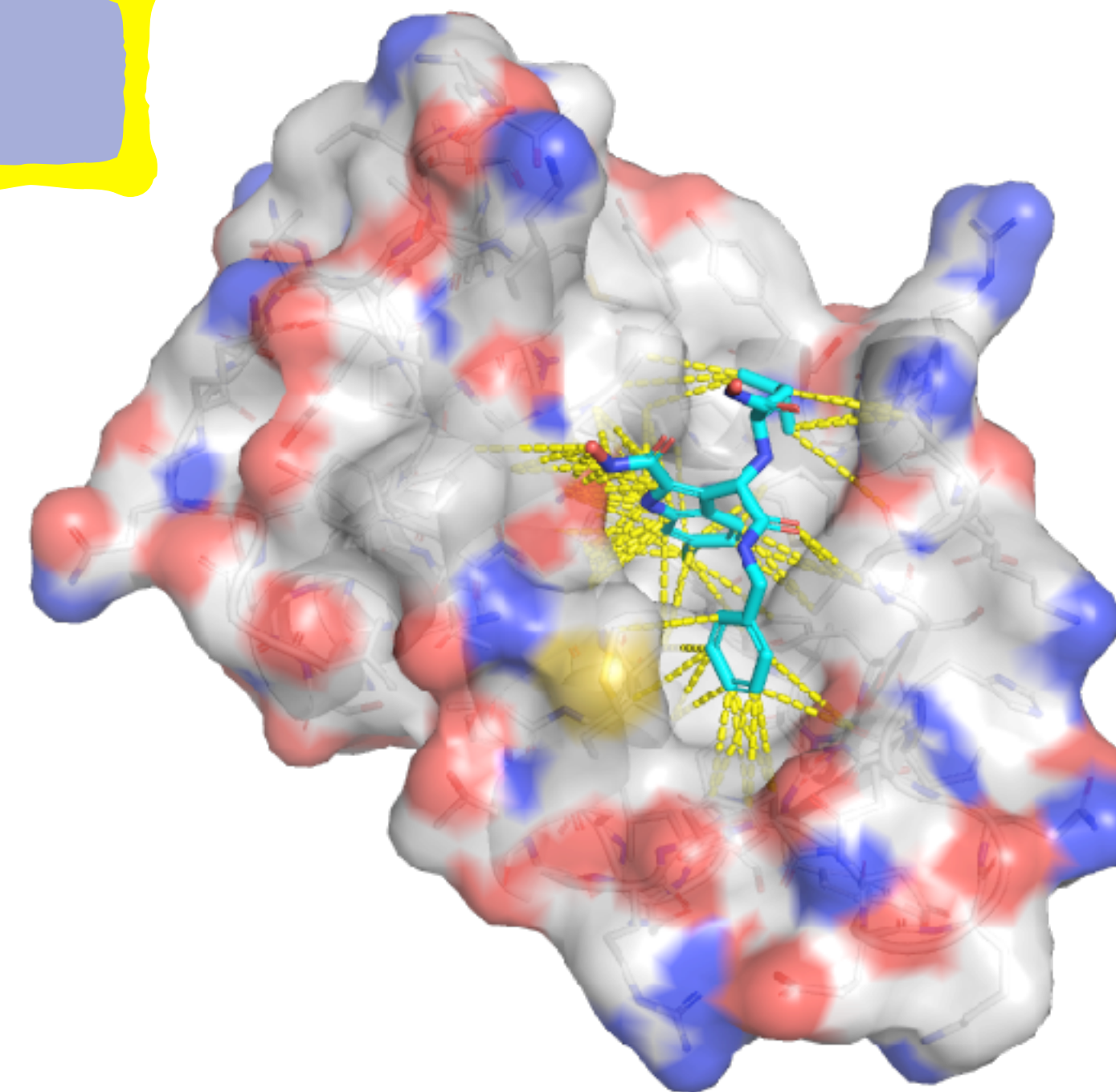
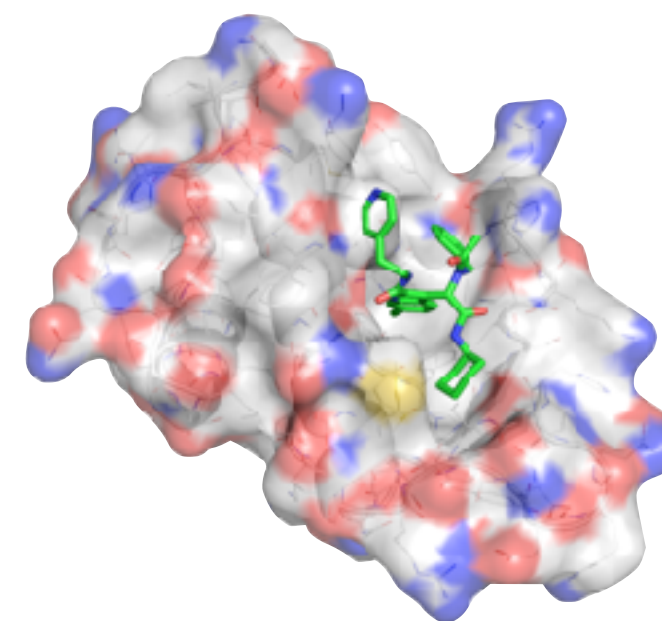
Accessible

Drug Discovery Funnel


Matching


Scoring

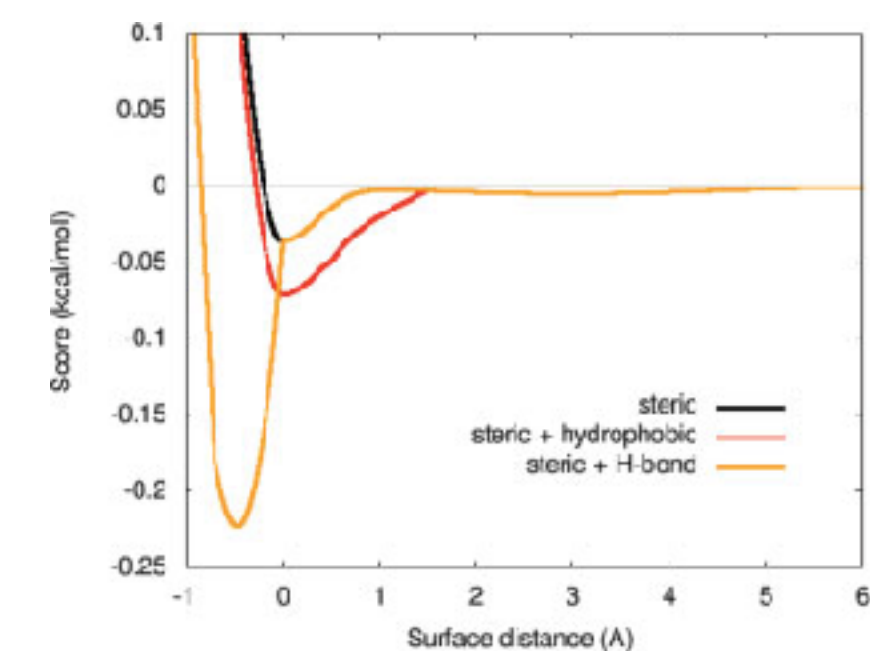

Dynamics



$$\begin{aligned}\text{gauss}_1(d) &= w_{\text{gauss}_1} e^{-(d/0.5)^2} \\ \text{gauss}_2(d) &= w_{\text{gauss}_2} e^{-((d-3)/2)^2} \\ \text{repulsion}(d) &= \begin{cases} w_{\text{repulsion}} d^2 & d < 0 \\ 0 & d \geq 0 \end{cases}\end{aligned}$$

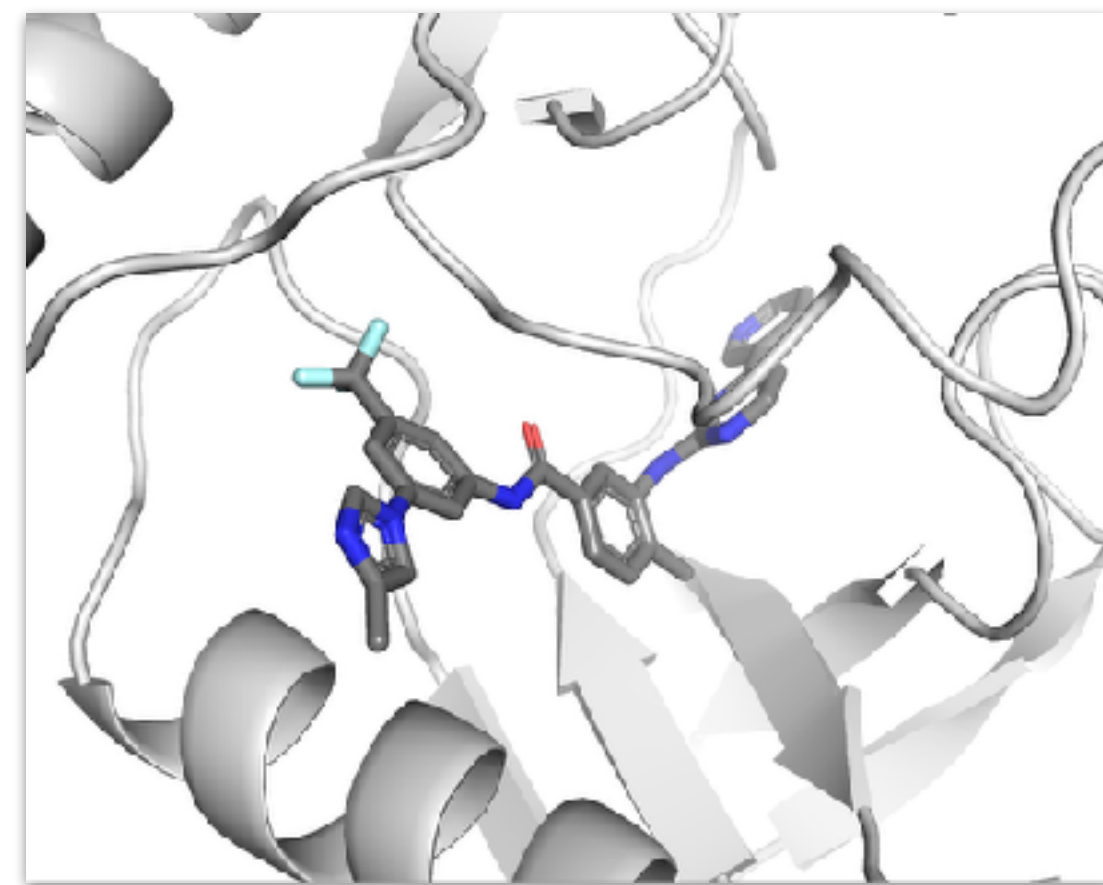
$$\text{hydrophobic}(d) = \begin{cases} w_{\text{hydrophobic}} & d < 0.5 \\ 0 & d > 1.5 \\ w_{\text{hydrophobic}}(1.5 - d) & \text{otherwise} \end{cases}$$

$$\text{hbond}(d) = \begin{cases} w_{\text{hbond}} & d < -0.7 \\ 0 & d > 0 \\ w_{\text{hbond}}(-\frac{10}{7}d) & \text{otherwise} \end{cases}$$



O. Trott, A. J. Olson, AutoDock Vina: improving the speed and accuracy of docking with a new scoring function, efficient optimization and multithreading, *Journal of Computational Chemistry* 31 (2010) 455-461

Protein-Ligand Scoring



Model

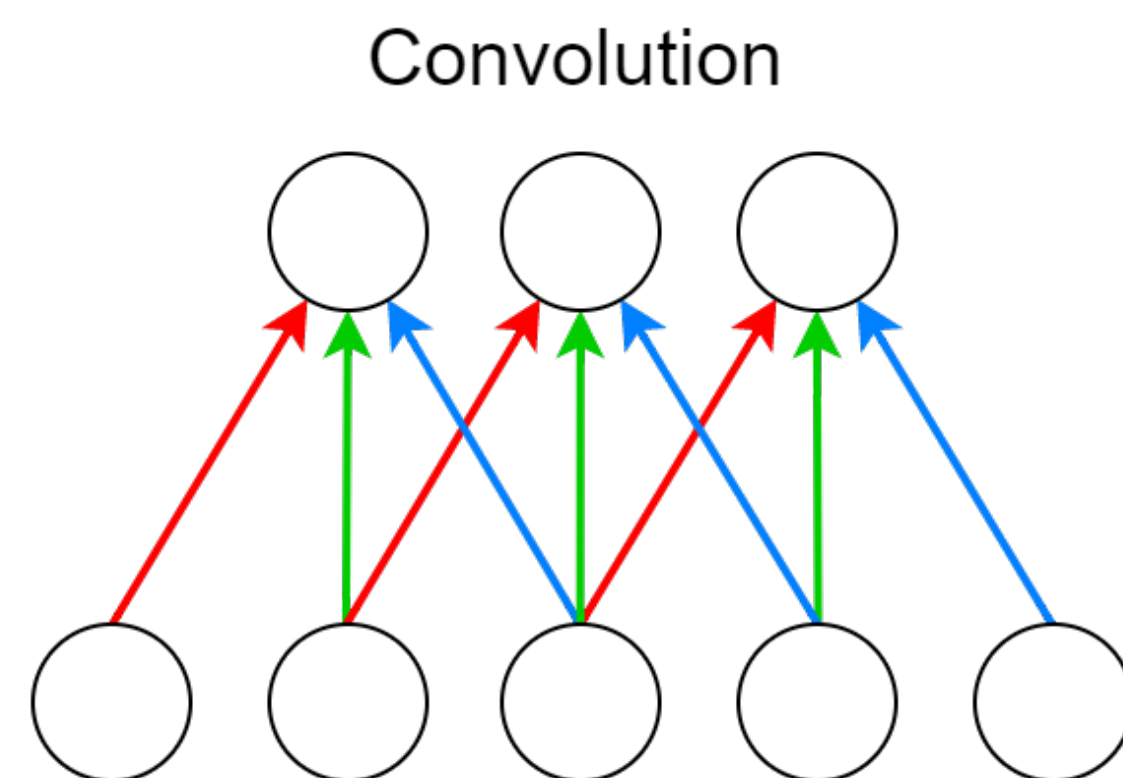
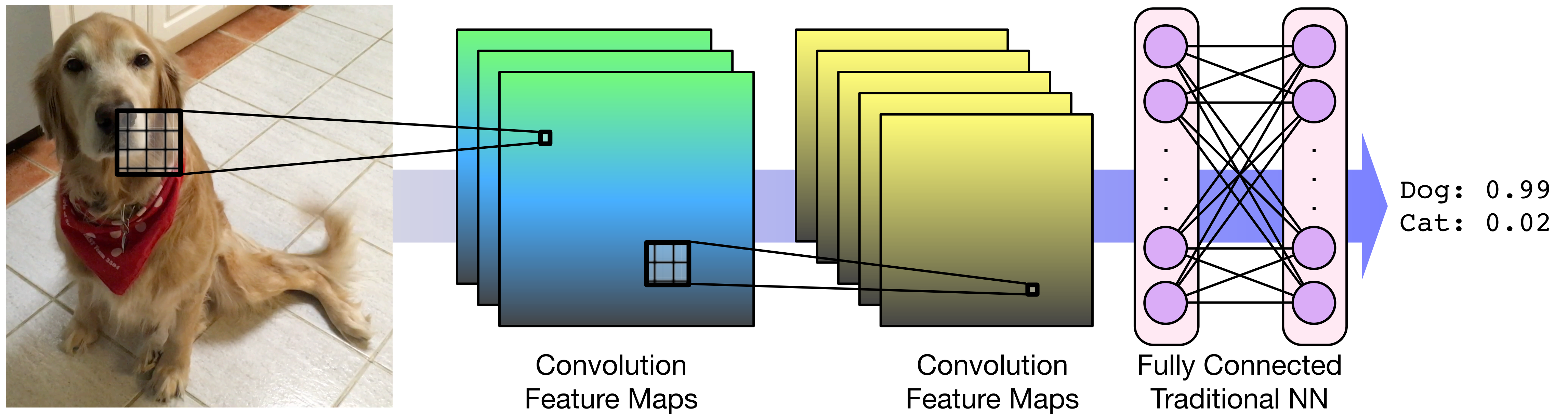


Pose Prediction

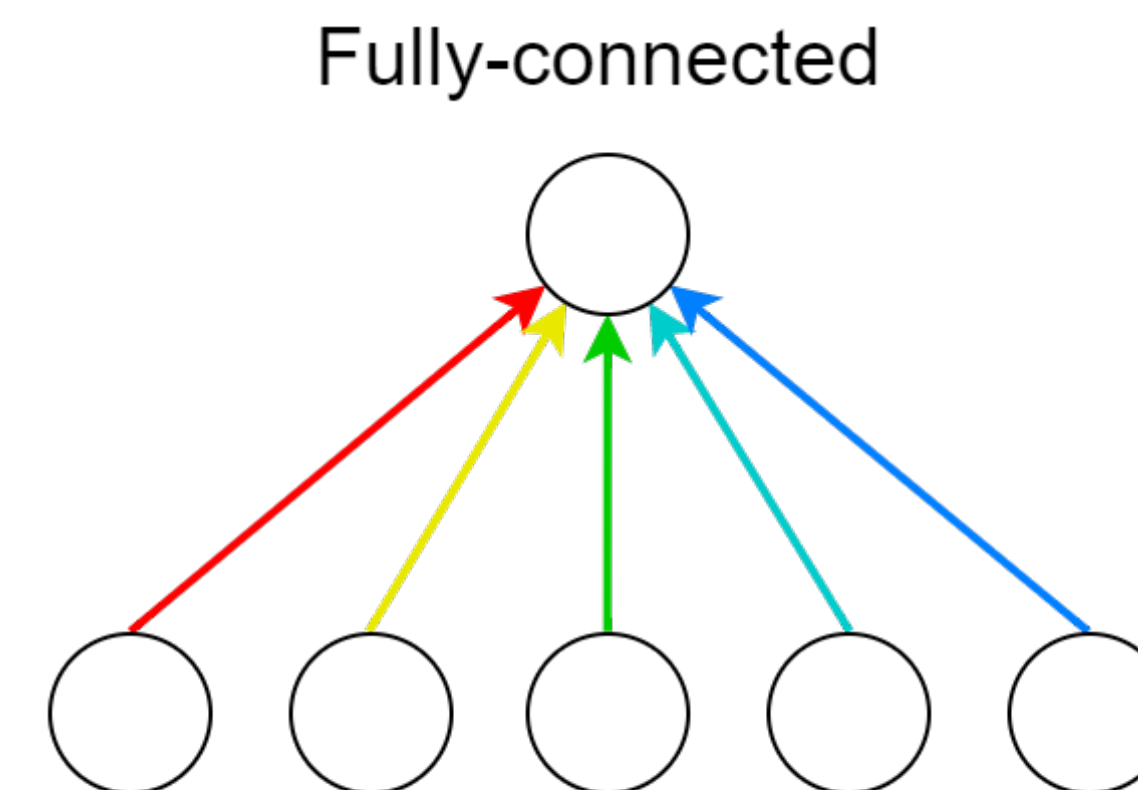
Binding
Discrimination

Affinity Prediction

Convolutional Neural Networks

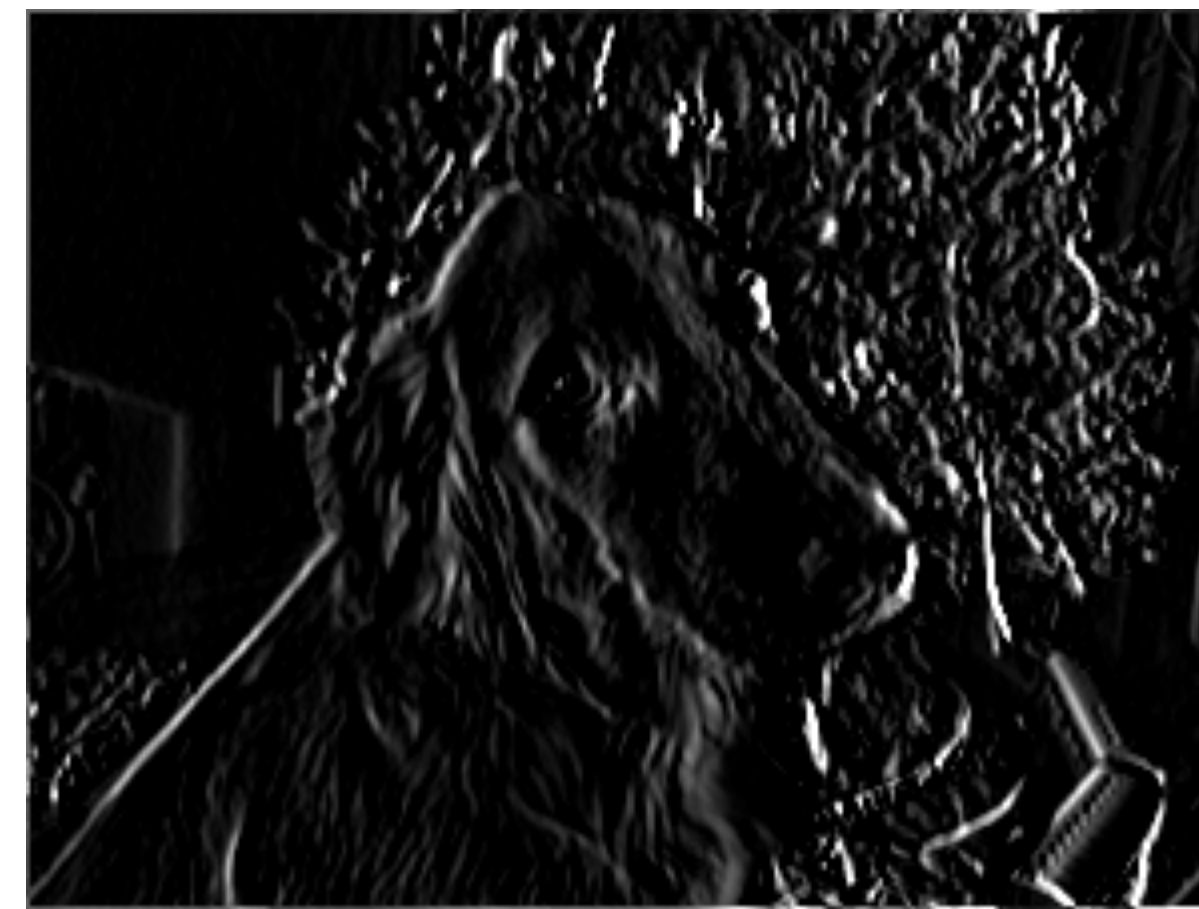
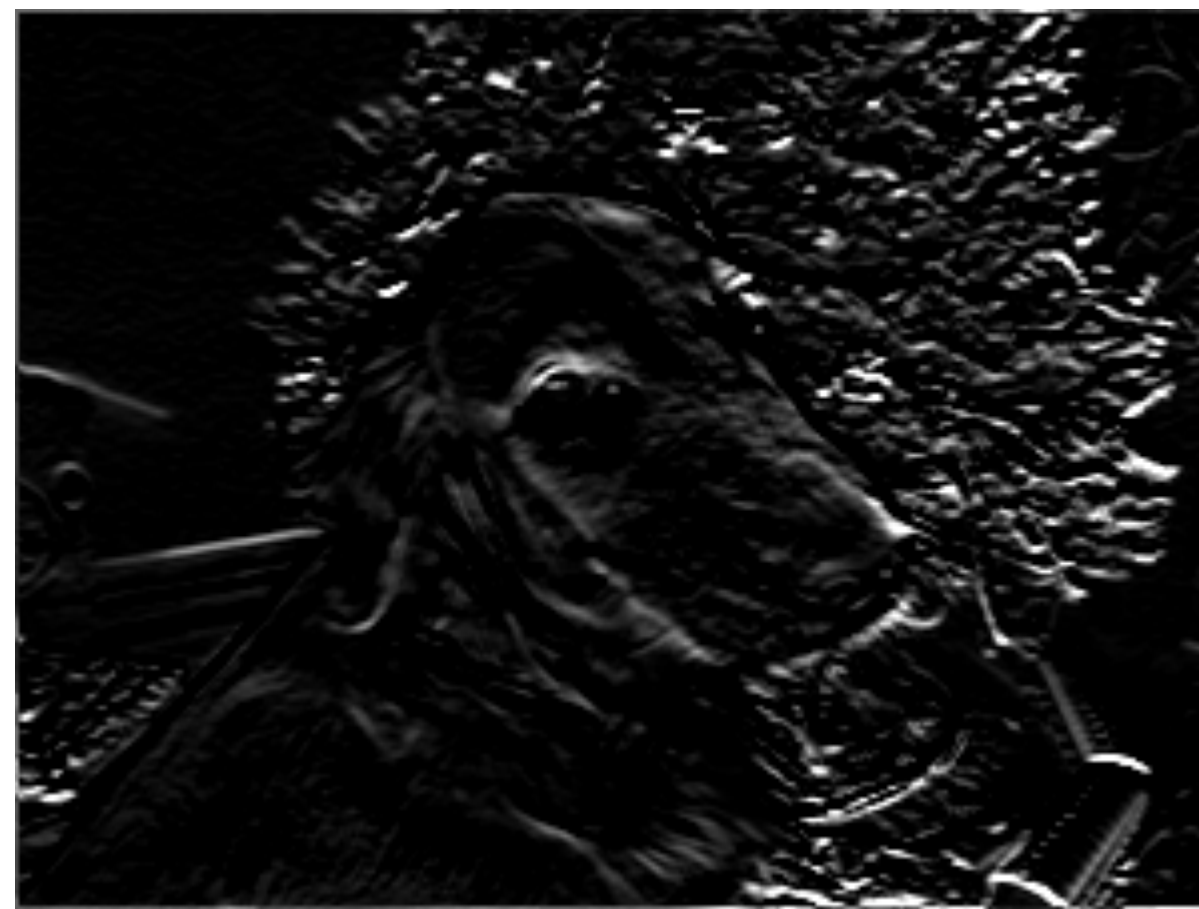


— weight 1
— weight 2
— weight 3



— weight 1
— weight 2
— weight 3
— weight 4
— weight 5

Convolutional Filters

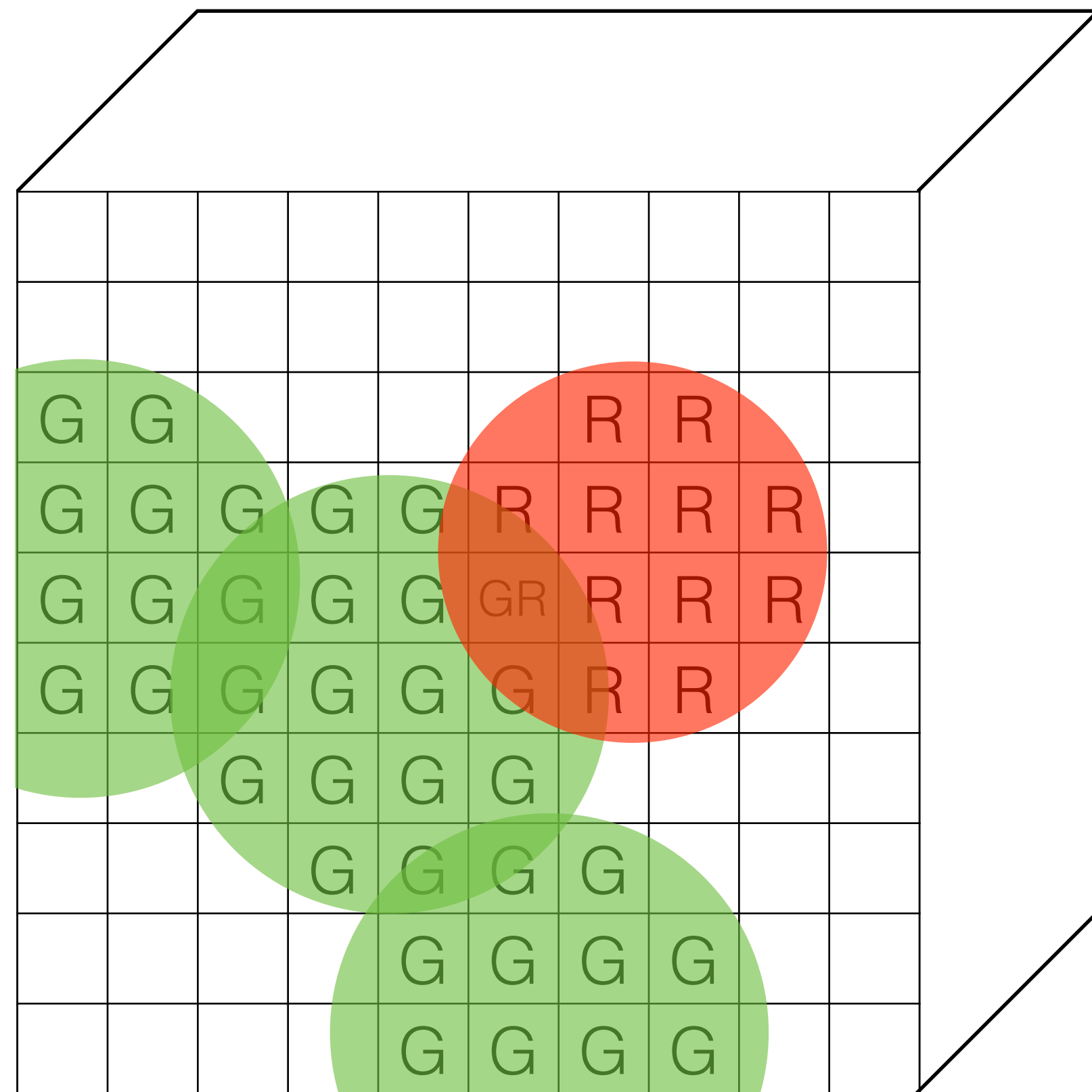


-1	-1	-1
0	0	0
1	1	1

-1	0	1
-1	0	1
-1	0	1

-1	-1	-1
-1	8	-1
-1	-1	-1

Protein-Ligand Representation



(R,G,B) pixel →

(Carbon, Nitrogen, Oxygen,...) **voxel**

The only parameters for this representation are the choice of **grid resolution**, **atom density**, and **atom types**.

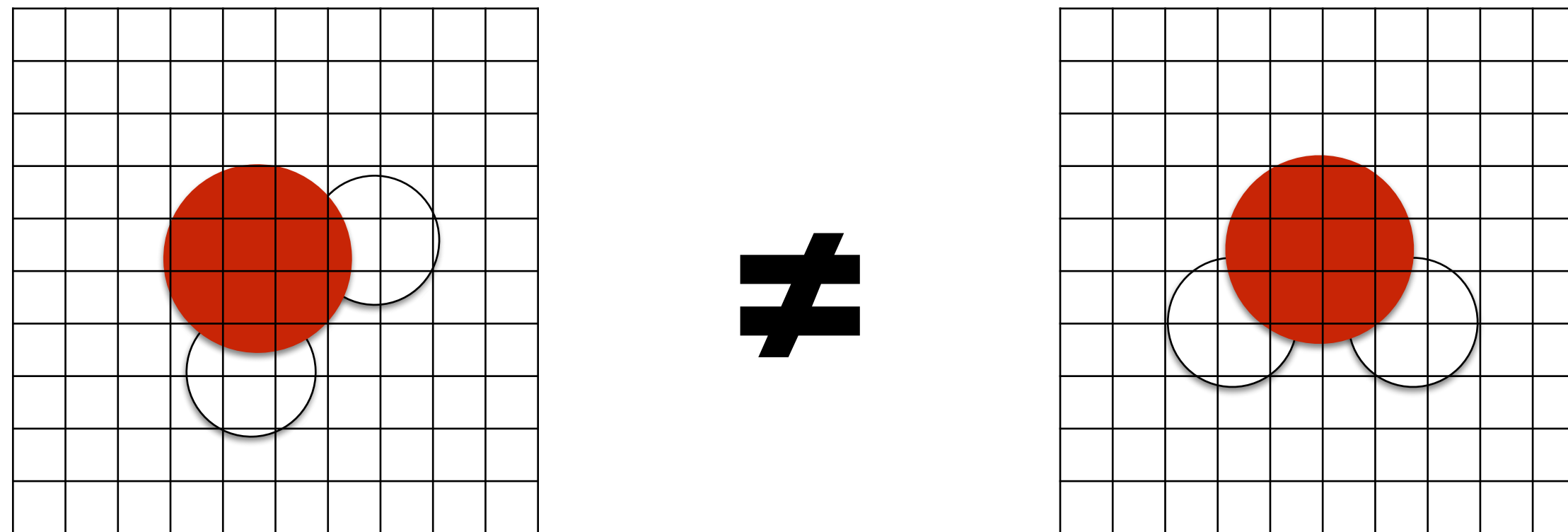
Why Grids?

Cons

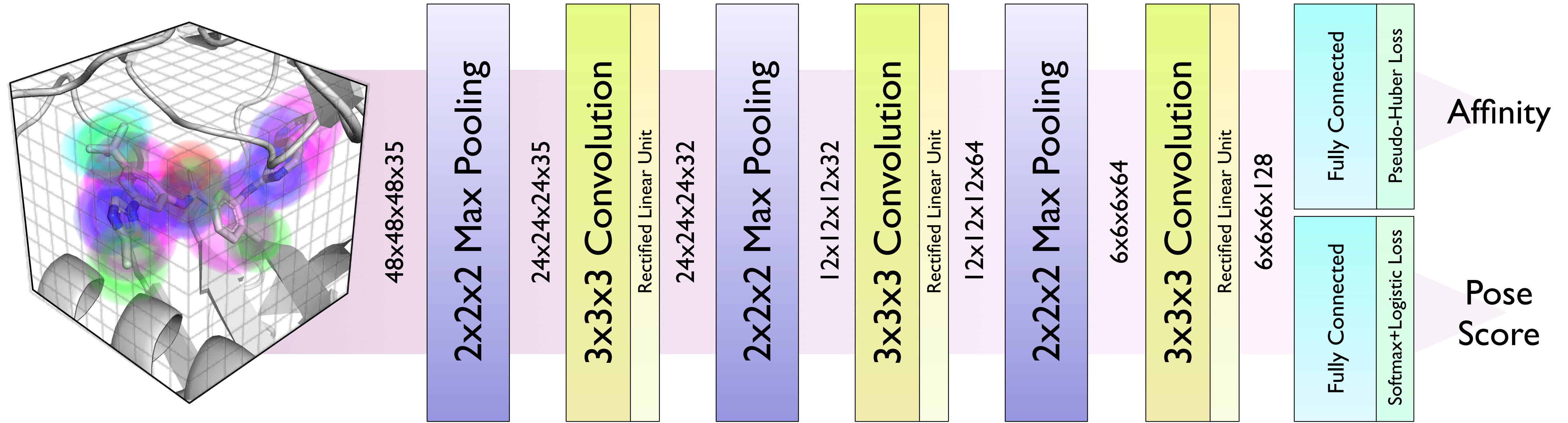
- *coordinate frame dependent*
- pairwise interactions not explicit

Pros

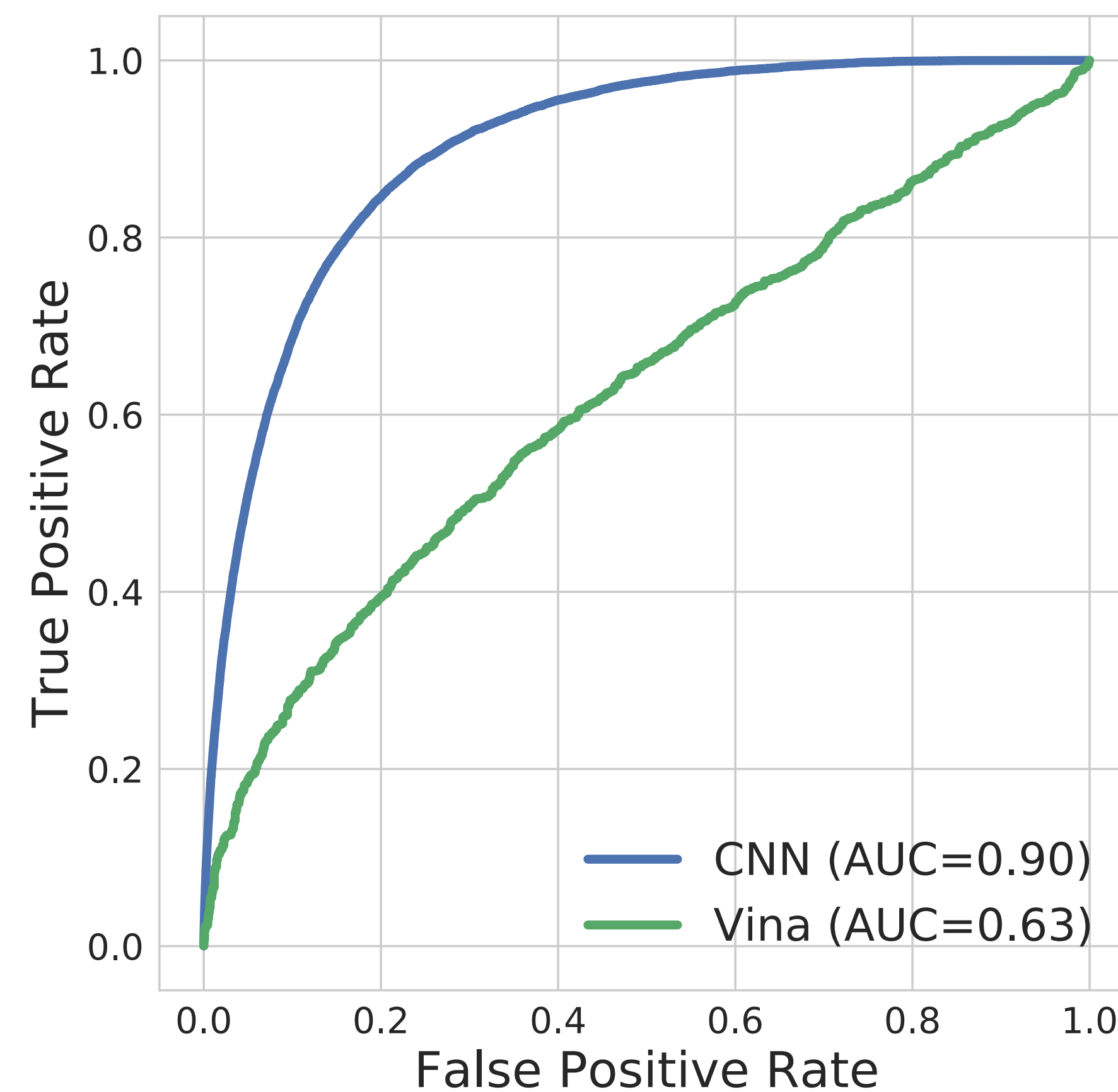
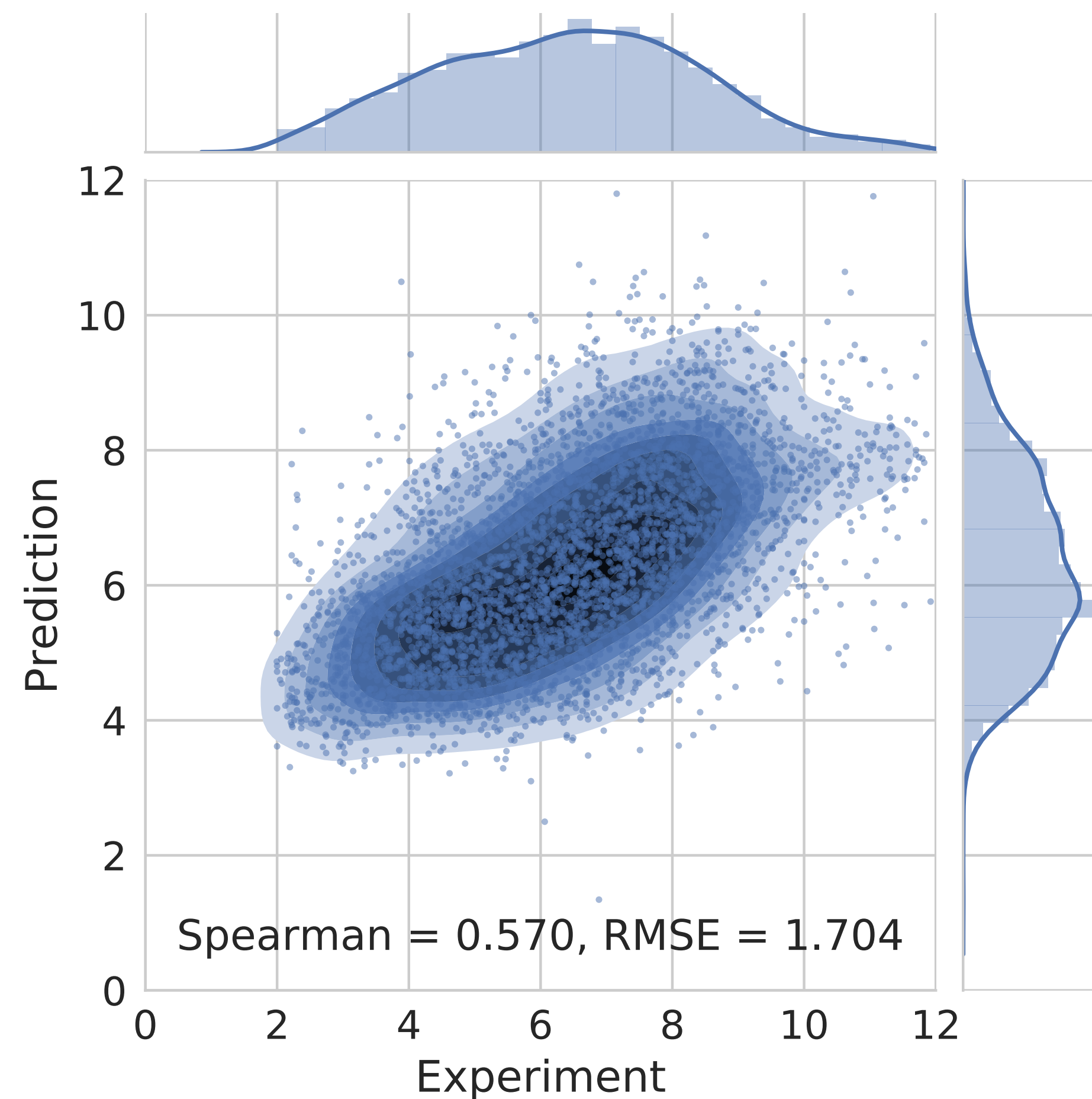
- clear spatial relationships
- amazingly parallel
- easy to interpret



Model



Results

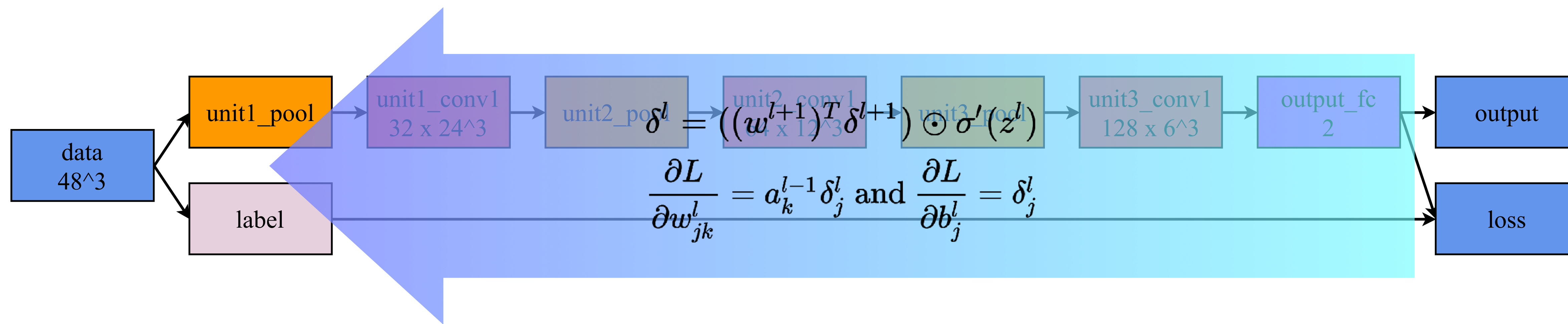


COMP 410: GNINA: Deep learning for molecular docking
Monday, Aug 20 8:00 PM
Exhibit Hall C, Boston Convention & Exhibition Center

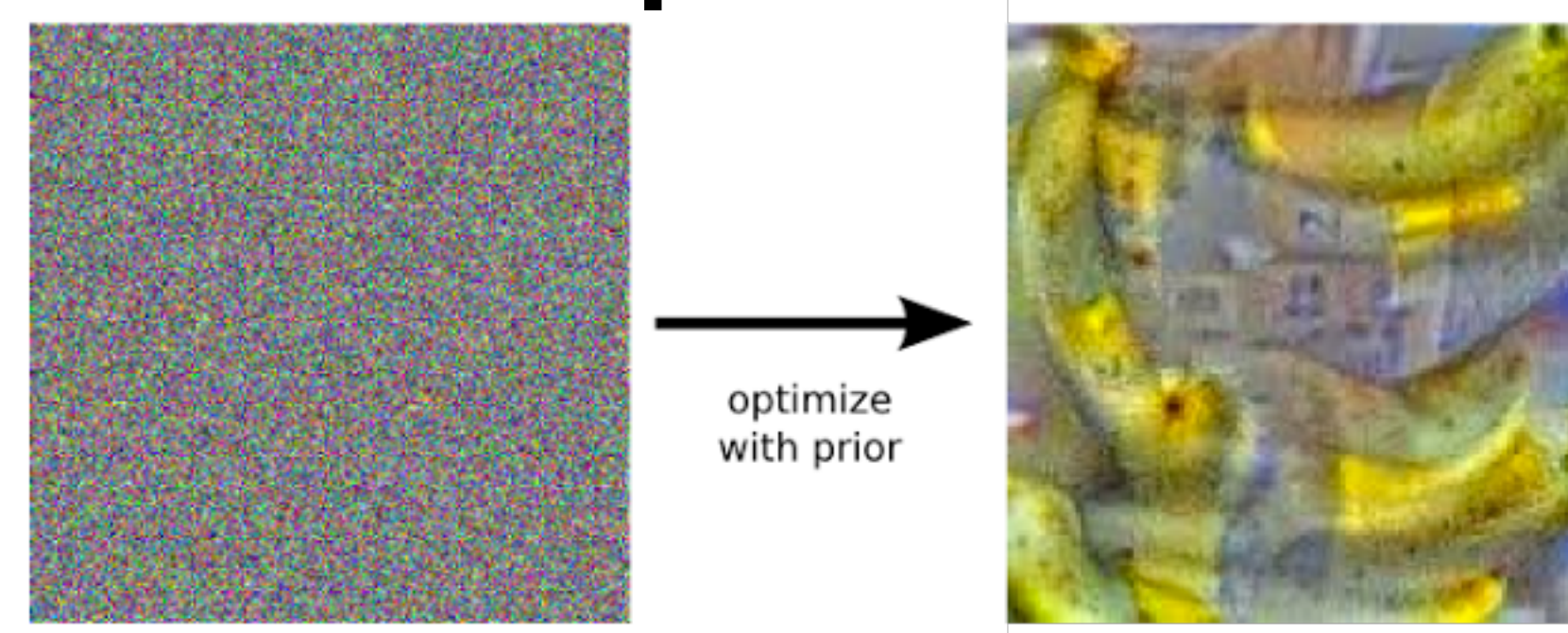


COMP: Poster Session
Tuesday, Aug 21 6:00 PM
Exhibit Hall B1, Boston Convention & Exhibition Center

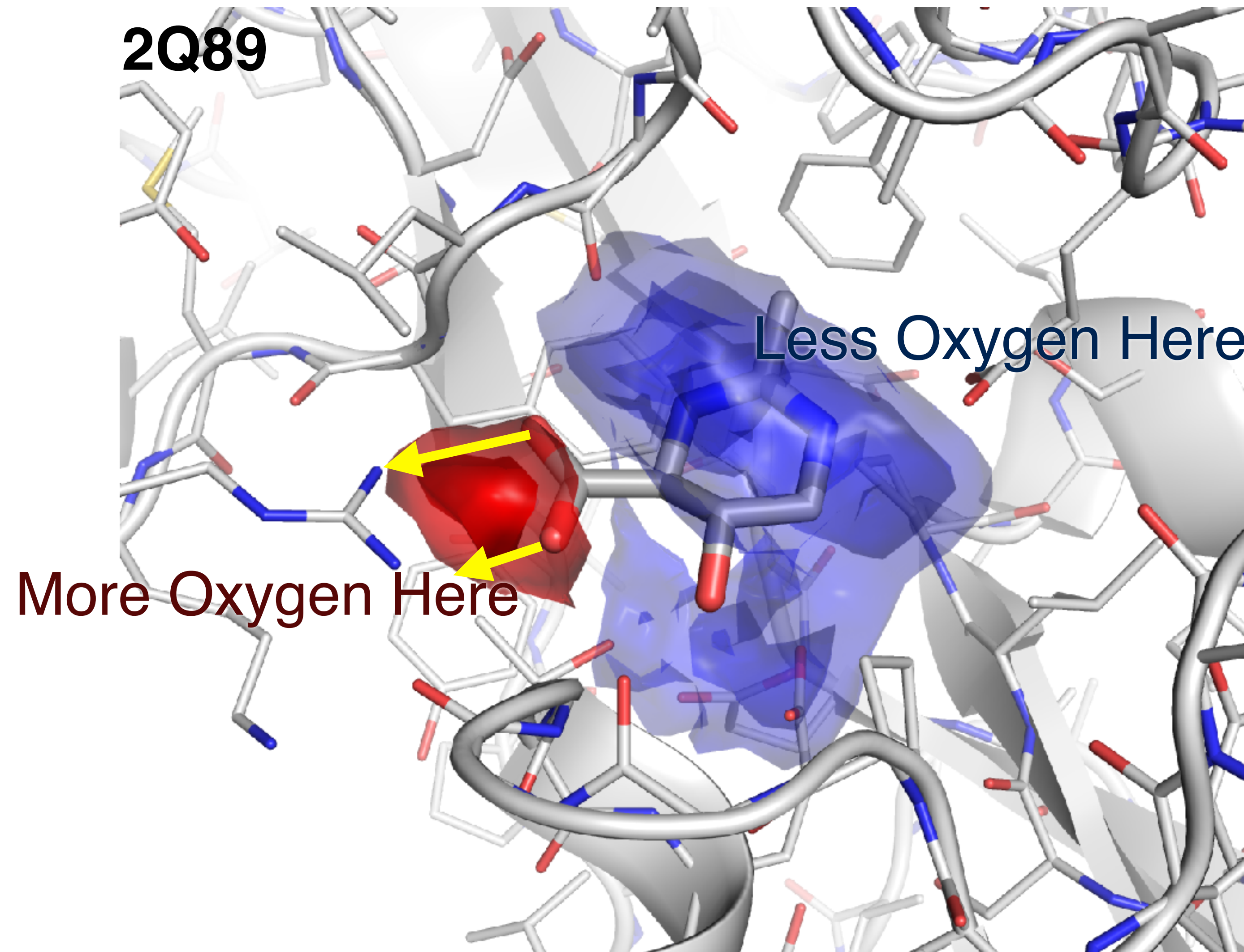
Beyond Scoring



Deep Dreams



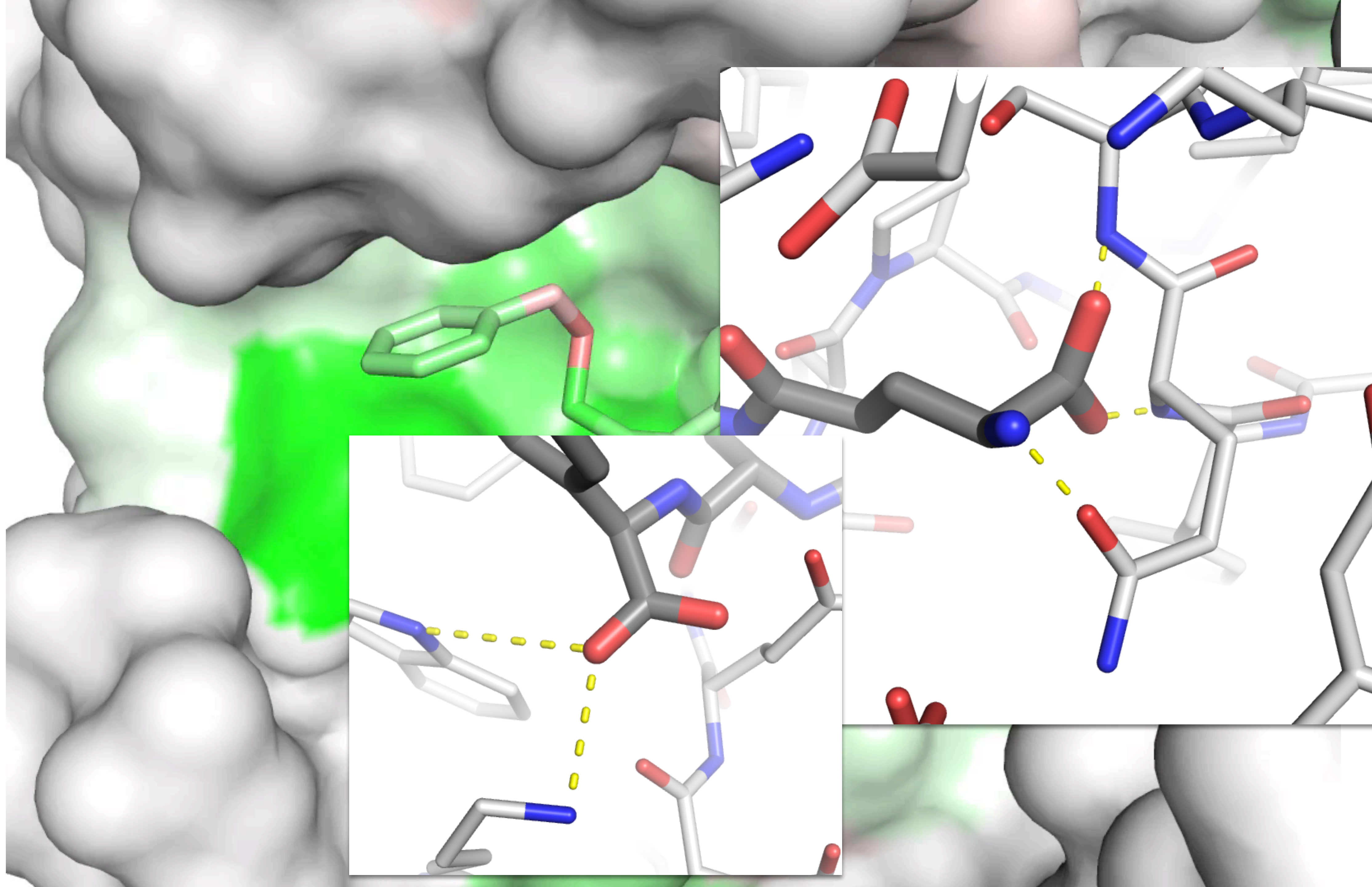
Beyond Scoring



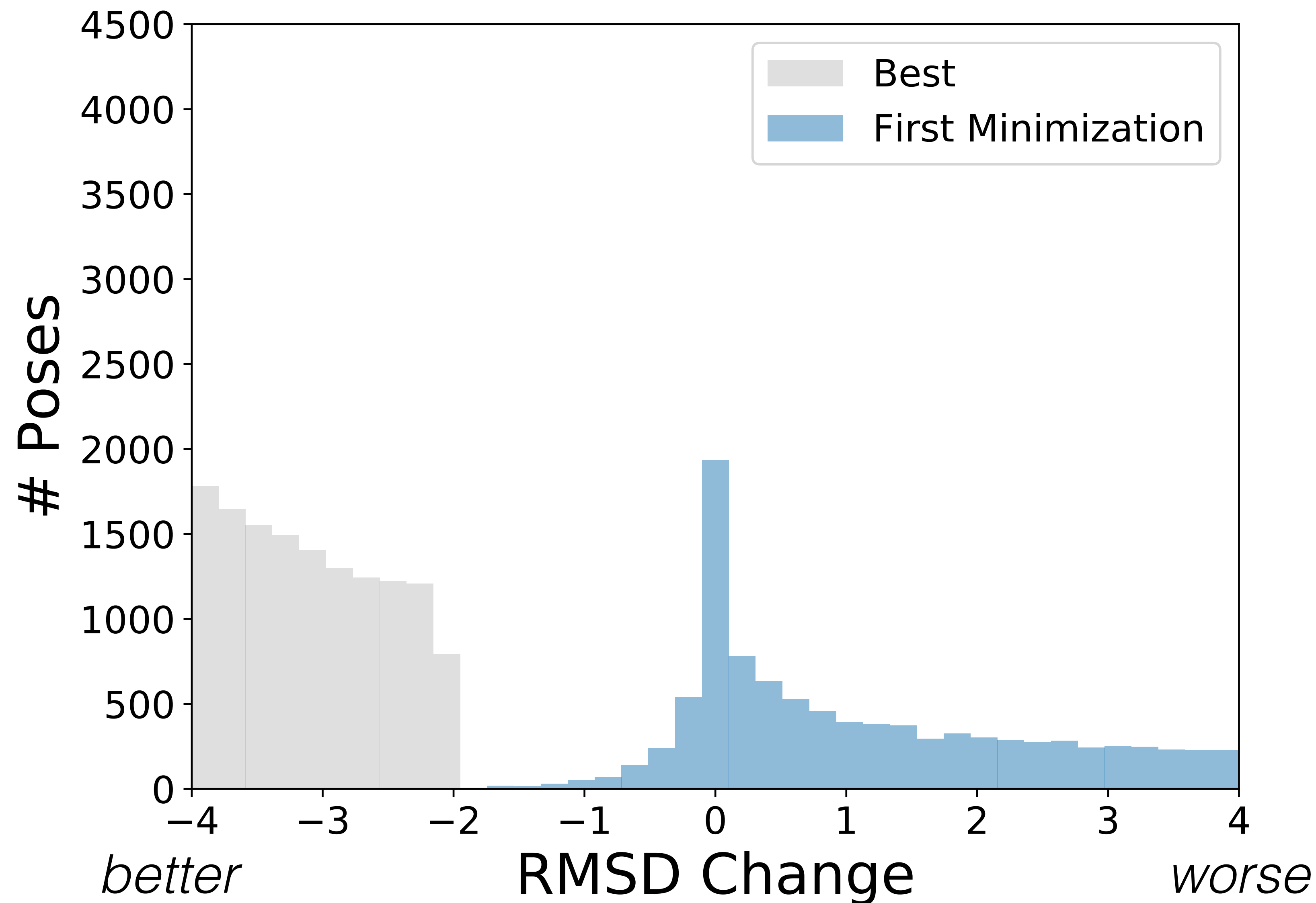
$$\frac{\partial L}{\partial A} = \sum_{i \in G_A} \frac{\partial L}{\partial G_i} \frac{\partial G_i}{\partial D} \frac{\partial D}{\partial A}$$

unit1_pool

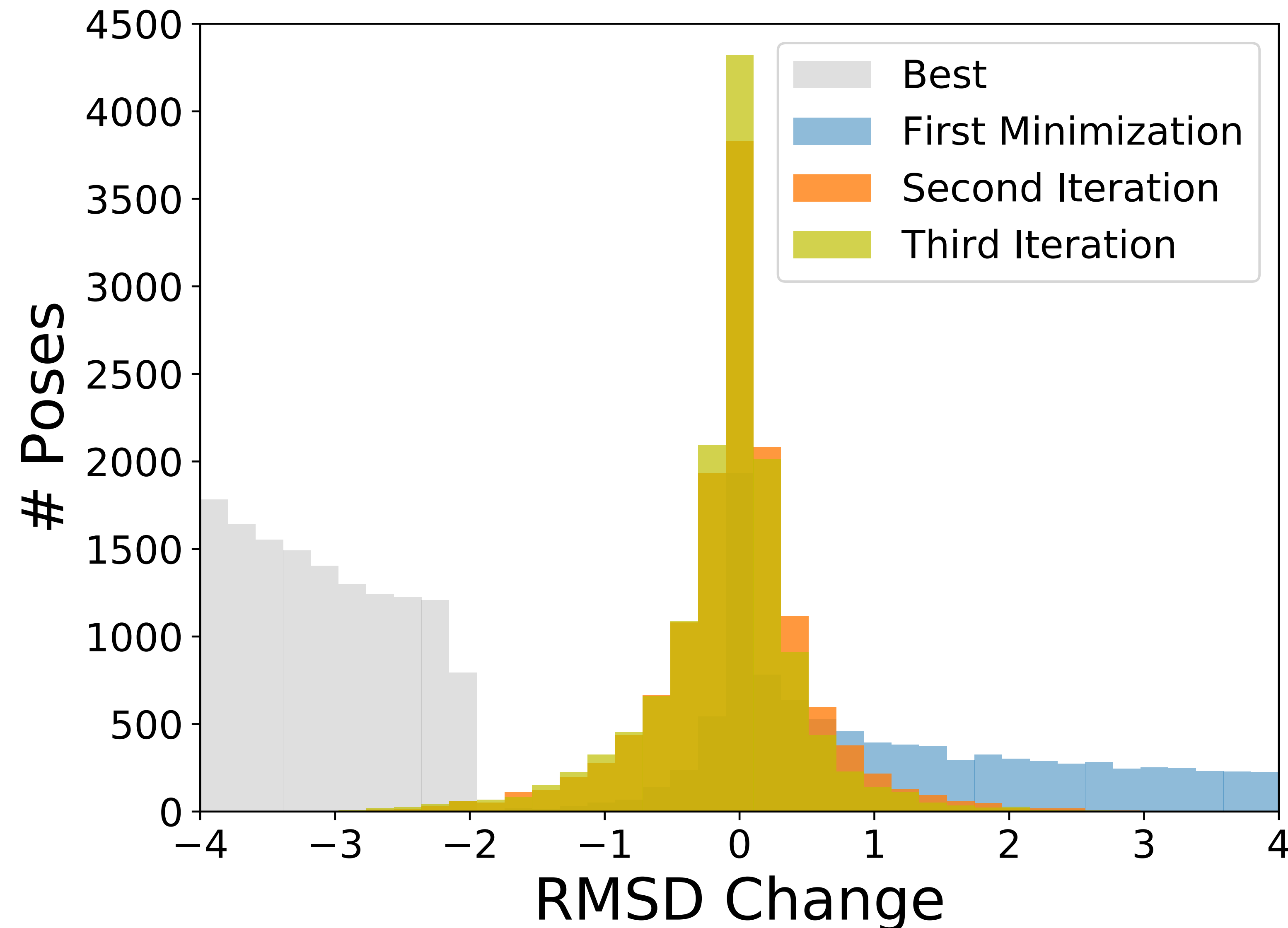
label

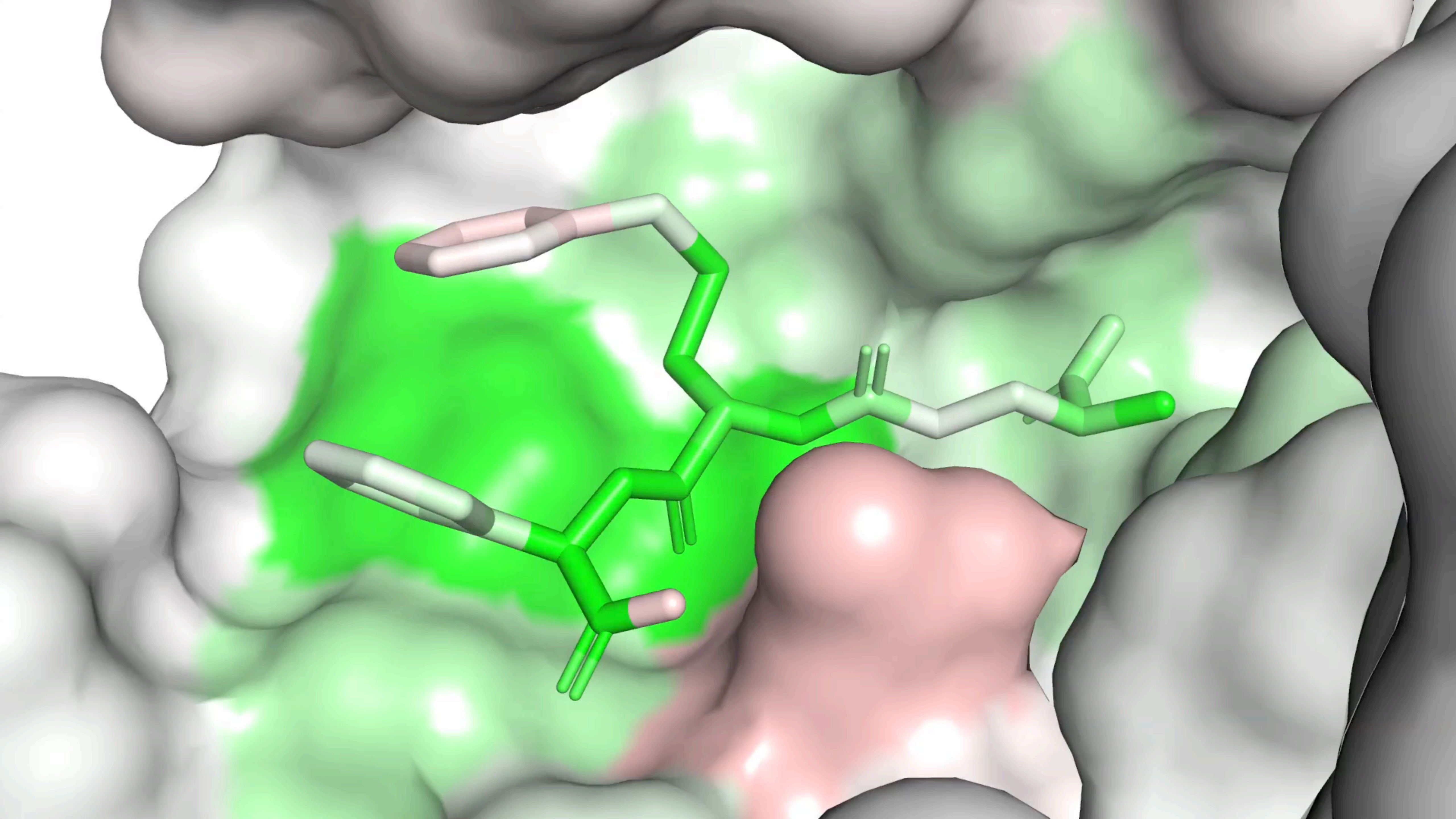


Minimizing Low RMSD Poses



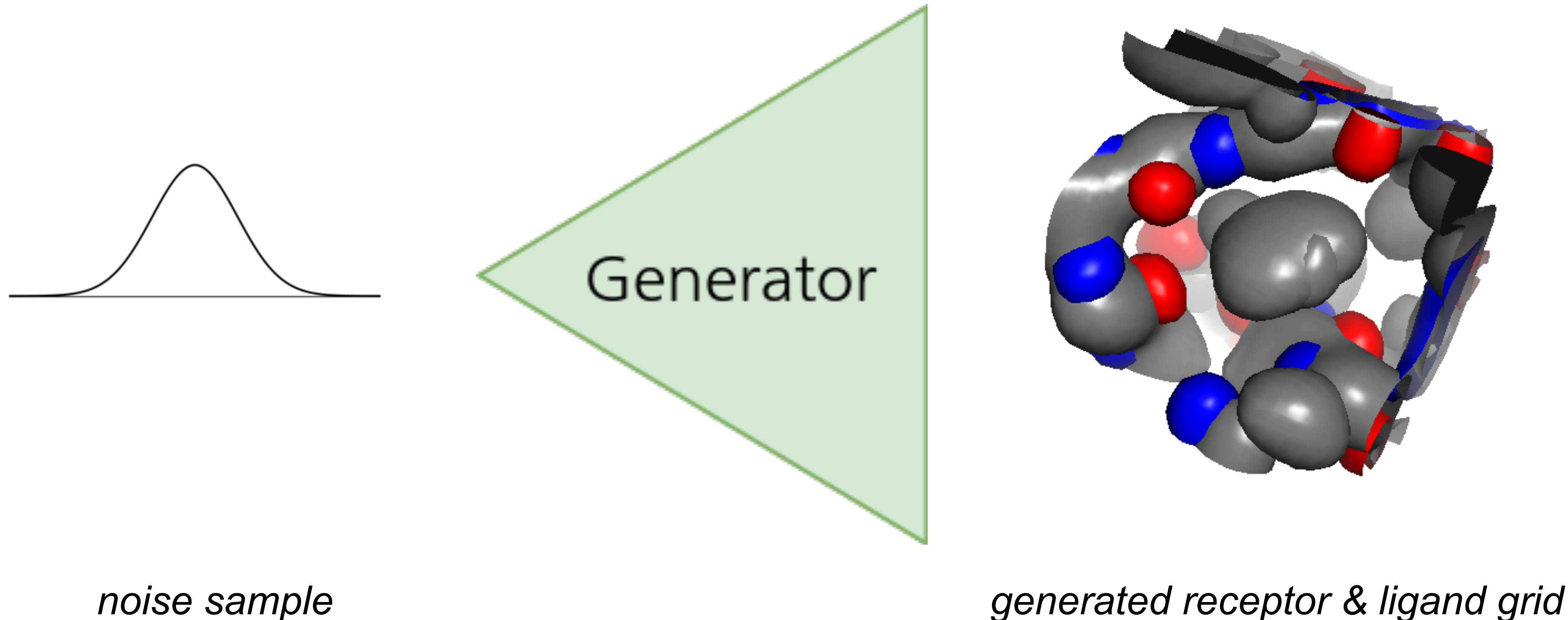
Iterative Refinement





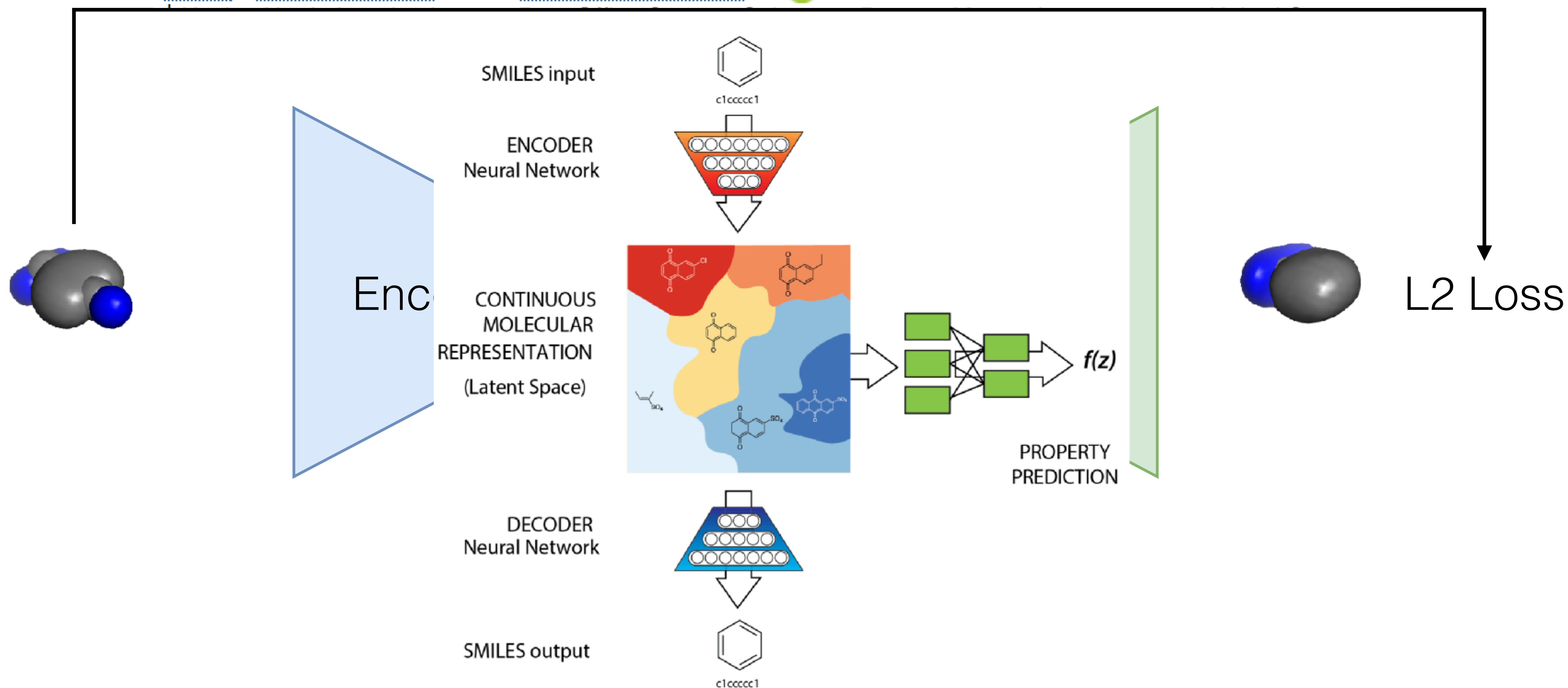
Generative Models

Generative models approximate a data distribution directly. They can map samples from one distribution (noise or input data) to realistic samples from an output distribution of interest.

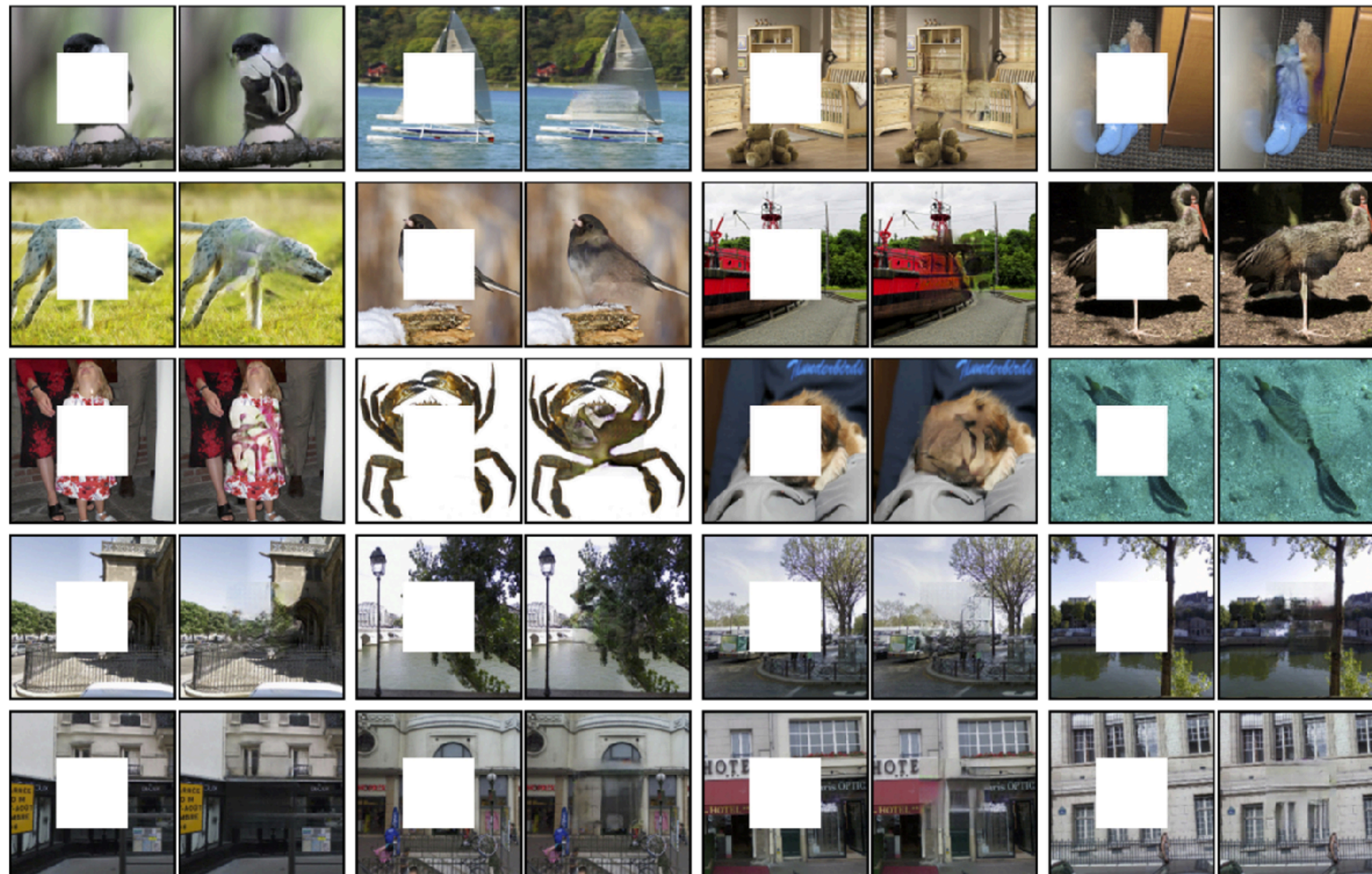


Automatic Chemical Design Using a Data-Driven Continuous Representation of Molecules

Rafael Gómez-Bombarelli^{†#} , Jennifer N. Wei^{‡#} , David Duvenaud^{¶#}, José Miguel Hernández-Lobato^{§#}, Benjamín Sánchez-Lengeling[‡], Dennis Sheberla[‡] , Jorge Aguilera-Iparraguirre[†], Timothy D. Hirzel[†], Ryan P. Adams^{¶†}, and Alán Aspuru-Guzik^{‡⊥} 

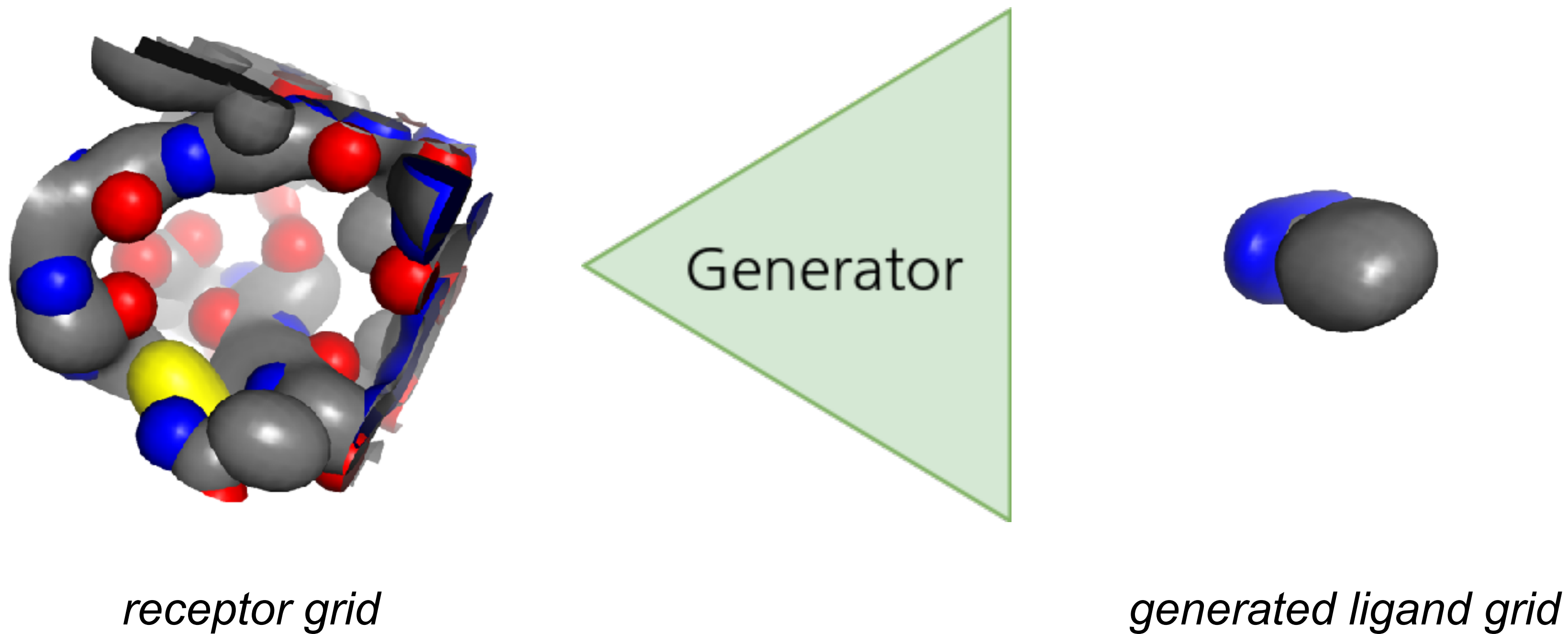


Context Encoding

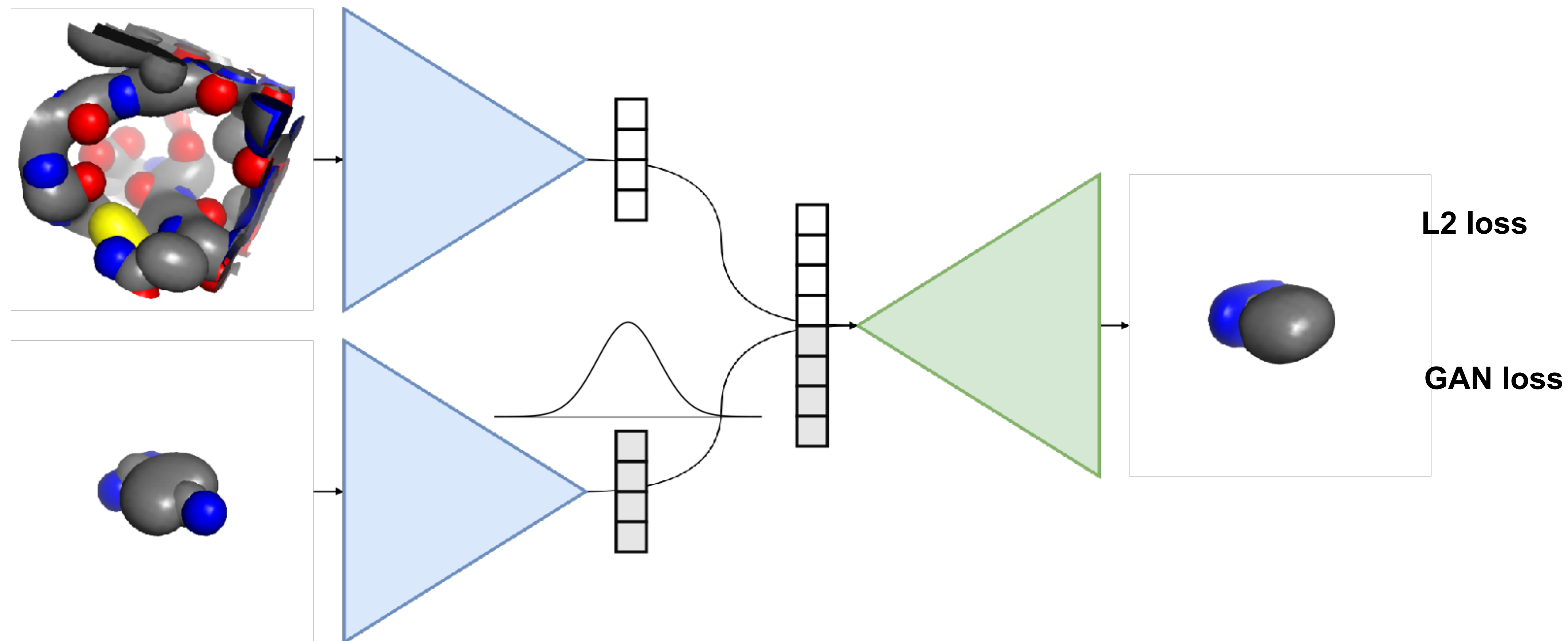


http://people.eecs.berkeley.edu/~pathak/context_encoder/

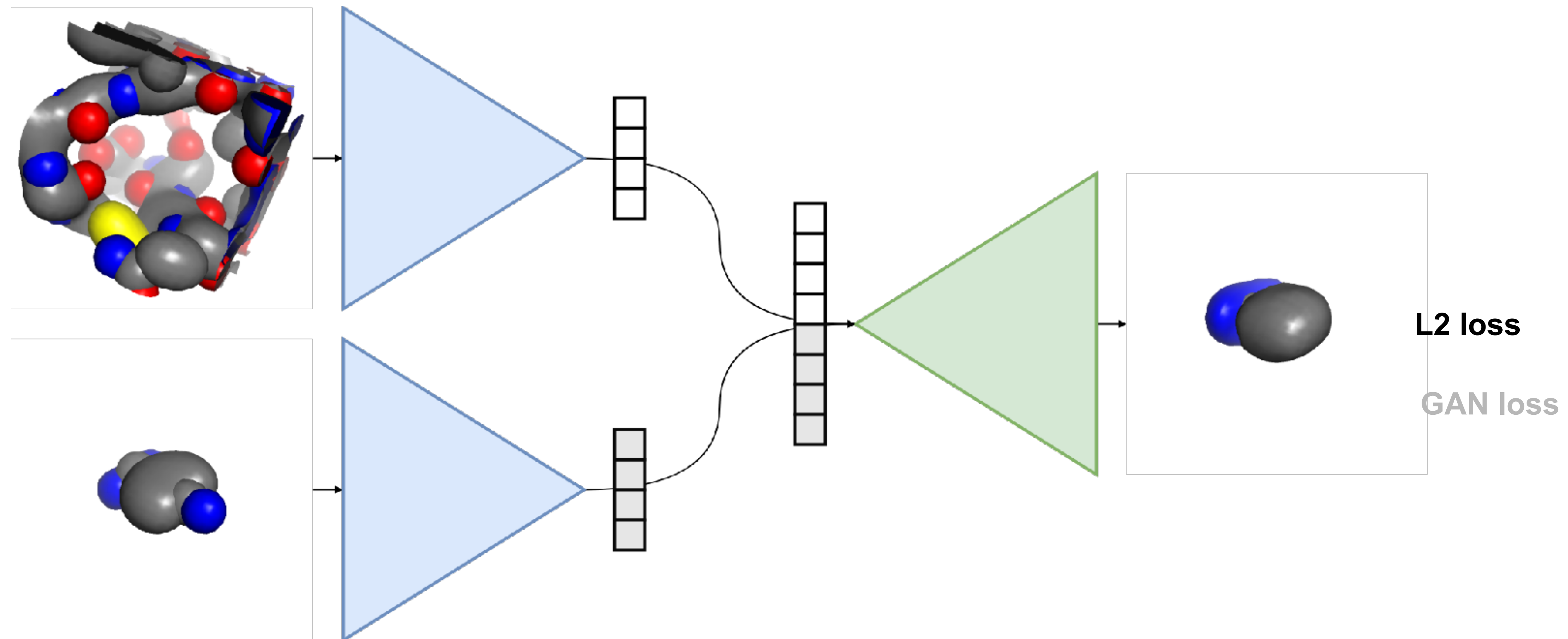
Context Encoding



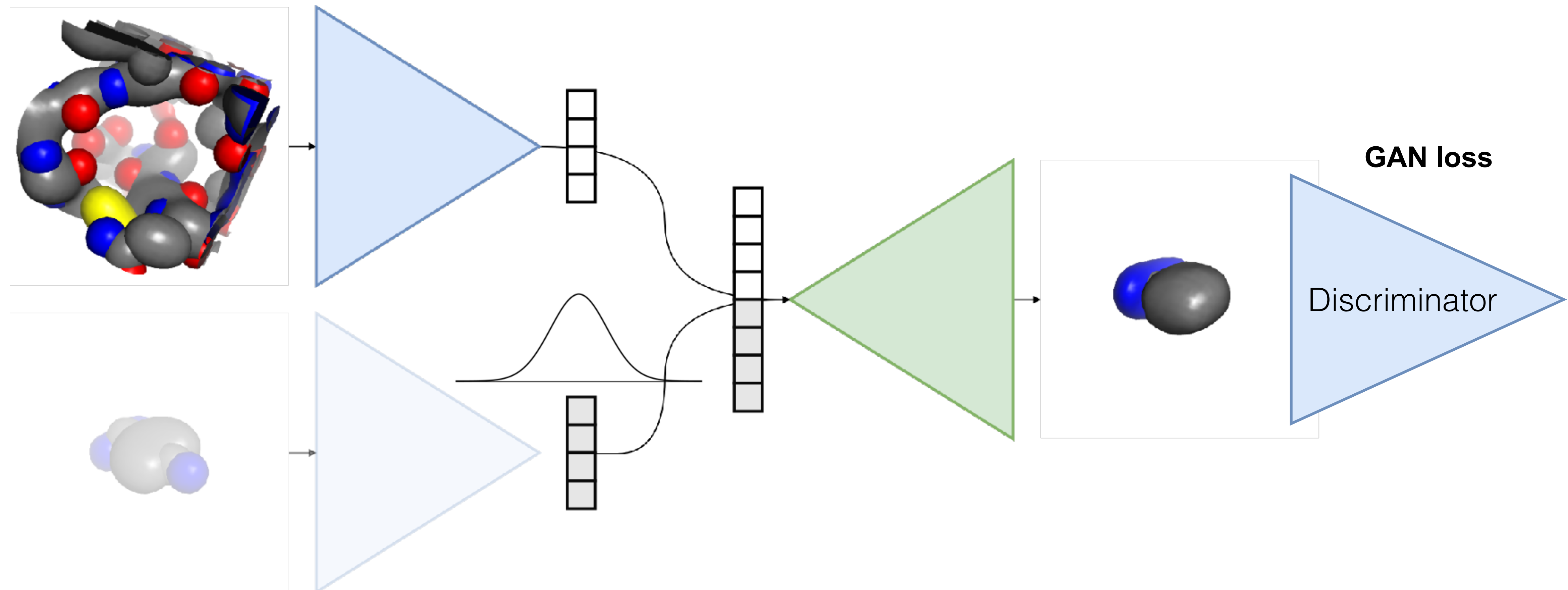
Receptor-Conditional Ligand-Variational Model

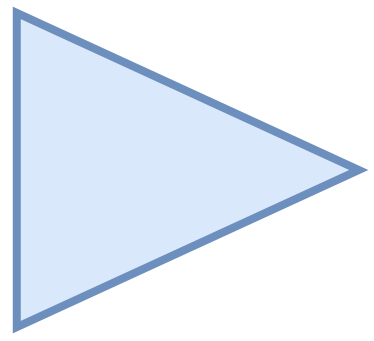


Receptor-Conditional Ligand-Variational Model

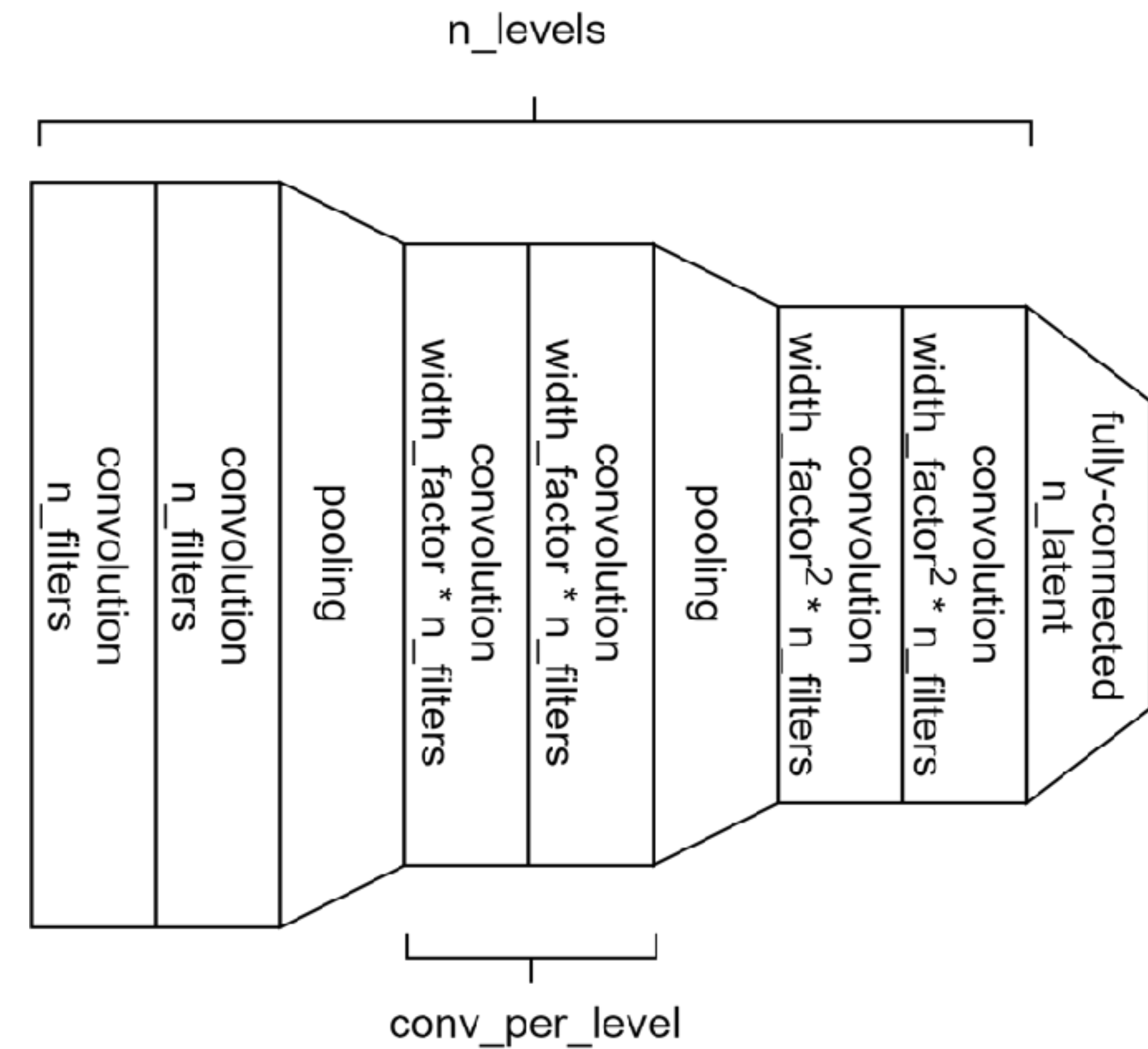
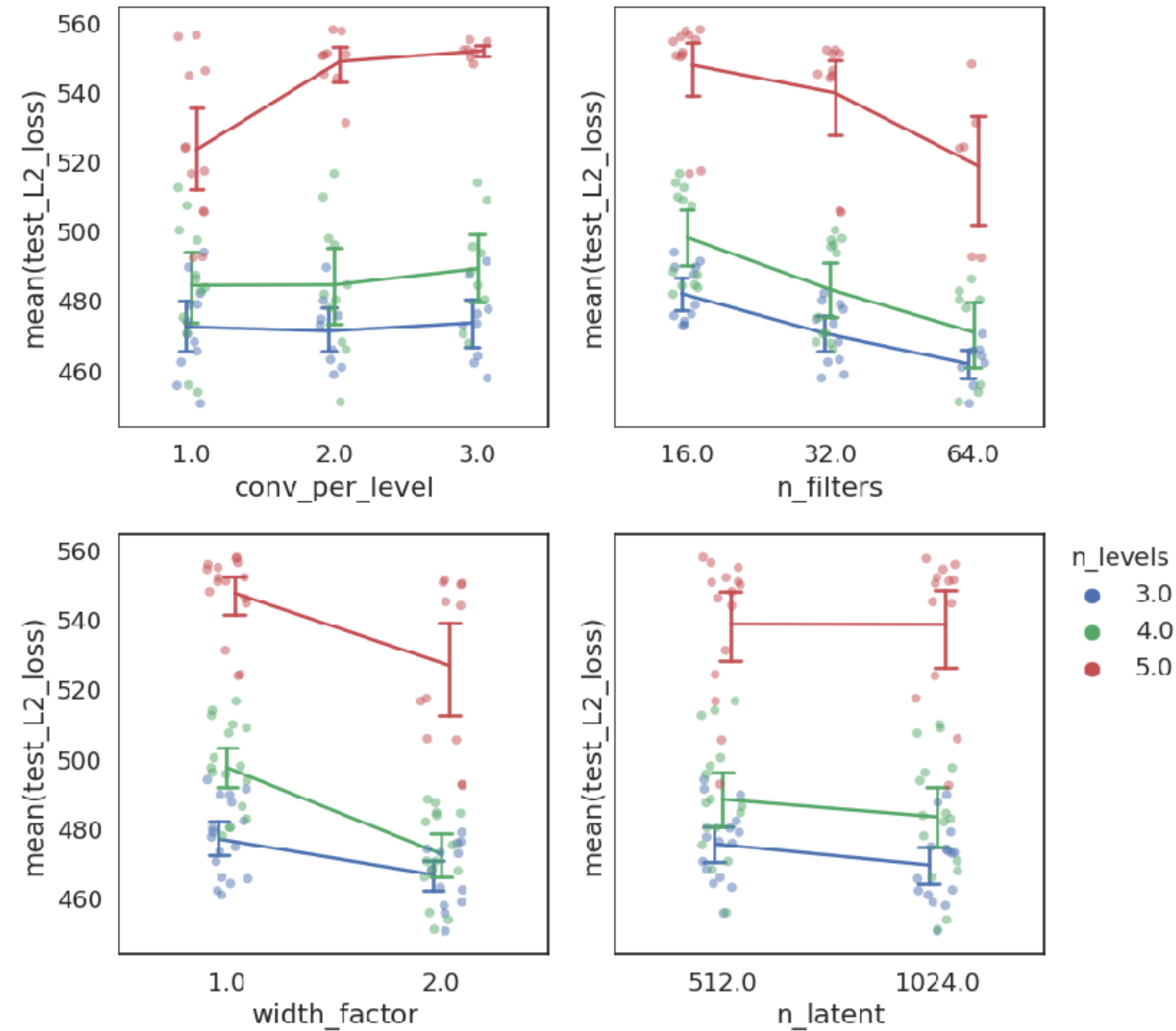


Receptor-Conditional Ligand-Variational Model

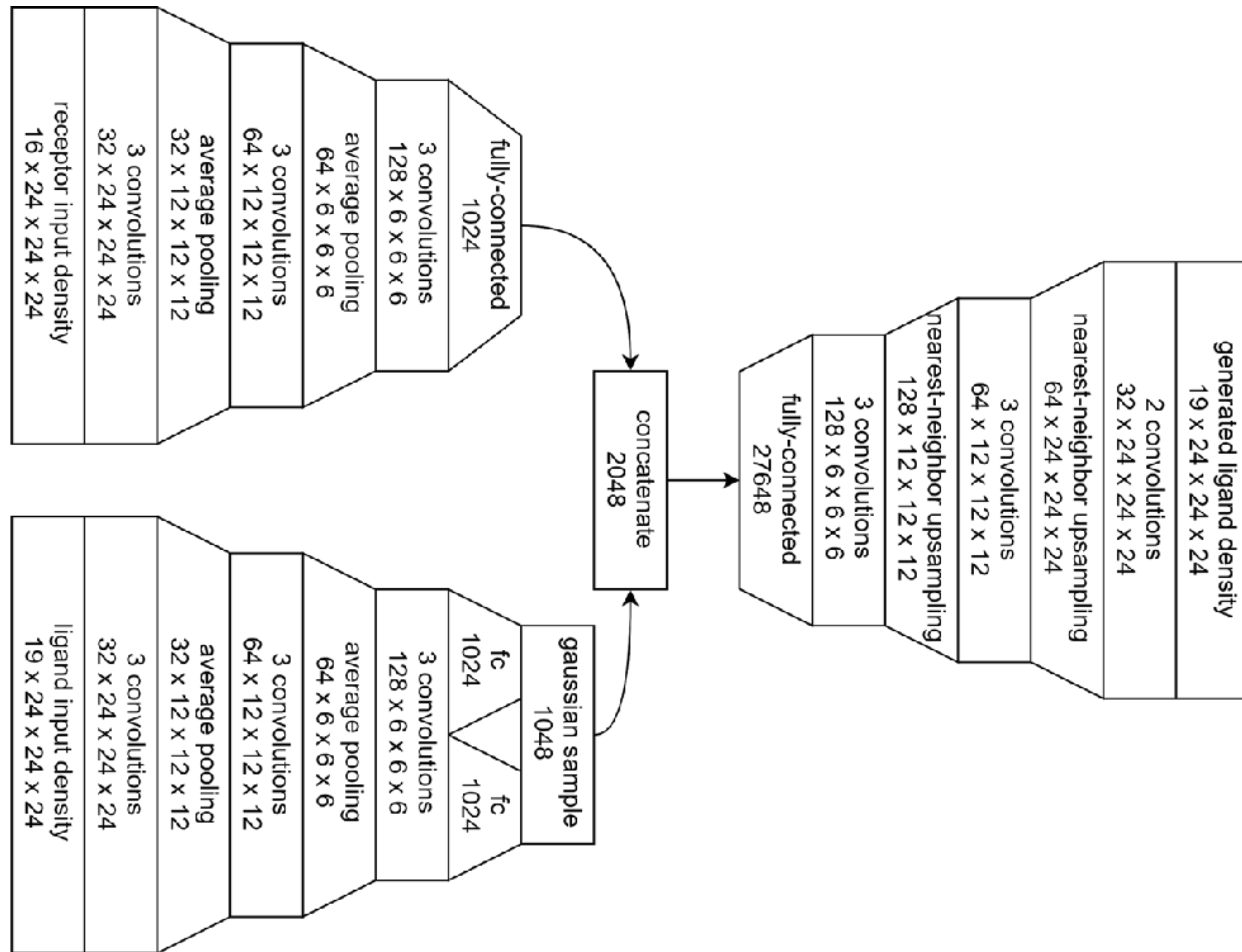




Model Architecture



Model Architecture



```
n_levels = 3
conv_per_level = 3
n_filters = 32
width_factor = 2
n_latent = 1024
```


Training Procedure

2016 PDBbind refined set

3765 crystal structures

Vina docking

RMSD < 2 Å from crystal pose

8648 poses (~2.3 per target)

random rotation & translation

Adam optimization

base_lr = 0.00001

momentum = 0.9

momentum2 = 0.999

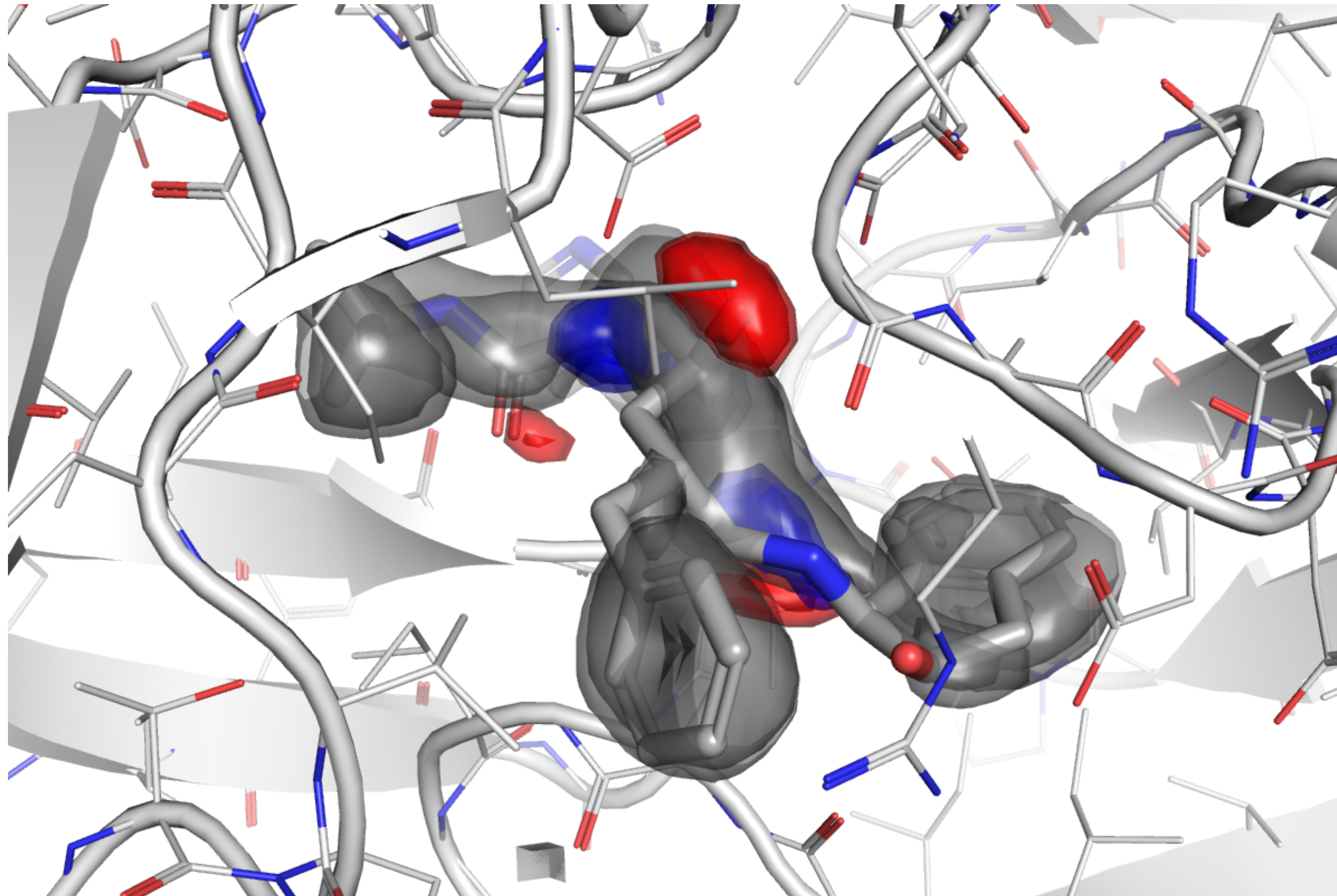
max_iter = 100000

batch_size = 50



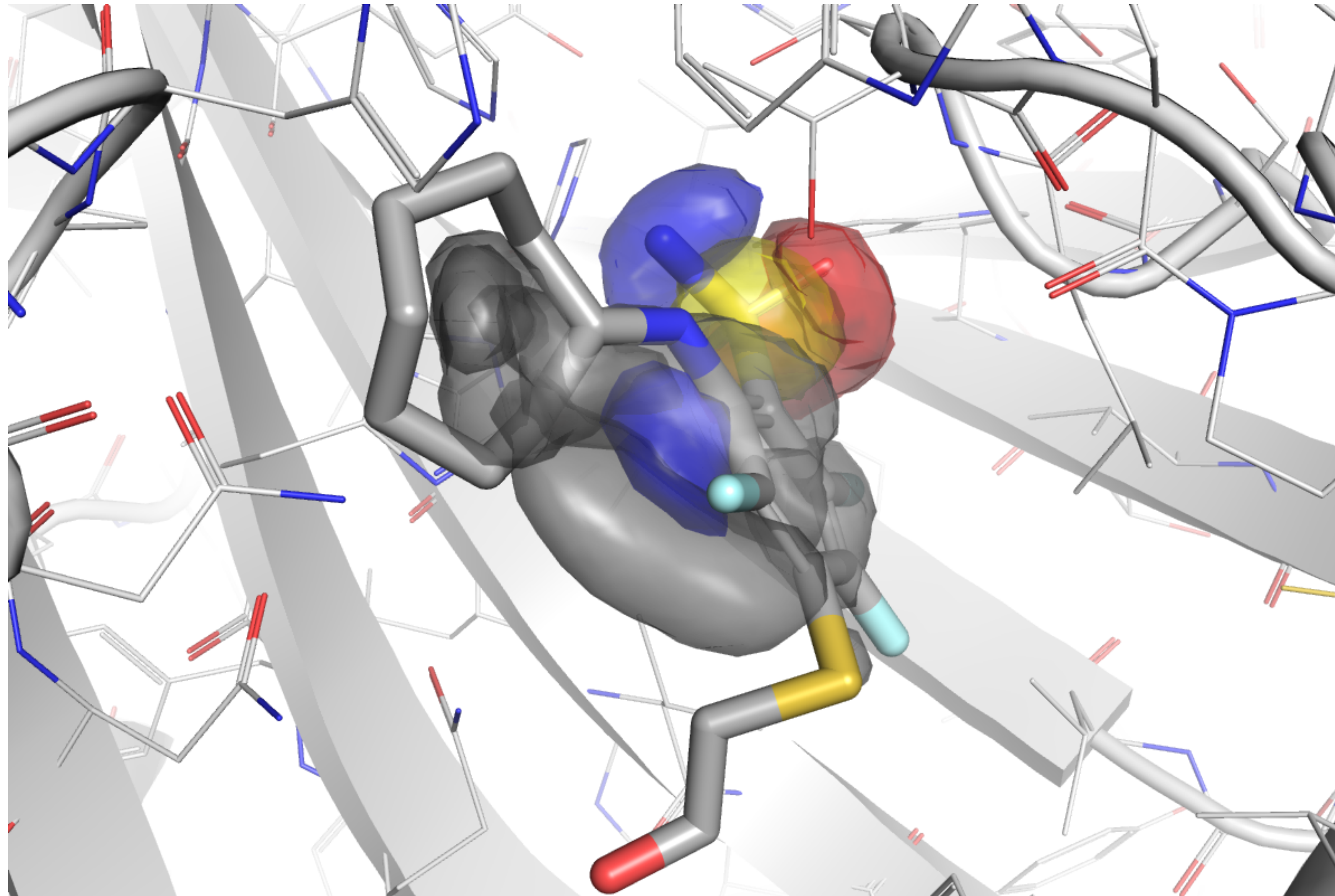
Caffe

Autoencoding Examples



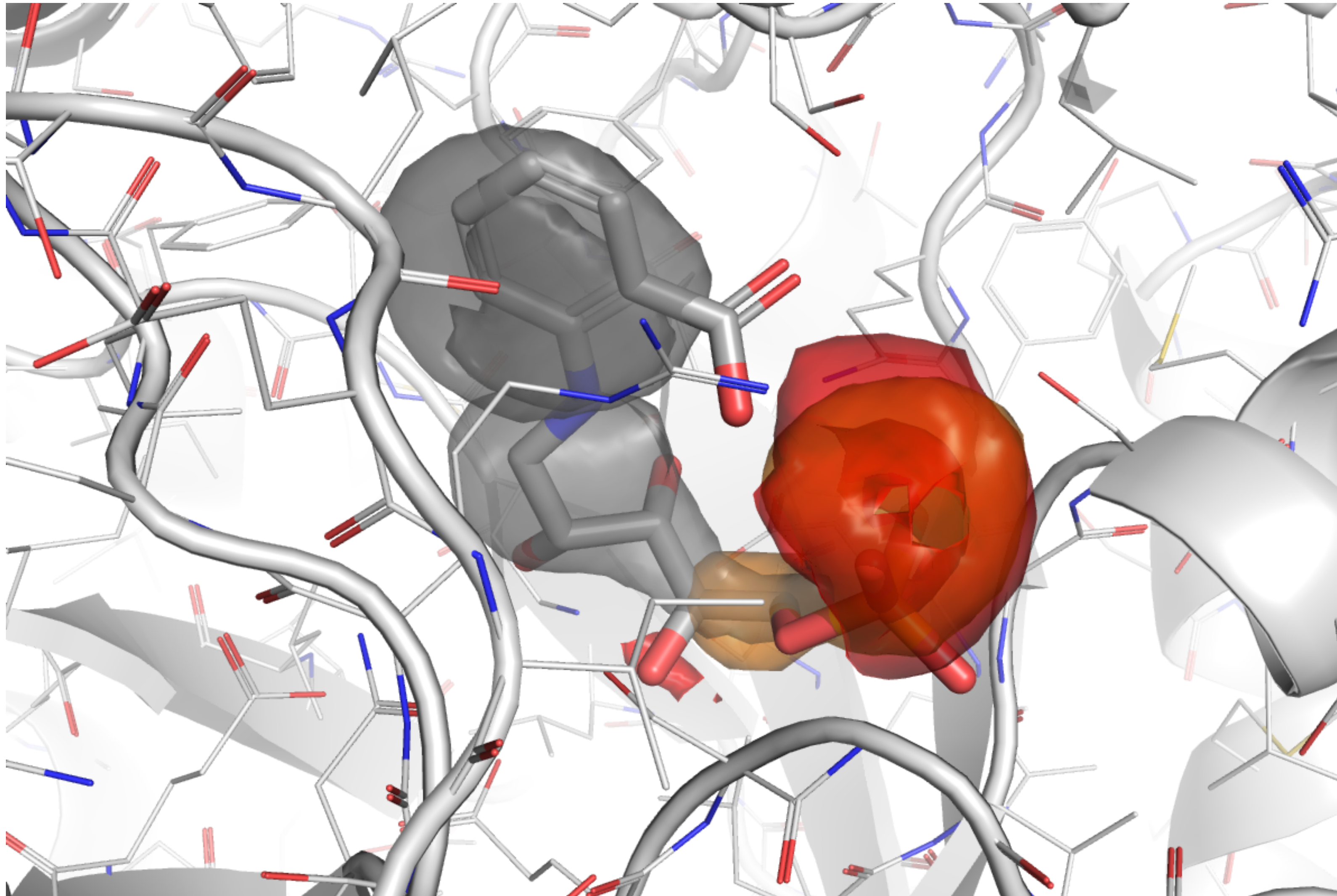
2AVO

Autoencoding Examples



4PYX

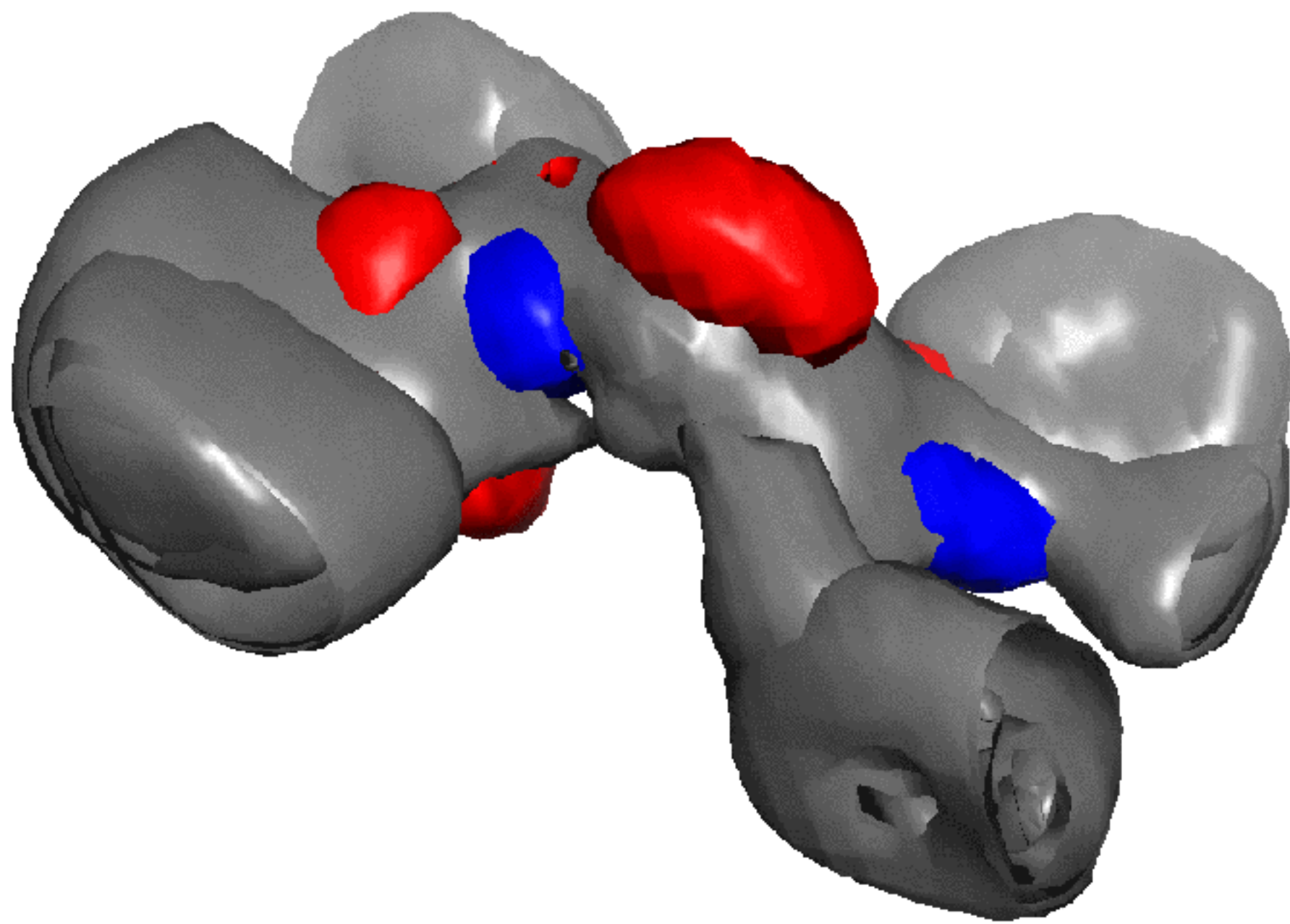
Autoencoding Examples



1LBF

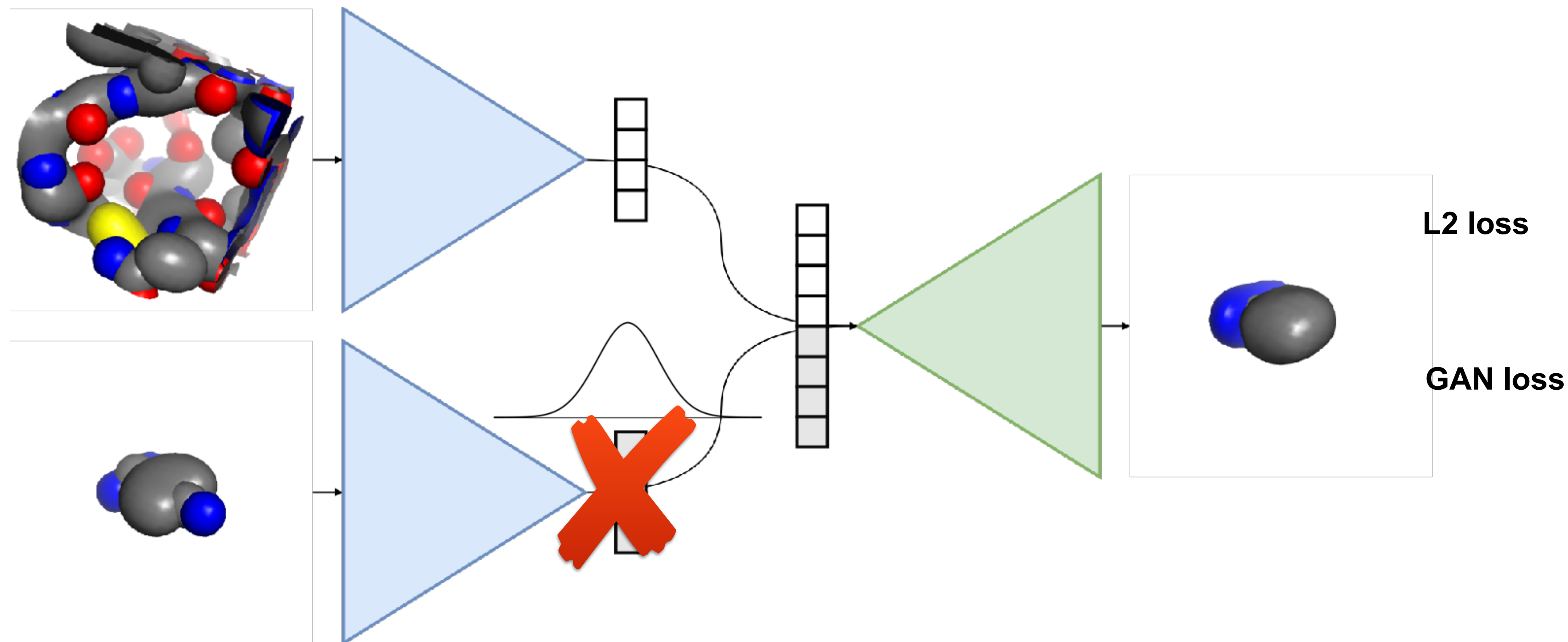
Atom Fitting

$$a^* = \operatorname{argmin}_a \|d - D(a)\|_2^2 + \lambda E(a)$$

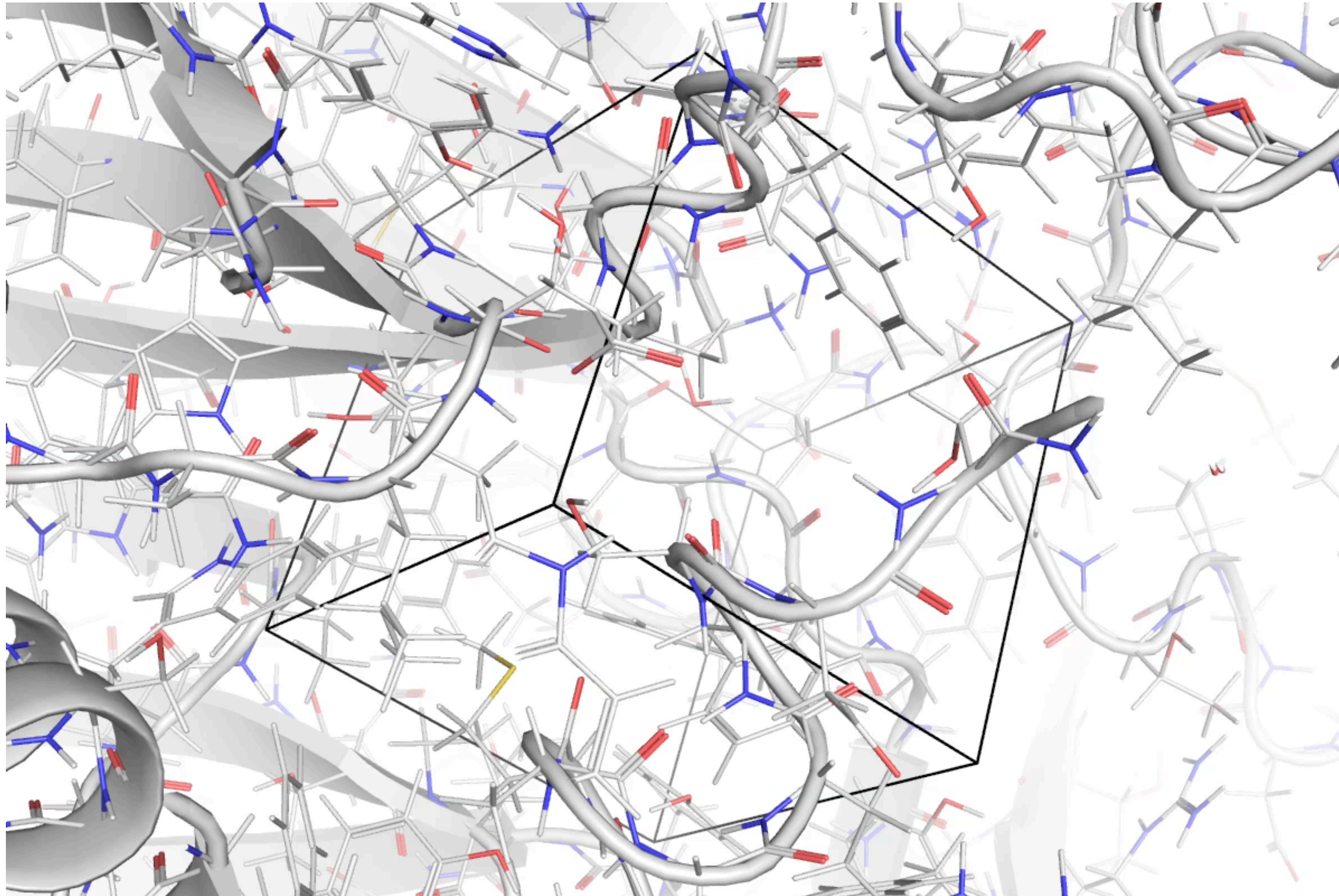


Ligand Variation

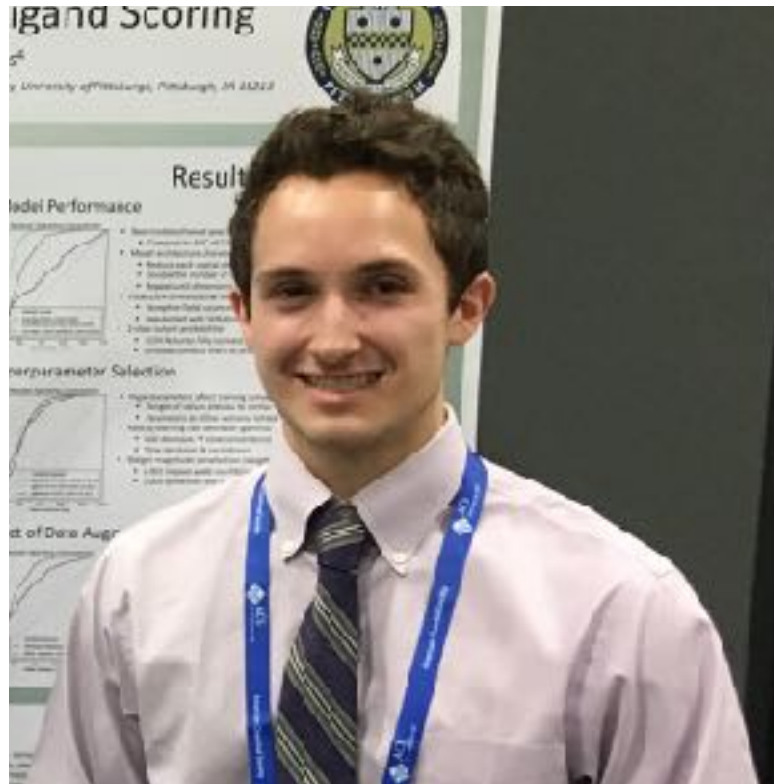
to be continued...



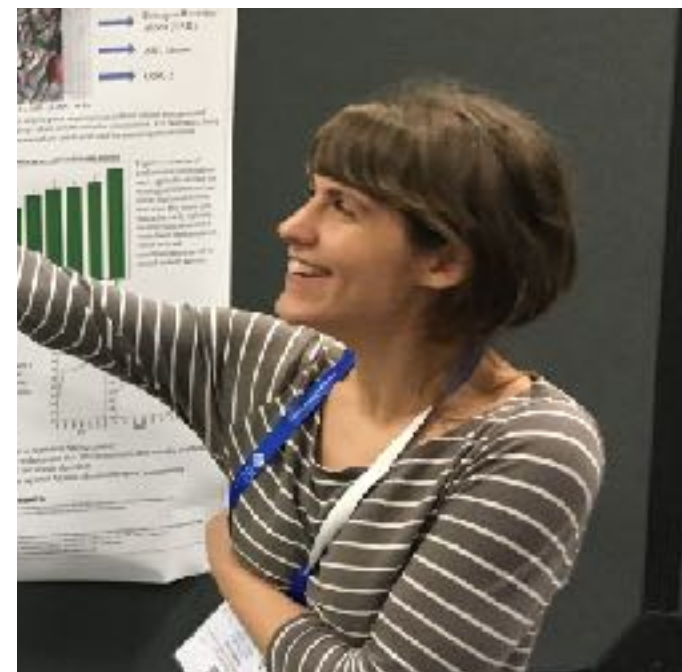
Conditioning on the Receptor



Acknowledgements



Matt Ragoza



Jocelyn Sunseri Paul Francoeur



Department of
Computational and
Systems Biology



National Institute of
General Medical Sciences
[R01GM108340](#)

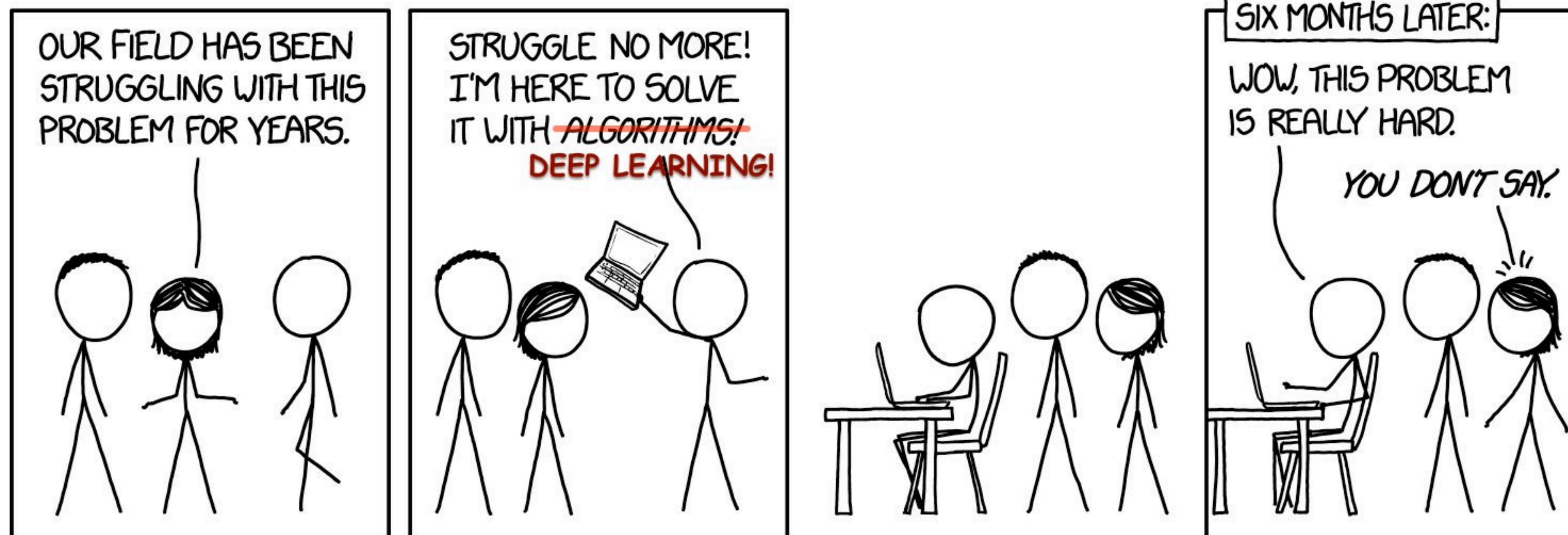


Google Cloud

 github.com/gnina

 <http://bits.csb.pitt.edu>

 @david_koes



COMP: Poster Session

Tuesday, Aug 21 6:00 PM

Exhibit Hall B1, Boston Convention & Exhibition Center



COMP 528: Structure-based searching of chemical space with Pharmit

Thursday, Aug 23 9:20 AM

Douglass, Westin Boston Waterfront