

Using AutoDock for Virtual Screening

CUHK Croucher ASI
Workshop
2011

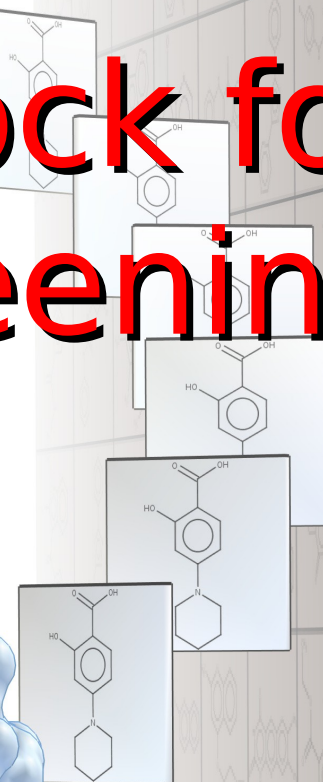
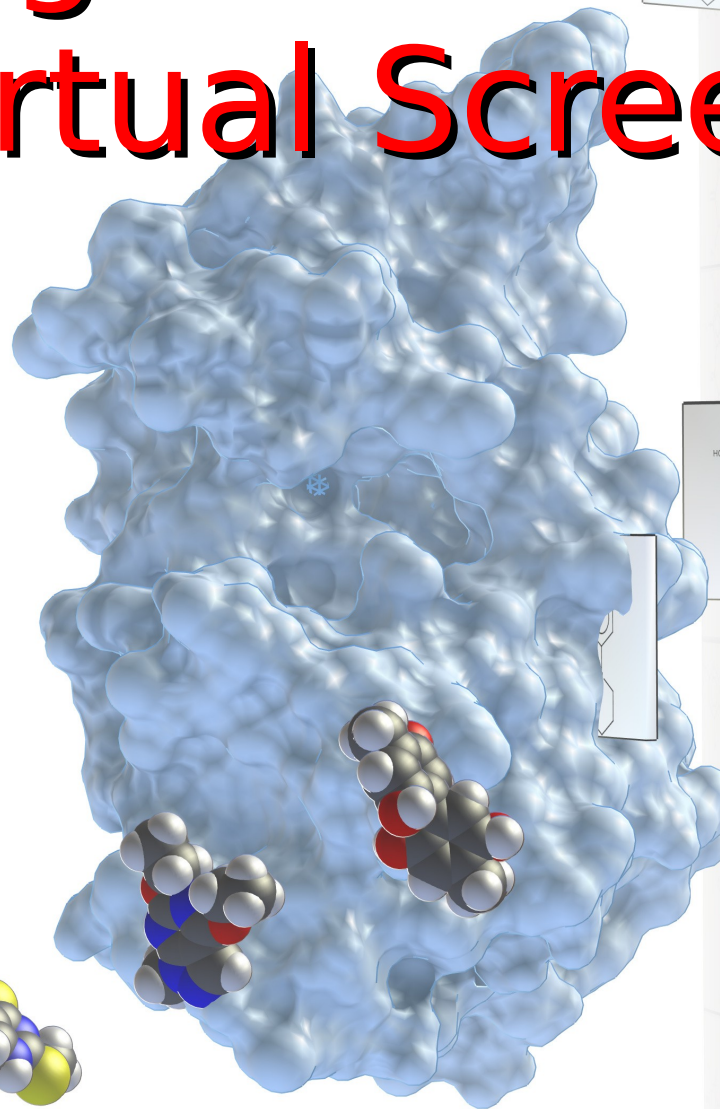
Stefano Forli, PhD
Prof. Arthur J. Olson, Ph.D



Molecular Graphics Lab



AutoDock



Screening and Virtual Screening

The ultimate tool for identifying active compounds is the biological test:

High-Throughput Screening

Expensive (both money and time)

Can be automated but it still needs a lot of human intervention

Not all assays can be automated

Screening and Virtual Screening

Compounds can be pre-screened *in silico* enriching the ligand set

Virtual



High-Throughput Screening

Cheap (saves both money and time)

Can be easily automated

Dramatic reduction of the number of:

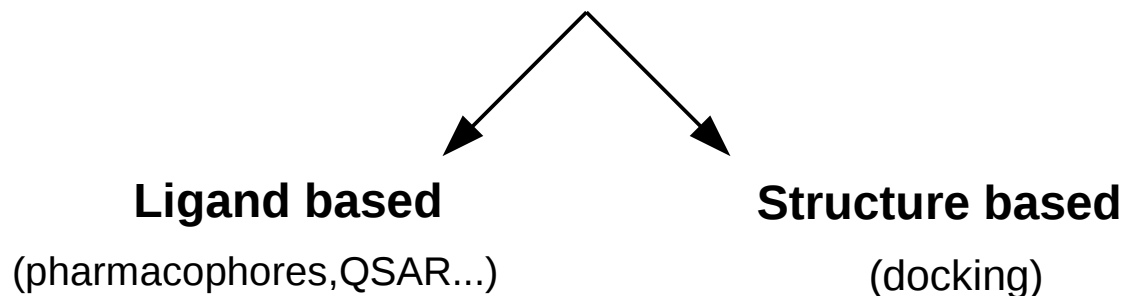
- compounds to be tested
- false negative

Virtual Screening

Definition

“Search for compounds with a defined biological activity using a computational model”

It's a *knowledge-based* method



Virtual Screening

Advantages

Relatively cheap filter

(save both time and money)

Enrich ligand libraries

Exploit the increase of target structures

(structural genomics and crystallography)

Allow to test *in silico* the “druggability” of
new targets

Virtual Screening

Advantages

- Relatively cheap filter
(save both time and money)
- Enrich ligand libraries
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(structural genomics and crystallography)
- Allow to test *in silico* the “druggability” of
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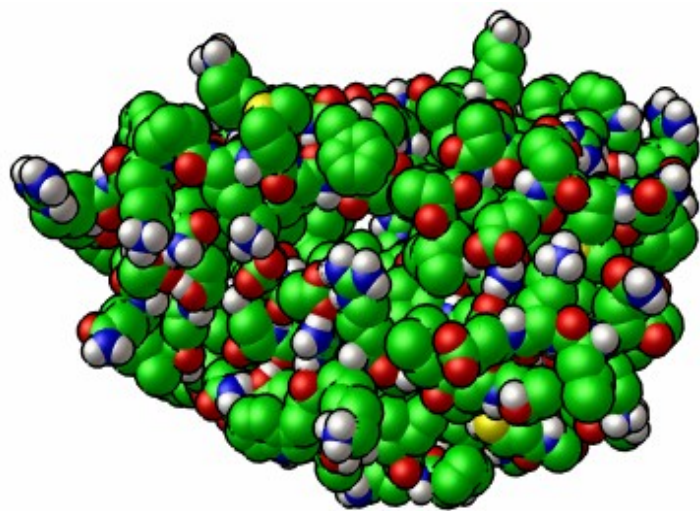
Disadvantages

- Often inaccurate
- Scoring-function dependent
- There is no method that's better than
others
- Strongly dependent on:
 - target
 - search method
 - chemical space sampled
- Always provides an answer
(McMaster competition 2005)

The Goal

Identify a molecule able to bind to a target providing a biological function

K_i / Energy



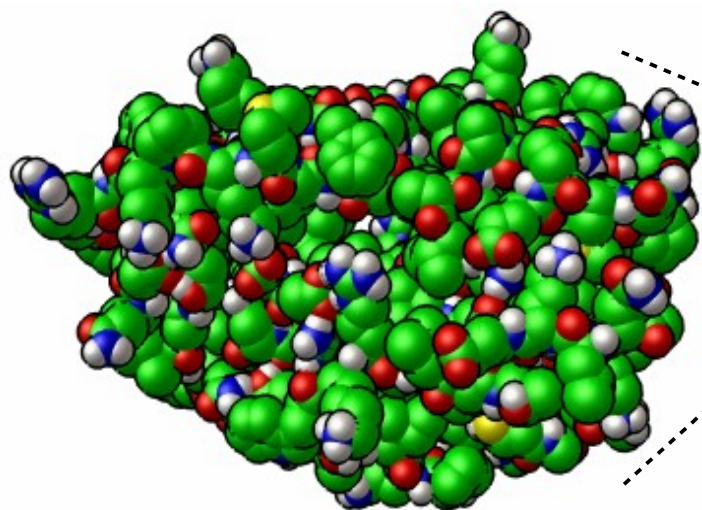
RECEPTOR

The Goal

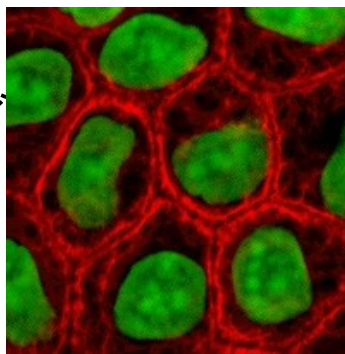
Identify a molecule able to bind to a target providing a biological function

K_i / Energy

Unusual elements (Pt, Ru, U...)
Reactive chemical groups
Over/Under-functionalization
Partition coefficient (logP)



RECEPTOR



CELL

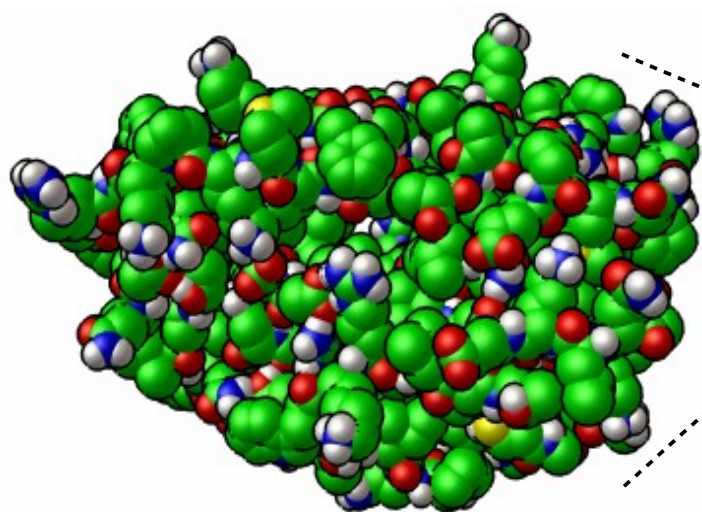
The Goal

Identify a molecule able to bind to a target providing a biological function

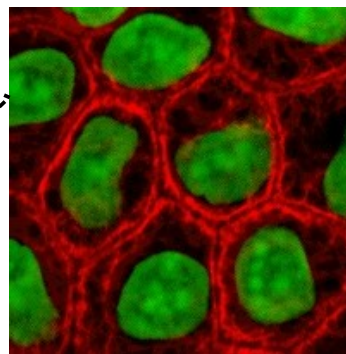
Absorption
Distribution + Tox
Metabolism
Excretion

K_i / Energy

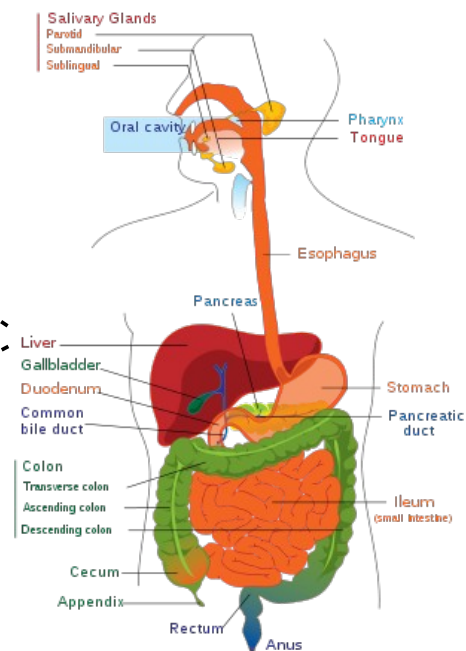
Unusual elements (Pt, Ru, U...)
Reactive chemical groups
Over/Under-functionalization
Partition coefficient (logP)



RECEPTOR



CELL



BODY

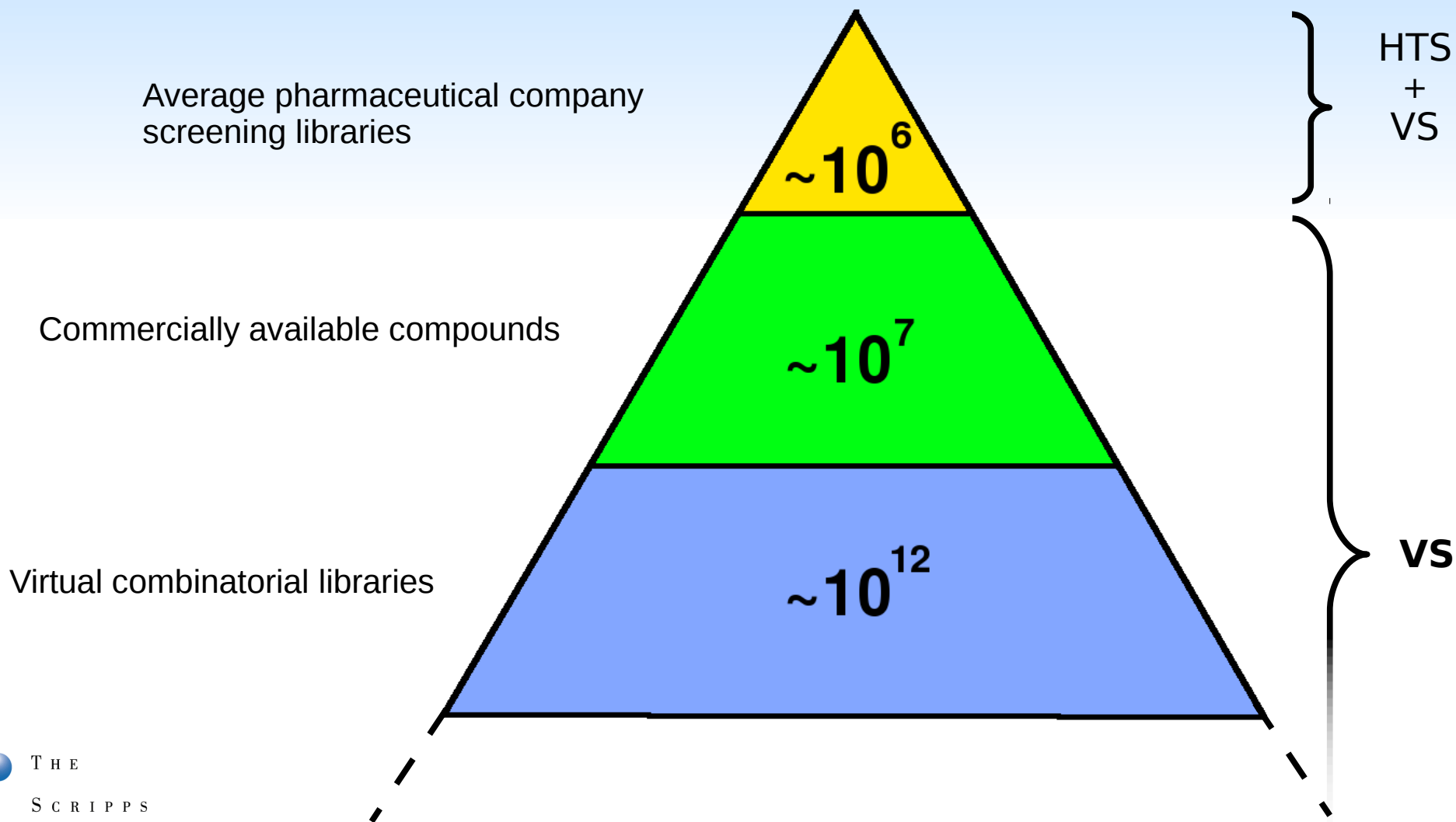
Virtual Screening

The Question

Which ligand binds in a target structure ?

Where to look for the answer

The Chemical Space



What the answer looks like

Hit low/medium target affinity

Lead sub-optimal target binding affinity

To be chosen for further development a **lead** compound should have the following properties:

- relatively simple chemical features (suitable for combinatorial/med-chem optimization, no/few chiral centers)
- well-established SAR series (similar compounds/chemical groups should present similar activity)
- good ADME properties
- [OPTIONAL] favorable patent situation

What the answer looks like

Filtering 'rules'

Drugs 'Rule of Five' (Lipinski rule)

Hydrogen bond donors ≤ 5
Hydrogen bond acceptors ≤ 10
Molecular weight ≤ 500 dalton
 $\text{Log}P_{w/o} < 5$

← Approved drugs

Hit Fragments 'Rule of Three'

Molecular weight ≤ 300 dalton
HB donor/Acceptors ≤ 3
 $\text{Clog}P \leq 300$
Nrot ≤ 3

← ASTEX frag hits

HTS efforts by using Lipinski-filtered libraries led to few micro-molar hits

LEADS are not DRUGS

“Rules” are good in principle, but they require to sample a huge chemical space to give really effective molecules.

What the answer looks like

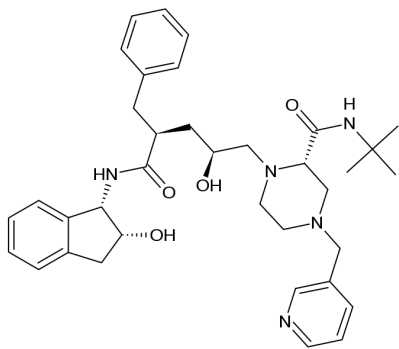
Rules 'Exceptions'

The nature and location of the target must be take into account for properties profile:

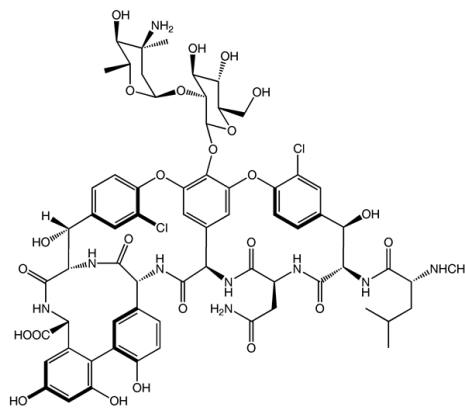
CNS molecule
(lipophilic blood-brain-barrier)

gastro-intestinal antibiotic
(highly soluble)

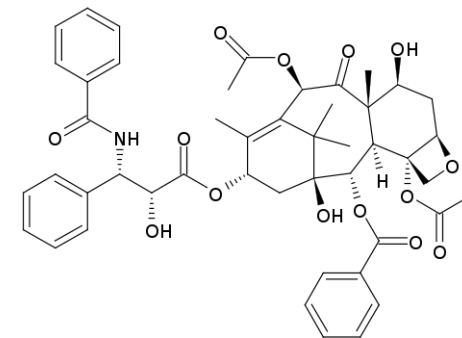
Natural compounds & Pro-drugs and "last resort" compounds



Indinavir

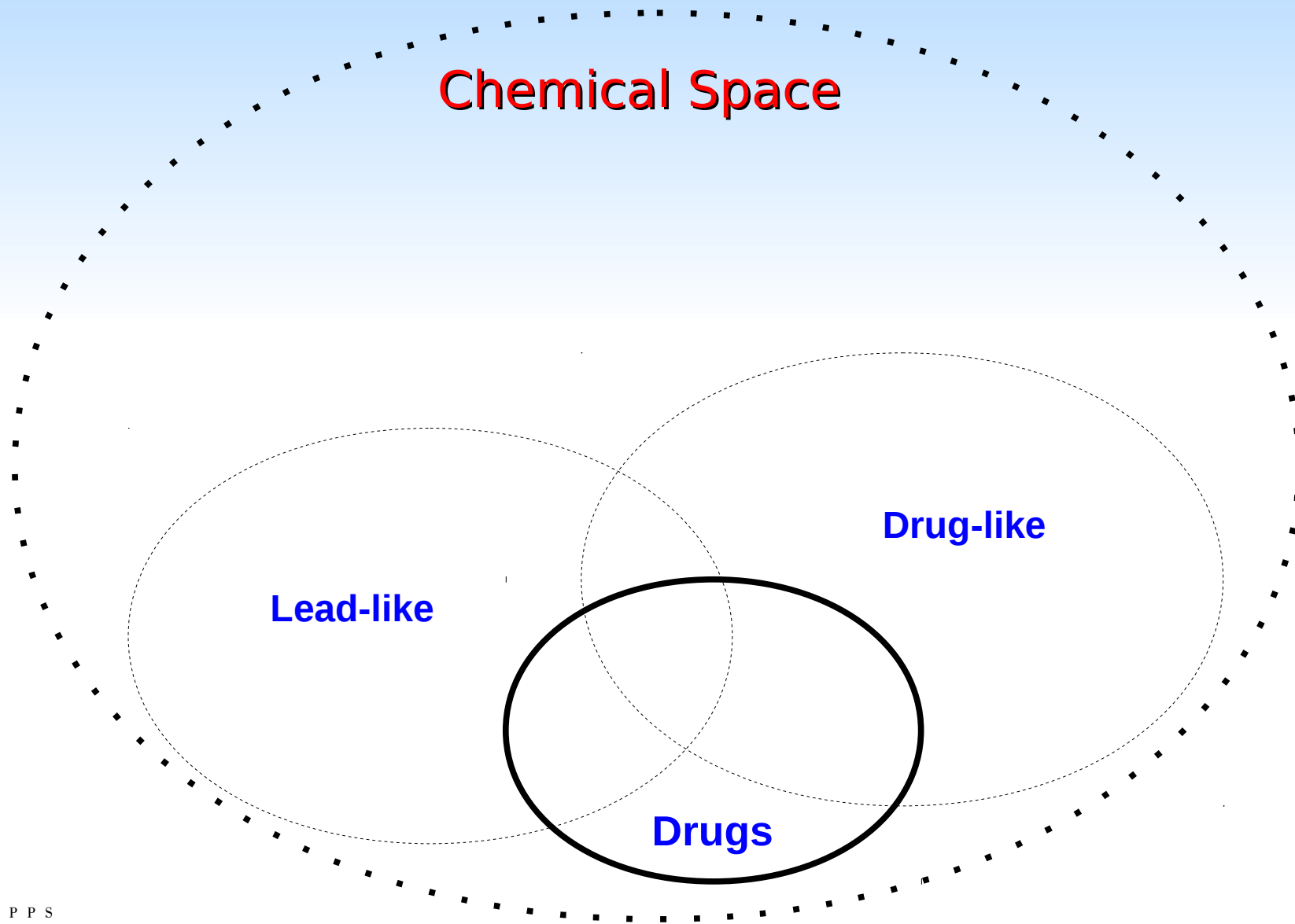


Vancomycin



Paclitaxel

What the answer looks like



Virtual Screening

The Question

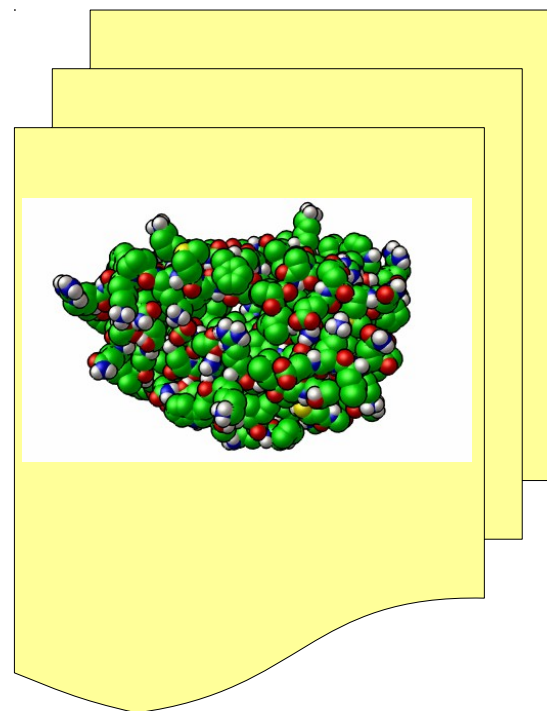
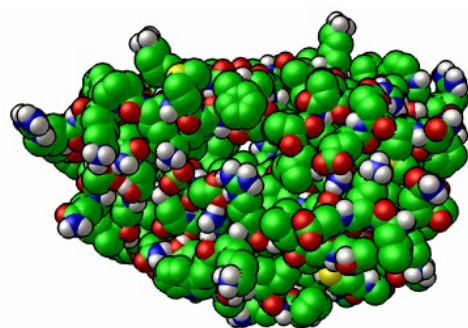
Which **LIGANDS** are *likely* to bind in a **target** structure ?

Where the answer should be found

Target state(s)

Hitting a moving target:

- *functional states (active-inactive)*
- *dynamic states (temperature)*
- *protonation/complexation states*



Virtual Screening

The Question

Which ligands are *likely* to bind the most probable state(s) of my target structure

Virtual Screening Hints

Prepare target and select ligand libraries with care

- Filter unusual elements
- Reliable 3D geometries
- Protonation states/tautomers

Reduce the space of your search

- diversity sets
- generic filtering
- target specific filtering (lipophilic VERSUS hydrophobic binding sites)

Use all available information to select results

- mutagenesis, SAR...

Try to sample different conformations of the protein

- reduce false negative

Use reference compounds whenever available

- Useful for comparing results with ligands with known activity

Available ligand libraries

PubChem

<http://pubchem.ncbi.nlm.nih.gov/>

All biological data related to a compound

2D structures

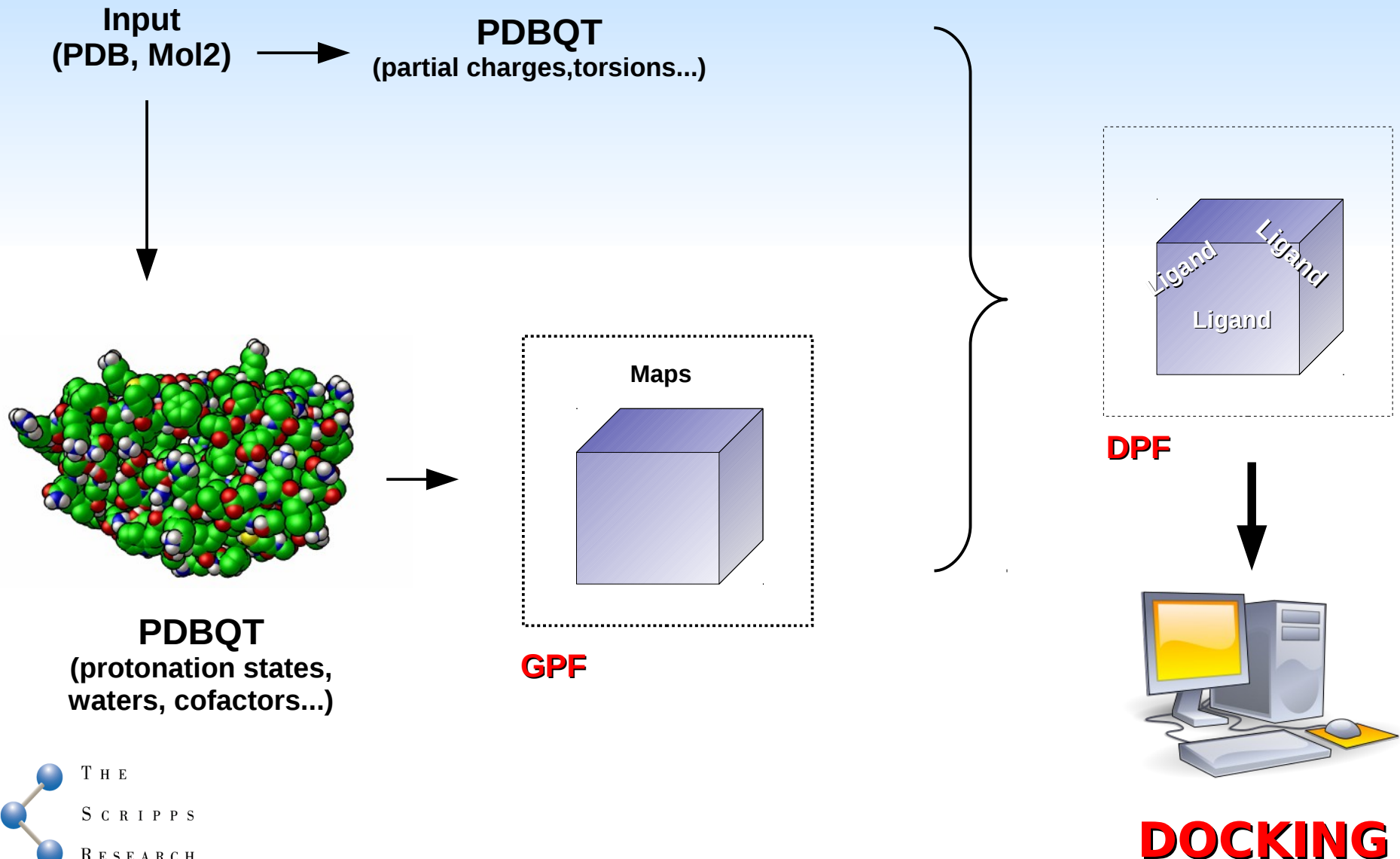
ZINC

<http://zinc.docking.org/>

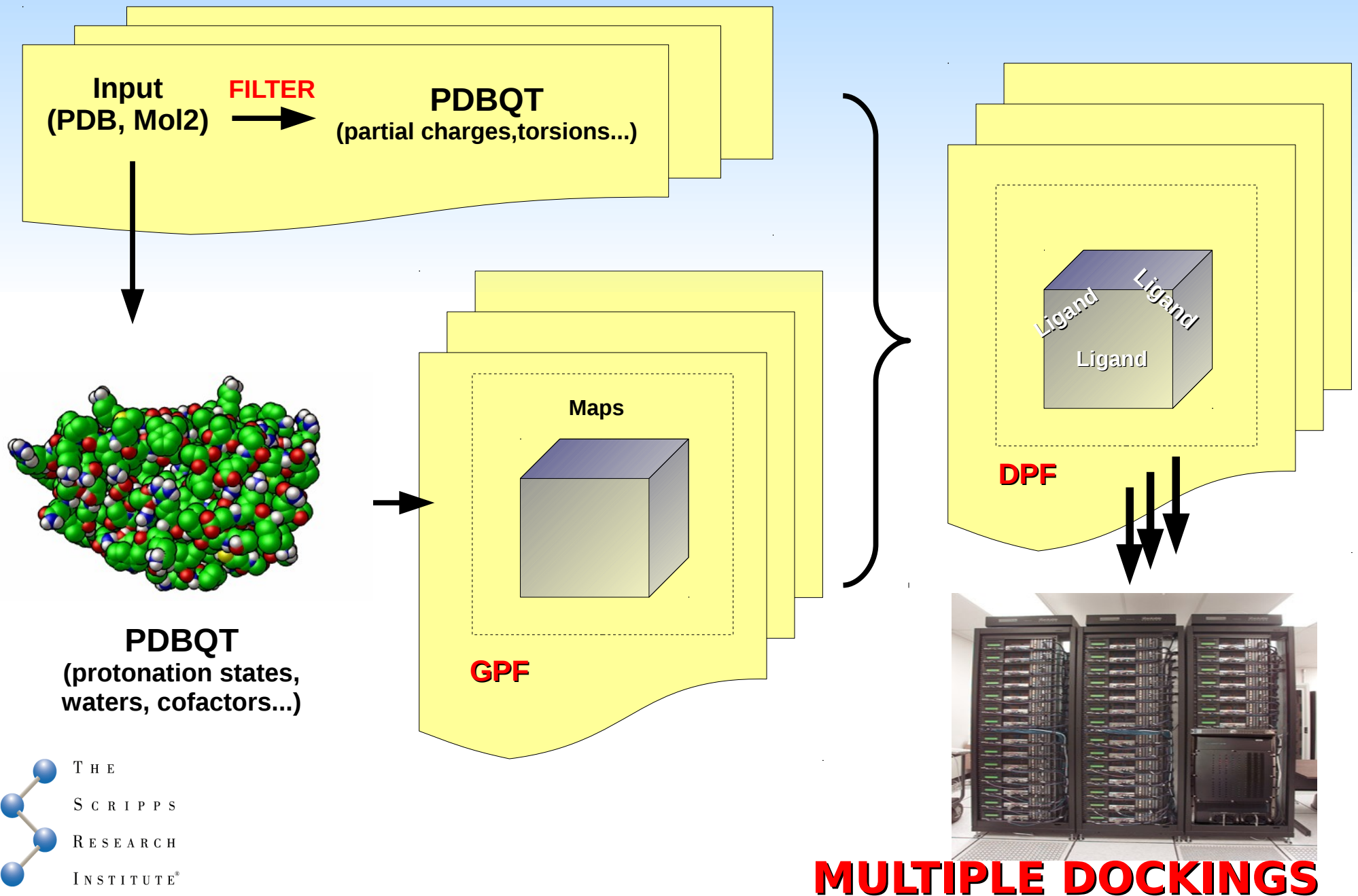
A free database of commercially available compounds for virtual screening

109 commercial compound suppliers, 30×10^6 compounds (non-unique)

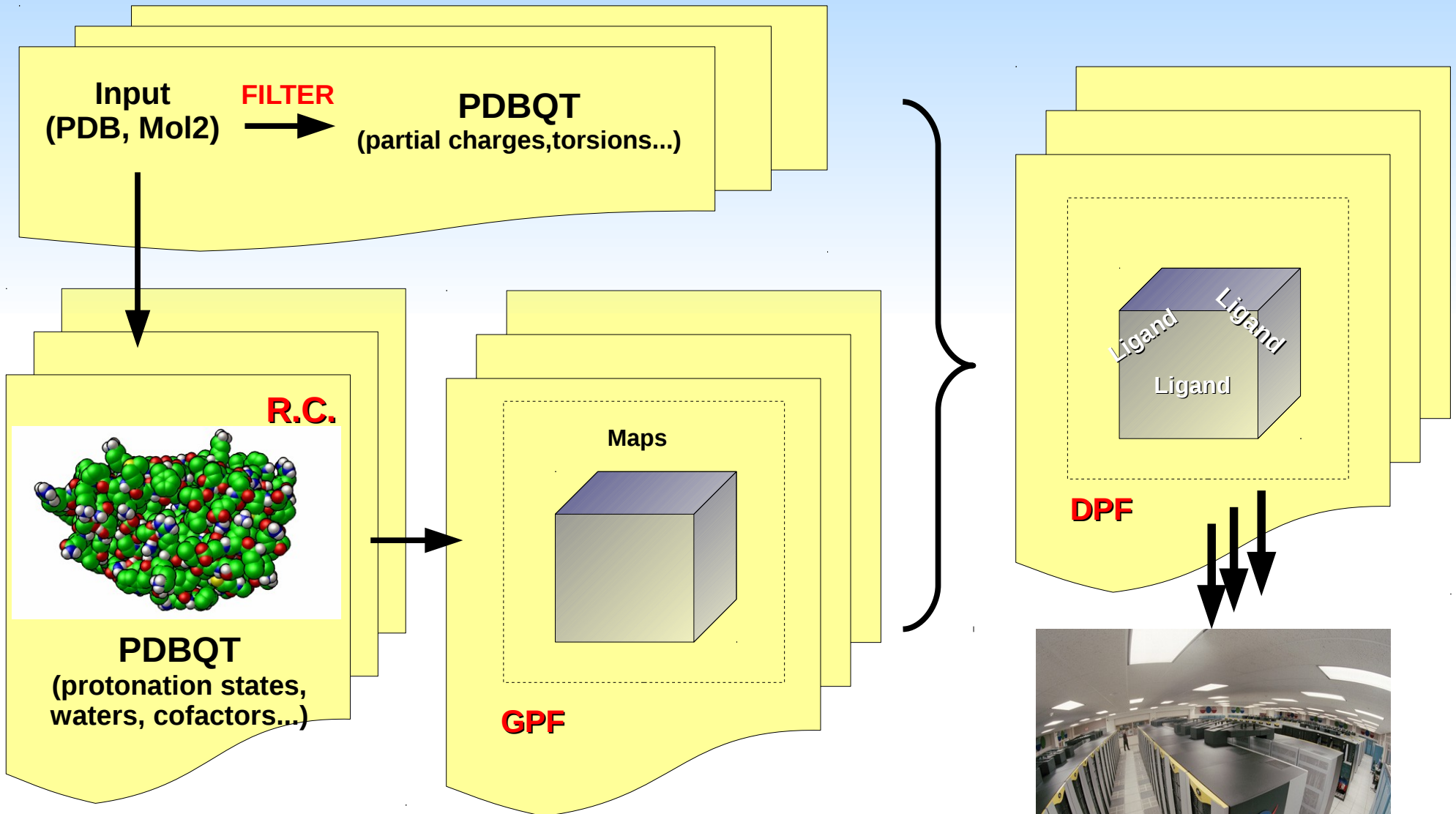
AutoDock Single Docking



AutoDock VS



AutoDock VS



How spot a good answer?

Ligand properties used for results analysis

Energy:

AutoDock score

Ligand Efficiency :

$$\Delta g = \frac{-RT \log K_d}{N_{\text{non-hydrogen atoms}}}$$

Cluster analysis:

- multiple poses clustering tolerance
- cluster size
- energy range

**Knowledge-base
analysys**

- chemical similarities with known binders
- mutagenesis data
- structure/sequence homology

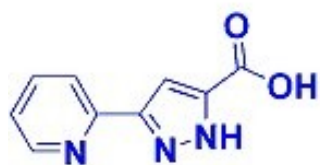
**REDUCE THE NUMBER OF RESULTS TO ANALYZE
AND (HOPEFULLY) ENRICH THE QUALITY**

How spot a good answer?

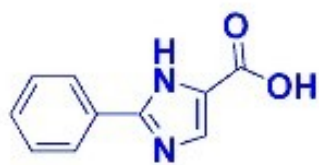
Ligand properties used for results analysis

OPTIMIZATION

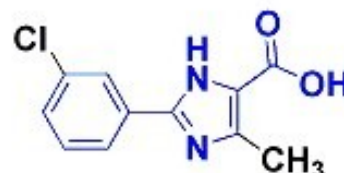
←
ligand efficiency



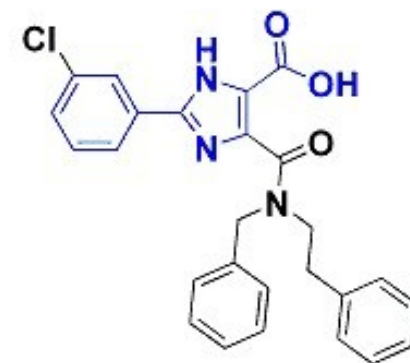
Compound 3
 $IC_{50} = 720 \mu M$
 $LE = 0.31$



Compound 5
 $IC_{50} = 180 \mu M$
 $LE = 0.36$



Compound 10e
 $IC_{50} = 20 \mu M$
 $LE = 0.40$



Compound 20
 $IC_{50} = 0.83 \mu M$
 $LE = 0.25$
 $GI_{50} = 13 \mu M$

How spot a good answer?

Results clustering

Number of distinct conformational clusters found = 2, out of 100 runs,
Using an rmsd-tolerance of 2.0 A

CLUSTERING HISTOGRAM

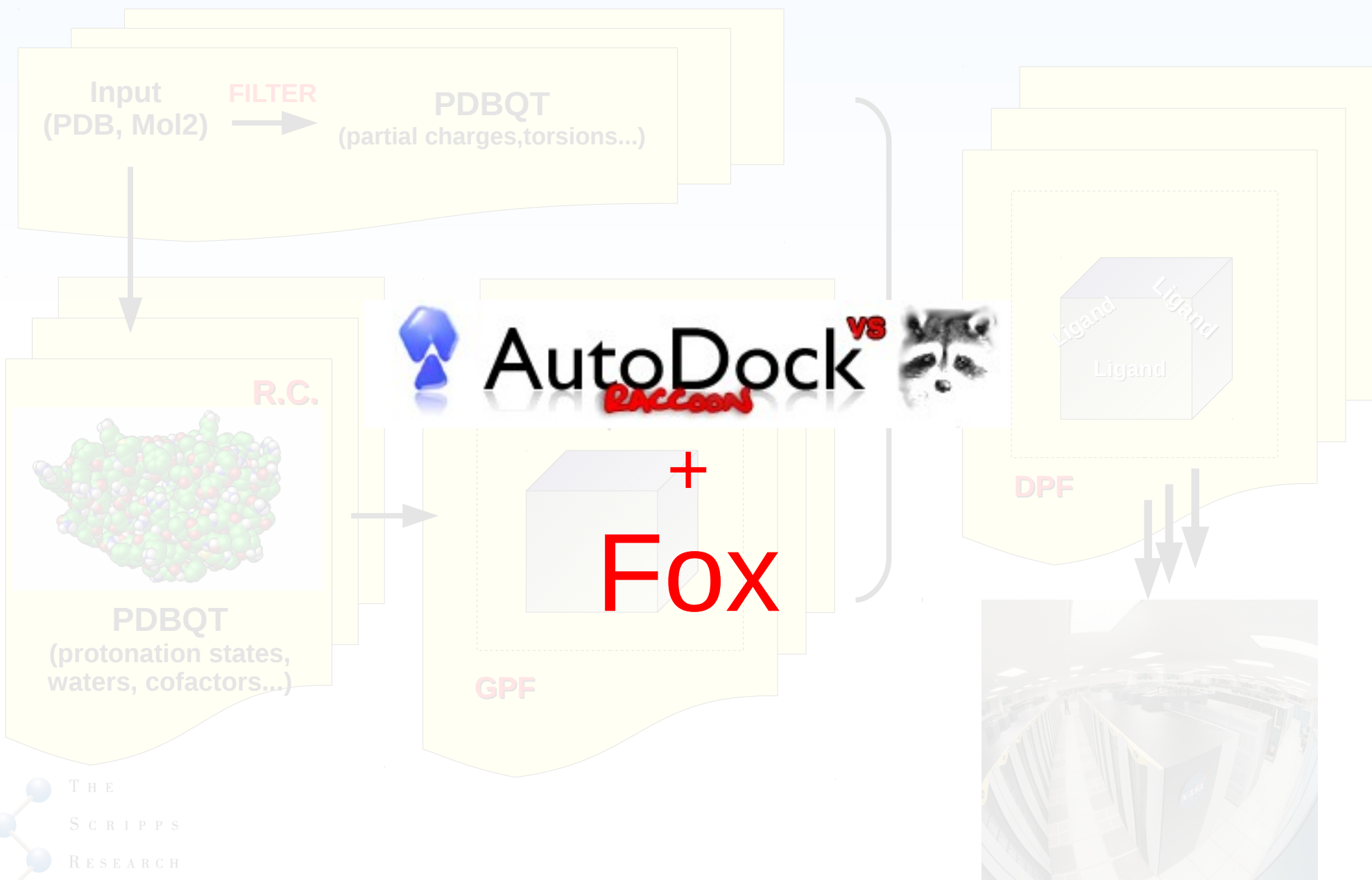
Clus-ter Rank	Lowest Binding Energy	Run	Mean Binding Energy	Num in Clus	Histogram							
					5	10	15	20	25	30	35	
1	-7.52	14	-7.52	7	#####							
2	-7.39	60	-7.39	93	#####	#####	#####	#####	#####	#####	#####	#####

BEST ENERGY?

MOST POPULATED CLUSTER?

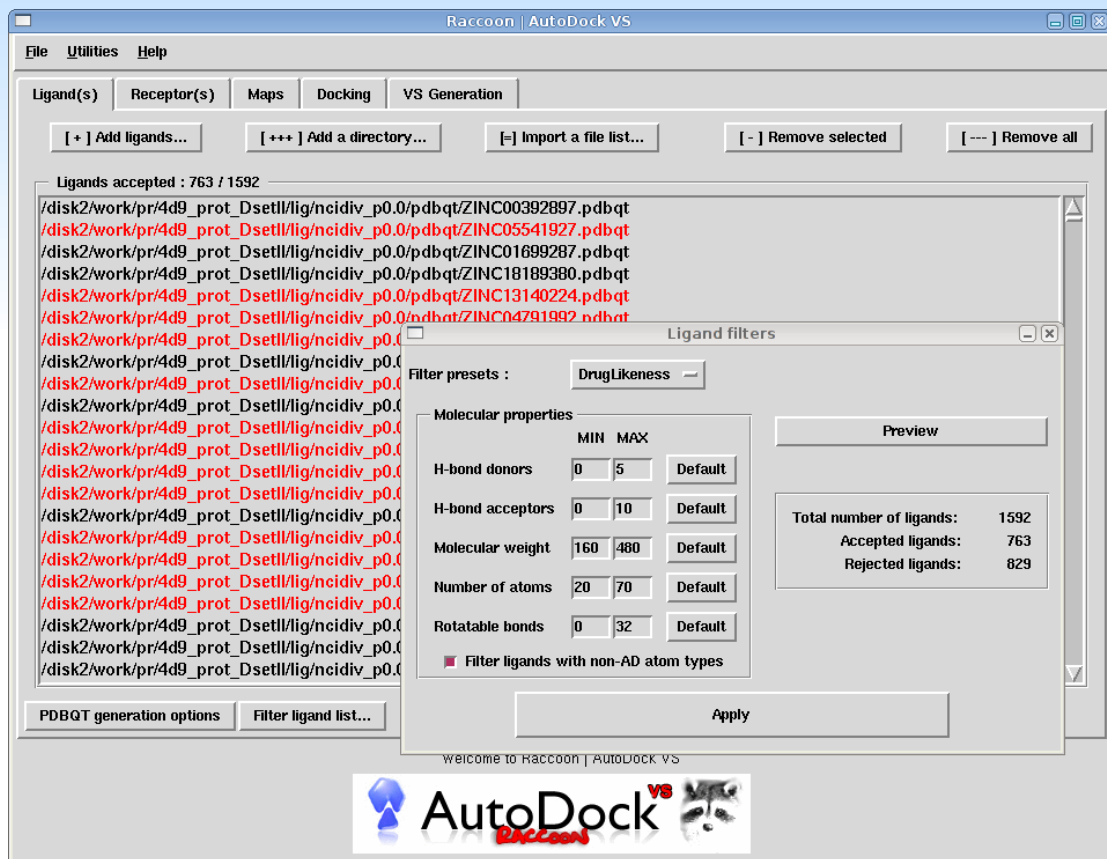
Number of multi-member conformational clusters found = 2, out of 100 runs.

AutoDock VS

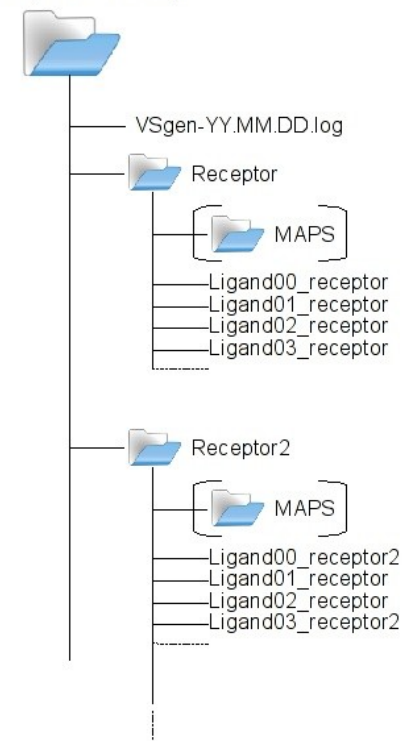


AutoDockVS | Raccoon

- input preparation and filtering
- file-system organization
- parameter files generation
- automated calculation scripts
- generation data logging



VS output directory



AutoDockVS | Fox

Fox | AutoDock VS **TESTING**

File Mode Analysis Wizard Help

Input Filter & analysis Viewer Export

Total ligands: Ligands :2767
Total accepted: 1837 [150.6260%] Score Profiler(TM)

Filter set: <default> Save Delete

Pose selection: Unique Lowest energy **Largest cluster** any

Energy: -5.34 Kcal/mol
Worst: -5.34
Best: -9.69
1837 accepted

Cluster size: 1.00 %
1837 accepted

Ligand efficiency: -0.10
Worst: -0.1
Best: -0.807
1837 accepted

Interactions: 1837 accepted

Filter

Fox | AutoDock VS

Input data Filter & Analysis Viewer Export

imatnib

Energy -15.39
Ligand efficiency -0.42
Active torsions 6
Clustering [100 runs @ 2.00 A tolerance]
clusters 2
cluster size 94.00% [94]
E range 1.63 Kcal/mol
Hydrogen bonds 3
vdW contacts 20

3D viewer
Center
Tgt
Grd
Lig
Snap!
Load

Energy profile
500 ligands, Lowest energy in largest cluster (2.0A RMSD)

Energy profile data (approximate):

Kcal/mol	%
-4	11
-5	51
-6	122
-7	132
-8	117
-9	52
-10	14
-11	0
-12	0
-13	0
-14	0
-15	1

Viewer option <<

Select	Ligand	E	L.eff.	Tors
1	imatnib	-15.39	-0.42	6
2	ZINC01572309	-10.94	-0.33	4
3	ZINC01639633	-10.81	-0.31	6
4	ZINC01081577	-10.21	-0.41	5
5	ZINC00155292	-10.16	-0.51	1
6	ZINC01578220	-10.12	-0.34	7
7	ZINC00161700	-10.02	-0.40	3
8	ZINC01559756	-9.92	-0.35	5
9	ZINC00393674	-9.88	-0.41	2
10	ZINC01640193	-9.56	-0.40	4
11	ZINC01574620	-9.51	-0.43	3
12	ZINC01655914	-9.24	-0.44	5
13	ZINC01574615	-9.16	-0.40	3
14	ZINC01563973	-9.16	-0.42	4
15	ZINC01573467	-9.11	-0.40	3
16	ZINC00247785	-9.09	-0.40	4

Select all Invert Deselect all Show only

Selected ligands : 0 / 81

3D viewer labels: THR310, LYS274, LYS286, TYR253, PHE382, PHE380, ASP381, HIS361, ARG362, LEU360

- clustering
- results analysis
- report tools

How to obtain good answers

Virtual Screening Hints

Pre-processing

- Choose with care which ligands to include in the screening
- Select representative target state(s)

Post-processing

- Efficiently filter results:
 - *avoid chemical complexity*
 - *search for specific interactions (polar residues)*
 - *use both energy score and ligand efficiency*
- Use knowledge-driven criteria
 - *use target information (function, mutagenesis)*
 - *use known binders references (if available)*

Recommended readings

“Is there a difference between leads and drugs? A historical perspective”

Oprea, T., I., Davis, A., M., Teague, S., J., Leeson, P., D.J. Chem. Inf. Comput. Sci. 2001, 41, 1308-1315

“A 'rule of three' for fragment based lead discovery?”

Congreve, M., Carr, R., Murray, C., Jhoti, H. 2001, Drug Discov. Today, 2003, v8, n19, p876

“Virtual screening - what does it give us?”

Köppen H. Curr Opin Drug Discov Devel. 2009 May;12(3):397-407

“Ligand efficiency: a useful metric for lead selection”

Hopkins AL, Groom CR, Alex A. Drug Discov Today. 2004 May 15;9(10):430-1.

“Experimental and computational approaches to estimate solubility and permeability in drug discovery and development settings”

C.A. Lipinski; F. Lombardo; B.W. Dominy and P.J. Feeney (1997). . Adv Drug Del Rev 23: 3–25