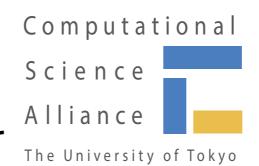
古典統計力学模型と数値計算

Classical Statistical Models and Numerical Simulation

理学系研究科 物理学専攻 大久保 毅

Department of Physics, Tsuyoshi Okubo





Background of the lecturer

大久保 毅(OKUBO Tsuyoshi)

Projecto Lecturer, Department of Physics, Sci. Bldg. #1 940

Research:

Statistical Physics, Condensed matter physics, Magnetism, (Computational Physics)

- Random packing of disks
- Mean-filed analysis of hierarchical society
- Ordering of (classical) frustrated spin system
 Skyrmion, multiple-Q states, Z₂-vortex

 Monte Carlo
 (Spin) dynamics
- Deconfined quantum criticality

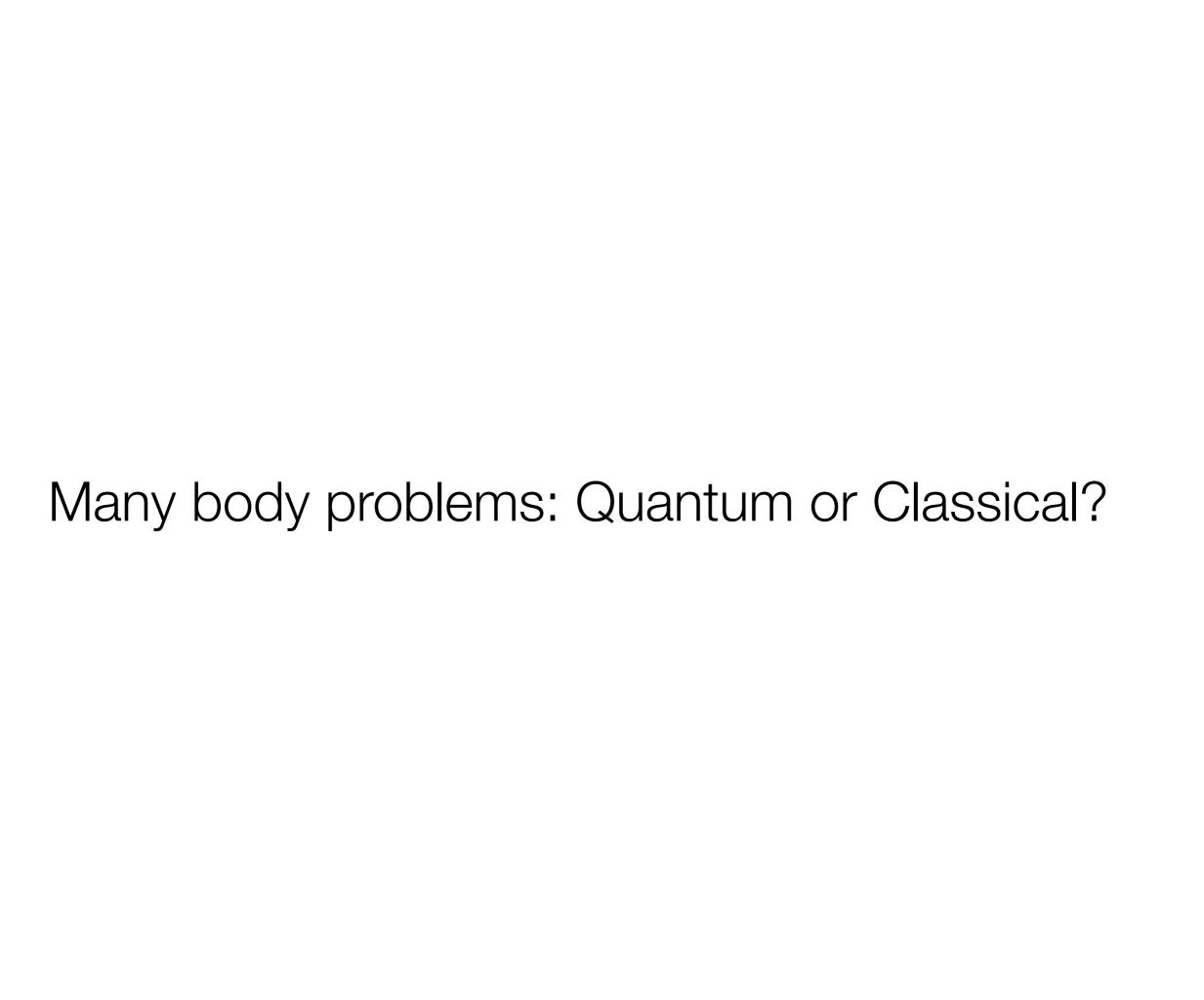
Tensor network

•

Quantum Monte Carlo

Outline

- Many-body problems: Quantum or Classical?
 - When we can use classical "models"?
- Targets of this lecture
 - Targets of computational sciences
 - Examples of classical models
- Computational science for classical statistical models
 - Statistical ensembles
 - Long time average and relaxation time



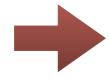
Many-body problems: Quantum or Classical?

Two types of classical many-body problems

1. Approximation of quantum problems

Nature: Elementary particles obey quantum mechanics.

$$i\hbar \frac{\partial}{\partial t} |\Psi\rangle = \mathcal{H} |\Psi\rangle$$



Classical mechanics is an approximation.

2. Pure classical problems

Classical problems not necessary based on quantum mechanics

- Percolation, covering, packing, ...
- · Stochastic process, dynamical system (力学系),..
- Critical phenomena (臨界現象)

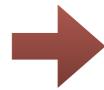
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Classical problems as an approximation: molecules

Interaction of molecules:

- Coulomb interactions of charges
- Van der Waals force
- •

For accurate treatments, we need to consider quantum mechanics.



However, we can approximate the system as a set of "classical" point particles.

Approximated two-body interactions between classical particles:

- Lennard-Jones potential for noble gas
- Effective potential for water
- •

Example: water (H₂O)

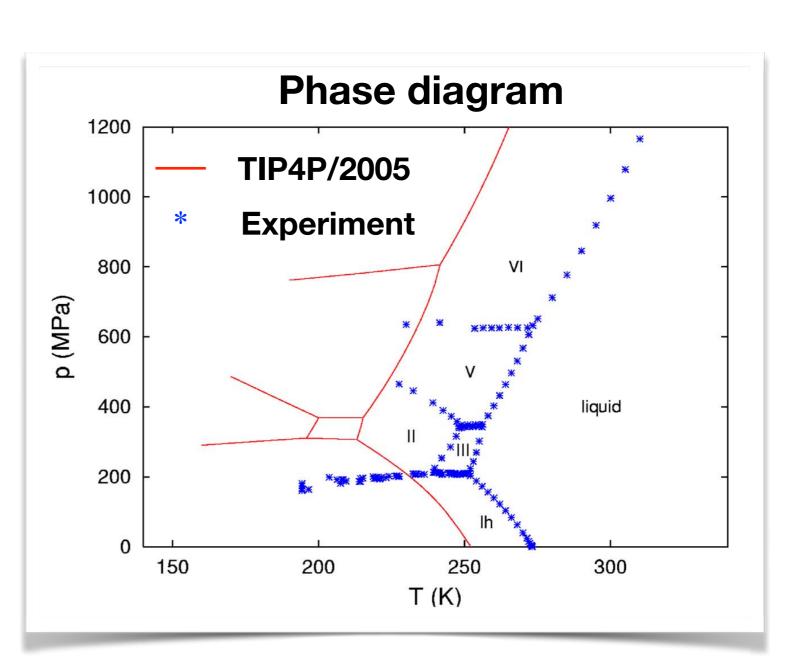
For H₂O, there are lots of effective potentials

Example: TIP4P/2005 (J. L. F. Abascala and C. Vega, J. Chem. Phys. 123, 234505(2005))

O: LJ potential
(Its charge is located at Q)
H: point charge
*Their relative locations are fixed.



Phase diagram of water is qualitatively reproduced!

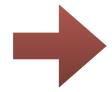


Classical problems as an approximation: magnetism

(Electron) spins: "Quantum" degree of freedom

For accurate treatment, the spin quantum number S is important:

$$S=1/2, 1, 3/2, \dots$$



However, we can approximate the system by taking the limit of $S \rightarrow \infty$.

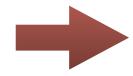
"classical" spin model

- Classical Heisenberg model
- Anisotropy: Ising model, XY model
- •

Example: ferromagnetism

Iron (Fe): Ferromagnet (強磁性体)

Below the Curie temperature $T_c \approx 1043 \text{ K}$, it exhibit spontaneous magnetization (自発磁化).



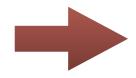
The most simple approximation for the ferromagnet:

Classical Heisenberg model

$$\mathcal{H} = -\sum_{(i,j)} J_{ij} S_i \cdot S_j$$

Heisenberg spin: $S_i = (S_i^x, S_i^y, S_i^z)$

Three component unit vector: $(S_i^x)^2 + (S_i^y)^2 + (S_i^z)^2 = 1$



The Heisenberg model on the bcc lattice shows a phase transition at $T_c \approx 2.054 J$.

Classical problems as an approximation

When a classical approximation becomes accurate?

- High temperature
 - We safely neglect quantum nature compared with thermal fluctuations.
- Low density
 - The interaction between particles is small (rare).
- Classical order (magnetism)
 - If the ground state is classical magnetic long range order, typically, classical approximation is not so bad.

Pure classical problems: Critical phenomena

Critical phenomena:

At the critical point, characteristic length scale diverges



Scale invariance

Several quantities show power-low behaviors

Correlation length : $\xi \sim |T - T_c|^{-\nu}$

Specific heat : $C \sim |T - T_c|^{-\alpha}$

Susceptibility: $\chi \sim |T - T_c|^{-\gamma}$

Order parameter: $M \sim (T_c - T)^{\beta}$

Exponent: $\alpha, \nu, \gamma, \beta, \dots$

 T_c

=Critical exponent

Pure classical problems: Critical phenomena

Universality

Critical exponents depends only on symmetry and spacial dimensions.

Ising model: the order parameter has Z₂ symmetry

Ising systems	$ $ α	β	γ	ν	η
2D-Ising(exact)	0	1/8=0.125	7/4=1.75	1/2=0.5	0
Fe film ^a	N/A	0.13 ± 0.02	1.74 ± 0.05	N/A	N/A
3D-Ising ^b	*0.10994	*0.3264	*1.23719	0.63002(10)	0.03627(10)
Dy ₃ Al ₅ O ₁₂ c,d	0.12 ± 0.03	0.26 ± 0.02	1.16±0.04	0.61 ± 0.02	N/A
LJ(model liquid)e	*0.11	0.3285(7)	*1.2	0.63(4)	*0.1
Xef	0.110 ± 0.003	0.325±0.002	1.241±0.002	0.630 ± 0.002	N/A

a:C.H. Back et al Nature (1995), b:M. Hasenbusch, PRB (2010), c:A Guttmann, J.Phys.C(1975), d:J.C.Norvell et al, Phys.Rev. (1969). e:H. Watanabe et al, JCP(2012), f: taken from table in K. Gills et al, PRE(2004).*: calculated assuming scaling relations.



A lot of critical phenomena are exactly understood from classical models.

Pure classical problems: other examples

- Percolation problem
 - Physics of Bingo game
- Sphere packing
 - What is the most dense packing in a box?
 - Packing structure of poly-disperse systems?
- Stochastic process
 - Dynamics of financial trades
 - Dynamics of population, society, ...

Target of this lecture

Target of studies: Static or Dynamic

Static properties:

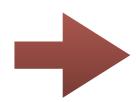
Physical properties independent on time.

(free) energy, specific heat, (static) susceptibilities, ...

Dynamical properties:

Related to a response to external forces.

Time-dependent susceptibilities, Time-Correlations,



By computational science, both types of quantities can be calculated, although the method could depend on the type.

(Typically, dynamical properties are more difficult to obtain.)

Target of studies: Equilibrium or Non-Equilibrium

Equilibrium system:

Systems are described by thermodynamics

Non-Equilibrium system:

Systems are not described by thermodynamics

Steady state:

Its physical quantities are independent of time.

Non-steady state:

Its physical quantities depend on time.

Typically, treatment of non-steady state is very difficult.

Target of my lecture

Steady state of classical system (not necessarily in equilibrium)

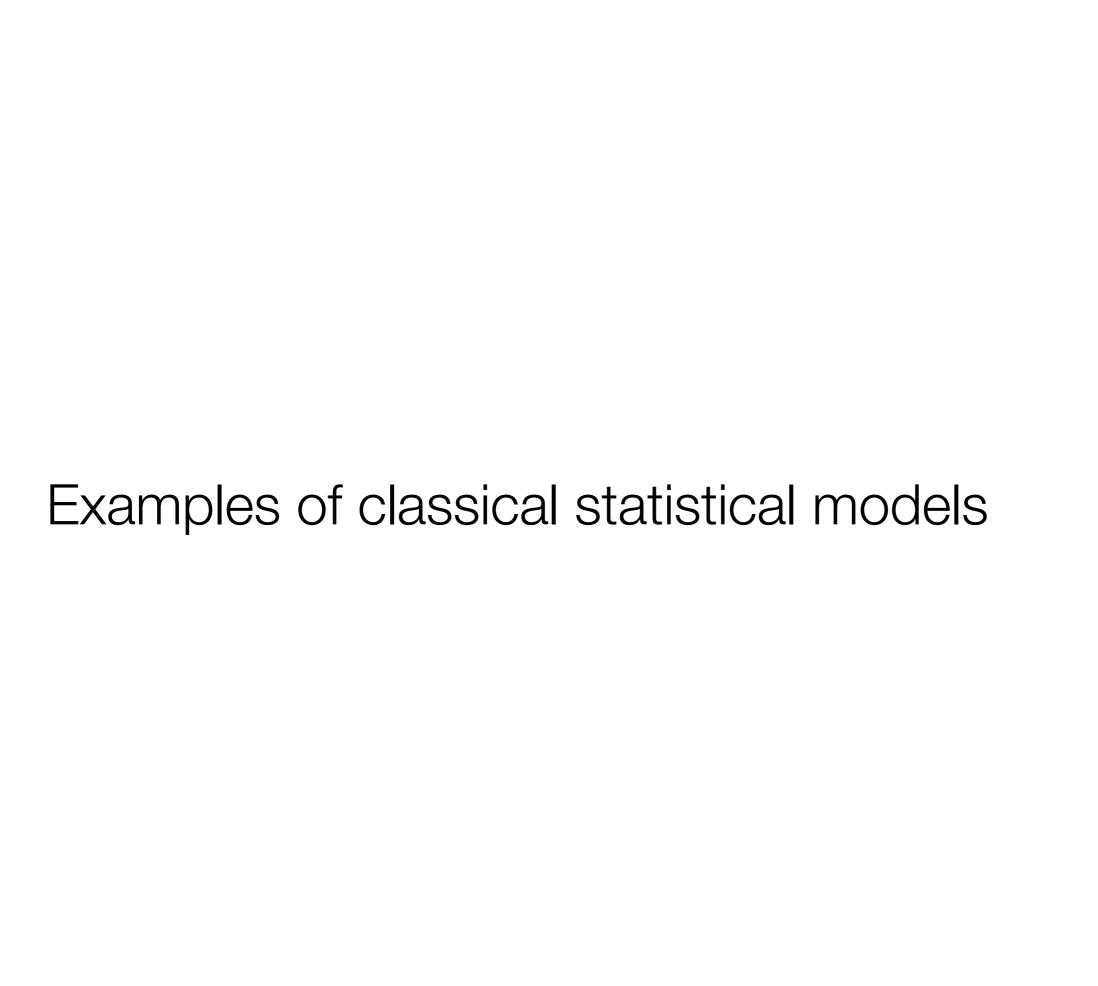
Physical quantities are calculated through steady state distribution $P(\Gamma)$

$$O = \langle \hat{O} \rangle = \operatorname{Tr}_{\Gamma} \left(\hat{O}(\Gamma) P(\Gamma) \right)$$

$$C(\tau) = \langle \hat{A}(t=0) \hat{B}(t=\tau) \rangle = \operatorname{Tr}_{\Gamma} \left(\hat{A}(\Gamma) \hat{B}(\Gamma(\tau)) P(\Gamma) \right)$$

$$\Gamma = \{S_i\}, \{q_i, p_i\}, \dots \text{ state in the phase space}$$

Q. Are you familiar with statistical physics?



Statistical mechanical models:

Models considered in this lecture:

- Classical Spin systems
 - Ising, XY, Heisenberg, ...
 - Frustration, DM interactions, Anisotropy, ...
- Particle systems
 - Point particles, Molecules, hard spheres,...

Models related to the methods presented in this lecture:

- Agent models of socio-physics
- Lattice models representing (non-equilibrium) steady state
 - ASEP (ASymmetric Exclusion Process), lattice gas, ...
- Langevin dynamics (Stochastic differential equation)
 - Brownian motion, econophysics, ...

Classical spin system: spin model on lattice

Spin systems:

Spin degree of freedoms defined on a lattice (they interact each other).

Lattice 1D Square lattice Kagame lattice 2D

Simple cubic, FCC lattice, BCC lattice, ...

Classical spin degree of freedom

Spin:

- 1. $S \to \infty$ limit of quantum spin
- 2. simple degree of freedom reflecting symmetry
- 1. Ising spin $S_i = \pm 1 = \uparrow, \downarrow$
 - Strong easy axis anisotropy
 - Representing underlying Z₂ symmetry
- 2. Heisenberg spin $S_i = (S_i^x, S_i^y, S_i^z)$

Three component unit vector: $(S_i^x)^2 + (S_i^y)^2 + (S_i^z)^2 = 1$

- 3. XY spin $S_i = (S_i^x, S_i^y)$ Two component unit vector: $(S_i^x)^2 + (S_i^y)^2 = 1$
 - Strong easy plane anisotropy
 - Representing underlying U(1) symmetry

Classical spin model: interactions

Heisenberg spin
$$S_i = (S_i^x, S_i^y, S_i^z)$$

Heisenberg interaction:

$$\mathcal{H} = J_1 \sum_{\langle i,j \rangle} S_i \cdot S_j + J_2 \sum_{\langle \langle i,j \rangle \rangle} S_i \cdot S_j$$

Single ion anisotropy

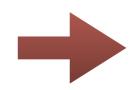
$$D\sum_{i} (S_{i}^{z})^{2} + E\sum_{i} \left[(S_{i}^{x})^{2} - (S_{i}^{y})^{2} \right]$$

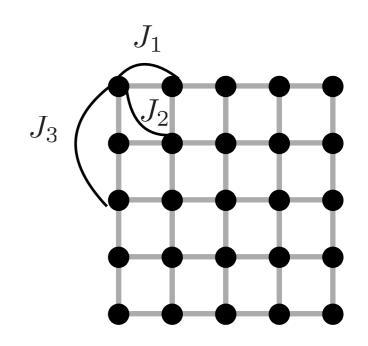
 $D \rightarrow +\infty$: XY spins

 $D \rightarrow -\infty$: Ising spins

Dzyaloshinskii-Moriya interaction

$$\sum_{\langle i,j\rangle} \vec{D} \cdot (S_i \times S_j)$$





A lot of "novel" magnetism appears even in classical spin system

Example: Magnetic skyrmion

T. Okubo et al Phys. Rev. Lett. 108, 017206 (2012).

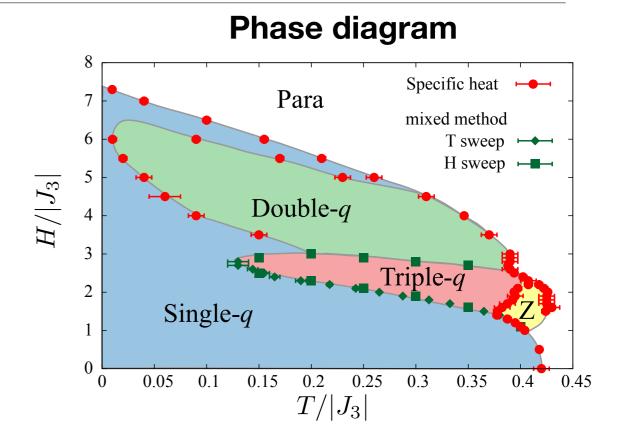
Classical antiferromagnetic Heisenberg model on triangular lattice under magnetic fields

By considering J_1 and J_2 (or J_3) interaction (effective model for NiGa₂S₄)

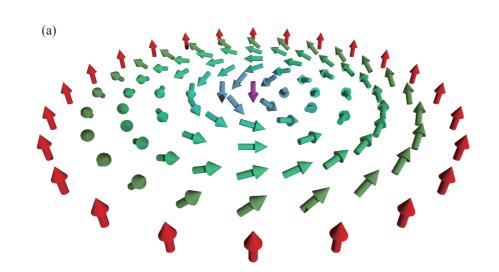


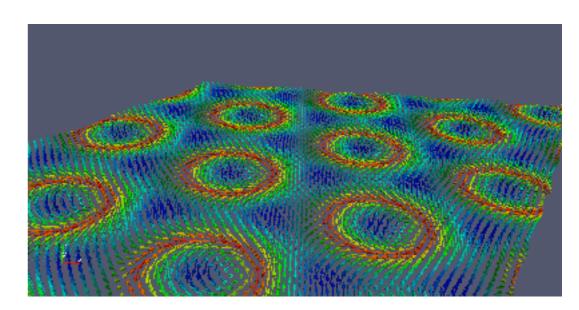
Novel multiple-q states are stabilized

One of them is identical with "magnetic skyrmion lattice"



This has been also investigated by **Monte Carlo simulation**.





Particle system:

Particle systems:

Particles moving in continuous space by interacting each other

Typically, their degree of freedoms are "positions" and "momentum"

Two components in Hamiltonian

Interacting potential: $V(\mathbf{r}_i - \mathbf{r}_j)$

Kinetic Energy: $\frac{p_i^2}{2m_i}$

Phase space: $\Gamma = \{ \boldsymbol{r}_i, \boldsymbol{p}_i \}$



N-particles= 2dN dimension

Variety of models: variety of interacting potentials

Hard sphere

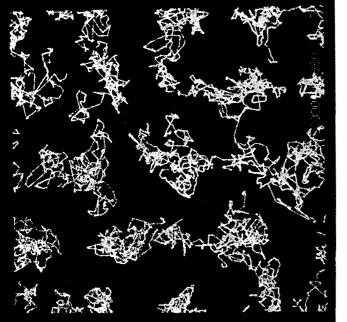
$$V(\boldsymbol{r}_i - \boldsymbol{r}_j) = egin{cases} 0 & (r > r_c) \\ \infty & (r \le r_c) \end{cases} \quad r = |\boldsymbol{r}_i - \boldsymbol{r}_j| \qquad V(r) \quad \stackrel{\infty}{\longleftarrow}$$

The first application of molecular dynamics

Alder and Wainwright, J. Chem. Phys. 27, 1208 (1957);31, 459 (1959)

Event driven molecular dynamics simulation

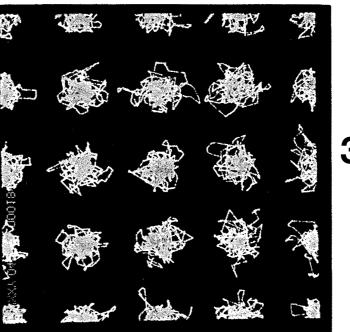




Phase transition
(Alder transition)



Crystal

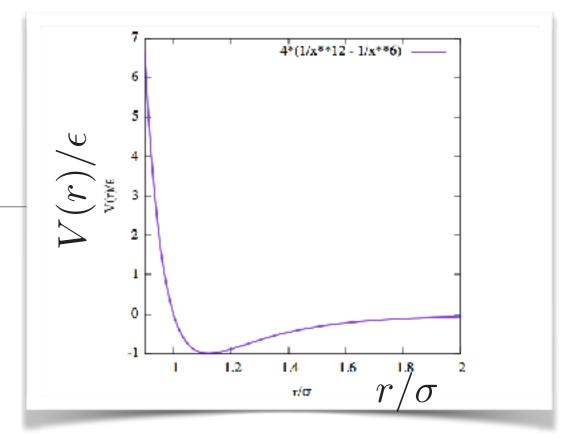


32 particle system

Lennard-Jones potential

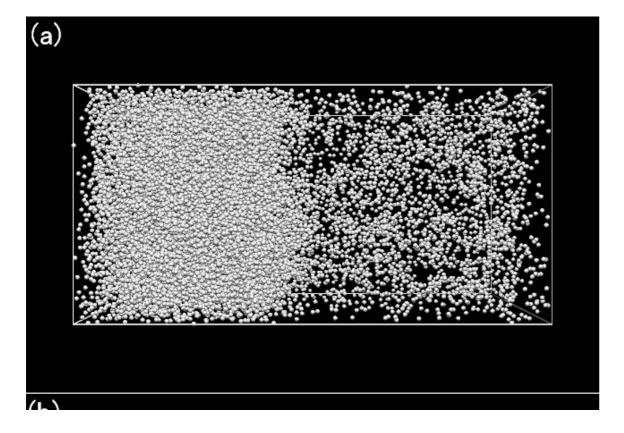
$$V(r) = 4\epsilon \left[\left(\frac{\sigma}{r} \right)^{12} - \left(\frac{\sigma}{r} \right)^{6} \right]$$

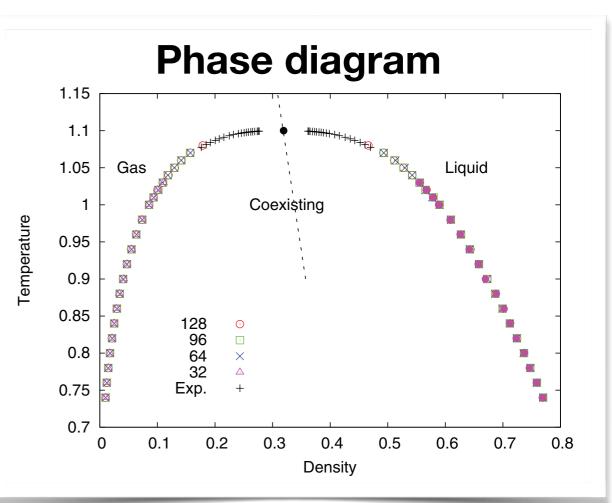
Model potential for noble gas (Ar, ...)



Recent simulation: H. Watanabe et al, J. Chem. Phys. **136**, 204102 (2012). (~1,000,000 particles)

Gas-Liquid coexistence





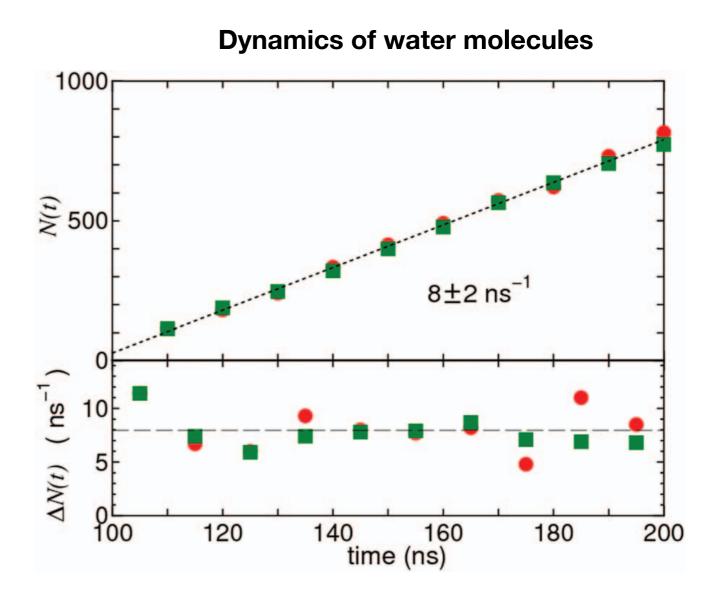
Complex systems

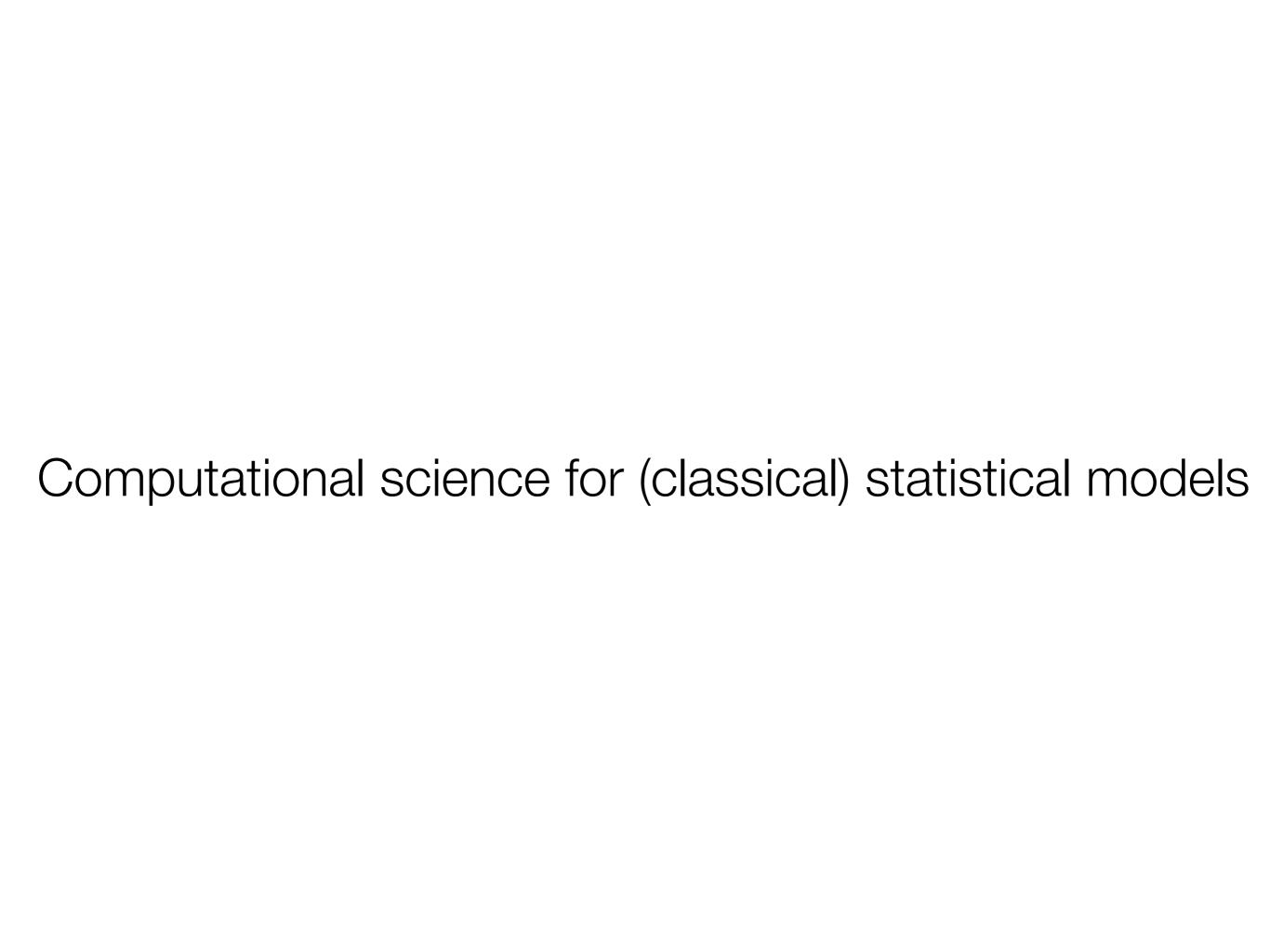
Eg. Poliovirus capsid in electrolyte solution (電解質溶液)

Y. Ando et al, J. Chem. Phys. 141, 165101(2014).

Long-range coulomb interaction

Poliovirus capsid





Statistical mechanics: Ensemble

Statistical mechanics:

Connect microscopic models to macroscopic observable

Example: Ising model

$$\mathcal{H} = -J \sum_{\langle i,j \rangle} S_i S_j - h \sum_i S_i$$

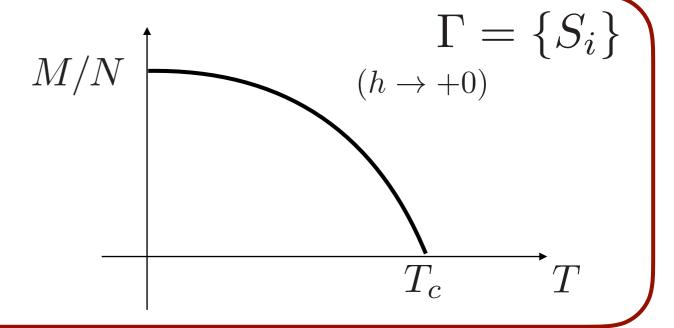
$$(S_i = \pm 1 = \uparrow, \downarrow)$$

Canonical ensemble (NVT-ensemble):

$$P(\Gamma; T) = \frac{1}{Z} \exp\left(-\frac{1}{k_B T} \mathcal{H}(\Gamma)\right)$$

Example: magnetization at T:

$$M(T) = \left\langle \sum_{i} S_{i} \right\rangle_{T}$$
$$= \sum_{\Gamma} \sum_{i} S_{i} P(\Gamma; T)$$



Statistical mechanics: important ensembles

Micro Canonical ensemble (NVE-ensemble):

$$P(\Gamma; E) \propto \sum_{\Gamma} \delta(E - \mathcal{H}(\Gamma))$$

E: energy

NPT-ensemble:

$$P(\Gamma; P, T) \propto \int dV e^{-\beta PV} \sum_{\Gamma(V)} e^{-\beta \mathcal{H}(\Gamma)}$$

P: pressure $\beta = \frac{1}{k_B T}$

Grand Canonical ensemble (µVT-ensemble):

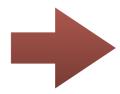
$$P(\Gamma;\mu,T) \propto \sum_N rac{1}{N!} e^{eta \mu N} \sum_{\Gamma(N)} e^{-eta \mathcal{H}(\Gamma)}$$
 μ : chemical potential

General ensemble:

- Not necessarily related to thermal equilibrium
- But, it may represent a steady state of a certain physical system
 - Non-equilibrium steady state

Computational science for statistical models

Purpose of computational science



Calculate ensemble averages numerically

Two types of approaches

- Evaluate ensemble average as a "time average" based on a special dynamics
 - Monte Carlo (MC) , Molecular Dynamics (MD)
 - Target of this lecture
- Calculate partition function directly
 - Transfer matrix method, Tensor network method
 - ・ It will be treated partly in "計算科学における情報圧縮 (A-term)"

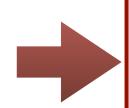
Long time average

Long time average for ensemble average

States depending on time

$$\Gamma(t) = \{q_i(t), p_i(t)\}, \{S_i(t)\}, \cdots$$





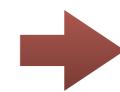
$$\langle \hat{O} \rangle = \lim_{T \to \infty} \frac{1}{T} \int_0^T \hat{O}(\Gamma(t)) dt$$
$$= \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^T \hat{O}(\Gamma(t))$$

 $\hat{O}(\Gamma)$: Observable such as

Energy, magnetization, momentum, force, ...

If we can find a good dynamics which satisfies

$$\lim_{T \to \infty} \frac{1}{T} \int_0^T \hat{O}(\Gamma(t)) = \int d\Gamma P(\Gamma)$$



We can calculate **ensemble averages** through **dynamical simulations**.

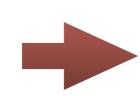
(Time average coincides with an ensemble average.)

Typical dynamics:

Molecular dynamics:

Dynamics of Γ obeys a differential equation (Newtonian equation).

$$\frac{d}{dt} \begin{bmatrix} q_i \\ p_i \end{bmatrix} = \begin{bmatrix} \frac{\partial \mathcal{H}}{\partial p_i} \\ -\frac{\partial \mathcal{H}}{\partial q_i} \end{bmatrix}$$



The Hamiltonian is constant of the motion.

The long time average gives us an average over micro canonical ensemble.

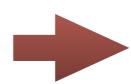
Markov Chain Monte Carlo:

Dynamics of Γ obeys a master equation.

$$\rho_{t+1}(\Gamma) - \rho_t(\Gamma) = \sum_{\Gamma'} W_{\Gamma' \to \Gamma} \rho_t(\Gamma') - \sum_{\Gamma'} W_{\Gamma \to \Gamma'} \rho_t(\Gamma)$$

 $ho_t(\Gamma)$:probability distribution

 $W_{\Gamma \to \Gamma'}$:transition probability



The long time average gives us a variety of ensemble averages depending on W.

Time Correlation and relaxation time

Time correlation function

$$C_{AB}(t) \equiv \langle \hat{A}(0)\hat{B}(t)\rangle - \langle \hat{A}\rangle\langle \hat{B}\rangle$$

Auto correlation function

$$C_{AA}(t) \equiv \langle \hat{A}(0)\hat{A}(t)\rangle - \langle \hat{A}\rangle^2$$

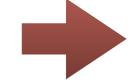
*Average over initial states

$$\langle \hat{O}(t) \rangle = \int d\Gamma \hat{O}(\Gamma(0)) P(\Gamma(0))$$

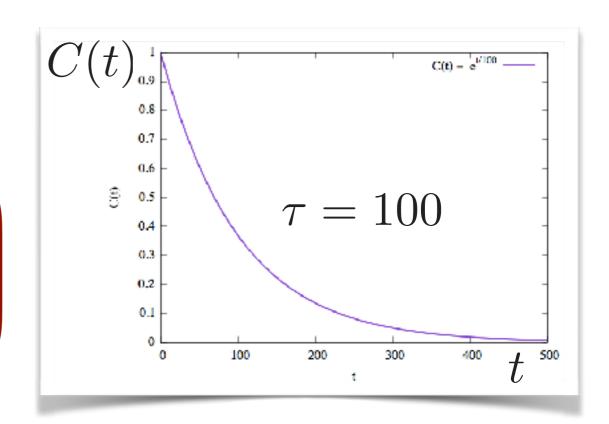
(It is different from the time average.)

Typical asymptotic behavior

$$C_{AA}(t) \sim e^{-t/\tau_A}$$
 exponential decay



Relaxation time: T_A



Relaxation time and sampling

Error due to finite number of sampling

$$\bar{A} \equiv \frac{1}{T} \sum_{t=1}^{T} \hat{A}(\Gamma(t))$$

Standard error: $\epsilon^2 = \langle \bar{A}^2 \rangle - \langle \bar{A} \rangle^2$

$$\epsilon^2 = \left\langle \frac{1}{T^2} \sum_{t_1=1}^{T} \sum_{t_2=1}^{T} A_{t_1} A_{t_2} \right\rangle - \left\langle \frac{1}{T} \sum_{t=1}^{T} A_{t} \right\rangle$$

$$= \frac{1}{T^2} \sum_{t_1=1}^{T} \sum_{t_2=2}^{T} C_{AA}(|t_2 - t_1|)$$

$$= \frac{1}{T^2} \sum_{\Delta t=1}^{T-1} 2(T - \Delta t) C_{AA}(\Delta t) + \frac{C_{AA}(0)}{T}$$

$$\underset{T\to\infty}{\sim} \frac{1+2\tau}{T} C_{AA}(0) \quad \blacksquare$$

$$\sum_{T \to \infty}^{\Delta t = 1} \frac{1 + 2\tau}{T} C_{AA}(0) \qquad \qquad \epsilon \propto \sqrt{\frac{1 + 2\tau}{T}}$$

⟨···⟩ :average over trajectories (initial condition)

 $C_{AA}(\Delta t) \sim C_{AA}(0)e^{-\Delta t/\tau}$ $\Delta t = |t_2 - t_1|$

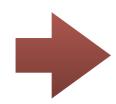
In order to reduce the error, we want to reduce τ .

Phenomena with large relaxation time

- Critical phenomena
 - $\tau \sim (T-T_c)^{-\nu z}$ with standard algorithm (critical slowing down)
 - z can be significantly reduced by using "global update"
- Glass transition (structural glass, spin glass), protein folding, first order phase transitions
 - $\tau \sim \exp(a/T)$ or $\exp(a/|T-T_c|)$
 - Exponential can be reduce to polynomial by using extended ensemble methods.

Information for future exercises

I will provide sample python codes.



By using these codes, you will experience simulations explained in lectures.

Q. Are you familiar with running python codes?

Unfortunately, there is **no enough time** to explain "how to use them". Instead, I will prepare a FAQ site for these python code.

In addition, we will provide informations of open source softwares related to the topics.

Some of them run, at least, on ECCS with default configurations.

I recommend you to get ECCS account to test them, including the above python codes.

(ECCS = Educational Campus-wide Computing System)

Classical

Next week

1st: Introduction

2nd: Difficulties in many-body problems

3rd: Classical statistical models and numerical simulation

4th: Classical Monte Carlo method and its applications

5th: Molecular dynamics simulation and its applications

6th: Extended ensemble method for Monte Carlo methods

7th: Quantum statistical models and numerical simulation

8th: Quantum Monte Carlo methods

9th: Applications of quantum Monte Carlo methods

10th: Quantum many-body problems and huge sparse matrices

11th: Krylov subspace methods and its applications

12th: Sparse matrices and quantum statistical mechanics

13th: Parallelized algorithm in many-body problems