AND/OR Branch-and-Bound for Computational Protein Design Optimizing K*

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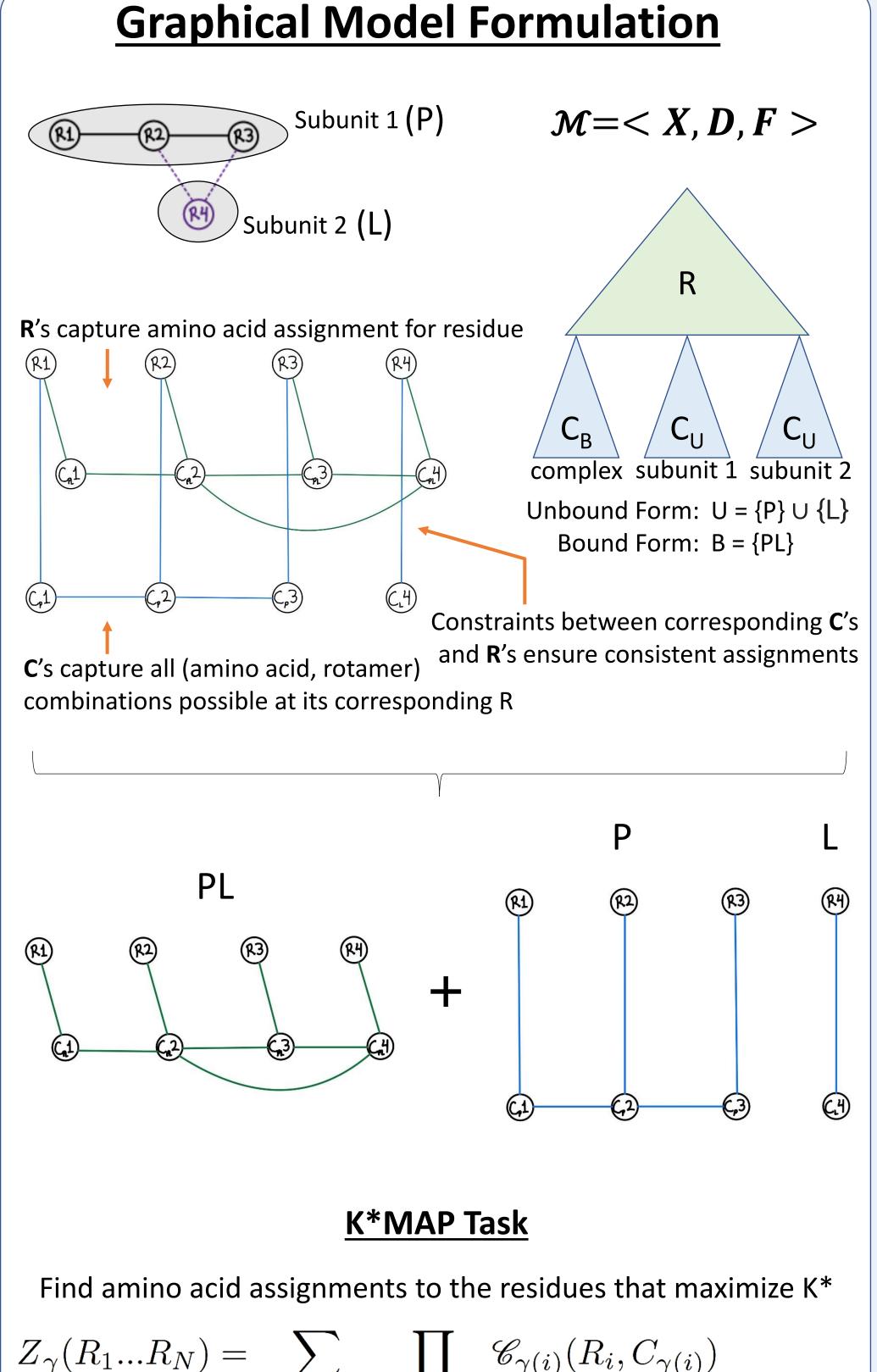
Overview

RVINE

The objective of this work is to (1) create a framework for future advancements for protein design via K* optimization (ie. K*MAP) leveraging powerful MMAP algorithms, (2) explore new related bounded heuristics, and (3) create a foundation for efficient algorithms solving such protein design problems.

Contributions:

- 1. Formulation of K*MAP as a graphical model
- 2. wMBE-K*, a weighted mini-bucket scheme for K*MAP enhanced with a domain partitioning scheme
- 3. AOBB-K*, a depth-first branch-and-bound algorithm over AND/OR search spaces for solving K*MAP
- 4. A thresholding scheme introducing and exploiting determinism with correctness guarantees
- 5. Extensive analysis comparing these schemes to state-of-the-art BBK* illustrating their potential



AOBB-K*

□ Branch-and-bound algorithm over AND/OR search spaces

AOBB-K* is exact

□ Can use wMBE-K* to guide search

Exploits determinism by using constraint propagation

□ Incorporates a global constraint enforcing biologically relevant solutions

Subunit Stability Constraints

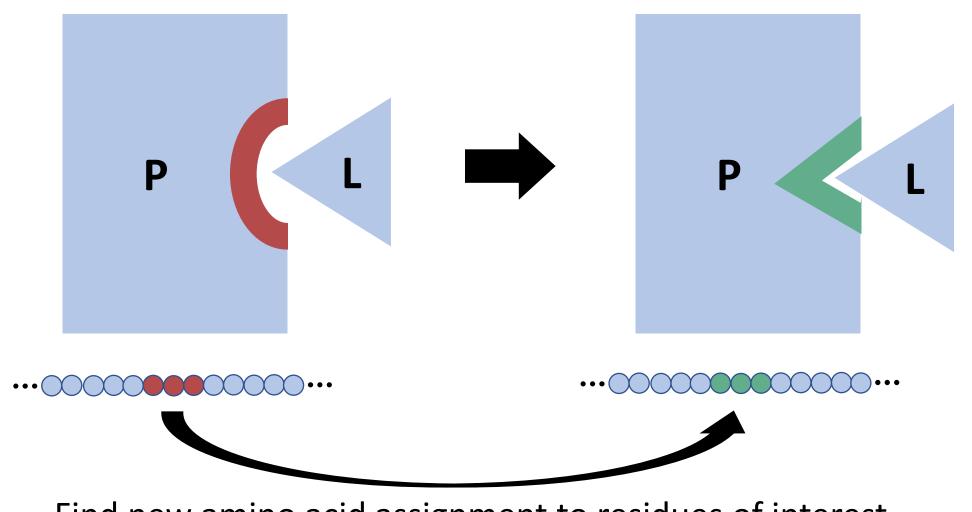
Condition to enforce the stability of each subunit to be no less than a given threshold from that of the wild-type stability

 $Z_{subunit i}(r) > Z_{subunit i}(r^{wt}) * \exp\{-5/\mathcal{R}T\}$

Stability of naturally occurring version Constant factor for thresholding

Problem

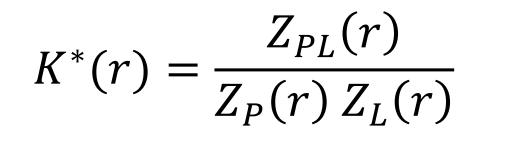
Redesign of proteins to form higher affinity complexes



Find new amino acid assignment to residues of interest that optimize affinity between interacting subunits

K* Objective

An approximation of binding affinity between molecules (based on the biological association constant known as K_a)



$$(R_1...R_N) = \sum_{\substack{C_1,...,C_N \ \mathscr{C}_{\gamma(i)} \in \mathscr{C}}} \prod_{\substack{\varphi(i) \in \mathscr{C} \\ \mathcal{C}_{\gamma(i)} \in \mathscr{C}}} \mathscr{C}_{\gamma(i)}(R_i, C_{\gamma(i)})} \\ \prod_{\substack{E_{\gamma(i)}^{sb} \in \mathbf{E}_{\gamma}^{sb}}} e^{-\frac{E_{\gamma(i)}^{sb}(C_{\gamma(i)})}{\mathscr{R}T}} \cdot \prod_{\substack{E_{\gamma(ij)}^{pw} \in \mathbf{E}_{\gamma}^{pw}}} e^{-\frac{E_{\gamma(ij)}^{pw}(C_{\gamma(i)}, C_{\gamma(j)}}{\mathscr{R}T}}}$$

 $K^*(R_1, ..., R_N) = Z_B(R_1, ..., R_N) / Z_U(R_1, ..., R_N)$

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task: K^*MAP = \max_{R_1,...,R_N} K^*(R_1,...,R_N)
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Infusing Determinism: τ-Underflows

Replace extremely unfavorable assignments with hard constraints taking exploiting the strength of constraint propagation

- Let *f* be a non-negative function
- Consider $\tau \in \mathbb{R}^+$
- Then the τ underflow of f is...

 $f(x) = \begin{cases} f(x), & f(x) \ge \tau \\ 0, & otherwise \end{cases}$

Empirical Analysis

Competing Scheme: BBK*

[Ojewole et al., 2018]

State-of-the-art protein redesign algorithm, part of the software package, OSPREY, developed for over ten years for protein design • A*-like best first • utilizes dynamic optimistic greedy heuristic • approximate scheme w/ tightness parameter

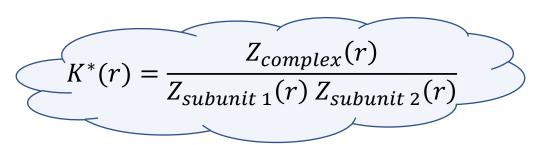
Empirical Results

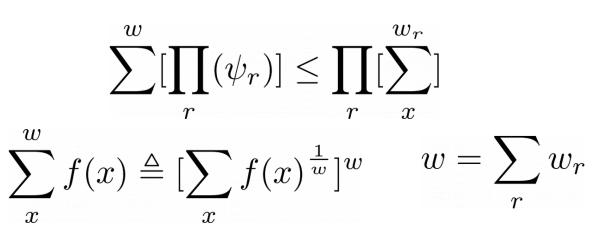
	1	AOBB-K [°]	any-AOBB-K [*]				
Dataset	$\mathbf{K}^{*} \ge$	K *>	time<	$\mathbf{K}^{*} \geq$	$\mathbf{K}^* >$		
(#instances)	(F1,F2)	(F1,F2)	(F1,F2)	(F1,F2)	(F1,F2)		
Orig. (30)	30,30	2,2	23,28	30,30	2,2		
Expand. (12)	6,11	0,4	2,4	11,11	1,4		

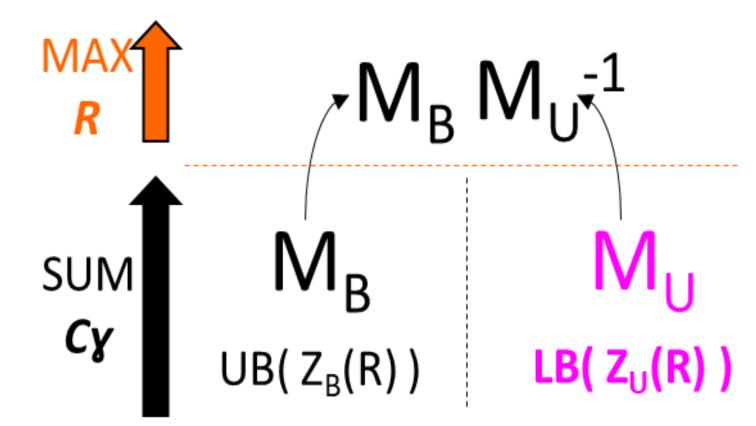
benchmarks				(203 ≤ Dmax ≤ 206)			[ω,τ]-AOBB-K*			BBK*			
(3 MAP Variables)	ω	τ	iB	w*	d	X	UB	pre-t	search	time	K *	time	K *
1gwc_00021*	-	-	4	4	7	13	28.8	123.8	81.3	205.1			
	0.001	-	4	4	7	13	28.8	124.3	12.1	136.4	11.9	551.3	11.
	-	1E-05	4	4	7	13	28.8	117.1	3.5	120.7			
2hnv_00025*	-	-	4	6	9	17	42.3	109.8	44.0	153.8			
	0.001	-	4	6	9	17	42.3	109.3	12.2	121.5	16.2	880.5	13.
	-	1E-05	4	6	9	17	42.3	100.8	1.7	102.4			
2rf9_00013*	-	-	4	6	9	17	37.7	83.0	17.8	100.8			
	0.001	-	4	6	9	17	37.7	82.8	1.6	84.4	15.0	39.2	15.
	_	1E-05	4	6	9	17	37.7	71.4	0.4	71.8			
2rfe_00012*	-	-	4	5	8	15	34.1	58.3	2.6	60.9			
	0.001	-	4	5	8	15	34.1	58.6	0.3	58.9	13.9	11.8	13.
	-	1E-05	3	5	8	15		5.5	14.9	20.3			
2rfe_00014*	-	-	4	5	-	_	35.1	58.2	2.4	60.6			
	0.001	-	4	5	8	15	35.1	58.2	1.3		14.4	44.9	14.
	-	1E-05	3	5	8	15		4.9	15.2				
2rfe_00017*	-	-	5		8	15	26.4	166.8	167.8				
	0.001		4				27.4	89.1	5.0		10.9	78.0	10
	-	1E-05					27.4	85.7					
2rfe_00030*	-	-	4					115.2		276.6			
	0.001	-	4					101.4		101.9		275.4	11.
	-	1E-05						105.4		108.9			
2xgy_00020*	-	-			8	15	26.2	81.8	278.9	360.7			
	0.001	-	4	5	8	15	27.2	60.4	8.2	68.6	11.0	1388.1	11.
	-	1E-05	4	5	8	15	27.2	60.1	23.8	83.9			
3u7y_00009*	-	-	4	4	7	13	11.4	62.6	36.8	99.5			
	0.001	-	4	4	7	13	11.4	62.5	2.1	64.7	4.5	215.8	4.!
	-	1E-05	4	4	7	13		61.3	5.1	66.4			
3u7y_00011*	-	-	4	4	7	13	28.3	74.0	2.1	76.1	11.9		
	0.001	-	4	4	7	13	28.3	83.4	0.1	83.5		26.6	11.
	-	1E-05					28.3	80.7	0.5	81.2			
4wwi_00019*	-	-	5				37.0	169.2			15.0		
	0.001	-	4				38.0	62.0	7.2	69.2		34.0	15.
	-	1E-05	4	5	8	15		54.2	8.4	62.7			

wMBE-K*

Precompiled K* heuristic to guide search, based on dynamic programming message-passing Mini Bucket Elimination







Domain-Partitioned wMBE-K*

$$Z_{\gamma}(r) = \sum_{c \in C_{\gamma}(r)} \exp\{-E_{\gamma}(c)/\mathcal{RT}\}$$
captures
captures
the goodness of

captures

the subunit(s) in

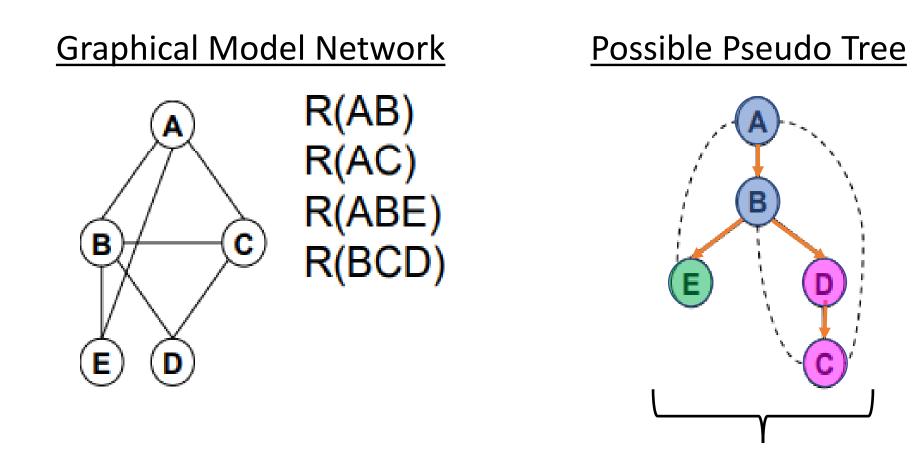
form $\gamma \in \{P, L, PL\}$

r = amino acid assignments to residues C(r) = possible conformations given rE(c) = energy given conformation c \mathcal{R} = universal gas constant

T = absolute temperature (Kelvin)

AND/OR Search

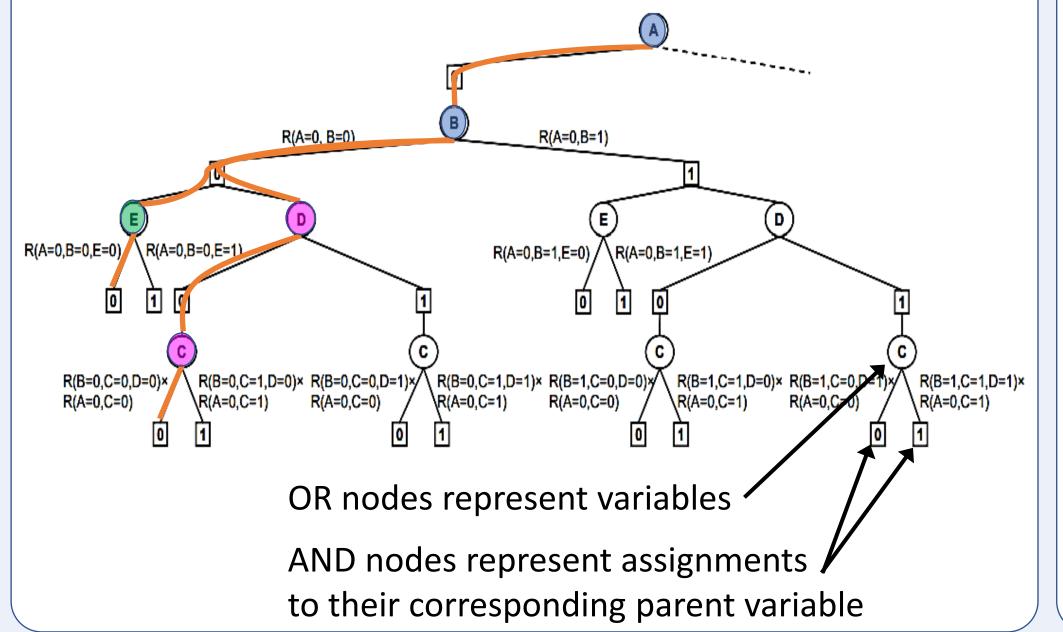
Compact search space taking advantage of conditional independences present in the model



Directed tree (based on a variable ordering) that branches when

conditional independences exist given assignments to ancestors.

The pseudo tree is used to construct the AND/OR search space



Strategy to improve lower bounds generated by wMBE-K*

- Let X, Y, and Z be three variables
- Let $obj = \sum_{X} f(x, y) \cdot g(x, z)$
- Let $X' = \{x \in X | g(x, z) \neq 0\}$ s.t. $\epsilon_{X'} = \min_{x \in X'} g(x, z)$
- Since ϵ_{X} , > 0, we can derive...

 $obj = \sum_{x} f(x, y) \cdot g(x, z)$ $obj = \sum_{x \in X'} f(x, y) \cdot g(x, z) + \sum_{x \in X \setminus X'} f(x, y) \cdot g(x, z)$ $obj = \sum_{x \in Y} f(x, y) \cdot g(x, z) \ge \epsilon_{X'} \cdot \sum_{x \in Y'} f(x, y) > 0$

Summary

- □ AOBB-K* shows promise vs. state-of-the-art BBK*
 - Competitive run-times
 - □ Can find better solutions
- \Box τ -AOBB-K* can greatly improve runtimes
- □ AOBB-K* has scalability issues as the number of MAP variables increase

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