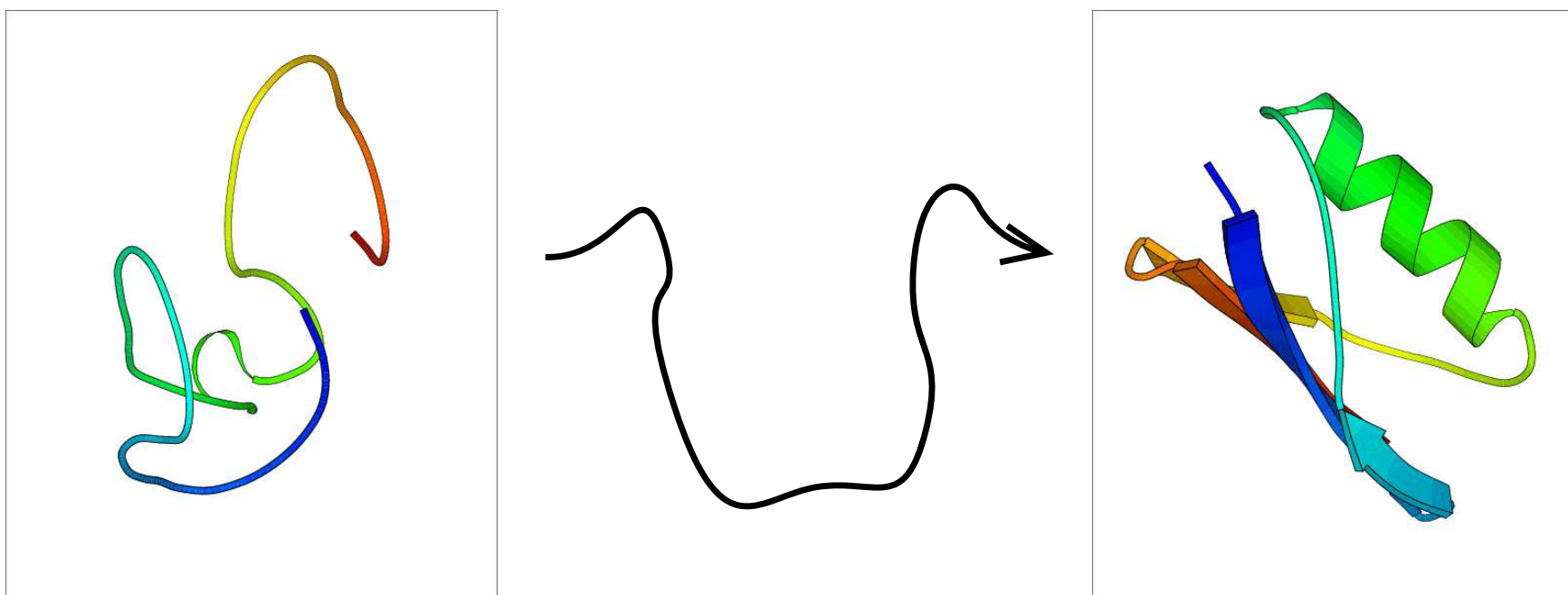


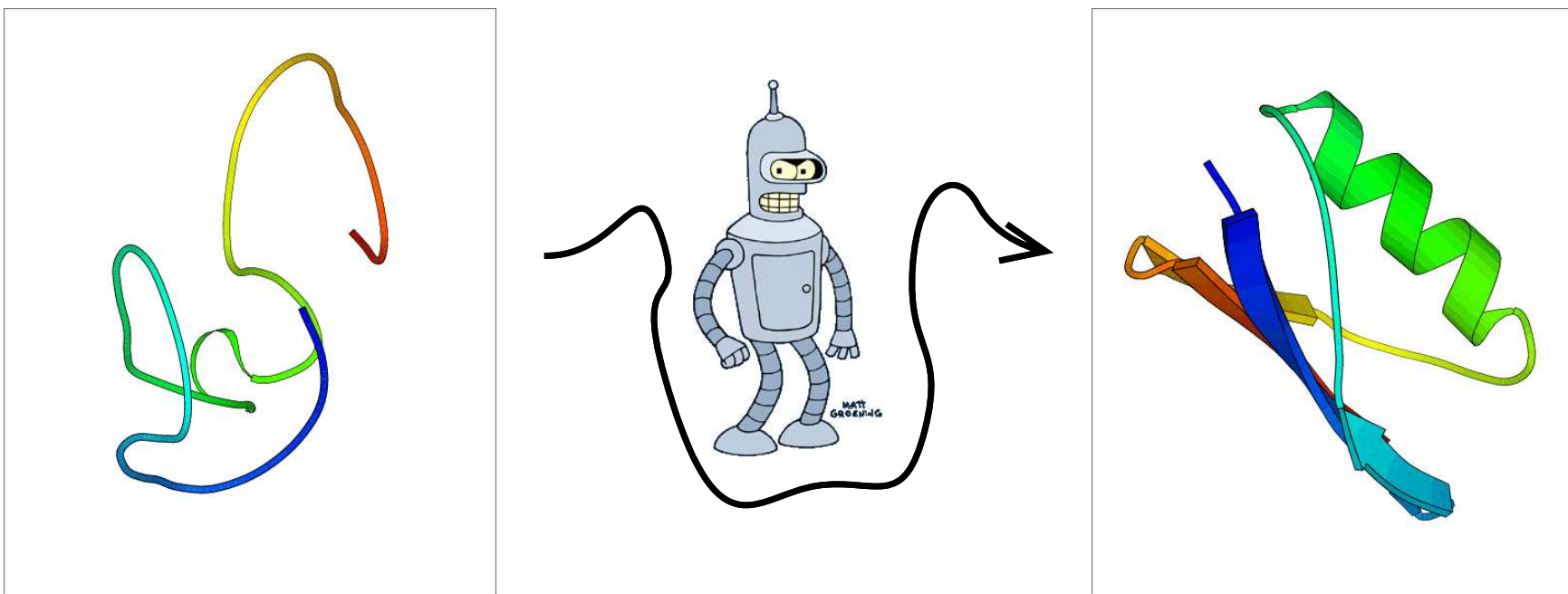
# Protein Folding by Robotics

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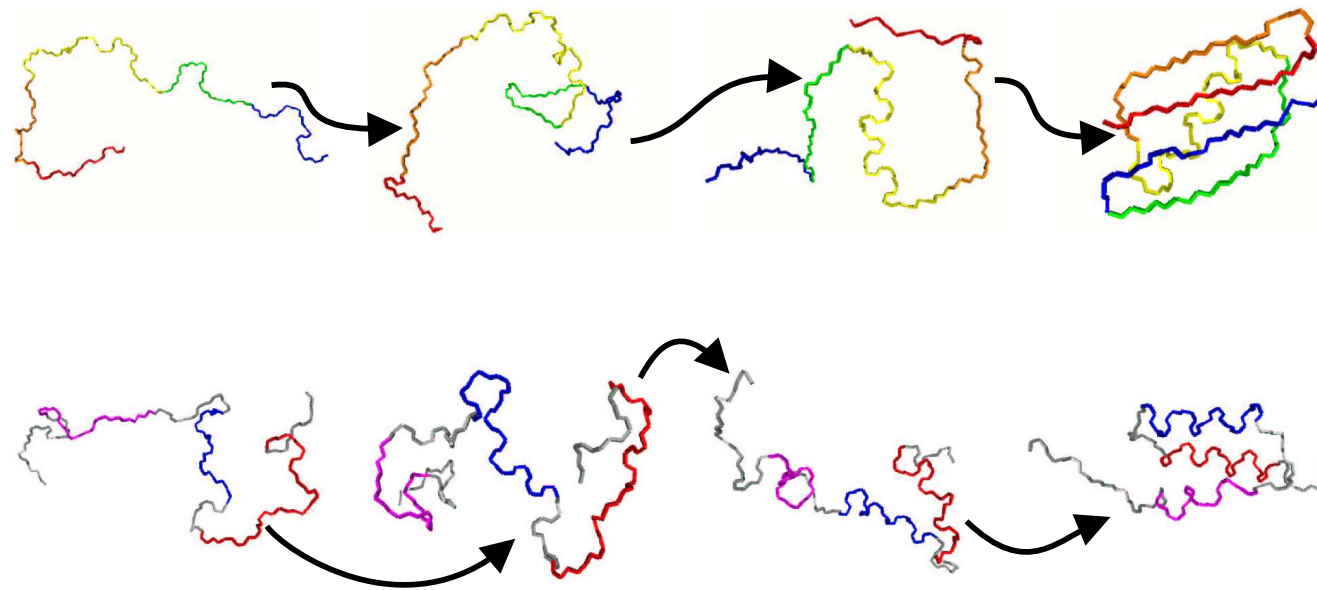




## Probabilistic Roadmap Planning (PRM)

[ Thomas, Song, Amato. *Protein folding by motion planning*. Phys. Biol., 2005 ]

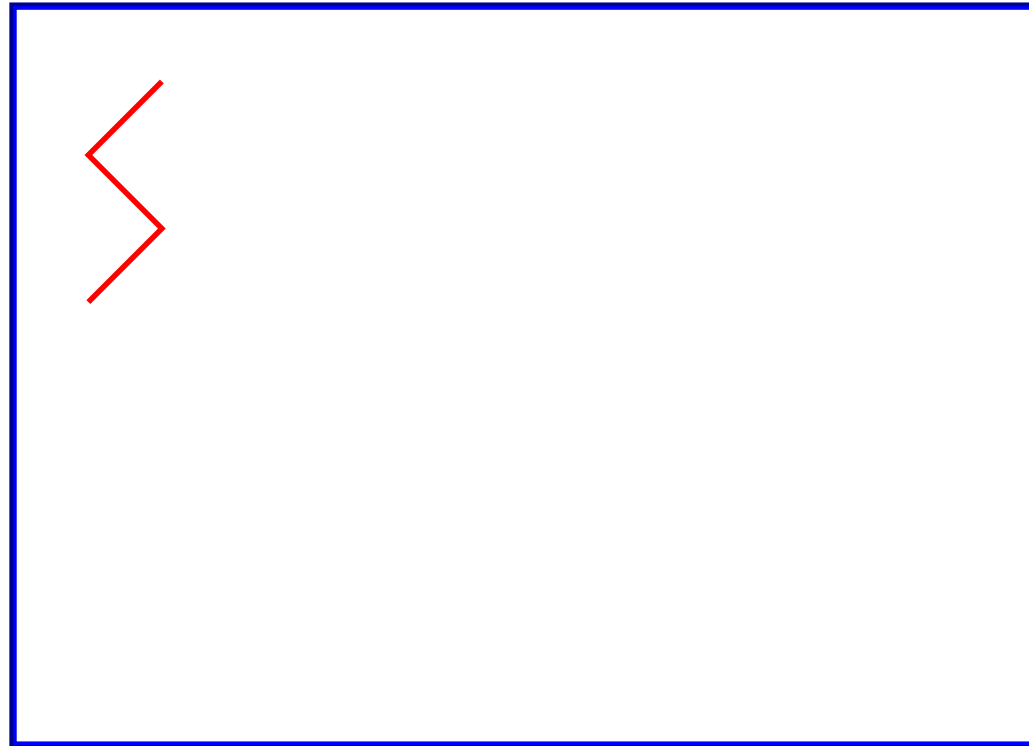
- Find good quality folding paths (into given native structure)
  - no structure prediction!
- Predict formation orders (of secondary structure)



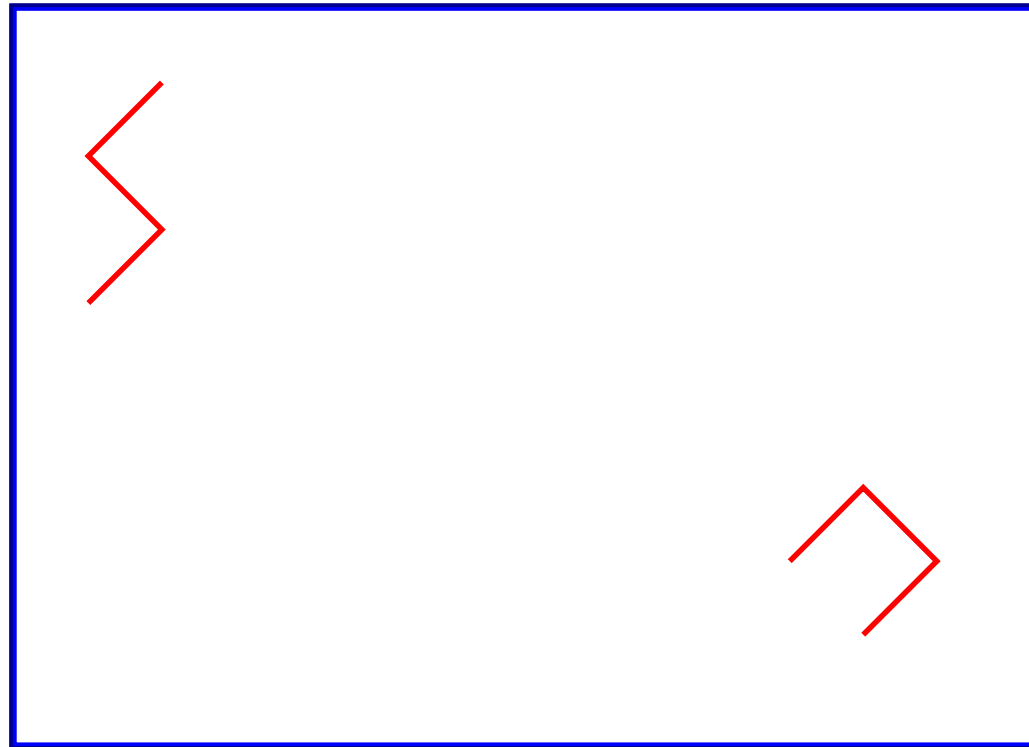
# Motion planning

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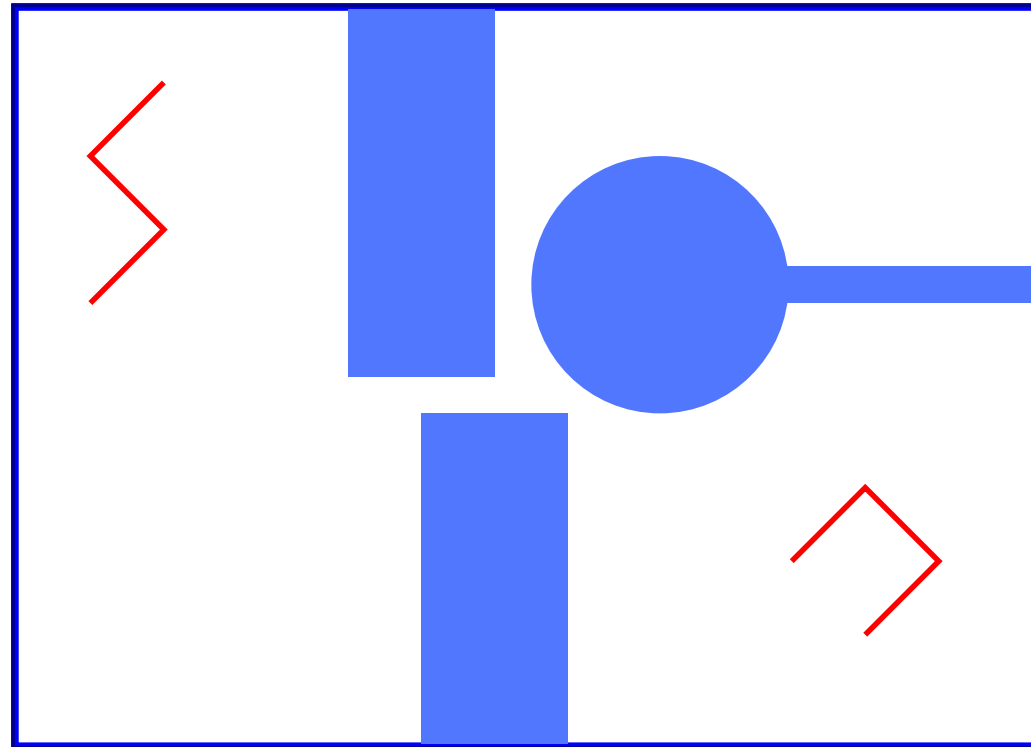
## ● Motion planning



● Motion planning



- Motion planning

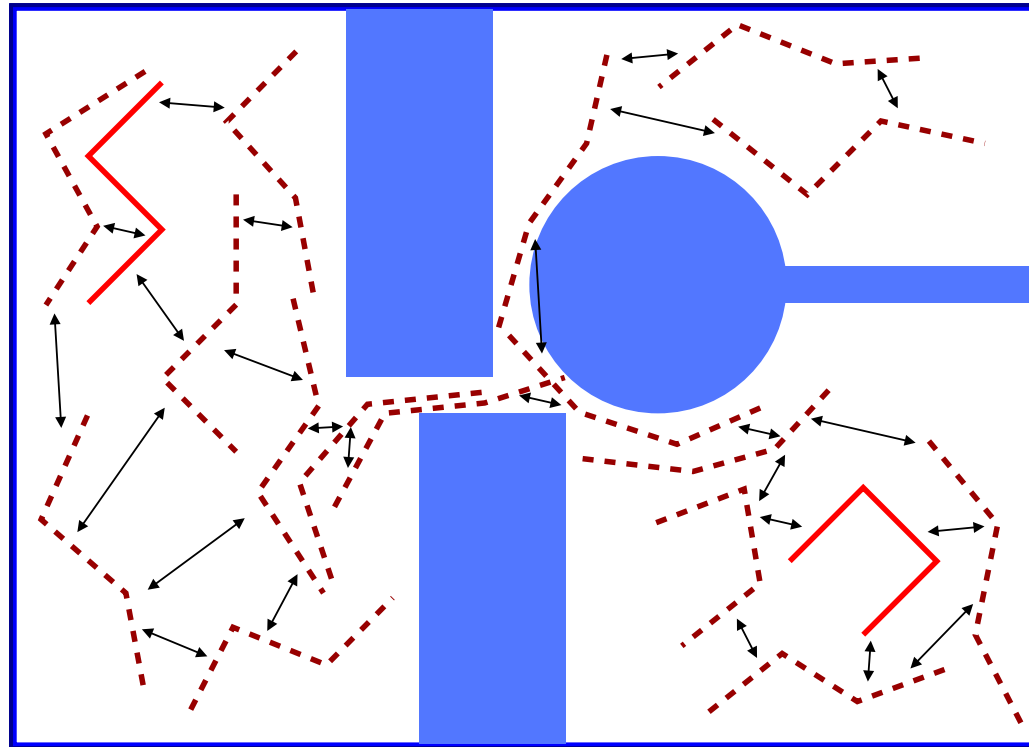


- Probabilistic roadmap planing





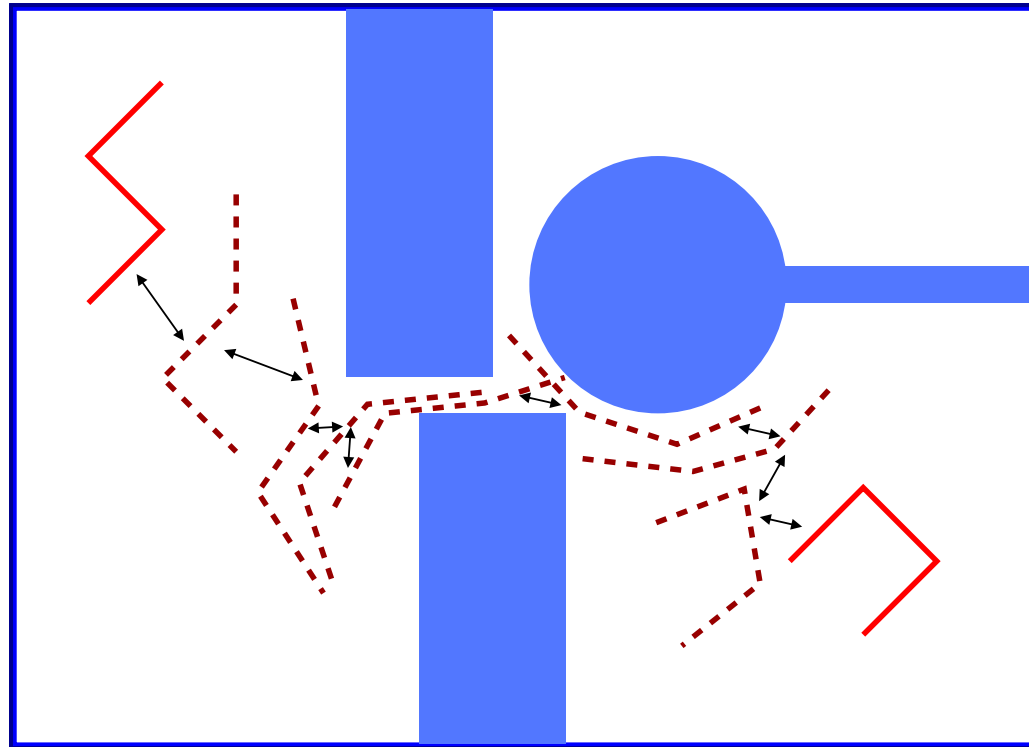
## ● Motion planning



## ● Probabilistic roadmap planning

- Sampling of configuration space  $Q$
- Connecting nearest configurations by a (simple) *local planner*

## ● Motion planning

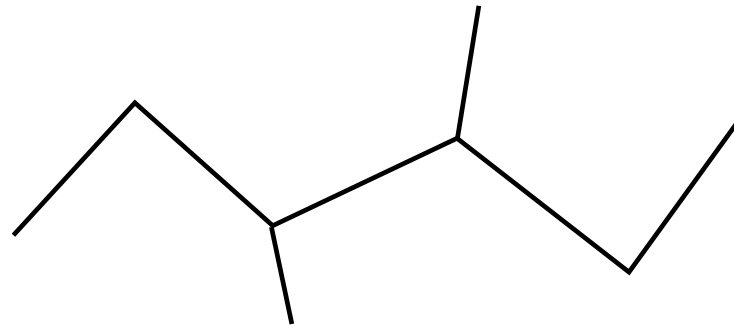


## ● Probabilistic roadmap planning

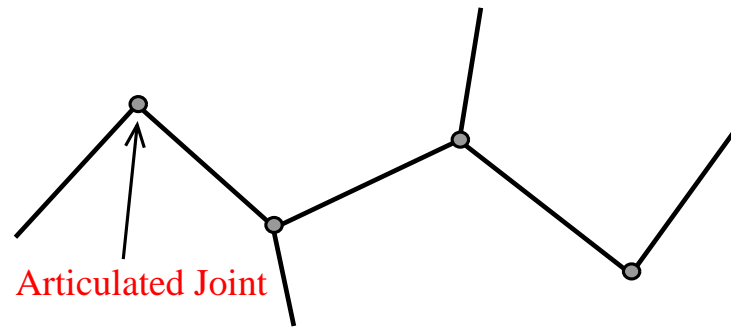
- Sampling of configuration space  $Q$
- Connecting nearest configurations by a (simple) *local planner*
- Apply graph algorithms to “roadmap”: Find shortest path

# More on PRM for motion planning

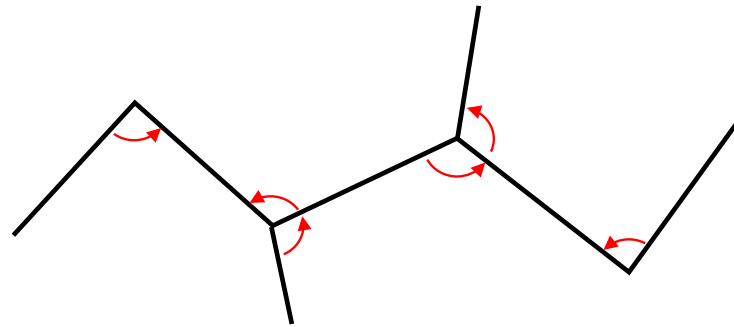
● tree-like robots



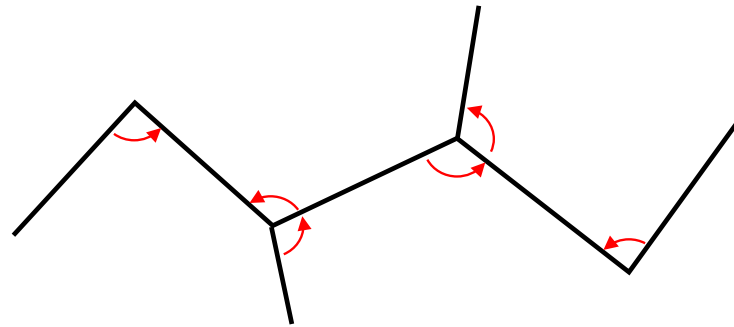
- tree-like robots (*articulated robots*)



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- tree-like robots (*articulated robots*)



- configuration = vector of angles
- configuration space

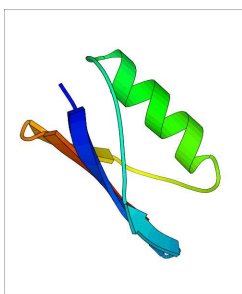
$$Q = \{q \mid q \in S^n\}$$

- $S$  — set of angles
- $n$  — number of angles = degrees of freedom (dof)

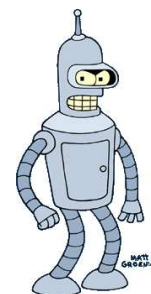
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● Obvious similarity



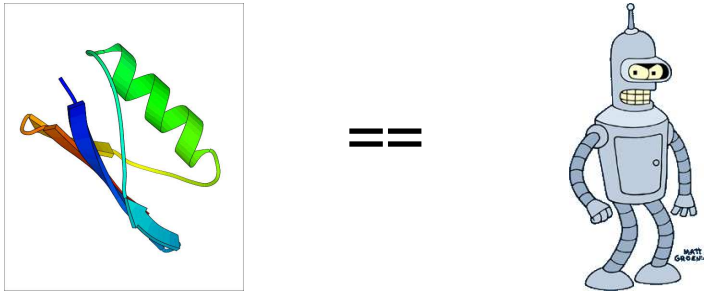
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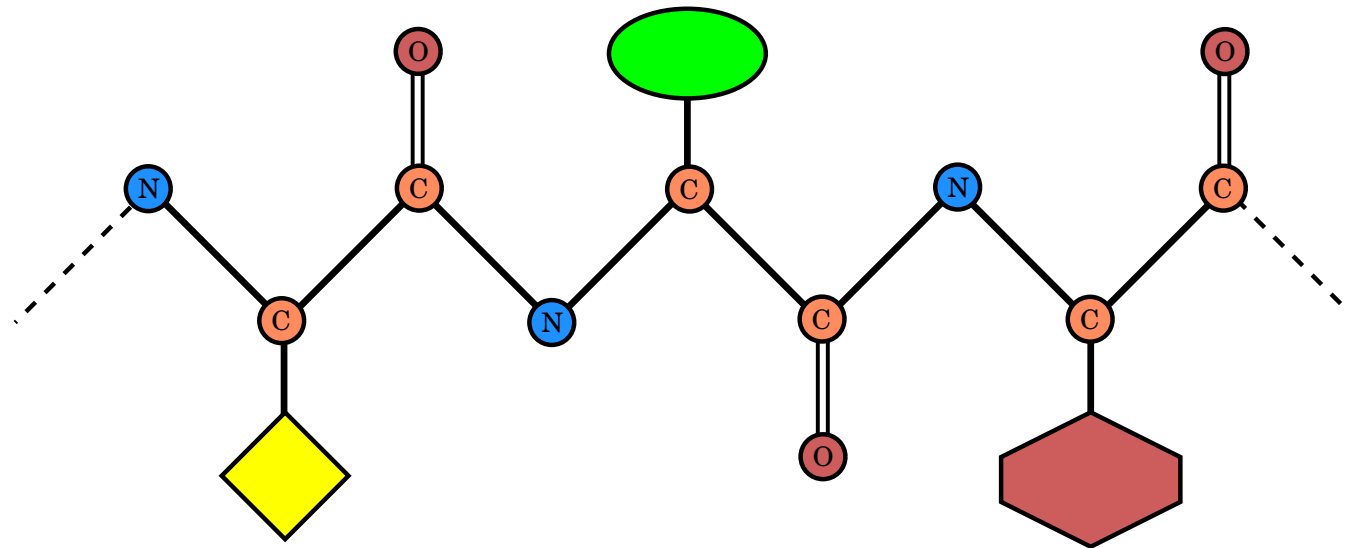
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● Our model

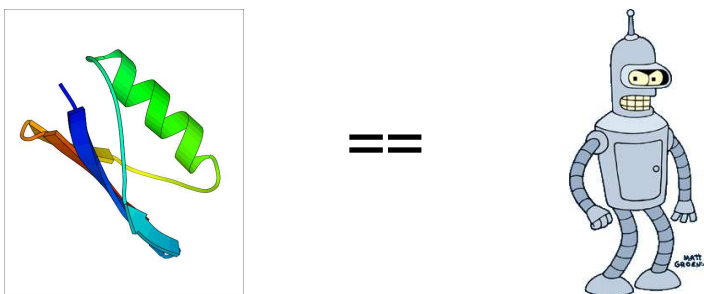




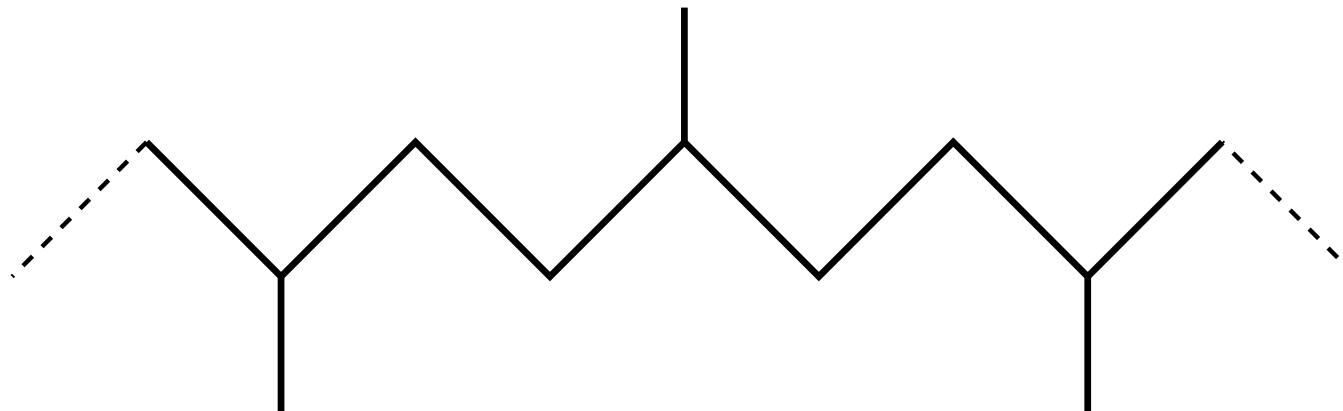
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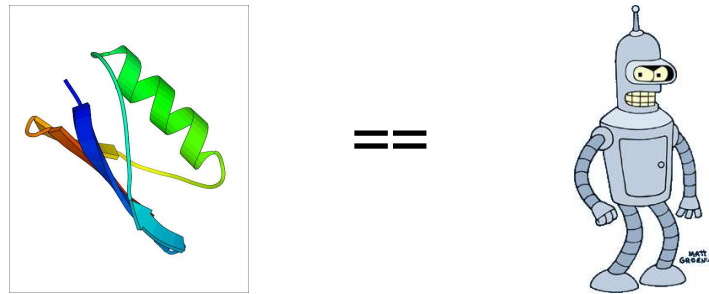
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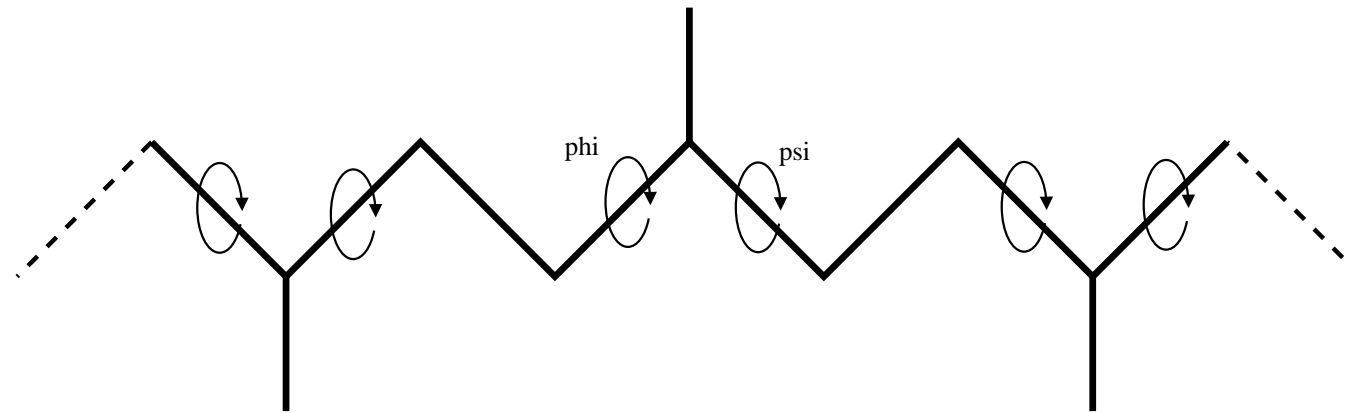
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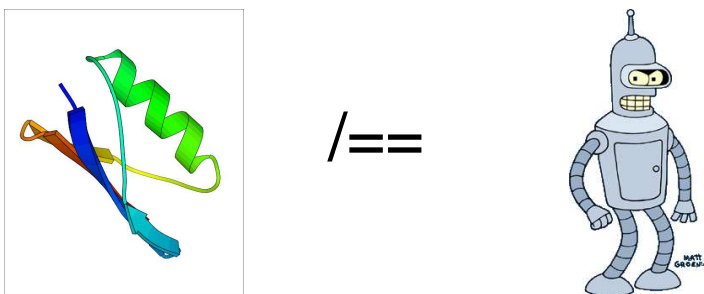
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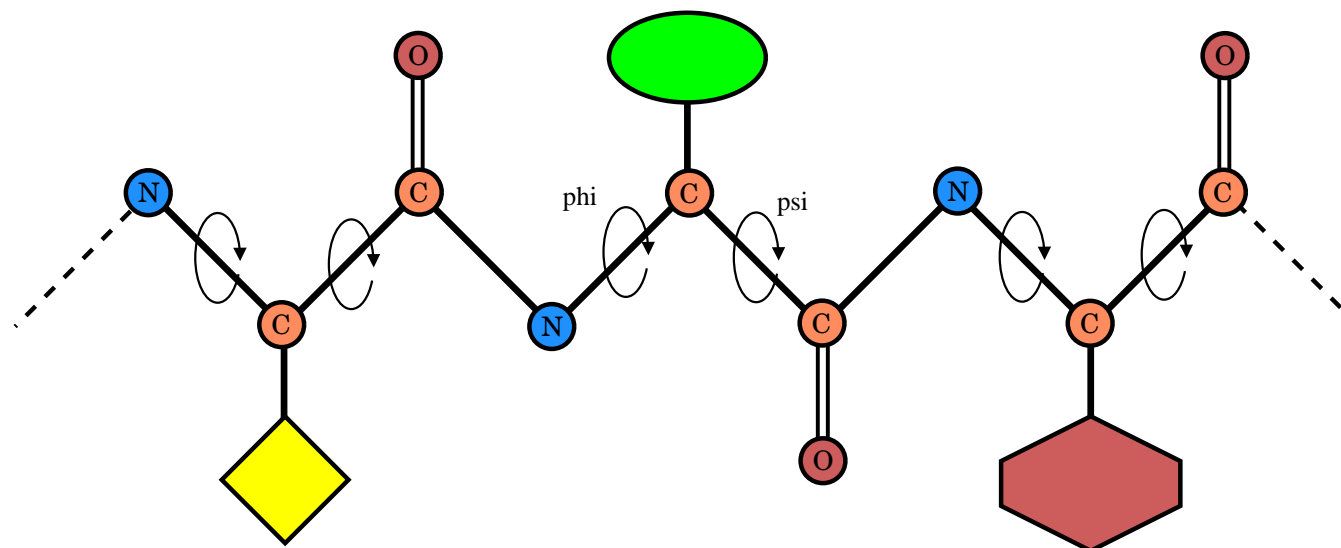
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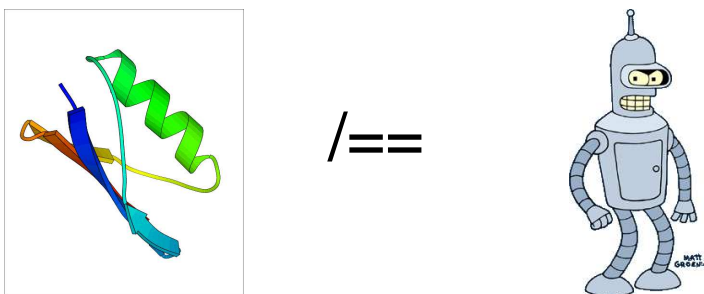


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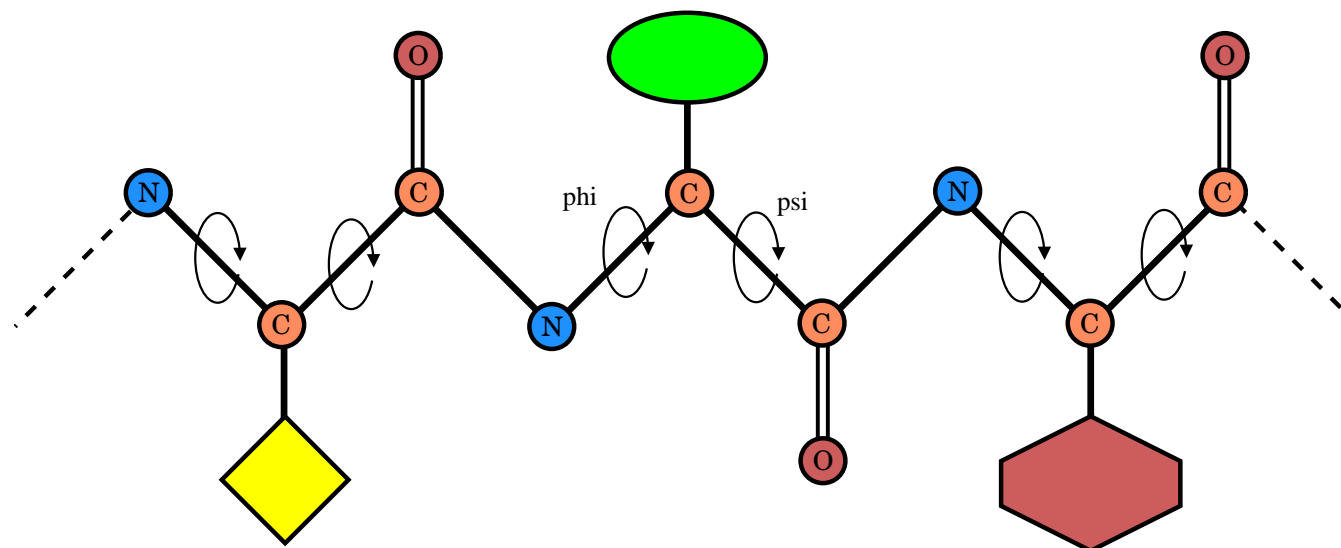


# Proteins are Robots (aren't they?)

- Obvious similarity ;-)



- Our model



- Protein == vector of phi and psi angles (treelike robot with  $2n$  dof)
- possible models range from only backbone up to full atom

# Differences to usual PRM

- no external obstacles, but
  - self-avoidingness
  - torsion angles
- quality of paths
  - low energy intermediate states
  - kinetically preferred paths
  - highly probable paths

# Energy Function

- method can use any potential

- method can use any potential
- Our coarse potential  
[Levitt. J.Mol.Biol., 1983. ]
  - each sidechain by only one “atom” (zero dof)

$$U_{tot} =$$

- method can use any potential

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[Levitt. J.Mol.Biol., 1983. ]

- each sidechain by only one “atom” (zero dof)

$$U_{tot} = \sum_{\text{restraints}} K_d \{ [(d_i - d_0)^2 + d_c^2]^{\frac{1}{2}} - d_c \}$$

- **first term** favors known secondary structure through main chain hydrogen bonds and disulphide bonds



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[Levitt. J.Mol.Biol., 1983. ]

- each sidechain by only one “atom” (zero dof)

$$U_{tot} = \sum_{\text{restraints}} K_d \{ [(d_i - d_0)^2 + d_c^2]^{\frac{1}{2}} - d_c \} + E_{hp}$$

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- **second term** hydrophobic effect

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- Van der Waals interaction modeled by step function

- All-atom potential: EEF1

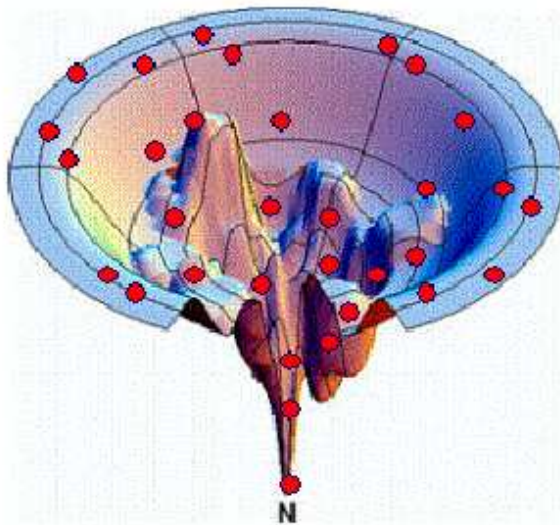
[Lazaridis, Karplus. Proteins, 1999. ]

# PRM method for Proteins

1. Motivation
2. Motion Planning
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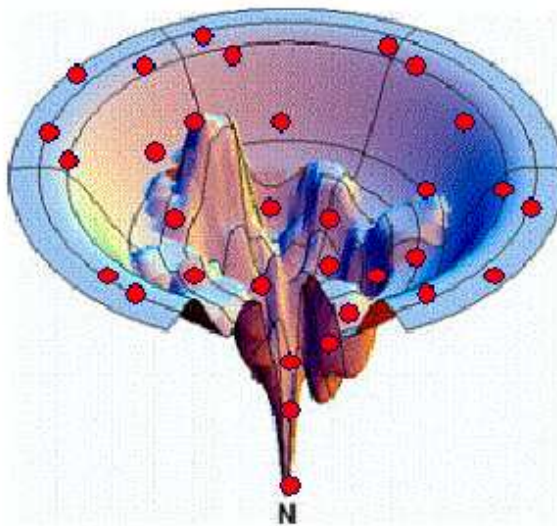
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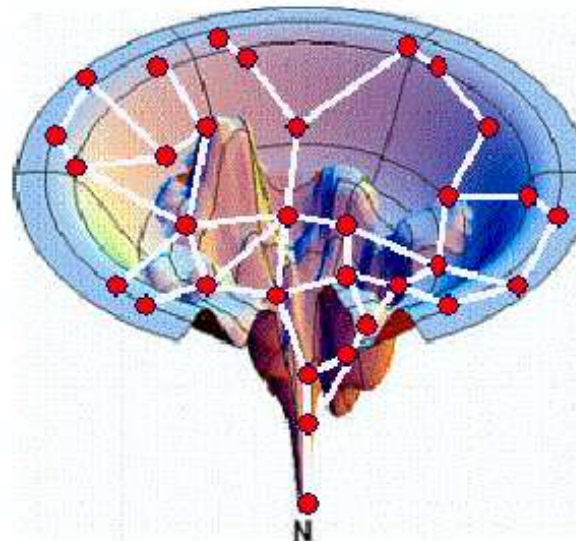
 Sampling

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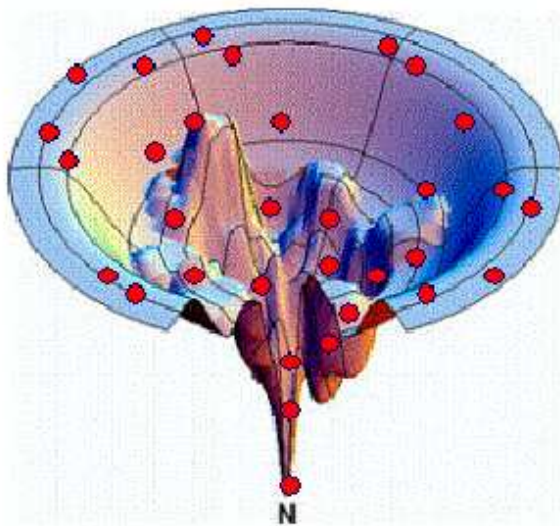
● Sampling



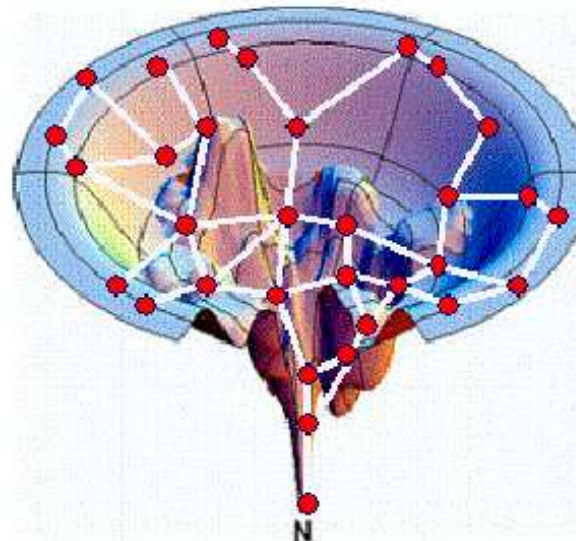
● Connecting

# PRM method for Proteins

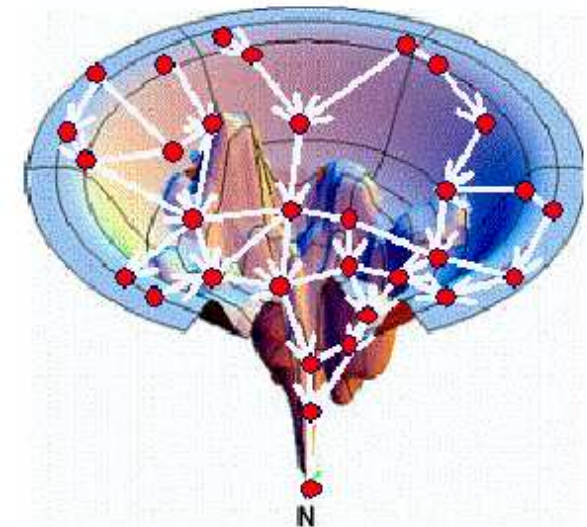
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● Sampling



● Connecting

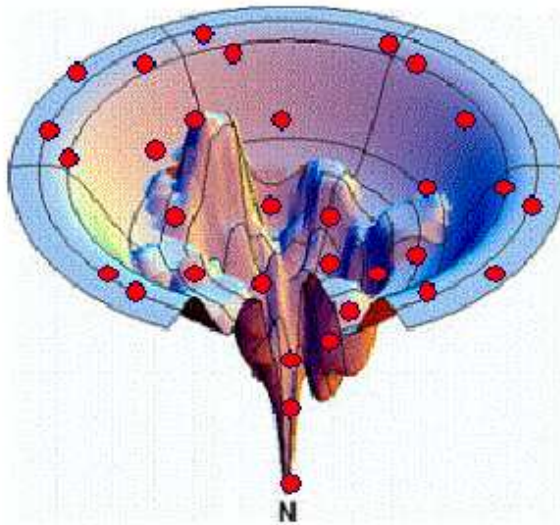


● Extracting

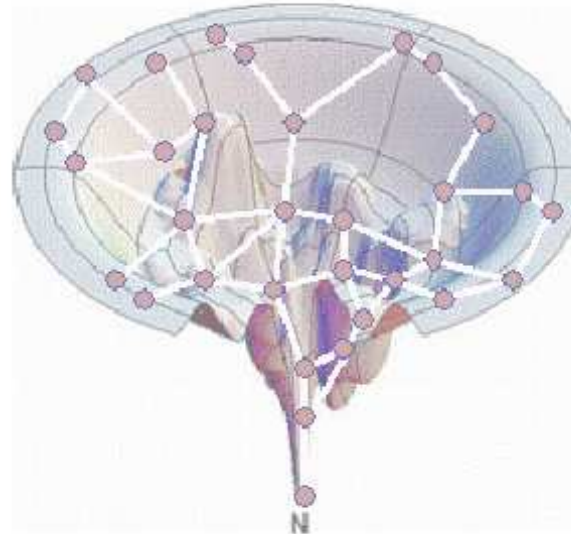


# Sampling — Node Generation

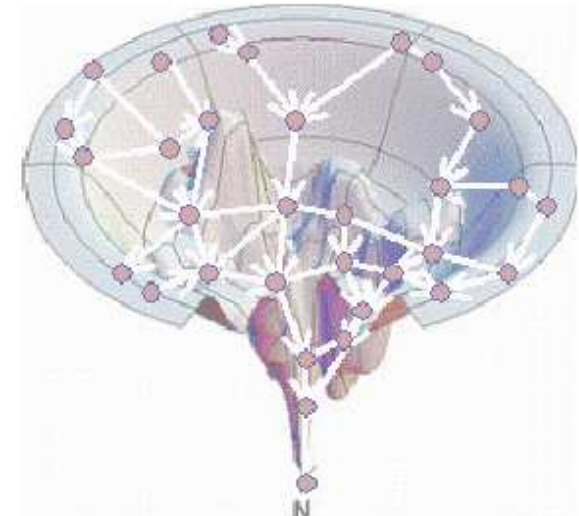
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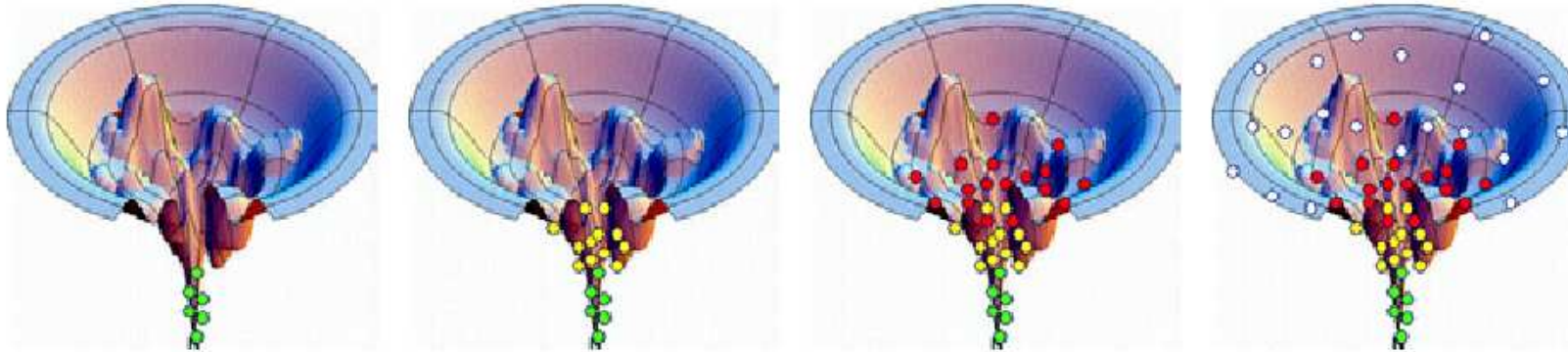
- No uniform sampling
  - configuration space too large
  - $\Rightarrow$  need biased sampling strategy

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- Gaussian sampling
  - centered around native conformation
  - with different STDs  $5^\circ, 10^\circ, \dots, 160^\circ$
  - ensure representants for different numbers of native contacts

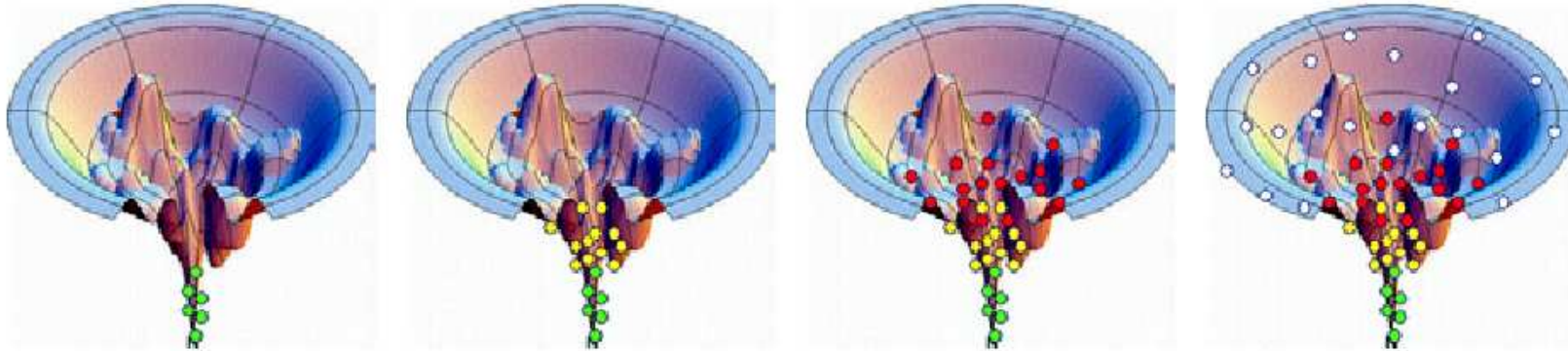
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- Gaussian sampling
  - centered around native conformation
  - with different STDs  $5^\circ, 10^\circ, \dots, 160^\circ$
  - ensure representants for different numbers of native contacts
- Selection by energy

$$P(\text{accept } q) = \begin{cases} 1 & \text{if } E(q) < E_{\min} \\ \frac{E_{\max} - E(q)}{E_{\max} - E_{\min}} & \text{if } E_{\min} \leq E(q) \leq E_{\max} \\ 0 & \text{if } E(q) > E_{\max} \end{cases}$$

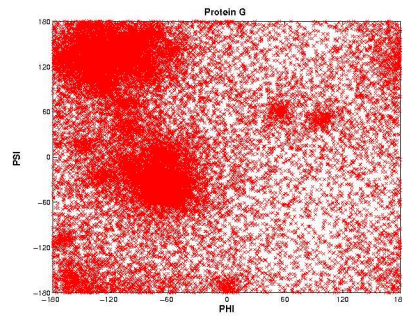
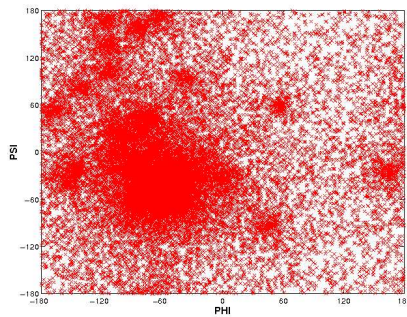
● Visualization of Sampling Strategy



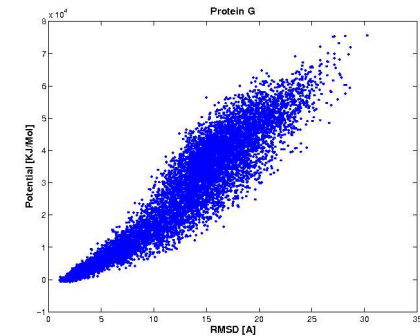
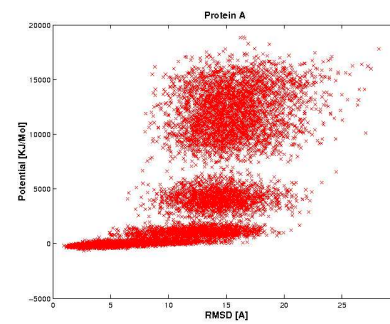
## Visualization of Sampling Strategy



## Distribution



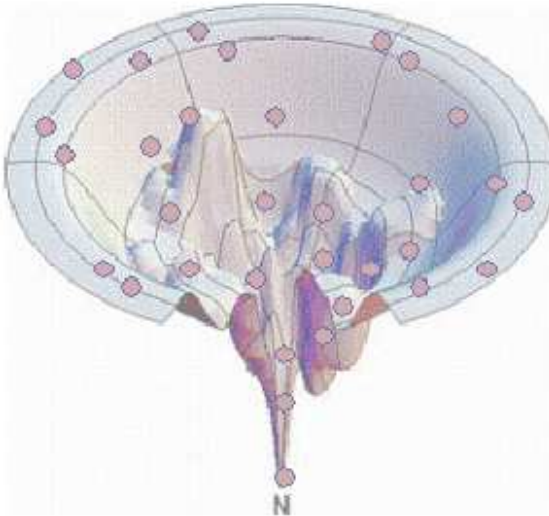
Psi and Phi angles



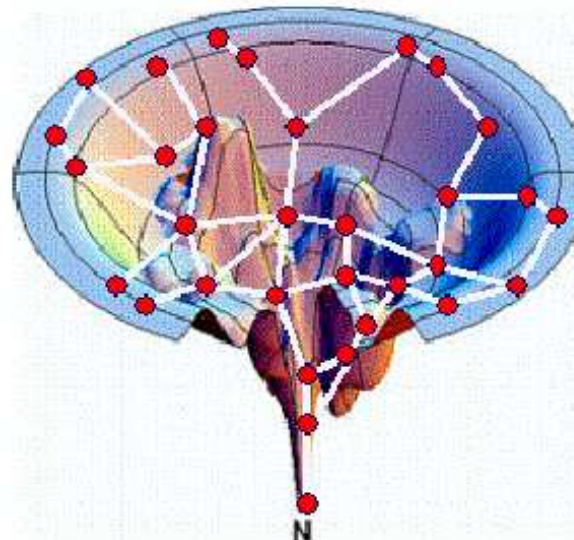
RMSD vs. Energy

# Node Connection

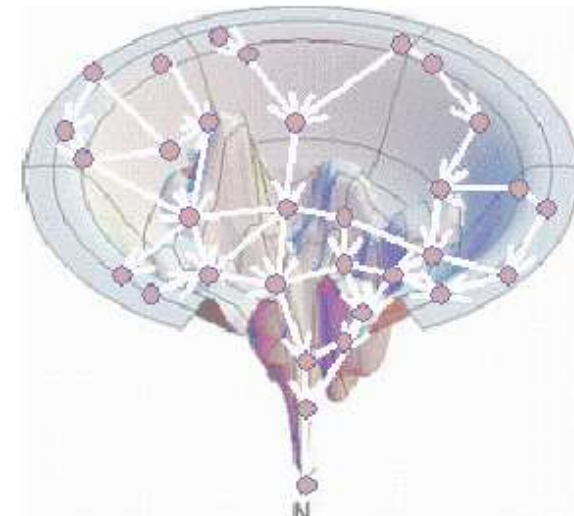
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● Connecting



● Extracting

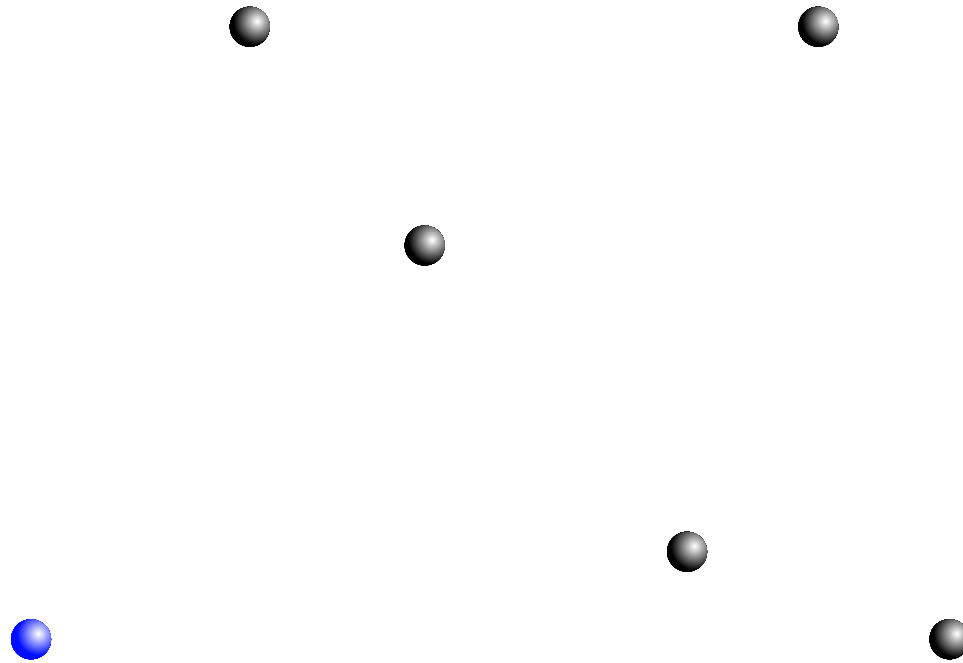


# Connecting Nodes by Local Planner

- connect configurations in close distance
- generate N intermediary nodes by local planner

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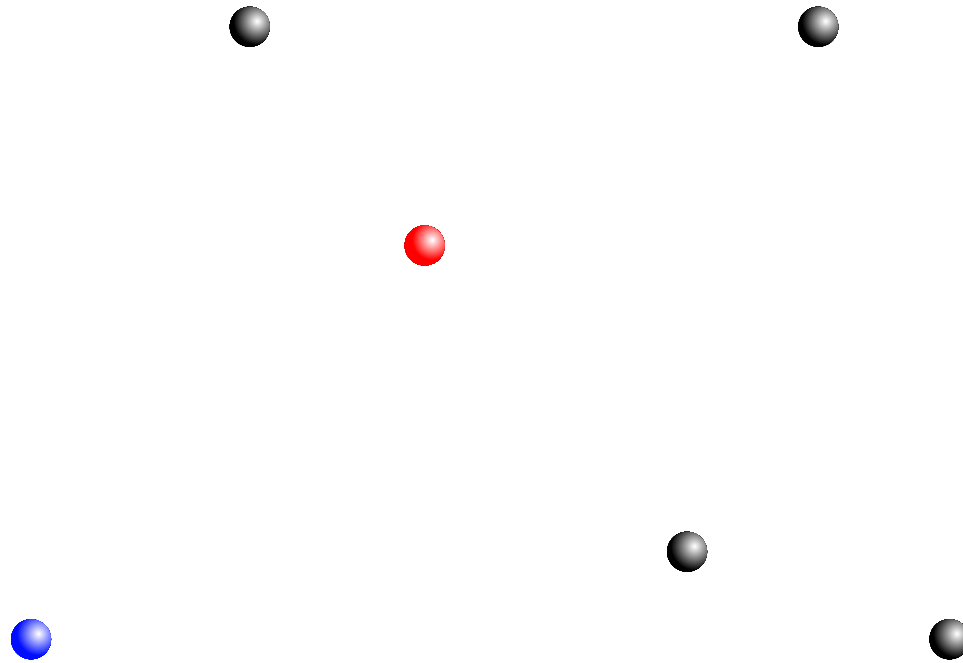
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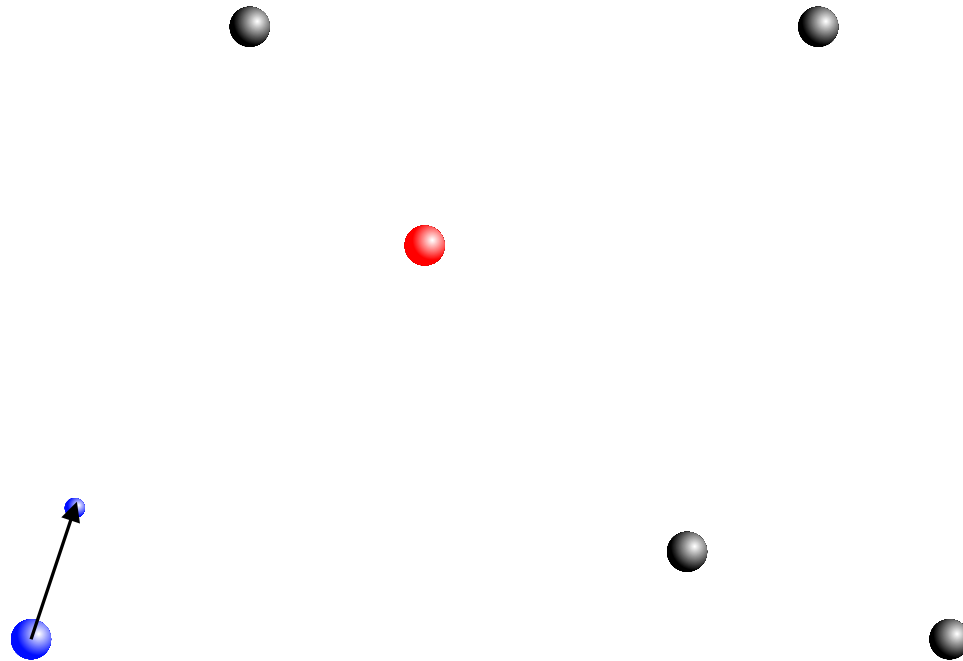
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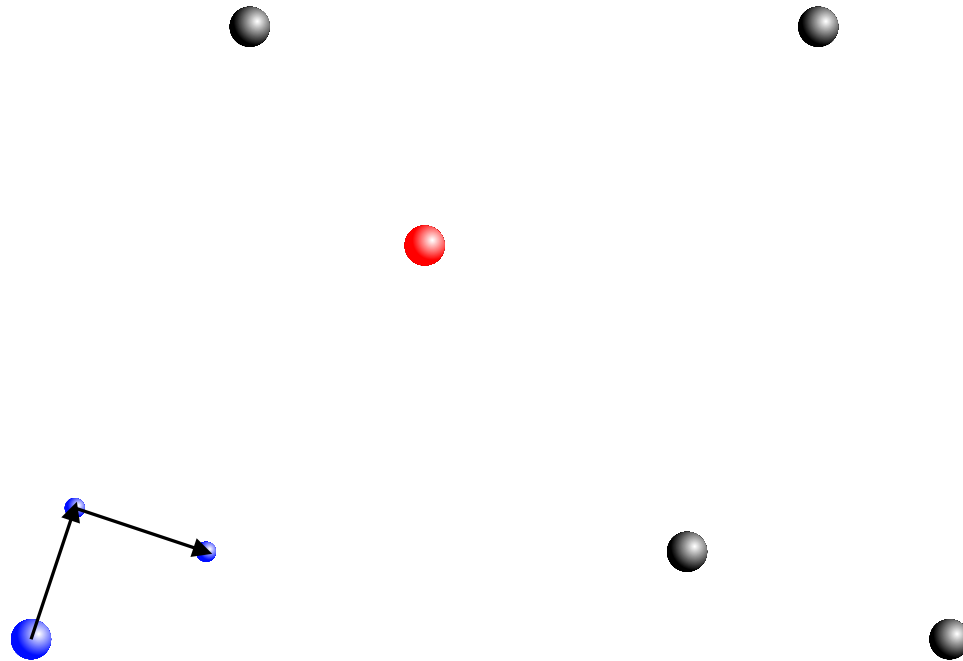
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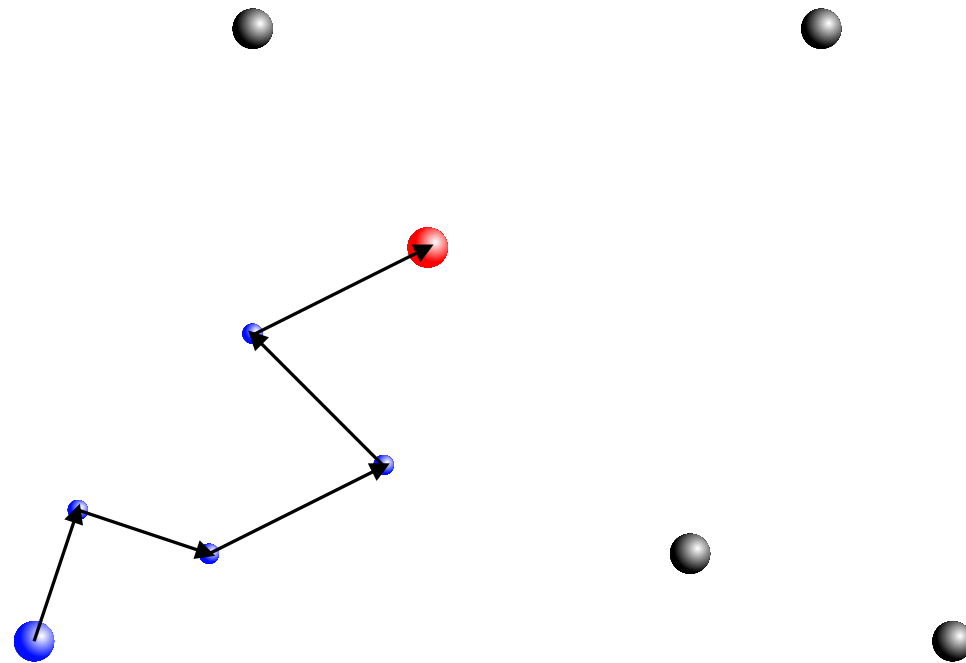
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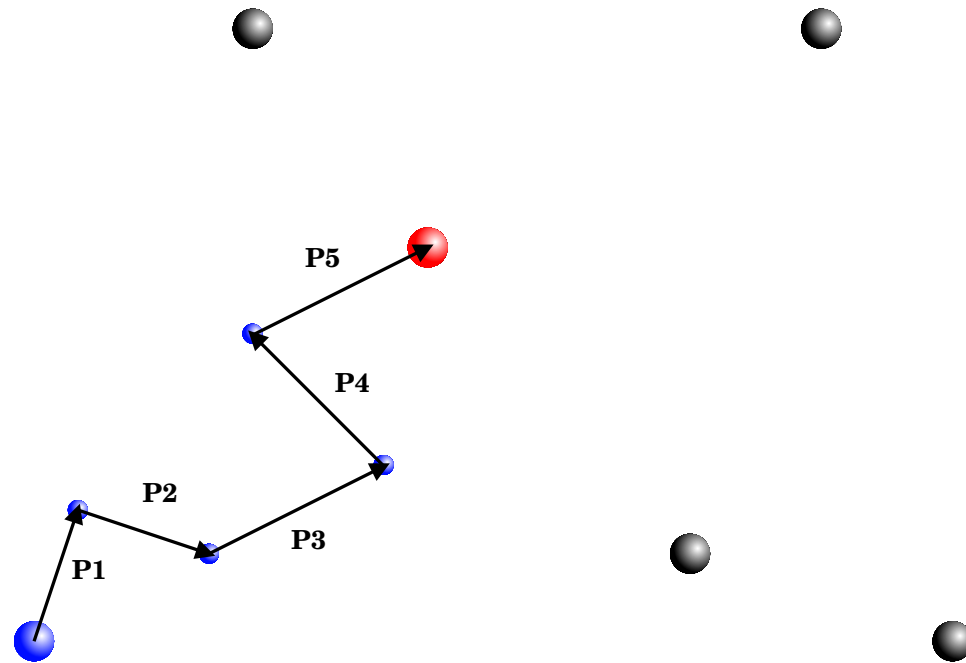


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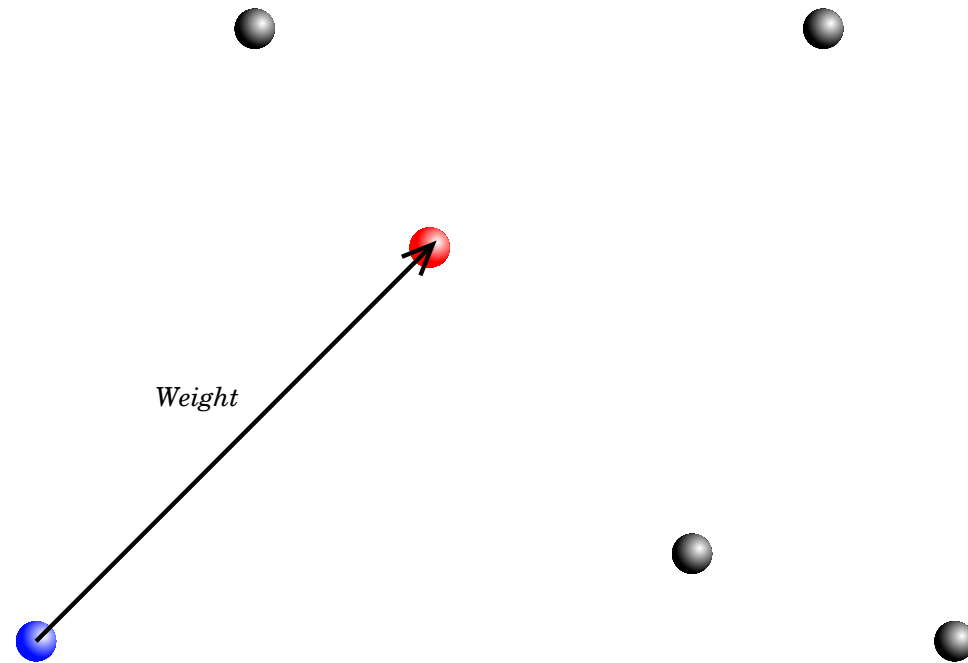


- assign weights to edges

$$P_i = \begin{cases} e^{-\frac{\Delta E}{kT}} & \text{if } \Delta E > 0 \\ 1 & \text{if } \Delta E \leq 0 \end{cases}$$

# Connecting Nodes by Local Planner

- connect configurations in close distance
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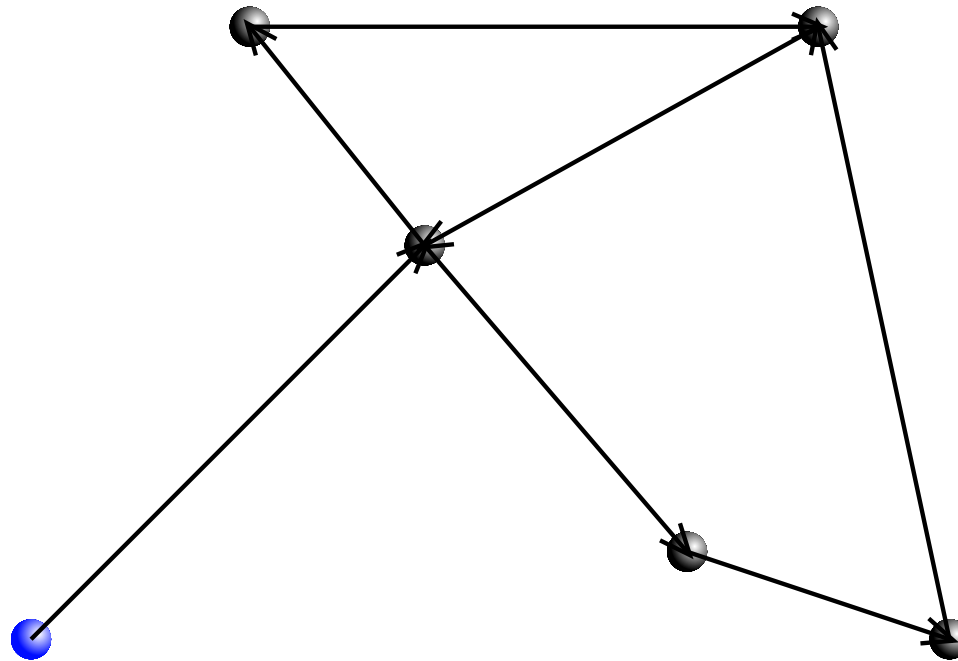


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- connect configurations in close distance
- generate  $N$  intermediary nodes by local planner



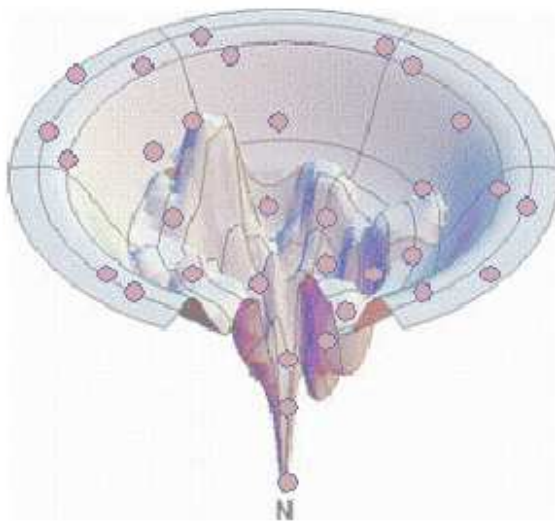
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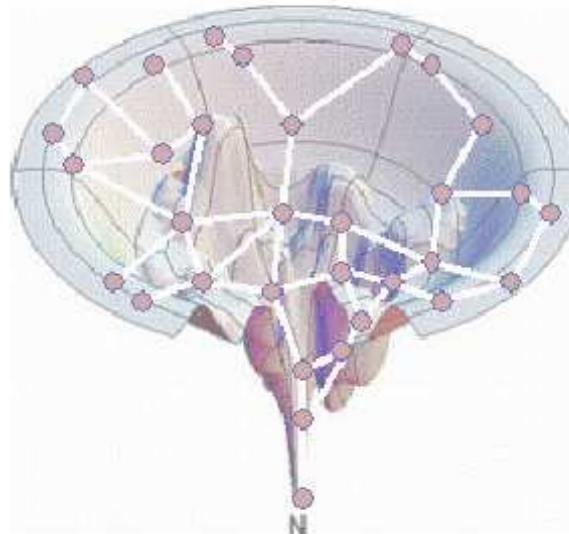
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# Extracting Paths

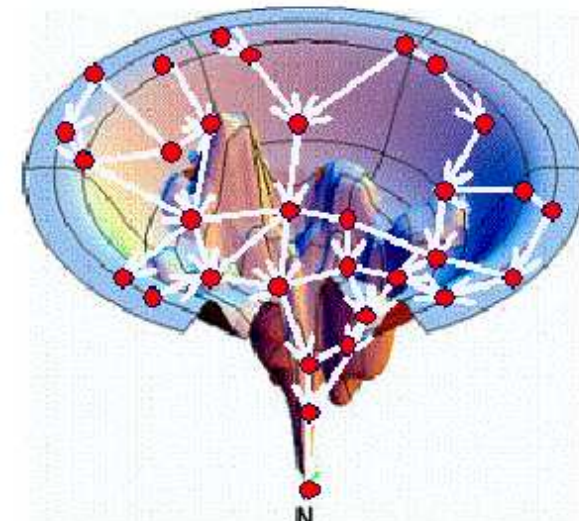
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 Extracting



## ● Shortest Path

- extract one shortest path
- from some starting conformation, one path at a time

## ● Shortest Path

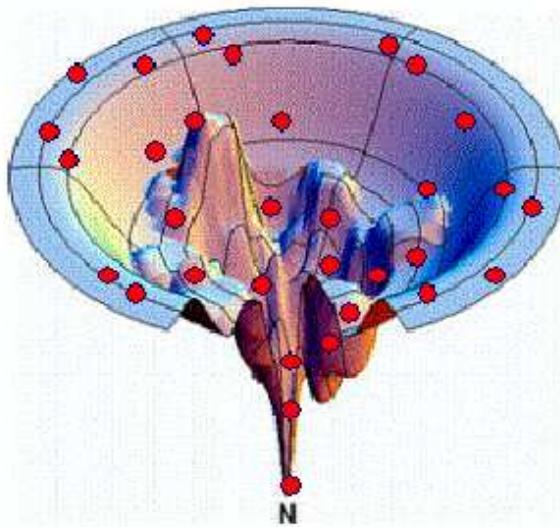
- extract one shortest path
- from some starting conformation, one path at a time

## ● Single Source Shortest Paths (SSSP)

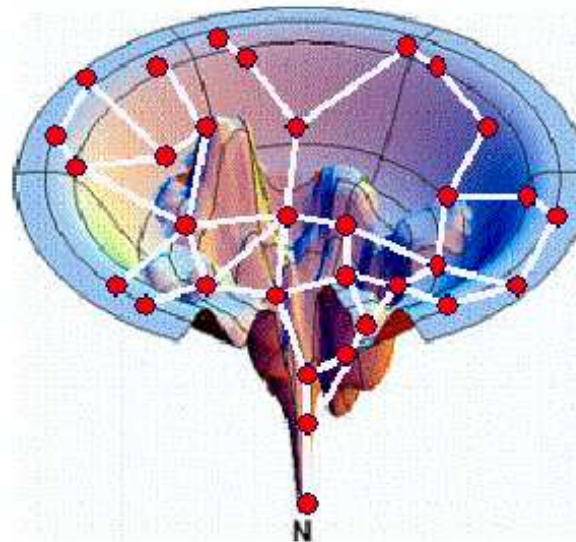
- extract shortest paths from all starting conformation
- compute paths simultaneously
- generate tree of shortest paths (SSSP tree)

# Big Picture

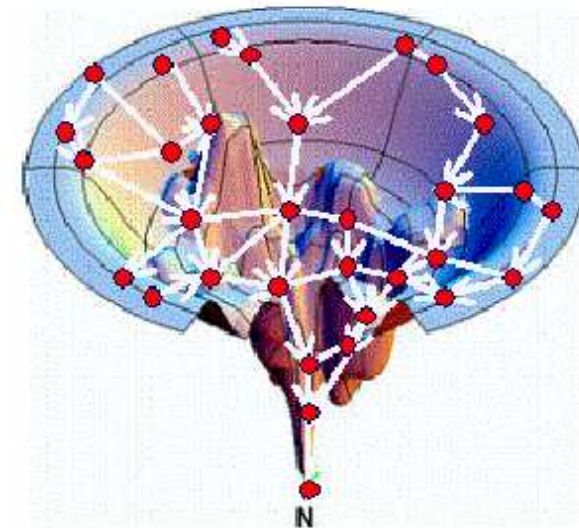
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● Sampling



● Connecting



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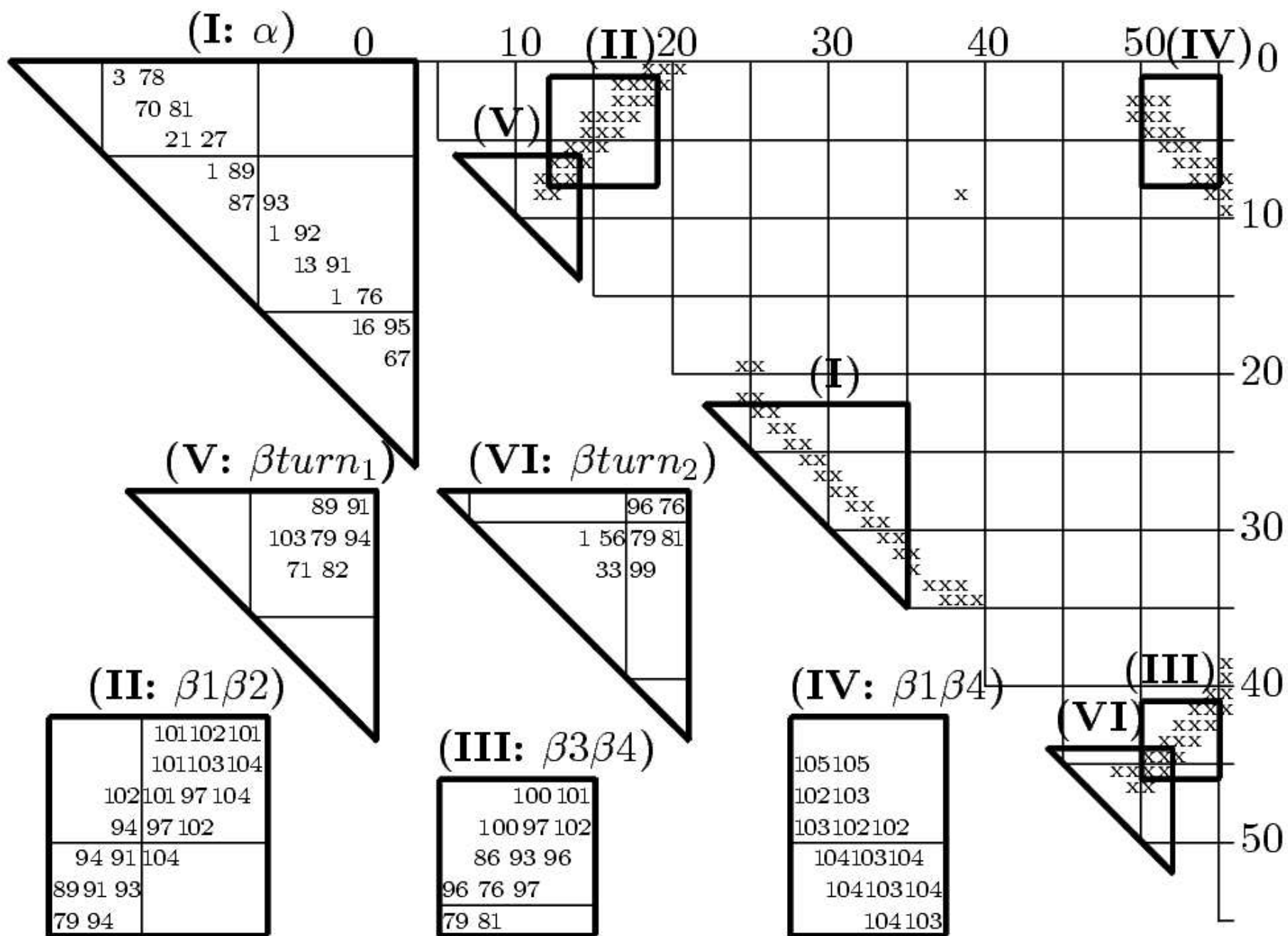
● Overview of studied proteins, roadmap size, and construction times

pdb	Description	Length	SS	# Nodes	Time (h)
1gb1	Protein G domain B1	56	$1\alpha + 4\beta$	8 000	6.400
2crt	Cardiotoxin III	60	$5\beta$	8 000	6.430
1bdd	Staphylococcus protein A	60	$3\alpha$	10 000	10.400
1shg	SH3 domain $\alpha$ -spectrin	62	$5\beta$	10 000	8.344
2ptl	Protein L, B1 domain	62	$1\alpha + 4\beta$	4 000	3.104
1coa	CI2	64	$1\alpha + 4\beta$	10 000	9.984
1srl	SH3 domain src	64	$5\beta$	8 000	5.990
1nyf	SH3 domain fyn	67	$5\beta$	10 000	8.418
2ait	Tendamistat	74	$7\beta$	10 000	13.327
1ubq	Ubiquitin	76	$1\alpha + 5\beta$	8 000	10.381
1pks	SH3 domain PI3 kinase	79	$1\alpha + 5\beta$	10 000	14.446
1pba	Procarboxypeptidase A2	81	$3\alpha + 3\beta$	8 000	10.845

- formation order of secondary structure for verifying method
- formation orders can be determined experimentally  
[ Li, Woodward. Protein Science, 1999. ]
  - Pulse labeling
  - Out-exchange
- prediction of formation orders
  - single paths
  - averaging over multiple paths (SSSP-tree)

# Timed Contact Maps

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# Formation Order

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2. Motion Planning
3. Protein Model
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- 5. Results**
6. Conclusion

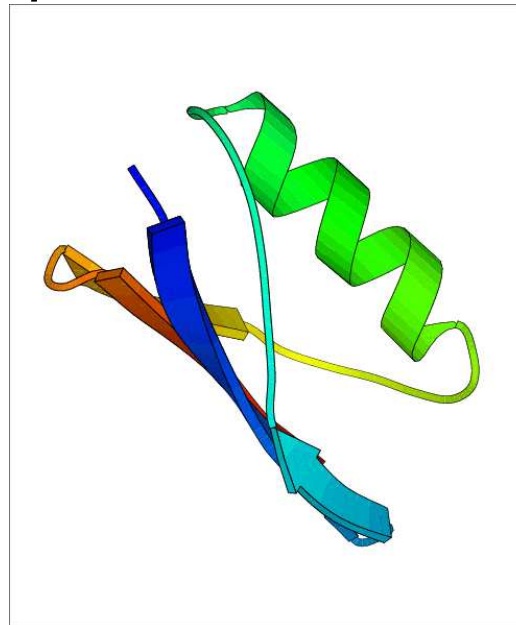
pdb	Out exchange	Pulse labeling	Our SS formation order	Comp.
1gb1	$[\alpha, \beta_1, \beta_3, \beta_4], \beta_2$	$[\alpha, \beta_4], [\beta_1, \beta_2, \beta_3]$	$\alpha, \beta_3-\beta_4, \beta_1-\beta_2, \beta_1-\beta_4$	Agreed
2crt	$[\beta_3, \beta_4, \beta_5], [\beta_1, \beta_2]$	$\beta_5, \beta_3, \beta_4, [\beta_1, \beta_2]$	$\beta_1-\beta_2, \beta_3-\beta_4, \beta_3-\beta_5$	Not sure
1bdd	$[\alpha_2, \alpha_3], \alpha_1$	$[\alpha_1, \alpha_2, \alpha_3]$	$[\alpha_2, \alpha_3], \alpha_1, \alpha_2-\alpha_3, \alpha_1-\alpha_3$	Agreed
1shg	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_5, \beta_1-\beta_2$	N/A
2ptl	$[\alpha, \beta_1, \beta_2, \beta_4], \beta_3$	$[\alpha, \beta_1], [\beta_2, \beta_3, \beta_4]$	$\alpha, \beta_1-\beta_2, \beta_3-\beta_4, \beta_1-\beta_4$	Agreed
1coa	$[\alpha, \beta_2, \beta_3], [\beta_1, \beta_4]$	N/A	$\alpha, \beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_4$	Agreed
1srl	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_5, \beta_1-\beta_2$	N/A
1nyf	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_2, \beta_1-\beta_5$	N/A
2ait	$[\beta_1, \beta_2], [\beta_3, \beta_4, \beta_5, \beta_6, \beta_7]$	N/A	$\beta_1-\beta_2, \beta_3-\beta_4, [\beta_2-\beta_5, \beta_3-\beta_6], \beta_3-\beta_5$	Agreed
1ubq	$[\alpha, \beta_1, \beta_2], [\beta_3, \beta_5], \beta_4$	N/A	$\alpha, \beta_3-\beta_4, \beta_1-\beta_2, \beta_3-\beta_5, \beta_1-\beta_5$	Agreed
1pks	N/A	N/A	$\beta_3-\beta_4, \beta_1-\beta_5, [\beta_1-\beta_2, \beta_2-\beta_3]$	N/A
1pba	N/A	N/A	$[\alpha_1, \alpha_3], [\beta_1-\beta_2, \beta_1-\beta_3]$	N/A

pdb	Out exchange	Pulse labeling	Our SS formation order	Comp.
1gb1	$[\alpha, \beta_1, \beta_3, \beta_4], \beta_2$	$[\alpha, \beta_4], [\beta_1, \beta_2, \beta_3]$	$\alpha, \beta_3-\beta_4, \beta_1-\beta_2, \beta_1-\beta_4$	Agreed
2crt	$[\beta_3, \beta_4, \beta_5], [\beta_1, \beta_2]$	$\beta_5, \beta_3, \beta_4, [\beta_1, \beta_2]$	$\beta_1-\beta_2, \beta_3-\beta_4, \beta_3-\beta_5$	Not sure
1bdd	$[\alpha_2, \alpha_3], \alpha_1$	$[\alpha_1, \alpha_2, \alpha_3]$	$[\alpha_2, \alpha_3], \alpha_1, \alpha_2-\alpha_3, \alpha_1-\alpha_3$	Agreed
1shg	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_5, \beta_1-\beta_2$	N/A
2ptl	$[\alpha, \beta_1, \beta_2, \beta_4], \beta_3$	$[\alpha, \beta_1], [\beta_2, \beta_3, \beta_4]$	$\alpha, \beta_1-\beta_2, \beta_3-\beta_4, \beta_1-\beta_4$	Agreed
1coa	$[\alpha, \beta_2, \beta_3], [\beta_1, \beta_4]$	N/A	$\alpha, \beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_4$	Agreed
1srl	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_5, \beta_1-\beta_2$	N/A
1nyf	N/A	N/A	$\beta_3-\beta_4, \beta_2-\beta_3, \beta_1-\beta_2, \beta_1-\beta_5$	N/A
2ait	$[\beta_1, \beta_2], [\beta_3, \beta_4, \beta_5, \beta_6, \beta_7]$	N/A	$\beta_1-\beta_2, \beta_3-\beta_4, [\beta_2-\beta_5, \beta_3-\beta_6], \beta_3-\beta_5$	Agreed
1ubq	$[\alpha, \beta_1, \beta_2], [\beta_3, \beta_5], \beta_4$	N/A	$\alpha, \beta_3-\beta_4, \beta_1-\beta_2, \beta_3-\beta_5, \beta_1-\beta_5$	Agreed
1pks	N/A	N/A	$\beta_3-\beta_4, \beta_1-\beta_5, [\beta_1-\beta_2, \beta_2-\beta_3]$	N/A
1pba	N/A	N/A	$[\alpha_1, \alpha_3], [\beta_1-\beta_2, \beta_1-\beta_3]$	N/A

- no (reported) contradictions between prediction and validation
- different kind of information from experiment and prediction



- Studied in more detail
- good test case
- structurally similar:  $1\alpha + 4\beta$



- fold differently
  - Protein G:  $\beta$ -turn 2 forms first
  - Protein L:  $\beta$ -turn 1 forms first

# Comparison of Analysis Techniques

## $\beta$ -Turn Formation

1. Motivation
2. Motion Planning
3. Protein Model
4. Roadmaps
- 5. Results**
6. Conclusion

Name	Contacts considered	Energy function	Secondary structure formation order	Analyze first $x\%$ contacts						
				20	40	60	80	100		
Protein G	All	Our	$\alpha$ , turn 2, turn 1	53	52	52	50	50		
			turn 2, $\alpha$ , turn 1	15	9	17	22	22		
			$\alpha$ , turn 1, turn 2	25	33	26	23	24		
		All-atom	$\alpha$ , turn 2, turn 1	36	37	55	55	57		
			turn 2, $\alpha$ , turn 1	3	0	0	0	0		
			$\alpha$ , turn 1, turn 2	50	63	45	45	43		
	Hydrophobic	Our	$\alpha$ , turn 2, turn 1	96	96	85	96	87		
			$\alpha$ , turn 1, turn 2	4	4	12	2	11		
			All-atom	$\alpha$ , turn 2, turn 1	76	78	78	92	69	
			$\alpha$ , turn 1, turn 2	24	22	22	8	31		
		Protein L	All	Our	$\alpha$ , turn 1, turn 2	24	30	37	38	41
					turn 1, $\alpha$ , turn 2	3	4	4	4	6
$\alpha$ , turn 2, turn 1	73				63	60	48	39		
All-atom	$\alpha$ , turn 1, turn 2			25	25	48	43	41		
	$\alpha$ , turn 2, turn 1			75	75	52	57	59		
	Hydrophobic			Our	$\alpha$ , turn 1, turn 2	72	68	72	70	69
turn 1, $\alpha$ , turn 2			5		9	5	7	15		
$\alpha$ , turn 2, turn 1			23		22	22	23	15		
All-atom	$\alpha$ , turn 1, turn 2		66	76	78	95	97			
	turn 1, $\alpha$ , turn 2		3	0	0	0	0			
	$\alpha$ , turn 2, turn 1		31	24	22	5	3			

# Conclusion

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- PRM can be applied to “realistic” protein models

# Conclusion

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- Predictions are in good accordance to experimental data
- Interesting relations to e.g. computation of barrier trees