

FGS4411/9411 FEB 18

$$E[E_L(\vec{\alpha})] = \int d\vec{r} P(\vec{r}, \vec{\alpha}) E_L(\vec{r}, \vec{\alpha})$$
$$(\langle E_L(\vec{\alpha}) \rangle)$$

$$P(\vec{r}, \vec{\alpha}) = \frac{|\psi_T(\vec{r}, \vec{\alpha})|^2}{\int d\vec{r} |\psi_T(\vec{r}, \vec{\alpha})|^2}$$

$$E_L(\vec{r}, \vec{\alpha}) = \frac{1}{\psi_T(\vec{r}, \vec{\alpha})} H(\vec{r}) \psi_T(\vec{r}, \vec{\alpha})$$

$$\psi_T(\vec{r}, \vec{\alpha}) \rightarrow \psi(\vec{\alpha})$$

$$\frac{\partial E[E_L(\vec{\alpha})]}{\partial \vec{\alpha}} = 0$$

$$= \int d\vec{r} \left[\frac{dP(\vec{\alpha})}{d\alpha} E_L(\vec{\alpha}) + p(\vec{\alpha}) \frac{dE_L(\vec{\alpha})}{d\alpha} \right]$$

$$\text{Example: } \psi(\vec{\alpha}) = \psi(\alpha)$$
$$= e^{-\frac{1}{2}\alpha^2 x^2}$$

$$\frac{d p(\alpha)}{d \alpha} = \frac{d}{d \alpha} \frac{|e^{-\frac{1}{2}\alpha^2 x^2}|^2}{\int \dots \dots - \alpha^2 x^2}$$

$$\begin{aligned}
 & \alpha \alpha \int \alpha x e \\
 = & -2\alpha x^2 e^{-\alpha^2 x^2} \int dx e^{-\alpha^2 x^2} \\
 & + \left[\int 2\alpha x^2 e^{-\alpha^2 x^2} \right] \cdot e^{-\alpha^2 x^2}
 \end{aligned}$$

$$\begin{aligned}
 & \frac{(\int dx e^{-\alpha^2 x^2})^2}{\int e^{-\alpha^2 x^2} dx} \\
 = & \frac{-2\alpha x^2 e^{-\alpha^2 x^2}}{\int e^{-\alpha^2 x^2} dx} + \frac{e^{-\alpha^2 x^2} \int 2\alpha x^2 e^{-\alpha^2 x^2} dx}{\int e^{-\alpha^2 x^2} dx \int e^{-\alpha^2 x^2} dx} \\
 & p(\alpha) \quad \boxed{p(\alpha)} \int 2\alpha x^2 p(\alpha) dx
 \end{aligned}$$

$$\begin{aligned}
 & -2\alpha x^2 \frac{e^{-\alpha^2 x^2/2}}{e^{-\alpha^2 x^2/2}} = 2 \left(\frac{\frac{d\psi(\alpha)}{d\alpha}}{\psi(\alpha)} \right)
 \end{aligned}$$

$$= 2 \frac{d \ln \psi(\alpha)}{d\alpha}$$

$$-2 \int p(\alpha) \frac{d \ln \psi(\alpha)}{d\alpha} dx$$

$$\int dx \frac{dp(\alpha)}{d\alpha} E_2(\alpha)$$

$$= 2 \left[\int dx \left\{ \frac{d \ln \psi(x)}{dx} E_L(x) - \frac{P(x) E_L(x) \int \frac{d \ln \psi(x)}{dx} P(x)}{P(x)} \right\} \right]$$

$$= 2 \left[E \left[\frac{d \ln \psi(x)}{dx} E_L(x) \right] - E \left[\frac{d \ln \psi(x)}{dx} \right] E \left[E_L(x) \right] \right] = 0$$

new integral, new integral
multi-dim evaluate
by MC integration

$$\frac{d E[E_L(x)]}{dx}$$

in general $\vec{\nabla}_{\vec{\alpha}} E[E_L(\vec{\alpha})]$

steepest descent

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

solve iteratively

$$\vec{\alpha}^{(k+1)} = \vec{\alpha}^{(k)} - \underbrace{\eta}_{\substack{\text{learning} \\ \text{rate}}} \vec{\nabla}_{\vec{\alpha}} [E[\mathcal{E}_L(\vec{\alpha})]]_{\vec{\alpha}^{(k)}}$$

stop when

$$\|\vec{\alpha}^{(k+1)} - \vec{\alpha}^{(k)}\|_2 \leq \delta \sim 10^{-8}$$

Example : 2 electrons
in two-dim
interact via
an electrostatic
potential

$$\psi_T(\vec{R}, \alpha, \beta) = e^{-\frac{\alpha^2}{2}(\vec{r}_1^2 + \vec{r}_2^2)} \times J(r_{12})$$

$$\vec{R} = \{\vec{r}_1, \vec{r}_2\}$$

$$r_i = \sqrt{x_i^2 + y_i^2}$$

$$r_{12} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

$$J(r_{12}) = \frac{r_{12}}{e^{1 + \beta r_{12}}}$$

— code ;

(+) importance sampling

+ analytical E_L

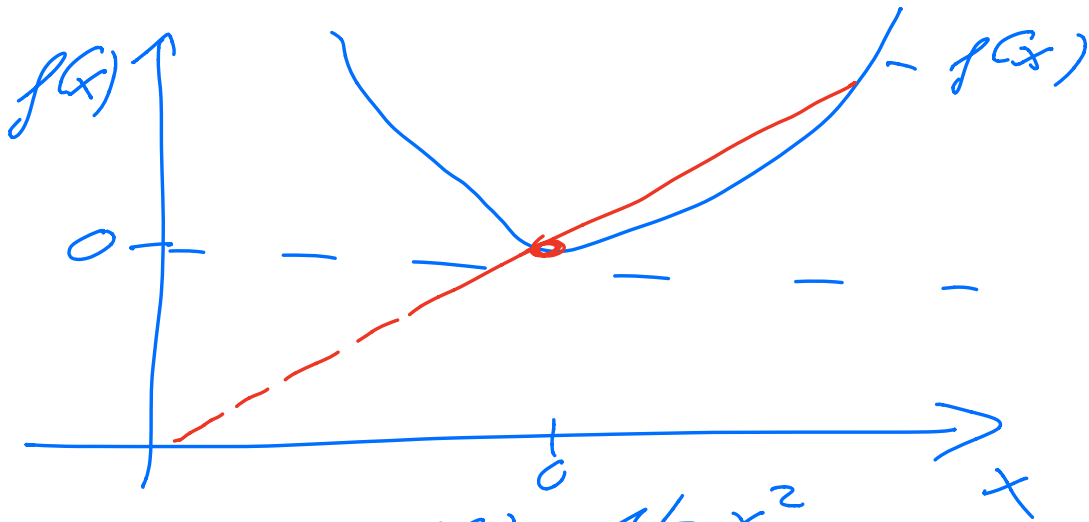
+ — 1 — quantum
force

\Rightarrow + numerical $\vec{\nabla}_{\alpha, \beta} [E[E(\alpha, \beta)]]$

— Gradient algos —

$$E[E_L(\vec{x})] \rightarrow f(\vec{x})$$

$$\vec{\nabla}_{\vec{x}} f(\vec{x}) = \vec{\nabla} f(\vec{x}) = 0$$



$$f(x) = 1/2 x^2$$
$$f'(x) = x$$

$$f'(x) = 0, \text{ min.}$$

$$x < 0$$

$$f'(x) < 0$$

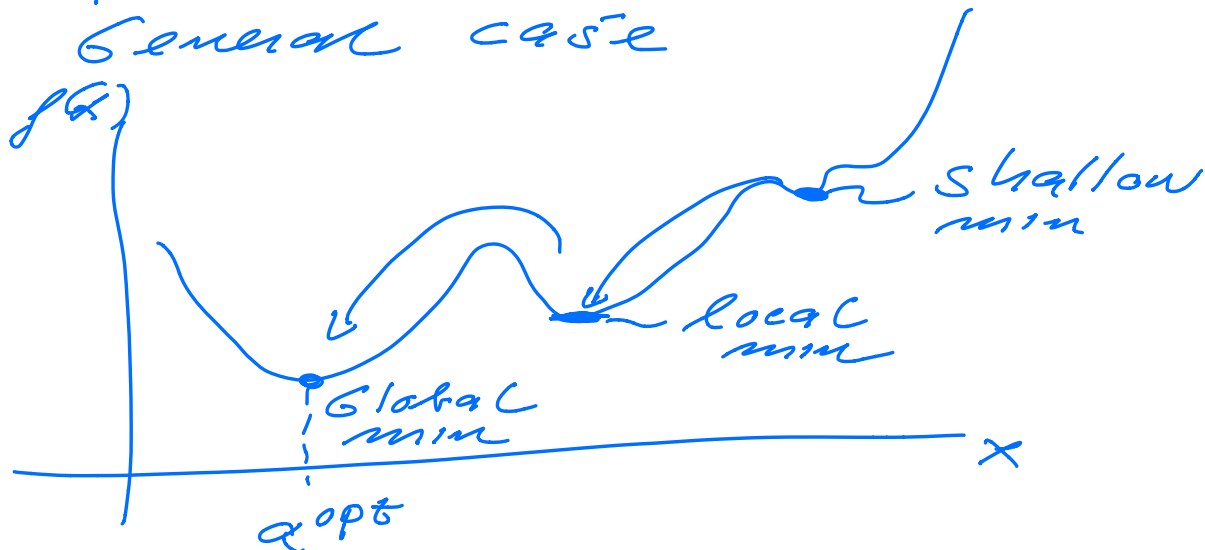
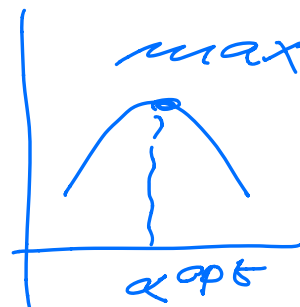
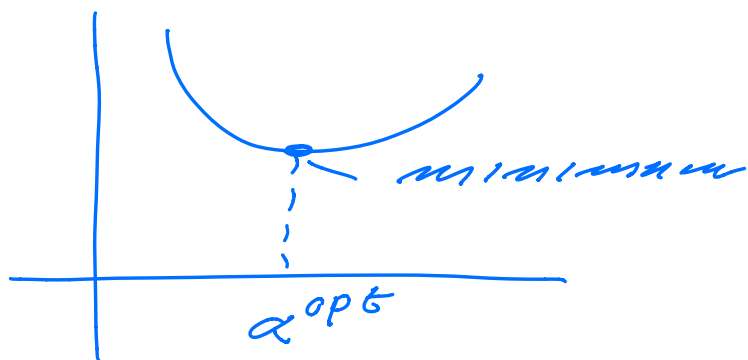
$f(x)$ is decreased
by moving to

$$x > 0$$

$$f'(x) > 0$$

move to
the left.

the right



2nd derivative :

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = H_{ij} = \text{Hessian matrix}$$

$$= H_j^i$$

In most cases H is positive definite, all eigenvalues are larger than zero
 \Rightarrow convex optimization

Taylor - expansion of $f(\vec{x})$ around \vec{x}_0

$$f(\vec{x}) \approx f(\vec{x}_0) + \underbrace{(\vec{x} - \vec{x}_0)^T}_{\vec{x} \vec{g}^T} \vec{g}$$

($\vec{g} = \nabla f(\vec{x})$)

$$+ \frac{1}{2} (\vec{x} - \vec{x}_0)^T H (\vec{x} - \vec{x}_0)$$

use a learning rate γ
 new point:

$$\vec{x} \approx \vec{x}_0 - \gamma \cdot \vec{g}$$

$$f(\vec{x}) = f(\vec{x}_0 - \gamma \vec{g}) \approx f(\vec{x}_0) - \gamma \vec{g}^T \vec{g} + \frac{1}{2} \gamma^2 \vec{g}^T H \vec{g}$$

optimal $\gamma \quad \frac{df(\vec{x})}{d\gamma} =$

$$\vec{g}^T \vec{g} = \gamma \vec{g}^T H \vec{g} \Rightarrow$$

— +

—

$$\underline{x^{opt}} = \frac{\vec{g}' \vec{g}}{\vec{g}^T \underline{H} \vec{g}}$$

Newton-Raphson

$$\vec{x}^{(k+1)} = \vec{x}^{(k)} - \left[\underline{H}(f(\vec{x}^{(k)})) \right]^{-1} \times \vec{\nabla} f(\vec{x}^{(k)})$$