First-principle-based and data-driven design platform for small molecule drugs and antimicrobial peptides

Acknowledgement: Profs Yunching Becky Chen, Vincent Shu, Chin Yu, Qing Zhang, Praexisio Inc. and students/postdoc researchers in my lab

Professor and Director, Inst. of Bioinformatics and Structural Biology, NTHU, Taiwan; (楊立威) Director of PhD program in Biomedical Artificial Intelligence, NTHU Group coordinator, Complex Systems and Mathematical Biology, National Center for Theoretical Sciences (Physics Division); TIGP Bioinformatics & CBMB PhD program, Academia Sinica; Honorary Professor, University of Liverpool, UK NCTS Winter School Visiting Professor, University of Osaka (2018), 02/2202 Co-founder of Praexisio Inc. (Drug discovery with harnessing the dancing targets)

Talk overview

- Small drug design state of the art for MD-aided drug screening and new drug discovery
- Find PPI blockers, re-define specificity
- Therapeutic peptides
- Other methods to explore protein dynamics – Normal Mode Analysis and Linear Response Theories

Current pipeline in Yang's lab to screen drugs with protein dynamics accentuated



BETWEEN™ (LWY's <u>Lin.,2020</u>):

- A drug screening that integrates docking, entropy-weighted contact, MDrefined bind free energy
- For screening the binding interface

DRDOCK™ (LWY's <u>Tsai et al.2021</u>):

- A drug screening that integrates docking, AI-based ranking score and MD-refined bind free energy
- For the druggable site that has a cavity





http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.113.6936&rep=rep1&type=pdf

Automated Docking Using a Lamarckian Genetic Algorithm and an Empirical **Binding Free Energy Function**

GARRETT M. MORRIS,¹ DAVID S. GOODSELL,¹ ROBERT S. HALLIDAY,² RUTH HUEY,¹ WILLIAM E. HART,³ RICHARD K. BELEW,⁴ ARTHUR J. OLSON¹

¹ Department of Molecular Biology, MB-5, The Scripps Research Institute, 10550 North Torrey Pines Road, La Jolla, California 92037-1000 ² Hewlett-Packard, San Diego, California

- ³ Applied Mathematics Department, Sandia National Laboratories, Albuqurque, NM
- ⁴ Department of Computer Science & Engineering, University of California, San Diego, La Jolla, CA

Simulated Annealing (Goodsell et al. 1990)



https://en.wikipedia.org/wiki/Simulated_annealing



Genetic algorithm (Morris et al. 1998)

Use of a Genetic Algorithm as a sampling method

- Each conformation is described as a set of rotational angles.
- 64 possible angles are allowed to each of the bond in the ligand.
- Each plausible dihedral angle is codified in a set of binary bits (2⁶=64)
- Each conformation is codified by a so called chromosome with 4 x 6 bits (0 or 1)





General Coordinate System

 $\Phi_1 = 1 \times 2^5 + 1 \times 2^4 + 1 \times 2^3 + 0 \times 2^2 + 1 \times 2^1 + 0 \times 2^0 = 58^\circ$

Genetic algorithm

Population (ie, set of chromosomes or configurations)





Genetic algorithm



Genetic algorithm



Monte Carlo Sampling



Step I. set initial temperature and use random number generator generate random molecular conformation Step 2. generate a new molecular conformation and calculate molecular conformation energy

Step3. Compare energy between previous(EA) and current (EB) conformations. $P = \begin{cases} 1 & , if \ \Delta E \le 0 \\ e^{\frac{-\Delta E}{T}} & , if \ \Delta E > 0 \end{cases}$

Step4. simulated annealing iterates over time until one of the termination criteria is met. termination criteria: predetermined number of iterations, or termination temperature is reach.



Lamarckian genetic algorithm



The local search method is *adaptive*, in that it adjusts the step size depending upon the recent history of energies:

I.a user-defined number of consecutive failures, or increases in energy, cause the step size to be doubled

2.a user-defined number of consecutive successes, or decreases in energy, cause the step size to be halved

translational step size :0.2 A° orientational and torsional step sizes :58°



Problems - affinity and specificity/selectivity



Current pipeline in Yang's lab to screen drugs with protein dynamics accentuated

Huang et al.,2019): An allosteric site predictor based on Linear response theory Al ranking model based on different 2000~4000+ feature distributions between targeted FDA drugs and those are not FDA drugs ATG4R in Active For ocking Pose: Rank 6 Oncogene CALLTM Old drugs or X-ray + MDleads that sampled inhibit the alternative target protein conformation (oncogene) **BETWEEN**^{TN} binding interface Druggable site of protein target

BETWEEN™ (LWY's <u>Lin.,2020</u>):

- A drug screening that integrates docking, entropy-weighted contact, MDrefined bind free energy
- For screening the binding interface

DRDOCK[™] (LWY's <u>Tsai et al.2021</u>):

• A drug screening that integrates docking, AI-based ranking score and MD-refined bind free energy

CALL[™] (LWY's Yang et al. 2014; Li et al., 2017;

For the druggable site that has a cavity



LOD Score of pose
$$x = \sum_{f}^{\square} \square \log \frac{P_{f}^{T}(f(x))}{P_{f}^{F}(f(x))}$$

, where x represented a sampled docked pose. f represented the feature generation function that took an input pose x and returned the corresponding feature value. $f \in \{$ the docking affinity, the distance to the drug target site, \leftarrow the size of poses cluster $\}$. P_f^T was the value distribution of feature f for a docked pose sampled from a true binder. P_f^F was the value distribution of feature f for a docked pose sampled from a decoy. Thus, the LOD score represented how more likely a sampled pose was resulted from a true binder or decoy. The distribution of P_f^T and P_f^F were derived from the docking results of the 2016 drugs on 16 selected crystallized complex structures composing of proteins as drug targets and FDAapproved drugs that was also included in the 2016 drugs according to Westbrook et al., 2019 (Table SX). The 2016 drugs including the one originally in the complex were

Find New Leads for EgIN2 but not EgIN1



DRDOCKTM

BETWEEN™

Old drugs or leads that inhibit the target protein (oncogene)

10.20 ns

Potential allosteric site

sampled

alternative

conformation

Oncogene

4

New drug derived from combining fragments from on-target drugs and systemic drugs (100 times better than the best of the 80 compounds screened and

provided by a leading Al-based drug discovery company)

On-target drug efficiency Identify systemic drug

(FDA 2)

(FDA I)

(FDA I) (FDA 2)

The new drug integrate from on-target fragment and systemic fragments

> $IC50 \le 20$ nM

4 FDA drugs, A-X, A'''-C, A*-D, A'''-B, were screen out from **DRDOCKTM** to inhibit EglN2's active site.

Immunoblotting assays showed A"-B is the best drug in molecular level.

(Unpublished data, confidential)

At the cellular level, A-X shows a strong tumor suppressor effect on breast ductal carcinoma (MCF7, T47D), but less on non-tumorigenic breast epithelial cell line (MCF10A). New drug (A"-X) that integrates fragment A" from on-target drug (A"-B) and fragment X from systemic drug Only ~400 nM of A"-X (A-X) together also showed specific inhibition to EgIN2 but not to EgIN1 which share 70% sequence identity.

can inhibit 50% of the breast ductal carcinoma.

> Data are by courtesy of collaborator Prof. Q Zhang

Using pharmacophors analysis to add one functional group to boost the efficacy of Atomwise's top compound (IC50=2500nM; EC50>11,000nM)

Our new drug: IC50 = 50nM; EC50 = 200nM

Triple negative breast cancer cell line MDA-MB-231

By the end of next year, we can make similar design with a bigger database in 10 days. 6 out of 7 drugs/leads we screened/designed were effective, while Atomwise gave 1/80. (Unpublished data, confidential)



Table 2. Rank of the docking results for effective FDA drugs repurposed to inhibit EglN24

	drugid	name	docking_rank_in_egIn2_X_ray	docking_rank_in_egIn2_c0	docking_rank_in_egIn2_c1
1	01025	A‴- C	74	224	94
2	01426	A - X	296	170	12
3	01631	A" - B	191	119	208
4	01450	A* - D	197	222	245

EgIN2 and the best FDA drugs were more prioritized in MD conformations than that with the x-ray one

As previously discussed with Figure 3, A"-B is the most inhibitory at the molecular level (with cell-free translation and Western Blot) and A-X is the most breast-cancersuppressive. The two drugs were prioritized by alternative conformations C0 and C1, where A-X is much favored in C1 conformation and A"-B is prioritized by C0 among a total of 2000+ FDA drugs. The ranking of the drug in EglN1 is only 129 higher than that using the EglN2 x-ray structure, when at least 400 higher is needed as the selection criterium. The second best EglN2 inhibitor, A*-D cannot be selected for a similar reason.

Conventional thinking of the pharma: high affinity = specificity



Yet, evolution-imposed similarity for functional lives at molecular level makes off-target effects inevitable



FDA/Old drugs (and/or their fragments) are mostly safer, synthesizable, cell-penetrating











Table 1. List of ATG4B inhibitors←

Name/compound ID	ATG4B conformation	Ligand binding sites<-	IC50← ²	References ^{ረ⊒} ∢
NSC185058←	Closed-form←	The exit of the active site nearby the ATG4B N-terminus	51 <u>µ</u> M्≓	Akin et al., 2014 ^{←2} ∢
LV-320	Closed-form←	The exit of the active site nearby the ATG4B N-terminus [←]	24.5 μ∭<⊐	Bosc et al., 2018€
S130⊄	Closed-form←	The groove formed by the folded N-terminal tail	3.24 µM	Fu et al., 2018≪ ² ∢
<mark>Tioconazole</mark> < ^근	<mark>Open-form</mark> ←	The entry of the active site ←	<mark>1.79 µM</mark> ← ⁻	Liu et al., 2018
Compound 1 and 17	Open-form< [→]	The entry of the active site ←	10 and 12 µM←	Endo et al., 2019
VB←	Open-form< [→]	The interface of LC3 binding site ←	~5 µM←	Yang et al≮ [⊇]
Allo1 and Allo2	Open-form<⊐	Potential Allosteric site	~10 µM←	Yang et al [←]
N7 and N9	Open-form	Intermolecular allosteric site on LC3	N.A.←	Yang et al [←]



FDA/Old drugs (and/or their fragments) are mostly safer, synthesizable, cell-penetrating





Synergistic effects (協同效應) by co-drugging active site and protein-protein interface for Cancer cure and SARS-CoV2 suppression









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MD (sampling) \rightarrow Docking \rightarrow MD (binding affinity)

What is DRDOCK?

DRDOCK is a web server that performs online automatic virtual drug screening of 2016 FDA–approved drugs on a user–submitted target protein. Its goal is to facilitate the drug repurposing to extend the possible treatments toward life–threaten and epidemic diseases. This is achieved by combining the molecular docking and molecular dynamic (MD) simulations to prioritize drugs of strong binders from non–binder. The only things the user required to provide are a well–patched protein structure made of a single peptide chain in PDB format and the target residues IDs to which the drugs expected to bind. *DRDOCK* is freely accessed without login requirements. Find more in Tutorials.



PDB file:	選擇檔案未選擇任何檔案
Chain ID:	ex: A Model No: ex: 1
Residues range:	ex: 1-100
Target sites:	ex: 101-102,201
Email:	
Rolay the structur	e by MD before docking

or AlphaFold2 modeling

Submit





Reference: Tsai,KL. and and Yang,LW. (2021) <u>DRDOCK: A DrugRepurposing platform integrating automated docking, simulation</u> and a log-odds-based drug ranking scheme. **doi:** 10.1101/2021.01.31.429052 (*To be peer-reviewed*)

Contact: The server is maintained by the <u>Yang Lab</u> at the <u>Institute of Bioinformatics and Structural Biology</u> at National Tsing Hua University, Taiwan.

For questions and comments please contact Kun-Lin Tsai.



MD (sampling) \rightarrow Docking \rightarrow MD (binding affinity)

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Protein sequence:

AlphaFold2 (Al-based structure prediction)

>6WKS_1|Chain A[auth AAA]|2'-Omethyltransferase|Severe acute> SSQAWQPGVAMPNLYKMQRMLLEKCDLQNYGDSATLPKGIMMNVA KYTQLCQYLNTLTLAVPYNMRVIHFGAGSDKGVAPGTAVLRQWLP TGTLLVDSDLNDFVSDADSTLIGDCATVHTANKWDLIISDMYDPK

CTLLVDSDLNDFVSDADSTLIGDCATVHTANKWDLIISDMYDPK CKNVTKENDSKEGFFTYICGFIQQKLALGGSVAIKITEHSWNADL KLMGHFAWWTAFVTNVNASSSEAFLIGCNYLGKPREQIDGYVMH ANYIFWRNTNPIQLSSYSLFDMSKFPLKLRGTAVMSLKEGQINDM

Target sites: ex: 101-102,201

Relax the structure by MD before docking
Submit

or Upload protein structure





Reference: Tsai,KL. and and Yang,LW. (2021) <u>DRDOCK: A DrugRepurposing platform integrating automated docking, simulation</u> and a log-odds-based drug ranking scheme. (*To be peer-reviewed*)

Contact: The server is maintained by the <u>Yang Lab</u> at the <u>Institute of Bioinformatics and Structural Biology</u> at National Tsing Hua University, Taiwan.

Antimicrobial peptides (AMPs)



Therapeutic Peptide Design

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Helical structure motifs made searchable for functional peptide design

Cheng-Yu Tsai, Emmanuel Oluwatobi Salawu, Hongchun Li, Guan-Yu Lin, Ting-Yu Kuo, Liyin Voon, Adarsh Sharma, Kai-Di Hu, Yi-Yun Cheng, Sobha Sahoo, Lutimba Stuart, Chih-Wei Chen, Yuan-Yu Chang, Yu-Lin Lu, Simai Ke, Christopher Llynard D. Ortiz, Bai-Shan Fang, Chen-Chi Wu, Chung-Yu Lan , <u>Hua-Wen Fu</u> & Lee-Wei Yang

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Antimicrobial peptides (AMPs)



 It is a innate immune defensive system, which are wide spread in bacteria to amphibians, insects, fish, plants, mammals, and even viruses.

 Almost the antimicrobial peptides (generally 12~50 residues) have the common properties : cationic and amphipathic



Nature Immunology 2001, 2, 1133

Secondary Protein Structure





TRENDS in Biotechnology





#	υ# s	Matcheo Sequence	d Mato (MS) Patt	ched cern	Full	Helix	(FH)	PDB ID:	Chain	(MS),	Posit (FH)	ions in & File	PDB Download	Helical Propensity:	Contact :	Inte: Par	ractir tners	ng	Helicity%;
1	1 🕅	VLEWIRW	W2W2	W DVQQ	LLIWLEWI	RWESD		4eba:F		(287,	<u>293) (</u>	280,296)		1.189	8.857	4eba:F	(324,	338)	0.360
10	2 🔟	VQQWLNW	W2W2	W DLAT	FWQQWLN	1		<u>3tsu</u> :A		(651,	<u>657) (</u>	646,657)		1.131	7.857				0.392
11	3 🔟	VORWENW	W2W2	W VNSY	LWORWEN	FWNVTL	R	2lzq:A		(10,1	<u>6) (5,</u>	23)		1.105	8.000				0.385
12	4 <u>N</u>	VDAWLNW	W2W2	W WDAW	LNWFR			<u>lz8h</u> :D		(198,	204) (198,206)		1.089	7.286				0.410
13	5 🚺	KCWARW	W2W2	W <u>NVED</u>	WKCWARW	RLIRARA		<u>3zuk</u> :B		(283,	289) (279,296)	-	1.055	9.143	3zuk:B	(415,	434)	0.339
15	6 <u>M</u>	NAWWISW	W2W2	W <u>AGEW</u>	LGSWTIFY	WAWWIS	WSPFVGMFLAR	<u>411h</u> :A		(371,3	<u>377) (</u>	359,387)		1.039	10.571	411h:A 411h:A 411h:A	(449, (511, (527,	479) 525) 545)	0.285
25	7 🔟	<u>VDWWQW</u>	W2W2	W QWVD	WOWWVK			<u>4n7k</u> :L		(259,	<u>265)</u> (258,268)	-	0.985	7.286	4n7k:M 4n7k:M	(81, 8 (178,	88) 192)	0.402
86	8 🚺	NKDWESW	W2W2	W <u>SVLR</u> QSF	KALHDSLH	IDCSHWF	YTRWKDWESWYS	3zrh:A		(481,	<u>487) (</u>	460,492)		0.799	8.857	3zrh:A	(522,	533)	0.330
87	9 🔟	TAWSTW	W2W2	W WTAW	STWKYC			<u>3cb7</u> :A		(106,	<u>112) (</u>	106,115)		0.638	7.714				0.360
88	10 <u></u>	PEWWNW	W2W2	W <u>GWPE</u>	WNWWLE			<u>3wmm</u> :L		(268,	<u>274) (</u>	267,277)	-	0.345	8.857	3wmm:M 3wmm:M	(82, 9 (180,	0) 193)	0.296
89	11 🚺	VPEWWGW	W2W2	W WPEW	WGWWL			7prc:L		(259,	265) (259,267)		-0.020	8.429				0.284

*At a minimum, 7-8 amino acids are needed for isolated helices due to hydrogen bond formation

*Helicity% for matched sequence in this Table ranges from 0 to 1.

*The 3D visualization is empowered by 3Dmol (Rego and Koes, 2015, Bioinformatics, 31, 1322–1324)



Name⇔	Sequence	MIC ₉₀ vs. <i>C. albicans</i> ↔ (µg/mL)↔	MIC ₉₀ vs. <i>E. coli</i> ↔ (µg/mL)↔	MHC₅↩ (µg/mL)↩
W3_p1↩	KK <u>WRK WLK WLA</u> KK₽	7.5€	15€	120
W3_p2	KK <u>WLK WLK</u> KK∉	7.5↩	15⇔	90∢⊐
<mark>W3_db5</mark> ↩	KK <u>WKC WAR WRL</u> KK	<mark>3.75</mark> ←	<mark>30</mark> ←	<mark>>> 240</mark> €⊒ √
W3_n1₽	KK <u>WGN WGG WRL</u> KK∉	N/A<⊐	>> 120	N/A←
W3_n2€	KK <u>WKD WES WRL</u> KK 🕘	N/A<⊐	>> 120	N/A←

Therapeutic Index = MHC/MIC ~= 80 times better than the original template AMPs.





Supplementary Figure 4 The overview of Sgo1-PP2A protecting centromeric cohesin. During mitosis, phosphorylation of SA2 and Sororin cause cohesin to dissociate from the chromosome arm. Cdk1-mediated phospho-Sgo1 recruits PP2A at centromere to counteract phosphorylation of SA2 and Sororin and maintains centromeric cohesin to tether sister chromatids together. Image is adopted from Fig. 3 in Marston's review paper⁹ where the permission (Permission for the reuse of Supplementary Figure 4.pdf) is obtained through the Copyright Clearance Center of the publisher (https://marketplace.copyright.com/rs-ui-web/mp).



Supplementary Table 1. PP2A-like patterns searched against the developed helical peptide database

Pattern	Query	# of Peptides Found	# of Unique Peptides Found
K *** G ** Y	K 3 G 2 Y	398	69
A *** K *** G	A 3 K 3 G	2981	391
G ** Y *** A	G 2 Y 3 A	2079	225
A *** K *** G ** Y	A 3 K 3 G 2 Y	15	3
K *** G ** Y *** A	K 3 G 2 Y 3 A	3	2
A *** K *** G ** Y *** A	A 3 K 3 G 2 Y 3 A	0	0
A**/***K**/***G**/***Y**/***A	A 2,3 K 2,3 G 2,3 Y 2,3 A	34	3



US, Taiwan & China Patent : https://patentscope.wipo.int/search/en/detail.jsf?docId=US192676438



US, Taiwan & China Patent : https://patentscope.wipo.int/search/en/detail.jsf?docId=US192676438



Amino Acid	Hydrophobicity
Ala	0.310
Arg	-1.010
Asn	-0.600
Asp	-0.770
Cys	1.540
Gln	-0.220
Glu	-0.640
Gly	0.000
His	0.130
Ile	1.800
Leu	1.700
Lys	-0.990
Met	1.230
Phe	1.790
Pro	0.720
Ser	-0.040
Thr	0.260
Trp	2.250
Tyr	0.960
Val	1.220



Figure 18. Spearman correlation for all 4 series of peptides at 20 to 40ns

Figure 19. Precision for all 4 series of peptides at 20 to 40ns

Table 2. Circular permutants of peptide FK13

Mutants	Peptide Name	Sequence
Wild Type	FK13_W	FKRIVQRIKDFLR
Mutant 1	FK13_2	KRIVQRIKDFLRF
Mutant 2	FK13_3	RIVQRIKDFLRFK
Mutant 3	FK13_4	IVQRIKDFLRFKR
Mutant 4	FK13_5	VQRIKDFLRFKRI
Mutant 5	FK13_6	QRIKDFLRFKRIV
Mutant 6	FK13_7	RIKDFLRFKRIVQ
Mutant 7	FK13_8	IKDFLRFKRIVQR
Mutant 8	FK13_9	KDFLRFKRIVQRI
Mutant 9	FK13_10	DFLRFKRIVQRIK
Mutant 10	FK13_11	FLRFKRIVQRIKD
Mutant 11	FK13_12	LRFKRIVQRIKDF
Mutant 12	FK13_13	RFKRIVQRIKDFL

Mutants	Peptide Name	Sequence
Wild Type	CM15_W	KWKLFKKIGAVLKVL
Mutant 1	CM15_2	WKLFKKIGAVLKVLK
Mutant 2	CM15_3	KLFKKIGAVLKVLKW
Mutant 3	CM15_4	LFKKIGAVLKVLKWK
Mutant 4	CM15_5	FKKIGAVLKVLKWKL
Mutant 5	CM15_6	KKIGAVLKVLKWKLF
Mutant 6	CM15_7	KIGAVLKVLKWKLFK
Mutant 7	CM15_8	IGAVLKVLKWKLFKK
Mutant 8	CM15_9	GAVLKVLKWKLFKKI
Mutant 9	CM15_10	AVLKVLKWKLFKKIG
Mutant 10	CM15_11	VLKVLKWKLFKKIGA
Mutant 11	CM15_12	LKVLKWKLFKKIGAV
Mutant 12	CM15_13	KVLKWKLFKKIGAVL
Mutant 13	CM15_14	VLKWKLFKKIGAVLK
Mutant 14	CM15_15	LKWKLFKKIGAVLKV

Table 3. Circular permutants of peptide R5KT8W

Mutants	Peptide Name	Sequence
Wild Type	R5KT8W_W	GLLKKIKWLL
Mutant 1	R5KT8W_2	LLKKIKWLLG
Mutant 2	R5KT8W_3	LKKIKWLLGL
Mutant 3	R5KT8W_4	KKIKWLLGLL
Mutant 4	R5KT8W_5	KIKWLLGLLK
Mutant 5	R5KT8W_6	IKWLLGLLKK
Mutant 6	R5KT8W_7	KWLLGLLKKI
Mutant 7	R5KT8W_8	WLLGLLKKIK
Mutant 8	R5KT8W_9	LLGLLKKIKW
Mutant 9	R5KT8W_10	LGLLKKIKWL

Collaborators Prof Yunching Becky Chen, Prof Vincent Shu, Prof Chin Yu, Prof Chin Yu, Prof Qing Zhang, Prof Bai-Shan Fang Prof Bai-Shan Fang Prof Hua-Wen Fu Prof Chung-Yu Lan Prof Chung-Yu Lan Prof Zhong-Hong Lin Praexisio Inc

Computing resources

National Center High Performance Computing (NCHC), Taiwan

Former and Current Lab members

Dr Hongchun Li Dr Emmanuel O Salawu Dr Kun-Lin Tsai Dr Anny Cheng Dr Bang-Chieh Huang Dr Yuan-Yu Chang Cheng-Yu Tsai Christopher L Ortiz Liyin Voon Kai-Di Hu Sobha Sahoo Lutimba Stuart

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