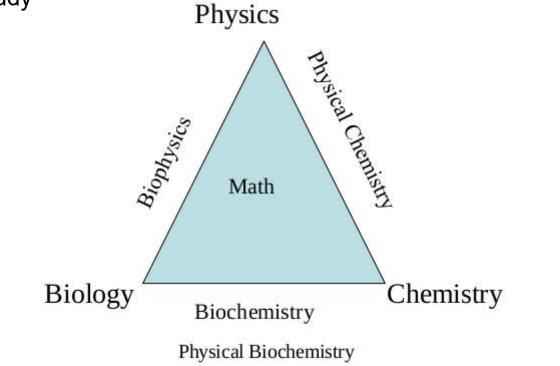
# Why biophysics and biochemistry

Systems under study



Principles models methods

# A bit of biology



Ознаки "життя":

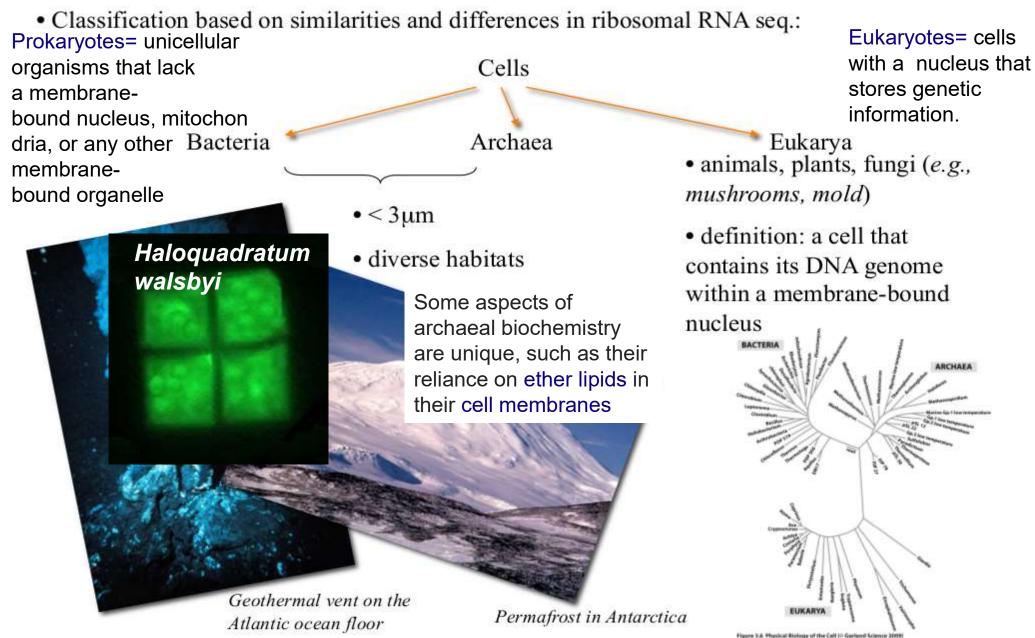
отримання і перетворення енергії з середовища - метаболізм

самоорганізація через використання енергії — синтез, утворення макромолекулярних комплексів

здатність запам`ятовувати свою будову – генетичний код

здатність давати потомство - розмноження

# **Diversity of life forms**

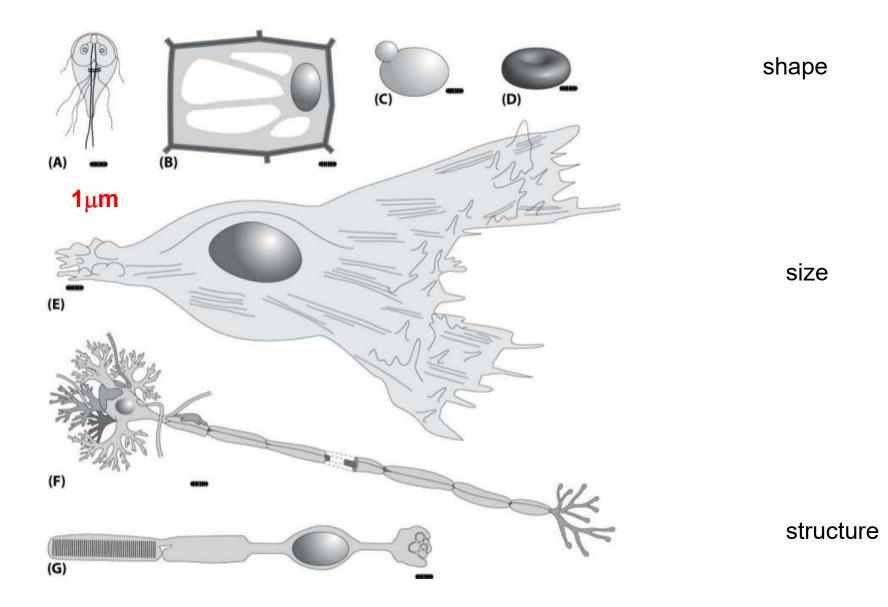


# **Structural hierarchy in eukaryotes**



Illustration by <u>Cell Imaging Core</u> of the Center for Reproductive Sciences.

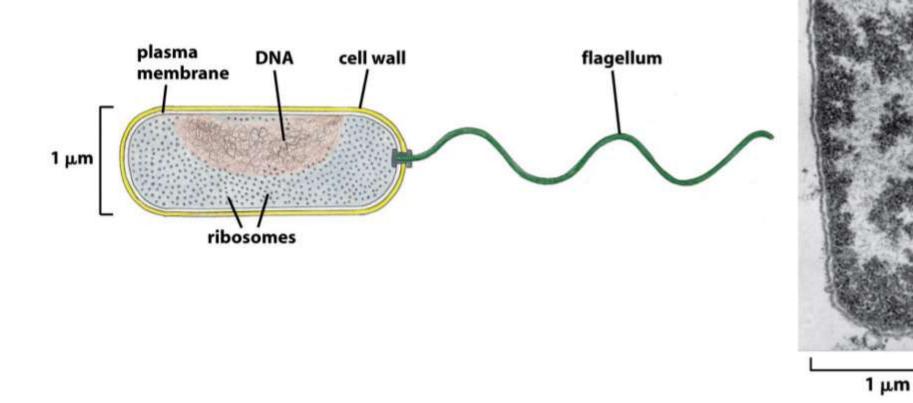
## **Great diversity of cells**



## **Cell structure**

Кишкова паличка

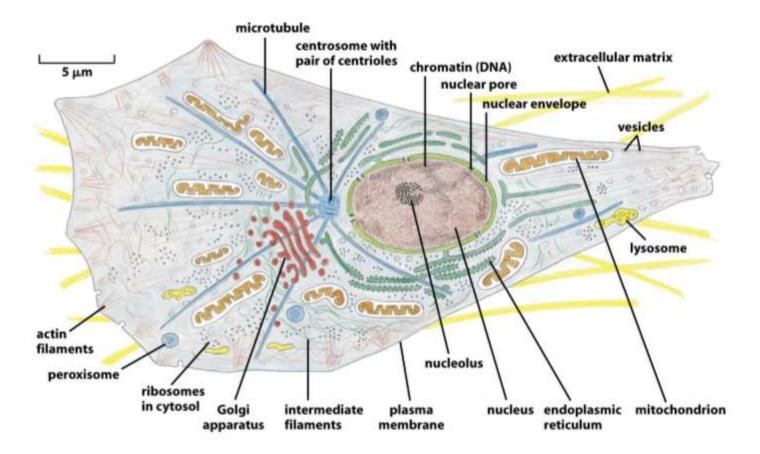
E. Coli (model prokaryotic cell)



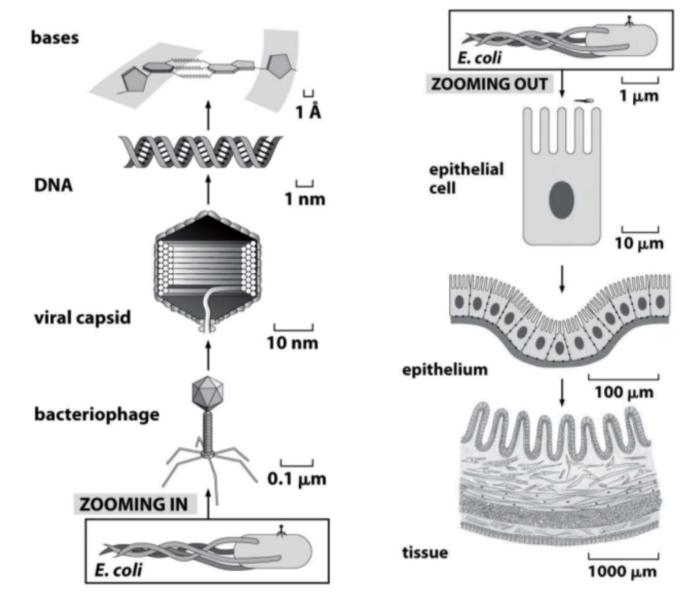
#### **Cell structure**

Фібропласт – клітина сполучної тканини (колаген для загоювання ран)

Fibroblast (model higher eukaryotic cell)

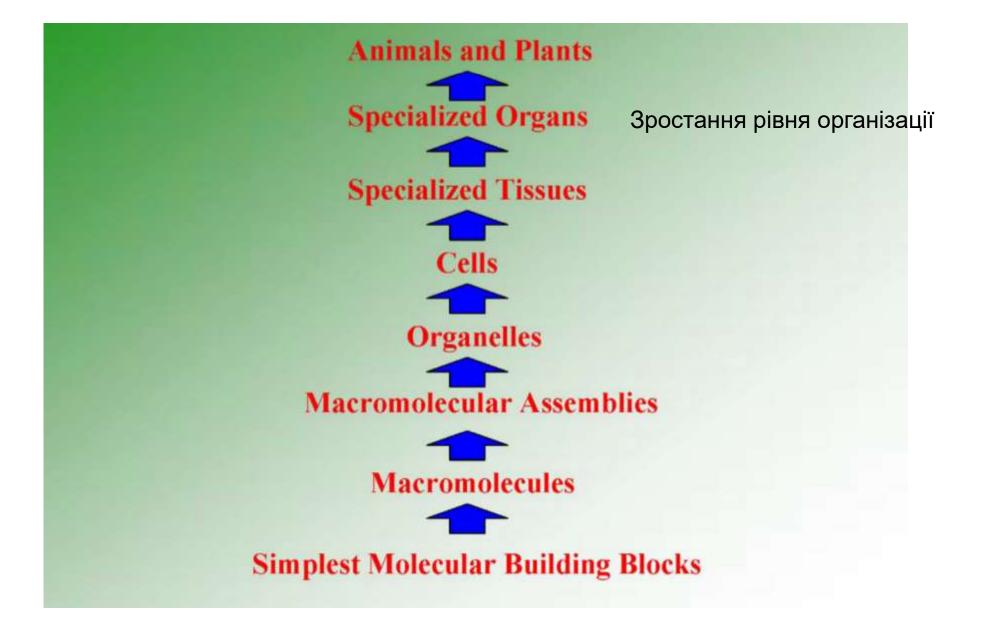


## **Biological length scales**

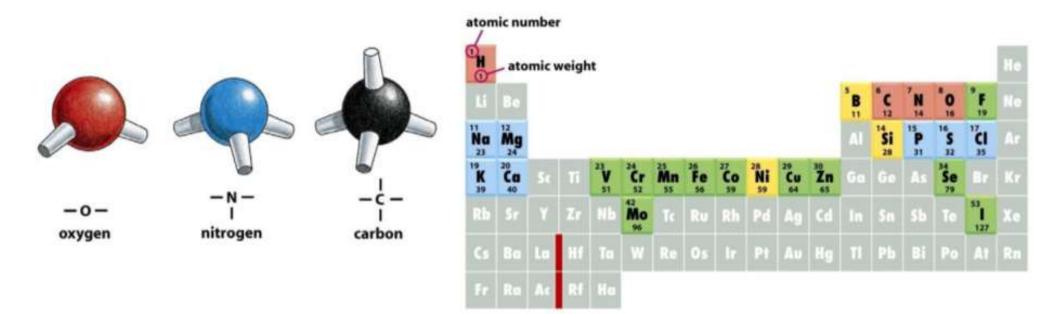


http://learn.genetics.utah.edu/content/begin/cells/scale/

# **Hierarchical organization**

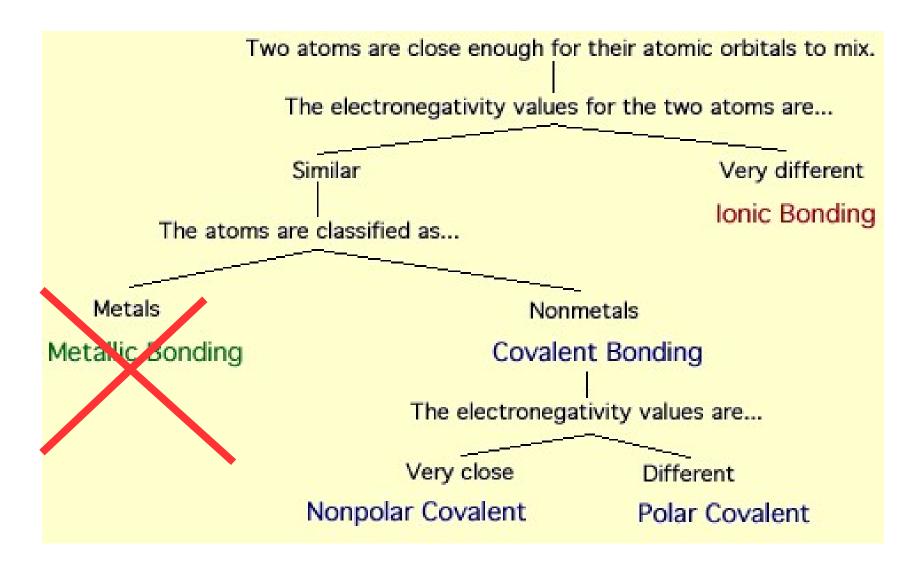


#### **Cell atoms**

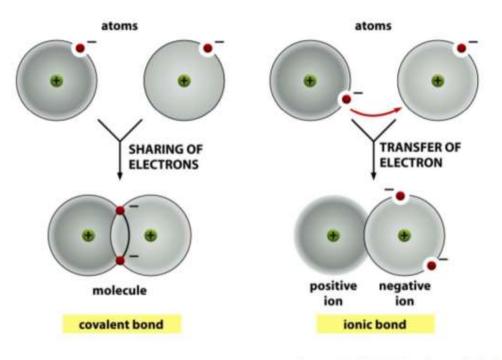


Organic Atoms (H, C, N, O) Ions (Na, K, Mg, Ca, P, S, Cl) 99% of cells 0.9%

# **Chemical bonds in biology**



## **Covalent bonds**



Polar Bond Creates permanent dipoles Nonpolar Bond oxygen When <u>sodium</u> (Na) and <u>chlorine</u> (Cl) are combined, the sodium atoms each lose an <u>electron</u>, forming cations (Na<sup>+</sup>), and the chlorine atoms each gain an electron to form anions (Cl<sup>-</sup>). These ions are then attracted to each other in a 1:1 ratio to form sodium chloride (NaCl).

 $Na + CI \rightarrow Na^+ + CI^- \rightarrow NaCI$ 

## **Noncovalent bonds**

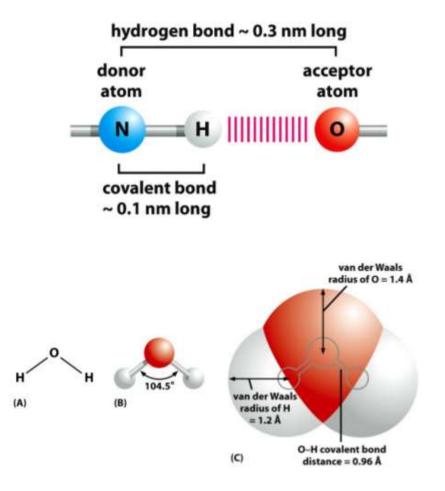
#### Hydrogen Bond

Electropositive hydrogen atom is shared by two electronegative atoms. Covalent bond is partially distorted. Interaction is weak, last a short period of time due to thermal motion.

Molecules that contain polar bonds and that can form H-bonds in water dissolve easily in water (hydrophilic). Nonpolar molecules do not dissolve in water (hydrophobic)

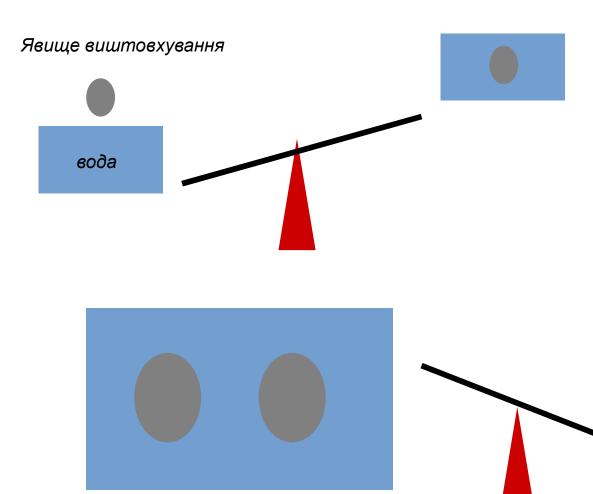
#### Van der Waals Interaction

The electron cloud of an atom fluctuates, producing a flickering dipole. Such dipoles induce oppositely flickering dipoles in a nearby atom, generating a weak interaction.



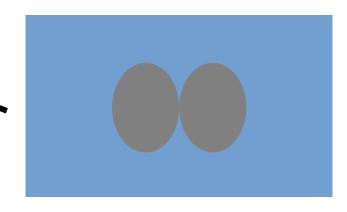
# **Hydrophobic interactions**

Гідрофоб – речовина яка не змішується з водою, олії, нафта та інші вуглеводні

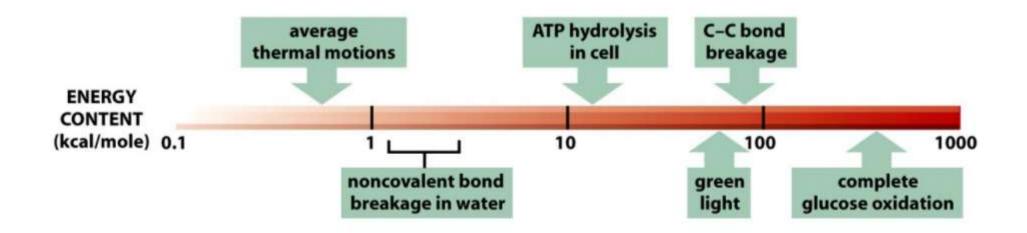




Гідрофобні частинки злипаються – ефективне притягання



# **Energy scale**

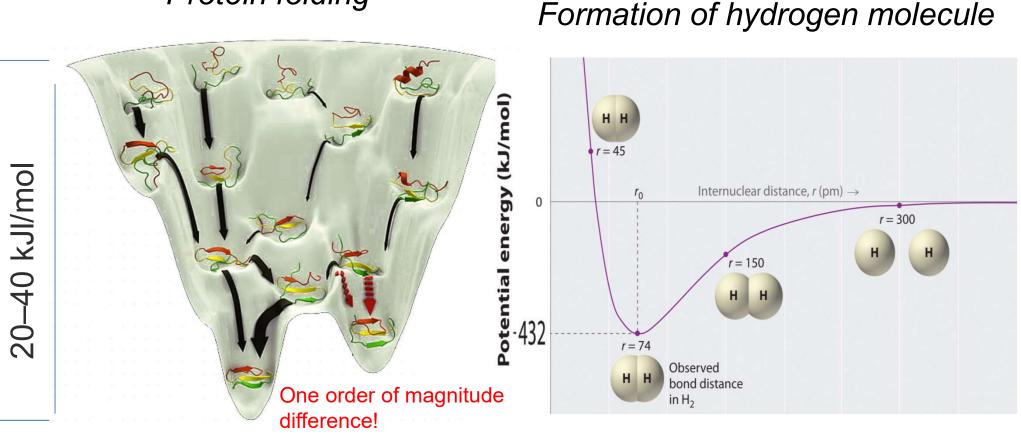


- Molecules do not fall apart by thermal agitation.
- The energy of noncovalent interactions are in the range of thermal noise in the environment.
- ATP hydrolysis energy exceeds noncovalent interactions and thermal motions
- Covalent bond energy can be used to synthesize multiple ATPs

# **Specifics of biological systems**

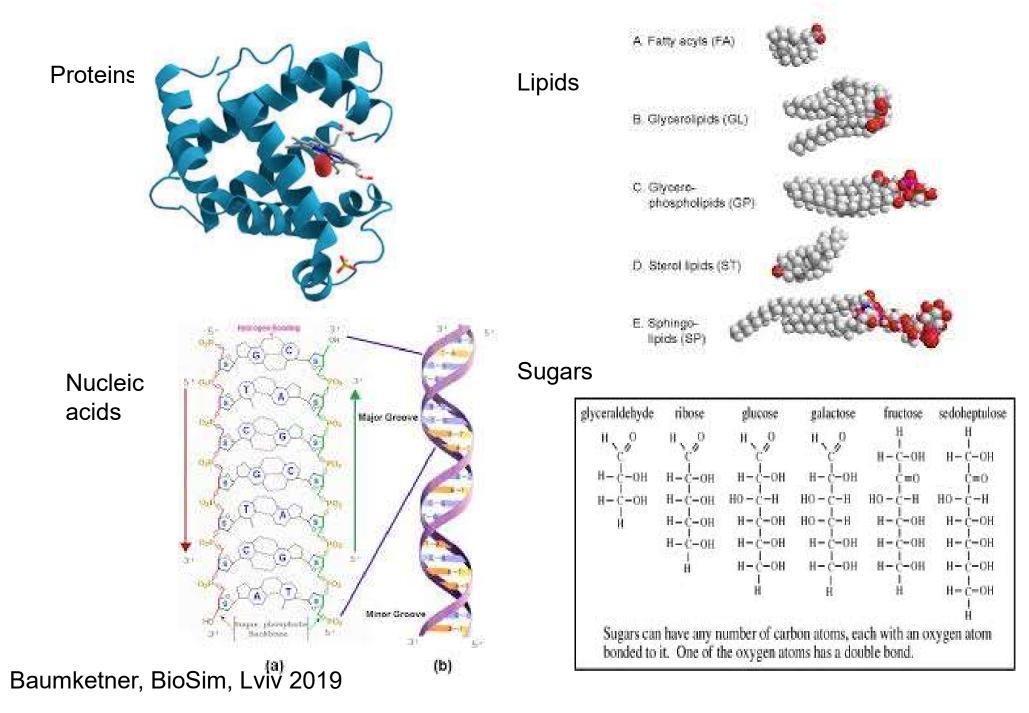
1) Processes are driven by free energy not internal energy

#### Protein folding



- a) Strong influence of thermal fluctuations and entropy
- b) Important role of non-covalent and solvent-mediated interactions
- c) Very little chemistry other than in enzymes

# **Biological molecules**

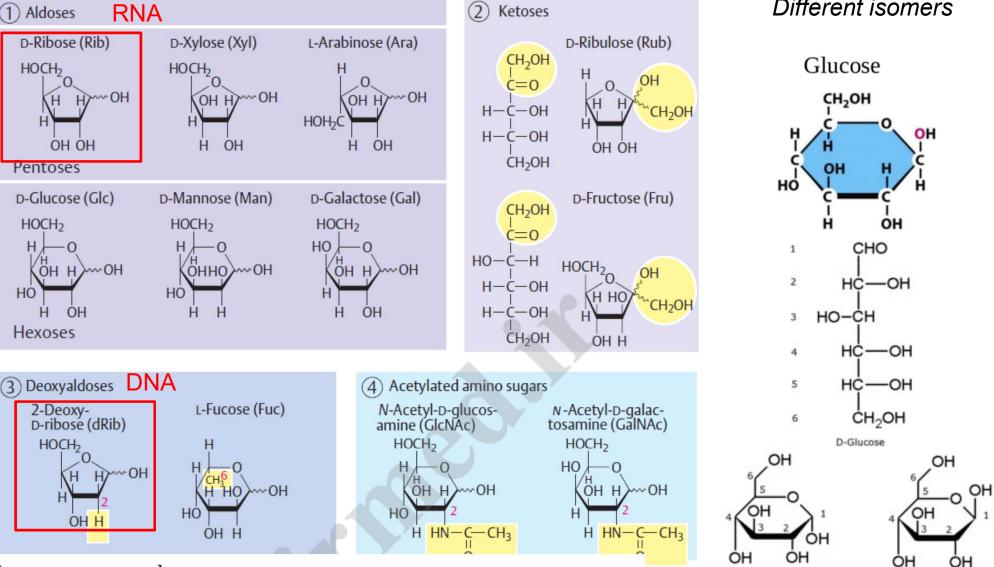


#### Different monosaccharides

# **Sugars**

Carbohydrates with hydroxyl groups

Different isomers



Energy source and storage.

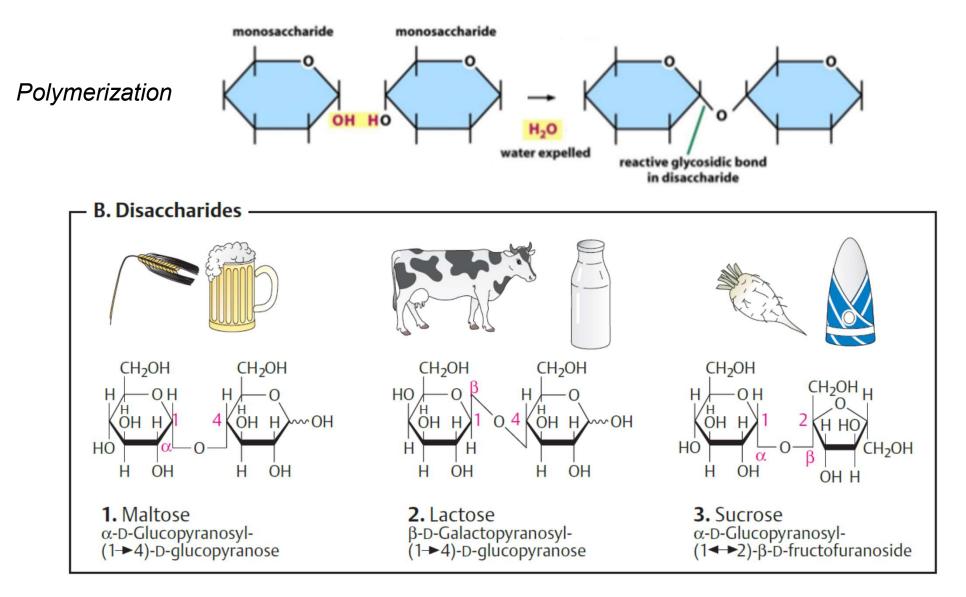
Cell wall (mechanical support)

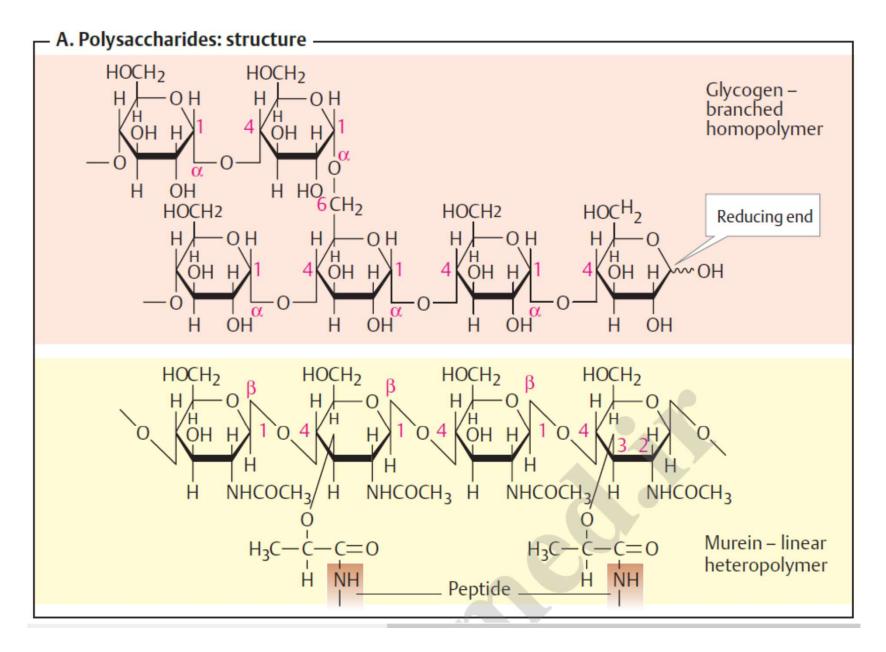
Glycoproteins, glycolipids (surface adhesion, extracellular signaling, cell-cell interactions)

Baumketner, BioSim, Lviv 2019

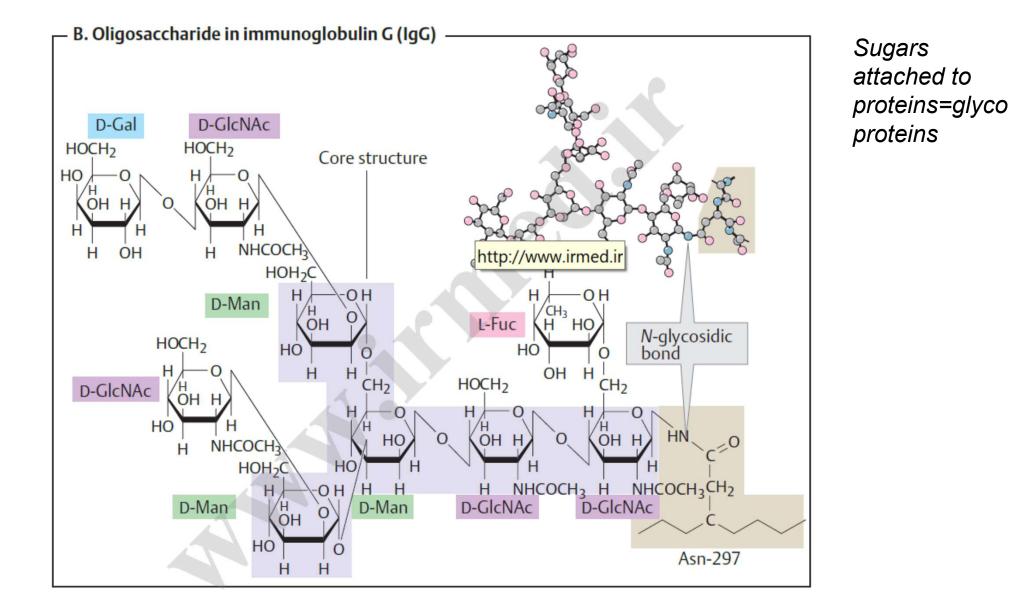
β-D-Glucose

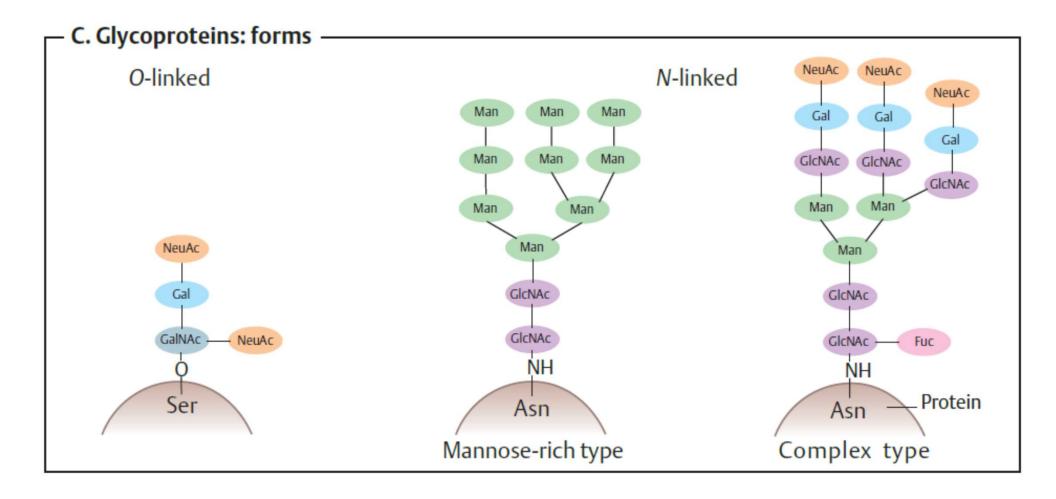
a-D-Glucose

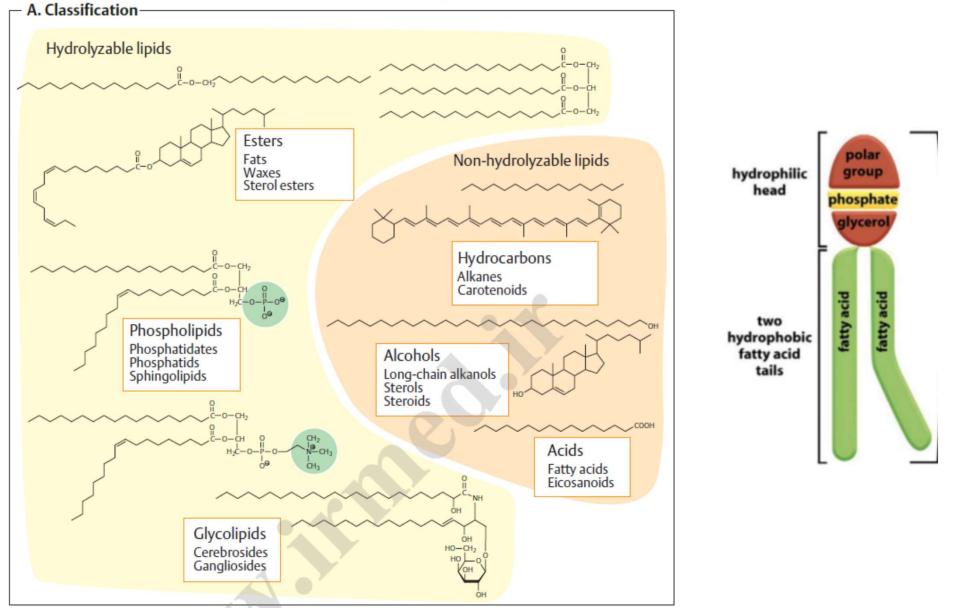


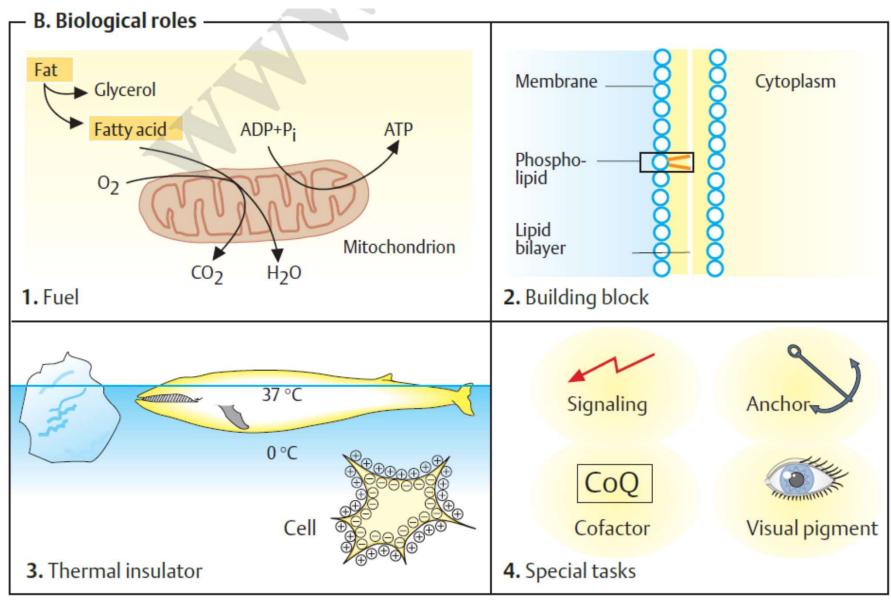


– B. Important polysaccharides –							
Poly- saccharide	Mono- saccharide1	Mono- saccharide 2	Linkage	Branch- ing	Occurrence	Function	
<b>Bacteria</b> Murein Dextran	D-GlcNAc D-Glc	D-MurNAc <sup>1)</sup>	$\beta 1 \rightarrow 4$ $\alpha 1 \rightarrow 6$	 α1→3	Cell wall Slime	SC WB	
Plants Agarose Carrageenan Cellulose Xyloglucan Arabinan Amylose Amylopectin Inulin	D-Gal D-Gal D-Glc D-Glc L-Ara D-Glc D-Glc D-Fru	L-aGal <sup>2)</sup>  D-Xyl (D-Gal, L-Fuc) 	$ \begin{array}{c} \beta 1 \rightarrow 4 \\ \beta 1 \rightarrow 3 \end{array} \\ \beta 1 \rightarrow 4 \\ \beta 1 \rightarrow 4 \\ \alpha 1 \rightarrow 5 \\ \alpha 1 \rightarrow 4 \\ \alpha 1 \rightarrow 4 \\ \beta 2 \rightarrow 1 \end{array} $		Red algae (agar) c://www.irmed.ir Cell wall Cell wall (Hemicellulose) Cell wall (pectin) Amyloplasts Amyloplasts Storage cells	WB WB SC SC SC RC RC RC RC	
Animals Chitin Glycogen Hyaluronic acid	D-GlcNAc D-Glc D-GlcUA	 D-GlcNAc	$ \begin{array}{c} \beta 1 \rightarrow 4 \\ \alpha 1 \rightarrow 4 \\ \beta 1 \rightarrow 4 \\ \beta 1 \rightarrow 3 \end{array} $	α <u>1</u> →6	Insects, crabs Liver, muscle Connective tissue	SK RK SK,WB	





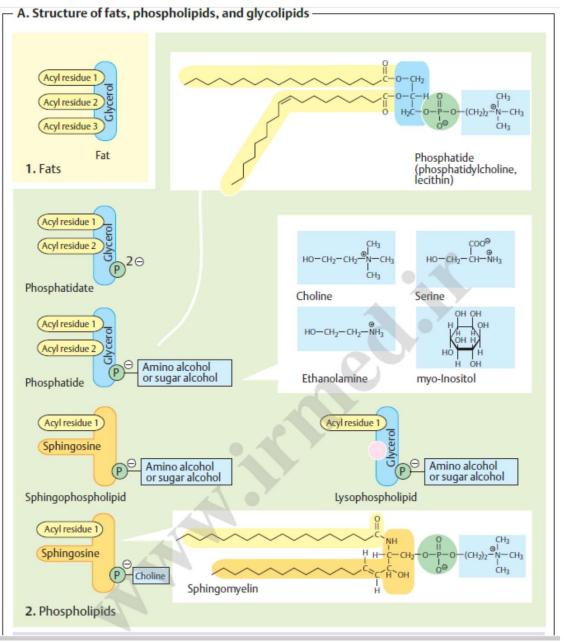


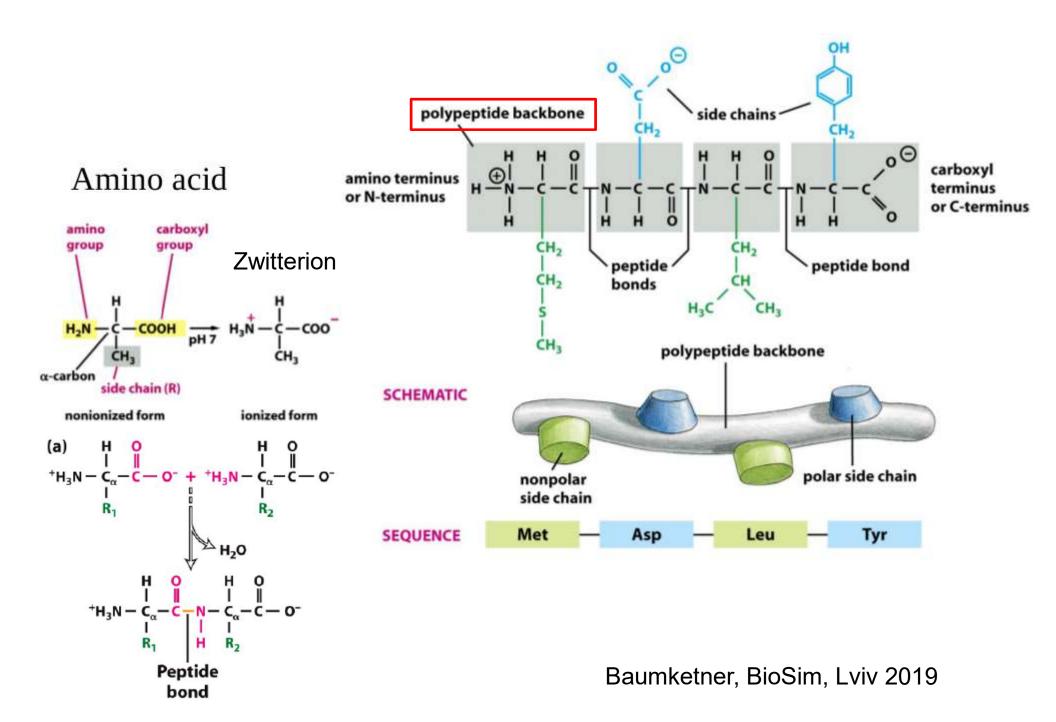


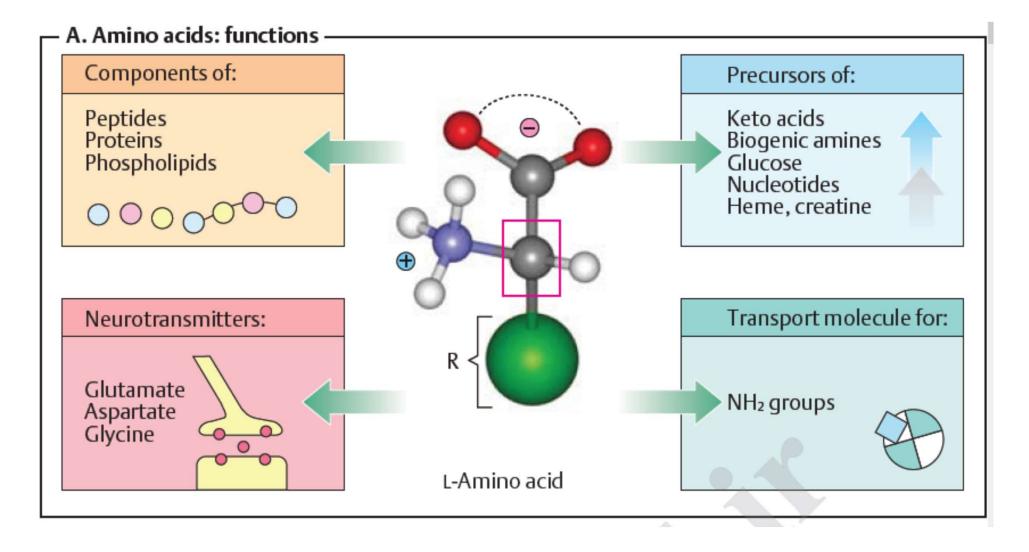
Baumketner, BioSim, Lviv 2019

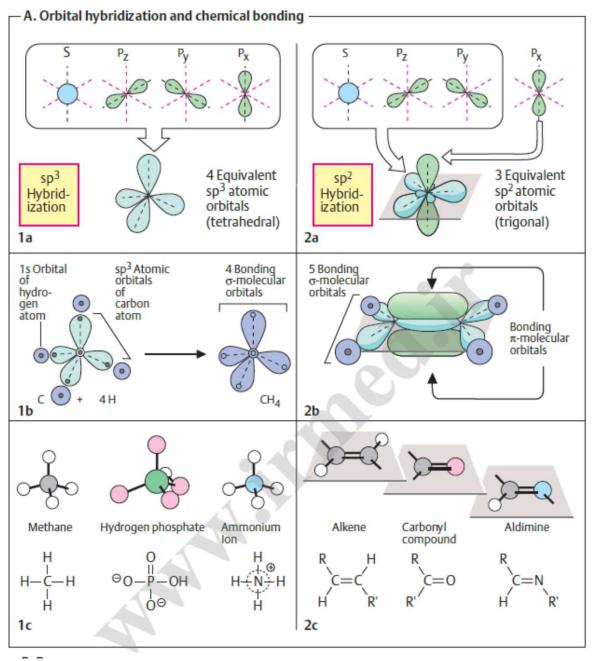
Name	Number of carbons					
		<ul> <li>Number of double bonds</li> <li>Position of double bonds</li> </ul>				
Formic acid	1:0	<ul> <li>Not contained</li> </ul>				
Acetic acid	2:0	Q in lipids				
Propionic acid	3:0					
Butyric acid	4:0	0				
Valerianic acid	5:0	Q				
Caproic acid	6:0	О HOOC-CH2-CH2-CH2-CH2-CH3				
Caprylic acid	8:0	Caproic acid				
Capric acid	10:0	٩				
Lauric acid	12:0					
Myristic acid	14:0					
Palmitic acid	16:0					
Stearic acid	18:0					
Oleic acid	18:1; 9	0				
🎋 Linoleic acid	18:2; 9,12	0				
🔆 Linolenic acid	18:3; 9,12,15					
Arachidic acid	20:0					
🎋 Arachidonic acid	20:4; 5,8,11,14					
Behenic acid	22:0	Q				
Erucic acid	22:1; 13					
Lignoceric acid	24:0	••••••				
Nervonic acid	24:1; 15	0				

Fatty acids



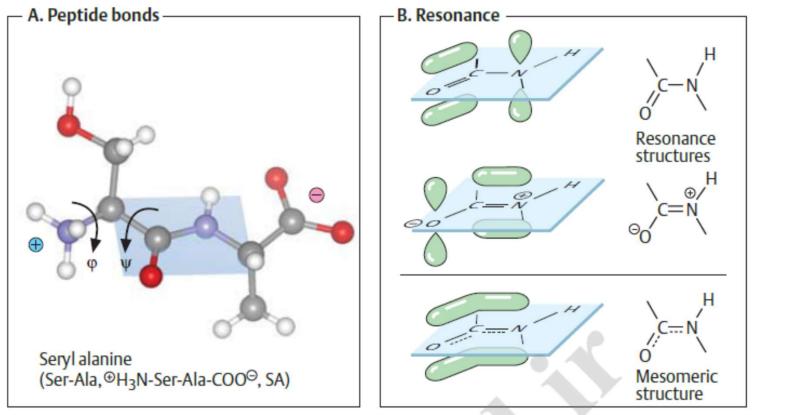






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No rotation around double bonds!



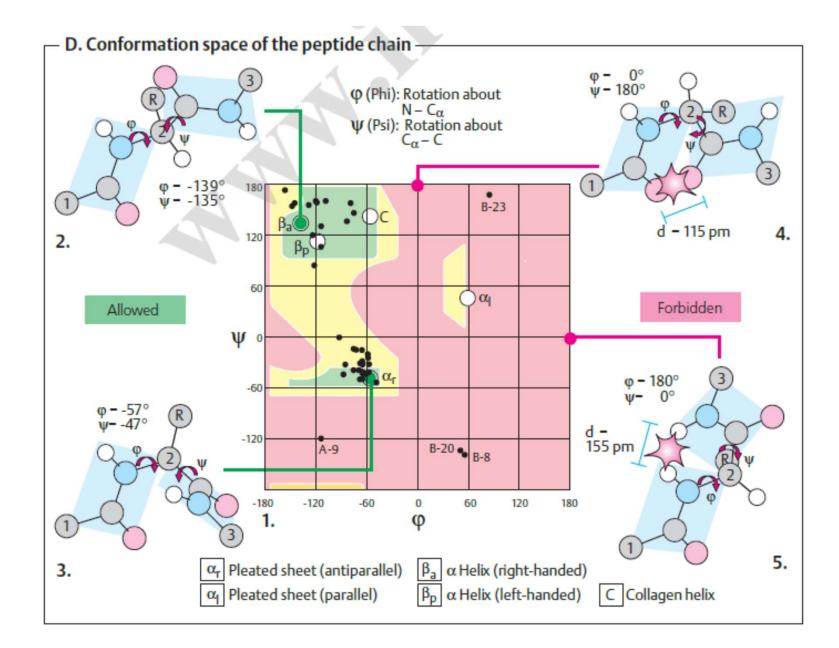
Cost of rotation is 90kJ/mol. Compare to 2.5kJ/mol of thermal energy at 300K

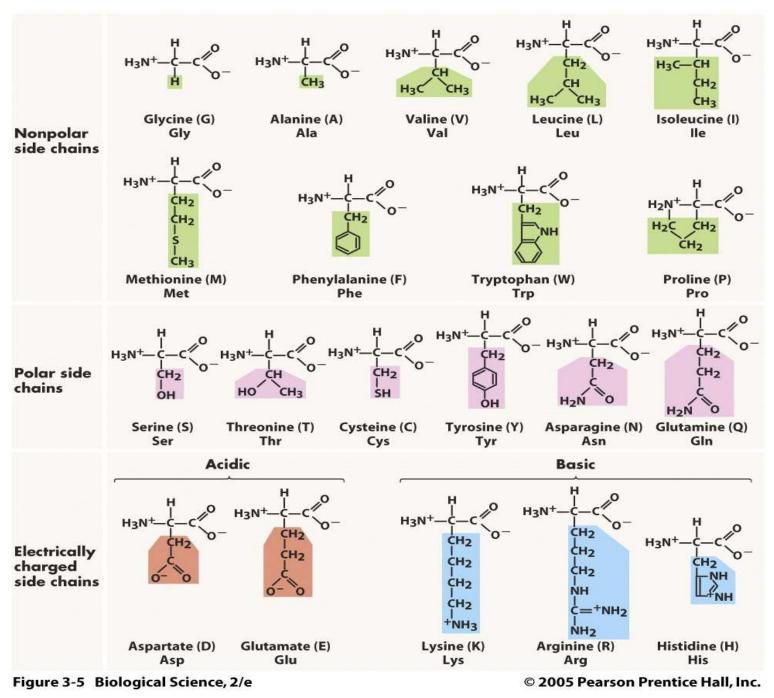
No rotation around C-N or O-C bonds.

The peptide bond is planar and rigid!

Phi/Psi angles are the only real degrees of freedom of the protein backbone

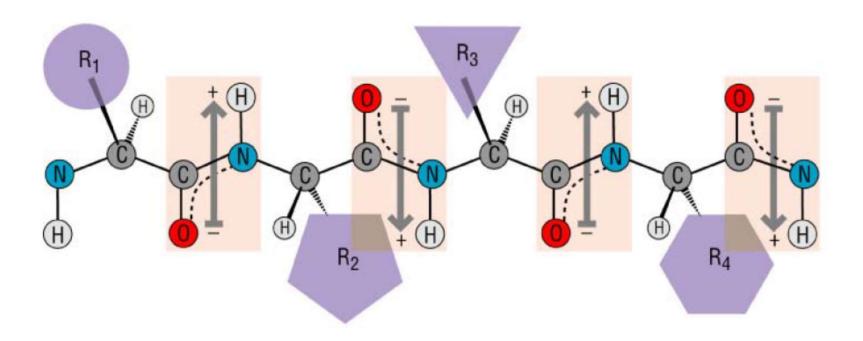
## **Ramachandran plot**





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## **Primary structure**

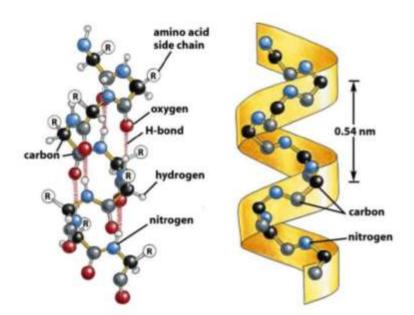


...-ASP-ALA-VAL-ILE-ASP-SER-GLU-PRO-THR-...

#### ...DAVIDSEPT...

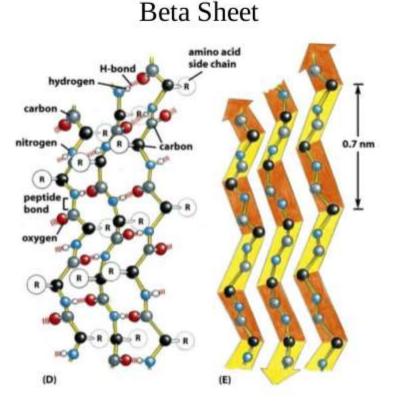
# **Secondary structure**

H- bonding between N-H and C=O groups without involving side chains.



Alpha Helix

C=O of one residue bond to N-H of the fourth residue 3.6 amino acid residues per turn. Helical pitch is 0.54 nm.



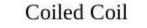
C=O of one residue bond to N-H of a residue on another strand 0.48 nm between strands 0.35 nm per residue

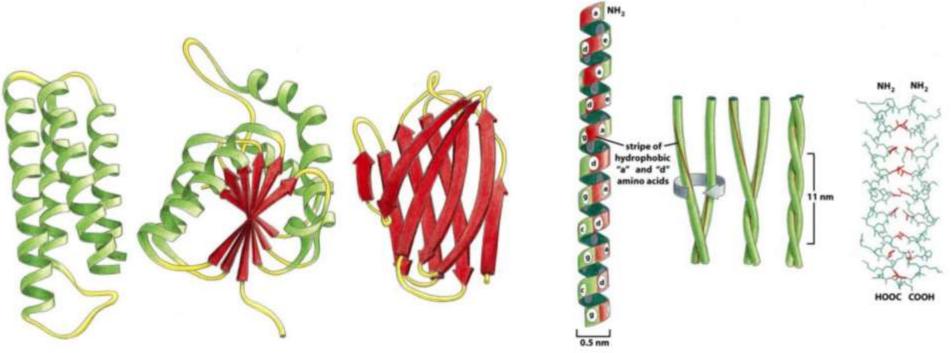
# **Tertiary structure**

- Helices and sheets often combine in various ways.
- Certain combinations of  $\alpha$  and  $\beta$  repeat over and over, called MOTIFS

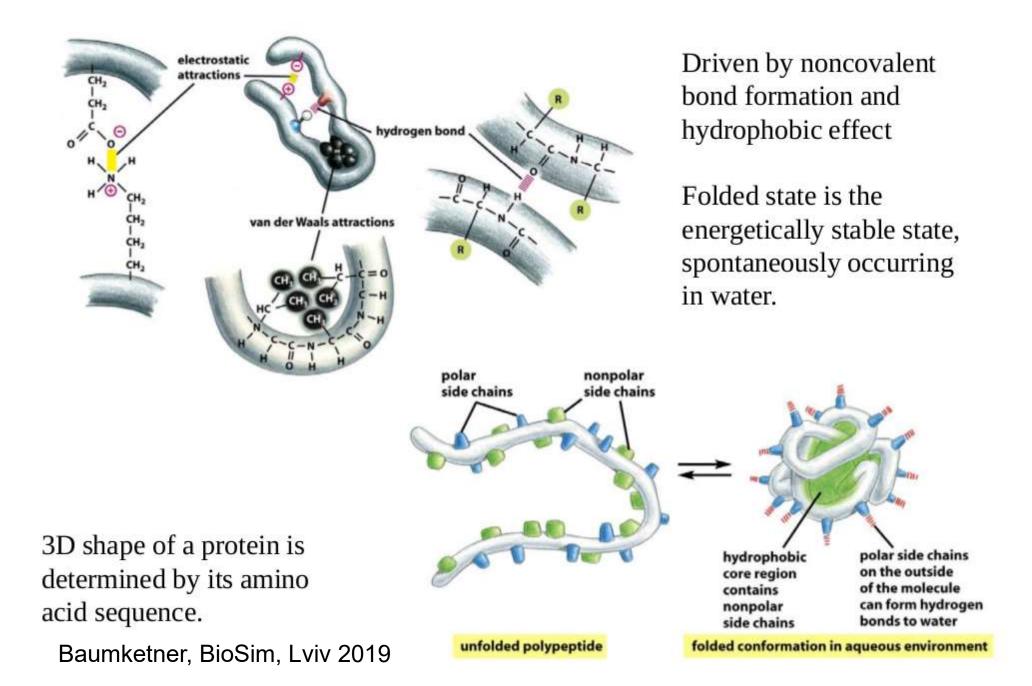
Four Helix Bundle

Beta Barrel

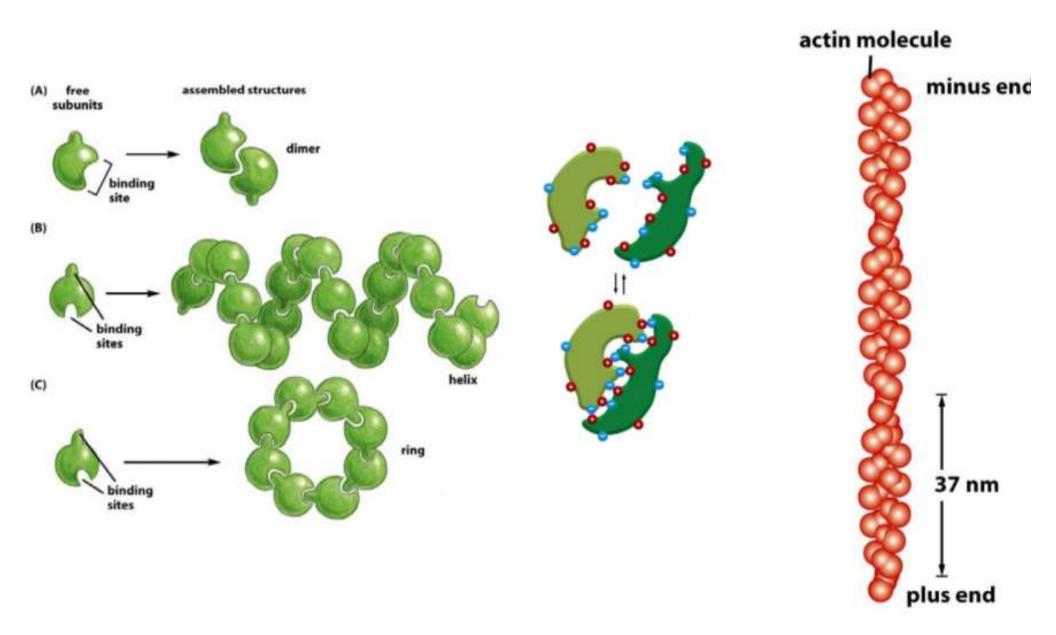


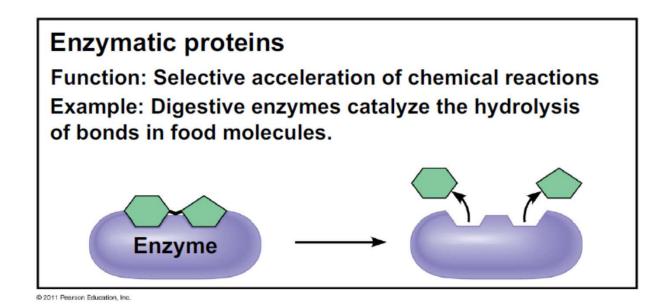


# **Protein folding**



### Interactions between proteins



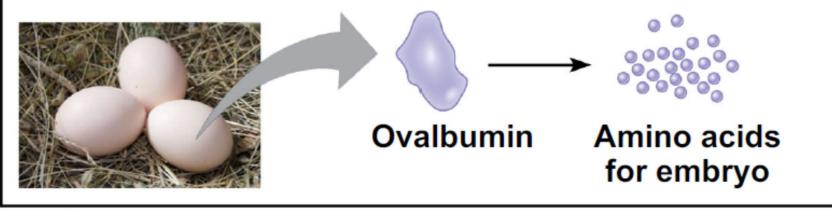


- Enzymes are a type of protein that acts as a catalyst to speed up chemical reactions
- Enzymes can perform their functions repeatedly, functioning as workhorses that carry out the processes of life
- http://www.biotopics.co.uk/other/morinf.html

### Storage proteins

Function: Storage of amino acids

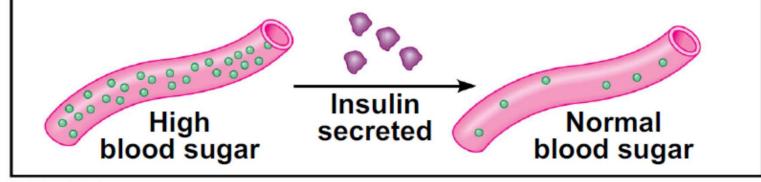
Examples: Casein, the protein of milk, is the major source of amino acids for baby mammals. Plants have storage proteins in their seeds. Ovalbumin is the protein of egg white, used as an amino acid source for the developing embryo.



@ 2011 Pearson Education, Inc.

### **Hormonal proteins**

Function: Coordination of an organism's activities Example: Insulin, a hormone secreted by the pancreas, causes other tissues to take up glucose, thus regulating blood sugar concentration



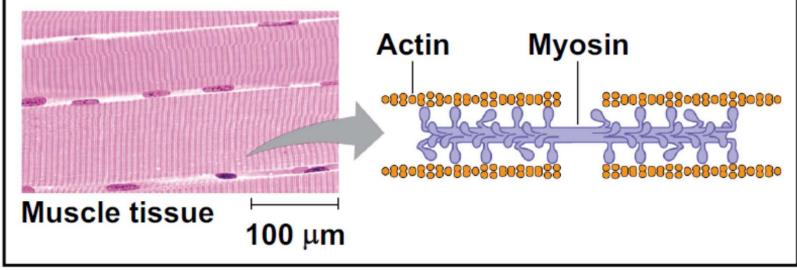
@ 2011 Pearson Education, Inc.

#### Insulin protein entry: https://www.ncbi.nlm.nih.gov/protein/AAA59172.1

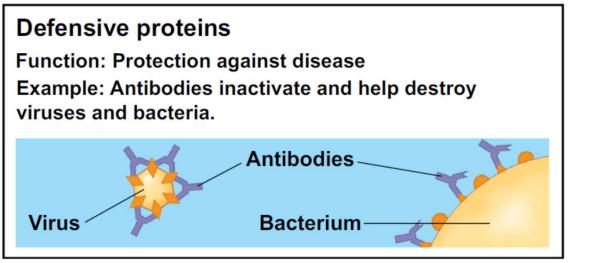
### **Contractile and motor proteins**

**Function: Movement** 

Examples: Motor proteins are responsible for the undulations of cilia and flagella. Actin and myosin proteins are responsible for the contraction of muscles.



@ 2011 Pearson Education, Inc.



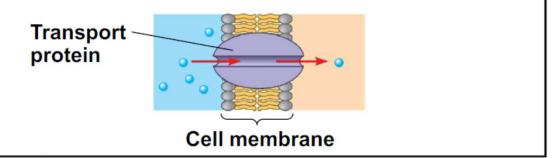
Recognizes pathogen (antigen) via fragment antigen binding motif

@ 2011 Pearson Education, Inc.

#### **Transport proteins**

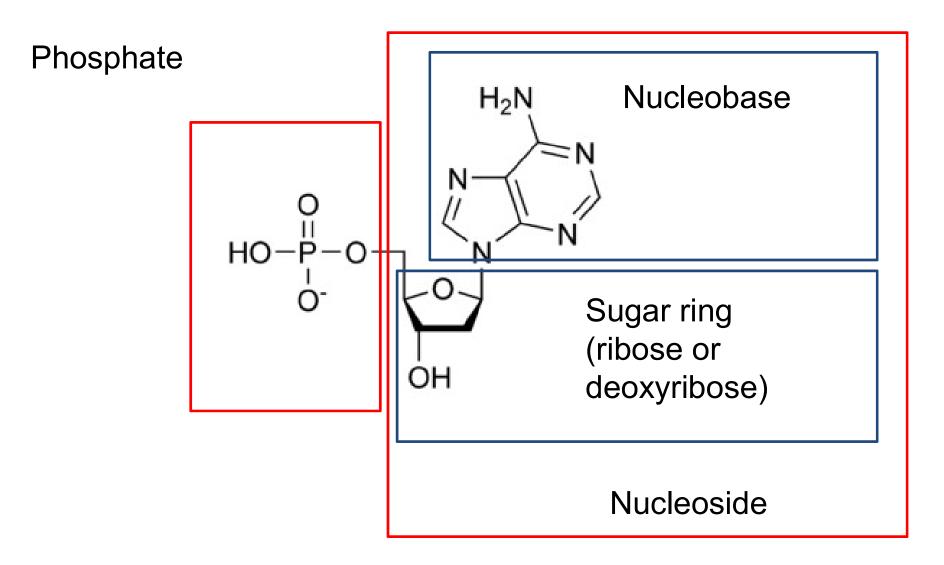
**Function: Transport of substances** 

Examples: Hemoglobin, the iron-containing protein of vertebrate blood, transports oxygen from the lungs to other parts of the body. Other proteins transport molecules across cell membranes.

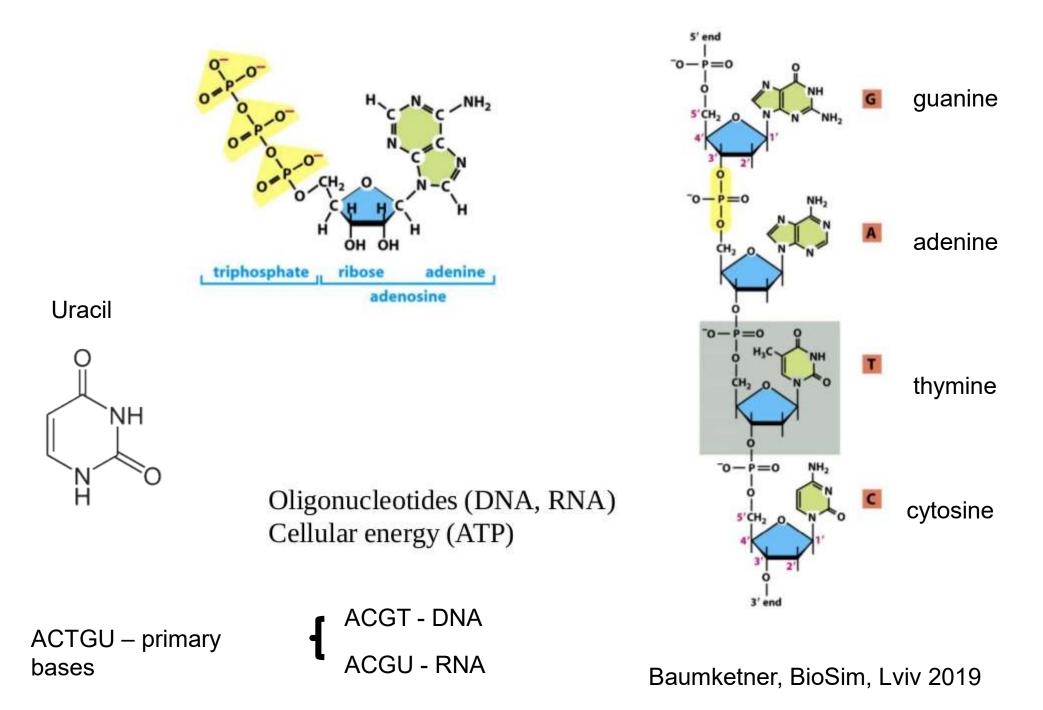


© 2011 Pearson Education, Inc.

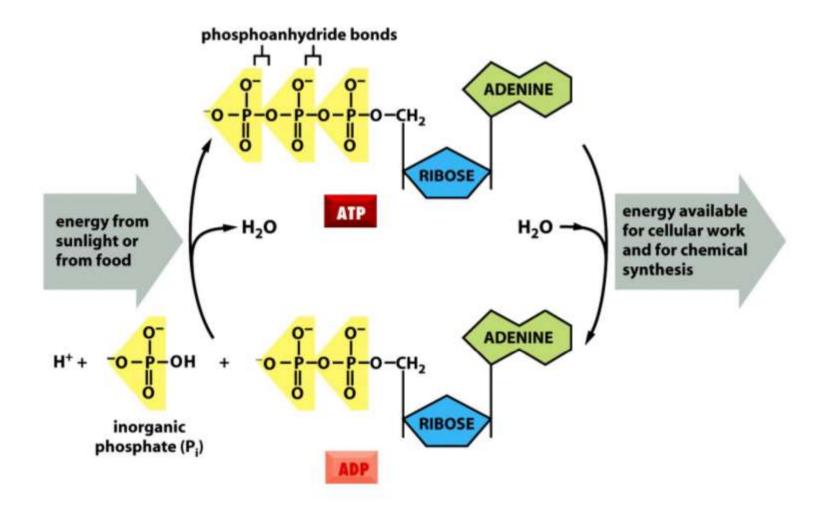
### **Nucleotides**



## Nucleic acids=poly-nucleaotides



### **ATP** as energy source



### **DNA structure**

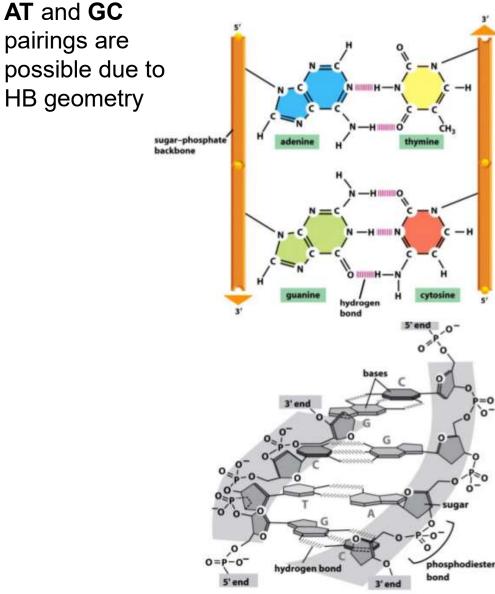
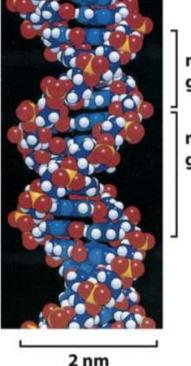


Figure 1.3b Physical Biology of the Cell (1) Garland Science 2008)



• Forms a double helix.

nucleotide pairs.

nucleotide

• Each turn is made of 10

• 3.4 nm between adjacent

minor groove

major groove

Play DNA packaging movie! http://www.youtube.com/watch?v=gbSIBhFwQ4s

### **Genetic code**

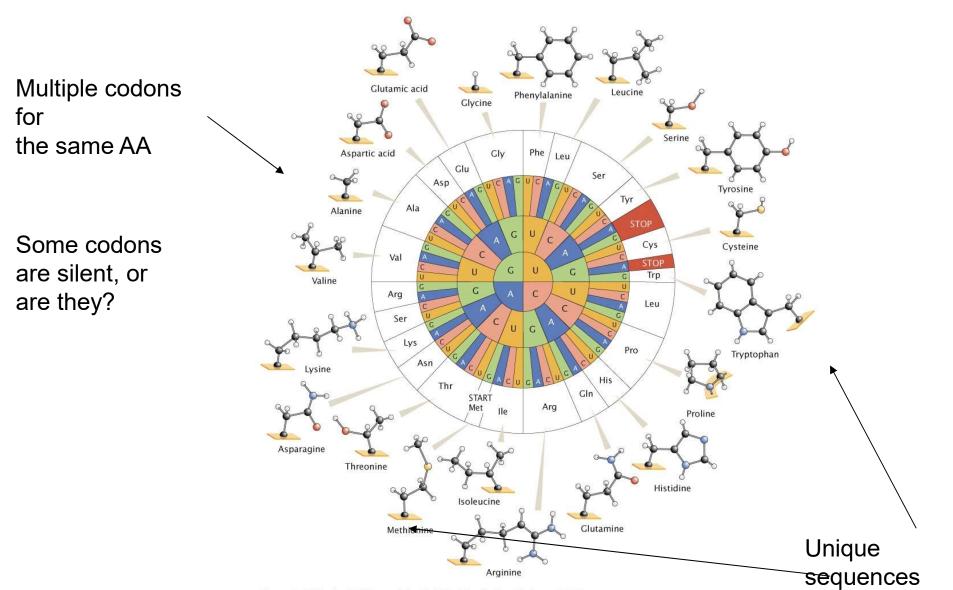
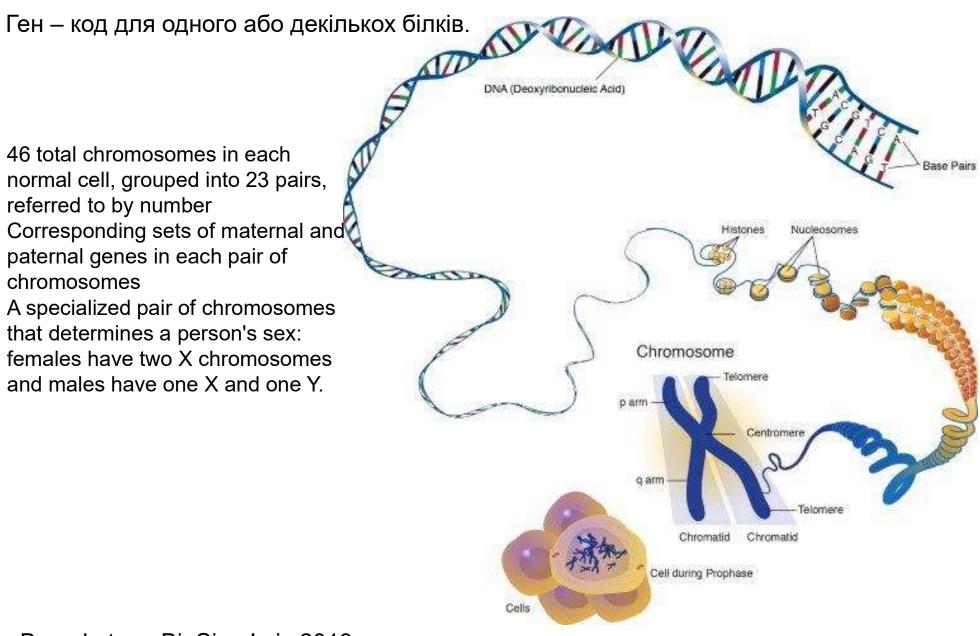
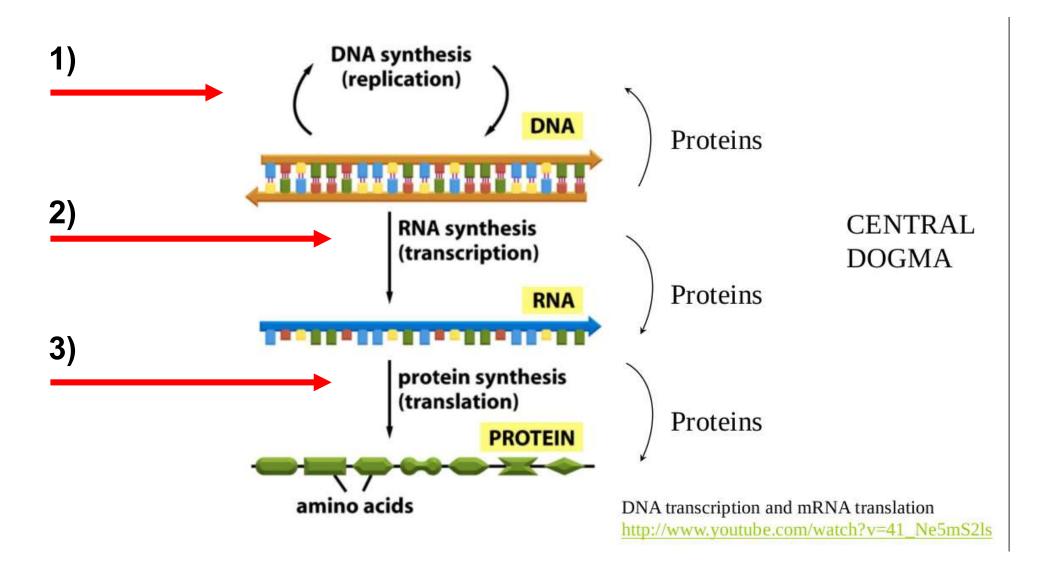


Figure 1.4 Physical Biology of the Cell, 2ed. (© Garland Science 2013)

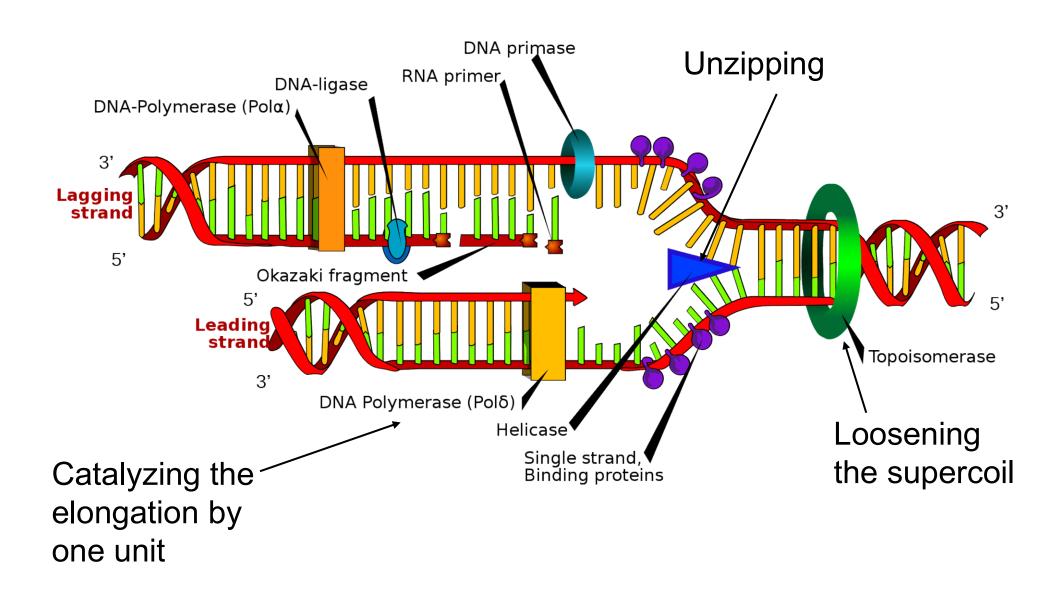
# How is genetic information stored?



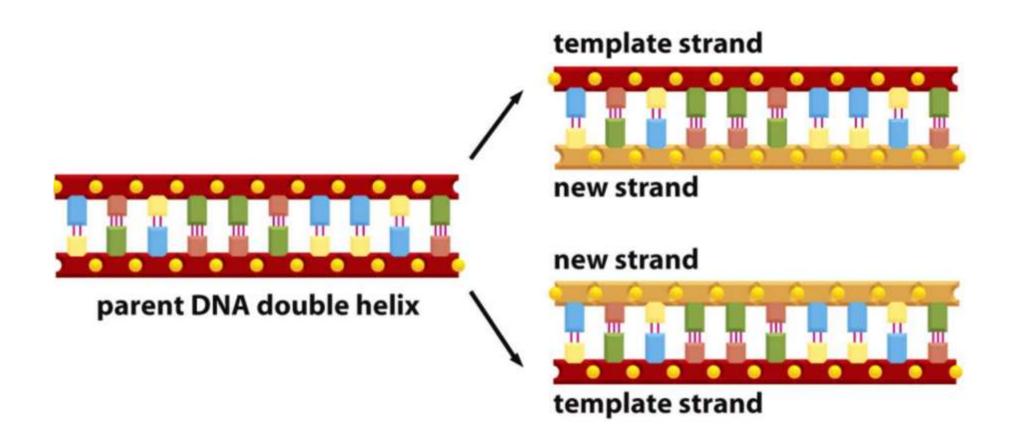
### **Transcription + translation**



# **DNA replication**



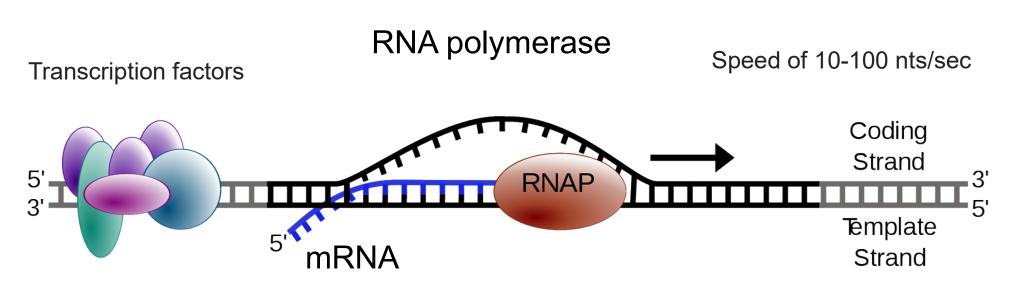
# **DNA replication**



Show DNA polymerase advanced

http://www.youtube.com/watch?v=I9ArIJWYZHI&feature=related

# Transcription



1.RNA polymerase, together with one or more general transcription factors, binds to promoter DNA.

2.RNA polymerase creates a transcription bubble, which separates the two strands of the DNA helix. This is done by breaking the hydrogen bonds between complementary DNA nucleotides.

3.RNA polymerase adds RNA nucleotides (which are complementary to the nucleotides of one DNA strand).

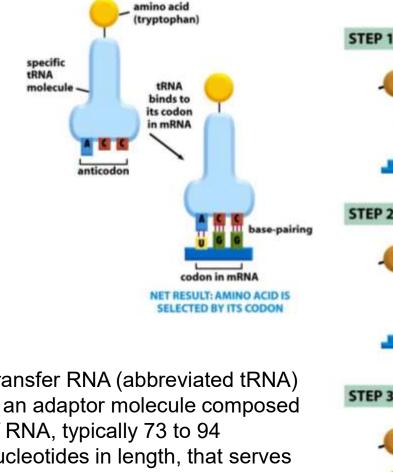
4.RNA sugar-phosphate backbone forms with assistance from RNA polymerase to form an RNA strand.

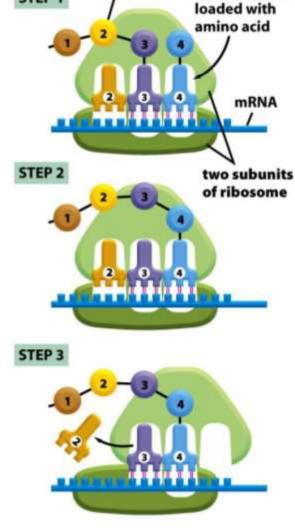
5.Hydrogen bonds of the RNA–DNA helix break, freeing the newly synthesized RNA strand.

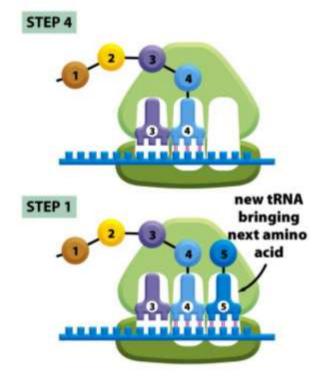
# **Protein synthesis=translation**

growing polypeptide chain

incoming tRNA

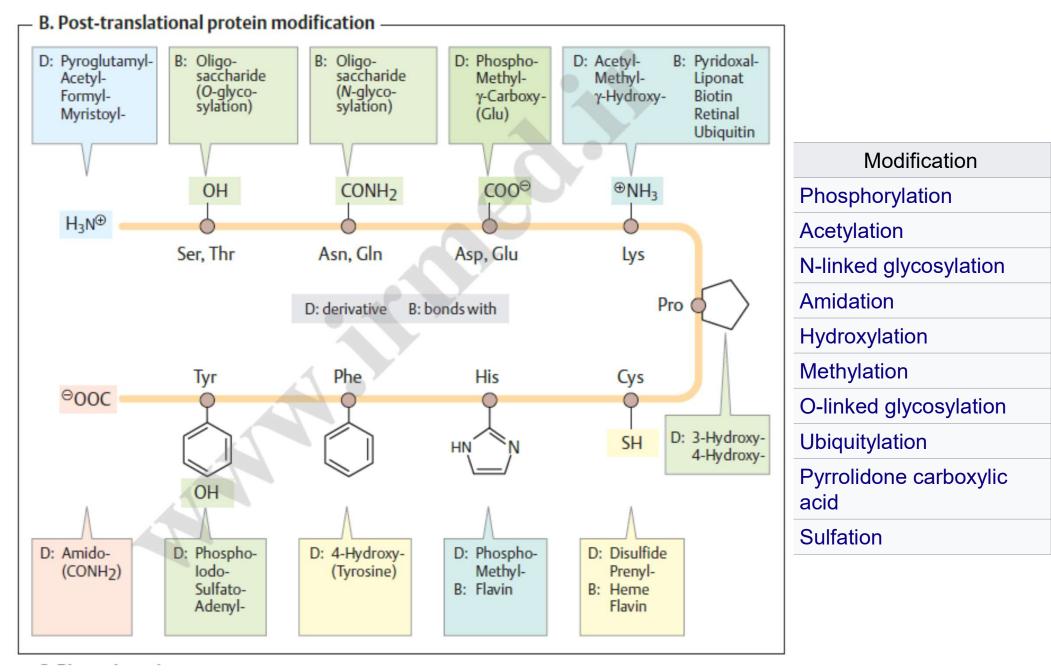






Transfer RNA (abbreviated tRNA) is an adaptor molecule composed of RNA, typically 73 to 94 nucleotides in length, that serves as the physical link between the nucleotide sequence of nucleic acids (DNA and RNA) and the amino acid sequence of proteins.

### **Proteins modifications**



### Абетки життя

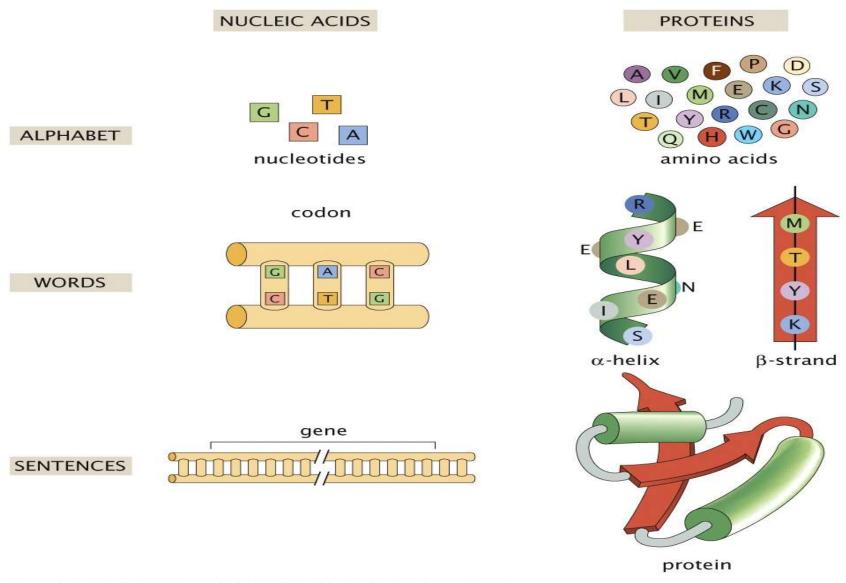
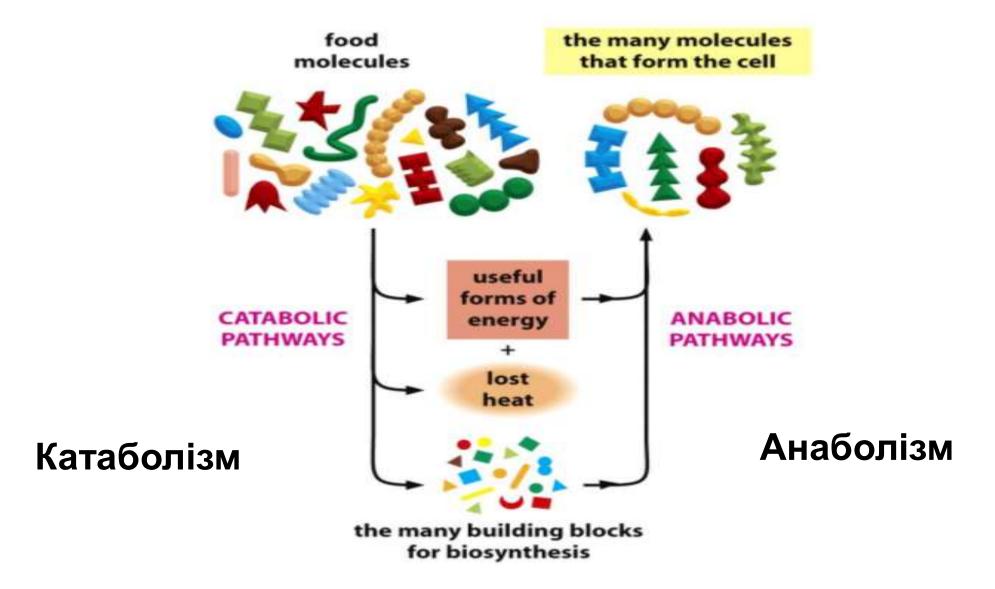


Figure 1.2 Physical Biology of the Cell, 2ed. (© Garland Science 2013)

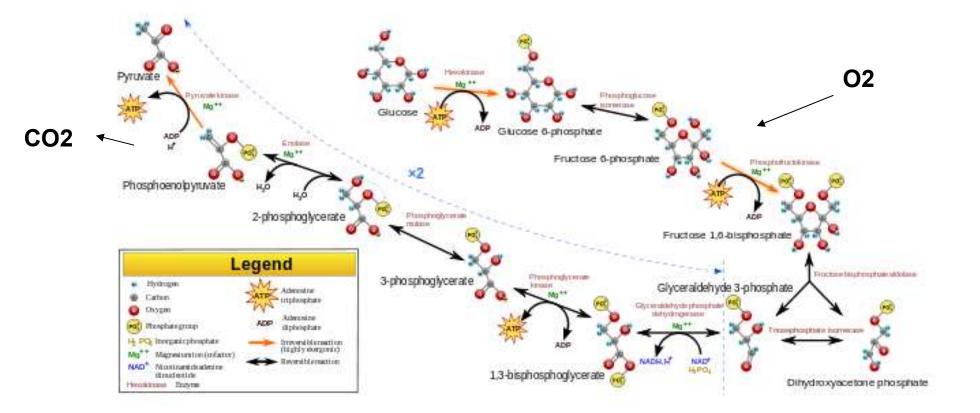
### **Metabolism**

Процес перетворення енергії в клітинах

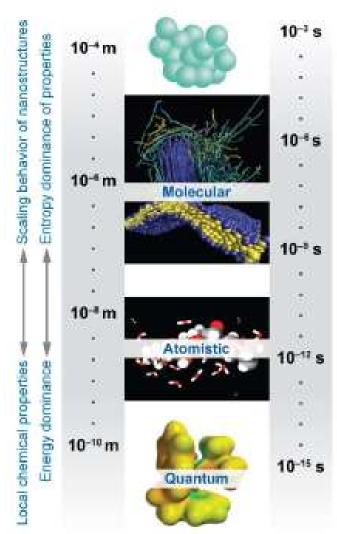


# Приклад катаболізму: Гліколіз

Процес перетравлювання цукру (глюкози) досить складний. В результаті утворються молекули **ATP** та піруват. Споживається кисень для реакції оксидації та виділяється дво-окис вуглецю.



#### How to model biological molecules



Praprotink M, et al. 2008. Annu, Rev. Phys. Chem. 59:545-71.

#### MACRO

Finite-element calculations Continuum hydrodynamics Dissipative particle dynamics

MD-MC-Lattice Boltzmann

#### MESO

MICRO

Car-Parrinello MD

Quantum MC

MC statics/dynamics MD, NEMD

Classical force field MD, MC

Quantum chemical methods

For harmonic

oscillator, for

XTZ=L)

instance:

1) Adiabatic approximation. Nuclei are moving in the field created by the electrons.

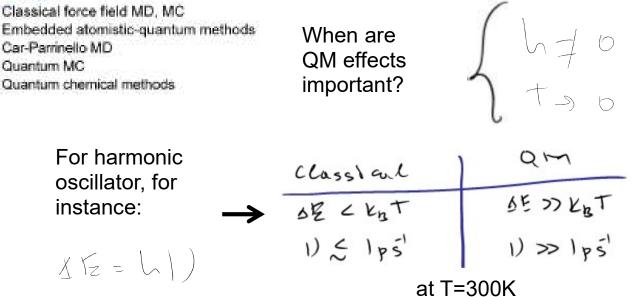
> 2) Relaxation processes taking place on picosecond timescale and slower.

Very little chemistry happens during the

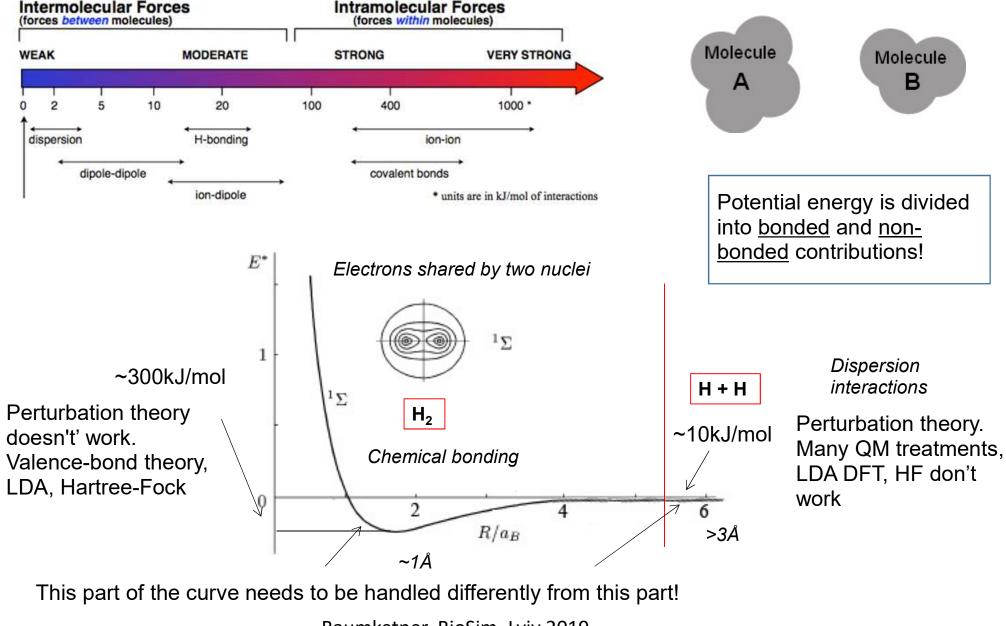
appropriate level of description is

classical. This entails:

majority of all biological processes so the

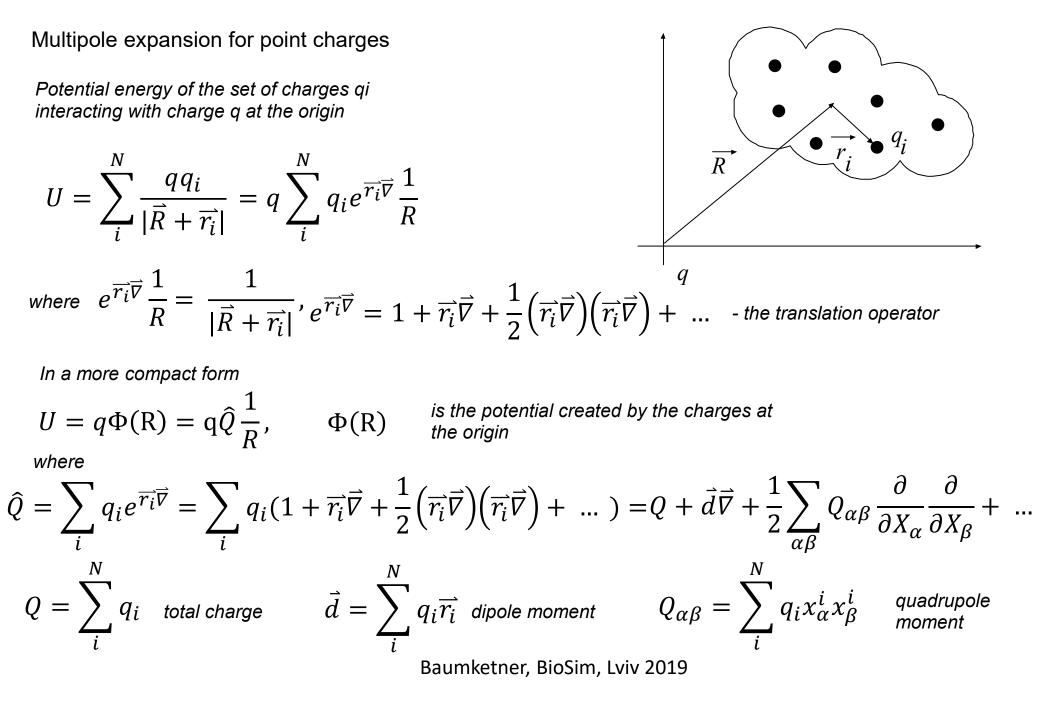


Baumketner, BioSim, Lviv 2019



#### Separation into bonded and non-bonded energy terms

#### Non-bonded energy



Potential energy then can be written as series:

$$\begin{split} U &= q \Phi(R) = q \varphi_m(R) + q \varphi_d(R) + q \varphi_Q(R) + \dots \\ \varphi_m &= \frac{Q}{R} \qquad \text{potential created by the monopole=total charge} \quad \sim \frac{1}{R} \\ \varphi_d &= -\frac{\vec{d}\vec{R}}{R^3} \quad \text{potential created by point dipole (at vector} - \vec{R}) \sim \frac{1}{R^2} \\ \varphi_Q &= \frac{1}{2} \sum_{\alpha\beta} Q_{\alpha\beta} \left( \frac{3X_{\alpha}X_{\beta}}{R^2} - \delta_{\alpha\beta} \right) \frac{1}{R^3} \quad \text{potential created by point quadrupole} \quad \sim \frac{1}{R^3} \end{split}$$

Another way to look the interaction energy is to compute interaction of point multipoles with the field created by the charge at the origin

$$U = Q \frac{q}{R} \qquad -\vec{d}\vec{E} \qquad -\frac{1}{2} \sum_{\alpha\beta} Q_{\alpha\beta} \frac{\partial}{\partial X_{\alpha}} E_{\beta}$$

potential created at the location of the charge distribution by point charge at the origin

Monopole "interacts" with the potential

$$\vec{E} = -q\vec{\nabla}\frac{1}{R} = \frac{q\vec{R}}{R^3}$$

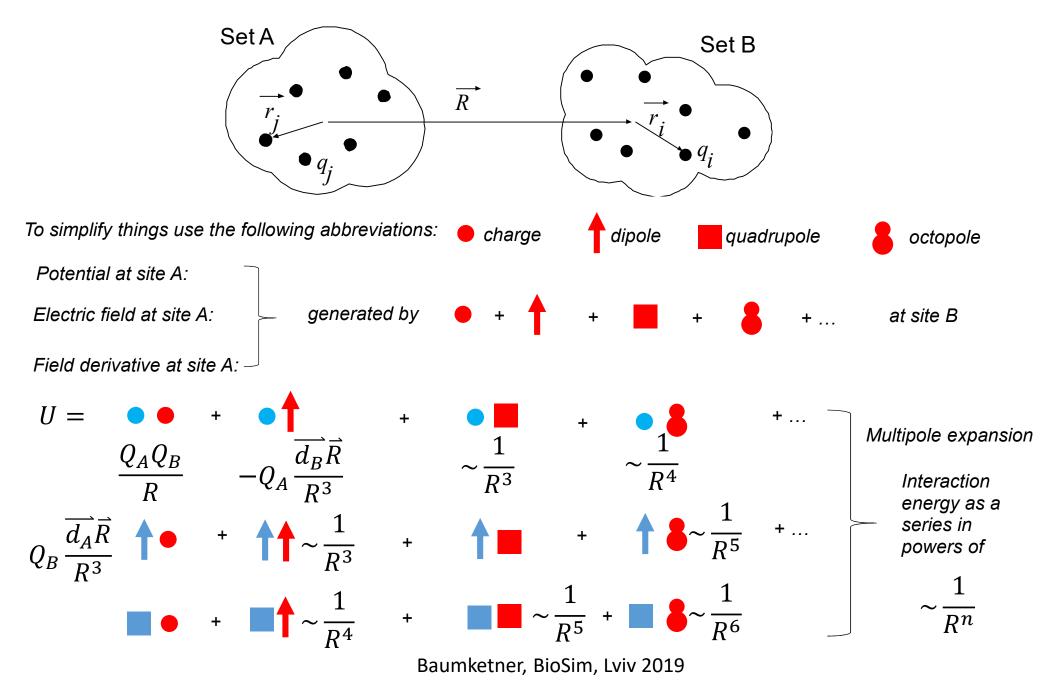
field created by the point charge at the location of the dipole

Dipole "interacts" with the field

derivatives of the electric field created by the point charge

Quadrupole "interacts" with the field derivative

Apply these formulas to two distributions of charges



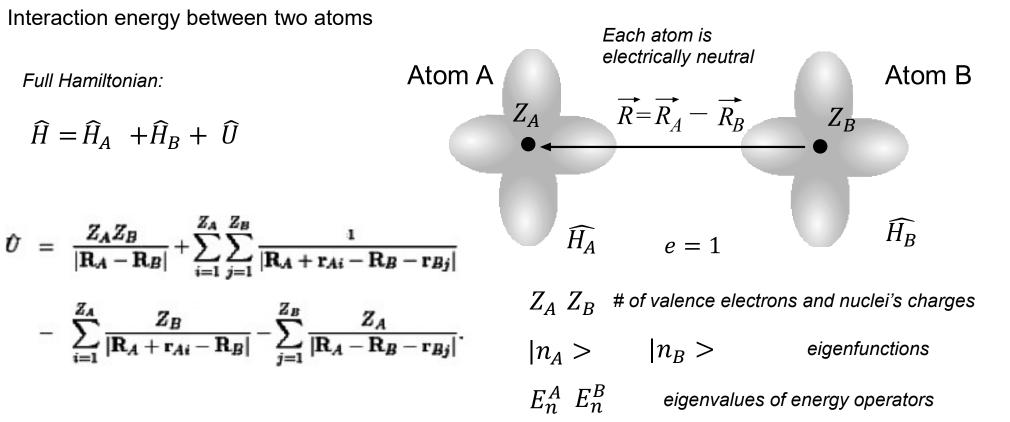
#### A table of the order of different interactions

	•	1		8
	$\sim \frac{1}{R}$	$\sim \frac{1}{R^2}$	$\sim \frac{1}{R^3}$	$\sim \frac{1}{R^4}$
1		$\sim \frac{1}{R^3}$	$\sim \frac{1}{R^4}$	$\sim \frac{1}{R^5}$
			$\sim \frac{1}{R^5}$	$\sim \frac{1}{R^6}$
8				$\sim \frac{1}{R^7}$

Interaction energy between two atoms

Full Hamiltonian:

 $\widehat{H} = \widehat{H}_A + \widehat{H}_R + \widehat{U}$ 



Compute the total energy by the perturbation theory:

$$\widehat{H_0} = \widehat{H_A} + \widehat{H_B}$$
 zero-order  
Hamiltonian  
 $\widehat{U}$  perturbation term

$$E = E^{(0)} + E^{(1)} + E^{(2)} + \cdots$$

 $E^{(0)} = E_0^A + E_0^B$ 

first-order term

ground state of individual atoms

Baumketner, BioSim, Lviv 2019

second-order term

 $E^{(0)} = \langle 0_A 0_B | \widehat{H_0} | 0_A 0_B \rangle$ 

Using the translation vector formula:

$$e^{\mathbf{r}_{Ai}\mathbf{\nabla}}e^{-\mathbf{r}_{Bj}\mathbf{\nabla}}\frac{1}{R} = \frac{1}{|\mathbf{R} + \mathbf{r}_{Ai} - \mathbf{r}_{Bj}|}, \qquad \longrightarrow \hat{U} = \sum_{i=1}^{Z_A} \sum_{j=1}^{Z_B} (e^{\mathbf{r}_{Ai}\mathbf{\nabla}} - 1) (e^{-\mathbf{r}_{Bj}\mathbf{\nabla}} - 1) \frac{1}{R}$$
Upon introducing charge operators:  

$$\hat{Q}_A = \sum_{i=1}^{Z_A} (e^{\mathbf{r}_{Ai}\mathbf{\nabla}} - 1)$$
Perturbation term can be written as:  

$$\hat{U} = \hat{Q}_A \hat{Q}_B^+ \frac{1}{R}$$
Multipole moments of atoms A and B  
First-order term:  

$$E^{(1)} = \langle 0|\hat{U}|0\rangle = \langle 0_A 0_B |\hat{Q}_A \hat{Q}^+_B \frac{1}{R}| 0_A 0_B \rangle = \langle 0_A |\hat{Q}_A |0_A \rangle \langle 0_B |\hat{Q}_B^+|0_B \rangle \frac{1}{R}$$
Let see the first few terms explicitly:  

$$\hat{Q}_A = \sum_i \left(1 + \left(\overline{r_i}^A \vec{\nabla}\right) + \frac{1}{2} \left(\overline{r_i}^A \vec{\nabla}\right) \left(\overline{r_i}^A \vec{\nabla}\right) + \dots - 1\right) = \overline{d^A} \vec{\nabla} + \frac{1}{2} \sum_{\alpha\beta} Q^A_{\alpha\beta} \frac{\partial}{\partial x_\alpha} \frac{\partial}{\partial x_\beta} + \dots$$

$$\hat{Q}_B^+ = \sum_i \left(1 - \left(\overline{r_i}^B \vec{\nabla}\right) + \frac{1}{2} \left(\overline{r_i}^B \vec{\nabla}\right) \left(\overline{r_i}^B \vec{\nabla}\right) + \dots - 1\right) = \overline{-d^B} \vec{\nabla} + \frac{1}{2} \sum_{\alpha\beta} Q^B_{\alpha\beta} \frac{\partial}{\partial x_\alpha} \frac{\partial}{\partial x_\beta} + \dots$$

If atoms have non-zero charge:  $\hat{Q}_A = Q_A + (\vec{d}^A \vec{\nabla}) + \frac{1}{2} \sum_{\alpha\beta} Q^A_{\alpha\beta} \frac{\partial}{\partial X_{\alpha}} \frac{\partial}{\partial X_{\beta}} + \dots$ 

Taking the expectation value:

$$< 0_{A} |\hat{Q}_{A}| 0_{A} > = < \vec{d^{A}} > \vec{\nabla} + \frac{1}{2} \sum_{\alpha\beta} < Q_{\alpha\beta}^{A} > \frac{\partial}{\partial x_{\alpha}} \frac{\partial}{\partial x_{\beta}} + \dots$$

$$< 0_{B} |\hat{Q}^{+}{}_{B}| 0_{B} > = - < \vec{d^{B}} > \vec{\nabla} + \frac{1}{2} \sum_{\gamma\delta} < Q_{\gamma\delta}^{B} > \frac{\partial}{\partial x_{\gamma}} \frac{\partial}{\partial x_{\delta}} + \dots$$

$$= \int_{\alpha\beta} (<\vec{d_{A}} > \vec{\nabla}) (<\vec{d_{B}} > \vec{\nabla}) \frac{1}{R} + \sum_{\alpha\beta} < d_{\alpha}^{A} > < d_{\alpha}^{B} > (\frac{3X_{\alpha}X_{\beta}}{R^{5}} - \frac{\delta_{\alpha\beta}}{R^{3}}) \sim \frac{1}{R^{3}}$$

$$= \int_{\alpha\beta} (<\vec{d_{A}} > \vec{\nabla}) (<\vec{d_{B}} > \vec{\nabla}) \frac{1}{R} + \sum_{\alpha\beta} < d_{\alpha}^{A} > < d_{\alpha}^{B} > (\frac{3X_{\alpha}X_{\beta}}{R^{5}} - \frac{\delta_{\alpha\beta}}{R^{3}}) \sim \frac{1}{R^{3}}$$

$$= \int_{\gamma\delta} (<\vec{d_{A}} > \vec{\nabla}) < Q_{\gamma\delta}^{B} > - (<\vec{d_{B}} > \vec{\nabla}) < Q_{\gamma\delta}^{A} > \frac{\partial}{\partial X_{\gamma}} \frac{\partial}{\partial X_{\delta}} \frac{1}{R} - \frac{1}{R^{4}}$$

$$+ \frac{1}{4} \sum_{\alpha\beta\gamma\delta} < Q_{\alpha\beta}^{A} > < Q_{\gamma\delta}^{B} > \frac{\partial}{\partial X_{\alpha}} \frac{\partial}{\partial X_{\beta}} \frac{\partial}{\partial X_{\gamma}} \frac{\partial}{\partial X_{\delta}} \frac{1}{R} + \cdots \sim \frac{1}{R^{5}}$$

$$= \frac{C^{(3)}}{R^{3}} + \frac{C^{(4)}}{R^{4}} + \frac{C^{(5)}}{R^{5}} + \cdots = \frac{Q_{A}Q_{B}}{R} + \frac{C^{(2)}}{R^{2}} + \frac{C^{(3)}}{R^{3}} + \frac{C^{(4)}}{R^{4}} + \frac{C^{(5)}}{R^{5}} + \cdots$$

$$= \frac{vansion if atoms have uncompensated charge$$

#### Second-order term:

$$E_n^{(2)} = \sum_{m(n \neq m)} \frac{|U_{mn}|^2}{E_n^{(0)} - E_m^{(0)}}$$

matrix element is over double indices

$$U_{mn} = < m_A, m_B \left| \widehat{U} \right| n_A, n_B >$$

Correction to the ground-state energy relies on the matrix entry:

$$U_{m0} = \langle m | \hat{U} | 0 \rangle = \langle m_A | \hat{Q}_A | 0_A \rangle \langle m_B | \hat{Q}_B^+ | 0_B \rangle \frac{1}{R},$$

which has to be substituted into the energy formula:

$$E_0^{(2)} = \sum_{m_A, m_B} \frac{|\langle m_A | \hat{Q}_A | 0_A \rangle \langle m_B | \hat{Q}_B^+ | 0_B \rangle \frac{1}{R} |^2}{E_0^A - E_{m_A}^A + E_0^B - E_{m_B}^B} = E_{0,ind}^{(2)} + E_{0,disp}^{(2)}$$

note that since the denominator is always negative and nominator – positive the correction is negative and corresponds to attraction

#### Induction energy

Summation is performed while keeping one of the atoms in the ground state  $E_{ind}(A) = \sum_{m_B} \frac{|\langle 0_A | \hat{Q}_A | 0_A \rangle \langle m_B | \hat{Q}^+{}_B | 0_B \rangle \frac{1}{R} |^2}{E_0^B - E_{m_B}^B} + \sum_{m_A} \frac{|\langle m_A | \hat{Q}_A | 0_A \rangle \langle 0_B | \hat{Q}^+{}_B | 0_B \rangle \frac{1}{R} |^2}{E_0^A - E_{m_A}^A}$ 

non-zero starting from non-zero multipole.

The induction energy is non-zero starting from non-zero multipole terms.

Examples:

1) Atoms have non-zero dipole in the ground state  $E_{ind}(A) \sim \left| < \overrightarrow{d^A} > \overrightarrow{\nabla} < m_B \right| \left| \widehat{Q}^+_B \right| |0_B| > \frac{1}{R} \right|^2 = \frac{I^{(6)}}{R^6} + \cdots$ 

*is the lowest term in expansion which has to squared* 

2) Atoms have non-zero charge and may or may not have dipole moment

$$Q_{A} + \langle \vec{d^{A}} \rangle \vec{\nabla} + \dots \qquad \text{is the leading term}$$

$$\int_{V} E_{ind}(A) \sim |\langle 0_{A} | \hat{Q}_{A} | 0_{A} \rangle \langle m_{B} | \hat{Q}^{+}{}_{B} | 0_{B} \rangle \frac{1}{R} |^{2} = |Q_{A} \langle m_{B} | \hat{Q}^{+}{}_{B} | 0_{B} \rangle \frac{1}{R} |^{2} = \frac{I^{(4)}}{R^{4}} + \dots$$

A convenient way to view induction energy is by introducing the concept of polarization. Assume that the dipole moment induced by external field can be written as:

 $\vec{\mu} = \alpha \vec{E}$  where  $\alpha$  is the polarizability constant (tensor in general)

The interaction energy of that moment with the field then is:  $E_{ind} = -\vec{\mu}\vec{E} = -\alpha E^2$ If polarization is caused by point charge,  $E \sim \frac{1}{R^2}$  and so  $E_{ind} \sim \frac{1}{R^4}$  •  $\mathbf{r}$  interaction of charge with induced dipole for the interaction of dipole  $E \sim \frac{1}{R^3}$  and so  $E_{ind} \sim \frac{1}{R^6}$  •  $\mathbf{r}$  interaction of dipole with induced dipole  $E \sim \frac{1}{R^3}$  and so  $E_{ind} \sim \frac{1}{R^6}$  •  $\mathbf{r}$  A formal expression for the induction energy:

$$\begin{split} E_{ind}(A) &= -\frac{1}{2} \alpha_{\alpha\beta}(A) E_{\alpha}(A) E_{\beta}(A) - \frac{1}{3} A_{\alpha,\beta\gamma}(A) E_{\alpha}(A) E_{\beta\gamma}(A) - \\ &- \frac{1}{6} C_{\alpha\beta,\gamma\delta}(A) E_{\alpha\beta}(A) E_{\gamma\delta}(A) + \dots \end{split}$$

molecular polarizabilities **α, Α, C** specific for the molecule

$$E_{\alpha}(A) = -\frac{X_{\alpha}}{R^{3}}Q_{B} + \sum_{\beta} \left(\frac{3X_{\alpha}X_{\beta}}{R^{5}} - \frac{\delta_{\alpha\beta}}{R^{3}}\right)d_{\alpha}(B) + \cdots \qquad \text{electric field due to atom B}$$

$$E_{\alpha\beta}(A) = -\left(\frac{3X_{\alpha}X_{\beta}}{R^5} - \frac{\delta_{\alpha\beta}}{R^3}\right)Q_B + \cdots$$

*derivative of the electric field due to atom B* 

#### Dispersion energy

Second-order correction when the summation is performed over excited states of both atoms:

$$E_{0,disp}^{(2)} = \sum_{m_A, m_B \neq 0} \frac{|\langle m_A | \hat{Q}_A | 0_A \rangle \langle m_B | \hat{Q}^+{}_B | 0_B \rangle \frac{1}{R} |^2}{E_0^A - E_{m_A}^A + E_0^B - E_{m_B}^B}$$

Keeping only the lowest-order dipolar term:  $\hat{Q}_A = \overline{d^A} \vec{\nabla}$   $\hat{Q}^+_{\ B} = -d^B \vec{\nabla}$ 

$$E_{0,disp}^{(2)} = \sum_{m_A,m_B \neq 0} \frac{|(< m_A | \vec{d}^A | 0_A > \vec{\nabla})(< m_B | \vec{d}^B | 0_B > \vec{\nabla}) \frac{1}{R} |^2}{E_0^A - E_{m_A}^A + E_0^B - E_{m_B}^B} = \frac{D^{(6)}}{R^6}$$
  
For charged systems

Dispersion, London, van der Waals interaction

Has dipole-induced dipole interpretation. Not everyone agrees with it. See J. O. Hirschfelder; C. F. Curtiss & R. B. Bird (1954), Molecular Theory of Gases and Liquids, New  $\hat{Q}_{A} = Q_{A} + \overrightarrow{d^{A}} \overrightarrow{\nabla}$  0 because of orthogonality condition  $< m_{A} | \hat{Q}_{A} | 0_{A} > = Q_{A} < m_{A} | 0_{A} > + < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left| \overrightarrow{d^{A}} \overrightarrow{\nabla} \right| 0_{A} > = < m_{A} \left|$ 

is genuinely the lowest order term in the dispersion interaction SO

Some general properties of dispersion interactions

attractive regardless of molecule orientation

weaker than normal covalent and ionic bonds

strength is proportional to the polarizability of the atom

additive and cannot be saturated

short-range forces and hence only interactions between the nearest particles need to be considered

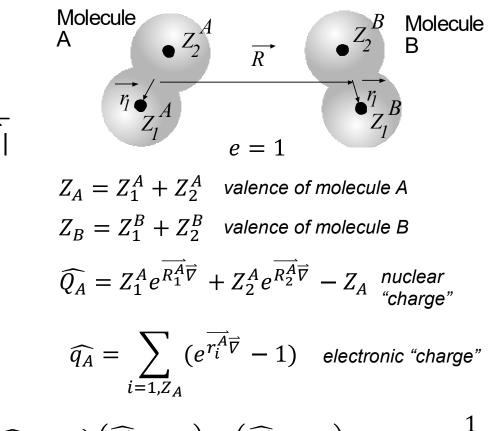
#### Extension to molecules

Nuclear interaction

$$\frac{Z_1^A Z_1^B}{|\vec{R} - \overline{R_1^B} + \overline{R_1^A}|} + \frac{Z_1^A Z_2^B}{|\vec{R} - \overline{R_2^B} + \overline{R_1^A}|} + \frac{Z_2^A Z_1^B}{|\vec{R} - \overline{R_1^B} + \overline{R_2^A}|} + \frac{Z_2^A Z_2^B}{|\vec{R} - \overline{R_2^B} + \overline{R_2^A}|} = (\widehat{Q_A} + Z_A)(\widehat{Q_B^+} + Z_B)\frac{1}{R}$$

Electrons with nuclei

$$-1\sum_{i=1,Z_A} \{\frac{Z_1^B}{\left|\vec{R} - \overline{R_1^B} + \overline{r_i^A}\right|} + \frac{Z_2^B}{\left|\vec{R} - \overline{R_2^B} + \overline{r_i^A}\right|}\} +$$



$$-1\sum_{j=1,Z_B}\left\{\frac{Z_1^A}{\left|\vec{R}+\vec{R_1^A}-\vec{r_j^B}\right|}+\frac{Z_2^A}{\left|\vec{R}+\vec{R_2^A}-\vec{r_j^B}\right|}\right\} = -\left\{\left(\widehat{Q_A}+Z_A\right)\left(\widehat{q_B^+}+Z_B\right)+\left(\widehat{Q_B^+}+Z_B\right)\left(\widehat{q_A}+Z_A\right)\right\}\frac{1}{R}$$

Electrons with electrons

$$\sum_{i=1,Z_A} \sum_{j=1,Z_B} \frac{1}{\left|\vec{R} - \vec{r_j^B} + \vec{r_i^A}\right|} = (\widehat{q_A}\widehat{q_B^+} + Z_A\widehat{q_B^+} + Z_B\widehat{q_A} + Z_AZ_B)\frac{1}{R}$$

Full perturbation potential

$$\widehat{U} = \{\widehat{Q}_A \widehat{Q}_B^+ + \widehat{q}_A \widehat{q}_B^+ - \widehat{Q}_A \widehat{q}_B^+ - \widehat{q}_A \widehat{Q}_B^+\} \frac{1}{R}$$

Additional terms:

$$E_{0,n}^{(1)} = <0\left|\widehat{Q_A}\widehat{Q_B^+}\right| 0 > \frac{1}{R} = \widehat{Q_A}\widehat{Q_B^+}\frac{1}{R} = \frac{N^{(3)}}{R^3} + \cdots$$

*multipole expansion for the nuclear subsystem. Starts with dipole-dipole interactions for neutral molecules* 

$$E_{0,n}^{(2)} \sim \langle m_A \left| \widehat{Q_A} \widehat{Q_B^+} \right| 0_A \rangle = \widehat{Q_A} \widehat{Q_B^+} \langle m_A | 0_A \rangle = 0$$

because of the orthogonality of the excited states to the ground-state wave function

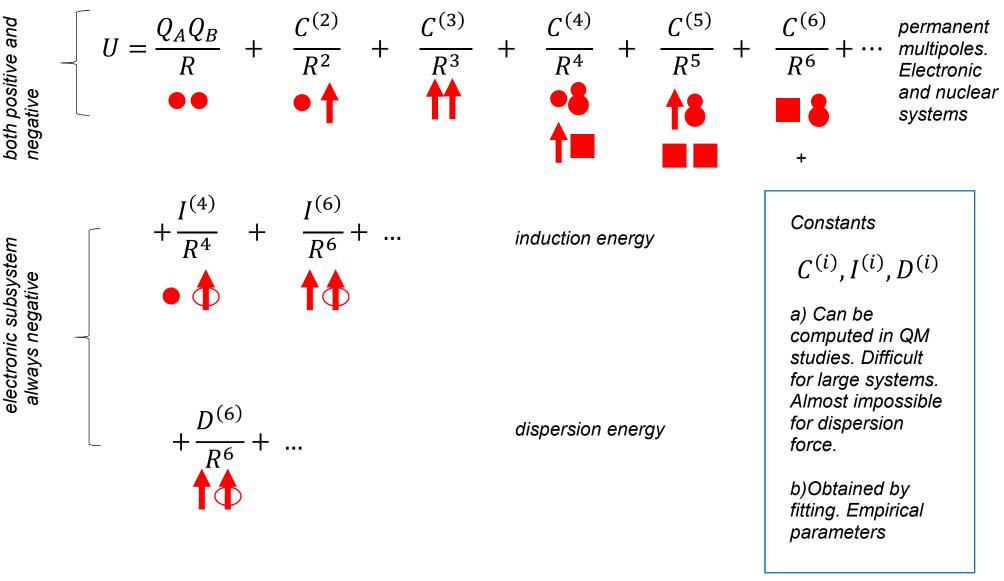
$$E_{0,c}^{(1)} = <0\left|\widehat{Q_{A}}\widehat{q_{B}^{+}}\right| 0 > \frac{1}{R} = \widehat{Q_{A}} < 0\left|\widehat{q_{B}^{+}}\right| 0 > \frac{1}{R} = \frac{CN^{(3)}}{R^{3}} + \cdots$$

$$E_{0,c}^{(2)} \sim \sum_{m \neq 0} |<0|\widehat{Q_{A}}\widehat{q_{B}^{+}}| m > \frac{1}{R}\Big|^{2} = \sum_{m \neq 0} \left|\widehat{Q_{A}} < 0\left|\widehat{q_{B}^{+}}\right| m > \frac{1}{R}\Big|^{2} = \frac{CN^{(6)}}{R^{6}} + \cdots$$

$$Cross terms. combined effect of electronic and nuclear permanent dipoles$$

Nuclear degrees of freedom contribute additional terms to the multipole expansion corresponding to the permanent moments

Putting all summands together one arrives at the most general representation of the interaction energy between two molecules:



# Atom-pair potential approximation

Proteins are modeled at the classical level. 1) Not much chemistry happens but 2) QM calculations are way too expensive

Interaction energy U(R) can be used to model the dynamics of the nuclei in the Born-Oppenheimer approximation. Adiabatic approximation.

Two options of how to proceed:

Option #1:

Assign <u>proper</u> (valence) charges to each nucleus and a certain number of permanent moments. These can be taken from QM calculations or some other source (from experiment in case of dipole moment for instance). The moments have to be attached to the local geometry of the molecules. As the local reference frame moves (rotates) the moments have to be recomputed.

#### Drawbacks:

1) Algorithms are not always straightforward to implement. It may be difficult to compute forces acting on each nucleus, especially for higher moments. See Stockmayer fluid for example. Torques are not always computed in a pairwise summation (i acting on j is not the opposite of j acting on i).

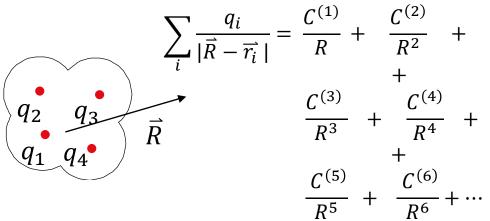
2) The procedure is tedious and expensive. Each molecule has to have its moments recomputed at each step as it rotates in the course of the simulation.

3) A large amount of data needs to be stored.

4) A large number of parameters – dipole, quadrupole and higher moments, makes parametrization very challenging.

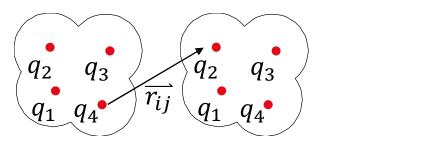
Option #2:

1) Assign partial charges to each nucleus. These will generate multipole series of permanent dipoles.



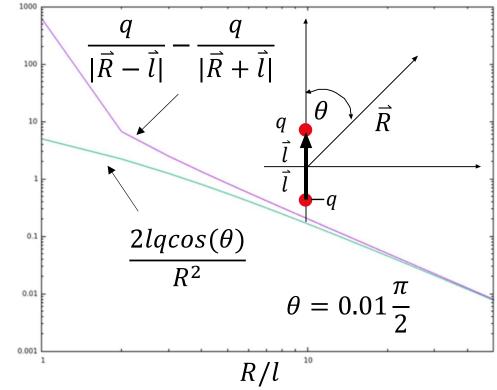
Important: the series will contain all powers of 1/R, not just ones specific for a particular dipole.

2) Add polarization and dispersion interactions to each nucleus.



*3)* Add repulsion at short distances to prevent nuclei overlapping

Baumketner, BioSim, Lviv 2019



The field created by two charges is different from the field of a point dipole !

$$\sum_{i,j} \left( \frac{D_{ij}^{(4)}}{r_{ij}^4} + \frac{D_{ij}^{(6)}}{r_{ij}^6} + \frac{D_{ij}^{(7)}}{r_{ij}^7} + \frac{D_{ij}^{(8)}}{r_{ij}^8} \dots + \frac{D_{ij}^{(12)}}{r_{ij}^{12}} \right)$$

Parameters: 
$$q_1 \dots q_N$$
  
 $D_{ij}^{(n)}$ ,  $n = 4,6,7,8 \dots 12$  for each pair  $q_i, q_j$ 

Can the atom-pair approximation work?

The method of Clementi

1) Approximation: cut all terms with powers  $1/R^7$  and higher. This will lower the number of parameters

2) Compute potential energy for a two-molecule system in QM calculations.

A= amino acids and some other systems. 25 in total

**B=** water molecule

 $\Delta E_{AB}(R, \theta, \varphi)$  interaction energy as a function of mutual distance and orientations. 10,000 different values

The interaction potential

$$\Delta E = \sum_{a(X)} \sum_{b(W)} \{ c_{ab}^{(1)} / R_{ab} + c_{ab}^{(4)} / R_{ab}^4 + c_{ab}^{(6)} / R_{ab}^6 + c_{ab}^{(12)} / R_{ab}^{12} \}$$

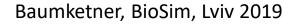
Results:

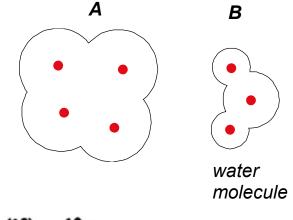
1) Way too many parameters to perform a fit for all atoms. Introduce atom types. Typical types:

sp3, sp3 hybridized carbon, carbon in aromatic residues etc. ~30 different classes

2) Electrostatic contribution can be well approximated by charges:

$$c_{ab}^{(1)} = q_a q_b$$





3) Keeping the 1/R<sup>4</sup> term doesn't improve the quality of the fit

4) Certain rules for cross terms seem to work well. For instance:

$$c_{a(X)H(W)}^{(12)} = c_{a(X)}^{(12)} c_{H(W)}^{(12)}$$
$$c_{a(X)O(W)}^{(12)} = c_{a(X)}^{(12)} c_{O(W)}^{(12)}$$

5) Coefficients  $C_{ab}^{(6)}$  are too small and can't be determined reliably. This is the consequence of the dispersion interactions not being well described by the QM approximation.

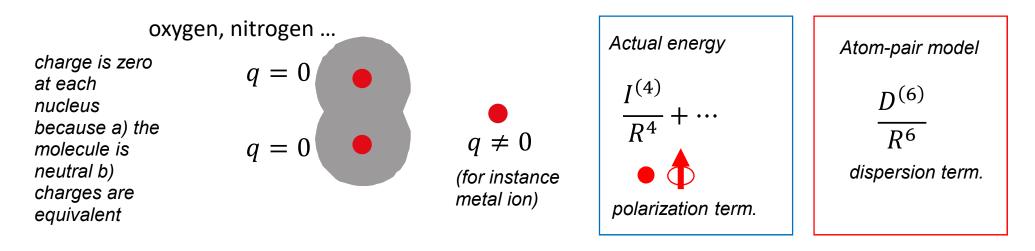
Conclusions

The following model of potential energy will work well for proteins:

$$U = \sum_{i,j} \{ \frac{q_i q_j}{r_{ij}} + c_{ij}^{(12)} / r_{ij}^{12} - c_{ij}^{(6)} / r_{ij}^6 \}$$

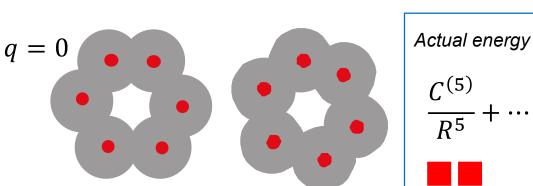
Adjustable parameters  $q_1 \dots q_N$  partial charges  $c_{ij}^{(12)}, c_{ij}^{(6)} > 0$ 

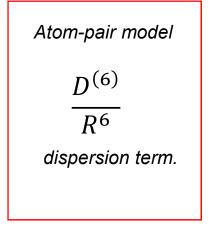
#### Examples of when this approximation will fail



benzene

Molecules that have <u>zero</u> <u>charge, zero</u> <u>dipole</u> moment but non-zero <u>quadrupole</u> moment



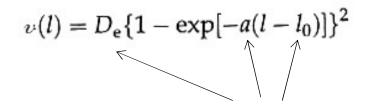


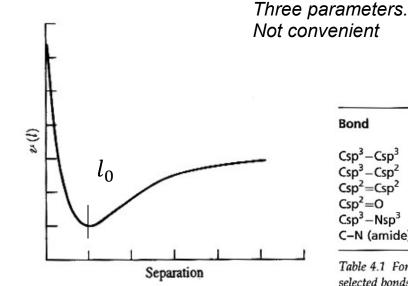
# Bonded energy

QM calculations predict certain geometry for the studied molecule. Distortions from that geometry are described by a number of potential energy terms that collectively are known as "bonded energy"

# Bond-stretching potential

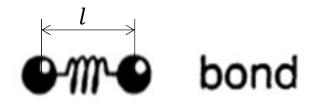
Morse potential (some basis in QM calculations)



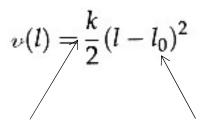


Bond	10 (Å)	k (kcal mol <sup>−1</sup> Å <sup>−2</sup> )		
Csp <sup>3</sup> -Csp <sup>3</sup>	1.523	317		
Csp <sup>3</sup> -Csp <sup>2</sup>	1.497	317		
Csp <sup>2</sup> =Csp <sup>2</sup>	1.337	690		
Csp <sup>2</sup> =0	1.208	777		
Csp <sup>3</sup> -Nsp <sup>3</sup>	1.438	367		
C-N (amide)	1.345	719		

Table 4.1 Force constants and reference bond lengths for selected bonds [Allinger 1977].



Harmonic approximation (typically used)



Force constant. Source: normal mode analysis of QM, vibrational spectra

Reference bond length. Source: crystal structures, QM calculations

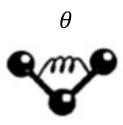
# Angle bending potential

#### Harmonic approximation

 $v(\theta) = \frac{k}{2}(\theta - \theta_0)^2$ 

Force constant. Source: normal mode analysis of QM, vibrational spectra

Reference bond angle. Source: crystal structures, QM calculations



$\theta_0$	k (kcal mol <sup>-1</sup> deg <sup>-1</sup> )
109.47	0.0099
109.47	0.0079
109.47	0.0070
117.2	0.0099
121.4	0.0121
122.5	0.0101
	109.47 109.47 109.47 117.2 121.4

Table 4.2 Force constants and reference angles for selected angles [Allinger 1977].

Higher-order approximations approximation:

$$v(\theta) = \frac{k}{2}(\theta - \theta_0)^2 [1 - k'(\theta - \theta_0) - k''(\theta - \theta_0)^2 - k'''(\theta - \theta_0)^3 \dots]$$

# Dihedral angle potential

Several functional forms are in use

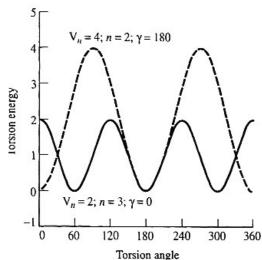
$$v(\mathbf{\phi}) = \sum_{n \neq 0}^{N} \frac{V_n}{2} \left[1 + \cos(n\mathbf{\phi} - \gamma)\right]$$

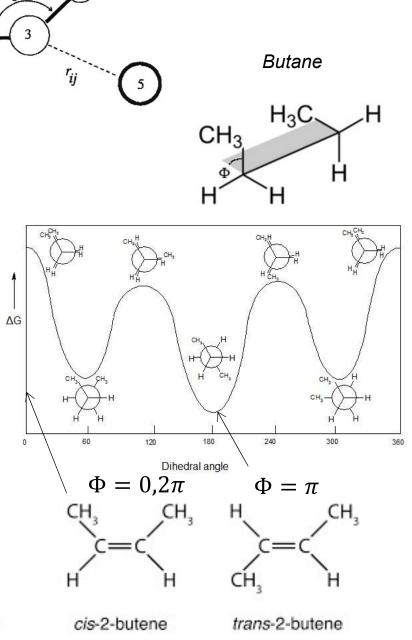
Barrier height. Provides an idea on qualitative level about the barrier to rotation around particular bond.

4.0

Multiplicity. Determines how many minima the potential has. Depends on the chemistry of the central two atoms. For sp3 atoms, n=3, giving 3 minima. For sp2 atoms, n=2, leading to 2 minima.

The phase factor, Determines where the potential passes through a minimum.





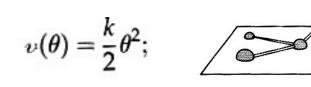
3.5 3.0 Energy (kcal/mol) 2.5 2.0 1.5 1.0 0.5 01 0 60 120 180 240 300 360 Torsion angle

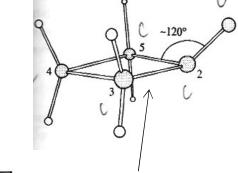
AMBER force field with O-C-C-O torsion angle

# Improper dihedrals

Chemical compounds in which four nonconsecutive atoms have to lie in-plane. This can't be achieved with the help bond, angle and dihedral energy alone.

Improper dihedral energy:

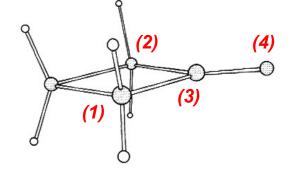




Conformation

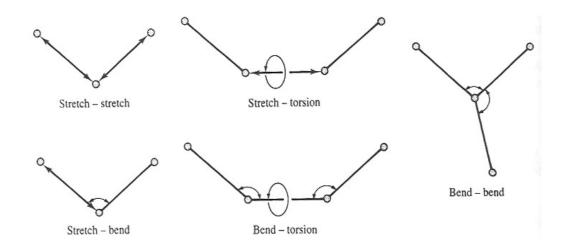
angle terms

favored by bond-



Experimentally observed conformation. Four atoms (1)(2)(3)(4) lie in the same plane.

Bonded cross-terms



Apply in Class II forcefields as opposed to Class I force-fields relying on fixed-charge model

Typically used in highly specialized force-fields such as MM2/MM3

Baumketner, BioSim, Lviv 2019

## Cyclobutanone

# Parametrization

# Partial charges

1) First principle approaches:

a) Partial charge is not an experimentally observable quantity. Can't be determined directly

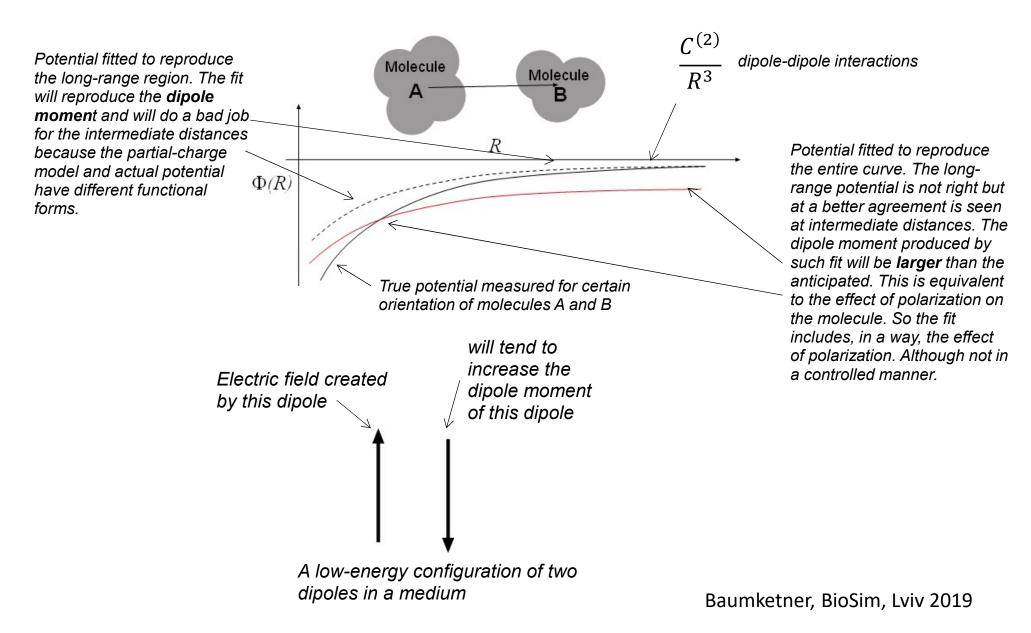
a) In QM calculations partial charges can't be determined unambiguously. Many schemes exist. Mulliken charges are meant for intra-molecular interactions. They depend on the molecule chemistry, number of nuclei etc. Can't be used to describe interactions between molecules.

2) Fitting :

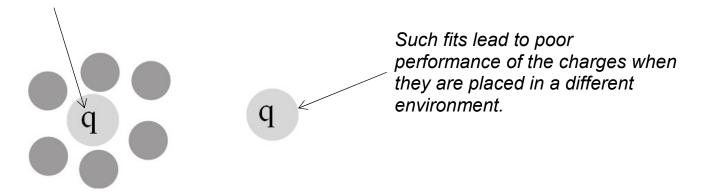
*a)* Partial charges are fitted to reproduce certain thermodynamic properties of the studied system. See for instance OPLS/AA.

b) Partial charges are adjusted to reproduce electrostatic potential created around the molecule of interest. The latter are obtained in QM calculations. See AMBER and CHARMM.

In principle there is no guarantee that such fit should be successful. Much depends on how fitting is performed. In all cases errors will be present.



c) Charges that are buried are statistically underdetermined. Difficult to obtain meaningful values.



The problem can be addressed by introducing weight factors for the charges. Example **RESP** charges of AMBER

*d)* The same set of charges cannot describe the potential equally well for different configurations of the target molecules.

Some force-fields consider multiple configurations so that the fitted charge produces the best agreement for the entire ensemble of structures. See AMBER.

*e)* The best performing fixed-charge model produce **5-15%** relative error in electrostatic potential with respect to QM results. For comparison, polarizable force-fields can achieve less than 1% accuracy.

# Van der Waals parameters

$$V_{LJ}(r_{ij}) = 4\epsilon_{ij} \left( \left( \frac{\sigma_{ij}}{r_{ij}} \right)^{12} - \left( \frac{\sigma_{ij}}{r_{ij}} \right)^6 \right)$$

Combination rules

$$\sigma_{ij} = \sqrt{\sigma_i \sigma_j} \qquad \sigma_{ij} = \frac{1}{2} (\sigma_i + \sigma_j)$$
  
$$\epsilon_{ij} = \sqrt{\epsilon_i \epsilon_j} \qquad \text{Lorentz rule}$$

In almost all force-fields the vdW parameters to reproduce

- a) Constants in molecular crystals
- b) Heat of vaporization
- c) Liquid densities

# Bonded potentials

Bond-stretching, angle bending – normal modes, vibrational spectra. Most transferable part of force-field

Torsion potential.

QM calculations of potential energy as a function of the particular dihedral angle.

# General scheme

*Typically, parametrization of a force-field proceeds in three steps:* 

- 1) Bond-stretching and angle-bending parameters are set. Perhaps by borrowing values from AMBER.
- 2) Charges are fitted
- 3) Vdw parameters are fitted. The rule for 1-4 interactions is set.
- *4)* Torsion potentials are fitted on QM simulations of dipeptides.

These are coupled. Don't use torsion potentials obtained in one force-field in a different force-field!

# Force-fields in general use

AMBER

OPLS

CHARMM

Force field	Potential type	Key references
BUFF	All Atom	Carlson, 2000
CEDAR	All Atom	Hermans et al., 1984; Hu et al., 2003
CVFF	All Atom	Kitson and Hagler, 1988
DISCOVER	All Atom	Maple et al., 1998
ECEPP/3	All Atom, Torsional	Némethy et al., 1993
ENCAD	All Atom	Daggett and Levitt, 1993;
		Levitt et al., 1995
GROMOS87	United Atom	van Gunsteren and
		Berendsen, 1987
GROMOS96	United Atom	Scott <i>et al.</i> , 1999
MM2	All Atom	Lii et al., 1989
MM3	All Atom	Lii et al., 1991
MM4	All Atom	Langley and Allinger, 2002
MMFF	All Atom	Halgren, 1996a,b,c,d
NEMO	Polarizable	Hermida-Ramón et al., 2003
PROSA	Polarizable	Stern et al., 1999
SCHRODINGER	Polarizable	Kaminski et al., 2002
SDFF	Polarizable	Palmo et al., 2003
SIBFA	Polarizable	Gresh, 1997; Guo et al., 2000
SPASIBA	All Atom	Derreumaux and Vergoten, 1995
TRIPOS	All Atom	Clark et al., 1989
UCSD-WILSON	All Atom	Mackay et al., 1984
UFF	All Atom	Rappé <i>et al.</i> , 1992
UPJOHN	All Atom	Oie et al., 1981
YETI	United, Torsional	Vedani, 1988

TABLE I	
Other Force Fields for Peptide and Protein Modeling	

# AMBER

#### History

ff84 u

united atom

ff94, ff96,ff99 all-atom

ff02 polarizable

#### Charges

Fritted to reproduce electrostatic potential of model peptides, ESP and then RESP charges.

In ff99 refitted using higher-order QM energies

## vdW parameters

Combination rules:

 $\epsilon_{ij} = \sqrt{\epsilon_i \epsilon_j}$  geometric mean

$$\sigma_{ij} = \frac{1}{2}(\sigma_i + \sigma_j)$$
 arithmetic mean

Density and enthalpy of vaporization of CH4,C2H6,C3H8 and C4H10 liquids -> sp3 carbon and aliphatic hydrogen. sp2 carbon and aromatic H from liquid benzene. All others borrowed from OPLS/UA

# 1-4 interactions

Scaling factor of 0.5 in ff84 and 0.83 in all-atom force fields

# Bonded

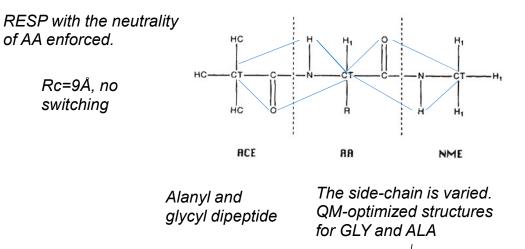
QM data and vibrational spectra

# $E_{\text{total}} = \sum_{\text{bonds}} K_r (r - r_{\text{eq}})^2 + \sum_{\text{angles}} K_{\theta} (\theta - \theta_{\text{eq}})^2 + \sum_{\text{dihedrals}} \frac{V_n}{2} [1 + \cos(n\phi - \gamma)] + \sum_{i < j} \left[ \frac{A_{ij}}{R_{ij}^{12}} - \frac{B_{ij}}{R_{ij}^{6}} + \frac{q_i q_j}{\epsilon R_{ij}} \right]$

Torsions

Energy function

#### QM HF-6-31G\* set. Multiple conformations.



QM on GLY and ALA dipeptides as a function of rotation angles

# CHARMM

## History

charmm19	united atom
charmm22, charmm27	all-atom
charmm36	polarizable

#### Charges

Supramolecular approach. QM energies are computed for AA-Water complexes. For neutral systems the energy is divided by 1.16. Charges are fitted to reproduce AA-Water interactions. TIP3P with non-zero vdW on H is used for water.

7.5-8.5A W-W

9.5A S-W

Rc=

## vdW parameters combination rules

Density and heat of vaporization.

$$\epsilon_{ij} = \sqrt{\epsilon_i \epsilon_j}$$
 geometric mean  
 $\sigma_{ij} = \frac{1}{2}(\sigma_i + \sigma_j)$  arithmetic mean

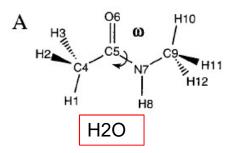
## Bonded

QM data and vibrational spectra

## 1-4 interactions

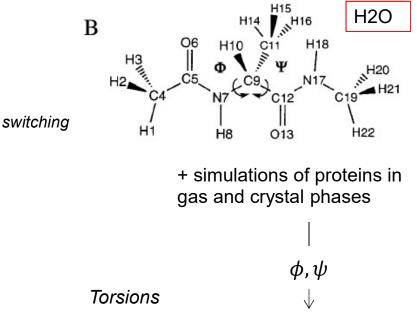
No scaling. Scaling factor of 1.0

# NMA water complexes



Backbone: QM yields geometry + force constants for bonds, angles. Water is important for geometry. Charges + vdW parameters

Alanyl dipeptide with water



QM on dipeptides. Matching of energy of different minima, C7, aR etc.

# OPLS

History

opls-UA

united atom

opls-AA

all-atom

# Charges

Fitted to reproduce interaction energy of model compounds with water estimated in QM simulations. Dipole moments are set about 15% larger than in gas phase to take polarization into account. TIP4P water is used in MM part, but TIP3P and SPC are also suitable. Concept of neutral groups is introduced, which reduces the number of requisite charges,.

## 1-4 interactions

Scaling factor of 0.83 in OPLS-UA and 0.5 in Rc= 10-12Å depending on OPLS-AA

# vdW parameters

Experimental density and enthalpy of vaporization in liquid state are reproduced in MC simulations of model compounds that correspond to the peptide bond and side chains .

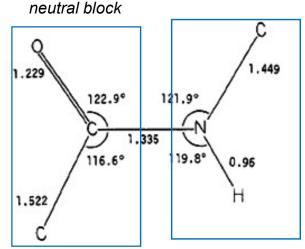
$$\epsilon_{ij} = \sqrt{\epsilon_i \epsilon_j} \qquad \sigma_{ij} = \sqrt{\sigma_i \sigma_j}$$

geometric mean

## Bonded

Borrowed from AMBER94 force-field

NMA is used as the model of peptide bond. Geometry from crystal structure. Charges from solute-water interactions.



Parameters of CH3(C-O) are taken from hydrocarbons. After charges are fitted, the number of unknown parameters is equal the number of experimental measurements

## Torsions

Adopted from AMBER94 in OPLS-UA. Fitted to QM energy functions computed for AA dipeptides for OPLS-AA/L

# Convergence of force-fields

United-atom force-fields show large variation in charges:

	Amber 84	Amber 94/99	CHARMM19	CHARMM22/27	OPLS-UA	OPLS-AA	GROMOS96	BUF
N	-0.463	-0.4157	-0.35	-0.47	-0.57	-0.50	-0.28	-0.749
HN	0.252	0.2719	0.25	0.31	0.37	0.30	0.28	0.328
CA	0.035	-0.0249	0.10	0.07	0.20	0.14	0.00	0.189
HA	0.048	0.0843		0.09		0.06		0.048
С	0.616	0.5973	0.55	0.51	0.50	0.50	0.38	0.828
0	-0.504	-0.5679	-0.55	-0.51	-0.50	-0.50	-0.38	-0.679
СВ	0.018	0.2117	0.25	0.05	0.265	0.145	0.15	0.296
HB	0.119	0.0352		0.09		0.06		0.006
OG	-0.55	-0.6546	-0.65	-0.66	-0.70	-0.683	-0.548	-0.764
но	0.31	0.4275	0.40	0.43	0.435	0.418	0.398	0.491

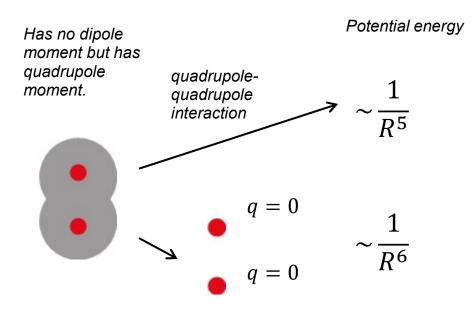
All-atom force-fields appear to converge

# Problems, ways to improve

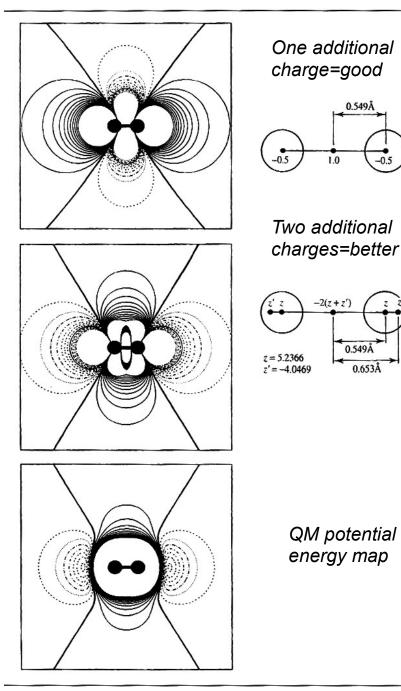
# Intrinsic deficiencies

The ansatz of partial charges placed at positions of nuclei not always is appropriate. It may not yield proper permanent dipoles. This can be fixed by adding more charges. Also atom-based multipole moments.

Example: nitrogen molecule



the fixed-charge model has no moments so the first term is dispersion energy



# Problems, ways to improve

# Polarization

Molecules in condensed-phase environment acquire additional moments. This is a very strong effect that is seen even in molecular geometry, Polarization causes N-C distance in peptide bond to shorten while that of C-O bond to lengthen.

		Experimental			MP2/6-31 G(d) <sup>b</sup>	
infest.	Gas <sup>c</sup>	Crystal <sup>d</sup>	Survey <sup>c</sup>	Gas	3H <sub>2</sub> O	H <sub>2</sub> O,2FM
Bonds						
C <sub>m</sub> —C	1.520 (5)	1.515 (3)	1.52(1)	1.514	1.510	1.512
C—N	1.386 (4)	1.325 (3)	1.33 (1)	1.365	1.339	1.337
N—C <sub>m</sub>	1.469 (6)	1.454 (3)	1.45 (2)	1.448	1.454	1.454
C=O	1.225 (3)	1.246 (2)	1.23 (1)	1.232	1.255	1.254
Angles						
C <sub>m</sub> —C—N	114.1 (15)	116.3 (6)	116 (2)	115.3	117.1	116.6
O=C-N	121.8 (4)	121.7 (6)	123 (1)	123.1	122.1	122.6
C <sub>m</sub> -C=O	124.1	121.9 (6)	121 (4)	121.6	120.9	120.9
C-N-Cm	119.7 (8)	121.3 (6)	122 (1)	122.1	121.1	121.3

Table 1. Comparison of Peptide Bond Geometries from QM and Experimental Methods.

Polarization is taken into account implicitly by:

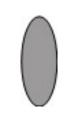
- 1) Errors in QM theory
- 2) Adding water molecules to the model compounds in QM calculations
- 3) Taking molecular geometry from crystal structures
- 4) Increasing the dipole moment of studied compounds by about 15%
- 5) Optimizing dihedral angles against NMR data in liquid state or proteins in solution

Still fixed-charge force-fields are only about 5-15% accurate. The chemical accuracy of 1kCal/mol is out of reach.

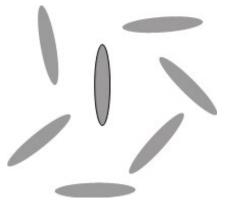
# Polarization in local environment

Better parametrization is unlikely to improve fixed-charge models by much. The fundamental problem is that they include polarization in an average sense.

Molecule in gas. Small dipole

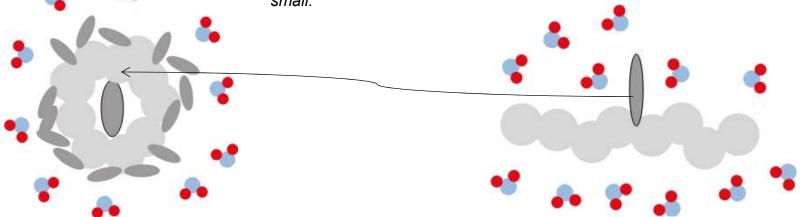


Same molecule in polar medium, perhaps its own liquid. Increased dipole.



What happens during protein folding

The environment of target molecule changes. Could be transferred from polar medium where it's polarized to non-polar medium where it's dipole moment is small.



Polarization has to be included explicitly in order to make progress

# Polarizable force-fields

Three basic methods:

- 1) Fluctuating charge model
- 2) Drude oscillator
- 3) Induced dipole models

$CH_3 CH_3$ $CH_3 CH_3$ $O_1 H_1 O$ $CH_3 CH_3$ $CH_3 CH_3$	H CH <sub>3</sub> O CH <sub>3</sub> O CH <sub>3</sub> O	H <sub>3</sub> N H H H H H H H H H H H H H	СН <sub>3</sub> СН <sub>3</sub> СН <sub>3</sub> Н
Energy Model	cis-NMA	β-sheet	ΔΕ
OPLS-AA	-11.5	-16.9	-5.4
CHARMM27	-11.6	-16.9	-5.3
AMBER ff94	-11.3	-14.8	-3.5
AMBER ff02	-13.5	-14.8	-1.3
АМОЕВА	-18.5	-12.6	+5.9
SIBFA	-18.7	-17.1	+1.6
MP2/(CEP)4-31G+(2d)	-20.5	-17.5	+3.0
BP/DZVP (BSSE corrected)	-16.2	-8.4	+7.8

Polarization seems to get the ordering of different structures right

# Two different types of physical processes, deterministic and stochastic

# Deterministic behavior:

The outcome of an experiment <u>can</u> be predicted exactly. Applies to many laws of physics: Newton's laws, Maxwell equations etc.

Example: Dice



## Stochastic behavior:

The outcome of an experiment <u>cannot</u> be predicted exactly. This could be an intrinsic property of the physical object – quantum mechanics. Or, the lack of knowledge about the object= statistical mechanics. Fundamentally, all processes in nature are stochastic.

1) The outcome of rolling dice "experiment" consists of 6 different realizations. It can be fully described by a discrete variable g that takes on 6 values:

 $g_1, g_2, g_3, g_4, g_5, g_6$ 

2) Although the laws of solid body mechanics are known, there is no way of predicting exactly the outcome of any experiment. Too many unknowns are involved: asymmetry in the mass distribution in the dice, temperature/pressure fluctuations, convection etc

For quantitative description of stochastic processes one needs the concept of distribution.

# **Distributions:**

Are easiest to introduce for discrete variables. Averages:  $g_2$  seen 3 times By definition: 91 - -- 9m possible realizations  $\langle g \rangle = \frac{1}{M} \sum_{k=1}^{M} g_{k} = \frac{1}{M} (g_{1} + g_{2} + g_{2} + g_{2} + g_{3} + \cdots) =$ of *auantity* g If after M experiments value  $g_i$  is seen  $Mp(g_i)$  times then k= sum over different experiments  $p(g_i)$  = probability distribution function  $= \frac{1}{M} \sum_{i}^{N} M p(g_i) g_i = \sum_{i}^{N} p(g_i) g_i$ Important properties:  $p(g_i) >= 0$ , always positive or zero i= sum over different realizations of variable q  $(A) = \sum_{i=1}^{H} f(g_i) \cdot P(g_i)$ f(g;)=1 has to be normalized, the sum is finite For any function of gand normalized dist.: For any distr. funct.:  $\langle f \rangle = \frac{\sum_{i=1}^{N} f(g_i) P(g_i)}{\sum_{i=1}^{N} P(g_i)}$ Most generally:  $P(g_i) \rightarrow \frac{P(g_i)}{\sum_{i=1}^{N} P(g_i)}$ For continuous variables sum are replaced with integrals:  $X \in [9, 4]$  P(X) dX is the probability of seeing x in the interval  $[X, X+b]_{Y}$ r(x) =probability distribution function

Normalization condition:  $\int f(x) dx = 1$ 

U

Averages:  $(f) = \int f(x) \cdot F(x) dx$ 

# Some basic definitions for distributions

$$\int u^{n} = \int (x - y^{n})^{2} P(x) dx$$

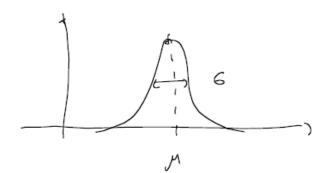
$$\int G^{2} = \int (x - y^{n})^{2} P(x) dx$$

$$\int u^{n} = \int (x - y^{n})^{n} P(x) dx$$

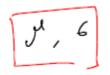
mean value

standard deviation

n-order moment (may or may not exist)



Geometrical interpretation



can be estimated from sampling

Say we have a sequence of measurements:

Average over the sample will approximate the mean value

Square deviation from the average will approximate the standard deviation:

$$S = \left| \begin{array}{c} L \\ L \\ h - l \end{array} \right| \left| \begin{array}{c} X_{i} - X_{i} \right|^{2} \\ h - l \end{array} \right| \left| \begin{array}{c} X_{i} - X_{i} \right|^{2} \\ H - l \end{array} \right| \left| \begin{array}{c} X_{i} - X_{i} \right|^{2} \\ H - l \end{array} \right| \left| \begin{array}{c} X_{i} - X_{i} \right|^{2} \\ H - l \\ H - l \end{array} \right| \left| \begin{array}{c} X_{i} - X_{i} \right|^{2} \\ H - l \\ H - l$$

(*n-1* comes from Bessel correction for finite *n*)

#### **Error** estimate

# Independent measurements

SE = 
$$\frac{S}{\Box}$$
 sample error  
SD =  $\frac{S}{\Box}$  standard error

Correlated measurements

SE =  $\frac{S}{F_{H}} \left\| \frac{1+(h-1)p}{1-p} \right\|$  $l = \mathcal{L}(\frac{1}{2})$  correlation coefficient

 $q = - \infty$  for independent events

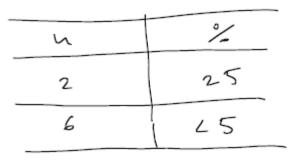
Examples:  $P(x) = \begin{bmatrix} 1 \\ 26^{2} \\ \pi e \end{bmatrix}$ 

normal distribution

Relative error:  $\mathcal{B}\mathcal{B} = \frac{Sp}{p} \rightarrow \frac{S}{p} \frac{F}{p}$ 

declines as inverse square root of the number of  $\mathcal{L} = \mathcal{J}^{\mathcal{L}}$ measurements. n must be large to achieve good accuracy

Accuracy of SE



It's safe to use SE to estimate the error in the measurement for n>10

Wide distributions require larger number of steps to converge

#### Transforming distribution functions

 $\times$  – is a stochastic variable characterized by  $\mathcal{P}(\times \mathbb{N})$ 

$$\gamma = f(x)$$
 Q: what is distribution  $P(\gamma) = ?$ 

From the definition of the probability distribution:

$$P(x)dx = P(y) \cdot dy - 9$$
  
-9 P(y) = 
$$\frac{P(x(y))}{\left|\frac{dy}{dx}(y)\right|}$$
(pr  
tra

(probability density transformation theorem)

This can be written in a more convenient form :

$$P(y) = \frac{P(x(y))}{\int \frac{dA}{dx}(x(y))} = \int \delta(y - f(x)) P(x) dx = \langle \delta(y - f(x)) \rangle$$
change of variables rule for delta function
$$y' = f(x), \ dx = \frac{dy'}{\left|\frac{df}{dx}(x(y'))\right|}$$

$$\int \delta(g(x)) f(g(x)) |g'(x)| \ dx = \int \delta(u) f(u) du$$
Paumkatner PieSim, with 2010

# Examples of probability transformations

1) Normal distribution with zero mean and  $\sigma=1$   $P_{h}(x) = \int_{\sqrt{2\pi}} e^{-\frac{x}{2}}$ 

Q: what is the distribution of the linear transformation of variable x?

$$X = \frac{y - v}{6} - 9 + \frac{y}{6}(X(y)) = \int_{2\pi}^{1} e^{-\frac{y}{2\pi}}$$
  
 $y = y + 6 \cdot X - 9 = 5T = 6$ 

 $P(y) = \frac{1}{1266^2} e^{-\frac{(y-y)}{262}}$ 

M= J+ 6.X

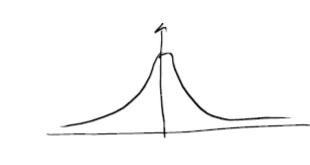
The shape of the distribution doesn't change. But now it is characterized by new mean and variance

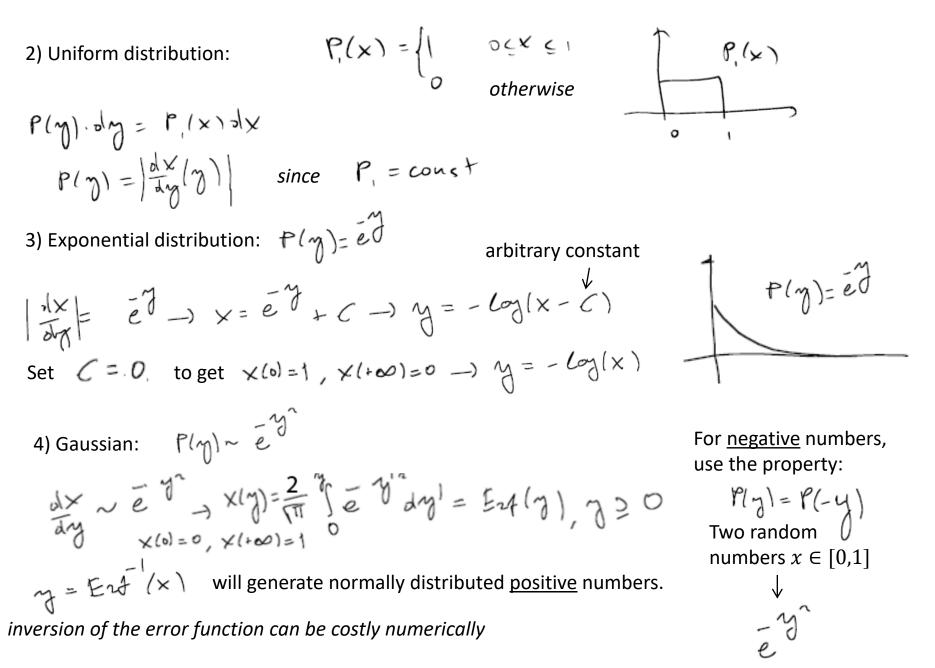
$$\begin{array}{c}
6 \neq 1 \\
\hline
6 \neq 1 \\
\hline
6 \\
\hline
7 \\
\hline
7
\end{array}$$

N/N-M

1

Normal distribution with zero mean and unit standard deviation can be used to generate Gaussians with arbitrary mean and variance through linear transformation of the variable!





5) For distributions of arbitrary shapes: <u>cumulative distribution</u> transformation theorem

$$P(y), y \in [y_1, y_2] \text{ target distribution. Define: } F(y) = \int_{y_1}^{y} P(x')dx' \text{ cumulative dist.}$$

$$z = F^{-1}(x) \text{ what's dist. for this variable } P_n(Z)? \text{ indeed, the desired distribution}}$$

$$P_n(z)dz = 1dx \rightarrow P_n(z) = \frac{d}{dz}x(z), \ x(z) = F(z), \ \frac{dx}{dz} = \frac{dF(z)}{dz} = P(z), \ P_n(z) = P(z)$$

#### Multivariate distributions

Multiple events can be observed simultaneously. For two variables x and y one introduces:

$$\Gamma = (\times, \mathcal{J}) \quad \text{to denote a joint event}$$
Joint distribution function  $\mathcal{P}(\times, \mathcal{J})$  is introduced so that  $\mathcal{P}(\times, \mathcal{J}) \, d \times \, d \mathcal{J}$ 
is the probability of seeing  $\times \mathcal{A} = [\times, \times + \Im \times]$  and  $\mathcal{J} = \mathcal{L} = [\mathcal{D}, \mathcal{J}^{+} \, d \mathcal{J}]$ 

Distributions for individual variables:

Normalization condition:

$$P(x) = \int P(x,y) dy, P(y) = \int P(x,y) dx \qquad \int P(x,y) dx dy = 1$$

#### Conditional probabilities

MAB М Assume 2-D for simplicity A: [X, X+8×] B: [y, 7+67] Event Event ゾ X+PX Mn = total 📱 🕂 2D events М  $= H \circ A$   $M_{AB} = H \circ f$  both  $A \circ A \circ B$  occurring at the same time Ч, = H of B P(A,B)=MAB joint probability

Define conditional probability:

$$P(A|B) = \text{ prob. of } A \text{ once } B \text{ occurred } =$$

$$= \frac{M_{A}B}{M_{B}} = \frac{H_{-} H_{A}B}{H_{-} H_{B}} = \frac{P(A|B)}{P(B)} \int \frac{P(A|B)}{P(B)} = \frac{P(A)}{P(B)}$$

$$P(B|A) = \frac{H_{A}B}{H_{A}} = \frac{P(A|B)}{P(A)}$$

$$P(A|B) = P(B|A) \frac{P(A)}{P(B)}$$
Bayes' theorem
Bayes' theorem

#### Concept of independent events

Assume that event A is not conditioned upon event B. The conditional probability then is equal to the simple probability of event A:

$$P(A|B) = P(A)$$

The joint probability then becomes:

$$P(A,B) = P(A) \cdot P(B)$$

If this condition is met the events are known as <u>independent</u>. The distribution can be used to judge the degree of independence or correlation.

Quantitatively this can be measured by  
correlation coefficient:  

$$\ell = \frac{\langle \Delta \times \cdot \Delta \gamma \rangle}{\sqrt{\Delta \times^2}} \qquad \text{where } x \text{ and } y \text{ are two}$$
stochastic variables and  

$$\Delta \times = \times - \langle \times \rangle, \Delta \gamma = \tilde{\gamma} - \langle \gamma \rangle$$
Case 1: x and y are independent:  

$$\langle \Delta \times \cdot \Delta \gamma \rangle = \int [\langle \times - \langle \times \rangle, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle \times \cdot \gamma, \gamma - \langle \gamma \rangle] \cdot P(x, \gamma) \Delta \omega d\gamma =$$

$$\int [\langle - \langle - \langle - \rangle \rangle] \cdot P(x) \cdot P(y) \Delta \omega d\gamma =$$

$$\int [\langle - \langle - \rangle \rangle] \cdot P(x) \cdot P(y) \Delta \omega d\gamma =$$

$$\int [\langle - \langle - \rangle \rangle] \cdot P(x) \cdot P(y) \Delta \omega d\gamma =$$

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$$\int [\langle - \langle - \rangle \rangle] \cdot P(x) \cdot P(y) \Delta \omega d\gamma =$$

$$\int [\langle - \langle - \rangle \rangle] \cdot P(x) \cdot P(y) \Delta \omega d\gamma =$$

Case 2: *x* and *y* are fully correlated *x*= $\alpha y$ ,  $\alpha > 0$ 

$$(4x \cdot ay) = d \cdot (4y^2), \quad l = \frac{d \cdot (4y^2)}{[d^2(4y^2)^2]} = 1$$

Case 3: *x* and *y* are fully anti-correlated *x=-\alpha y, \alpha > 0* 

$$(\Delta x A y) = - d (A y^2), p = \frac{- d (A y^2)}{d (A y^2)} = -1$$

#### What multivariate distributions can be used for

Generation of normal distributions. Let *x* and *y* be random variables uniformly distributed between 0 and 1. Introduce new variables:

$$X' = \sqrt{-2\log(x)} \cos(2\pi y)$$
  

$$X' + y'' = -2\log(x) - 1 \quad X = e^{-2(x'^2 + y''^2)}$$
  

$$Y' = \sqrt{-2\log(x)} \sin(2\pi y)$$

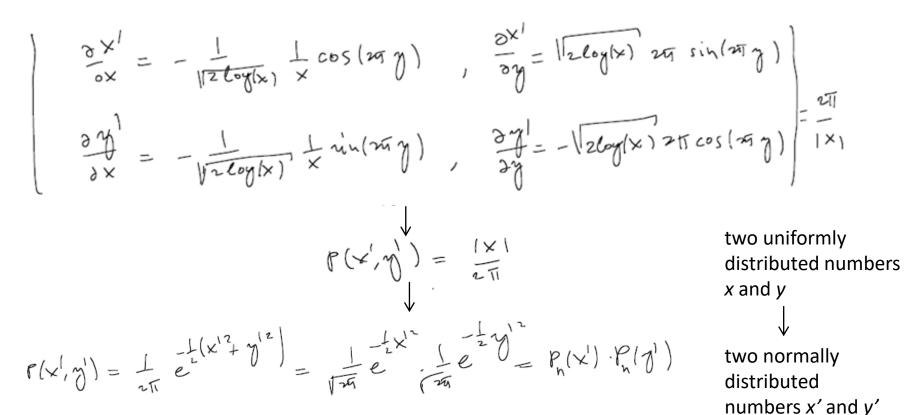
Transformation of the joint distribution function:

$$P(x) = P_{i}(x), P(g) = P_{i}(g)$$

$$P(x', g') | \exists x' \exists g' = P_{i}(x) \cdot P_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot \forall x \exists y = -p_{i}(x) \cdot p_{i}(g) \cdot p_{i}$$

$$\rightarrow P(x', \eta') = \frac{1}{|\frac{\partial(x', \eta')}{\partial(x, \eta)}|}$$

Jacobian of the transformation



# Statistical mechanics = theory to extract <u>macroscopic</u> properties from <u>microscopic</u> variables

Microscopic description:

2N-D phase space:

$$\begin{bmatrix} (q, P_1) & (q_1, \dots, q_m)^2 \\ (q_1, P_1) & (q_1, \dots, q_m)^2 \\ (q_1, P_1) & (q_1, \dots, q_m) \end{bmatrix} (q_1, P) = P$$

Coordinates + momenta fully define the state of a system with N degrees of freedom

Measuring property  $A(\Gamma)$  always yields time average (take pressure in tires for example):

$$A_{ols} = (A)_{time} = (A(\Gamma(H))_{time} = \lim_{t \to l_s} \int_{\Delta} (\Gamma(H))_{time} = \lim_{t \to l_s} (\Gamma(H))_{tim} = \lim_{t \to l_s} (\Gamma(H))_{time} = \lim_{t \to l_s} (\Gamma(H))_{time}$$

real or virtual experiment

Observation time  $t_{obs}$  is always finite. Furthermore, in practice it is always discretized so that the integral can be carrier out.:

$$+_{0As} = SJ \cdot T_{0As} - T_{0S} = \#$$
 of steps/events in the observation  $\{$ 

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must be large

- r enough to eliminate
- dependence on the initial conditions

The expression for the observable now reads:

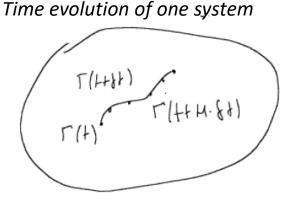
(\*) 
$$A_{pls} = (A)_{time} = \frac{1}{\tau_{obs}} \frac{\tau_{obs}}{\tau_{abs}} A(\Gamma(\tau))$$
,  $\tau$  is now just a blind index that enumerates all measurements

Recall how we computed averages for random variables:

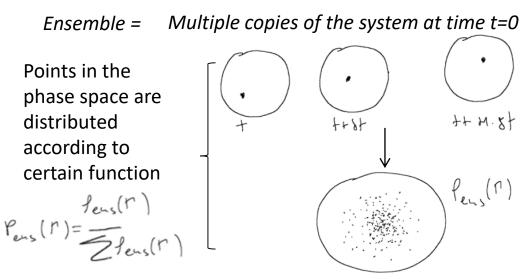
$$\langle g \rangle = \frac{1}{M} \sum_{k}^{M} g_{k} = \frac{1}{M} (g_{1} + g_{2} + g_{2} + g_{2} + g_{3} + \cdots)$$
 it's the same formula

On one hand we have <u>time evolution</u> but on the other – different realizations of some random variables that can be described by certain <u>distribution</u>. Both descriptions lead to the same average. The one based on distributions is the subject of statistical mechanics.

#### The concept of ensembles

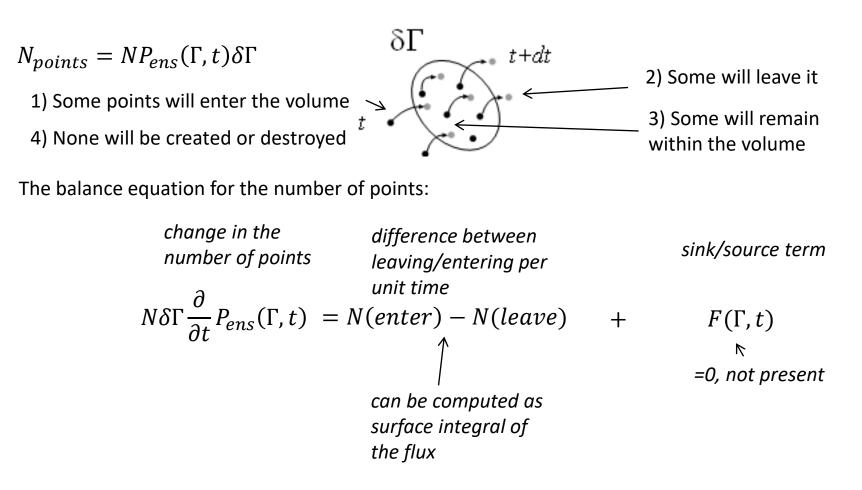


The same state point  $\Gamma$  can be visited multiple times

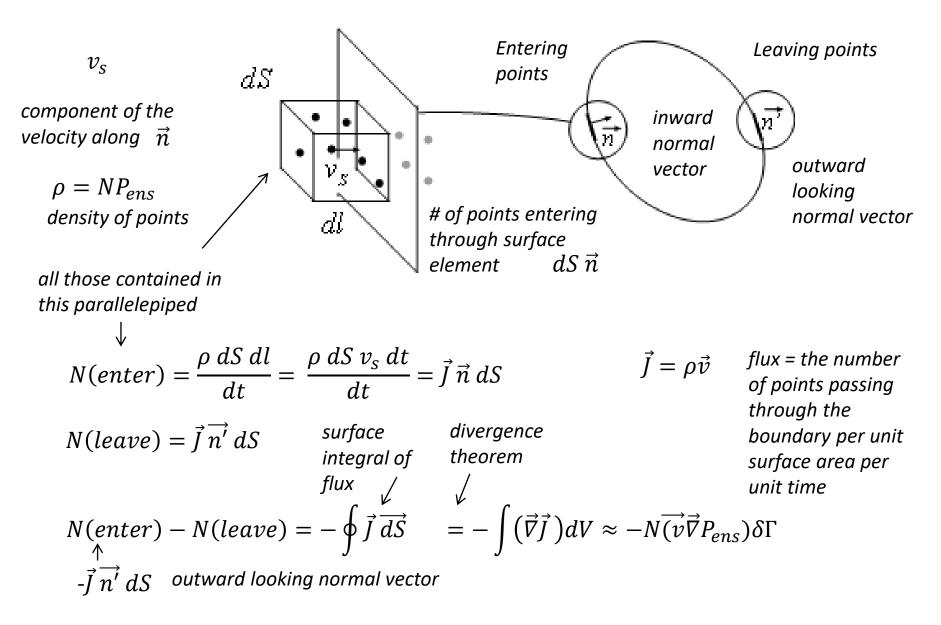


At first glance the connection between <u>time average</u> and <u>ensemble average</u> appears to be straightforward. But there are important subtleties.

Let us consider N members of the ensemble, each corresponding to a gamma point  $\Gamma$ i. Consider that in general the distribution function may have explicit dependence on time. See what happens in a certain volume  $\delta\Gamma$  when the time changes from t to t+dt.



Let's forget about momenta in  $\Gamma$  for the moment and focus on Cartesian coordinates only



Putting the estimate into the balance equation:

$$N\delta\Gamma\frac{\partial}{\partial t}P_{ens}(\Gamma,t) = -N(\vec{v}\vec{\nabla}P_{ens})\delta\Gamma$$

$$\downarrow$$

$$\frac{\partial}{\partial t}P_{ens}(\Gamma,t) + (\vec{v}\vec{\nabla}P_{ens})=0$$

$$\downarrow$$

$$\frac{\partial}{\partial t}P_{ens}(\Gamma,t) + \dot{\vec{r}}\frac{\partial}{\partial \vec{r}}P_{ens}=0$$

If we add momenta back to the equation we will get (by analogy):

$$\frac{\partial}{\partial t}P_{ens}(\Gamma,t) + \dot{\vec{r}}\frac{\partial}{\partial \vec{r}}P_{ens} + \dot{\vec{p}}\frac{\partial}{\partial \vec{p}}P_{ens} = 0$$

$$\downarrow$$

$$\left(\frac{\partial}{\partial t} + \dot{\vec{r}}\frac{\partial}{\partial \vec{r}} + \dot{\vec{p}}\frac{\partial}{\partial \vec{p}}\right)P_{ens}(\Gamma,t) = 0$$

$$Liouville equation$$

$$\frac{dP_{ens}(\Gamma,t)}{dt} = 0 \quad \frac{d\rho_{ens}(\Gamma,t)}{dt} = 0.$$
The probability distribution is constant along any trajectory

In equilibrium the probability distribution can not depend on time. Because otherwise the averages would depend on time as well. That contradicts the definition of "equilibrium". Therefore:

$$P_{ens}(\Gamma, t) = P_{ens}(\Gamma) \longrightarrow \frac{\partial}{\partial t} P_{ens}(\Gamma, t) =$$
  
 $N(enter) - N(leave) = 0$ 

The system is evolving in is such a way that

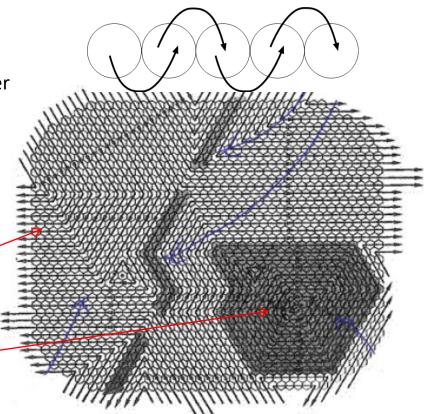
 $P_{ens}(\Gamma) = const$  at each point

As one point exits certain cell in the phase space, another point immediately enters it. As a result, all points are moving in concert in what resembles a Conga line.

The line snakes around the phase space as time passes by. How this happens has important consequences.

<u>Option 1</u>. The snakes passes through all points available in the phase space. The entire phase space is accessible. <u>Ergodic</u> behavior.

<u>Option 2</u>. There are regions in the phase space from which the snake cannot break out. It moves in a circular manner. <u>Non-ergodic</u> behavior. for any point in the phase space. The number of points occupying it is conserved.



In ergodic systems, all phase points are visited multiple times during a simulation. Only in this case is the time average equal to ensemble average (with particular distribution function)

$$A_{obs} = \langle A \rangle_{time} = \langle A \rangle_{eus} = \frac{\sum A_i(r) \cdot P_{eus}(r)}{\sum P_{eus}(r)}$$

1) Determining whether or not a system is ergodic is not a trivial task. Rigorous proof exists only for a few model systems, such as coupled harmonic oscillators.

2) There are different reasons for non-ergodicity

a) Frustration – multiplicity of potential energy minima of the same depth prevents their thorough exploration
b) Low temperature. Creates very high barriers in the free energy landscape that can be overcome. The system becomes locked up in certain parts of the phase space. Glass transition is one example.

3) Certain models are known to be non-ergodic. For instance, certain lattice models of proteins

4) It's easy to design a non-ergodic system. All it takes is to arrange a circular movement in the phase space. Can be achieved through specific Monte Carlo moves.

#### Stat mech. .vs. thermodynamics

Normalization constant of the probability distribution is not needed to compute averages. Consider

 $\rho_{ens}(\Gamma)$  and another distribution proportional to it  $\rho'_{ens}(\Gamma) = \alpha \rho_{ens}(\Gamma)$ 

According to the definition:

$$' = \sum\_{\Gamma} A\(\Gamma\)\rho'\_{ens}\(\Gamma\) / \sum\_{\Gamma} \rho'\_{ens}\(\Gamma\) = \sum\_{\Gamma} A\(\Gamma\)\alpha\rho\_{ens}\(\Gamma\) / \sum\_{\Gamma} \alpha\rho\_{ens}\(\Gamma\) =$$
$$= \sum_{\Gamma} A(\Gamma)\rho_{ens}(\Gamma) / \sum_{\Gamma} \rho_{ens}(\Gamma) =$$

But this quantity is central to establishing link between <u>microscopic</u> description in terms of coordinates/momenta and <u>macroscopic</u> description in terms of thermodynamic functions

minimum in equilibrium.

#### Common ensembles

Microcanonical ensemble (NVE)

Distribution function:

$$\rho_{\rm ens} \sim \delta(E - H(\Gamma))$$

Hamiltonian:

$$H(\Gamma) = E_k + E_p = \sum_{i} \frac{\vec{p_i}^2}{2m_i} + U(\vec{q_1}, \cdots, \vec{q_N})$$

Partition function:

$$Q_{NVE} = \sum_{\Gamma} \delta(E - H(\Gamma))$$
 volume of the hypersurface that corresponds to energy  $E$ 

proportionality constant first introduced on the grounds of dimensionalities. Then recognized as the Plank constant when QM came about

$$Q_{NVE} = \frac{1}{N! h^{3N}} \int d\vec{p} d\vec{q} \delta(E - H(\Gamma))$$

takes care of the distinguishability of the particles

entropy

equiprobable

Thermodynamic potential:

$$\Psi_{NVE} = -k\log(Q_{NVE}) = -S(N, V, E)$$

Boltzmann's constant

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all configurations with energy E are *Physical equivalent= an* isolated system NVE  $E = H(\Gamma)$ F 出 1 2 Æ 生 2

> the integral counts these contributions twice

Canonical ensemble (NVT)

Distribution function:

$$\rho_{NVT}(\Gamma) \sim e^{-\beta H(\Gamma)}, \beta = \frac{1}{kT}$$

external parameter that is associated with temperature

Partition function:

$$Q_{\text{NVT}} = \sum_{\Gamma} e^{-\beta H(\Gamma)} = \sum_{E} n(E) e^{-\beta E}$$
 states

separation of the partition function

$$Q_{NVT} = \frac{1}{h^{3N}N!} \int d\vec{p} d\vec{q} e^{-\beta H(\Gamma)} = \frac{1}{h^{3N}N!} \int_{\Lambda} d\vec{p} e^{-\beta E_K} \int_{\Lambda} d\vec{q} e^{-\beta U(\vec{q})} =$$

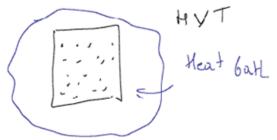
$$kinetic \ part \qquad configuration \\ integral \qquad configuration \\ integral \qquad configuration \\ NVT \times Q_{NVT}^{ex} \quad Q_{NVT}^{id} = \frac{V^N}{N! \lambda^{3N}}, \lambda = \sqrt{h^2/2\pi mkT} \quad Q_{NVT}^{ex} = \frac{Z_{NVT}}{V^N}, Z_{NVT} = \int d\vec{q} e^{-\beta U(\vec{q})}$$

density of

Thermodynamic potential:

$$\Psi_{NVT} = F(N, V, T) = -kT\log(Q_{NVT}) = F_{id}(N, V, T) + F_{ex}(N, V, T)$$
  
Helmholtz free energy ideal gas part excess part (due to interactions)  
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Physical equivalent= system exchanging heat with the environment



multiple hypersurfaces are populated with the probability  $\sim n(E)e^{-\beta E}$  Distribution function:

 $\rho_{NPT}(\Gamma) \sim e^{-\beta(H(\Gamma,V)+PV)}$ 

Partition function:

external parameter associated with pressure

$$Q_{NPT} = \sum_{V} \sum_{\Gamma} e^{-\beta(H(\Gamma, V) + PV)} = \sum_{V} Q_{NVT} e^{-\beta PV}$$

separation of the partition function

$$Q_{NPT} = \frac{1}{h^{3N}N!V_0} \int dV \int d\vec{p} d\vec{q} e^{-\beta(H(\Gamma,V)+PV)} = \frac{1}{h^{3N}N!V_0} \int d\vec{p} e^{-\beta E_K} X$$

$$X \int dV e^{-\beta PV} \int d\vec{q} e^{-\beta U(q)} = \frac{1}{N!\lambda^{3N}V_0} Z(N, P, T)$$

$$Z(N, P, T) = \int dV e^{-\beta PV} Z_{NVT}$$
configuration integral

Thermodynamic potential:

$$\frac{Thermodynamic potential:}{\Psi_{NPT}} = G(N, P, T) = -kT\log(Q_{NPT}) = G_{id}(N, P, T) + G_{ex}(N, P, T)$$

Gibbs free energy

(both contain contributions from configuration integral)

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ideal gas part

*Physical equivalent= system* under a piston

both energy and  
volume are allowed to  
change  
$$E = H(\Gamma, V)$$

Distribution function:

$$\rho_{\mu VT}(\Gamma) \sim e^{-\beta(H(\Gamma,V)-\mu N)}$$

no separation but the kinetic part can be integrated

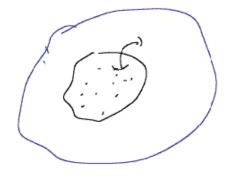
Partition function:

explicitly

external parameter associated with chemical potential

$$Q_{\mu VT} = \sum_{N} \sum_{\Gamma} e^{-\beta (H(\Gamma, V) - \mu N)} = \sum_{N} Q_{NVT} e^{\beta \mu N}$$

*Physical equivalent=* system exchanging heat and particles with the environment



energy and number of particles are allowed to  $Q_{\mu VT} = \sum_{N} e^{\beta \mu N} Q_{NVT}^{id} Q_{NVT}^{ex} = \sum_{N} e^{\beta \mu N} \frac{1}{N! \lambda^{3N}} Z(N, V, T)$ change

key property to be evaluated

Thermodynamic potential:

$$\Psi_{\mu VT} = \Phi_{G}(\mu, V, T) = -kT\log(Q_{\mu VT}) = F - \mu N = -PV$$

$$\swarrow$$
grand canonical
potential
chemical potential

#### Summary on ensembles/thermodynamic functions

Microcanonical (primary)

$$\frac{S(N,V,E)}{k} = \log(Q_{NVE}) \qquad entropy$$

Canonical

$$F(NTV) = -kT\log(Q(NTV)) = E - TS$$

Isobaric-isothermic

$$G(NPT) = -kT\log(Q(NPT)) = F + PV$$

Grand canonical

$$\Phi(\mu TV) = -kT\log(Q(\mu TV)) = F - \mu N = -PV$$
 Grand canonical or Hill free energy

Link to thermodynamics

Fundamental law:

μ*TP* is not an ensemble. it contains only intensive variables some of which are related

Helmholz free energy

Gibbs free energy

# Monte Carlo method

Monte Carlo – a class of algorithms that rely on random sampling to obtain numerical results

a) Developed by Ulam, von Nuemann and Metropolis in the 40's to model diffusion of neutrons in fissile material.

b) The term is the codename coined after Monte Carlo casino where Ulam's uncle used to borrow money to gamble.

c) Many flavors exist designed to address specific problems

d) Use in math: applied statistics – the inference problem, integration, optimization, inverse problems etc.

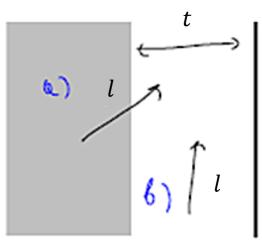
e) Under the name of Markov Chain Monte Carlo (MCMC), used widely in physics, chemistry, biology, finance, quantitative linguistics etc

The main idea: use *stochastic* methods (random sampling) to solve *deterministic equations.* 

How is that possible? Why is that needed?

Example: Buffon's needle experiment

A needle of length *I* is thrown onto a striped field. What is the probability that the needle will cross the middle line?



Two outcomes of the experiment: a) Needle crosses the middle line b) Needle doesn't cross the line

The state of the needle is defined by two variables:

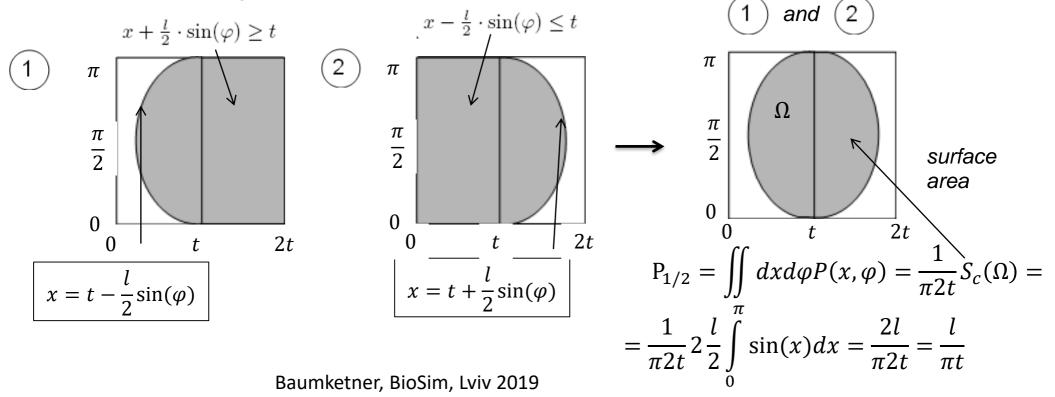
a) x – the center of the needle a) $\varphi$ – the angle it makes with the vertical axis

x and  $\varphi$  are random variables, independently distributed.

 $P(x), P(\varphi), P(x, \varphi) \in$  are all uniform distributions – no preferential x or  $\varphi$ .

$$P(x,\varphi) = \frac{1}{\pi} \cdot \frac{1}{2t}, \qquad \int P(x,\varphi) dx d\varphi = 1$$

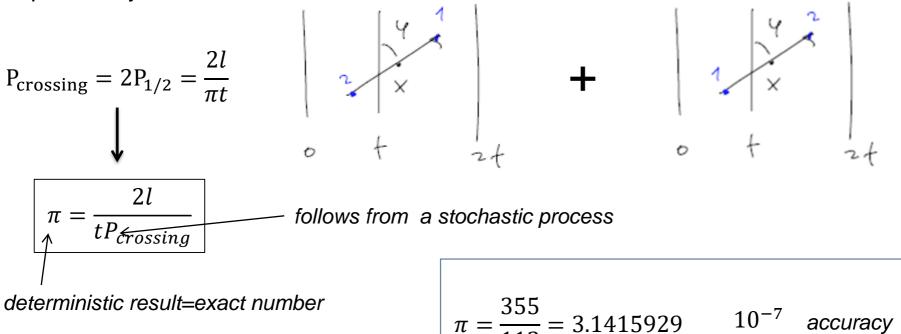
The needle crosses the line when x coordinate of points 1 and 2 satisfies the following conditions:



2D configuration space

 $x \in [0, 2t],$  $\varphi \in [0, \pi]$ 

Full probability:



Lazzarini's experiment:3408 trials

# $\pi = \frac{355}{113} = 3.1415929$

#### **Example:** hit and miss integration

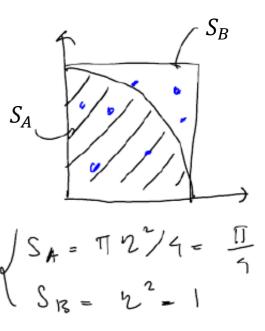
Throw particles (generate pairs of random numbers) on this square and count how many fall within the circle r = 1. The goal is to compute  $\pi$ .

If particles are distributed uniformly then:

 $P_A$  - probability to hit circle

 $P_{\rm R}$  - probability to square

$$\begin{cases} P_A \approx S_A = \frac{\pi}{4} \\ P_B \approx S_B = 1 \\ \downarrow \\ \frac{P_A}{P_B} = \frac{S_A}{S_B} = \frac{\pi}{4} \end{cases}$$



If the number of particles hitting the circle is  $n_A$  and those hitting the square is  $n_B$ :

$$\pi = \frac{4n_A}{n_B}$$

Accuracy estimates:

 $\swarrow$  10<sup>-4</sup> accuracy Hit & miss: **3.141 7 3** after 10<sup>7</sup> shots

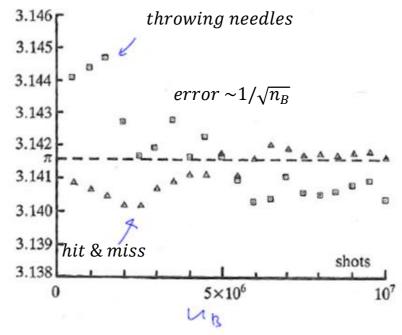
 $\swarrow$  10<sup>-3</sup> accuracy Needles: **3.14 0 472** after 10<sup>7</sup> shots

Conclusion: Lazzarini was able to compute  $\pi$  with 10<sup>-7</sup> accuracy after ~10<sup>4</sup> shots so he:

a) cheated

b) had a VERY lucky afternoon with numbers!



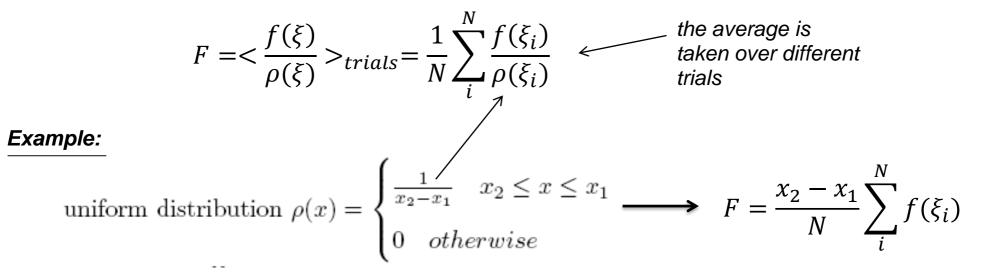


#### Sample mean integration

Hit & miss experiment is an example of the "sample mean" integration method.

Goal: compute 
$$F = \int_{x_1}^{x_2} f(x) dx$$
  
.  
Rewrite  $F = \int_{x_1}^{x_2} f(x) dx = \int_{x_1}^{x_2} \frac{f(x)}{\rho(x)} \cdot \rho(x) dx = \begin{cases} \rho(x) - \text{arbitrary} \\ distribution \\ function \end{cases}$ 

If  $N_{\tau}$  trials are performed to sample random variable  $\xi$ , distributed according to  $\rho(\xi)$ , then

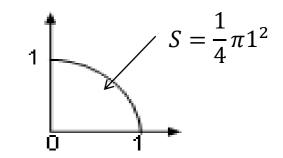


Compute  $\pi$  number by the sample mean method:

$$f(x) = \sqrt{1 - x^2}, x \in [0, 1], \int_0^1 \sqrt{1 - x^2} dx = \frac{\pi}{4}$$

$$\pi \approx 3.14 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \text{for } N = 10^7 \qquad \text{same ac}$$

$$10^{-4} \text{ accuracy}$$



same accuracy as the hit and miss method

Simpson's integration rule:

$$\pi = 3.141593$$
 after  $10^4$  steps!  
 $10^{-6}$  accuracy

The stochastic method is not competitive!

The cost of Simpson's rule (or similar quadrature method based on interpolation) is prohibitive for multi-dimensional integrals!

$$D = n \longrightarrow \int f(\vec{x}) dx_1 \dots dx_n \quad n_s - \text{number of sample points per} \qquad n_s^n - \text{number of function} \\ n = 300 \quad \text{for an ensemble of 100} \\ n_s = 10 \quad \text{particles} \qquad \boxed{10^{300} \qquad \begin{array}{c} \text{function evaluations. That's an} \\ \text{astronomical number that no computer} \\ \text{can handle!} \end{array}}$$

For integrals of high dimensionality stochastic methods remain the only viable option

Two steps involved in the integration using uniform  $\rho$ :

*(in math this method is known as random Monte Carlo integration)* 

1) Pick a point in the configuration space  $(\overrightarrow{r_1} ... \overrightarrow{r_N})$  by generating 3N random numbers <u>uniformly</u>

2) Compute the potential energy  $U(\overrightarrow{r_1} ... \overrightarrow{r_N})$  and the integrand for select  $\beta$ 

Repeat these steps  $N_s$  times and compute the configuration integral as:

$$Z(N, V, T) = \frac{1}{N_s} \sum_{i=1}^{N_s} e^{-\beta U(\overrightarrow{r_1}(i) \dots \overrightarrow{r_N}(i))}$$

Problems with the uniform  $\rho$ :

1)  $N_s$  has to be VERY large. For most systems of practical interest in physics convergence is not attainable.

2) Ensemble averages

$$< A > = \frac{\sum A_i e^{-\beta U_i}}{\sum e^{-\beta U_i}}$$

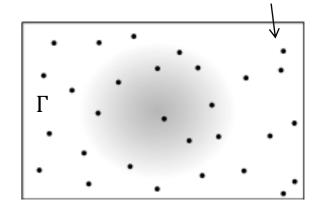
Focus on the configuration integral of the canonical ensemble.

$$Z(N, V, T) = \int e^{-\beta U(\overrightarrow{r_1} \dots \overrightarrow{r_N})} d\overrightarrow{r_1} \dots d\overrightarrow{r_N}$$

$$\uparrow$$
Cartesian coordinates

the integral has to converge with  $N_s$ 

for many evaluation points  $e^{-\beta U} \sim 0$ 



are even less accurate and in most cases meaningless

a number with large uncertainty in the denominator

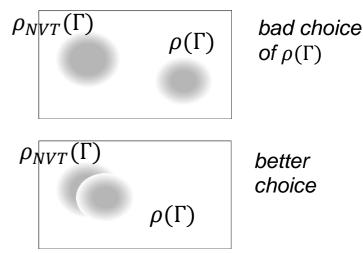
# Importance sampling

To reduce the number of zeroes choose a distribution function  $\rho(\Gamma)$  that has a strong overlap with the integrand.

For the canonical ensemble:

$$< A >_{NVT} = \frac{\int A(\Gamma)\rho_{NVT}(\Gamma)d\Gamma}{\int \rho_{NVT}(\Gamma)d\Gamma} = \frac{\_{trials}}{<\rho\_{NVT}/\rho >\_{trials}}$$

$$\rho - sampling \ distribution$$



Specific choice  $\rho(\Gamma) = \rho_{NVT}(\Gamma)$  is known as <u>importance sampling</u>:

$$<\frac{\rho_{NVT}}{\rho}>_{trials} = <1>_{trials} =1$$

$$< A >_{NVT} = < A >_{trials}$$

How does one generate a sequence of configurations  $\Gamma_1 \dots \Gamma_N$  that satisfy the given distribution  $\rho(\Gamma)$ ?

Answer: design a Markov chain of states whose limiting distribution is  $\rho(\Gamma)$ !

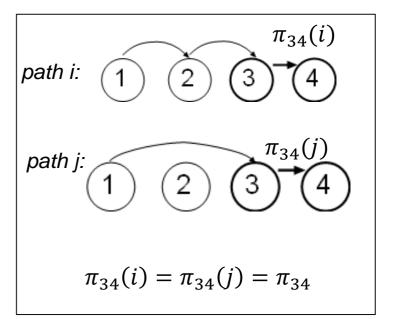
(the corresponding method is known as Markov Chain Monte Carlo (MCMC))

# Markov chains

What does it mean "Markov chain"? Stochastic process in which:

a) there is a finite (countable) set of configurations in the phase space {  $\Gamma_1 ... \Gamma_N$  }.

b) transition from state *i* to state *j* does not depend on the history prior to state *i*. There is no memory. Correlation only between neighboring sites.



Transition probabilities among states make a matrix  $\hat{\pi}$ :

 $\pi_{mn}$  probability of making a transition from state *m* to state *n*.

$$\sum_{n\neq m}\pi_{mn}$$

probability of transitioning to any state

 $\pi_{mm}$ probability of remaining in state m. $\sum_{n} \pi_{mn} = 1$ consequence of the phase space finiteness

### How are $\pi_{mn}$ and $\rho(\Gamma)$ related?

#### **Example:** prediction of computer's up time

Computer can be either up or down. So the phase space consists of two states  $|\uparrow>$  and  $|\downarrow>$ 

day before

down the day before

Computer has:

Transition matrix from day 1 to day 2

70% chance of being down today if it was  $\hat{\pi} = \begin{pmatrix} \pi(\uparrow\uparrow) & \pi(\uparrow\downarrow) \\ \pi(\downarrow\uparrow) & \pi(\downarrow\downarrow) \end{pmatrix} = \begin{pmatrix} 0.6 & 0.4 \\ 0.3 & 0.7 \end{pmatrix}$ 

60% chance of being up today if it was up the

**Day 3**: 
$$\rho(\uparrow) = 0.6 * 0.6 + 0.4 * 0.3 = 0.48$$
  
 $\rho(\downarrow) = 0.4 * 0.7 + 0.6 * 0.4 = 0.52$   
 $(0.48\ 0.52) = (0.6\ 0.4) \begin{pmatrix} 0.6 & 0.4 \\ 0.3 & 0.7 \end{pmatrix} = (1\ 0) \begin{pmatrix} 0.6 & 0.4 \\ 0.3 & 0.7 \end{pmatrix}^2$ 

$$\hat{\rho}(3) = \hat{\rho}(2) \cdot \hat{\pi} = \hat{\rho}(1) \cdot \hat{\pi} \cdot \hat{\pi} = \hat{\rho}(1) \cdot \hat{\pi}^2$$

Day N:

 $\hat{\rho}(N) = \hat{\rho}(1) \cdot \hat{\pi}^{N-1}$ 

probability on day N depends on probability on day 1

Is there a limiting probability for large N in which the dependence on the initial state disappears?

 $\lim_{N \to \infty} \hat{\rho}(N) = \bar{\rho} \quad \text{does this limit exist?}$ 

If it does, then the probability becomes independent of time so it is equal for day N+1 and day N:

$$\hat{\rho}(N+1) = \hat{\rho}(N) = \bar{\rho}$$

However,

$$\hat{\rho}(N+1) = \hat{\rho}(N) \cdot \hat{\pi} \longrightarrow \bar{\rho} = \bar{\rho} \cdot \hat{\pi}$$
 an equation distribution

an equation for the limiting distribution

Eigenvector eigenvalue problem

$$\rho = \sum_{m} \rho_m \pi_{mn}$$

 $\bar{o} = \bar{o} \cdot \hat{\pi}$ 

limiting distribution  $\overline{\rho}$  is the left eigenvector of the transition matrix  $\hat{\pi}$  that corresponds to the eigenvalue 1

 $\hat{\pi}$  is a **stochastic matrix** – its rows sum up to 1. We will also assume that it is an irreducible matrix which means that all states are accessible leading to ergodic behavior.

**Perron-Frobenius theorem** for stochastic irreducible matrices: The maximum eigenvalue is  $\lambda(1) = 1$ . It's simple (non-degenerate). Its eigenvector is real. No other real eigenvector exists.

Consequences: a) limiting distribution  $\bar{\rho}$  exists

b) eigenvalues  $\lambda(n), n > 1$  control the convergence rate to  $\bar{\rho}$ 

# Application to the canonical configuration integral

The transition matrix  $\hat{\pi}$  is unknown. But we know the limiting distribution  $\rho_m = \rho_{NVT}(\Gamma_m)$ 

Some rules for constructing  $\hat{\pi}$ 

a) avoid the need to compute  $Q_{NVT} = \sum_{m} \rho_{m}$ b) Detailed balance :  $\rho_{n}\pi_{nm} = \rho_{m}\pi_{mn}$ Take the sum over m:  $\sum_{m} \rho_{n}\pi_{nm} = \rho_{n}\sum_{m} \pi_{nm} = \rho_{m}\pi_{mn}$   $\sum_{m} \rho_{n}\pi_{nm} = \rho_{n}\sum_{m} \pi_{nm} = \rho_{n} = \sum_{m} \rho_{m}\pi_{mn}$  $\rho_{n}$  is the desired eigenvector

A number of methods are available to build  $\hat{\pi}$  that satisfies detailed balance

Metropolis-Hastings

Wood/Glauber/Barker Kawasaki

Metropolis-Hastings method: asymmetrical solution

1

$$\begin{aligned} \pi_{mn} &= \alpha_{mn} \quad \rho_n \ge \rho_m \quad m \neq n \\ \pi_{mn} &= \alpha_{mn} \cdot \frac{\rho_n}{\rho_m} \quad \rho_n < \rho_m \quad m \neq n \\ \pi_{mm} &= 1 - \sum_{m \neq n} \pi_{mn} \longrightarrow \sum_n \pi_{mn} = 1 \end{aligned}$$

$$\alpha_{mn} = \alpha_{nm}$$
 a symmetric stochastic matrix underlying Markov chain

Proof that the solution satisfies the detailed balance:

$$(m \to n \text{ for lower final } \rho)$$

$$(n \to m \text{ for higher final } \rho)$$

$$\rho_n \leq \rho_m: \quad \rho_n \pi_{nm} = \rho_n \alpha_{nm} = \rho_m \alpha_{nm} \frac{\rho_n}{\rho_m} = \rho_m \alpha_{mn} \frac{\rho_n}{\rho_m} = \rho_m \pi_{mn}$$

$$\rho_n > \rho_m: \quad \rho_n \pi_{nm} = \rho_n \alpha_{nm} \frac{\rho_m}{\rho_n} = \alpha_{nm} \rho_m = \alpha_{mn} \rho_m = \rho_m \pi_{mn}$$

$$(n \to m \text{ for lower final } \rho) \quad \checkmark$$
Important point:  $\pi_{nm}$  depends on the ratio  $\rho_n / \rho_m$  but not on these quantities individually

One needs to know  $\rho_n$  up to a multiplicative constant to arrange a Markov chain. The normalizing factor  $Q_{NVT} = \sum_n \rho_n$  is not required.

# Symmetric solution

$$\begin{cases} \pi_{mn} = \alpha_{mn} \frac{\rho_n}{\rho_n + \rho_m} & m \neq n \\ \pi_{mm} = 1 - \sum_{n \neq m} \pi_{mn} & \alpha_{mn} = \end{cases}$$

 $\alpha_{mn} = \alpha_{nm}$  a symmetrical stochastic matrix Wood & Jacobson 1954 Flinn & McManus 1961 Glauber 1963(Spin systems) Barker 1965(liquids)

Proof that the solution satisfies the detailed balance:

$$\rho_n \pi_{nm} = \rho_n \alpha_{nm} \frac{\rho_m}{\rho_n + \rho_m} = \rho_m \alpha_{mn} \frac{\rho_n}{\rho_n + \rho_m} = \rho_m \pi_{mn}$$

# Which solution is better?

Statistical inefficiency to measure the rate of convergence to the limiting distribution: low inefficiency=fast convergence

s is anti-correlated with the off-diagonal entries in  $\hat{\pi}$  matrix

	Asymmetrical	Symmetrical
$\rho_n \ge \rho_m$	$\alpha_{mn}$	$> \qquad \alpha_{mn} \frac{\rho_n}{\rho_n + \rho_m}$
$\rho_n < \rho_m$	$\alpha_{mn} \frac{\rho_n}{\rho_m}$ >	> $\alpha_{mn} \frac{\rho_n}{\rho_n + \rho_m}$

$$s = \frac{\tau_{run}\sigma^2(\langle A \rangle_{run})}{\sigma^2(A)}$$

$$\begin{split} & [\hat{\pi}_1]_{nm} > [\hat{\pi}_2]_{nm} \quad m \neq n \\ & s(\pi_1) < s(\pi_2) \end{split}$$

Metropolis algorithm has faster convergence rate

# MC in canonical ensemble

Let's see how Monte Carlo can be applied to simulate liquids, in particular Lennard-Jones liquid.

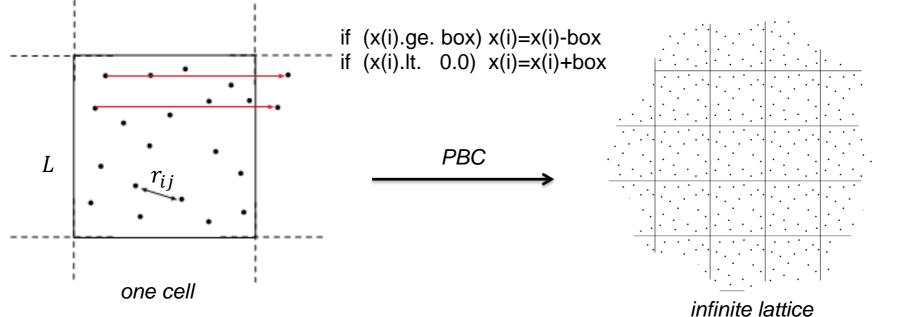
Configuration space:

Probability distribution:

$$\Gamma = (\overrightarrow{r_1}, \dots, \overrightarrow{r_N})$$
$$U(\Gamma) = \frac{1}{2} \sum_{i \neq j}^{N} U_{LJ}(r_{ij})$$

 $\rho_{NVT}(\Gamma) \sim e^{-\beta H(\Gamma)}, \beta = \frac{1}{kT}$ 

Periodic boundary conditions (PBC) are applied to remove the surface artifacts



Baumketner, BioSim, Lviv 2019

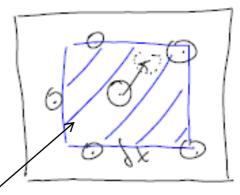
 $U_{LJ}(r) = 4\epsilon \left(\left(\frac{\sigma}{r}\right)^{12} - \left(\frac{\sigma}{r}\right)^{6}\right)$  $\sigma 2^{1/6}$  $-\epsilon$ .....

# How to design MC moves

In order to run MC one needs to select the symmetric matrix  $\hat{\alpha}$ .

For simplicity the matrix  $\alpha_{nm} = \alpha_{mn} = \alpha$  is assumed to be a constant

One possible choice for this constant is related to how new configurational states  $r_n$  are generated.



Assume new **trial** states are generated by random displacement of atom *i* by vector:  $\delta \vec{r} = (\xi_1 \delta x, \xi_2 \delta x, \xi_3 \delta x)$  where  $\delta x$  is the maximum allowed displacement and  $\xi_i \in [0,1]$  are random numbers

If the initial state is n, then the final states m will make a cube with side  $\delta x$ . This cube will contain a large but finite (on computers) number of points  $N_k$ .

Any one of these points will have an  $\frac{1}{N_k}$  probability of being occupied upon transition.

Therefore random displacements occur with transition probability  $\frac{1}{N_k} = \pi_{nm} = \alpha_{nm}$ 

A natural choice:

$$\alpha = \frac{1}{N_k}$$
 so  $\alpha$  will be set by the magnitude of  $\delta x$ 

#### Simulation scheme

The system is in an initial state n. Potential energy is available.

 $\rightarrow$  **<u>Step 1</u>**: pick a random displacement vector. This will happen with probability  $\alpha$ .

**<u>Step 2</u>**: If the resulting  $\rho_m > \rho_n$ , accept the move as this means  $\pi_{nm} = \alpha$  transition probability.

- Step 3: If the resulting  $\rho_m < \rho_n$ , accept the move with  $\frac{\rho_m}{\rho_n}$  probability. This means

$$\pi_{nm} = \alpha \frac{\rho_m}{\rho_n}$$
 transition probability

For  $\rho_n \sim e^{-\beta E_n}$  and  $\Delta E = E_m - E_n$ , the algorithm can be written as follows:

Accept  $\underline{n} \to \underline{m}$  move with  $\min\{1, e^{-\beta \Delta E}\}$  probability

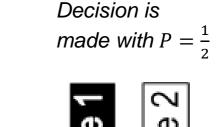
How to decide whether a given move should be accepted or rejected based on its desired probability *P*?

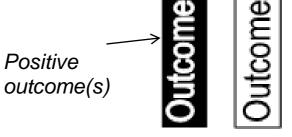
The outcome is stochastic so it has to rely on a stochastic/random process. The simplest method is to flip a coin or roll a dice.

# Coin example:

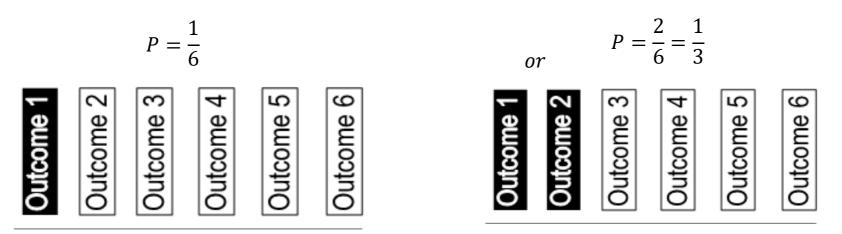
If we don't want/are unable to make a decision we leave it to chance.

If we flip a coin, the positive outcome of the decision will have  $\frac{1}{2}$  probability





If we roll a dice, the positive outcome of the decision may have probability 1/6 or a number of other values



In general, a dice with N sides may encode N - 1 distinct probabilities:

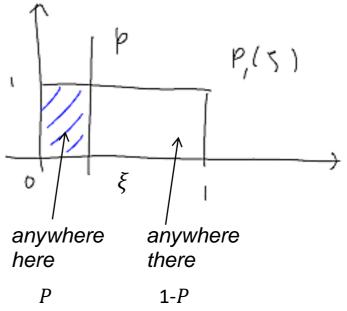


Generalization to continuous P:

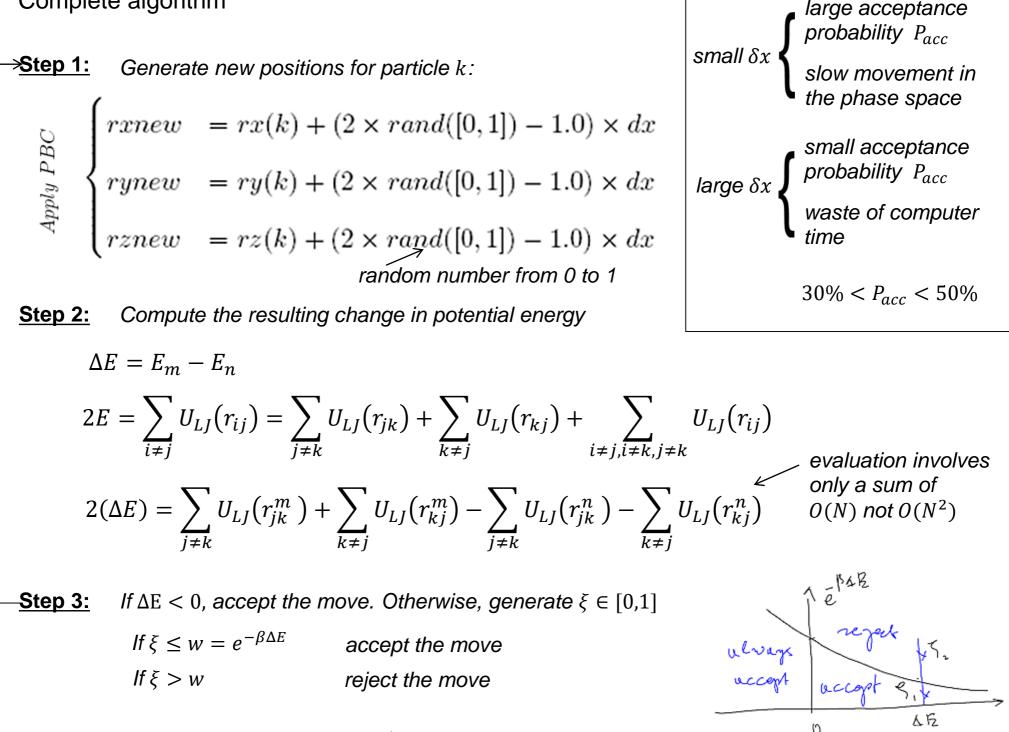
 $\xi \in [0,1]$  a random number  $P_1(\xi)$  uniform distribution

The event that  $\xi$  is below *P* will occur with *P* probability

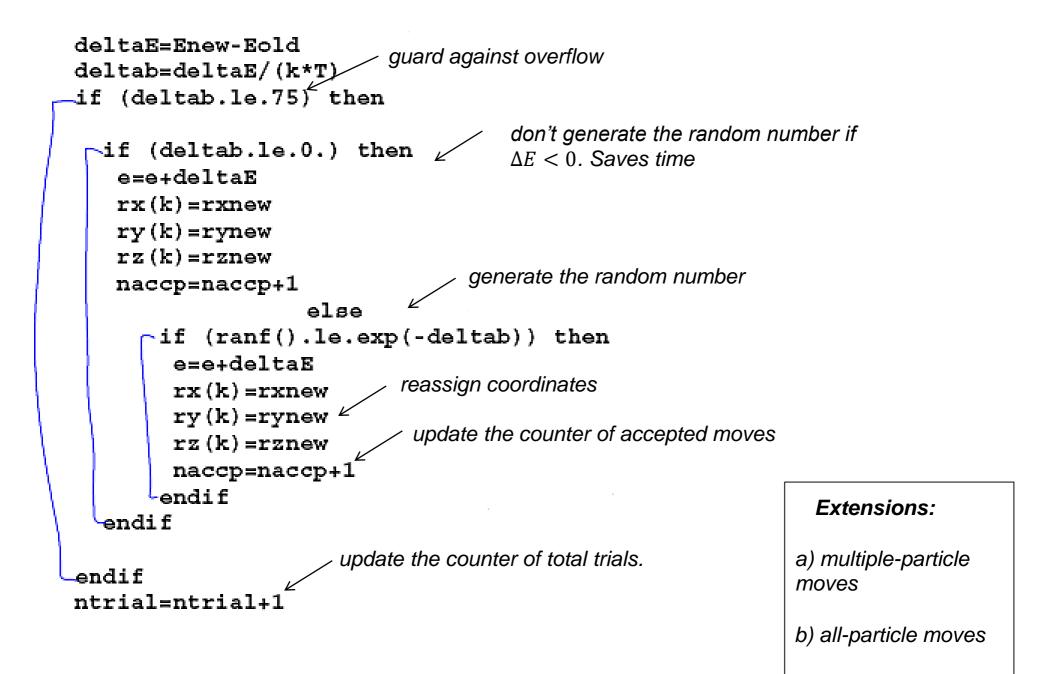
Generate a random number  $\xi$ . If it is below *P* - accept the move, otherwise – reject it.



# Complete algorithm



Implementation example in Fortran. One particle moves at a time



# Isothermal-isobaric simulations

The goal is to reproduce the NTP ensemble. Volume now has to be treated as a dynamical variable.

Phase space: $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V)$  $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V+\delta V)$ After relaxation, particles<br/>will fill up the box $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V)$  $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V-\delta V)$  $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V-\delta V)$  $(\overrightarrow{r_{1}}...,\overrightarrow{r_{N}},V)$ <td

Alternative approach: introduce scaled coordinates

old variables:

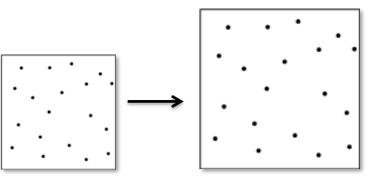
new variables:

 $\overrightarrow{(r_1} \dots \overrightarrow{r_N}, V)$ 

$$\overrightarrow{(s_1} \dots \overrightarrow{s_N}, V)$$

$$\overrightarrow{r} = V^{\frac{1}{3}} \cdot \overrightarrow{s}, \ (s_x, s_y, s_z) \in [0, 1], \ d\overrightarrow{r_i} = V \cdot d\overrightarrow{s_i}$$

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The box will experience uniform

expansion or contraction

$$d\overrightarrow{r_i} = V \cdot d\overrightarrow{s_i}$$

$$< A >_{NPT} = \frac{\int dV e^{-\beta PV} \int d\vec{r} e^{-\beta U(\vec{r})} A(\vec{r})}{\int dV e^{-\beta PV} \int d\vec{r} e^{-\beta U(\vec{r})}} = \frac{\int dV e^{-\beta PV} V^N \int d\vec{s} e^{-\beta U(\vec{s})} A(\vec{s})}{\int dV d\vec{s} e^{-\beta U(\vec{s})} e^{-\beta PV} e^{N \log(V)} A(\vec{s})} = \frac{\int dV d\vec{s} e^{-\beta U(\vec{s})} + PV - kTN \log(V)}{\int dV d\vec{s} e^{-\beta U(\vec{s})} + PV - kTN \log(V)} A(\vec{s})} = < A >_{sV}$$

Sample from NVT ensemble for the extended system defined by phase space coordinates  $\Gamma = (\vec{s_1} \dots \vec{s_N}, V)$  with the limiting distribution function:

$$\rho(\Gamma) = e^{-\beta(U(\vec{s}) + PV - kTN\log(V))}$$

#### Algorithm:

Simulation is conducted as in NVT ensemble except that now we have **two types** of moves.

1) Coordinate moves:  

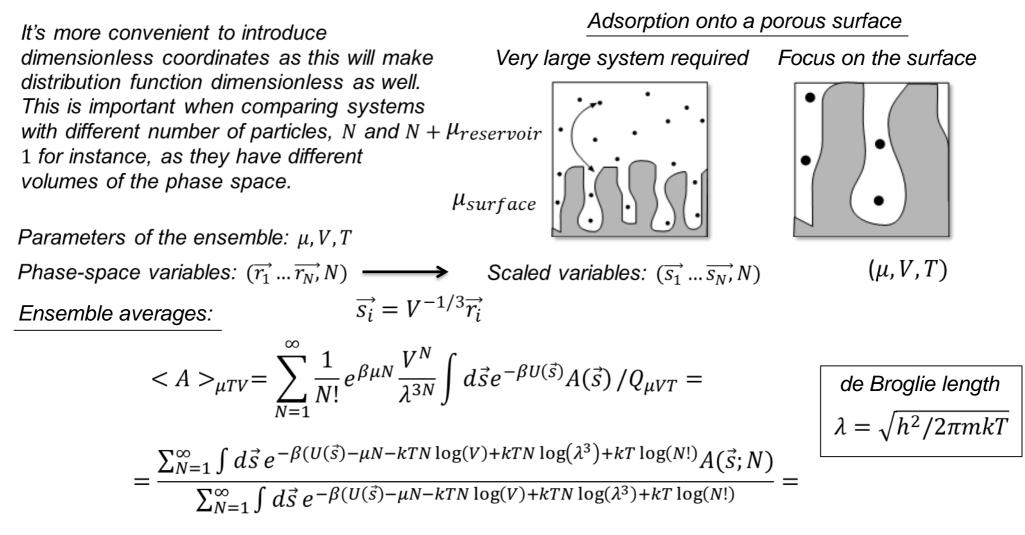
$$\overrightarrow{s}_{i}^{m} = \overrightarrow{s}_{i}^{n} + \delta x (2 \cdot \xi - 1) \quad \xi \in [0,1]$$
2) Volume changes:  

$$V^{m} = V^{n} + \delta V (2 \cdot \xi - 1) \longleftarrow \qquad \text{these are expensive so should} \\ be attempted rarely$$
Moves accepted  
with the probability:  

$$P = \min\{1, e^{-\beta \Delta E}\}, \Delta E = E_{m} - E_{n} + P(V_{m} - V_{n}) - kT \log(\frac{V_{m}}{V_{n}})$$

## Grand canonical ensemble

# Both coordinates and the number of particles are allowed to change



*Limiting distribution in MC chain:* 

$$\rho(\overrightarrow{s_1} \dots \overrightarrow{s_N}, N) = e^{-\beta(U(\overrightarrow{s}) - \mu N - kTN \log(V) + kTN \log(\lambda^3) + kT \log(N!))}$$

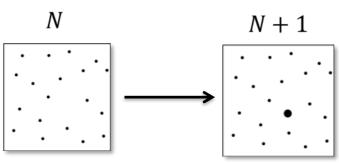
There are a number of implementations of GCMC that differ in how particles are added to/removed from the system

Three types of moves:

**1)** Coordinate moves:

$$\overrightarrow{s}_{i}^{m} = \overrightarrow{s}_{i}^{n} + \delta x (2 \cdot \xi - 1) \qquad \xi \in [0, 1]$$
$$P = \min\{1, e^{-\beta \Delta U}\}$$

2) Particle creation:



N - 1

for fastest convergence choose  $P_1 = P_2 = P_3 = \frac{1}{3}$ 

*insertion at a random positon. Difficult in dense fluids because of steric clashes* 

$$P \sim \frac{\rho_m(\vec{s}, N+1)}{\rho_n(\vec{s}, N)} = \min\left\{1, e^{-\beta \Delta U + \log \frac{ZV}{N+1}}\right\}$$

Ν

 $\Delta U = U(\vec{s}, N + 1) - U(\vec{s}, N)$  $z = e^{\beta \mu} / \lambda^3 \quad \text{activity}$ 

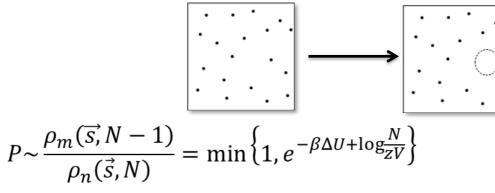
> deletion of a random particle. Difficult in dense fluids because the particle may experience strong attraction in the media

$$\Delta U = U(\vec{s}, N - 1) - U(\vec{s}, N)$$

# averages obtained from simulation

may not be accurate because of large fluctuation in <N>

**3)** *Particle destruction:* 



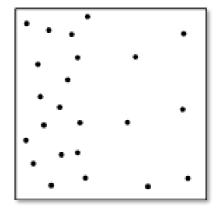
Direct computation of free energy in GCMC:

$$A/N = \mu - \langle P \rangle_{\mu VT} V / \langle N \rangle_{\mu VT}$$

### Gibbs-ensemble simulations

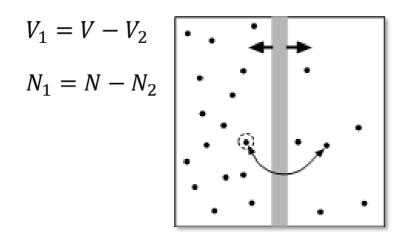
This method is designed to simulate phase equilibria.

$$\begin{array}{c} \mbox{Liquid} \\ \mbox{Liquid} \\ \mbox{} P_l = P_g \\ \mbox{} T_l = T_g \end{array}$$



The best choice for these experimental conditions is  $\mu PT$  "ensemble" One of the state variables has to be extensive (N or V)

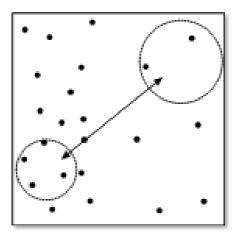
Consider two coupled systems with the total V and N fixed:



V2 Exchange of particles and volume is allowed. This enables coexistence between two phases. The advantage is that there is no interface. Molecules in system 1 and 2 do not interact with one another.

Such ensemble does not exist!

If both N and V are allowed to change a simulation box can't be defined uniquely



The partition function:

$$Q_G(N, V, T) = \sum_{n_1=0}^{N} \frac{1}{V\lambda^{3N}n_1! (N-n_1)!} \int_0^V dV_1 V_1^{n_1} (V-V_1)^{N-n_1} \times \int ds_1^{n_1} e^{-\beta U(s_1)} \int ds_2^{N-n_1} e^{-\beta U(s_2)}$$

Variables:  
$$\left(\overrightarrow{s_{1}} \dots \overrightarrow{s_{n_{1}}}, n_{1}, V_{1}\right)$$
  
 $\left(\overrightarrow{s_{1}} \dots \overrightarrow{s_{N-n_{1}}}\right)$ 

Distribution function:

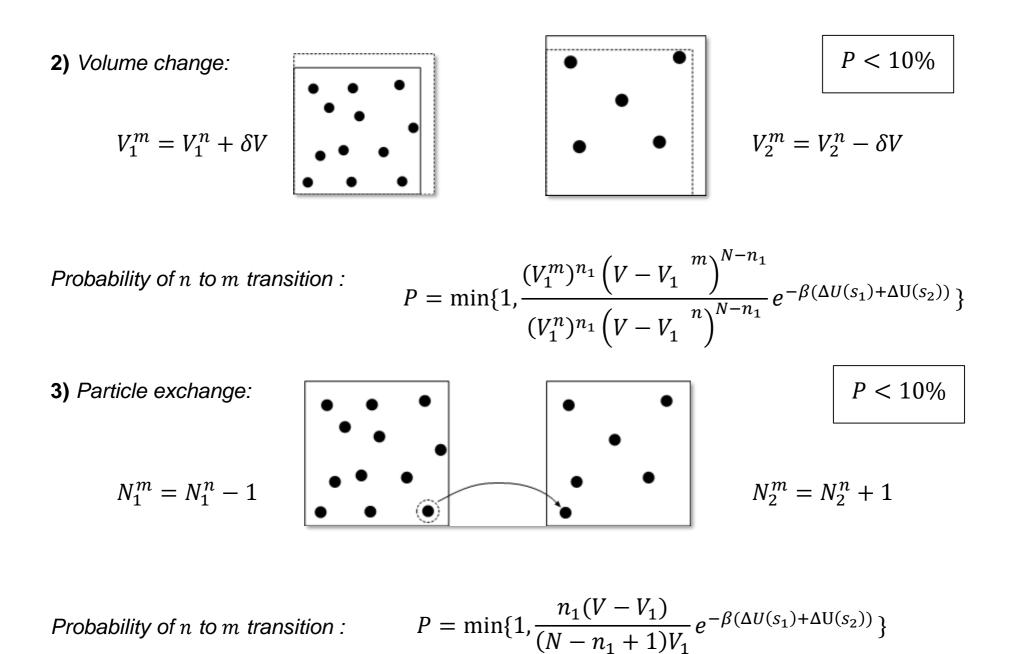
scaled coordinates of system 2

$$\rho(n_1, V_1, s_1, s_2) = \frac{V_1^{n_1}(V - V_1)^{N - n_1}}{n_1! (N - n_1)!} e^{-\beta(U(s_1) + U(s_2))}$$

$$\int_{\text{scaled coordinates of system 1}}^{N}$$

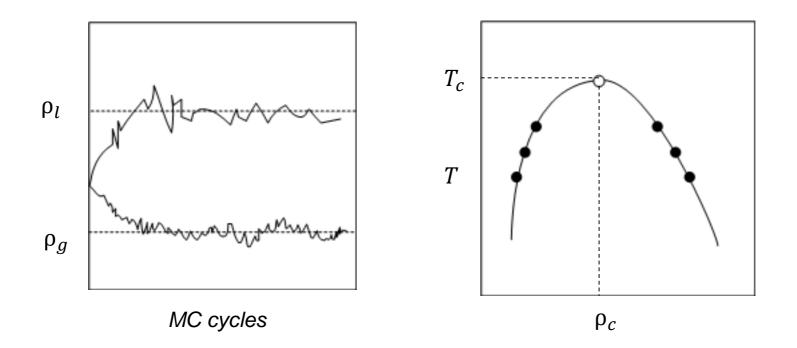
MC process that samples from that distribution:

**1)** Coordinate moves applied in both systems independently:



Typical results:

After initial relaxation, densities in the two boxes will settle down to their equilibrium values



In the coexistence region  $T < T_c$  there will be two distinct densities corresponding to two distinct phases.

In the supercritical region  $T > T_c$  there will be only one density. Boxes may have different sizes and numbers of particles.

Large finite size effect for gas-lattice models. Minimal effects for continuous models. Systems with <100 particles are OK for LJ model in both 2D and 3D.

# Electrostatics in biomolecular systems

Couloud Distension behaven two degre 
$$U_{C}(x) = \frac{\pi}{4} \frac{\pi}{4}$$
  
Et cut off  $e_{C}$  is Distributed, we with  $U_{C}$  factorial, the long range connection is  
 $\pi H = e \int e^{-x} V_{C}(x) dx = \pi H = e^{-x} H = e$ 

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(see Figure 3).

[1] Reaction Held corrections (WF method) Compute controbutions of the truncated long-range port of the using contituur electrociations models. For homogeneous nears: Atowic representation continuum representation E - dielectric an kg/ constant of the meadure Electrostations of changes on splended conditions ' Podsson equation relating potential & and change tenning f: 725  $\int \Delta P_{1}(\vec{r}) = -4\pi l(\vec{z}) \quad z \leq 4$ l(デ)= y- f(デージョ  $\left( \Delta \Phi_{\underline{q}}(\overline{z}) \right) = 0$ لر ) م  $\int_{r}^{0} P_{E}(n=a) = P_{E}(n=a) - potential is continuous at the boundary$  $<math display="block">\int_{r}^{0} P_{E}(n=a) = f \frac{\partial P_{E}(n=a)}{\partial n} - nontrue derived ave, on douplacement <math>\vec{D} = \epsilon \cdot \vec{E},$  R continuous

For the potential decode the calling:  

$$\Phi_{t}(\bar{z}) = \frac{4}{|\bar{z}-\bar{z}_{s}|} + \Phi_{k}(\bar{z})$$
as next contained becadioon holds recalling for the polenospation at the polenospation at the bolectric meddle in the bolectric me

It wold have 
$$dW = \Phi_{k}(a) dy$$
 work against that potential to add by charge  
at the certa. the lotal work accocines with creating charge  $y = -\frac{1}{2} \frac{1}{2} \frac{1}{$ 

6) charge periode x2. More has to be done ayabet it own nearboun  
Held:  

$$4F_{1} = \int_{1}^{\infty} \left[ -\frac{q(t-1)}{a-t} + \frac{q}{a^{5}} \frac{2(n-t)}{2(t+1)} z_{1}^{*} \right] dy = -\frac{1}{a} \frac{q^{2}(t+1)}{a-t} + \frac{1}{2} \frac{q^{2}}{a^{5}} \frac{2(n-t)}{2(t+1)} z_{2}^{*} = \Delta G_{1}$$
and ugalish the nearbounded cheated by the Abst period is:  

$$4F_{2} = \int_{1}^{\infty} \left( f(-\frac{1}{a}) \right) dy' = \int_{1}^{\infty} \left[ -\frac{q(t-1)}{a-t} - \frac{1}{a^{5}} \frac{2(n-t)}{2(t+1)} z_{2}^{*} \right] dy' =$$

$$= \frac{q^{2}(f(-\frac{1}{a})) dy'}{a-t} + \frac{q}{a^{5}} \frac{2(n-t)}{2(t+1)} z_{2}^{*}$$
Puttbug three terms to gether:  $\Delta F = ag_{1} + aF_{2} + \Delta F_{3} = \frac{2}{a} \frac{q}{a^{2}} \frac{2(n-t)}{2(t+1)} z_{2}^{*}, (q^{2}s)^{2} = \frac{M^{2}}{4}$ 
In the bluit 4 point whole,  $z_{1} \to 0$ ,  $M = const$ :  

$$\Delta f_{0} = \frac{1}{a^{2}} \frac{1-G}{2(t+1)} - \frac{M^{2}}{a} \frac{1}{a} \frac{1-G}{a} M^{2} - \frac{1}{a} \frac{M^{2}}{a} \frac{1}{a} \frac{1}{a} \frac{1-G}{a} M^{2} - \frac{1}{a} \frac{1}{a$$

The diargony free every an also be determined on differentiation of the depole  
with its own reaction total. Elegence holds created at  
the center by a change of a predition is:  

$$\vec{E}(\vec{2}) = -\frac{2}{9} \frac{\Phi_{e}(\vec{1})}{2\pi} = -\frac{4}{4\pi} \frac{2(t-1)}{2t+1} \vec{2s} + O(1\vec{21})$$
  
Ef there's more than one change,  $\eta_{1}, \tilde{z}_{1}$ :  
 $\vec{E}(\vec{1}) = -\frac{1}{4\pi} \frac{2(t-1)}{2t+1} \vec{z}_{1}, \vec{z}_{1} = -\frac{1}{4\pi} \frac{2(t-1)}{2t+1} \vec{m} - \vec{m}$  dispole moment of a group  
of changes. The field  
let's assume now that the field or created by  
 $\vec{m} = 2q \cdot \vec{z}_{2}$ . Adding -  $\eta_{1} \cdot \vec{z}_{1}$  so that depend on their location  
 $\vec{m} = 2q \cdot \vec{z}_{2}$ . Adding -  $\eta_{1}$  and  $q_{1}$  is so that depend on their location  
 $\vec{m} = 2q \cdot \vec{z}_{3}$ . Adding -  $\eta_{1}$  and  $\eta_{2}$  is determined to the second the these partially here  
changes that zero with regulate work.  
 $\left[\frac{dy}{d} = -\frac{1}{4\pi} \frac{2(t-1)}{2t+1}, 2\vec{z}_{3}, q', d'_{3} = -\frac{4}{2} \frac{2(t-1)}{4\pi} \frac{1}{2t+1} = \frac{1}{4\pi} \frac{1-t}{2t+1}, \vec{m}^{2} = \Delta f_{0}$ .  
 $\vec{p}$ 

On seyen solvation energy Baumketner, BioSim, Lviv 2019

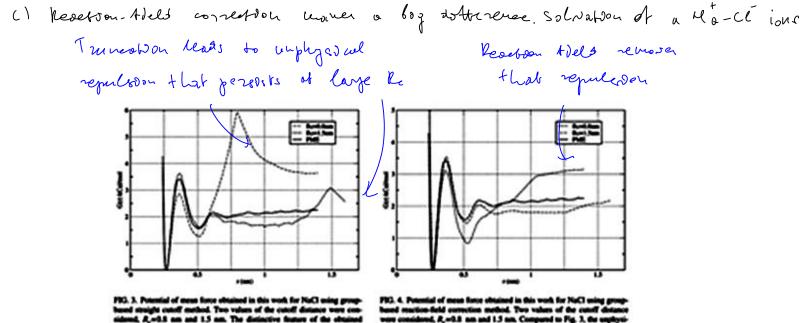
Why it a c called "solution" energy?  
Acsume X denotes controputations of our indemle & interest. Etc energy or  
Northin D. U. (X). Probability & selly X  
P(N) ~ 
$$E^{RO_{1}(N)}$$
  
Cf. The indecale is placed on a medium,   
 $solution = Sellin = e^{RO_{1}(N)}$   
 $solution = Sellin = e^{RO_{1}(N)}$   
 $= e^{RO_{1}(N)}$   
Cf. The indecale is placed on a medium,   
 $= e^{RO_{1}(N)}$   
 $= e^{RO_{1}(N)}$ 

Elled & Welectroz contonnum

potential during in vacuum  
United during in vacuum  
Up (c) = U<sub>x</sub>(v) + 
$$kb(v)$$
  
potential during direc energy  
du volwart dotter (during)  
path : a) decherging 0  
(a)  $kc_z = a (b_x(x))$   
Davidgy a changing / Se duringing 0  
path : a) decherging 0  
(a)  $kc_z = a (b_x(x))$   
Davidgy a changing / Se duringing 0  
(b)  $kc_z = a (b_x(x))$   
Davidgy a changing / Se duringing 0  
(c)  $kc_z = a (b_x(x))$   
(c)  $kc_z = a (b_x(x)$ 

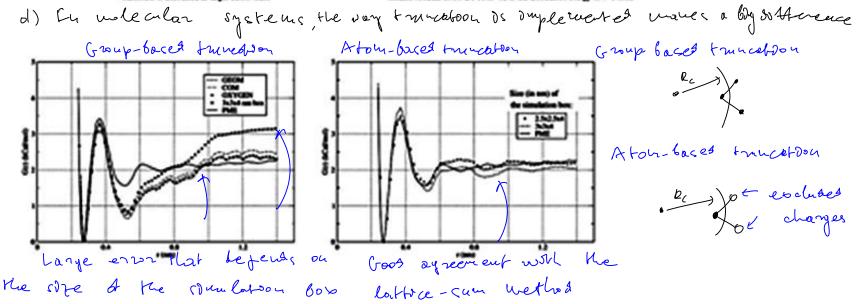
Moving boundary reaction to solythe electric tills creates at  
the contex by a source change 
$$q_{12}$$
:  
 $\vec{E}_{R}(\vec{z}=0) = -\frac{2}{2} \frac{P_{R}(\vec{z})}{2} = \frac{q_{12}}{12} \frac{2(t-1)}{2(t+1)} \frac{1}{2}$   
Force corrected by the probe change  $q_{12}$  at the  
center due to polarization is:  
 $\vec{F} = q_{11} \vec{E}_{R}(\vec{z}=0) = \frac{q_{11}}{n} \frac{2(t-1)}{2(t+1)} \vec{z}_{2}$  (ronce from its own polarization or zero  
This torce can be modeled by dutroducing an effective potential acting  
between particles  $i$  and  $j$ :  $U_{eff}(r_{0}) = \frac{q_{11}q_{12}}{2(t+1)} \vec{z}_{2}$   
 $\vec{F}_{1} = -\vec{F}_{1} = \frac{2}{2r_{1}} U_{eff}(r_{2}) = \frac{q_{11}q_{12}}{n} \frac{2(t-1)}{2(t+1)} \vec{z}_{2}$   
The total horce acting between changes  $q_{13}$  and  $q_{13}$  of  $n \in A$  is:  
 $U_{RF}(2) = U_{C}(n) + U_{eff}(n) = \frac{q_{11}q_{12}}{n} + \frac{q_{12}q_{12}}{n} \frac{\xi-1}{2\xi+1} \cdot r_{1}^{2} = \frac{q_{12}q_{12}}{n} (1+\frac{\xi-1}{2\xi+1}(\frac{n}{2})^{5})$ 

The reaches wheth results is a unstabled Coulous provided of 
$$a = k_c$$
.  
In one office aspects siturdation are the same.  
A) hadded is applicable to low geneon system only.  
The area particle at the sphere of this approved matrix is  
the to be longeneon contribution.  
Applies to some potential apply to wort  
solve atoms  
 $i = \frac{1}{k_c}$   
b) the undities potential is still long-ranges.  
 $U_{ep}(z = k_c) = \frac{1}{k_c} \frac{3}{z_{eff}} = \frac{2}{z_{eff}} \frac{9ifs}{k_c} = \frac{3}{z} U_c(k_c)$   
The potential or show significant at the  
cut-off datance. The force is stor continuates  
to which are the contrologion of the  
to which are the contrologion of the  
the undities the contrologion of the

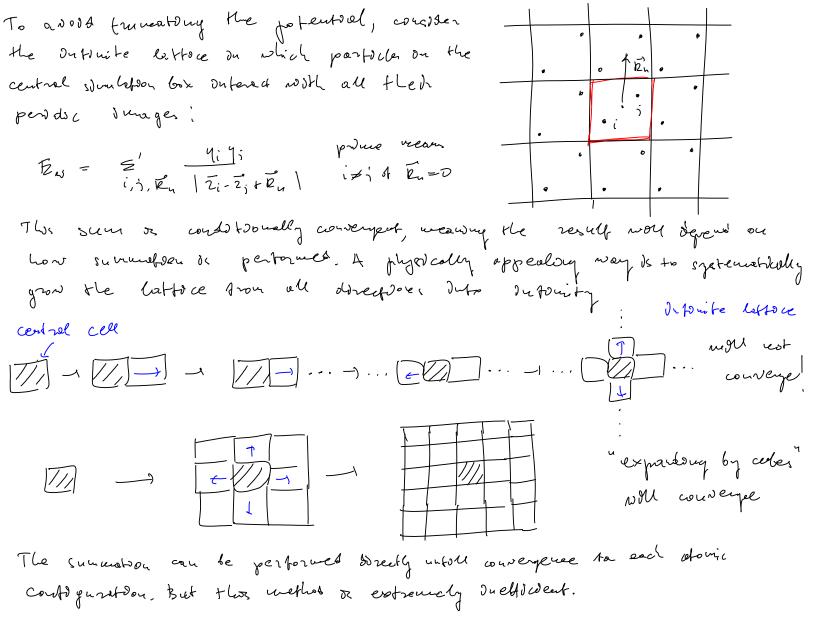


PMPs is a strong and unphysical maximum at roll,. The strength of the nanimum is attenuated at larger cutoff radii.

waw considered, R,=0.8 am and 1.5 am. Compared to Fig. 3, the angle cal maxima studing from the potential transition at roll, are pose. Sig-milicant modual errors are observed in the association energy of two iron.



Ewald summatson



Each drange de the Evald see Detender  
with the Detrive California (alfornia)  
change g: change creating the Wold "created"  

$$i = \frac{1}{1 + i} + \frac{1}{1 + i}$$

The sum on the long-range part on the supplements of the 
$$i=j, E_{u}=0$$
 term  
 $\frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}+\overline{n}_{u}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}+\overline{n}_{u}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} q_{i} P_{6}(\overline{n}_{ij}+\overline{n}_{u}) = \frac{1}{2}\sum_{i,j,E_{u}}^{-1} P_{6}(\overline{n}_$ 

Polison equation reads:  

$$E^{n} + \frac{1}{4} [E] = -4\pi l_{1} [E]$$

For the Dubrite lattice 4 background change!  

$$l_{1}(\vec{z}) = \sum_{j, E_{u}} l_{0}^{i} (\vec{z} - \vec{z}_{j} + \vec{b}_{u}) = -\binom{\mu}{\pi} \sum_{j, E_{u}}^{2} q_{j} e^{-\nu(\vec{z} - \vec{z}_{j} + \vec{b}_{u})}$$

$$l_{1}(\vec{z}) = \sum_{j, E_{u}}^{2} l_{j}^{i} (\vec{z} - \vec{z}_{j} + \vec{b}_{u})^{2} (\vec{z} - \vec{z}_{j})^{2} (\vec{z} - \vec{z})^{2} (\vec{z} - \vec{$$

$$= 2\pi \sqrt{2} \int_{\mathbf{k}}^{-\mathbf{k}} e^{-4\lambda} \left( i|\vec{\mathbf{k}}| \cdot l_i(-\vec{\mathbf{k}}) - 2\pi \sqrt{2} \int_{\mathbf{k}}^{-\mathbf{k}} e^{-4\lambda} \left| l_i(\vec{\mathbf{k}}) \right|^2$$

Beckground change contribution can be computed on the Fourier quee:  

$$E_{i} = \pi \nabla \sum_{k} \frac{1}{k} e^{\frac{k^{2}}{4k}} |l_{i}(\vec{k})|^{2}$$

$$E_{i} = \frac{1}{k} e^{\frac{k^{2}}{4k}} |l_{i}(\vec{k})|^{2}$$

$$E_{i$$

$$\begin{split} |l_{i}||\vec{k}||^{n} &= \frac{1}{\sqrt{n}} \left( \left( \vec{k} \cdot \vec{q}_{i}\right)^{n} + kn^{n} \left( \vec{k} \cdot \vec{q}_{i}\right)^{2} - kn^{n} \vec{k} \cdot \vec{q}_{i} \vec{k} \cdot \vec{q}_{i}\right) + O(kn^{n}) \right) \\ C(\vec{k}) &= \frac{1}{\sqrt{n}} \frac{e^{\frac{k^{n}}{2}}}{e^{\frac{k}{2}}} \frac{1}{k^{n}} \left( \left( \vec{k} \cdot \vec{q}_{i}\right)^{n} + kn^{n} \left( \vec{k} \cdot \vec{q}_{i}\right)^{2} - kn^{n} \vec{k} \cdot \vec{q}_{i} \vec{k} \cdot \vec{q}_{i}\right) \right) + O(kn^{n}) \\ C(\vec{k}) &= \frac{1}{\sqrt{n}} \frac{e^{\frac{k^{n}}{2}}}{e^{\frac{k}{2}}} \frac{1}{k^{n}} \left( \left( \vec{k} \cdot \vec{q}_{i}\right)^{n} + kn^{n} \left( \vec{k} \cdot \vec{q}_{i}\right)^{2} - kn^{n} \vec{k} \cdot \vec{q}_{i} \vec{k} \cdot \vec{j}\right) \right) + O(kn^{n}) \\ Acsume - diarge-neutral comulation cell  $\vec{k} \cdot \vec{q}_{i} = 0. \\ C(\vec{k}) &= \frac{1}{\sqrt{n}} \cdot \frac{e^{\frac{k^{n}}{2}}}{k^{n}} \frac{1}{k^{n}} \left( kn \cdot \vec{q}_{i}\vec{k} \cdot \vec{l} \right)^{n} = \frac{1}{\sqrt{n}} \frac{e^{\frac{k^{n}}{2}}}{k^{n}} \frac{1}{k^{n}} \left( \vec{k} \cdot \vec{M} \right)^{n} \quad \vec{m} = \vec{k} \cdot \vec{q}_{i}\vec{k} \cdot \vec{l} \\ The Outil depends on direction drow where  $0$  is approached? Her simulation cell  $k^{n}$   $k$$$$

En obten voorde, et chould change along the diagonal to be appropriate for the  
chosen summation method, but there's more than 1 diagonal on the E-speed  
((E) ender on the control of  
Founder transforms. There are miles  
in Founder transforms thanklong  
der continuous Auncho one  
to uside 1-0 case:  
the 1 - 0 case:  
the line 
$$\frac{1}{2\pi}$$
 field  $e^{-ikx}$   
the line  $\frac{1}{2\pi}$  field  $e^{-ikx}$   
the line  $\frac{1}{2\pi$ 

$$\tilde{E}_{1}$$
 30 there are  $g$  dragonal to reach  $\tilde{E}_{20}$ . Set  $p$  a reacy producted  
 $\tilde{E} = P/\sqrt{3} (E^{1}, \Xi^{1}, \Xi^{1}, \Xi^{1}) - would grove all  $g$  dragonals  
For outsure,  $\tilde{E}_{1} = \frac{P}{\sqrt{3}} (1, 1, 1), \quad \kappa_{1}^{2} = P^{2}, \quad kru \quad G(\tilde{k}_{1}) = \frac{1}{3\kappa^{2}} (M_{x} + M_{y} + M_{y})^{2}$   
 $\tilde{E}_{1} + D$$ 

Takony all 8 hourits: 
$$G(0) = \frac{1}{8} \lim_{i=1}^{8} G(\vec{k}_i) = \frac{1}{3} \sqrt{(M_{12}^{2} + M_{11}^{2} + \delta M_{12}^{2})}$$
  
Those groves for the background energy!

$$E_{4} = \frac{2\pi}{3\sqrt{2}} \left( \frac{z}{z} q_{1} z_{1}^{2} \right)^{2} + 2\pi\sqrt{2} \frac{1}{k} e^{-4\lambda} \left| l_{1}(\vec{k}) \right|^{2}$$

$$E_{\neq D}$$

ĺ

Puttory all terms together:  

$$\frac{1}{2} = \frac{1}{2} = \frac{1}{2} \left( \frac{1}{2} \left( \frac{1}{2} \right) + \frac{1}{2} + \frac{1}{2} \left( \frac{1}{2} + \frac{1}{2} \right) + \frac{1}{2} + \frac{1}{2} \left( \frac{1}{2} + \frac{1}{2} \right) + \frac{1}{2} + \frac{1}{2} \left( \frac{1}{2} + \frac{1}{2} \right)^{2}, \quad l_{i} \left( \frac{1}$$

Assume that the Numberto Cyclic 3: considered on  
a dielease measure and not on Jacana.  
Periods Images a the central cell will  
gradually full up space on approximately central action  
Aseld which will controllate to the solution  
the energy of the central cell AG. Since on  
the energy of the central cell will shown  
to a point, one can use dipole opproximation:  

$$E = -\frac{1}{2^3} \frac{2(1-E)}{2EH} the, the the only de moment of the apple books
 $M_1 = \frac{2}{3} q_1(2r+E_1) = N \cdot M$ ,  $M = dipole moment a the central colors in the splore
 $M_2 = -\frac{4}{3} t - \frac{1-4}{3} t - \frac{1$$$$

The solveton every an le couboued with the 
$$\vec{b} = 0$$
 entry to give  
 $\vec{T}_{2NF} = \frac{1}{2} \sum_{i,5,K_{11}}^{2} (S_{c}(\vec{T}_{ij} + \vec{k}_{11}) + T_{c} \times \sum_{k=0}^{2} \frac{1}{k^{2}} e^{-\frac{k^{2}}{4L_{2}}} |l_{i}(\vec{k})|^{2} - \sum_{i} q_{i}^{2} |\frac{t}{\pi}|^{2} + \frac{T_{c}}{4} \frac{T_{c}}{(2F+1)} (\sum_{i} q_{i} \cdot \vec{T}_{i}|^{2})^{2}$ 

A canacy and complexity  
one adjustable parameter - d  
The error is controlled by how many terms are retroved in the  
real and inverse parts. Accume as another orthodoces for the real part,  
and the time downerse part. Les = 24 / 1. he. The error on them be  
estimated:  
She 
$$\approx Q \cdot \left\| \frac{\mu_{e}}{\nu_{L}} - \frac{1}{(Fk_{e})} e^{-\frac{\mu_{e}}{F}k_{e}^{-1}} - \frac{\mu_{e}}{F}k_{e}^{-1} - \frac{\mu_{e}}{F}k_{e}^{$$

Computational effort  
Total computational expense:  

$$T = T_{k} \cdot M_{k} + T_{p} \cdot M_{k}$$

$$T = T_{k} \cdot M_{k} + T_{p} \cdot M_{k}$$

$$T = T_{k} \cdot M_{k} + T_{p} \cdot M_{k}$$

$$M_{k} = M_{k} \cdot M_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$T_{p} - H_{k} - H_{k} + T_{p} \cdot M_{k}$$

$$M_{k} = M_{k} \cdot M = \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T}$$

$$M_{k} = -H_{k} \cdot M = \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T}$$

$$M_{k} = -H_{k} \cdot M = \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T}$$

$$M_{k} = -H_{k} \cdot M = \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{M_{k}}{T}$$

$$M_{k} = -\frac{M_{k}}{T} \cdot \frac{M_{k}}{T} \cdot \frac{$$

TK/TE vation can be determined in short structured

#### Poisson-Boltzmann (PB) model

In canonical ensemble:

Partition function:

$$\rho_{NVT}(\Gamma) \sim e^{-\beta H(\Gamma)}, \beta = \frac{1}{kT} \qquad \qquad Q_{NVT} = \frac{1}{h^{3N}N!} \int d\vec{p} d\vec{q} e^{-\beta H(\Gamma)} = \overset{\text{local part}}{Q_{NVT}^{id}} \times Q_{NVT}^{ex}$$

$$Q_{NVT}^{id} = \frac{V^N}{N!\,\lambda^{3N}}, \lambda = \sqrt{h^2/2\pi mkT} \qquad \qquad Q_{NVT}^{ex} = \frac{Z_{NVT}}{V^N}, Z_{NVT} = \int d\vec{q} e^{-\beta U(\vec{q})}$$

Free energy splits into two parts as well:

$$F = -kT \log Q_{NVT} = F^{id} + F^{ex}$$

Ideal part

Gibbs free energy: 
$$G = F + PV = F^{id} + F^{ex} + (P^{id} + P^{ex})V = G^{id} + G^{ex}$$

Chemical potential: 
$$\mu = \frac{G}{N} = \mu^{id} + \mu^{ex}$$
 where  
 $\mu^{id} = kTlog(\lambda^3) + kTlog(\rho) = kTlog(\frac{\rho}{n_Q})$  particle density  
 $n_Q = \lambda^{-3}$   $\mu^{ex} = U^{ex} - TS^{ex} + P^{ex}V$ 

Assume the following approximation for the ions solvated near a charged wall: number density of ions

$$U^{ex} + \mu^{id} = q\varphi + kTlog(\frac{\rho}{n_Q})^{\downarrow}$$

total interaction energy is approximated by the electrostatic potential. The potential needs calibration.

 $\mu =$ 

excess parts of entropy and pressure are neglected (not too bad)

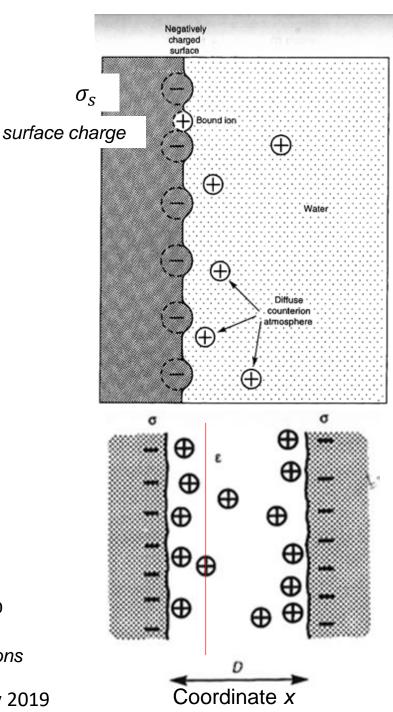
Consider system of ions confined between two surfaces. All properties depend on coordinate x.

In the state of equilibrium, or more generally stationary state, the chemical potential should not depend on x to avoid exchange of particles between different parts of the system.

Boltzmann distribution prescribing how density of ions will change depending on the potential

0 *0*<sup>0</sup>  $p(\lambda$ 

calibration conditions



Density and the potential are connected by laws of electrostatics:

displacement created by displacement created by charge distribution  
In polarizable media: 
$$\vec{D}(x) = \epsilon(x)\vec{E}(x) = -\epsilon(x)\vec{\nabla}\varphi(x)$$
  
For vacuum:  $-\vec{\nabla}\vec{E}(x) = \Delta\varphi = -4\pi q\rho(x)$  Poisson equation for computing potential created by charge density  
 $\frac{d^2\Delta\varphi}{dx^2} = -4\pi q\rho^0 e^{-\beta q\varphi(x)}$   
Poisson-Boltzmann (PB) equation  
PB gives ion density, potential and electric field at any point within the system

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x = D/2

x = 0

x = -D/2

#### How well does the PB model work?

Analytical solution:

$$\rho(x) = \rho_0 e^{-q\beta\varphi(x)} = \rho_0 / \cos^2(Kx)$$

$$-\frac{2K}{\beta q} \tan\left(\frac{KD}{2}\right) = \sigma_s \quad \text{equation for K}$$

The agreement is remarkably good for concentrations in the range up to 16M!

# PB underestimates the density at the surface PB = 15.5 M $P_{g} = 15.5 \text{ M}$ Broken line = PB Solid line = MC ODistance x (nm)

#### Extension to mixtures

Assume that we have a mixture of ions with varying valency. The condition on the constancy of the chemical potential has to be satisfied for each component.

$$\mu_i = q_i \varphi + kT \log(\frac{\rho_i}{n_Q}) \longrightarrow \rho_i(x) = \rho_i^0 e^{-\beta q_i \varphi(x)}$$

Poisson equation

$$\Delta \varphi = -4\pi \sum_{i} q_{i} \rho_{i}(x) \longrightarrow \Delta \varphi = -4\pi \sum_{i} q_{i} \rho_{i}^{0} e^{-\beta q_{i} \varphi(x)} \qquad \text{PB equation}$$

Linearize the RHS

$$e^{-\beta q_i \varphi(x)} = 1 - \beta q_i \varphi(x) + \cdots$$

$$4\pi \sum_{i} q_i \rho_i^0 e^{-\beta q_i \varphi(x)} = 4\pi \sum_{i} q_i \rho_i^0 (1 - \beta q_i \varphi(x) + \cdots) = 4\pi \sum_{i} q_i \rho_i^0 - 4\pi \sum_{i} q_i^2 \rho_i^0 \beta \varphi(x) + \cdots$$

$$\approx -\kappa^2 \varphi$$

$$\kappa = \sqrt{4\pi\beta \sum_{i} q_i^2 \rho_i^0} \qquad \text{inverse screening length}$$

After putting everything together:

$$\Delta \varphi - \kappa^2 \varphi = 0$$

linear PB (LPB) for multicomponent systems

#### Limitations of the PB model

The key approximation:

 $\mu = U^{ex} + \mu^{id} = q\varphi + kTlog(\frac{\rho}{n_Q})$ 

The total energy is approximated by the electrostatic component only. What's neglected:

 a) other energy contributions, excluded volume, vdW etc. The size of the ions is missing
 b) the electrostatic energy is included at the mean-field level. Approximated by the average value.

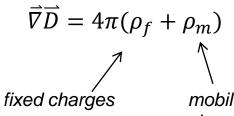
2) Full entropy is approximated by its ideal part. Effect of particle-particle interactions on the excess entropy is neglected. In particular:

a) steric effects are missing

3) Discreetness of surface charge. May contribute additional attraction when discrete surface charges are mobile.

How can PB model be used for biomolecules?

Extension of the Poisson equation to multiple media with fixed and mobile charges:



*mobile ions charge density* 

Electric field in the continuum approximation:

$$\vec{D}(\vec{r}) = \epsilon(\vec{r})\vec{E}(\vec{r})$$

$$\downarrow$$

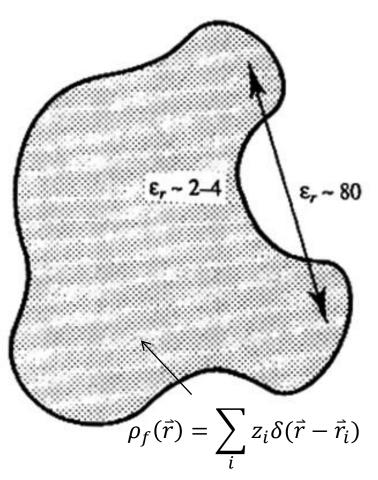
$$\vec{\nabla}(\epsilon(\vec{r})\vec{E}(\vec{r})) = -4\pi(\rho_f(\vec{r}) + \rho_m(\vec{r}))$$

$$\downarrow$$

$$\vec{\nabla}(\epsilon(\vec{r})\vec{\nabla}\varphi(\vec{r})) = -4\pi(\rho_f(\vec{r}) + \sum_i q_i\rho_i^0 e^{-\beta q_i\varphi(\vec{r})}$$

$$\downarrow$$

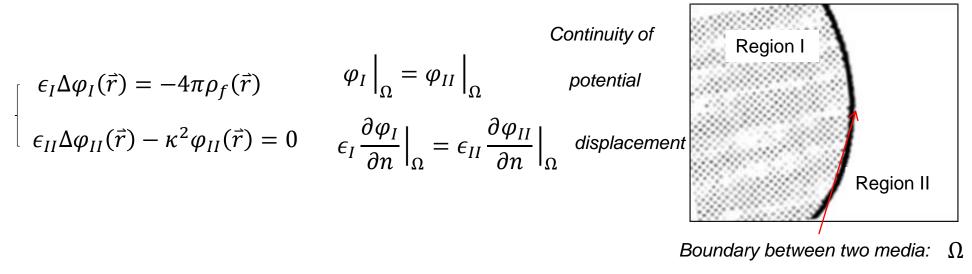
$$\vec{\nabla}\left(\epsilon(\vec{r})\vec{\nabla}\varphi(\vec{r})\right) - \kappa^2(\vec{r})\varphi(\vec{r}) = -4\pi\rho_f(\vec{r})$$



sum over fixed-charge points that make up the interior of the solute molecule

LPB equation

LPB can be solved numerically subject to specific boundary conditions (constant charge):



Computation of the charging free energy

Recall that the potential in solvent (continuum approximation) is :

 $U_M(\Gamma) = U_V(\Gamma) + \Delta G(\Gamma)$  where  $\Delta G(\Gamma)$  is the free energy associated with turning the solvent "on".  $U_V(\Gamma)$  electrostatic energy in vacuum

Also recall that  $\Delta G(\Gamma) = \Delta G_{ch}(\Gamma) - U_V(\Gamma)$ 

$$\Delta G_{ch}(\Gamma) = \int dq \, \varphi$$

charging free energy. Work needed to create charge in a medium

Since the PBL equation is linear:

$$\Delta G_{ch}(\Gamma) = \frac{1}{2} \sum_{i} q_i \varphi_{sol}(i)$$

potential acting on charge qi obtained for particular solute in solvent with  $\epsilon = 80$ 

Potential energy in vacuum:

$$U_V = \frac{1}{2} \sum_i q_i \varphi_{vac}(i)$$

potential acting on charge qi in vacuum or solvent with  $\epsilon = 1$ 

Combining the formulas:

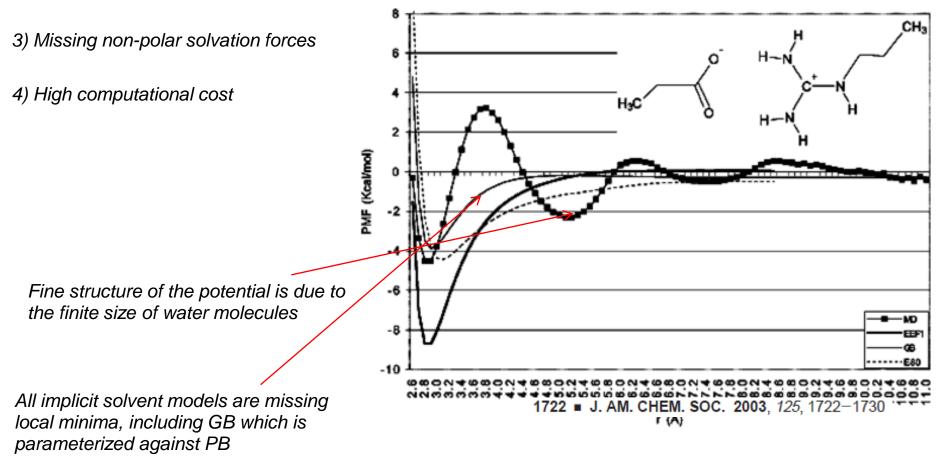
$$\Delta G(\Gamma) = \frac{1}{2} \sum_{i} q_i(\varphi_{sol}(i) - \varphi_{vac}(i)) = \Delta G_{PB}$$
  
this is the term that needs to be added to the potential energy in order to include the effect of the solvent.

The approach that combines certain force-field with PB equation for solvation energy is known as **PB/MM** model

### Limitations of the PB/MM model

1) All that apply to PB equation.

2) Error due to continuum approximation for water. Model breaks down on length scales comparable to the size of water molecule.



### Generalized Born (GB) model

Numerical solutions of PB for real molecular shapes are very costly. Much faster implicit solvation models are needed.

Draw an analogy with the Born solvation energy:

Approximate solvation energy for a molecule:

*Empirical function:* 

 $\Delta G_{Born} = \frac{1}{2} \left(\frac{1}{\epsilon} - 1\right) \frac{q^2}{a}$  $\Delta G_{GB} = \frac{1}{2} \left(\frac{1}{\epsilon} - 1\right) \sum_{i,j} \frac{q_i q_j}{f_{ij}}$ 

Generalized Born (GB) model

$$f_{ij} = \sqrt{r_{ij}^2 + R_i R_j e^{-r_{ij}^2/4R_i R_j}}$$
Still's formula
$$R_i$$
is the effective Born
radius for atom i

If there's only one atom in the system:

$$f_{ij} = R_i$$
,  $\Delta G_{GB} = \frac{1}{2} \left( \frac{1}{\epsilon} - 1 \right) \frac{q_i^2}{R_i} = \Delta G_{Born}$  Born ensuring with radius with radius and the second second

Born energy for particle with radius Ri

For two charges at a large separation:  $r_{12} \ge R_1, r_{12} \ge R_2, f_{ij} \approx r_{ij}$ 

$$\Delta G_{GB} = \frac{1}{2} \left( \frac{1}{\epsilon} - 1 \right) \frac{q_1^2}{R_1} + \frac{1}{2} \left( \frac{1}{\epsilon} - 1 \right) \frac{q_2^2}{R_2} + \left( \frac{1}{\epsilon} - 1 \right) \frac{q_1 q_2}{r_{12}}$$

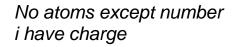
Full electrostatic interaction then is:

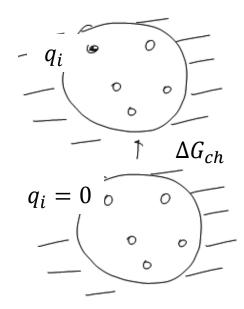
$$U_{ele}(r_{12}) = \frac{q_1 q_2}{r_{12}} + \Delta G_{GB} = \frac{1}{2} \left( \frac{1}{\epsilon} - 1 \right) \frac{q_1^2}{R_1} + \frac{1}{2} \left( \frac{1}{\epsilon} - 1 \right) \frac{q_2^2}{R_2} + \frac{q_1 q_2}{\epsilon r_{12}}$$

$$(\Box q)$$
Self-energy of the two ions
$$Coulomb \text{ interaction in a continuum}}$$

To retain their physical meaning, Born radii are introduced via charging free energy:

$$R_i = \frac{2\Delta G_{ch}}{q_i^2} \frac{\epsilon}{1-\epsilon}$$





Coulomb field approximation for the Born radii

Another way to compute electrostatic work is via scalar product of the displacement vector with the vector of electric field:

$$W = \frac{1}{8\pi} \int \mathbf{E} \cdot \mathbf{D} dV$$

Assume that the displacement vector created by charge qi retains its Coulomb form even outside of the solute molecule:

$$\mathbf{D}_i \approx rac{q_i \mathbf{r}}{r^3}$$

Work needed to move charge qi from infinity to its proper location:

$$W = \frac{1}{8\pi} \int \left( \mathbf{D}/\varepsilon \right) \cdot \mathbf{D} dV \approx \frac{1}{8\pi} \int_{in} \frac{q_i^2}{r^4} dV + \frac{1}{8\pi} \int_{out} \frac{q_i^2}{r^4\varepsilon} dV$$

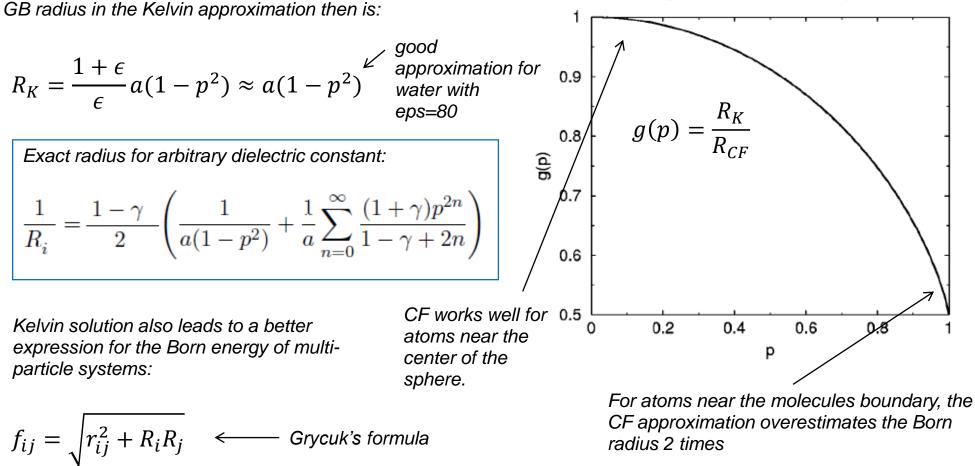
To compute electrostatic solvation energy one needs to subtract the same quantity evaluated at 
$$\varepsilon = 1 \longrightarrow \Delta G_{ch} = \frac{-1}{8\pi} \left( 1 - \frac{1}{\varepsilon} \right) \int_{out} \frac{q_i^2}{r^4} dV$$

One then arrives at the following formula:

$$R_i^{-1} = \frac{1}{4\pi} \int_{out} r^{-4} dV$$

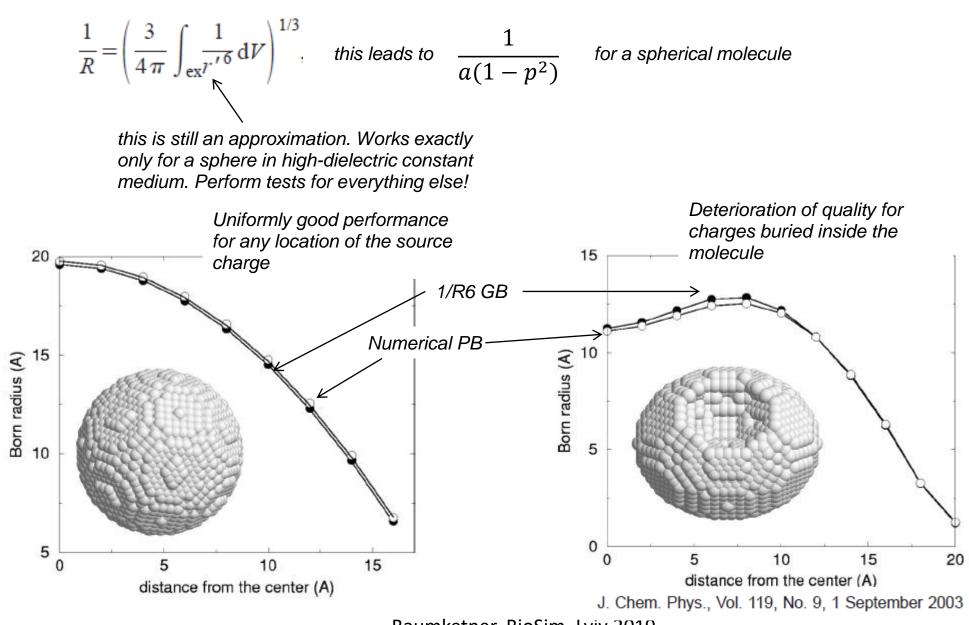
charged line that extends The Born radius in CF approximation can be evaluated exactly for the spherical to infinity geometry. The integral can be taken analytically to yield:  $\epsilon$  $R_{CF} = \frac{4\pi}{\int_{out} r^{-4} dV} = 2a \left( \frac{1}{1-p^2} + \frac{1}{2p} \ln \frac{1+p}{1-p} \right)^{-1}, \ p = \frac{r_s}{a}$  $q_K$ q а  $\vec{r}_K$ The spherical geometry has an exact solution. In particular, the reaction field is a sum of the field created by Kelvin image and a charged ray:  $\varphi_{RF}(\bar{r}) = \varphi_K(\bar{r}) + \varphi_{line}(\bar{r})$ terms of order 1 terms of orders and  $1/\epsilon$ higher than  $1/\epsilon$ Kelvin charge image.  $\vec{r}_{K} = \frac{q^{2}}{r_{c}}$   $q_{K} = \gamma \frac{a q}{r_{s}}$   $\gamma = \frac{1 - \epsilon}{1 + \epsilon}$ Reaction filed at the location of the source charge:  $\varphi_{RF}(\vec{r_s}) = \frac{q_K}{r_K - r_s} = \frac{1 - \epsilon}{1 + \epsilon} \frac{aq}{a^2 - r_s^2}$  $\Delta G_{ch} = \int dq \ \varphi_{RF} = \frac{1}{2} \frac{1-\epsilon}{1+\epsilon} \frac{aq^2}{a^2-r_c^2} = \frac{1}{2} \left(\frac{1}{\epsilon}-1\right) \frac{q^2}{R_{\nu}}$ Charging free energy: Baumketner, BioSim, Lviv 2019

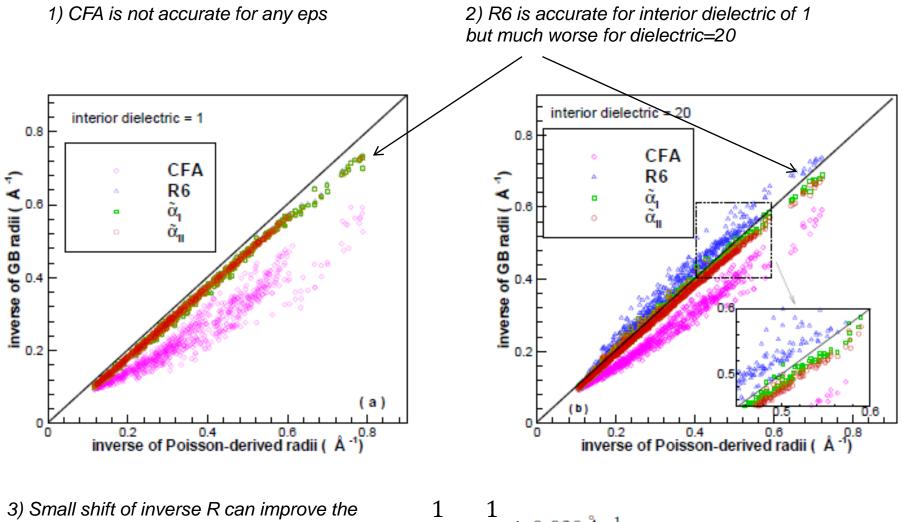
J. Chem. Phys., Vol. 119, No. 9, 1 September 2003



 $f_{ij} = \sqrt{r_{ij}^2 + R_i R_j e^{-r_{ij}^2/4R_i R_j}} \leftarrow \text{Still's formula}$ 

To evaluate Born radius for non-spherical objects, an empirical formula is proposed:





agreement with PB a lot. Reason – unknown

 $\frac{1}{R_i} = \frac{1}{R_i} + 0.028 \mathring{A}^{-1}$ 

## Non-polar solvation

Non-polar molecules tend to minimize exposure to solvent. As a result, configurations with minimal surface area are assumed. Solvation free energy is assumed to be proportional to the surface area exposed to solvent:

solvation energy of the molecule with all non-polar groups hidden from water

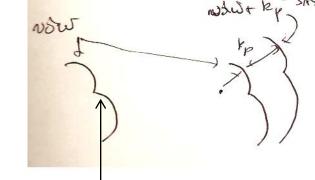
$$\Delta G_{np} = \gamma(SA) + b$$

empirical parameter. May depend on the curvature of the solvent molecule. Typical value

 $\gamma = 72 \, cal \, mol^{-1} \text{\AA}^{-1}$ 

SASA constructed as the surface area of a figure swept by the center of a probe molecule rolled on the surface of the solute molecule

 $R_p = 1.4 \text{\AA}$  typically used for water



vdW surface = SASA with the probe radius set to zero

Molecular surface is made by the points of closest approach of the probe to the solute

1) Parametrizations by many groups (Sitkoff, Sheraga etc.)

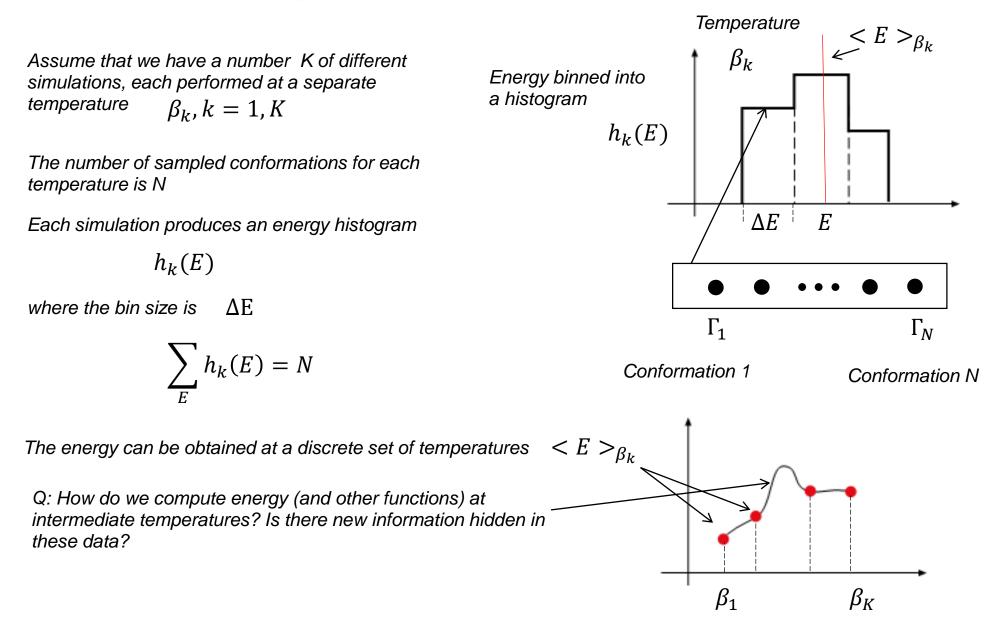
2) Only part or the whole molecule can be treated as non-polar. Separate parameters can be introduced for polar and non-polar groups.

3) Several definitions of "accessible surface" are in use.

 $\Delta G = \Delta G_{PB/GB} + \gamma \Delta S$ 

common models PB/SA or GB/SA

# Weighted histogram analysis method (WHAM)



Sampled histograms can be used to estimate density of states:

$$h_k(E) = Nn_k(E)e^{-\beta_k(E-f_k)} \longrightarrow n_k(E) = \frac{h_k(E)}{N}e^{\beta_k(E-f_k)}$$
density of states,  $f_k$  is the free energy

Most accurate for energy levels close  $to < E >_{\beta_k}$ 

 $f_k$  is the free energy at temperature  $\beta_k$ 

Let us combine histograms at all temperatures in order to obtain a more accurate estimate of the density of states:

$$n(E) = \sum_{i=1}^{K} w_i n_i(E)$$

$$\sum_{i=1}^{K} w_i = 1$$

$$\sum_{i=1}^{K}$$
normalization condition that the coefficients

If the density of states is known, energy distribution at any temperature can be computed as follows  $(\mathbf{r}) - \beta \mathbf{E}$ 

$$P_{\beta}(E) = \frac{n(E)e^{-\beta E}}{\sum_{E} n(E)e^{-\beta E}}$$

#### How to compute the weight coefficients?

Let us estimate the error in the density of states and try to minimize it. This will produce an optimal set of weights.

If we perform multiple experiments = sets of measurements, the resulting energy histograms will fluctuate. This will lead to fluctuations in the estimate of the density of states.

$$n_k(E) = \frac{h_k(E)}{N} e^{\beta_k(E-f_k)} \longrightarrow \delta n_k(E) = \frac{\delta h_k(E)}{N} e^{\beta_k(E-f_k)}$$

fluctuation in the density of states

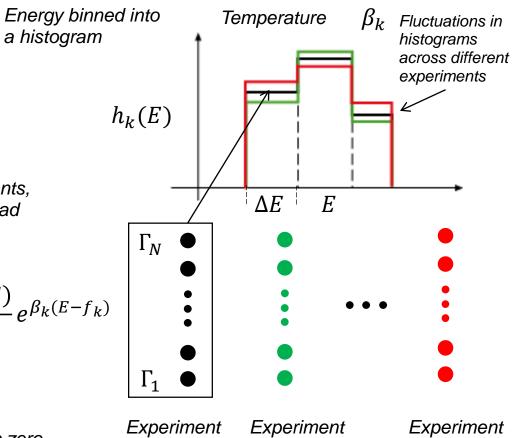
The average of fluctuations across many experiments is zero

$$< \delta n_k(E) >_{exp} = 0$$

Fluctuation of the weighted density of states:

$$\delta n(E) = \sum_{i=1}^{K} w_i \, \delta n_i(E) \quad \longrightarrow \quad < \delta n(E) > = \sum_{i=1}^{K} w_i < \delta n_i(E) > = 0$$

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The error can be estimated from fluctuation squared:

Average fluctuations in the density of states at fixed temperatures can be estimated as follows:

$$(\delta n_k(E))^2 = \frac{(\delta h_k(E))^2}{N^2} e^{2\beta_k(E-f_k)} \longrightarrow < (\delta n_k(E))^2 > = \frac{<(\delta h_k(E))^2 >}{N^2} e^{2\beta_k(E-f_k)}$$

Let us rewrite the squared fluctuation of the histogram in explicit form:

 $<(\delta h_k(E))^2> = < h_k^2(E)> - < h_k(E)>^2$ 

By definition:

$$h_{k}(E) = \sum_{i=1}^{N} \delta_{E,E_{i}} \quad \text{where} \quad \delta_{E,E_{i}} = \frac{1}{2} \left( \Theta(E_{i} - E) + \Theta(E + \Delta E - E_{i}) \right) = - \begin{bmatrix} 1 & \text{if} & E \le E_{i} \le E + \Delta E \\ 0 & \text{otherwise} \end{bmatrix}$$

$$<(h_{k}(E))^{2}>=<\sum_{i=1,j=1}^{N}\delta_{E,E_{i}}\delta_{E,E_{j}}>=<\sum_{i=1}^{N}\delta_{E,E_{i}}^{2}>+<\sum_{i\neq j}^{N}\delta_{E,E_{i}}\delta_{E,E_{j}}>$$

$$<\sum_{i=1}^{N}\delta_{E,E_{i}}>\sum_{i\neq j}^{N}\langle\delta_{E,E_{i}}\rangle<\langle\delta_{E,E_{i}}\rangle<\langle\delta_{E,E_{j}}\rangle$$

$$=Ng$$
For canonical distribution, quantity g can be evaluated directly:
$$N(N-1)g^{2} \qquad g =<\delta_{E,E_{i}}>$$

$$number that shows how likely a random conformation at temperature \beta is to have energy  $\in [E \in +\Delta E]$$$

$$g = \frac{\int_{E}^{E+\Delta E} \delta_{E,E_{i}} n(E) e^{-\beta E} dE}{\int n(E) e^{-\beta E}} \approx n(E) e^{-\beta(E-F(\beta))} \Delta E$$

 $\lim_{\Delta E\to 0}g=0$ 

SO

Average square:

$$< h_k (E) >^2 = < \sum_{i=1}^N \delta_{E,E_i} > < \sum_{j=1}^N \delta_{E,j} > = N^2 g^2$$

$$< (\delta h_k(E))^2 > = < h_k^2(E) > - < h_k(E) >^2 = Ng + N(N-1)g^2 - N^2g^2 = Ng - Ng^2$$

$$\approx Ng = < h_k(E) >$$
if  $g^2 \ll g$  which can always be achieved by making an appropriate choice for  $\Delta E$ 

Going back to the estimate of error in the density of states:

$$<(\delta n_k (E))^2>=\frac{<(\delta h_k(E))^2>}{N^2}e^{2\beta_k(E-f_k)}=\frac{}{\sqrt{N^2}}e^{2\beta_k(E-f_k)}$$

The best estimate of the average histogram can be obtained from the improved density of states:

$$< (\delta h_k(E))^2 > = g_k < h_k(E) >$$

more general expression where the g factor may include the effect of energyenergy correlations

The error in the improved density of states finally:

$$< (\delta n(E))^{2} > = \sum_{i=1}^{K} w_{i}^{2} < (\delta n_{i}(E))^{2}) > = \sum_{i=1}^{K} w_{i}^{2} \frac{n(E)}{N} e^{\beta_{i}(E-f_{i})}$$

Let us consider the relative error in the density of states estimate:

$$F(w_1, \dots, w_K) = \frac{\langle (\delta n_k(E))^2 \rangle}{n(E)} + \lambda \sum_{i=1}^K w_i = \sum_{i=1}^K w_i^2 \frac{1}{N} e^{\beta_i(E-f_i)} + \lambda \sum_{i=1}^K w_i$$

Minimize the cost function:

$$\frac{\partial F(w_1, \dots, w_K)}{\partial w_l} = \frac{2w_l}{N} e^{\beta_l (E - f_l)} + \lambda = 0 \qquad l = 1, K$$
$$\downarrow$$
$$w_l = -\frac{\lambda N}{2} e^{-\beta_l (E - f_l)}$$

undefined coefficient designed to enforce the normalization constraint on weight factors

Use the constraint to determine  $\lambda$ 

$$\sum_{l=1}^{K} w_l = -\frac{\lambda N}{2} \sum_{l=1}^{K} e^{-\beta_l (E-f_l)} = 1 \longrightarrow -\frac{\lambda N}{2} = \frac{1}{\sum_{l=1}^{K} e^{-\beta_l (E-f_l)}} \longrightarrow \qquad w_l = \frac{e^{-\beta_l (E-f_l)}}{\sum_{l=1}^{K} e^{-\beta_l (E-f_l)}}$$

The best estimate of the density of states:

The best estimate of the density of states:  

$$n_i(E) = \frac{h_i(E)}{N} e^{\beta_i(E-f_i)}$$

$$p_i(E) = h_i(E)/N$$

$$m(E) = \sum_{i=1}^K w_i n_i(E) = \frac{\sum_{i=1}^K n_i(E)e^{-\beta_i(E-f_i)}}{\sum_{i=1}^K e^{-\beta_i(E-f_i)}} = \frac{\sum_{i=1}^K n_i(E)e^{-\beta_i(E-f_i)}}{\sum_{i=1}^K e^{-\beta_i(E-f_i)}} = \frac{\sum_{i=1}^K p_i(E)}{\sum_{i=1}^K e^{-\beta_i(E-f_i)}}$$
normalized energy histogram

Density of states can be evaluated from energy histograms at all temperatures and free energies.

By definition:

$$e^{-\beta_i f_i} = \sum_E n(E) e^{-\beta_i E}$$

Then one obtains a set of coupled equations:

$$n(E) = \frac{\sum_{i}^{K} p_i(E)}{\sum_{i}^{K} e^{-\beta_i(E-f_i)}} \qquad (1)$$
$$e^{-\beta_i f_i} = \sum_{E} n(E) e^{-\beta_i E} \qquad (2)$$

Reweighting: 
$$P_{\beta}(E) = \frac{n(E)e^{-\beta E}}{\sum_{E} n(E)e^{-\beta E}}$$

WHAM equations can be solved by iterations:

Step 1: Adopt some values for the free energies  $f_1 \dots f_K$ Step 2: Compute the density of states using eq. (1) Step 3: Obtain more accurate free energy from eq. (2) Step 4: Go back to step 1. Continue until convergence. Non-iterative WHAM: JCP 135 (2011) 061103 WHAM with faster convergence: Mol Sim 42 (20016) 1079 Outcome:

1) Relative free energy for a set of temperatures. f1 has to be fixed.

2) Density of states so energy dist. for any temperature Pitfalls:

1) Temperatures have to be narrowly spaced for energy distributions to overlap

2) Energy distributions have to be converged. Problems at low temperature may arise in some systems

### **Two-dimensional WHAM**

Imagine that it's some structural parameter X for which we seek temperature dependence.

To obtain reweighted function one needs to consider joint distribution of that parameter with E

$$P_{i}(E,X) = \frac{n_{i}(E,X)e^{-\beta_{i}E}}{\sum_{E,X}n_{i}(E,X)e^{-\beta_{i}E}} = n_{i}(E,X)e^{-\beta_{i}(E-f_{i})} \longrightarrow n_{i}(E,X) = P_{i}(E,X)e^{\beta_{i}(E-f_{i})}$$

$$\sum_{E,X}P_{i}(E,X) = 1 \qquad \text{2D density of states} \qquad \text{free energy} \qquad P_{i}(X) = \sum_{E}P_{i}(E,X)$$

$$P_{i}(X) = \sum_{E}P_{i}(E,X)$$

$$P_{i}(X) = \sum_{E}P_{i}(E,X)$$

$$P_{i}(E,X) = \sum_{E}P_{i}(E,X)$$

better estimate of the density of states:

$$n(E,X) = \sum_{i} w_{i}n_{i}(E,X) \longrightarrow w_{l} = \frac{e^{-\beta_{l}(E-f_{l})}}{\sum_{k=1}^{K} e^{-\beta_{k}(E-f_{k})}}$$

2D WHAM equations:  

$$n(E, X) = \frac{\sum_{i}^{K} P_{i}(E, X)}{\sum_{i}^{K} e^{-\beta_{i}(E-f_{i})}}$$

$$e^{-\beta_{i}f_{i}} = \sum_{E, X} n(E, X)e^{-\beta_{i}E}$$

Distribution function at any temperature by reweighting:  $< X^2 >_{\beta} - < X >_{\beta}^{2}$  $P_{\beta}(X) = \frac{\sum_{E} n(E, X) e^{-\beta E}}{\sum_{E, X} n(E, X) e^{-\beta E}}$  $\langle X \rangle_{\beta} = \sum_{x} X P_{\beta}(X), \langle X^{2} \rangle_{\beta} = \sum_{X} X^{2} P_{\beta}(X)$ ß

transition point

### Umbrella sampling

The idea of combining multiple trajectories can be used to obtain distributions along selected degrees of freedom with the help of biased simulations.

Recall that for a degree of freedom X:

Not normalized distribution function

$$P(X) = \sum_{E} P(E,X) = \frac{\sum_{E} n(E,X)e^{-\beta E}}{\sum_{E,X} n(E,X)e^{-\beta E}} = \frac{P_0(X)}{\sum_{X} P_0(X)} = P_0(X)e^{\beta F(\beta)} \qquad P_0(X) = \sum_{E} n(E,X)e^{-\beta E}$$

$$i \text{ joint normalized} \qquad 2D \text{ density of} \qquad \text{free energy at} \\ i \text{ temperature} \\ 1/beta \qquad \qquad \sum_{X} P_0(X) = e^{-\beta F}$$

Imagine that we apply external potential to bias the value of coordinate X sampled in simulations

 $E \rightarrow E + \frac{\alpha}{2} (X - X_i)^2$ biasing "umbrella" potential

Distribution in the umbrella simulation:

$$P_{i}(X) = \sum_{E} n(E, X) e^{-\beta E} e^{-\beta \frac{\alpha}{2} (X - X_{i})^{2}} e^{f_{i}} = P_{0}(X) e^{-\beta \frac{\alpha}{2} (X - X_{i})^{2}} e^{f_{i}}$$

$$\sum_{X} P_i(X) = 1$$

some normalization constant specific to Xi

Unbiased distribution can be recovered as follows:

$$P_0^i(X) = P_i(X)e^{\beta\frac{\alpha}{2}(X-X_i)^2} e^{-f_i} \longrightarrow \sum_X P_0^i(X)e^{-\beta\frac{\alpha}{2}(X-X_i)^2} = e^{-f_i}$$

this is normalized histogram from biased simulation

Let us now conduct multiple biasing simulations to obtain improved distribution:

$$P_0(X) = \sum_i w_i P_0^i(X) \qquad \sum_i w_i = 1$$

Follow the WHAM procedure to estimate the error and then minimize it:

$$(\delta P_0^i(X))^2 = (\delta P_i(X))^2 e^{2\beta \frac{\alpha}{2}(X-X_i)^2} e^{-2f_i} = P_0(X) e^{\beta \frac{\alpha}{2}(X-X_i)^2} e^{-f_i}$$
$$(\delta P_0^i(X))^2 = \sum_i w_i^2 (\delta P_0^i(X))^2 = \sum_i w_i^2 e^{\beta \frac{\alpha}{2}(X-X_i)^2} e^{-f_i} P_0(X)$$

The function to be minimalized:

$$F = \sum_{i} w_{i}^{2} e^{\beta \frac{\alpha}{2} (X - X_{i})^{2}} e^{-f_{i}} + \lambda \sum_{i} w_{i} \longrightarrow \qquad w_{l} = \frac{e^{-\beta \frac{\alpha}{2} (X - X_{l})^{2} + f_{l}}}{\sum_{i} e^{-\beta \frac{\alpha}{2} (X - X_{i})^{2} + f_{i}}}$$

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WHAM equations:

Let X be some generalized coordinate. By definition:

$$P_{0}(X) = \frac{\sum_{i} P_{i}(X)}{\sum_{i} e^{-\beta \frac{\alpha}{2} (X-X_{i})^{2} + f_{i}}}$$

$$P(X) = \int \delta(X - X(\Gamma)) e^{-\beta U} d\Gamma Z^{-1} = \frac{\int e^{-\beta U} d\Gamma_{X}}{\int e^{-\beta U} d\Gamma} = \frac{Z(X)}{Z}$$

$$d\Gamma = dX d\Gamma_{X}$$

$$d\Gamma = dX d\Gamma_{X}$$

$$d\Gamma_{1} \dots d\Gamma_{N} =$$

$$dr_{N} \text{ other than } X \text{ (orthogonal variables)}$$

$$d\Gamma = average \text{ force that corresponds to the coordinate.}}$$

$$Reweighting:$$

$$P(X) = \frac{P_{0}(X)}{\sum_{X} P_{0}(X)}$$

$$reweighting:$$

$$reweighting:$$

$$P(X) = \frac{P_{0}(X)}{\sum_{X} P_{0}(X)}$$

$$reweighting:$$

#### Free energy estimation

Key thermodynamic function that helps to describe stability of condensed matter systems

1) Phase equilibria, transitions

2) Binding strength for macro complexes ...

By definition:

Partition function Ideal part  $\mathcal{E}$  Excess part=due to interactions  $F(N,V,T) = -kT\log(Q_{NVT}) = F_{id}(N,V,T) + F_{ex}(N,V,T)$  $F_{id}(N, V, T) = \frac{N}{\beta} \log(\rho) + \frac{N}{\beta} \log\left(\frac{1}{\lambda^3}\right) - \frac{N}{\beta}, \qquad \rho = \frac{N}{V}$  $F_{ex}(N,V,T) = -kTlog(Q_{NVT}^{ex}) \qquad Q_{NVT}^{ex} = \frac{Z_{NVT}}{V^N}, \qquad Z_{NVT} = \int d\Gamma e^{-\beta U(\Gamma)}$   $\int \int d\Gamma e^{-\beta U(\Gamma)} d\Gamma e^{-\beta U(\Gamma)}$   $\int \int d\Gamma e^{-\beta U(\Gamma)} d\Gamma e^{-\beta U(\Gamma)}$   $\int \int d\Gamma e^{-\beta U(\Gamma)} d\Gamma e^{-\beta U(\Gamma)}$ Configuration integral

Not formulated as an average over ensemble so difficult to estimate in simulations

### 1) Hit and miss method

 $Z_{NVT}$  is an integral in multidimensional space. The most efficient integration method is sample mean.

$$Z_{NVT} = \int e^{-\beta U(\Gamma)} d\Gamma = < \frac{e^{-\beta U(\Gamma)}}{\rho(\Gamma)} >_{\rho} \int \rho(\Gamma) d\Gamma$$

sampling from the given distribution

The scheme can have multiple realizations:

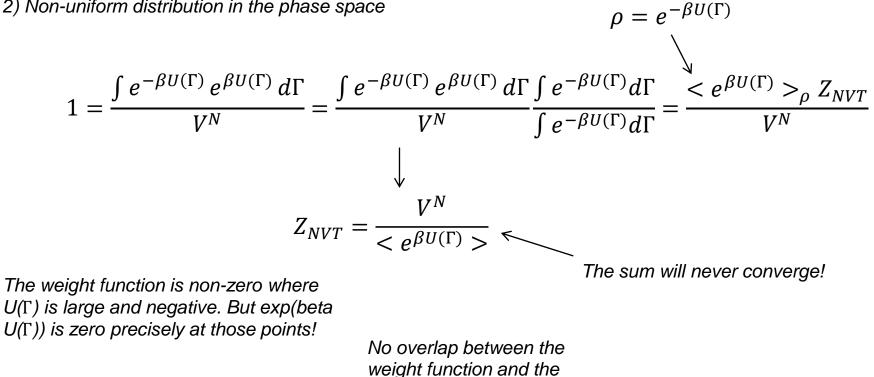
1) Uniform distribution in the phase space  $\rho = \frac{1}{V^N}$ 

$$\rho = \frac{1}{V^N}, \quad \int d\Gamma \,\rho(\Gamma) = 1$$

$$Z_{NVT} = V^N < e^{-\beta U(\Gamma)} >$$

Configurations are generated by randomly displacing particles anywhere in the available volume V

Due to overlaps between particles, very few entries in this sum will be non-zero. The sum will never converge 2) Non-uniform distribution in the phase space



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integrand

### 2) Thermodynamic integration

1) Integration over density

$$dF = -PdV - SdT \longrightarrow P = -\left(\frac{\partial F}{\partial V}\right)_{T}$$

$$F(V) - F(V_{0}) = -\int_{V_{0}}^{V} P(V)dV = N\int_{\rho_{0}}^{\rho} d\rho \frac{P(\rho)}{\rho^{2}} \longleftarrow dV = -\frac{N}{\rho^{2}}d\rho$$

$$\downarrow \int_{\rho_{0}}^{\rho} d\rho \frac{P(\rho)}{\rho^{2}}$$

$$F(\rho) = F(\rho_{0}) + N\int_{\rho_{0}}^{\rho} d\rho \frac{P(\rho)}{\rho^{2}}$$

$$Free energy has to be known exactly for this density$$

$$Certain density for which free energy is supposed to be known$$

Let's pick density sufficiently low so that the system can be approximated by ideal gas

$$F(\rho_0) = F_{id}(\rho_0) = \frac{N}{\beta}\log(\rho_0) + \frac{N}{\beta}\log\left(\frac{1}{\lambda^3}\right) - \frac{N}{\beta}$$

Then the ideal part at low density can be written in terms of the ideal part at any density:

$$F_{id}(\rho_{0}) = \frac{N}{\beta}\log(\rho) - \frac{N}{\beta}\log(\rho) + \frac{N}{\beta}\log(\rho_{0}) + \frac{N}{\beta}\log\left(\frac{1}{\lambda^{3}}\right) - \frac{N}{\beta} = F_{id}(\rho) + \frac{N}{\beta}\log(\rho_{0}) - \frac{N}{\beta}\log(\rho)$$

$$\downarrow$$

$$F_{id}(\rho_{0}) = F_{id}(\rho) - \frac{N}{\beta}\int_{\rho_{0}}^{\rho}d\rho\frac{1}{\rho}$$

$$F(\rho) = F(\rho_{0}) + N\int_{\rho_{0}}^{\rho}d\rho\frac{P(\rho)}{\rho^{2}} = F_{id}(\rho) - \frac{N}{\beta}\int_{\rho_{0}}^{\rho}d\rho\frac{1}{\rho} + N\int_{\rho_{0}}^{\rho}d\rho\frac{P(\rho)}{\rho^{2}} = F_{id}(\rho)$$

$$+ N\int_{\rho_{0}}^{\rho}d\rho\frac{\beta P - \rho}{\beta\rho^{2}} = F_{id}(\rho) + N\int_{\rho_{0}}^{\rho}d\rho\frac{P^{ex}(\rho)}{\rho^{2}} = F_{id}(\rho) + N\int_{0}^{\rho}d\rho\frac{P^{ex}(\rho)}{\rho^{2}}$$

$$F_{ex}(\rho) = N\int_{0}^{\rho}d\rho\frac{P^{ex}(\rho)}{\rho^{2}}$$

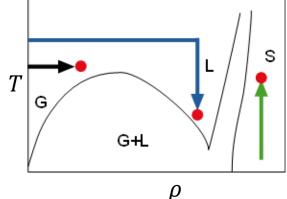
2) Integration over temperature

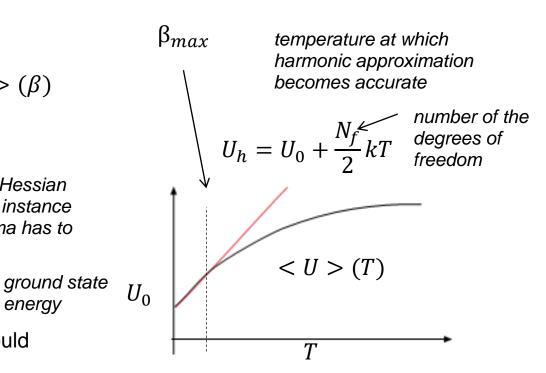
$$F(\beta) = \frac{\beta_{max}}{\beta} F_0(\beta_{max}) - \frac{1}{\beta} \int_{\beta}^{\beta_{max}} d\beta < U > (\beta)$$

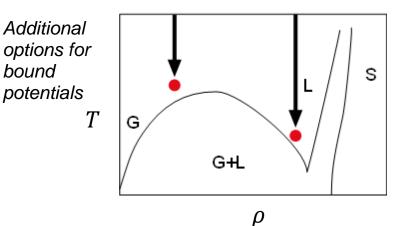
Free energy in harmonic approximation. Involves Hessian matrix. Easy to compute for a single structure, for instance in crystals. For liquids, an ensemble of local minima has to be considered

Thermodynamic integration: integration paths should not cross phase boundaries!

Suggested paths to determine absolute free energy in liquid and solid states







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energy

### 3) Thermodynamic perturbation

Assume that we want to measure free energy difference between two different systems described by Hamiltonian A and B

Free energy of system B is expressed in terms of free energy of system A and some average obtained in ensemble A

3) A path between two states A and B can be constructed that contains intermediate states with mutual overlap

#### 4) "Artificial" thermodynamic integration

Let's consider the same problem with two different systems A and B.  $U_A = U_B$ 

Introduce a variable that transforms one system into another

$$U(\lambda) = U_A + \lambda(U_B - U_A) = U_A + \lambda \Delta U$$
$$U(\lambda = 0) = U_A, \qquad U(\lambda = 1) = U_B$$

Partition function that depends on  $\lambda$ 

$$Z(\lambda) = \int d\Gamma e^{-\beta(U_A + \lambda \Delta U)} \longrightarrow \frac{\partial Z(\lambda)}{\partial \lambda} = \int d\Gamma - \beta \Delta U e^{-\beta(U_A + \lambda \Delta U)} = -\beta < \Delta U >_{\lambda} Z(\lambda)$$

$$d\log(Z(\lambda)) = -\beta < \Delta U >_{\lambda} d\lambda \quad \longrightarrow \quad \log(Z(\lambda)) = \log(Z(0)) - \beta \int_{0}^{\lambda} < \Delta U >_{\lambda} d\lambda$$

$$F(B) = F(A) + \int_{0}^{1} \langle \Delta U \rangle_{\lambda} d\lambda$$

The most reliable and widely used method

1) Integral has to be evaluated for a number of intermediate points. Each point has to be computed in a separate simulation

2) May have issues with integrand not being smooth enough

3) Applied to a large variety of tasks, for instance mutations

Perturbation and artificial integration are equivalent when the difference between the systems is small.

Free energy for a small  $\lambda^*$ 

$$F(\lambda^*) = F(A) + \int_0^{\lambda^*} \langle \Delta U \rangle_{\lambda} \, d\lambda = F(A) + \langle \Delta U \rangle_A \, \lambda^* \qquad \text{if } \lambda^* \sim 0$$

In perturbation theory:

$$\begin{split} U_{B'} &= U_A + \lambda^* (U_B - U_A) \longrightarrow \Delta U' = U_{B'} - U_A = \lambda^* (U_B - U_A) = \lambda^* \Delta U \\ F(B') &= F(A) - \frac{1}{\beta} \log < e^{-\beta \Delta U'} >_A = F(A) - \frac{1}{\beta} \log < e^{-\beta \lambda^* \Delta U} >_A \approx F(A) + \lambda^* < \Delta U >_A \\ \log(1 - \beta \lambda^* < \Delta U >_A + \cdots) = \beta \lambda^* < \Delta U >_A \end{split}$$

#### 5) Method of Einstein crystal

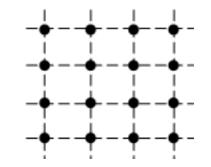
Can be used to compute absolute free energy of crystals

Introduce an artificial Hamiltonian that will drive the system into a state with known free energy

 $U(\lambda) = \lambda U + (1 - \lambda)U_H$ system where particles are  $U(\lambda = 0) = U_H$  held at their positions by harmonic potentials  $U(\lambda = 1) = U$ actual system  $F(\lambda) = F(0) + \int_{0}^{\lambda} \langle U - U_{H} \rangle_{\lambda} d\lambda$ free energy of harmonic oscillator

the integrand is well behaved if particles occupy the same position at the start and the end of the integration (in both Hamiltonians)

The system is defined by a set of positions on a lattice



$$U_H(\Gamma) = \frac{1}{2} \alpha \sum_{i}^{N} (\overline{r_i} - \overline{r_i^0})$$

### 6) Widom's particle insertion method

accessible in simulation through virial

Free energy can be computed from the chemical potential:  $F(NVT) = G - PV = N\mu - PV$ 

According to the definition:

$$G(N,TP) = N\mu \longrightarrow \mu = G(N+1,PT) - G(N,PT)$$

$$G(N,PT) = -kT \log(Q(NPT)) \longrightarrow \mu = -kT \log(\frac{Q(N+1,PT)}{Q(N,PT)})$$

$$Volume distribution function:$$

$$P(V) = \frac{e^{-\beta PV}Z(NVT)}{\int dV e^{-\beta PV}Z(NVT)}$$

Recall the definition of the partition function in NPT ensemble:

 $Q(N,PT) = \frac{1}{N!\lambda^{3N}V_0} Z(N,PT), \qquad Z(N,PT) = \int dV e^{-\beta PV} Z(NVT) \longleftarrow \begin{array}{c} \text{canonic canonic configuration} \\ \text{integral} \\ \text{integral} \\ \end{array}$ 

$$\int dq_1 dq_2 \dots dq_N e^{-\beta U(q_1 \dots q_N)}$$

average over

Evaluate the N+1 term first:

Similar expression for the N-particle term:

Chemical potential can be evaluated from simulations in canonical ensemble:

$$\mu^{ex} = G^{ex}(N+1,PT) - G^{ex}(N,PT) = F^{ex}(N+1,TV) - F^{ex}(N,TV) + (P^{ex}(N+1) - P^{ex}(N))V \qquad \begin{array}{c} \text{canonical ensemble} \\ \text{ensemble} \\ \text{with } N \\ \text{particles} \\ \end{array}$$

$$F^{ex}(NVT) = -kT\log(Q(NVT)) \longrightarrow F^{ex}(N+1,VT) - F^{ex}(N,VT) = -kT\log(\frac{Q(N+1,VT)}{Q(N,VT)}) \qquad \begin{array}{c} \text{particles} \\ \text{particles} \\ \text{particles} \\ \end{array}$$

$$Configuration integral explicitly: \qquad -kT\log(e^{-\beta U_1} - e^{-\beta U_1}) = \frac{1}{V^{N+1}} \int dq_1 e^{-\beta U_1} dq_2 \dots dq_{N+1} e^{-\beta U(q_2 \dots q_{N+1})} = \frac{1}{V^N} < e^{-\beta U_1} > Z(NVT) = < e^{-\beta U_1} > Q(NVT)$$

K

average in

Pressure contribution:  

$$p - \rho = \frac{1}{V}$$

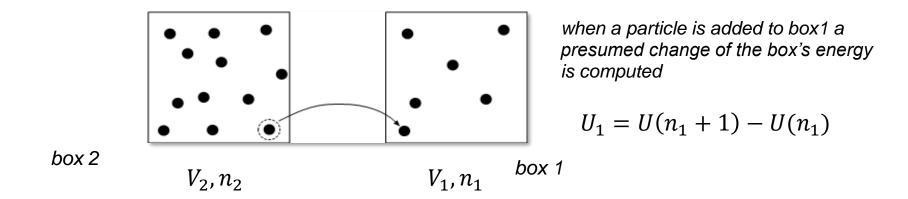
$$P^{**}(N+1) = P^{**}(\rho) = \frac{N+1}{V} \approx P^{**}(\rho) = \frac{N}{V} + \frac{dP^{**}(\rho)}{d\rho} (\rho' - \rho) = P^{**}(N) + \frac{K^{**}}{\rho} \frac{1}{V}$$
bulk modulus
$$K^{**} = \rho \frac{dP^{**}(\rho)}{d\rho} = a\rho^{2} + b\rho^{3} + \dots$$
from virial expansion
Two terms together:  

$$\mu^{**} = -kT \log(\langle e^{-\rho U_{1}} \rangle) + \frac{K^{**}}{\rho} \bigwedge^{a\rho} + b\rho^{2} + \dots$$
this summand vanishes at low densities
but doesn't disappear when N tends to
infinity
$$\mu^{**} \approx -kT \log(\langle e^{-\rho U_{1}} \rangle) = F^{**}(N+1,VT) - F^{**}(N,VT) = \frac{F^{**}(N+1,VT) - F^{**}(N,VT)}{N+1-N} \approx \frac{\partial F^{**}(NVT)}{\partial N}|_{vT} = \mu^{**}$$
the original Widom's formula. Due to large

fluctuations it applies only at low densities. So it's safe to use it there. At high densities, large variations in  $U_1$  resulting from particle overlaps hinder convergence.

#### 7) Chemical potential from the Gibbs ensemble simulations

Two boxes in GEMC simulations are maintained at constant temperature and pressure. The Widom formula for the NPT ensemble can be used to estimate chemical potential during the transfer move.



The volume and the number of particles change so the average includes both of them:

$$\mu = -kT\log(\frac{1}{(N+1)\lambda^3} < Ve^{-\beta U_1} >) \longrightarrow \mu = -kT\log(\frac{1}{\lambda^3} < \frac{V_1e^{-\beta U_1}}{n_1 + 1} >)$$

$$NPT$$
Gibbs ensemble

1) The identity of box 1 can't change during chemical potential evaluation. If it's vapor it has to remain vapor to the end of the simulation. Similarly for liquid. This is easy to achieve unless the system is near critical point.

2) If box 1 contains all particles of the system (the other box is empty) one should still attempt to add a particle to it to evaluate  $U_1$ . This step is not executed in normal GEMC.

#### 8) Multiple Bennett acceptance ratio (MBAR) method

Imagine that we have a number of trajectories simulated at a set of temperatures. WHAM can be used to combine the energy histograms and obtain a) density of states and b) relative free energies. The relevant equations are:

$$n(E) = \frac{\sum_{i}^{K} p_{i}(E)}{\sum_{i}^{K} e^{-\beta_{i}(E-f_{i})}}$$
$$e^{-\beta_{i}f_{i}} = \sum_{E} n(E)e^{-\beta_{i}E}$$

Histograms are built assuming certain size of the bins  $\Delta E$ . The bin size has to be a) small so that the density of states is constant within  $[E, E + \Delta E]$  and b) large so that reasonable statistics of n(E) is obtained. The finite size of  $\Delta E$  introduces errors. If only the free energies are of interest, the error can be minimized by taking the limit  $\lim \Delta E \to 0$ . The WHAM equations then can be reduced to a simpler form.

Let us introduce an indicator function which is unity if energy of a given configuration k is within  $\Delta E$  of E and zero otherwise:

$$\delta_{E,E_k} = \frac{1}{2} \Big( \Theta(E_k - E) + \Theta(E + \Delta E - E_k) \Big) = - \begin{cases} 1 & \text{if } E \leq E_k \leq E + \Delta E \\ 0 & \text{otherwise} \end{cases}$$

The energy histogram for temperature i is

$$p_i(E) = \sum_k \delta_{E,E_k}$$

summation runs over all sampled conformations

The density of states then can be re-written:

$$n(E) = \frac{\sum_{i}^{K} p_i(E)}{\sum_{l}^{K} e^{-\beta_l(E-f_l)}} = \frac{\sum_{i}^{K} \sum_{j} \delta_{E,E_j}}{\sum_{l}^{K} e^{-\beta_l(E-f_l)}}$$

for sufficiently small  $\Delta E$  the indicator function will kill the summation over E

Let us substitute this expression into the second WHAM equation:

$$e^{-\beta_{s}f_{s}} = \sum_{E} \frac{\sum_{i}^{K} \sum_{j} \delta_{E,E_{j}}}{\sum_{i}^{K} e^{-\beta_{l}(E-f_{l})}} e^{-\beta_{s}E} = \sum_{i} \sum_{E} \frac{\sum_{j} \delta_{E,E_{j}}^{L} e^{-\beta_{s}E}}{\sum_{i}^{K} e^{-\beta_{l}(E-f_{l})}} = \sum_{j} \sum_{i} \sum_{j} \frac{e^{-\beta_{s}E_{j}}}{\sum_{i}^{K} e^{-\beta_{l}(E_{j}-f_{l})}}$$

$$MBAR \text{ equations}$$

$$MBAR \text{ equations}$$

$$MBAR \text{ equations}$$

$$g_{s}f_{s} = -\log\{\sum_{i} \sum_{j} \frac{e^{-\beta_{s}E_{j}}}{\sum_{i}^{K} e^{-\beta_{l}(E_{j}-f_{l})}}\}$$

$$1) \text{ Non-linear set of equations for } f_{i}$$

$$2) \text{ Can be solved by iterations}$$

$$\beta_{s}f_{s} + A$$

$$\beta_{s}f_{s} + A$$

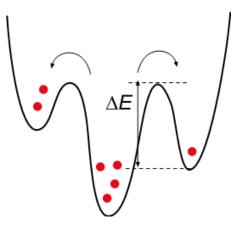
4) Solution is not unique. Only relative free energies are obtained

#### Other methods:

9) Grand canonical ensemble (covered)

10) Methods for approximate evaluation of the free energy: chemical Monte Carlo, lamba dynamics, linear response theory, ....

# MC simulations in generalized (non-Boltzmann) ensembles



# Outline

#### Introduction

• Generalized ensembles:

-multicanonical ensemble -Tsallis statistics -Wang-Landau method -1/k ensemble -**J-**walking algorithm -expanded-ensemble method

- Replica-exchange (REX) approach
- Applications:

-replica-exchange simulations of peptide aggregation -folding of a short  $\beta$ -peptide in explicit water

# Introduction

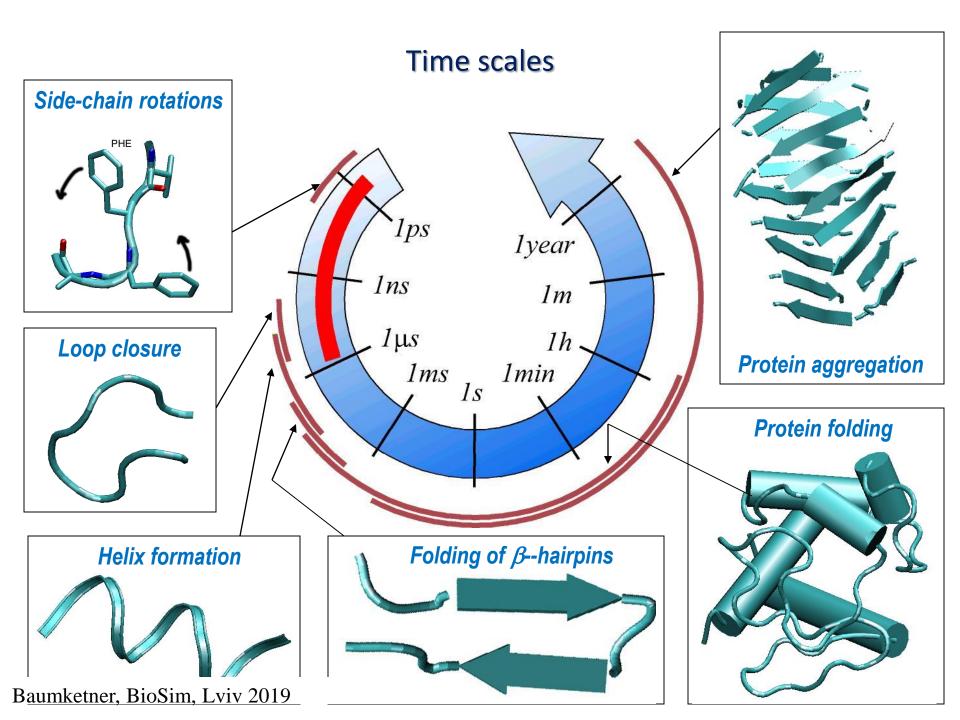
• Why do we need *generalized* ensembles ?

• Two ingredients of a successful simulation:

(I) accurate representation of the **system** and **solvent** 

(II) adequate **sampling** of the conformational space

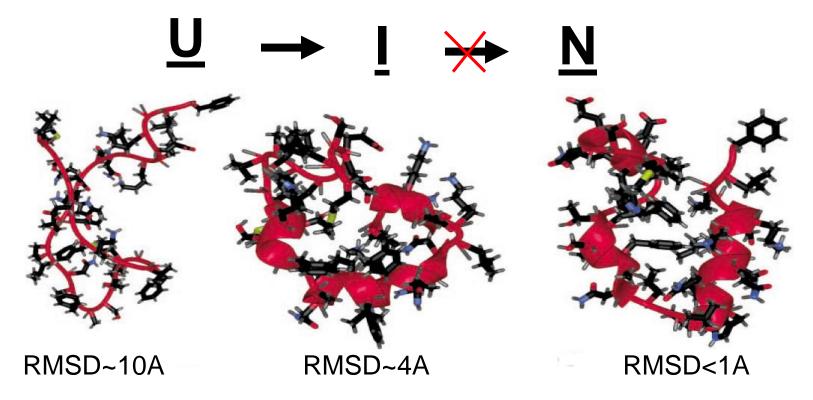
Simulation times must be at least <u>10 times</u> longer than the relevant relaxation time !



# Brute force approach

<u>Y. Duan & P. Kollman</u>, Science 282,(1998),740, "Pathways to a protein folding intermediate observed in a 1-microsecond simulation in aqueous solution"

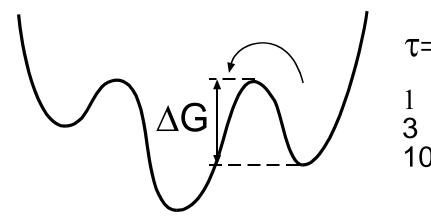
• Villin headpiece subdomain,256 CPUs of Cray T3E.



# **Rugged potential energy landscapes**

• Why are the relaxation times so long?

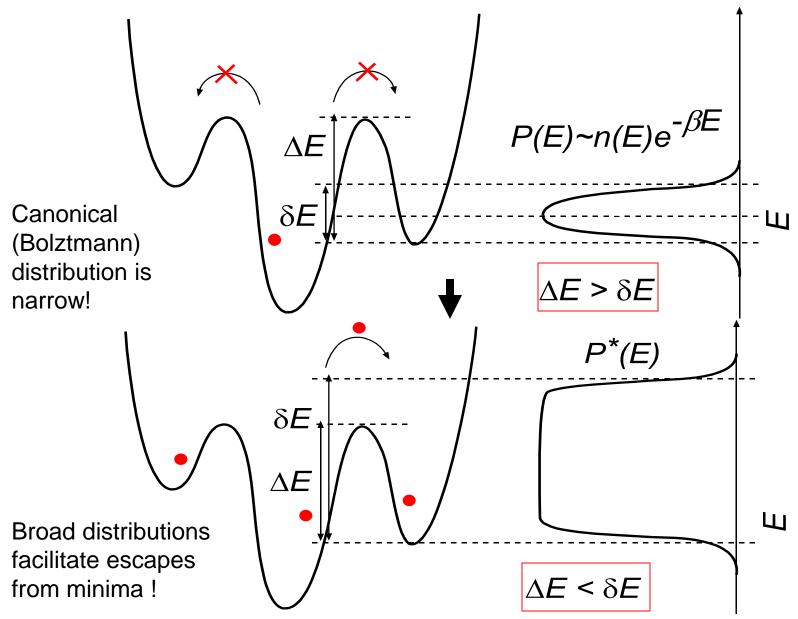
-number of local potential energy minima grows exponentially with N



$$\tau_0 \exp(\Delta G/\kappa_b T) \quad \tau_0 \sim 1 \text{ ps}$$
  
kcal/mol:~1.2 ps  
kcal/mol:~1.5 ns  
0kcal/mol:~1 ms and longer

-each minimum acts as a kinetic trap. The relaxation time is determined by the escape time from the minima

#### **Generalized ensembles**



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#### **Multicanonical ensemble**

• sampling on a "deformed" potential energy surface W(E):

$$P^{*}(E) \sim n(E)e^{-\beta W(E)}$$
(1)

• *flat* energy distribution for multicanonical ensemble:

$$P^{*}(E) = P_{\mu}(E) \sim const$$
$$W_{\mu}(E) = ?$$

• equation (1) can be rewritten as a non-linear equation in  $W_{\mu}(E)$  (valid up to a constant which drops during normalization):

$$W_{\mu}(E) = \frac{1}{\beta} [\ln n(E) - \ln P_{\mu}(E)] = \frac{1}{\beta} \ln n(E)$$
(2)

• density of states is estimated from a simulation. It depends (as a functional) on  $W_{\mu}(E)$  and simulation parameters:  $n(E)[W_{\mu}; param]$ . Simplest solution to equation (2) is given by successive iterations:

$$W_{\mu}^{n+1}(E) = \frac{1}{\beta} \ln n^{n}(E)$$
(3)

#### Multicanonical ensemble

• final result: 
$$W_{\mu}^{n+1}(E) = W_{\mu}^{0}(E) + \frac{1}{\beta} \ln[P_{\mu}^{0}(E) \cdots P_{\mu}^{n}(E)]$$
 (4)

• an example:  $W_{\mu}^{0}(E) = E$ , zero energy distribution  $P_{\mu}^{0}(E)$  is canonical and equation (4) is the standard *multicanonical recursion*:

$$W_{\mu}^{n+1}(E) = E + \frac{1}{\beta} \ln[P_{\beta}(E) \cdots P_{\mu}^{n}(E)]$$
(5)

• canonical distribution can be recovered from  $P_{\mu}(E)$  through a reweighting procedure:

$$P_{\beta}(E) \sim P_{\mu}(E) \ e^{\beta(W_{\mu}(E) - E)} \tag{6}$$

• three steps of a multicanonical simulation:

- (i) generating  $W_{\mu}(E)$  in successive iterations
- (ii) equilibrium sampling

(iii) recovering canonical expectations for various observables

#### Monte Carlo studies of spin glasses

• <u>B. A. Berg & T. Neuhaus</u>, *PRL* 68,(1992),9, "*Multicanonical ensemble: A new approach to simulate first-order phase transitions*"

• <u>B. A. Berg & T. Celik</u>, *PRL* 69,(1992),2292, "*New approach to spin-glass simulations*" - multicanonical recursions

2D 10-state Potts model

• No exponential increase in the tunneling time between two free energy minima

• Speedup up to 2 orders of magnitude compared to standard simulations

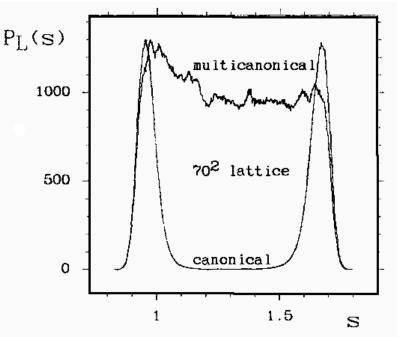


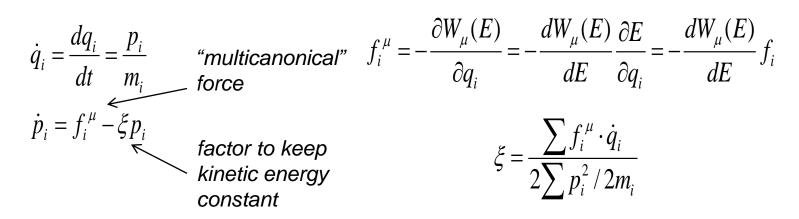
FIG. 2. Multicanonical action density distribution  $\mathcal{P}_{70}(s)$  together with its reweighted distribution  $P_{70}(s)$ .

## Molecular dynamics simulations

• <u>U. H. E. Hansmann, Y. Okamoto and F. Eisenmenger</u>, *Chem. Phys. Lett* 259,(1996),321, "*Molecular dynamics, Langevin and hybrid Monte Carlo simulations in a multicanonical ensemble*"

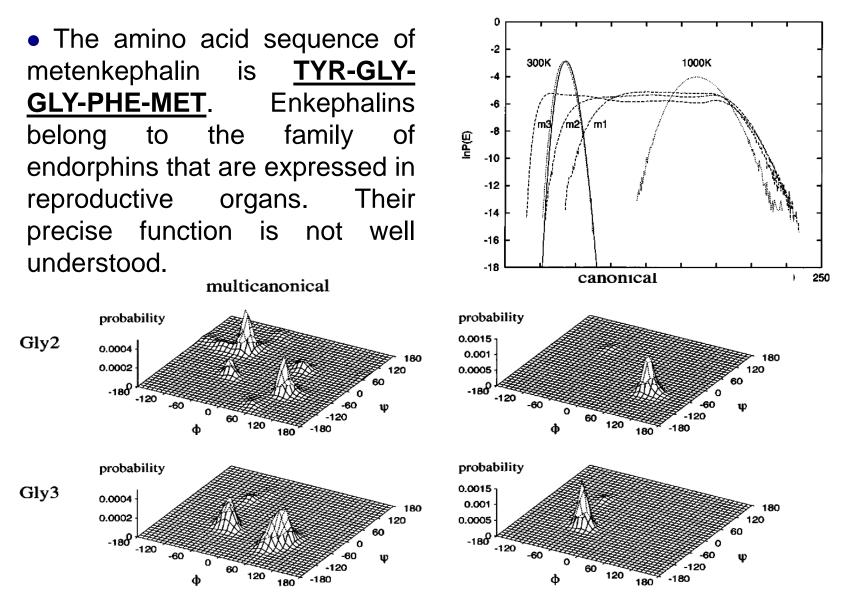
• <u>N. Nakajima, H. Nakamura and A. Kidera</u>, *J. Phys. Chem. B* 101, (1997), 817, "*Multicanonical ensemble generated by molecular dynamics simulations for enhanced conformational sampling*"

• Equations of motion:



• The only modification is in how *forces* are calculated !

# Simulations of met-enkephalin



# Summary

#### Advantages:

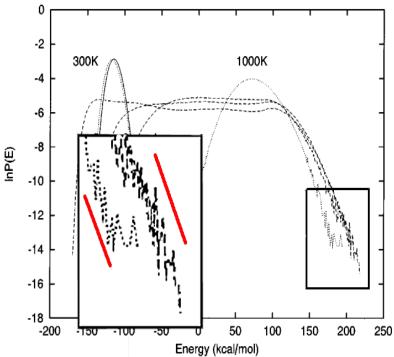
(i) multicanonical simulations do not get trapped in local minima
 (ii) various thermodynamic quantities are obtained as a function of temperature from a single run. No need to run multiple simulations at different temperatures

#### • Disadvantages:

(i) the energy transformation function  $W_{\mu}(E)$  is non-analytical. Several preliminary simulations are needed to generate it

(ii) these simulations can not be run in parallel

(iii) convergence is sensitive to the details of numerical implementation. Can be quite poor if  $P_{\mu}^{0}(E)$  is not accurately determined



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## **Tsallis energy transformation**

• <u>U. H. E. Hansmann & Y. Okamoto</u>, *PRE* 56, (1997), 2228, "Generalized-ensemble Monte Carlo method for systems with rough energy landscape "

• *analytical* form for the multicanonical weight factor. *Non-exponential falloff* at large *E*:

$$w_T(E) = [1 + x\beta(E - E_0)]^{-\frac{1}{x}} \xrightarrow[x \to 0]{-\beta(E - E_0)} e^{-\beta(E - E_0)}$$

energy transformation:

$$W_T(E) = \frac{1}{x\beta} \ln[1 + x\beta(E - E_0)]$$

• at low temperature the density of states can be calculated in harmonic approximation:  $N_F$ 

$$n(E) \sim (E - E_0)^{\frac{N_F}{2}}$$

- if low-energy states are to be populated:
- $x < x_{c} = 2 / N_{F}$

$$x_0 = 0.5 x_c$$

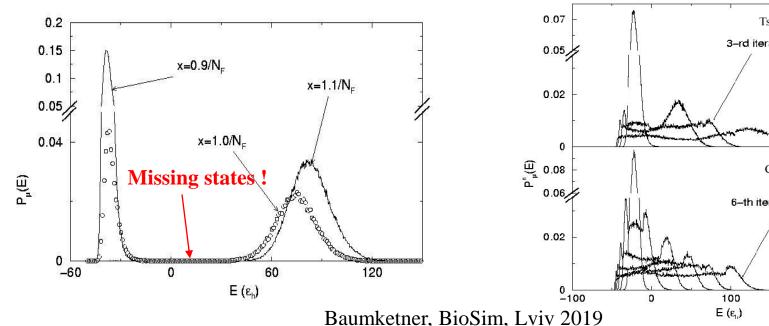
• optimal value for *x*:

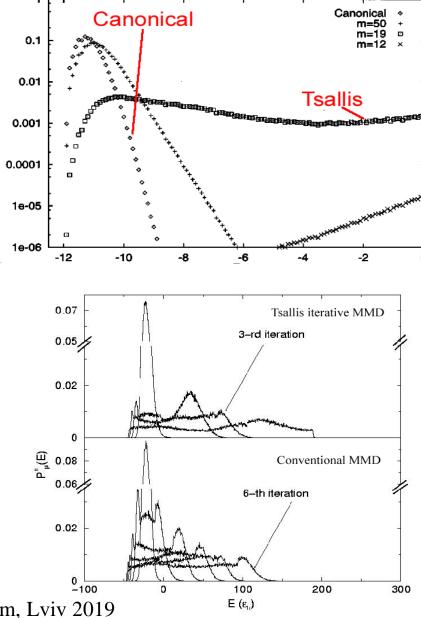
# Applications

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• progressive *broadening* of the potential energy distribution of a metenkephalin model as *x* is reduced

- same  $x_0$  does not work for all systems !
- simulations of HT protein model
   [AB & Y. Hiwatari, JPSJ, 71, (2002),
   1001]. MMD iterations

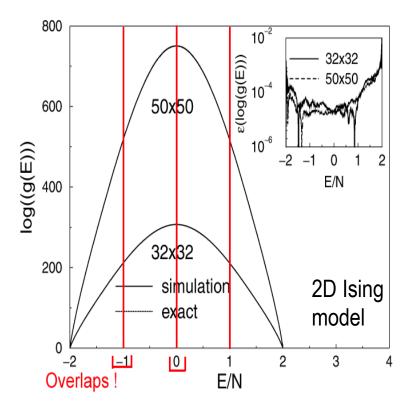




# Wang-Landau method

- <u>F. Wang & D. P. Landau</u>, *PRL* 86, (2001), 2050, "*Efficient, multiple*range random walk algorithm to calculate the density of states"
- Acceptance probability of a Monte Carlo move  $i \rightarrow j$ : min {  $n(E_i)/n(E_j), 1$ }
- Algorithm:
- 0) *n*(*E*)=1 for all *E*, *f*~3
- 1) every time an energy level *E* is visited, n(E)=f n(E)2) simulation is continued until energy histogram H(E)is "flat". H(E) for all *E* is not less than 80% of  $\langle H(E) \rangle$ 3) change the factor  $f_{i+1} = \sqrt{f_i}$
- 4) if  $f_{i+1} > f_c (\sim 1.001)$  set H(E)=0 and return to step 1
  - Detailed balance is satisfied at *f*=1
  - Applicable to *large* systems. The desired energy interval can be broken into smaller pieces which are simulated in *parallel*
  - <u>Caveat</u>: Make energy intervals large enough to avoid trapping !
  - Application to proteins: [A. Cavalli et al., Biophys J. 88, (2005), 3158]

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# 1/k ensemble

• <u>B. Hesselbo & R. B. Stinchcombe</u>, *PRL* 74, (1995), 2151, "*Monte Carlo simulation and global optimization without parameters*"

• Acceptance probability of a Monte Carlo move  $i \rightarrow j$  : min {  $w_j / w_i, 1$ } Metropolis (canonical distribution)  $w_i = e^{-\beta E_i}$ 

Multicanonical, Wang-Landau 1/k ensemble

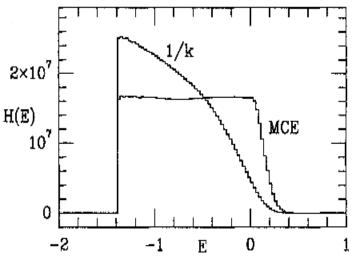
$$w_i = 1/k_i, \qquad k_i = n(E_i)$$
$$w_i = 1/k_i, \qquad k_i = \int_{E < E_i} dE n(E_i)$$

• Definitions of entropy:

 $S(E) = k \log(n(E))$   $S^*(E) = k \log(\int_{E' < E} dE' n(E'))$  are equivalent in the therm. limit:

$$S^*(E) = S(E) + O(\log(N)), N \to \infty$$

Differ for finite *N*. Energy distribution is not flat.



# J-walking algorithm

• <u>D. D. Frantz, D. L. Freeman and J. D. Doll</u>, *JCP* 93, (1990), 2769, "Reducing quasi-ergodic behavior in Monte Carlo simulations by **J**walking: Applications to atomic clusters"

• It's easier to overcome potential energy barriers at *high T* (low  $\beta$ )!

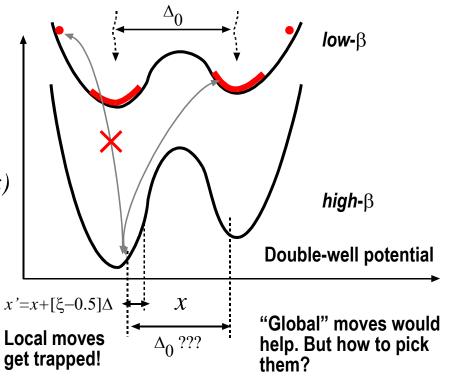
• two types of Monte Carlo moves: *local* to sample free energy minima and *global* to transition among minima

• J-walks (global moves) are generated at high T F(x)

too high T = low acceptance rate

- too low T = ergodicity problems

Low- $\beta$  distribution provides an "intrinsic" size of a global move !



#### Expanded-ensemble concept

• <u>E. Marinari & G. Parisi</u>, *Eur. Phys. Lett.* 19, (1992), 451, "Simulated tempering: a new Monte Carlo scheme"

• <u>A. P. Lyubartsev</u> et al., JCP 96, (1992), 1776, "New approach to Monte Carlo calculation of the free energy: Method of expanded ensembles"

• temperature  $\beta$  is treated as a *dynamical variable*. Canonical ensembles for each  $\beta$  are treated as sub-ensembles of a larger, *expanded* ensemble. Distribution function in this larger ensemble is defined through a supplementary function  $\alpha(\beta)$ :

$$P^{*}(\beta,\Gamma) = \frac{\exp(-\beta\alpha \ (\beta) - \beta \ H(\Gamma))}{Z^{*}}, \qquad Z^{*} = \sum_{\beta} \exp(-\beta\alpha \ (\beta))Z(\beta), \qquad Z(\beta) = 1/N! \int d\Gamma \exp(-\beta \ H(\Gamma))$$

• probability to occupy states with temperature  $\beta$ :  $P^*(\beta) = \exp(-\beta \alpha(\beta))Z(\beta)/Z^*$ 

• free energy difference for two temperatures: available from simulations

$$\beta_2 F(\beta_2) - \beta_1 F(\beta_1) = \beta_1 \alpha \ (\beta_1) - \beta_2 \alpha \ (\beta_2) - \log \left\{ P^*(\beta_1) / P^*(\beta_2) \right\}$$
  
given by the model

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main result

# MC in expanded ensembles

• MC algorithm:

(I) Standard Metropolis moves for fixed  $\beta$ .  $p = \min \{ \exp(-\beta \Delta E), 1 \}$ 

(II) Temperature swaps:  $\beta_1 \rightarrow \beta_2$  with probability:

$$p = \min \{ \exp(((\beta_1 - \beta_2)E + \beta_2\alpha(\beta_2) - \beta_1\alpha(\beta_1), 1) \}$$

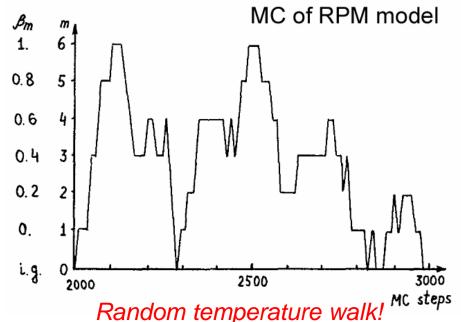
(III) Total time spent at each temperature is accumulated in histograms and used for estimating  $P^*(\beta)$ 

• Random walk in temperature is realized for:

 $\alpha(\beta) = F(\beta) = 1/\beta \log(Z(\beta))$ 

•  $\alpha(\beta)$  are determined in successive iterations

- For each β canonical distributions are recovered!
- The algorithm is also known as simulated tempering



#### Replica-exchange algorithm

• <u>R. H. Swendsen & J.-S. Wang</u>, *PRL 5*7, (1986), 2607, *"Replica Monte Carlo simulation of spin-glasses"* 

• <u>M. C. Tesi</u> et al., *J. Stat. Phys.* 82, (1996), 155, "Monte Carlo study of the interacting self-avoiding walk model in three dimensions"

• <u>K. Hukushima & K. Nemoto</u>, *JPSJ*, 65, (1996), 1604, "Exchange Monte Carlo method and application to spin glass simulations"

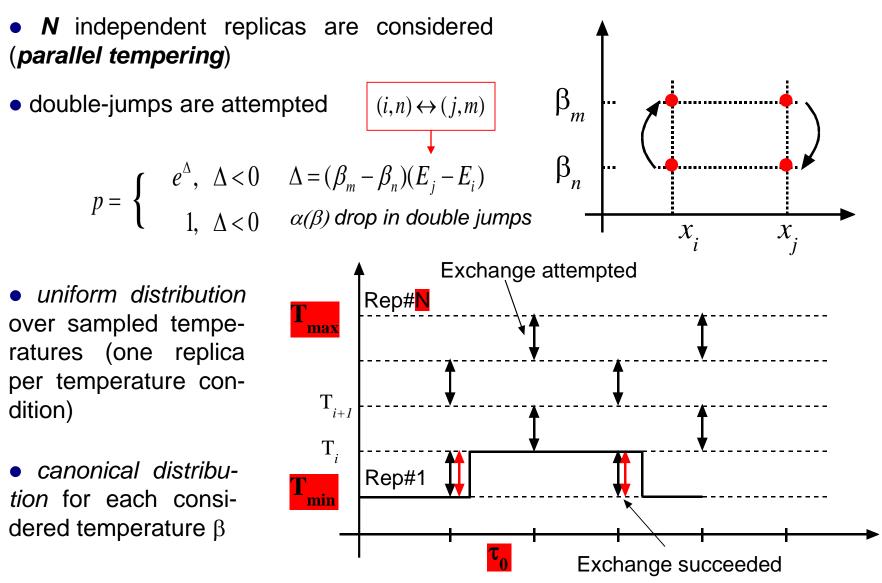
• <u>U. H. E. Hansmann</u>, Chem. Phys. Lett., 281, (1997), 140, "Parallel tempering algorithm for conformational studies of biological molecules"

• <u>Y. Sugita & Y. Okamoto</u>, *Chem. Phys. Lett.*, 314, (1999), 141, *"Replica-exchange molecular dynamics method for protein folding"* 

Replica-exchange (REX) = parallel tempering = multiple Markov chain method

#### Replica-exchange algorithm

• the method is based on the **expanded-ensemble** idea  $P^*(\beta,\Gamma) \sim \exp(\beta \alpha(\beta) - \beta H(\Gamma))$ 



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# **Practical points**

• Four parameters need to be set:  $T_{\text{max}}$ ,  $T_{\text{min}}$ , N,  $\tau_0$ 

 $T_{\rm max}$ the higher the better(~500-700K). Typical relaxation time at this temperature should be ~1-100ps P(E), T<sub>min</sub> P(E), T<sub>max</sub> the temperature of your interest (300K?)  $T_{\rm min}$ N large enough to ensure 10-50% acceptance probability P(E) for swaps between replicas  $N \sim \frac{\delta E}{\Delta E} \sim \frac{N_F}{\sqrt{C}} \sim \frac{N_F}{\sqrt{N_F}} \sim \sqrt{N_F}$ the longer the better. Typically 100-1000  $\tau_0$ Ε simulation time steps δE What to look out for: Nadler[PCL B 112 (2008) replica-exchange acceptance ratio is more than 10% (1) $N = 1+0.594\sqrt{C} \ln T_{max}/T_{min}$ each replica visits *Tmin* and *Tmax* at least several times (iii) all *relevant* order parameters undergo sufficient relaxation

# Kinetic data from REX simulations

• There is no physical kinetics in the REX simulations. A number of approaches to extract kinetic information:

Andrec [PNAS 102 (2005) 6801] van der Spoel [PRL 96 (2006) 238102] Yang[JMB 372 (2007) 756] Buchete[JPC B 112 (2008) 6057 Muff [JPC B 113 (2009) 3218] Chodera[JCP 134 (2011) 244107]

• Most approaches rely on the following ingredients:

a) discretization of the available configuration space
b) obtaining rates of transition between the identified states
c) solving master equation to generate reaction time
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Example: ETNA of Muff and Caflisch

Folding time for a  $\beta$ -sheet peptide predicted for varying temperature over a range that spans an order of magnitude

# Replica-exchange flavors

- *REX* coupled with Tsallis energy deformation function:
- Muticanonical *REX* and *REX* multicanonical:
- *REX* in constant pressure (CPT) ensemble:
- Mutidimensional **REX:** <u>Sugita, Kitao & Okamoto, JCP</u>, 114 (2000)
   6042
- Ab initio Monte Carlo **REX:** <u>Ishikawa et al.</u>,Chem. Phys. Lett., 333 (2001) 199
- Hamiltonian *REX:* <u>Fukunishi, Watanabe & Takada</u>, *JCP*, 116
   (2002) 905

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<u>Hansamann</u>, Chem. Phys. Lett, 281(1997) 140
 <u>Jang et al.</u>, PRL, 91 (2003) 058305

<u>Sugita & Okamoto, Chem. Phys. Lett</u>, 329 (2000) 261

<u>Okabe</u> et al. Chem. Phys. Lett, 335 (2001) 435

nonsional **PEV** Sugita Kita

# Replica-exchange flavors

- *REX* coupled with RISM: <u>Mitsutake et al.</u>, *J. Phys. Chem. B*, 108 (2004) 19002
- Local *REX:* <u>Cheng</u> *et al.*, *J. Phys. Chem. B*, 109 (2005) 8220
- Non-equilibrium switches
   *REX:*

Ballard and Jarzynski, PNAS, 106 (2009) 12224

• Further reading:

Review paper by K. Tai, <u>Biophys. Chem</u>., 107 (2004) 213
 Special issue of <u>J. Mol. Graph. Mod.</u>, 22, (2004) 317

## Multiple-histogram reweighting technique

- <u>A. M. Ferrenberg & R. H. Swendsen</u>, PRL 63, (1989), 1195, "Optimized Monte Carlo data analysis"
- Chodera et al, JCTC 3, (2007), 26, "WHAM for REX simulations"
- i=1,m temperatures, Ni samples,  $H_i(E)$  energy histograms

$$P_i(E) = H_i(E) / N_i = n(E) \exp(-\beta_i(E - f_i))$$

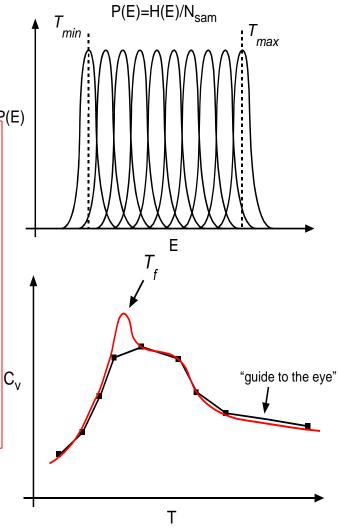
- by definition, free energy:  $\exp(-\beta_i f_i)$ ) =  $\sum_{E_k} n(E_k) \exp(-\beta_i E_k)$  (E)
- inaccurate estimate of the density of states from simulation at temperature *i*:

$$n_i(E) = P_i(E) \exp(\beta_i(E - f_i))$$

• improved density of states:  $n(E) = \frac{\sum_{i} g_i n_i(E)}{\sum_{i} g_i}$ 

•  $\delta n(E)^2 / n(E)$  is minimized with respect to weighting  $g_i$  coeff.  $\sum B(E)$ 

• set of non-linear equations in  $f_i : n(E) = \frac{\sum_i P_i(E)}{\sum_i \exp(-\beta_i(E - f_i))}$ 



# Summary

• Why is replica exchange the method of choice in biomolecular simulations?

• Parallelism

- No empirical parameters or fitting involved
- Access to low free energy minima through accelerated relaxation
- Availability of all thermodynamical properties as a function of temperature through histogram reweighting techniques