

## Multidim minimization (very similar)

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Consider scalar function  $\phi$  of many words

$$x_0, x_1, \dots, x_{n-1} \Rightarrow \phi(\vec{x})$$

Taylor expand about small step  $\vec{x} + \vec{\xi}$

$$\phi(\vec{x} + \vec{\xi}) = \phi(\vec{x}) + (\nabla \phi(\vec{x}))^T \vec{\xi} + \frac{1}{2} \vec{\xi}^T H(\vec{x}) \vec{\xi} + O(\xi^3)$$

$$\nabla \phi(\vec{x}) \equiv \text{gradient vector} = \left[ \frac{\partial \phi}{\partial x_0} \quad \frac{\partial \phi}{\partial x_1} \quad \dots \quad \frac{\partial \phi}{\partial x_{n-1}} \right]^T$$

$$\text{or } (\nabla \phi(\vec{x}))^T \vec{\xi} = \sum \frac{\partial \phi}{\partial x_i} \xi_i$$

To first order in slightly diff notation

$$\phi(\vec{x} + d\vec{x}) = \phi(\vec{x}) + \underbrace{\nabla \phi \cdot d\vec{x}}$$

maximum when  $d\vec{x}$  points along  $\nabla \phi(\vec{x})$

If local minima is  $\vec{x}^*$

$$\phi(\vec{x}^* + \vec{\xi}) \approx \phi(\vec{x}^*) + (\nabla \phi(\vec{x}^*))^T \vec{\xi}$$

largest decrease when  $\vec{\xi}$  points opposite  $\nabla \phi(\vec{x}^*)$

but we are at minima so we can't get lower

$$\Rightarrow \nabla \phi(\vec{x}^*) = 0 \quad \text{multidimensional critical point}$$

$$\nabla \phi(\vec{x}) = 0 = \vec{f}(\vec{x}) \quad \text{Same problem we already solved}$$

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recall old solution 
$$\vec{J}(\vec{x}^{(k-1)}) (\vec{x}^{(k)} - \vec{x}^{(k-1)}) = -\vec{f}(\vec{x}^{(k-1)})$$

$$\Rightarrow \vec{J}_{\nabla \phi}(\vec{x}^{(k-1)}) * (\vec{x}^{(k)} - \vec{x}^{(k-1)}) = -\nabla \phi(\vec{x}^{(k-1)})$$

where  $\vec{J}_{\nabla \phi}(\vec{x}) = H(\vec{x}) \equiv \text{Hessian}$

$$H(\vec{x}) = \left\{ \frac{\partial^2 \phi}{\partial x_i \partial x_j} \right\} = \begin{bmatrix} \frac{\partial^2 \phi}{\partial x_0^2} & \dots & \frac{\partial^2 \phi}{\partial x_0 \partial x_{n-1}} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 \phi}{\partial x_{n-1} \partial x_0} & \dots & \frac{\partial^2 \phi}{\partial x_{n-1}^2} \end{bmatrix}$$

### Action

Single particle in one-dim ( $x$ )

$$KE = \frac{1}{2} m \dot{x}^2 \quad \dot{x} = dx/dt = v$$

$$V = V(x(t)) \quad \text{potential}$$

Lagrangian 
$$L(x(t), \dot{x}(t)) = KE(\dot{x}(t)) - V(x(t))$$

We study particle from  $t=0$  to  $t=T$  and

define the action functional

$$S[x(t)] = \int_0^T dt L(x(t), \dot{x}(t))$$

$S$  is a functional  $\Rightarrow$  function of a function  $S-12$

$f(x) \rightarrow S \rightarrow \#$  depends on all values of  $x$   
but not of  $t$

For given trajectory  $x(t)$  from  $t=0$  to  $t=T$

$S[x(t)]$  gives a single number

Hamilton's principle: particle follows a trajectory  
that minimizes the action

(Similar to Fermat's principle for path of least  
time for light)

Algorithm: Discretize time  $t_k = k \frac{T}{n-1} = kh_t$

where  $k=0, 1, \dots, n-1$  Let  $x_k = x(t_k)$

We will compute an integral by a rectangle approx  
and use forward diff. for  $\dot{x}$

$$S_n = \sum_{k=0}^{n-2} h_t \left[ \underbrace{\frac{1}{2} m \left( \frac{x_{k+1} - x_k}{h_t} \right)^2}_{\text{rect height}} - V(x_k) \right]$$

rect width

We keep  $x(0)$  and  $x(T)$  fixed by definition

$S_n = S_n(x_1, x_2, \dots, x_{n-2}) \leftarrow$  need its minimum  
like  $\phi(\vec{x})$  problem

Solution

$$J_{\nabla \phi}(\vec{x}^{(k-1)}) (\vec{x}^{(k)} - \vec{x}^{(k-1)}) = -\nabla \phi(\vec{x}^{(k-1)})$$

where we use  $S$  instead of  $\phi$

$$\nabla S_i = \frac{\partial S_n}{\partial x_i} = \sum_{k=0}^{n-1} h_t \left[ \frac{M}{h_t^2} (x_{k+1} - x_k) (\delta_{i,k+1} - \delta_{i,k}) - \frac{\partial V(x_k)}{\partial x_i} \delta_{i,k} \right]$$

$$= \frac{M}{h_t} (2x_i - x_{i-1} - x_{i+1}) - h_t \frac{\partial V(x_i)}{\partial x_i}$$

also need  $J_{\nabla S} \Rightarrow$  take another derivative

(Eg. 5.137)