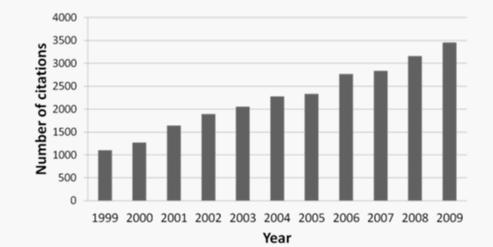
#### Focusing Conformational Ensembles on Bioactive-Like Conformations

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3rd Strasbourg Summer School on Chemoinformatics, Strasbourg, France, 25-29 June 2012

#### **Presentation Outline**

- Bioactive conformations: Definition and importance
- Experimental and computational identification of bioactive conformations
- Challenges in identifying and scoring bioactive conformations
- Bioactive conformational biasing
- Bioactive conformations of drugs: Preliminary analysis
- Conclusions and future directions

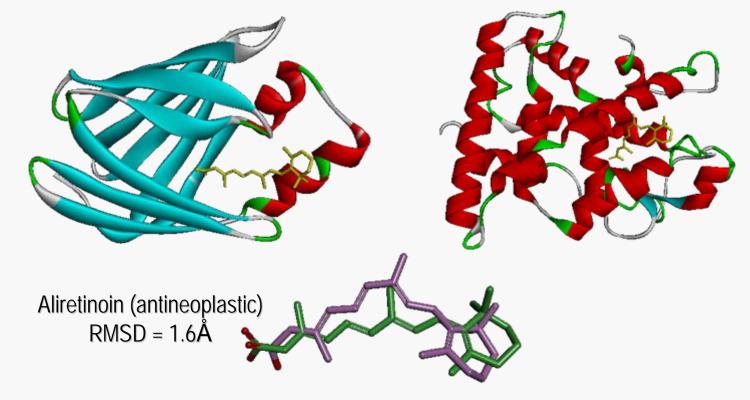


#### **Bioactive Conformations**

- The conformation adopted by a compound when bound to its bio-target
- The conformation responsible for the biological activity
- Bioactive conformations are target-dependent

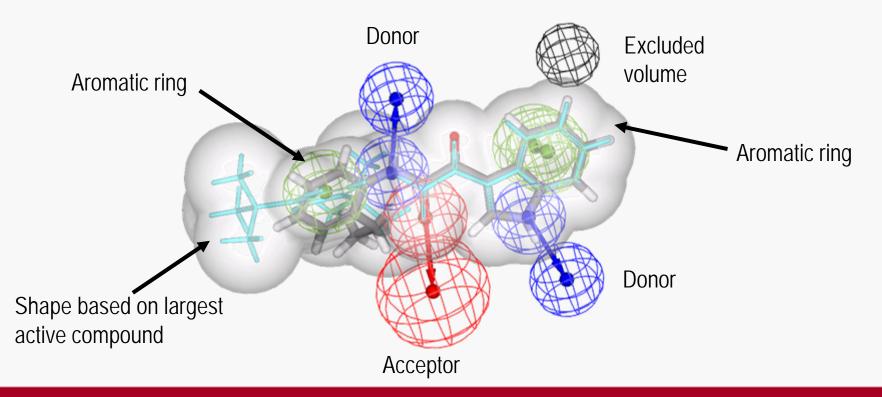
Retinoic acid binding protein

Nuclear receptor



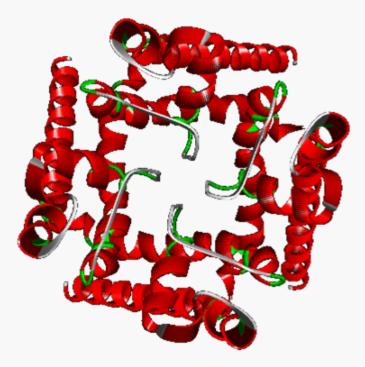
## Ligand-Based Drug Design: Pharmacophore

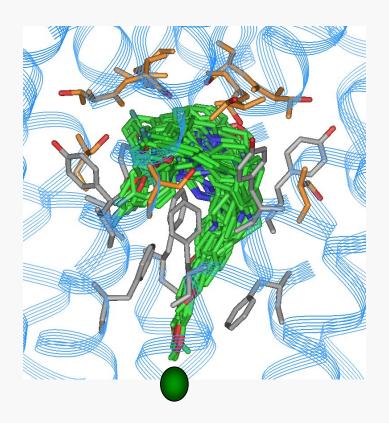
- Pharnacophore: A 3D arrangement of function groups which is responsible for the biological activity
  - Obtained by the superposition of active (and inactive) compounds
  - Assumption: Compounds represented by their bioactvie conformations



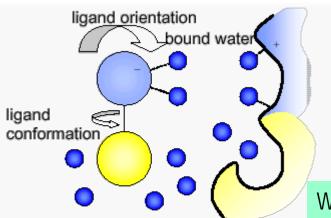
## Target-Based Drug Design: Docking

- Determine the most probable binding mode
- Approximate binding free energy
- Knowledge of bioactive conformation can eliminate erroneous binding modes

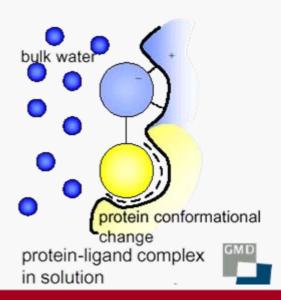




#### Target-Based Drug Design: Scoring



ligand and protein in solution



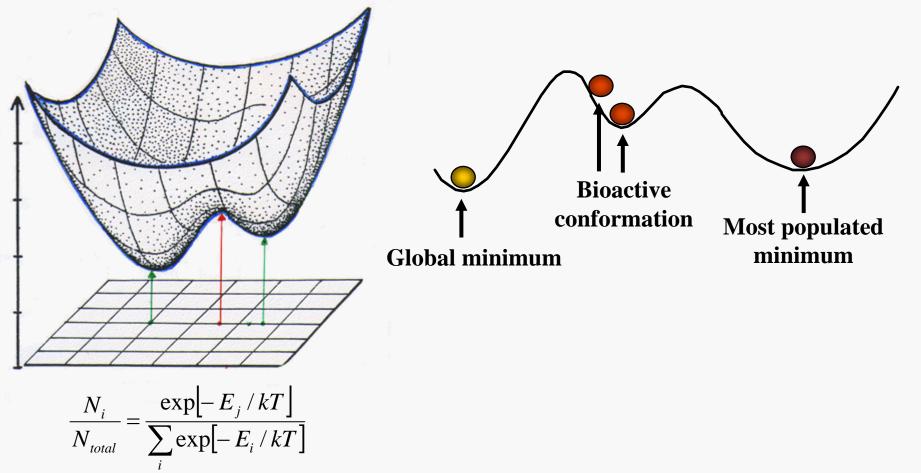
Contribution of Conformer Focusing to the Uncertainty in Predicting Free Energies for Protein-Ligand Binding (Tirado-Rives and Jorgensen, J. Med. Chem., 2006, 49, 5880-5884)

$$\Delta G_{cf} = \left(\varepsilon_k - \varepsilon_1\right) + \beta^{-1} \ln \left[\sum_i n_i \exp(-\beta(\varepsilon_i - \varepsilon_1))\right]$$

When a ligand binds to a protein, it is typically not in the lowestenergy conformation for the unbound ligand and there is also a loss of conformational degrees of freedom. The free-energy change for this "conformer focusing" is addressed here formally, and the associated errors with its estimation or neglect are considered in the context of scoring functions for protein-ligand docking and computation of absolute free energies of binding. Specific applications for inhibition of HIV-1 reverse transcriptase are reported. It is concluded that the uncertainties from this source alone are sufficient to preclude the viability of current docking methodology for rank-ordering of diverse compounds in high-throughput virtual screening.

## Potential Energy Surface (PES)

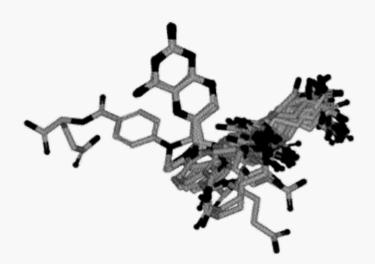
 An N atoms ligand is defined by 3N Cartesian coordinates or 3N-6 internal coordinates



## **Experimental Sources for Bioactive Conformations**

- Solid state (X-ray)
  - PDB (82,522 structure, 24,517 complexes ("has ligand" AND "300 < MW < 800"))</li>
  - CSD (596,810 entries; January 1<sup>st</sup> 2012)
  - Potentially subjected to crystal packing forces
  - Represent a single conformer
- Solution (NMR)
  - Analysis complicated by multiple conformations
  - Only few studies

Methotrexate Foloppe and Chen, Curr. Med. Chem. 2009, 16, 3381



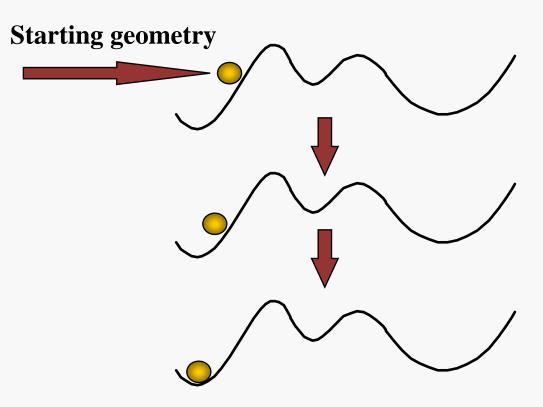
## **Computational Derivation of Bioactive Conformations**

- Approximate the true PES
  - ✤ Force Field:

$$V(r^{N}) = \sum_{bonds} \frac{k_{i}}{2} (l_{i} - l_{i,0})^{2} + \sum_{angles} \frac{k_{i}}{2} (\theta_{i} - \theta_{i,0})^{2} + \sum_{torsions} \frac{V_{n}}{2} (1 + \cos(n\omega - \gamma))$$
$$+ \sum_{i=1}^{N} \sum_{j=i+1}^{N} \left( 4\varepsilon_{ij} \left[ \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{12} - \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{6} \right] + \frac{q_{i}q_{j}}{4\pi\varepsilon_{0}r_{ij}} \right] + \text{cross terms}$$

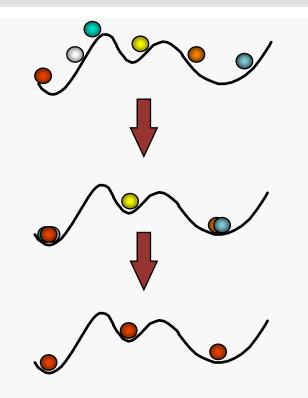
- \* QM:  $H\Psi = E\Psi$
- ✤ QM/MM
- Sample the PES
  - ✤ Minimization
  - Conformational search
  - Molecular dynamics (MD)
  - ✤ Monte Carlo (MC)

# **Energy Minimization**



- Depends on starting geometry
- Can only go down hill

## **Conformational Search**

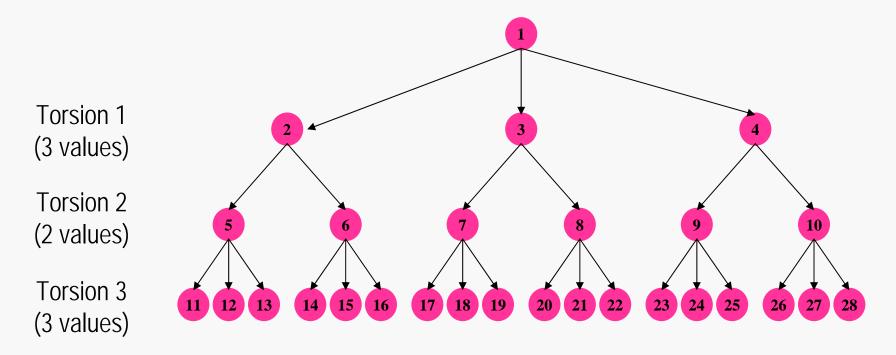


- Randomly or systematically generated starting geometries
- Energy minimization

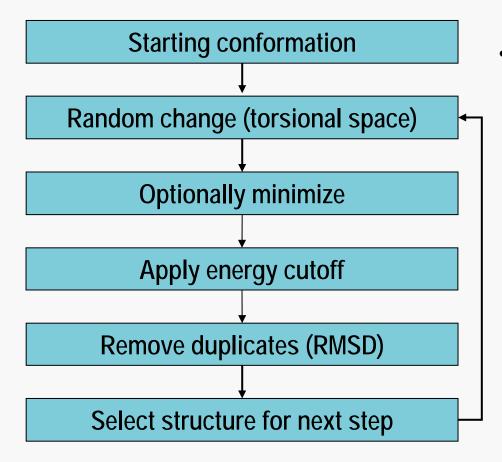
- <u>Duplicates elimination</u>
- Representative structures for each potential minimum
- Gives coverage of potential surface.
- · Combinatorial growth.
- Resulting ensemble reflects enthalpy only.

#### Systematic Search

- Test all combinations of all (torsional) DOF
- · Screen each torsion with a pre-defined granularity
- Optionally minimize structures
- · Computational cost is exponential with number of torsions



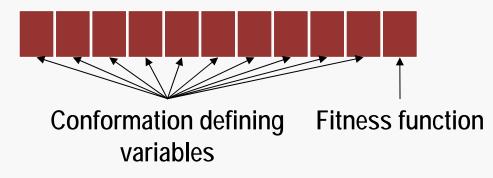
#### Stochastic Search

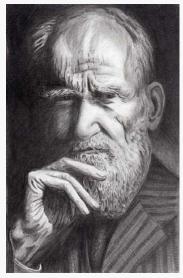


- Factors affecting performances
  - ✤ # cycles
  - ✤ Energy cutoff
  - RMSD threshold
  - ✤ Starting structure for next cycle

## Genetic Algorithm

- Create a random populations of conformations (chromosomes)
- For each chromosome calculate a fitness value (conformational energy)
- Evolve population using genetic operators (selection of the fittest, mutations, cross-over)
- Optimize fitness function

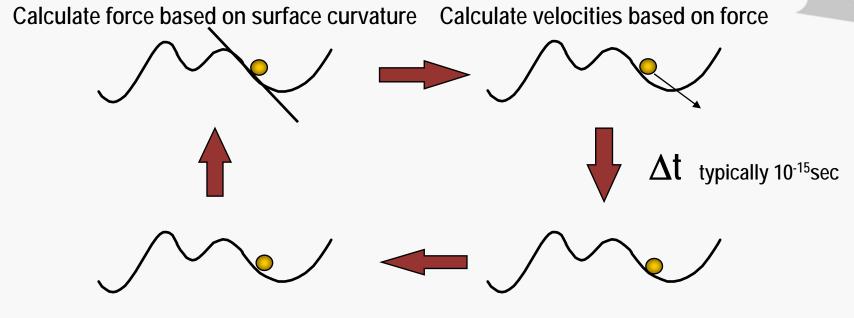




## Additional Conformation Search Methods

- Rule based (e.g., Omega)
  - Use pre-defined fragment conformations obtained, e.g., from CSD
- Tabu search (e.g., Catalyst's poling)
  - Avoid re-visiting already samples regiond of the PES
- Distance geometry
  - Used to derive structures from NMR data
- And many others...

## Molecular Dynamics

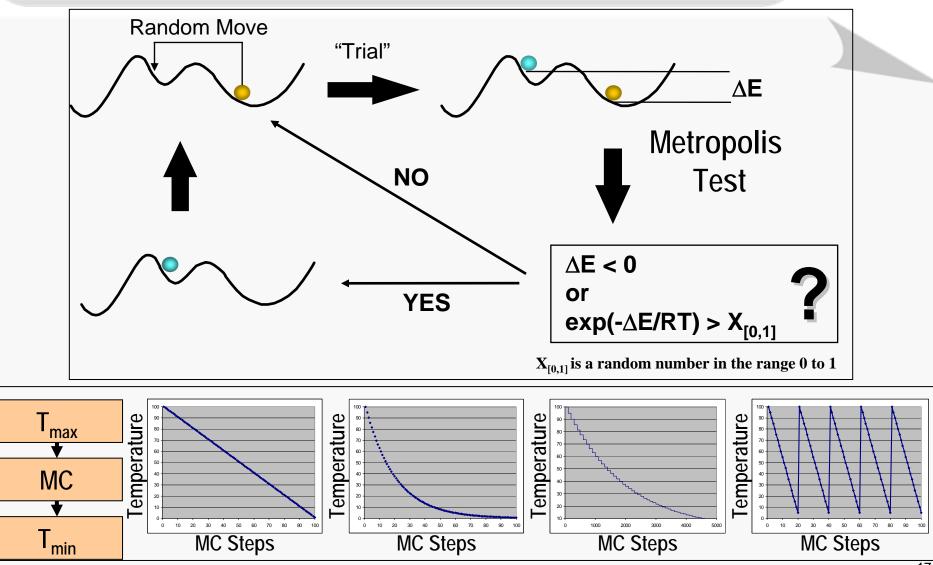


Save energy and geometry for average

Calculate new position

- Gives average quantities which reflect free energy
- Slow to cross barriers ~2-3 kcal/mol

#### Monte Carlo/Simulated Annealing (MC/SA)



17

#### Performances of CS Methods

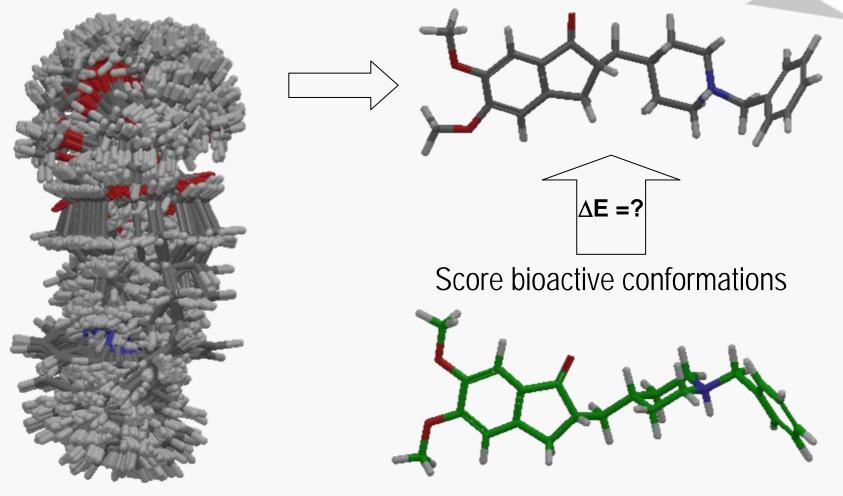
- Success determined in terms of having at least one structure close to the bioactive conformation
- All methods produce many conformations remote from the bioactive one, hence the need for focusing

Software	Dataset	Performances
Balloon	311	90% with RMSD < 2A
CAESAR	918	60% with RMSD < 1A
CAESAR	510	90% with RMSD < 2A
	32	47-50% with RMSD < 0.5A
	150	20% with RMSD < 0.5A
Catalyst		69% with RMSD < 1A
Gatalyst	193	70% with RMSD < 1A
	510	80% with RMSD < 1.5A
		93% with RMSD < 2A
ConfGen	253	80% with RMSD < 1A
Confort	32	34% with RMSD < 0.5A
Cyndi	742	MECMB: 54% with RMSD < 1A
Cyndi		FFMB: 37% with RMSD < 1A
Flo99	32	62-66% with RMSD < 0.5A
ІСМ	150	20% with RMSD < 0.5A
		69% with RMSD < 1A
MacroModel: LMCS	32	69% with RMSD < 0.5A
MOE	256	95% with RMSD < 1.5A
	32	41-50% with RMSD < 0.5A
Omogo	36	56-78% with RMSD < 0.5A
Omega	150	27% with RMSD < 0.5A
		69% with RMSD < 1A

#### Challenges in the Field of Bioactive Conformations

Produce conformational ensemble

Identify bioactive conformation(s)



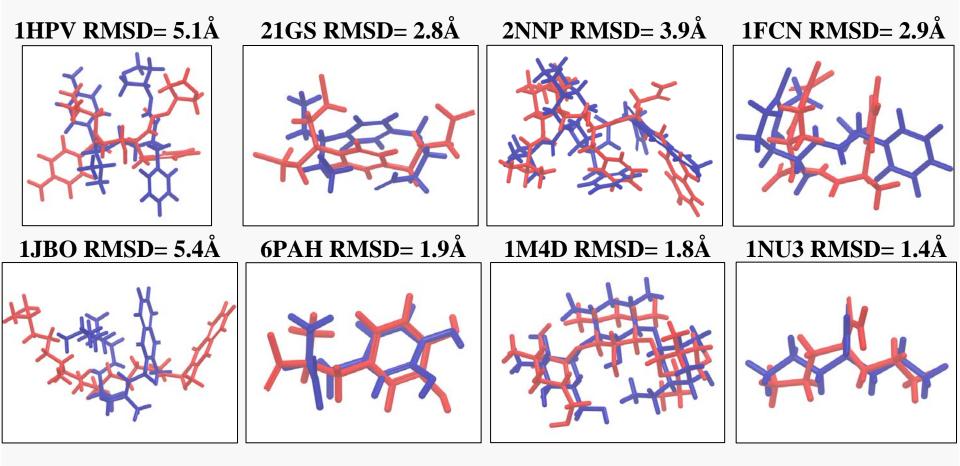
#### Challenges in Defining the Bioactive Structure

- Assume: crystal conformation represents the bioactive conformation
- Assumption questionable (but not enough solution phase data)



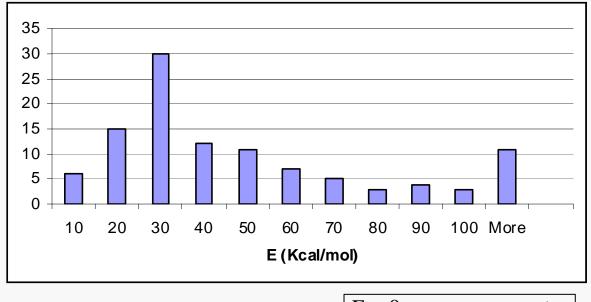
## Identify Bioactive Conformations: Structure

 Assumption: Bioactive conformations more elongated than global energy minima



#### Challenges in Determining the Bioactive Conformational Energy

 $E_{bioactive}$ - $E_{closest\_minima}$  (OPLS-AA; Kcal/mol; RMSD = 0.5±0.1)



- Unconstrained minimization
- Protein-constrained minimization
- Flat-bottom constrained minimization
- B-Factor constrained minimization -

$$E = 0 \qquad r \le \sigma$$
$$E = k(r - r_0)^2 \qquad r > \sigma$$
$$r = |r - r_0|$$

$$E = k(r - r_0)^2; k = 4\pi^2 k_B T / B$$

#### Minimization

E = 232 Kcal/mol	PDB	Unconstrained	Protein constrained	B-factor constrained
ML. IN	1BZM	0.39	0.61	0.12
M M	1CBX	0.56	0.76	0.07
	1FKF	0.38	0.57	0.06
	1HPV	0.74	0.51	0.12
E = 34 Kcal/mol	1HVR	1.11	0.56	0.05
	1ADD	0.51	0.85	0.06
my w	1CPS	0.37	0.55	0.16
* With	1PSO	0.88	0.58	0.11
	1TLP	0.50	0.62	0.12
	2GBP	0.17	0.29	0.00
	Ave	0.56 <b>±</b> 0.28	0.59 <b>±</b> 0.15	0.09 <b>±</b> 0.05

# Identify Bioactive Conformations: Energy

- Assumption: Bioactive conformations reside within well defined energy windows relative to global energy minima
- Reality: Not necessarily
- Some estimates are clearly unreasonable
- Discrepancies from
  - Inappropriate definition of bioactive conformations
  - ✤ Inappropriate force fields
  - Different data sets
  - Low resolution structures

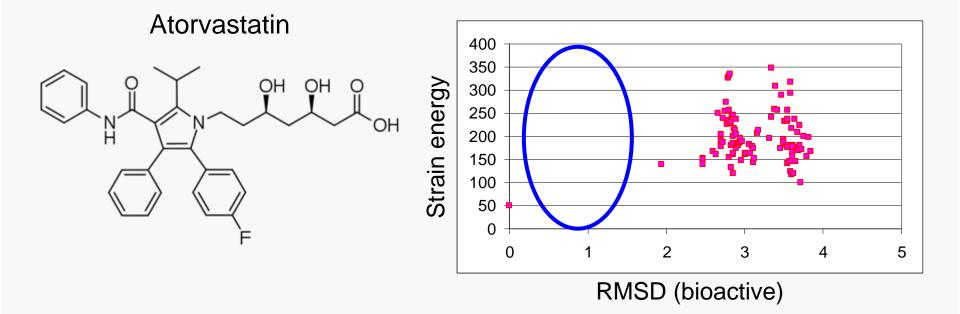
Program	Force field	Energy cutoff (kcal/mol)
Catalyst	Modified CHARMM	20
Catalyst	Modified CHARMM	<b>10,</b> 20
Catalyst	Modified CHARMM	20
Catalyst	Modified CHARMM	7, 12, 15, <b>20,</b> 30, 40
MOE	MMFF94x	7, 12, 15, 20, 30, 40, > <b>15</b>
MacroModel	AMBER & MM3	12
MOE	MMFF94x	20
OMEGA	MMFF	3.3, 6.9, <b>50</b>
OMEGA	MMFF94s	3, <b>5,</b> 7
OMEGA	MMFF94s	5

## Bioactive Conformational Biasing: A New Method for Focusing Conformational Ensembles on Bioactive-Like Conformers

- Goal
  - Enrich conformational ensembles by bioactive-like conformations (RMSD < 1Å)</li>
  - Retain a sufficiently large number of bioactive-like conformations
  - ✤ De-rich conformational ensembles by non-bioactive conformations (RMSD > 2.5Å)
- Dataset
  - ✤ 71 ligands (47 in training, 24 in test)
  - Ligand and protein diversity
  - High resolution proteins
- Conformational ensembles generated in MacroModel

#### **Pre-Filtration**

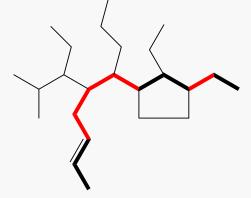
• Can we always identify bioactive conformations?



#### **Pre-Filtration: M-PROB**

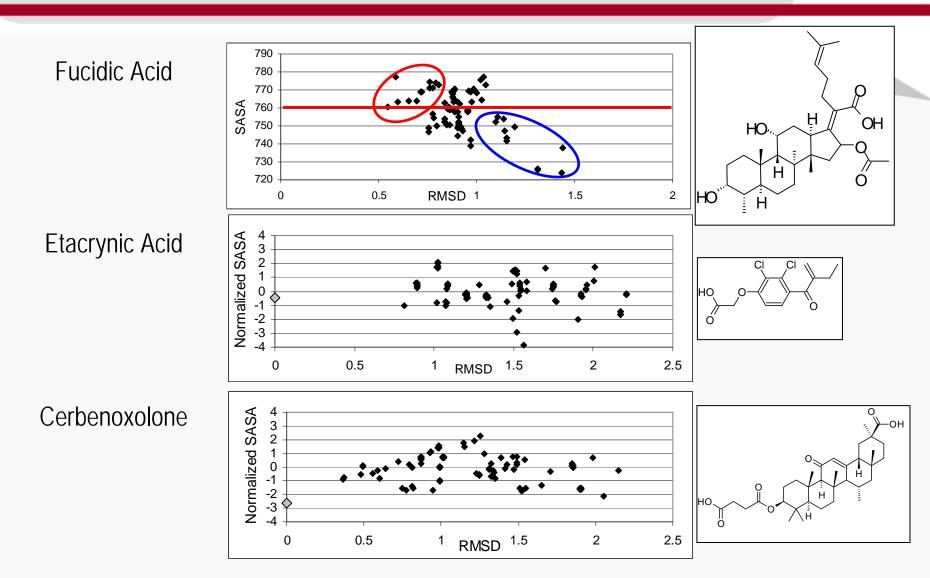
• Can we always identify bioactive conformations? NO!

M-PROB: No. of rotatable bonds along maximal path

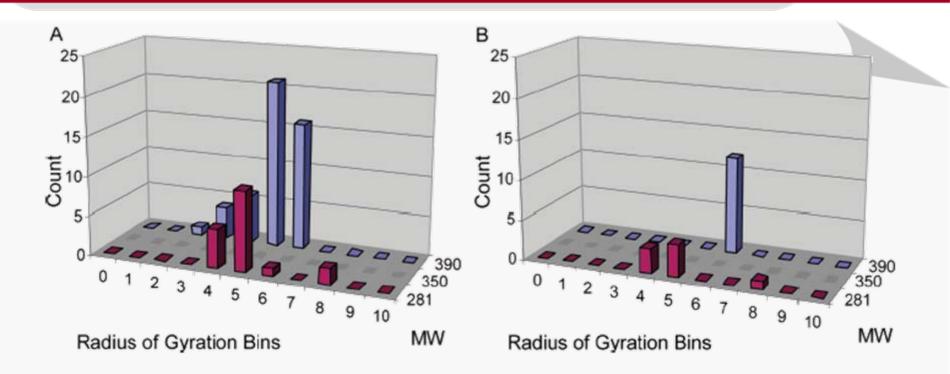


M-PROB	1-3	4-5	6-7	8-9	10-18
# ligands	16	10	11	5	5
# "good" ligands	16	7	9	0	3
# "bad" ligands	0	1	2	5	2

#### Single 3D Descriptors: SASA

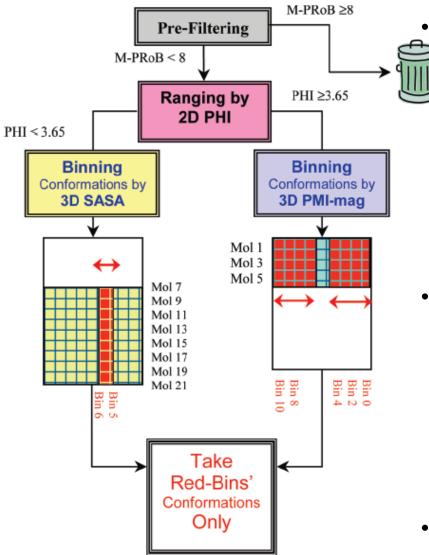


#### 2D-3D Combination: MW & ROG



MW > 350  $\Rightarrow$  bin 6 (retrieve bioactive conformations of cyclothiazide; blue) MW < 350  $\Rightarrow$  bins 4,5 (retrieve bioactive conformations of flufenamic acid; red)

## 2D-3D-3D Models

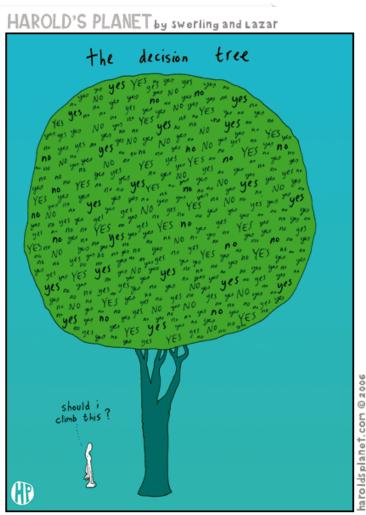


#### Pre-filtration

- ✤ 5 compounds pre-filtered
- ✤ 1 with a single bioactive conformations
- ✤ Sensitivity 80%
- 2 compounds with no bioactive conformation not filtered
- Filtration
  - ✤ 36% of all conformations removed
  - ✤ 39% of "bad" conformations removed
  - \* 26% of "good" conformations removed
  - 74% compounds retained sufficiently large number of "good" conformations
- Overall success rate: 75%

## Interim Conclusions & Future Work

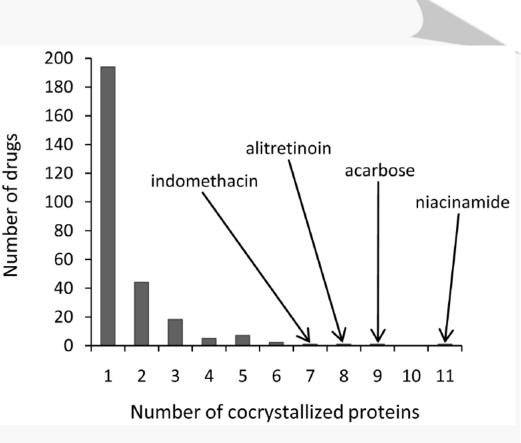
- Conformational ensembles could be focused on • bioactive conformations using ligand characteristics
- A larger data set
- Incorporate target information ٠
  - Bioactive conformations are target dependent
- A more flexible algorithm
  - Test more descriptors combinations



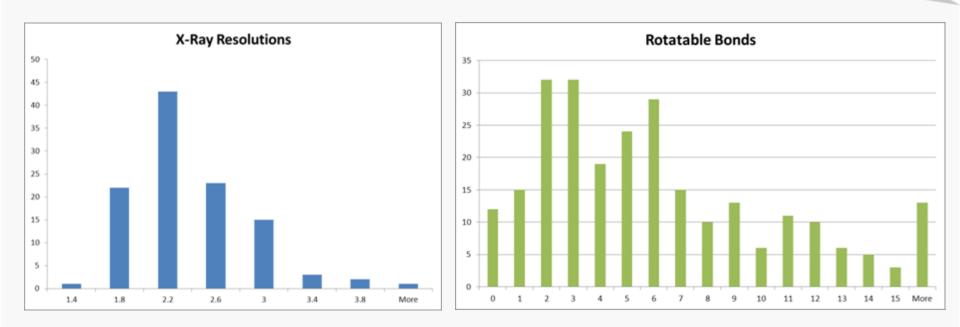
# A Drug Binding Site Database

(Kinnings et al. PLoS Computational Biology, 2010, 6, 1)

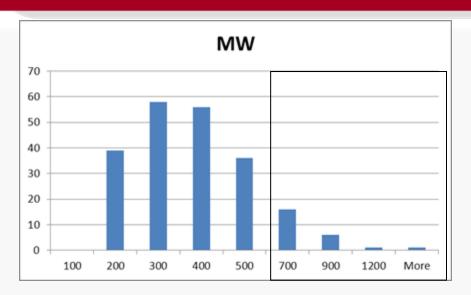
- 274 approved drugs
- 962 drug binding sites
- 194 drugs co-crystallized with a single unique protein
- Multiple drugs crystallized with multiple proteins
  - Indomethacin (non-steroidal antiinflamatory)(7)
  - Alitretinoin (antineoplastic)(8)
  - Acarbose (anti-diabetic)(9)
  - Niacinamide (vitamin)(11)

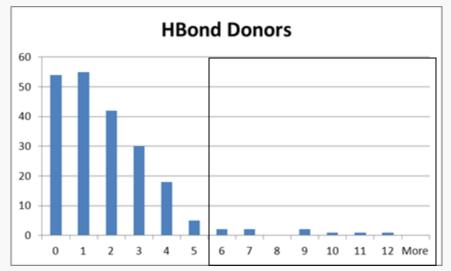


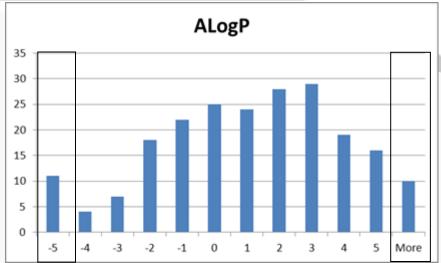
#### **Database Characteristics**

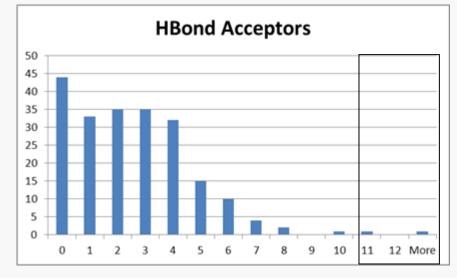


#### Database Characteristics: Lipinski's Rules



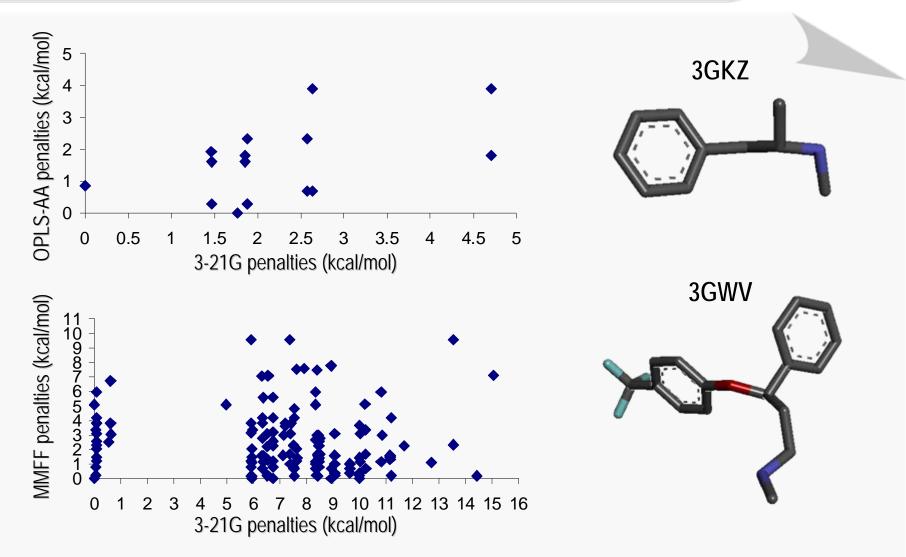






#### The Workflow **Produce conformational ensembles** Score conformational ensembles Focus on bioactive conformations Nrot $\leq 6$ (123) **Conformational Search Pick Bioactive** Database LMCS/MCMM (OPLS, MMFF) Conformation Nrot > 7 Catalyst (CHARMm) (77) **Data Analysis Minimization Torsional Clustering** (30°) **Global Minimum** 3-21G, 6-31G\*, OPLS-AA, **Pick Centroids** "Bioactive" conformation MMFF, CHARMm

#### Did We Really Need to Work That Hard (~15K QM Calc.)?



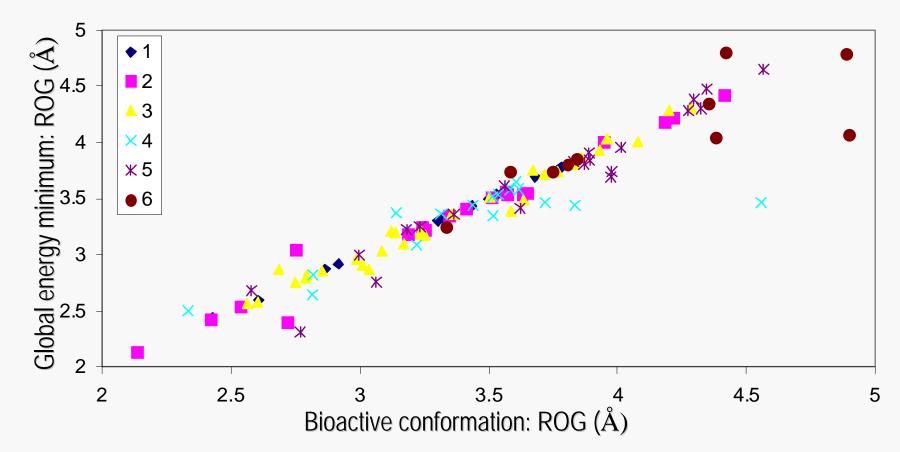
## Can CS Methods Generate Bioactive Conformations?

	# ligands	RMSD < 0.5Å	RMSD < 1.0Å	RMSD < 1.5Å	RMSD < 2.0Å	RMSD > 2.0Å
OPLS-AA	117	0.62/ <mark>0.22</mark>	0.91/ <mark>0.56</mark>	0.97/ <mark>0.73</mark>	0.99/ <mark>0.88</mark>	0.01/ <mark>0.12</mark>
MMFF	119	0.63/ <mark>0.20</mark>	0.92/0.54	0.98/0. <mark>7</mark> 9	1.00/0.93	0.00/0.07
CHARMm	120	0.78/ <mark>0.20</mark>	0.97/ <mark>0.52</mark>	1.00/0.74	1.00/ <mark>0.91</mark>	0.00/0.09
	# ligands	RMSD < 0.5Å	RMSD < 1.0Å	RMSD < 1.5Å	RMSD < 2.0Å	RMSD > 2.0Å
OPLS-AA	110	0.75 <mark>/0.28</mark>	0.98/ <mark>0.67</mark>	1.00/0.81	1.00/0.93	0.00/0.07
MMFF	110	0.74/ <mark>0.26</mark>	0.98/ <mark>0.58</mark>	1.00/0.80	1.00/0.95	0.00/0.05
CHARMm	110	0.78 <mark>/0.23</mark>	0.98/ <mark>0.56</mark>	1.00/0.75	1.00/0.92	0.00/0.08
3-21G	110	0.73 <mark>/0.2</mark> 1	0.98/ <mark>0.5</mark> 1	1.00/0.75	1.00/ <mark>0.94</mark>	0.00/0.06
6-31G*	88	0.83/ <mark>0.32</mark>	0.99/ <mark>0.66</mark>	1.00/0.83	1.00/ <mark>0.97</mark>	0.00/0.03

- In general, our workflow can produce bioactive conformations slightly better than "standard" CS methods
- From within the methods tested in this work, OPLS-AA and 6-31G\* perform the best

#### Identify Bioactive Conformation: The Structure

- Assumption: Bioactive conf. more elongated than global energy minima
- Reality: Not necessarily



## Hydrophobicity Dependent Ligand Unfolding

• Hydrophilic ligands tend to fold in their binding sites

RotBond = 5, 6	n	ClogP	ROG <sub>bioactive</sub> - ROG <sub>global minimum</sub>
Hydrophilic ligands (ClogP < 0)	12	-1.9±1.1	-0.14±0.27
Hydrophobic ligands (ClogP > 0)	19	2.5±1.5	-0.02±0.17

$$2ZQ9: ClogP = -1.13$$

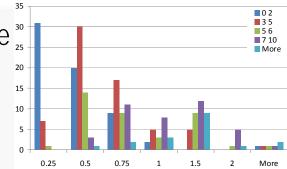
$$ROG_{bioactive} - ROG_{global minimum} = -0.83$$

$$3CLB: ClogP = 1.15$$

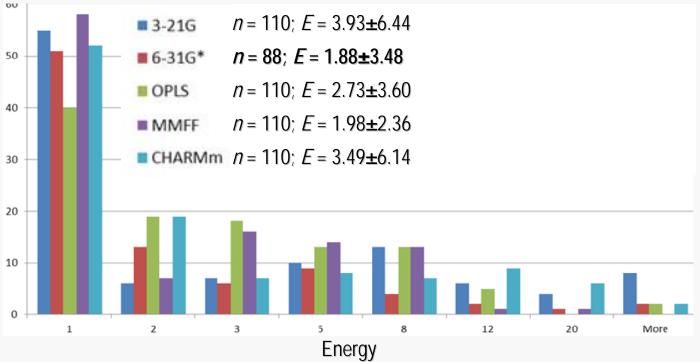
$$ROG_{bioactive} - ROG_{global minimum} = 0.39$$

#### Force Field-Based Conformational Focusing Energies

 Conformational focusing energies calculated relative to the constrained-free minimized bioactive conformation



# Conformational Focusing Energies (kcal/mol)



#### Comparison with Docking

- Glide docking with default parameters
- Success defined according to lowest energy structures

	# ligands	Average	SD	RMSD < 0.5Å	RMSD < 1.0Å	RMSD < 2Å
Docking	110	0.78	0.61	0.42	0.83	0.95
3-21G	110	1.05	0.63	0.21	0.51	0.75
6-31G*	88	0.84	0.57	0.32	0.66	0.97
OPLS-AA	110	0.92	0.62	0.28	0.67	0.93
MMFF	110	0.94	0.60	0.26	0.58	0.95
CHARMm	110	1.04	0.68	0.23	0.56	0.92

# Conclusions I

- Bioactive conformations are important and interesting
- Can CS methods generate bioactive conformations?
  - For rigid ligands (# RotBonds ≤ 6) a bioactive conformation is likely to be found in the conformational ensemble, although not as the global minimum.
  - For more flexible ligands (# RotBonds ≥ 8) the probability of identifying bioactive conformations is lower
  - Our workflow performs better in these respect thans "simple" CS methods
  - Medium level QM calculations show promise
- Could bioactive conformations be identified based on their structures?
  - Probably but more work is needed
  - ✤ Bioactive conformations are not necessarily more elongated than global minima ones

## Conclusions II

- Could bioactive conformations be identified based on their energies?
  - Our data support energy cutoffs in the order of 5-6 kcal/mol for force field calculations
  - QM data show a trend towards lower penalties as the size of the basis set increases
- How well do CS methods reproduce bioactive conformations compared with docking simulations?
  - ✤ Docking is better than CS but medium level QM is not far behind
  - What does this tell us about our scoring functions?
  - Should we re-visit rigid docking?

#### Acknowledgments

#### Lab members

- Hannah Avgy
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- Lubov Simhaev
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- Michael Zenin

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• Dr. Boaz Musafia

