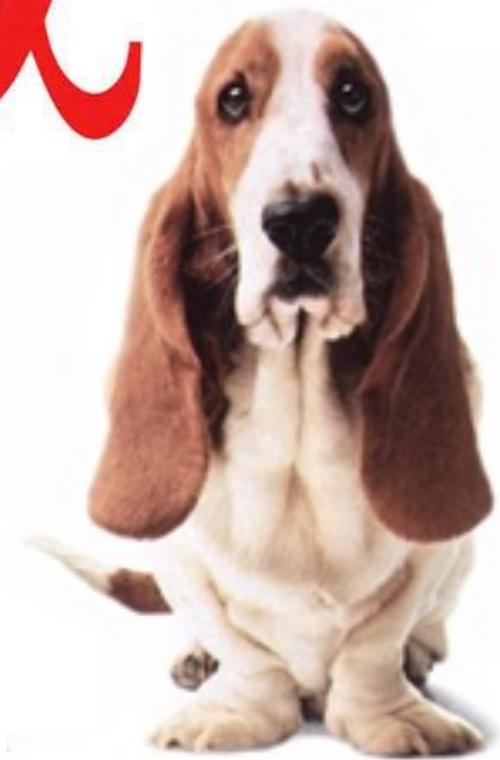


Machine learning on molecular simulation

Hongbin Ren (任宏斌) | 2016.11.30 | IOP. CAS

ALPHA α



how can machine learning help
physicist, based on my understanding, I
think it makes material simulation based
on DFT possible to be implemented in
large scale calculation

现阶段工业和制药中采用的材料计算方法:

经典分子动力学, 力常数方法, 经验参数

机器学习使得**更精确的**大规模
材料计算成为现实.....

Benefits



Medicine



Industry

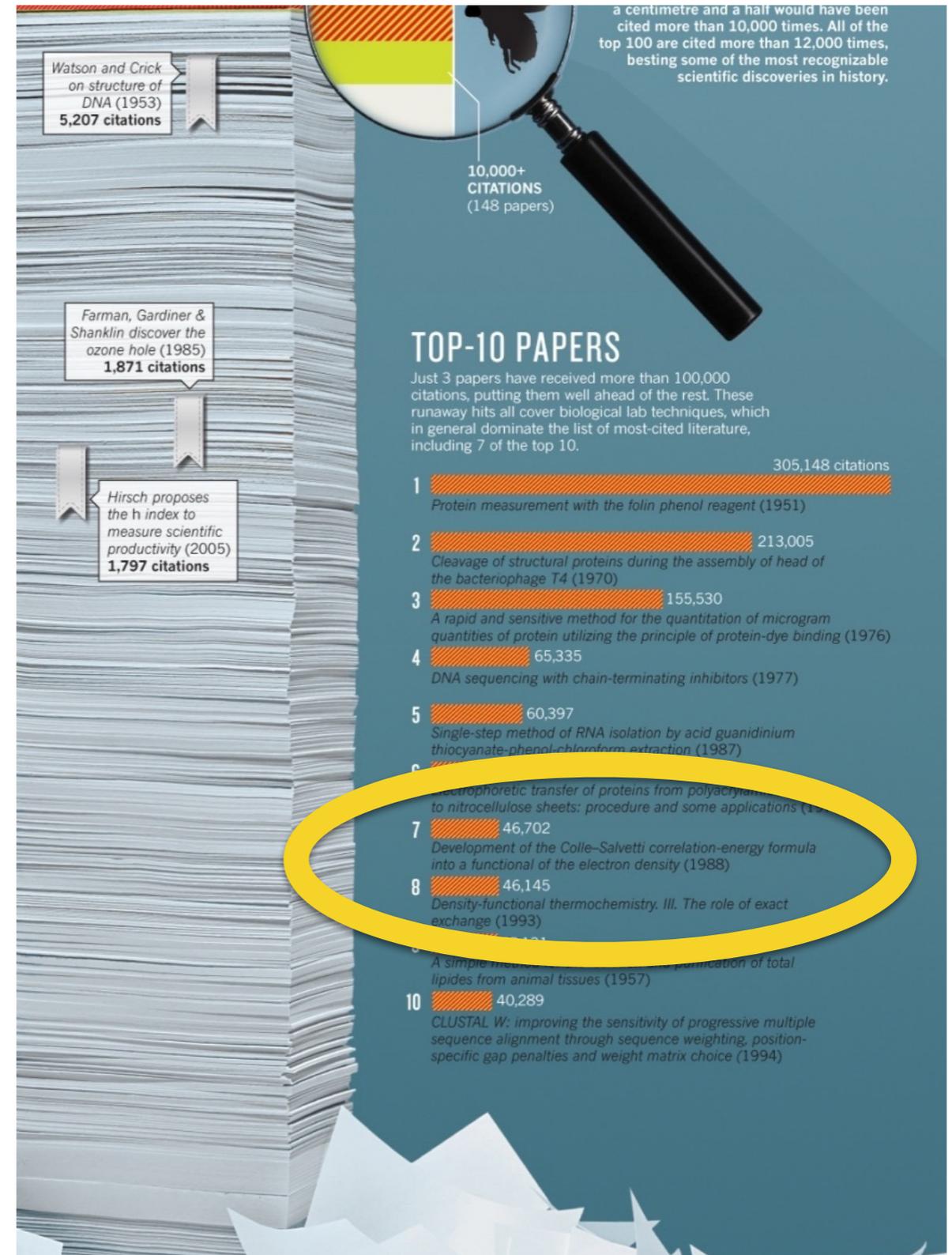
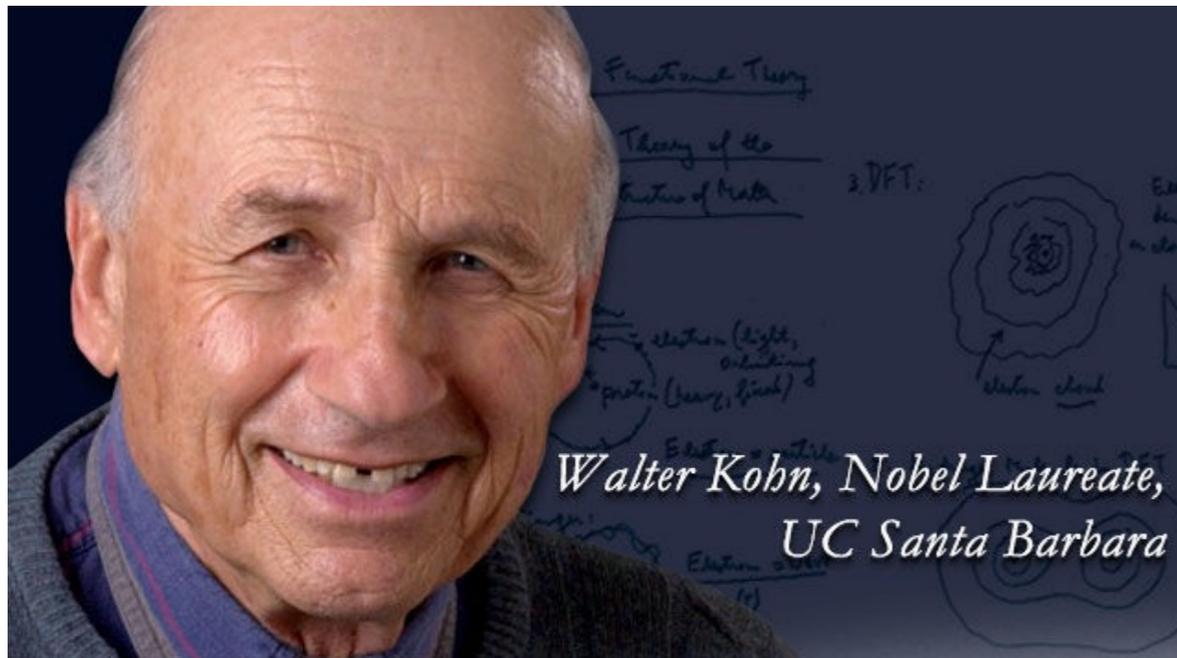
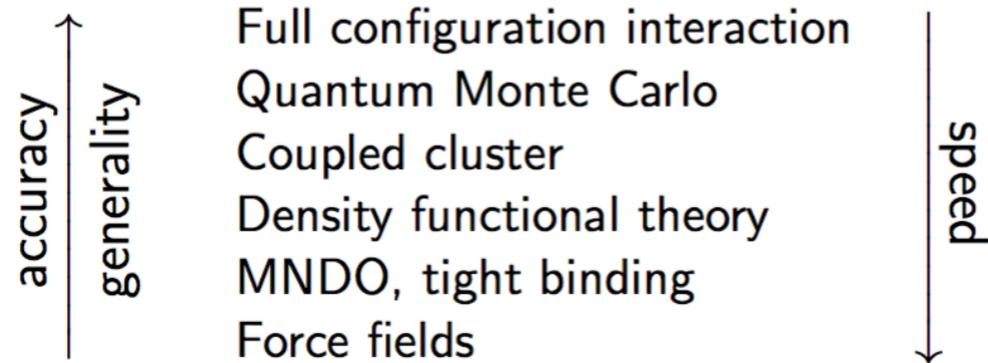
Outline

- DFT in nutshell
- Why machine learning (**Supervised learning**) ?
- Physics+Technology=?
- Summary

DFT in nutshell

DFT:

(Density functional theory)



DFT overview

self-consistent loop (on the board)
approximation

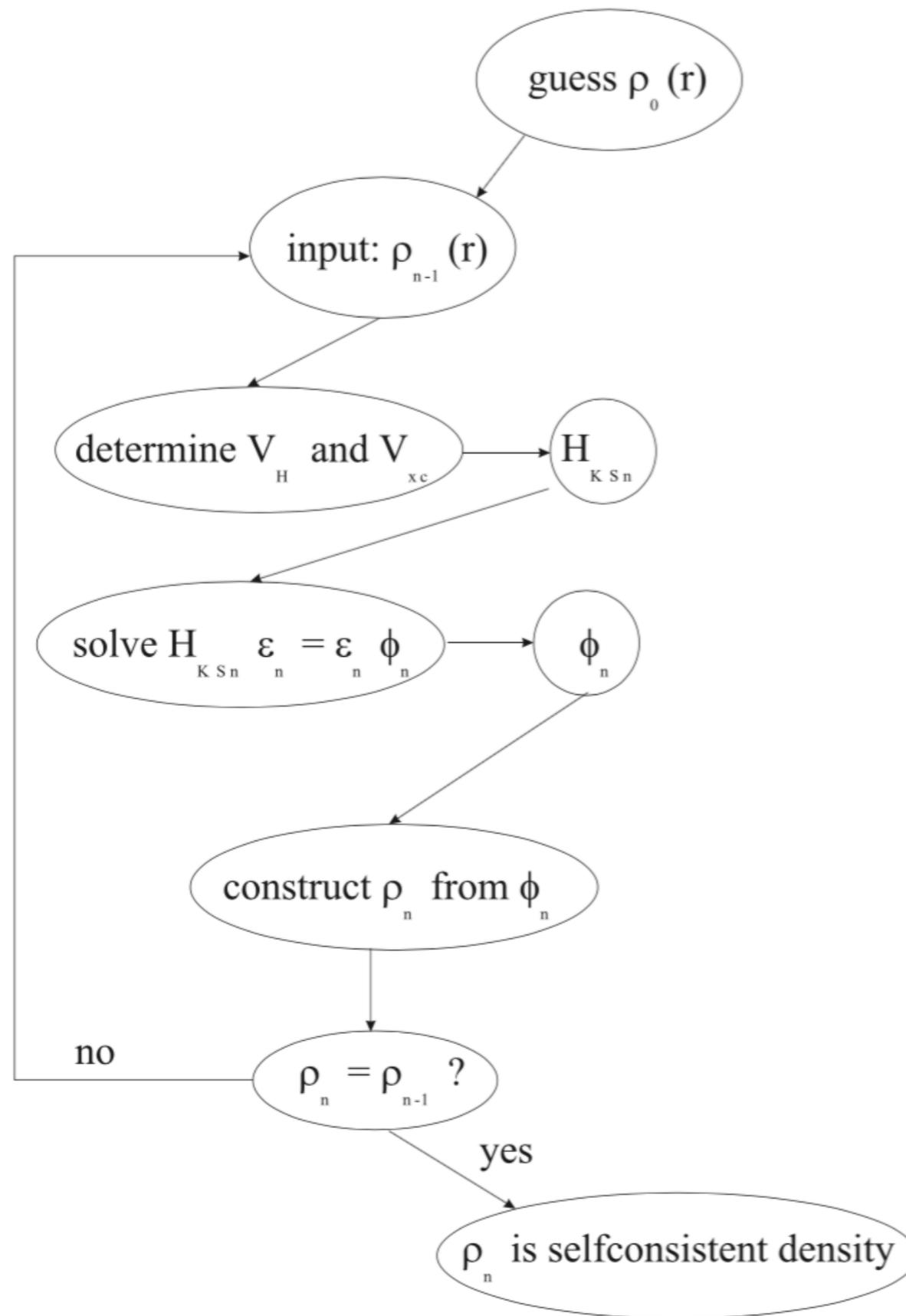
$$\hat{H} = -\frac{\hbar^2}{2} \sum_i \frac{\nabla_{\vec{R}_i}^2}{M_i} - \frac{\hbar^2}{2} \sum_i \frac{\nabla_{\vec{r}_i}^2}{m_e} - \frac{1}{4\pi\epsilon_0} \sum_{i,j} \frac{e^2 Z_i}{|\vec{R}_i - \vec{r}_j|} + \frac{1}{8\pi\epsilon_0} \sum_{i \neq j} \frac{e^2}{|\vec{r}_i - \vec{r}_j|} + \frac{1}{8\pi\epsilon_0} \sum_{i \neq j} \frac{e^2 Z_i Z_j}{|\vec{R}_i - \vec{R}_j|}$$

Many-body Hamiltonian

Interacting ground state
Non-interacting ground state

Single particle Hamiltonian

$$\begin{aligned} \hat{H}_{KS} &= \hat{T}_0 + \hat{V}_H + \hat{V}_{xc} + \hat{V}_{ext} \\ &= -\frac{\hbar^2}{2m_e} \nabla_i^2 + \frac{e^2}{4\pi\epsilon_0} \int \frac{\rho(\vec{r}')}{|\vec{r} - \vec{r}'|} d\vec{r}' + V_{xc} + V_{ext} \end{aligned}$$



For any new and complex system, it need vast amount of time to reformulate the information needed.

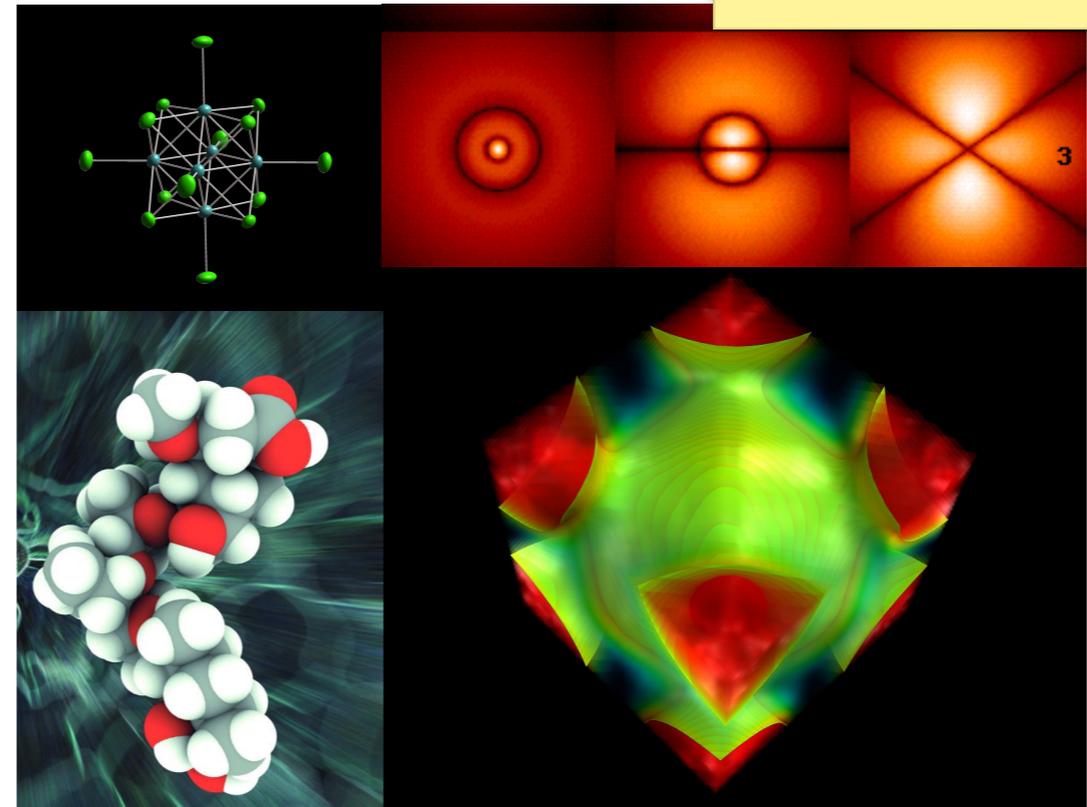
It is called "Ab init", because every time when you start a new calculation, you need to do all the initial settings again.

Setting parameter is an art more than science, relies heavily on experience. Therefore, beginner may be "too young, too simple, sometime naive"

Characters of traditional

1. DFT calculations cover from single atom all way up to solid
2. It is called first principle because it is based on the quantum mechanic principle with nearly no or fewer empirical factors
3. However, due to the limited computing power, DFT can't work efficiently when system contains more than ? of atoms
4. Doing DFT calculation is really time consuming and therefore is not applicable to fields that need instant results.

- Generally applicable
- No or few parameters
- Limited system size
- Time consuming



Why machine learning ?

Because

Database Statistics

67,317

INORGANIC COMPOUNDS

52,336

BANDSTRUCTURES

21,954

MOLECULES

530,243

NANOPOROUS MATERIALS

3,859

ELASTIC TENSORS

941

PIEZOELECTRIC TENSORS

3,628

INTERCALATION ELECTRODES

16,128

CONVERSION ELECTRODES

<https://materialsproject.org>

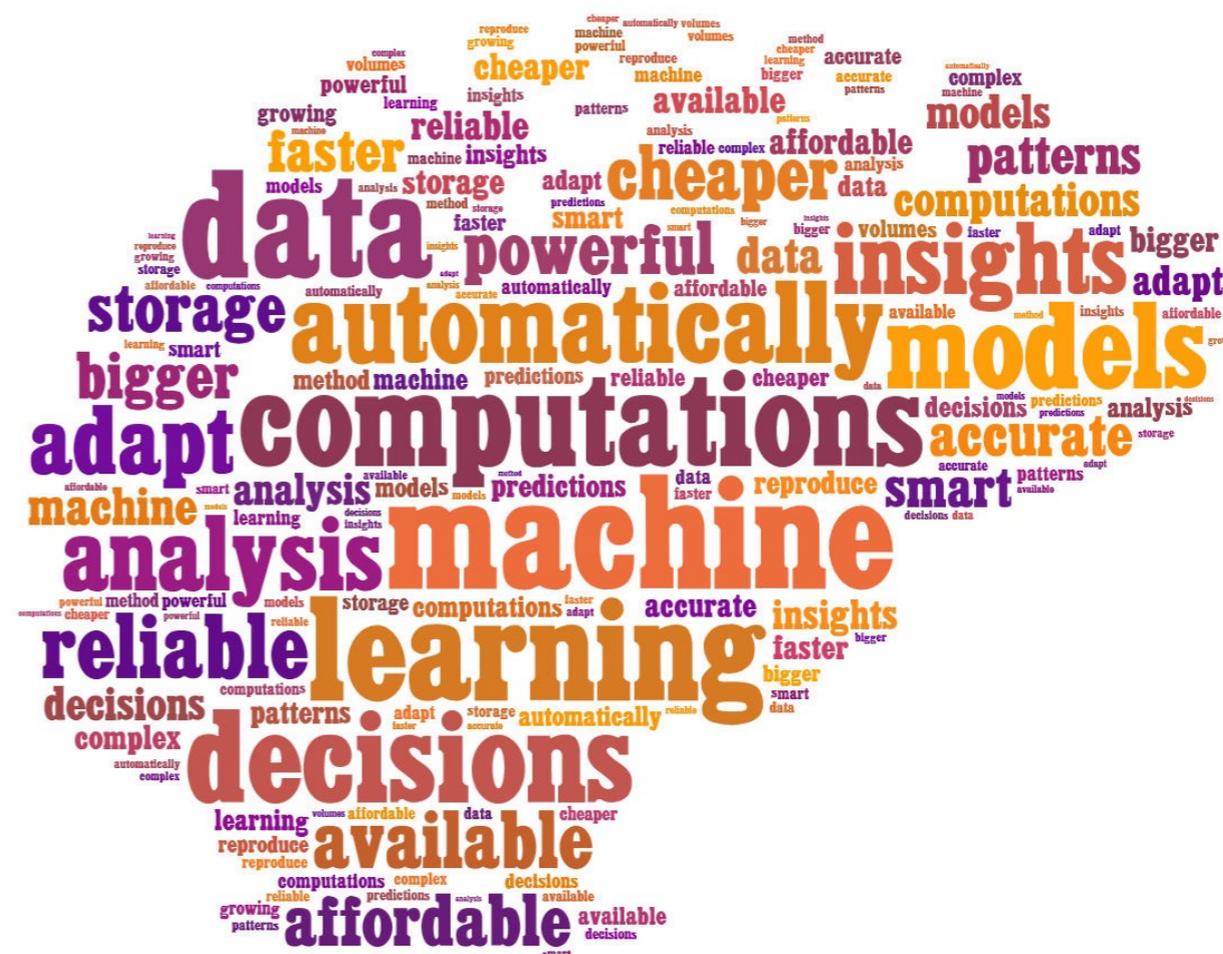
Power of machine lea

Since the first demonstration of the DFT method, it has been used in fields involving chemical compounds. Therefore, it has accumulated a large amount of data, e.g. Materials Project

We want our DFT calculation to be more smart, and more adaptive to various conditions.

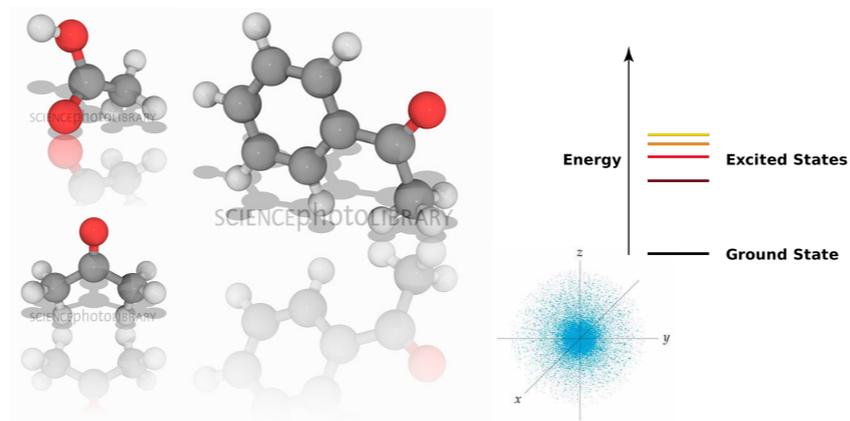
The prediction is able to be made within $O(N)$ time.

- **Experienced** learn from the existing knowledge
- **Accurate** training and testing scheme
- **Efficient** predict from the model learned

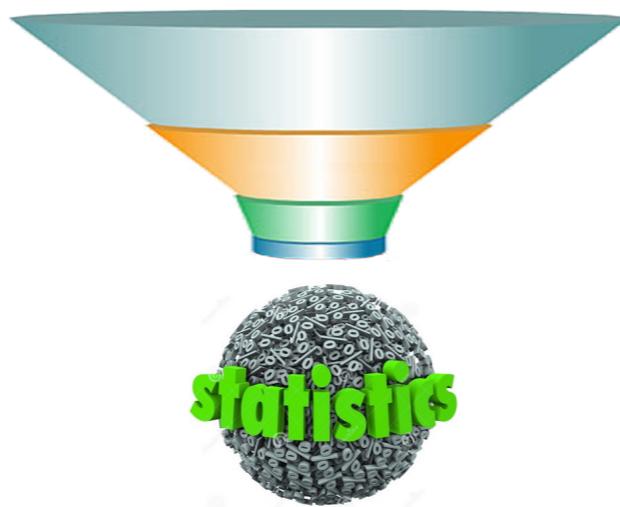


In the following content, machine learning is regarded as an efficient tool, physics ends in the DFT part.

Physics+Technology= \equiv ?

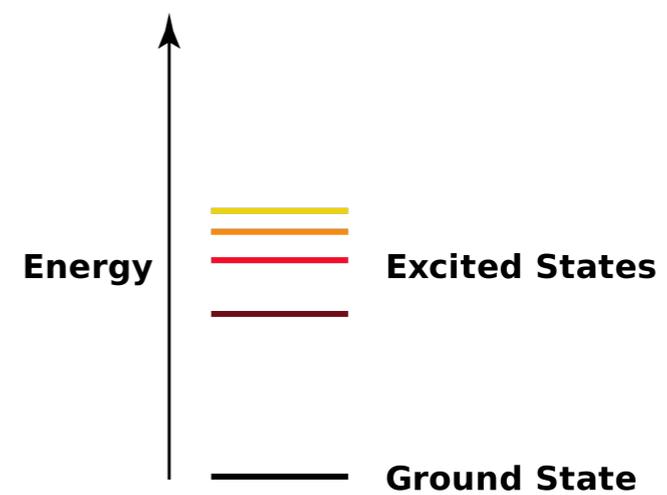
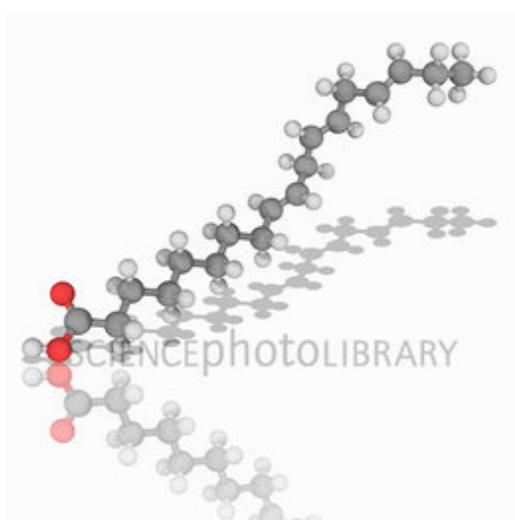


database construction:
 (maybe update)
 1. wave function orientation
 2.



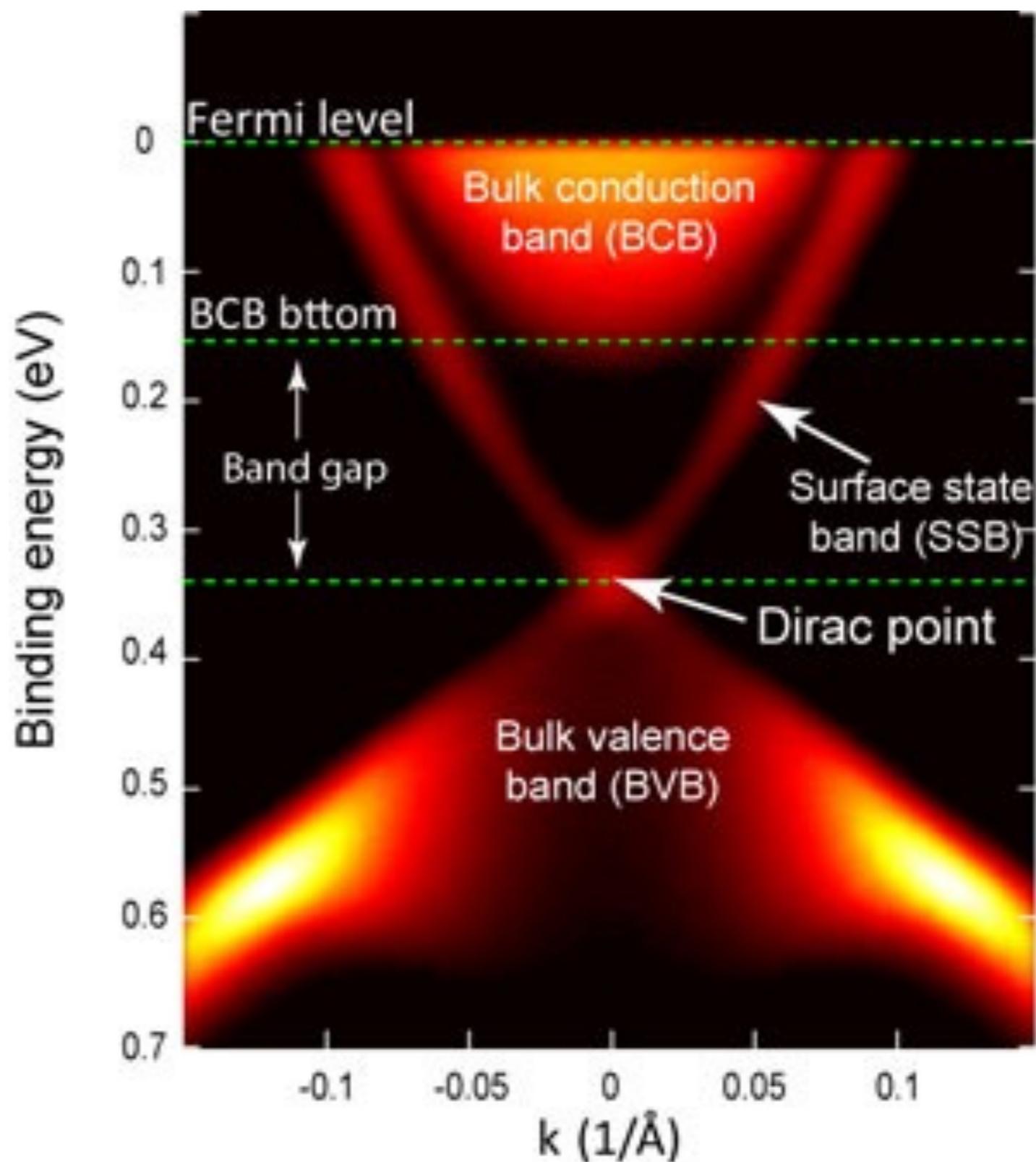
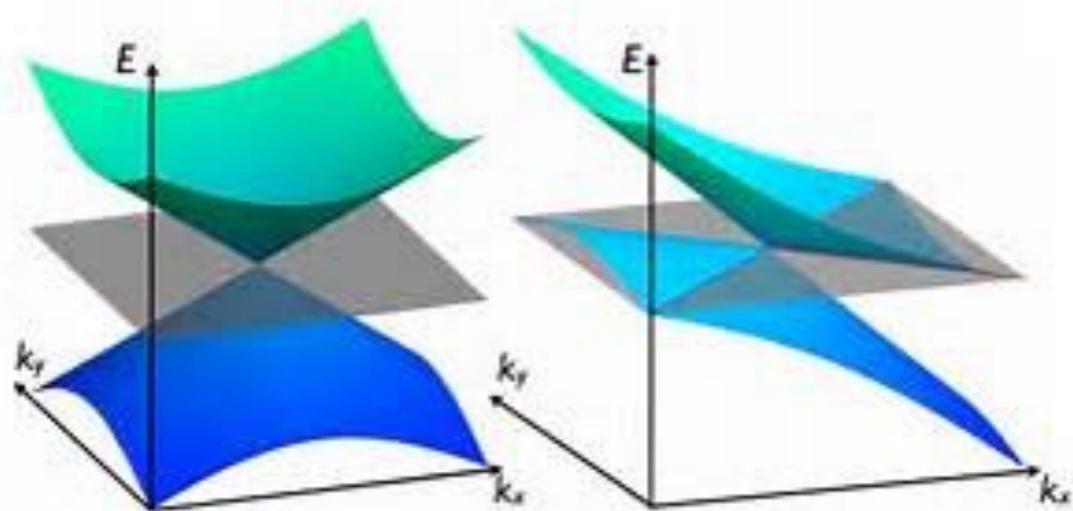
New molecule

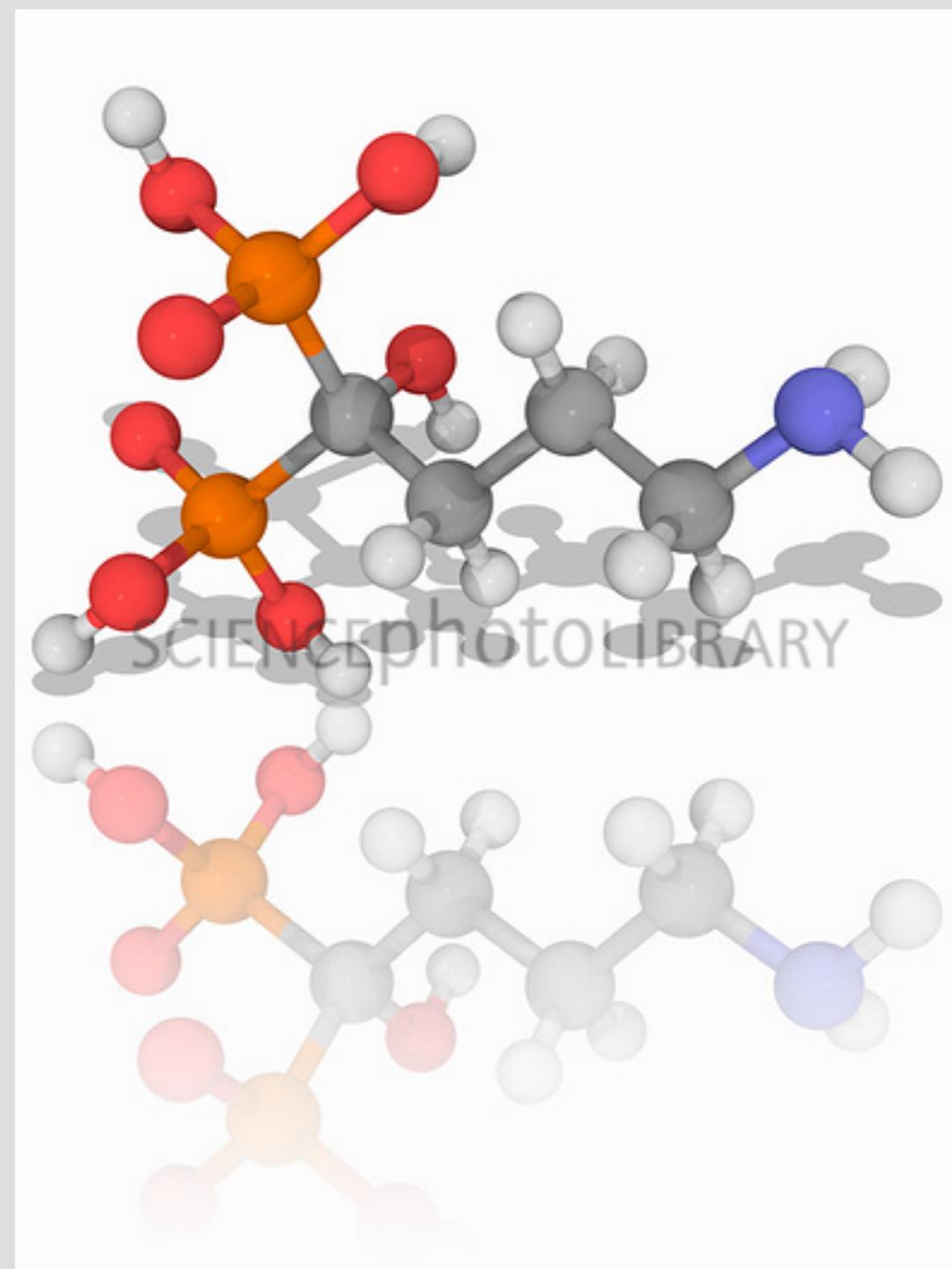
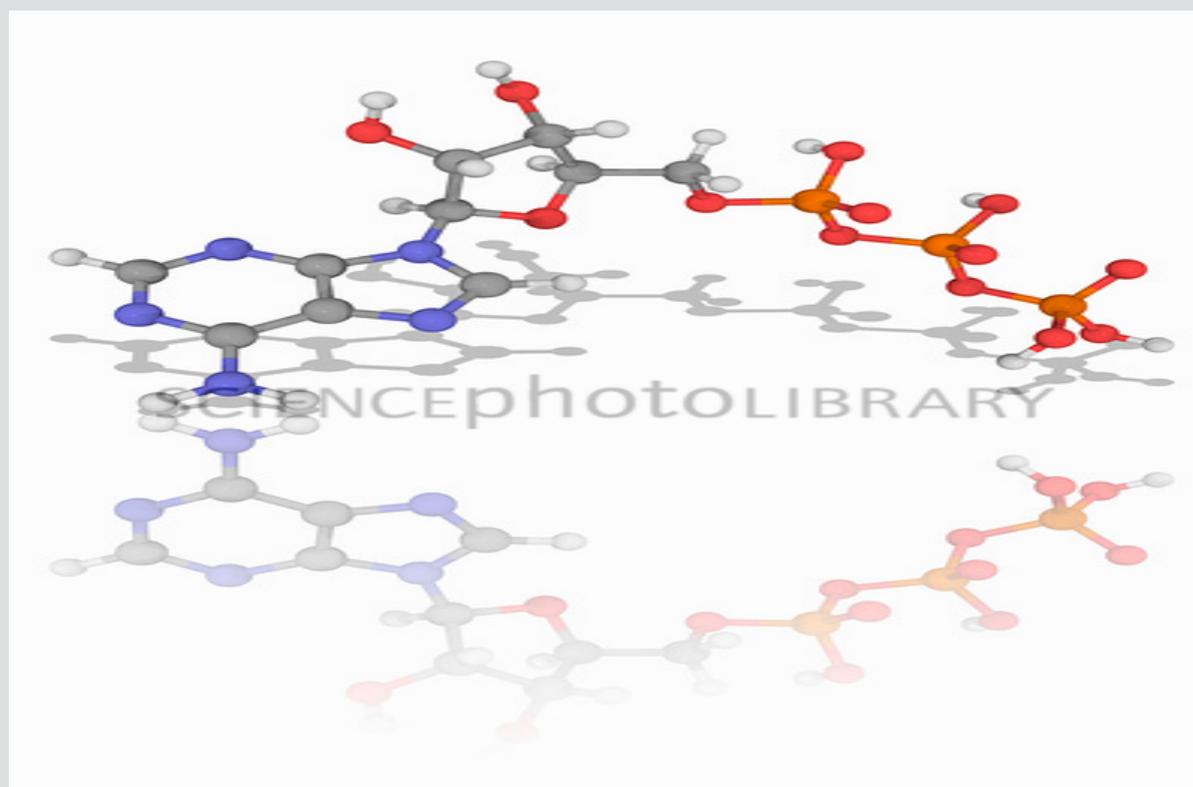
Properties



physicsworld

TOP 10
BREAKTHROUGH
2015





Simple ORGANIC COMPOUNDS:

There structure and ground state energy



Database



Regression



Prediction

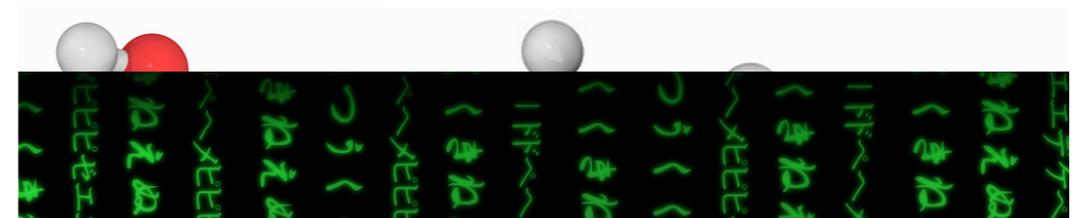
Database

extract **GEOMETRIC** information

动画效果
tell machine learning it's a 3D system
add on lattice

+features: Coulomb matrix
+targets: ground state energy

- **Basic Feature** atoms' position & charge
- **Interaction** Coulomb interaction
- **Other** symmetry



$$M_{ij} = \begin{cases} 0.5Z_i^{2.4} & i=j \\ \frac{Z_i Z_j}{\|\mathbf{R}_i - \mathbf{R}_j\|_2} & i \neq j \end{cases}$$



Kernel: ?

1. kernel theory
2. functional form
3. linear

Regression

build **GEOMETRY-ENERGY** map

how to validate it's a right kernel

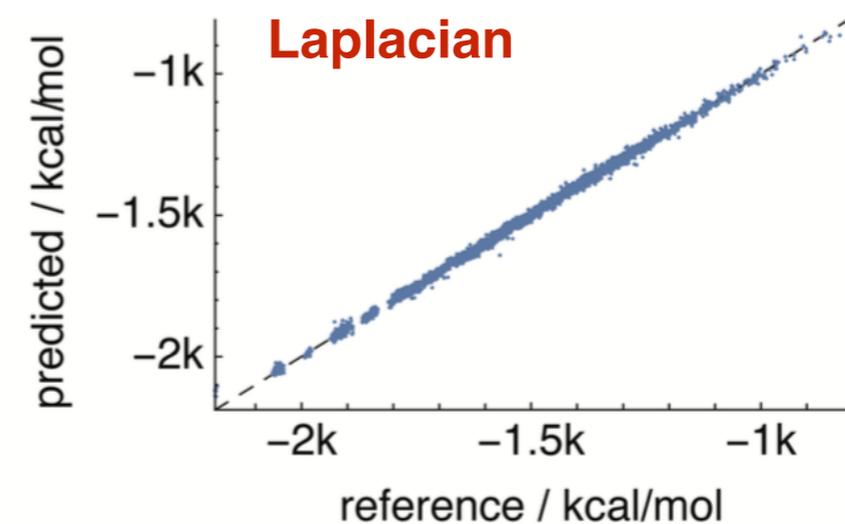
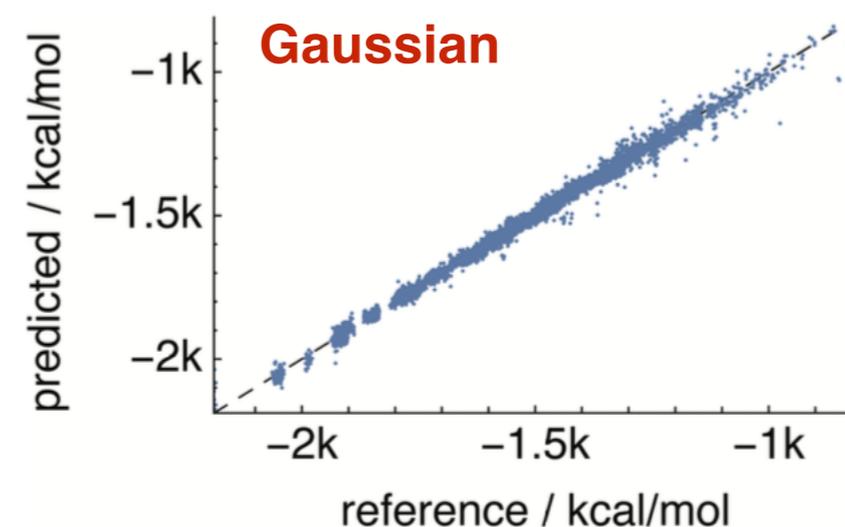
the relationship between geometry and energy is complex, maybe non-linear, therefore, we use KRR as a tool to build our map

acceptance ratio ?

time complexity ?

- **Non-linear** kernel trick
(Gaussian kernel, Laplacian kernel
- **Kernel Ridge Regression**

M. Rupp. Int. J. Quantum Chem. 2015, 115,
1058–1073. DOI: 10.1002/qua.24954



Limitation & Outlook

- Limits:
 - the training data (DFT generated)
 - interpolation
- Future work:
 - universal functional (electron only term)
 - connections among different materials (kernel)

instead of considering a single microscopic system, we should pay more attention to multiple such system and find their connections

rethink the red part

Summary

- DFT: generally implementable, time consuming
- ML: experienced, accurate, efficient
- Able to do large scale computation more precisely

Reference

- S. Cottenier, Density Functional Theory and the family of (L)APW-methods: a step-by-step introduction, 2002-2013 (2nd edition), ISBN 978-90-807215-1-7 (freely available at http://www.wien2k.at/reg_user/textbooks).
- M. Rupp. Int. J. Quantum Chem. 2015, 115, 1058–1073. DOI: 10.1002/qua.24954
- Rasmussen, Williams: Gaussian Processes for Machine Learning, MIT Press, 2006.
- Justin Domic: Kernel method and SVM, Lecture notes.
- The Top 100 papers, Nature vol.514, Oct.30, 2014

Thank you for your
attention