

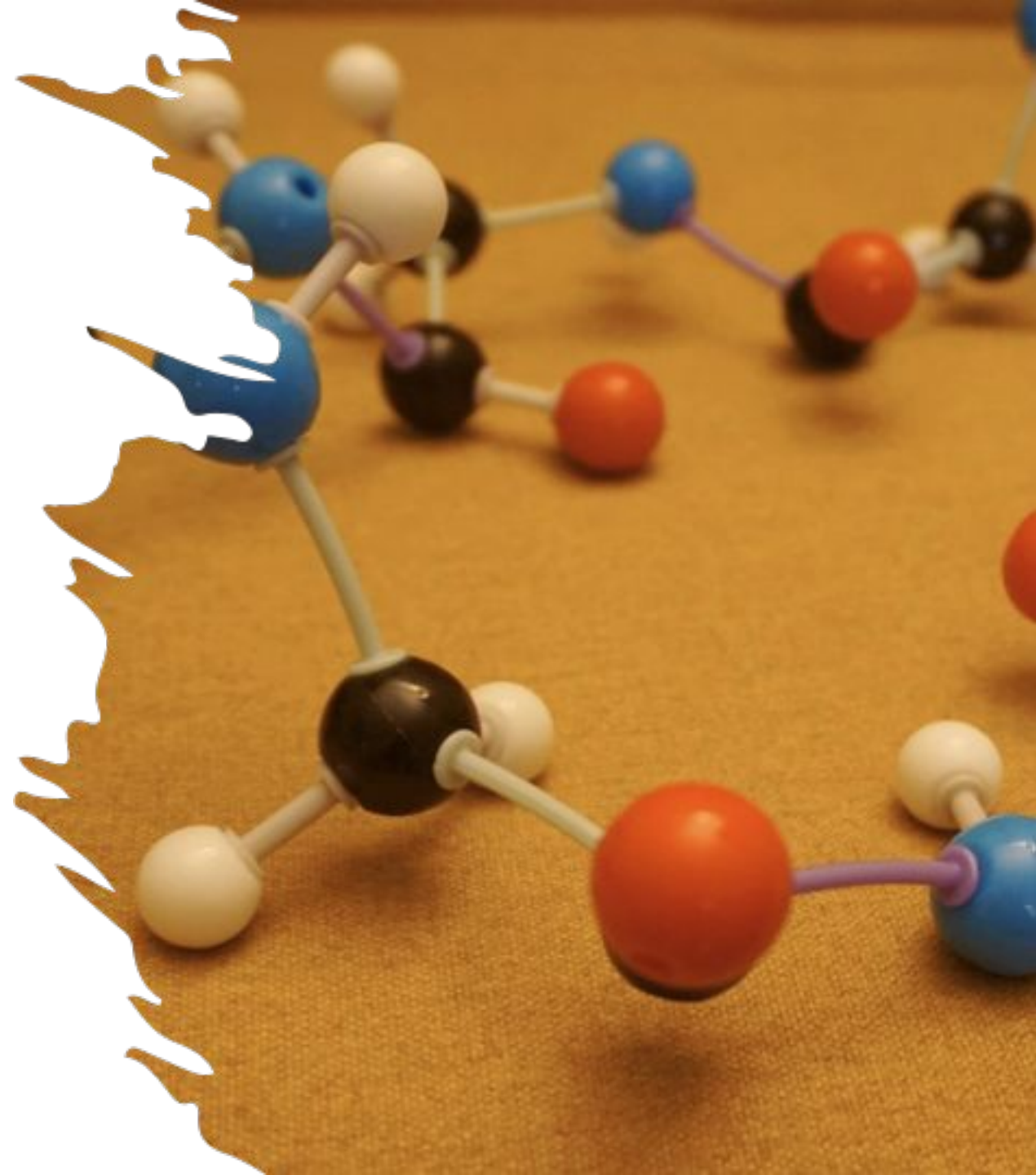
# Heuristic energy-based cyclic peptide design

Qiyao Zhu (NYU, now Simons  
Foundation),

Vikram Mulligan (Simons  
Foundation), and

**Dennis Shasha**

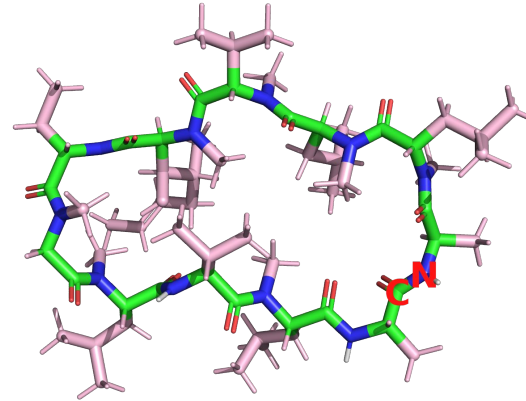
(New York University)



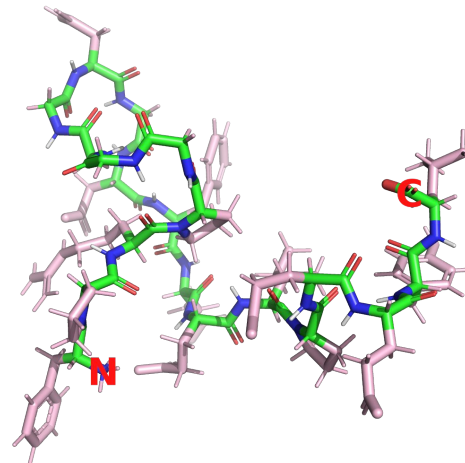
# Why Cyclic Peptides?

- **Definition:** A chain of 7+ amino acids (residues), with the N- and C-termini connected to form a closed loop
- **Why good:**
  - More rigid conformations and resistance to degradation compared to **linear peptides**
  - Potentially superior binding affinity and selectivity compared to **small molecules**
  - Immune system (e.g. exopeptidase) doesn't recognize them as well as linear peptide (especially when mixing L- with D-).

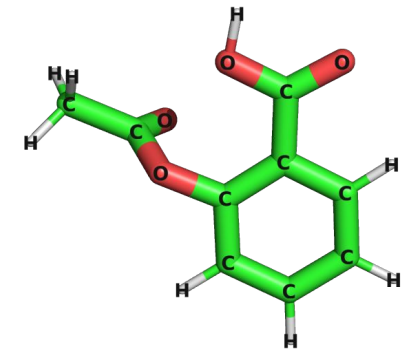
Cyclic peptide drug:  
Cyclosporine (1.2 kDa)



Linear peptide drug:  
Bivalirudin (2.18 kDa)

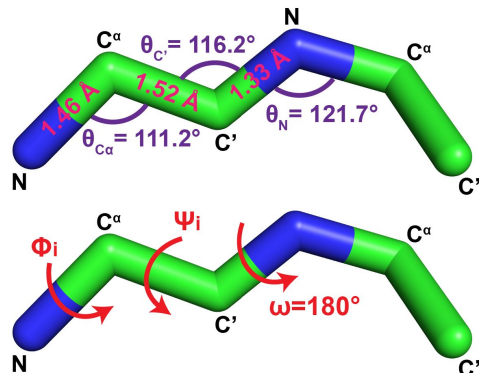


Small molecule drug:  
Aspirin (0.18 kDa)

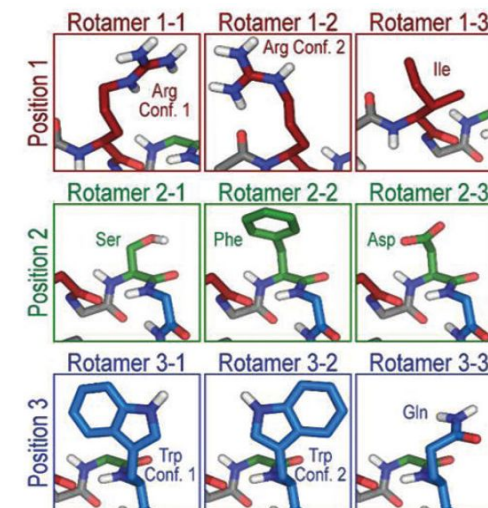
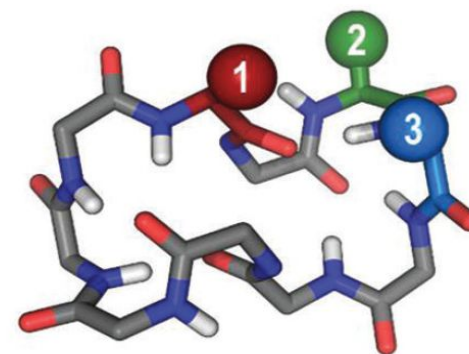
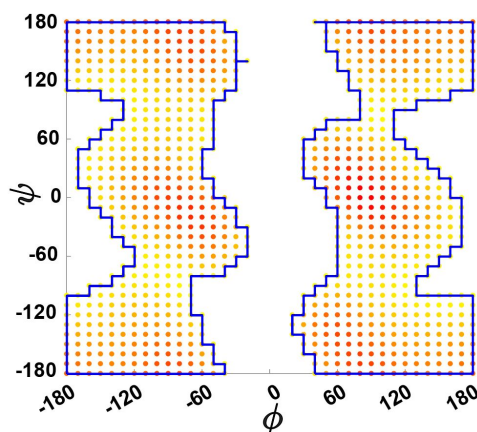


# Cyclic Peptide Design Pipeline

## $\phi$ , $\psi$ torsion angle variables



## Ramachandran space



## Backbone search: High dimensionality challenge

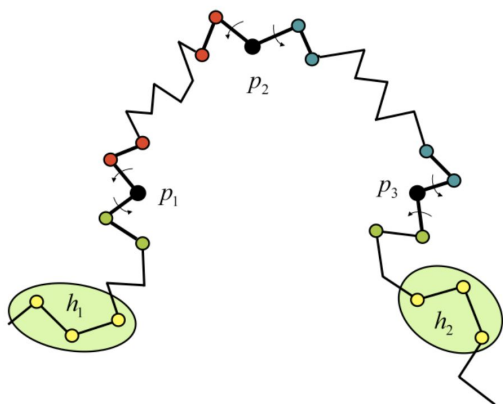
- For  $n$ -residue peptide, backbone has  $n$  pairs of  $(\phi, \psi)$  torsion angle variables
- Each pair  $(\phi, \psi) \in$  Ramachandran space
- The search space grows **exponentially** with peptide size

## Side-chain optimization: exponential combinatorial problem

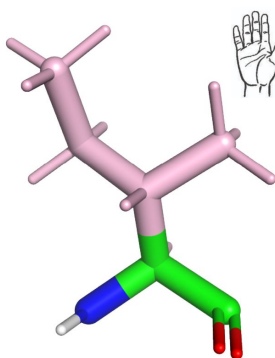
- There are 20 natural amino acids
- Sequence design has at least  $20^n$  choices
- Many more if allow non-canonicals (e.g., D- and artificial amino acids)

# Prior Work: Physics-based design in *Rosetta*

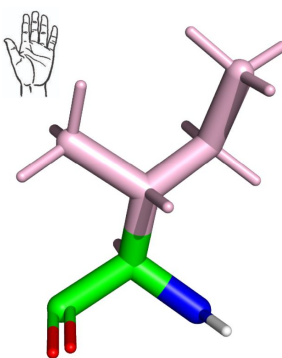
Kinematic loop closure



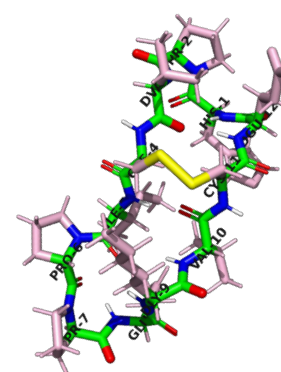
L-conformer



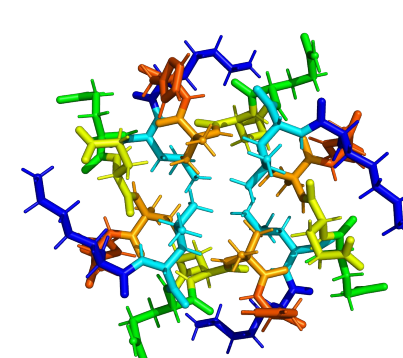
D-conformer



Cross-link



S4 symmetry



## Algorithm

- Backbone: Use **kinematic loop closure** to algebraically solve the cyclic constraint <sup>[1]</sup>
- Side-chain: Use **Monte Carlo simulated annealing** to minimize the energy <sup>[2]</sup>

## Pros

- Design can include **D-amino acids**, which are more resistant to peptidase degradation
- Can design **non-canonicals**, thus expanding chemical diversity even more

## Cons

- Backbone sampling works efficiently only for **7-10** residues
- To exceed this size limit, researchers use disulfide cross-links (**11-26** residues <sup>[3, 4]</sup>) or symmetry (**15-24** residues <sup>[5]</sup>)

[1] D. Mandell, et al. *Nature Methods*, 6:551-552, 2009.

[2] A. Leaver-Fay, et al. *Methods Enzymol.*, 487:545-574, 2011.

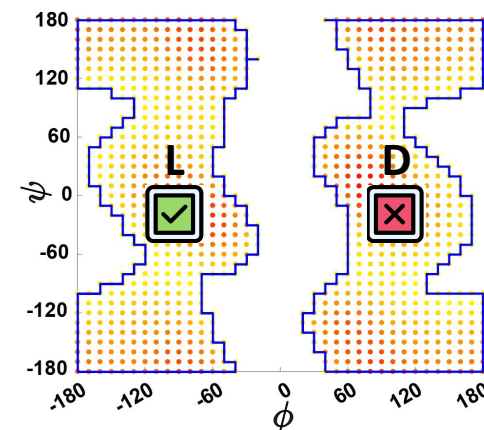
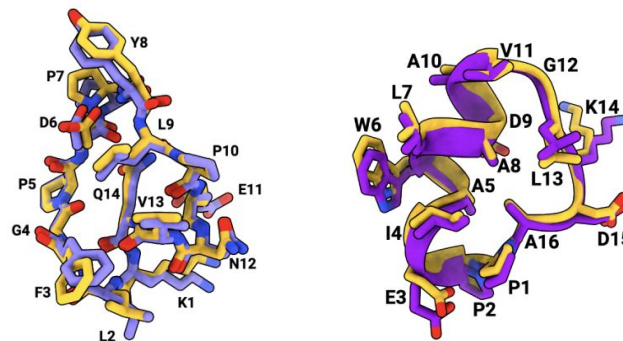
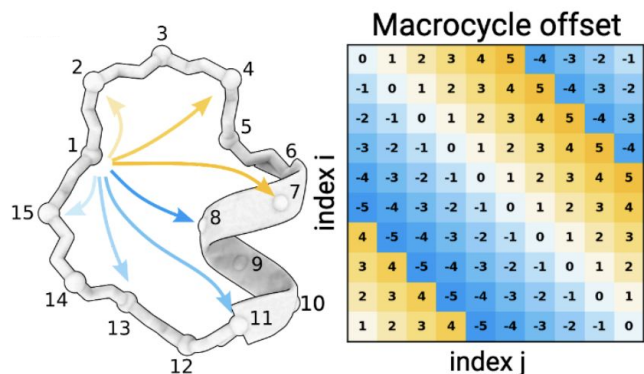
[3] P. Hosseinzadeh, et al. *Science*, 358:1461-1466, 2017.

[4] G. Bhardwaj, et al. *Nature*, 538:329-335, 2016.

[5] V. Mulligan, et al. *Protein Sci.*, 29:2433-2445, 2020.



# Prior: Deep-learning design led by *AlphaFold*



## Algorithm

- Base on *AlphaFold* or *RFdiffusion*
- Encode the cyclic backbone constraint into their amino acid relative position matrix

## Pros

- Can design slightly larger sizes of **7-16** residues <sup>[1, 2]</sup> due to *AlphaFold*'s protein training data
- Can predict **12-39** residues <sup>[3]</sup>

## Cons

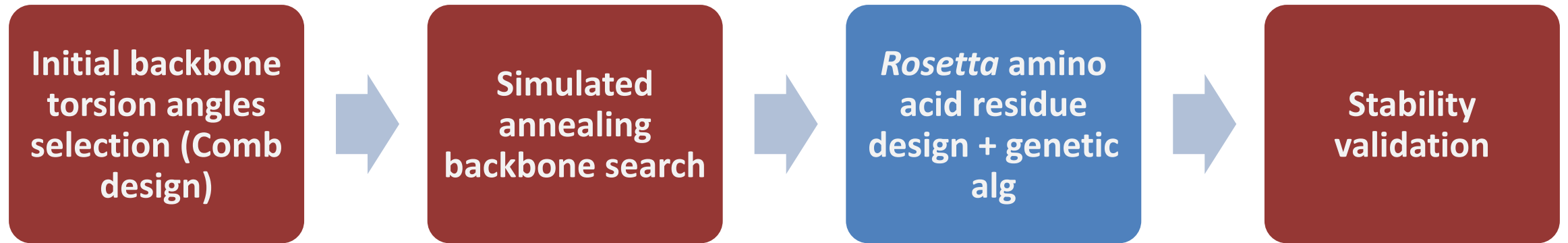
- Trained on natural L-amino acids, so:
- Not good for designing non-canonicals or mixed chirality
- Therefore: restricted design search space

[1] S. Rettie, et al. *bioRxiv*, doi:10.1101/2023.02.25.529956, 2023.

[2] S. Rettie, et al. *bioRxiv*, doi:10.1101/2024.11.18.622547, 2024.

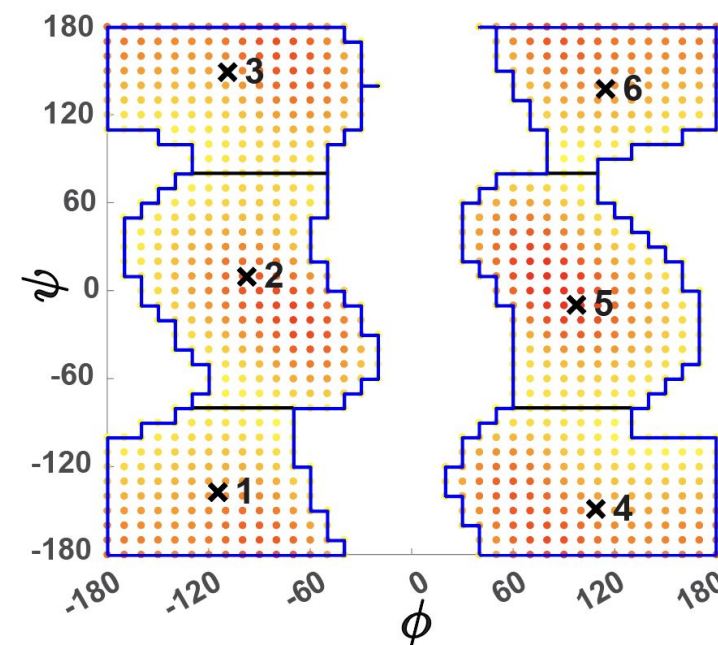
[3] C. Zhang, et al. *Brief Bioinform.*, 25:bbae215, 2024.

# Our *CyclicChamp* Design Pipeline

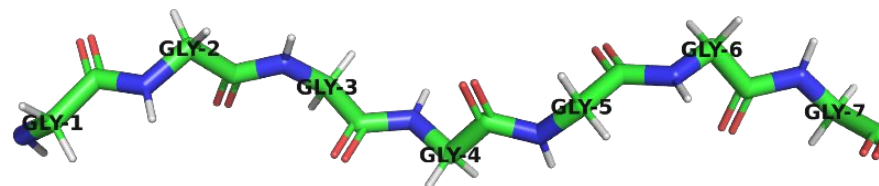


# Initial Backbone Torsion Angles Selection

- Initial backbones are chains of glycine residues, with  $(\phi, \psi)$  chosen from the six torsion bin centers of the Rama space.
- For  $n$ -residue peptide,  $\sim 6^n/n$  combinations subject to cyclic permutations.
- Use combinatorial design to obtain well-spaced random samples from all possible combinations <sup>[1]</sup>.



Example initial backbone with all torsion angles chosen as center 1

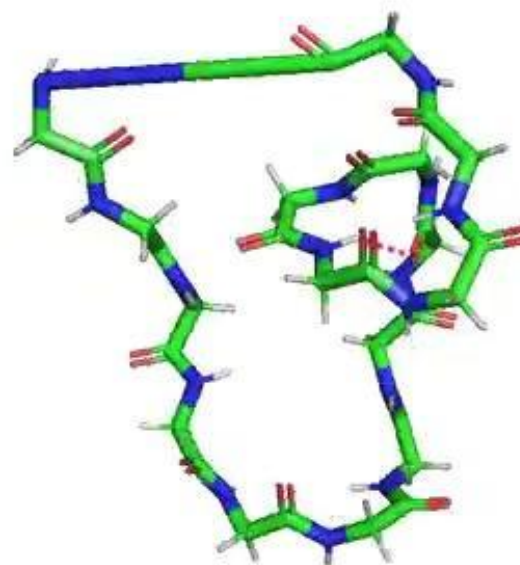


[1] C. Colbourn, et al. *J. Combin. Designs*, 14:124-138, 2006.

# Active Search for Backbone: Simulated Annealing

- Start from “well-spaced” random initial configurations
- At each step, add perturbations and accept based on the Metropolis acceptance criterion
- Close the backbone into cycle, but also seek desirable features like hydrogen bonds and low steric clashes

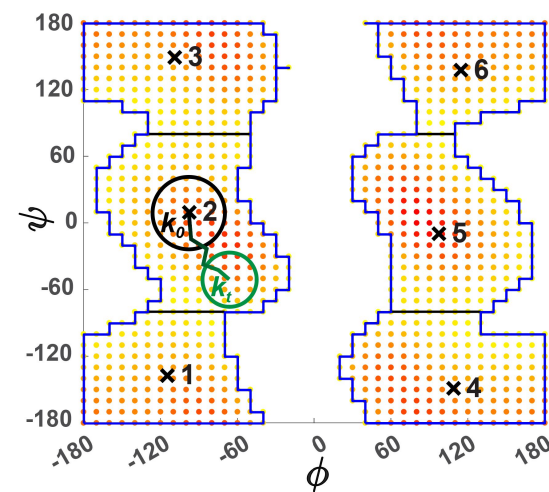
**Rama = 106.13, Repulsive = 20.18, Cyclic = 92.41, H-bond = 1**



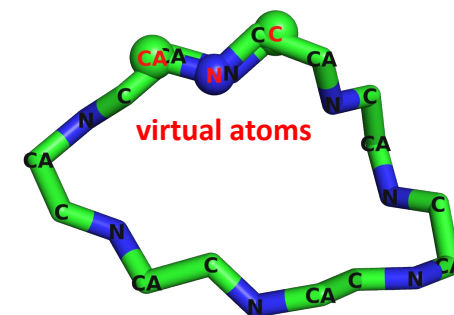


# How *CyclicChamp* Simulated Annealing Works

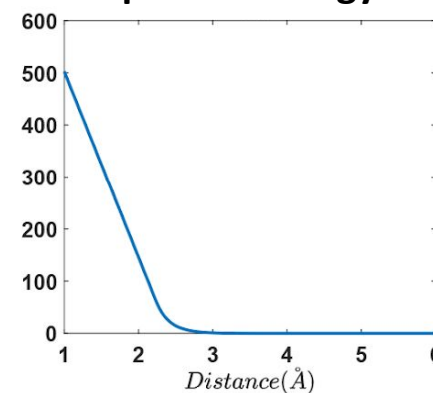
- Goal: find **cyclic** backbones with **low repulsive energy** and **sufficient hydrogen bonds**
- $E_{total} = w_{cyc} * E_{cyc} + w_{rep} * E_{rep} + w_{hbond} * E_{hbond}$
- At each step  $t$ , generate random moves in a shrinking disk of radius  $k_t = \frac{k_0}{1 + b * t/M}$ ,  $M=10000$  steps.
- Accept new configuration if (*Metropolis acceptance*)
  - Its energy  $E_{new} \leq E_{total}$
  - Or  $\text{rand}(0,1) \leq e^{(E_{total}-E_{new})/T_t}$ ,  $T_t = \frac{T_0}{1+c*t/M}$
- Parameters including *weights*  $w$ , *initial disk radius*  $k_0$  and its *dropping rate*  $b$ , *initial temperature*  $T_0$  and its *dropping rate*  $c$  vary using **combinatorial design** in test runs.



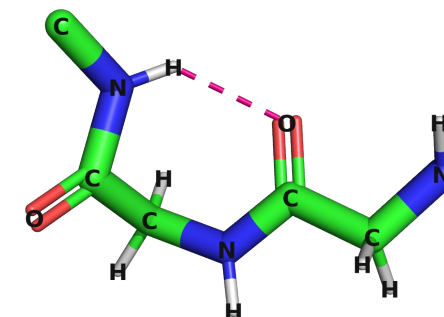
Cyclic error = 0.14



Repulsive energy <sup>[1]</sup>



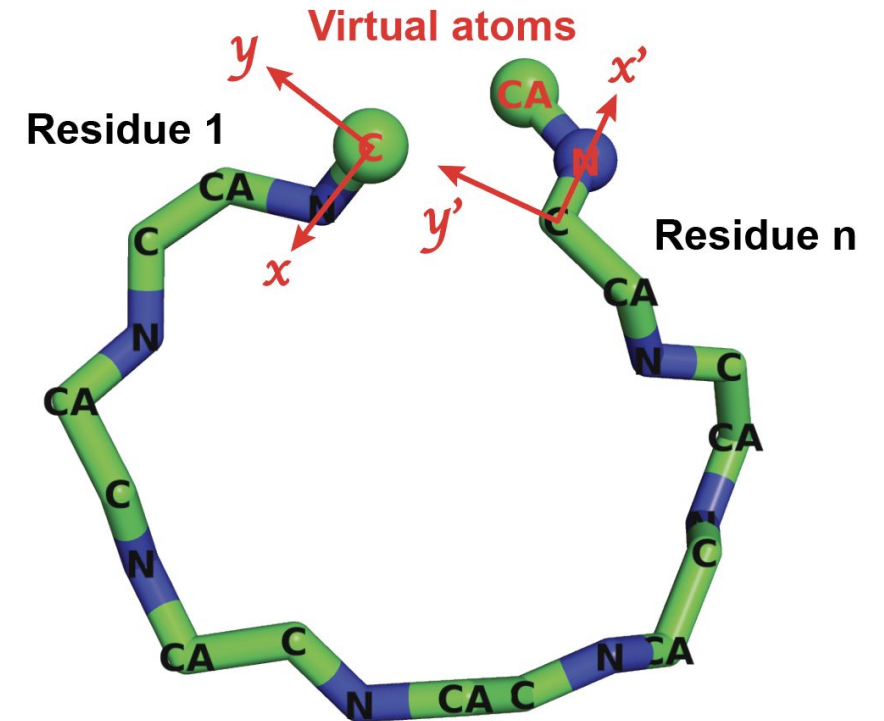
Hydrogen bond <sup>[1]</sup>



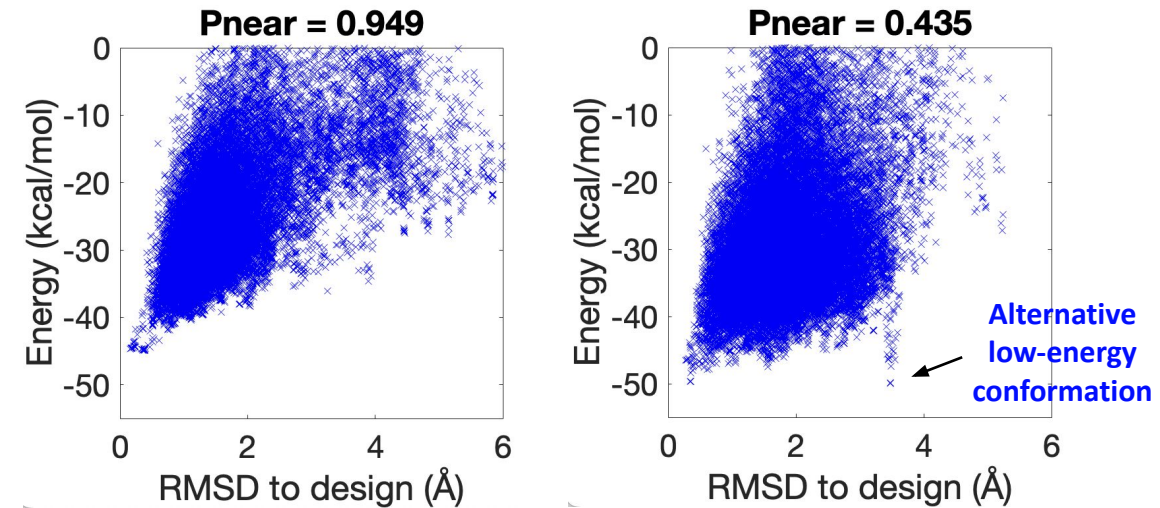
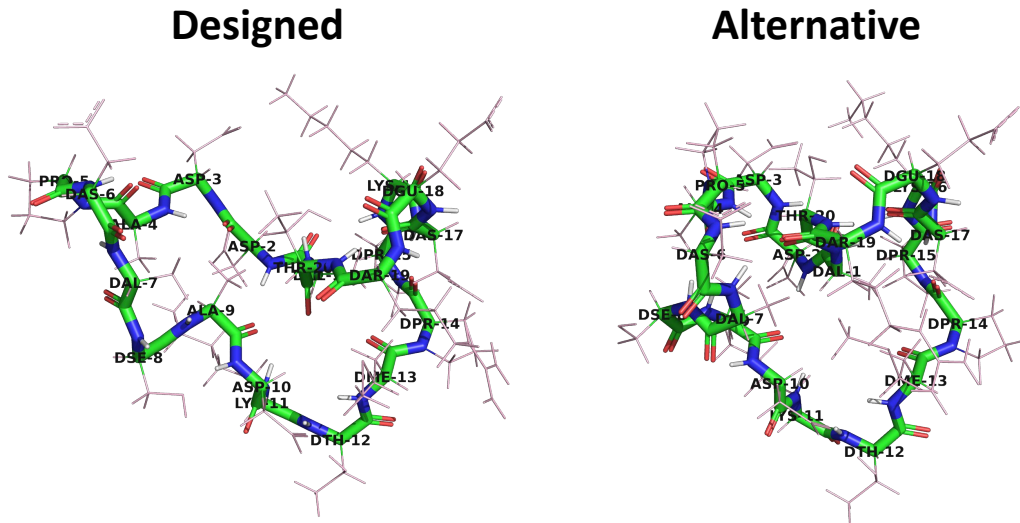
# Cyclic Backbone Constraint Modeled as Cyclic Error

- Generate a virtual atom  $C_{virtual}$  at the origin before the  $N$  terminus
- The first  $N$  atom lies on the standard  $x$ -axis, and the first CA atom lies in the standard  $xy$ -plane
- For a given set of  $\phi, \psi$  torsion angle values, compute the coordinates of all backbone atoms using
  - Ideal bond angles and bond lengths
  - Ideal torsion  $\omega = 180^\circ$  at peptide bond (C-N)
- Two virtual atoms  $N_{virtual}, CA_{virtual}$  after the C terminus also computed
- Construct unit vector  $x'$  pointing from  $C_n$  to  $N_{virtual}$ , and its perpendicular  $y'$  such that  $CA_{virtual}$  lies in the  $x'y'$ -plane
- The cyclic error

$$E_{cyc} = \sqrt{\|C_n - C_{virtual}\|^2 + \|x - x'\|^2 + \|y - y'\|^2}$$



# Stability Validation by Sampling Alternative Conformations



## Sample energy landscapes

- For a designed amino acid sequence, the **full-energies** of alternative conformations, together with their backbone root-mean-square-deviations (**RMSDs**) from the designed structure, form the energy landscape
- Stable** design if all low-energy conformations align closely to the backbone conformation

## Stability = probability to fold into backbone

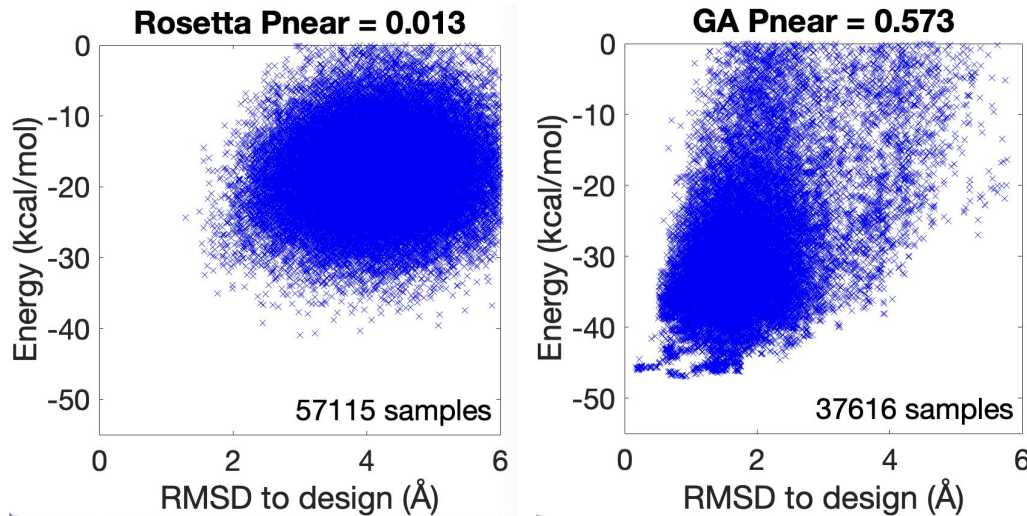
- To quantitatively measure stability, use

$$P_{Near} = \frac{\sum_{i=1}^N \exp\left(\frac{-RMSD_i^2}{\lambda^2}\right) \exp\left(\frac{-E_i}{k_B T}\right)}{\sum_{i=1}^N \exp\left(\frac{-E_i}{k_B T}\right)}, \quad \lambda \sim 1, \quad k_B T = 0.62$$

- $P_{Near} > 0.9$  experimentally shown to be indicative of stability <sup>[1]</sup>

[1] P. Hosseinzadeh, et al. *Science*, 358:1461–1466, 2017.

# Genetic Algorithms to Avoid Local Minima

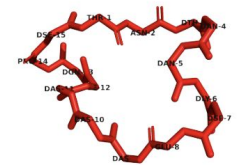


## Rosetta's failure to sample thoroughly

- The conformational space grows **exponentially** with the peptide size.
- *Rosetta's random sampling* approach <sup>[1]</sup> yields many false-negatives when validating 15 residue designs, and generates unusable energy landscapes for 20 and 24 residues.

## Crossover

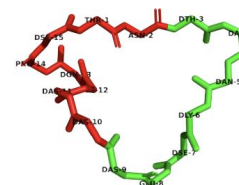
Parent 1



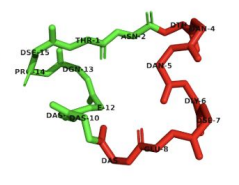
Parent 2



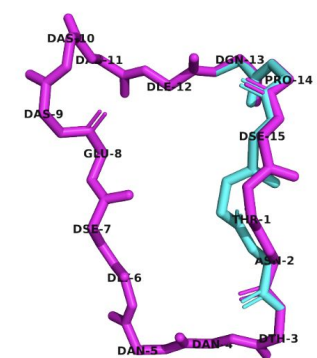
Child 1



Child 2



## Mutation



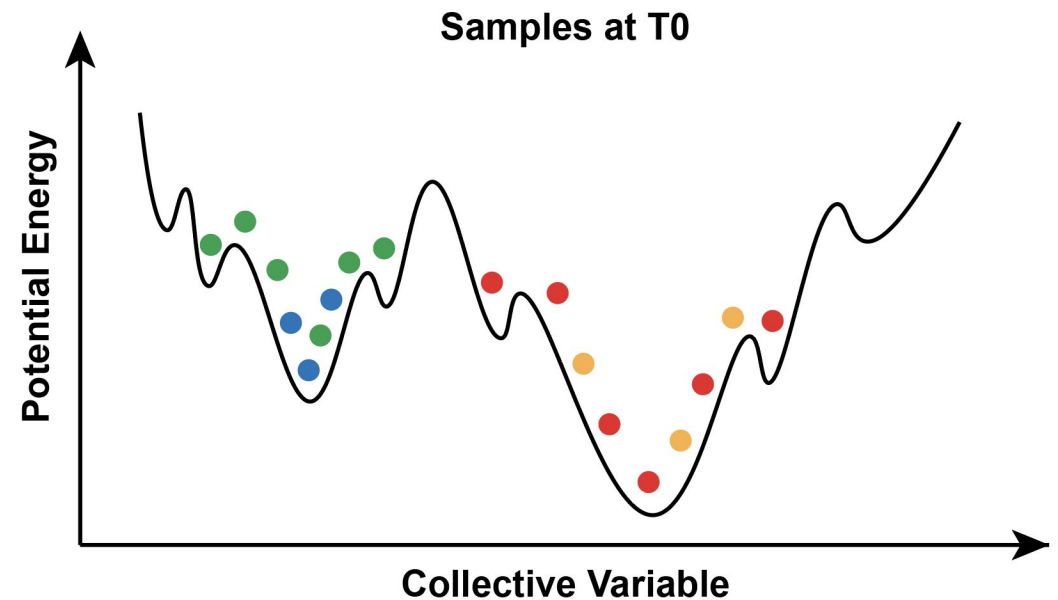
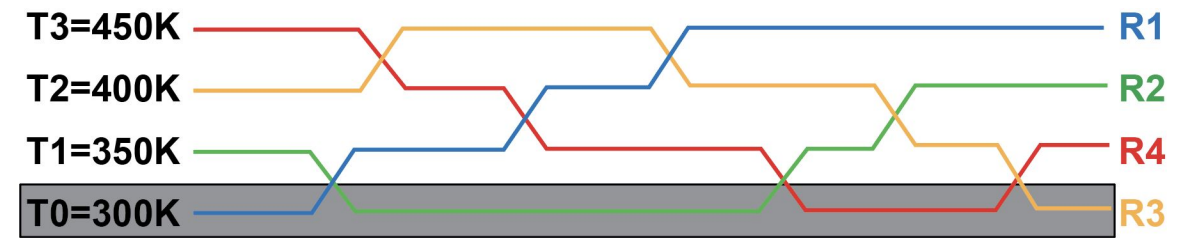
## What genetic algorithms accomplish

- Using **simulated annealing** alone may find only shallow minima in a rugged energy landscape
- Explore potential energy minima via **genetic algorithms** that perform crossover and mutation on low-energy conformations

[1] P. Hosseinzadeh, et al. *Science*, 358:1461–1466, 2017.

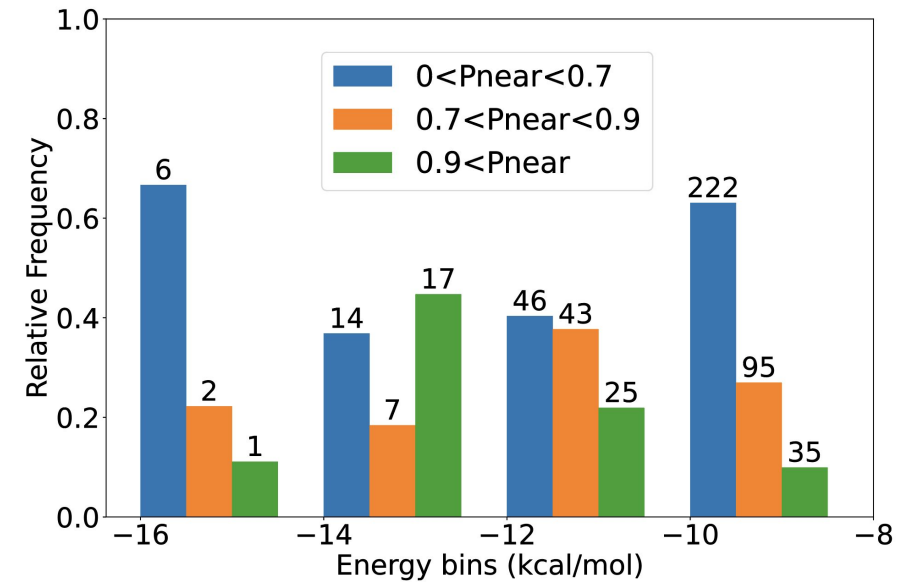
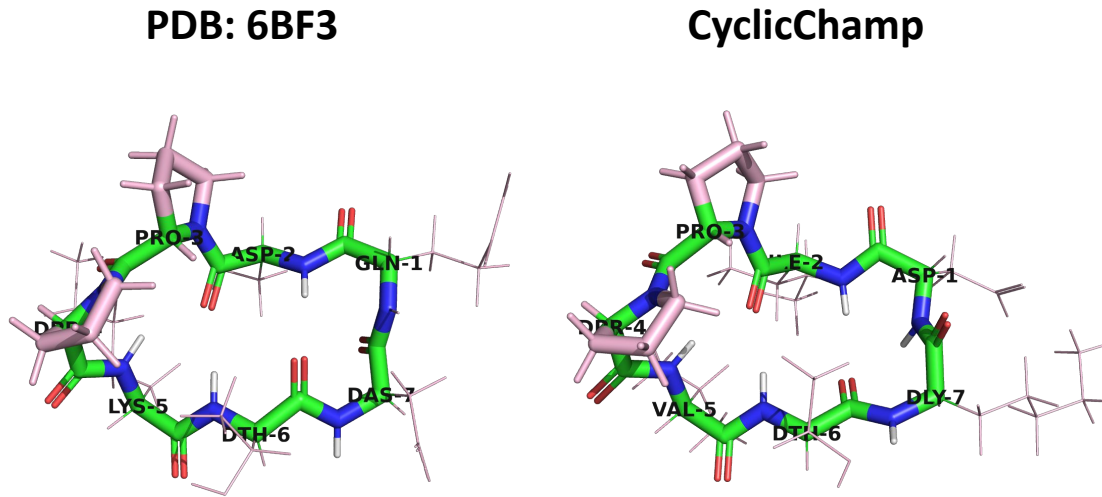
# Validation by Replica Exchange Molecular Dynamics

- For **top designs with high  $P_{Near}$** , perform *replica exchange molecular dynamics (REMD)* simulations as a validation method
- Identical replicas of designed peptides in solvent (water) box copied for different temperatures, and undergo regular molecular dynamics simulations <sup>[1]</sup>
- Periodically **swap** temperatures for neighboring replicas, so that each replica has chance to explore behavior at high temperatures to overcome **energy barriers**
- Collect and analyze conformations sampled at reference temperature  $T_0$





# Faster 7-residue Macrocycle Design with $P_{Near}$ Insights



## Four times faster to design a stable peptide

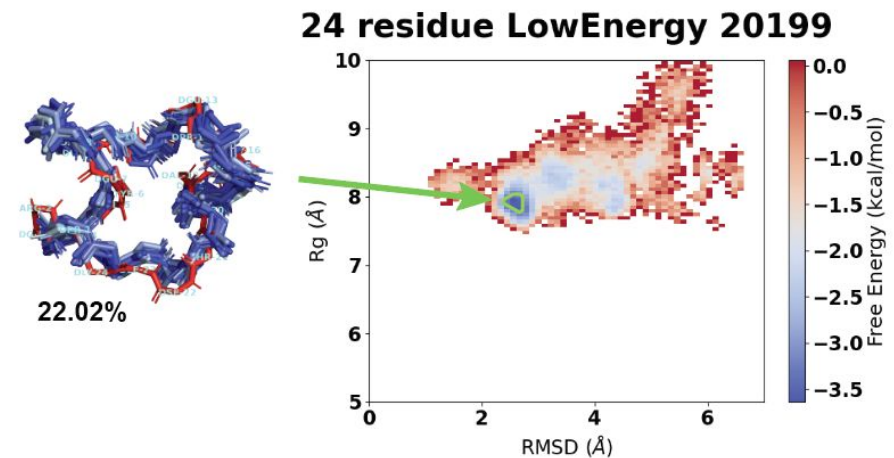
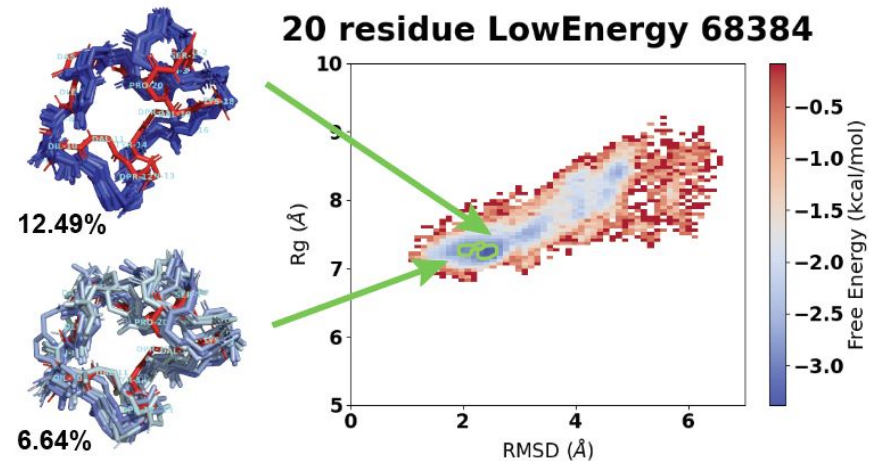
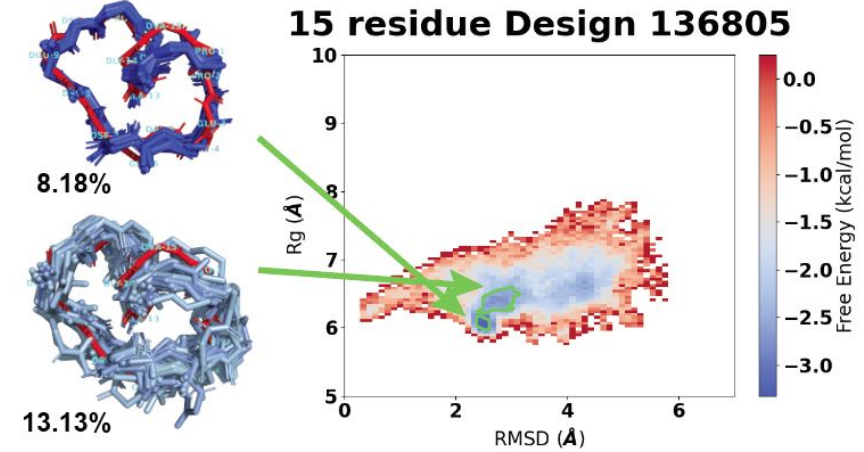
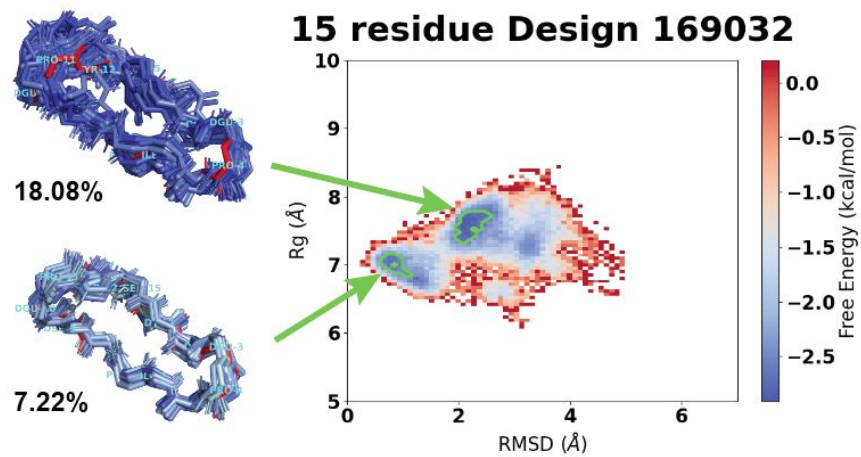
- Allocating equivalent computation time for backbone sampling, *CyclicChamp* found **4.5 times** as many stable designs as *Rosetta*.
- CyclicChamp* also recovered the experimentally validated conformations designed by *Rosetta* [1].

## Low energy $\neq$ High $P_{Near}$

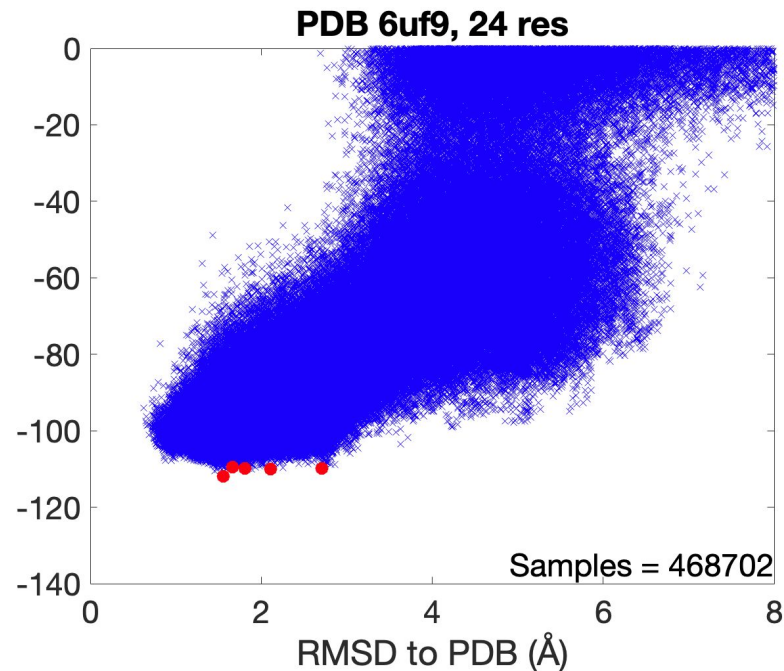
- The second-lowest energy bin had the largest probability of high  $P_{Near}$  values
- Low energy alone not sufficient for stability
- Other features like tight hydrogen bond networks often enhance stability

[1] P. Hosseinzadeh, et al. *Science*, 358:1461–1466, 2017.

# REMD Validated 15-24 residue Large Macrocyclic Designs



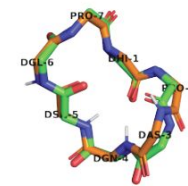
# Structure Predictions for Previously Known Macrocycles



## Only amino acid sequence known

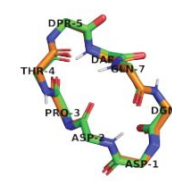
- Generated energy landscapes using only the amino acid sequences as input
- Clustered the 50 lowest-energy conformations and selected the 5 lowest-energy cluster centers as predictions

**6bew, 7 res**



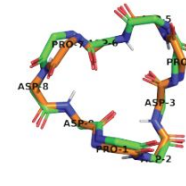
**0.802 Å**

**6be7, 8 res**



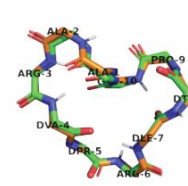
**0.277 Å**

**6ugc, 9 res**



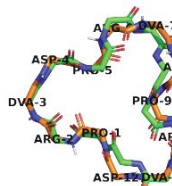
**1.0182 Å**

**6beq, 10 res**



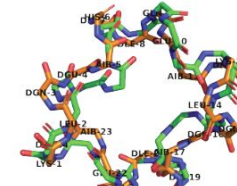
**0.380 Å**

**6ug6, 12 res**



**1.333 Å**

**6uf9, 24 res**



**1.559 Å**

## Accurate predictions for 7-24 residues

- Predicted 17 existing macrocycles without cross-links, whose experimentally-solved structures deposited in the Protein Data Bank
- Predicted backbones have RMSDs of 0.277-1.836 Å from experimental structures

# Conclusion

- We have addressed the high dimensionality challenge in backbone search by
  - Transforming the cyclic backbone constraint into an error function
  - Employing simulated annealing for backbone sampling
  - Employing genetic algorithms for thorough exploration of energy minima
  - Employing combinatorial design for initial configuration and parameter selection
- We have achieved
  - Faster speed for designing small (e.g. 7-residue) macrocycles
  - Unique ability to design 15-24 residue large macrocycles with mixed-chirality
  - Accurate predictions for existing macrocycles deposited in PDB
- Codes available at <https://github.com/qiyaozhu/CyclicPeptide>

# Future Work

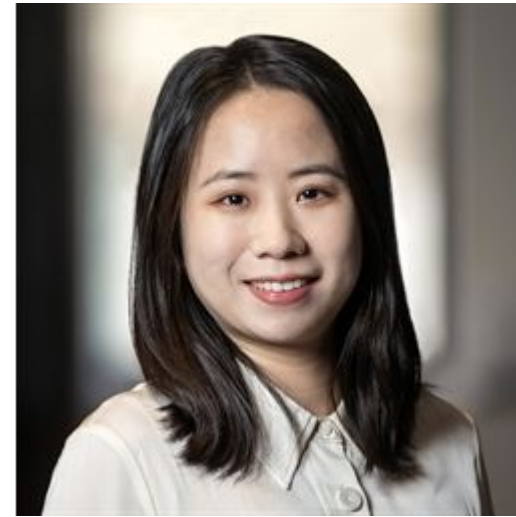
- Design cyclic peptide-binders to druggable protein sites as novel therapeutics
- Add option for sampling backbones with disulfide cross-links
- Incorporate into *Rosetta* for smooth transition between *CyclicChamp*'s backbone sampling and *Rosetta*'s sequence design, and user friendliness
- Add GPU support for further speed up



# Acknowledgements



**Vikram Mulligan**  
Research Scientist at Flatiron  
Institute



**Qiyao Zhu**  
Research Fellow at  
Flatiron Institute



What is combinatorial design? Well-spaced sampling.

Suppose you are a thief...

**Combinatorial Safe:** 10 switches with 3 settings each. Over 59,000 ( $3^{10}$ ) possible configurations. However there is a certain pair of switches (you don't know which pair) and a certain pair of values of those switches that will open the safe.

**Illustration:**

S1 S2 S3 **S4** S5 S6 **S7** S8 S9 S10  
          C          A

**Challenge:**

Open the safe in as few switch configurations as possible. How many? How to do?

# Safecracking Solution

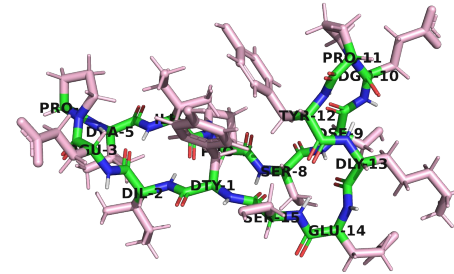
(X = Don't care)

- **Number S1 S2 S3 S4 S5 S6 S7 S8 S9 S10**
- **1: A A A A A A A A A A**
- **2: A B B B B B B B B B**
- **3: A C C C C C C C C C**
- **4: B A B C A B C A B C**
- **5: B B C A B C A B C A**
- **6: B C A B C A B C A B**
- **7: C A C B A C B A C B**
- **8: C B A C B A C B A C**
- **9: C C B A C B A C B A**
- **10: X A A A B B B C C C**
- **11: X A A A C C C B B B**
- **12: X B B B A A A C C C**
- **13: X B B B C C C A A A**
- **14: X C C C A A A B B B**
- **15: X C C C B B B A A A**

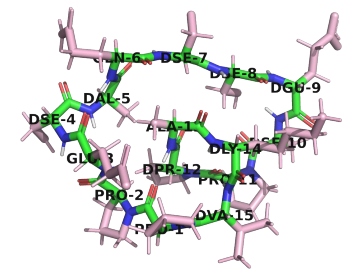
# Faster design & Larger macrocycles

- For 7 residues, our *CyclicChamp* takes **one-fourth** the time of *Rosetta*'s to find a stable design. Advantage increases with size.
- de novo* design of the first **15-24 residue** mixed-chirality macrocycles, without relying on additional cross-links or symmetry
- Computationally validate using molecular dynamics

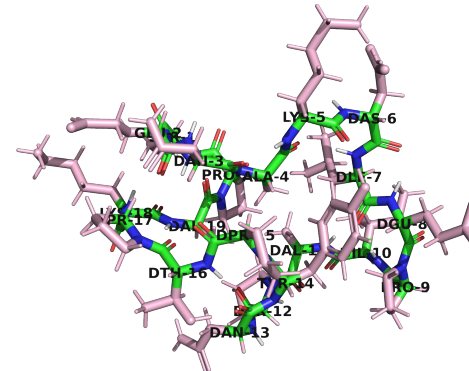
15 residue



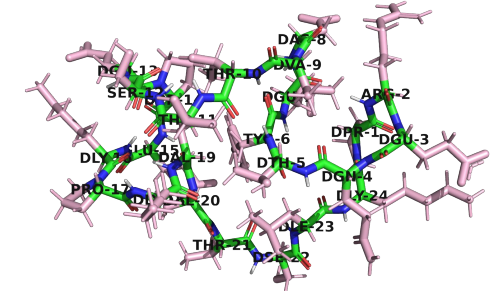
15 residue



20 residue

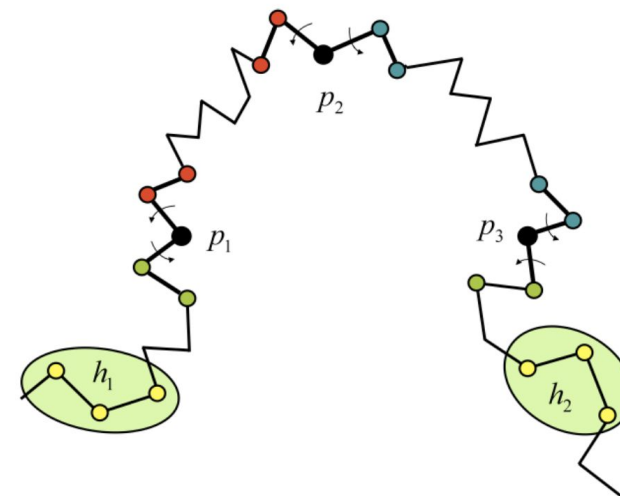
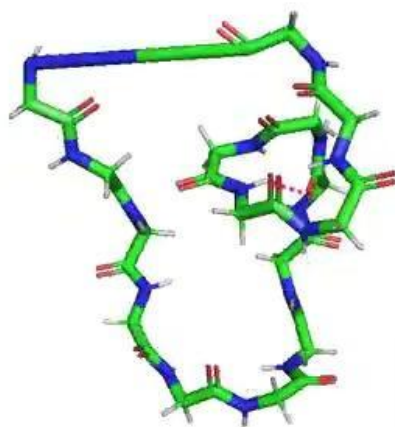


24 residue



# Our active search vs. *Rosetta*'s random sampling

Rama = 106.13, Repulsive = 20.18, Cyclic = 92.41, H-bond = 1



## Our backbone simulated annealing search <sup>[1]</sup>

- Start from “well-spaced” random initial configurations
- At each step, add perturbations and accept based on the Metropolis acceptance criterion
- Close the backbone into cycle, but also seek desirable features like hydrogen bonds

## *Rosetta*'s backbone kinematic closure <sup>[2]</sup>

- Besides the three pivot points  $p_1$ ,  $p_2$ ,  $p_3$ , all other segments' torsion angles are randomly sampled
- Algebraically solve for the six torsions of  $p_1$ ,  $p_2$ ,  $p_3$  to satisfy loop closure
- Fast solution, but hit desirable features by chance

[1] Q. Zhu, et al. *PLoS Comput. Biol.* 2025.

[2] D. Mandell, et al. *Nature Methods*, 6:551-552, 2009.