STRUCTURAL BIOINFORMATICS

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University of Michigan

http://tinyurl.com/bioinfl7

HILLIAN HARRING

MODULE OVERVIEW

Objective: Provide an introduction to the practice of bioinformatics as well as a practical guide to using common bioinformatics databases and algorithms

- 1.1. Introduction to Bioinformatics
- 1.2. Sequence Alignment and Database Searching
- 1.3 > Structural Bioinformatics
- 1.4 Genome Informatics: High Throughput Sequencing Applications and Analytical Methods

WEEKTWO REVIEW

Answers to last weeks homework:

Answers week 2

- Muddy Point Assessment (Only 25 responses):

 Responses
 - "More time to finish the assignment"
 - "The [NCBI] sites were so slow"
 - "More time with HMMER would be helpful"
 - "Very nice lab"

Q18: NW DYNAMIC PROGRAMMING

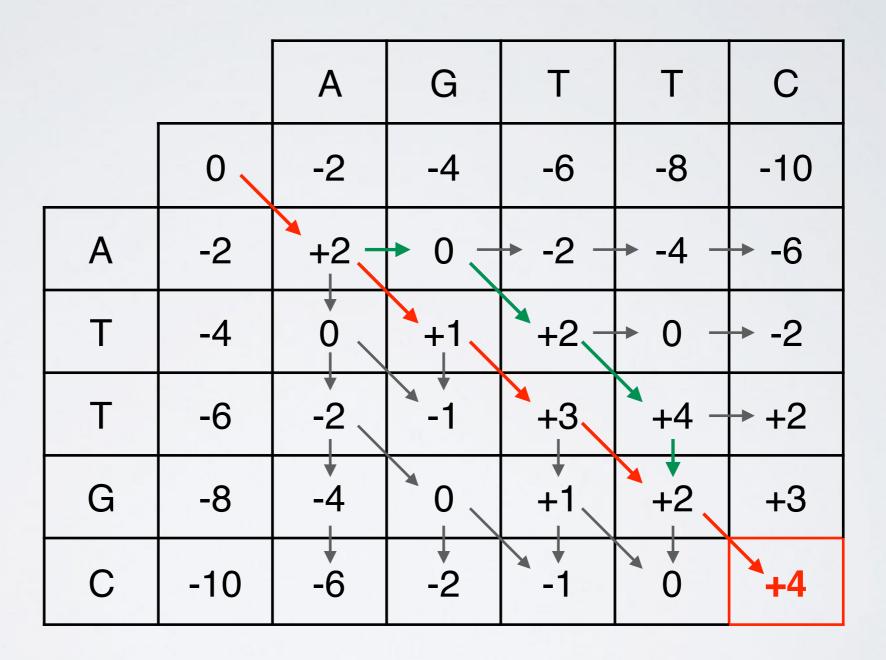
Match: +2

Mismatch: - I

Gap: -2

ATTGC IIII AGTTC

A - TTGC
IIII
AGTT-C



THIS WEEK'S HOMEWORK

- Check out the "Background Reading" material online:
 - Achievements & Challenges in Structural Bioinformatics
 - Protein Structure Prediction
 - ▶ Biomolecular Simulation
 - Computational Drug Discovery
- Complete the lecture 1.3 homework questions: http://tinyurl.com/bioinf525-quiz3

"Bioinformatics is the application of <u>computers</u> to the collection, archiving, organization, and analysis of <u>biological data</u>."

... A hybrid of biology and computer science

"Bioinformatics is the application of <u>computers</u> to the collection, archiving, organization, and analysis of <u>biological data</u>."

Bioinformatics is computer aided biology!

"Bioinformatics is the application of <u>computers</u> to the collection, archiving, organization, and analysis of <u>biological data</u>."

Bioinformatics is computer aided biology!

Goal: Data to Knowledge

		 L <mark> </mark>			<u> </u>
SO Wha					
So wha	l IO		NIVI		

So what is structural bioinformatics?

... computer aided structural biology!

Aims to characterize and interpret biomolecules and their assembles at the molecular & atomic level

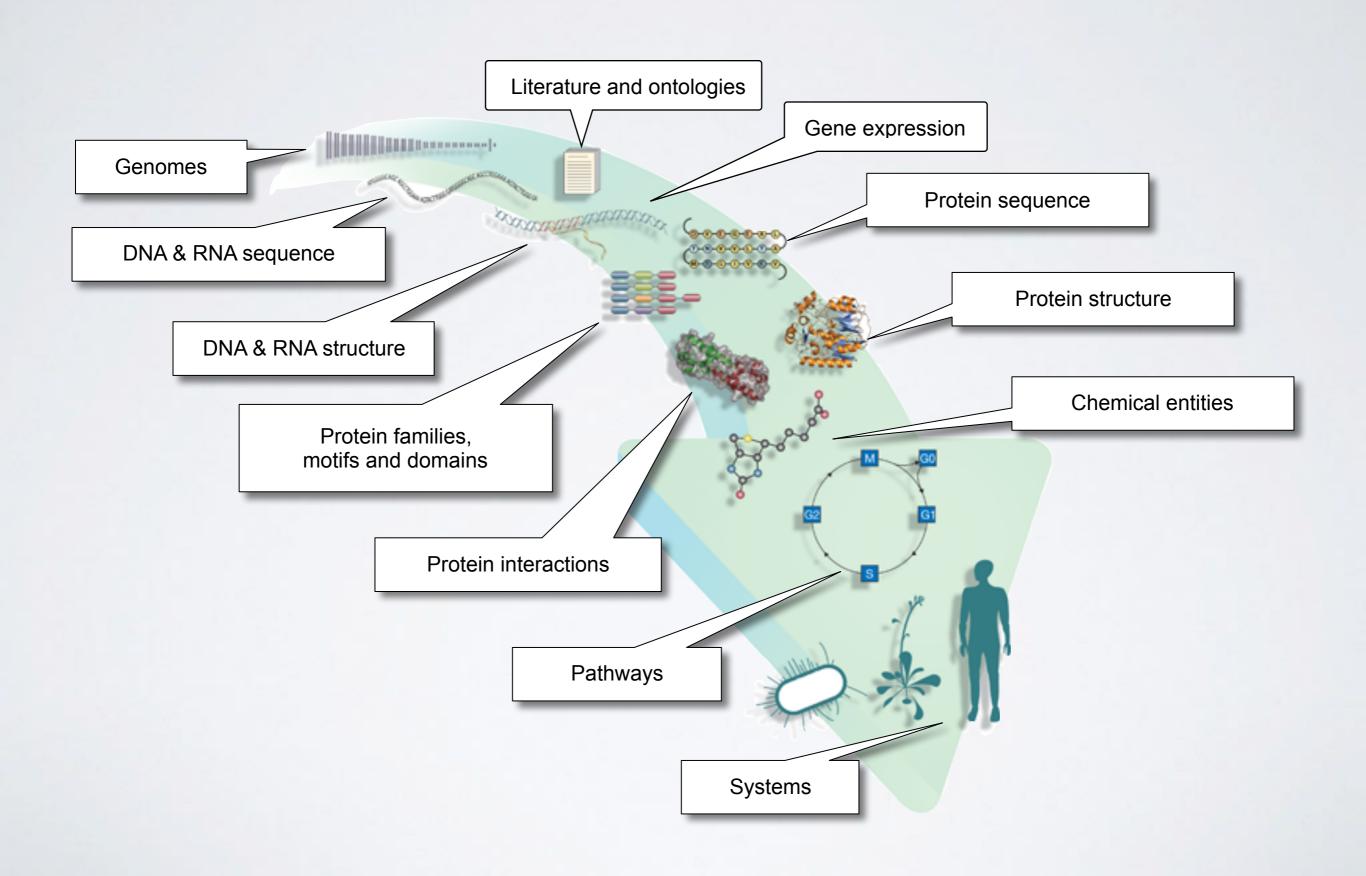
Why should we care?

Why should we care?

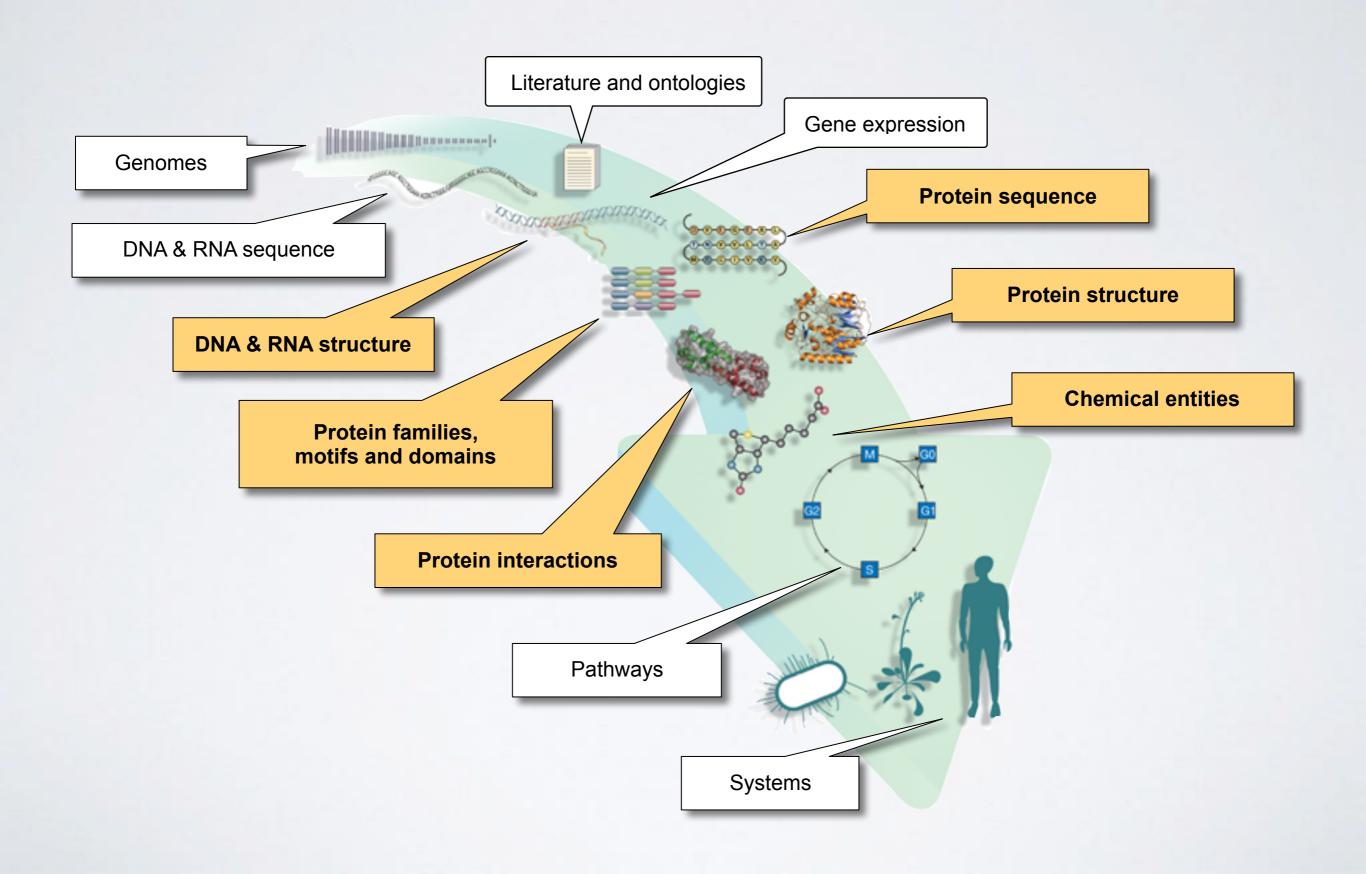
Because biomolecules are "nature's robots"

... and because it is only by coiling into specific 3D structures that they are able to perform their functions

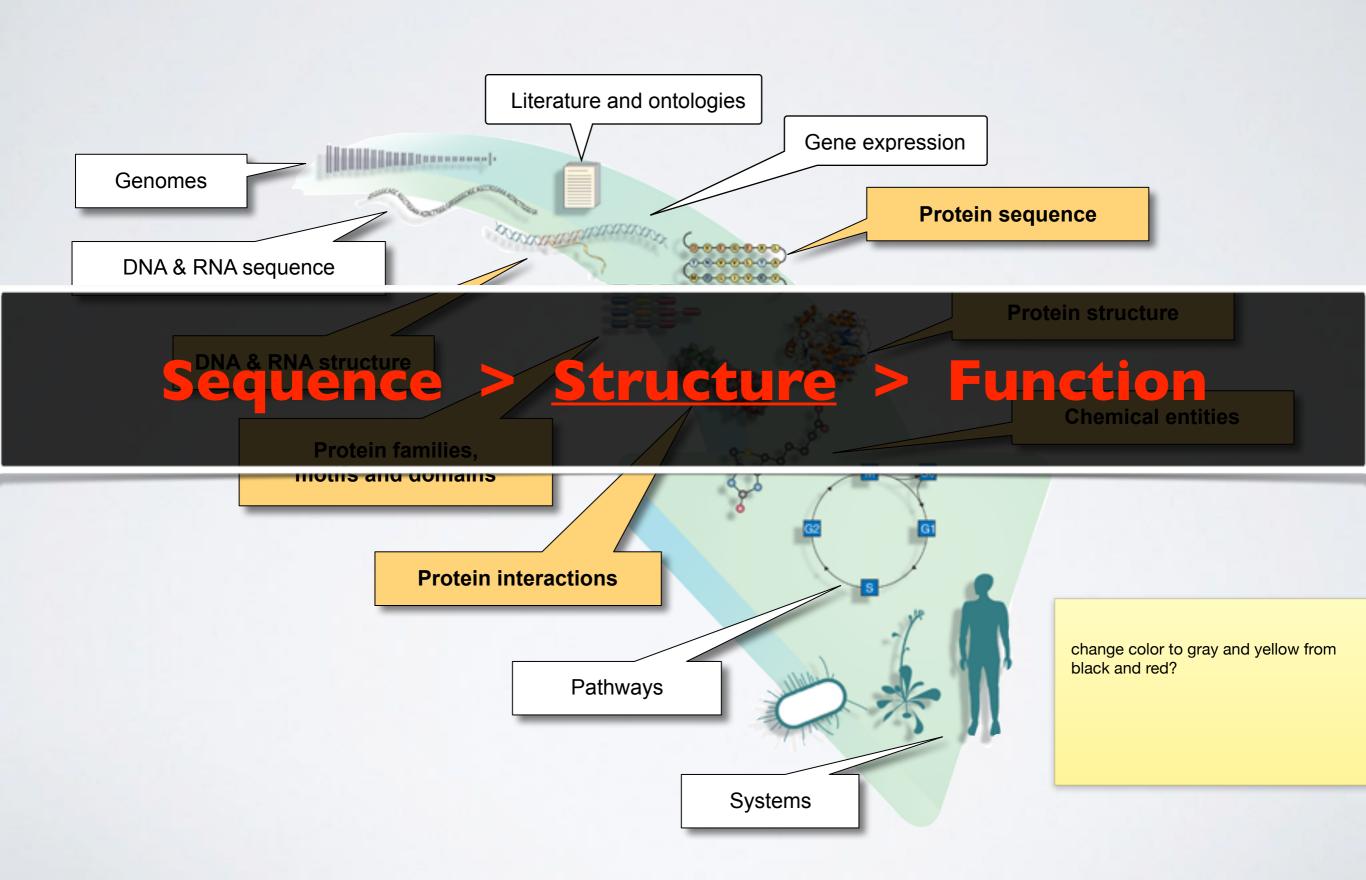
BIOINFORMATICS DATA



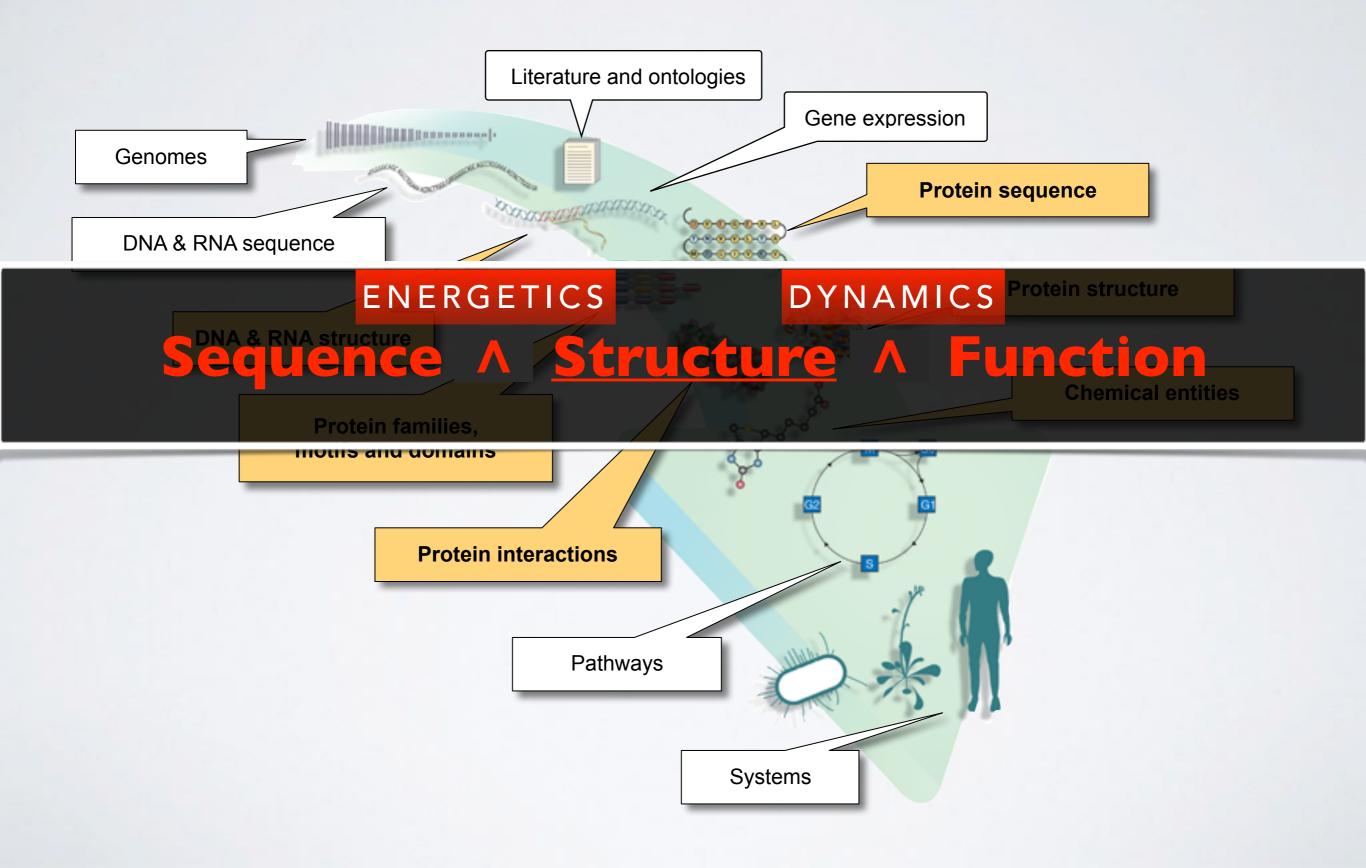
STRUCTURAL DATA IS CENTRAL

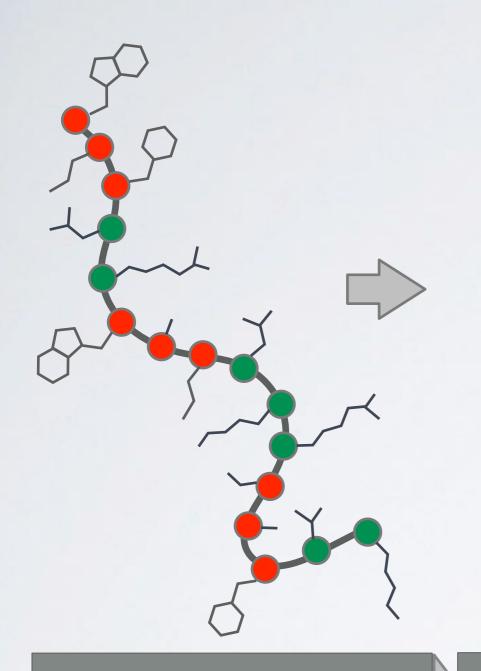


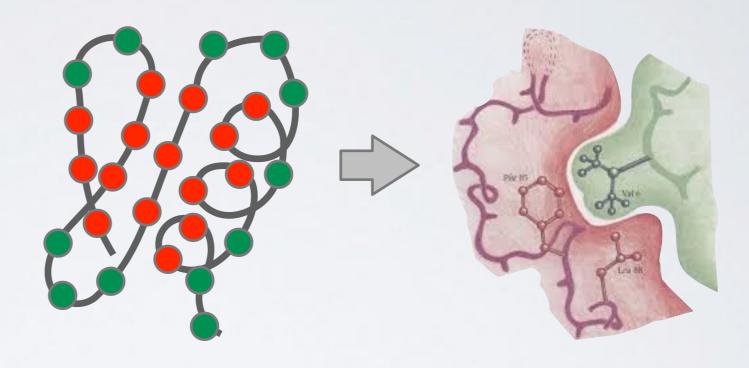
STRUCTURAL DATA IS CENTRAL



STRUCTURAL DATA IS CENTRAL







Sequence

- Unfolded chain of amino acid chain
- Highly mobile
- Inactive

Structure

- Ordered in a precise 3D arrangment
- Stable but dynamic

Function

- Active in specific "conformations"
- Specific associations
 & precise reactions

In daily life, we use machines with functional *structure* and *moving parts*





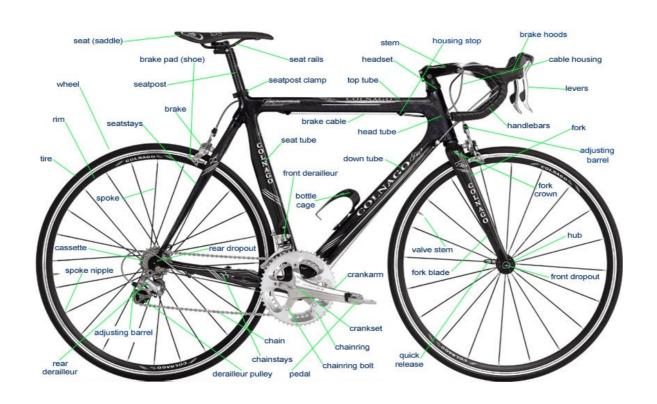
Genomics is a great start

Track Bike - DL 175

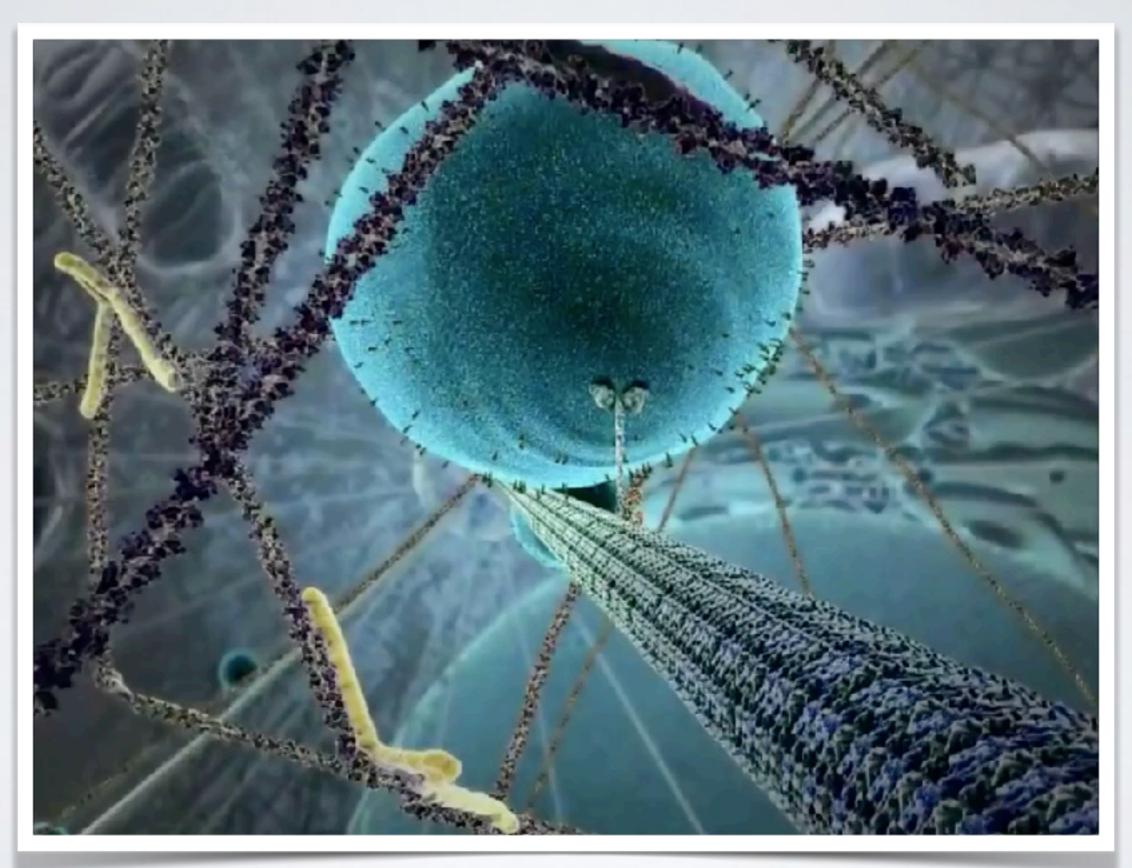
REF. NO.	IBM NO.	DESCRIPTION				
1	156011	Track Frame 21", 22", 23", 24", Team Red				
2	157040	Fork for 21" Frame				
2 2 2	157039	Fork for 22" Frame				
2	157038	Fork for 23" Frame				
2 3 4	157037	Fork for 24" Frame				
3	191202	Handlebar TTT Competition Track Alloy 15/16"				
		Handlebar Stem, TTT, Specify extension				
5	191278	Expander Bolt				
6	191272	Clamp Bolt				
7	145841	Headset Complete 1 x 24 BSC				
8	145842	Ball Bearings				
9	190420	175 Raleigh Pistard Seta Tubular Prestavalve 27"				
10	190233	Rim, 27" AVA Competition (36H) Alloy Prestavalve				
11	145973	Hub, Large Flange Campagnolo Pista Track Alloy (pairs)				
12	190014	Spokes, 11 5/8"				
13	145837	Sleeve				
14	145636	Ball Bearings				
15	145170	Bottom Bracket Axle				
16	145838	Cone for Sleeve				
17	146473	L.H. Adjustable Cup				
18	145833	Lockring				
19	145239	Straps for Toe Clips				
20	145834	Fixing Bolt				
21	145835	Fixing Washer				
22	145822	Dustcap				
23	145823	R.H. and L.H. Crankset with Chainwheel				
24	146472	Fixed Cup				
25	145235	Toe Clips, Christophe, Chrome (Medium)				
26	145684	Pedals, Extra Light, Pairs				
27	123021	Chain				
28	145980	Seat Post				
29	E Walter	Seat Post Bolt and Nut				
30	167002	Saddle, Brooks				
31	145933	145933 Track Sprocket, Specify 12, 13, 14, 15, or 16 T.				

But a parts list is not enough to understand how a bicycle works

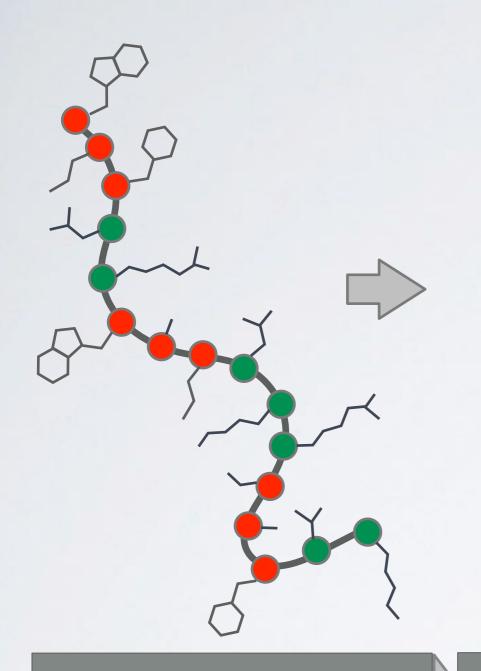
... but not the end

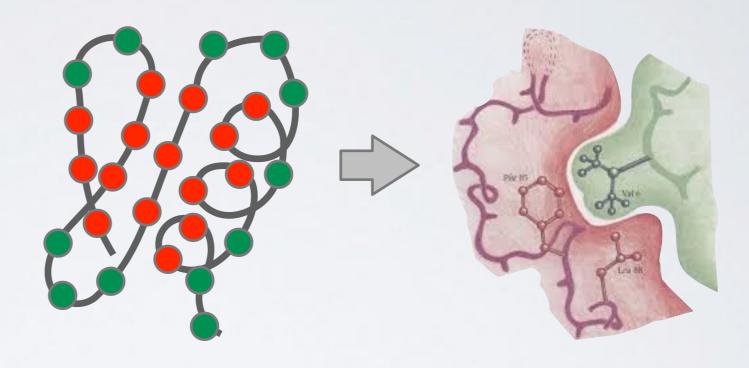


- We want the full spatiotemporal picture, and an ability to control it
- Broad applications, including drug design, medical diagnostics, chemical manufacturing, and energy



Extracted from The Inner Life of a Cell by Cellular Visions and Harvard [YouTube link: https://www.youtube.com/watch?v=y-uuk4Pr2i8]





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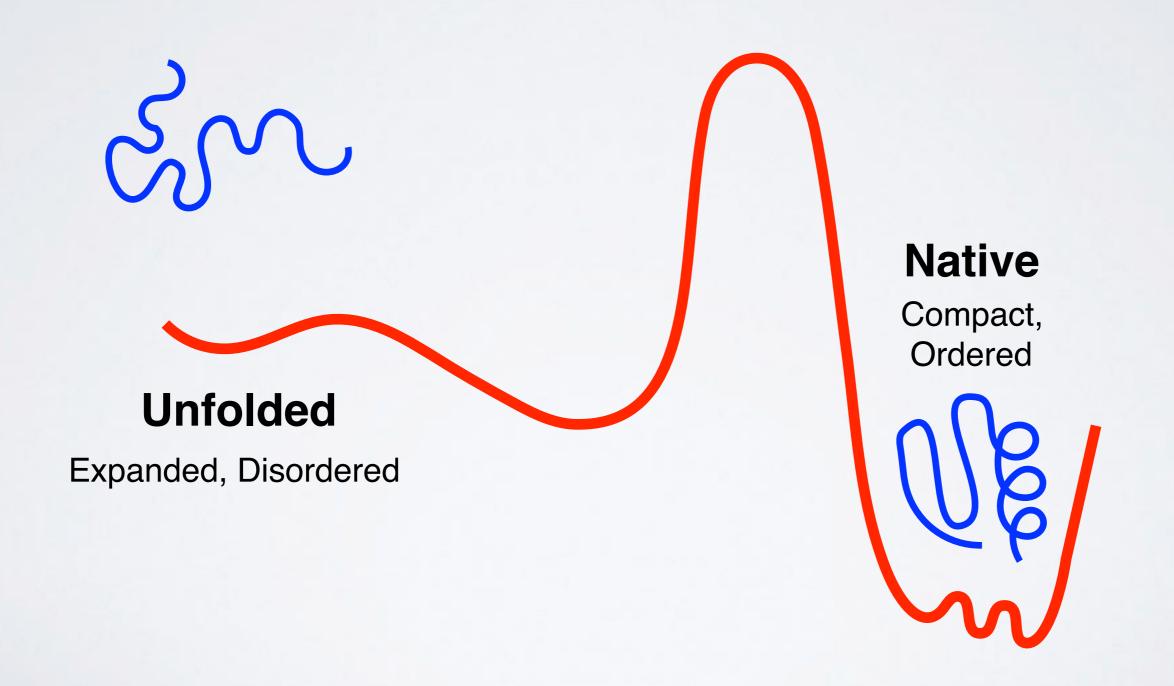
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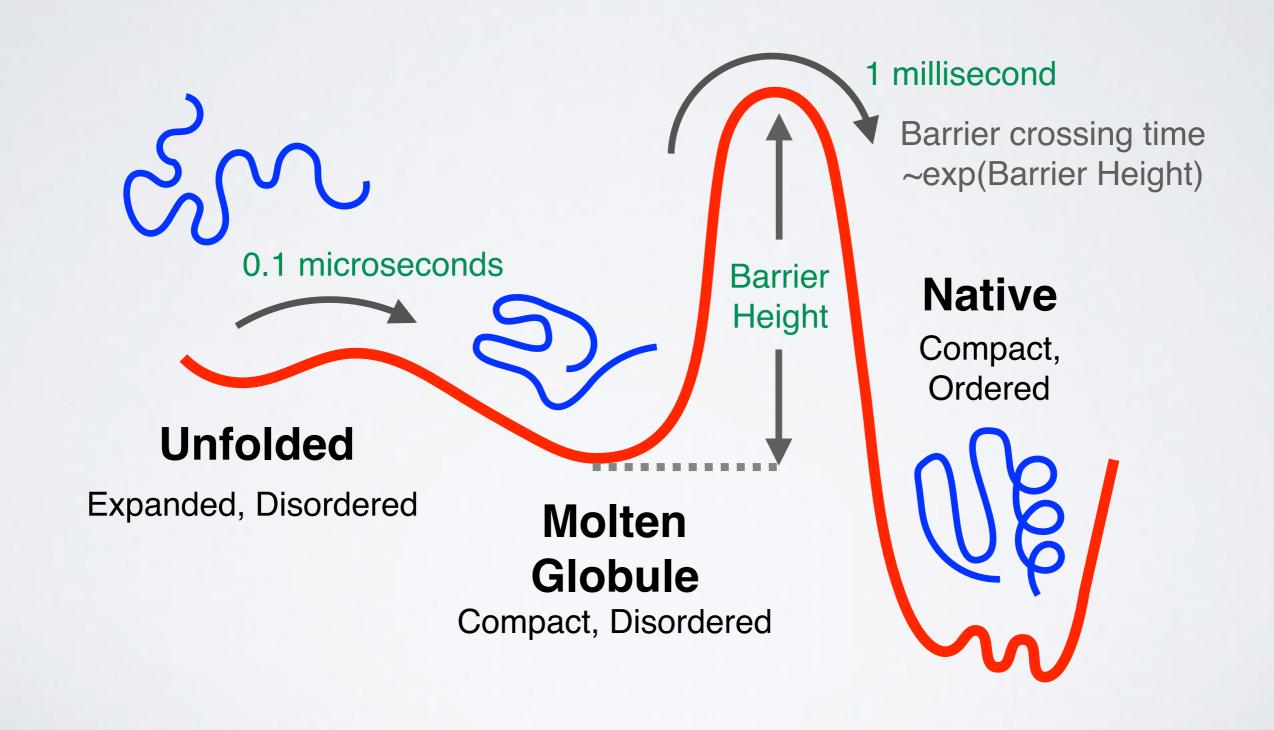
Function

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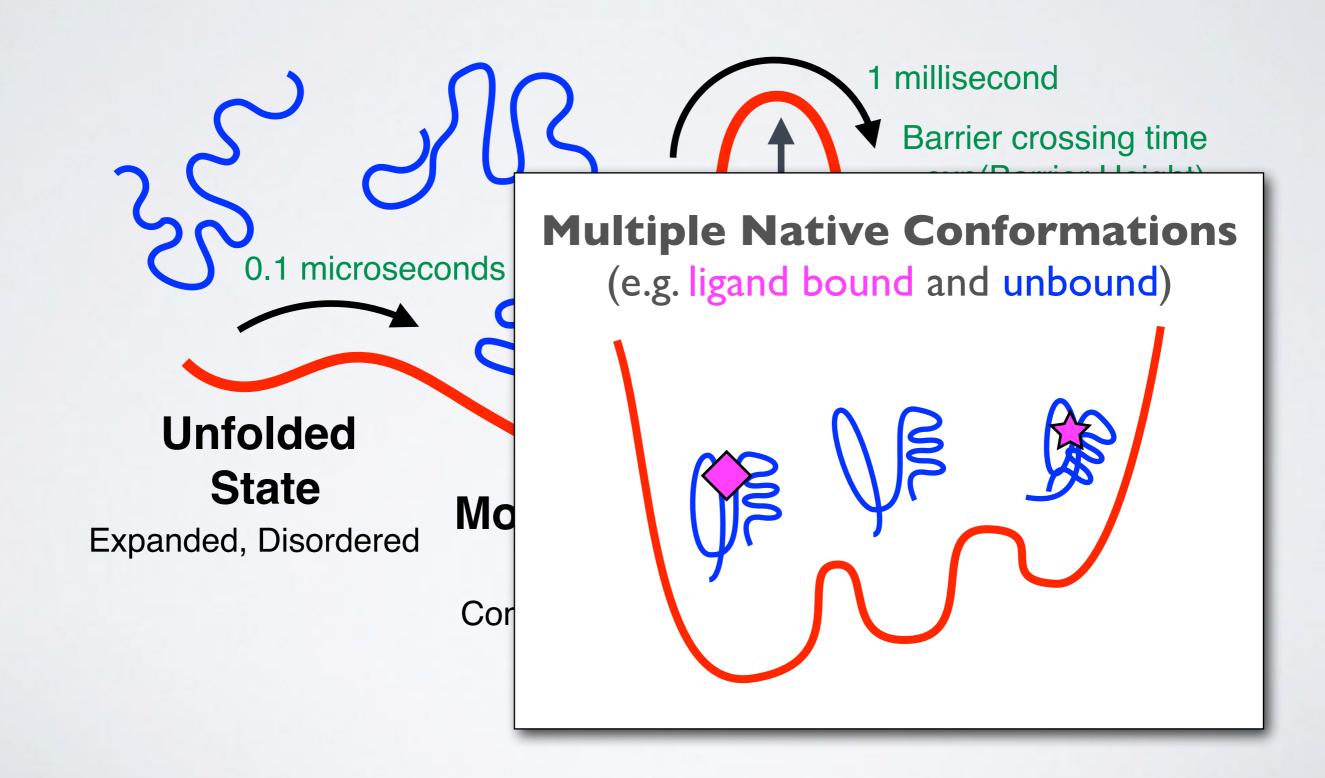
KEY CONCEPT: ENERGY LANDSCAPE



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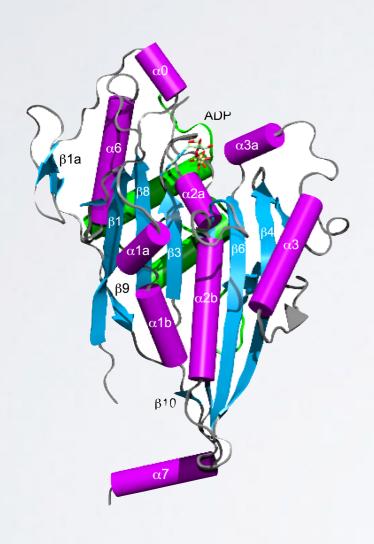
OUTLINE:

- Overview of structural bioinformatics
 - Major motivations, goals and challenges
- Fundamentals of protein structure
 - Composition, form, forces and dynamics
- Representing and interpreting protein structure
 - Modeling energy as a function of structure
- Example application areas
 - Predicting functional dynamics & drug discovery

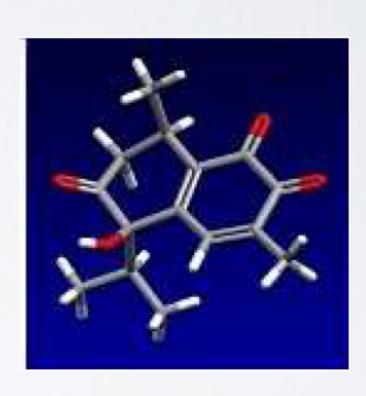
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TRADITIONAL FOCUS PROTEIN, DNA AND SMALL MOLECULE DATA SETS WITH MOLECULAR STRUCTURE







Protein (PDB)

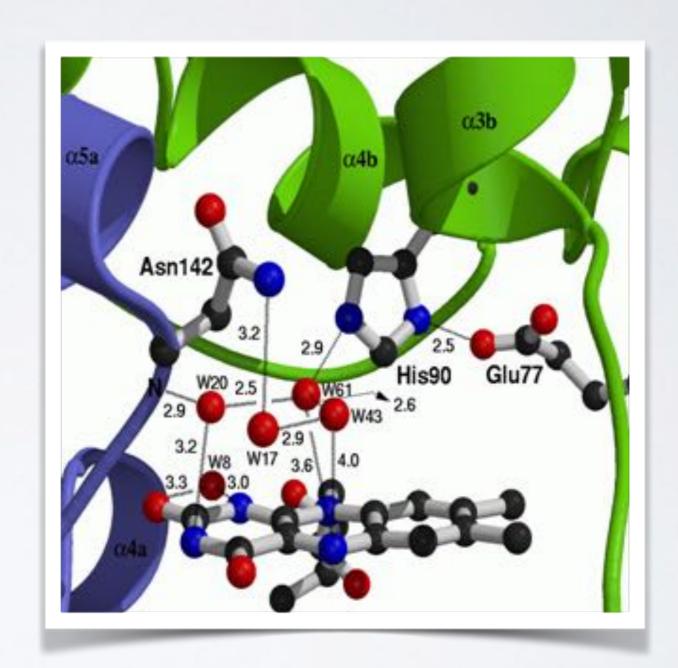
DNA (NDB)

Small Molecules (CCDB)

Motivation 1:

Detailed understanding of molecular interactions

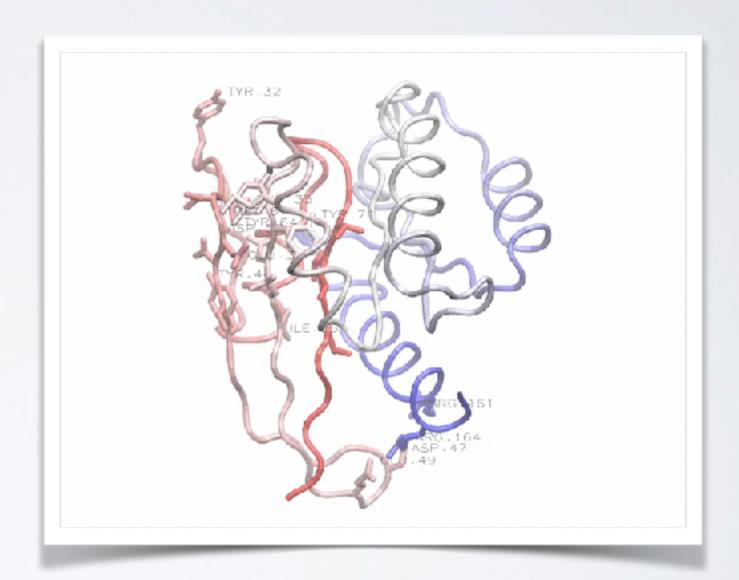
Provides an invaluable structural context for conservation and mechanistic analysis leading to functional insight.



Motivation 1:

Detailed understanding of molecular interactions

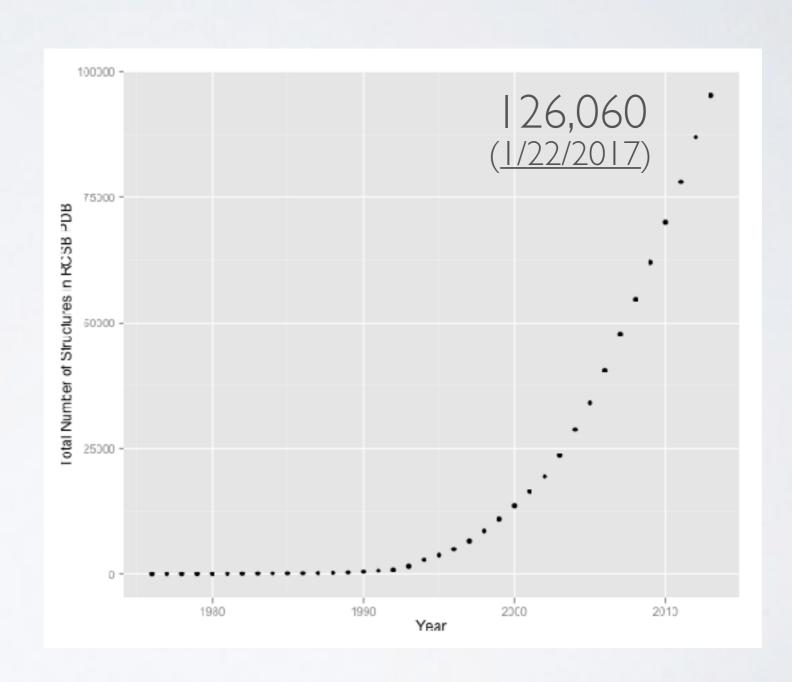
Computational modeling can provide detailed insight into functional interactions, their regulation and potential consequences of perturbation.



Motivation 2:

Lots of structural data is becoming available

Structural Genomics has contributed to driving down the cost and time required for structural determination

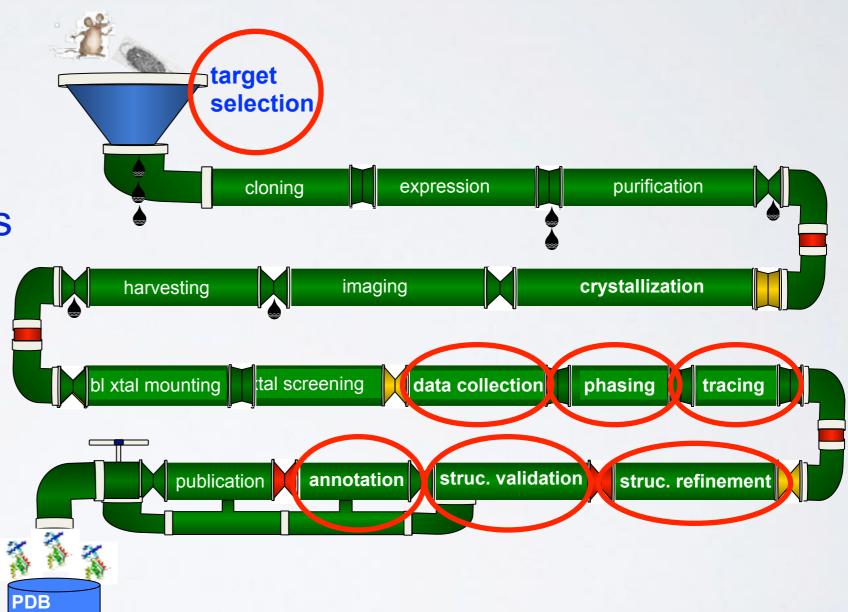


Data from: http://www.rcsb.org/pdb/statistics/

Motivation 2:

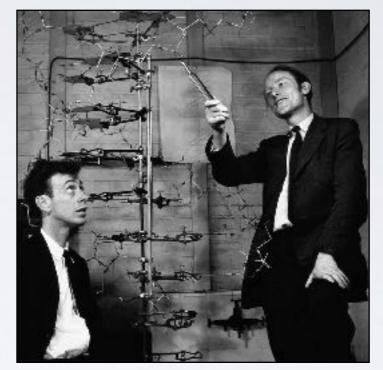
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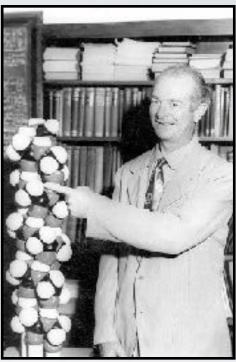
Structural Genomics has contributed to driving down the cost and time required for structural determination



Motivation 3:

Theoretical and computational predictions have been, and continue to be, enormously valuable and influential!







SUMMARY OF KEY MOTIVATIONS

Sequence > Structure > Function

 Structure determines function, so understanding structure helps our understanding of function

Structure is more conserved than sequence

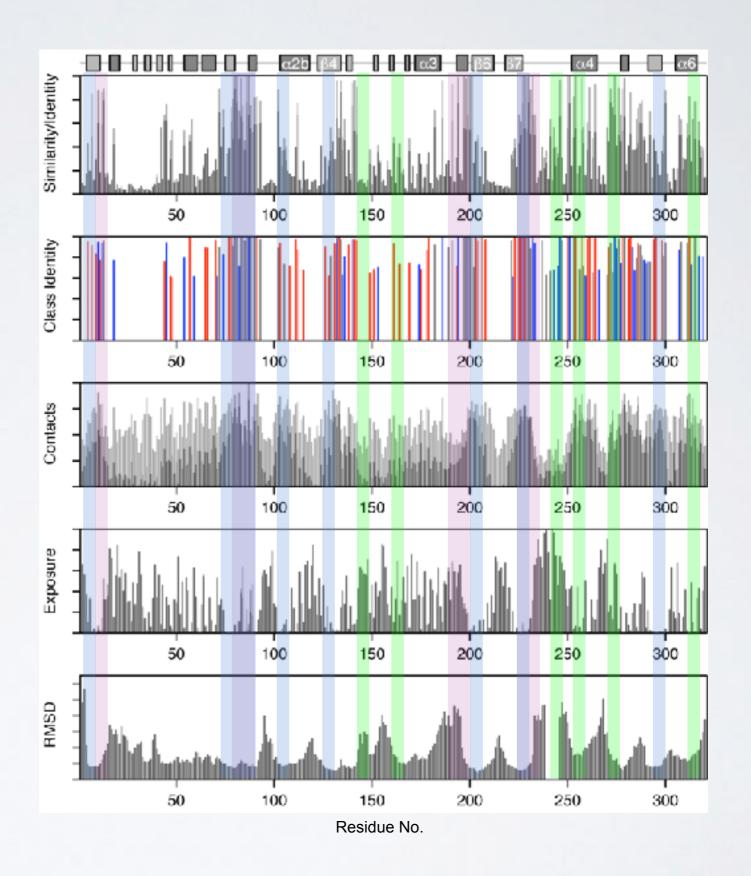
Structure allows identification of more distant evolutionary relationships

Structure is encoded in sequence

 Understanding the determinants of structure allows design and manipulation of proteins for industrial and medical advantage

Goals:

- Analysis
- Visualization
- Comparison
- Prediction
- Design

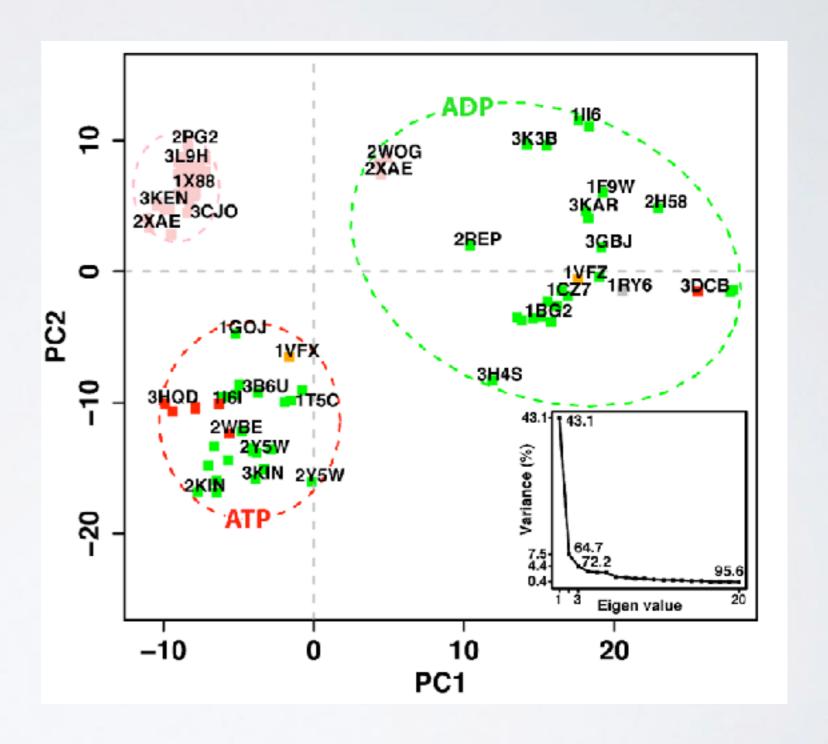


Goals:

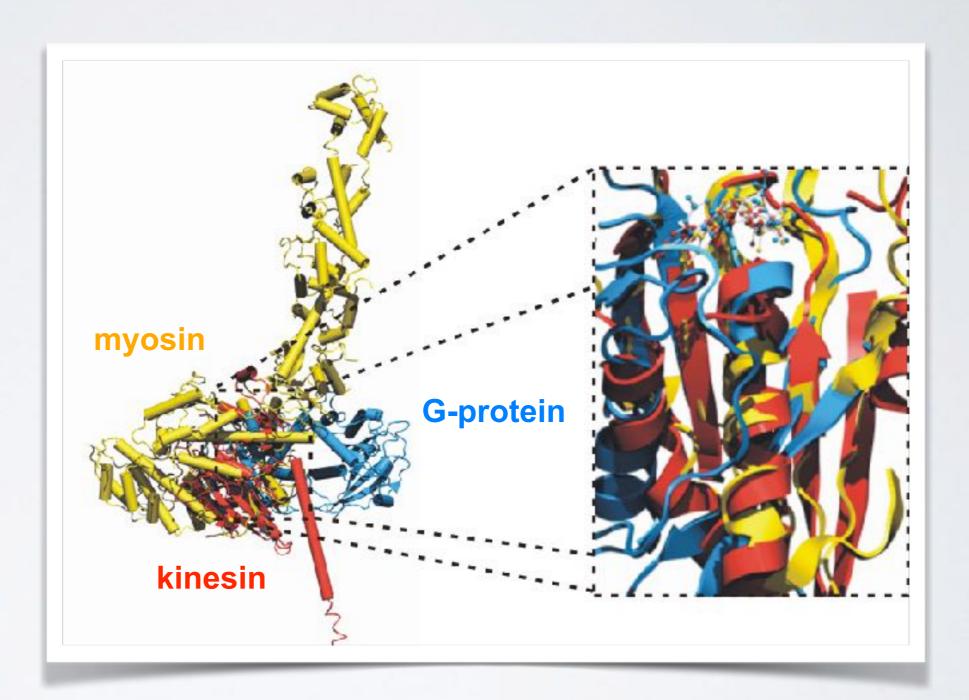
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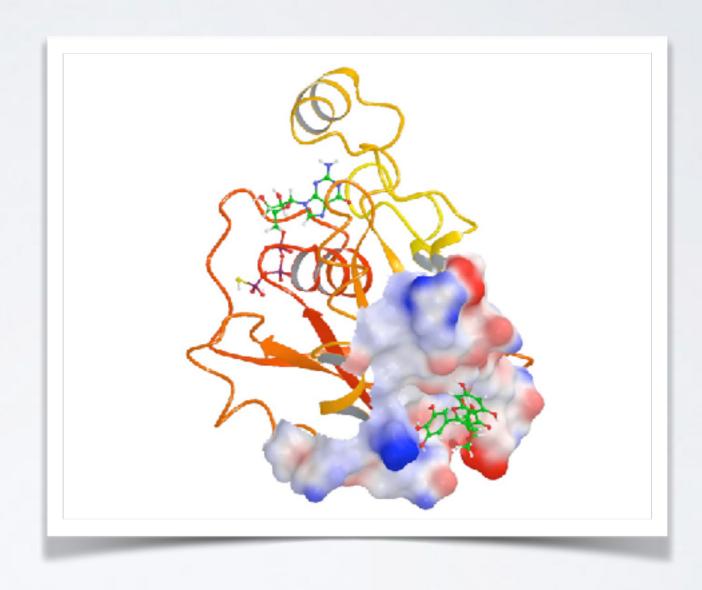
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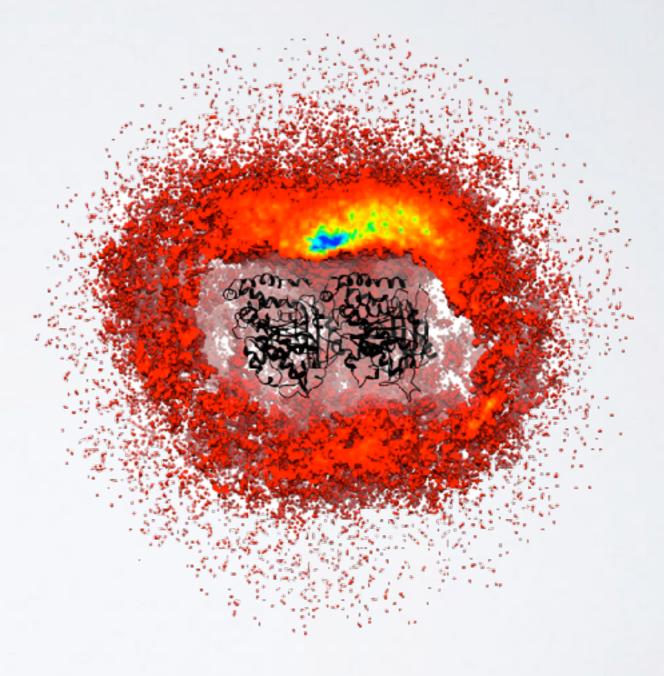


- Analysis
- Visualization
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Grant et al. PLoS One (2011, 2012)

- Analysis
- Visualization
- Comparison
- Prediction
- Design



Grant et al. PLoS Biology (2011)

MAJOR RESEARCH AREAS AND CHALLENGES

Include but are not limited to:

- Protein classification
- Structure prediction from sequence
- Binding site detection
- Binding prediction and drug design
- Modeling molecular motions
- Predicting physical properties (stability, binding affinities)
- Design of structure and function
- etc...

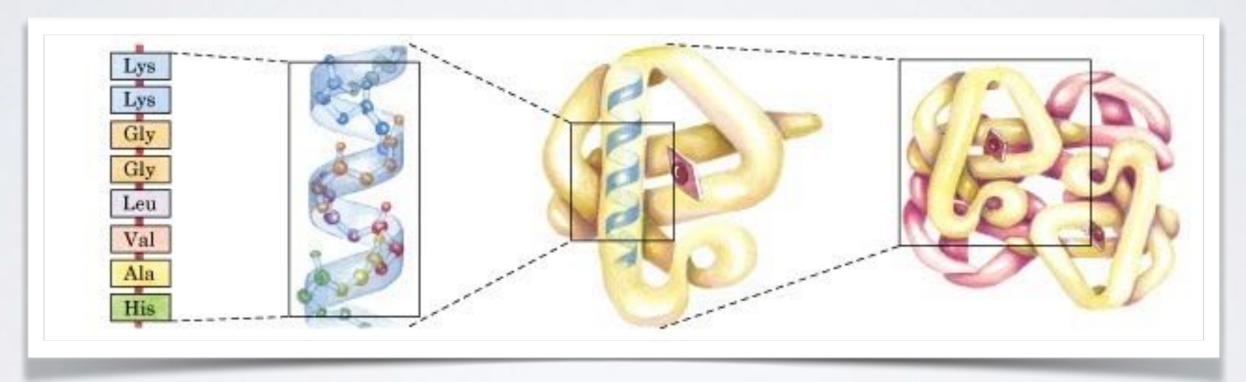
With applications to Biology, Medicine, Agriculture and Industry

NEXT UP:

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HIERARCHICAL STRUCTURE OF PROTEINS

Primary > Secondary > Tertiary > Quaternary

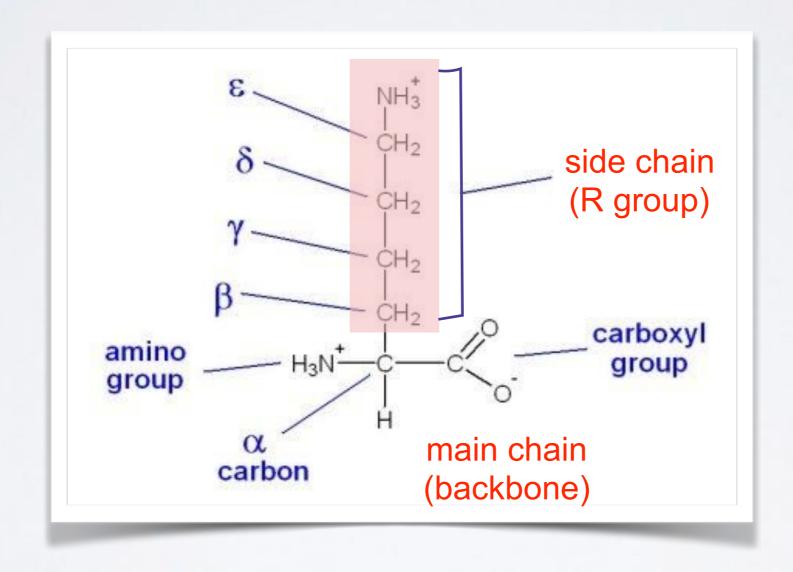


amino acid residues

Alpha helix Polypeptide chain

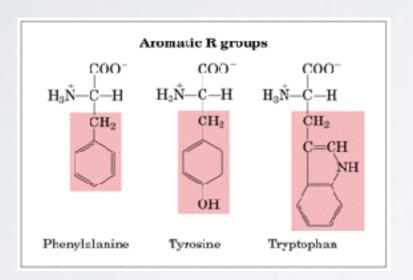
Assembled subunits

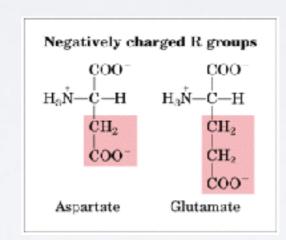
RECAP: AMINO ACID NOMENCLATURE

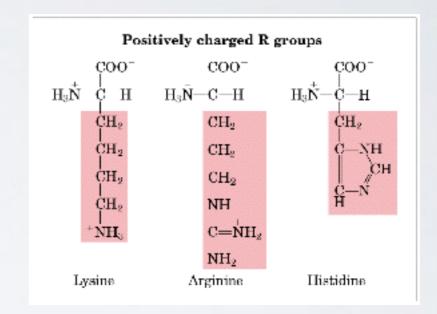


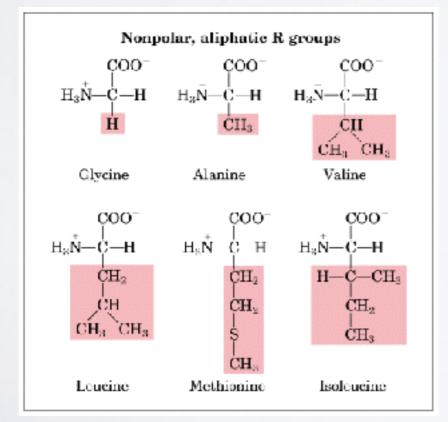
AMINO ACIDS CAN BE GROUPED BY THE

PHYSIOCHEMICAL PROPERTIES









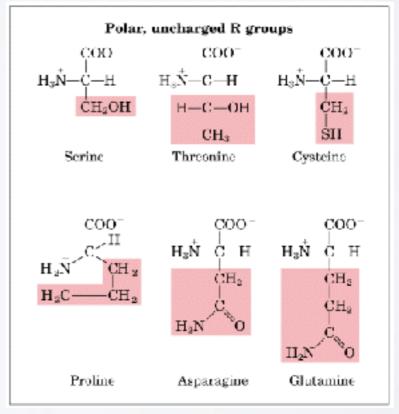
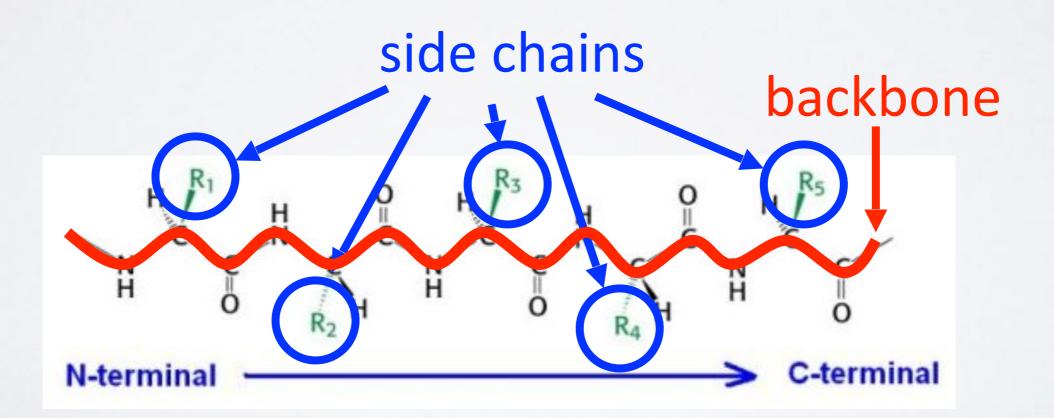
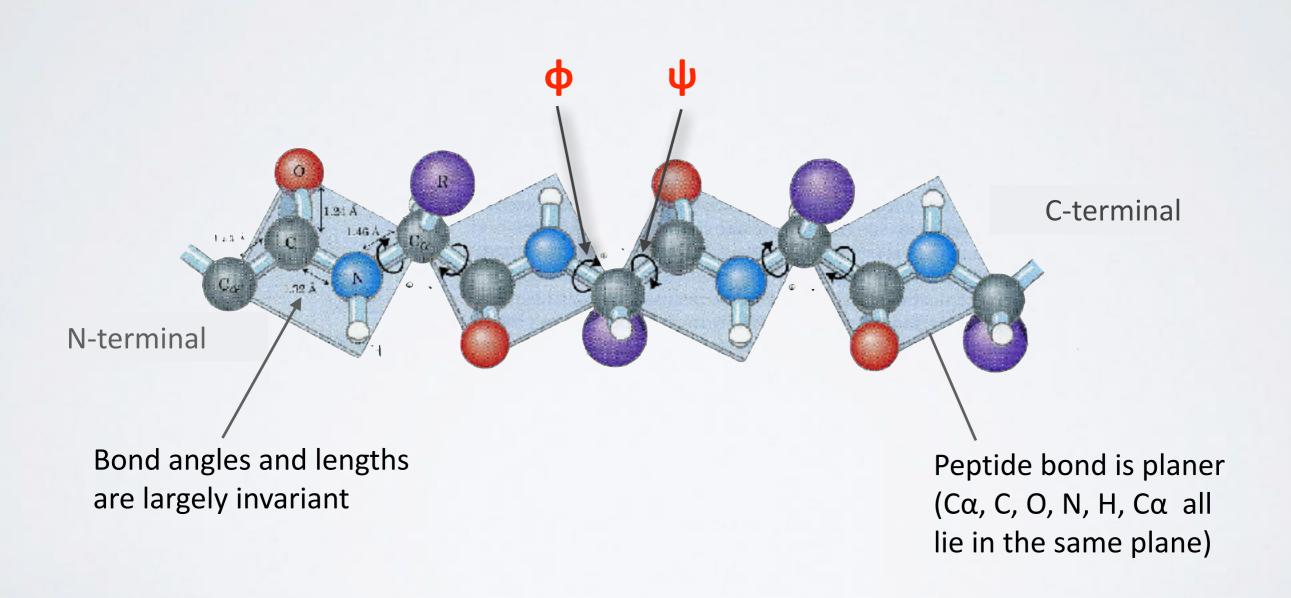


Image from: http://www.ncbi.nlm.nih.gov/books/NBK21581/

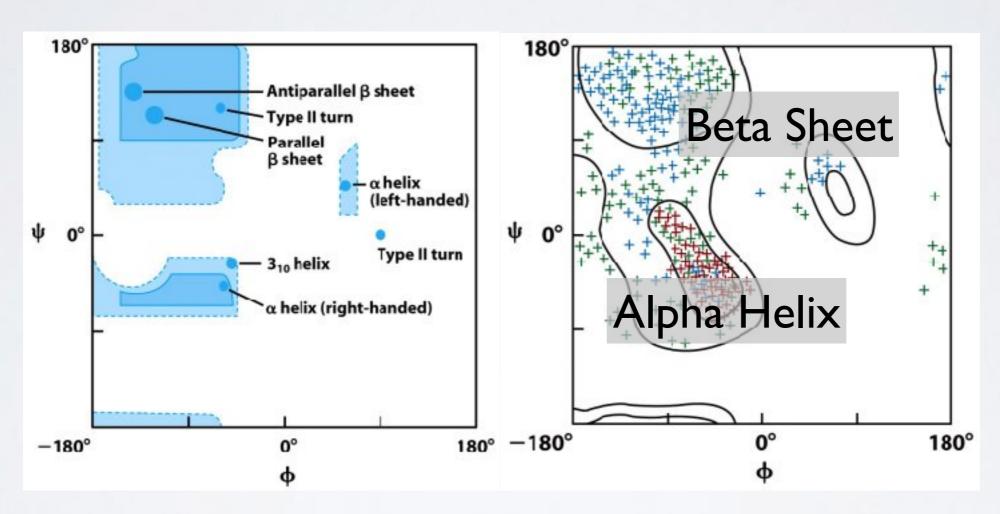
AMINO ACIDS POLYMERIZE THROUGH PEPTIDE BOND FORMATION



PEPTIDES CAN ADOPT DIFFERENT CONFORMATIONS BY VARYING THEIR PHI & PSI BACKBONE TORSIONS

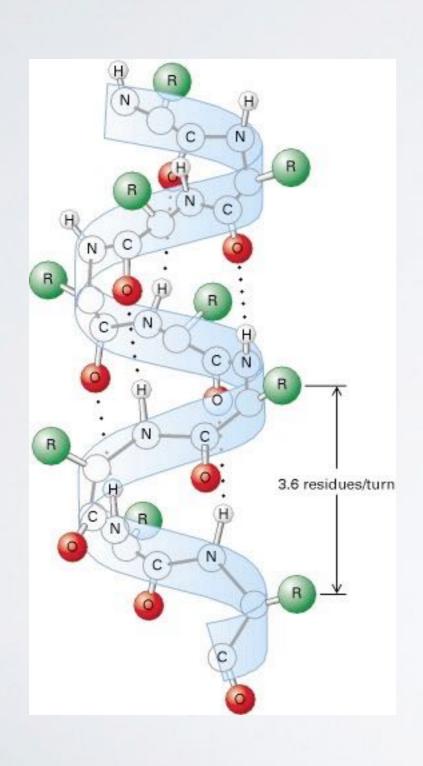


PHI vs PSI PLOTS ARE KNOWN AS RAMACHANDRAN DIAGRAMS



- Steric hindrance dictates torsion angle preference
- Ramachandran plot show preferred regions of ϕ and ψ dihedral angles which correspond to major forms of **secondary structure**

MAJOR SECONDARY STRUCTURE TYPES ALPHA HELIX & BETA SHEET

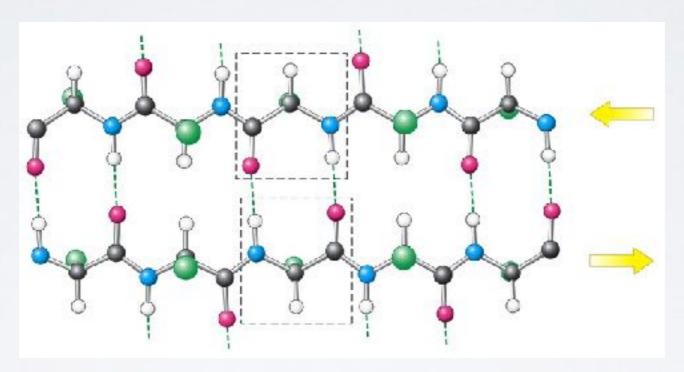


α-helix

- Most common from has <u>3.6 residues per turn</u> (number of residues in one full rotation)
- Hydrogen bonds (dashed lines) between residue <u>i and i+4</u> stabilize the structure
- The side chains (in green) protrude outward
- 3_{10} -helix and π -helix forms are less common

Hydrogen bond: i→i+4

MAJOR SECONDARY STRUCTURETYPES ALPHA HELIX & BETA SHEET

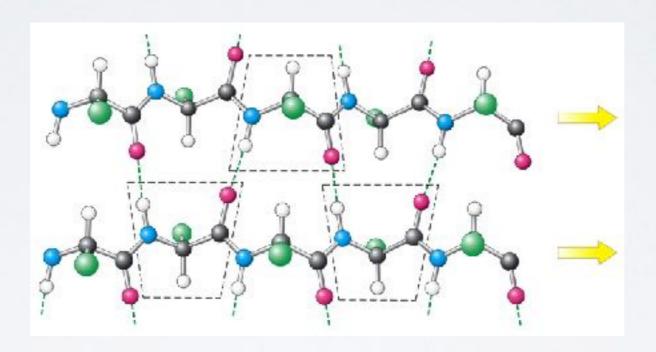


In antiparallel β -sheets

- Adjacent β-strands run in opposite directions
- Hydrogen bonds (dashed lines) between NH and CO stabilize the structure
- The side chains (in green) are above and below the sheet

Image from: http://www.ncbi.nlm.nih.gov/books/NBK21581/

MAJOR SECONDARY STRUCTURETYPES ALPHA HELIX & BETA SHEET

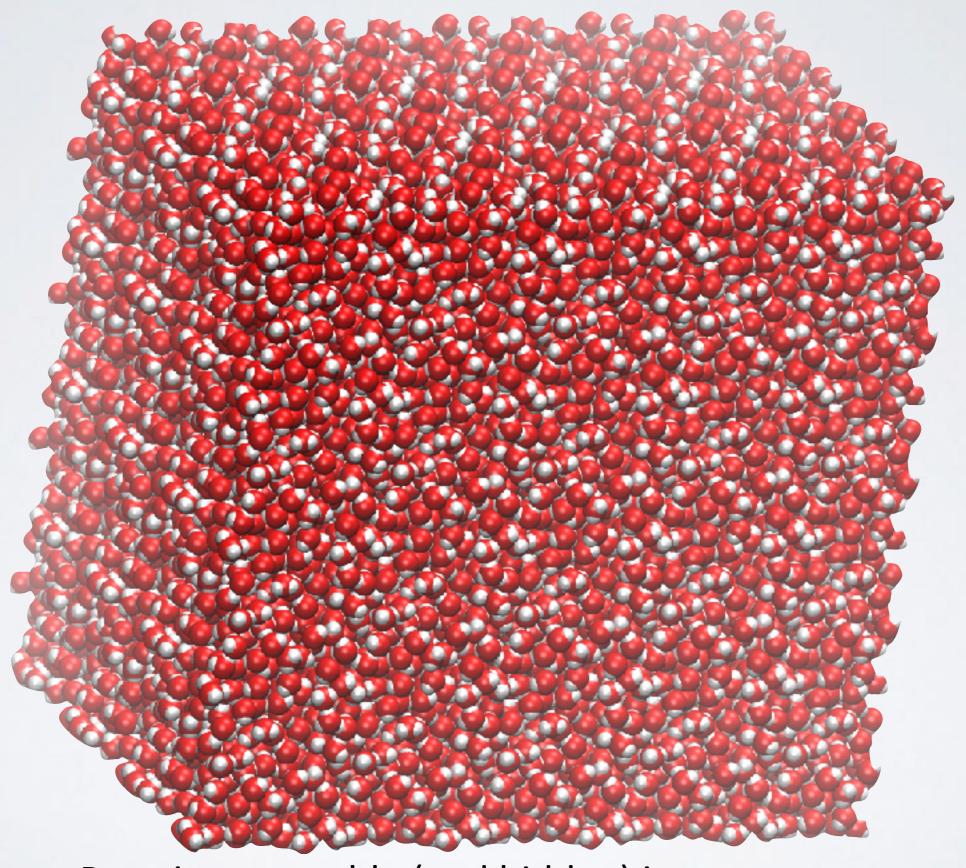


In parallel β -sheets

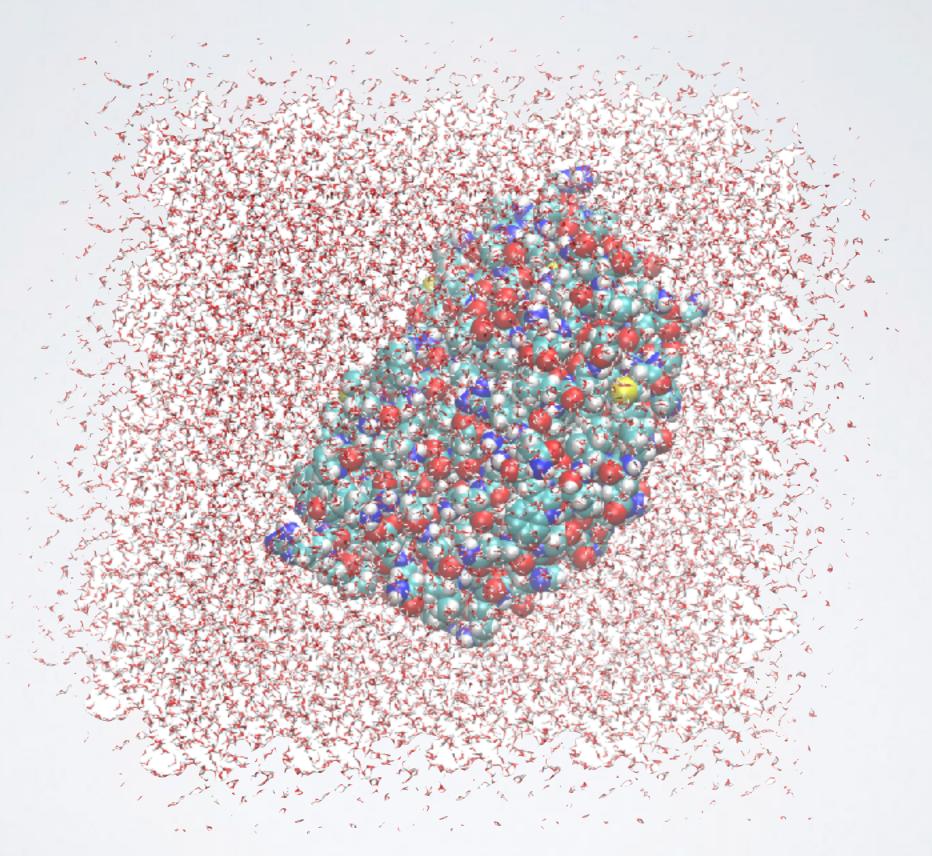
- Adjacent β-strands run in <u>same</u> direction
- Hydrogen bonds (dashed lines) between NH and CO stabilize the structure
- The side chains (in green) are above and below the sheet

Image from: http://www.ncbi.nlm.nih.gov/books/NBK21581/

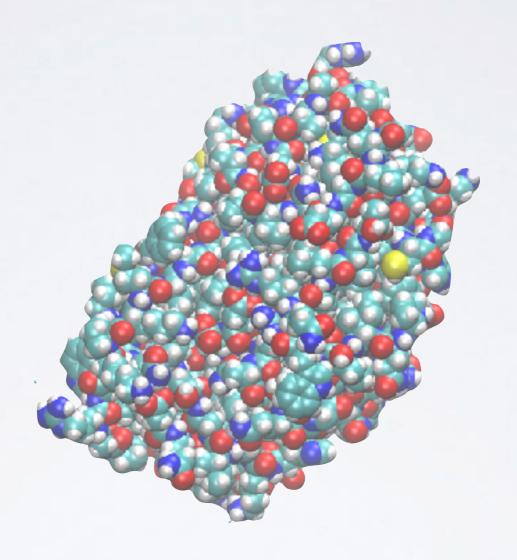
What Does a Protein Look like?



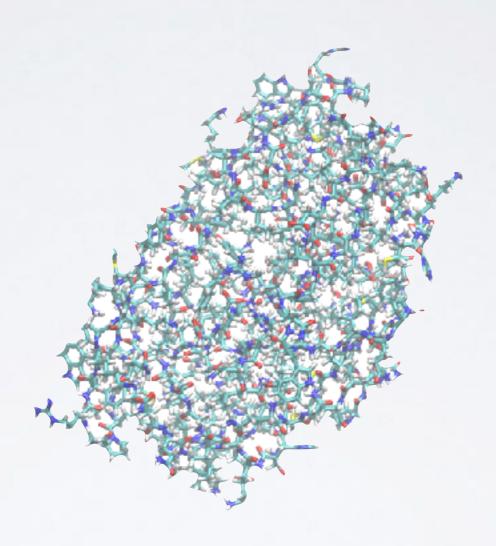
• Proteins are stable (and hidden) in water



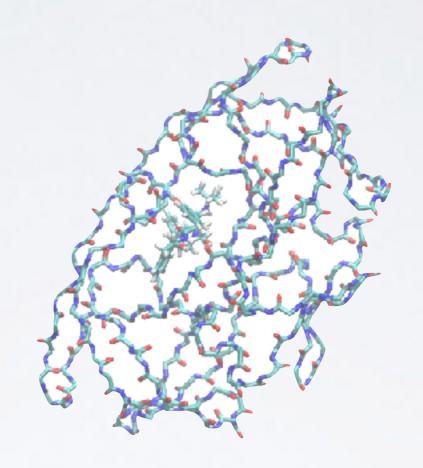
Proteins closely interact with water



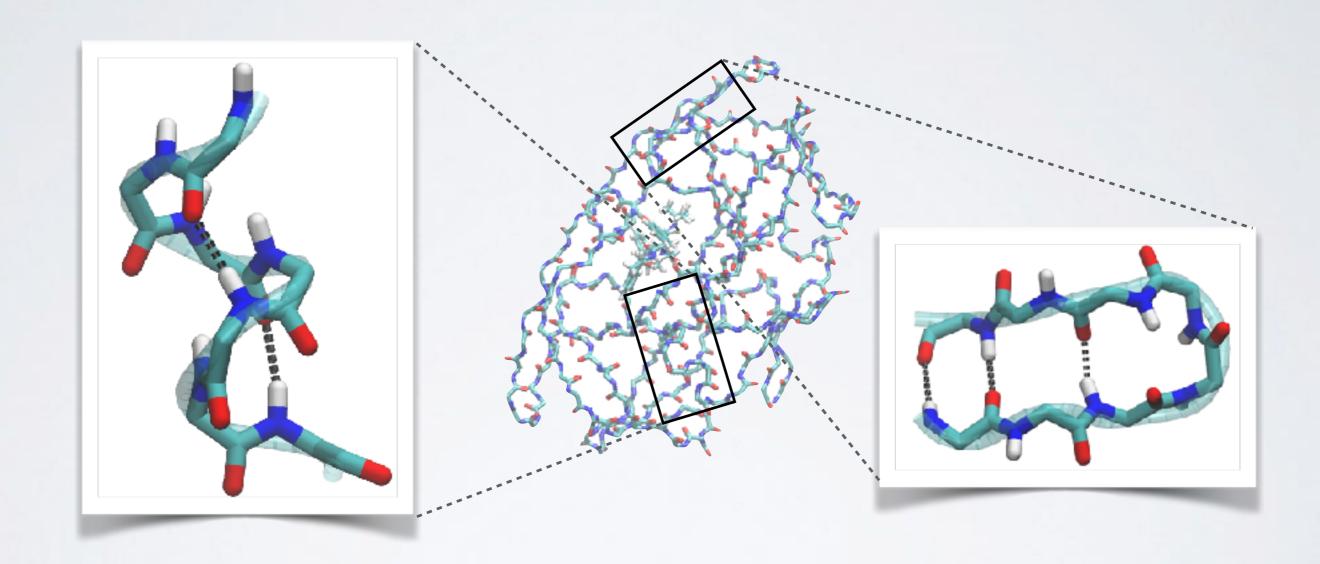
Proteins are close packed solid but flexible objects (globular)



• Due to their large size and complexity it is often hard to see whats important in the structure



 Backbone or main-chain representation can help trace chain topology

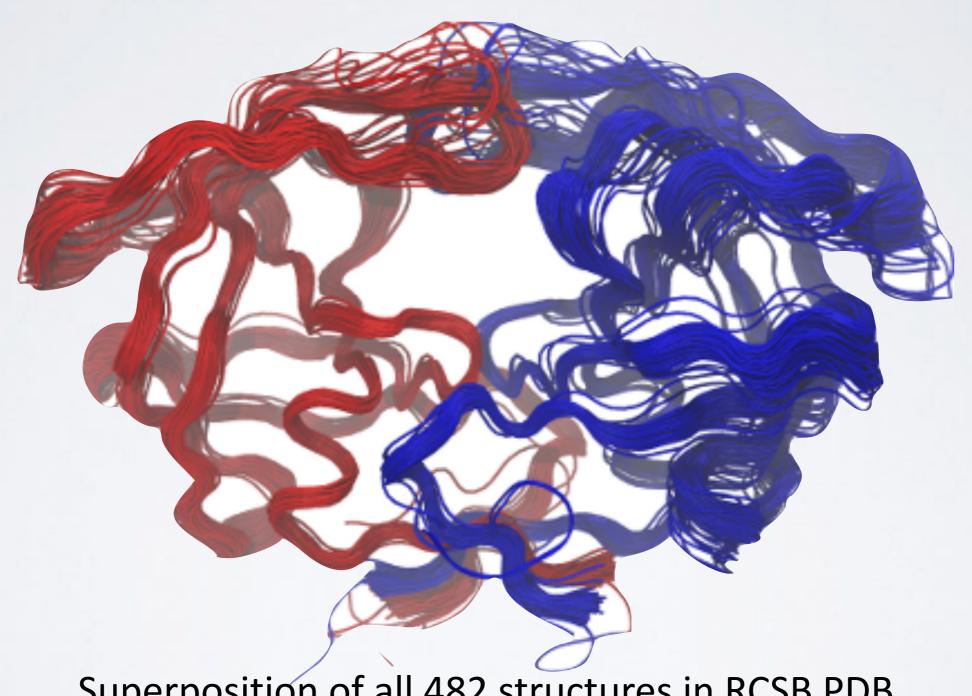


 Backbone or main-chain representation can help trace chain topology & reveal secondary structure



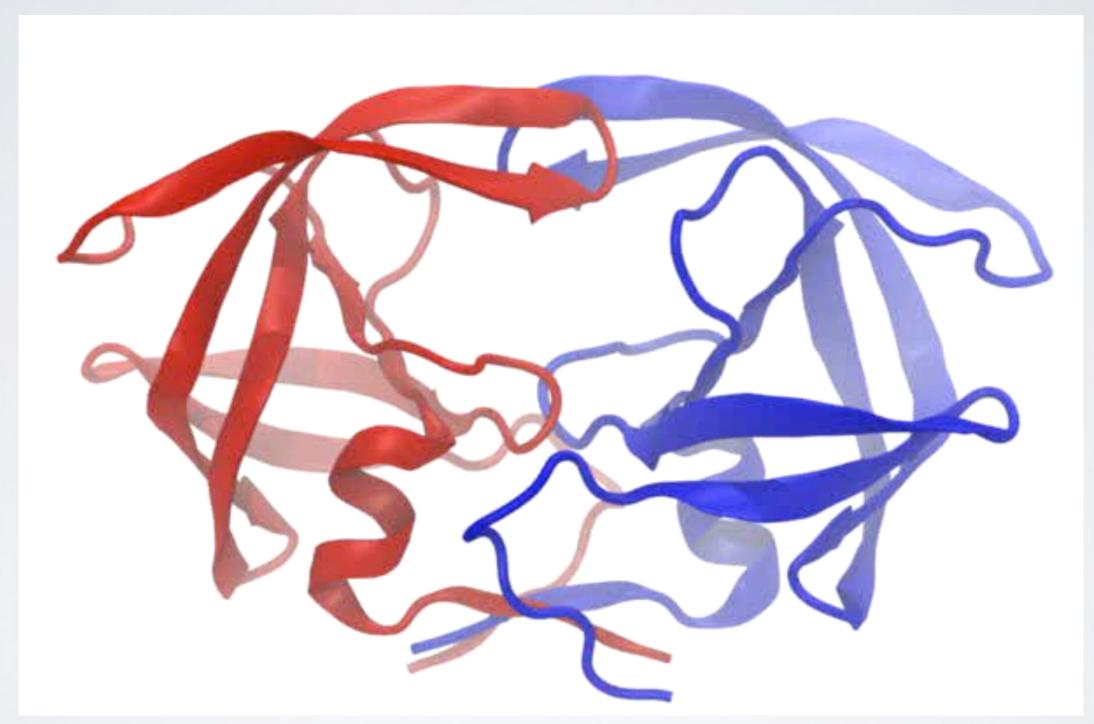
- Simplified secondary structure representations are commonly used to communicate structural details
- Now we can clearly see 2°, 3° and 4° structure
- Coiled chain of connected secondary structures

DISPLACEMENTS REFLECT INTRINSIC FLEXIBILITY



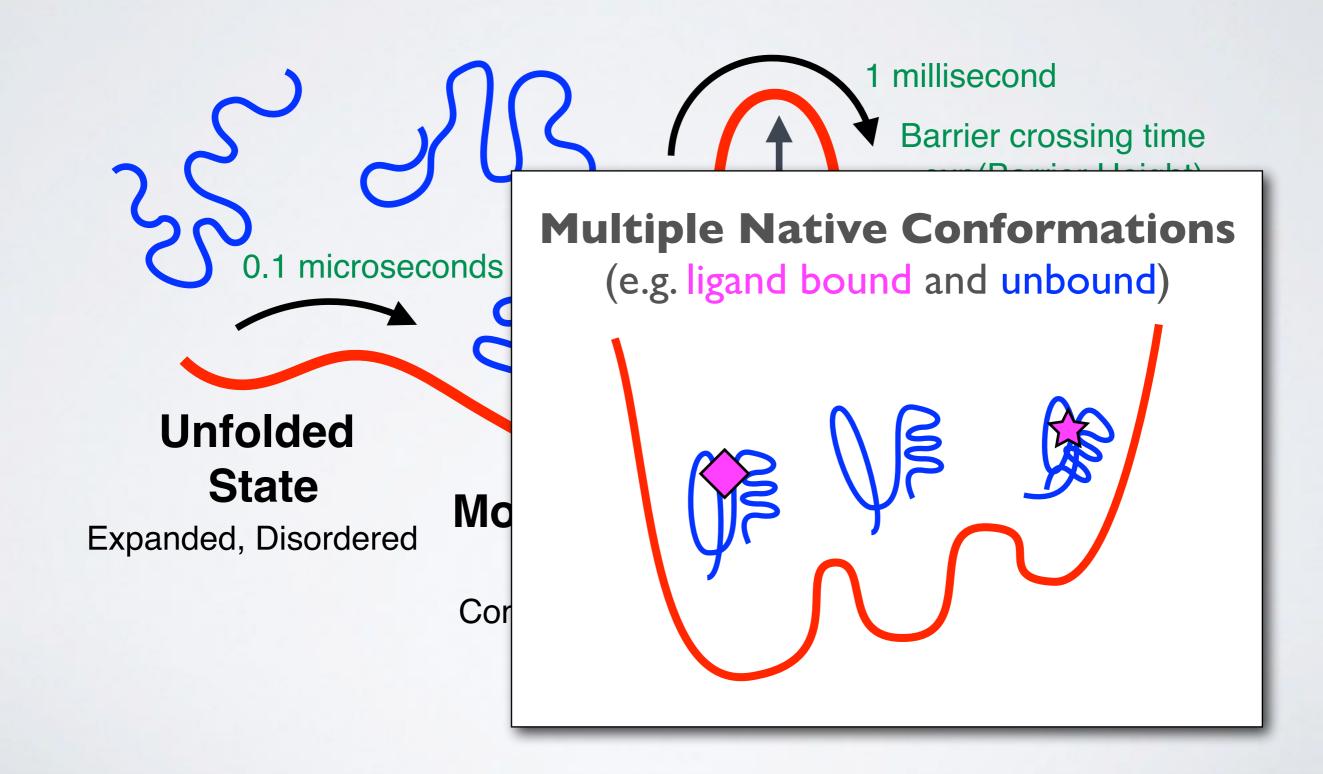
Superposition of all 482 structures in RCSB PDB (23/09/2015)

DISPLACEMENTS REFLECT INTRINSIC FLEXIBILITY



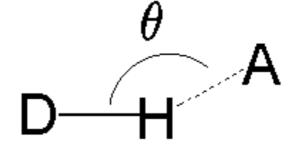
Principal component analysis (PCA) of experimental structures

KEY CONCEPT: ENERGY LANDSCAPE



- H-bonding
- Van der Waals
- Electrostatics
- Hydrophobicity

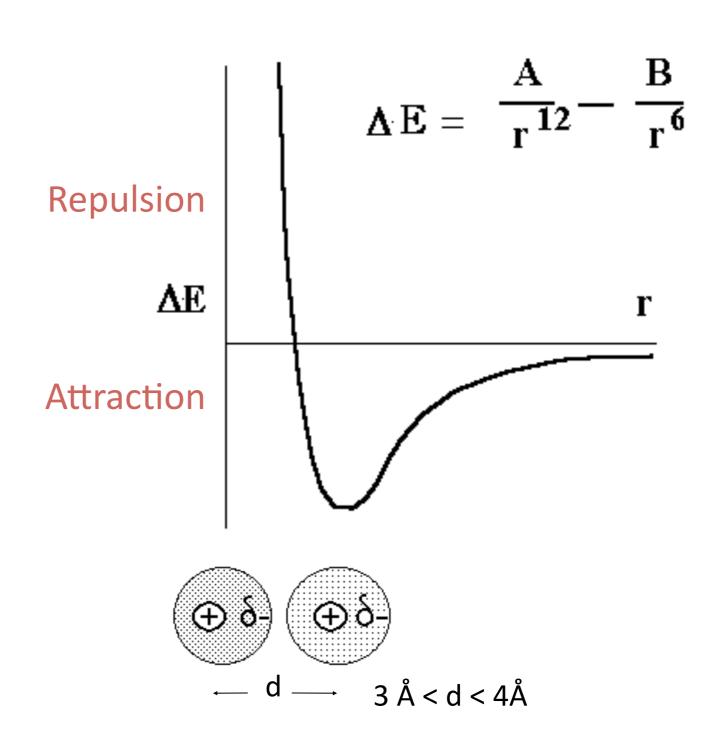
Hydrogenbond donor bond acceptor



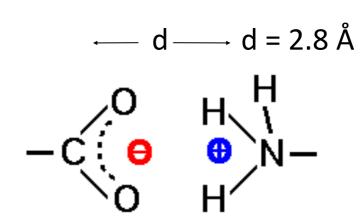
2.6 Å < d < 3.1Å

 $150^{\circ} < \theta < 180^{\circ}$

- H-bonding
- Van der Waals
- Electrostatics
- Hydrophobicity



- H-bonding
- Van der Waals
- Electrostatics
- Hydrophobicity



carboxyl group and amino group

(some time called IONIC BONDs or SALT BRIDGEs)

Coulomb's law

$$q_1 q_2$$
 $O r O$

$$E = \frac{K q_1 q_2}{D r}$$

E = Energy

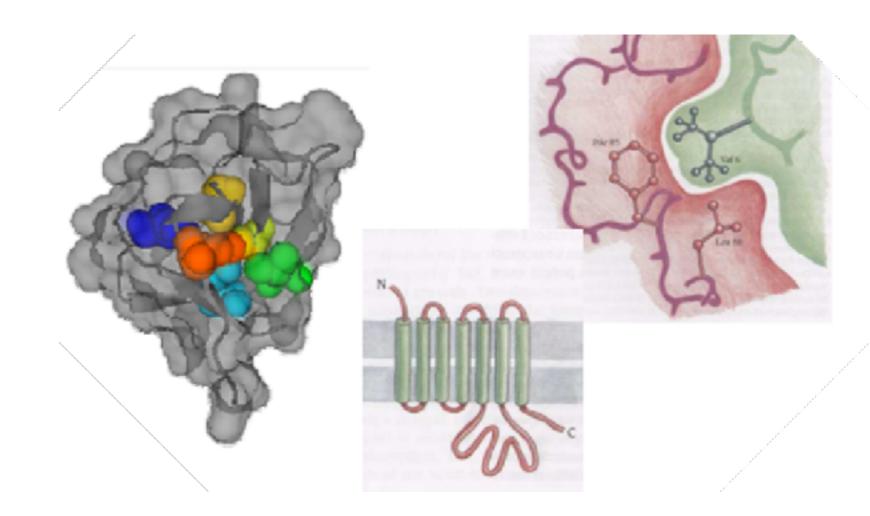
k = constant

D = Dielectric constant (vacuum = 1; $H_2O = 80$)

 $q_1 \& q_2 = electronic charges (Coulombs)$

r = distance (Å)

- H-bonding
- Van der Waals
- Electrostatics
- Hydrophobicity



The force that causes hydrophobic molecules or nonpolar portions of molecules to aggregate together rather than to dissolve in water is called <u>Hydrophobicity</u> (*Greek, "water fearing"*). This is not a separate bonding force; rather, it is the result of the energy required to insert a nonpolar molecule into water.

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KEY CONCEPT: POTENTIAL FUNCTIONS DESCRIBE A SYSTEMS ENERGY AS A FUNCTION OF ITS STRUCTURE

Two main approaches:

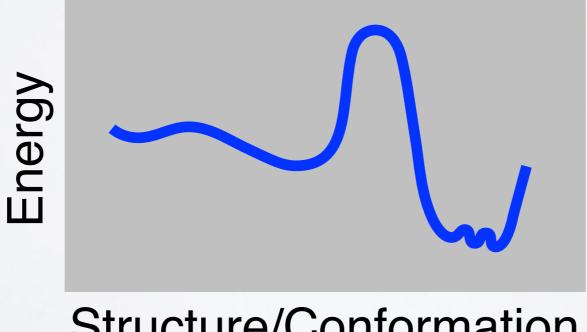
- (1). Physics-Based
- (2). Knowledge-Based

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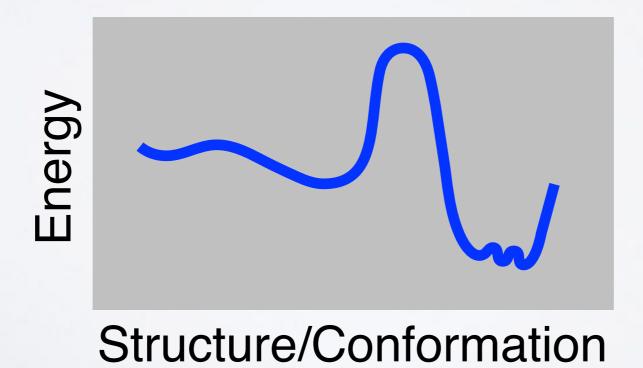
Structure/Conformation

KEY CONCEPT: POTENTIAL FUNCTIONS DESCRIBE A SYSTEMS ENERGY AS A FUNCTION OF ITS STRUCTURE

Two main approaches:

(1). Physics-Based

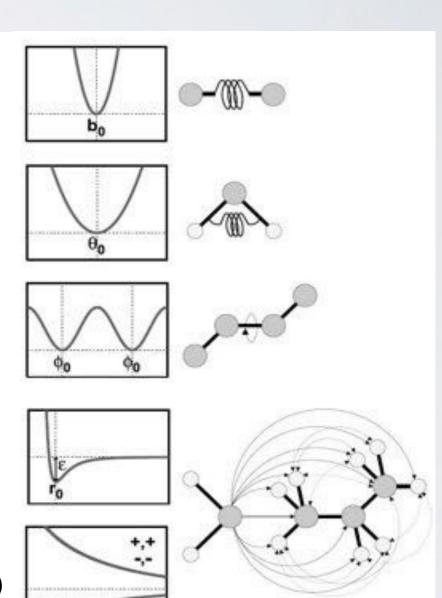
(2). Knowledge-Based



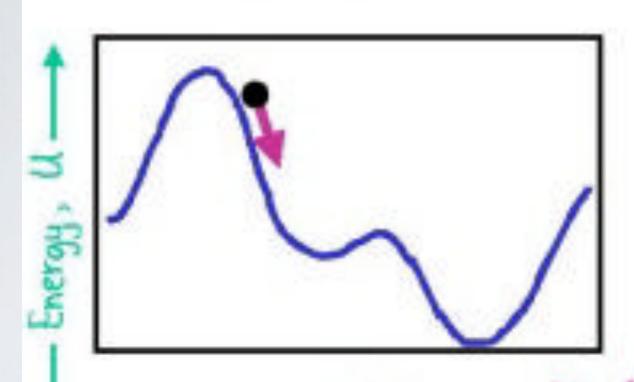
PHYSICS-BASED POTENTIALS ENERGY TERMS FROM PHYSICAL THEORY

$$U(\vec{R}) = \underbrace{\sum_{bonds} k_i^{bond} (r_i - r_0)^2 + \sum_{angles} k_i^{angle} (\theta_i - \theta_0)^2 + \sum_{U_{bond}} k_i^{dihe} [1 + \cos(n_i \phi_i + \delta_i)] + \sum_{dihedrals} \underbrace{\sum_{j \neq i} 4\epsilon_{ij} \left[\left(\frac{\sigma_{ij}}{r_{ij}}\right)^{12} - \left(\frac{\sigma_{ij}}{r_{ij}}\right)^6 \right] + \sum_{i} \sum_{j \neq i} \frac{q_i q_j}{\epsilon r_{ij}}}_{U_{nonbond}}$$

 U_{bond} = oscillations about the equilibrium bond length U_{angle} = oscillations of 3 atoms about an equilibrium bond angle $U_{dihedral}$ = torsional rotation of 4 atoms about a central bond $U_{nonbond}$ = non-bonded energy terms (electrostatics and Lenard-Jones)



TOTAL POTENTIAL ENERGY



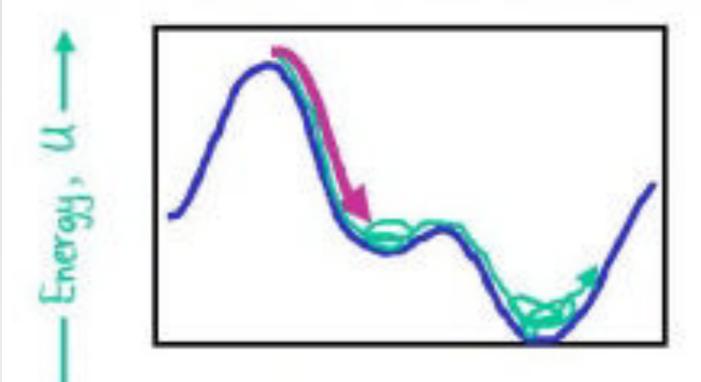
- The total potential energy or enthalpy fully defines the system, U.
- The forces are the gradients of the energy.

F(x) = -dU/dx • The energy is a sum of independent terms for:

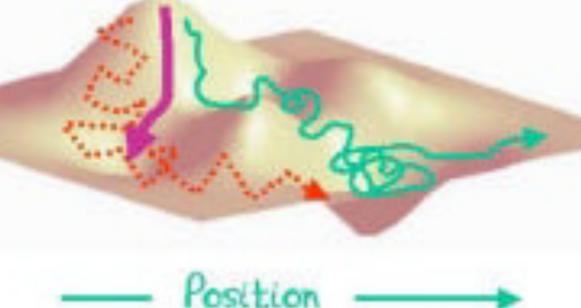
Bond, Bond angles, Torsion angles and nonbonded atom pairs.

Slide Credit: Michael Levitt

MOVING OVER THE ENERGY SURFACE



- Energy Minimization drops into local minimum.
- Molecular Dynamics uses thermal energy to move smoothly over surface.



 Monte Carlo Moves are random. Accept with probability exp (-∆U/kT).

Slide Credit: Michael Levitt

PHYSICS-ORIENTED APPROACHES

Weaknesses

Fully physical detail becomes computationally intractable
Approximations are unavoidable
(Quantum effects approximated classically, water may be treated crudely)
Parameterization still required

Strengths

Interpretable, provides guides to design Broadly applicable, in principle at least Clear pathways to improving accuracy

Status

Useful, widely adopted but far from perfect Multiple groups working on fewer, better approxs

Force fields, quantum entropy, water effects

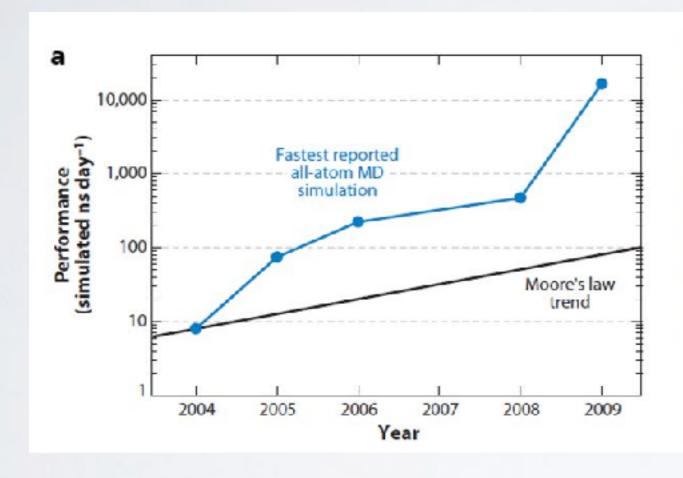
Moore's law: hardware improving

HOW COMPUTERS HAVE CHANGED

DATE	CONT			
1967	1408	0.1 MH	1 M8	MAT
1013	14,000	164	10 GB	LAPTOP
CHANGE	10,000	10,000	10,000	10,000

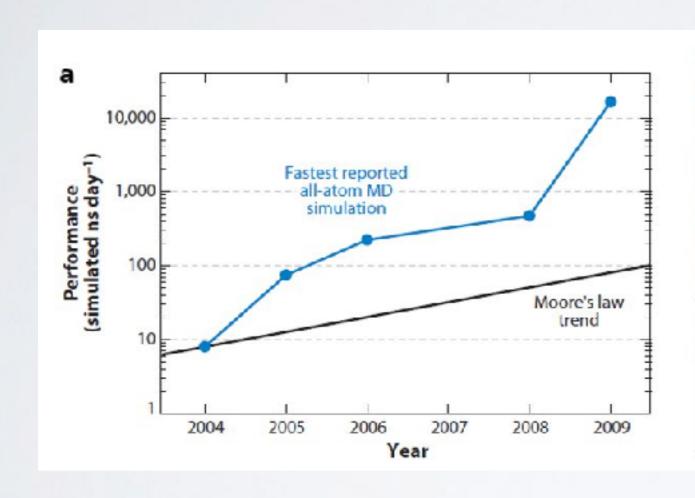
It cars were the computers then a new Volice would cost \$3, would have a top speed of 1,000,000 km/hr, would carry \$0,000 adults and would park in a shocker.

SIDE-NOTE: GPUS AND ANTON SUPERCOMPUTER





SIDE-NOTE: GPUS AND ANTON SUPERCOMPUTER





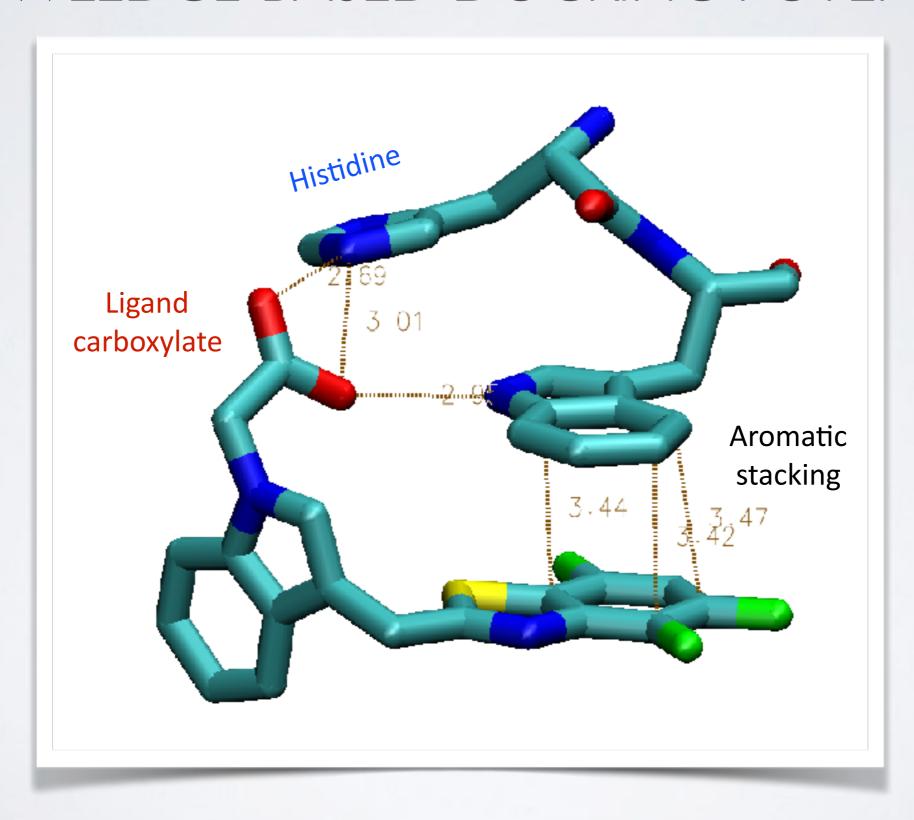
KEY CONCEPT: POTENTIAL FUNCTIONS DESCRIBE A SYSTEMS ENERGY AS A FUNCTION OF ITS STRUCTURE

Two main approaches:

(1). Physics-Based

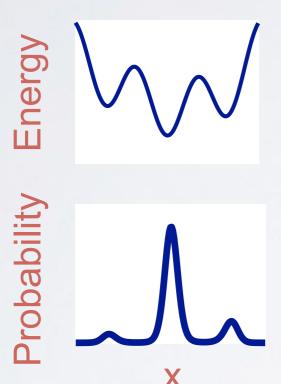
(2). Knowledge-Based

KNOWLEDGE-BASED DOCKING POTENTIALS



ENERGY DETERMINES PROBABILITY (STABILITY)

Basic idea: Use probability as a proxy for energy



Boltzmann:

$$p(r) \propto e^{-E(r)/RT}$$

Inverse Boltzmann:

$$E(r) = -RT \ln \left[p(r) \right]$$

Example: ligand carboxylate O to protein histidine N

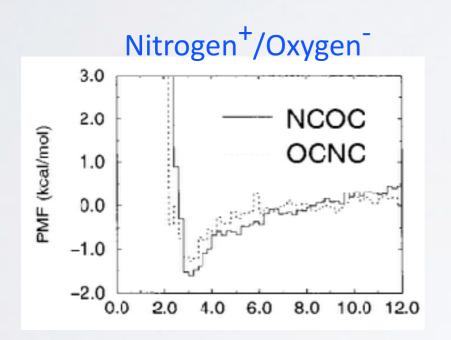
Find all protein-ligand structures in the PDB with a ligand carboxylate O

- 1. For each structure, histogram the distances from O to every histidine N
- 2. Sum the histograms over all structures to obtain $p(r_{O-N})$
- 3. Compute $E(r_{O-N})$ from $p(r_{O-N})$

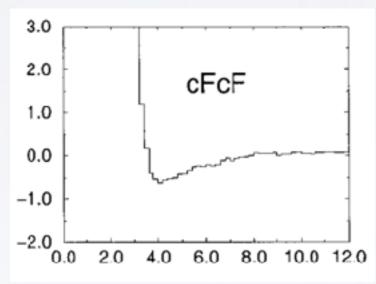
KNOWLEDGE-BASED DOCKING POTENTIALS

"PMF", Muegge & Martin, J. Med. Chem. (1999) 42:791

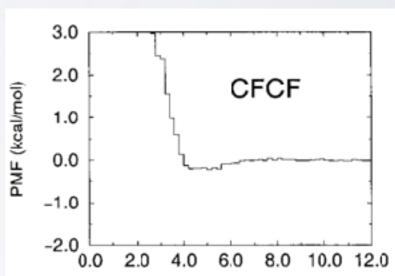
A few types of atom pairs, out of several hundred total







Aliphatic carbons



Atom-atom distance (Angstroms)

$$E_{prot-lig} = E_{vdw} + \sum_{pairs (ij)} E_{type(ij)}(r_{ij})$$

KNOWLEDGE-BASED POTENTIALS

Weaknesses

Accuracy limited by availability of data

Strengths

Relatively easy to implement Computationally fast

Status

Useful, far from perfect
May be at point of diminishing returns
(not always clear how to make improvements)

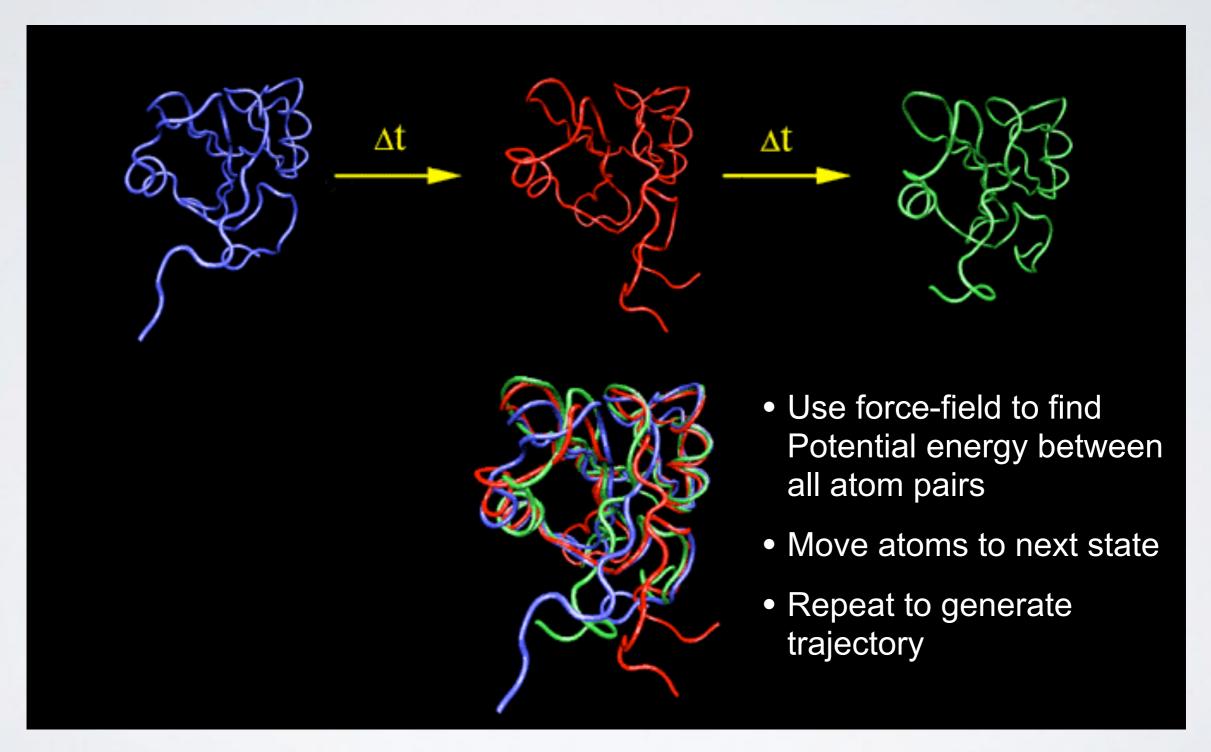
NEXT UP:

- Overview of structural bioinformatics
 - Major motivations, goals and challenges
- Fundamentals of protein structure
 - Composition, form, forces and dynamics
- Representing and interpreting protein structure
 - Modeling energy as a function of structure
- Example application areas
 - Predicting functional dynamics & drug discovery

PREDICTING FUNCTIONAL DYNAMICS

- Proteins are <u>intrinsically flexible</u> molecules with internal motions that are often intimately coupled to their biochemical function
 - E.g. ligand and substrate binding, conformational activation, allosteric regulation, etc.
- Thus knowledge of dynamics can provide a deeper understanding of the <u>mapping of structure to function</u>
 - Molecular dynamics (MD) and normal mode analysis (NMA) are two major methods for predicting and characterizing molecular motions and their properties

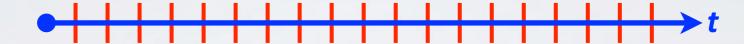
MOLECULAR DYNAMICS SIMULATION



McCammon, Gelin & Karplus, *Nature* (1977)

[See: https://www.youtube.com/watch?v=ui1ZysMFcKk]

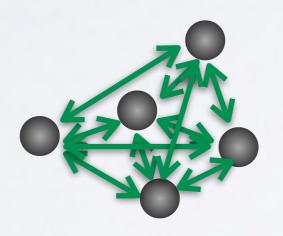
Divide time into discrete (~1fs) time steps (Δt) (for integrating equations of motion, see below)



Divide time into discrete (~1fs) time steps (Δt) (for integrating equations of motion, see below)



At each time step calculate pair-wise atomic forces (F(t)) (by evaluating force-field gradient)



Nucleic motion described classically

$$m_i rac{d^2}{dt^2} ec{R}_i = - ec{
abla}_i E(ec{R}_i)$$

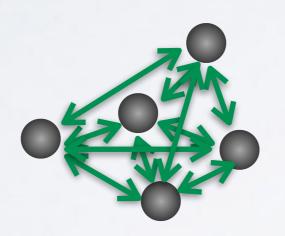
Empirical force field

$$E(\vec{R}) = \sum_{\text{bonded}} E_i(\vec{R}) + \sum_{\text{non-bonded}} E_i(\vec{R})$$

Divide time into discrete (~1fs) time steps (Δt) (for integrating equations of motion, see below)



At each time step calculate pair-wise atomic forces (F(t)) (by evaluating force-field gradient)



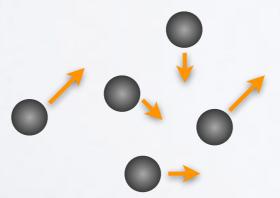
Nucleic motion described classically

$$m_i rac{d^2}{dt^2} ec{R}_i = - ec{
abla}_i E(ec{R})$$

Empirical force field

$$E(\vec{R}) = \sum_{\text{bonded}} E_i(\vec{R}) + \sum_{\text{non-bonded}} E_i(\vec{R})$$

Use the forces to calculate velocities and move atoms to new positions (by integrating numerically via the "leapfrog" scheme)



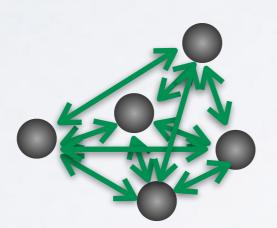
$$egin{array}{ccc} oldsymbol{v}(t+rac{\Delta t}{2}) & = & oldsymbol{v}(t-rac{\Delta t}{2})+rac{oldsymbol{F}(t)}{m}\Delta t \ oldsymbol{r}(t+\Delta t) & = & oldsymbol{r}(t)+oldsymbol{v}(t+rac{\Delta t}{2})\Delta t \end{array}$$

BASIC ANATOMY OF A MD SIMULAT

Divide time into discrete (~1fs) time steps (Δt) (for integrating equations of motion, see below)



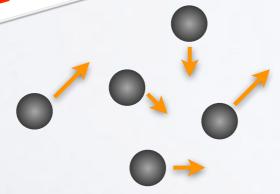
 \triangleright At each time step calculate pair-wise atomic forces (F(t)) (by evaluating force-field gradient)



$$m_i \frac{d^2}{dt^2} \vec{R}_i = -\vec{\nabla}_i E(\vec{R})$$

Use the REPEAT, (iterate many, many times... 1ms = 1012 time steps)

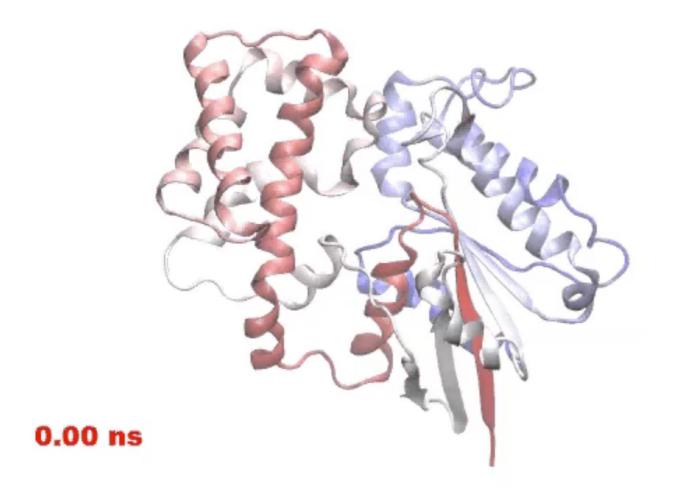
REPEAT, (iterate many, many times... 1ms = 1012 time steps)



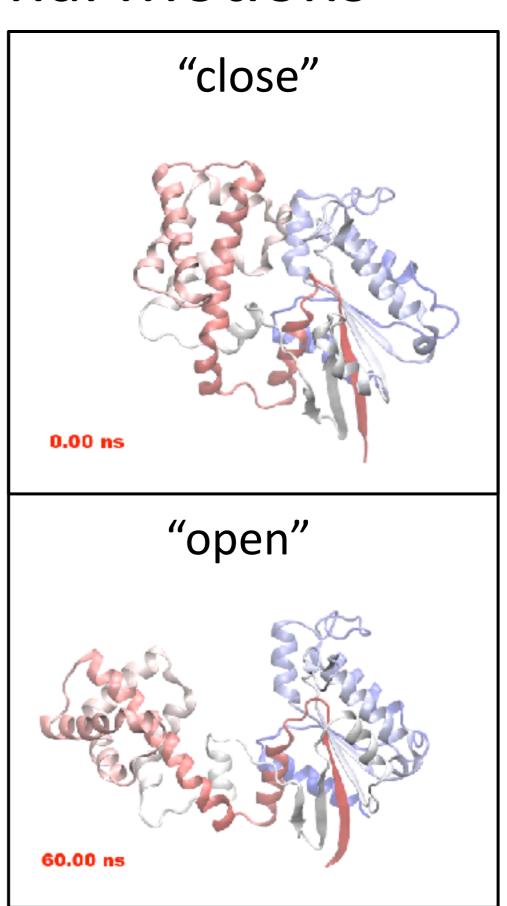
$$egin{array}{cccc} oldsymbol{v}(t+rac{\Delta t}{2}) & = & oldsymbol{v}(t-rac{\Delta t}{2})+rac{oldsymbol{F}(t)}{m}\Delta t \ oldsymbol{r}(t+\Delta t) & = & oldsymbol{r}(t)+oldsymbol{v}(t+rac{\Delta t}{2})\Delta t \end{array}$$

MD Prediction of Functional Motions

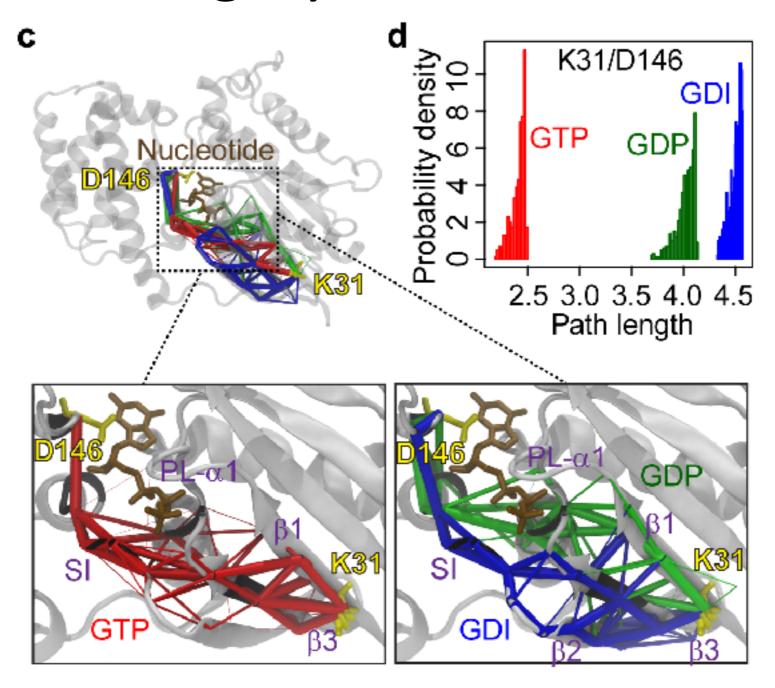
Accelerated MD simulation of nucleotide-free transducin alpha subunit



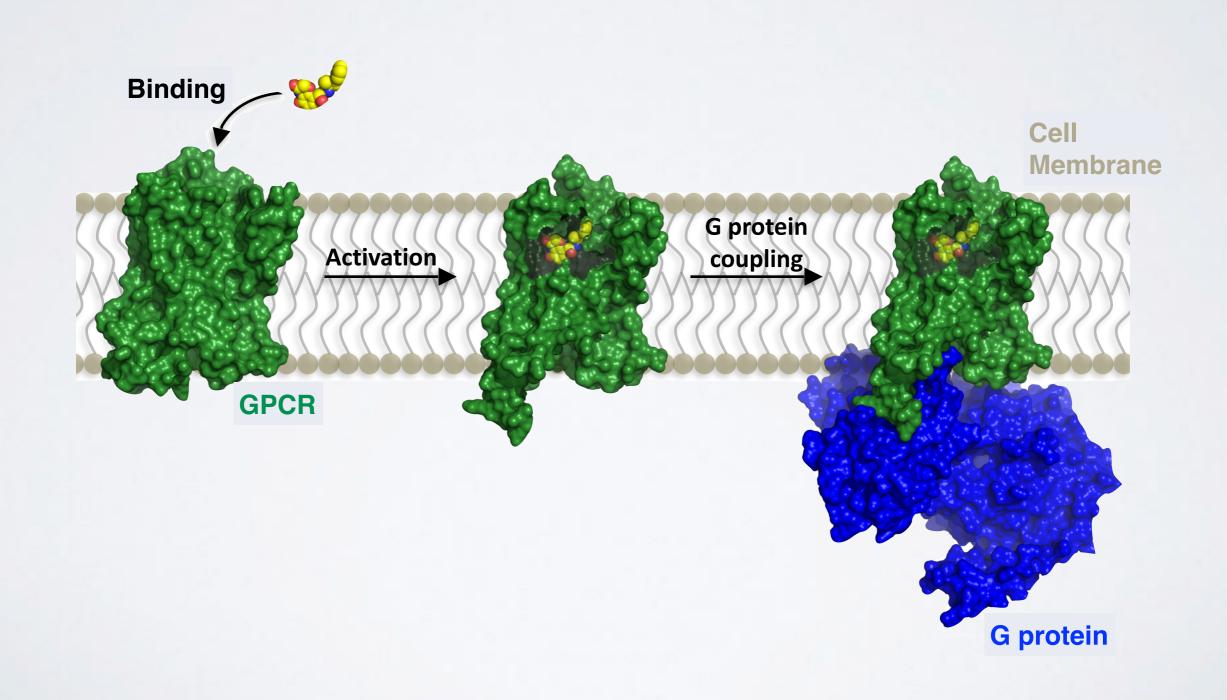
Yao and Grant, Biophys J. (2013)



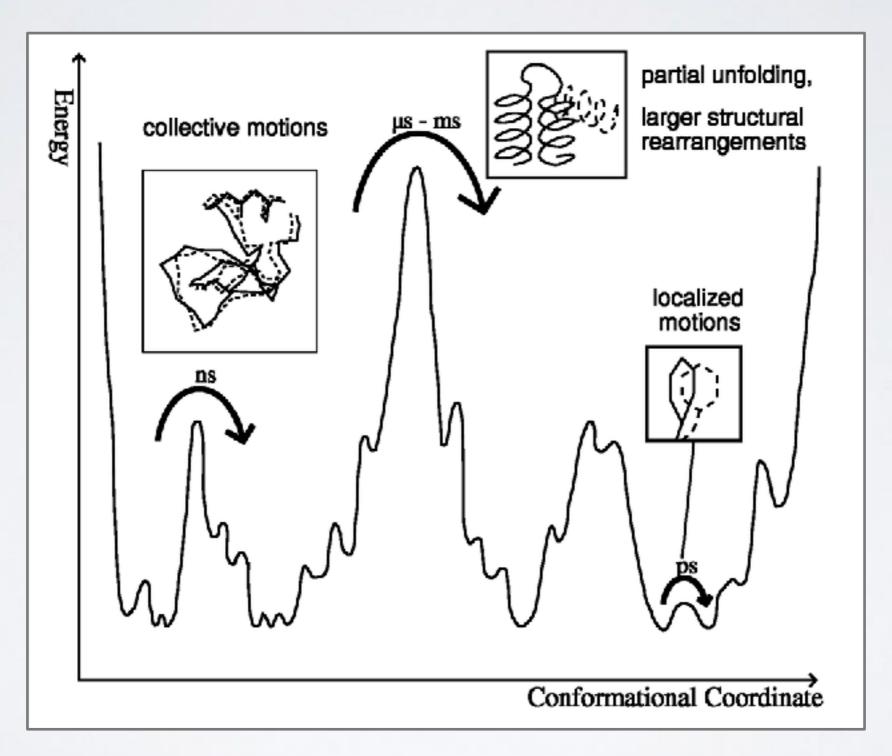
Simulations Identify Key Residues Mediating Dynamic Activation



EXAMPLE APPLICATION OF MOLECULAR SIMULATIONS TO GPCRS



PROTEINS JUMP BETWEEN MANY, HIERARCHICALLY ORDERED "CONFORMATIONAL SUBSTATES"



H. Frauenfelder et al., *Science* **229** (1985) 337

Improve this slide

MOLECULAR DYNAMICS IS VERY

Example: F₁-ATPase in water (183,674 atoms) for 1 nanosecond:

=> 10⁶ integration steps

=> 8.4 * 10¹¹ floating point operations/step

[n(n-1)/2 interactions]

Total: 8.4 * 10¹⁷ flop

(on a 100 Gflop/s cpu: ca 25 years!)

... but performance has been improved by use of:

multiple time stepping ca. 2.5 years

fast multipole methods ca. 1 year

parallel computers ca. 5 days

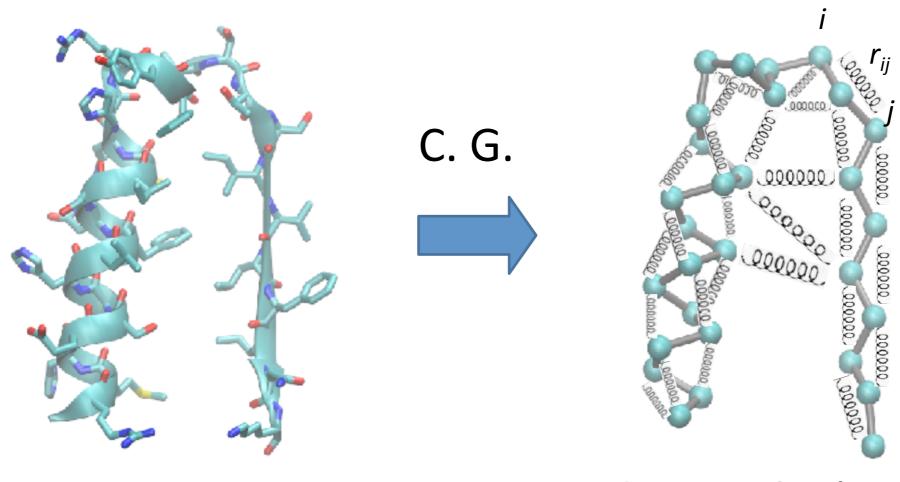
modern GPUs ca. 1 day

(Anton supercomputer ca. minutes)

COARSE GRAINING: NORMAL MODE ANALYSIS

(NMA)

- MD is still time-consuming for large systems
- Elastic network model NMA (ENM-NMA) is an example of a lower resolution approach that finishes in seconds even for large systems.

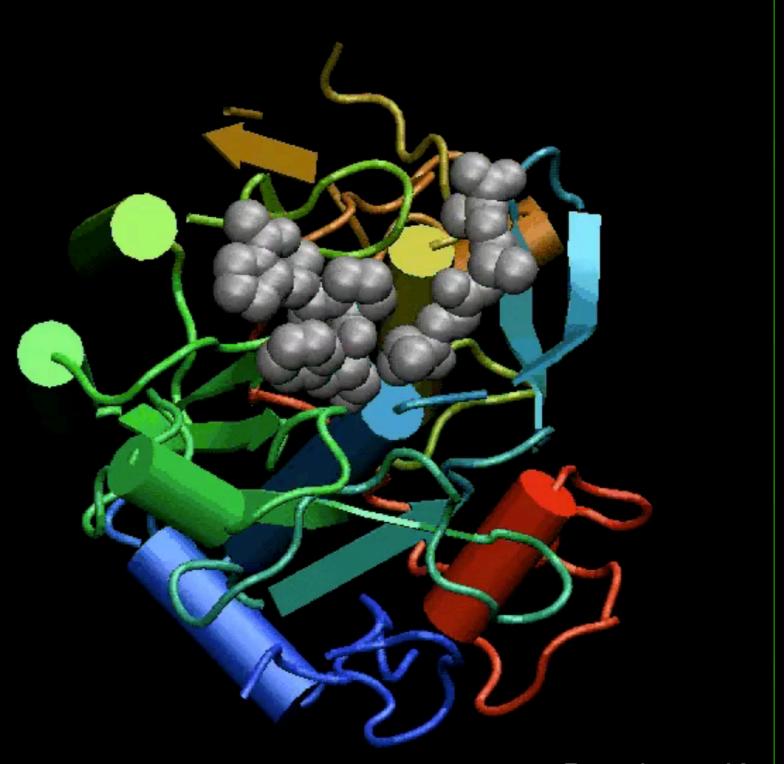


Atomistic

- 1 bead /1 amino acid
- Connected by springs

Coarse Grained

NMA models the protein as a network of elastic strings



Proteinase K

NEXT UP:

- Overview of structural bioinformatics
 - Major motivations, goals and challenges
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- Example application areas
 - Predicting functional dynamics & drug discovery

THE TRADITIONAL EMPIRICAL PATH TO DRUG DISCOVERY

Compound library

(commercial, in-house, synthetic, natural)

High throughput screening

(HTS)

Hit confirmation

Lead compounds

(e.g., μM K_d)

Lead optimization

(Medicinal chemistry)

Animal and clinical evaluation



Potent drug candidates

 $(nM K_d)$

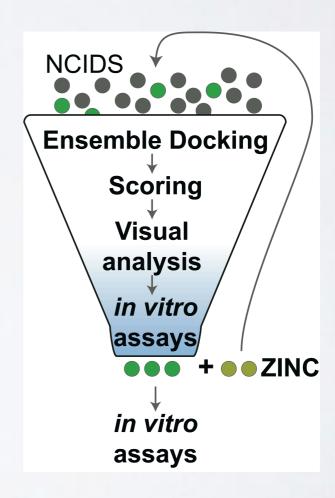
COMPUTER-AIDED LIGAND DESIGN

Aims to reduce number of compounds synthesized and assayed

Lower costs

Reduce chemical waste

Facilitate faster progress



Two main approaches:

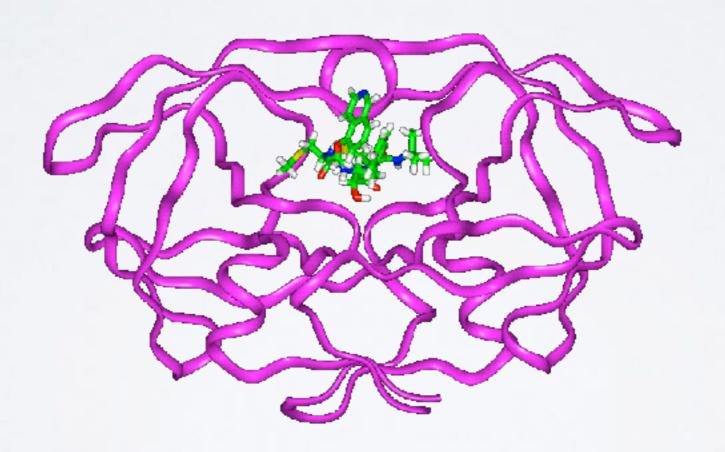
- (1). Receptor/Target-Based
- (2). Ligand/Drug-Based

Two main approaches:

- (1). Receptor/Target-Based
- (2). Ligand/Drug-Based

SCENARIO I: RECEPTOR-BASED DRUG DISCOVERY

Structure of Targeted Protein Known: Structure-Based Drug Discovery

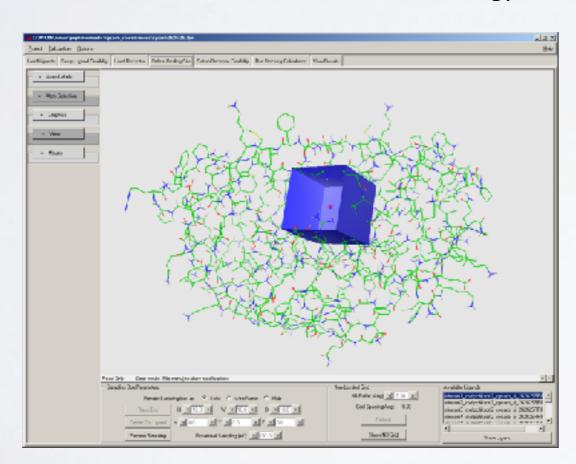


HIV Protease/KNI-272 complex

PROTEIN-LIGAND DOCKING

Structure-Based Ligand Design

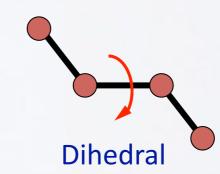
Docking software
Search for structure of lowest energy



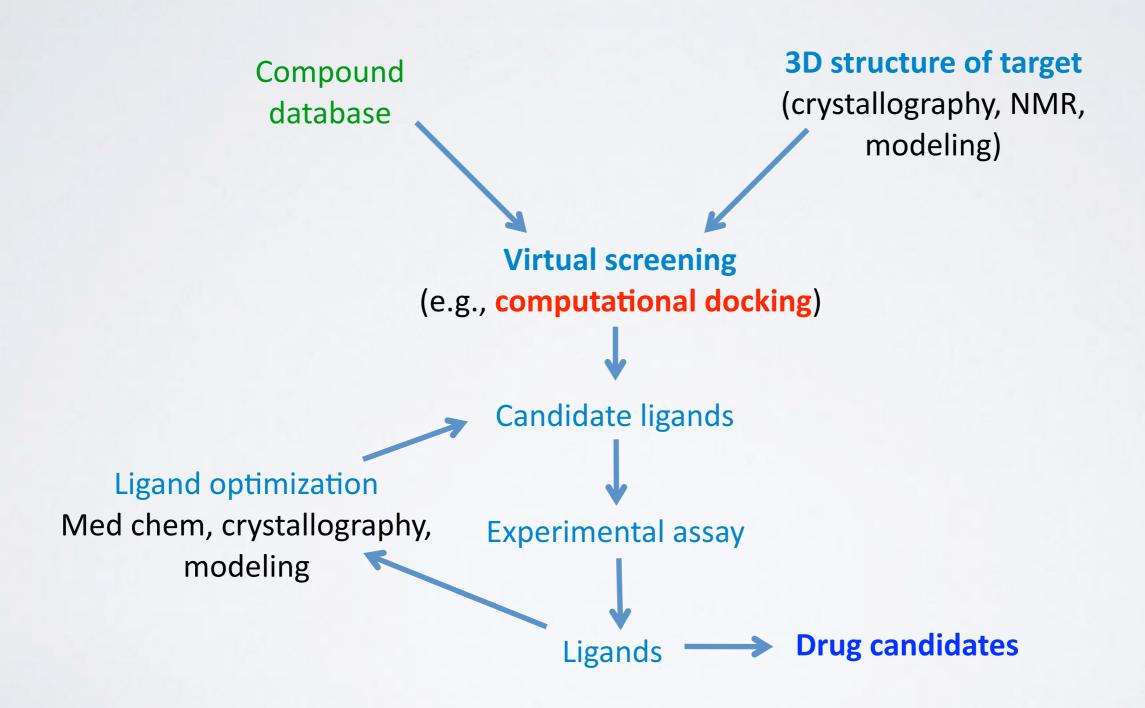
Potential function Energy as function of structure







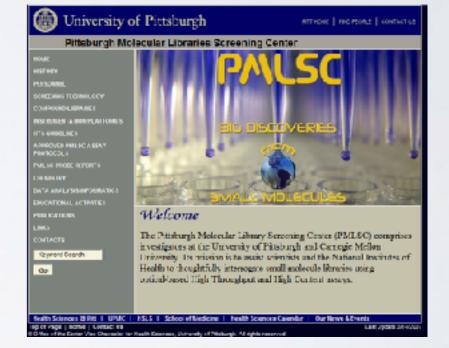
STRUCTURE-BASED VIRTUAL SCREENING



COMPOUND LIBRARIES





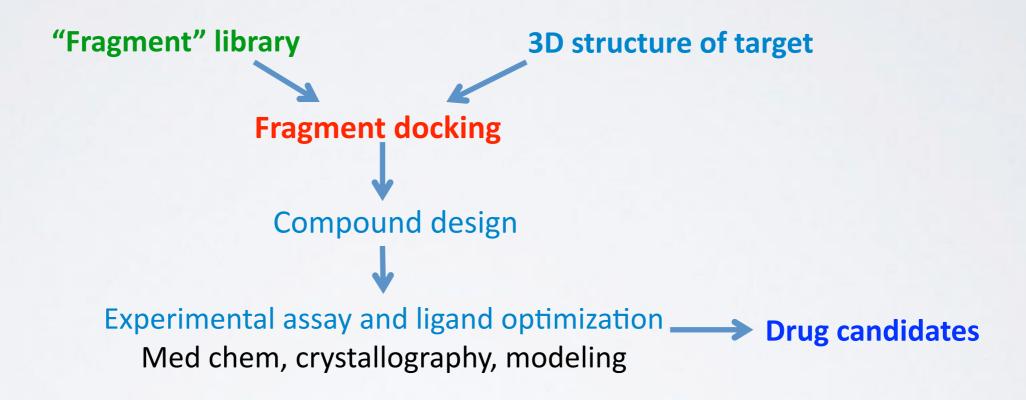


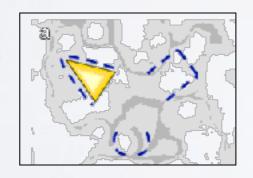
Commercial (in-house pharma)

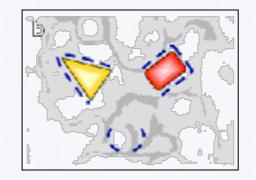
Government (NIH)

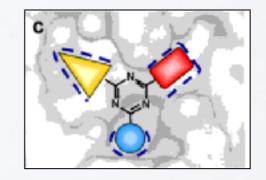
Academia

FRAGMENTAL STRUCTURE-BASED SCREENING



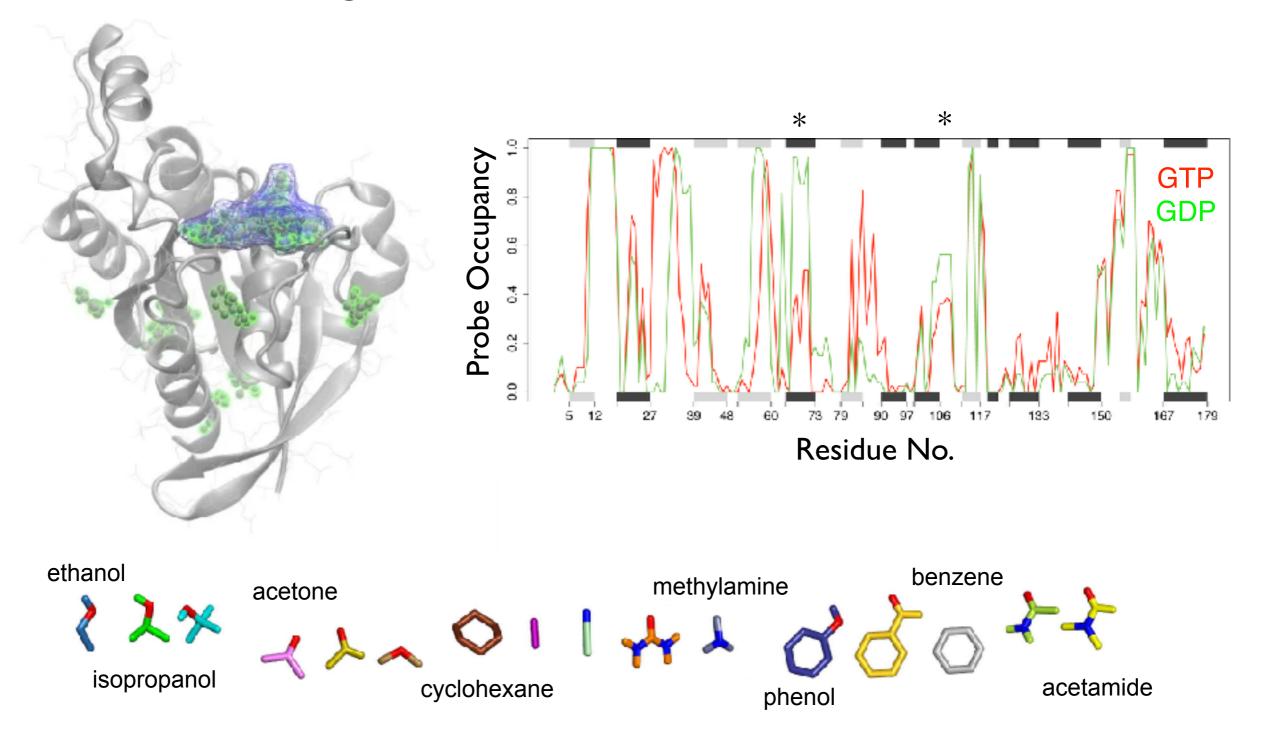






Multiple non active-site pockets identified

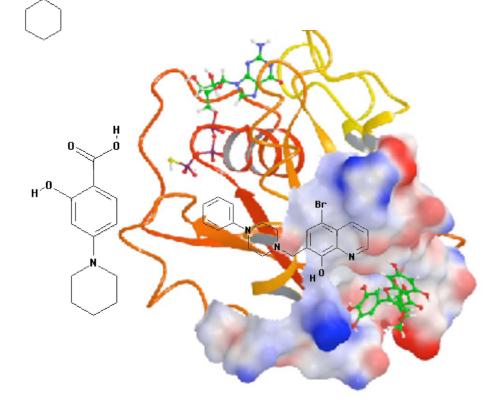
Small organic probe fragment affinities map multiple potential binding sites across the structural ensemble.



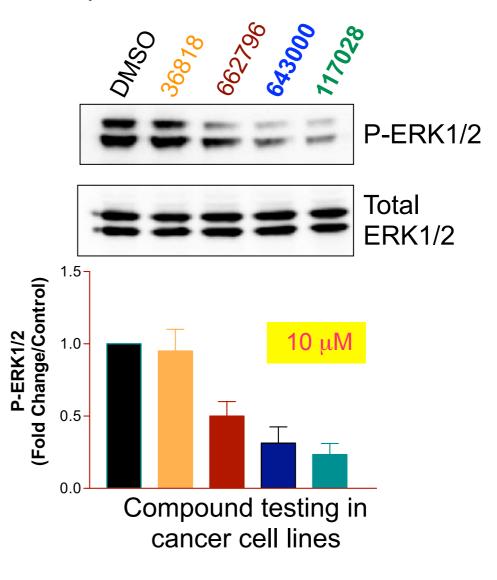
Ensemble docking & candidate inhibitor testing

Top hits from ensemble docking against distal pockets were tested for inhibitory effects on basal ERK activity in glioblastoma cell lines.

Ensemble computational docking

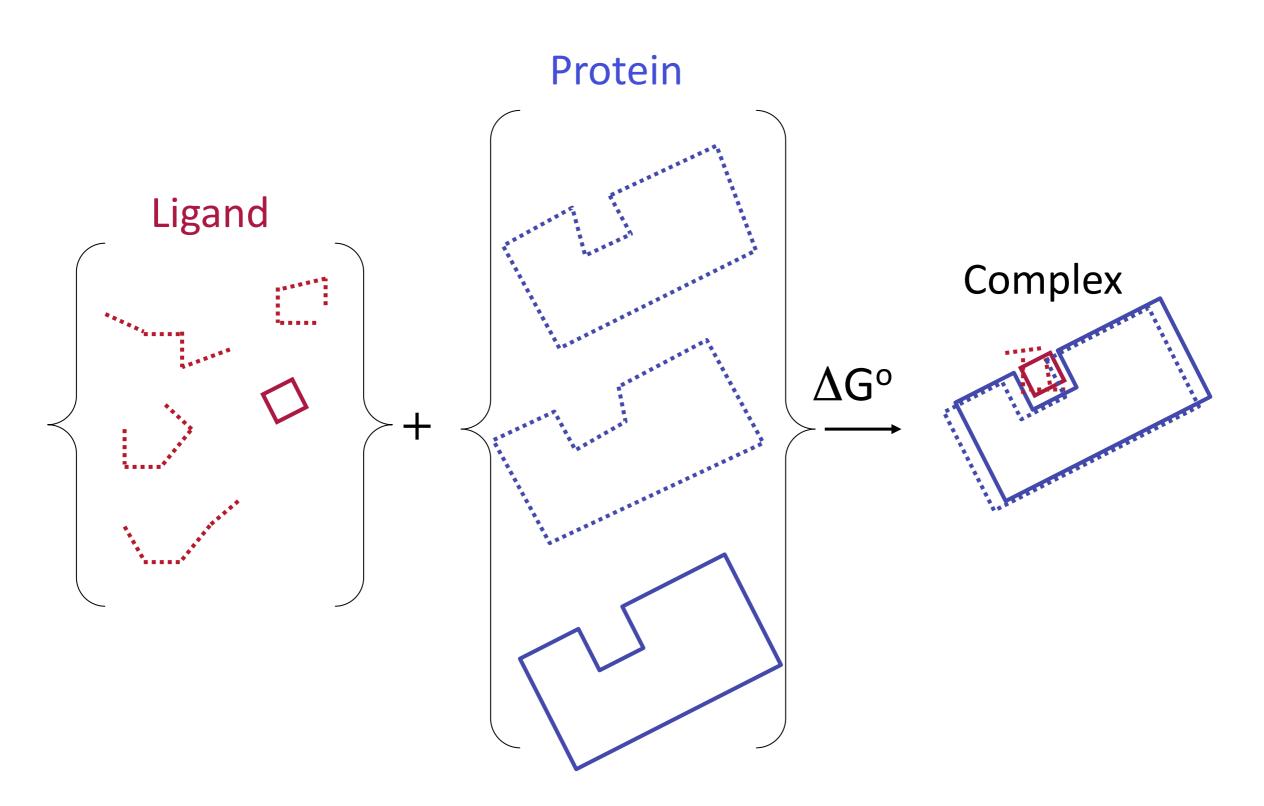


Compound effect on U251 cell line



PLoS One (2011, 2012)

Proteins and Ligand are Flexible



COMMON SIMPLIFICATIONS USED IN PHYSICS-BASED DOCKING

Quantum effects approximated classically

Protein often held rigid

Configurational entropy neglected

Influence of water treated crudely

Two main approaches:

(1). Receptor/Target-Based

(2). Ligand/Drug-Based

Experimental screening generated some ligands, but they don't bind tightly

A company wants to work around another company's chemical patents

A high-affinity ligand is toxic, is not well-absorbed, etc.

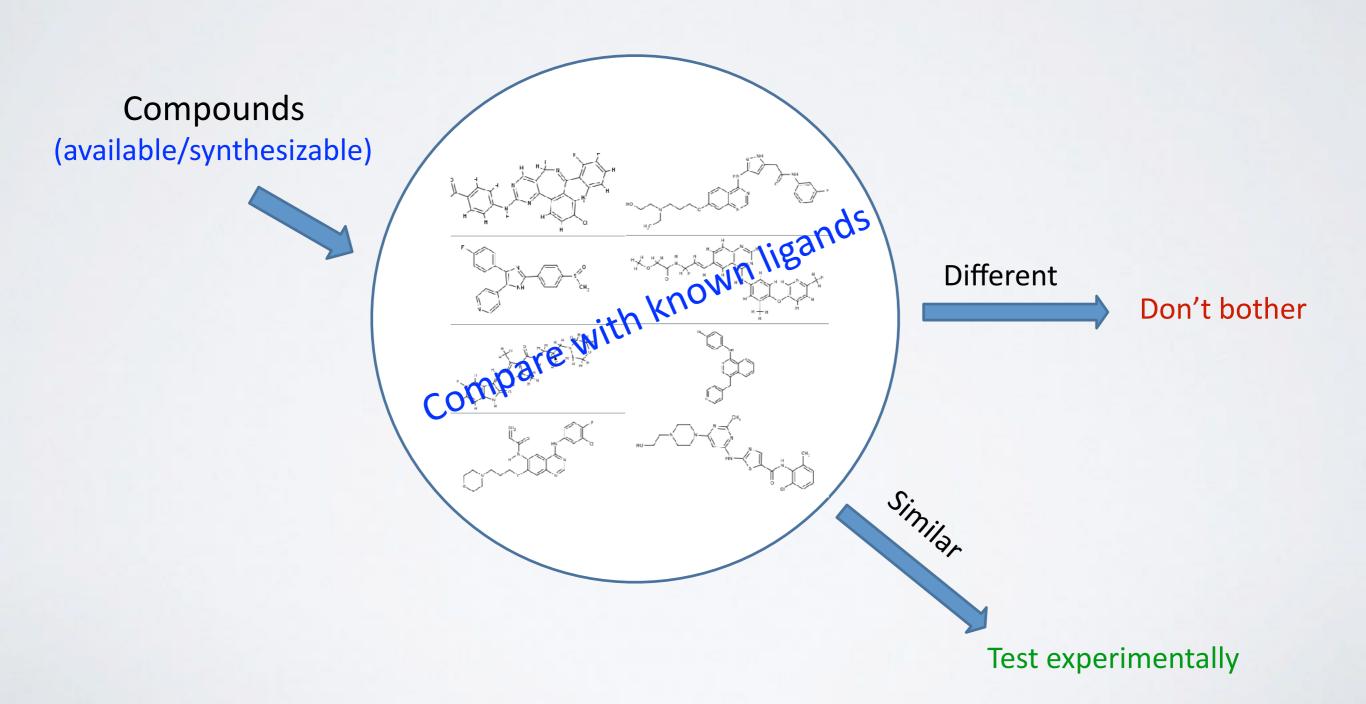
Scenario 2

Structure of Targeted Protein Unknown: Ligand-Based Drug Discovery

e.g. MAP Kinase Inhibitors

Using knowledge of existing inhibitors to discover more

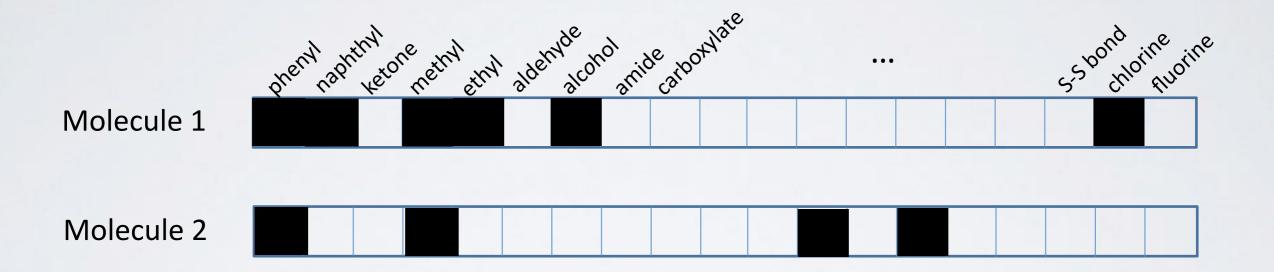
CHEMICAL SIMILARITY LIGAND-BASED DRUG-DISCOVERY



CHEMICAL FINGERPRINTS BINARY STRUCTURE KEYS

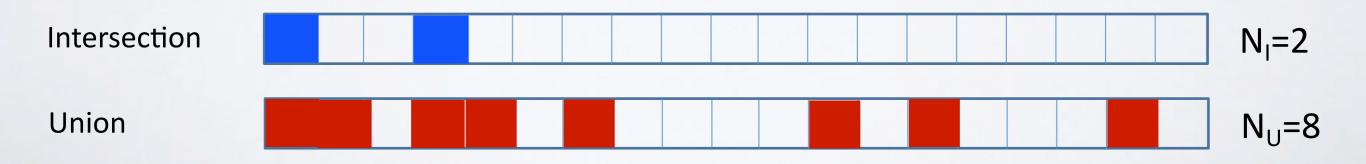


CHEMICAL SIMILARITY FROM FINGERPRINTS



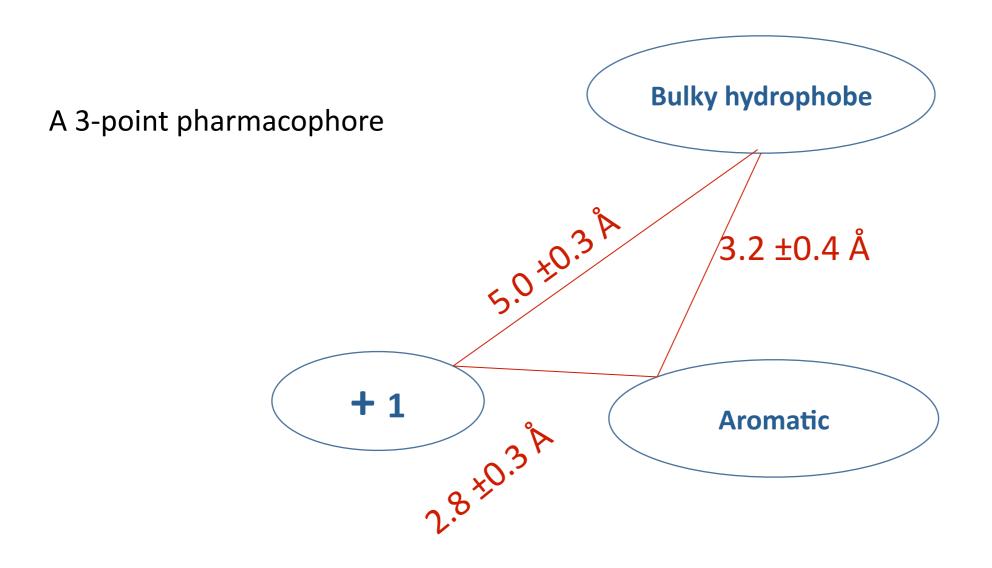
Tanimoto Similarity (or Jaccard Index), T

$$T \equiv \frac{N_I}{N_U} = 0.25$$



Pharmacophore Models

Φάρμακο (drug) + Φορά (carry)

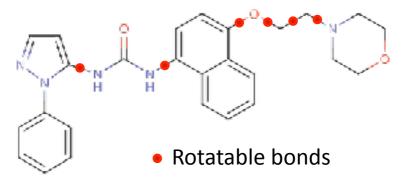


Molecular Descriptors

More abstract than chemical fingerprints

Physical descriptors

molecular weight charge dipole moment number of H-bond donors/acceptors number of rotatable bonds hydrophobicity (log P and clogP)



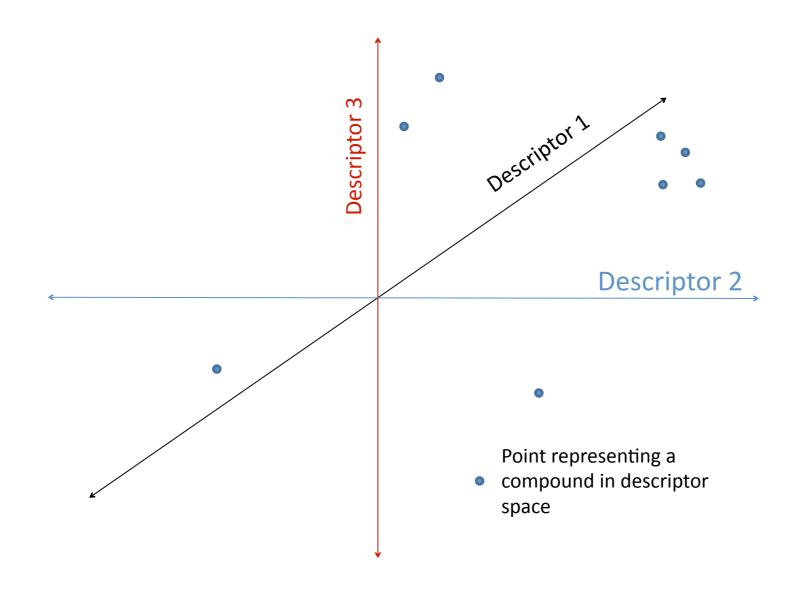
Topological

branching index measures of linearity vs interconnectedness

Etc. etc.

A High-Dimensional "Chemical Space"

Each compound is at a point in an n-dimensional space Compounds with similar properties are near each other



Apply multivariate statistics and machine learning for descriptor-selection. (e.g. partial least squares, support vector machines, random forest, etc.)

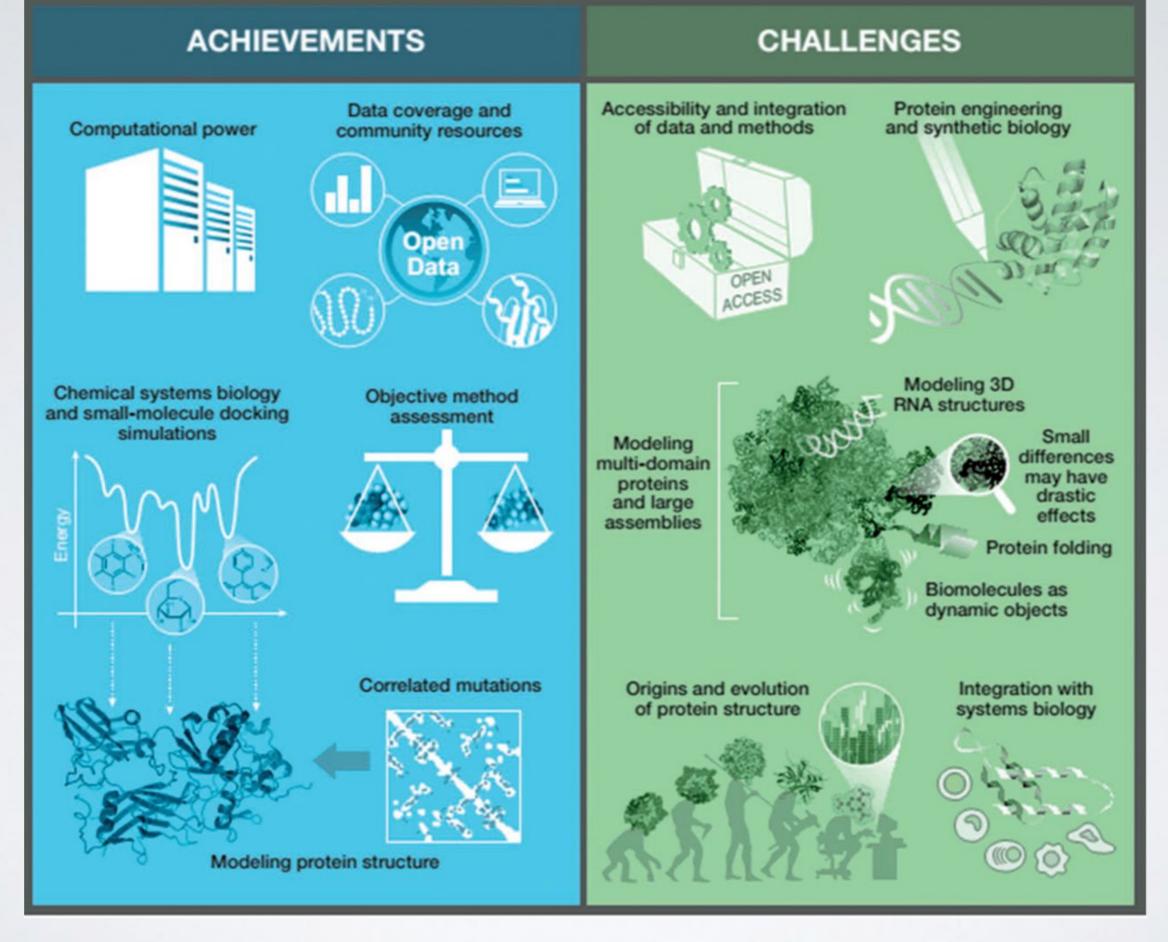
CAUTIONARY NOTES

- "Everything should be made as simple as it can be but not simpler"
 - A model is **never perfect**. A model that is not quantitatively accurate in every respect does not preclude one from establishing results relevant to our understanding of biomolecules as long as the biophysics of the model are properly understood and explored.
- Calibration of the parameters is an ongoing and imperfect process
 Questions and hypotheses should always be designed such that they do not depend crucially on the precise numbers used for the various parameters.
- A computational model is rarely universally right or wrong

A model may be accurate in some regards, inaccurate in others. These subtleties can only be uncovered by comparing to all available experimental data.

SUMMARY

- Structural bioinformatics is computer aided structural biology
- Described major motivations, goals and challenges of structural bioinformatics
- Reviewed the fundamentals of protein structure
- Introduced both physics and knowledge based modeling approaches for describing the structure, energetics and dynamics of proteins computationally



Ilan Samish et al. Bioinformatics 2015;31:146-150

INFORMING SYSTEMS BIOLOGY?

