

FYS 4411/9411, FEB 16, 2023

Continuous Markov Chain

$$W(\vec{y}, t + \Delta t) = \int_{x \in D} W(\vec{y}, t + \Delta t | \vec{x}, t) \\ \times W(\vec{x}, t) d\vec{x}$$

How does this link with QM?

$$\hat{H} |\phi_0\rangle = E_0 |\phi_0\rangle$$

$$\hat{H} \hat{H}^{-1} = \hat{H}^{-1} \hat{H} = \mathbb{1} \quad \hat{H}^{-1} = \hat{H}^\dagger$$

$$\hat{H}^{-1} \hat{H} |\phi_0\rangle = E_0 \hat{H}^{-1} |\phi_0\rangle$$

\hat{H} is a differential operator

1-particle

$$\hat{H} = -\frac{\hbar^2 \nabla^2}{2m} + V(\vec{r})$$

\hat{H}^{-1} is an integral operator

insert $\int_{-\infty}^{\infty} |\vec{x}\rangle \langle \vec{x}| d\vec{x}$

and multiply from the left
with $\langle \vec{y} |$

$$\langle \vec{y} | \phi_0 \rangle = \Phi_0(\vec{y})$$

$$= E_0 \int_{-\infty}^{\infty} \langle \vec{y} | \hat{H}^{-1} | \vec{x} \rangle \underbrace{\langle \vec{x} | \phi_0 \rangle}_{\Phi_0(\vec{x})} d\vec{x}$$

Green's function / propagator

$$G(\vec{y}, \vec{x}) = \langle \vec{y} | \hat{H}^{-1} | \vec{x} \rangle$$

probability of making a transition from $\vec{x} \rightarrow \vec{y}$

$$\begin{aligned} \Phi_0(\vec{y}) &= \hat{H}(\vec{y}) \hat{H}^{-1} \Phi_0(\vec{y}) \\ &= \int_{-\infty}^{\infty} \hat{H}(\vec{y}) G(\vec{y}, \vec{x}) \Phi_0(\vec{x}) d\vec{x} \end{aligned}$$

$$\hat{H}(\vec{y}) G(\vec{y}, \vec{x}) = \delta(\vec{y} - \vec{x})$$

$$\hat{H}(\vec{x}) G(\vec{x}, \vec{y}) = \delta(\vec{x} - \vec{y})$$

parallel to

$$\frac{\partial W(\vec{y}, t + \Delta t | \vec{x}, t)}{\partial t} =$$

$$1) \frac{\partial}{\partial \vec{x}^2} W(\vec{y}, t + \Delta t | \vec{x}^t)$$

$$W(\vec{y}, t + \Delta t | \vec{x}^t) =$$

$$\left(\frac{1}{\sqrt{4\pi D \Delta t}} \right) \exp \left(-\frac{(\vec{y} - \vec{x})^2}{4D \Delta t} \right)$$

Trial wf in code example

$$\hbar = m = e = \epsilon_0 = 1$$

$$H = -\frac{\nabla_1^2}{2} - \frac{\nabla_2^2}{2} + \frac{1}{2}r_1^2 + \frac{1}{2}r_2^2 + \frac{1}{|\vec{r}_1 - \vec{r}_2|}$$

$$\psi_T = e^{-\alpha^2(r_1^2 + r_2^2)/2} f(r_{12}, \beta)$$

$$r_{12} = |\vec{r}_1 - \vec{r}_2| = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$

$$f(r_{12}, \beta) = \exp \left\{ \frac{r_{12}}{1 + \beta r_{12}} \right\}$$

$$\vec{\alpha} = \{ \alpha, \beta \}$$

(i) Metropolis ratio

$$R = \frac{|\psi(\vec{R}_{\text{new}})|^2}{|\psi(\vec{R}_{\text{old}})|^2}$$

(ii) Quantum Force

$$\vec{F}_i = 2 \frac{1}{\psi} \vec{\nabla}_i \psi$$

(iii) Kinetic energy

$$\frac{1}{\psi} \left(-\frac{\nabla^2}{2} \psi \right)$$

(i) can move all particles

$$\vec{R}_{\text{old}} = \{ \vec{r}_{1\text{old}}, \vec{r}_{2\text{old}}, \dots, \vec{r}_{N\text{old}} \}$$

$$\vec{R}_{\text{new}} = \{ \vec{r}_{1\text{new}}, \vec{r}_{2\text{new}}, \dots, \vec{r}_{N\text{new}} \}$$

Then perform Metropolis's test, \vec{F} , + Kinetic energy.

(ii) Move one particle at the time, and then

test (R) and compute
 \bar{E} and K ,

Trial wf in \mathcal{P}_1 .

$$\psi_T(\vec{r}_1, \vec{r}_2, \dots, \vec{r}_N) \propto$$

$$\phi_{\alpha_1}(\vec{r}_1) \phi_{\alpha_2}(\vec{r}_2) \dots \phi_{\alpha_N}(\vec{r}_N)$$

$$R = \frac{\phi_{\alpha_1}(\vec{r}_{1, \text{new}}) \phi_{\alpha_2}(\vec{r}_{2, \text{old}}) \dots \phi_{\alpha_N}(\vec{r}_{N, \text{old}})}{\phi_{\alpha_1}(\vec{r}_{1, \text{old}}) \phi_{\alpha_2}(\vec{r}_{2, \text{old}}) \dots \phi_{\alpha_N}(\vec{r}_{N, \text{old}})}$$

$$= \frac{\phi_{\alpha_1}(\vec{r}_{1, \text{new}})}{\phi_{\alpha_1}(\vec{r}_{1, \text{old}})}$$

$$= e^{-\frac{1}{2}\alpha^2 (\vec{r}_{1, \text{new}} - \vec{r}_{1, \text{old}})^2}$$

Basic elements of VMC code

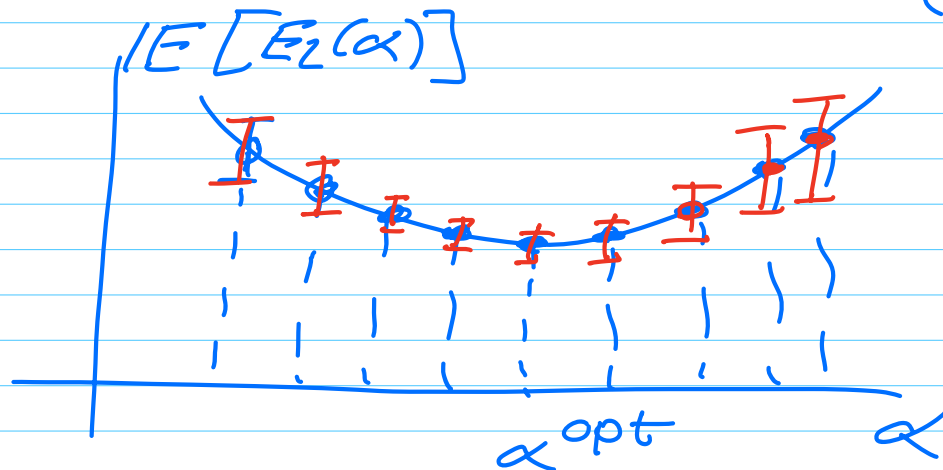
- Metropolis's + Markov chains
- Expression for $E_L(\vec{r}; \vec{\alpha})$
 $\psi_T(\vec{r}; \vec{\alpha})$, $P_T \sim |\psi_T|^2$

— importance sampling
(Metropolis-Hastings)

$$\vec{F} = 2 \frac{1}{\psi_T} \vec{\nabla} \psi_T$$

— optimization part

$$E[E_L(\vec{\alpha})] = \int_{\vec{R} \in D} d\vec{r} P(\vec{r}; \vec{R}) E(\vec{R}; \vec{\alpha})$$



each point is obtained with
the same amount of Monte
carlo cycles

$$\alpha^{opt} = \alpha = \arg \min_{\alpha \in \mathbb{R}^m} E[E_L(\alpha)]$$

Can we optimize the search
for $\hat{\alpha} = \alpha^{opt}$ with less

Monte Carlo?

yes \rightarrow gradient methods:

- gradient descent
- stochastic gradients
- stochastic reconfig.
- steepest descent
- conjugate descent