

Finding Many Stable Molecular Arrangements

Conformational Searching with Genetic Algorithms

Evan Curtin

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University of Illinois at Urbana-Champaign

Outline

1. Background Information
2. The Genetic Algorithm
3. Finding Low Energy Conformers of Dipeptides
4. Concluding Remarks

First-Principles Molecular Structure Search with a Genetic Algorithm

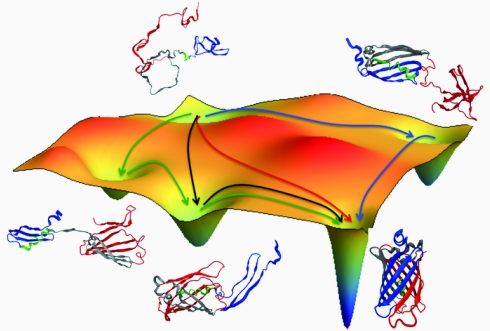
Supady, A.^{P1}; Blum, V.¹; Baldauf, C. J.^{1,2} Chem. Inf. Model. 2015, 55 (11), 23382348.

1. Fritz-Haber-Institut der Max-Planck-Gesellschaft, Berlin
2. Department of Mechanical Engineering & Materials Science, Duke University

Background Information

The Problem

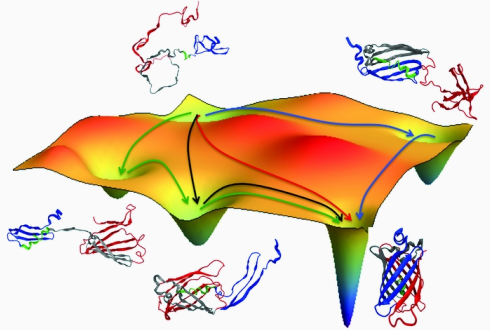
- Protein folding is important



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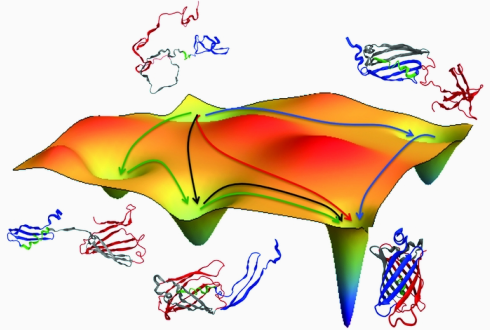
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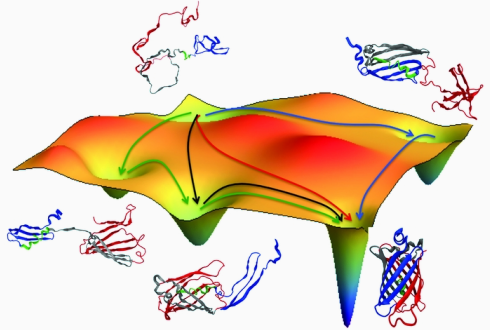
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The Problem

- Protein folding is important
- Peptides are building blocks of protein
- Peptide conformations → protein folding
- How do we understand peptide conformations?



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The Problem

Computational methods require knowledge of molecular structure

We need to find the lowest energy structure

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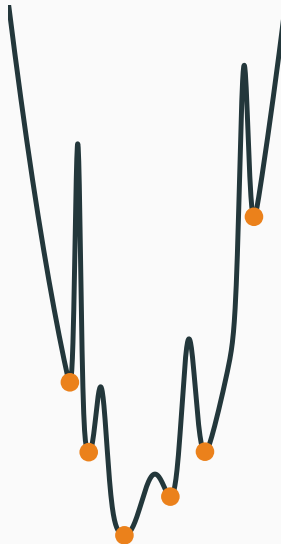
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- Ok, let's find them all!



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- Ok, let's find them all!
- Under a cutoff



Possible Solutions

- Many techniques are well established

Method	Implented in
grid-based	CEASAR, Open Babel , Confab , MacroModel, MOE
rule-based	ALFA , CONFECT , CORINA, ROTATE, COSMOS , OMEGA
population-based	Balloon , Cyndi
basin-hopping	ASE , GMIN , TINKER SCAN

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What Algorithmic Properties do we want for conformer search?

1. Accurate energies & Structures
2. Minimize # of geometry optimizations
3. Find many low energy conformations
4. Minimize human bias
5. Parallel

The Genetic Algorithm

- At least 23 years

Judson, R. S.; Jaeger, E. P.; Treasurywala, A. M.; Peterson, M. L. J. Comput. Chem. 1993, 14 (11), 14071414.

- Flexible ligand docking (Most cited: 7428)

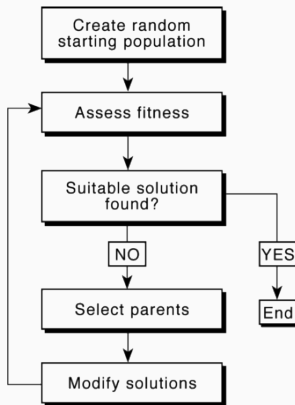
Morris, G. et al. J. Comput. Chem. 1998, 19 (14), 16391662.

- Precombustion CO₂ adsorbing MOFs (October 14th)

Chung, Y. G.; Gomez-Gualdron, D. A.; Li, P.; Leperi, K. T.; Deria, P.; Zhang, H.; Vermeulen, N. A.; Stoddart, J. F.; You, F.; Hupp, J. T.; Farha, O. K.; Snurr, R. Q. Sci. Adv. 2016, 2 (10)

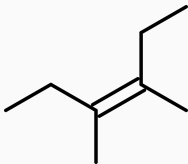
Outline

- Inspired by biological evolution
- Evolve a population over generations
- Survival of the fittest
- Requirements:
 - Represent individuals as vector
 - Fitness function
- $V = (x_1 \ y_1 \ z_1 \ x_2 \ y_2 \ z_2 \ \dots \ x_N \ y_N \ z_N)$
- $F = \frac{E_{\max} - E}{E_{\max} - E_{\min}}$

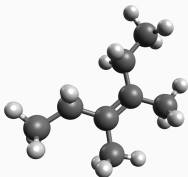


The Many Representations of a Molecule

2D Image



3D Image



Name

(3Z)-3,4-Dimethyl-
3-hexene

SMILES

CCC(C)=C(C)CC

InChI

1S/C8H16/c1-5-
7(3)8(4)6-2/h5-
6H2,1-4H3/b8-7-

Cartesian Coords

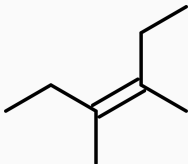
	x	y	z
C	0.90	-0.25	0.02
C	2.35	0.15	-0.17
C	2.91	1.30	-0.67

Internal Coords

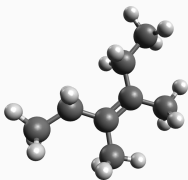
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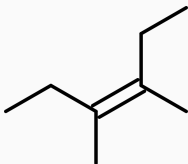
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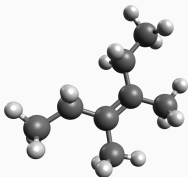
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Selecting Parents

Roulette Wheel Method

1. Reinforce good characteristics

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2. Still give losers a chance

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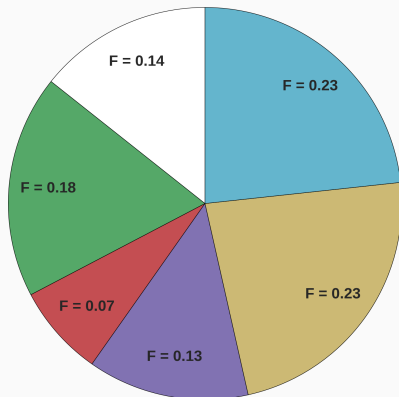


Sum of Fitness Scores = 1.0

Selecting Parents

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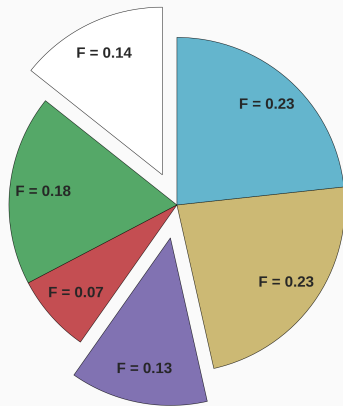
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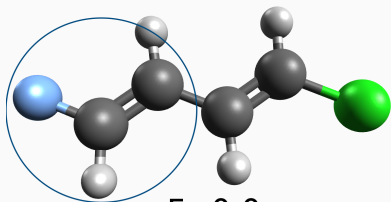
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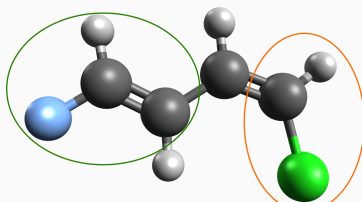
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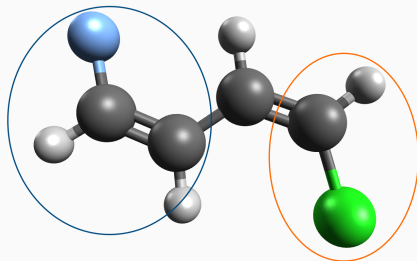
The Next Generation



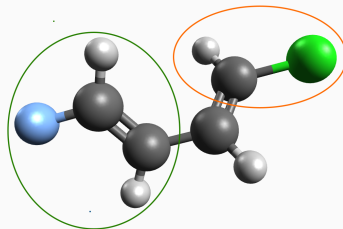
$F=0.0$



$F=0.95$



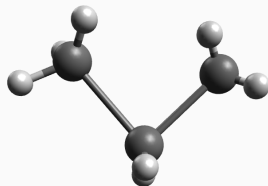
$F=1.0$



$F=0.86$

The Whole Algorithm

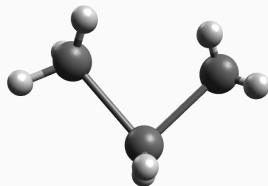
1. Generate N random, sensible geometries



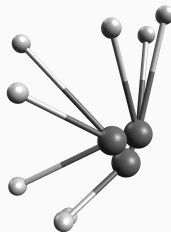
sensible

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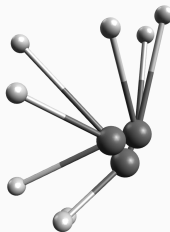
utter nonsense

The Whole Algorithm

1. Generate N random, sensible geometries
2. Optimize



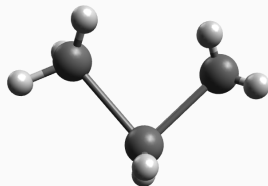
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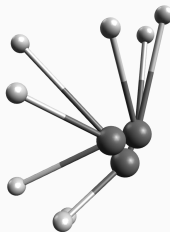
utter nonsense

The Whole Algorithm

1. Generate N random, sensible geometries
2. Optimize
3. Select Parents



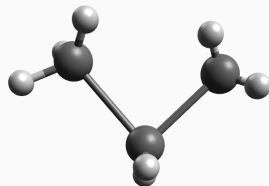
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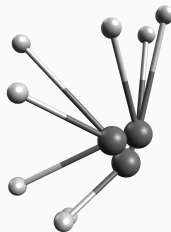
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The Whole Algorithm

1. Generate N random, sensible geometries
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3. Select Parents
4. Crossover & Mutate



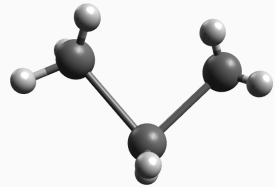
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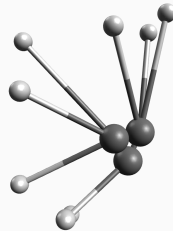
utter nonsense

The Whole Algorithm

1. Generate N random, sensible geometries
2. Optimize
3. Select Parents
4. Crossover & Mutate
5. Add Children to population



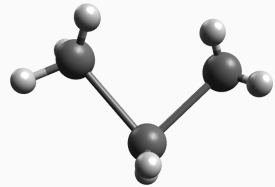
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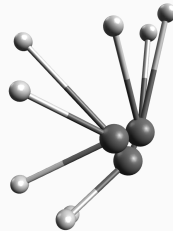
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6. Remove the unfit



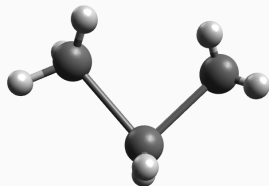
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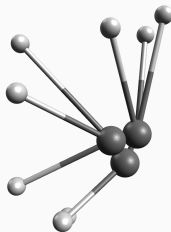
utter nonsense

The Whole Algorithm

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7. If converged:
 - Done!



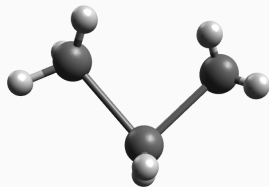
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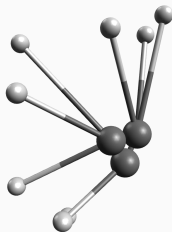
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7. If converged:
 - Done!Otherwise:
 - Go to 2



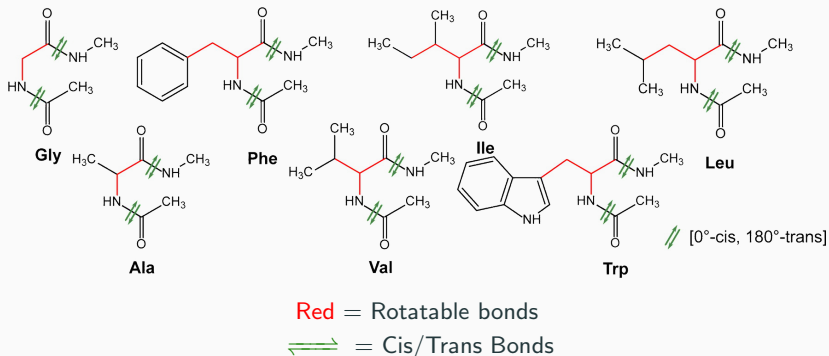
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utter nonsense

Finding Low Energy Conformers of Dipeptides

"Dipeptide" Structures

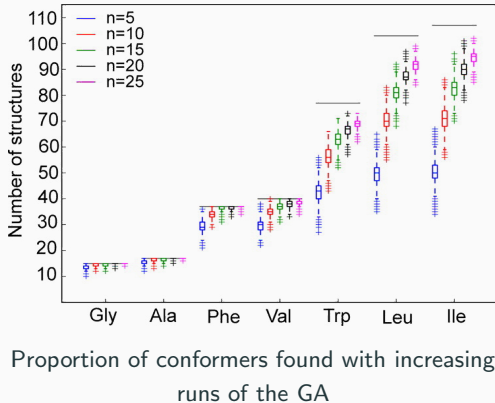


"We use the term dipeptide for amino acids with an acetylated N terminus and an amino-methylated C terminus"

	Molecule	N	# Rotatable +	# Conformers
			# Cis/Trans Bonds	
• GA beats other methods if space is large	Gly	19	2 + 2	15
	Ala	22	2 + 2	28
	Phe	32	4 + 2	64
• Space gets large fast	Val	28	3 + 2	60
	Trp	36	4 + 2	141
	Leu	31	4 + 2	183
	Ile	31	4 + 2	176

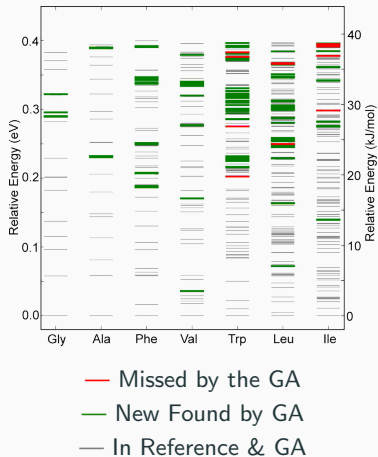
Coverage

- Smaller systems are reliably sampled
- As # of conformers increases, miss more and more
- Is there a pattern to what is missed?



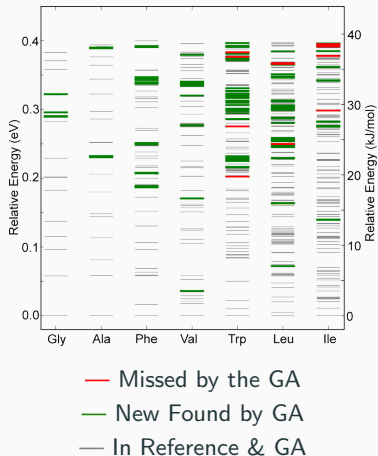
Coverage

- Most misses are very high energy



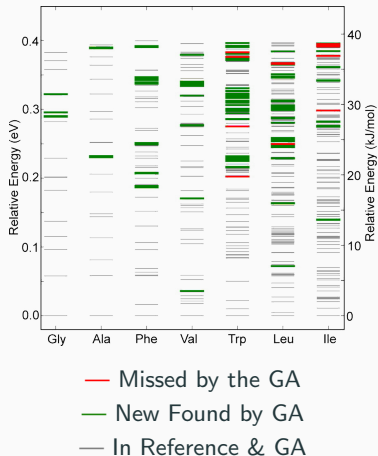
Coverage

- Most misses are very high energy
- Algorithm favors low energy areas of the space

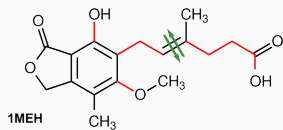


Coverage

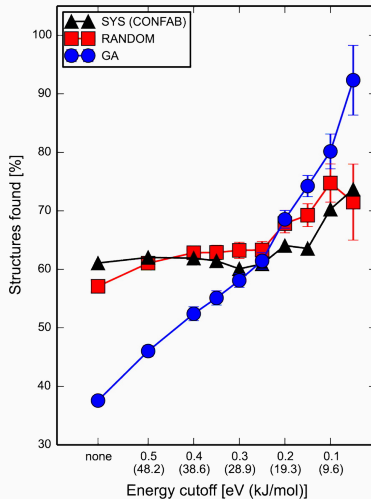
- Most misses are very high energy
- Algorithm favors low energy areas of the space
- Features low in energy are favored and recombined



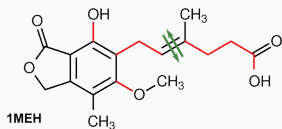
Energy Cutoff



Mycophenolic Acid

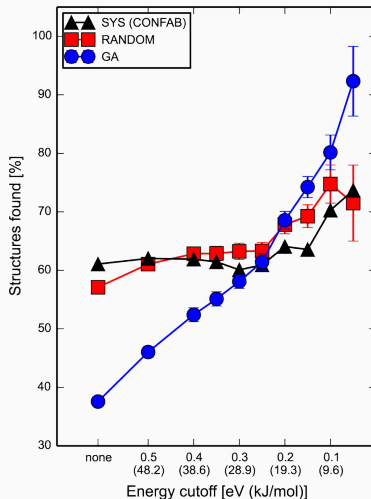


Energy Cutoff

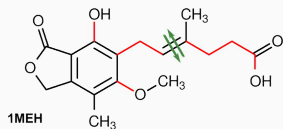


Mycophenolic Acid

- GA is more sensitive to energy cutoff

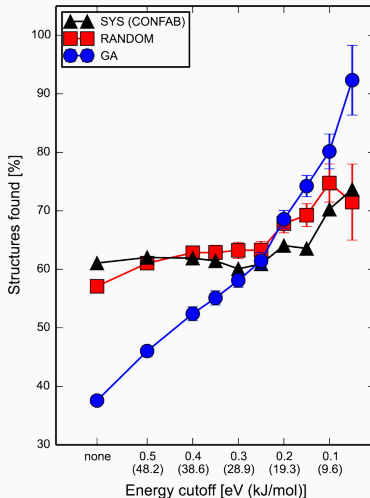


Energy Cutoff



Mycophenolic Acid

- GA is more sensitive to energy cutoff
- For finding low energy ensemble, GA outperforms purely stochastic/deterministic method



Concluding Remarks

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Review

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Concluding Remarks

Review

- Conformational searching is expensive
- The Genetic Algorithm is a guided global search
- It shines when asked to find many low energy solutions
- GA can be used with any electronic structure package
- This one is available under the GNU Lesser General Public License:
<https://github.com/adrianasupady/fafoom>

Questions?

- Geometry optimization step makes the algorithm more Lamarckian (Jean Baptiste Lamarck, [1744-1829])

Genetic Algorithm Parameters

Geometry Optimization: DFT PBE + VdW, *tier1* basis in FHI-aims¹.
Convergence at 0.005 eV / Å

	parameter	value
molecule	SMILES	<chem>CC(=O)N[C@H](C(=O)NC)[C@H](CC)C</chem>
	distance_cutoff_1	1.2 Å
	distance_cutoff_2	2.0 Å
	rmsd_cutoff_uniq	0.2 Å
	chiral	true
run settings	max_iter	10
	iter_limit_conv	10
	energy_diff_conv	0.001 eV
GA settings	popsize	5
	energy_var	0.001 eV
	selection	roulette wheel
	fitness_sum_limit	1.2
	prob_for_crossing	0.95
	cross_trial	20
	prob_for_mut_cistrans	0.5
	prob_for_mut_rot	0.5
	max_mutations_cistrans	1
	max_mutations_torsions	2
	mut_trial	100

GA Parameters for Isoleucine Dipeptide²

(1) Blum, V. et. al., M. Comput. Phys. Commun. 2009, 180 (11), 21752196.

(2) Supady, A.; Blum, V.; Baldauf, C. J. Chem. Inf. Model. 2015, 55 (11), 23382348.