On the frustration to predict binding affinities from protein-ligand structures with deep neural networks.

Mikhail Volkov,[†] Joseph-André Turk, [#] Nicolas Drizard,[#] Nicolas Martin,[#] Brice Hoffmann,[#] Yann Gaston-Mathé[#] and Didier Rognan[†]*

⁺ Laboratoire d'innovation thérapeutique, UMR7200 CNRS-Université de Strasbourg, 74 route du Rhin, 67400 Illkirch, France.

^{*} Iktos, 65 rue de Prony, 75017 Paris, France.

* To whom correspondence should be addressed (phone: +33 3 68 85 42 35, fax: +33 3 68 85 43 10,

email: rognan@unistra.fr)

Figure S1. Location and pharmacophoric properties of protein pseudoatoms.

Figure S2. Performance of modular MPNN models in predicting affinities for specific target classes of the 2019 hold-out set.

Figure S3. Influence of the number of closest ligands or proteins used to average binding affinities in the performance of simple memorization models.

Figure S4. PDBbind low sparsity subset.

Figure S5. Chemical diversity of PDBbind ligands.

Table S1. Structure-based deep neural networks to predict protein-ligand binding affinities.

Table S2. Geometric rules to define protein-ligand non-covalent interactions.



Figure S1. Location and pharmacophoric properties of protein pseudoatoms (grey, aliphatic; red, hydrogen-bond acceptor; cyan, hydrogen-bond donor; green, aromatic; metal-chelating, steel blue)



Figure S2. Performance of modular MPNN models in predicting affinities for specific target classes of the 2019 hold-out set. Mapping of protein target classes (GPCRs, G-protein-coupled receptor; NRs, Nuclear hormone receptors) from the Pharos database (https://pharos.nih.gov/) to PDB entries was performed using the Pharos-to-PDB code (https://github.com/ravila4/Pharos-to-PDB).



Figure S3. Influence of the number of closest ligands or proteins used to average binding affinities in the performance of simple memorization models, assessed by the Pearson r correlation coefficient.



Figure S4. PDBbind low sparsity subset. **A)** Split into four subsets for training, validation and external test sets (core 2016, hold-out 2019), **B)** Distribution of experimental affinities for the training (n=1,505), core (n=49) and hold-out sets (n=329). The boxes delimit the 25th and 75th percentiles, and the whiskers delimit the 1st and 99th percentiles. The median and mean values are indicated by a horizontal line and a filled square in the box, respectively. Outliers are indicated by a diamond.



Figure S5. Chemical diversity of PDBbind ligands. **A)** Pairwise similarity of Murcko superstructures for ligands from the training, 2016 core and 2019 hold-out sets. The similarity is expressed by the Tanimoto coefficient computed from ECFP4 fingerprints. **B)** Uniform Manifold Approximation and Projection (UMAP) of PDBbind ligands, performed in umap-learn 0.5.3 with a number of neighbours of 30 and a dice distance metric. The Morgan fingerprints of radius 2 (nBits=1024) were computed in rdkit v.2020.09.1.

Model	Туре	Objects	Descriptor	Training set	Test set	Split	R <i>p</i>	RMSE	Reference
TNet-BP	CNN	PL	Topological fingerprints	PDBbind 2016 refined (n=3767)	PDBbind 2016 core (n=290)	PDBBind original	0.826	1.37	11
ACNN	CNN	P, L, PL	Atom type-labelled distances (Nat*25 atom types*12 closest neighbors)	PDBbind 2015 refined (n=2965)	PDBbind 2015 refined (n=741)	Temporal	0.727	-	12
Brendan	CNN	PL	3D grid (21*21*21 Å) * 256 bit SPLIF vector	PDBbind 2016 general (10000)	PDBbind 2016 general (1500)	Random	0.704	-	13
PotentialNet	GNN	P, L, PL	Protein-ligand graph	PDBbind 2007 refined (n=1095)	PDBbind 2007 core (n=195)	PDBBind original	0.822	1.39	14
KDEEP	CNN	L, PL	1-Å 3D grid (25*25*25 Å) * 16 features	PDBbind 2016 refined (n=3767)	PDBbind 2016 core (n=290)	PDBbind original	0.820	1.27	15
Pafnucy	CNN	L, PL	1-Å 3D grid (21*21*21 Å) * 19 features	PDBbind 2016 general (11906)	PDBbind 2016 core (n=290)	PDBBind original	0.780	1.42	16
DeepATom	CNN	PL	1-Å 3D grid (25*25*25 Å) * 24 features	PDBbind 2016 refined (n=3390)	PDBbind 2016 core (n=290)	PDBbind original	0.807	1.32	18
DeepBindRG	CNN	PL	ligand (84) * protein (41) atom pair distances < 4 Å	PDBbind 2018 general (n=13500)	PDBbind 2018 general (n=925)	Random	0.593	1.50	21
OnionNet	CNN	PL	Atom type-labelled distances (Nat*25 atom types*12 closest neighbors)	PDBbind 2016 general (n=11906)	PDBbind 2016 core (n=290)	PDBbind original	0.816	1.28	22
RosENet	CNN	PL	voxelized Rosetta interaction energies + pharmacophoric descriptors	PDBbind 2016/2018 refined (n=4463)	PDBbind 2016 core (n=290)	PDBBind original	0.820	1.24	23
graphDelta	GNN	L, PL	One-hot encoded ligand atoms + protein environmental descriptors (373)	PDBbind 2018 general (n=8766)	PDBbind 2016 core (n=285)	PDBbind original	0.870	1.05	24
AK-Score	CNN	PL	id Kdeep	PDBbind 2016 refined (n=3772)	PDBbind 2016 core (n=285)	PDBBind original	0.827	1.22	25
SE-OnionNet	CNN	PL	1-Å grid (21*21*21)* 64 protein-ligand element distance counts	PDBbind 2018 general (n=11663)	PDBbind 2018 refined (n=463)	Random	0.853	1.59	27
Progessive multitask network	CNN	P, L, PL	ligand ECFP + Protein ECFP + Protein-Ligand SPLIF	PDBbind 2016 refined (n=3568)	PDBbind 2016 core (n=290)	PDBbind original	0.740	0.98	28
ACNN	CNN	P, L, PL	Atom type-labelled distances (Nat*25 atom types*12 closest neighbors)	PDBbind 2015 refined (n=3706)	PDBbind 2015 core (n=195)	PDBBind original	0.730	-	29
Pair	CNN	PL	protein-ligand distance pairs	PDBBbind 2018 refined (n=2675)	PDBBbind 2018 refined (n=891)	Random split	0.660	1.61	30
DEELIG	CNN	L, PL	Atomic model: 3D grid (10*10*10 Å) * 19 bits (atomic model); Composite model: 3D grid (10*10*10 Å) * 44 bits (pocket) + 14716 bits (ligand)	in-house set (n=4041)	PDBbind 2016 core (n=290)	Random 80/10/10	0.889	-	31
Interaction GraphNet	GNN	P, L, PL	independent GNN for intra and inter- molecular interactions	PDBbind 2016 general (n=10366)	PDBbind 2016 core (n=290)	PDBBind original	0.837	1.22	32

Table S1. Structure-based deep neural networks to predict protein-ligand binding affinities.

midlevel fusion	CNN+GNN	PL	CNN: 1-Å grid (48*48*48)* 19 atomic features; GNN: covalent (d < 1.5 Å) and non-covalent edges (1.5 < d < 4.5 Å)	Pdbbind 2016 general+refined (13283)	PDB2016 core set (n=290)	PDBBind original	0.810	1.31	33
SMPLIP	RF+ CNN	L, PL	IFP (140) + interaction distances (140) + SMF descriptors (2282)	Pdbbind 2016 general+refined (13283)	PDB2016 core set (n=290)	PDBBind original	0.770	1.51	34
OctSurf	CNN	PL	1-Å 3D grid (64*64*64 Å) * 24 features/octant	PDBbind 2018 general (n=16126)	PDBbind 2016 core (n=285)	PDBBind original	0.793	1.45	35
ВАРА	CNN	PL	Protein-ligand interaction descriptors + 6 Vina terms	PDBbind 2016 refined (n=3689)	PDBbind 2016 core (n=285)	PDBbind original	0.819	1.31	36
APMNet	GNN+GNN	P, L	75 DeepChem atomic features	PDBbind 2016 general (n=11844)	PDBbind 2016 core (n=290)	PDBBind original	0.815	1.27	37
GraphBAR	GNN	PL	13 features * 200 protein-ligand atoms	PDBbind 2016 general (n=11146)	PDBbind 2016 core (n=290)	PDBbind original	0.764	1.44	38

Interaction	Rule 1 ^a	Rule 2 ^b
H-bond	$\left\ \overrightarrow{DA}\right\ \le 3.5 \mathring{A}$	$\left\langle \overrightarrow{DH},\overrightarrow{HA}\right\rangle \in \left[\frac{-\pi}{4},\frac{\pi}{4}\right]$
Ionic	$\overrightarrow{\ +-\ } \le 4.0 \mathring{A}$	
Hydrophobe	$\left\ \overline{Y_1Y_2}\right\ \le 4.5\text{\AA}$	
Aromatic (Face to face)	$\left\ ac_1 ac_2 \right\ \le 4.0 \text{ Å}$	$\left\langle \vec{n_1}, \vec{n_2} \right\rangle \in \left\lfloor \frac{-\pi}{6}, \frac{\pi}{6} \right\rfloor$
Aromatic (Edge to face)	$\left\ ac_1 ac_2 \right\ \le 4.0 \text{ Å}$	$\left\langle \overrightarrow{n_1}, \overrightarrow{n_2} \right\rangle \in \left[\frac{\pi}{6}, \frac{5\pi}{6} \right]$
pi-cation	$\ ac +\ \le 4.0 \text{\AA}$	$\left\langle \vec{n}, \overrightarrow{ac+} \right\rangle \in \left[\frac{-\pi}{6}, \frac{\pi}{6}\right]$
Metal	$\left\ \overrightarrow{MA}\right\ \le 2.8 \mathring{A}$	

Table S2. Geometric rules to define protein-ligand non-covalent interactions.

^a D: H-bond donor; A: H-bond acceptor; +: cation; -:anion; Y: hydrophobe; ac: geometric center of an aromatic ring; M: metal.

^b H: hydrogen; n: normal to the aromatic ring.