



1785

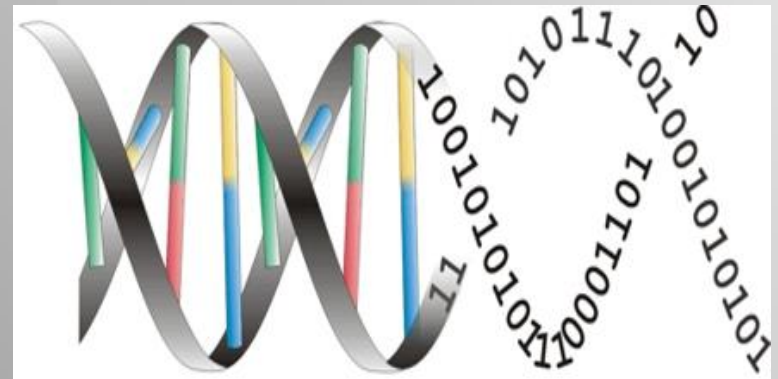
The University of Georgia



Programming for Computational & Systems Biology

Instructor: Paul Xie

Tue. & Thr. 9:35~10:50



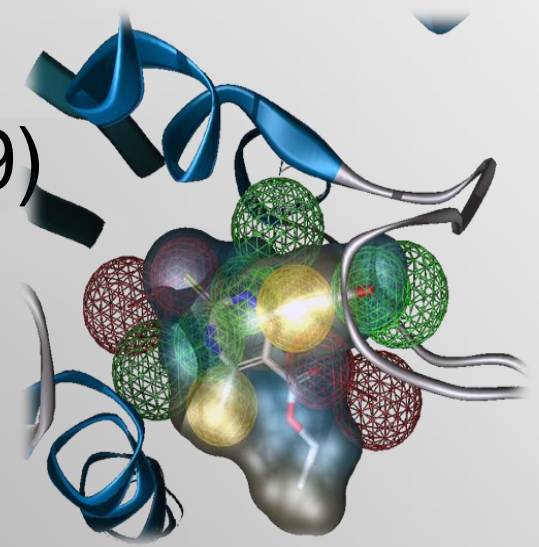
Course Format

- Computer labs + lectures (3 hours/week)
- Coding concepts (some knowledge about biological data)
- 6-8 assignments, published on eLC, (30-40%)
 - Please upload them by the due days
- Paper review (10-20%)
- 1 term paper (50-60%)



Docking/Simulation

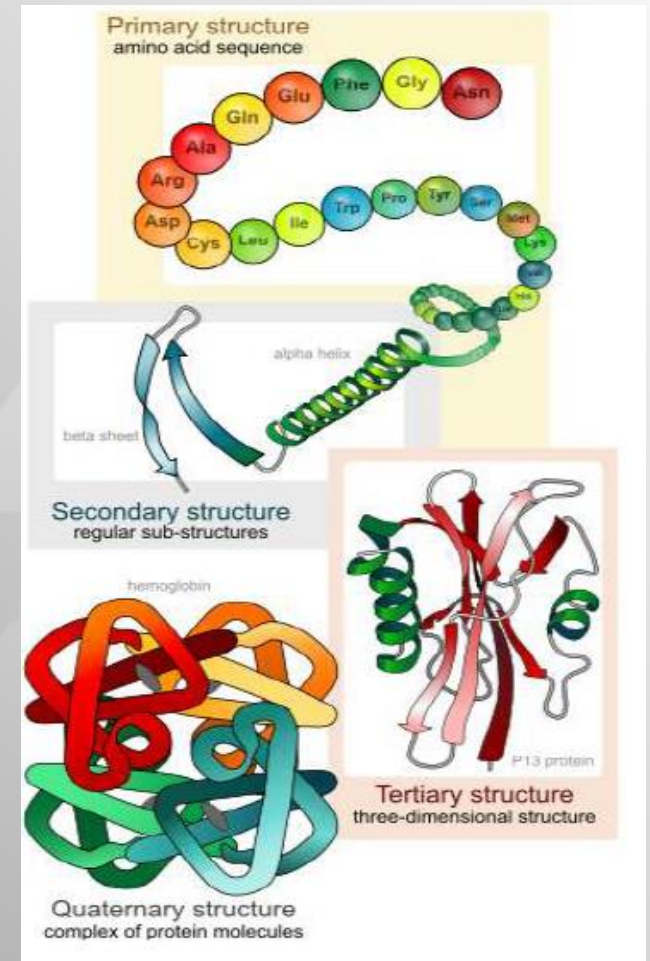
Instructor: Paul Xie (9)



Last Week

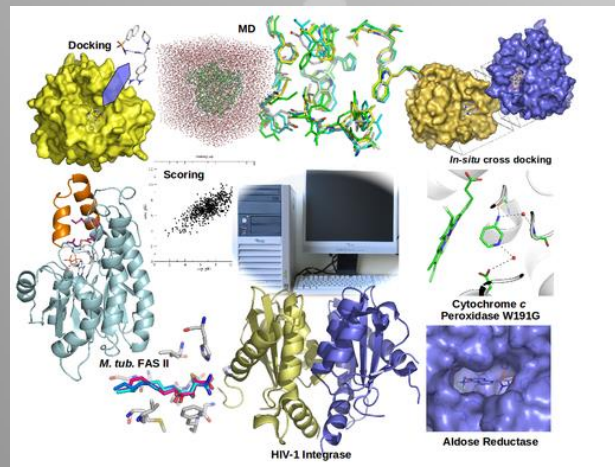


- Protein
- List & List Operation



This Week

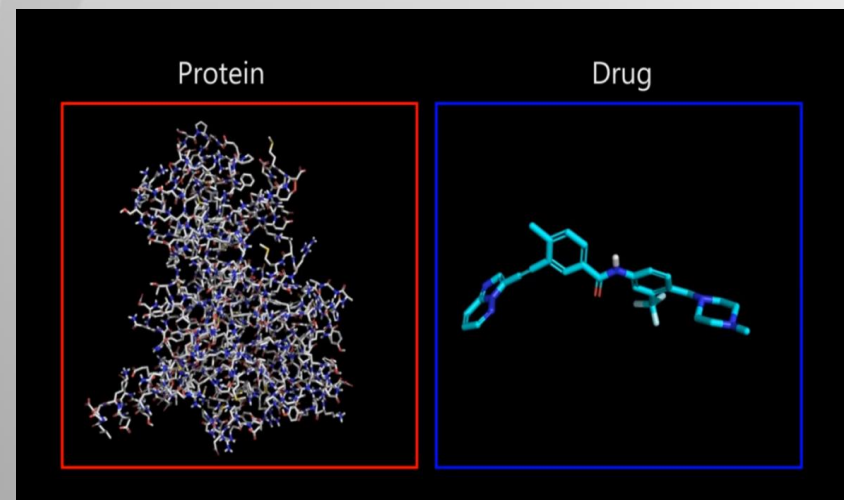
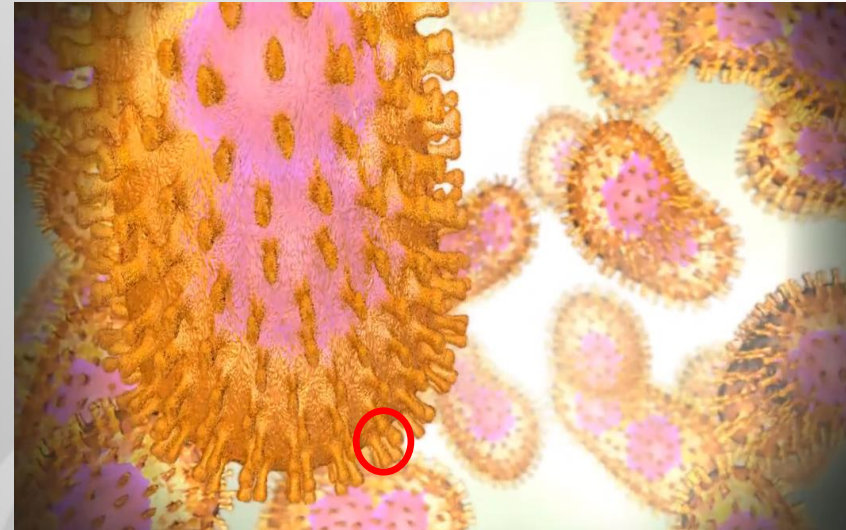
- Molecular docking
 - Virtual drug discovery
- List Operation → Modeling



Drug (Medicine) Discovery



- ❖ How to discover a drug?
 - Identify Targets
 - Proteins (or DNA/RNA)
 - Screen Drugs
 - Molecules can **bind** and **regulate** the activity of the target protein



Conventional vs. Computational Drug Discovery

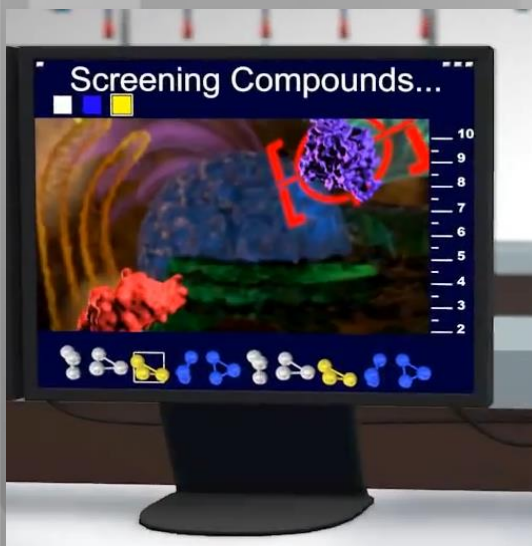
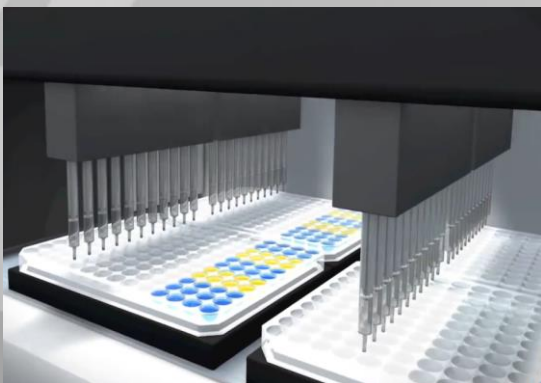


- ❖ **Challenges** of new drug discovery
- ❖ Comparison

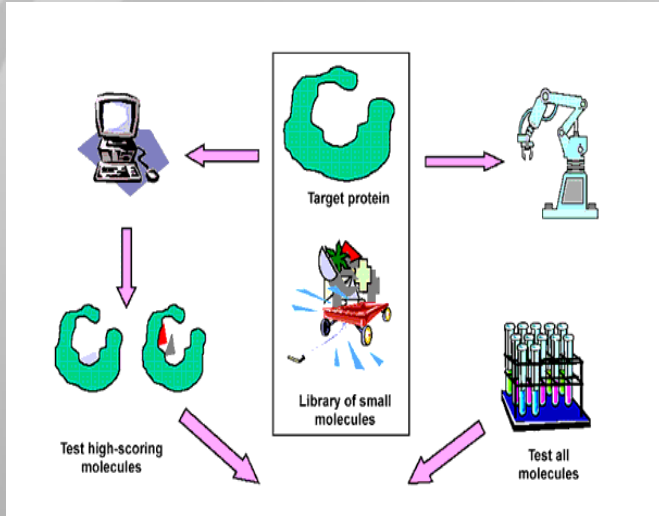
	Conventional	Computational
Venue	Labs	CPUs
Target Proteins	Culture, purify, ...	Download
Millions of compounds	Purchase, deliver, store,...	Download
Drug binding	Bio-essays	Software
Operators	Labors or machine	CPU & software

- ❖ **Advantages** of Computational Drug Discovery

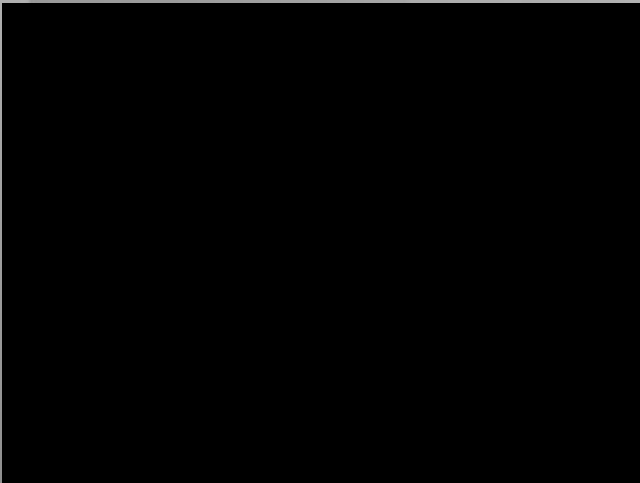
- Faster
- Cheaper
- More



Docking



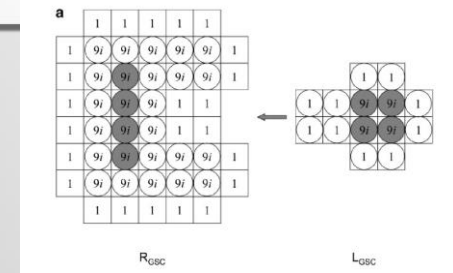
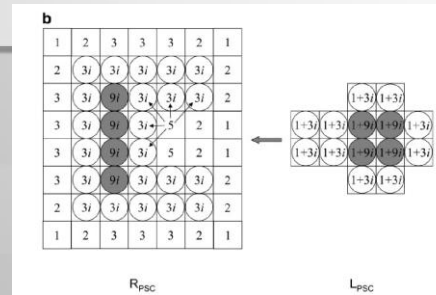
- To predict **whether** and **how well** one molecule bound to a second one to form a stable complex
- Application on medicinal chemistry & molecular biology
- Virtual screening



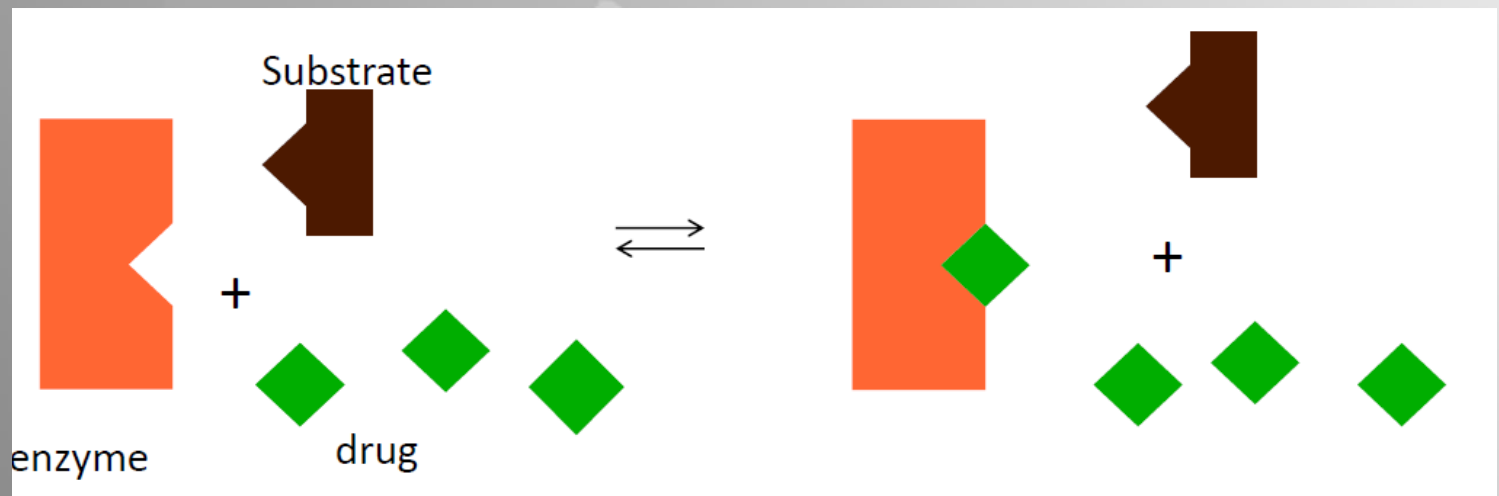
Basic Concept



- Shape complementarity



- Thermodynamic equilibrium $K_a = \frac{[A][B]}{[AB]} = \frac{[Protein][Ligand]}{[Complex]}$
- Affinity: $\Delta G = -RT \ln K_a$



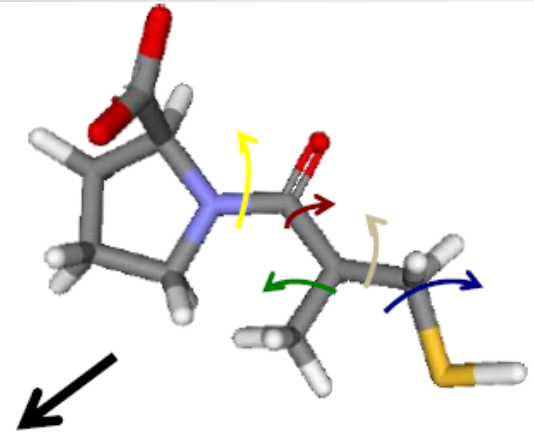
What are Key Scoring Functions of Components of Docking?

- ❖ Two components: Sampling and Scoring
 1. Generates a large number of poses of a molecule in the binding site
 2. Calculates a score or binding affinity for a particular pose
- ❖ Energy-based scoring functions:
 1. **Physics-based**: force-field or empirical
 2. **Knowledge-based**: statistical data to approximate binding energy

Genetic Algorithm



- ❖ Optimization
- ❖ To mimic evolution process
- ❖ Genes, individuals, and population
- ❖ Pose: location, orientation, conformation



Dihedral angles are translated in genes (binary)

101001010101001011001100111010101010



A random initial population is easily generated

001011010111000101001010011101010101
101010010111101110001010010100111010
110101101011100010100101001110101010
010111110110101110001010010100111010

Force Field



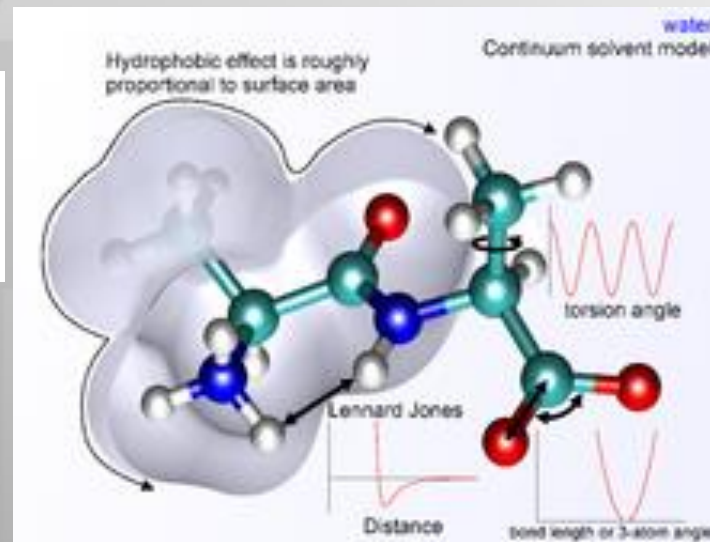
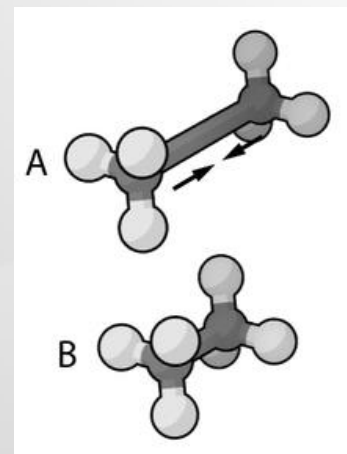
❖ Force-Field

- a physical- or statistical model describing the interaction energy

- $E_{total} = E_{bonded} + E_{nonbonded}$

$$E_{bonded} = E_{bond} + E_{angle} + E_{dihedral}$$

$$E_{nonbonded} = E_{electrostatic} + E_{van\ der\ Waals}$$



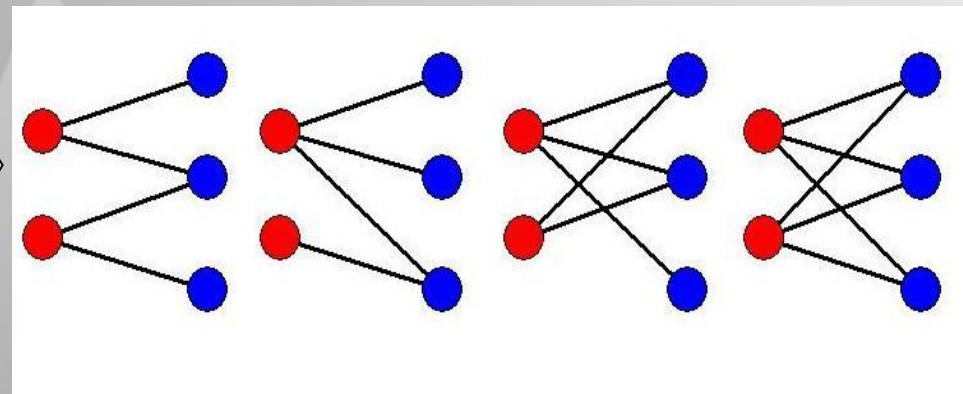
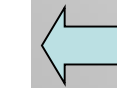
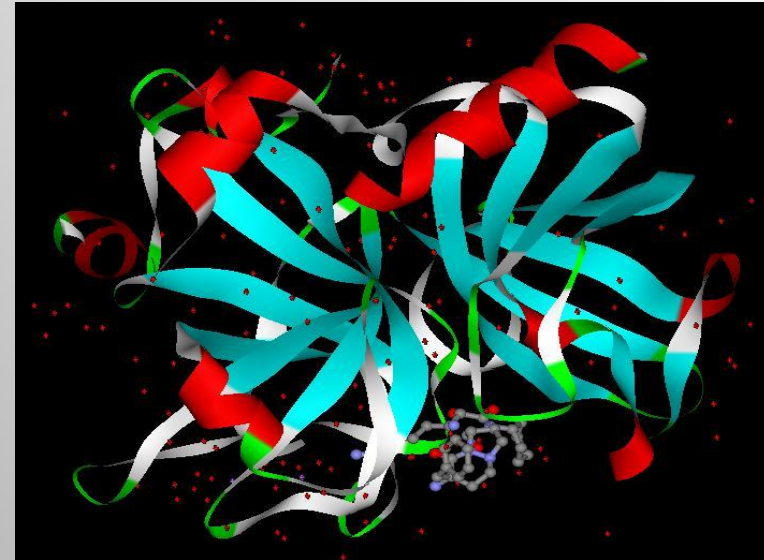
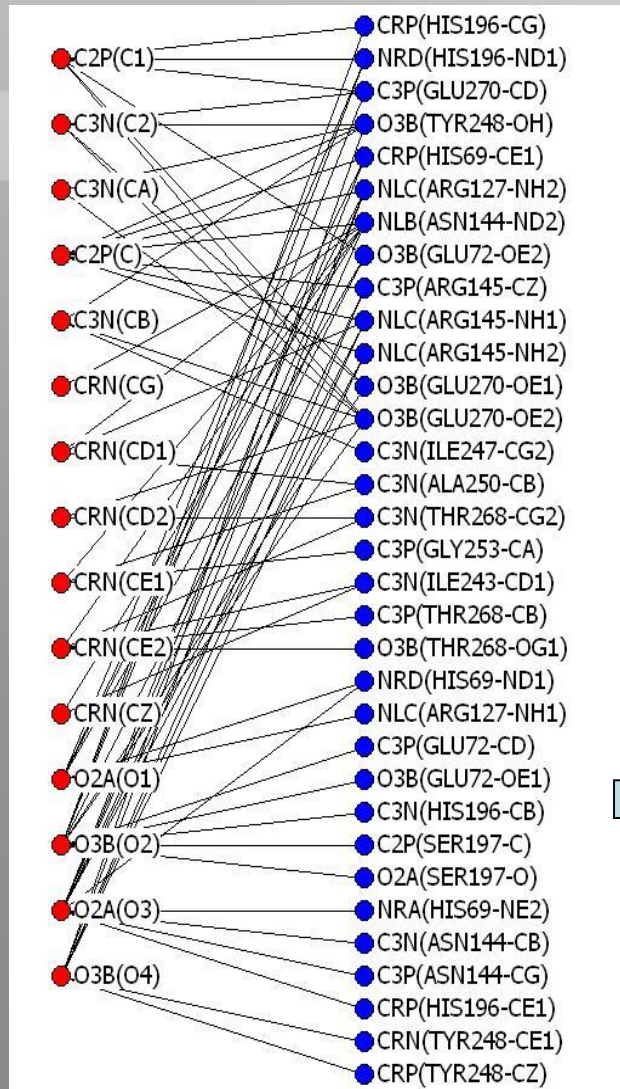
New Scoring Functions



- ❖ How to create a new docking scoring function?
 - New approach
 - Overcome the difficulties, e.g. structure flexibility



From 3D Structures to Interaction Motifs

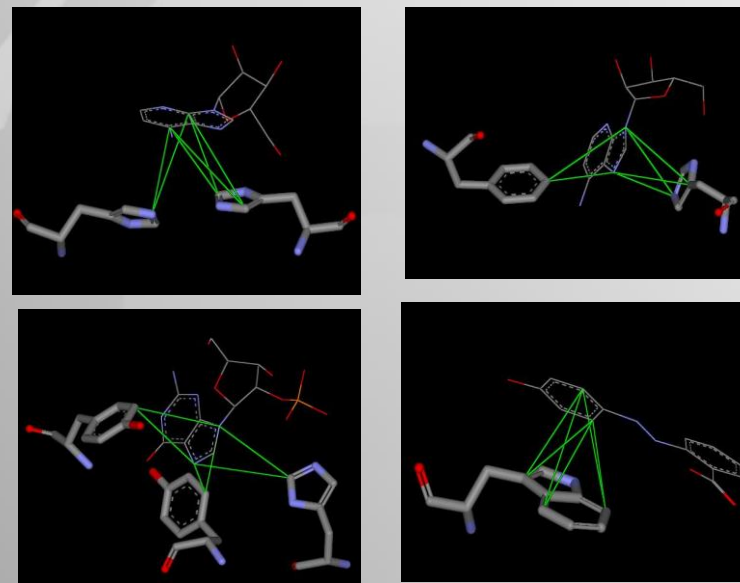


MotifScore

Atom Type	Description	Example
C2N	C, SP2, normal/non-polar	<chem>C=C</chem>
C2P	C, SP2, polar	<chem>C=O</chem>
C3N	C, SP3, normal/non-polar	<chem>C-C</chem>
C3P	C, SP3, polar	<chem>C-OH</chem>
CRN	C, aromatic, normal/non-polar	<chem>c1ccccc1</chem>
CRP	C, aromatic, polar	<chem>c1ccccc1Cl</chem>
O2A	O, SP2, hydrogen bond acceptor	<chem>>C=O</chem>
O3A	O, SP3, hydrogen bond acceptor	<chem>C-O-C</chem>
O3B	O, SP3, both	<chem>-OH</chem>
OLC	O, aliphatic, charge	<chem>-COO-</chem>
ORA	O, aromatic, hydrogen bond acceptor	<chem>c1ccoc1</chem>
NLA	N, aliphatic, hydrogen bond acceptor	<chem>-NR2</chem>
NLB	N, aliphatic, both	<chem>-NH1 or 2</chem>
NLC	N, aliphatic, charge	<chem>-NH3+</chem>
NRA	N, aromatic, hydrogen bond acceptor	<chem>c1ccncc1</chem>
NRD	N, aromatic, hydrogen bond donor	<chem>c1cc[nH]c1</chem>
NRE	N, aromatic, either H.B. donor or acceptor	<chem>c1cc[nH]c1</chem>
S3N	S, SP2, normal/non-polar	<chem>-SH</chem>
SFN	S, aromatic, hydrogen bond acceptor	<chem>c1ccsc1</chem>
SLC	S, aliphatic, charge	<chem>-SO4-2</chem>
P	P	
ME	metal	
HAL	F, Cl, Br, I	

➤ Automatic atom type assignment, graph converting, motif searching, & scoring

➤ Significant motifs



- 1st code : atom name (e.g., C, N, O, ME, HAL...)
- 2nd code: **2**-SP2; **3**-SP3; **1**-SP; **R**-aromatic; **L**-aliphatic
- 3rd code: **A**-HB acceptor; **D**-HB donor; **B**-Both; **N**-normal/neither, **E**-either, **C**-charge **P**-polar

Scoring Function

- Motif Gain → Relative abundance of a specific motif

$$SG_i = \log \left(\frac{OM_i/N_i}{\prod_{j=1}^5 (OA_j/M_j)} \right)$$

SG: Gain score

OM, *OA*: occurrence of motif/atom

N, *M*: number of specific type of motifs/atoms

$$Gain = \sum_{k=1}^n SG_k$$

- Penalty Function

$$Penalty = W \times NC$$

W: weight; *NC*: number of clash

- Overall Scoring Function

$$MotifScore = \frac{Gain}{Penalty+1}$$

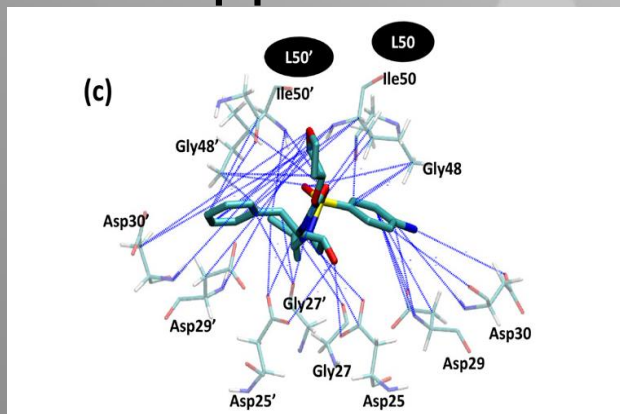
Comparison with Other Scoring Functions

Scoring function	Success rates (%) under different rmsd criteria ^a		
	$\leq 1 \text{ \AA}$	$\leq 2 \text{ \AA}$	$\leq 3 \text{ \AA}$
DrugScore ^{CSD}	83	87	* ^b
MotifScore	72	84	86
Cerius2/PLP	63	76	80
SYBYL/F-Score	56	74	77
Cerius2/LigScore	64	74	76
DrugScore ^{PDB}	63	72	74
Cerius2/LUDI	43	67	67
X-Score	37	66	74
AutoDock	34	62	72
Cerius2/PMF	40	52	57
SYBYL/G-Score	24	42	56
SYBYL/ChemScore	12	35	40

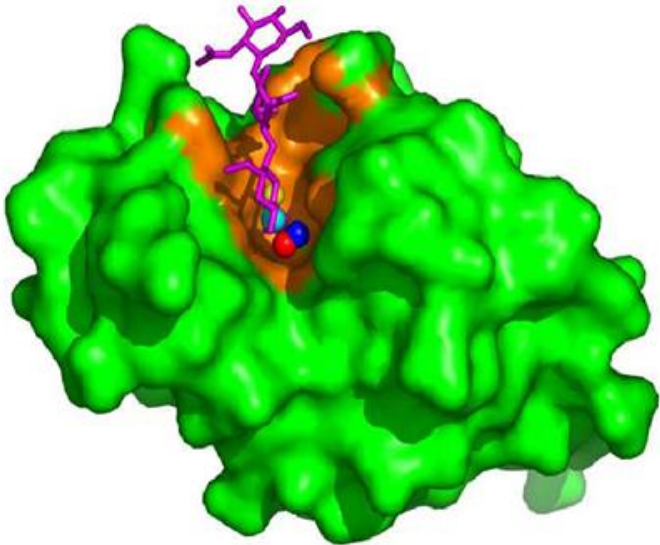
- **Comparable** to the best success rate of energy-based scoring functions
- To use the small molecule structure database, CSD
- Potential of Improvement

New Scoring Function

- ❖ Created a new docking scoring function
 - The **first** scoring function using network approach
 - More **tolerant** to structural flexibility
 - Good results compared with conventional approaches
 - **Complementary** with energy-based scoring functions
 - Has been applied to a study of **drug resistance of HIV**

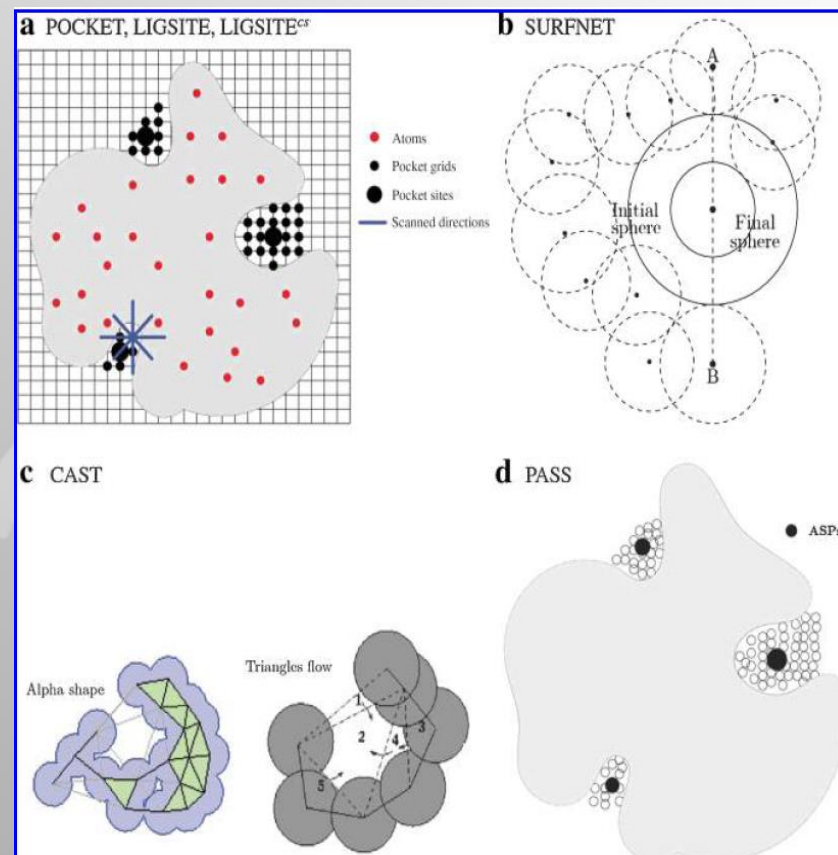


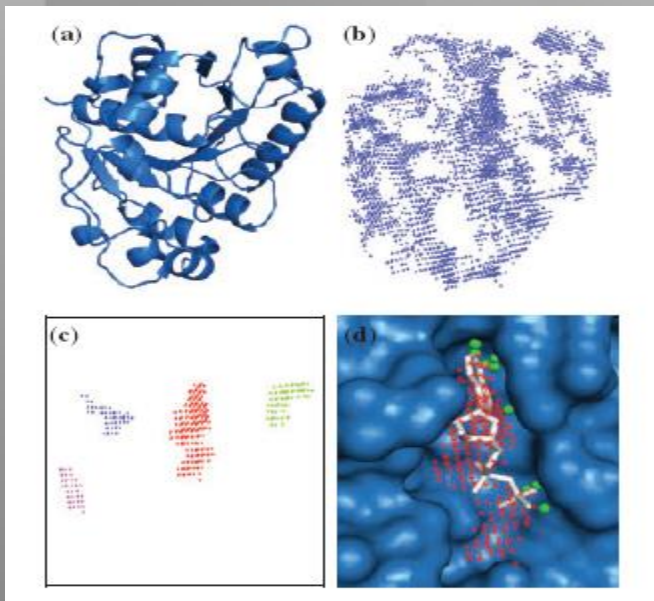
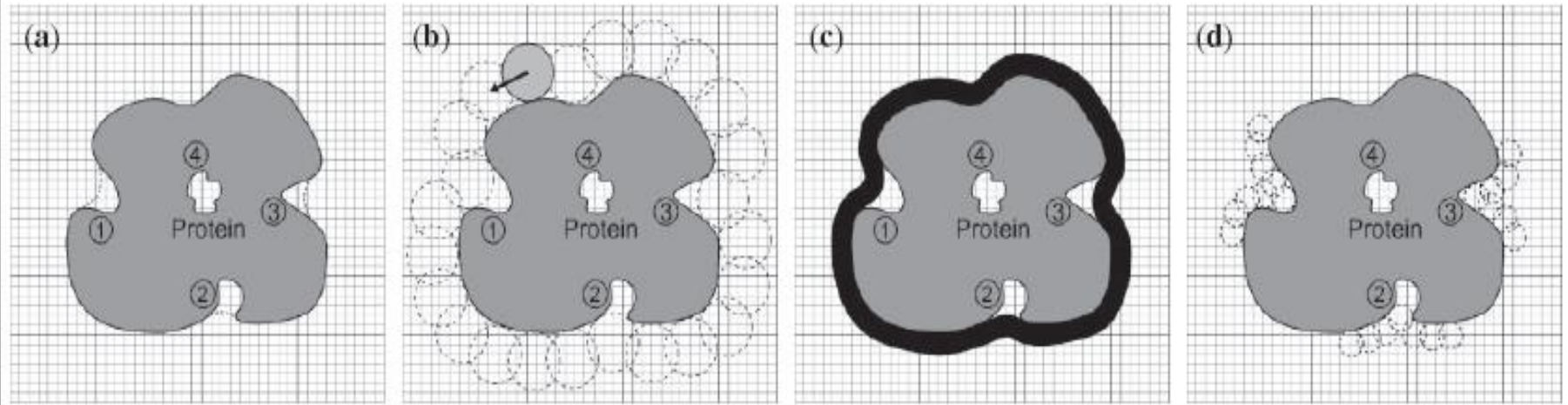
Before Docking



- ❖ Where is the binding site?
- ❖ Binding (Active) Site Prediction
 - To **reduce** computation load, and **narrow down** searching area on the protein
 - To predict protein functions

- From an observation
 - Small compounds often bind to **largest cavities**
 - New assumption
 - Geometry-based binding site prediction: to identify largest cavities
- Limitation: This assumption is **often**, but **not always** true





- Pocket: between protein & probe surfaces
- Diff. spheres create diff. cavities
- SPF: single point flag to remove noise

Limitation of Geometry-based Method

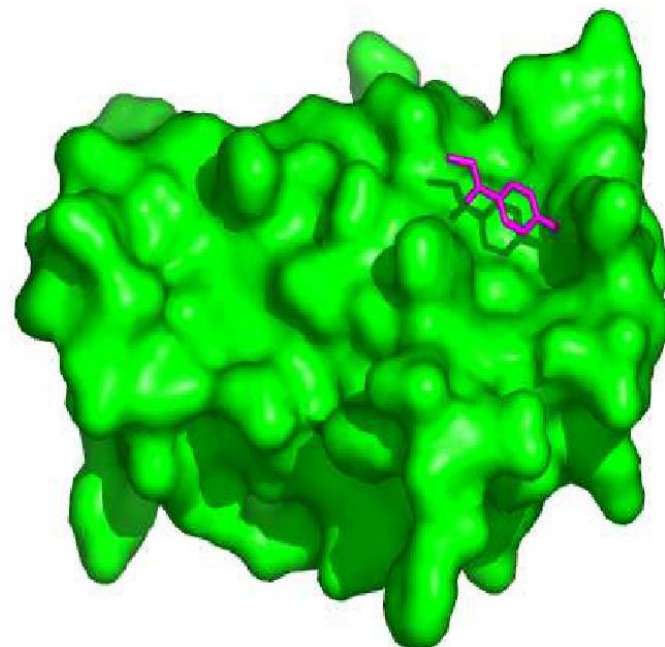
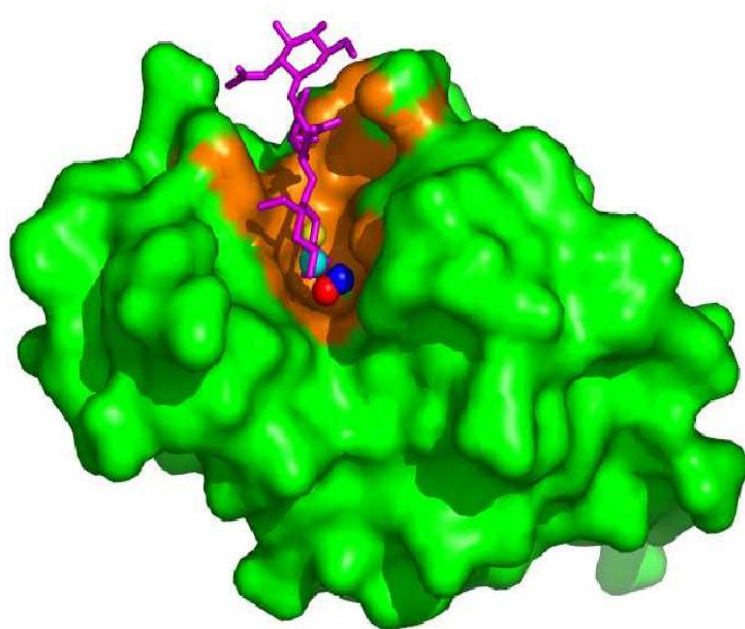


Table 3: Numbers of protein in each class for 210 bound structures.

Class	No. of proteins (as %)	Avg no. pocket points	Stdev
Class 1: Binding site in largest pocket	141/210 = 67%	209	185
Class 2: Binding site in second largest pocket	28/210 = 13%	66	64
Class 3: Binding site in third largest pocket	14/210 = 7%	40	41
Class 4: Binding site in none of above	27/210 = 13%		

Challenge



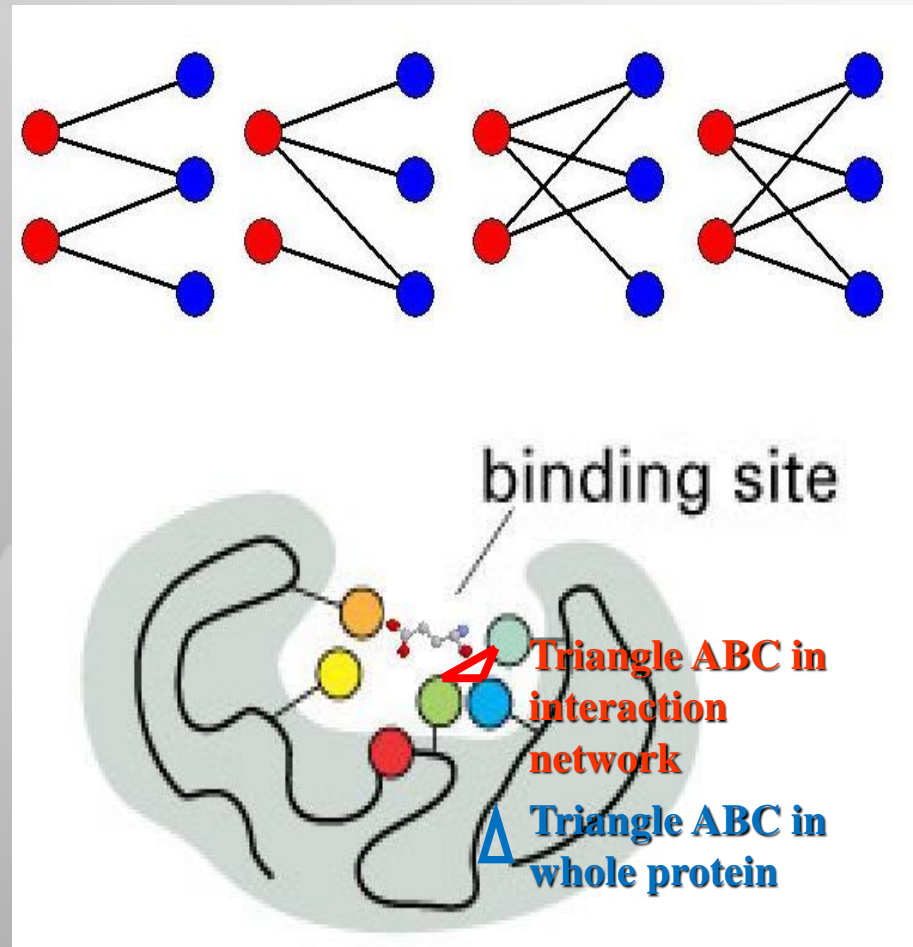
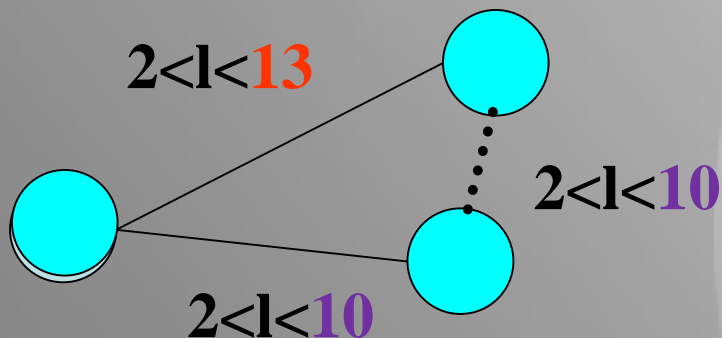
- ❖ How to create a new binding site prediction method?
 - New approach
 - Overcome the limitation



Using Graphs

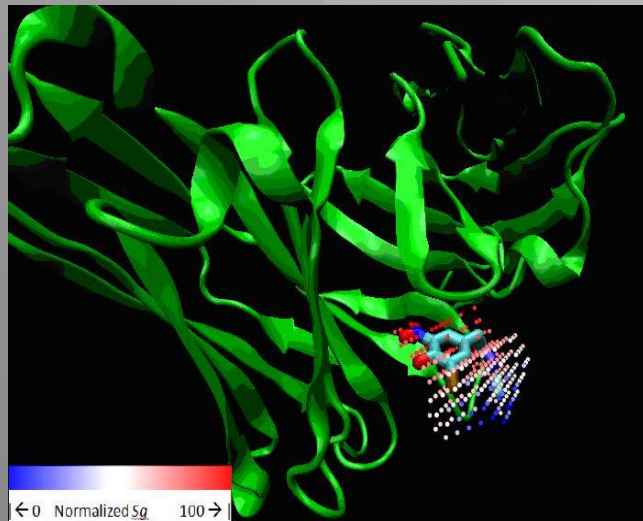
- Enriched in Motifs
- Side length thresholds (10, 10, 13 angstrom)
- Propensities of triangles

$$P_i = \frac{n_i / \sum_{i=1}^k n_i}{N_i / \sum_{i=1}^k N_i}$$



My Algorithm: LISE

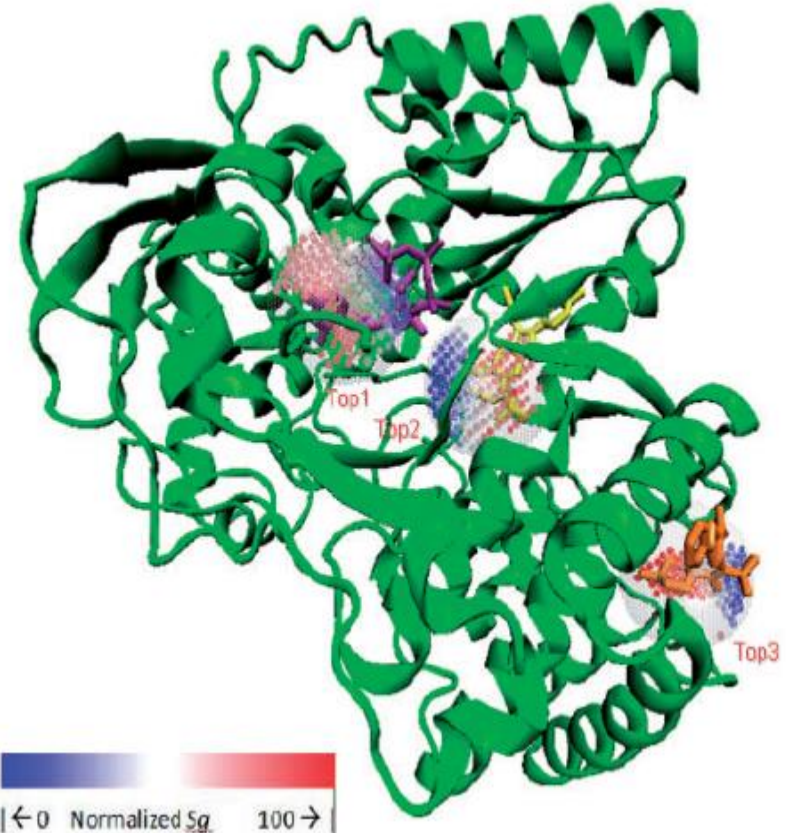
- Statistical data: Propensities
- Identify protein triangles and assign the scores
- Cluster high scored grids



Rank	Triangle	F_b
1	NLC-NLC-NLC	70.6
2	CRP-CRP-CRP	61.9
3	CRP-NLC-NLC	47.2
4	CRP-CRP-NLC	44.3
5	CRP-CRP-OLC	38.1
6	NLC-NLC-NRE	32.8
7	CRP-CRP-NRE	31.7
8	CRP-CRP-O3B	29.8
9	NLC-NLC-O3B	29.6
10	CRP-CRP-NLB	26.2
11	CRN-CRP-CRP	26.2
12	CRP-OLC-OLC	25.8
13	NLB-NLC-NLC	24.6
14	CRP-NRE-OLC	23.5
15	CRP-NLC-O3B	23.5
16	CRP-NLC-NRE	23.0
17	NRE-OLC-OLC	19.9
18	CRP-NRE-NRE	19.7
19	CRP-NLB-NLC	19.2
20	NLC-O3B-O3B	18.6

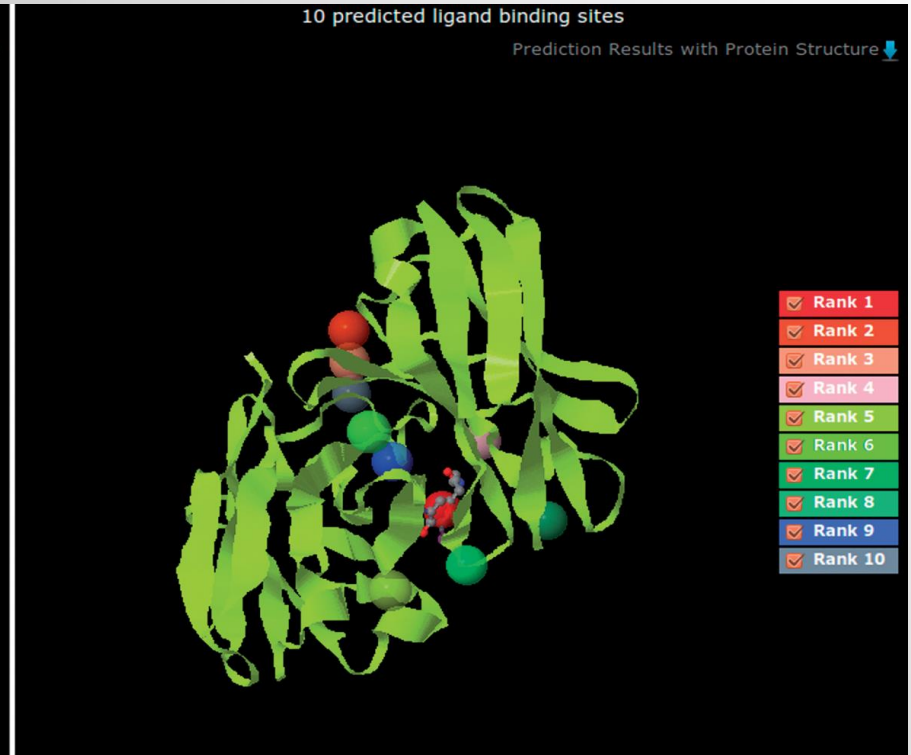
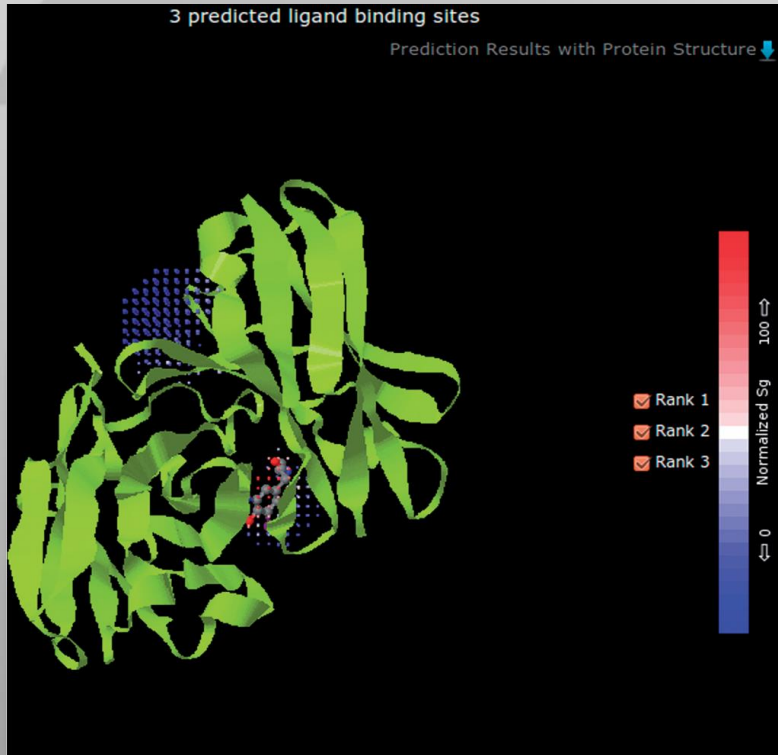
Results & Comparison (the Best Results So Far)

Methods	Bound		Unbound	
	Top1 (%)	Top3 (%)	Top1 (%)	Top3 (%)
LISE (this work) ^b	92	96	81	92
MPK2 (Zhang <i>et al.</i> , 2011)	85	96	80	94
VICE (Tripathi and Kellogg, 2010) ^c	85			
MPK1 (Huang, 2009)	83			
DoGSite (Volkamer <i>et al.</i> , 2010)	83			
Fpocket (Le Guilloux <i>et al.</i> , 2009)	83			
LIGSITE ^{CS} (Huang and Schroeder, 2006)	81			
LIGSITE ^{csc} (Huang and Schroeder, 2006)	79			
MSPocket (Zhu and Pisabarro, 2010)	77			
POCASA (Yu <i>et al.</i> , 2010)	77			
Q-SiteFinder (Laurie and Jackson, 2005) ^c	75			
PocketPicker (Weisel <i>et al.</i> , 2007)	72			
CAST (Liang <i>et al.</i> , 1998) ^c	67			
PASS (Brady and Stouten, 2000) ^c	63			
SURFNET (Laskowski, 1995) ^c	54			



“LISE” Web Server

The University
of Georgia

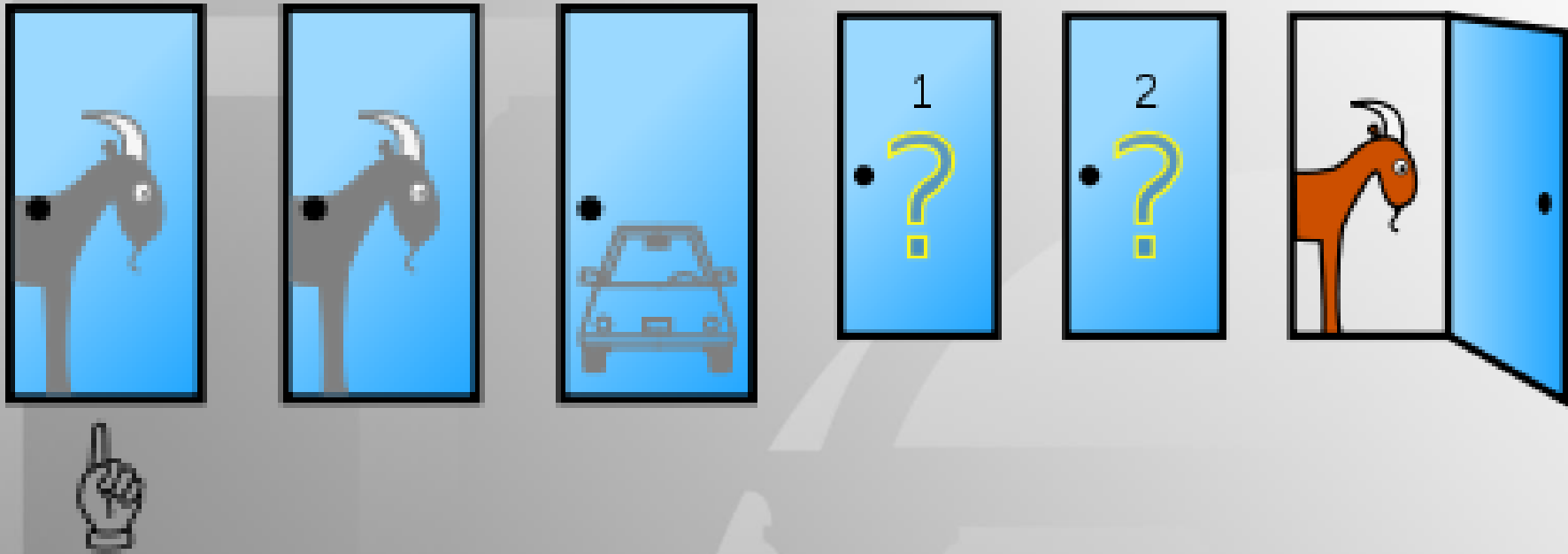


- A web server **established** and **published** on *NAR* 2013
- <http://lise.ibms.sinica.edu.tw>

Summary

- ❖ Created a new docking scoring function
 - The **first** scoring function using network approach
 - More **tolerant** to structural flexibility
 - Good results compared with conventional approaches
 - **Complementary** with energy-based scoring functions
 - Has been applied to a study of **drug resistance of HIV**

Monte Hall Problem



- What is the best strategy?
- Python simulation model

Python Time

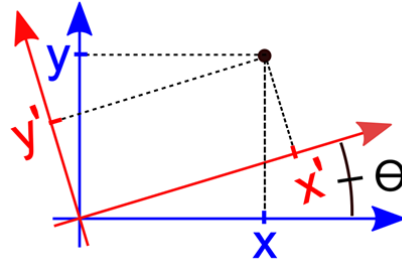


Rotation

➤ 2D rotation

$$x' = x \cos \theta + y \sin \theta$$

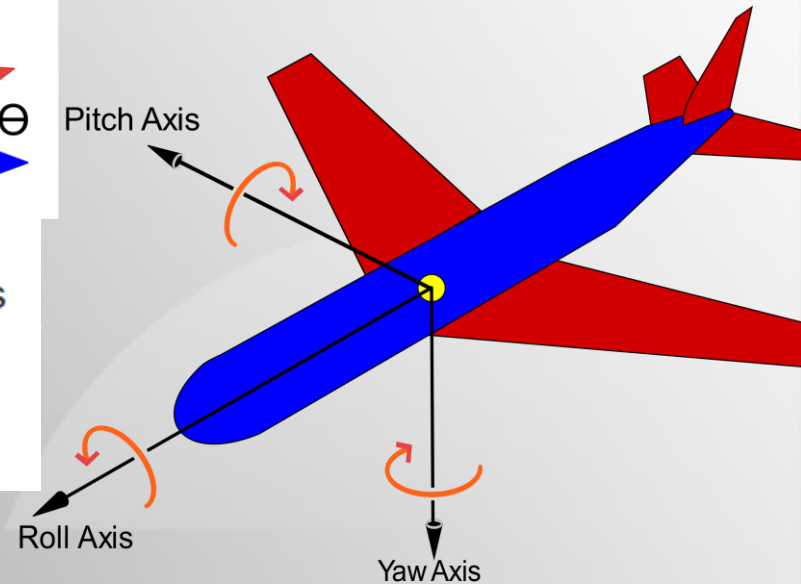
$$y' = -x \sin \theta + y \cos \theta.[7]$$



Equations (5) and (6) can be represented in matrix form as

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix},$$

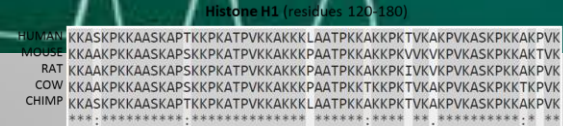
➤ 3D rotation



$$R = \begin{bmatrix} \cos \alpha \cos \beta & \cos \alpha \sin \beta \sin \gamma - \sin \alpha \cos \gamma & \cos \alpha \sin \beta \cos \gamma + \sin \alpha \sin \gamma \\ \sin \alpha \cos \beta & \sin \alpha \sin \beta \sin \gamma + \cos \alpha \cos \gamma & \sin \alpha \sin \beta \cos \gamma - \cos \alpha \sin \gamma \\ -\sin \beta & \cos \beta \sin \gamma & \cos \beta \cos \gamma \end{bmatrix}$$



The University
of Georgia



Non-conservative
Conservative

