

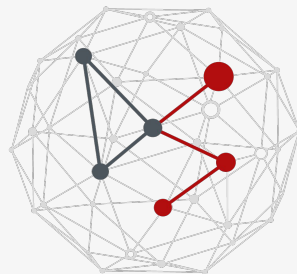
1222-2022
800 ANNI



UNIVERSITÀ
DEGLI STUDI
DI PADOVA



DIPARTIMENTO
MATEMATICA



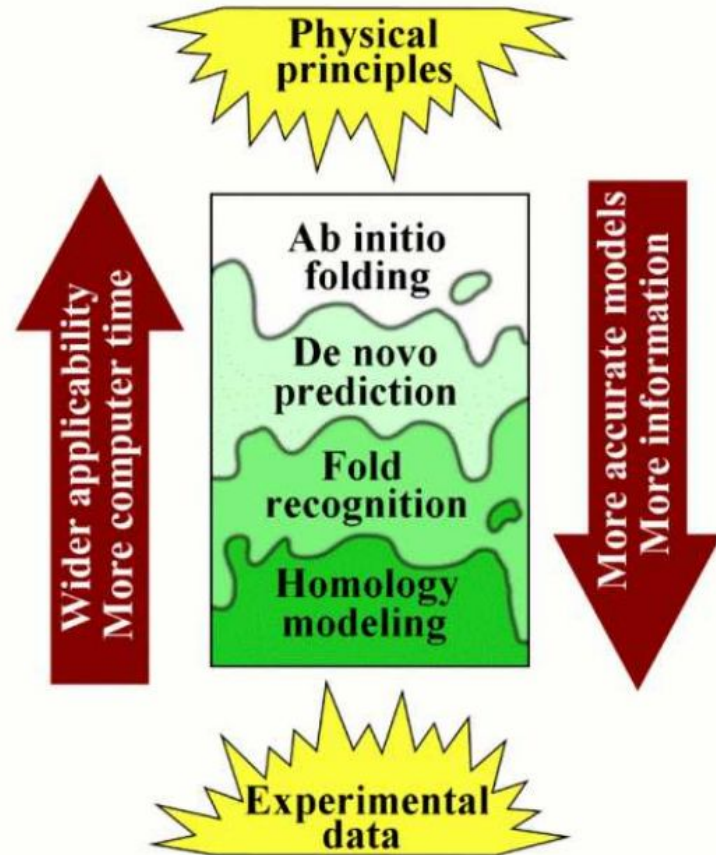
DATA SCIENCE
UNIVERSITY OF PADOVA

MOLECULAR DYNAMICS

Master of Science in Data Science

Damiano Piovesan





- **De novo prediction / Ab initio**

- Secondary structure prediction; conformation of short fragments (Rosetta); molecular dynamics; Monte Carlo; quantum mechanics (unfeasible)
- Tough computation

- **Fold recognition**

- Try to fit with known folds
- The fold space is not completely known (50% success)

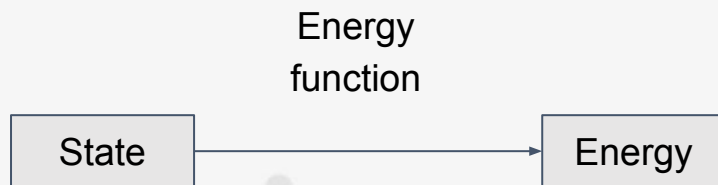
- **Homology modelling**

- Similar sequences have similar structures (+50% sequence identity)
- 40% of genes are not homologous to known structures



Energy functions

A mathematical algorithm that inputs the state of a system and outputs the energy



System state may include

- Coordinates
- Bonded structure
- External elements
- Empirical parameters
- Charge, spin

Energy function may include

- Logic
- Arithmetic
- Algebra
- Calculus
- Numerical procedures

Energy function can be

- Simple or complex
- Analytic or numerical
- QM or MM or other
- Ab initio or empirical
- Atomistic or Coarse-grained



Molecular Mechanics (MM)

A set of models which use an **empirical** (lot of parameters), **algebraic** (formulas), **atomistic** (individual atoms) energy function for chemical systems

$$E_{\text{total}} = E_{\text{bonded}} + E_{\text{non-bonded}}$$

$$E_{\text{bonded}} = E_{\text{bonds}} + E_{\text{angles}} + E_{\text{torsions}}$$

$$E_{\text{non-bonded}} = E_{\text{elst}} + E_{\text{vdw}}$$

Force field models

- Atoms: 3D point particles
- Structure: bonds, angles, torsions



Molecular Mechanics (MM)

Force fields vary in

- Energy function form
- Empirical parameters
- Simulation targets

Limitations

- Up to 1M of atoms
- Up to 10^{15} configurations
- Accuracy of energy
- Scope of parameters

Examples

- **AMBER**, assisted model building energy refinement (originally for DNA)
- **CHARM**, chemistry at harvard MM (Martin Karplus nobel 2013)
- **OPLS**, optimized potential for liquid simulations (small molecules)
- **GROMOS**, used by Gromacs software
- **MMFT**, Merk Molecular force field (pharmaceutical)



Force field parameters

An arbitrary constant whose value characterizes an element of a system

$$E_{total} = \sum_{bonds} K_b (r - r_{eq})^2 + \dots$$

$E \rightarrow [\text{kcal/mol}]$ $r \rightarrow [\text{\AA}]$

$R_{eq} \rightarrow [\text{\AA}]$ $K_b \rightarrow [\text{kcal/mol} \cdot \text{\AA}^2]$

Example

O-H in H₂O in AMBER95

$R_{eq} = 0.960 \text{ \AA}$ $k_b = 553.0 \text{ kcal/mol} \times \text{\AA}^2$

Sources

- Structures \rightarrow crystal, density
- Spectra \rightarrow IR, NMR
- Simulation \rightarrow PES (potential energy surface, quantum mechanics)

Desired properties

- General
- Transferable
- Accurate



Bond stretch terms

$$E_{\text{bonds}} = \sum_{\text{bonds}} K_b (r - r_{eq})^2$$

- Parameters

$r_{eq} \rightarrow$ equilibrium bond length

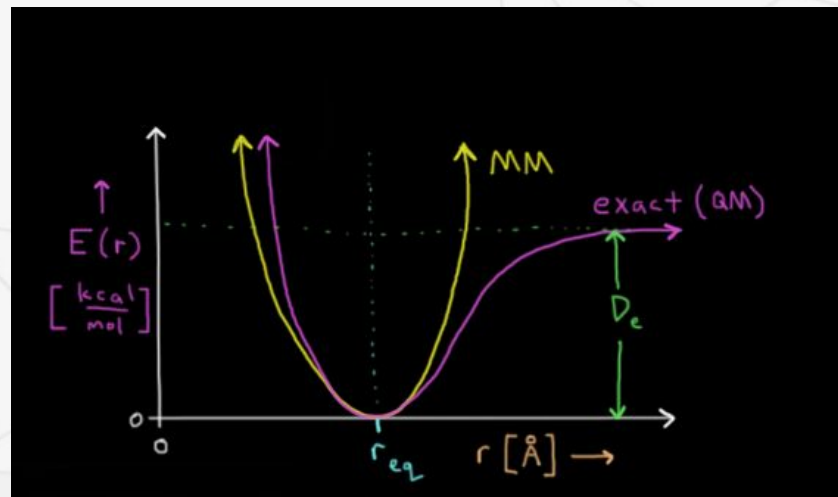
$K_b \rightarrow$ bond spring constant

- Variable

$r \rightarrow$ bond length

- $D_e \rightarrow$ dissociation energy

- Typical $K_b \approx 300\text{-}600 \text{ kcal/mol}\cdot\text{\AA}^2$



Angle bend terms

$$E_{\text{angles}} = \sum_{\text{angles}} K_a (\theta - \theta_{eq})^2$$

Parameters

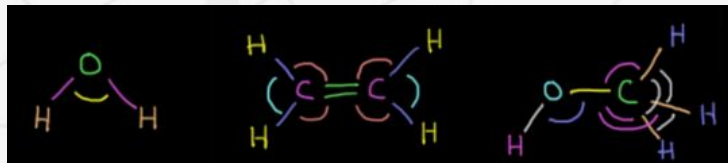
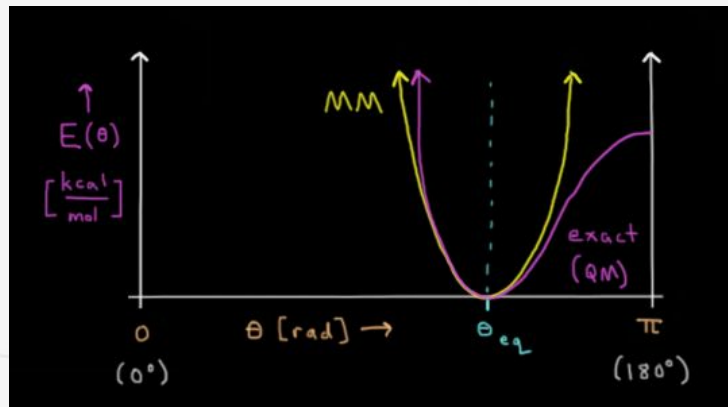
$\theta_{eq} \rightarrow$ equilibrium bond angle [rad]

$\theta_b \rightarrow$ angle spring constant

Variable

$\theta \rightarrow$ bond angle [rad], $0 \leq \theta \leq \pi$

Typical $K_a \approx 100\text{-}150 \text{ kcal/mol}\cdot\text{rad}^2$



Van der Waals terms

$$E_{vdw} = \sum_{i=1}^N \sum_{j=i+1}^N \epsilon_{ij} \left[\left(\frac{r_0}{r_{ij}} \right)^{12} - 2 \left(\frac{r_0}{r_{ij}} \right)^6 \right]$$

- Parameters

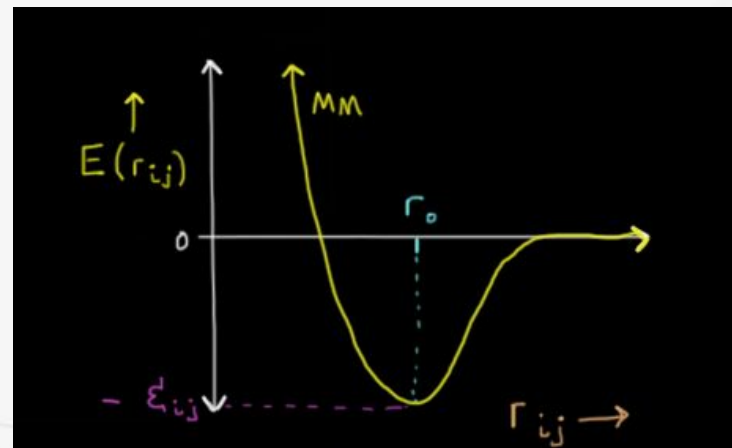
$\epsilon_{ij} \rightarrow$ interaction strength [kcal/mol]

$r_0 \rightarrow$ van der Waals radius (Å)

- Variable

$r_{ij} \rightarrow$ interatomic distance (Å)

- Short range \rightarrow exchange / steric repulsion (12)
- Long range \rightarrow London dispersion attraction (6)



How to define parameters for all possible pairs? \rightarrow “Combining rules”

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

“geometric mean”

$$R_0 = \frac{1}{2}(r_i + r_j)$$

“arithmetic mean”

$\epsilon_i, \epsilon_j \rightarrow$ atomic parameters



Electrostatics terms

$$E_{elst} = \sum_{i=1}^N \sum_{j=i+1}^N \frac{q_i q_j}{4\pi\epsilon_0 r_{ij}}$$

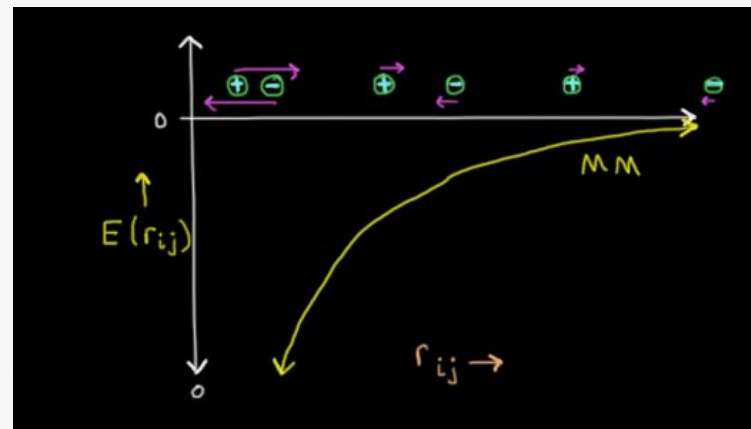
- Parameters

$q_i, q_j \rightarrow$ atomic partial charges (e)

- Variable

$r_{ij} \rightarrow$ interatomic distance (Å)

- Same charge \rightarrow repulsion
- Opposite charge \rightarrow attraction
- Q_{tot} usually is zero



$v_{dw} \propto \left(\frac{1}{r}\right)^6 \rightarrow$ quick decay

$e_{lst} \propto \left(\frac{1}{r}\right)^1 \rightarrow$ slow decay

Elst is rate limiting step of MM

- $O(N)$ bonded terms
- $O(N^2)$ non-bonded terms



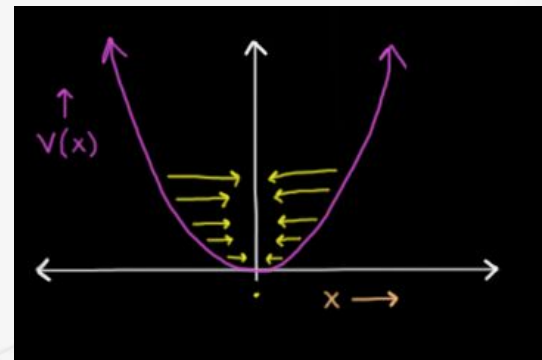
Energy gradient

 $V(x)$

→ potential energy (example: $\frac{1}{2} kx^2$)

$$F(x) = - \frac{dV(x)}{dx}$$

→ force (example: $-kx$)



In 3D

$V(x)$ → $V(x,y,z)$

$$- \frac{dV(x)}{dx} \rightarrow - \left(\frac{\partial V}{\partial x} \hat{x} + \frac{\partial V}{\partial y} \hat{y} + \frac{\partial V}{\partial z} \hat{z} \right)$$

- $\nabla V(x,y,z)$

“Gradient”

N atoms → 3N coordinates

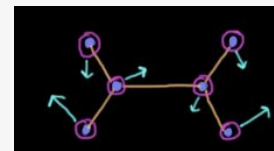
$$V = V(x_1, y_1, z_1, x_2, y_2, z_2, \dots, x_N, y_N, z_N)$$

$$= V(\vec{r}_1, \vec{r}_1, \dots, \vec{r}_N) \quad \vec{r}_1 = (x_i, y_i, z_i)$$

$$= V(\vec{r}^{3N})$$

$V(\vec{r}^{3N})$ → energy

$-\nabla V(\vec{r}^{3N})$ → force



Energy minimization

$$\frac{dV(x)}{dx} = 0$$

→ “stationary point”

$$\frac{d^2V(x)}{dx^2}$$

> 0 local minimum
 < 0 local maximum
 $= 0$ unknown (“saddle” point)

1D

→

3D

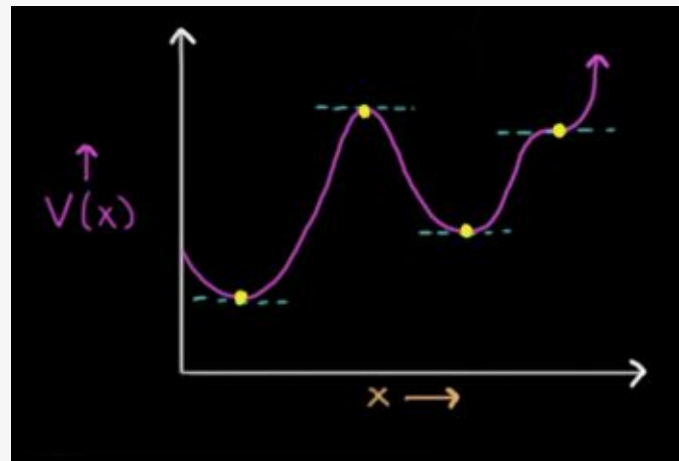
$$\frac{dV(x)}{dx} = 0$$

$$|\nabla V(\bar{r}^{3N})| = 0$$

$$\frac{d^2V(x)}{dx^2} > 0$$

$$\{\lambda_H\} \geq 0, H_{ij} = \frac{\partial^2 V(\bar{r}^{3N})}{\partial q_i \partial q_j}$$

$H \rightarrow 3N \times 3N$ real, symmetric “Hessian matrix”



- Lowest $V(\bar{r}^{3N})$ among local minima → global minimum
- “Geometry Optimization” → algorithm to find $\{\bar{r}^{3N}\}$ with minimum P.E.



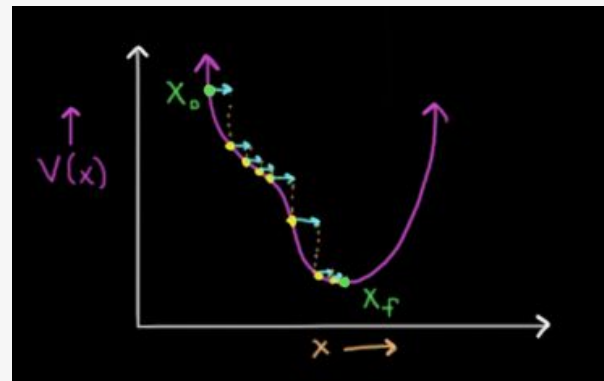
Steepest descent

Method for obtaining local stationary points of a multi-dimensional function

Simple method for geometry optimization

1. Guess X_0 “initial geometry”
2. Compute $V(x_i)$ and $\nabla V(x_i)$ energy and gradient
3. Update $x_{i+1} = x_i - \gamma_i \nabla V(x_i)$ displacement
4. Check for convergence
 - a. If yes: done $x_f = x_i$
 - b. If no: return to step 2

Various methods for choosing γ_n



Convergence checks

- $\|\nabla V(x_i)\| \approx 0$
- $|V(x_i) - V(x_{i-1})| \approx 0$
- $\|x_i - x_{i-1}\| \approx 0$

gradient

energy

displacement



Molecular dynamics (MD)

Calculate system properties by propagating through time and averaging

- Classical Mechanics → Newton's Laws ($F=ma$)
- MM → conservative (total energy is conserved, kinetic + potential energy), time-independent

$$F = ma = m \frac{d^2(x)}{dt^2} = \frac{d}{dt} \left(m \frac{d(x)}{dt} \right) = \frac{d}{dt}(mv) = \frac{dp}{dt}$$

$$F = - \frac{dV(x)}{dx}$$

$$p = mv = m \frac{dx(t)}{dt}$$

$$\frac{\partial p_{x_i}}{\partial t} = - \frac{\partial V}{\partial x_i}$$

Solve for all $3N$ coordinates

Can't solve exactly → approximate numerically



Molecular dynamics

1. Assign initial $x_0, q_0, t = 0$
 2. Compute $V(x_i)$ and $\nabla V(x_i)$
 3. Update $x_{i+1} = x_i + 1/m p_i \Delta t$
 4. Update $p_{i+1} = p_i - \nabla V(x_i) \Delta t$
 5. Repeat (steps 2-4) until $t \geq t_f$
 6. Compute desired properties
- $t = t + \Delta t$

$\Delta t \rightarrow$ timestep ($1\text{fs} = 10^{-15}\text{s}$)

$T \rightarrow$ depends on goal

- Vibrations $\rightarrow 10 - 1,000 \text{ fs}$
- Conformation changes $\rightarrow \text{ps} - \text{ns}$
- Diffusion / interaction $\rightarrow \text{ns} - \mu\text{s}$
- Protein folding $\rightarrow \mu\text{s} - \text{s}$



References & Links

TMP Chem (Trent Parker's YouTube channel)

<https://www.youtube.com/user/TMPChem>

Computational Chemistry

- 2.1, 2.2, 2.3
- 2.5, 2.6
- 2.9, 2.10
- 3.1, 3.2, 3.3
- 3.8

