

# Machine Learning for Material Science (a biased introduction)

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## Credits:

Emine Kucukbenli, Harvard (MA, USA)

Ruggero Lot, Univ Toulouse (F)

Franco Pellegrini, ENS Paris (F)

Yusuf Shaidu, Berkeley (CA, USA)



# **A few projects with Quantum ESPRESSO a personal selection**

Stefano de Gironcoli

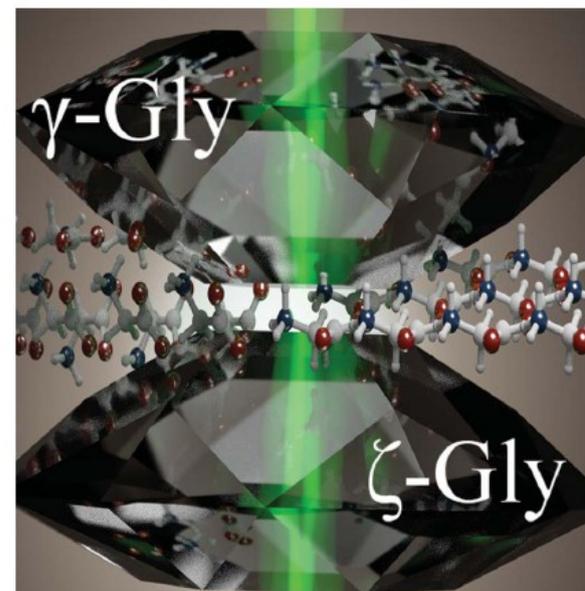
SISSA and CNR-IOM DEMOCRITOS



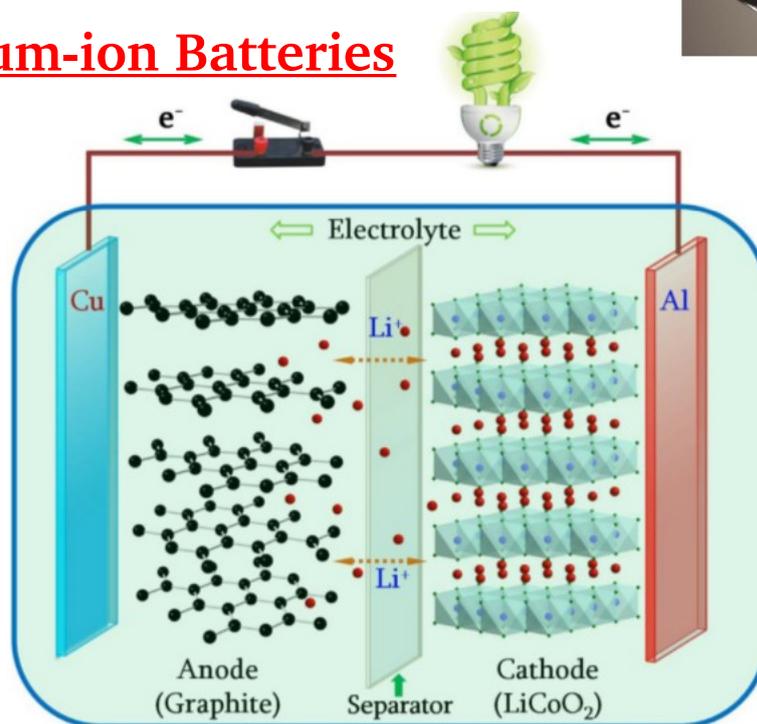
## Complete $^{13}\text{C}$ Chemical Shift Assignment for Cholesterol Crystal



## $\zeta$ -Glycine: Insight into the mechanism of a polymorphic phase transition



## Lithium-ion Batteries



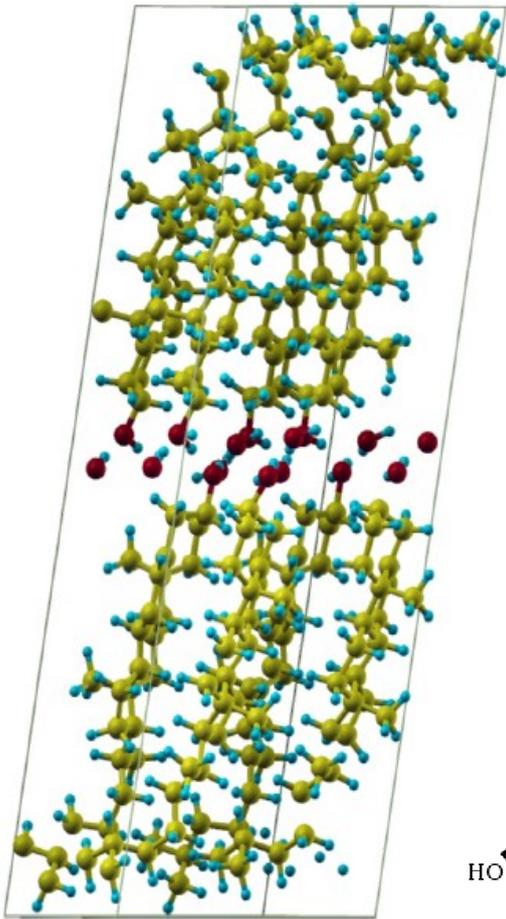


Gall stones associated to different pathologies have distinct NMR spectra.

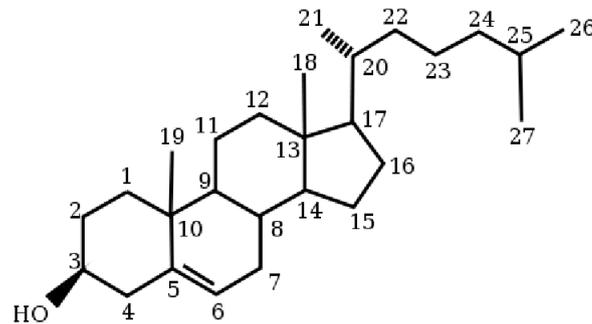
It would be important to understand the structural differences between these stones and the underlying reasons.

Can we distinguish the NMR spectra of different Cholesterol crystalline polymorphs ?

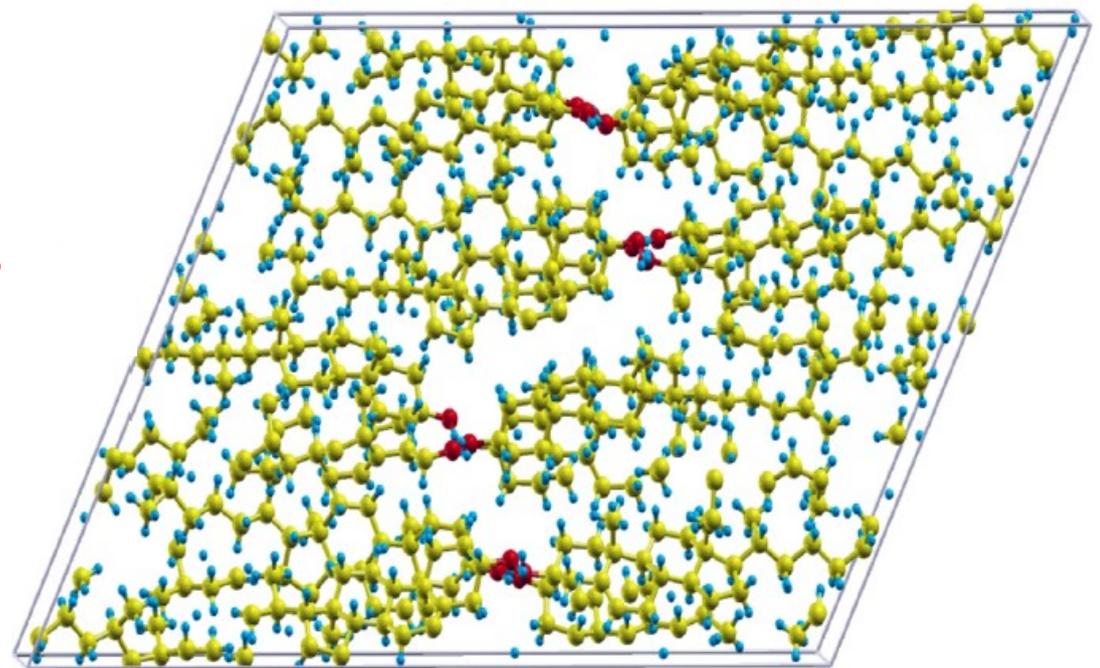




Monohydrate Cholesterol (ChM)  
8 CLR + 8 w molecules - 616 atoms



High temperature Anhydrous  
Cholesterol (ChAh)  
16 CLR mol - 1184 atoms

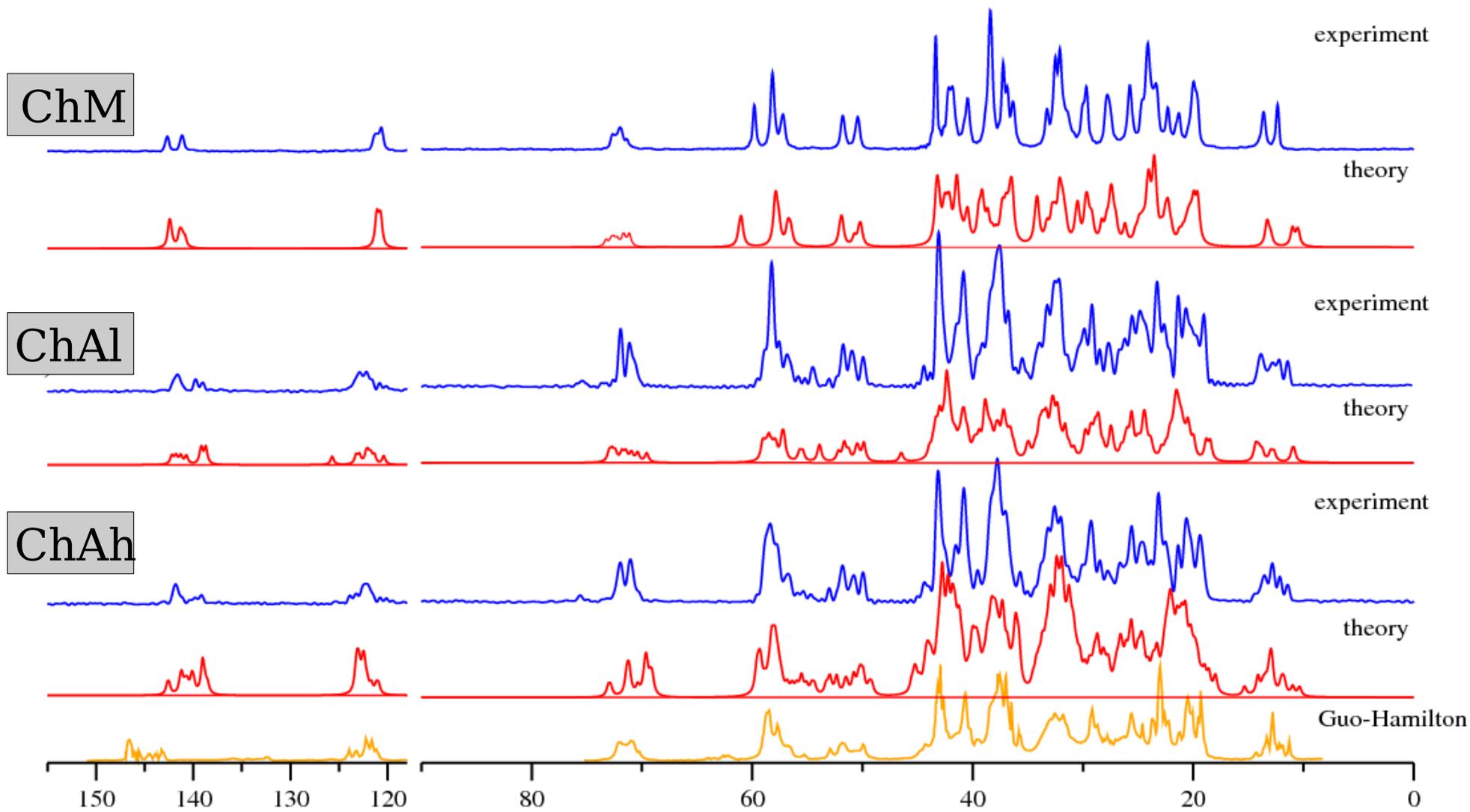


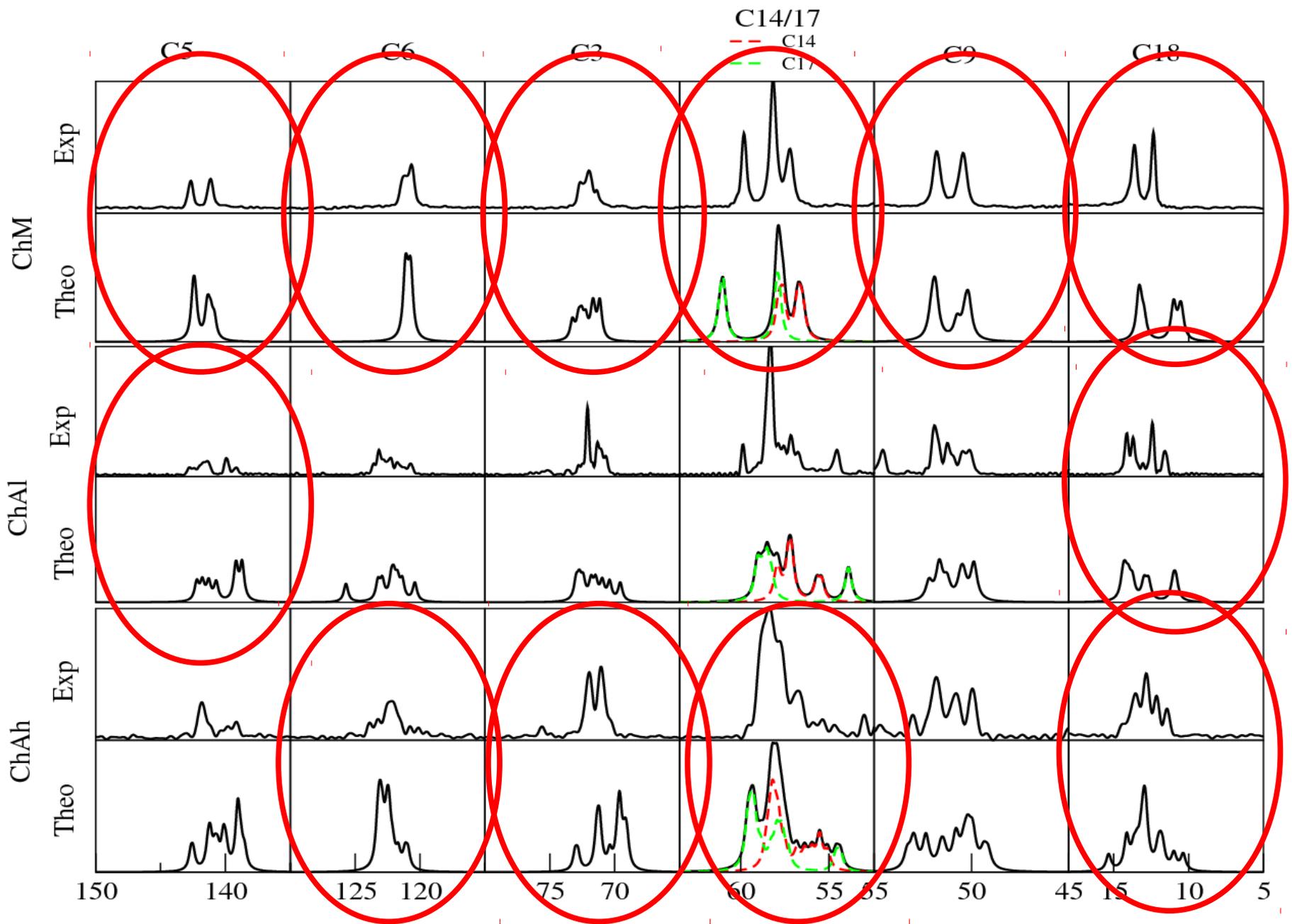
Low temperature Anhydrous  
Cholesterol (ChAl)  
8 CLR mol - 592 atoms

(not shown)

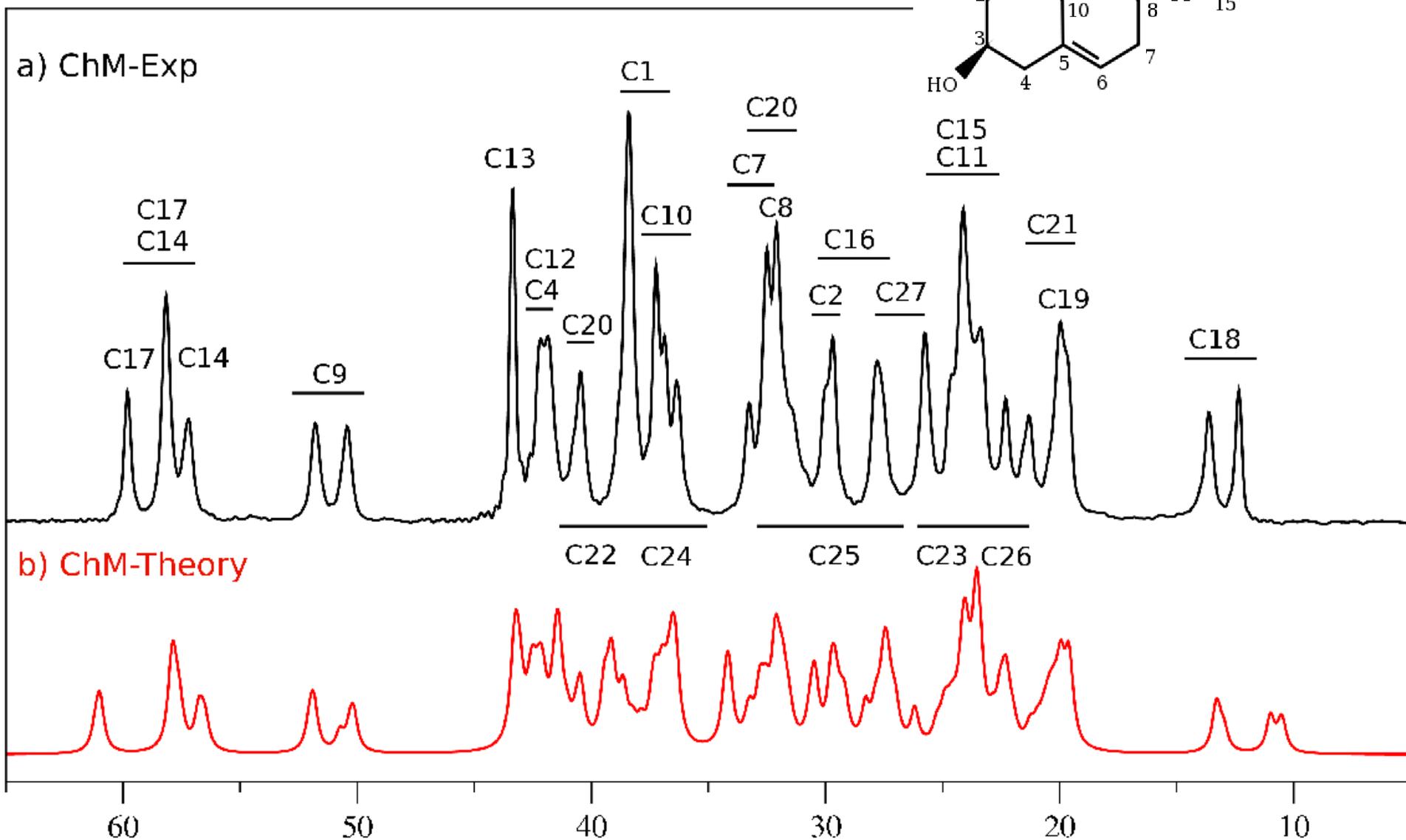
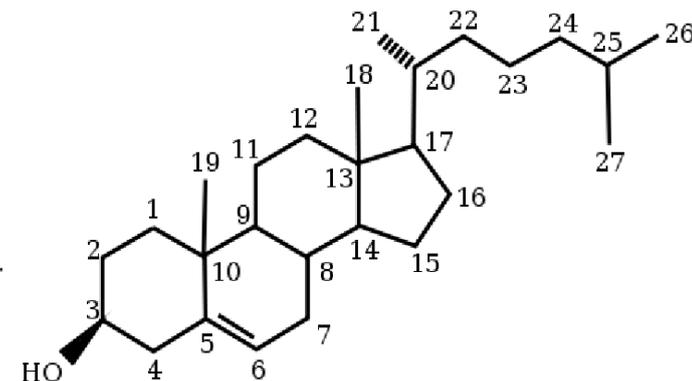
# Comparison with Experimental Spectra

(E.Kucukbenli, K.Sonkar, N. Shina, SdG, JPCA 2012)

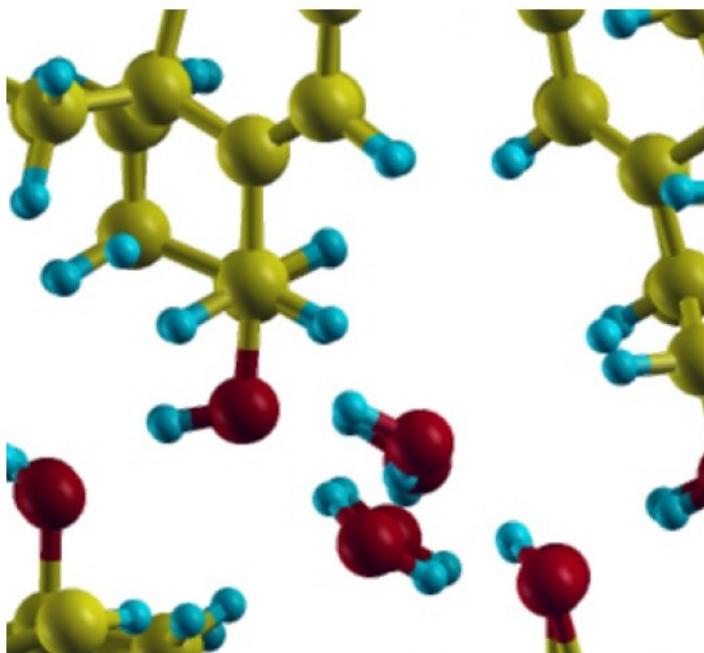




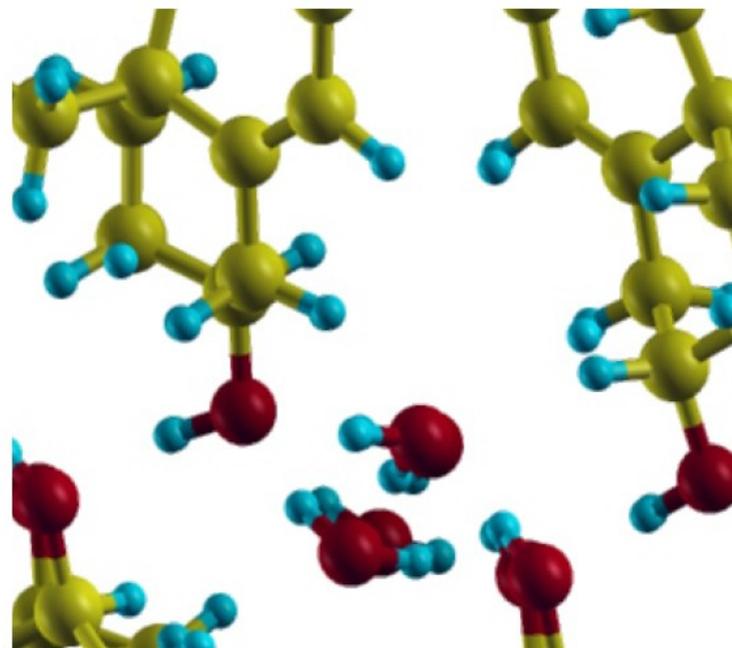
# Peak assignement in ChM



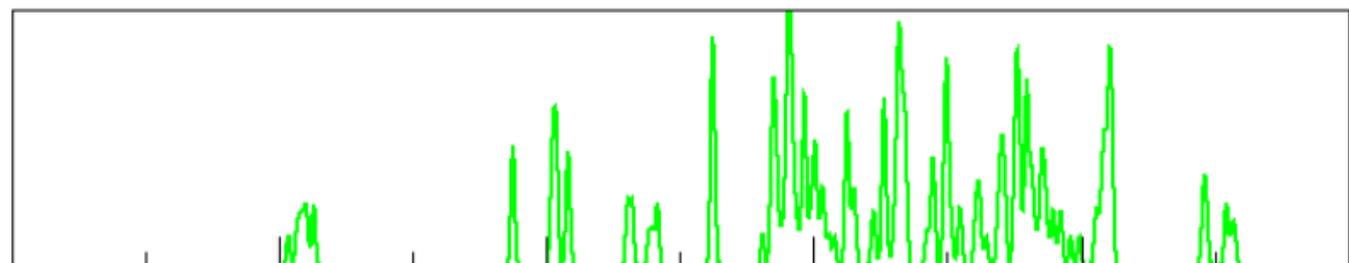
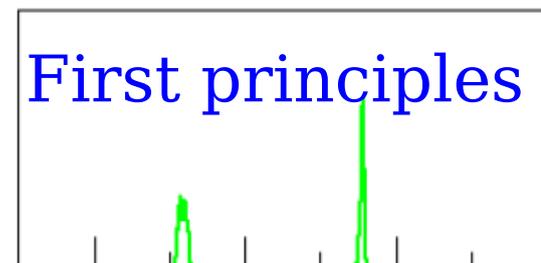
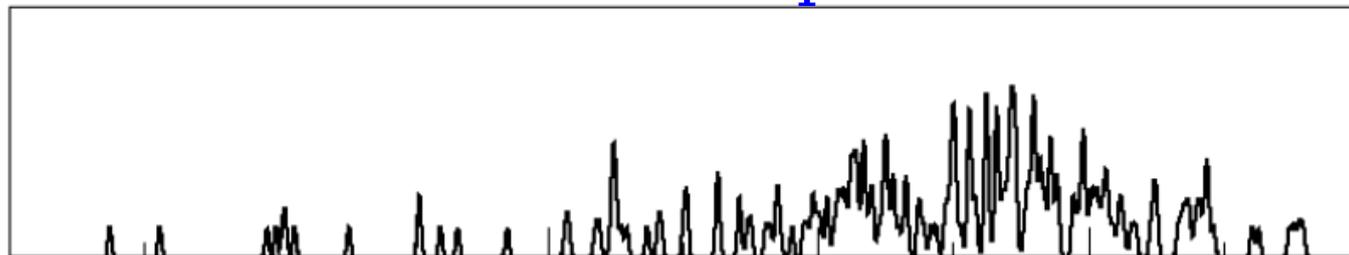
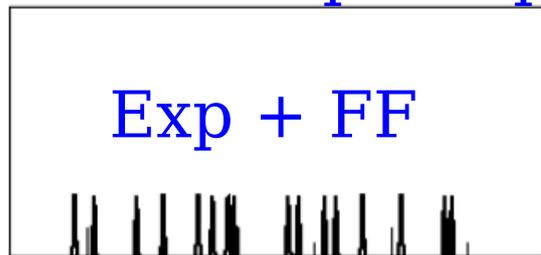
# Importance of accurate structural relaxation (ChM)



First principles



Exp + FF

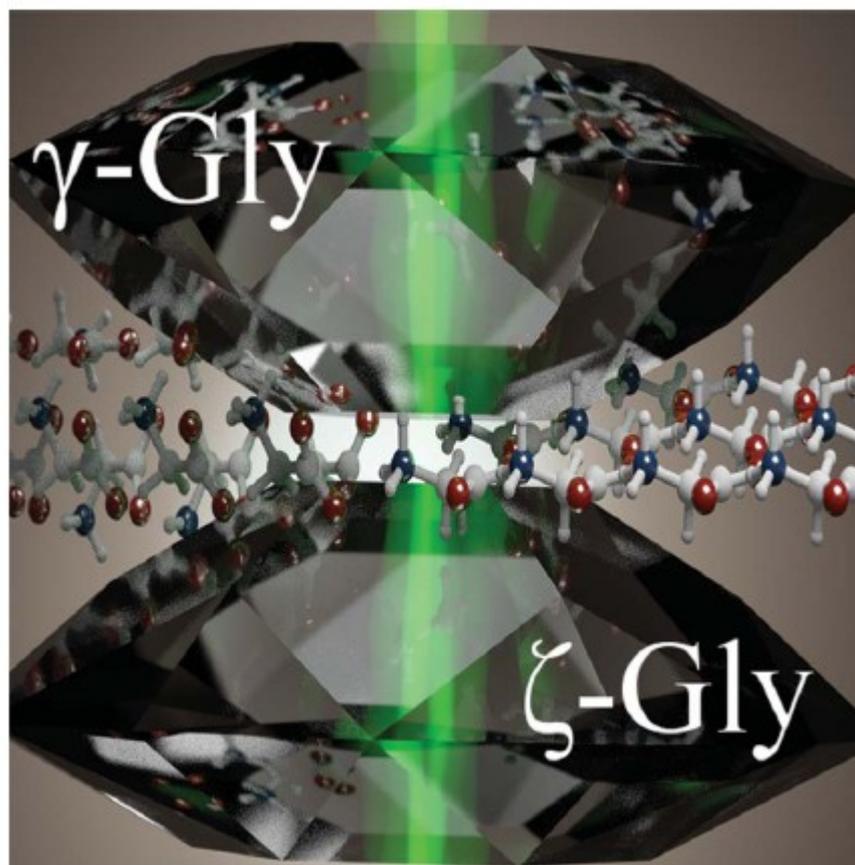


# Summary

- **Theory:**  
GIPAW + PAW fully implemented
- **$^{13}\text{C}$  NMR of Cholesterol Crystals**  
Calculations reproduce the main features of the spectra and are able to distinguish different polymorphs  
It is possible to provide a complete peak assignment, confirmed with spectral editing exp.
- **Search for unknown polymorphs would require a very accurate energy description at a fraction of the DFT cost**



# $\zeta$ -Glycine: Insight into the mechanism of a polymorphic phase transition

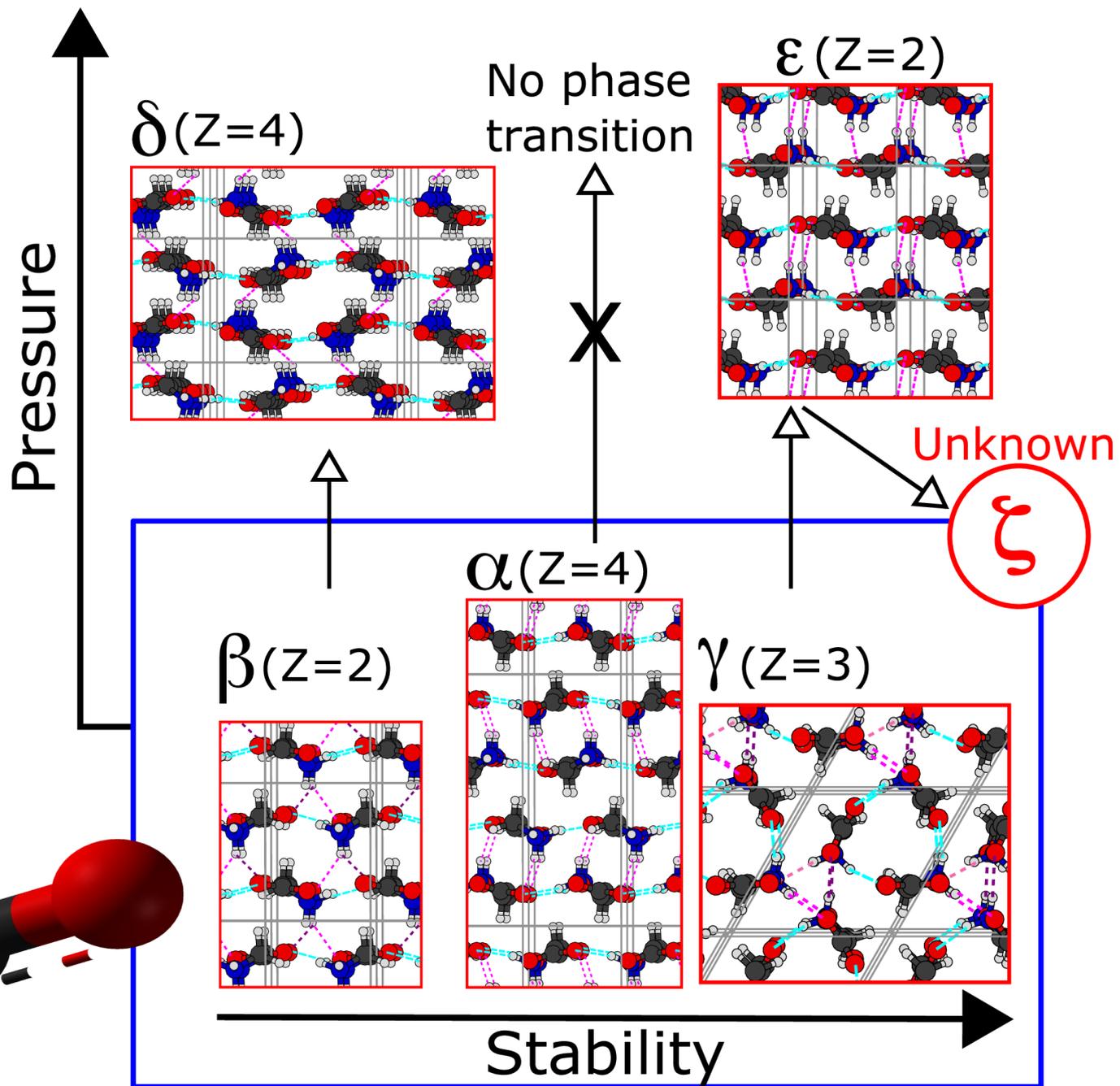
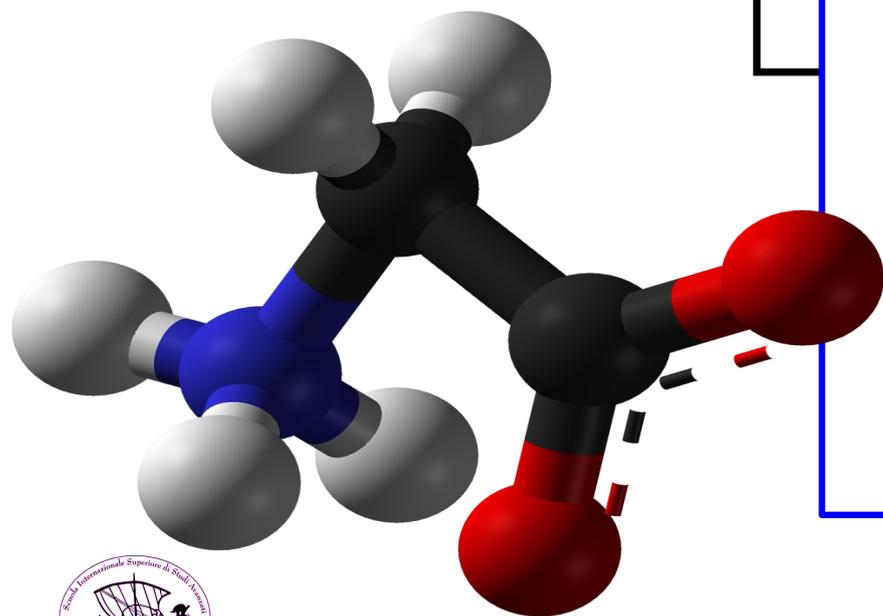


# CSP is a formidable task

- CSP problem: Name a chemical or stoichiometric formula; find the (local) minima of the free energy landscape under given thermodynamic conditions (often at certain T,P)
- “What is the most stable structure of glycine at ambient conditions?” “What is the carbon structure that is stable at very high pressures”
- Challenges:
  - A very vast space of possibilities.
  - Free energy landscape is very expensive to obtain accurately



# Glycine



# How to tackle CSP?

Explore: Use smart algorithms to explore as much of the landscape as possible

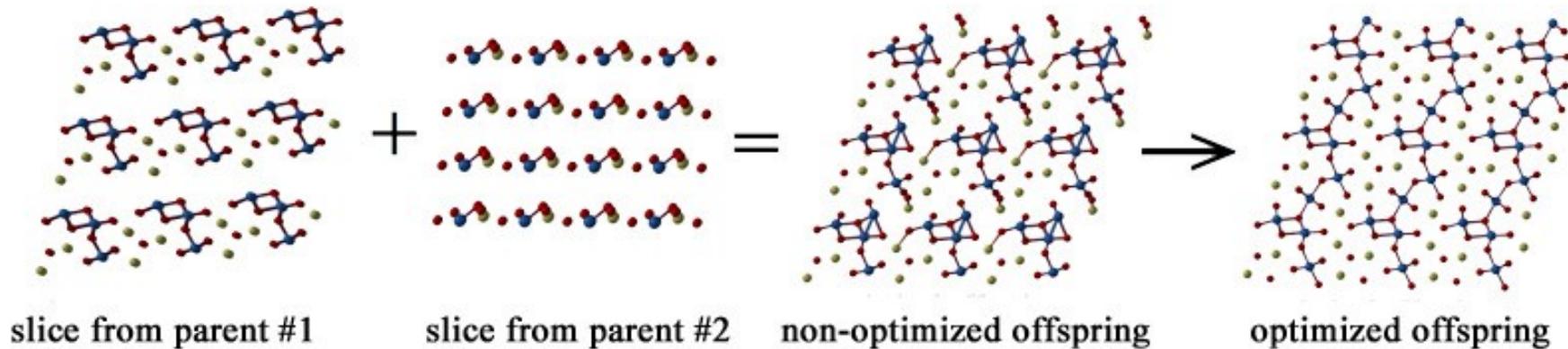
Molecular dynamics / Monte Carlo walkers

- Simulated annealing
- Metadynamics
- Basin hopping
- Minima hopping
- Genetic algorithm

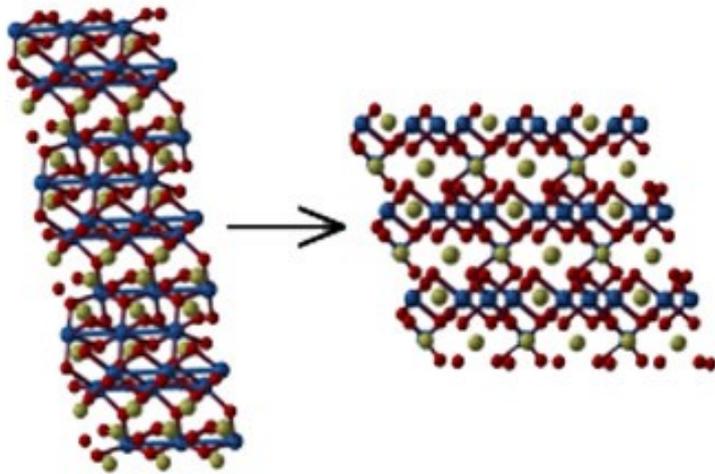


# Genetic algorithm

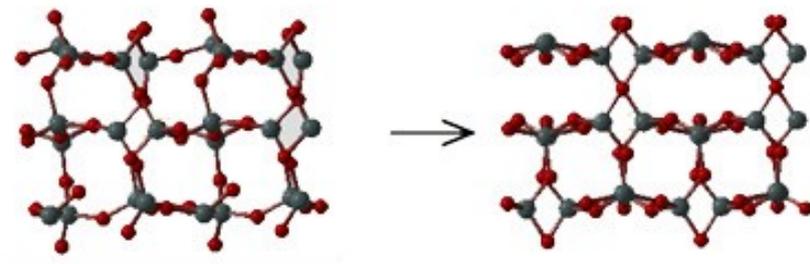
(a) heredity



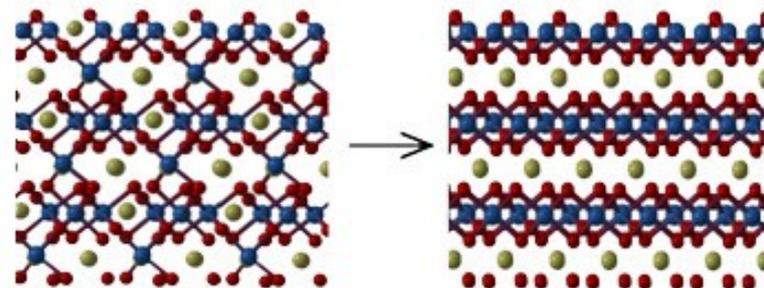
(b) lattice mutation



(c) softmode mutation



(d) permutation



USPEX operations

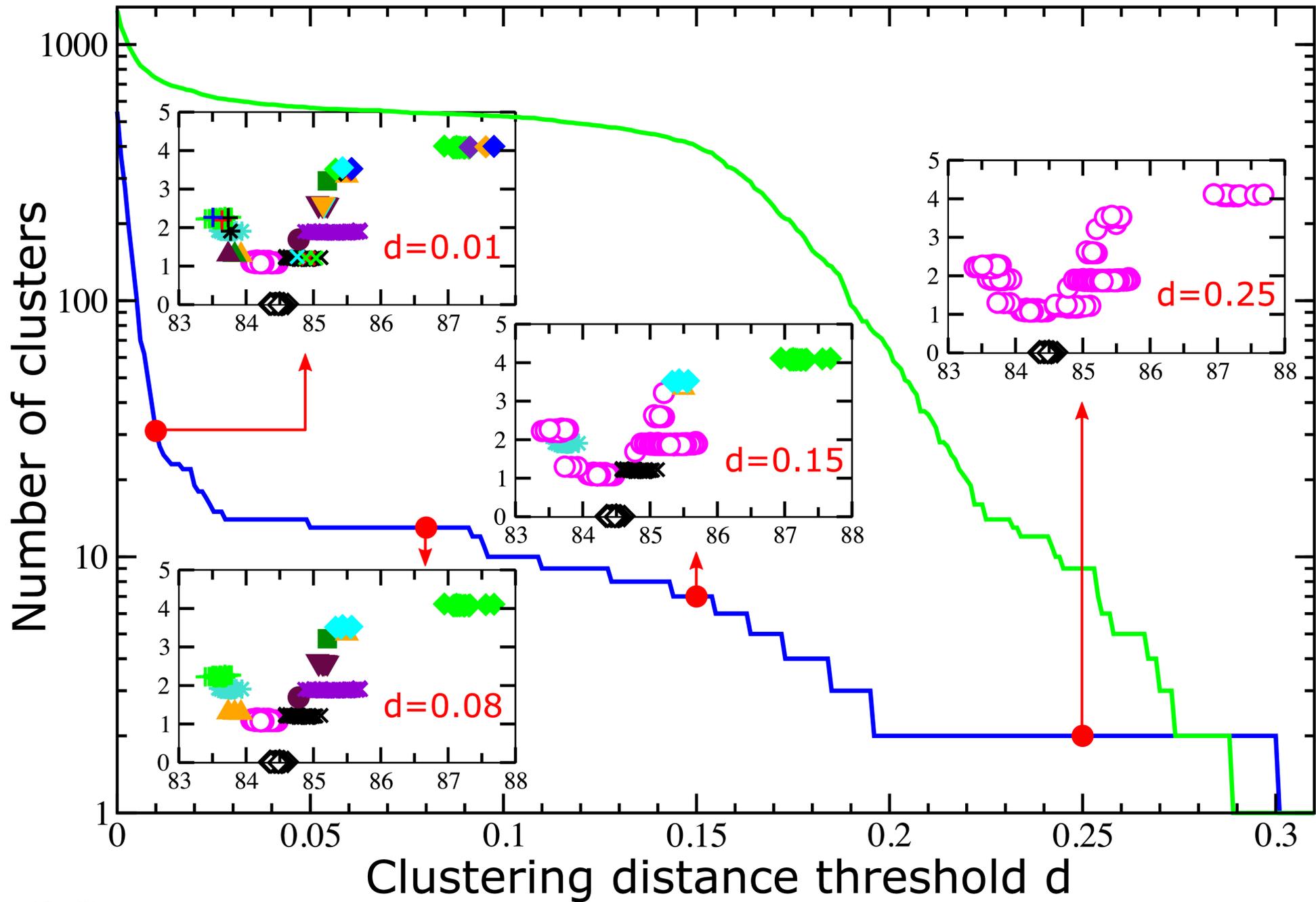
USPEX

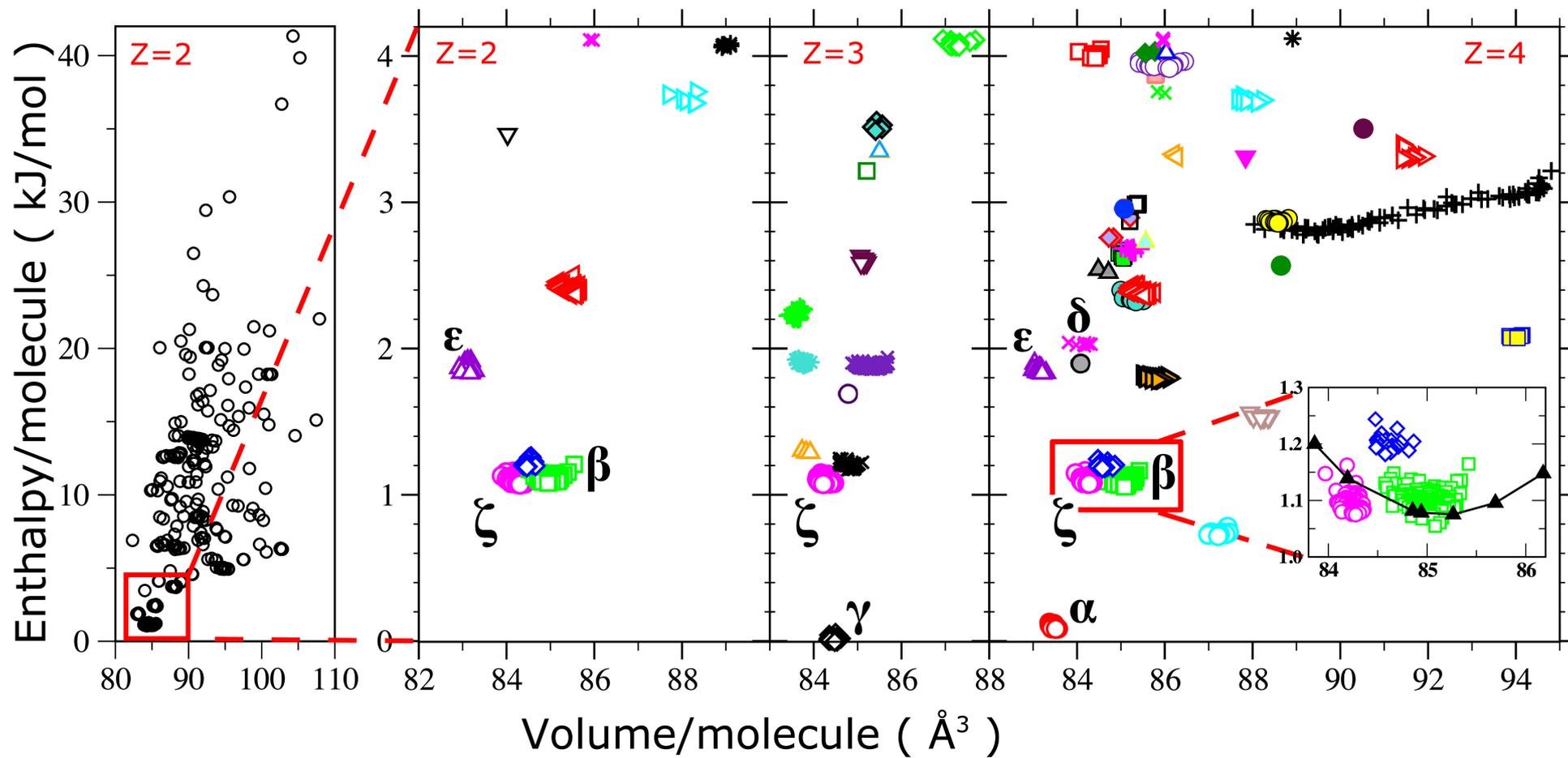


+



+ vdWDF + clustering





# $\zeta$ -phase

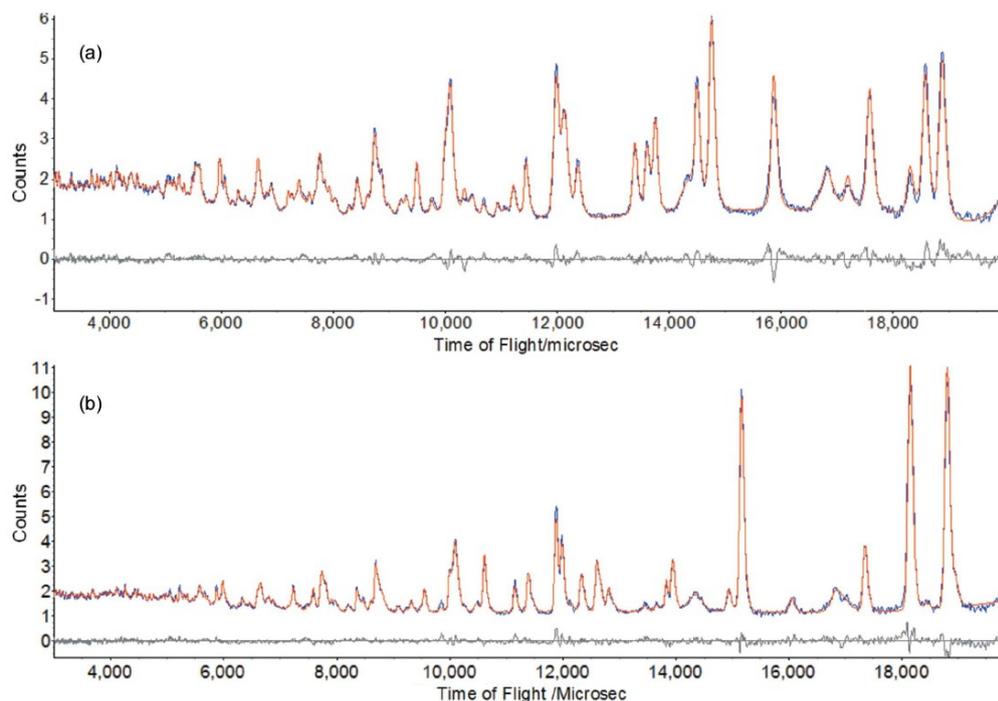


Figure 2  
 (a) Rietveld fit of the neutron powder diffraction pattern of  $\zeta$ -glycine at 100 K (blue = observed, red = calculated). In addition to the peaks  $\zeta$ -glycine, the pattern also shows the presence of residual  $\epsilon$ - and a trace of  $\gamma$ -glycine. Other peaks arise from the sample environment, namely the pressure marker and the  $\text{Al}_2\text{O}_3$  and  $\text{ZrO}_2$  components of the anvils of the pressure cell. (b) Rietveld fit of the neutron powder diffraction pattern of  $\zeta$ -glycine (contaminated with  $\epsilon$ - and a trace of  $\gamma$ -glycine) at 290 K. A  $1 \text{ \AA}$   $d$  spacing approximates to  $4837 \mu\text{s}$  in time-of-flight.

E Kucukbenli, CH Pham, SdG,  
C Bull, G Flowitt-Hill, HY Playford, M Tucker, S Parsons  
Int Union Crist J 4, 569-574 (2017)

Exploring the phase space for larger molecules (ex. CLR) requires fast and accurate energetics

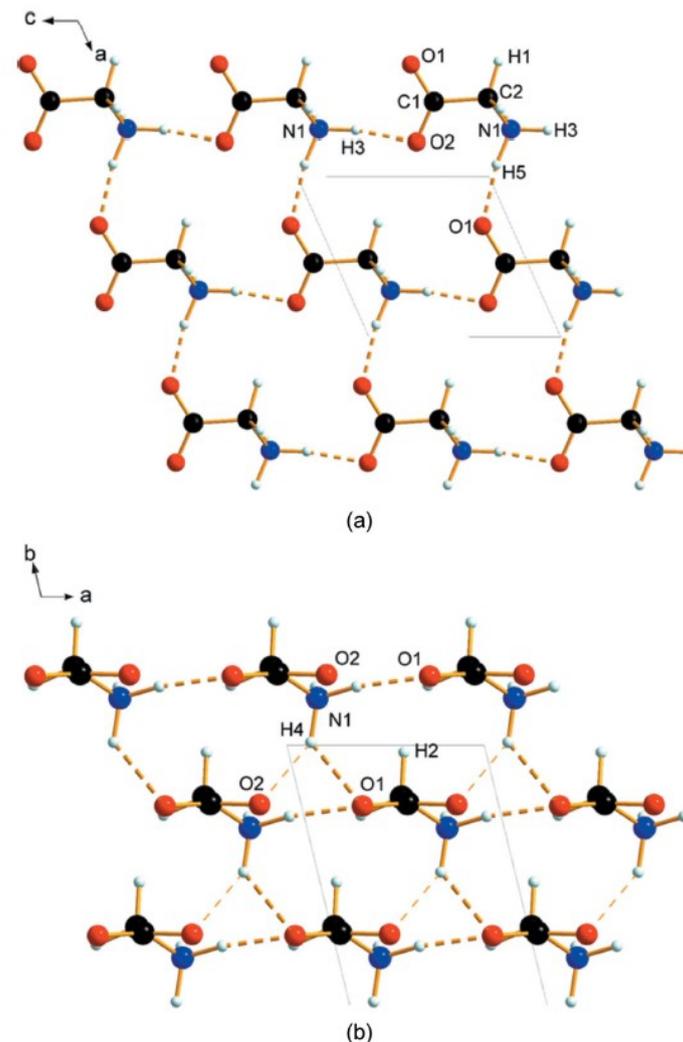


Figure 3  
 Intermolecular interactions in  $\zeta$ -glycine. (a) Layers formed in the  $ac$  plane, viewed along  $b$ . (b) Stacking of the layers, viewed along  $c$ .



# Lithium Interaction with Graphene Materials at Finite Temperature



~10Wh

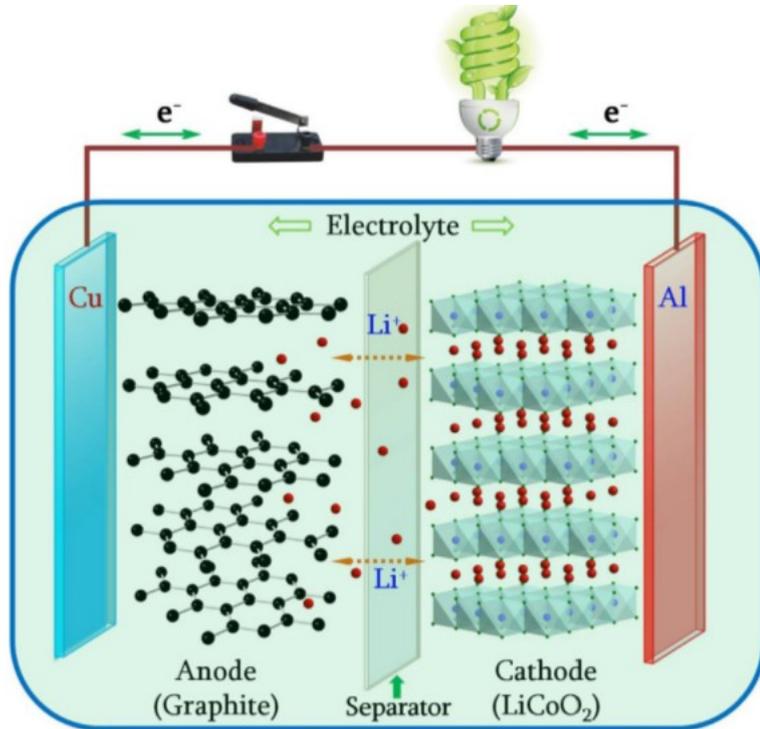


~100Wh



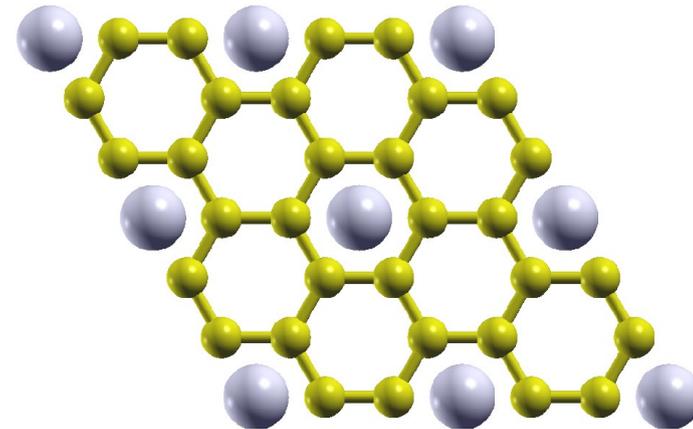
~10,000Wh

# Lithium ion battery



**Capacity:** The amount of Li absorbed by anode

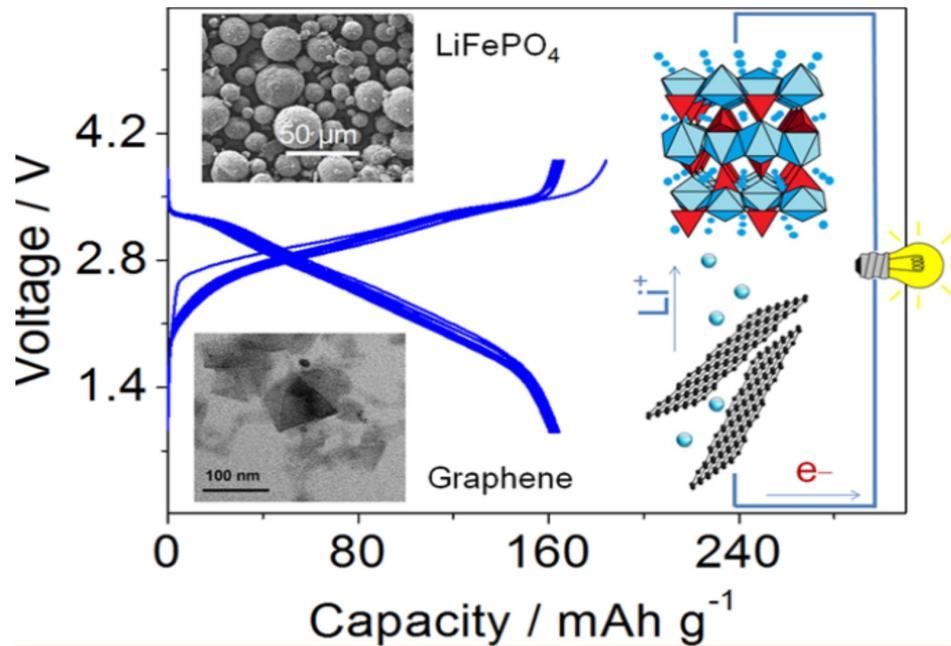
- Stoichiometry of Li adsorbed graphite is  $\text{LiC}_6$



- Cathode: Source of lithium
- Electrolyte: Ionic conductivity
- Anode: Lithium holder
- Current collectors

**Alternative anode materials :**  
Graphene due to its large surface to mass ratio and good electrical conductivity.

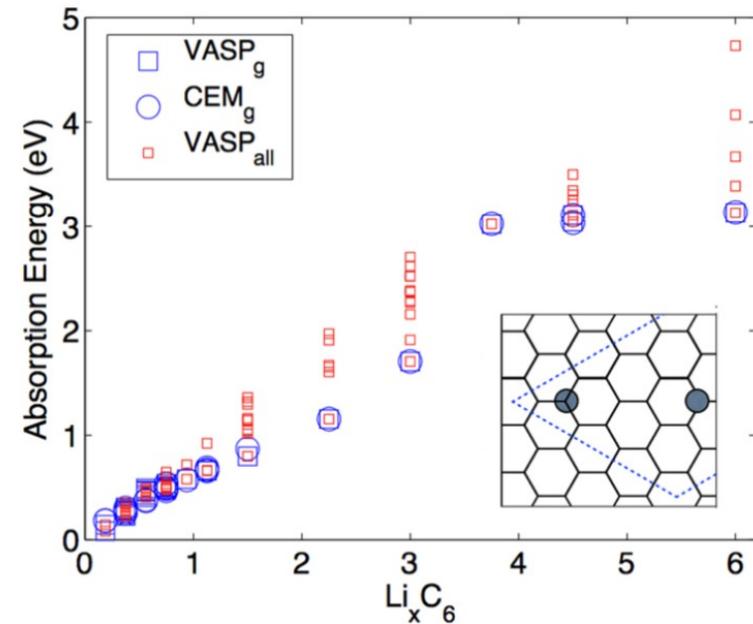
# Experiment



- Exploited graphene nanoflakes as alternative anode
- Flakes were ~30-100 nm lateral dimension
- **Very high Li uptake:  $\text{LiC}_2$**

Hassoun et al. Nano Lett. 2014, 14, 4901-4906

# DFT



High Li-concentration is unstable with respect to Li-metal.

**GOAL: Understand the nature of high Li uptake by graphene materials.**

Eunseok Lee and Kristin A. Persson, Nano Lett. 2012, 12, 4624-4630

# Li on graphene at 0K

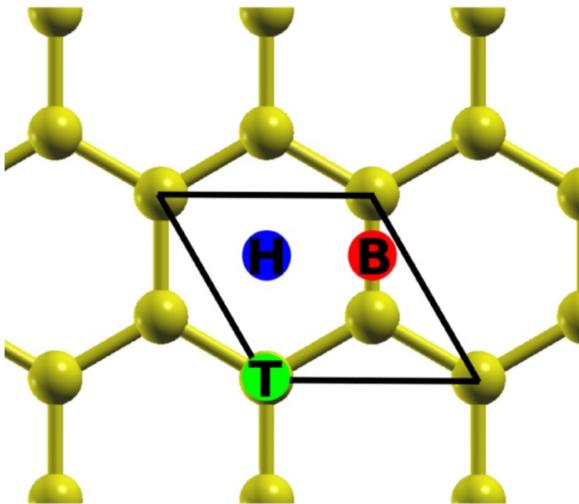
- Density functional theory ( DFT )
- rVV10 functional

## Adsorption energy



$$E_{ad}(n) = \frac{E(n) - E(n=0) - nE_{Libulk}}{n}$$

## Adsorption sites



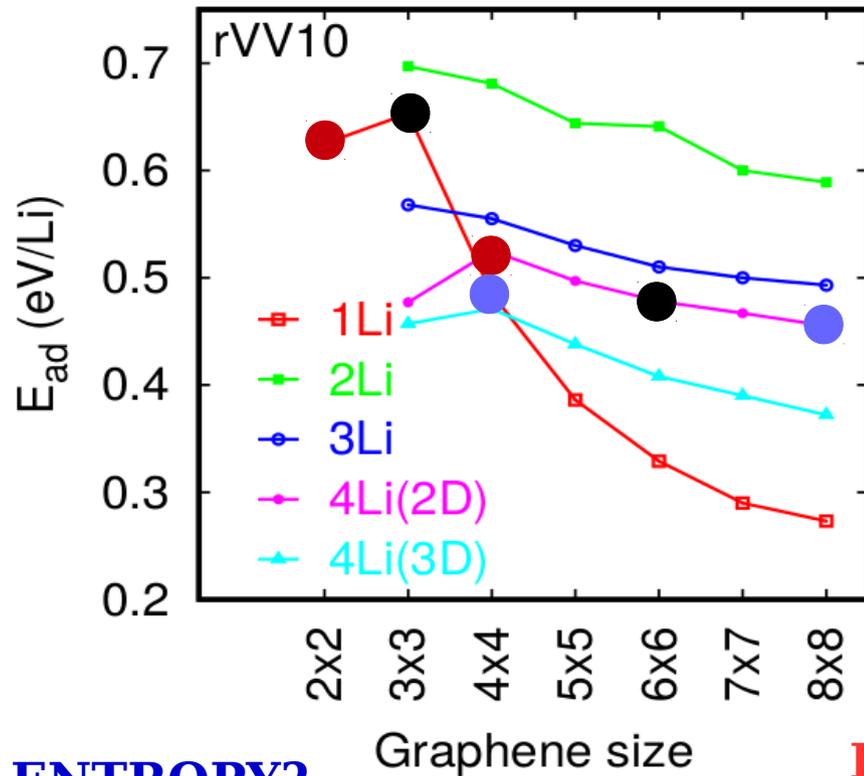
- Adsorption energy gives the stability of Li adsorbed graphene against phase separation into graphene and bulk Li.

System	$E_H^{ad}$ (eV)	$E_B^{ad}$ (eV)	$E_T^{ad}$ (eV)
<b>Li@Gr(2x2)</b>	0.625	0.759	0.767



# Results: Li on graphene at 0K

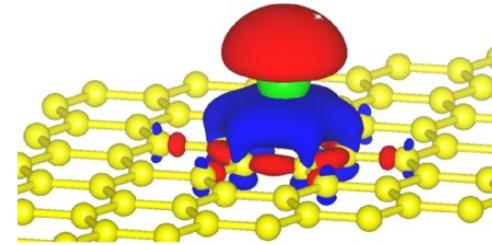
## Energetics



## ENTROPY?

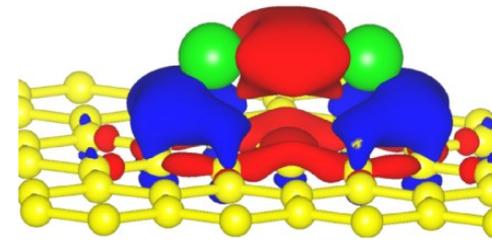
- **Adsorption energies are positive.**
- **Mechanism:** Mainly electrostatics
- **Charge distribution and energetics :** Li-atom vs Li-clusters

## Mechanisms



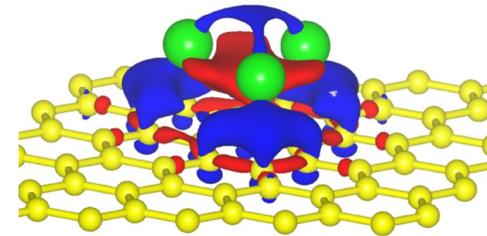
Li-atom

1 Li



Li-clusters

2 Li



3 Li

**Red (Blue)** positive (negative) charge density change upon adsorption of Li on graphene.

$$\Delta\rho = \rho(gr + nLi) - \rho(gr) - \rho(nLi)$$

# Finite temperature

## Grand Canonical Monte Carlo method (GCMC)

Compute thermodynamic properties at fixed  $\bar{\mu}$  and

$$\langle A \rangle = \frac{\sum_N \sum_{\{c_i\}} \exp(-\beta(U(\{c_i\}) - \mu N)) A(\{c_i\})}{\sum_N \sum_{\{c_i\}} \exp(-\beta(U(\{c_i\}) - \mu N))}$$

### configuration space is sampled:

- Select site at random
- Add particle if empty or remove if occupied
- Accept or reject the move according to

$$t_{\text{acc}}(\text{old} \rightarrow \text{new}) = \min(1, \exp(-\beta(\Delta U - \mu\Delta N)))$$

### System:

- 20x20 graphene supercell with 400 sites.
- Used periodic boundary conditions

**We need an AFFORDABLE  
interatomic potential**

# Cluster expansion

## Model:

- Map Li adsorption into a lattice model
- Assign Li occupation number to each site,  
 $c_i = 0$  if site  $i$  is empty  
 $c_i = 1$  if site  $i$  is occupied
- Configuration:

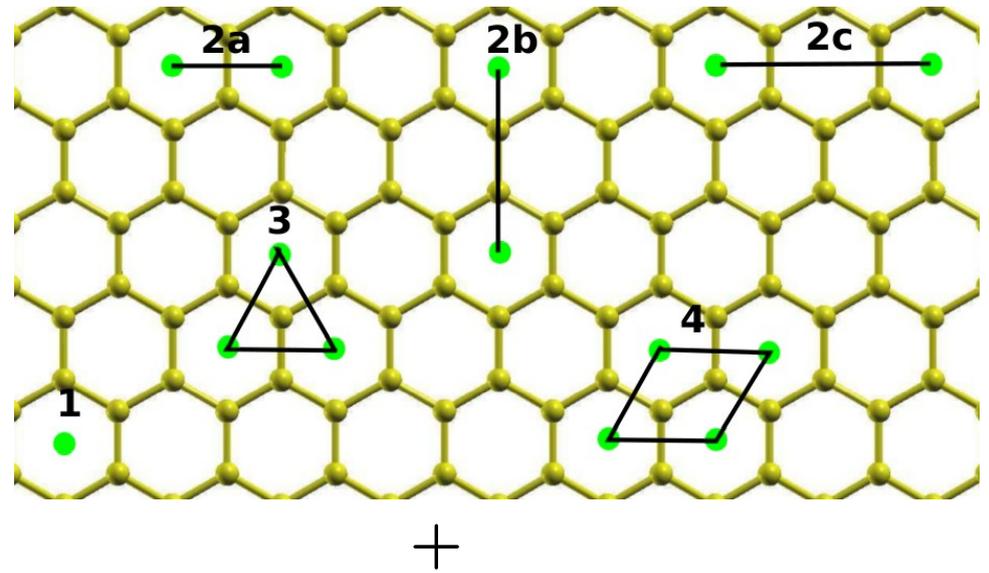
$$C_N = \{c_i\}, i = 1, \dots, N,$$

for  $N$  lattice sites

$$E_{CE}(C_N) = \sum_f J_f \Pi_f(C_N)$$
$$= \sum_f J_f \prod_{i \in f} c_i$$

## Approximations:

- Li adsorption geometry is restricted to 2D.
- **Expansion is truncated.**



**Long-range electrostatic contribution  
due to dipole interactions**

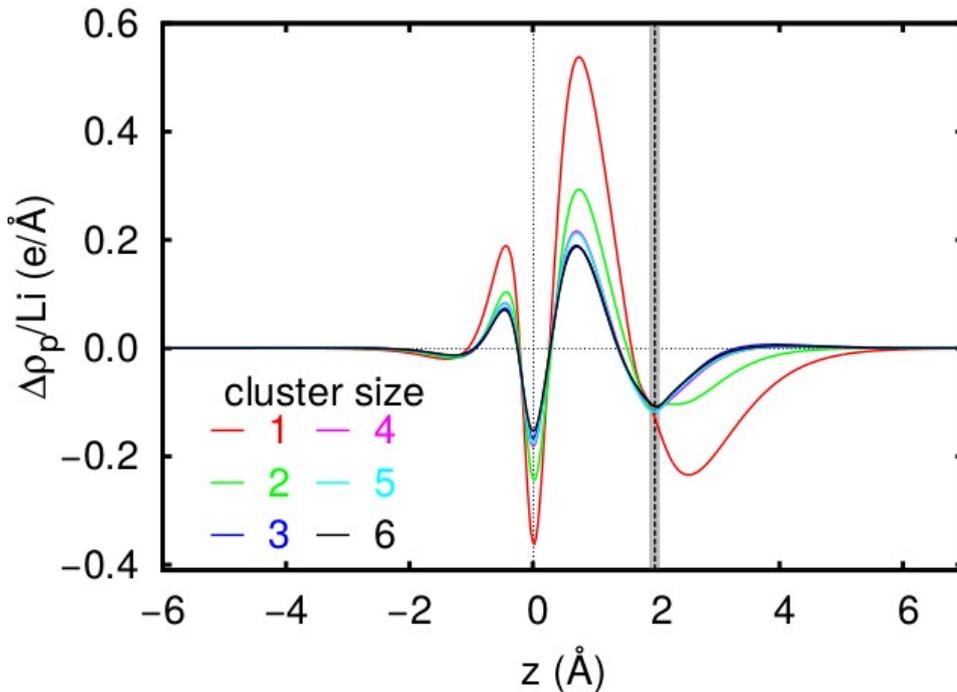
# Cluster expansion

$$E_{CE}(C) = J_1 \sum_{i \in f_1} c_i + \frac{1}{2} \sum_{p=a,b,c} J_{2p} \sum_{\{ij\} \in f_{2p}} c_i c_j$$

$$+ \frac{J_3}{6} \sum_{\{ijk\} \in f_3} c_i c_j c_k + \frac{J_4}{24} \sum_{\{ijkl\} \in f_4} c_i c_j c_k c_l$$

$$+ \frac{J_{dd}}{2} \sum_{ij, |\mathbf{r}_i - \mathbf{r}_j| > 2a_0} \frac{\alpha_i \alpha_j}{|\mathbf{r}_i - \mathbf{r}_j|^3} c_i c_j$$

## Li-atom vs Li-clusters



$$\alpha_i = \begin{cases} 1 & \text{if } NN_i = 0 \\ \gamma & \text{if } NN_i > 0 \end{cases}$$

$J_{dd}$  is the same for all sites

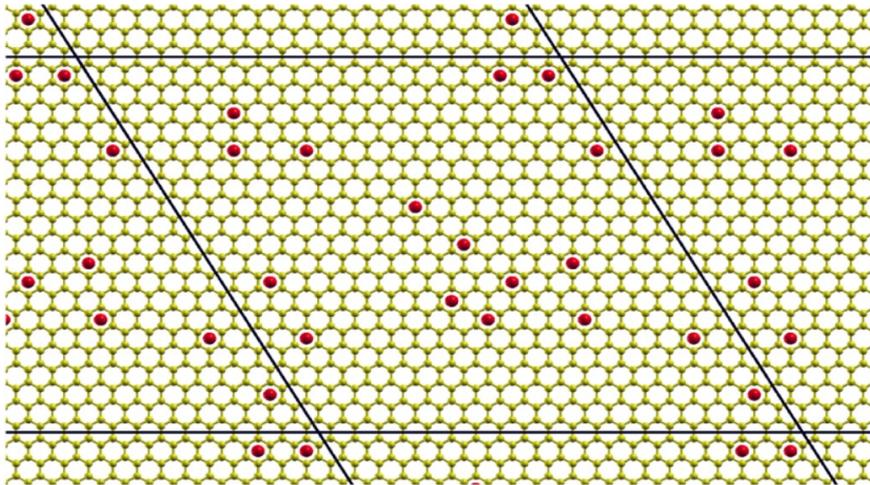
$\alpha$  distinguish the electrostatic interaction strength between isolated Li and clusters

**Fit model to DFT energies by minimizing square deviation.**

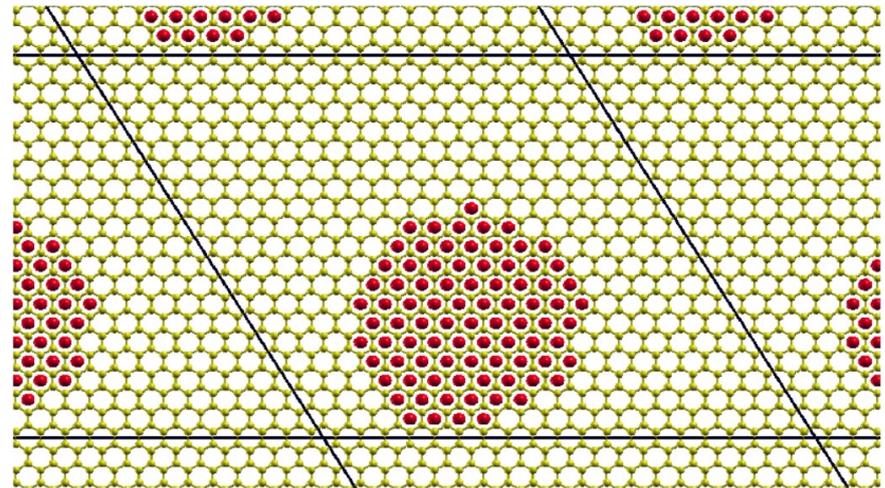
$$\sigma_{Li}^2 = \frac{1}{N_{config}} \sum_{i=1}^{N_{config}} \left[ \frac{E_{DFT}^i - E_{CE}^i}{N_{Li}} \right]^2 + t \sum_{i=1}^{N_J} J_i M_{ii} J_i$$

# Phases

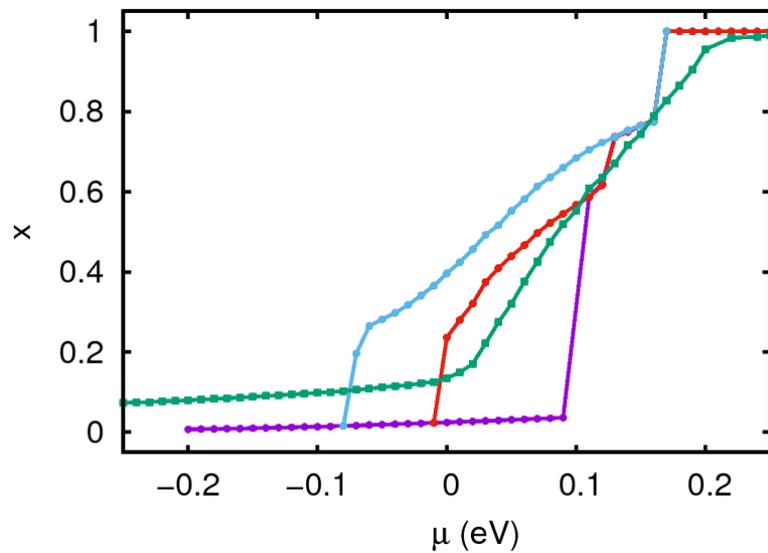
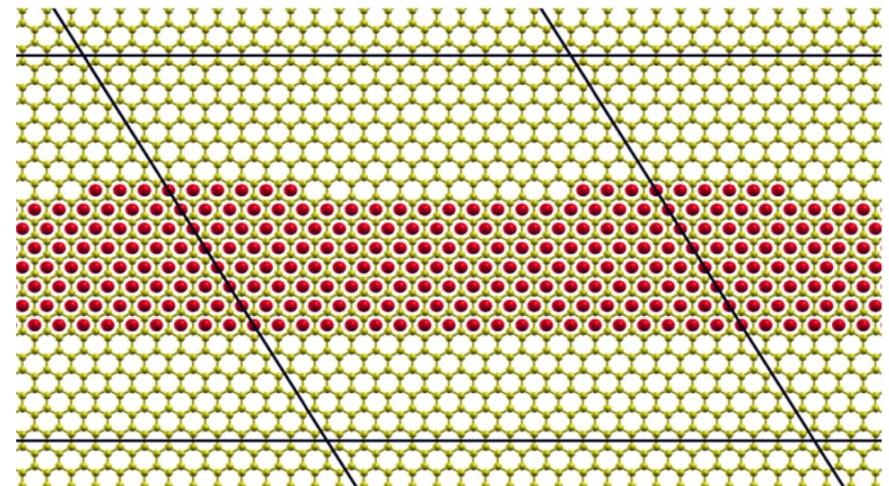
**a) Li-gas**



**b) Li-island**

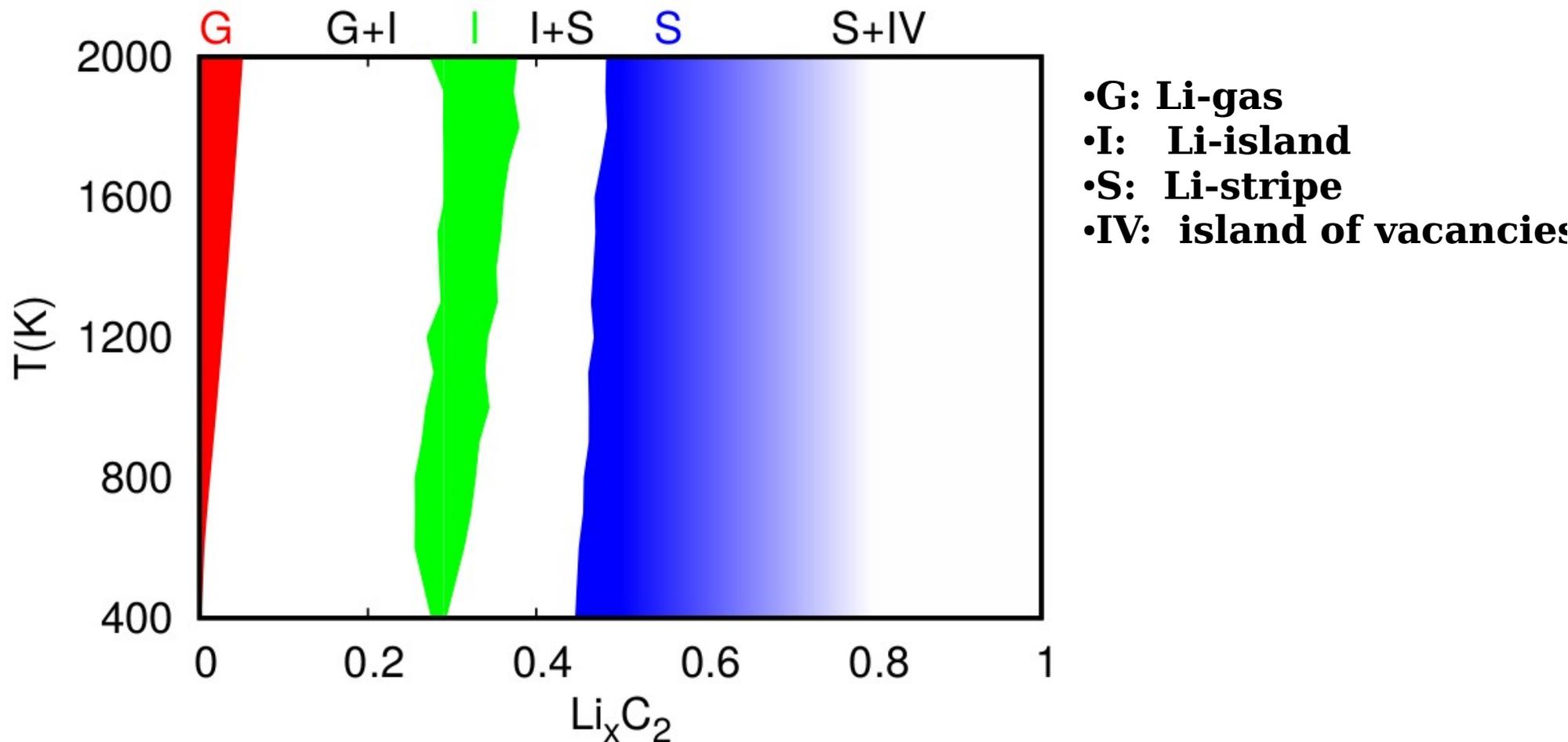


**c) Li-stripe**



**Red dots:** Lithium ions

# Results: Phase diagram

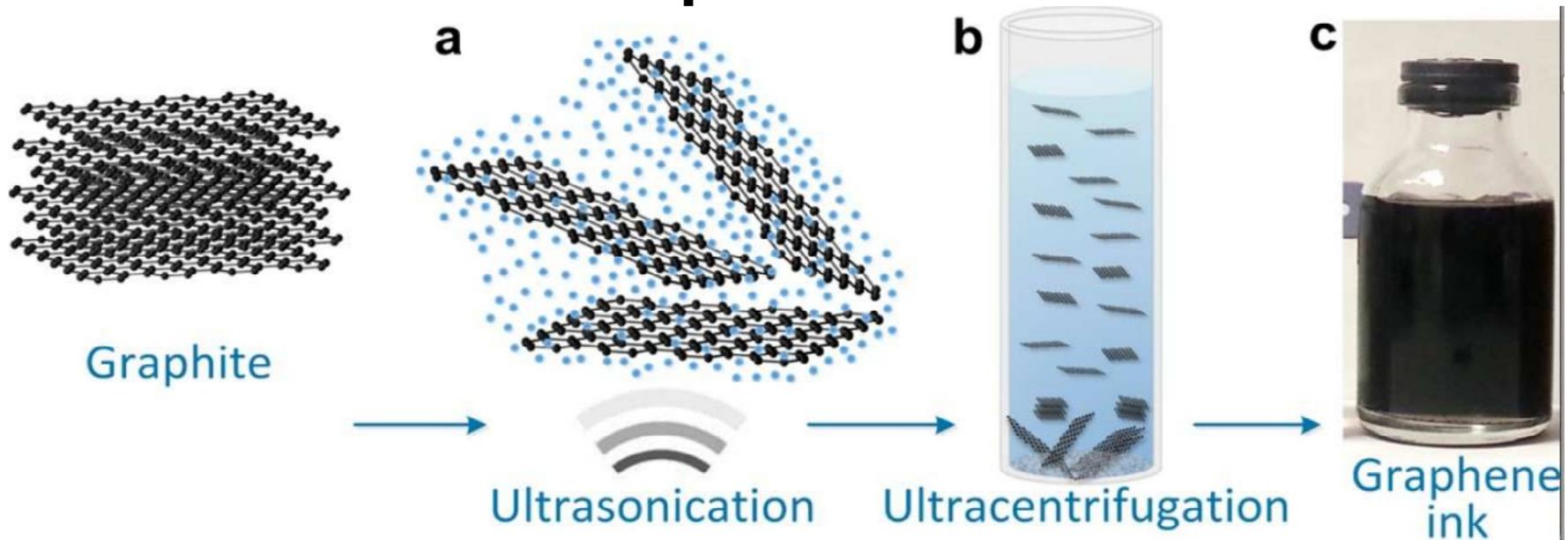


## Two main phases:

1. Random distribution of Li
2. 2D Li-clusters

**Is Li adsorption in carbon  
materials really 2D?**

# Limitations of Cluster expansion



- Applied to only well defined underlying lattice.
- The dynamics of Li must be restricted to the lattice sites.
- **This calls for an accurate and yet affordable Li/C interaction potential.**

## MACHINE LEARNING

Traditionally model potentials construction requires a lot of physical intuition and are strongly dependent on the available experimental information.

Not transferable to experimentally unexplored regions.

Limited accuracy due to rigid functional form.

DFT is a viable option to gather accurate information but requires a systematic approach to build a potential that can incorporate its features.





**Artificial  
Intelligence**  
is better than none

Replace the expensive DFT total energy calculations (or other accurate methods) with an interatomic potentials built to reproduce DFT data in a variety of environments

$$E(c) = \sum_{\alpha} \sum_{i \in \alpha} \varepsilon_{\alpha}(\mathbf{d}_i) + \text{long range contrib}$$


- Kernel Ridge Regression (and Gaussian Processes)
- Neural Networks
- local environment descriptors



# Force Matching Method

Furio Ercolessi, JB Adams

*“Interatomic potentials from first-principles calculations”*

MRS Online Proceedings Library Archive, 291

arXiv:cond-mat/9306054

Peter Brommer, Franz Gähler

*“Potfit: effective potentials from ab-initio data”*

Modelling and Simulation in Materials Science

and Engineering **15**, 295 (2007),

arXiv:0704.0185

$$Z = Z_F + Z_C,$$

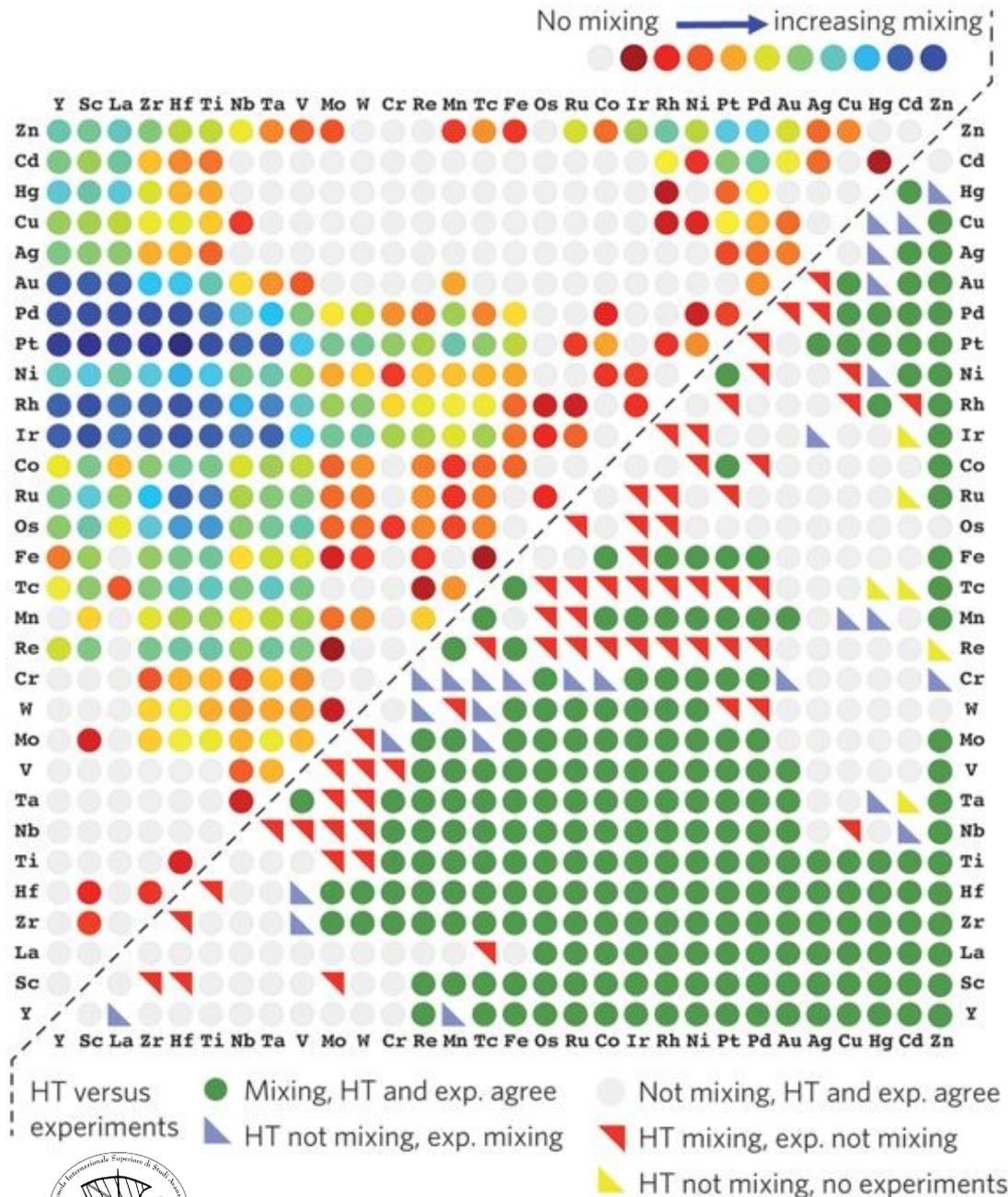
$$\text{with } Z_F = \sum_{j=1}^{N_A} \sum_{\alpha=x,y,z} W_j \frac{(f_{j\alpha} - f_{0,j\alpha})^2}{f_{0,j}^2 + \varepsilon_j},$$

$$\text{and } Z_C = \sum_{k=1}^{N_c} W_k \frac{(A_k - A_{0,k})^2}{A_{0,k}^2 + \varepsilon_k},$$

# The high-throughput highway to computational materials design

S Curtarolo, GLW Hart, M Buongiorno Nardelli, N Mingo, S Sanvito & O Levy

*Nature Materials* **12**, 191 (2013)



**Figure 1 | High-throughput analysis of binary intermetallics<sup>24</sup>.** Top left triangle: ordering tendency of the mixtures, as defined in the main text, for elements ordered by Pettifor's chemical scale<sup>54</sup>. Grey circles indicate no ordering, whereas darker blue circles indicate increasing capability to form stable compounds. Bottom right triangle: comparison of HT versus experimental results<sup>24</sup>. Green and grey circles denote agreement between calculation and experimental data on the existence (green) or absence (grey) of compounds. Purple (red) triangles indicate disagreement of HT predictions of compound absence (existence) versus experimental existence (absence). Yellow triangles indicate that data is unavailable for comparison.

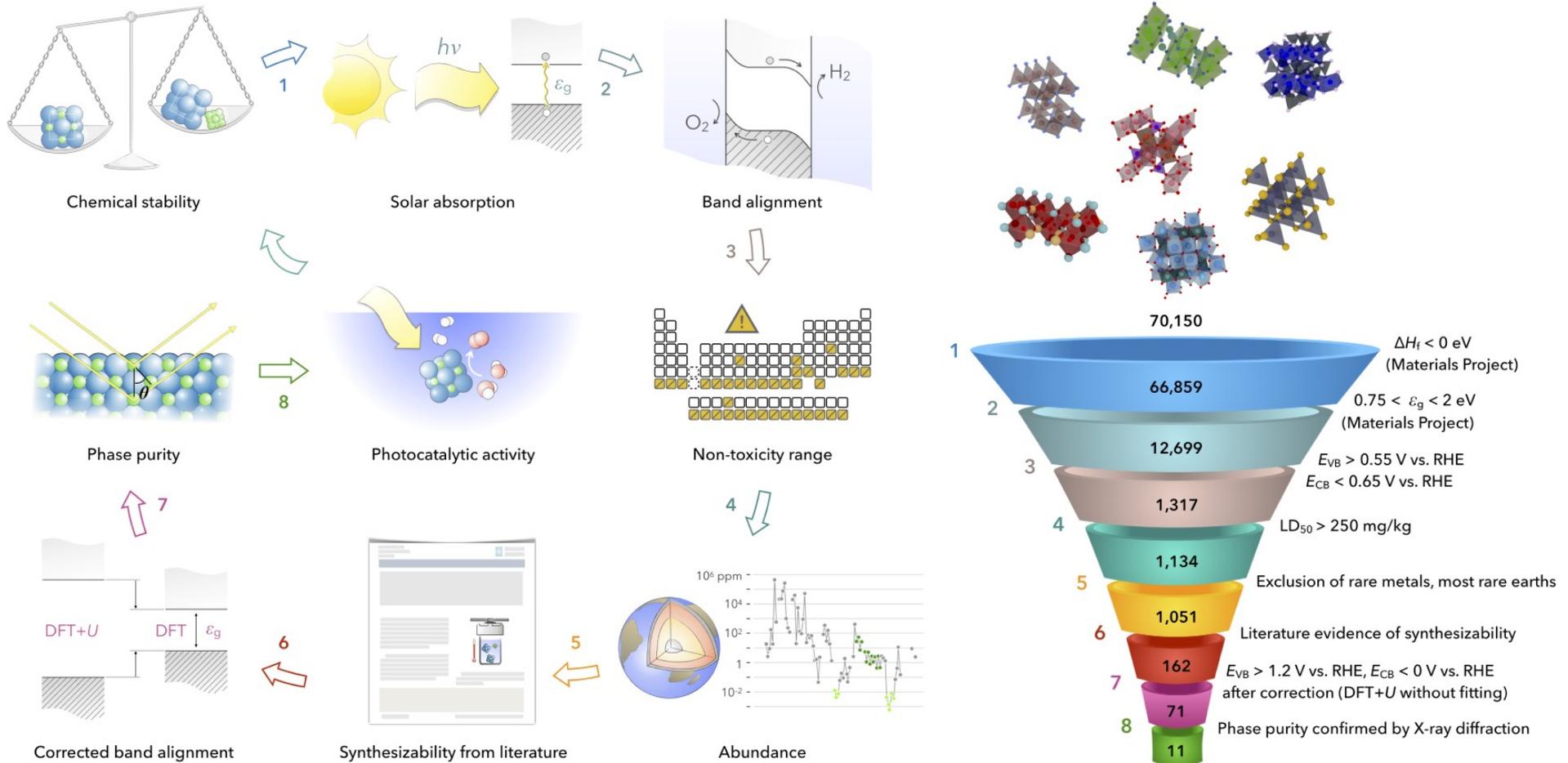


Marco is a scientist, composer and flutist at the

University of North Texas **SISSA PhD 1993**



# Optimizing accuracy and efficacy in data-driven materials discovery for the solar production of hydrogen”



Yihuang Xiong, Quinn T. Campbell, Julian Fanghanel, Catherine K. Badding, Huaiyu Wang, Nicole E. Kirchner-Hall, Monica J. Theibault, [Iurii Timrov](#), Jared S. Mondschein, Kriti Seth, Rebecca Katz, Andres Molina Villarino, Betül Pamuk, Megan E. Penrod, Mohammed M. Khan, Tiffany Rivera, Nathan C. Smith, Xavier Quintana, Paul Orbe, Craig J. Fennie, Senorpe Asem-Hiablíe, James L. Young, Todd G. Deutsch, [Matteo Cococcioni](#), Venkatraman Gopalan, Hector D. Abruña, Raymond E. Schaak, Ismaila Dabo

[arXiv:2102.01154](https://arxiv.org/abs/2102.01154)



Thank you for your attention

