

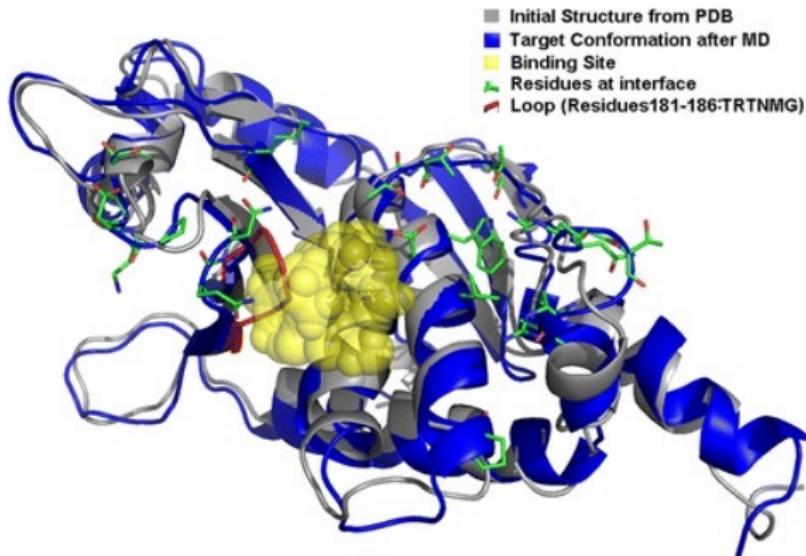
Comparative assessment of scoring functions *(Introduction to the CASF competition project)*

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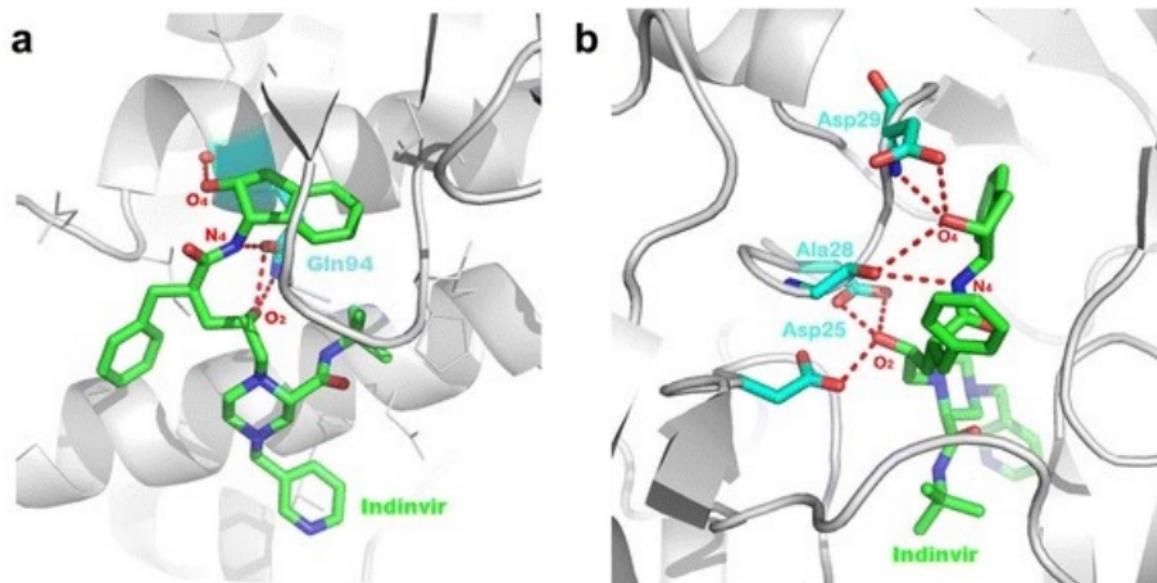
Protein-ligand docking problem and pharmacology



The binding interface of VP24 of Ebola with Karyopherin alpha

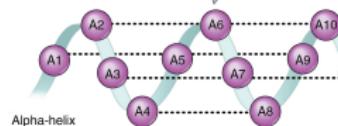
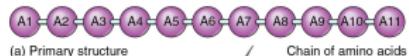
Drug to target Ebola virus replication and virulence using structural systems pharmacology by Zheng Zhao et al. //BMC Bioinf., 2016

It is important to select a ligand, which fits requirements

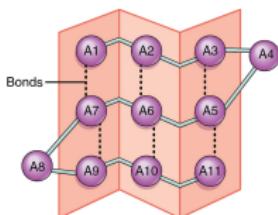


The predicted binding mode of Indinavir in VP24 of Ebola (a) and (b) the binding mode of Indinavir in HIV protease (PDB id 2AVO)

Amino-acids, proteins, and ligands

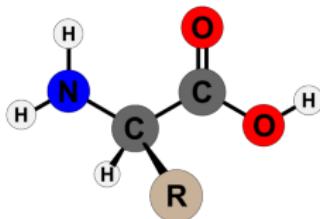


(b) Secondary structure (pleated sheet)

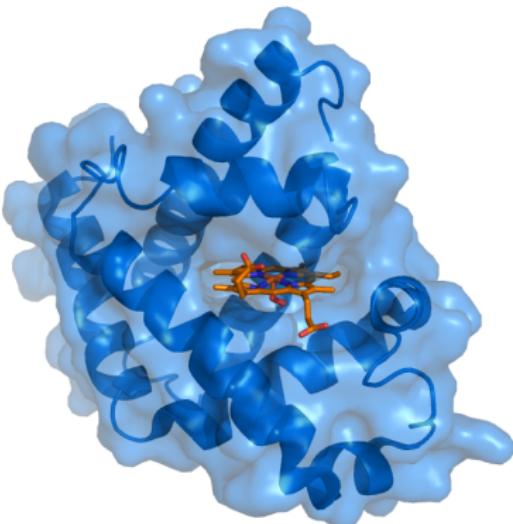


(d) Quaternary structure

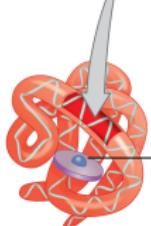
Hemoglobin
(globular protein)



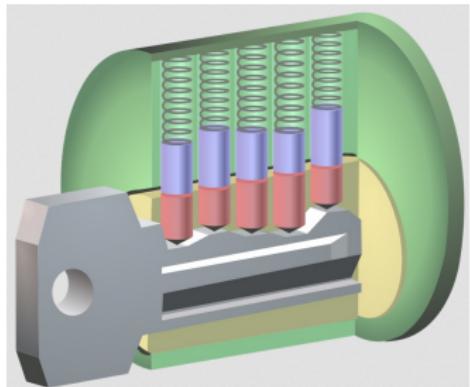
Amino-acid, 20 types



(c) Tertiary structure



Protein-ligand complex and scoring function to dock



Roles:

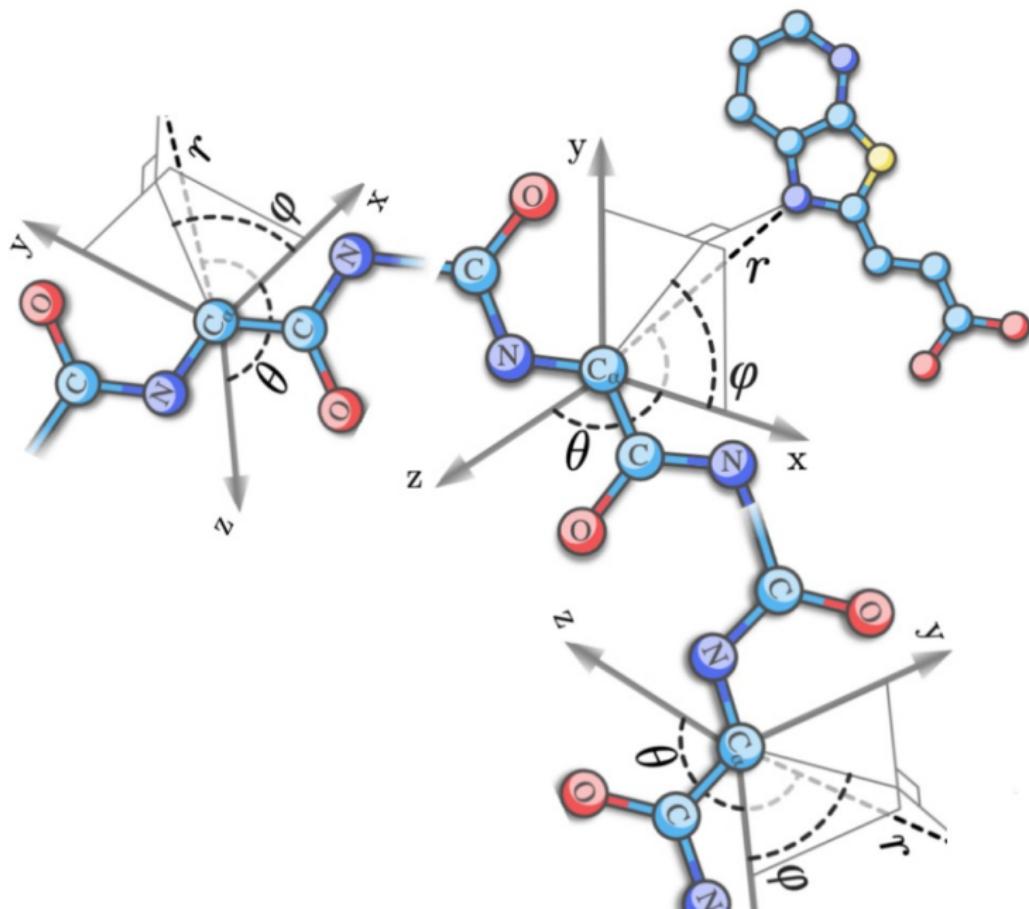
Protein: the lock

Ligand: the key

Scoring function: to move along

Native conformation: to open lock

Docking: a general view



Terminology of CASF

1. **Complex:** a subject to score $C(\text{prt}, \text{lig})$

supposed to be a stable couple protein-ligand, (an element of metric space).

2. The protein **residue types** corresponds to the 20 standard amino acids, indexed by $\text{aa} \in \{1, \dots, 20\} = \{\text{aa}\}$.

3. The set of 37 ligand **atom types**, indexed by $\text{atm} \in \{1, \dots, 37\} = \{\text{atm}\}$,

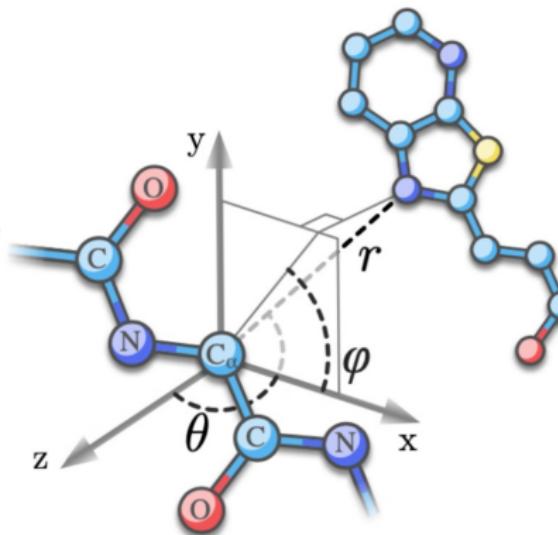
8 carbon types, 12 nitrogen, 7 oxygen, 4 sulfur, 2 phosphorus, and 4 halogens.

4. Frame: has a unique basis \mathbf{B} for any amino acid in a protein;

also a rigid body translation (affine transformation) between any pairs of frames is given.

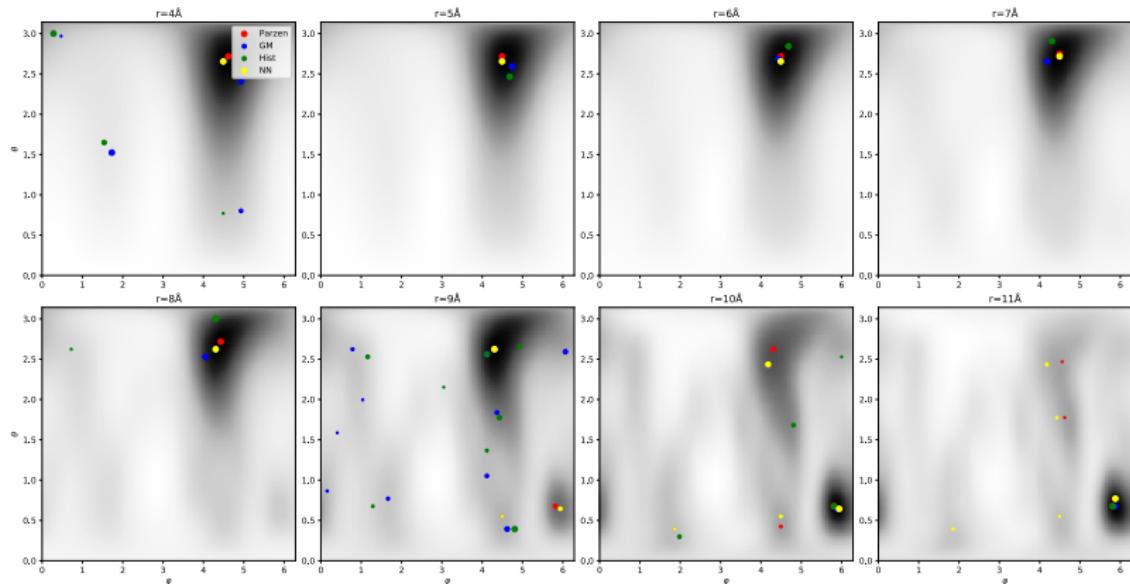
5. **Pose:** an orientation of a ligand (and so an atom) according to the frame, a triplet $[\theta, \varphi, r]^\top$

in spherical coordinates $\{0, \dots, 2\pi\}$, $\{0, \dots, \pi\}$, $\{3, \dots, 20\text{\AA}\}$



Каталог экстремумов (1)

Protein 0, ligand 2

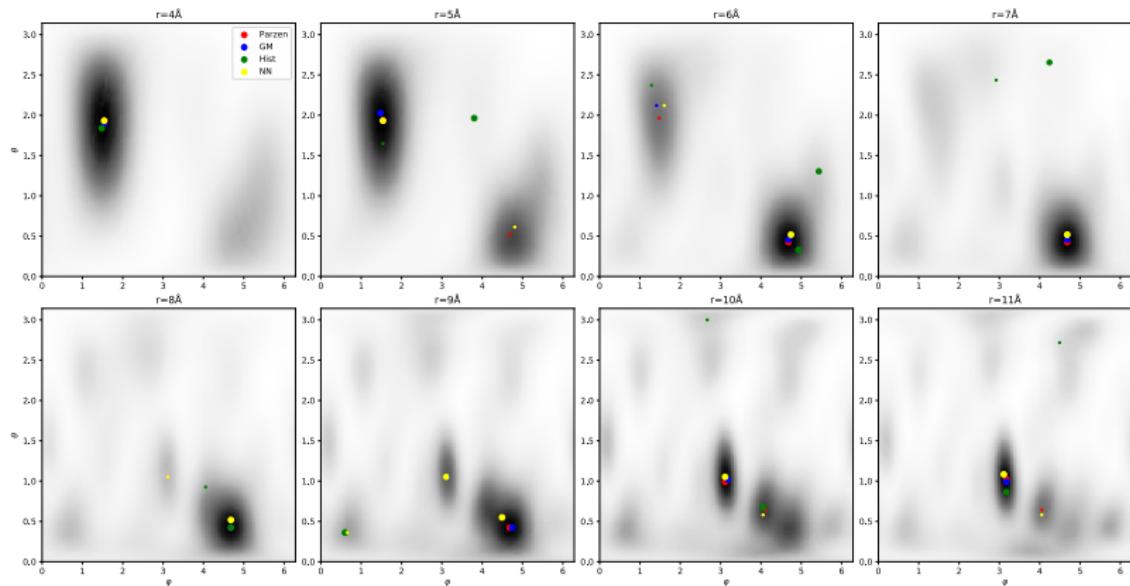


	Parzen	GM	Hist	NN
Parzen				
GM	28.98			
Hist	34.78	23.33		
NN	33.72	54.28	58.24	

MAPE, %

Каталог экстремумов (2)

Protein 10, ligand 23



	Parzen	GM	Hist	NN
Parzen				
GM	30.89			
Hist	60.94	48.88		
NN	39.61	59.71	86.75	

MAPE, %

Восстановление плотности распределения для построения метрического пространства

Модели \mathfrak{F} и оптимизируемые структурные параметры

- Гистограмма — размеры перцентиляй $dr, d\varphi, d\theta$.
- Окно Парзена — тип окна, ширина окна.
- Смесь гауссиан — число гауссиан (экстремумов).
- Нейросеть (2 скрытых слоя, 50 нейронов).

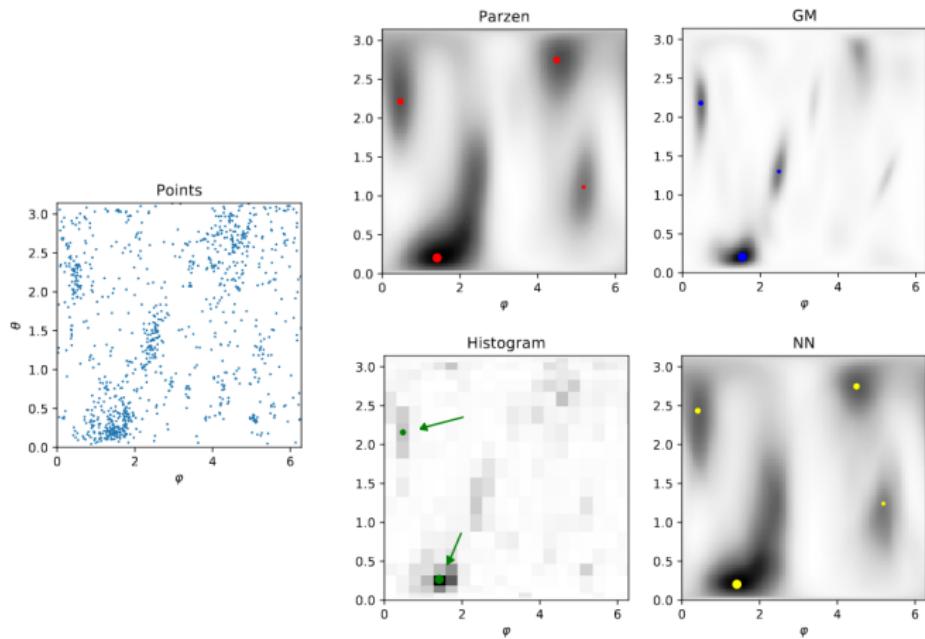
Критерии точности аппроксимации

Расхождение плотности усредняется по всем парам моделей:

$$L_1 = \sum_{1 \leq i < j \leq 4} \int_{\mathbb{R}^3} (f_i(\vec{r}, \hat{w}_i) - f_j(\vec{r}, \hat{w}_j))^2 d\vec{r},$$

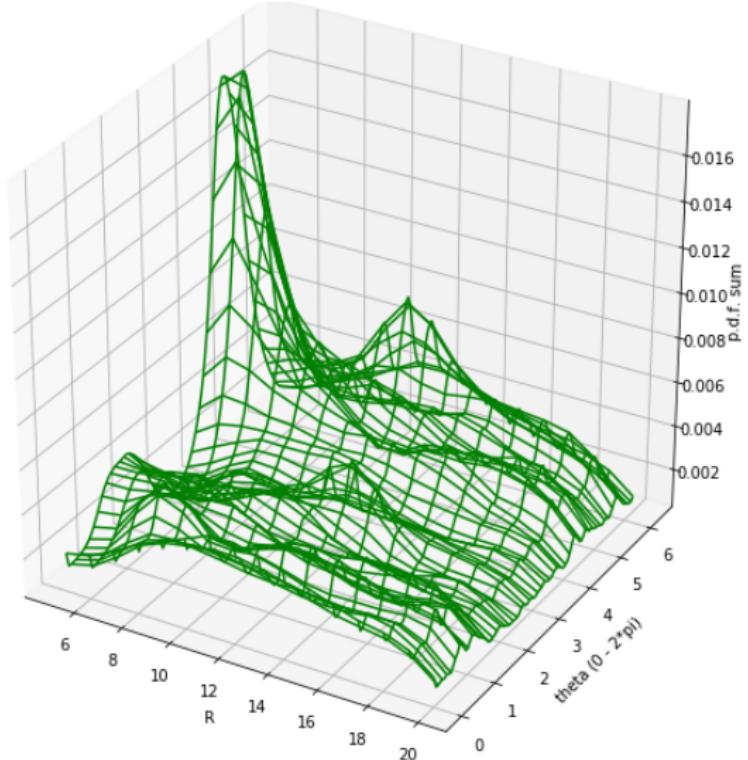
$$L_2 = \sum_{1 \leq i < j \leq 4} \int_{|f_i(\vec{r}, \hat{w}_i) - f_j(\vec{r}, \hat{w}_j))| > \varepsilon} d\vec{r}.$$

Восстановленная плотность $f(\varphi, \theta, r)$ при $r = 5\text{\AA}$



Для элемента $x = (4, 0)$. Стрелками отмечены согласованные экстремумы, попадающие в каталог.

Экстремумы плотности $f(r, \theta)$



Положение экстремумов на сфере меняется в зависимости от расстояния незначительно, что обуславливает структуру каталога.

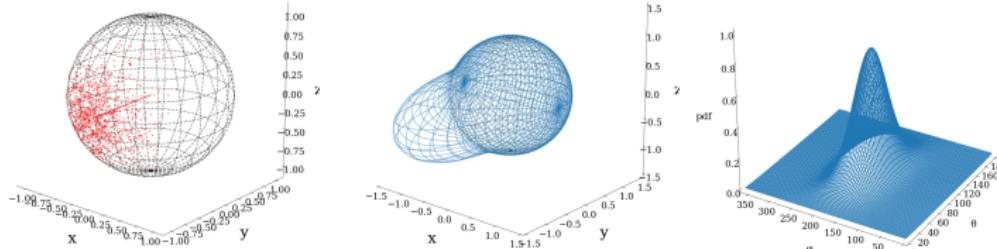
Переход к угловым переменным в распределении Кента

От компонент единичного вектора $[x_1, x_2, x_3]^T$ перейдём к сферическим углам $\theta \in [0, \pi]$, $\varphi \in [0, 2\pi]$:

$$x_1 = \cos \theta, \quad x_2 = \sin \theta \cos \varphi, \quad x_3 = \sin \theta \sin \varphi,$$

В таком случае плотность распределения обозначим

$$\mathcal{K}(\theta, \varphi | \kappa, \beta, \gamma_1, \gamma_2, \gamma_3) \text{ или кратко } \mathcal{K}(\theta, \varphi | \boldsymbol{\nu})$$



Иллюстрации плотности распределения типичного представителя семейства распределений Кента

Instances of f-divergence

Divergence	Corresponding $f(t)$
KL-divergence	$t \log t$
reverse KL-divergence	$-\log t$
squared Hellinger distance	$(\sqrt{t} - 1)^2, 2(1 - \sqrt{t})$
Total variation distance	$\frac{1}{2} t - 1 $
Pearson χ^2 -divergence	$(t - 1)^2, t^2 - 1, t^2 - t$
Neyman χ^2 -divergence (reverse Pearson)	$\frac{1}{t} - 1, \frac{1}{t} - t$
α -divergence	$\begin{cases} \frac{4}{1-\alpha^2}(1-t^{(1+\alpha)/2}), & \text{if } \alpha \neq \pm 1, \\ t \ln t, & \text{if } \alpha = 1, \\ -\ln t, & \text{if } \alpha = -1 \end{cases}$
Jensen-Shannon Divergence	$(t + 1) \log \left(\frac{2}{t + 1} \right) + t \log t$
α -divergence (other designation)	$\begin{cases} \frac{t^\alpha - t}{\alpha(\alpha-1)}, & \text{if } \alpha \neq 0, \alpha \neq 1, \\ t \ln t, & \text{if } \alpha = 1, \\ -\ln t, & \text{if } \alpha = 0 \end{cases}$

$$D_{\text{KL}}(P\|Q) = \int_{-\infty}^{\infty} p(x) \log \left(\frac{p(x)}{q(x)} \right) dx$$

Scoring function: the present state of research

There given P native protein-ligand complexes $C_{i0}, i \in \{1, \dots, P\}$. For each native (from database) configuration of the complex there exists D non-native configurations (decoys), $j \in \{1, \dots, D\}$. For each complex C_{ij} we have $D + 1$ conformations, 1 native and D non-native. We have to select a scoring function E , such that

$$E(C_{i0}) < E(C_{ij}), \text{ for alternatives } i \in \{1, \dots, P\}, j \in \{1, \dots, D\}.$$

Scoring function: a function to represent the integral binding energy; from a ligand native, non-native (a pose to be ranked).

$$E_{ij} = -RT \ln \frac{P_{aa,lig}^{\text{obs}}(\theta, \varphi, r) + z}{P_{\text{ref}}^{\text{obs}}(\theta, \varphi, r) + z}, \quad E = \sum_k E_k(\theta, \varphi, r).$$

A weighted variant:

$$E = \sum_i \sum_j r_i c_j E_{ij}(\theta, \varphi, r).$$

Tests of the competition CASF-16

Docking power

ability of a scoring function to predict the native or the best near-native docking pose among a set of computer-generated configurations.

Scoring power

correlation of scoring function predictions with the experimental binding affinity data.

Ranking power

ability of a scoring function to correctly rank a set of known ligands for a target protein. In CASF-2016, where five known ligands are available for each target protein, it is measured by Spearman's correlation coefficient.

Screening power

ability of a scoring function to identify true binders for a target protein among a set of small molecules.

Previous results with code

1. For probabilistic models of protein-ligand docking by Nikita Uvarov:
[thesis](#), [slides](#), [code](#) (the project to start with)
2. Mixture of spherical distributions by Sviatoslav Panchenko:
[thesis](#), [slides](#), [code](#)
3. Approximation the empirical distributions with neural networks by Natalia Varenik:
[thesis](#), [slides](#), [code](#)

References

1. CASF Project description page at m1p.org
2. Convex-PL: a novel knowledge-based potential for protein-ligand interactions deduced from structural databases using convex optimization by Maria Kadukova and Sergei Grudinin, 2017
3. Predicting Binding Poses and Affinities in the CSAR 2013–2014 Docking Exercises Using the Knowledge-Based Convex-PL Potential by Sergei Grudinin et al, 2016
4. Comparative Assessment of Scoring Functions: The CASF-2016 Update by Minyi Su et al., 2018
5. Docking rigid macrocycles using Convex-PL, AutoDock Vina, and RDKit in the D3R Grand Challenge 4 Maria Kadukova et al., 2020
6. Basic solution is a linear combination; it is described in draft

Docking: a residue, its frame and an atom

