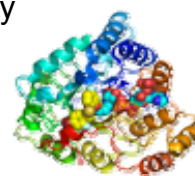


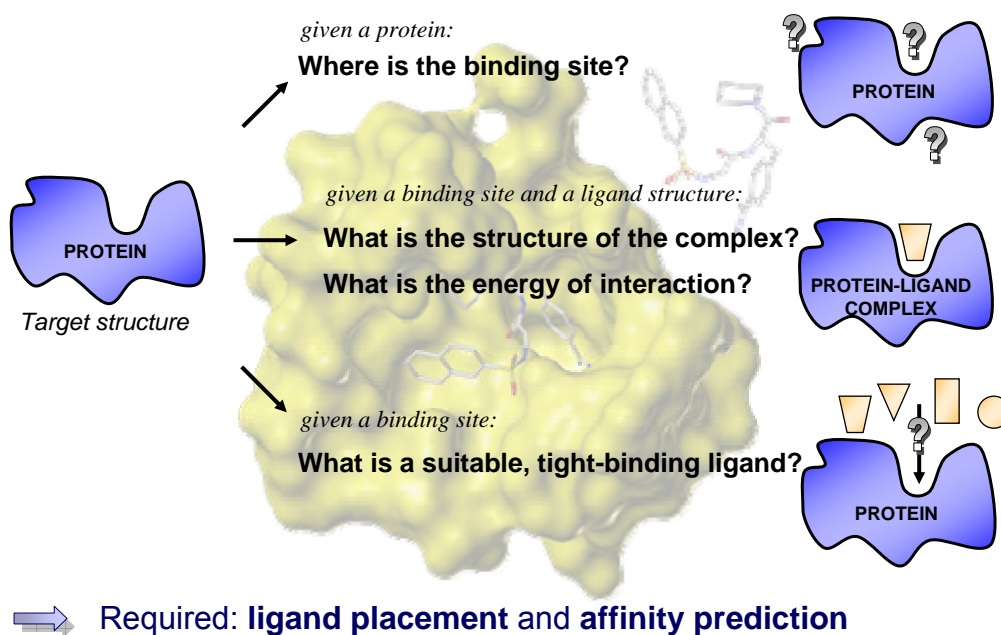
# Docking and scoring of protein-ligand complexes: *What is possible and what is not?*

Christoph Sotriffer

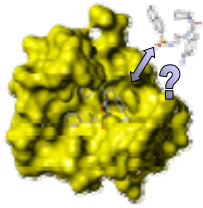
Institute of Pharmacy and Food Chemistry  
University of Würzburg  
Am Hubland  
D – 97074 Würzburg



## Key questions in structure-based drug design



## Docking problems & scoring tasks

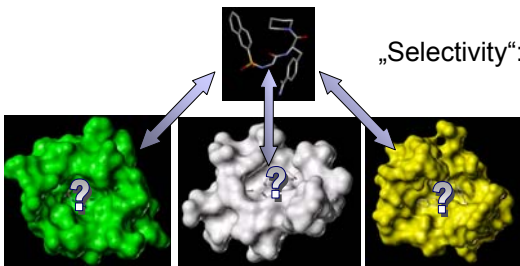
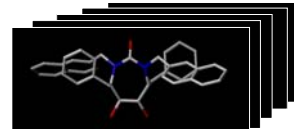


„Single Docking“: 1 protein – 1 ligand

looking for: binding mode (and affinity) of the ligand

„Virtual Screening“: 1 protein – many (potential) ligands

looking for: ligands with high affinity for target protein

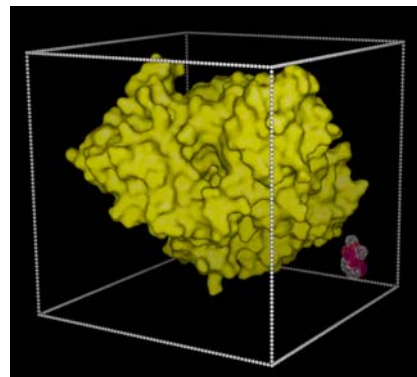


„Selectivity“: many proteins – one or more ligands

looking for: ligands with high selectivity for one target

## Why is docking a „problem“?

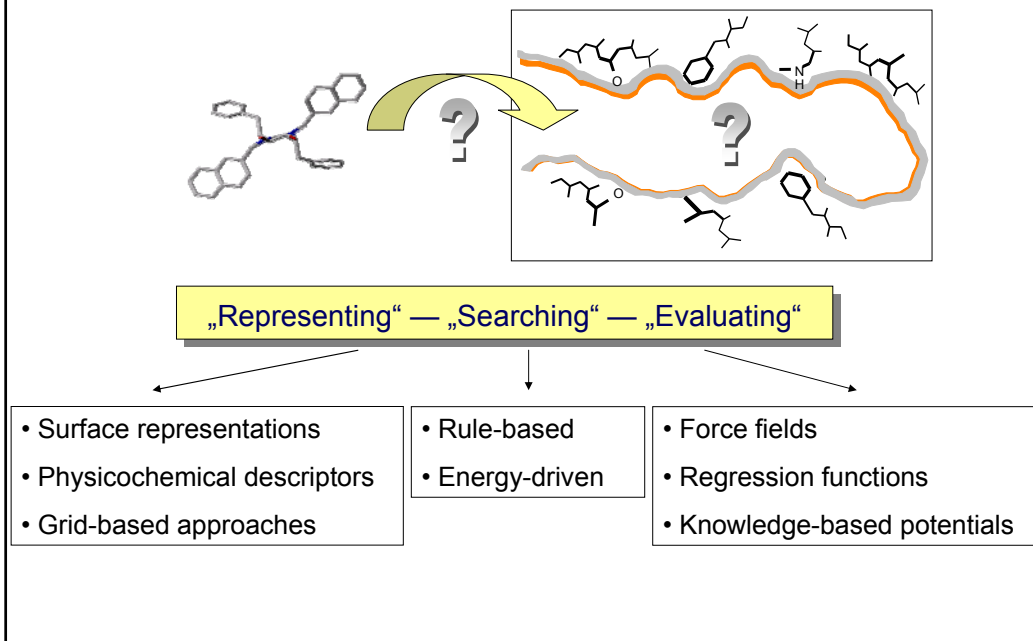
- complex 3D jigsaw puzzle
- conformational flexibility
- mutual adaptations („induced fit“)
- solvation in aqueous media
- complexity of thermodynamic contributions
- no easy route to  $\Delta G$  evaluation for scoring



Simplifications und heuristic approaches necessary

*Modelling and computer-aided drug design are frequently a quest for suitable simplifications*

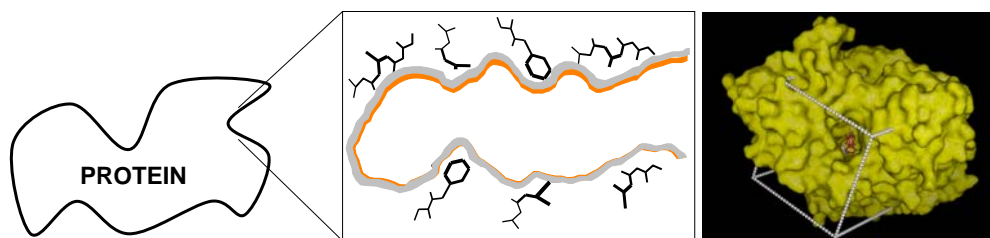
## Approaches to solve the docking problem



## „Representing“: Molecular representations for docking

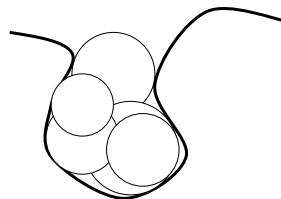
### A.) Protein

#### 0. Restricting the search space to the binding pocket



#### 1. Geometric surface descriptors

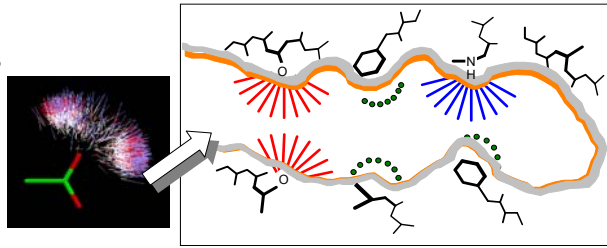
e.g., sphere representation of binding pockets  
(→ program DOCK)



## 2. Physicochemical descriptors

Interaction points and vectors

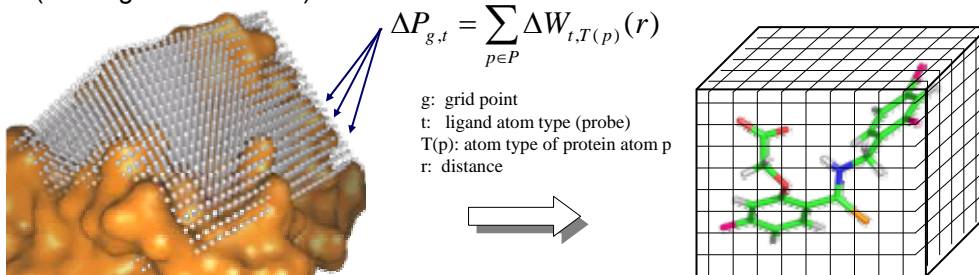
(→ Programs LUDI, FlexX)



## 3. Grid representations

Interaction potentials of probe atoms are mapped to grid points

(→ Program AutoDock)

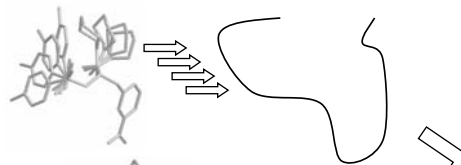


## B.) Ligand

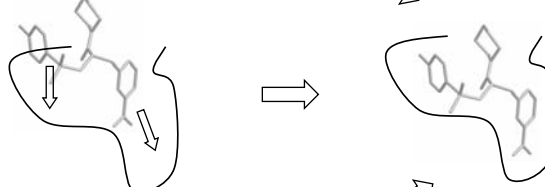
major problem: conformational flexibility

⇒ strategies for flexible ligand docking

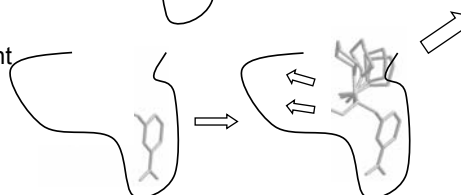
1.) rigid docking of conformers



2.) simultaneous optimization of orientation and conformation

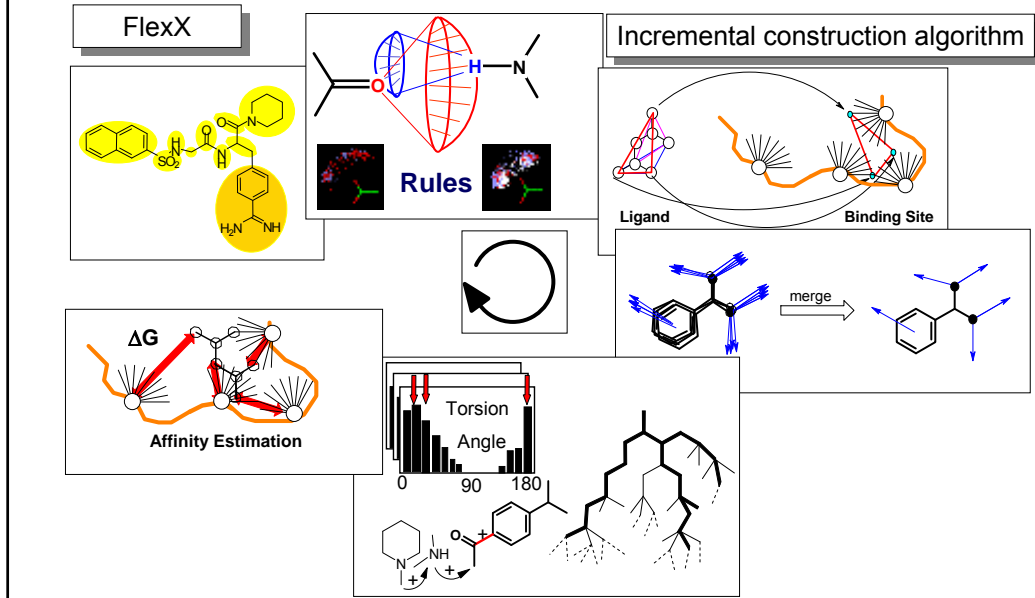


3.) placement of a base fragment followed by incremental construction



## „Searching“: Search algorithms for docking procedures

### 1.) Rule-based: geometric-combinatorial methods



## „Searching“: Search algorithms for docking procedures

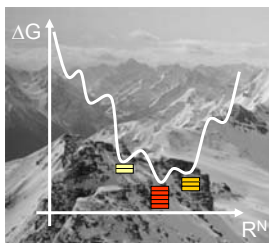
### 2.) Energy-driven: stochastic optimization methods

general assumption:

experimentally determined complex structure  
corresponds to global minimum of  $\Delta G_{\text{bind}}$



Docking = optimization problem



- Search for  $\min(\Delta G_{\text{bind}})$ -binding mode
- $\Delta G_{\text{bind}}$  approximated by scoring function
- „rugged“, multi-dimensional energy landscape



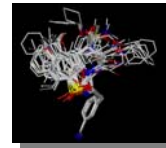
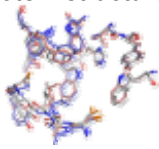
Monte-Carlo methods, genetic algorithms

examples: AutoDock, ICM, GOLD

## Before docking ...

... take care of the setup!

- Protein structures:
  - Protonation states and H-bonding networks
  - Quality and completeness of structural data
  - Location of binding site
  - Experimental data about water molecules and flexible regions
- Ligand structures:
  - Protonation states (influenced by protein!)
  - Tautomers
  - Conformers
- Docking program:
  - Choose suitable parameters
  - Validate, validate, validate (in particular for your system!)
- Know your program!
- Check structures and setup visually!
- Critically assess the quality of automated setup routines!



## „Evaluating“ / Scoring: Why is affinity prediction a challenge?

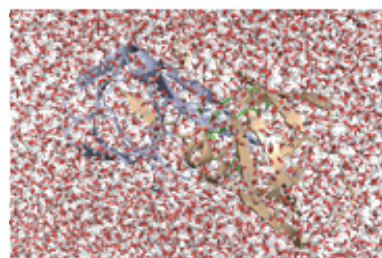
1.) Protein-ligand complexes are dynamic systems in aqueous solution

- huge number of particles
- simultaneous, unperiodic, continuously changing interactions

⇒ Simulation methods required!

Statistical thermodynamics: Calculation of  $\Delta G^\circ$  needs integration over entire phase space!

⇒ Computationally very expensive!



2.) The prediction methods need to be fast

Database screens:  $\sim 10^3 - 10^6$  molecules need to be compared

Docking runs:  $\sim 10^7 - 10^9$  configurations need to be evaluated

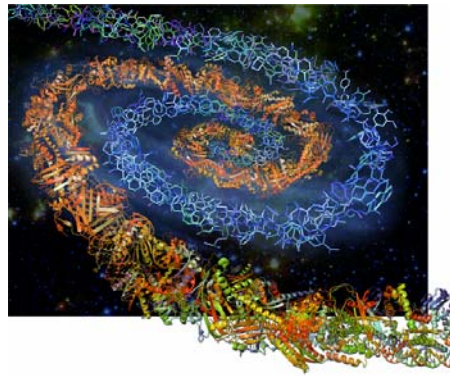
⇒ „Scoring functions“ required:

Fast, simplified, heuristic methods for prediction of binding strength

## Scoring functions: Goals

The ultimate goals of an ideal function:

- accurate within less than 1 pK<sub>D</sub> unit (<1.4 kcal/mol)
- generally valid (not system specific; large affinity range)
- robust (tolerant with respect to structural uncertainties)
- widely applicable (docking, virtual screening)
- physically meaningful (interpretable)
- fast and easy to compute



Ans: Niebe, Witzstoff/Design, 2. Aufl. © Spektrum Akademischer Verlag GmbH, 2009

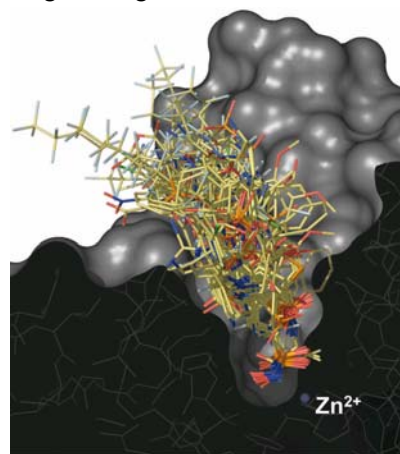
## Scoring functions: Tasks and types

Application tasks:

- A) Identification of the correct binding mode for a given ligand  
*Pose prediction in docking*
- B) Identification of new active ligands  
*Virtual screening*
- C) Affinity ranking for compound series  
*Ligand design, lead optimization*

Available approaches:

- Force field-based methods
- Knowledge-based scoring functions
- Empirical scoring functions



## Force field-based methods

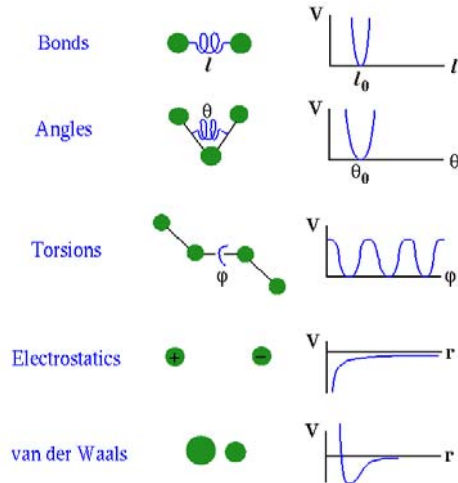
### Molecular Mechanics (MM):

- atoms → charged spheres
- bonds → springs
- classical potentials
- no electrons → no bond formation / cleavage
- typically parameterized to reproduce molecular potential energy surface (→ conformational  $\Delta H$  in the gas phase!)

➡ Scoring protein-ligand complexes:

- + for pose prediction in docking
- for ligand ranking by affinity

➡ Terms accounting for (de)solvation & entropic factors required (cf. MM-PBSA)



## Knowledge-based scoring functions

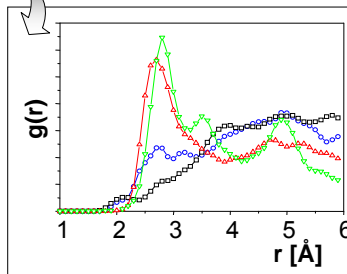
Derivation from crystal-structure data

$$P_{ij}(r) = -\ln \frac{g_{ij}(r)}{g_{ref}}$$

$P_{ij}$ : distance-dependent pair potential  
 $g_{ij}$ : frequency distribution of atom-atom contacts  
 $g_{ref}$ : reference distribution

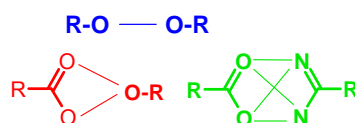
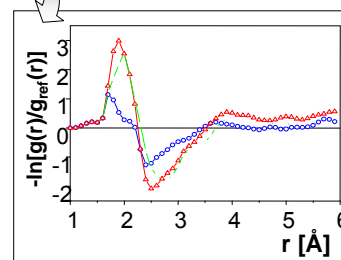


Frequency of occurrence



*No experimental affinities used!*

Statistical potential





## Empirical scoring functions

Regression-based:

$$pK_i = \sum pK_{i,n} f_n(\text{structure})$$

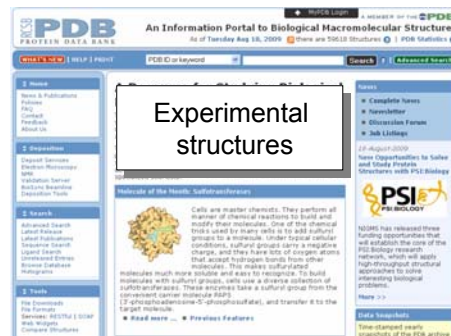
affinity

weighting factors

structure descriptors

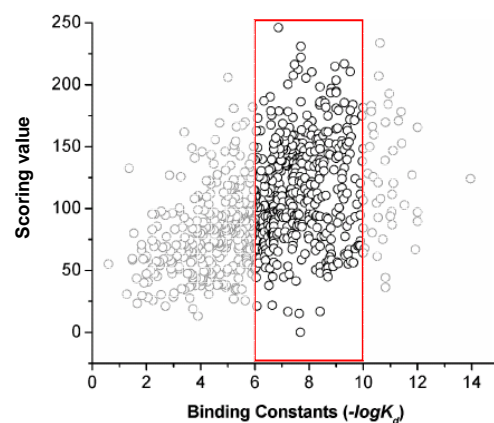
determined via regression analysis (MLR, PLS)

Data:



## Where do we stand with docking & scoring?

A not too unusual result ...



Correlation with affinity  
for a test set of 800  
known complexes:

*in general,*  
 $r < 0.55$  ( $r^2 < 0.3$ )

Wang et al., *J. Chem. Inf.  
Comp. Sci.* 44 (2004), 2114



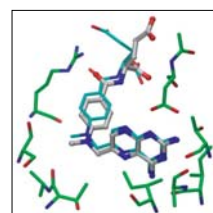
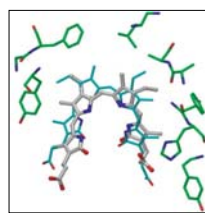
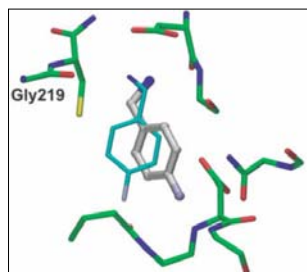
So, what is possible and what is not?

## I. Docking

### Preface: „Comparing protein-ligand docking programs is difficult“

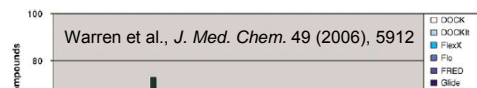
Cole et al., *Proteins* 60 (2005), 325

- Test sets needs to be carefully selected to
  - ensure sufficient diversity
  - provide good experimental reliability
  - avoid crystal packing effects
- Consider search complexity and timings
- RMSD values can be misleading
- Tests may cover different aspects, e.g.
  - redocking
  - crossdocking
  - blind docking
  - blind predictions



## I. Docking

### Comparative evaluations of docking programs



Success rate for reproducing exp. binding mode on top rank with RMSD < 2Å

- best approaches typically around 60%
- individual success rates up to 90%
- no approach consistently best
- highly target-dependent

Compiled by  
Moitessier et al.,  
*Br. J. Pharmacol.*  
153 (2008), S7

Figure 4 Co-workers, v

#### Similar general conclusions by recent studies:

- Cross et al., *J. Chem. Inf. Model.* 49 (2009), 1455 (68 complexes; DOCK, FlexX, Glide, ICM, PhDOCK, Surflex)
- Li et al., *J. Comput. Chem.* 31 (2010), 2109 (195 complexes; Glide, GOLD, LigandFit, Surflex)

## A critical issue: Conformational flexibility!

- Complex reconstruction from **rigid binding partners**: Essentially a solved problem!  
e.g.: RosettaLigand, 85 complexes (Astex diverse): 99% success rate; av. RMSD <1Å

Davis et al., *J.Mol.Biol.* 385 (2009), 381

- **Flexible ligand** – rigid protein docking: Standard, but not without problems

- docking success rate drops for more flexible ligands (>7-8 rotatable bonds)
- danger of insufficient sampling (correct conformation and pose is not generated)

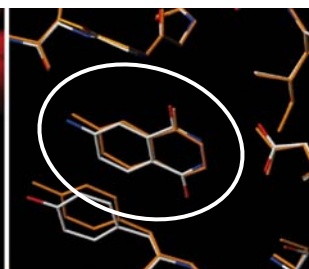
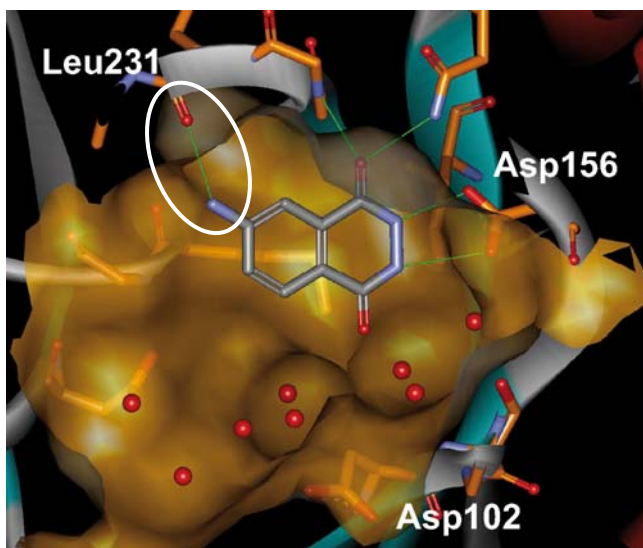
- Flexible ligand – **flexible protein** docking: Active field of development

- Modeling of protein flexibility:
- *before* ligand placement (e.g., ensemble docking)
  - *after* ligand placement (e.g., complex refinement)
  - *during* ligand placement (e.g., MC/MD techniques)



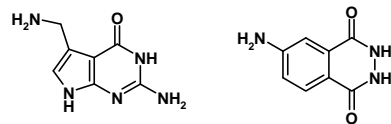
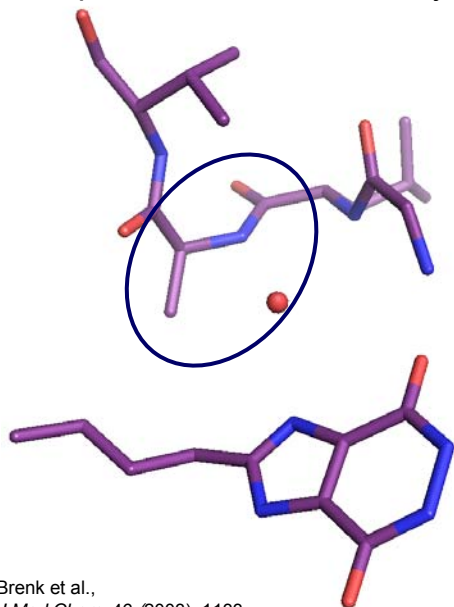
But: even „simple“ conformational changes can be out of reach!

## Example 1: TGT - Successful docking and ...

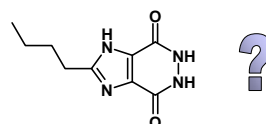


X-ray confirmed a perfect binding-mode-prediction for a new virtual-screening hit!

... surprises out of reach for any docking program

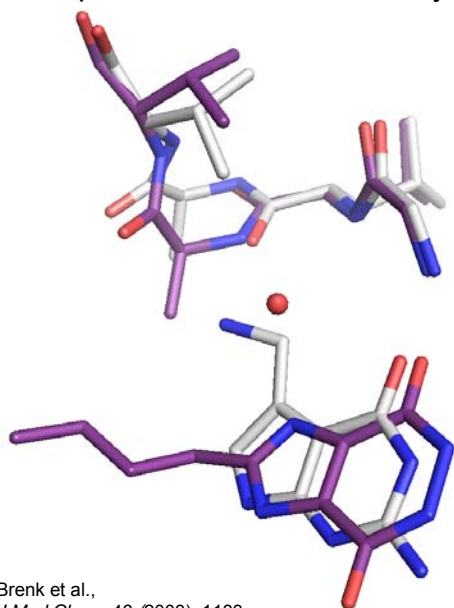


form H-bond with Leu231



Backbone flip at Leu231  
and water molecule  
mediate formation of new  
H-bond interaction!

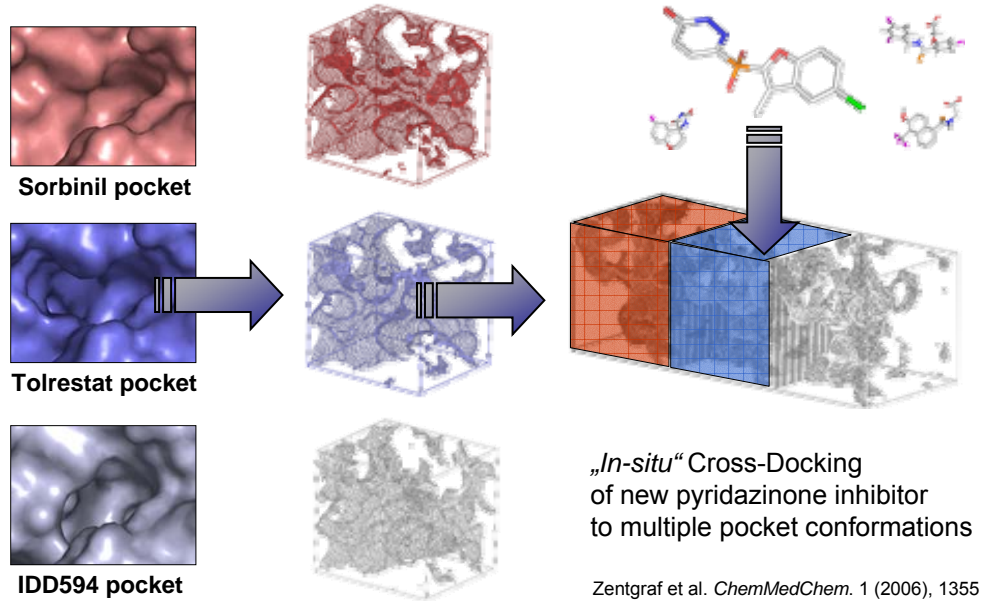
... surprises out of reach for any docking program



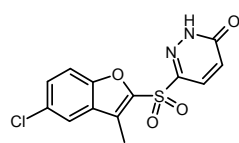
Virtually impossible to predict  
with current protein-flexibility  
docking approaches  
(unless alternative conformation  
is experimentally known in advance)

Backbone flip at Leu231  
and water molecule  
mediate formation of new  
H-bond interaction!

### Example 2: Aldose Reductase - docking to multiple pocket conformers

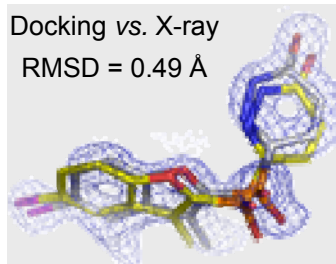


### Example 2: Aldose Reductase - docking to multiple pocket conformers



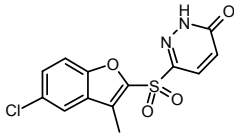
**binds to  
IDD594 pocket!**

Docking vs. X-ray  
RMSD = 0.49 Å



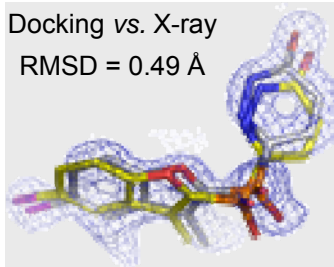
Steuber et al., *J. Mol. Biol.* 356 (2006), 45

### Example 2: Aldose Reductase - docking to multiple pocket conformers



**binds to  
IDD594 pocket!**

Docking vs. X-ray  
RMSD = 0.49 Å



Steuber et al., *J. Mol. Biol.* 356 (2006), 45

Reason for successful prediction:

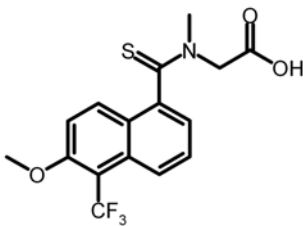
- ligand binds to protein conformer known from previous X-ray structures
- scoring function correctly scores the true binding mode much better than binding modes in alternative protein conformers



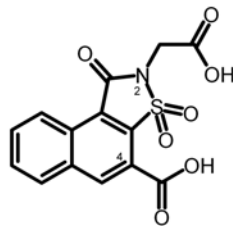
despite protein flexibility:

„easy task“ for common docking tools

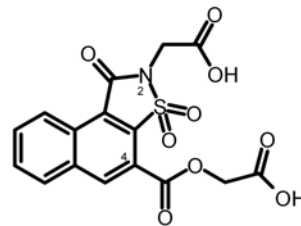
### Design of new inhibitors: Tolrestat analogues



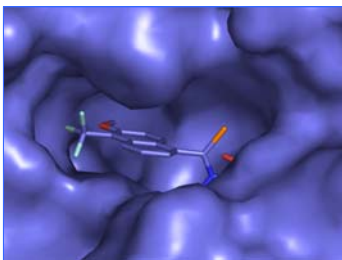
**tolrestat**



**1**



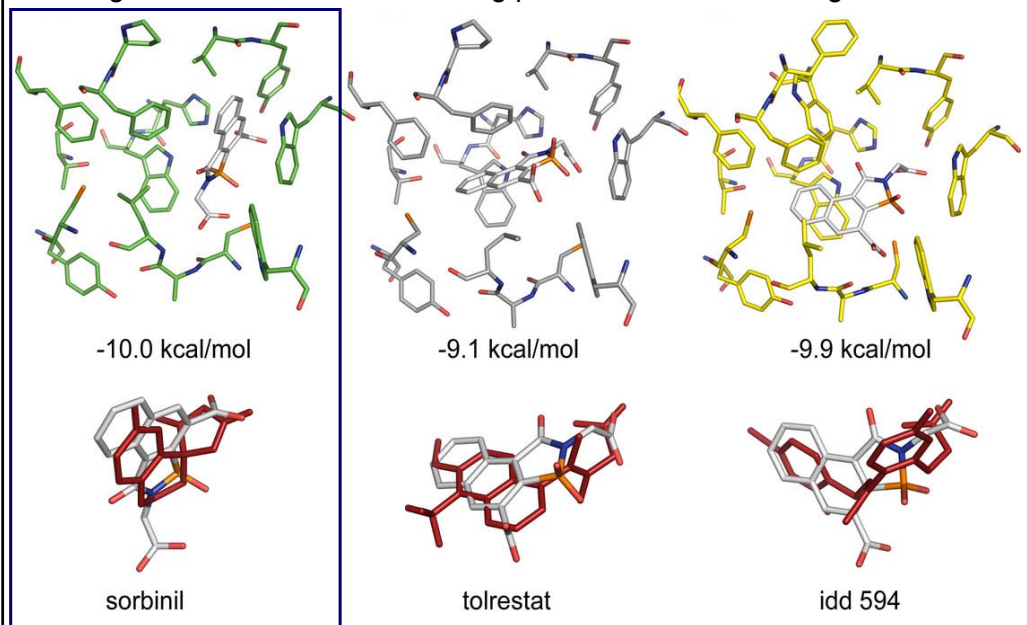
**2**



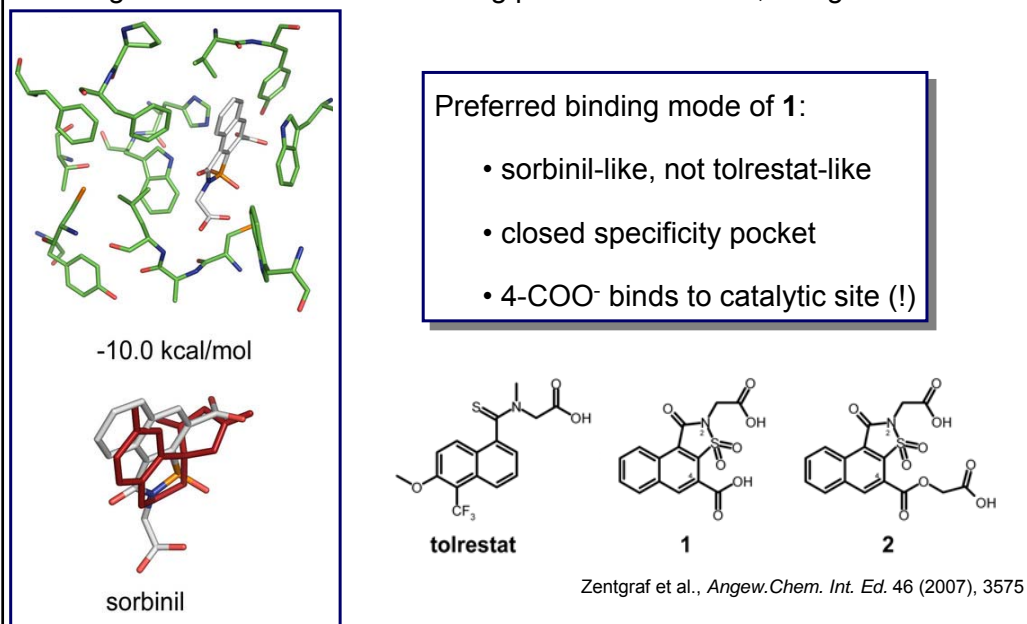
Da Settimo et al., *J. Med. Chem.* 48 (2005), 6897.  
*Naphtho[1,2-d]isothiazole acetic acid derivatives as  
a novel class of selective aldose reductase inhibitors.*

**Do the new compounds adopt  
the same binding mode as tolrestat?**

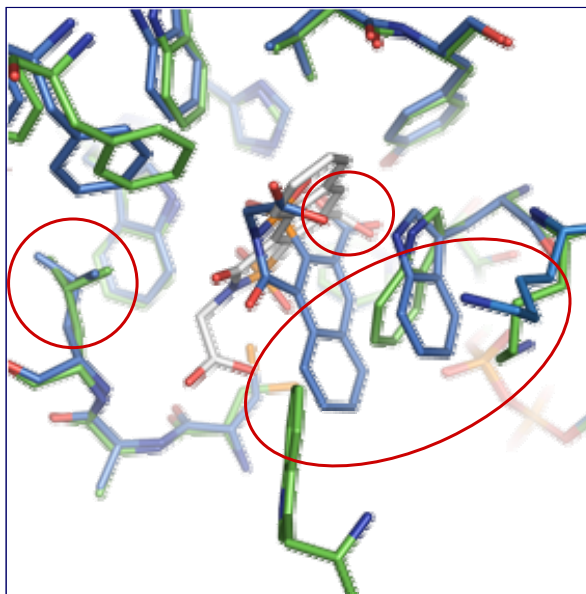
Docking of **1** to three different binding pocket conformers, using AutoDock



Docking of **1** to three different binding pocket conformers, using AutoDock



Docking result of 1 in comparison with crystal structure



- specificity pocket closed
- 4-COO<sup>-</sup> in catalytic site

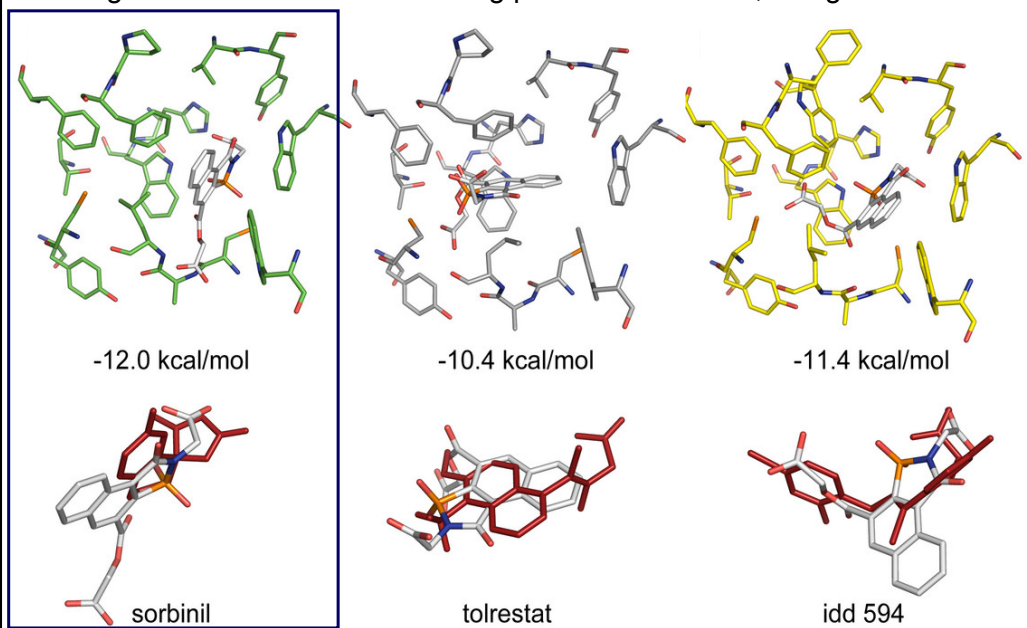
**But:**

Unexpected conformational changes!

- Trp 20 rotated by 35°
- Lys 21 salt bridge broken
- Trp 219 disordered

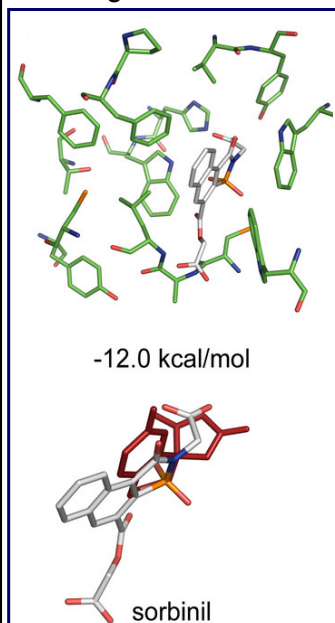
**Unpredictable with docking methods!**  
(incl. FlexX, GOLD, Glide)

Docking of 2 to three different binding pocket conformers, using AutoDock



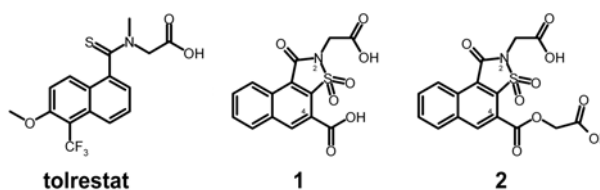


### Docking of **2** to three different binding pocket conformers, using AutoDock



#### Preferred binding mode of **2**:

- sorbinil-like, not tolrestat-like
- closed specificity pocket
- 2-COO<sup>-</sup> binds to catalytic site



Zentgraf et al., *Angew.Chem. Int. Ed.* 46 (2007), 3575

### Docking result of **2** in comparison with crystal structure



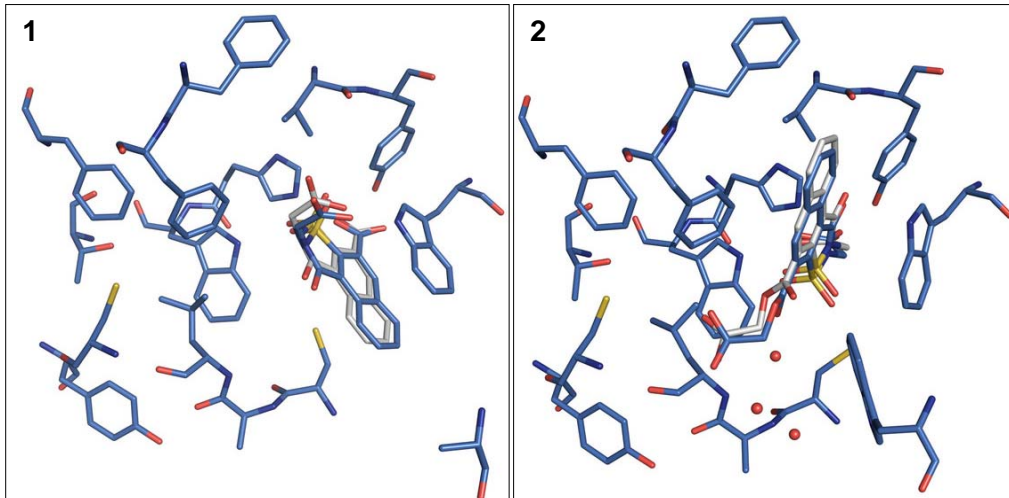
- specificity pocket closed
- 2-COO<sup>-</sup> in catalytic site
- no conformational changes!

#### **But:**

Water molecules  
immobilized in binding pocket!

3 very „similar“ ligands  
lead to  
3 very different binding modes!

AutoDock results obtained when using the „correct“ binding-site conformer



**Bindung mode exactly reproduced in both cases!**

### Protein flexibility and docking

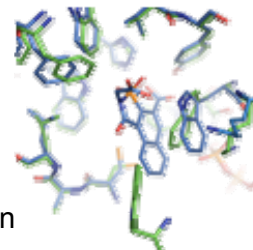
#### What's already possible:

- simultaneous docking to multiple protein conformers of arbitrary difference
- correct predictions if multiple protein conformers are known
- support by MD: generation of relevant conformers
- docking with explicit side-chain flexibility



#### What remains a problem:

- predicting: - the details
  - backbone mobility
  - large conformational changes
- fast estimate of energetic contributions from protein
- explicit consideration of full protein dynamics upon ligand binding



## II. Scoring

### Application tasks:

A) Identification of the correct binding mode for a given ligand

*Pose prediction in docking*

B) Identification of new active ligands

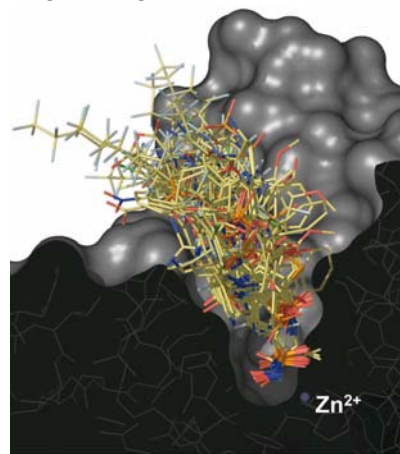
*Virtual screening*

C) Affinity ranking for compound series

*Ligand design, lead optimization*

### Available approaches:

- Force field-based methods
- Knowledge-based scoring functions
- Empirical scoring functions



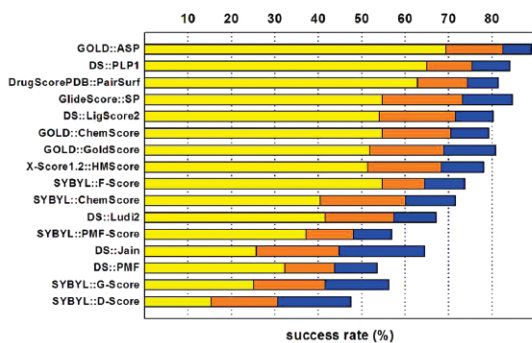
## II. Scoring

### A) Pose prediction in docking

Identification of near-native binding pose among a set of geometric decoys

- Test set of 195 complexes of 65 different targets
- 100 low-energy poses per complex (0-10 Å rmsd)
- 29 scoring functions tested

- native poses can be detected fairly well
- success rates of up to ~80%
- knowledge-based approaches work best



Success rate for identifying best-scored ligand binding pose with

- rmsd < 1.0 Å
- rmsd < 2.0 Å
- rmsd < 3.0 Å

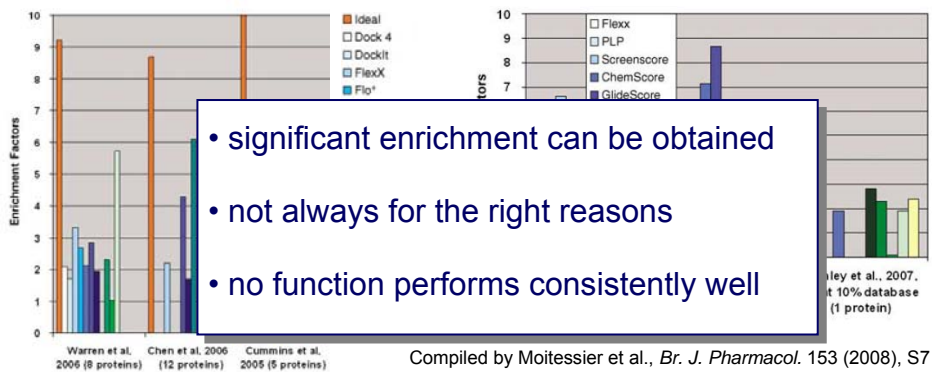
Cheng et al., *J. Chem. Inf. Model.* 49 (2009), 1079

## II. Scoring

### B) Virtual screening

Detection of active compounds in screening databases

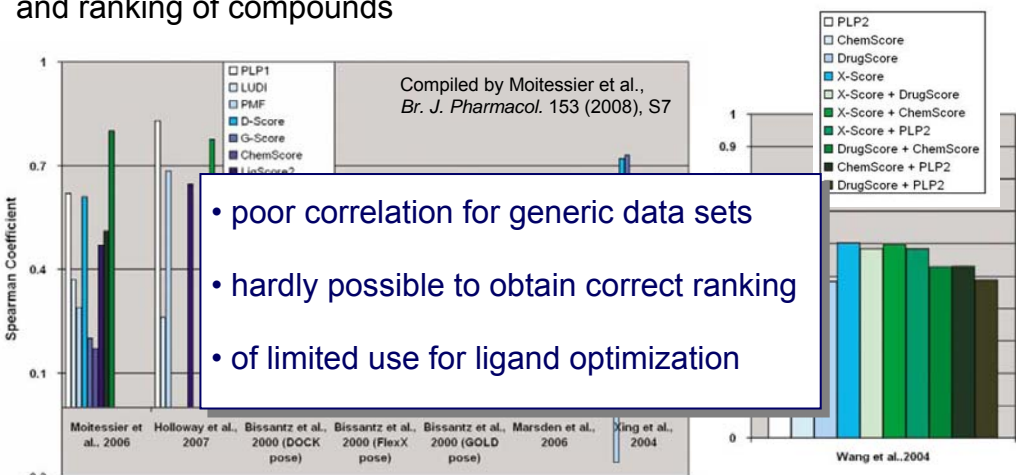
Problem: Testing scoring function performance in virtual screening is not trivial!



## II. Scoring

### C) Affinity prediction

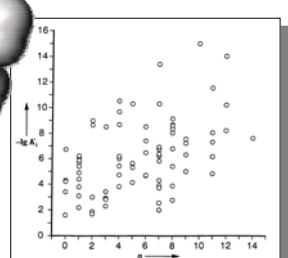
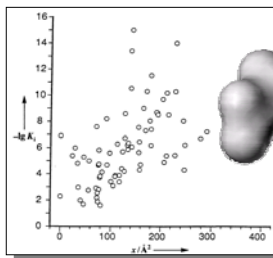
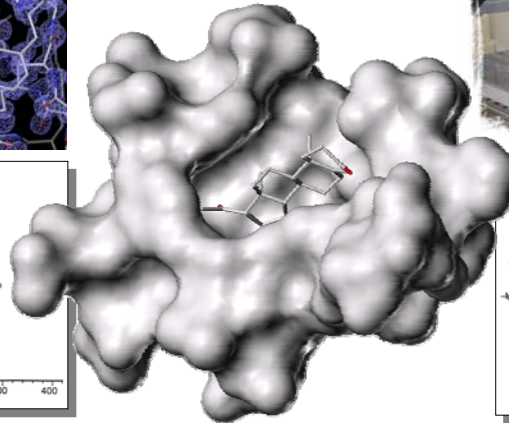
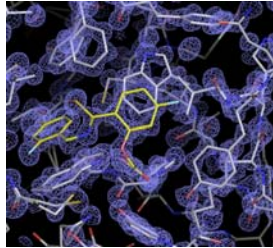
Correlation of scores with experimental binding affinities and ranking of compounds



## II. Scoring: What is possible and what is not?

Since all methods are of empirical nature:

Do more and „better“ experimental data  
lead to better functions?



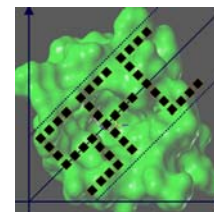
## II. Scoring: What is possible and what is not?

### SFCscore empirical scoring functions

SFC: Scoring Function Consortium

➡ Data collection from public & industry sources

- affinity data from literature for PDB complexes
- „diversity“ from PDB, SAR series from industry
- unique data format and encoding for industry data
- up to 58 complexes per target, 28 series, mostly  $IC_{50}$  (!)



➡ Raw data in total (public + industrial):

complexes from PDB:	440	filtered: 290
complexes from industry:	618	filtered: 565
total:	1058	855

SFCscore Training sets: Regression statistics

Function	Method	$N$	$k$	$r$	$r^2$	$s$	$F$
<i>sfc_290m</i>	MLR	290	7	0.843	0.711	1.085	99.2
<i>sfc_229m</i>	MLR	229	7	0.842	0.709	1.098	76.9
<i>sfc_frag</i>	MLR	130	4	0.810	0.656	0.973	59.8
sfc_855	PLS	855	6	0.770	0.593	0.994	205.9
sfc_ser	PLS	466	4	0.843	0.711	0.952	284.0
sfc_met	PLS	341	4	0.844	0.713	1.046	208.9
sfc_290p	PLS	290	5	0.867	0.751	1.005	171.3
sfc_229p	PLS	229	6	0.875	0.766	0.982	121.2

$N$ , number of complexes in the training set;  $k$ , number of components for PLS functions, number of variables for MLR functions;  $r$  and  $r^2$ , correlation coefficient and its square;  $s$ , standard error;  $F$ ,  $F$ -value.

Sotriffer et al., *Proteins* 73 (2008), 395

SFCscore Training sets: Internal cross validation

Function	$Q^2$	$s_{PRESS}$
<i>sfc_290m</i>	<i>0.692</i>	<i>1.121</i>
<i>sfc_229m</i>	<i>0.683</i>	<i>1.147</i>
<i>sfc_frag</i>	<i>0.627</i>	<i>1.015</i>
sfc_855	0.572	1.033
sfc_ser	0.692	1.028
sfc_met	0.688	1.135
sfc_290p	0.722	1.080
sfc_229p	0.723	1.086

For the functions derived by MLR, leave-one-out (LOO) cross-validation was used (lines highlighted in italics); for PLS functions, 10-fold cross-validation (20 runs) was applied and the average  $Q^2$  and  $s_{PRESS}$  of the 20 runs are reported.

Sotriffer et al., *Proteins* 73 (2008), 395

II. Scoring: What is possible and what is not?

Comparison with other scoring functions

	R	R <sup>2</sup>	s	F	Q <sup>2</sup>	S <sub>PRESS</sub>
SFCscore: sfc_290m ( k = 7, n = 290 )	0.843	0.711	1.09	99.2	0.692	1.12
X-CSCORE eq3 (Wang 2002): ( k = 4, n = 200 )	0.756	0.571	1.41	70.4	0.551	1.47
Chemscore (Eldridge 1997): ( k = 4, n = 82 )	0.843	0.710	1.40	47.1	0.658	1.52
Score2 (Böhm 1998): ( k = 7, n = 82 )	0.890	0.792	1.27	40.3		
Score1 (Böhm 1994): ( k = 4, n = 45 )	0.873	0.762	1.38	32.0		

II. Scoring: What is possible and what is not?

Function	R <sub>P</sub>	SD	ME
SFCscore:: sfc_met	0.585	1.80	1.37
SFCscore:: sfc_ser	0.572	1.82	1.40
SFCscore:: sfc_855	0.570	1.82	1.40
X-Score::HMScore	0.566	1.82	1.42
SFCscore:: sfc_290p	0.564	1.83	1.39
SFCscore:: sfc_229p	0.553	1.85	1.41
SFCscore:: sfc_229m	0.534	1.87	1.44
SFCscore:: sfc_290m	0.525	1.89	1.45
SFCscore:: sfc_frag	0.523	1.89	1.46
X-Score::HPScore	0.514	1.89	1.47
X-Score::HSScore	0.506	1.90	1.48
Sybyl::ChemScore	0.499	1.91	1.50
DrugScore:Pair/Surf	0.476	1.94	1.50
DrugScore: Pair	0.473	1.94	1.51
DrugScore: Surf	0.463	1.95	1.53
Cerius2:: PLP1	0.458	1.96	1.52
Sybyl:: G-Score	0.443	1.98	1.56
Cerius2:: LigScore	0.406	2.00	1.57
Cerius2:: LUDI2	0.379	2.04	1.62
GOLD:: GoldScore_opt	0.365	2.06	1.63
HINT	0.330	2.08	1.65
Cerius2:: PMF	0.253	2.13	1.71
Sybyl:: F-Score	0.141	2.19	1.77

Testing on external data set and comparison with other functions

800 PDB complexes with exp. pK<sub>i</sub>

Wang et al.,  
*J. Chem. Inf. Comp. Sci.* 44 (2004), 2114

→ improvement, but still  
only moderate correlation

New, carefully compiled test set of  
195 PDB complexes with exp. pK<sub>i</sub>:

Cheng et al.,  
*J. Chem. Inf. Model.* 49 (2009), 1079

Best functions:

	R <sub>P</sub>	SD
SFCscore:: sfc_met	0.646	1.82
X-Score::HMScore	0.644	1.83

II. Scoring: What is possible and what is not?

Why did many functions in the past appear more successful than they are?

➡ Very small external test sets of limited diversity

cf. how many of the now available complexes are well predicted by SFCscore!

Function	N	Residual < 1.5		
		$R_p$	$r_{pred}^2$	$SE_{pred}$
sfc_290m	551	0.874	0.763	0.809
sfc_229m	546	0.879	0.769	0.803
sfc_frag	417	0.915	0.818	0.835
sfc_855	555	0.850	0.720	0.820
sfc_ser	558	0.876	0.765	0.806
sfc_met	553	0.872	0.759	0.790
sfc_290p	559	0.875	0.765	0.796
sfc_229p	531	0.887	0.784	0.790

➡ CAVE with any conclusions derived from too small test sets!

II. Scoring: What is possible and what is not?

Have the limits of empirical approaches been reached?

➡ Consider quality and comparability of experimental data!

- Structural data (mainly X-ray) of protein-ligand complexes
  - multiple conformations (highly dynamic systems)
  - hydrogen atom positions (protonation states) not observable
  - side-chain orientation may be ambiguous (Asn, Gln, His)
  - water molecules are only partially observable
  - binding modes may depend on crystallization conditions and crystal packing
- Affinity data of protein-ligand complexes
  - may highly depend on pH, buffer, salt concentration, temperature
  - enzyme kinetics: inhibition mechanism must be known
  - $IC_{50} \leftrightarrow K_i \leftrightarrow K_d$

Knowledge-based and empirical scoring methods  
cannot be better than the exp. data they are based on!

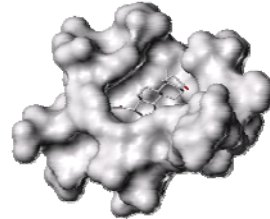


## Have the limits of empirical approaches been reached?

➡ For the development of generic scoring functions:  
Problems difficult to overcome, even by concerted efforts!

➡ Focus on target- or target-class-specific functions!

- Target-specific adaptation of existing functions
- Better comparability of experimental data
- Definition of standards for acquisition of new affinity data possible



## Recommendations ...

... for approaching the scoring problem:

- 1) Validate the scoring function for your system of interest
- 2) Train the scoring function for your system („Tailored scoring function“)
- 3) Try applying multiple scoring functions („Consensus Scoring“)
- 4) Tackle the problem with additional pre- and postfiltering steps

## Further developments required ...

... to overcome the most serious simplifications in scoring functions:

### „Flexibility – Water – Entropy“

- single configuration of the binding partners in the complex
- no consideration of the unbound state
- no or simplified consideration of the solvent
- focused on enthalpic contributions and interaction descriptors
- additivity of interaction terms

*A single model may not be sufficient to capture  
the complex interplay of  
residual mobility, desolvation, and interaction quality in protein-ligand complexes!*

## The wrong conclusion ...



## Acknowledgement



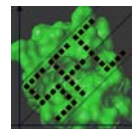
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Christine Topf  
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Armin Welker



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### Scoring Function Consortium

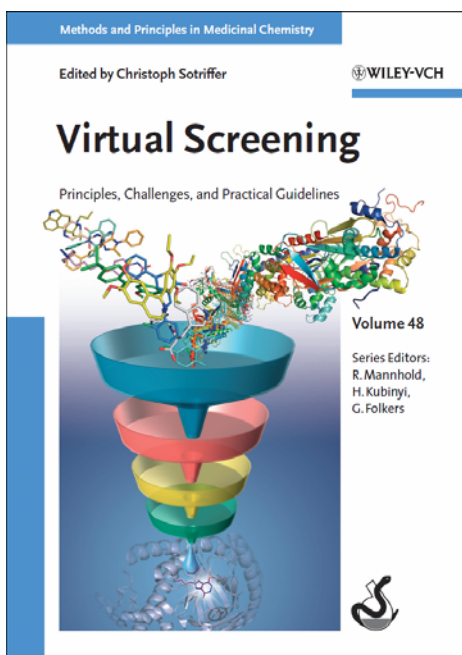


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available in autumn 2010