

Improving virtual screening through physics-based methods

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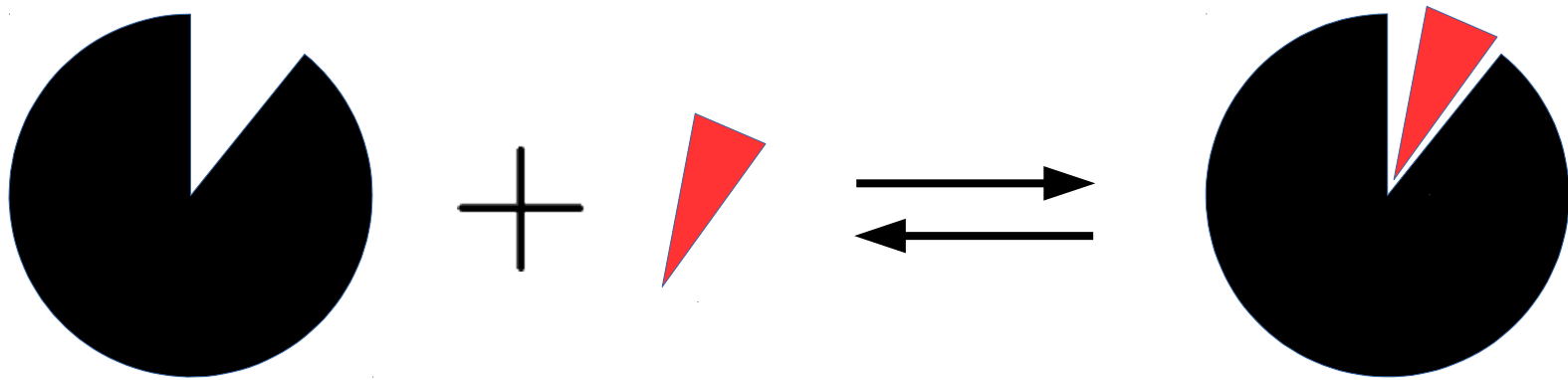
Motivation: drug discovery

- Problem: R&D is expensive – the space of possible small molecule drugs to synthesize and test is prohibitively large
- Accurate prediction of protein–ligand binding affinities desired from computational drug design
- Until recently, the value of computational screening in drug discovery has been limited

Relative Ligand Binding Potency in Prospective Drug Discovery by Way of a Modern Free-Energy Calculation Protocol and Force Field

L. Wang, *et al.* *J. Am. Chem. Soc.* 2015.

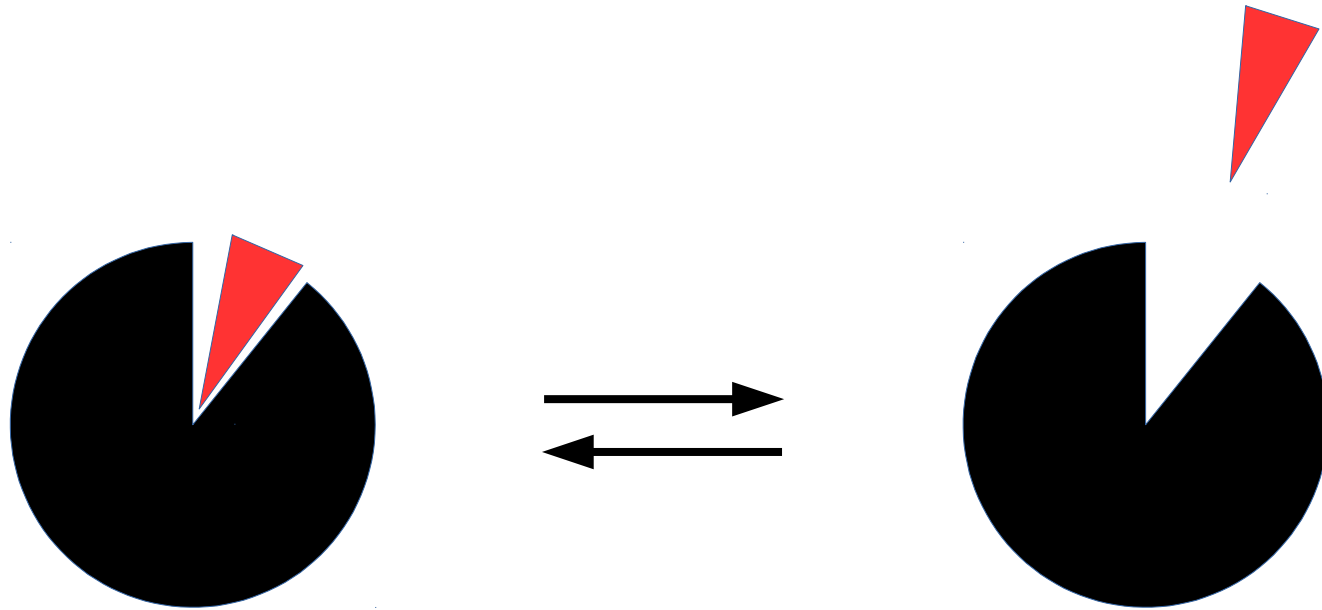
Definition: binding affinity



$$K_d \approx \frac{[\text{ligand}][\text{target}]}{[\text{complex}]}$$

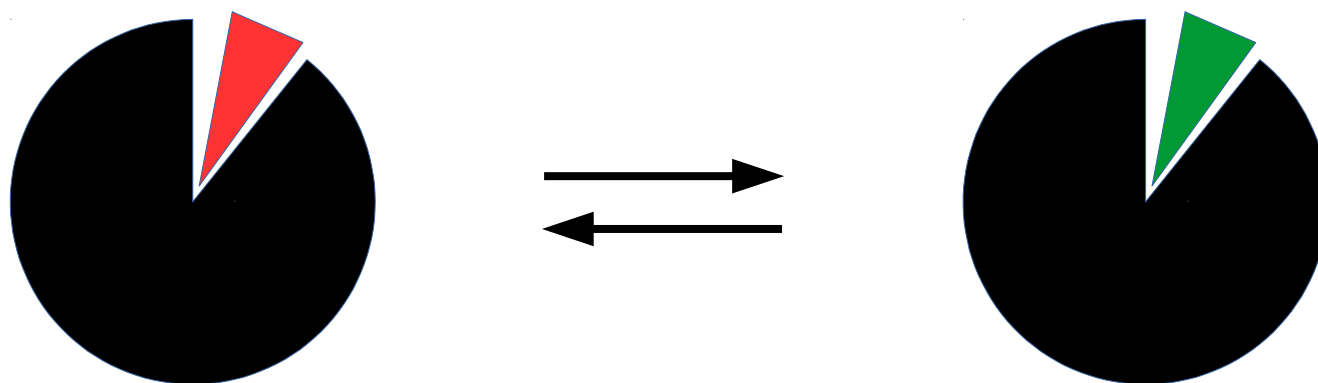
$$\Delta G_{\text{bind}}^0 = RT \ln(K_d)$$

Quantifying ligand binding



- Bimolecular molecular dynamics simulations
- Sampling problem: need simulations long enough to quantify fraction of time bound and unbound

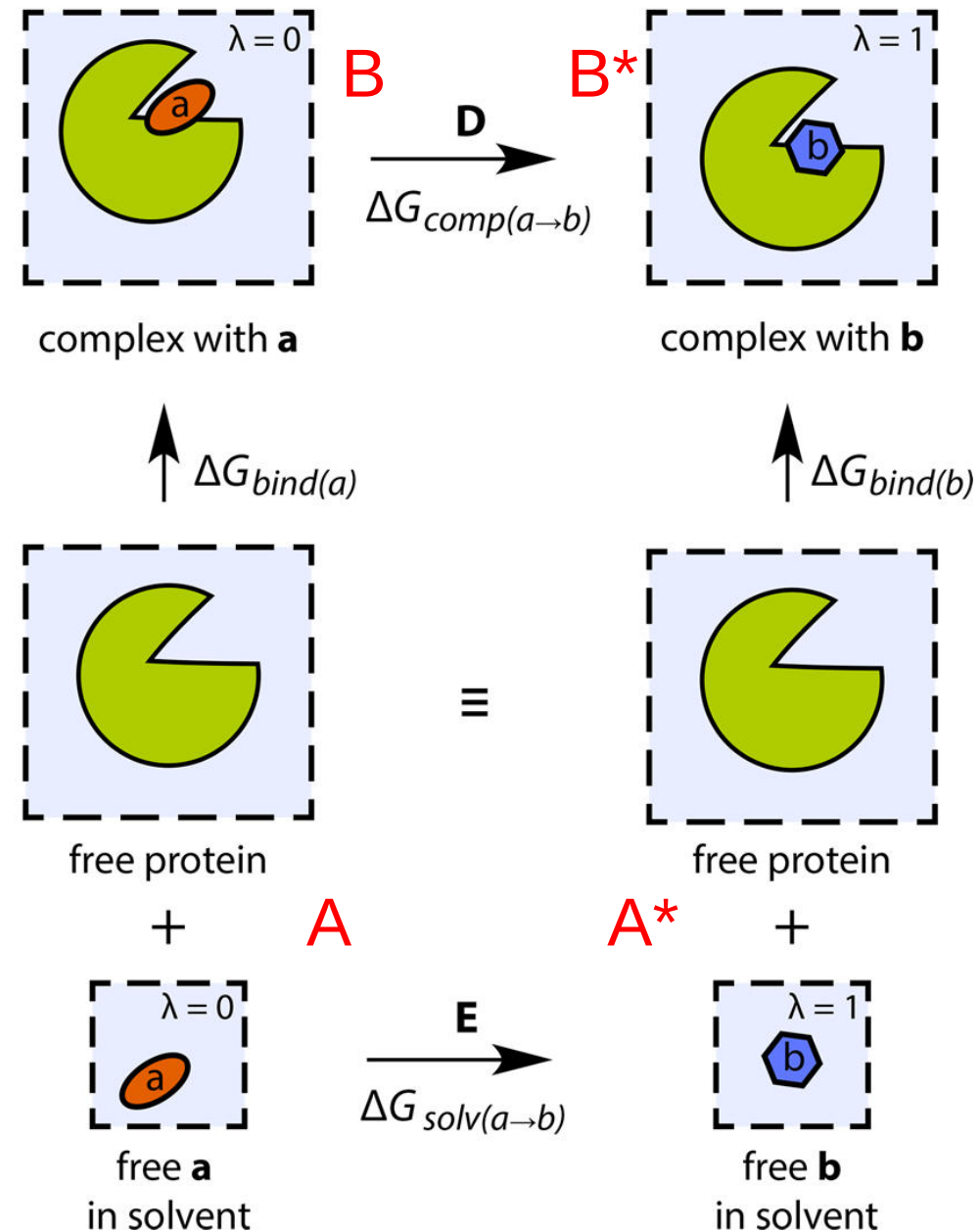
Quantifying ligand binding



- Free energy perturbation (FEP) methods are more efficient

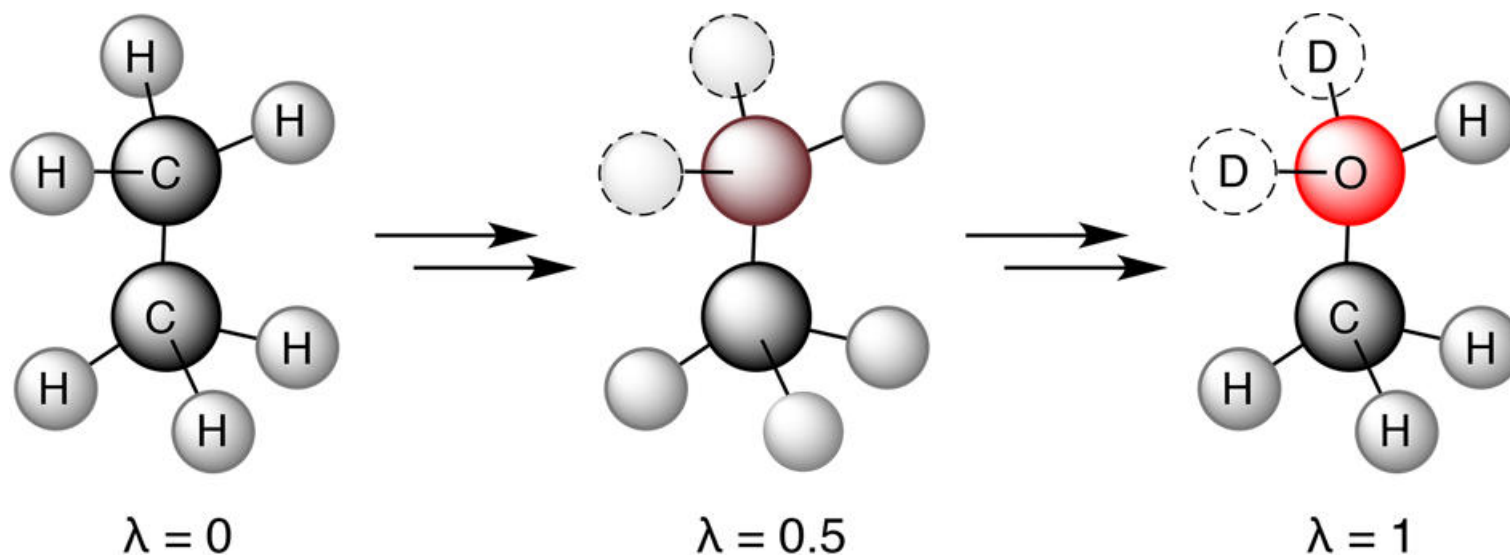
Free energy perturbation

- Morph the ligand from state **A** to state **A*** (or **B** to **B***) instead of simulating the binding event
- Simulation to allow systems **A** and **B** to sample different conformations

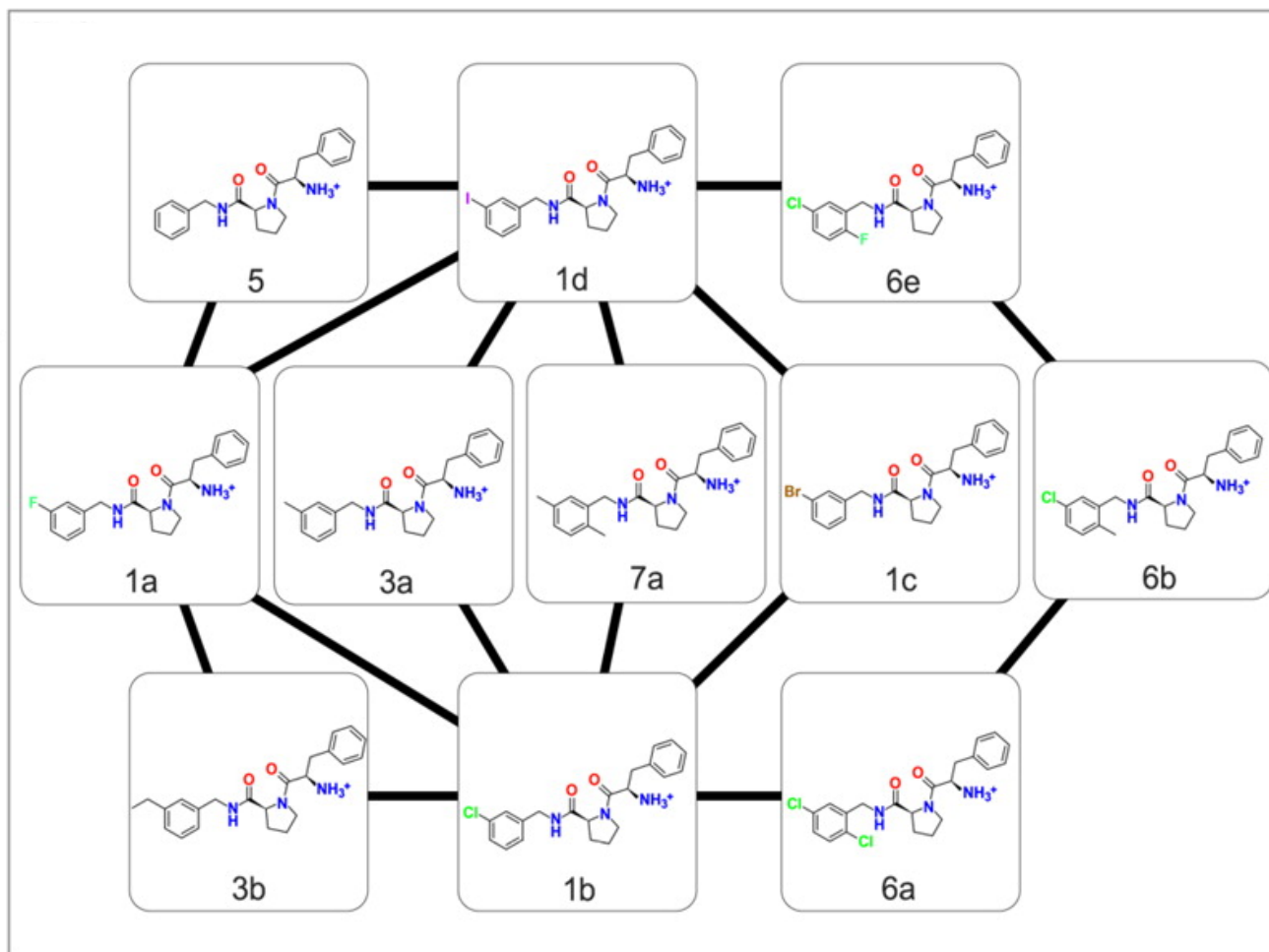


Free energy perturbation

- Transformation from A to A^* occurs over a number of discrete steps



Exploring the space of perturbations



Modern approach to FEP

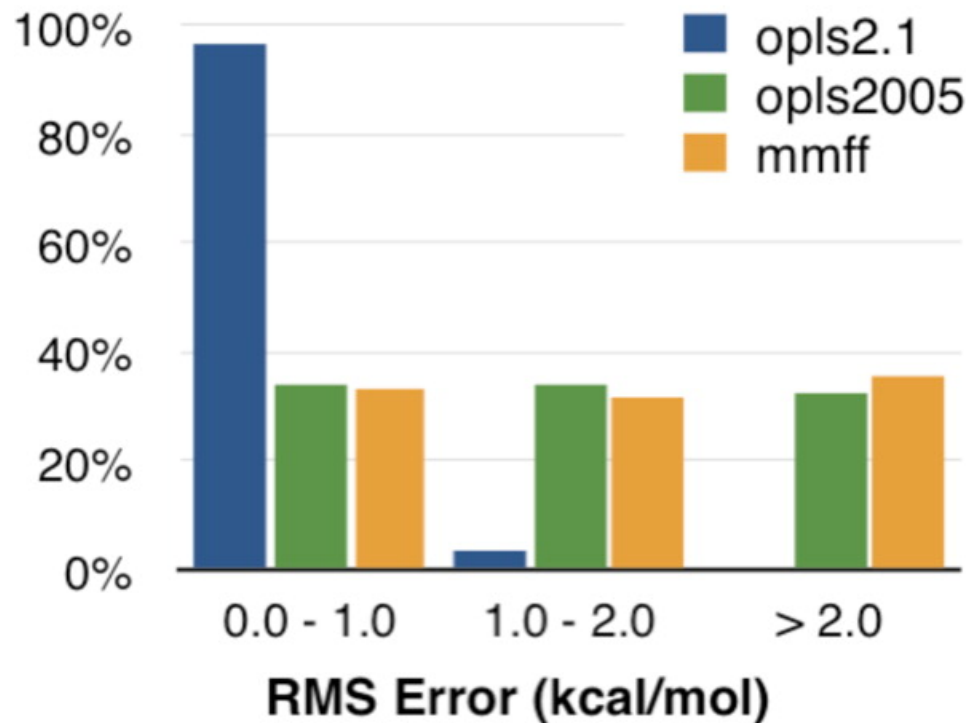
- FEP methods have been around for over 30 years, but previously limited by high computational cost
- High throughput screening possible thanks to the parallelization afforded by GPUs
- Accuracy suitable for guiding lead optimization due to force field and sampling algorithm improvements

OPLS2.1: Force field for drug-like molecules

- Optimized Potential for Liquid Simulations
- Force fields are usually not fit to data for drug-like molecules
- OPLS2.1 force field is more robust in the treatment of drug-like ligands.

OPLS2.1 in FEP

- If a missing torsion is identified, augment the force field with new fitted parameters
- 89/199 ligands had at least one missing torsion

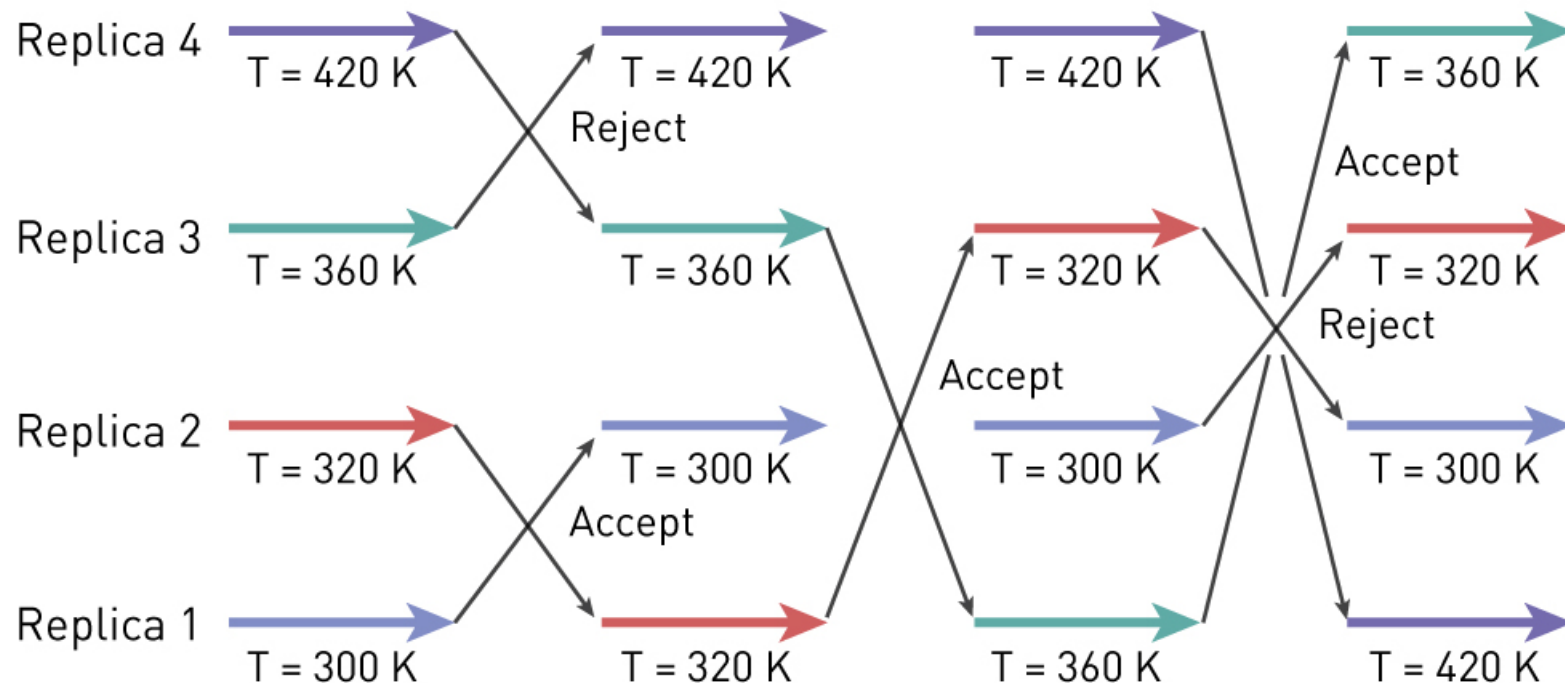


Sampling the conformation space

- Improving sampling in FEP by using replica exchange
- Required for accurate statistics and proper representation of the conformations sampled by the system

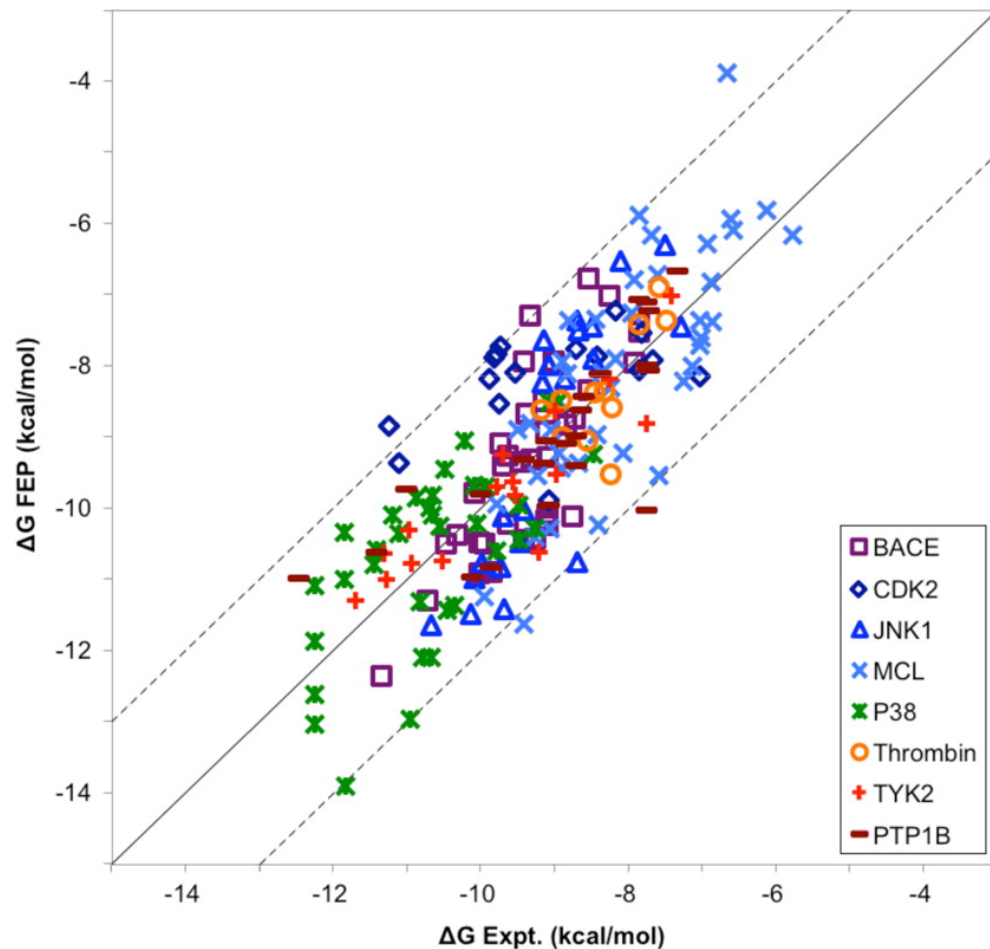
Replica exchange

- Replica systems run in parallel at different temperatures can exchange coordinates to allow for enhanced sampling of the phase space



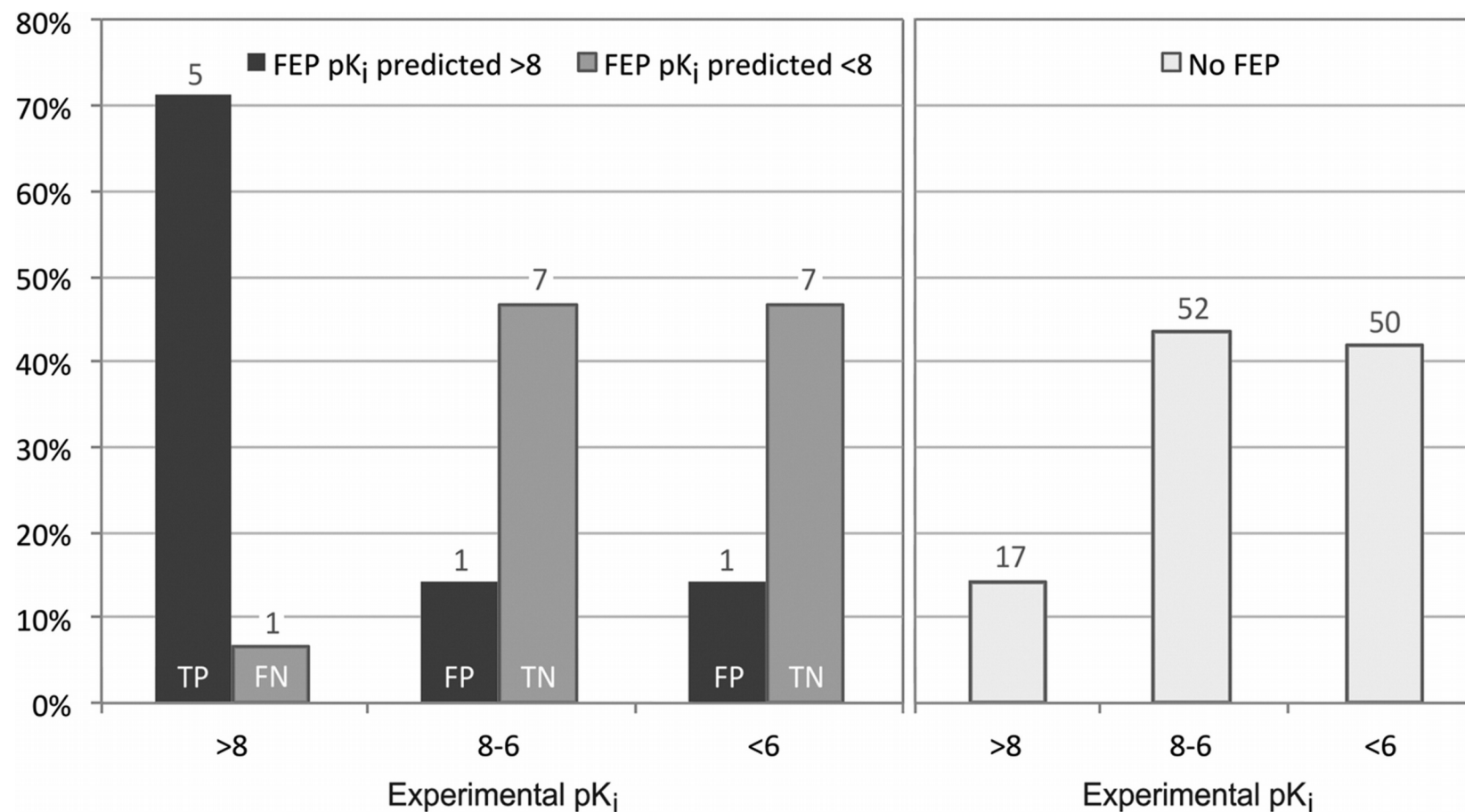
Results: method validation

- For eight different receptors, perturbed ligands are predicted to bind with affinities within 2 kcal/mol of experimental results.



Application to drug discovery

- Proof of principle on inhibitors for IRAK4
- F = False, T = True, P = Positive, N = Negative



Limitations

- Force field accuracy is benchmarked against other force fields and QM data (chemical torsions and conformational energies), but not validated against experiment.
- OPLS2.1 force field is possibly over fit.
- There are important constraints on the ligand (other than tightness of binding) that are important that are not addressed and the possible perturbations of candidate ligands is limited by the starting structure.

Incorporation of protein flexibility and conformational energy penalties in docking screens to improve ligand discovery

Marcus Fischer^{1,2†}, Ryan G. Coleman^{1†}, James S. Fraser^{3★} and Brian K. Shoichet^{1,2★}

Nikhil Goel

Problem: Proteins Fluctuate

[Conformation Sampling](#)

Existing Strategies

A battle of biases

Soft Docking

Bias: Flexibility

- Loosen the steric component.
- Which ligands *might* be accommodated by certain protein rearrangements?
- Consequence: Increased docking false positives.

Explicit Docking

Bias: Known Structures

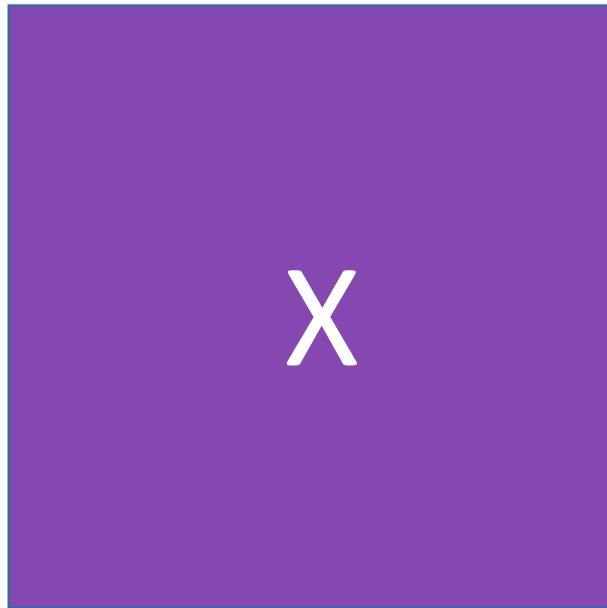
- Ensures accessible states.
- Which ligands *are* accommodated by certain protein rearrangements?
- Consequence: Limited # of states.

New Strategy

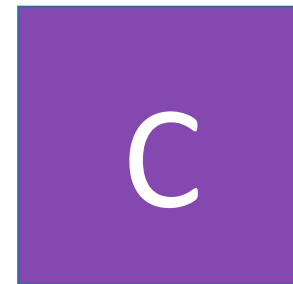
[Flexible Docking](#)

Higher-Energy Alternatives

Bias: Local Minima



* 10%

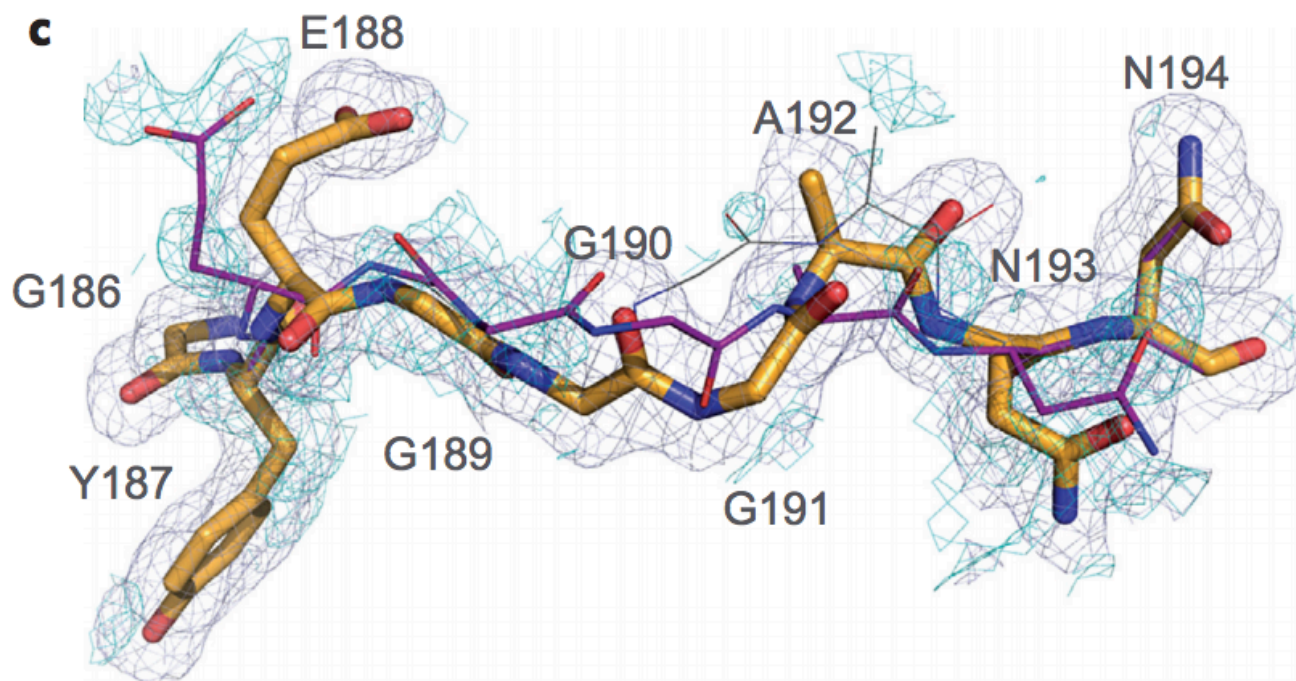


Anionic cavity site in cytochrome c peroxidase

583,363 compounds

x

16 energy-weighted
conformations

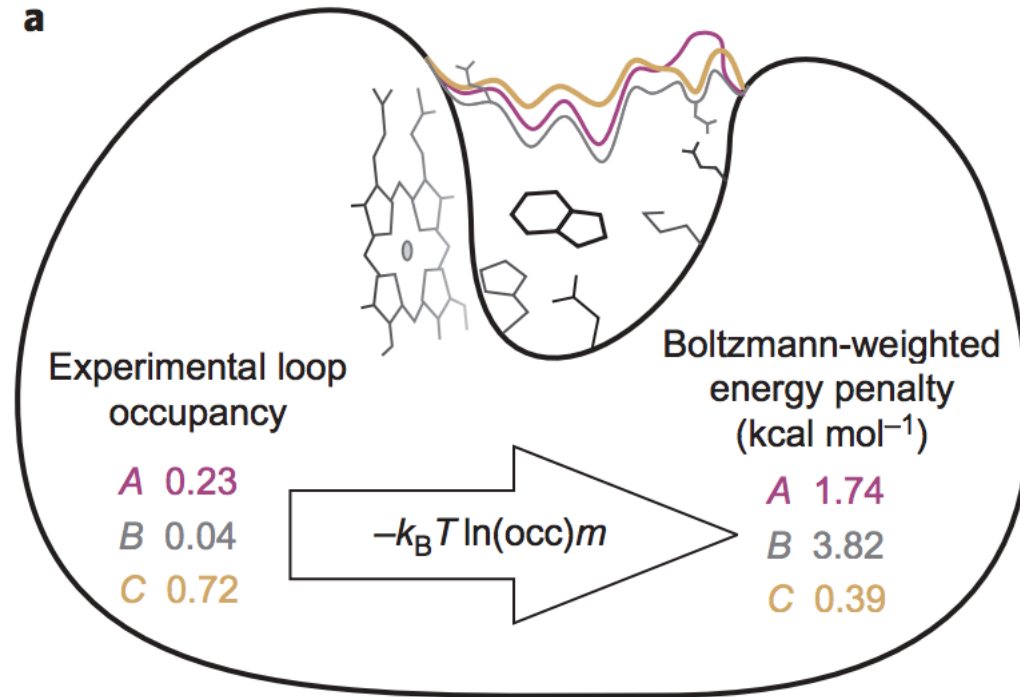


Decomposed interaction
energies into additive function

->

16 receptor states with
only 2.4x speed cost
compared with 1 state

Occupancies -> Energy Penalties

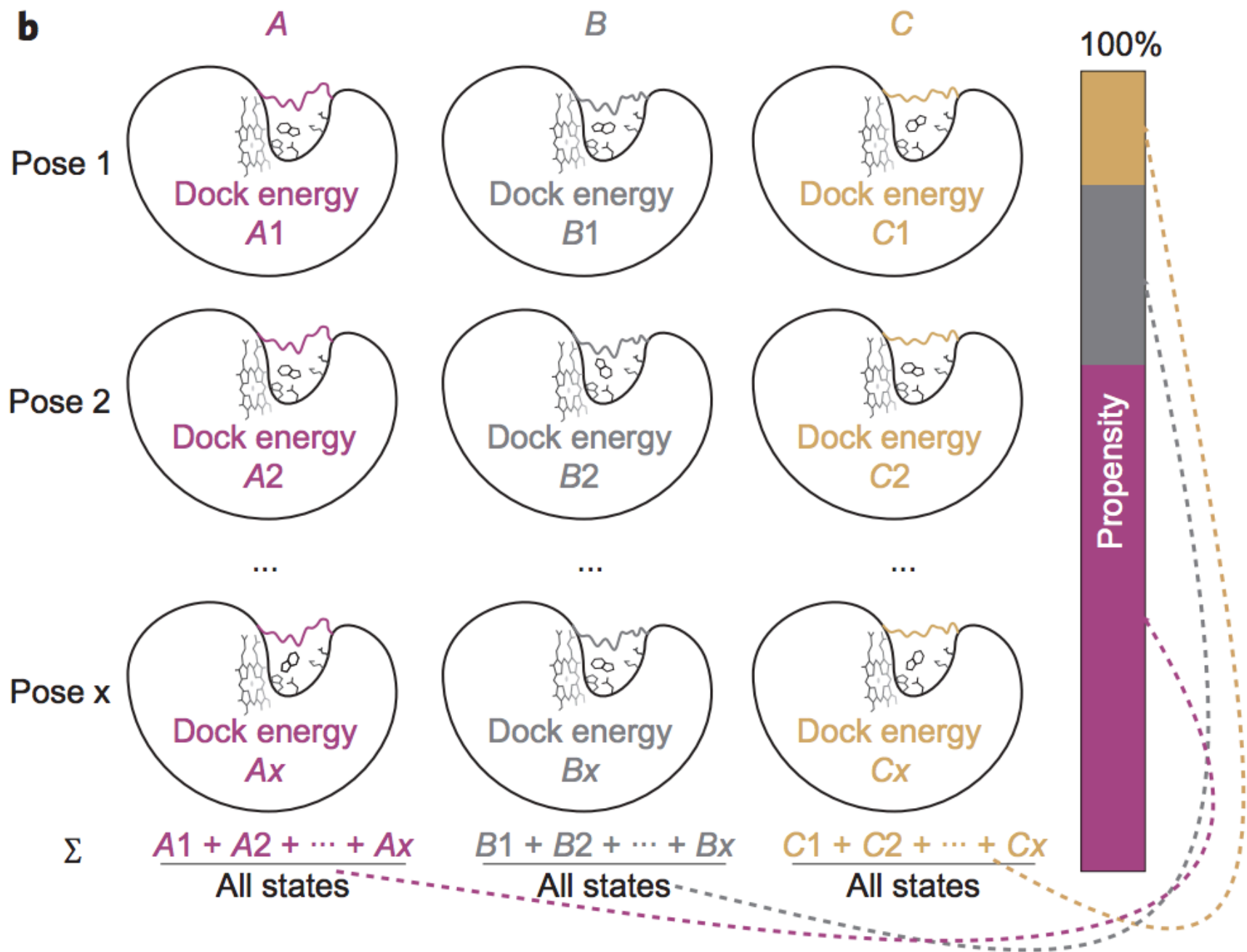


$$\text{energy penalty (conformation } A) = -k_B T \ln(\text{occ}(A))m$$

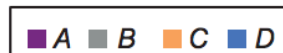
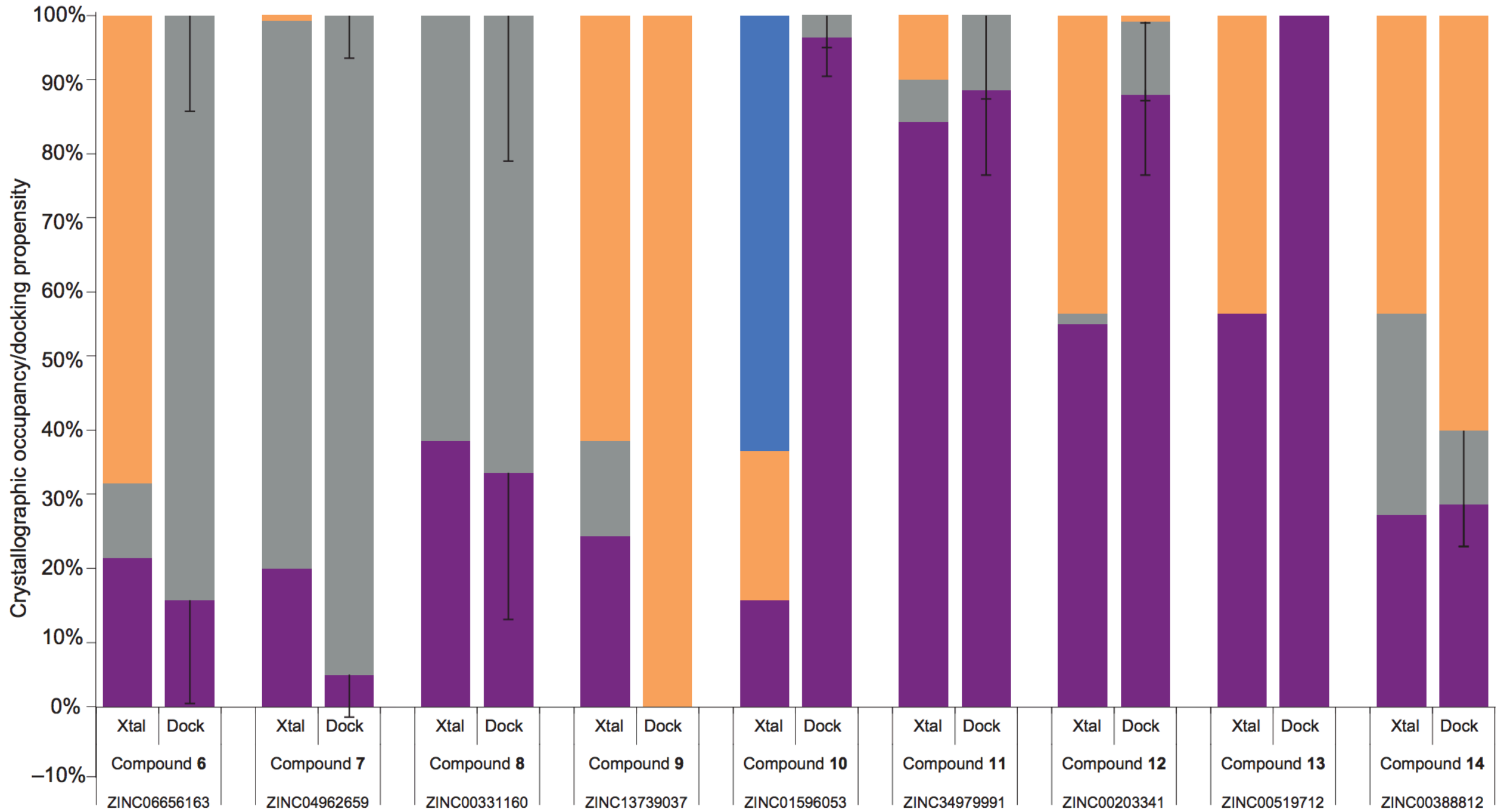
k_B = Boltzmann constant
 T = temperature (K)
 m = flexible weighting multiplier

$$\text{dock energy (loop } X, \text{ ligand } Z) = \text{energy penalty(loop } X) \\ + \sum_{\text{atom } z \in \text{ligand } z} V_{\text{dw}}(z) + \text{elstat}(z) + \text{ligand desol}(z)$$

$$\text{propensity}_{\text{ligand } Z, \text{loop } X} = \frac{\sum_{x \in \text{loop } X} e^{\text{dock energy}(x, Z) / kT}}{\sum_{y \in \text{all states}} e^{\text{dock engery}(y, Z) / kT}}$$



Results



Three Principle Observations

- 1) Alternative protein conformations with calculated energies.
- 2) Prediction of ligands with new properties.
- 3) We can apply this method to more proteins!

Strengths

- Novel Technique.
- Interesting findings in terms of the relationship between loop occupation and ligand propensity.
- Ligands with new phenotypes and chemical properties!

Limitations

- Data Availability
- Would this work for “messier” systems?
- In selecting a “simpler” system, have they created an ad hoc method?
- Docking scores make assumptions.