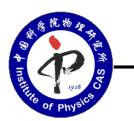
## 强关联电子系统的数值方法简介

## 杨义峰

## 中国科学院物理研究所



http://hf.iphy.ac.cn





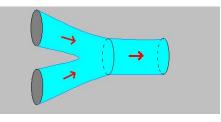


2018年科学计算论坛@中科院数学院

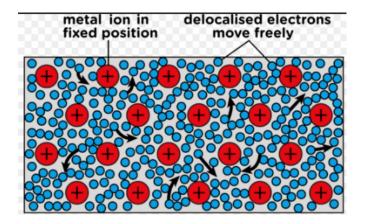
## High energy/particle physics



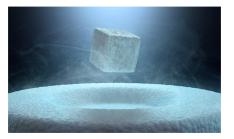
- ◎ 高能物理本质上是低能物理,从低能走向高能
- ☞ 借助加速器,观测身边"低能"世界的结构单元
- ⊌ 寻找更底层 / 高能的理论,解释这些单元的成因



## Condensed matter physics



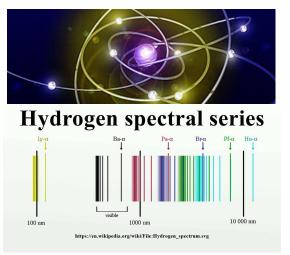
- ◎凝聚态物理本质上是高能物理,从高能走向低能
- ◎ 借助实验,观测电子等已知结构单元因相互作用而产生的复杂低能现象



Also known as "solid state physics" in 50s

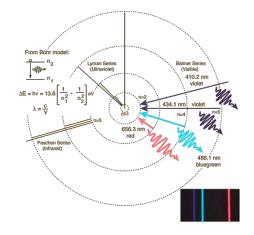
## It all begins with Quantum Mechanics/Statistics

## Quantum Mechanics

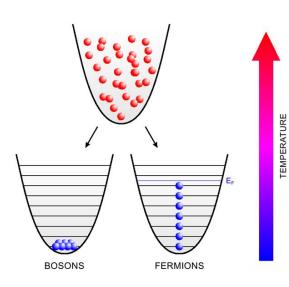


# Schröding $i\hbar \frac{\partial y}{\partial t} = -\frac{\hbar^2}{2m}$

#### 薛定谔方程的本征值H $\psi$ =E $\psi$ 即为电子轨道能量



#### Quantum Statistics



#### 电子为费米子,满足Pauli不相容原理

<i></i> 零温下 <i>ψ</i> (r₁,…,r <sub>N</sub> ) 满足反对
易关系,无相互作用时可写
为Slater行列式

$\Psi_{(x_1,x_2,\cdots,x_n)}=rac{1}{\sqrt{N!}}$	$\chi_{i(x_1)}$	$\chi_{j(x_1)}$	•••	$\chi_{k(x_1)}$
	$\chi_{i(x_2)}$	$\chi_{j(x_2)}$	• • •	$\chi_{k(x_2)}$
		÷	۰.	:
	$\chi_{i(x_n)}$	$\chi_{j(x_n)}$		$\chi_{k(x_n)}$

 $\psi(\dots,\mathbf{x}_{i},\dots,\mathbf{x}_{j},\dots) = -\psi(\dots,\mathbf{x}_{j},\dots,\mathbf{x}_{i},\dots)$ 

● 有限温度下用量子统计系综 Z 描述,引入配分函数

Z=Tr exp(-H/k<sub>B</sub>T)=∑ exp(-E<sub>i</sub>/k<sub>B</sub>T) ⟨O⟩=Z<sup>-1</sup>Tr[Oexp(-H/k<sub>B</sub>T)]

## Real materials: the density functional theory (DFT)

## The Hohenberg-Kohn theorem (1964)

$$\hat{H}^{el} = -\frac{\hbar^2}{2m_e} \sum_{i=1}^n \nabla_{r_i}^2 - \frac{1}{4\pi\varepsilon_0} \sum_{i=1}^n \sum_{\alpha} \frac{Z_{\alpha}e^2}{|R_{\alpha} - r_i|} + \frac{1}{4\pi\varepsilon_0} \sum_{i=1}^n \sum_{j>i} \frac{e^2}{|r_i - r_j|}$$

The Ground-State properties of any system of n-interacting particles are rigourously deduced from the electron density distribution  $\rho(r)$ .

$$E_{n}[\boldsymbol{\psi}_{n}] = \frac{\left\langle \boldsymbol{\psi}_{n}(x_{1},\cdots,x_{n}) \middle| \hat{H}^{el} \middle| \boldsymbol{\psi}_{n}(x_{1},\cdots,x_{n}) \right\rangle}{\left\langle \boldsymbol{\psi}_{n}(x_{1},\cdots,x_{n}) \middle| \boldsymbol{\psi}_{n}(x_{1},\cdots,x_{n}) \right\rangle}$$

$$E_{\nu}[\rho] = \min_{\rho} \left\{ F_{HK}[\rho] + \right\}$$



把对复杂多变量波函数的变分简化为对电子空间密度分布的变分 Nobel Prize in Cher

Walter Kohn was awarded with the Nobel Prize in Chemistry in 1998

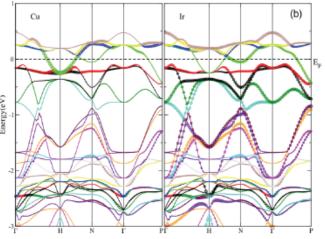
Figure Field Strain Strain Figure Fig

$$\rho_{s}(r) = \sum_{i=1}^{n} \left| \phi_{i}(r)^{2} \right| \qquad \qquad \sum_{i=1}^{n} \left\{ -\frac{1}{2m_{e}} \nabla_{i}^{2} + V_{eff}(r) \right\} \phi_{i}(r) = \sum_{i=1}^{n} \varepsilon_{i} \phi_{i}(r)$$

其中有效势场*Veff* 只存在近似公式,依赖于密度分布函数 ρ 或其空间梯度等,以上方程需自洽求解!

#### Very successful in explaning metal and semiconductor !!!

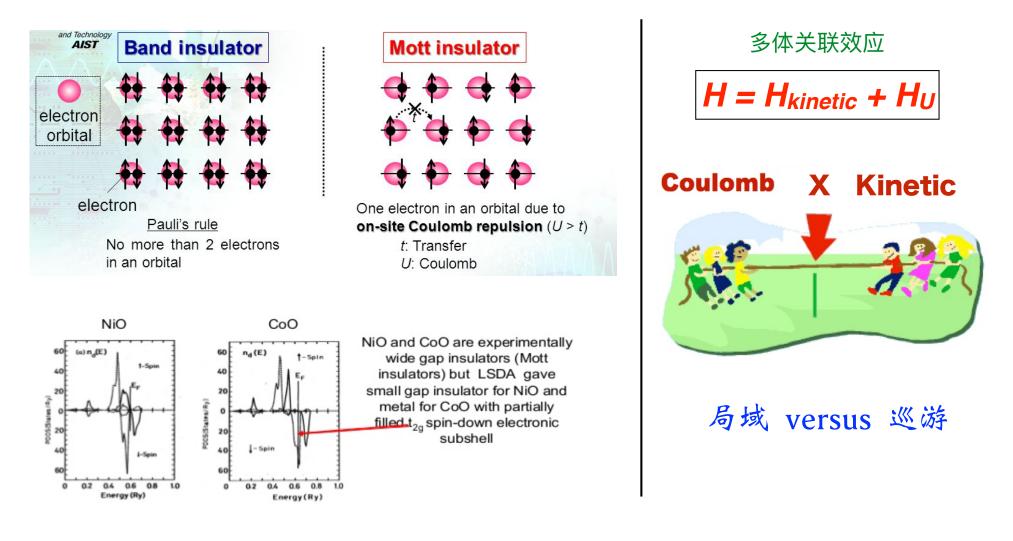




Physical Review Lett. **111,** 176403 (2013) arXiv: 1705.00846 (2017)

## Breakdown of the density functional theory (DFT)

## The role of electronic correlations: localization versus itinerancy



有趣的物理往往都发生在两者交界,如 高温超导 等等 缺乏共识,需要进行严格的数值求解以进行裁决! There are several roads to Rome

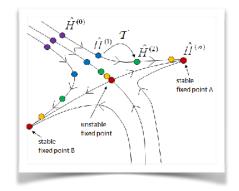
- Renormalization group approach ED/NRG/DMRG/TNRG/...
- Monte Carlo sampling MC/QMC/DQMC/CTQMC/...



每一种方法都有其优势,但又有一定的限制范围!

很不幸的是,这些范围都没能涵盖我们最关心的实际材料中的强关联物理!

## **Renormalization group approach** ED/NRG/DMRG/TNRG/...



## Let's start with the exact diagonalization (ED)

## The ultimate problem is the eigenproblem

$$H|\varphi\rangle = E|\varphi\rangle$$

$$|\phi\rangle = \sum_{\{n_i\}} \phi(n_1, n_2, ..., n_N) |n_1, n_2, ..., n_N\rangle$$

 $\varphi$ 为Hilbert态空间上的一个矢量; 其自然基底为每个格点上电子占据态的直积

$$\underbrace{\underbrace{H}}_{\varepsilon_{1}} \underbrace{\left\{ \begin{vmatrix} 0 \\ 1 \end{vmatrix}, \begin{vmatrix} 1 \\ 1 \end{vmatrix} \right\} \otimes \left\{ \begin{vmatrix} 0 \\ 2 \end{vmatrix}, \begin{vmatrix} 1 \\ 2 \end{vmatrix} \right\}}_{\left\{ \begin{vmatrix} 0, 0 \\ 0 \end{vmatrix}, \left\{ \begin{vmatrix} 0, 0 \\ 0 \end{matrix}, \left\{ \begin{vmatrix} 0, 0 \end{matrix}, \left\{ \begin{vmatrix} 0, 0 \\ 0 \end{matrix}, \left\{ \begin{vmatrix} 0, 0 \end{matrix}, \left\{ \begin{vmatrix} 0, 0 \\ 0 \end{matrix}, \left\{ \begin{vmatrix} 0, 0 \end{matrix},$$



- $\blacksquare$  Size of Hilbert space rise as  $M = s^N$
- $\blacksquare$  Typically only for N  $\lesssim 10$

求解基态可以采用Lanczos方法,求解激发态需要进行严格对角化, 但存在所谓的"指数墙"问题!!!

## Numerical renormalization group (NRG)

Reduce the Hilbert space by throwing away high energy states

$$H = \underbrace{V}_{\text{Imp}} \underbrace{t_{0}}_{0} \underbrace{t_{1}}_{2} \underbrace{t_{2}}_{3} \underbrace{t_{3}}_{4} \underbrace{t_{4}}_{5} \cdots H_{N+1} = H_{N} + H_{N+1}^{hop} \\ H_{N+1} = \sum_{\sigma} t_{N} c_{N\sigma}^{\dagger} c_{(N+1)\sigma} + \text{H.c.}$$

Iterative diagonalization & Truncation (keep fixed number of low energy states)



K. G. Wilson Nobel prize 1982

U=0.1

U=0.2

U=0.4

0.0

20.0

10.0

0.0

-0.2

A(w)

10

10<sup>4</sup>

'E 10<sup>3</sup> 10<sup>2</sup>

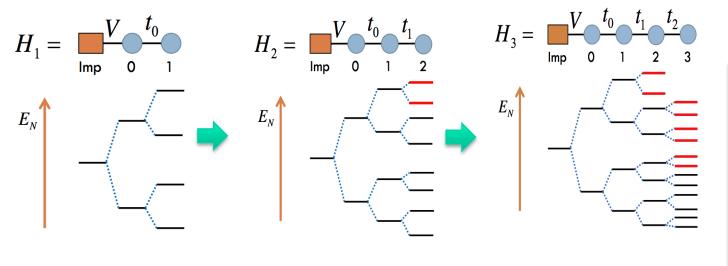
ω

0.00

0.20

0.2

20 0.40



require separation of energy scales ( $t_{N+1}/t_N \sim \Lambda < 1$ )

这解决了强关联物理的一大问题,即单格点(0维)的Kondo问题! NRG方法的背后,是重整化群的思想,亦即系统随尺寸flow到固定点! NRG方法给出了Kondo基态,但局限于较小的s(≤6),且无法处理lattice体系!

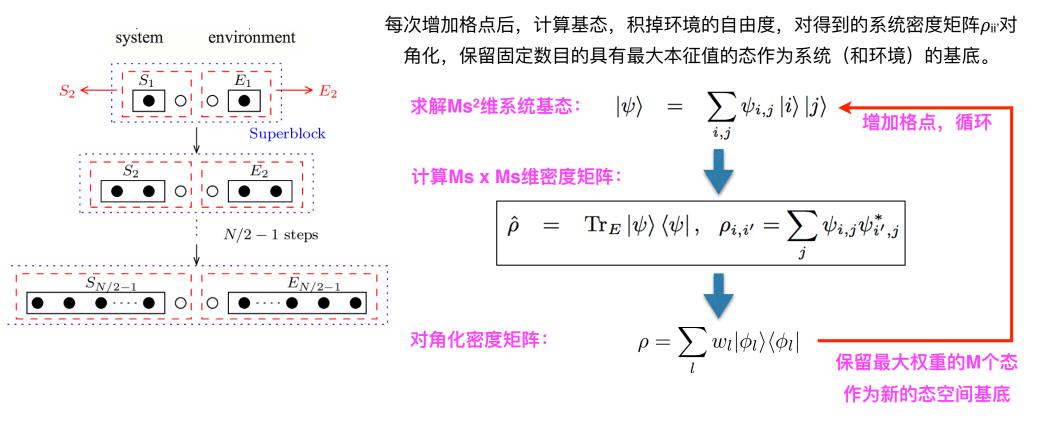
## **Density matrix renormalization group (DMRG)**

### Reduce the Hilbert space by keeping only states with higher weights



DMRG能够比较好地处理一维系统!

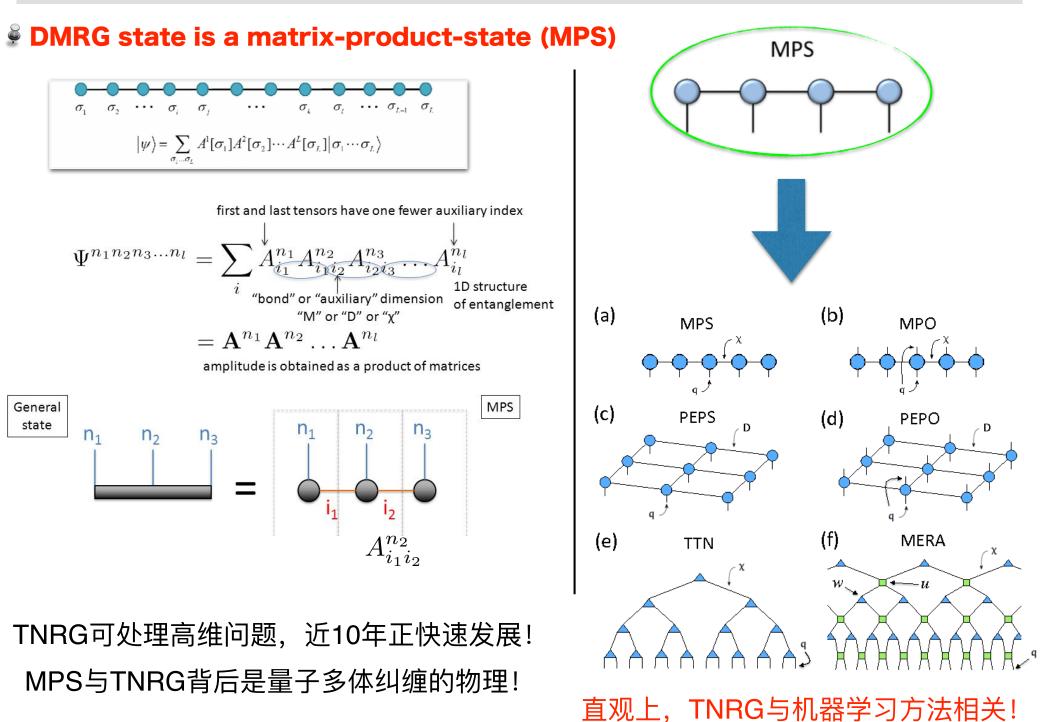
#### Iterative diagonalization & Truncation (keep states of higher weights)



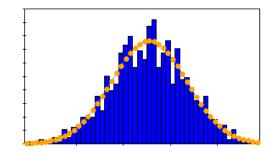
DMRG是处理一维问题的最好数值方法!

但在处理激发态与高维体系时比较困难,而现实材料很多都是2或3维的!

## **Tensor network renormalization group (TNRG)**

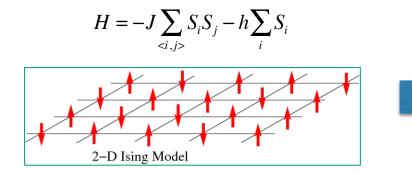


## Monte Carlo simulation MC/QMC/DQMC/CTQMC/...



## **Classical versus quantum Monte Carlo**

Classical Monte Carlo



### 对自旋空间的所有位形按照权重取样

$$Z = \sum_{\{S_i\}} e^{-\beta H(\{S_i\})}, \quad \langle m \rangle = \sum_{\{S_i\}} \frac{1}{Z} e^{-\beta H(\{S_i\})} m(\{S_i\}) = \sum_{\{S_i\}} w(\{S_i\}) m(\{S_i\})$$

Metropolis algorithm ▶随机选择z,翻转自旋:  $\left\{\overline{S_i}\right\} = (S_1^k, S_2^k, \dots, -S_z^k, \dots, S_N^k)$ ▶计算前后权重的比值:  $\alpha = \frac{w(\{\overline{S}_i\})}{w(\{S_i\})} = e^{-\beta(H(\{\overline{S}_i\}) - H(\{S_i\}_k))} = e^{-\beta\Delta E}$ 

▶选择随机数 $\gamma$ ,若 $\alpha \geq \gamma$ ,接受新位形,否则拒绝!

## Quantum Monte Carlo (QMC)

对任一位形,H({Si})为一数

 $H = U \sum_{i} c_{i\uparrow}^{\dagger} c_{i\uparrow} c_{i\downarrow}^{\dagger} c_{i\downarrow} - t \sum_{\langle ij \rangle \sigma} c_{i\sigma}^{\dagger} c_{j\sigma}$ TT

对任一状态,H({Si})不是数, 需要构造新的位形空间!

## 多种处理方法

☑辅助场QMC:引入合适的经典辅助场,将费米子态积掉, 得到辅助场的有效作用量,在辅助场的位形空间进行取样。 Hubbard-Stratonovich变换:

$$\exp\left[-\Delta\tau U(n_{\uparrow}n_{\downarrow}-\frac{1}{2}(n_{\uparrow}+n_{\downarrow}))\right]=\frac{1}{2}\mathrm{Tr}_{\sigma}[\exp[\lambda\sigma(n_{\uparrow}-n_{\downarrow})]$$

 $Z = \sum_{\{\sigma_i\}} D(\{\sigma_i\})$  After integrate out the "free" fermions, sample  $\{\sigma\}$  with the Metropolis algorithm

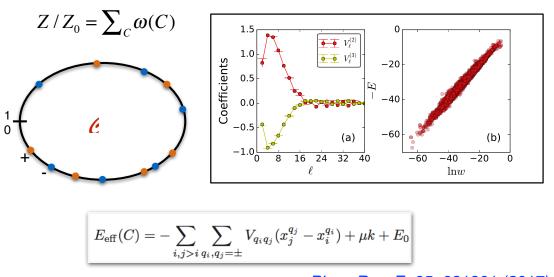
☑ 连续时间QMC: 在配分函数中将动能t项或相互作用U项做 微扰展开,以自由电子(t)或孤立原子(U)为背景,对微扰展 开项进行取样。

## **Comment on quantum Monte Carlo Simulations**

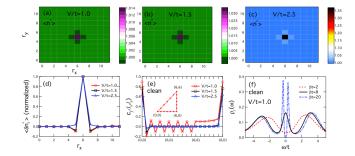
☑ 非常成功地处理一大批问题,是强关联主要方法之一 Kondo问题、Mott问题、玻色子系统等等

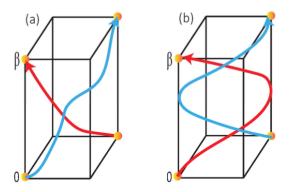
 ✓ 在很多重要的问题上,存在难以避免的"符号问题"
费米子的交换反对称性,导致配分函数权重可能为负 某些情况下,对称性可以抑制"符号问题"

☑ 在低温和自由度较多或体系尺寸大时,计算速度慢 要寻找可能的加速方法,如结合机器学习寻找推荐系统

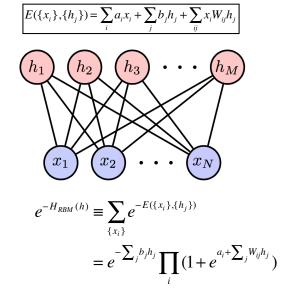


Phys. Rev. E 95, 031301 (2017)

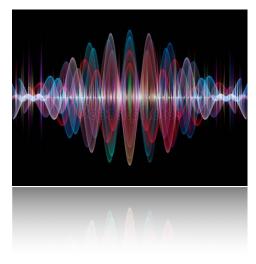




Restricted Boltzmann Machine



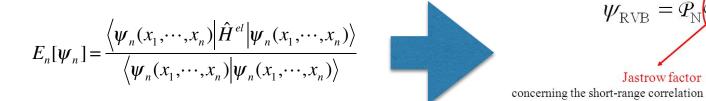
## Trial wave function/variational method Gutzwiller/BCS/Laughlin/...

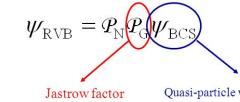


## **Construct trial wave function using neural network**

## An well-known example of the trial wave functions

The goal is to find a good approximation of the ground state wave function



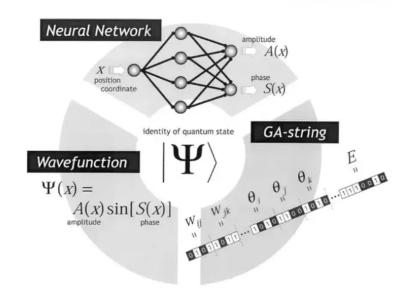


due to strong on-site repulsion

Quasi-particle wave function concerning the long-range correlation due to the BCS Hamiltonian

把复杂的求基态多体波函数的问题,转变为对有限几个自由参量求变分的问题

## The neural network as a trial wave function



就我目前了解,机器学习方法还没有能够 真正帮助解决凝聚态物理的任何困难问题; 反过来,凝聚态物理的方法似乎对理解神 经网络提供了一些新的视角。

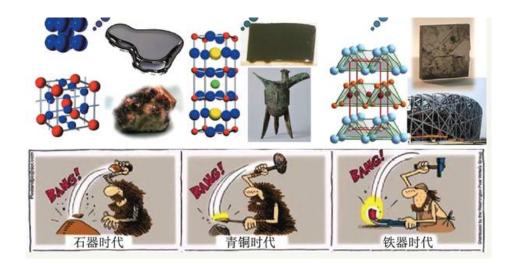
## Summary

Various approaches to solve correlated electron systems

weak correlation: density functional theory (DFT); *extension of DFT?* strong correlation: NRG/DMRG/*TNRG*; MC/QMC/CTQMC



- Each method has its own advantages and problems
  - ☑ computational cost, dimensionality, sign problem, uncontrolled approximation
- It is demanding in order to settle down the already exhausting debates
  - Too many uncertainties, no consensus so far; *is machine learning useful?*



Unusual richness of strongly correlated materials !!!

**Coulomb X Kinetic** 



局域 versus 巡游



2018年科学计算论坛@中科院数学院