

A still from the movie Doctor Strange in the Multiverse of Madness. Doctor Strange is in his Sanctum Sanctorum, wearing his dark blue robe and red cape. He is holding a glowing red orb in his right hand. The room is dimly lit with warm, golden light from wall sconces. The background shows a large, ornate wooden cabinet and a patterned rug.

CSC417 Physics-Based Animation

... starting at 3:10 pm





Capture and Modeling of Non-Linear Heterogeneous Soft Tissue | Bickel et al

Questions from Previous Lecture ?

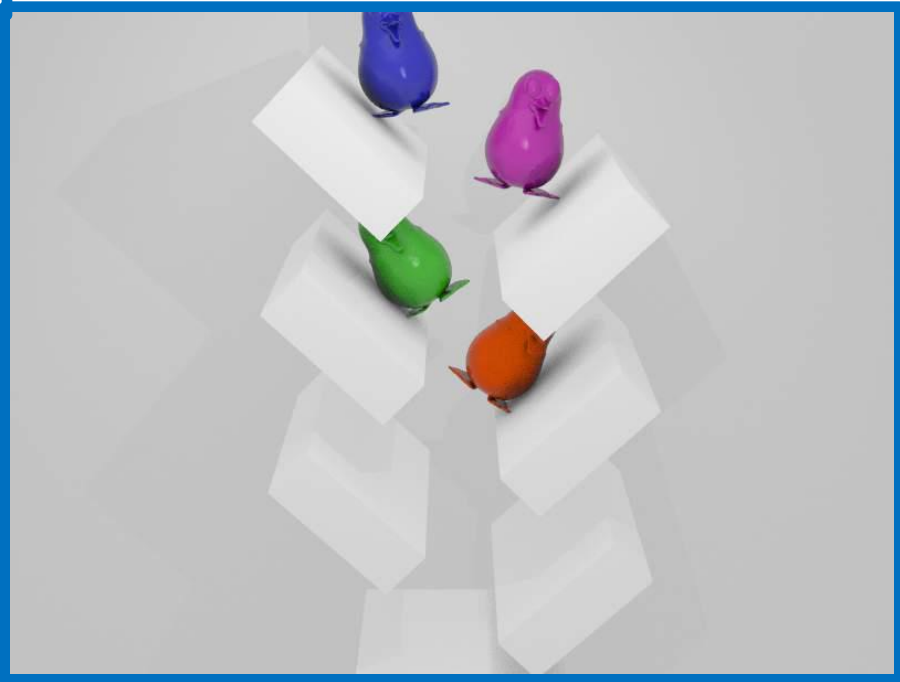
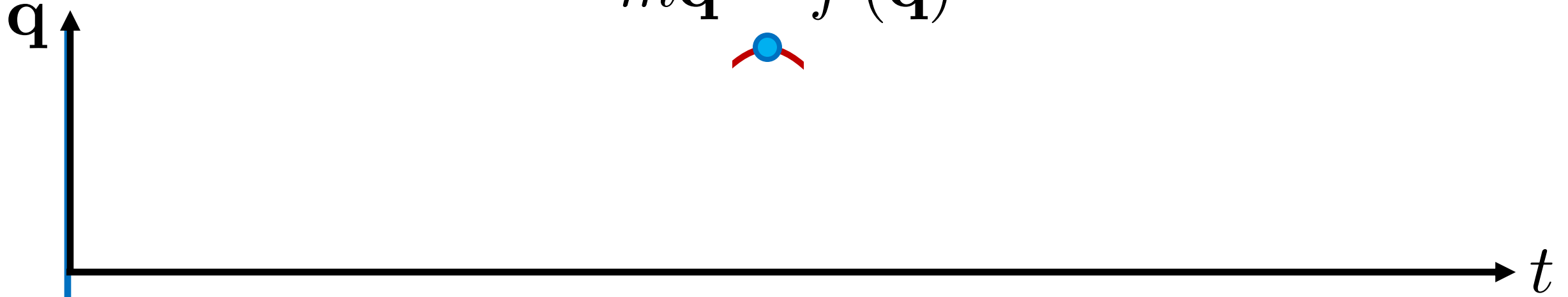
Equations of Motion

$$M\ddot{\mathbf{q}} = - \frac{\partial V}{\partial \mathbf{q}}$$



Time Integration

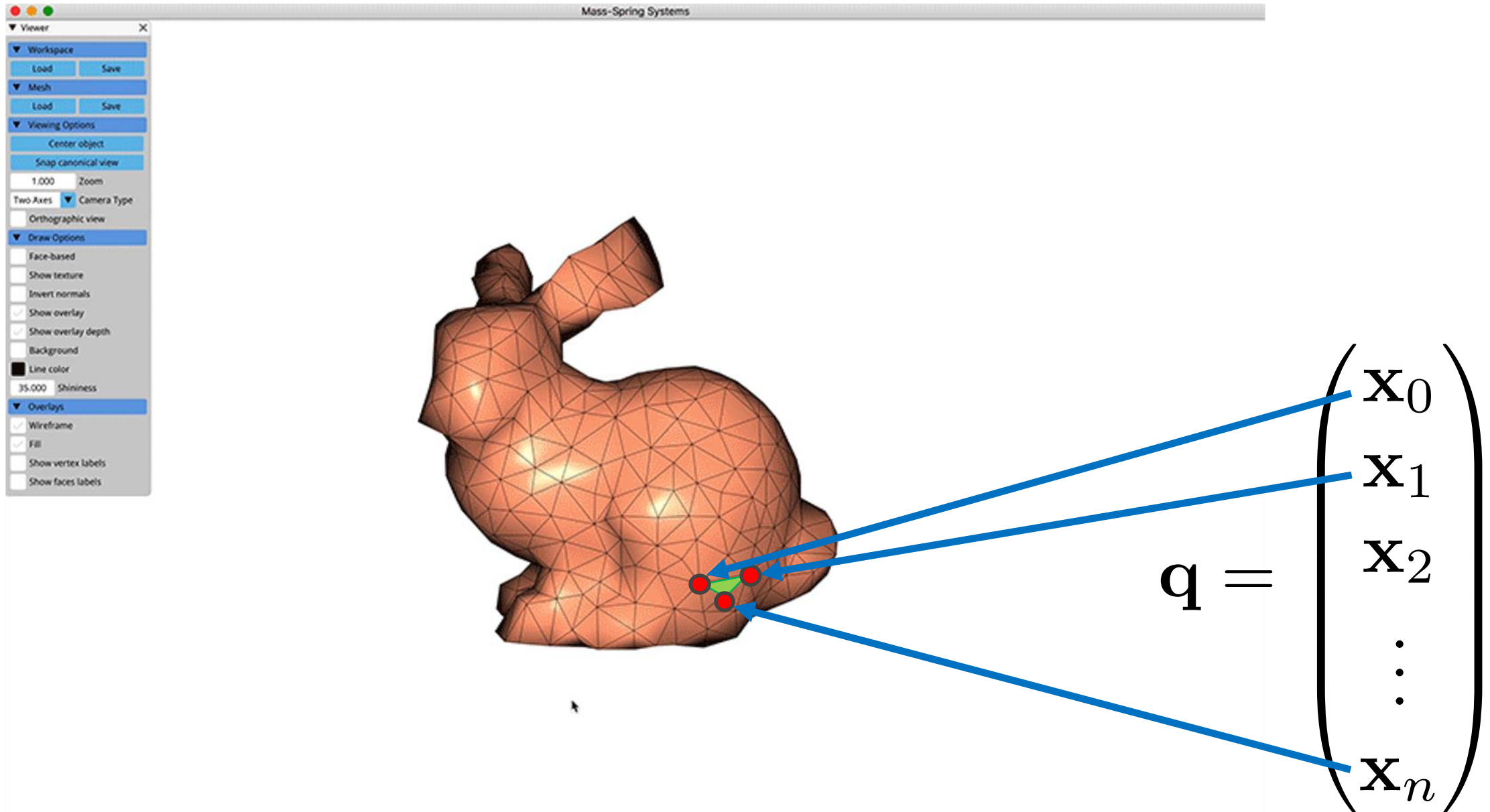
$$m\ddot{\mathbf{q}} = \mathbf{f}(\mathbf{q})$$



How to Solve This ?

$$\underline{M} \ddot{\mathbf{q}} = - \frac{\partial V}{\partial \mathbf{q}}$$

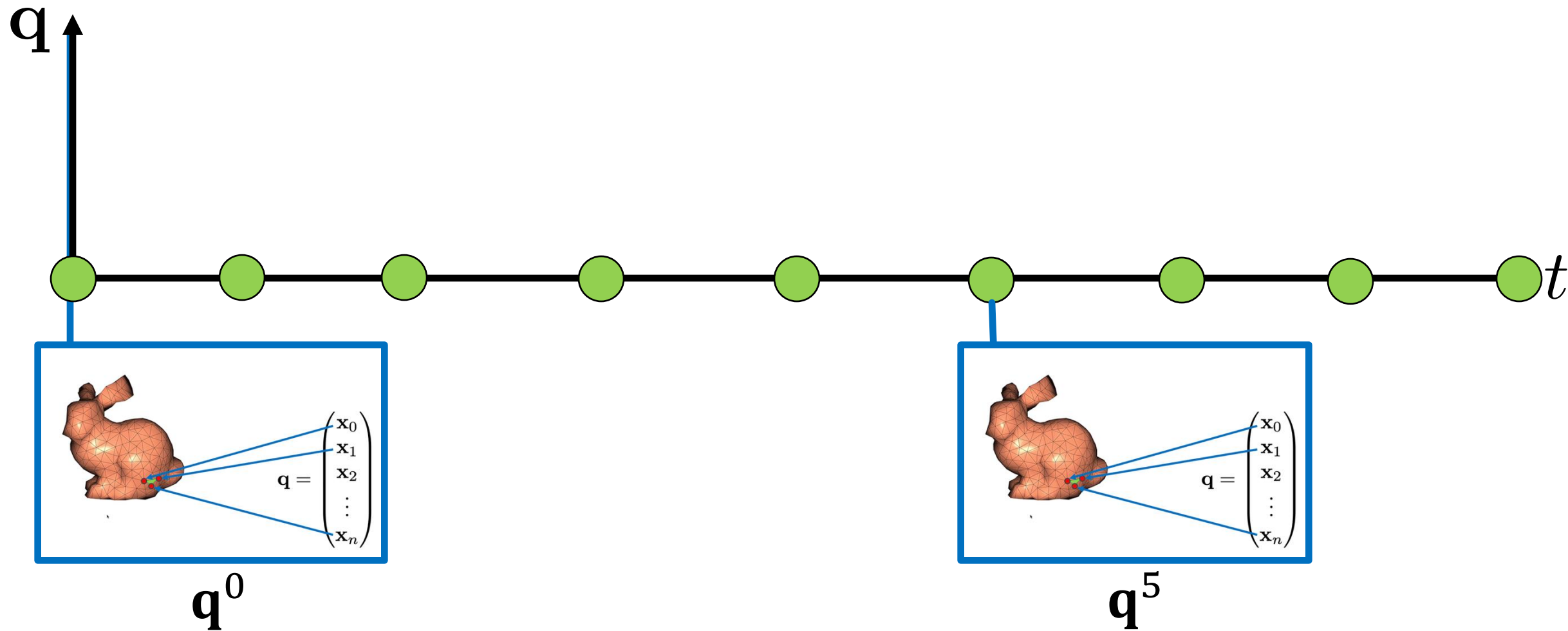
Spatial Discretization -- Finite Elements



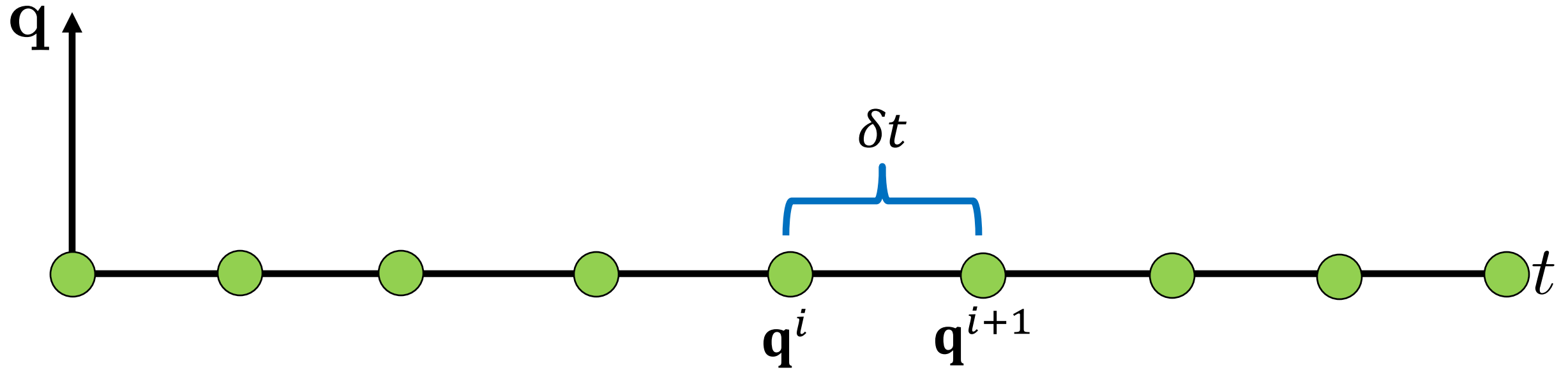
How to Solve This ?

$$M\ddot{\mathbf{q}} = - \frac{\partial V}{\partial \mathbf{q}}$$

Time Discretization



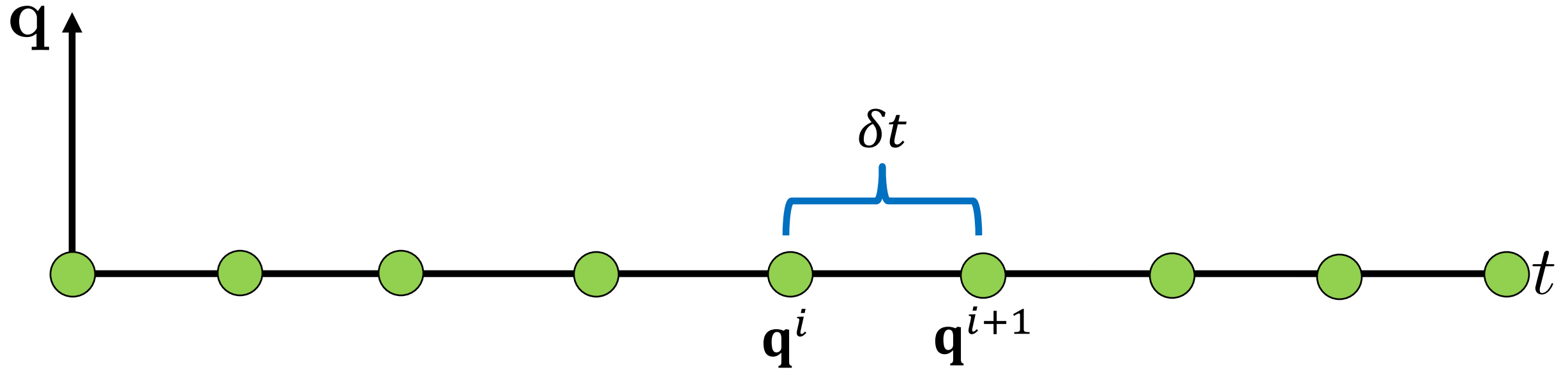
Time Discretization



Continuous Derivative

$$\dot{q} = \lim_{t \rightarrow 0} \frac{q(t + \delta t) - q(t)}{\delta t}$$

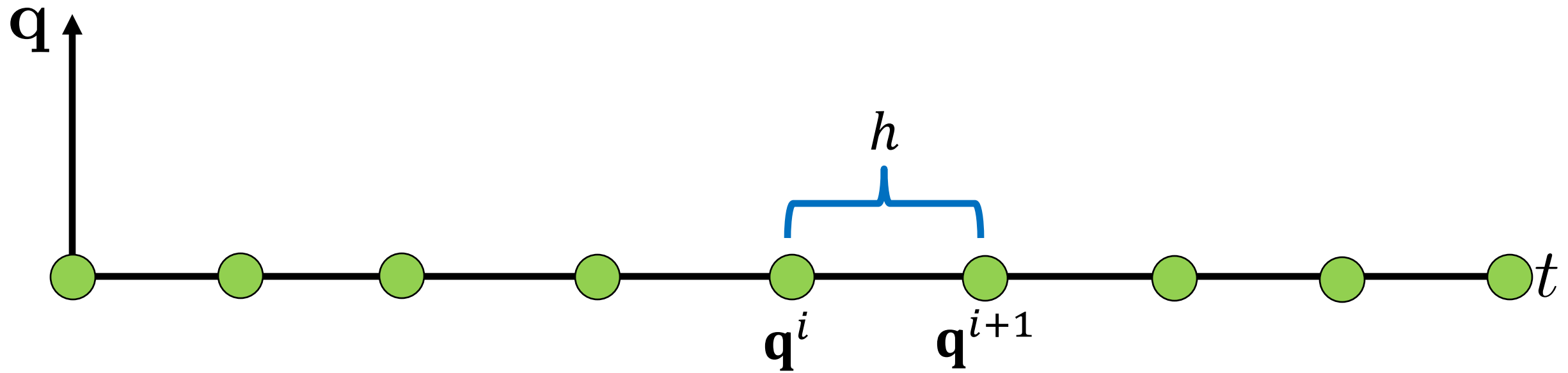
Time Discretization



Finite Difference Derivative

$$\dot{q} = \frac{q(t + \delta t) - q(t)}{\delta t}$$

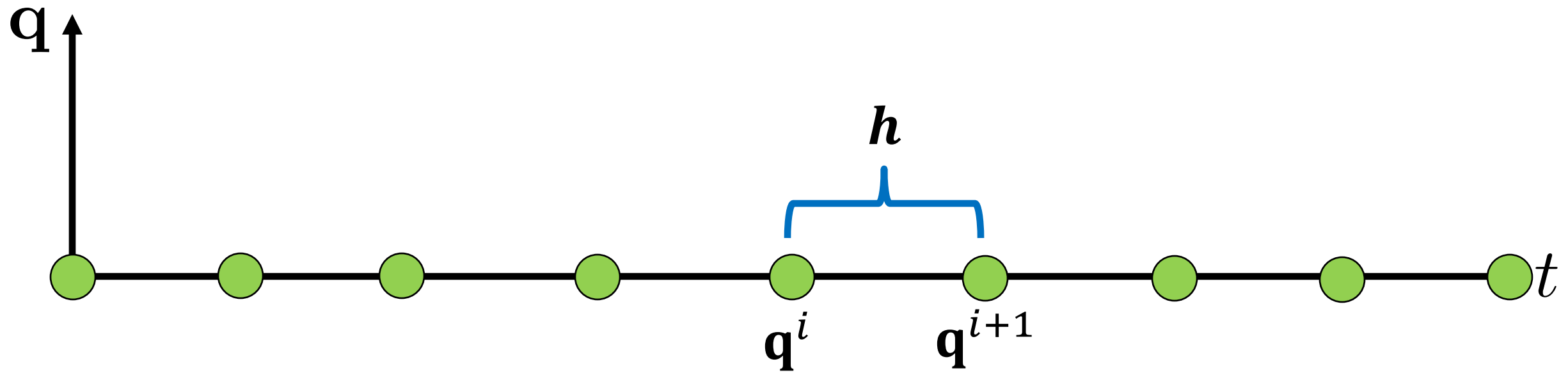
Time Discretization



Finite Difference Derivative

$$\dot{q}^{i+1} = \frac{q^{i+1} - q^i}{h}$$

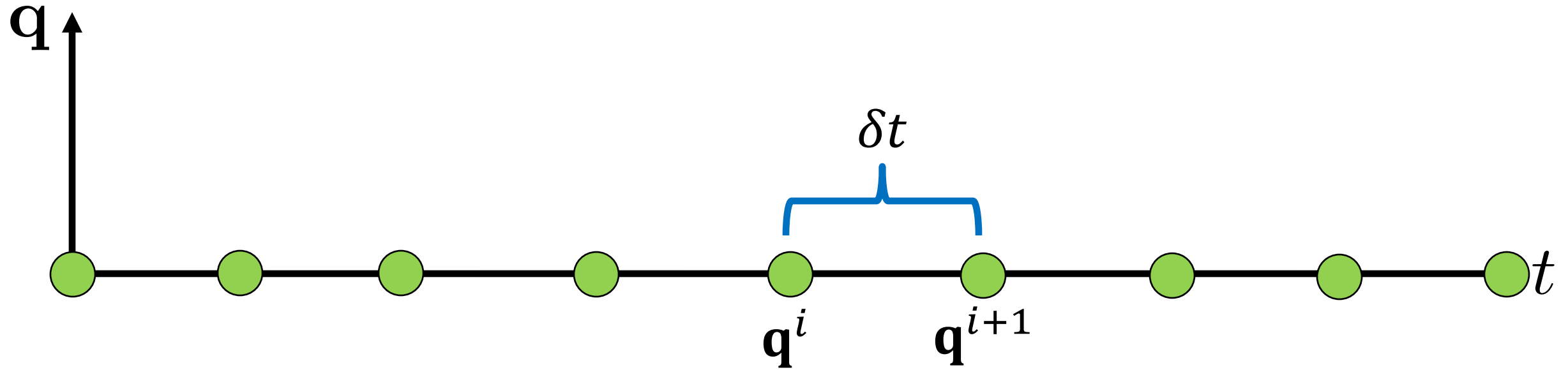
Time Discretization



Finite Difference

$$\ddot{q} = \text{?????}$$

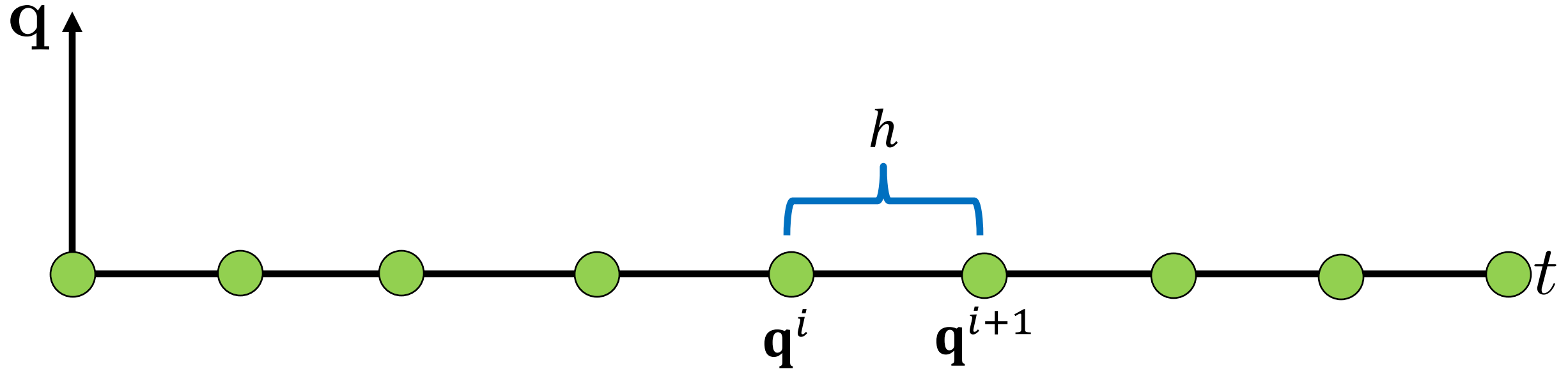
Time Discretization



Continuous Derivative

$$\ddot{\mathbf{q}} = \lim_{t \rightarrow 0} \frac{\dot{\mathbf{q}}(\mathbf{t} + \delta \mathbf{t}) - \dot{\mathbf{q}}(\mathbf{t})}{\delta t}$$

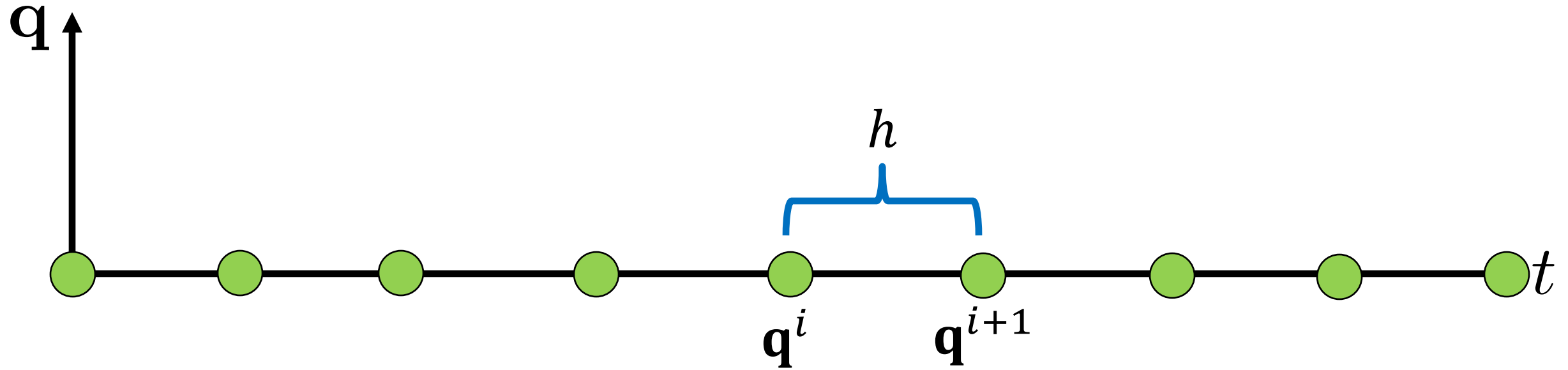
Time Discretization



Finite Difference Derivative

$$\ddot{q}^i = \frac{\dot{q}^{i+1} - \dot{q}^i}{h}$$

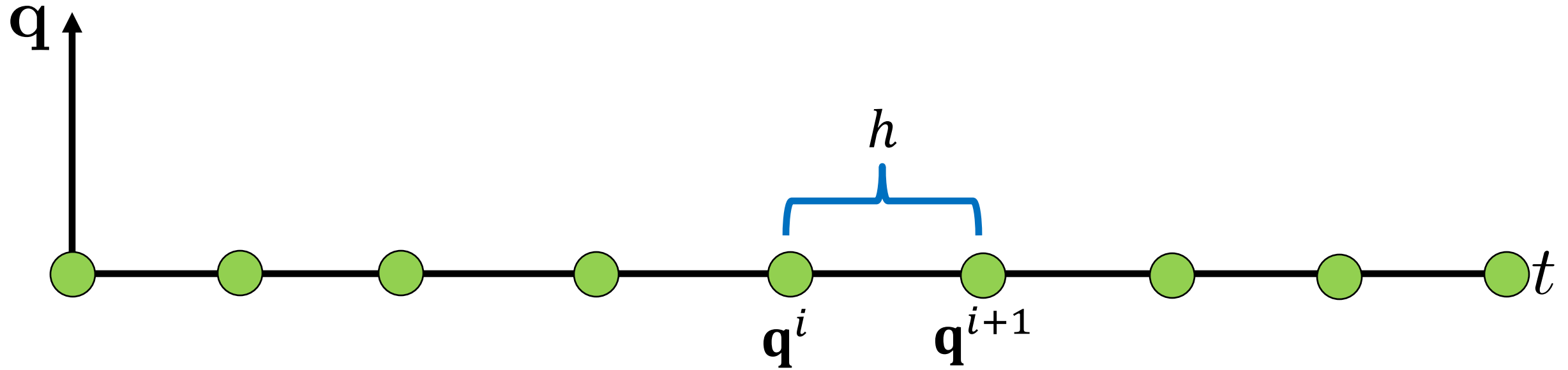
Time Discretization



Finite Difference Derivative

$$\ddot{q}^i = \frac{1}{h} \left(\frac{q^{i+1} - q^i}{h} - \frac{q^i - q^{i-1}}{h} \right)$$

Time Discretization




Finite Difference Derivative

$$\ddot{\mathbf{q}}^i = \frac{1}{h^2} \left(\mathbf{q}^{i+1} - \underbrace{2\mathbf{q}^i + \mathbf{q}^{i-1}}_{\tilde{\mathbf{q}}^i} \right)$$

Discretize in Time

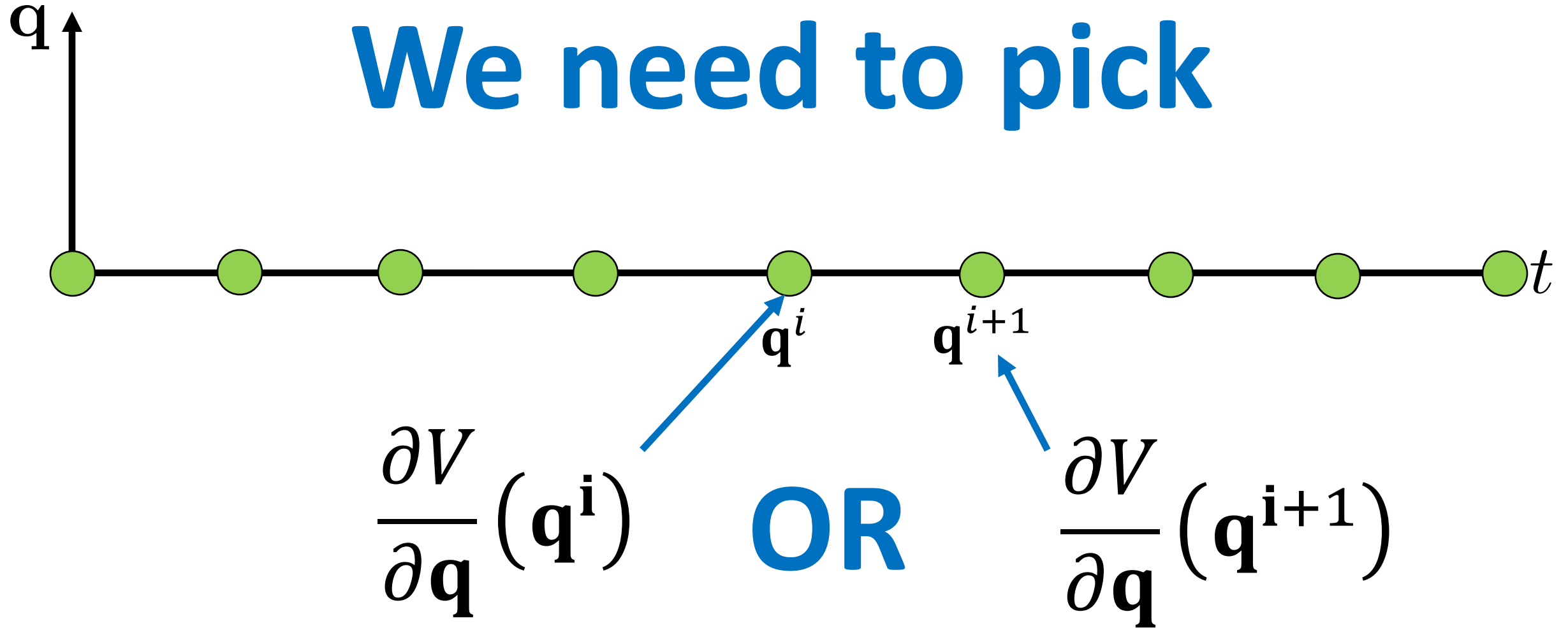
$$M\ddot{\mathbf{q}} = - \frac{\partial V}{\partial \mathbf{q}}$$

Discretize in Time

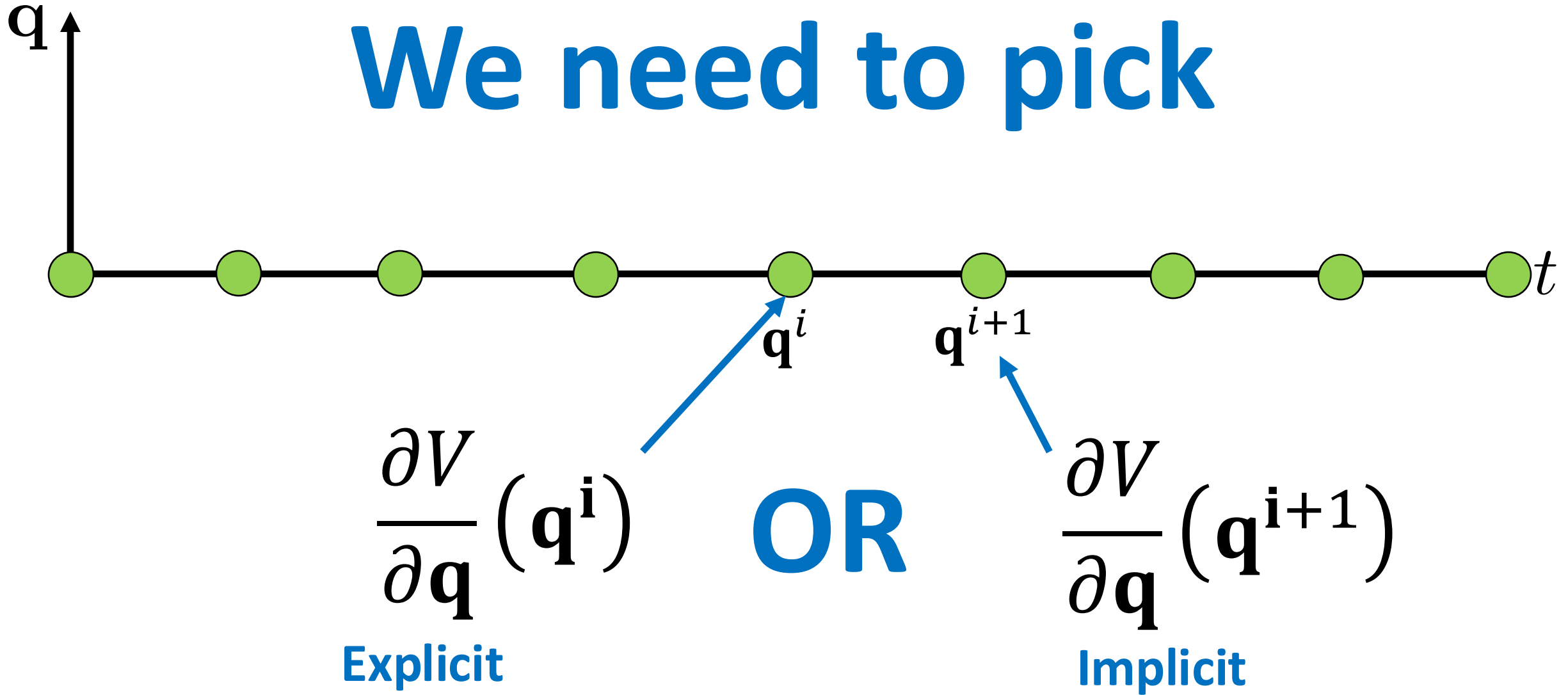
$$M \frac{1}{h^2} (q^{i+1} - \tilde{q}^i) = - \frac{\partial V}{\partial q}$$


What about this ?

We need to pick



We need to pick



Explicit Integrator

$$M\left(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i\right) = -h^2 \frac{\partial V}{\partial \mathbf{q}}\left(\mathbf{q}^i\right)$$

Forward Euler

Implicit Integrator

$$M(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) = -h^2 \frac{\partial V}{\partial \mathbf{q}}(\mathbf{q}^{i+1})$$

Backward Euler: More stable, harder to solve

▼ Viewer

▼ Workspace

Load Save

▼ Mesh

Load Save

▼ Viewing Options

Center object

Snap canonical view

1.000 Zoom

Two Axes ▼ Camera Type

☐ Orthographic view

▼ Draw Options

☐ Face-based

☐ Show texture

☐ Invert normals

☒ Show overlay

☒ Show overlay depth

☐ Background

☒ Line color

35.000 Shininess

▼ Overlays

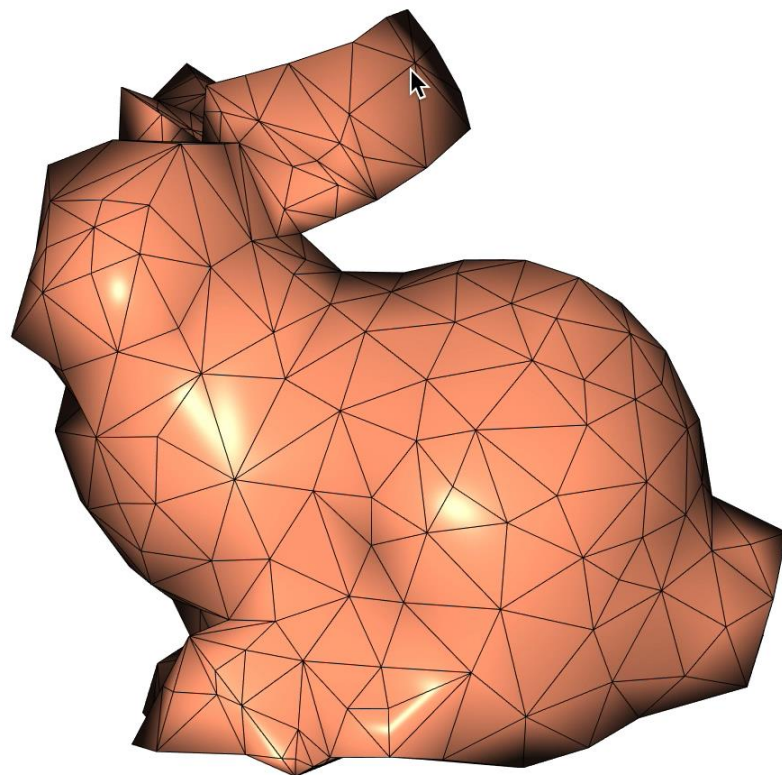
☒ Wireframe

☒ Fill

☐ Show vertex labels

☐ Show faces labels

► Energy Plot



How do we Solve This ?

$$M(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) = -h^2 \frac{\partial V}{\partial \mathbf{q}}(\mathbf{q}^{i+1})$$

Root Finding ?

$$M(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) + h^2 \frac{\partial V}{\partial \mathbf{q}}(\mathbf{q}^{i+1}) = 0$$

Nonlinear Root Finding is Hard

How do we Solve This ?

$$M(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) + h^2 \frac{\partial V}{\partial \mathbf{q}}(\mathbf{q}^{i+1}) = 0$$

What other type of problem involves finding the zero of a function?

Optimization

$$\nabla g(\mathbf{q}^{i+1}) = 0$$

Find where gradient is zero

How do we Solve This ?

$$M(\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) + h^2 \frac{\partial V}{\partial \mathbf{q}}(\mathbf{q}^{i+1}) = 0$$

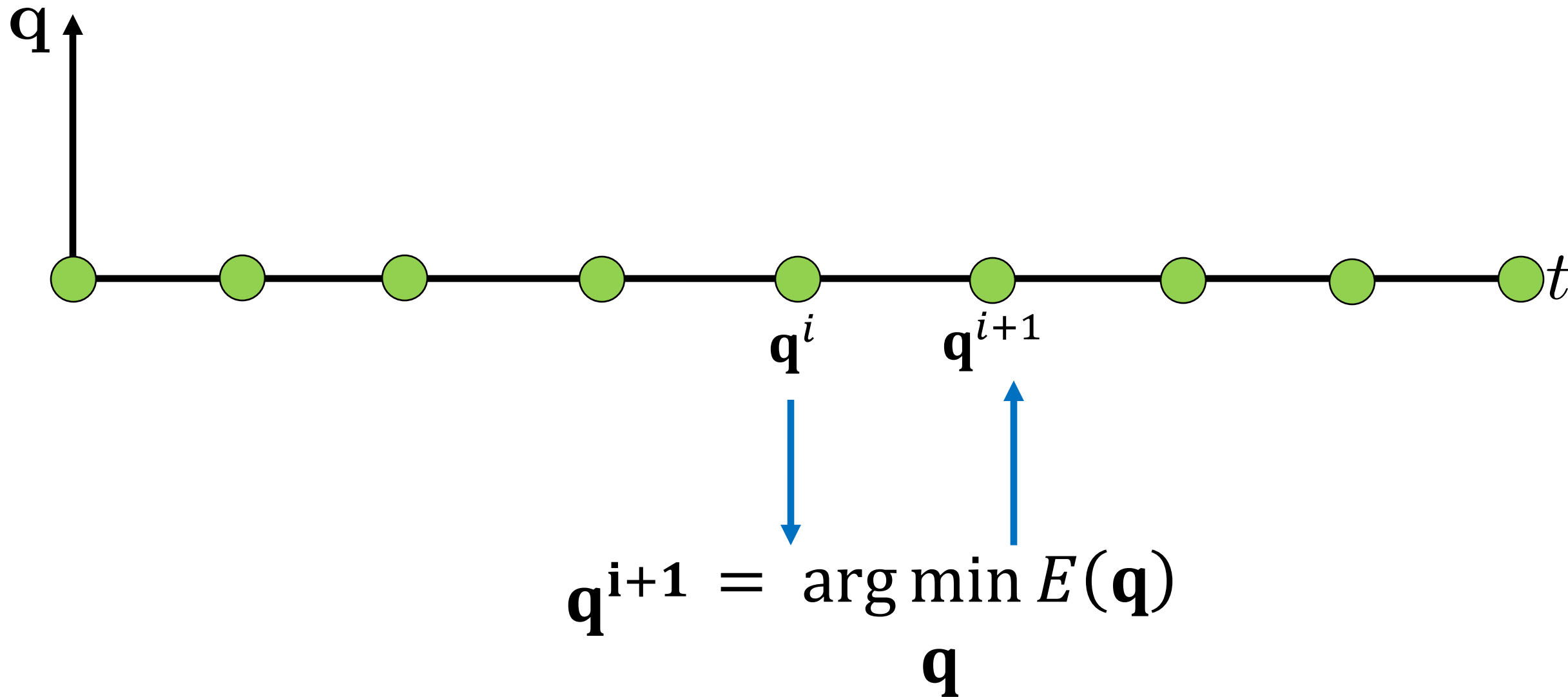
Gradient of what equals this ? Let's guess, then check

How do we Solve This ?

$$E(\mathbf{q}^{i+1}) = \frac{1}{2} (\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i)^T M (\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) + h^2 V(\mathbf{q}^{i+1})$$

Gradient of what equals this ? Let's guess, then check

For each Time Step, Use Optimization !



▼ Viewer

▼ Workspace

Load Save

▼ Mesh

Load Save

▼ Viewing Options

Center object

Snap canonical view

1.000 Zoom

Two Axes ▼ Camera Type

☐ Orthographic view

▼ Draw Options

☐ Face-based

☐ Show texture

☐ Invert normals

☒ Show overlay

☒ Show overlay depth

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☐ Line color

35.000 Shininess

▼ Overlays

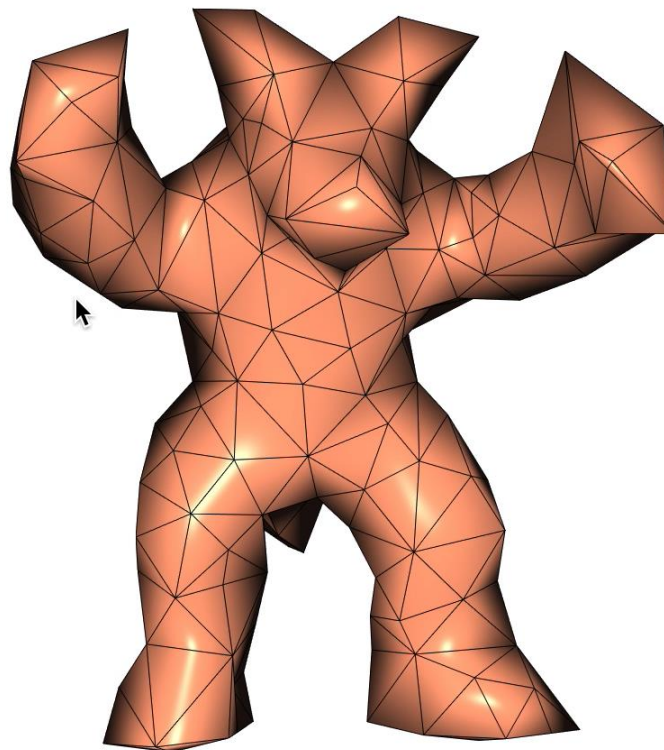
☒ Wireframe

☒ Fill

☐ Show vertex labels

☐ Show faces labels

► Energy Plot



▼ Viewer

▼ Workspace

LoadSave

▼ Mesh

LoadSave

▼ Viewing Options

Center object

Snap canonical view

1.000Zoom

Two Axes▼ Camera Type

☐ Orthographic view

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☐ Line color

35.000Shininess

▼ Overlays

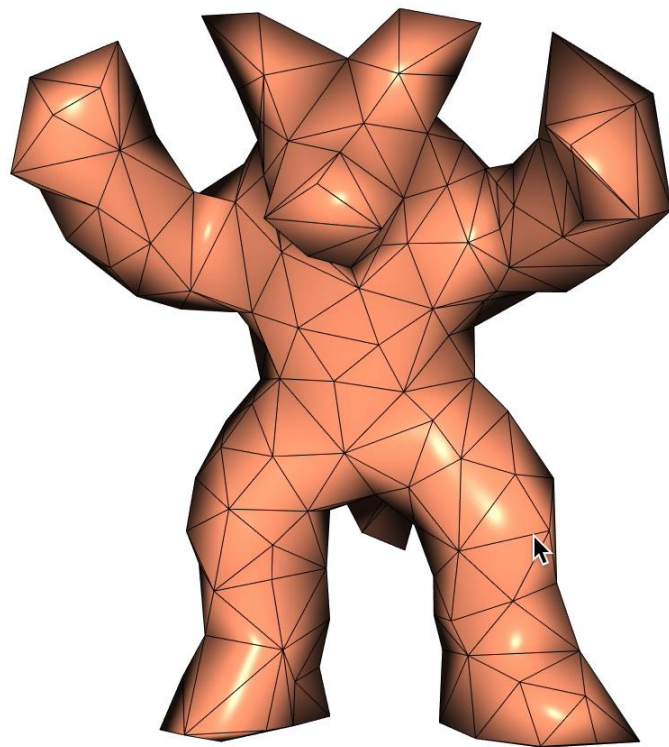
☒ Wireframe

☒ Fill

☐ Show vertex labels

☐ Show faces labels

► Energy Plot



How do we Solve This ?

$$E(\mathbf{q}^{i+1}) = \frac{1}{2} (\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i)^T M (\mathbf{q}^{i+1} - \tilde{\mathbf{q}}^i) + h^2 V(\mathbf{q}^{i+1})$$

Gradient of what equals this ? Let's guess, then check

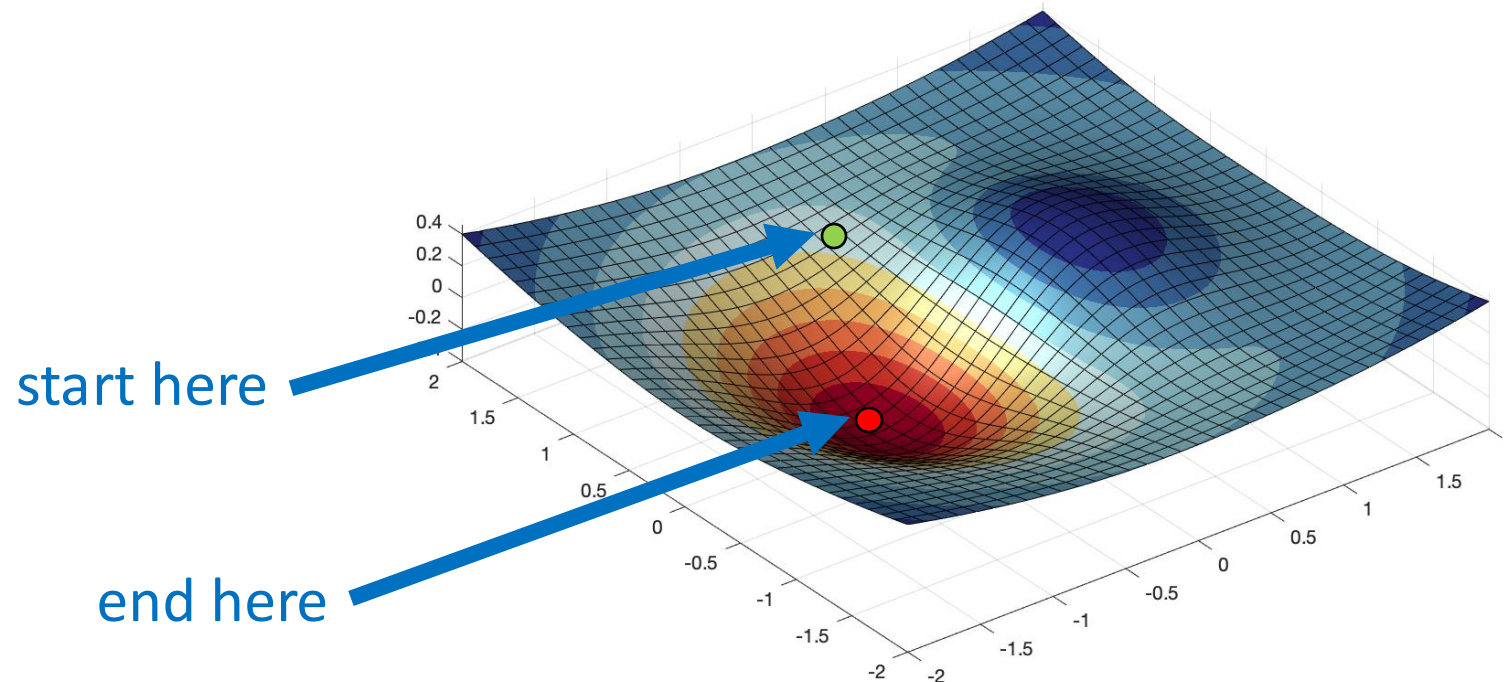
**WARNING I DID NOT HAVE
TIME TO RE-TYPESET THIS
MATH SO THE OPTIMIZATION
PROBLEM IS SLIGHTLY
DIFFERENT FROM THE ONE
ABOVE**

**BUT DON'T PANIC THE
ALGORITHM IS STILL THE SAME
!!!!**

Backward Euler using Optimization

$$\mathbf{v}^* = \arg \min_{\mathbf{v}} \frac{1}{2} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right)^T \mathbf{M} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right) + V \left(\mathbf{q}^t + \Delta t \mathbf{v} \right)$$

$E(\mathbf{v})$



Gradient-Based Optimization

Choose an initial guess

$$i = 0$$
$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{d} = \text{?????}$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$
$$i = i + 1$$

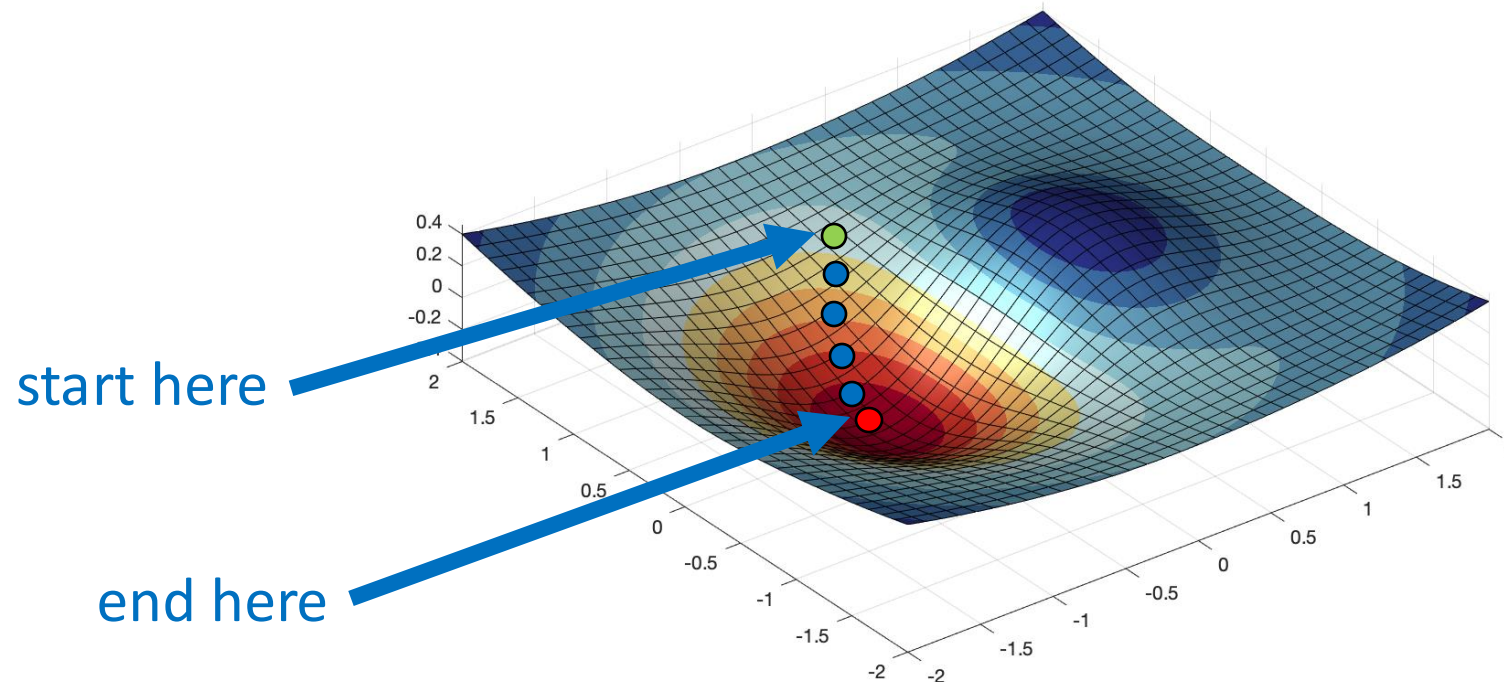
Repeat until converged



Backward Euler using Optimization

$$\mathbf{v}^* = \arg \min_{\mathbf{v}} \frac{1}{2} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right)^T \mathbf{M} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right) + V \left(\mathbf{q}^t + \Delta t \mathbf{v} \right)$$

$E(\mathbf{v})$



Gradient Descent

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{d} = - \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i}$$

Use search direction to update current guess

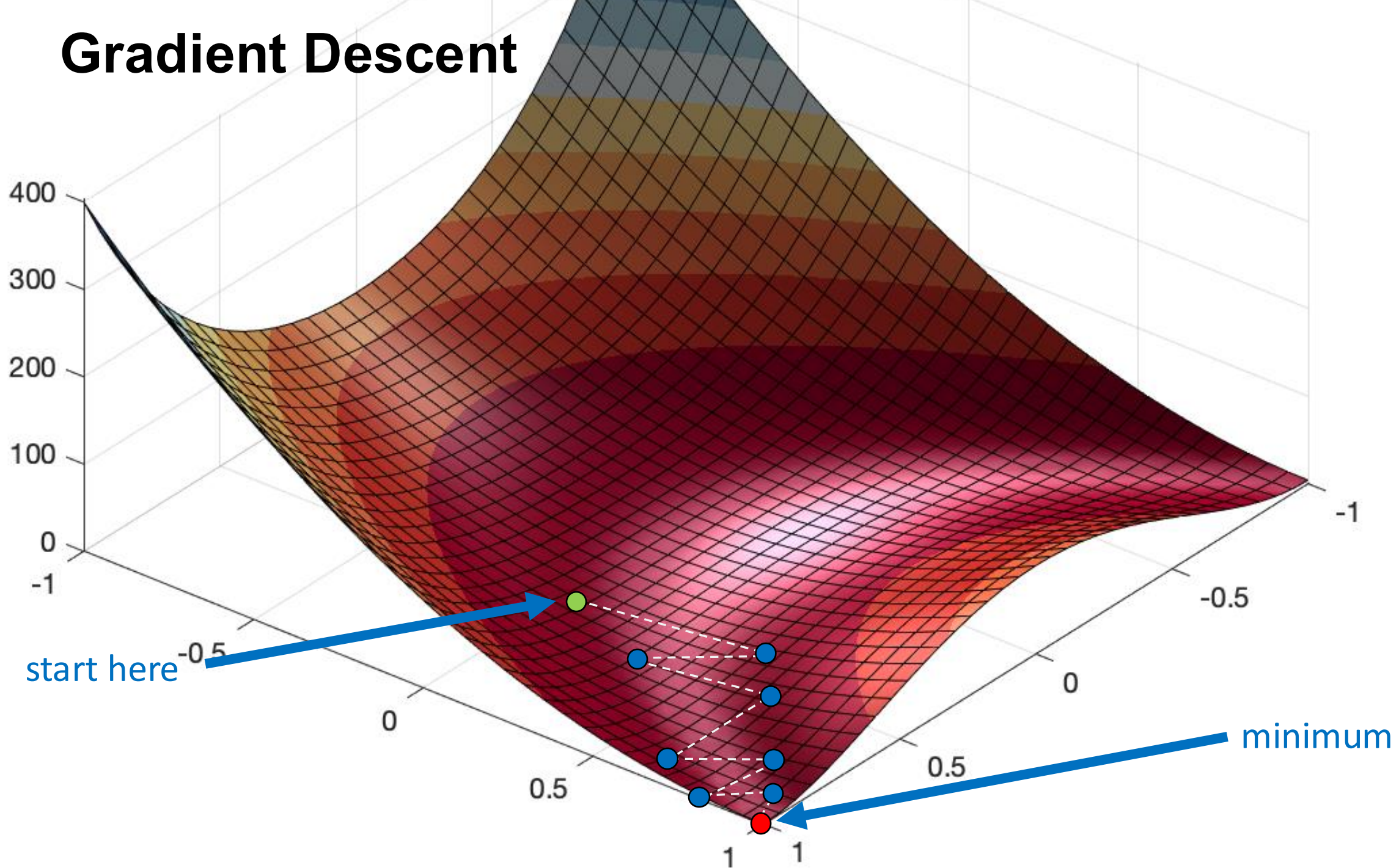
$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

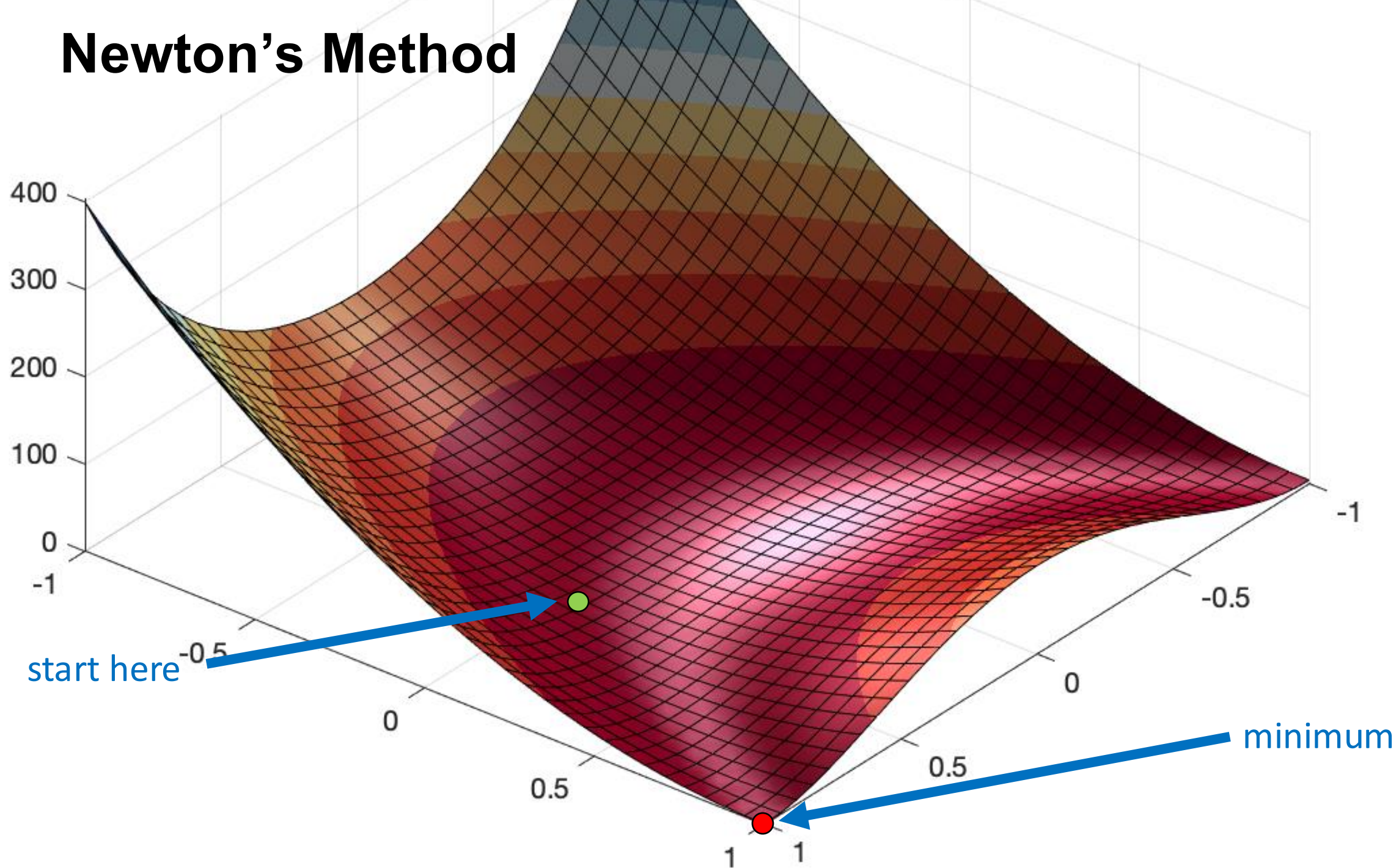
Repeat until converged



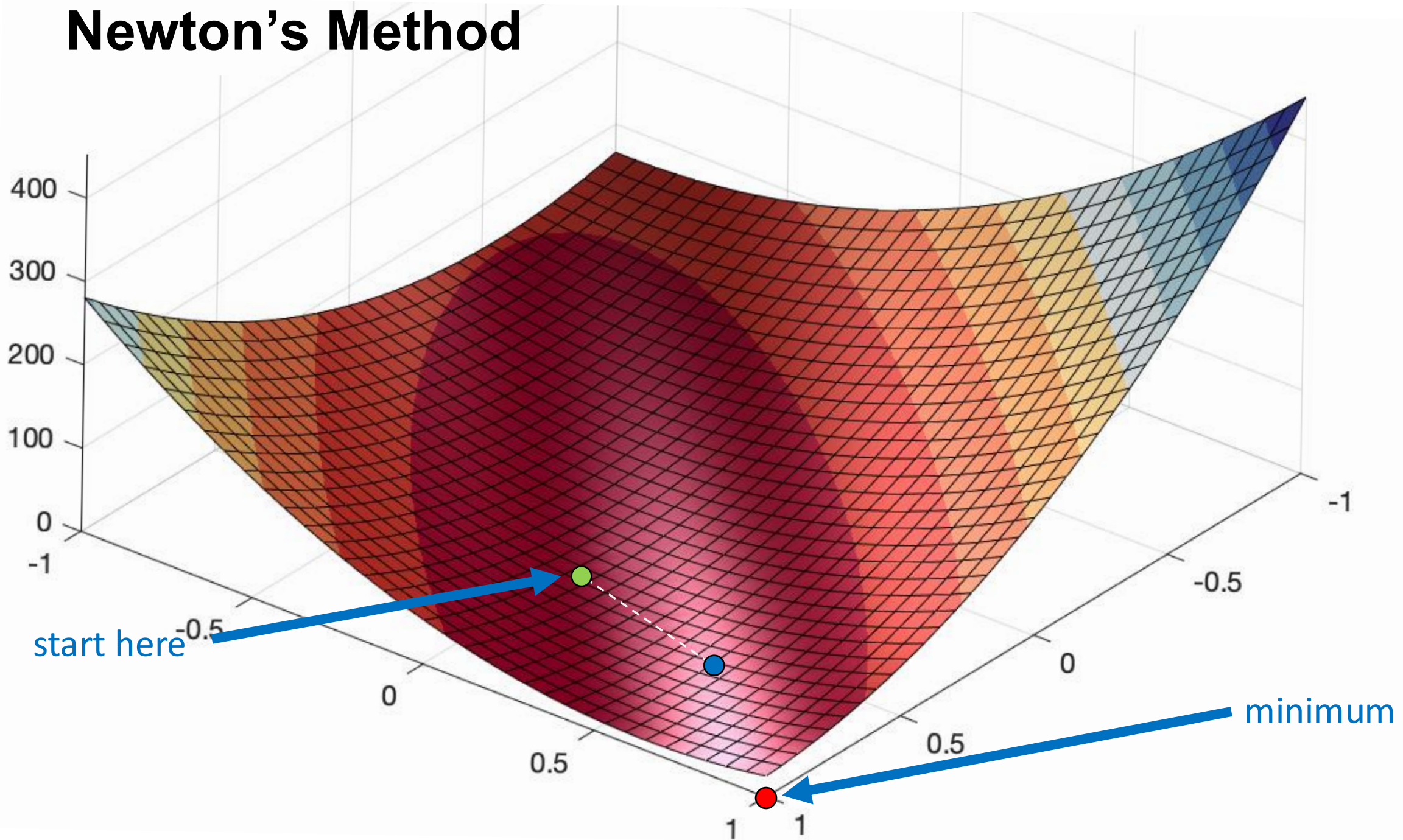
Gradient Descent



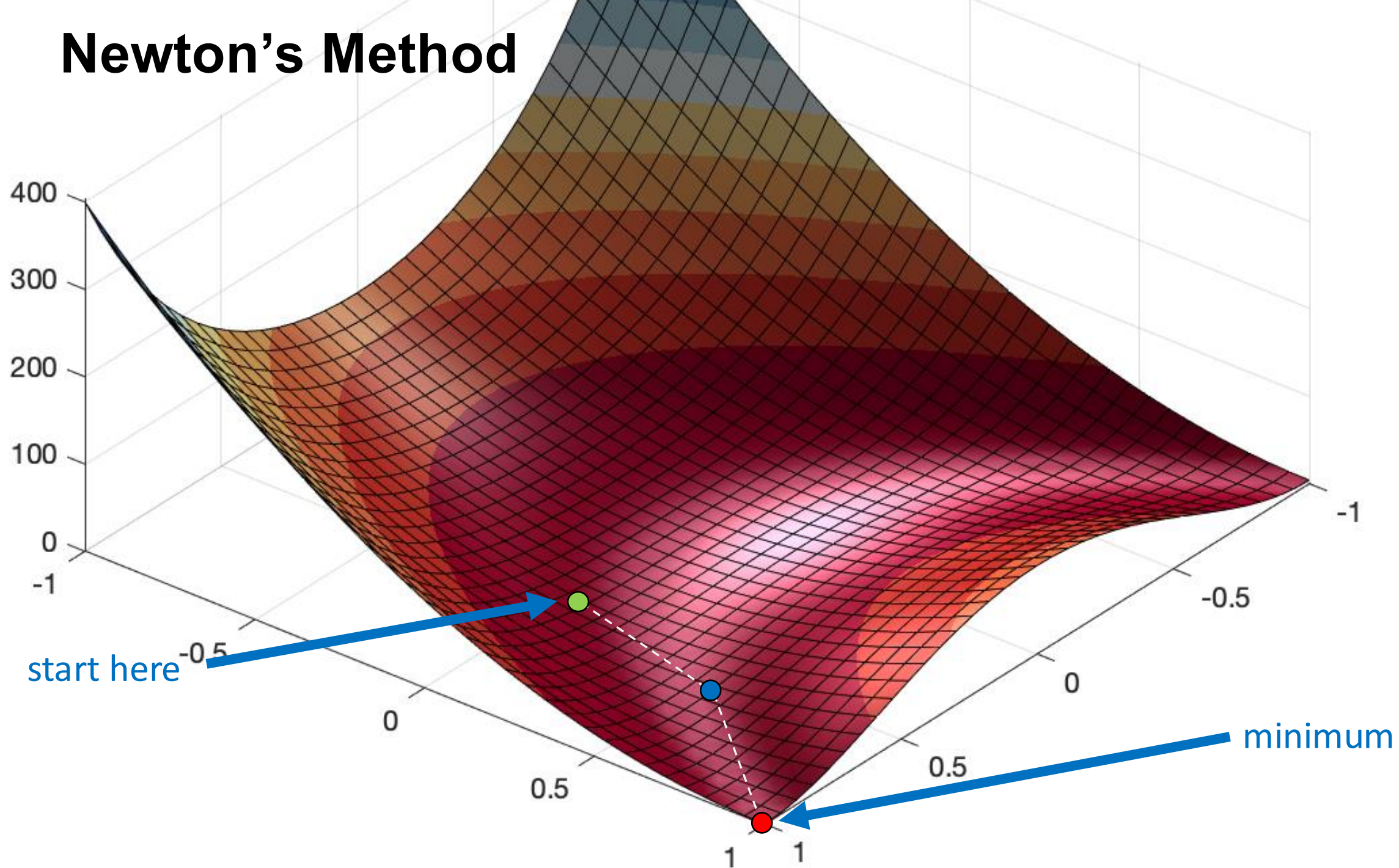
Newton's Method



Newton's Method



Newton's Method



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{d} = \text{Minimize quadratic approximation}$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



Aside: Quadratic Approximations

$$\underset{\text{optimal solution}}{\mathbf{y}^*} = \arg \min_{\mathbf{y}} \underset{\text{energy/cost function}}{E(\mathbf{y})} \quad \text{generic optimization problem}$$

$$\mathbf{d} = \arg \min_{\tilde{\mathbf{d}}} E(\mathbf{y}^i + \tilde{\mathbf{d}})$$

Second Order Taylor Approximation

$$\mathbf{d} = \arg \min_{\tilde{\mathbf{d}}} \frac{1}{2} \tilde{\mathbf{d}}^T \underset{\frac{\partial^2 E}{\partial \mathbf{y}^2} \big|_{\mathbf{y}^i}}{\mathbf{H}^i} \tilde{\mathbf{d}} + \tilde{\mathbf{d}}^T \underset{\frac{\partial E}{\partial \mathbf{y}} \big|_{\mathbf{y}^i}}{\mathbf{g}^i} + \cancel{\underset{E(\mathbf{y}^i)}{E^i}}$$



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{d} = \arg \min_{\tilde{\mathbf{d}}} \frac{1}{2} \tilde{\mathbf{d}}^T \mathbf{H}^i \tilde{\mathbf{d}} + \tilde{\mathbf{d}}^T \mathbf{g}^i .$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



Aside: Minimizing a Quadratic Function

$$\mathbf{d} = \arg \min_{\tilde{\mathbf{d}}} \frac{1}{2} \tilde{\mathbf{d}}^T \mathbf{H}^i \tilde{\mathbf{d}} + \tilde{\mathbf{d}}^T \mathbf{g}^i$$

Minimum when gradient is equal to zero

$$\mathbf{H}^i \mathbf{d} + \mathbf{g}^i = \mathbf{0}$$

$$\mathbf{H}^i \mathbf{d} = -\mathbf{g}^i$$

Solve linear system to get \mathbf{d}



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{H}^i \mathbf{d} = -\mathbf{g}^i \quad \text{Solve linear system to get } \mathbf{d}$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



Gradient and Hessian

$$E(\mathbf{v}) = \frac{1}{2} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right)^T \mathbf{M} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right) + V \left(\mathbf{q}^t + \Delta t \mathbf{v} \right)$$

$$\frac{\partial E}{\partial \mathbf{v}} = \mathbf{M} \left(\mathbf{v} - \dot{\mathbf{q}}^t \right) + \Delta t \underbrace{\frac{\partial V}{\partial \mathbf{q}} \Big|_{\mathbf{q}^t + \Delta t \mathbf{v}}}_{\text{negative generalized forces}}$$

$$\frac{\partial^2 E}{\partial \mathbf{v}^2} = \mathbf{M} + \Delta t^2 \underbrace{\frac{\partial^2 V}{\partial \mathbf{q}^2} \Big|_{\mathbf{q}^t + \Delta t \mathbf{v}}}_{\text{negative stiffness matrix}}$$



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{H}^i \mathbf{d} = -\mathbf{g}^i \quad \text{Solve linear system to get } \mathbf{d}$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



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Load Save

▼ Viewing Options

Center object

Snap canonical view

1.000 Zoom

Two Axes ▼ Camera Type

☐ Orthographic view

▼ Draw Options

☐ Face-based

☐ Show texture

☐ Invert normals

☒ Show overlay

☒ Show overlay depth

☐ Background

☐ Line color

35.000 Shininess

▼ Overlays

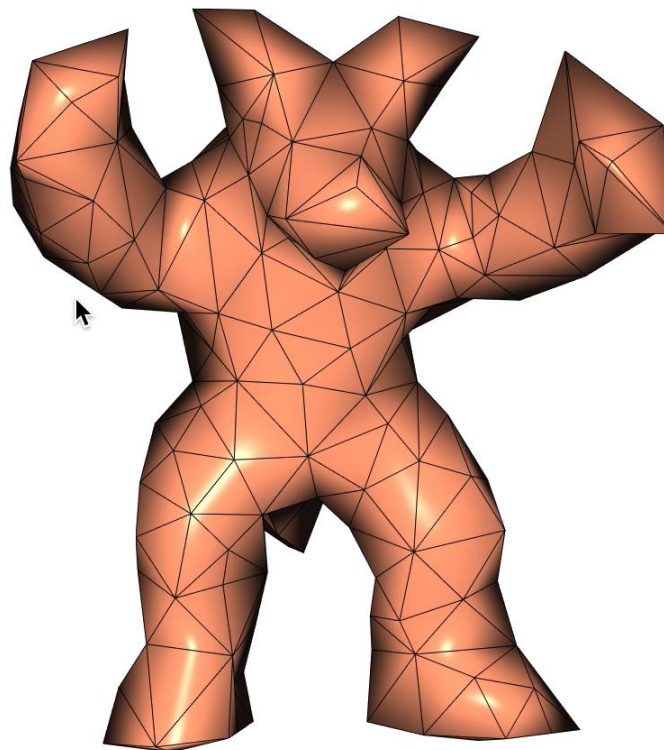
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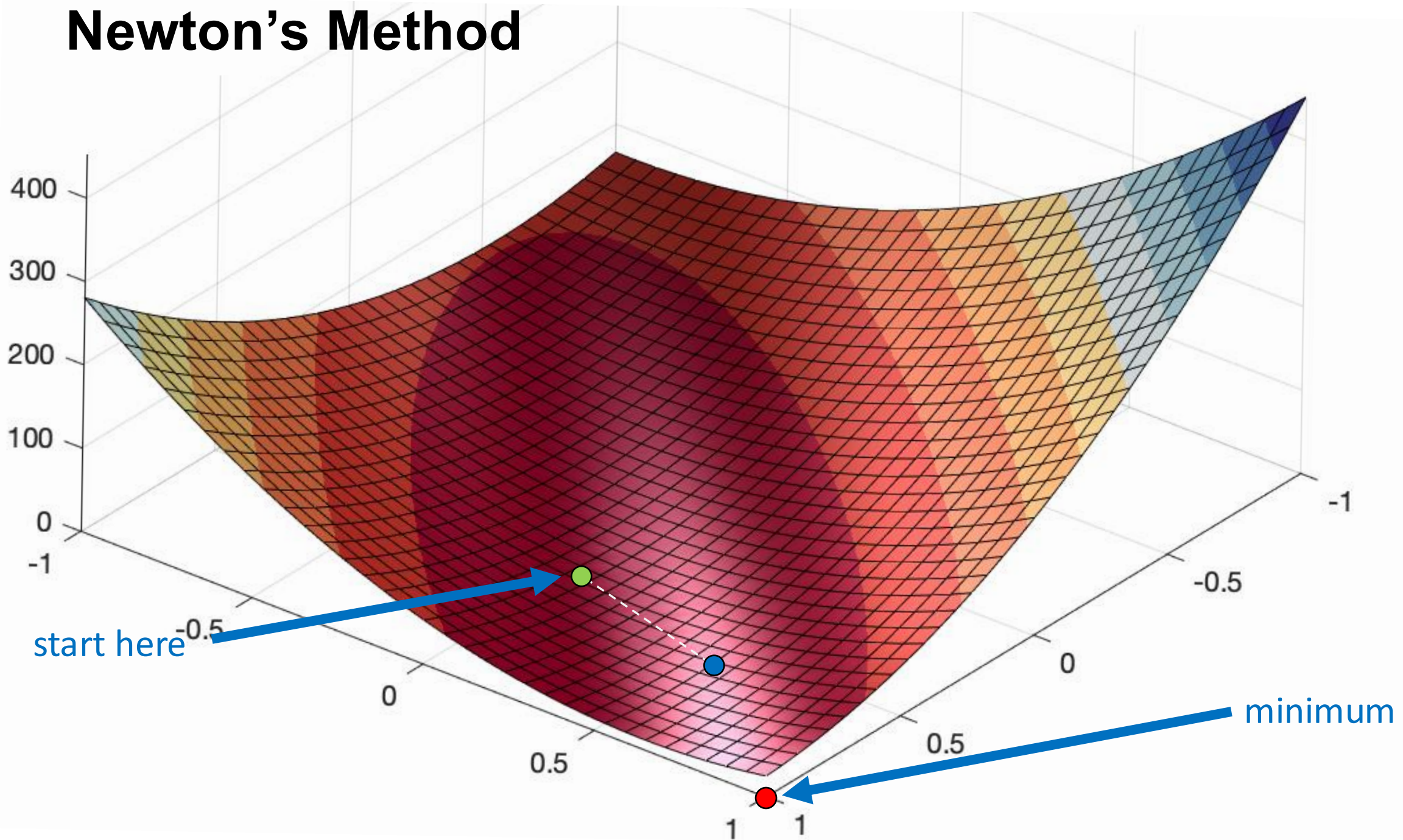
☐ Show vertex labels

☐ Show faces labels

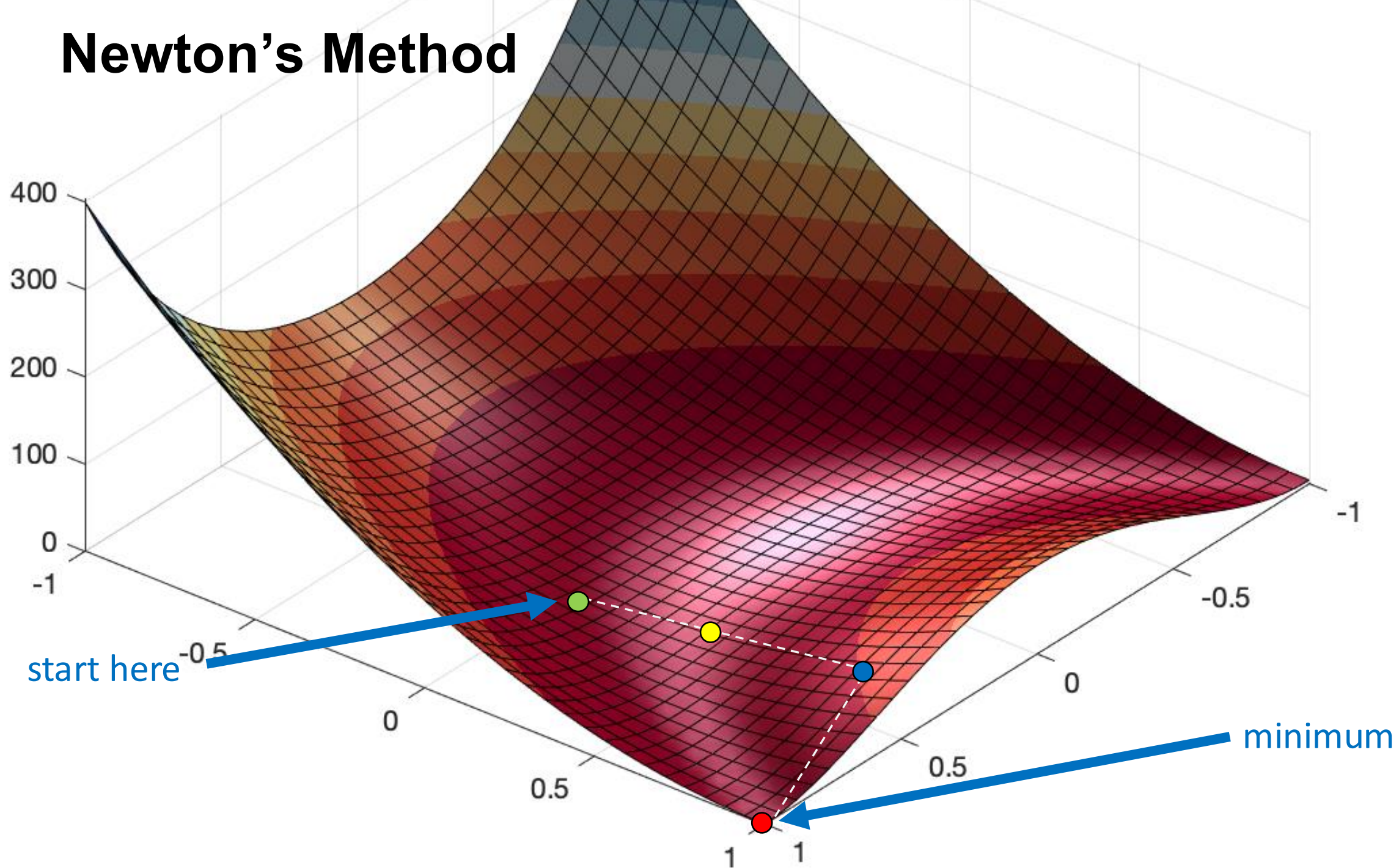
► Energy Plot



Newton's Method



Newton's Method



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{H}^i \mathbf{d} = -\mathbf{g}^i \quad \text{Solve linear system to get } \mathbf{d}$$

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



Newton's Method

Choose an initial guess

$$i = 0$$

$$\mathbf{v}^0 = \text{something}$$

Check for convergence

$$\left\| \frac{\partial E}{\partial \mathbf{v}} \Big|_{\mathbf{v}^i} \right\| < \text{tol}$$

Choose search direction

$$\mathbf{H}^i \mathbf{d} = -\mathbf{g}^i \quad \text{Solve linear system to get } \mathbf{d}$$

Choose α using line search

Use search direction to update current guess

$$\mathbf{v}^{i+1} = \mathbf{v}^i + \alpha \mathbf{d}$$

$$i = i + 1$$

Repeat until converged



Line Search

$$\mathbf{y}^* = \arg \min_{\mathbf{y}} E(\mathbf{y})$$

Once we compute \mathbf{d} ...

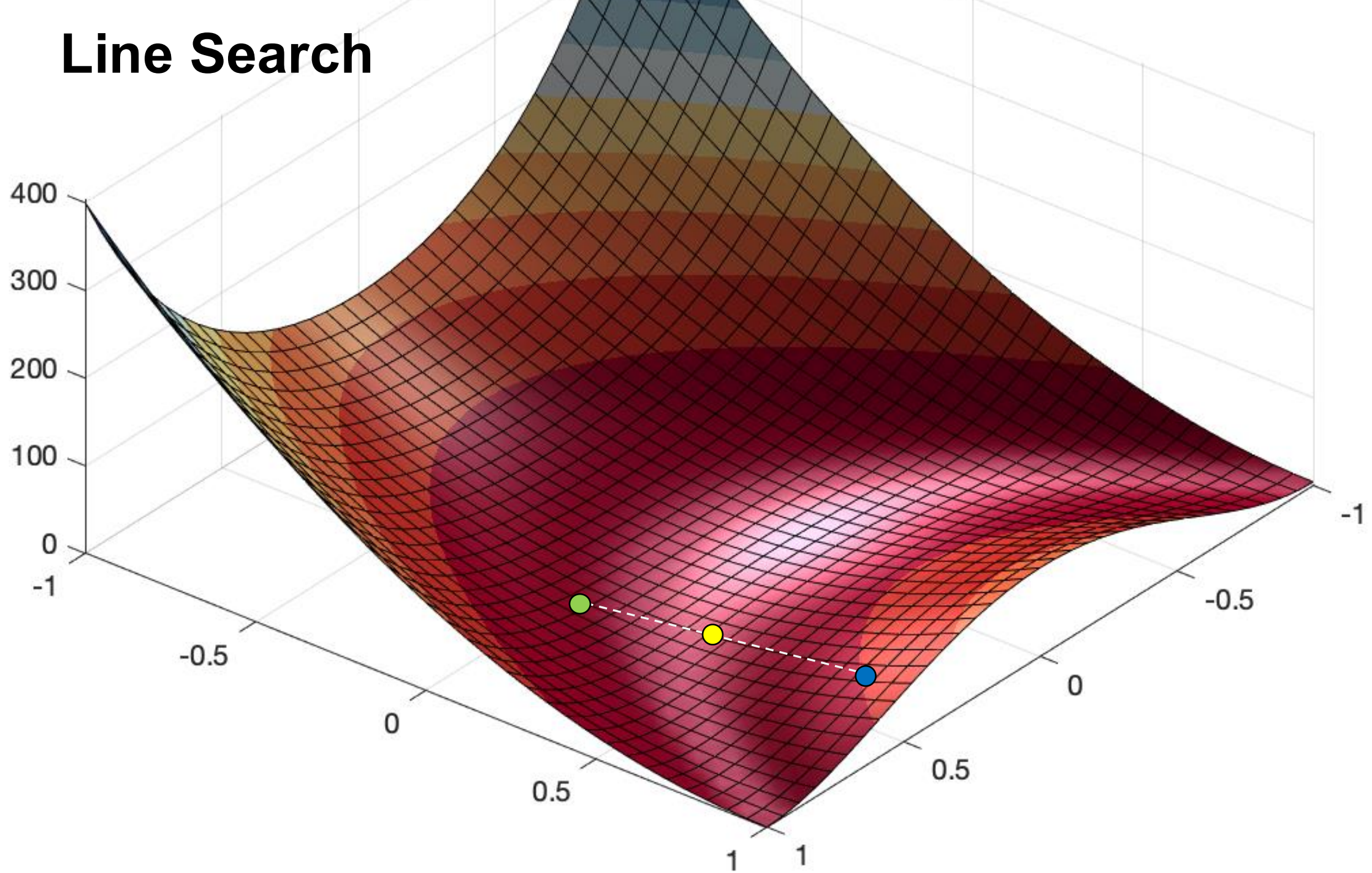
One-dimensional optimization

$$\alpha^* = \arg \min_{\alpha} E(\mathbf{y}^i + \alpha \mathbf{d})$$

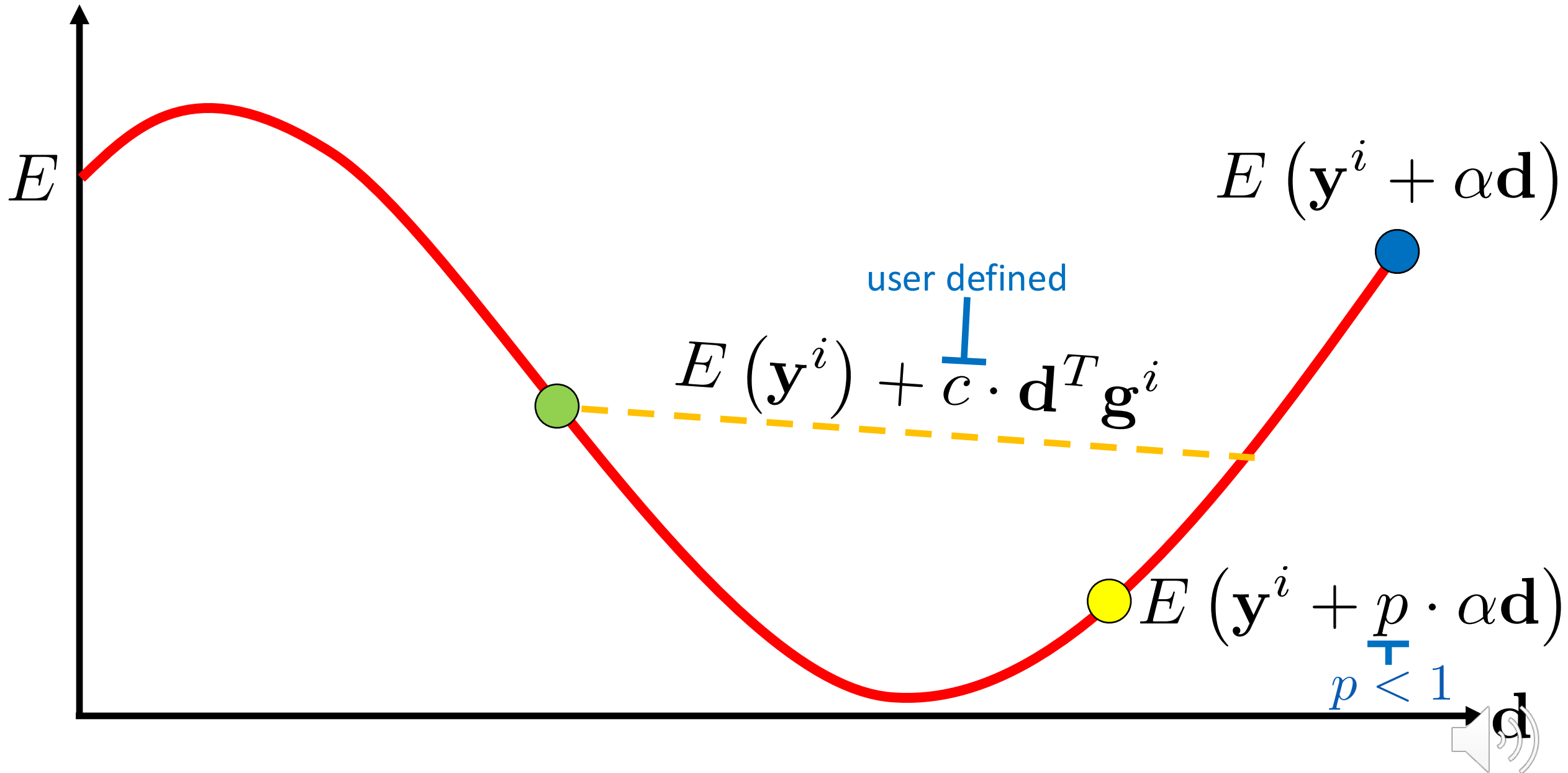
Solve by 1D Search



Line Search



Line Search



Backtracking Line Search

Choose an initial guess

$$\alpha = \alpha_{max}$$

Stop if sufficient decrease achieved or you get stuck

$$E(\mathbf{v}^i + \alpha \mathbf{d}) \leq E(\mathbf{v}^i) + c \cdot \mathbf{d}^T \mathbf{g}^i \text{ or } \alpha < \text{tol}$$

Reduce α

$$\alpha = p \cdot \alpha$$

Repeat



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LoadSave

▼ Viewing Options

Center object

Snap canonical view

1.000Zoom

Two Axes▼ Camera Type

☐ Orthographic view

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35.000Shininess

▼ Overlays

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