

Protein-Ligand Scoring with Convolutional Neural Networks

David Koes



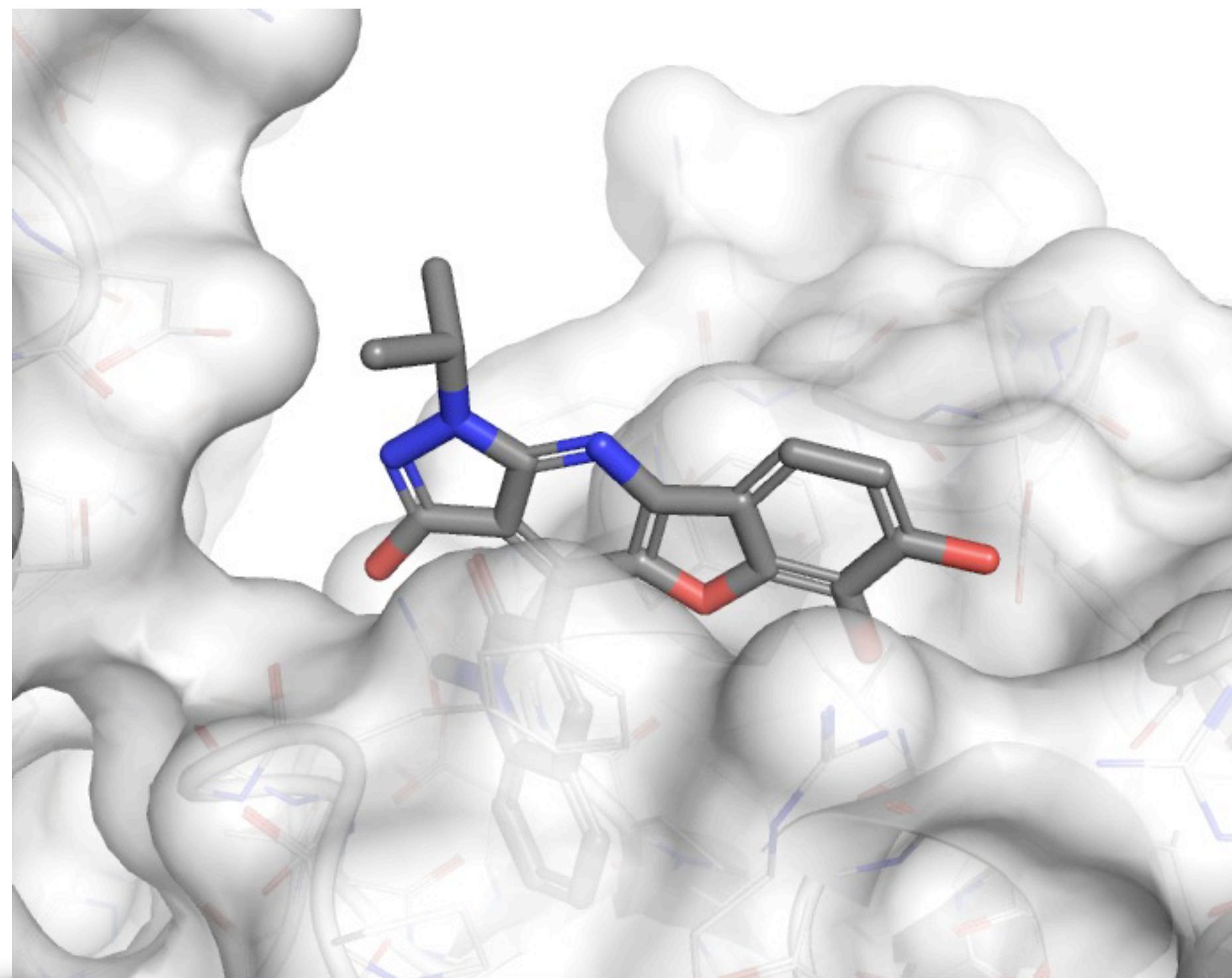
@david_koes

D3R Workshop
San Diego
February 22, 2018

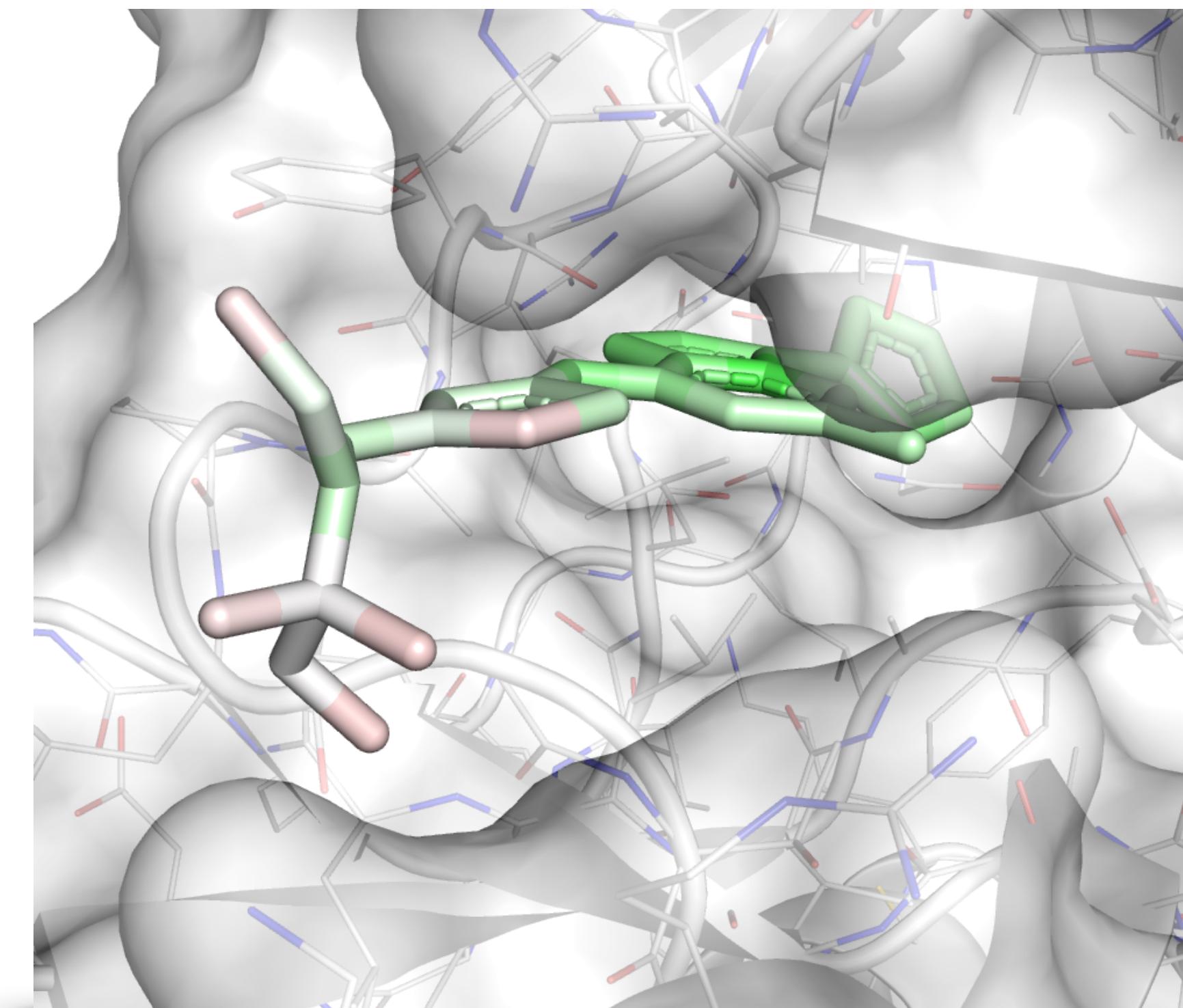


Structure Based Drug Design

Virtual Screening



Lead Optimization

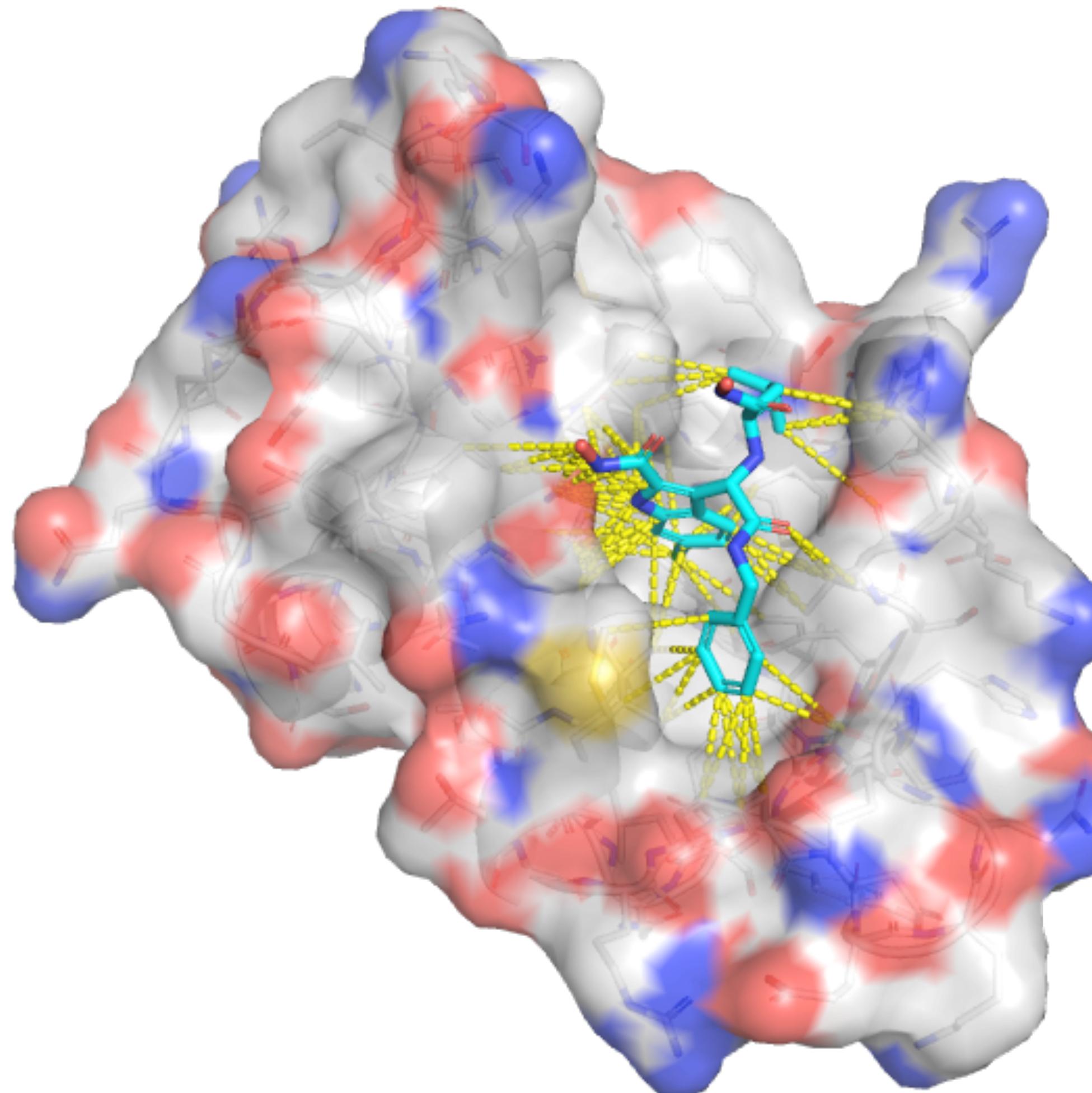


Pose Prediction

Binding Discrimination

Affinity Prediction

Protein-Ligand Scoring

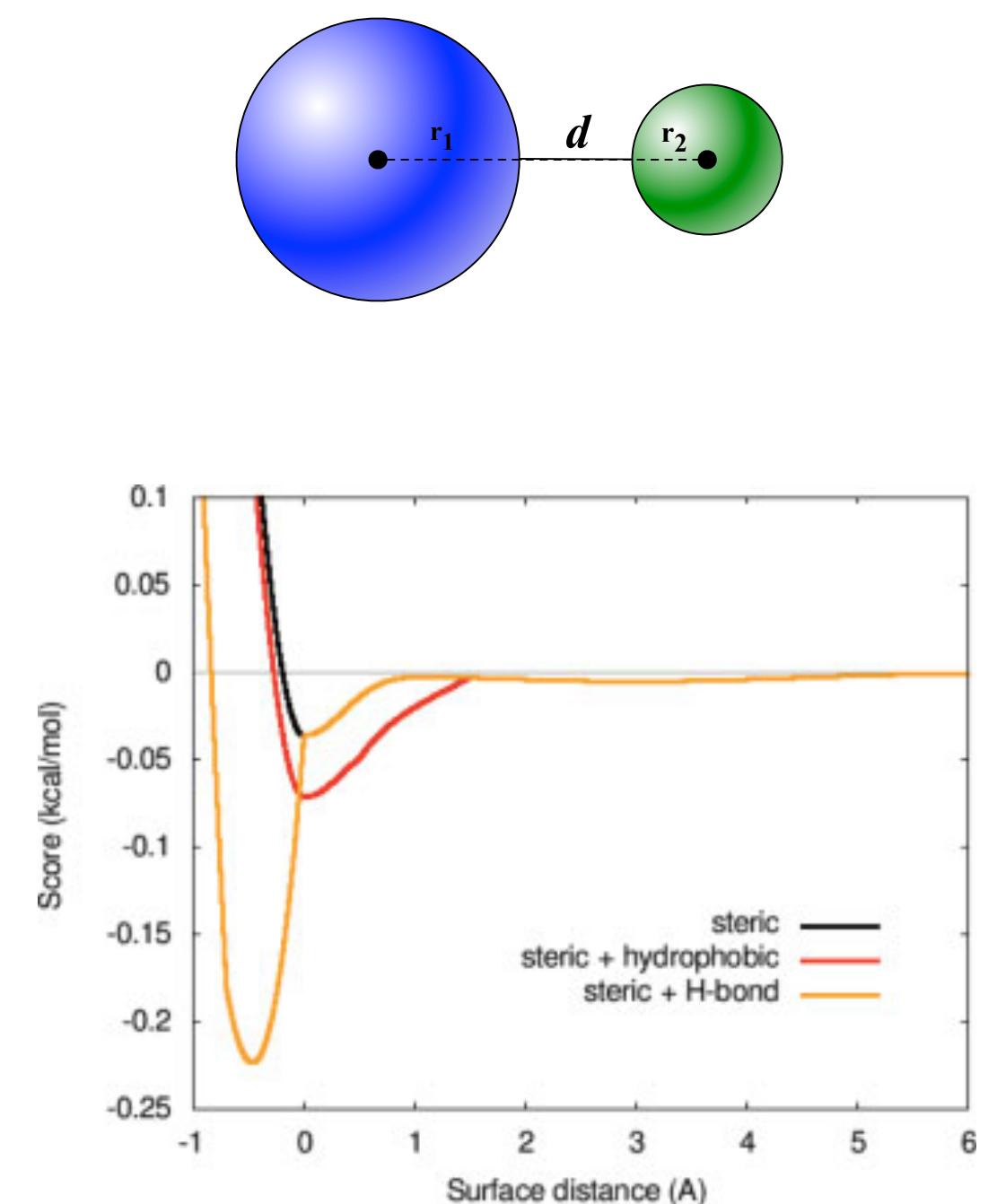


AutoDock Vina

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

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

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



Can we do better?

Accurate pose prediction, binding discrimination, **and** affinity prediction without sacrificing performance?

Key Idea: Leverage “big data”

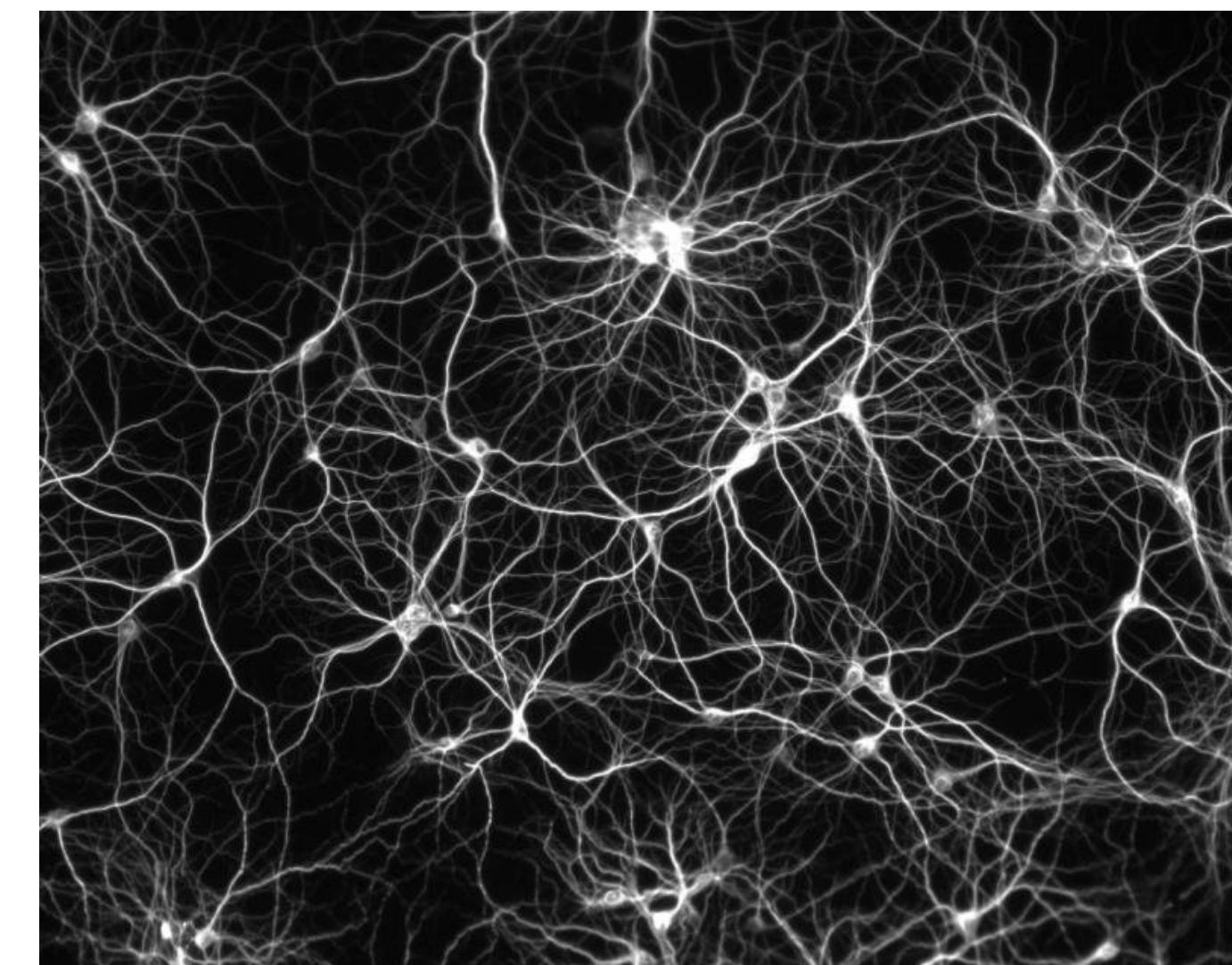
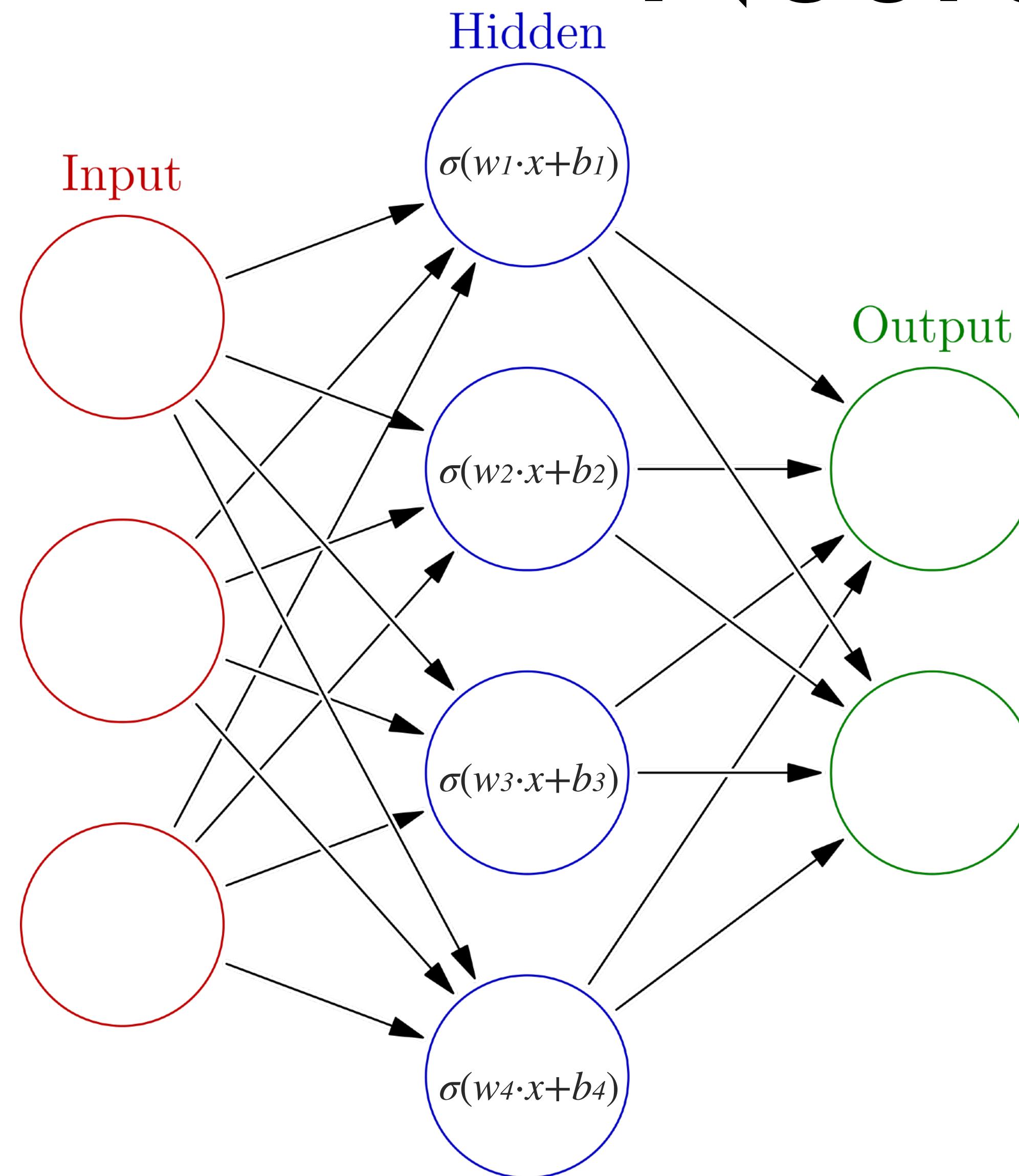
- 231,655,275 bioactivities in PubChem
- 125,526 structures in the PDB
- 16,179 annotated complexes in PDBbind



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

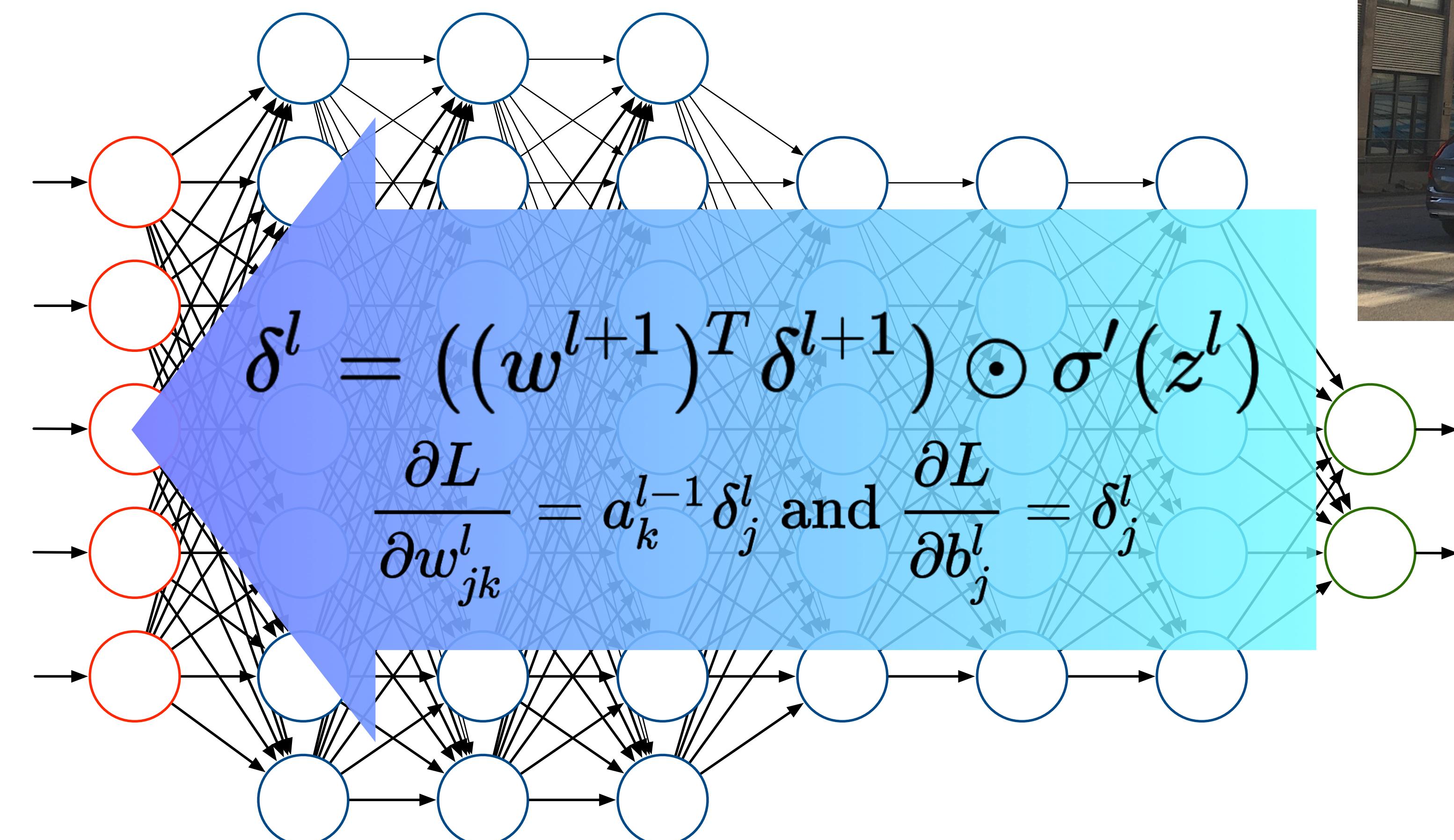
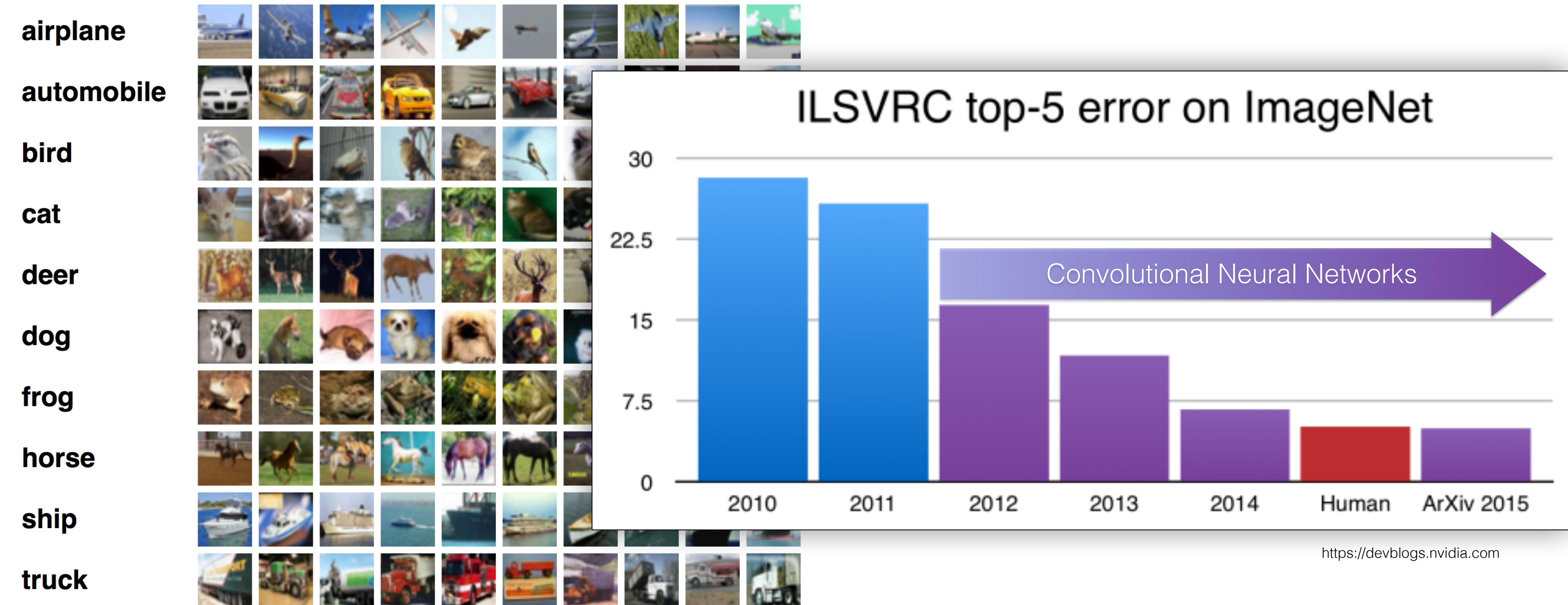
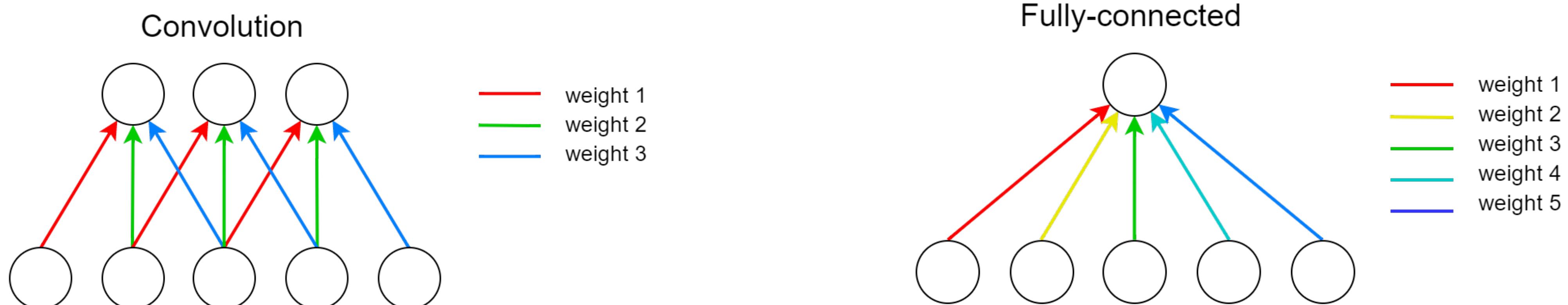
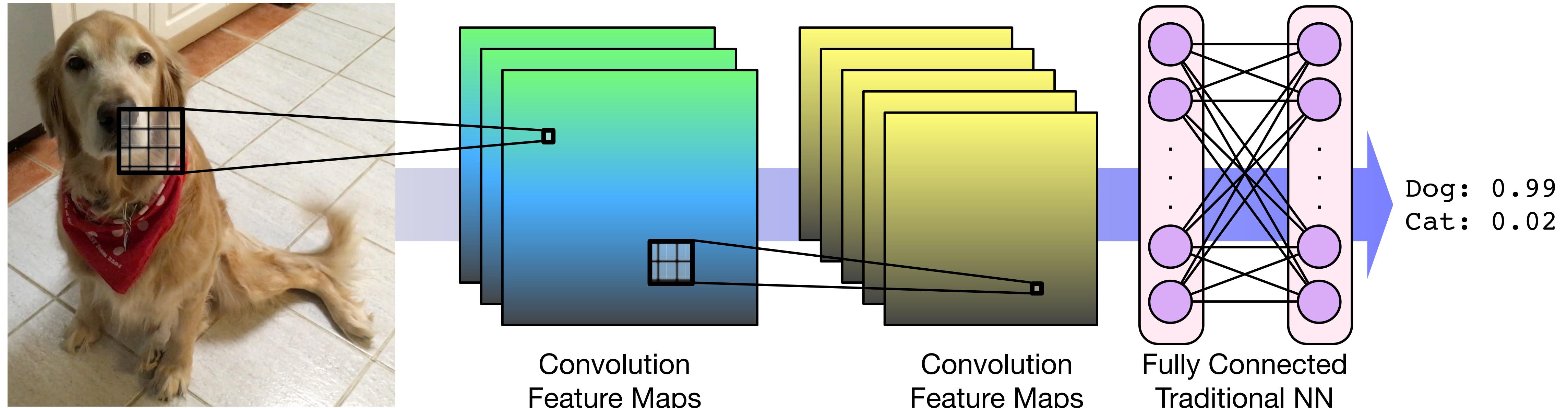


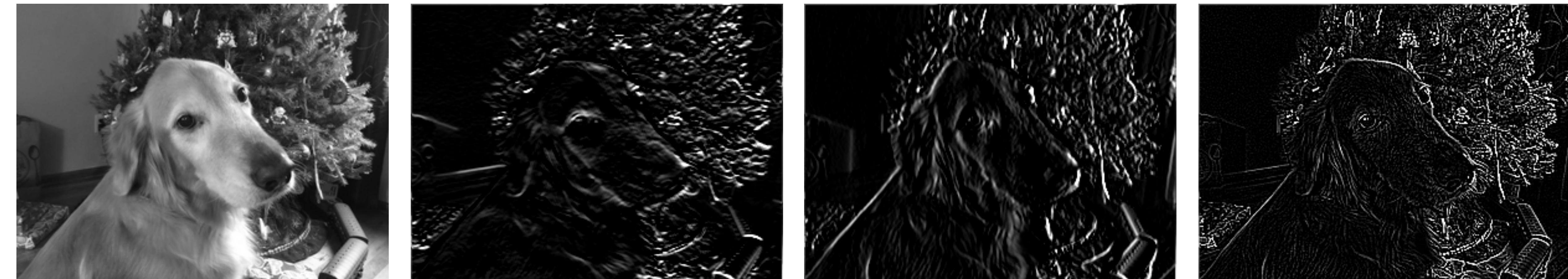
Image Recognition



Convolutional Neural Networks



Convolutional Filters



$$\begin{array}{ccc} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{array}$$

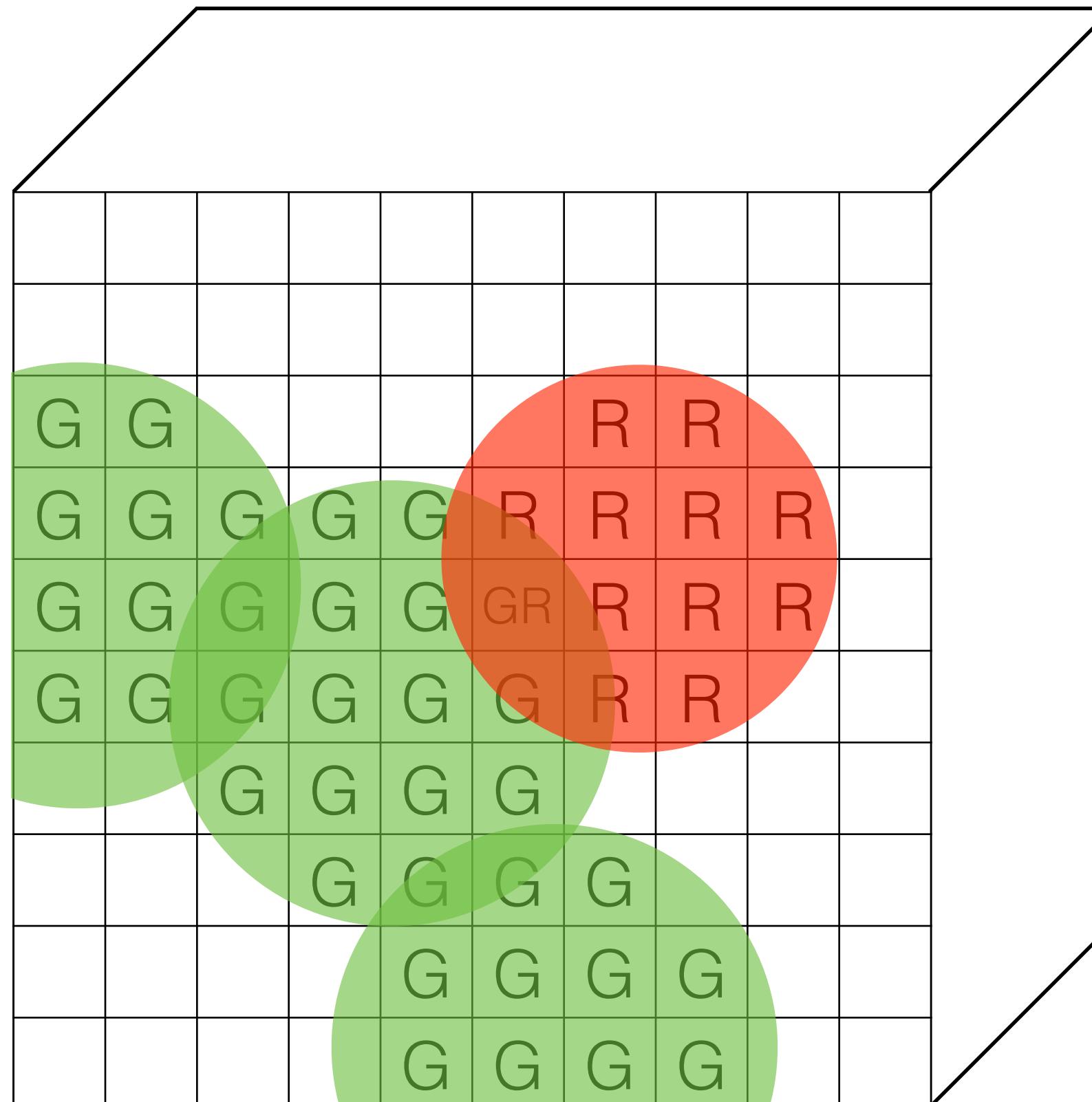
$$\begin{array}{ccc} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{array}$$

$$\begin{array}{ccc} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{array}$$

CNNs for Protein-Ligand Scoring



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**.

Training Data



Pose Prediction

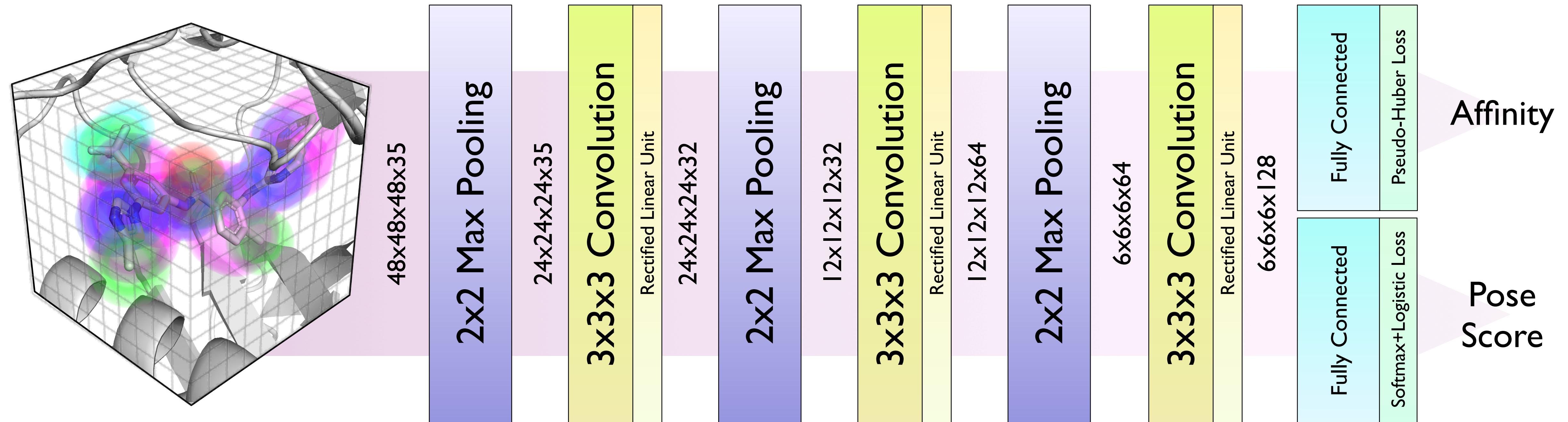
4056 protein-ligand complexes

- diverse targets
- wide range of affinities
- generate poses with AutoDock Vina
- include minimized crystal pose
 - 8,688 <2Å RMSD (actives)
 - 76,743 >4Å RMSD (decoys)

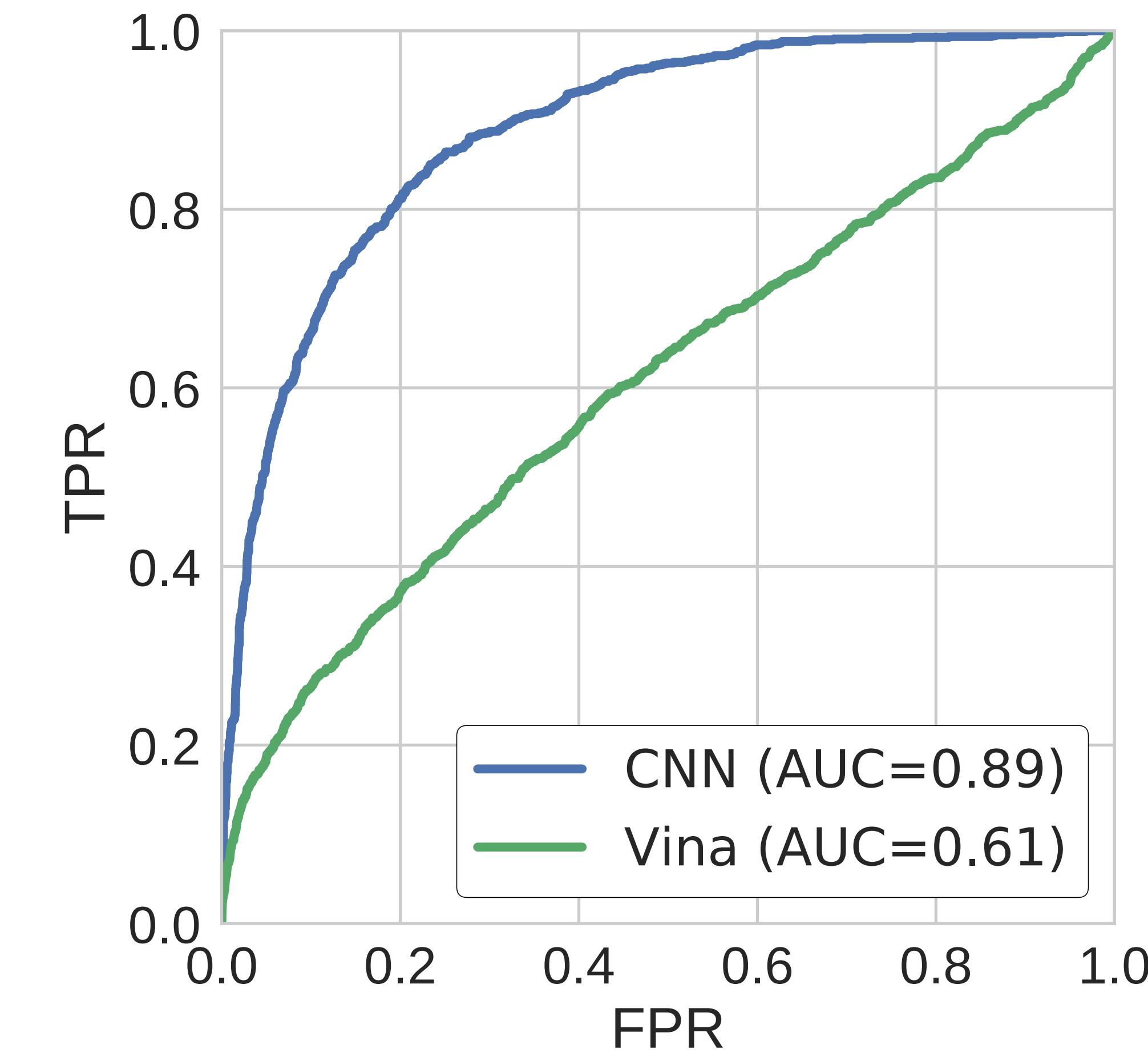
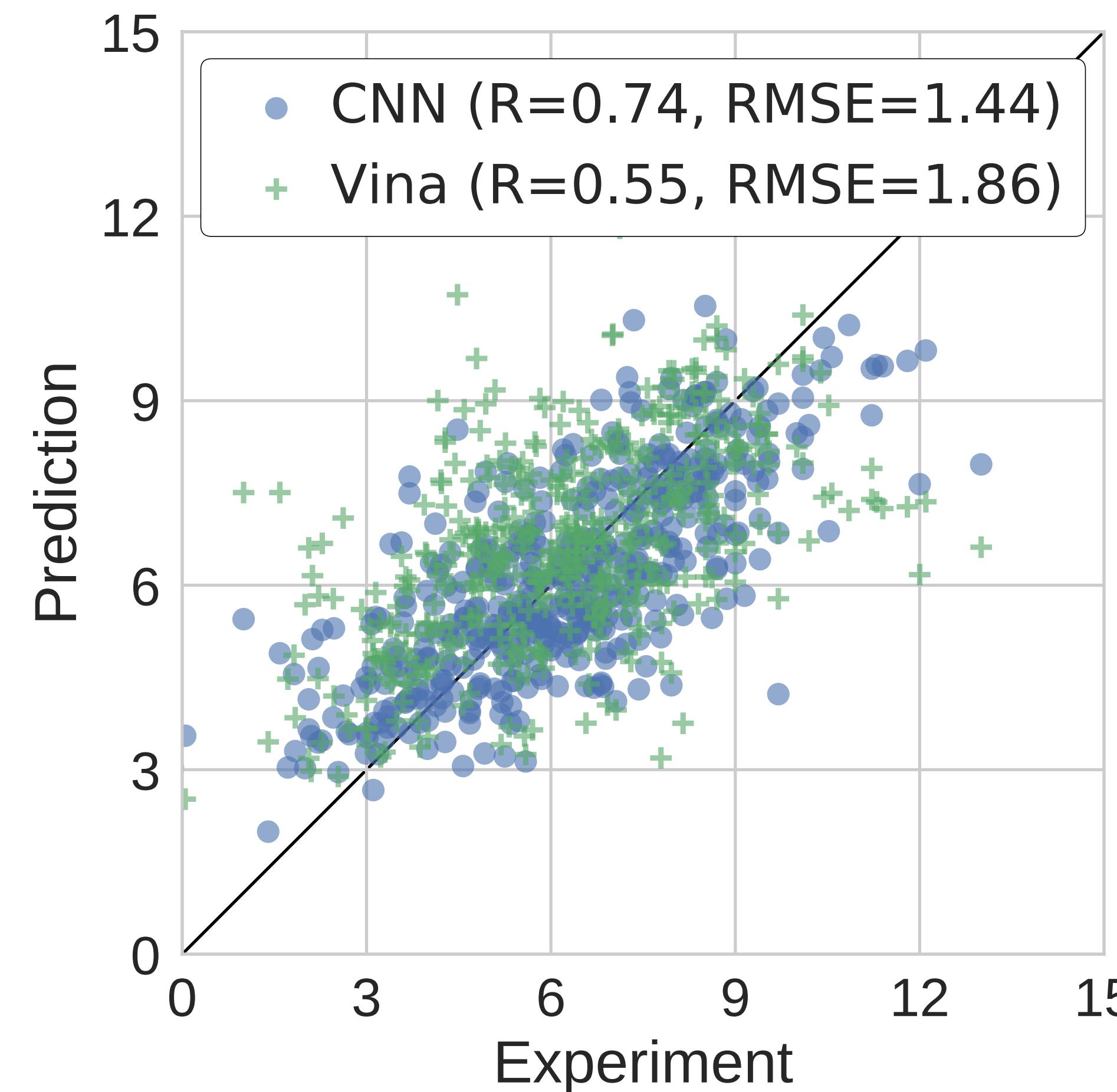
Affinity Prediction

- 8,688 low RMSD poses
- assign known affinity
- **regression problem**

Model

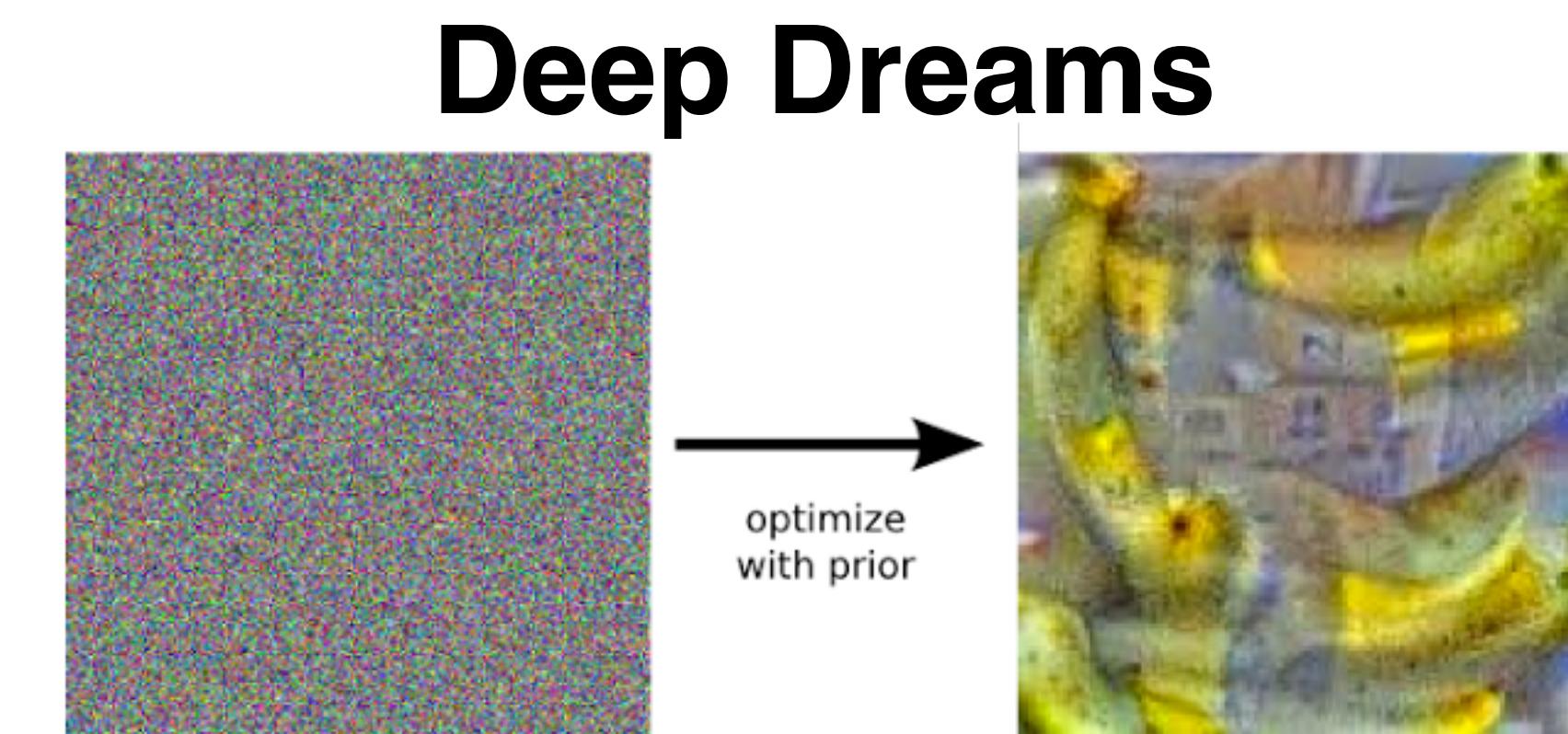
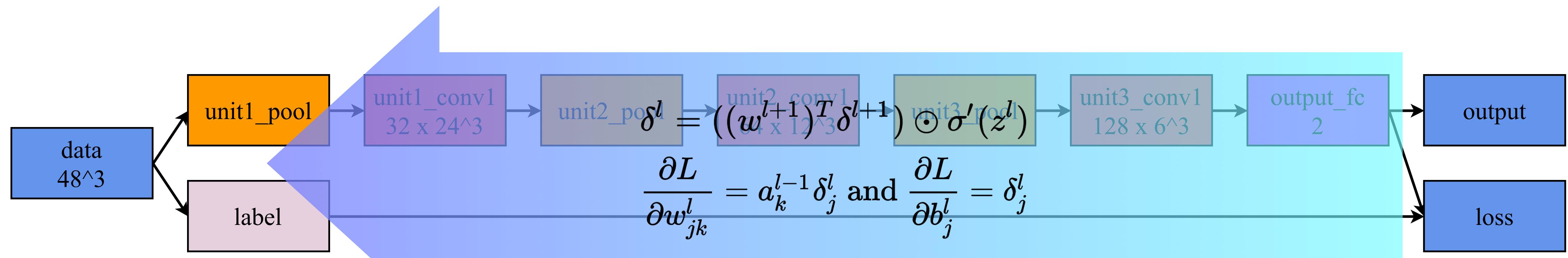


Results



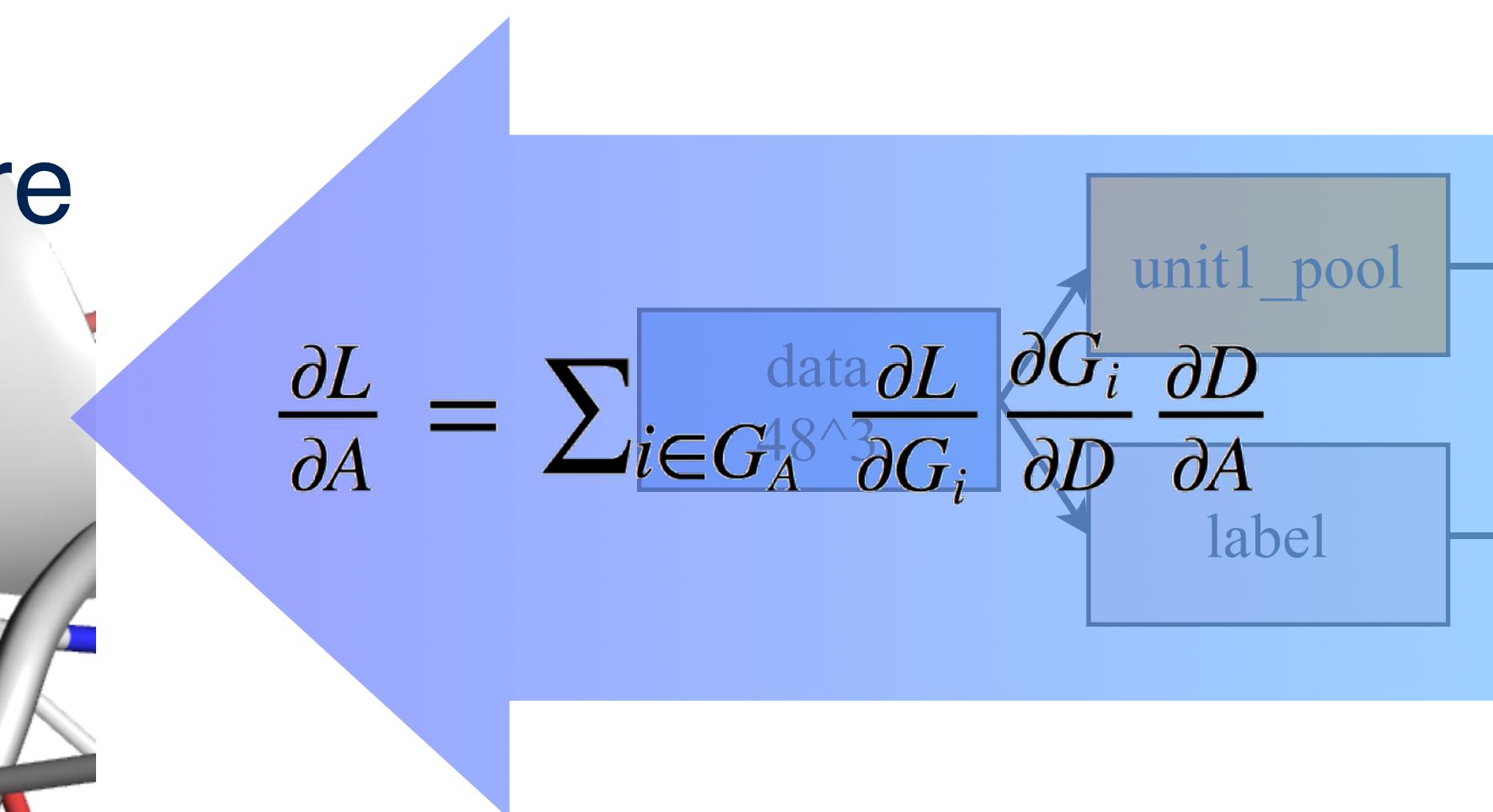
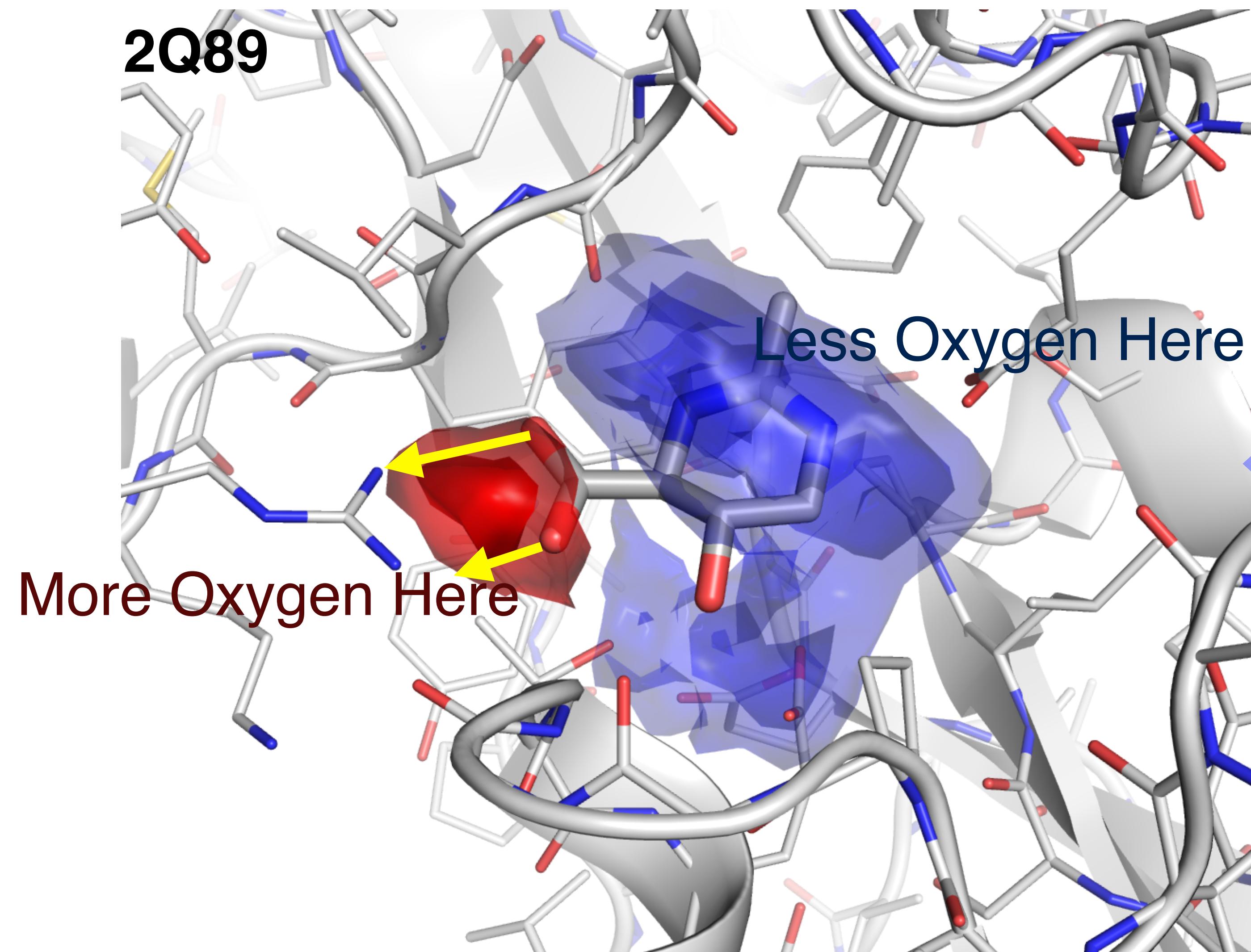
Trained on PDBbind refined; tested on CSAR

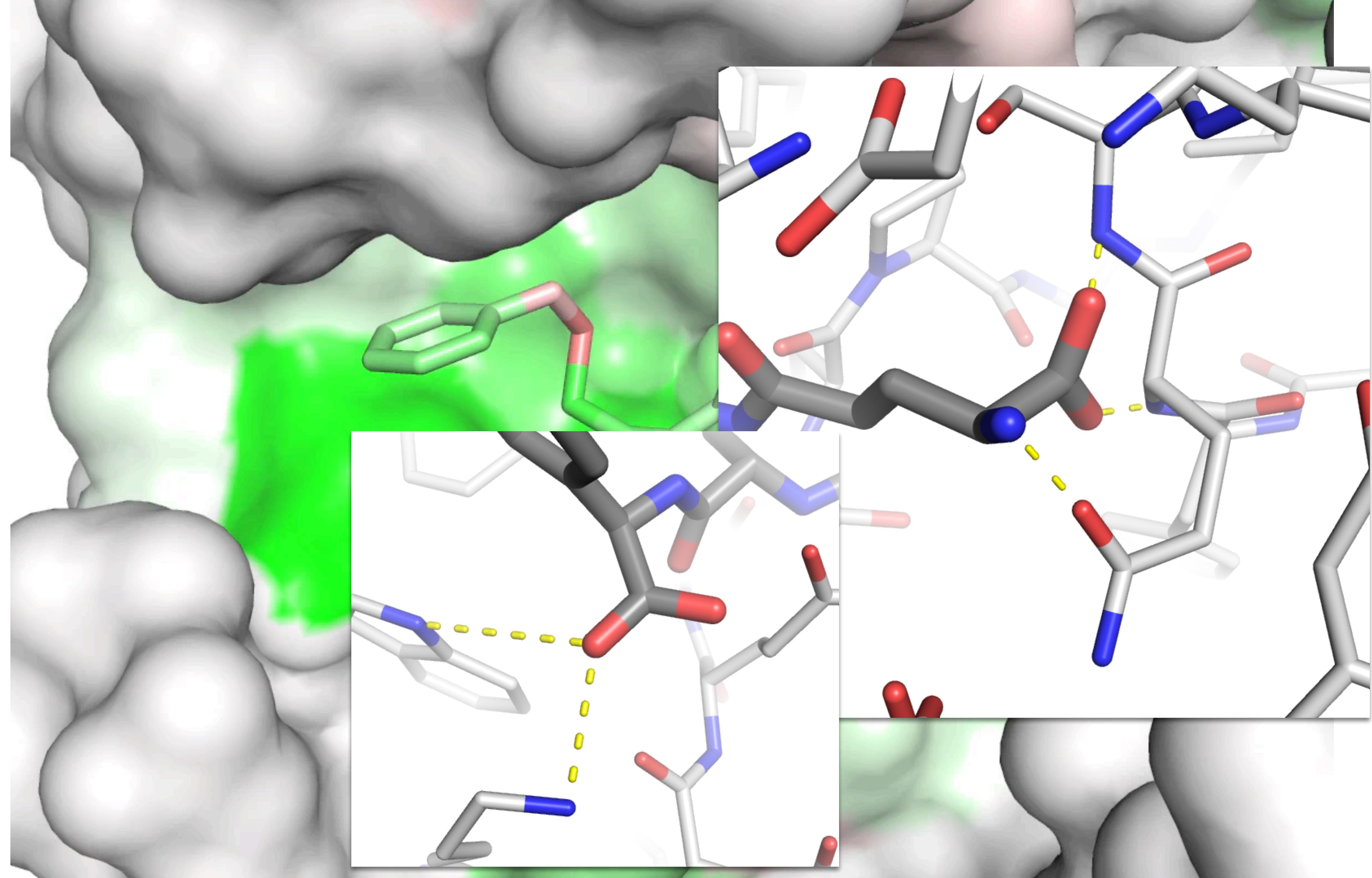
Beyond Scoring



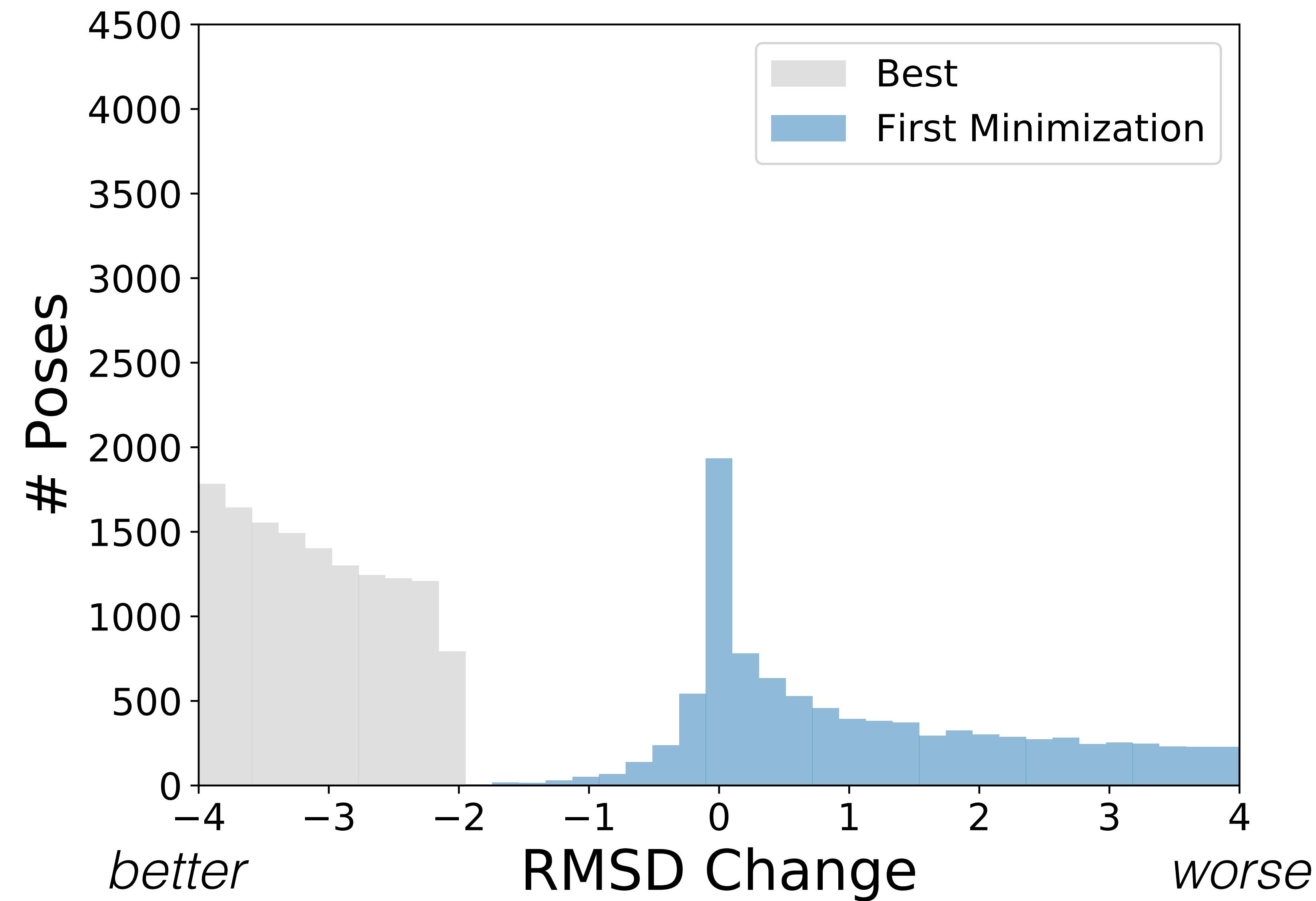
<https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html>

Beyond Scoring

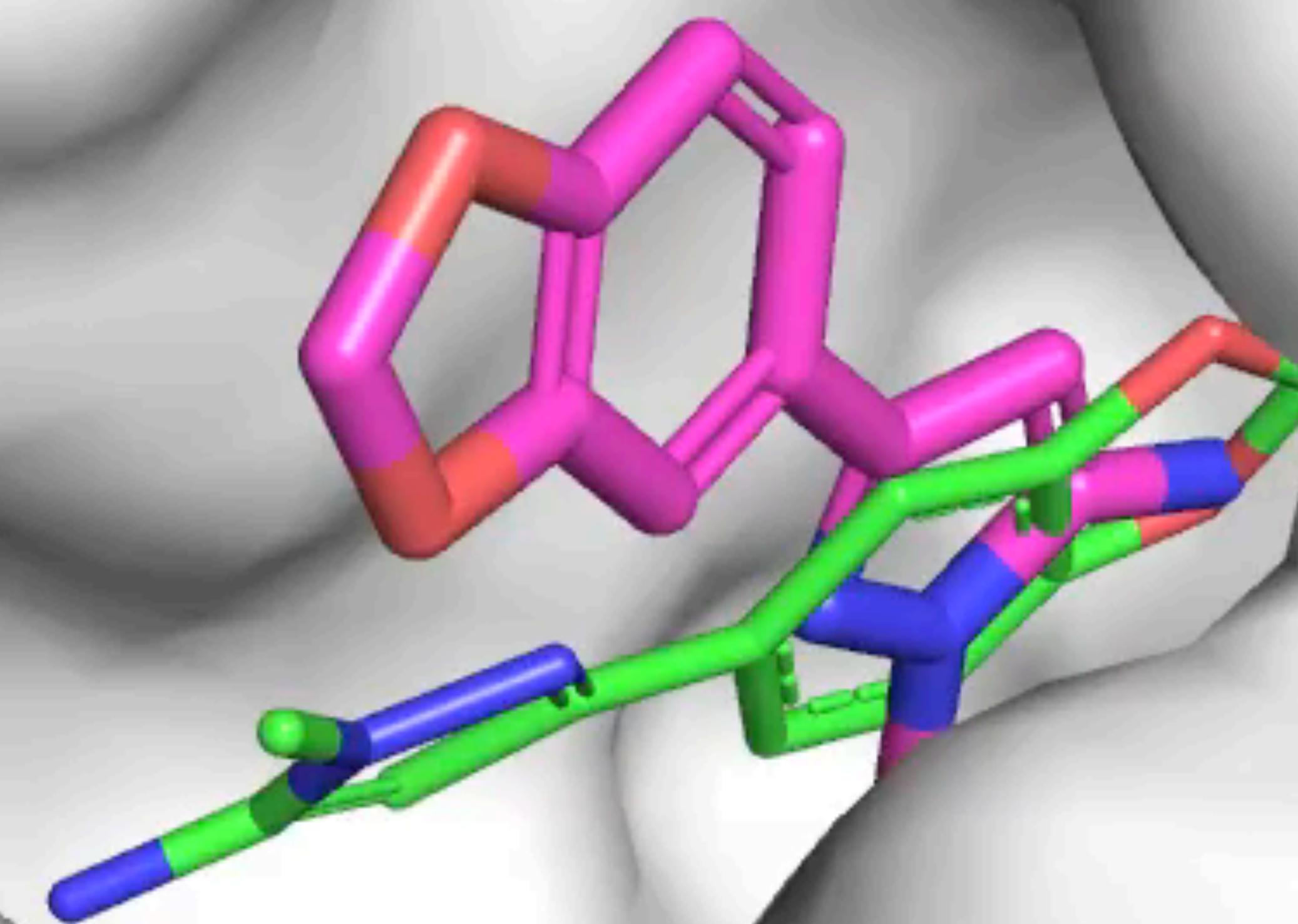




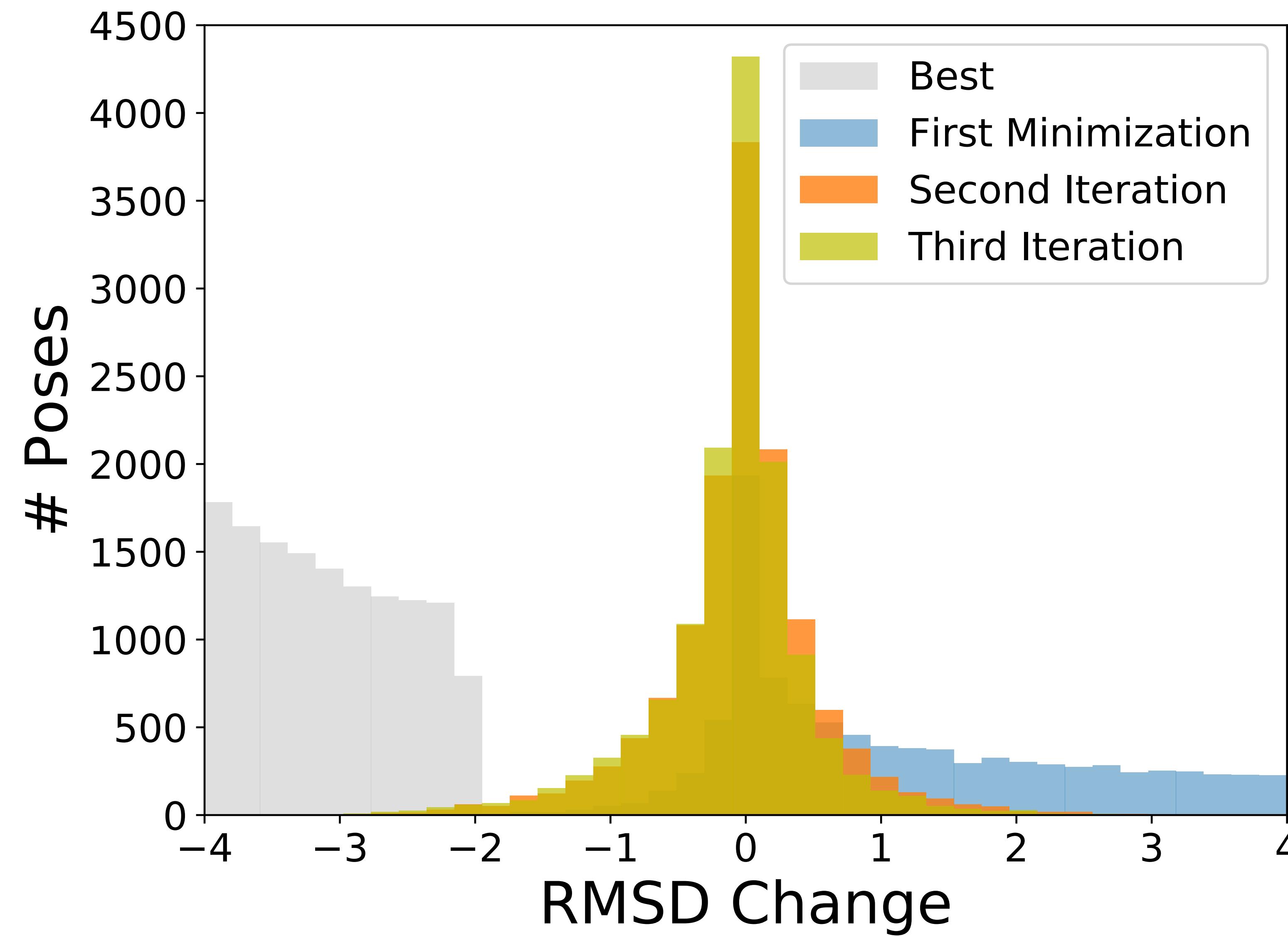
Minimizing Low RMSD Poses



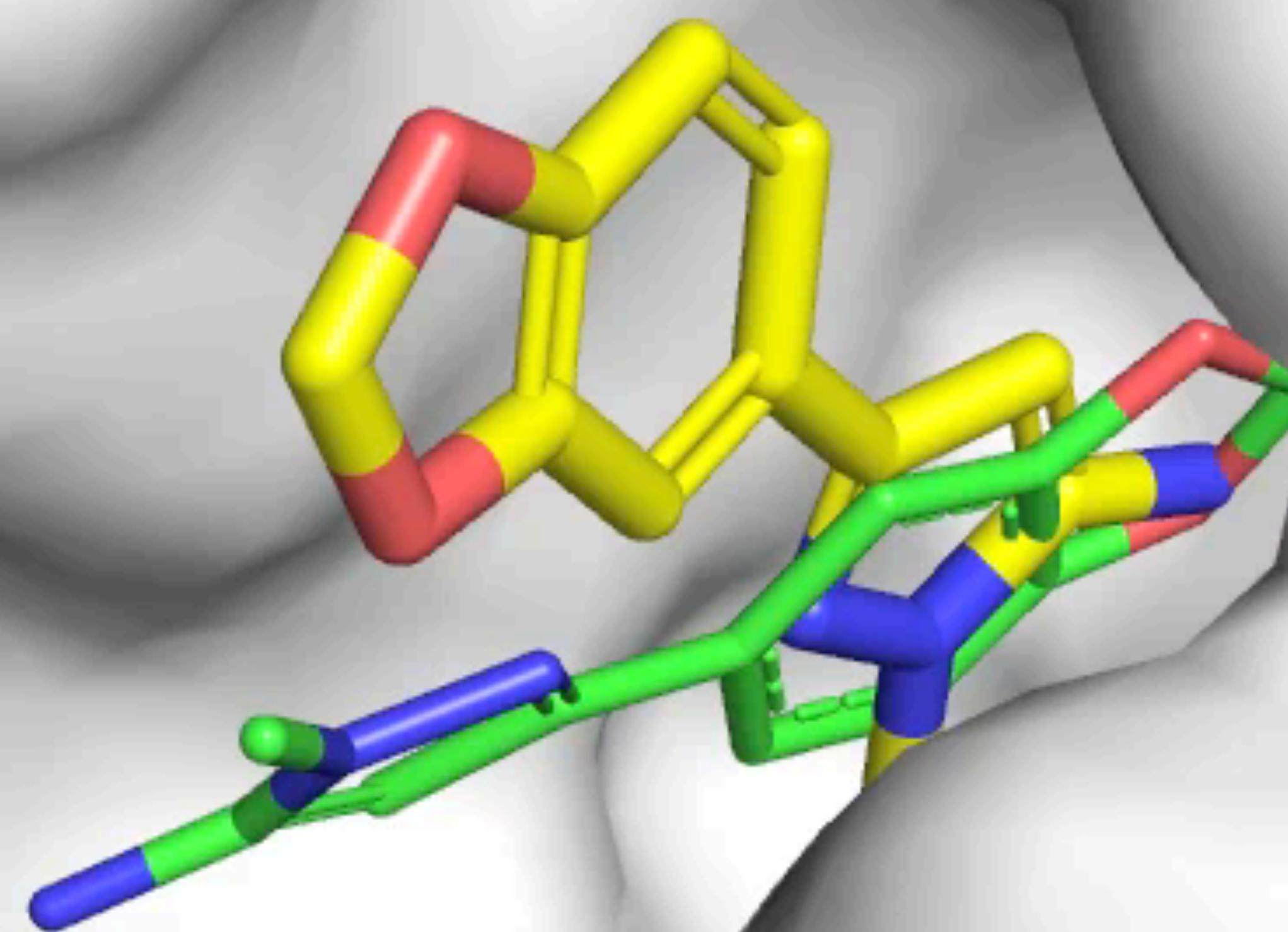
3AO4



Iterative Refinement



3AO4



Docking

vina/smina/gnina

Sampling

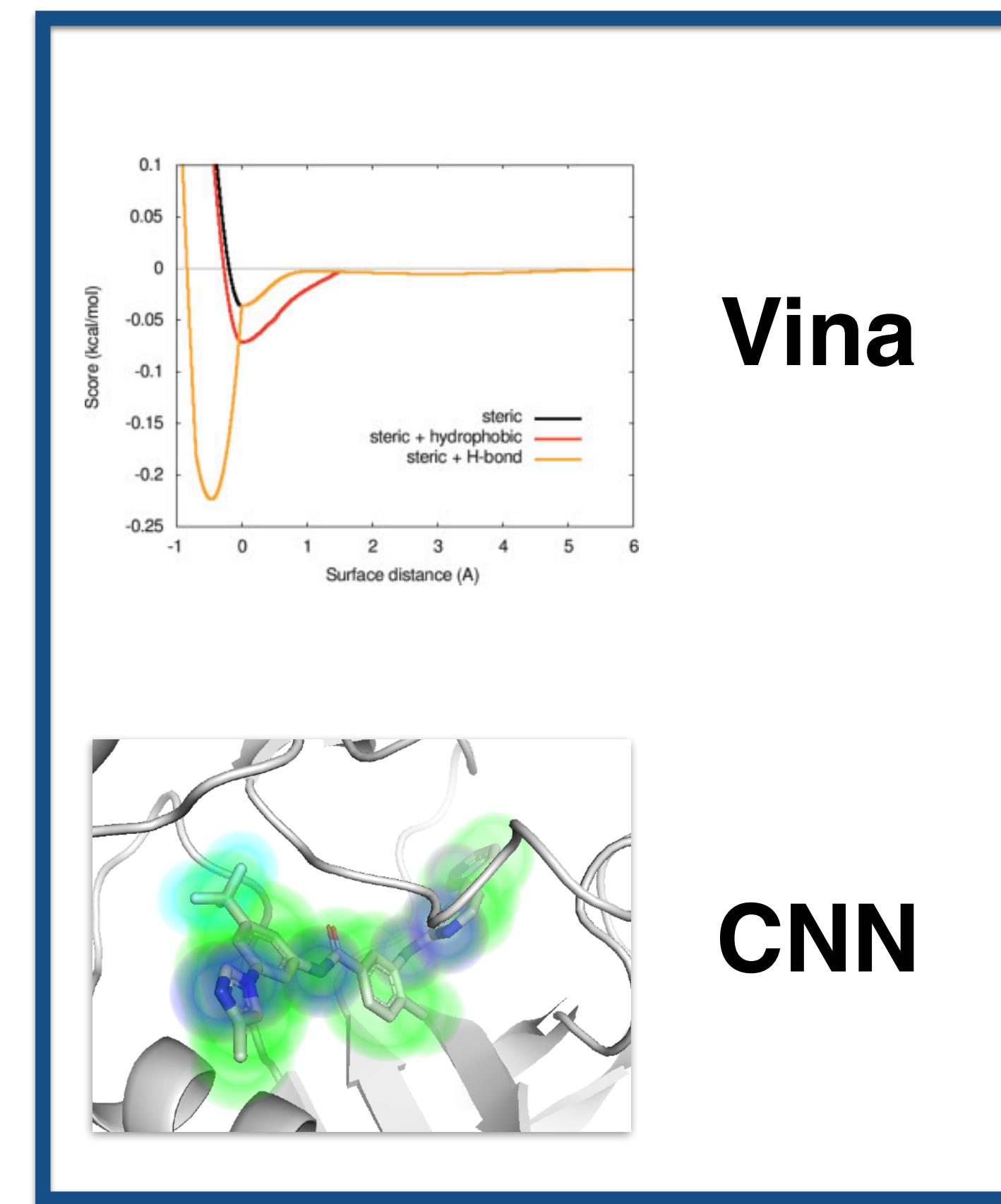
MCMC
MCMC
MCMC
MCMC
MCMC

:

N (50) independent Monte Carlo chains
Scored with grid-accelerated Vina
Best identified pose retained

best poses

Refinement



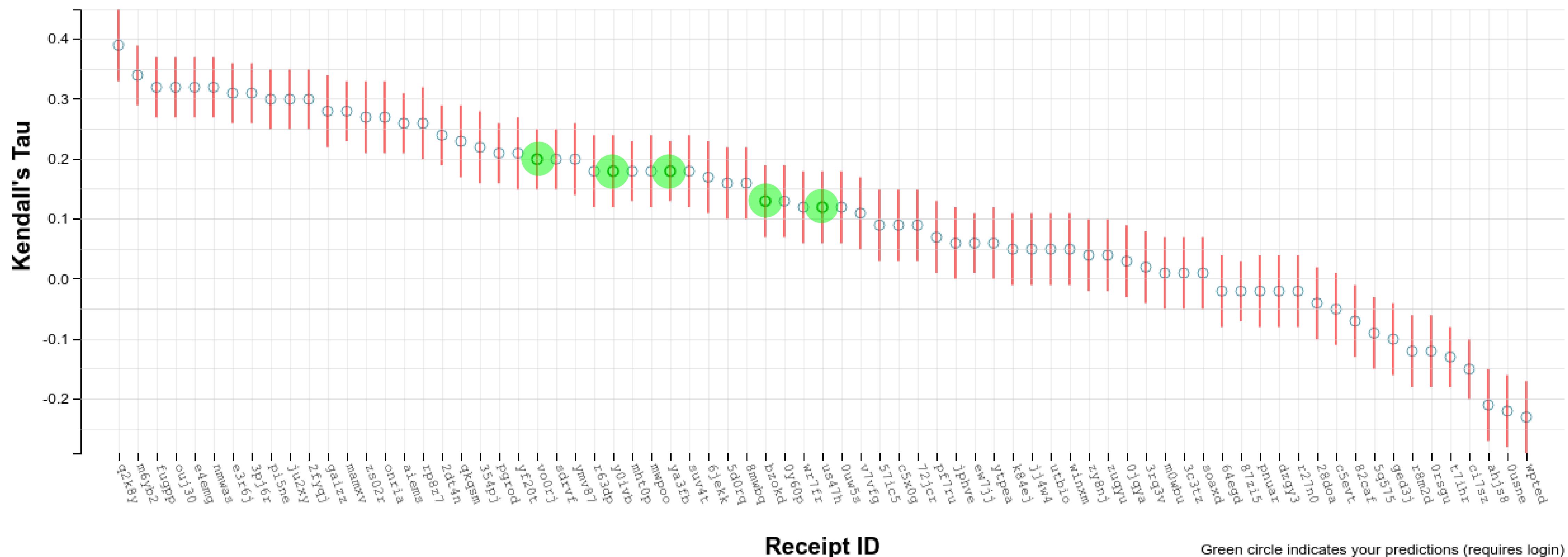
Rescoring
CNN
pose
affinity

D3R Results

Grand Challenge 3

Grand Challenge 3 - CatS_stage2

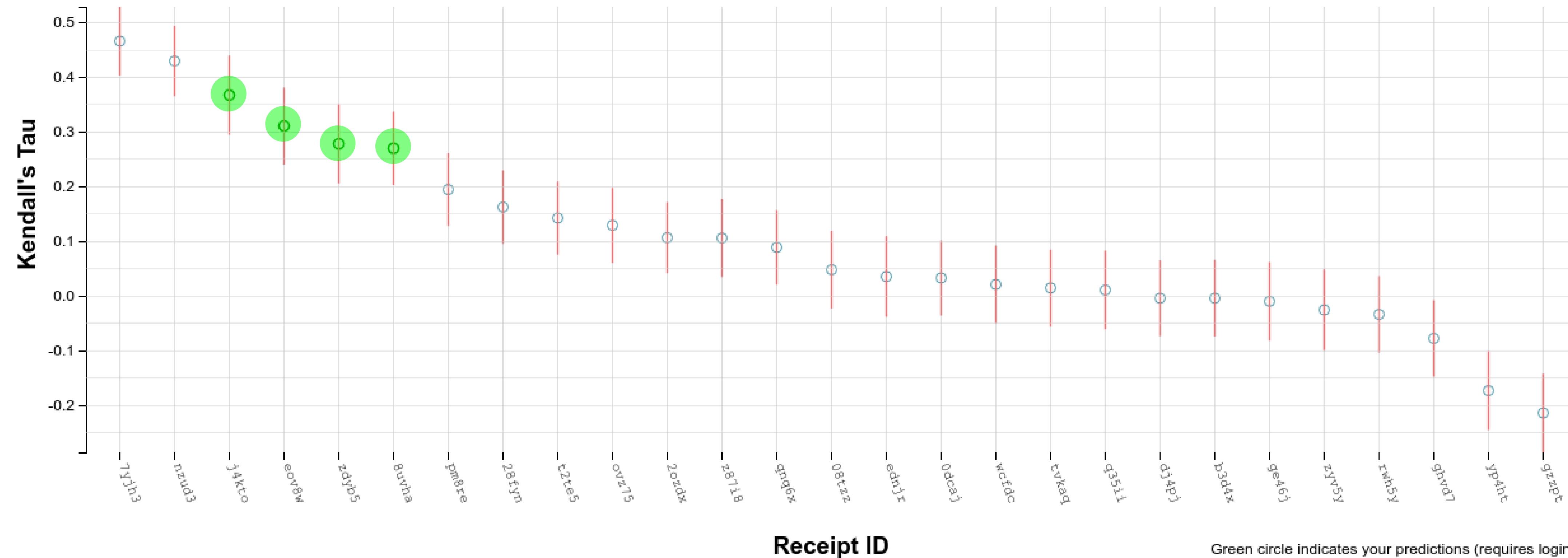
Affinity Ranking - Kendall's Tau



Grand Challenge 3

Grand Challenge 3 - JAK2_SC2

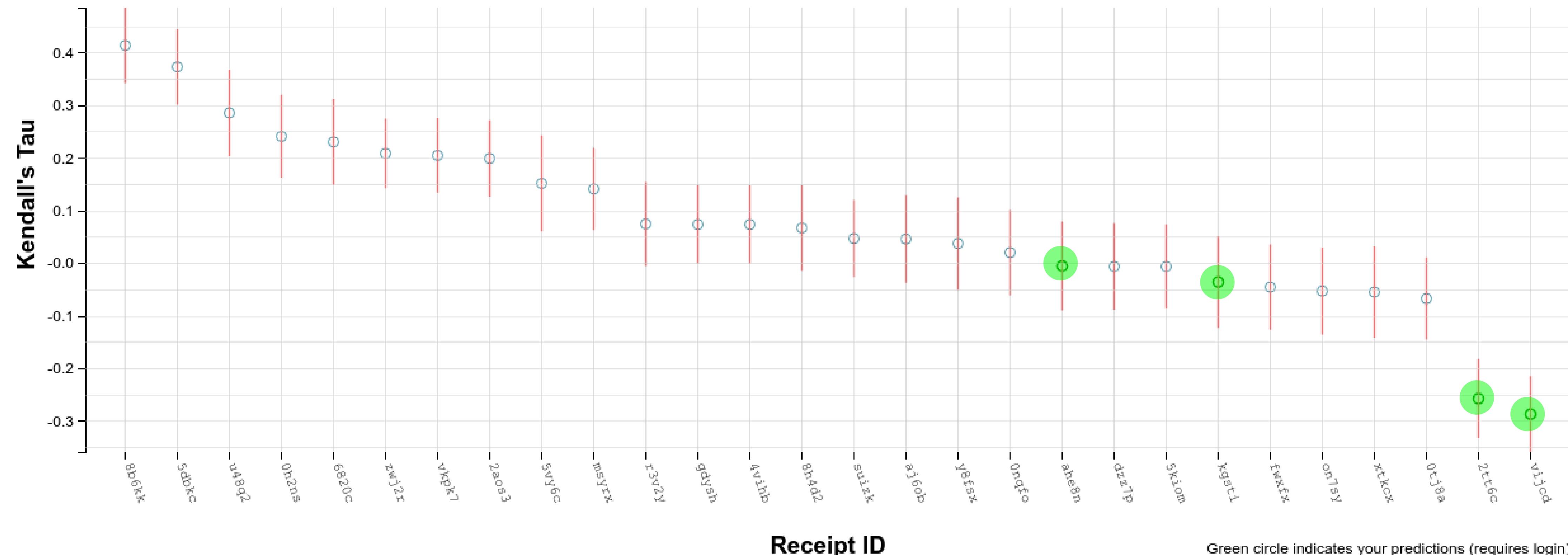
Affinity Ranking - Kendall's Tau



Grand Challenge 3

Grand Challenge 3 - p38a

Affinity Ranking - Kendall's Tau



Receipt ID

Green circle indicates your predictions (requires login)

Grand Challenge 3

Grand Challenge 3 - TIE2

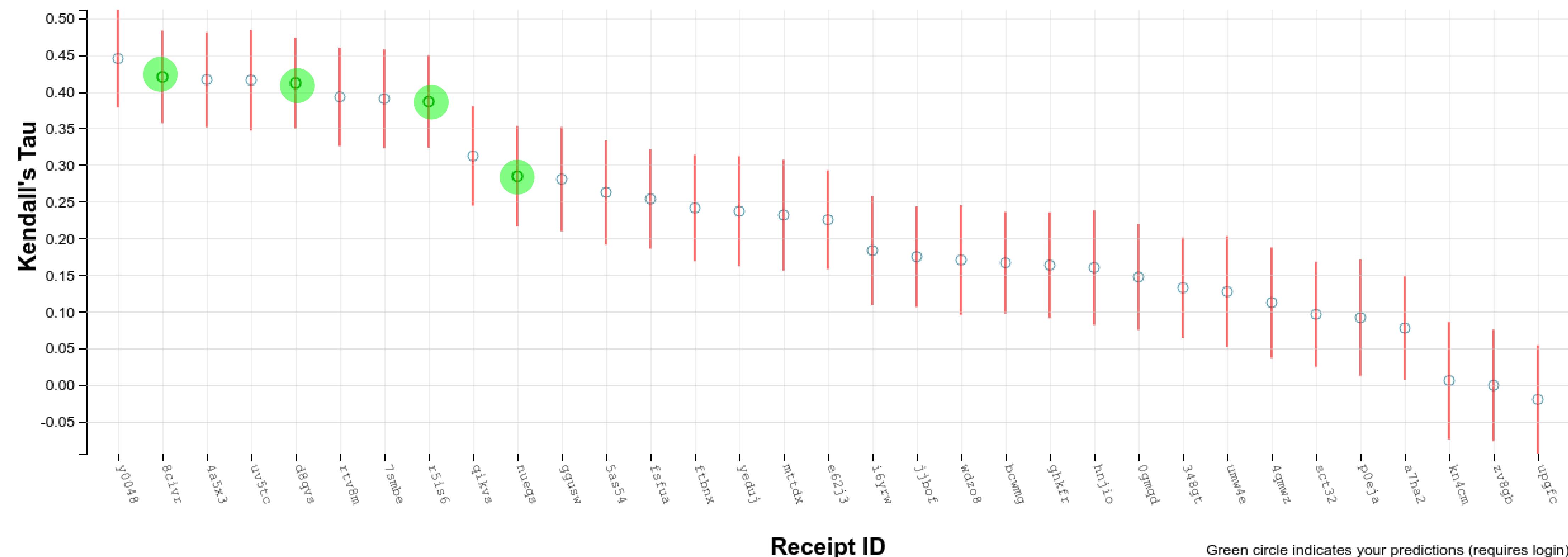
Affinity Ranking - Kendall's Tau



Grand Challenge 3

Grand Challenge 3 - VEGFR2

Affinity Ranking - Kendall's Tau



Grand Challenge 3

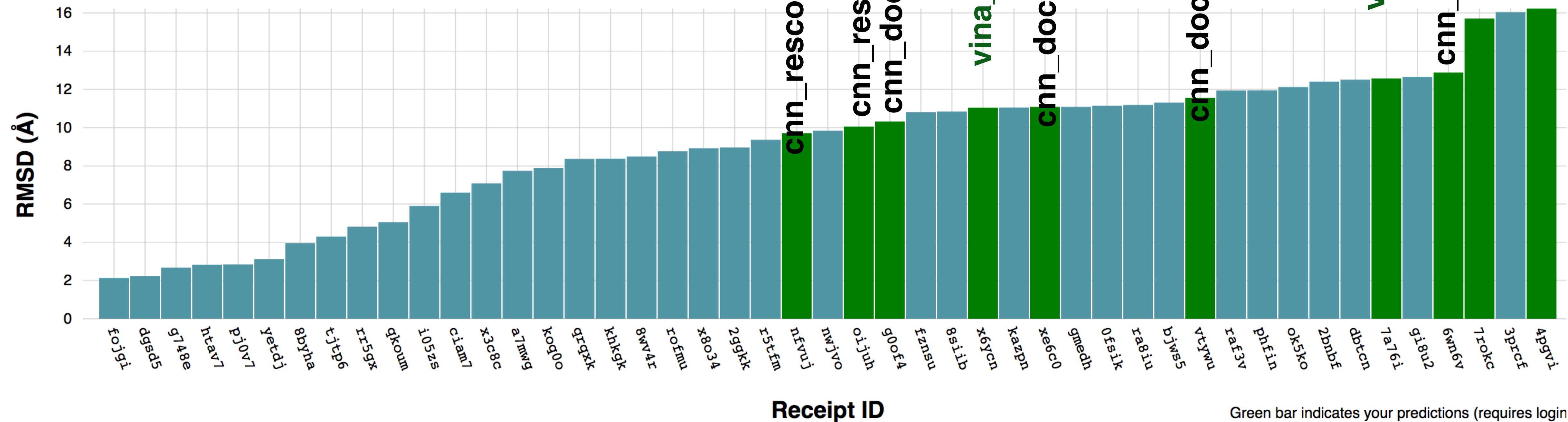
Spearman Correlation

	cnn_docked_affinity	cnn_rescore_affinity	cnn_docked_scoring	cnn_rescore_scoring	vina
cat	0.0701	0.154	-0.0351	0.178	0.179
p38a	-0.0784	-0.116	-0.329	-0.305	-0.0631
vegfr2	0.366	0.484	0.434	0.448	0.414
jak2	0.428	0.338	0.39	0.27	0.106
jak2_sub3	0.68	0.369	-0.372	0.159	-0.633
tie2	0.648	0.835	0.136	-0.078	0.561
abl1	0.634	0.745	0.005	0.182	0.713

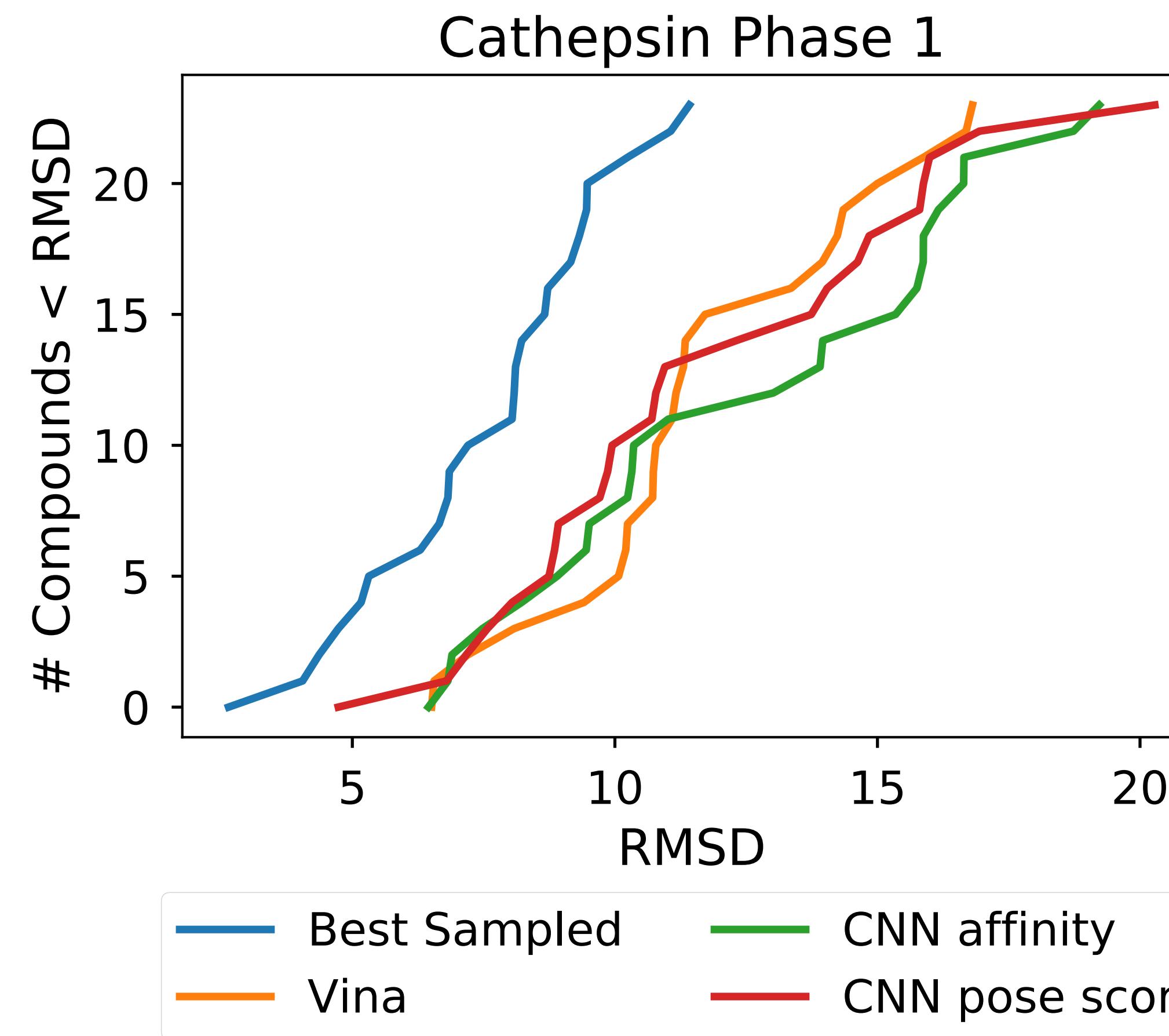
GC3: Pose Prediction

Pose RMSDs (\AA) - Compound: Average over all - Pose 1

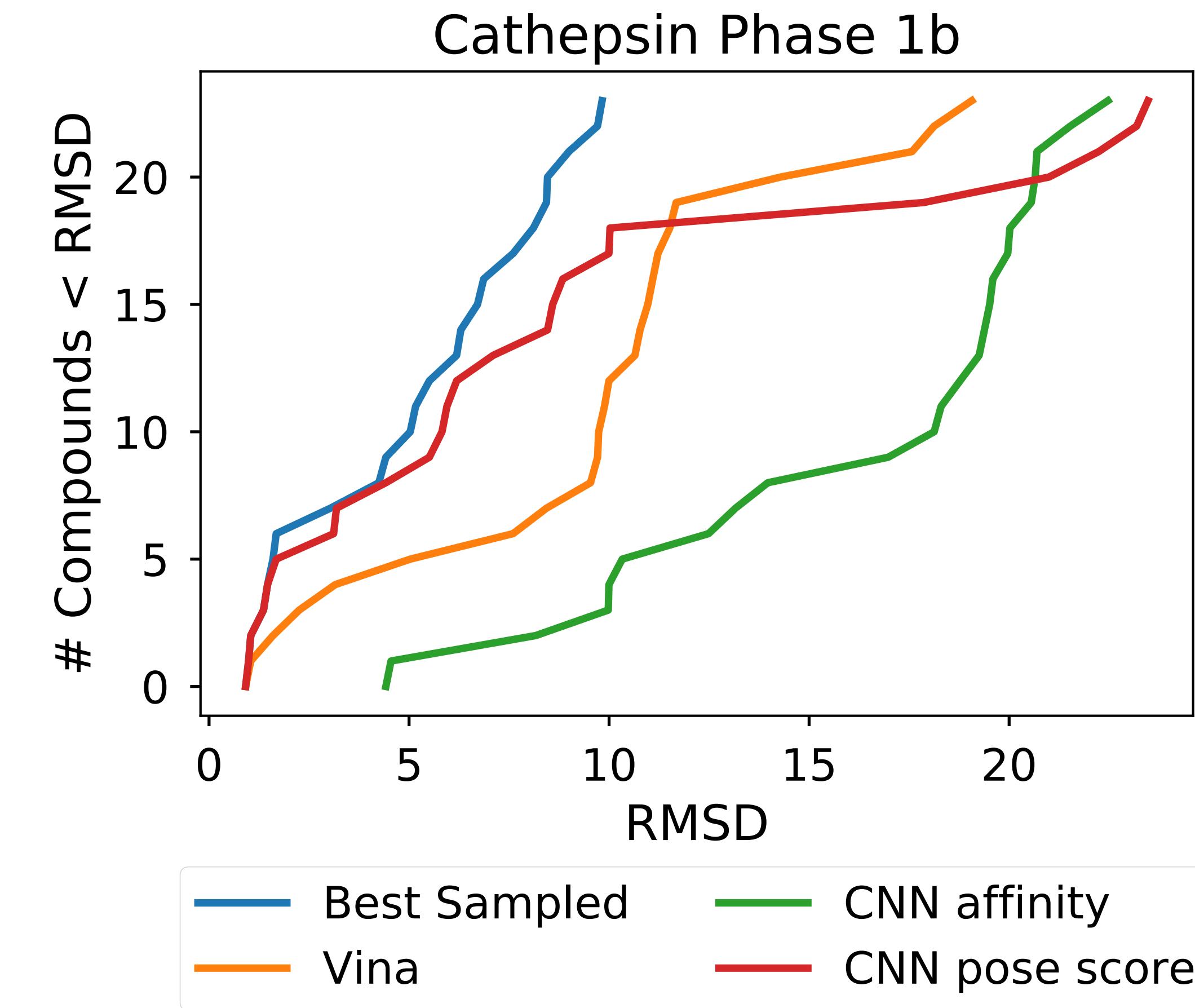
Compound:



GC3: Pose Prediction

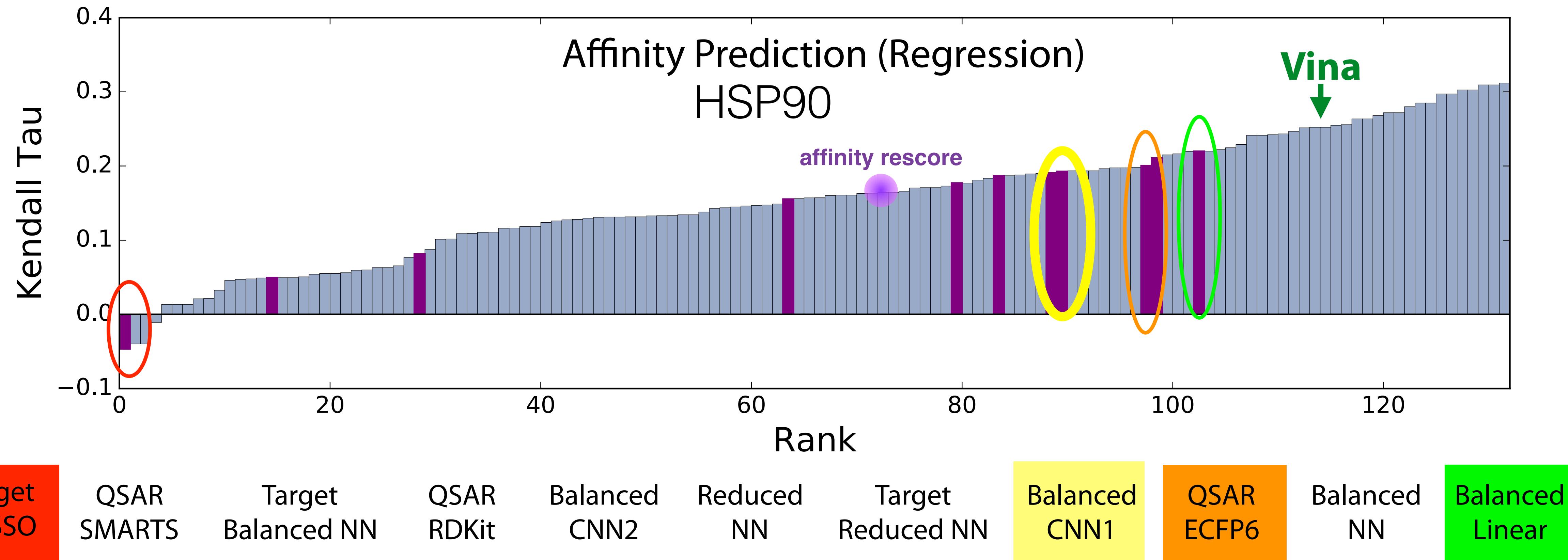


cross-docking



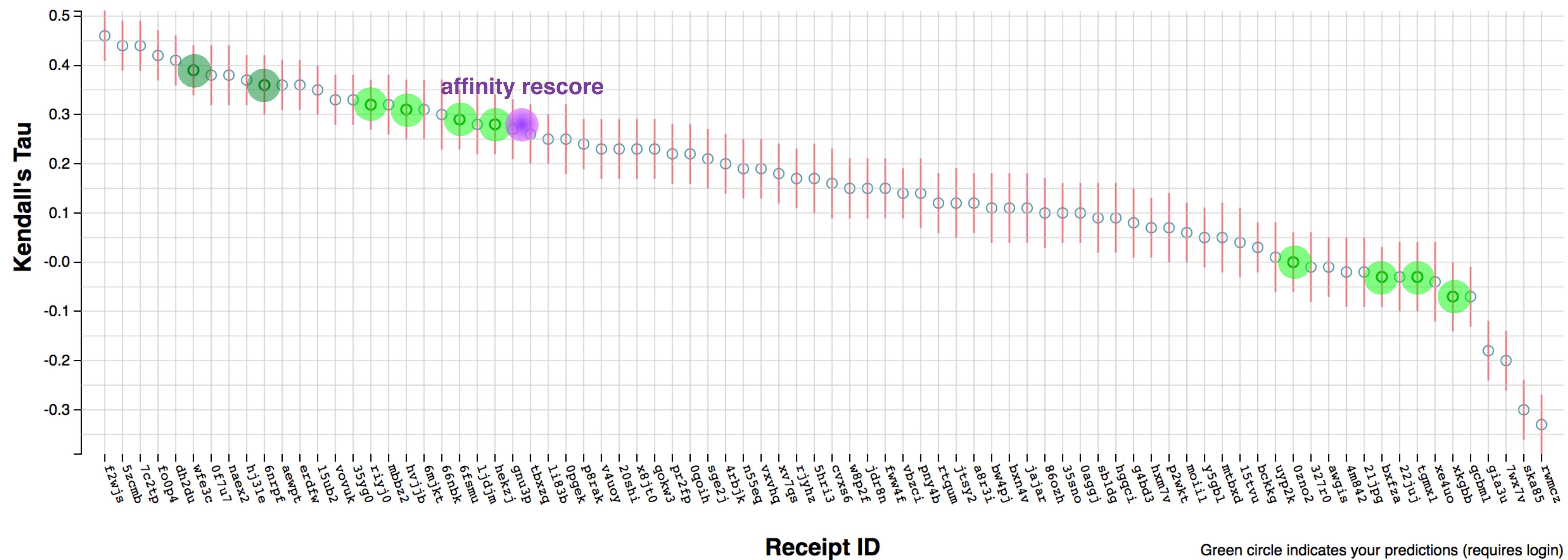
redocking

Grand Challenge 1



Grand Challenge 2

Affinity Ranking (Stage 2) - Kendall's Tau



Future Plans

Train CNN for docking

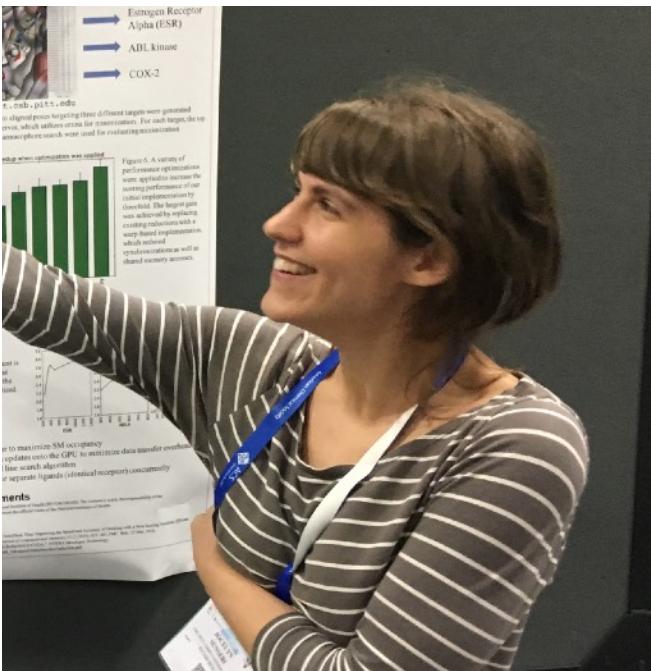
- iteratively train on docked poses
- train on cross-docked poses
- fully integrate CNN scoring into search

Continue to improve model/training parameters

Next Grand Challenge

- Finish fully automated predictions early
- Make automated+human insight submission

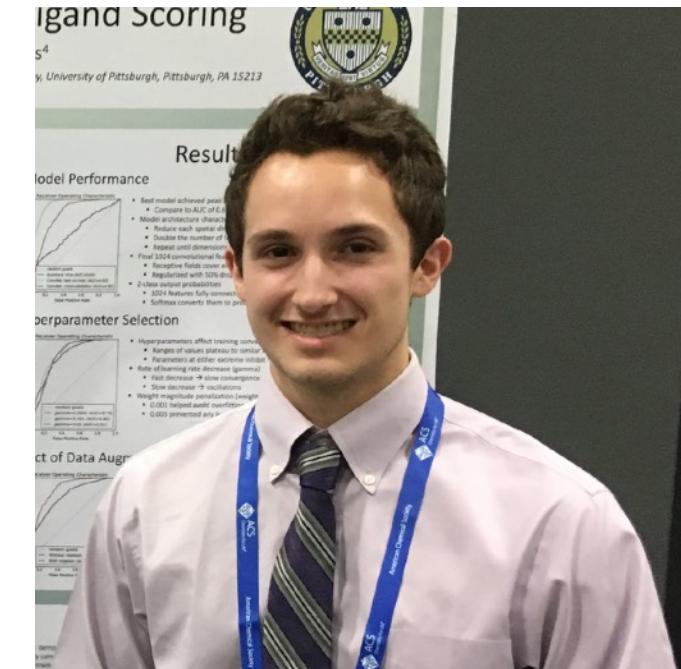
Acknowledgements



Jocelyn Sunseri



Josh Hochuli



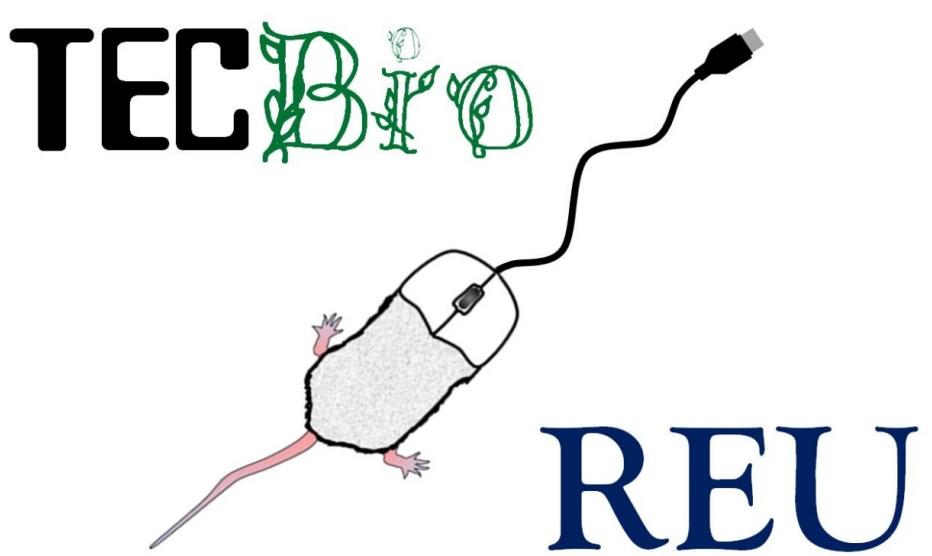
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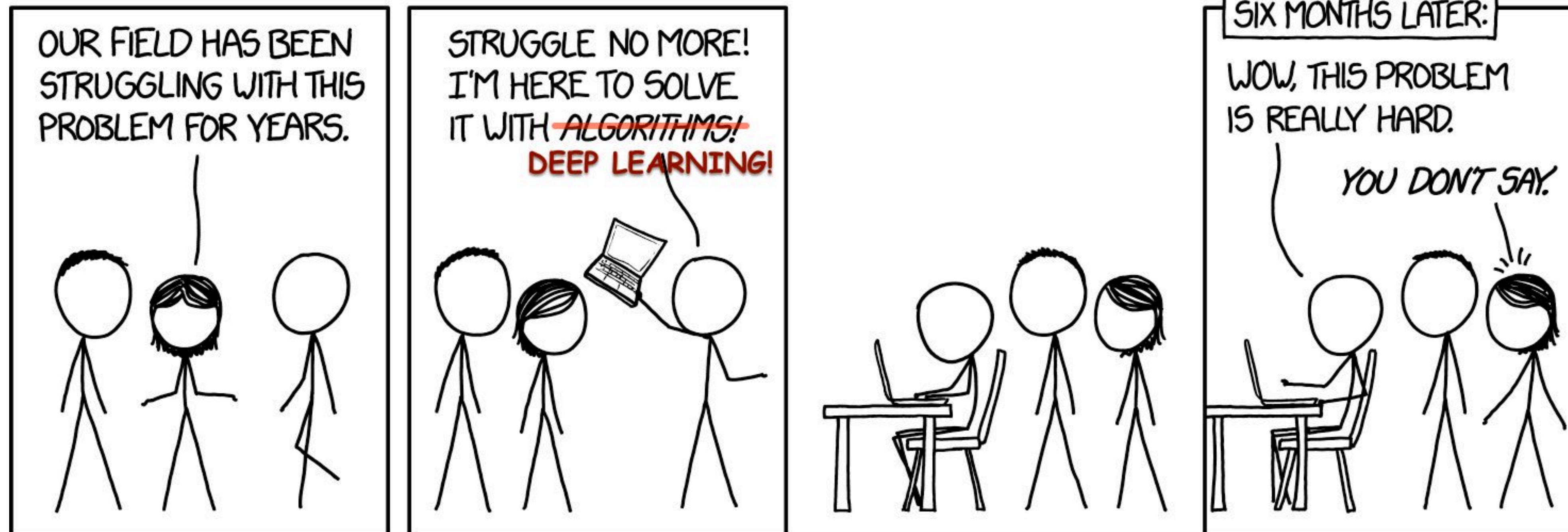
National Institute of
General Medical Sciences
R01GM108340



 github.com/gnina

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

 [@david_koes](https://twitter.com/david_koes)



Prospective Case Study: TIGIT

Can we block TIGIT/ PVR interaction with a small molecule?

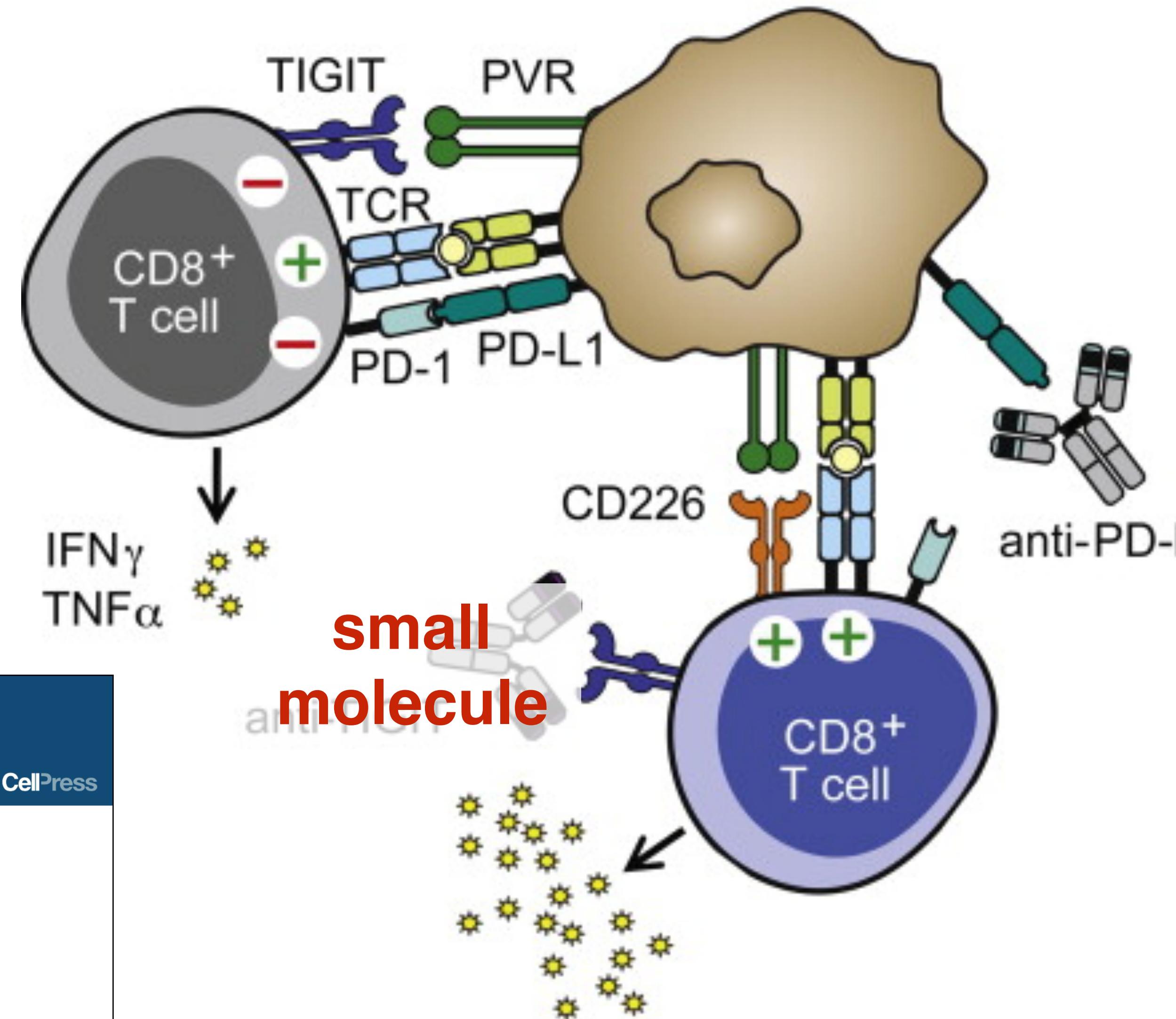
Cancer Cell Article

CellPress

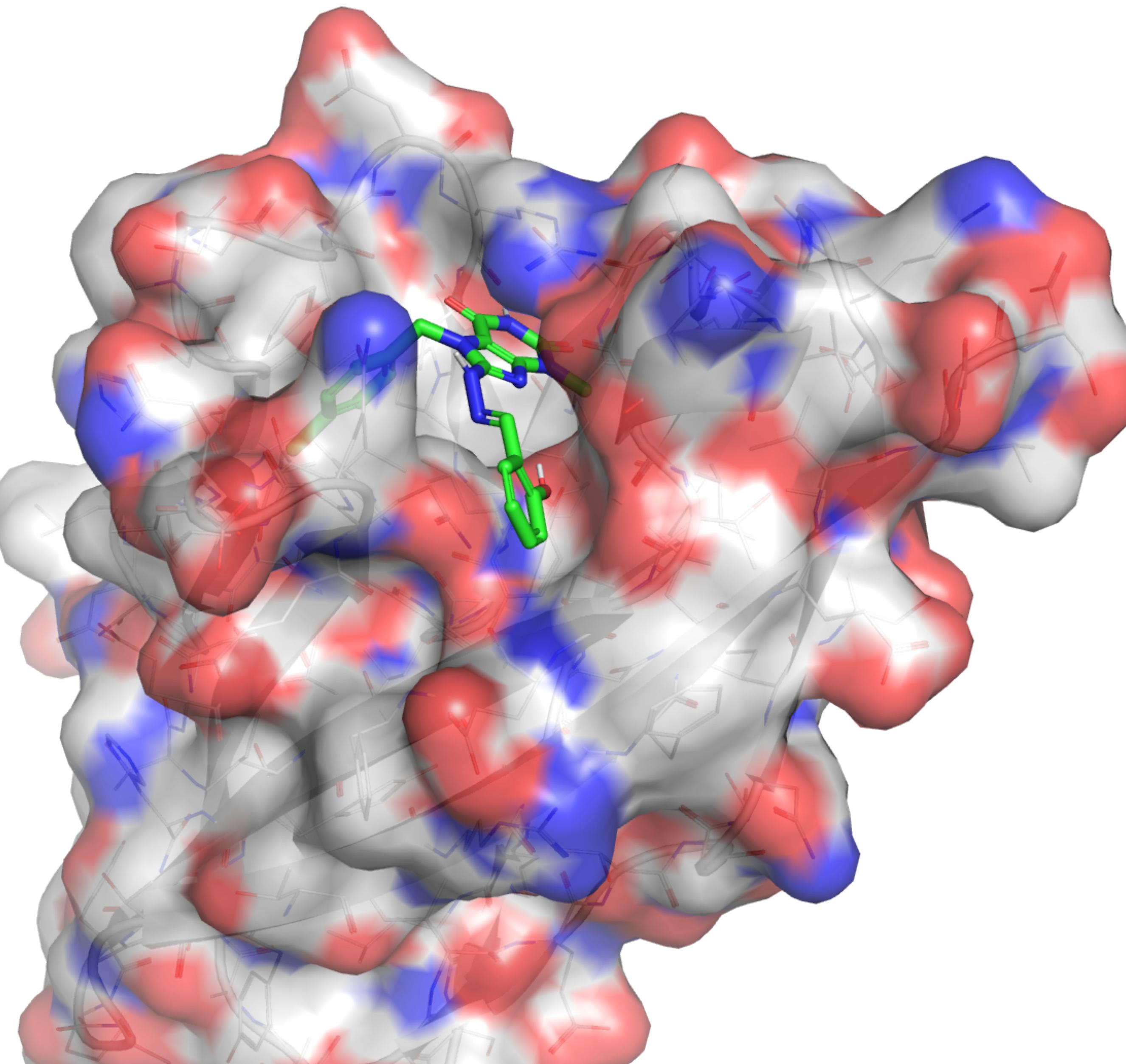
The Immunoreceptor TIGIT Regulates Antitumor and Antiviral CD8⁺ T Cell Effector Function

Robert J. Johnston,¹ Laetitia Comps-Agrar,² Jason Hackney,³ Xin Yu,¹ Mahrukh Huseni,⁴ Yagai Yang,⁵ Summer Park,⁶ Vincent Javinal,⁵ Henry Chiu,⁷ Bryan Irving,¹ Dan L. Eaton,² and Jane L. Grogan^{1,*}

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Genentech, 1 DNA Way, South San Francisco, CA 94080, USA
*Correspondence: grogan.jane@gene.com
<http://dx.doi.org/10.1016/j.ccr.2014.10.018>



Screening

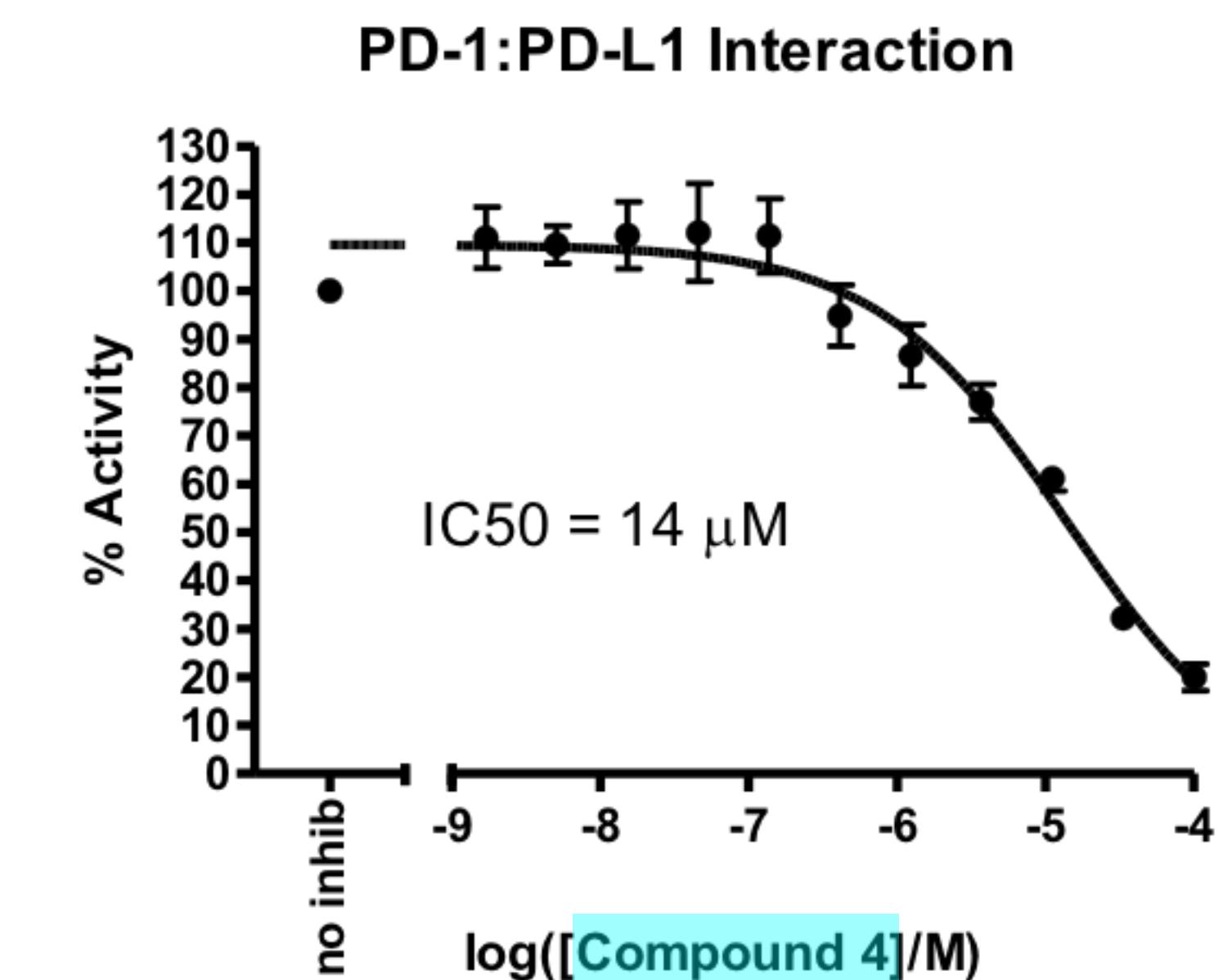
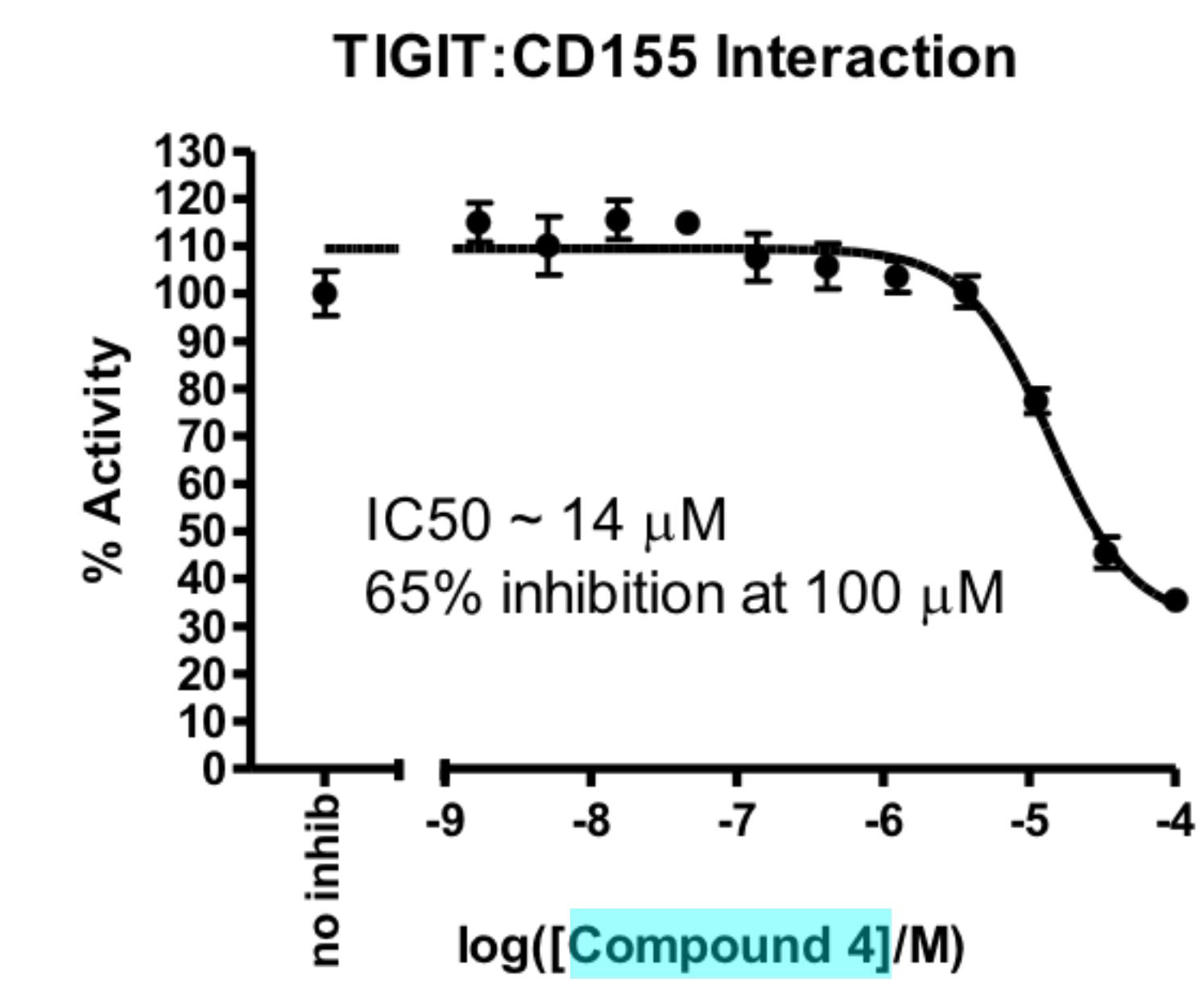
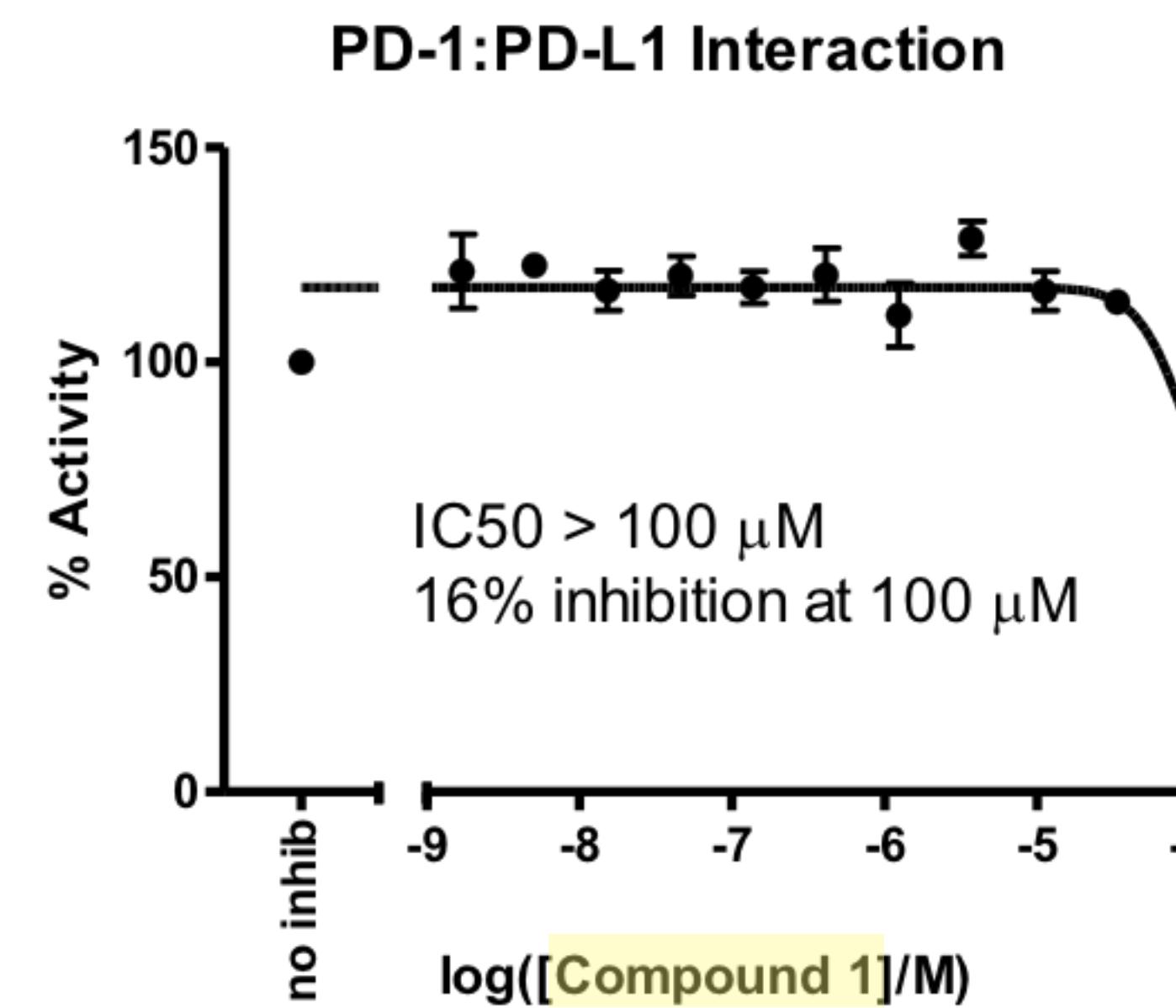
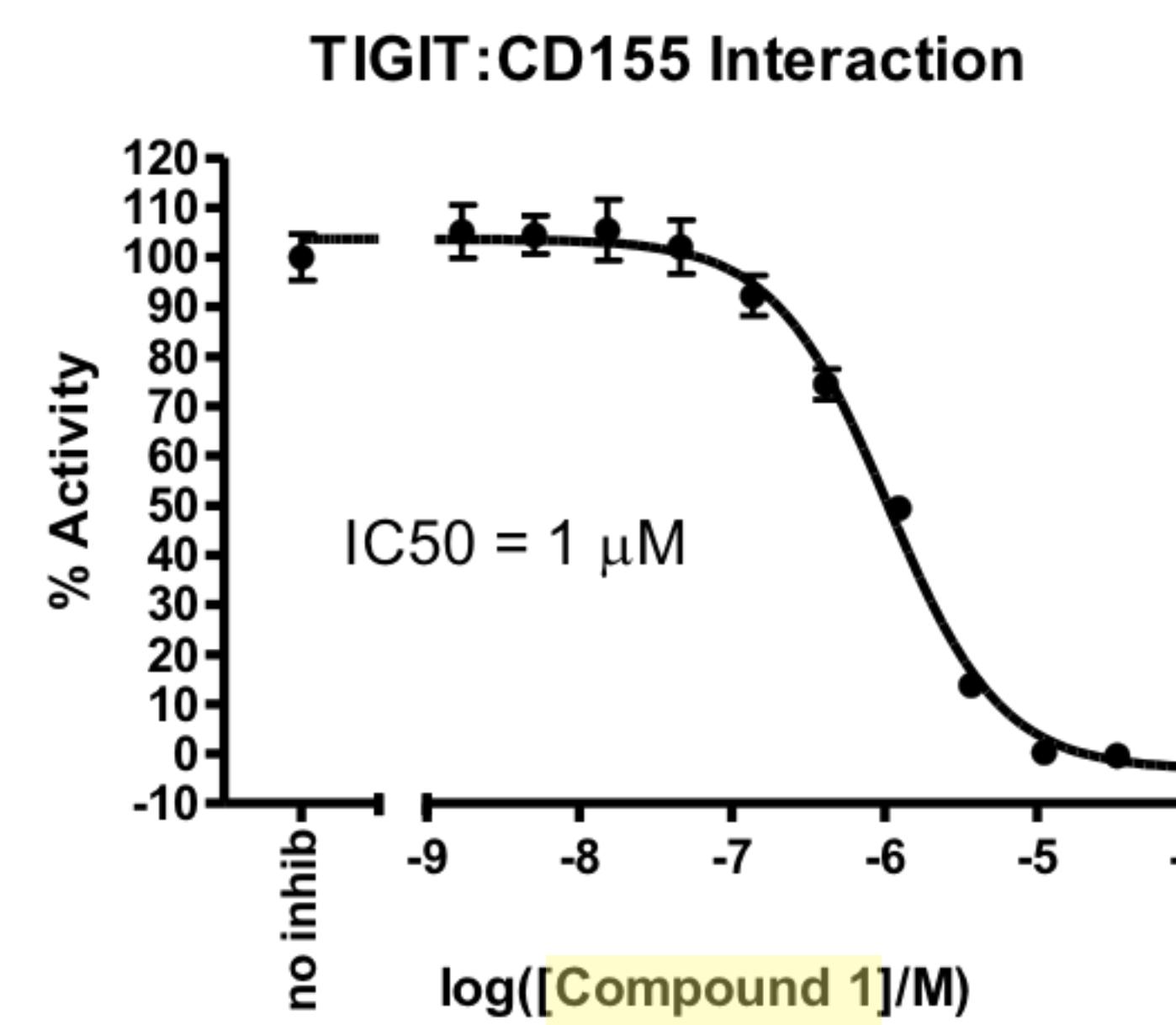
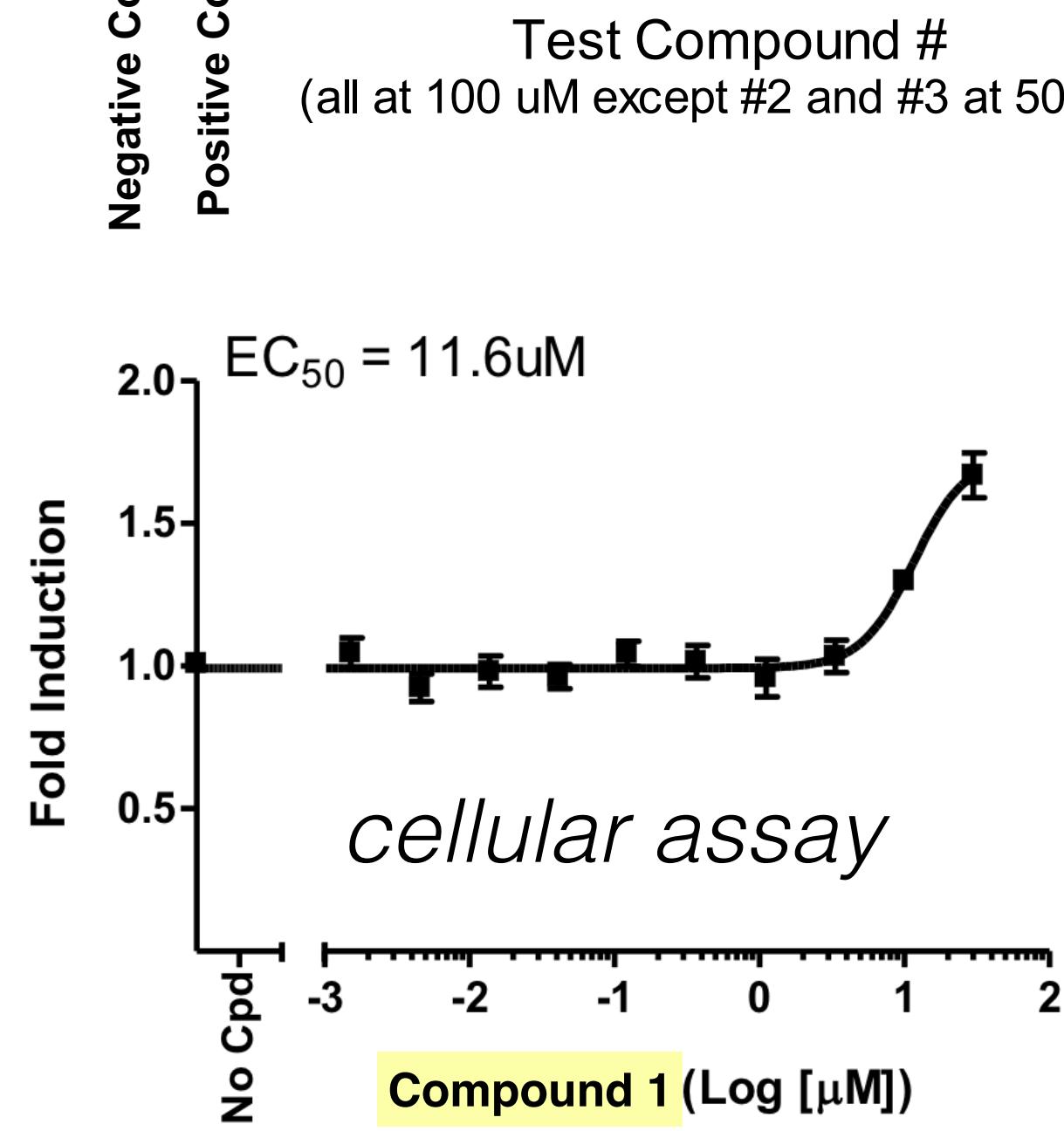
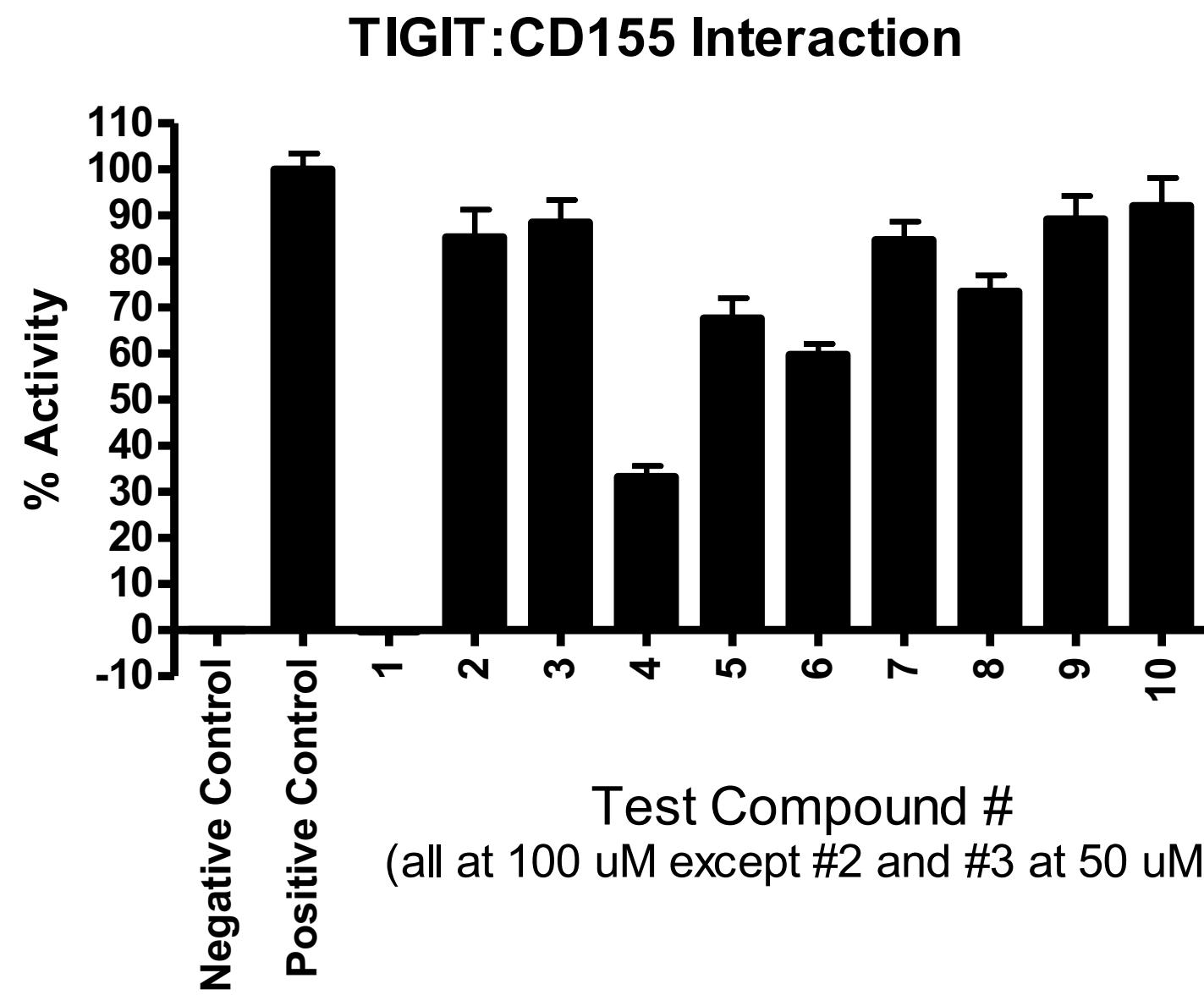


10 diverse compounds selected for screening

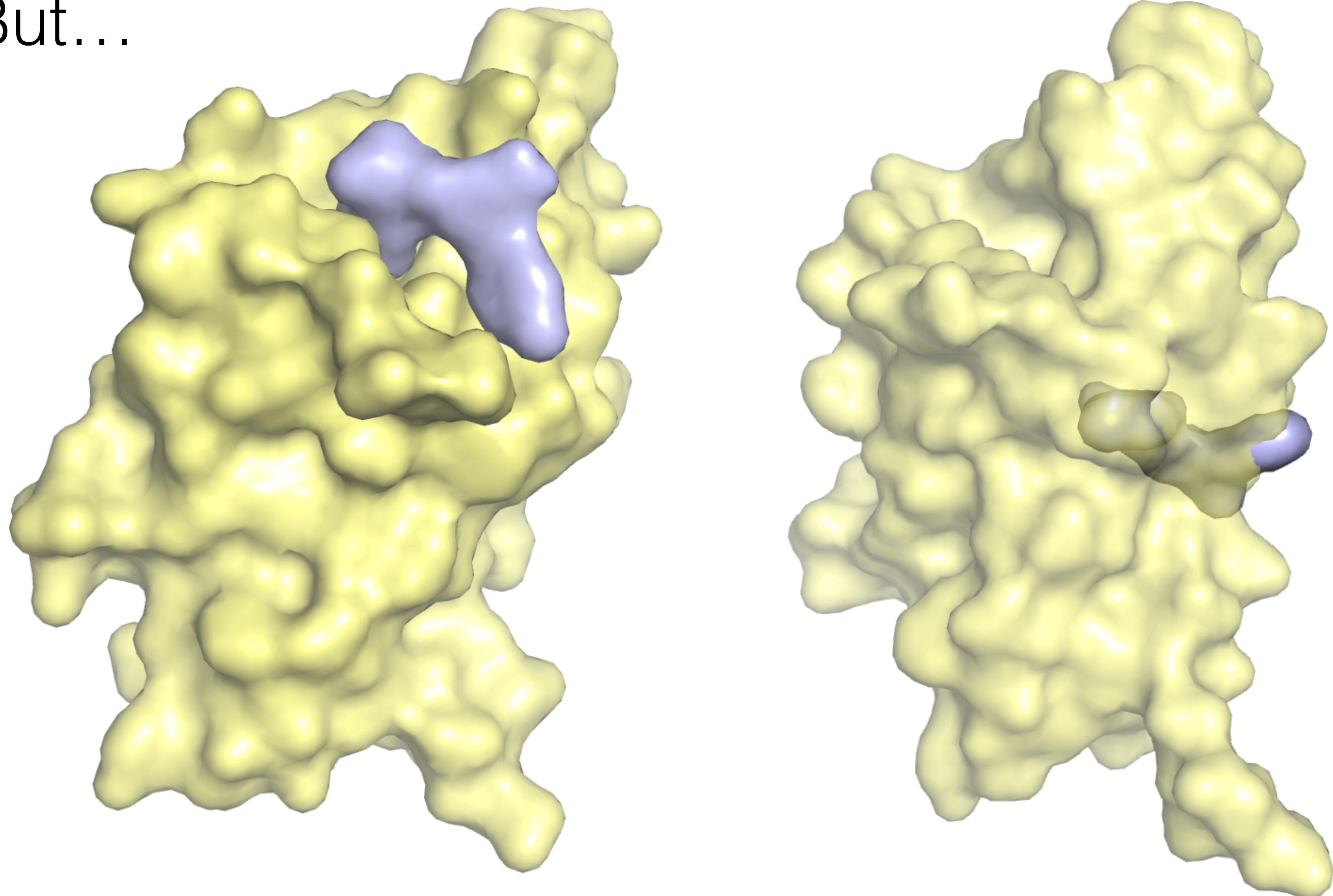
- top ranked by Vina
- top ranked by CNN

Name	CNN Affinity	CNN Score	Vina
Compound 1	7.69807	0.994763	85.95
Compound 2	5.57909	0.0180277	-8.12632
Compound 3	6.73692	0.0624742	-9.81935
Compound 4	6.87897	0.953488	-3.81378
Compound 5	6.32813	0.209807	-8.60293
Compound 6	5.689	0.0437	-8.991
Compound 7	4.368	0.022	-9.34722
Compound 8	4.81	0.072	-6.81787
Compound 9	5.22	0.032	-6.264
Compound 10	6.67	0.361	6.1053

Results



But...



Filter Visualization

