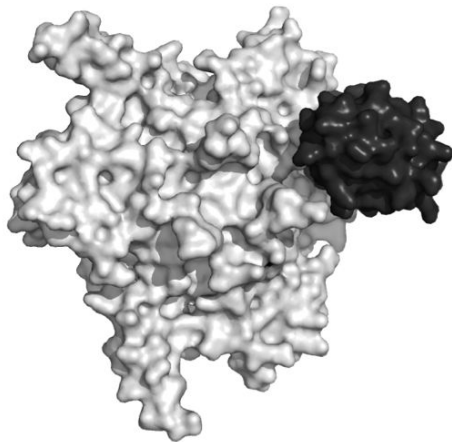


MEET-U - Scoring Group1

Maxime Borry, Guillaume Delevoye, François Gravey, Ilyes Abdelhamid, Paula Milan Rodriguez



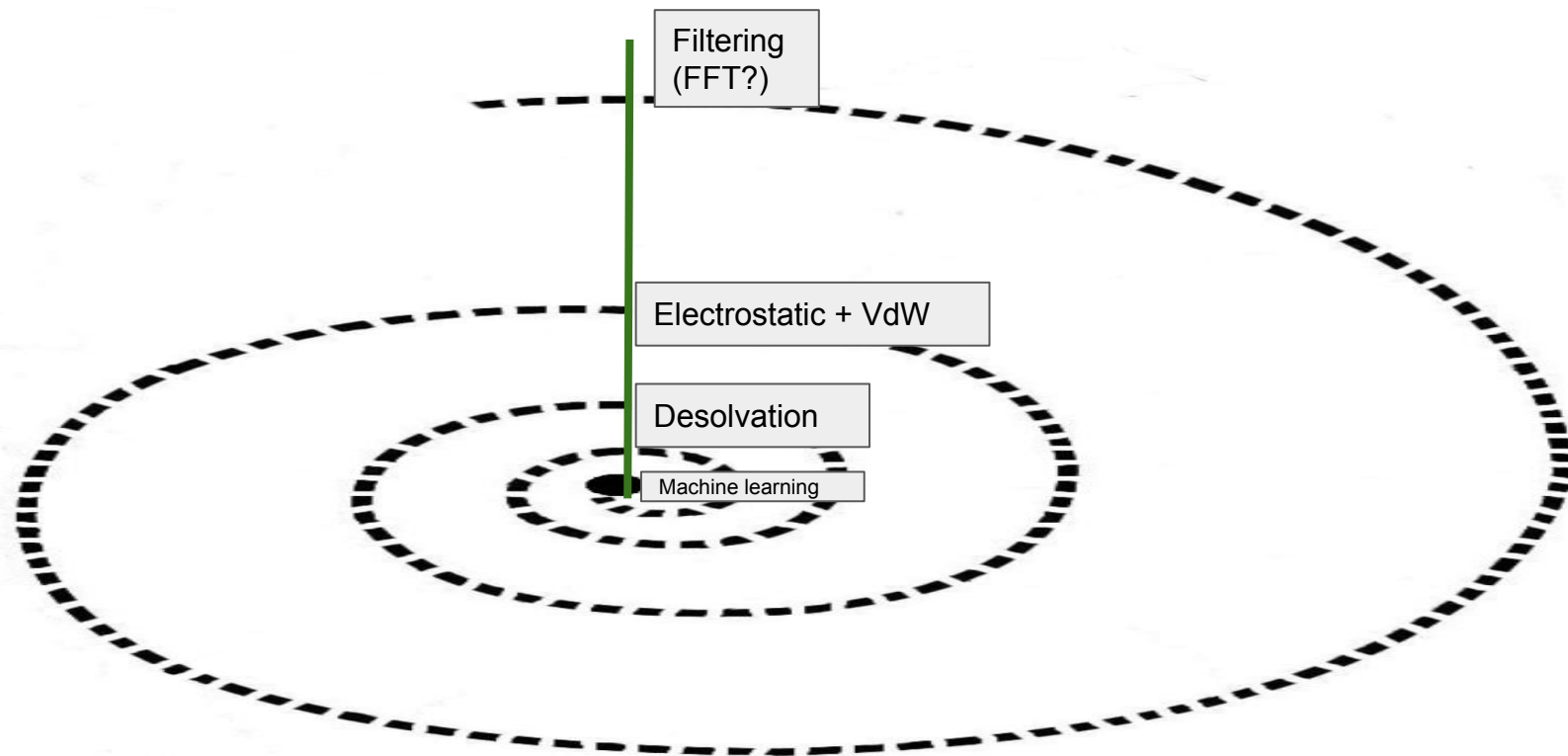
Meet-U

PROJET COLLABORATIF
PARIS 6 - PARIS 7 - PARIS 11 - EVRY

édition 2018

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DI
DEROT
PARIS 7

To implement



Shape Complementarity (SC) with FT

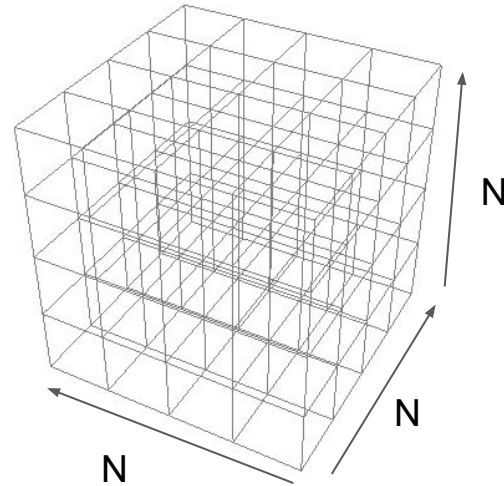
- $N \times N \times N$ grid
- grid point ($l, m, n = 1, 2, \dots, N$)
- **grid spacing** 1.2 Å
- N large enough for R and L

$$R_{SC}(l, m, n) = \begin{cases} 1 & \text{surface of } R \\ \rho i & \text{core} \\ 0 & \text{open space} \end{cases}$$

$$L_{SC}(l, m, n) = \begin{cases} 1 & \text{surface of } L \\ \rho i & \text{core} \\ 0 & \text{open space} \end{cases}$$

$$i = \sqrt{-1} \quad \rho = 9.$$

- Sample rotational ($360 \times 360 \times 360 / 15^3$), if angle step = 15°
- N^3 translations (x, y, z)



$$S_{SC} = \text{Re} \left[\frac{1}{N^3} \text{IFT}(\text{IFT}(R_{SC}) \cdot \text{DFT}(L_{SC})) \right] - \text{Im} \left[\frac{1}{N^3} \text{IFT}(\text{IFT}(R_{SC}) \cdot \text{DFT}(L_{SC})) \right]$$

(Zdock, Chen and Weng, 2002)

Protein-Protein Interface Size

Defining macromolecular interfaces based on solvent accessibility

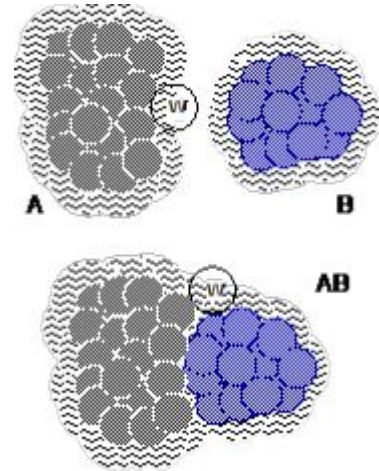
ASA accessible surface area
measures molecule-solvent contacts
with the
rolling ball algorithm
Lee & Richards, JMB, 1971

BSA buried surface area
measures molecule-molecule contacts
Chothia & Janin, Nature, 1975

Interface atoms or residues
are all atoms or residues that
contribute to the
BSA. On average, each interface atom
contributes $\approx 10 \text{ \AA}^2$

Hydrophobic effect

$$BSA = ASA_A + ASA_B - ASA_{AB}$$



Electrostatic and Van Der Waals

Electrostatic forces:

- Easy to compute
- Per residue (considered as points)
 - Charges in tables
- Cutoff to determine
- Only with closest residues within the interaction zone

$$\vec{F}_1(2) = q_2 \frac{q_1 \vec{e}_r}{4\pi\epsilon r_{12}^2} = q_2 \frac{q_1 \vec{r}_{12}}{4\pi\epsilon r_{12}^3} = -q_1 \frac{q_2 \vec{r}_{21}}{4\pi\epsilon r_{21}^3} = -\vec{F}_2(1)$$

Van der Waals:

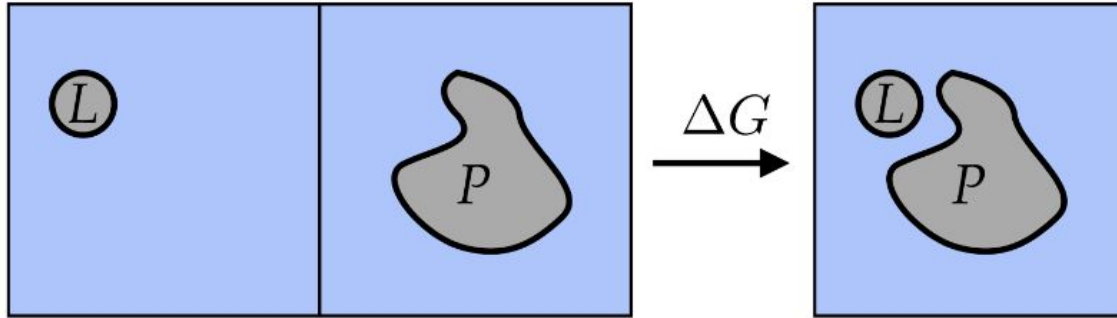
More complex computation due to induced dipole mechanism

$$E_{\text{van der Waals}} = -\frac{1}{r^6} \left[\underbrace{\frac{\mu_1^2 \cdot \mu_2^2}{3(4\pi \cdot \epsilon_0 \cdot \epsilon)^2 \cdot k_B \cdot T}}_{E_{\text{Keesom}}} + \underbrace{\frac{\mu_1^2 \cdot \alpha_2 + \mu_2^2 \cdot \alpha_1}{(4\pi \cdot \epsilon_0 \cdot \epsilon)^2}}_{E_{\text{Debye}}} + \underbrace{\frac{3}{4} \cdot \frac{h \cdot \nu \cdot \alpha_1 \cdot \alpha_2}{(4 \cdot \pi \cdot \epsilon_0)^2}}_{E_{\text{London}}} \right]$$

- Hydrogen Bonds ++ (gmx_hbond)
- PyPLIF (Other VDW)
- PPICP

Desolvation energy

No easy way: LIE / Umbrella / Alchemical ...



$$\frac{p_A}{p_B} = \exp \frac{F_B - F_A}{k_B T}$$

Short MD simulations needed → To do once only for separated L and P

- *Reasonable computational cost if we first filtered the samples

- *Pipeline (GROMACS / LOMAP - Alchemical setup)

Or implicit water models

- *More complex to implement

- *No shown benefit in our case

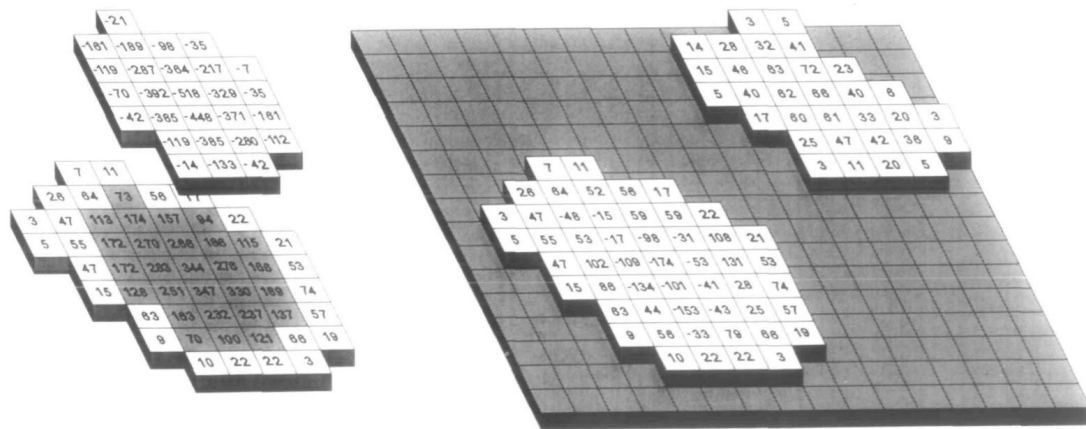
Machine learning

Score = $a \times \text{Desolvation} + b \times \text{Electrostatic} + c \times \text{VDW} + d \times \text{CFT} [\dots]$

→ How to combine our parameters to build a score function ?

Which kind of machine learning hasn't been determined yet

Image negative



(Vakser, 1995)

- Compute surface with ASA
 - Encode surface height in image with colors/grey levels
 - Ideal docking site is negative
 - Compute MSE
-
- Encode chemical/physical properties with colors
 - Machine Learning (NN?) on images for docking site recognition