

# Sampling with constraints

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**Thanks to:**

Jonathan Goodman

Emilio Zappa

US Dept of Energy

Problem:

Sample density  $\rho(x) = Z^{-1} f(x) \delta(q(x))$ .

$x \in \mathbb{R}^n$ ,  $f: \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $q: \mathbb{R}^n \rightarrow \mathbb{R}^m$  ("constraints".)

Why do this:

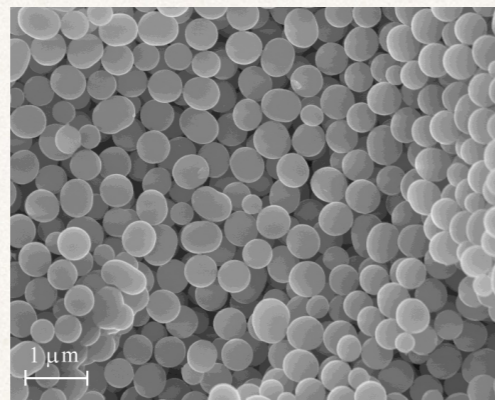
- Freeze out fast, vibrational degrees of freedom of strongly-bonded particles (e.g.  $q(x) = |x_1 - x_2|^2 - d^2$ )
- Compute Free Energy / Expectations at certain levels of a reaction coordinate
- Bayesian sampling — constraints on parameters (e.g.  $p_1 + p_2 + p_3 = 1$ )

# My interest = Colloids (colloidal particles)

- ❖ *Colloidal* particles: diameters  $\sim 10^{-8}$ - $10^{-6}$  m. ( $\gg$  atoms,  $\ll$  scales of humans)
- ❖ Building blocks for many materials
- ❖ Potential to make new materials ( $\because$  size  $\sim$  wavelength of light)



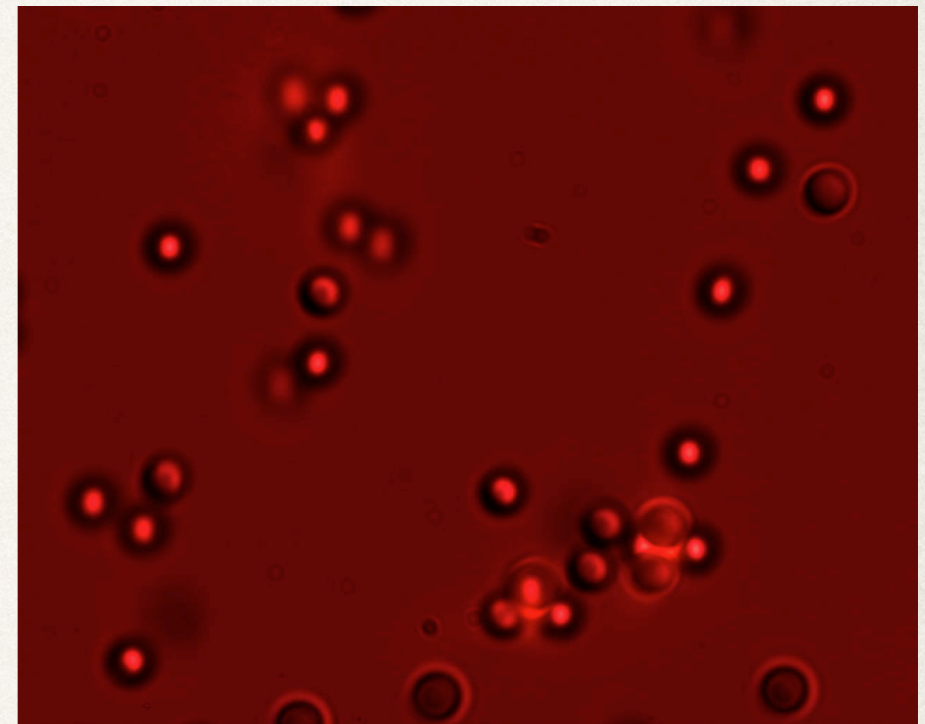
mayonnaise



red blood cells

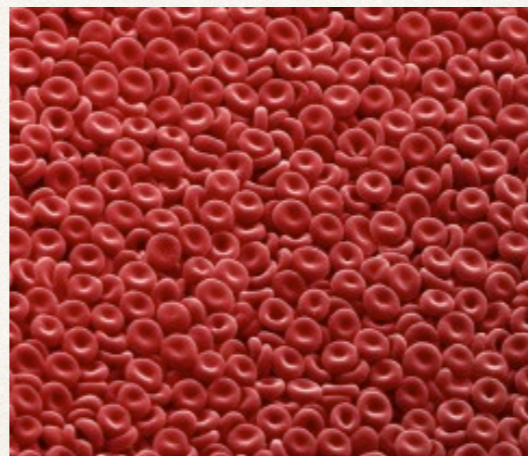
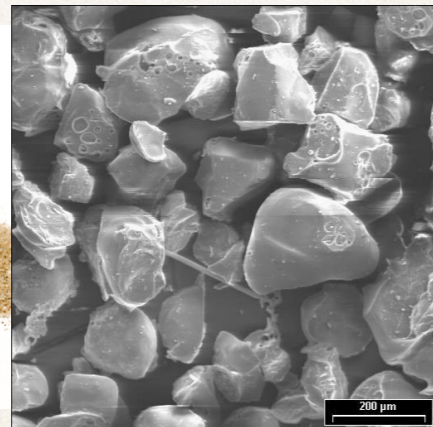


opal

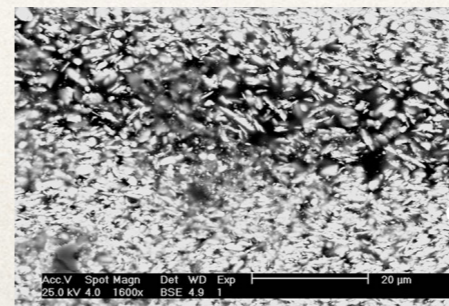
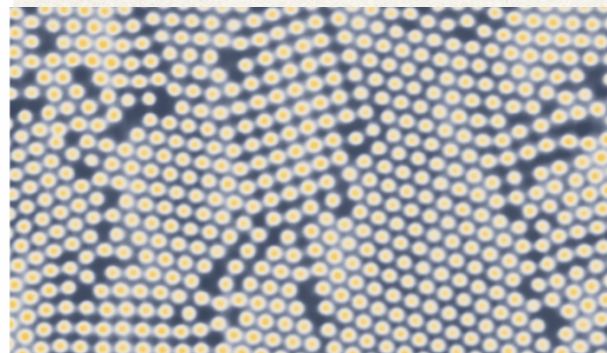


Schade, H.-C., et al. PRL (2013)

sand



cornstarch



paint



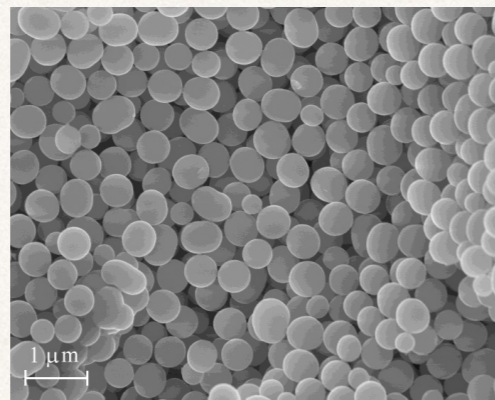
ketchup

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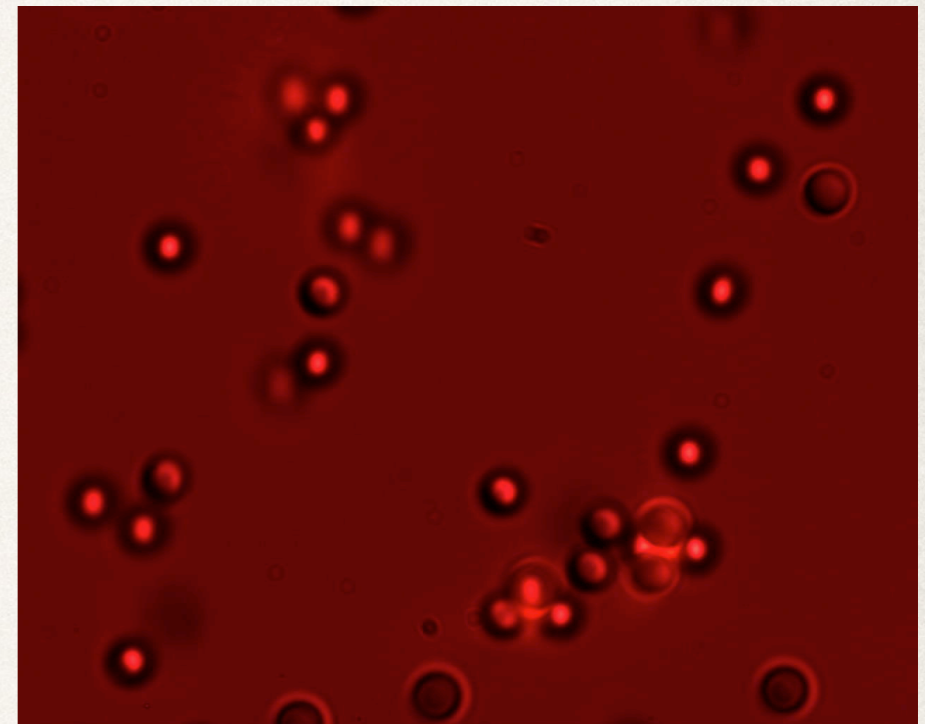
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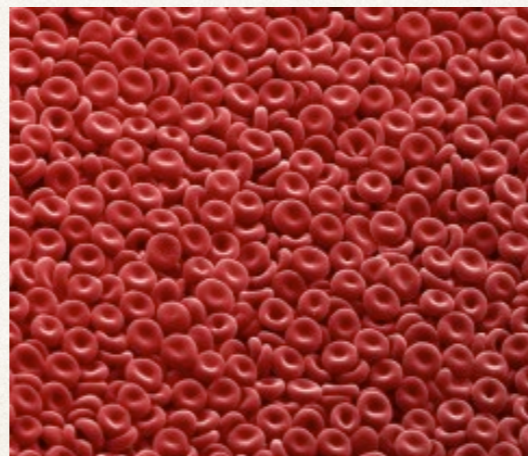
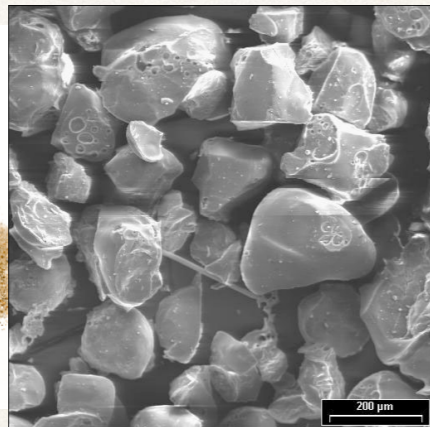
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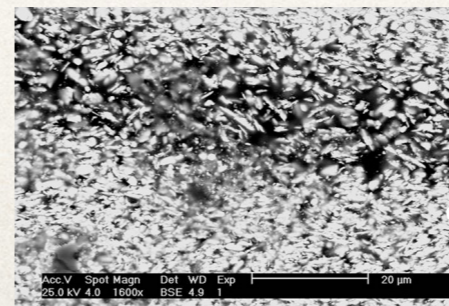
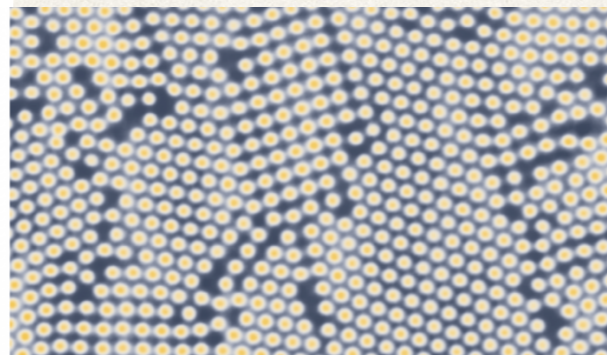
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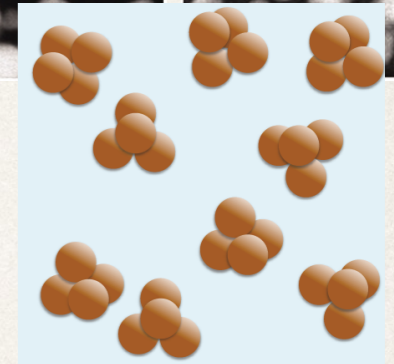
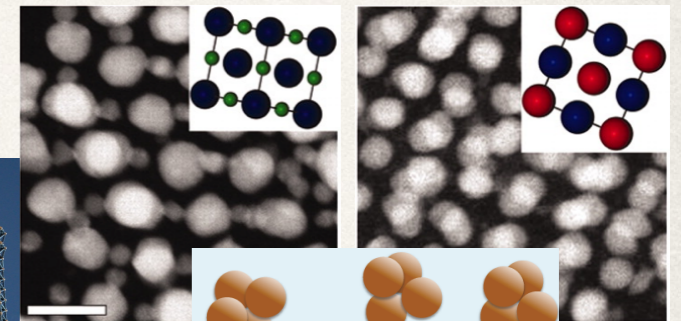
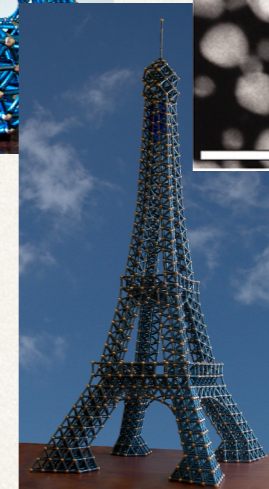
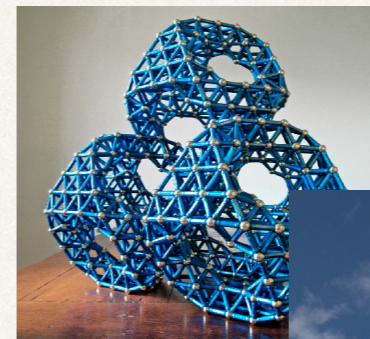
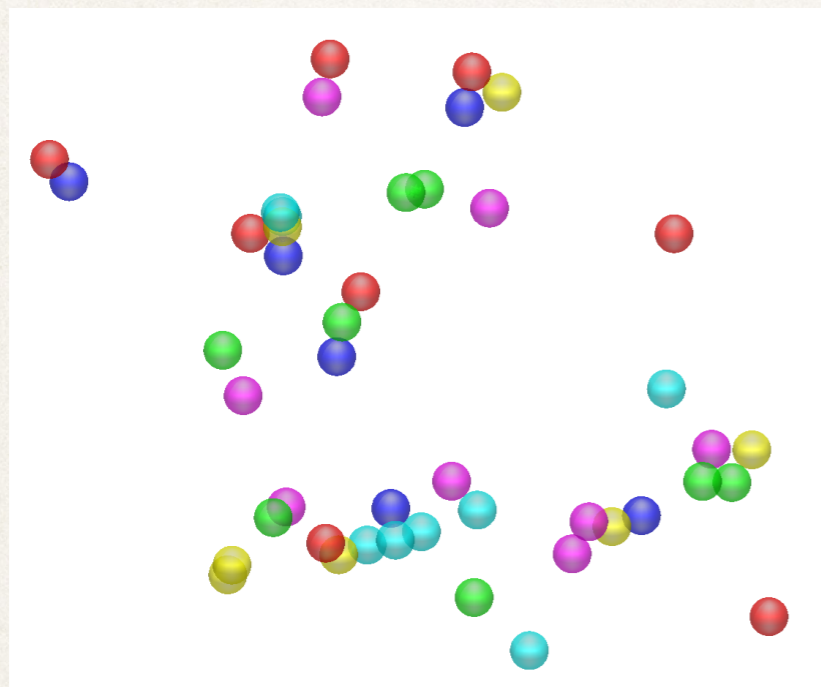
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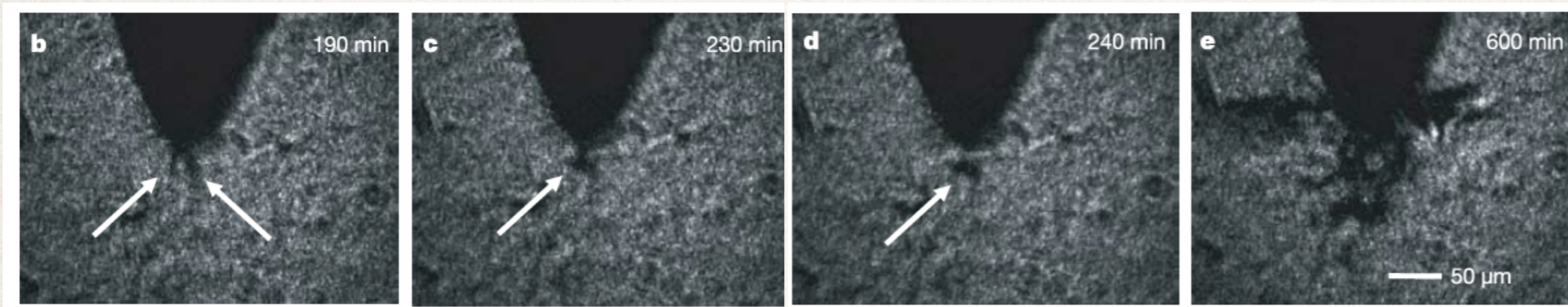
ketchup

# Scientific question:

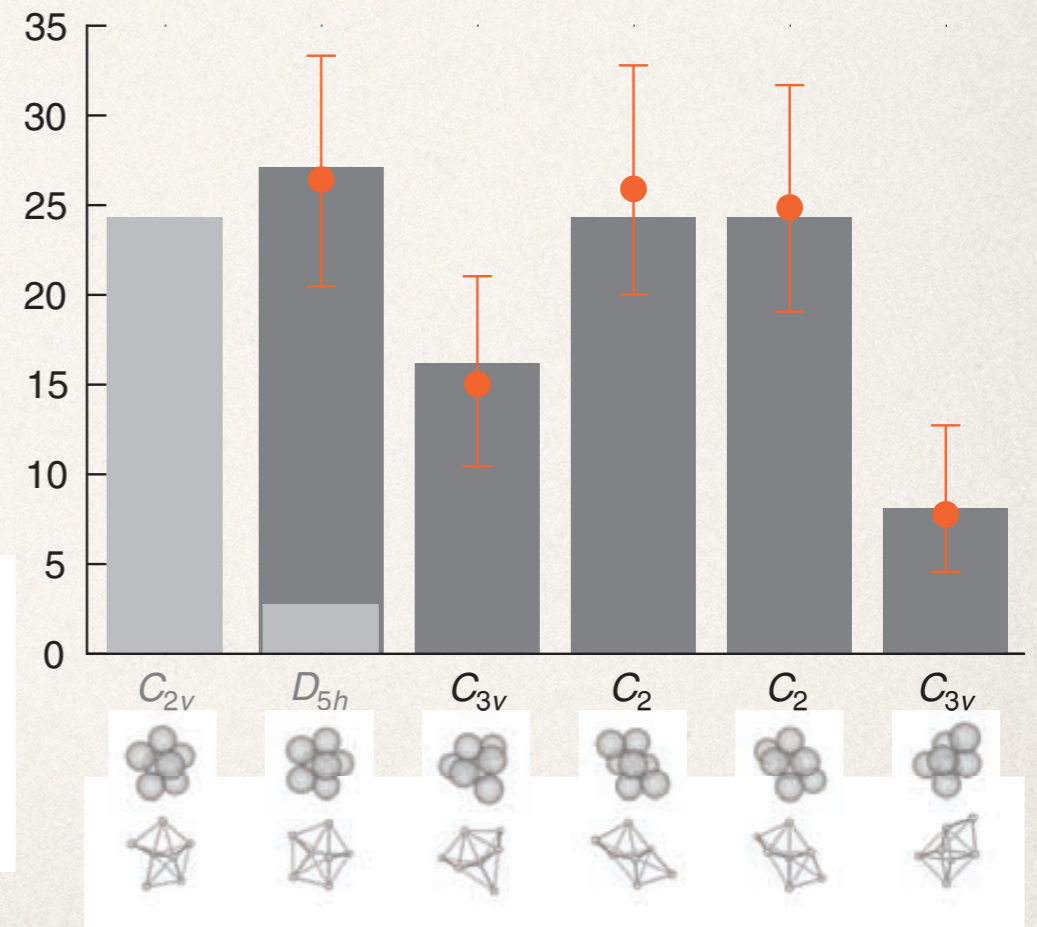
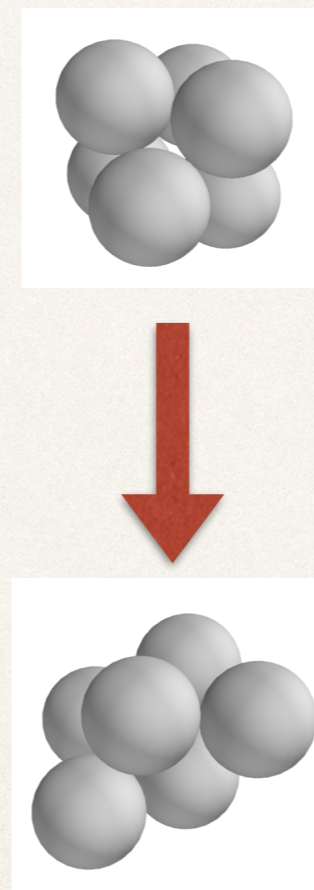
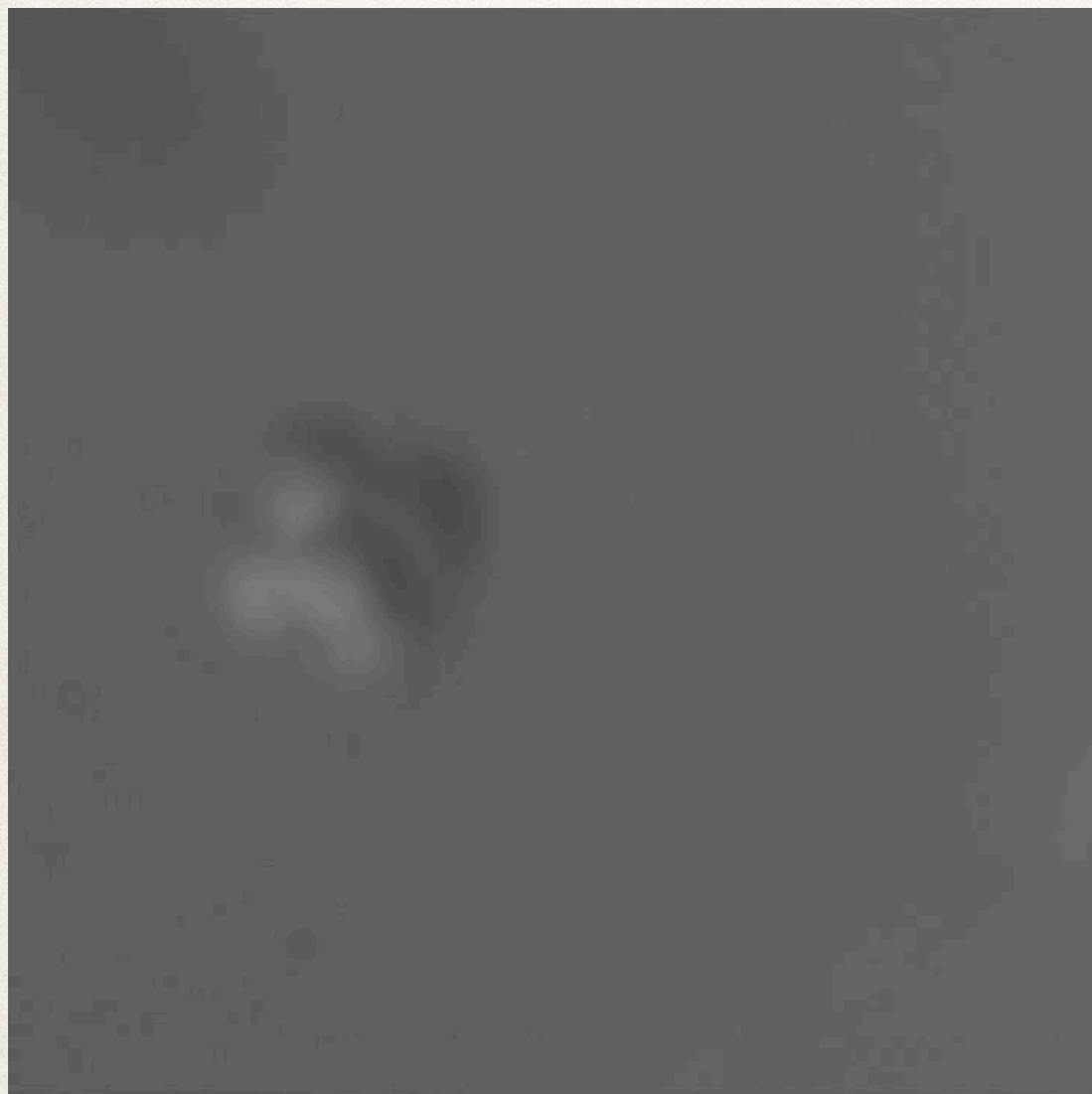
*How to design colloids to self-assemble into some desired structure?*



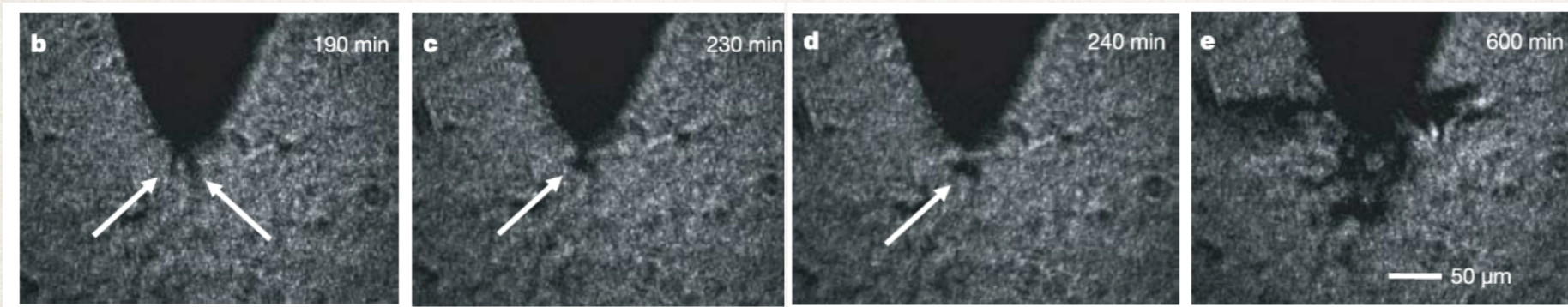
# Colloids are (sometimes) easy to study experimentally



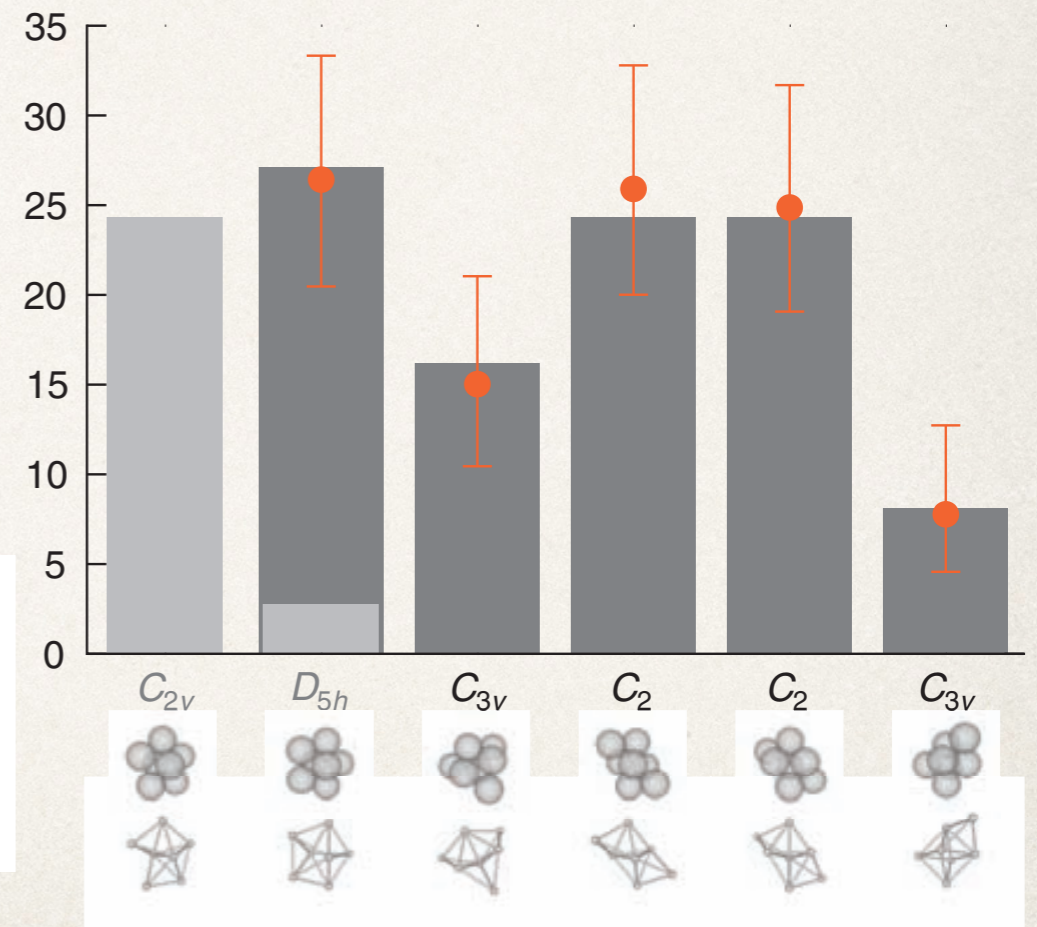
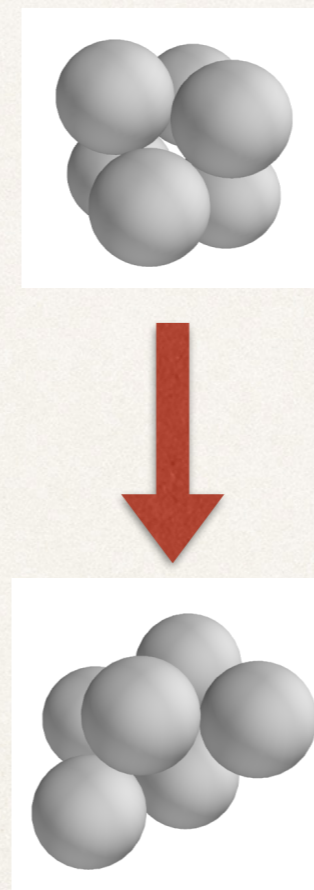
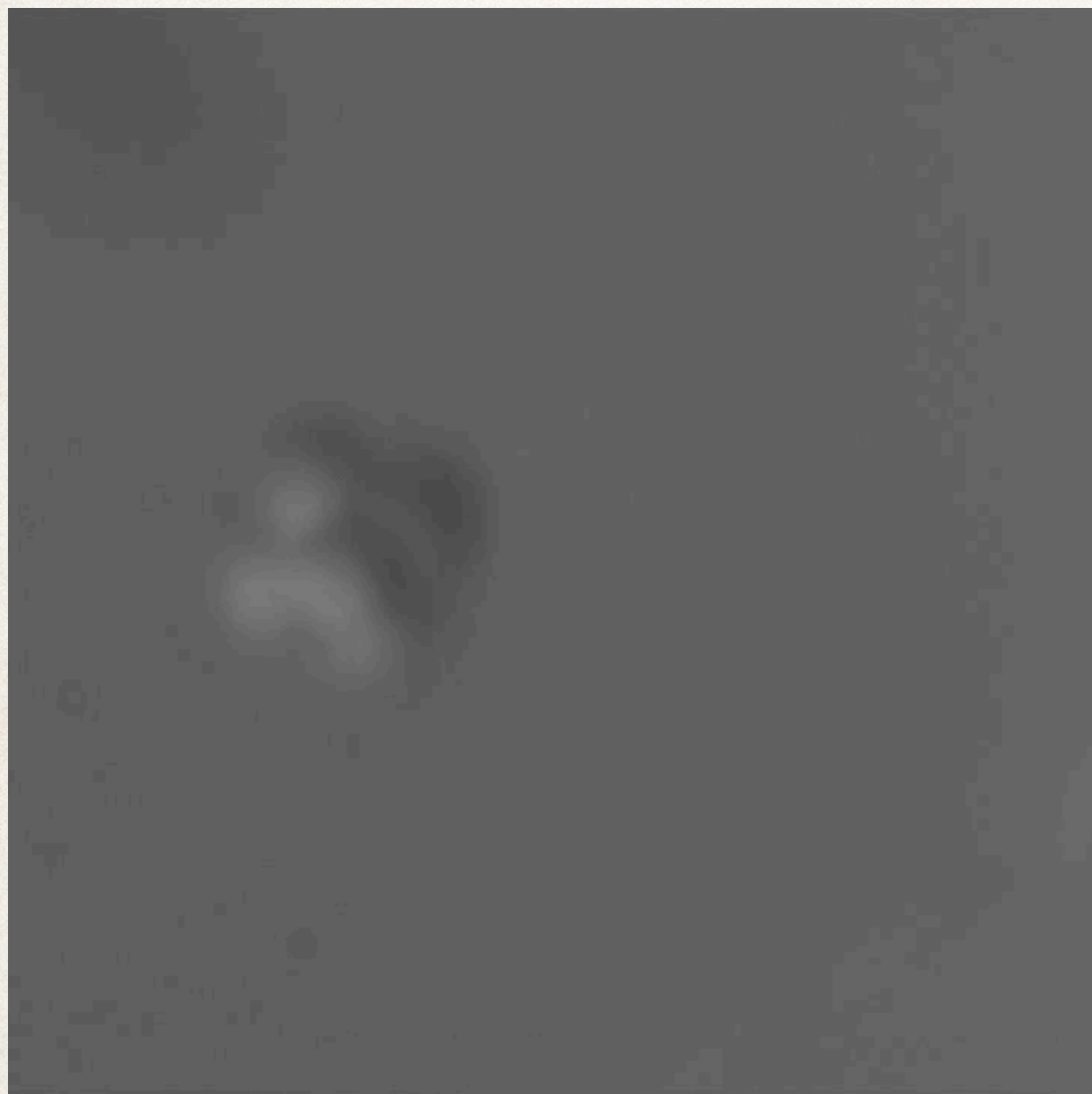
Schall et al, Nature (2006)



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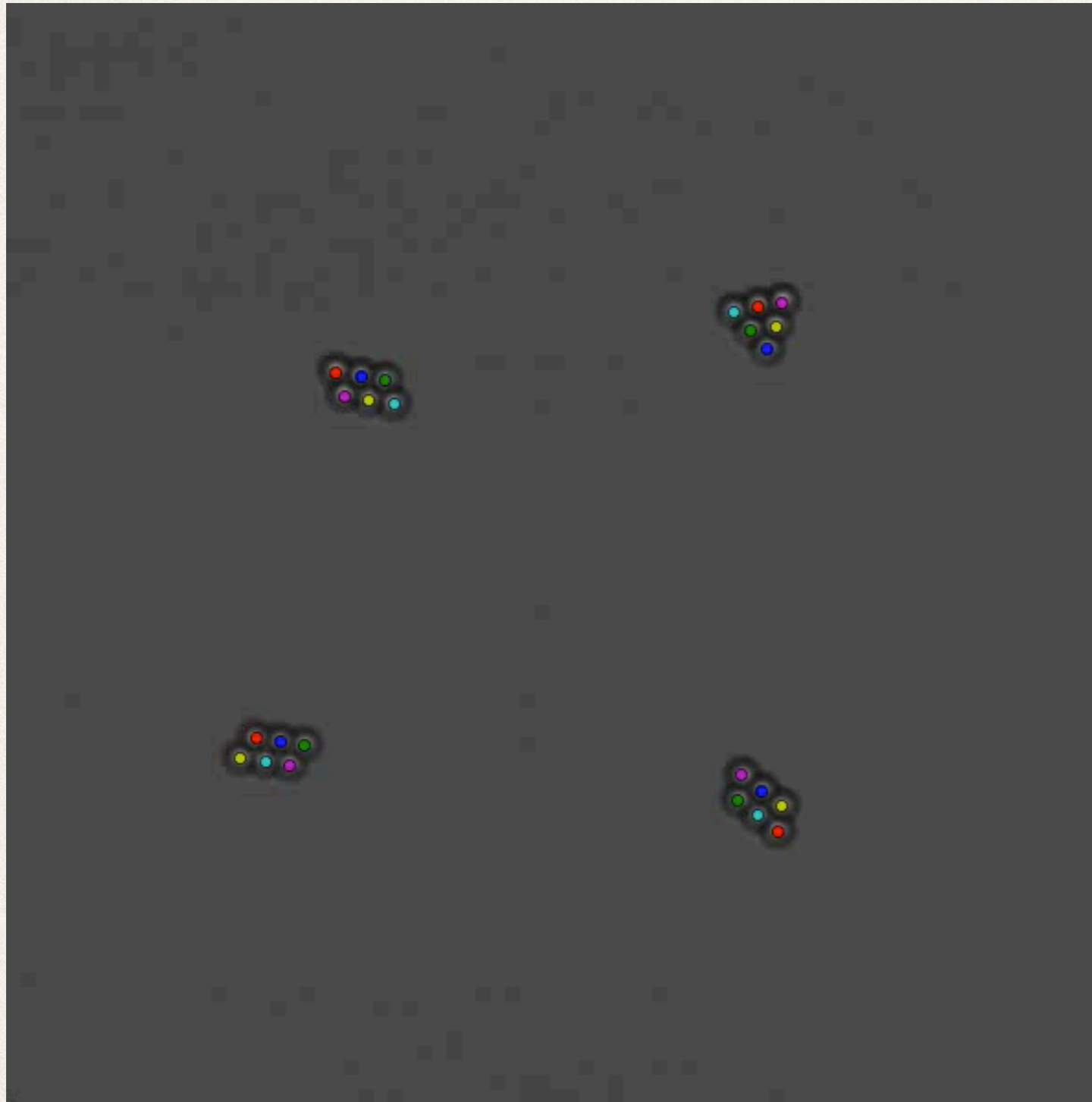
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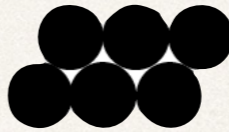
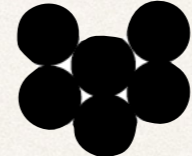
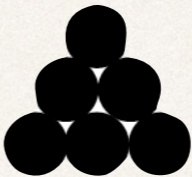
# We can even measure dynamics with high accuracy

Rebecca Perry  
(Manoharan lab)



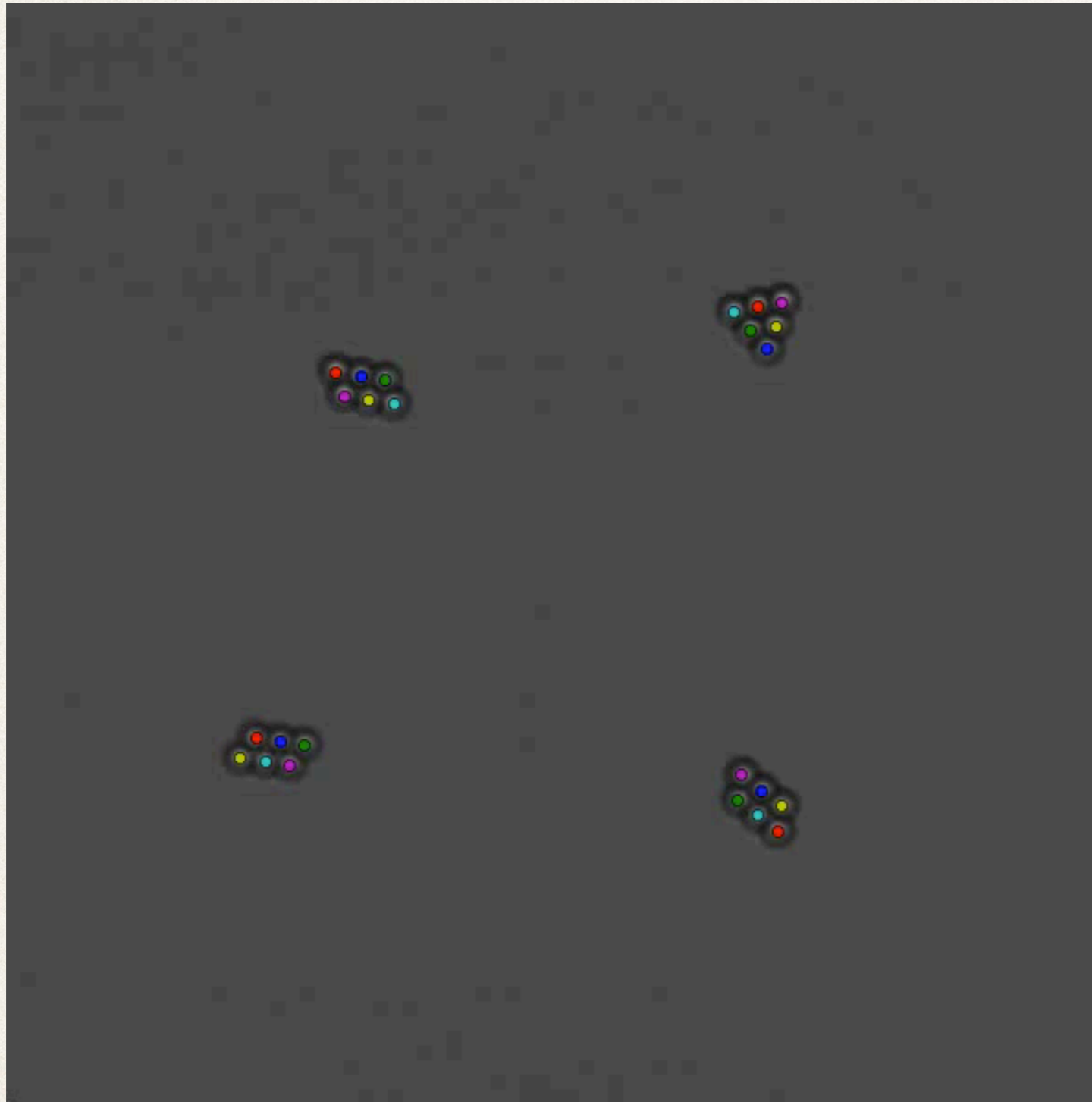
Diagrammatic representation of three particle clusters used in the table:

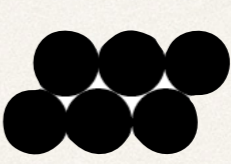
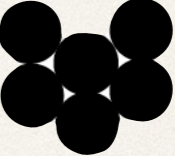
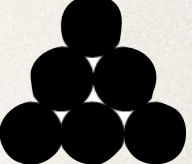
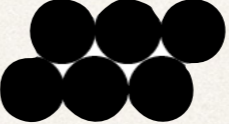
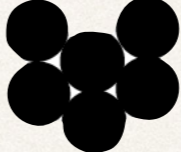
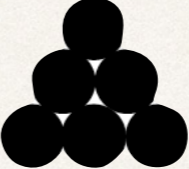
- Top-left: A cluster of 7 particles arranged in two rows (3 on top, 4 on bottom).
- Top-middle: A cluster of 7 particles arranged in two rows (3 on top, 4 on bottom).
- Top-right: A cluster of 7 particles arranged in two rows (3 on top, 4 on bottom).

	112	140	64
	138	198	49
	63	55	1

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## Colloids are a lot like atoms

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- Energy = pairwise interactions

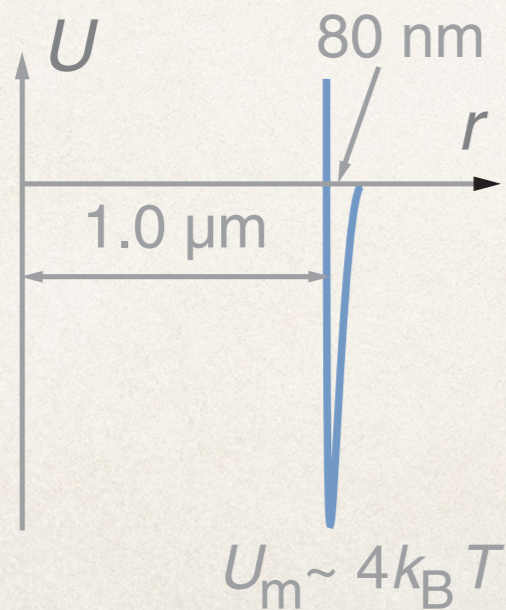
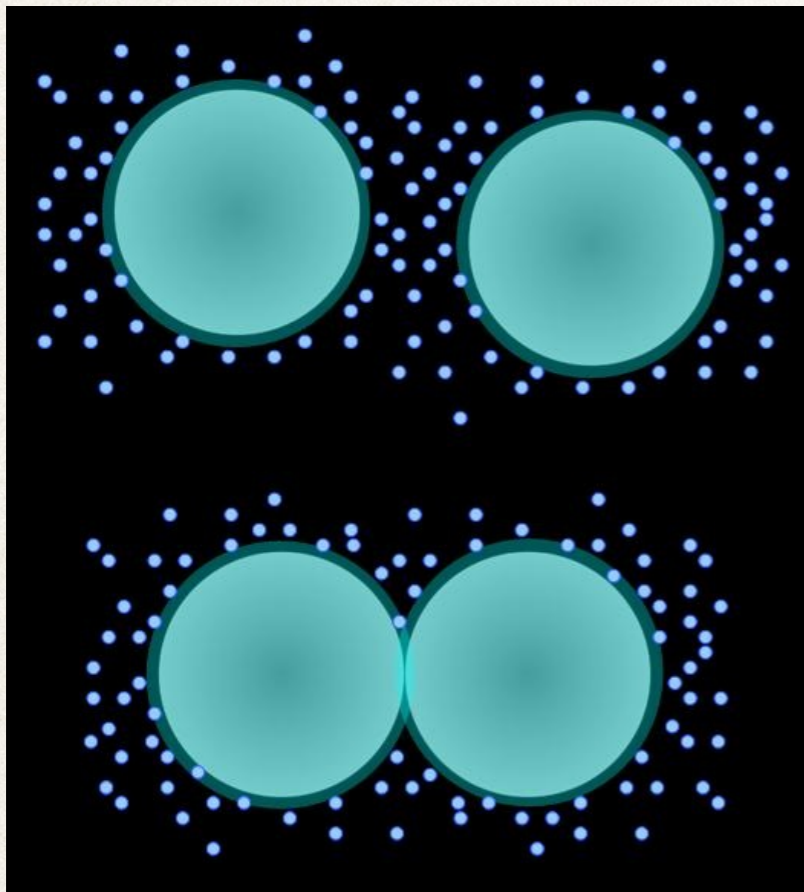
$$\pi(x) \propto e^{-\beta V(x)}, \quad V(x) = \sum_{i < j} U(|x_i - x_j|)$$

- Dynamics = overdamped Langevin

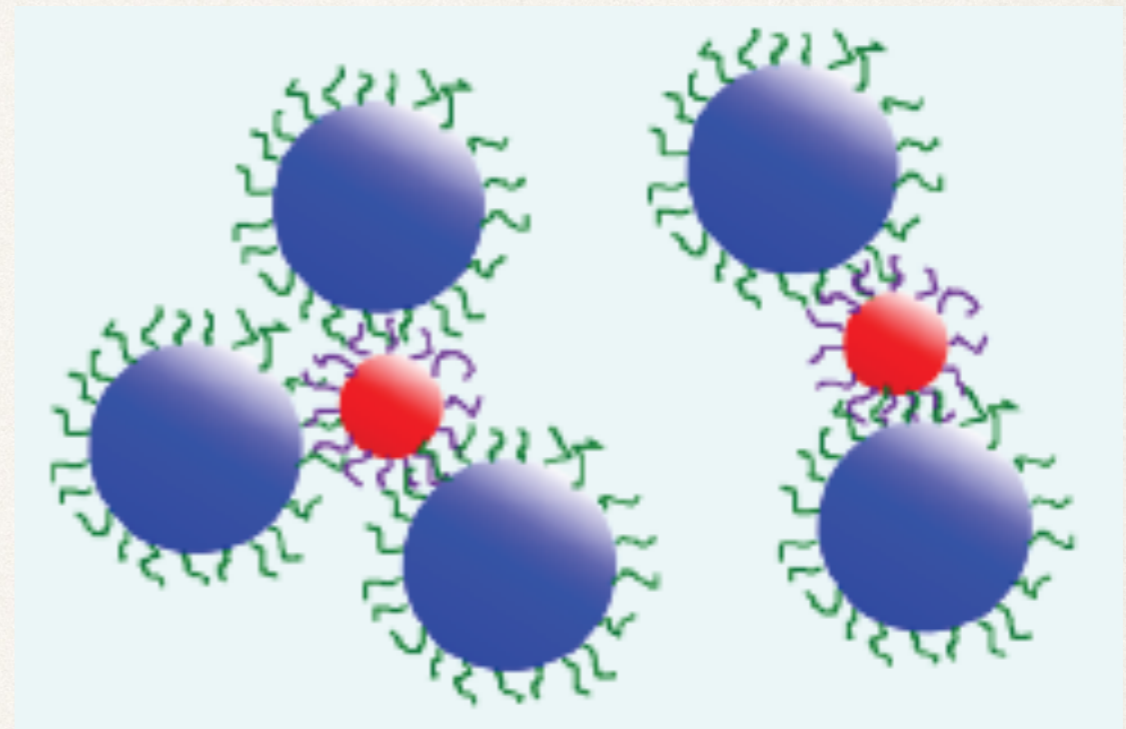
$$dX_t = \frac{-\nabla V(x)}{\gamma} dt + \sqrt{2k_B T \gamma^{-1}} dW_t$$

# Colloids have short-ranged attractive interactions (unlike atoms)

## Depletion



## DNA-mediated interactions



N. Seeman, 1982

⋮

Rothmund (2006)

⋮

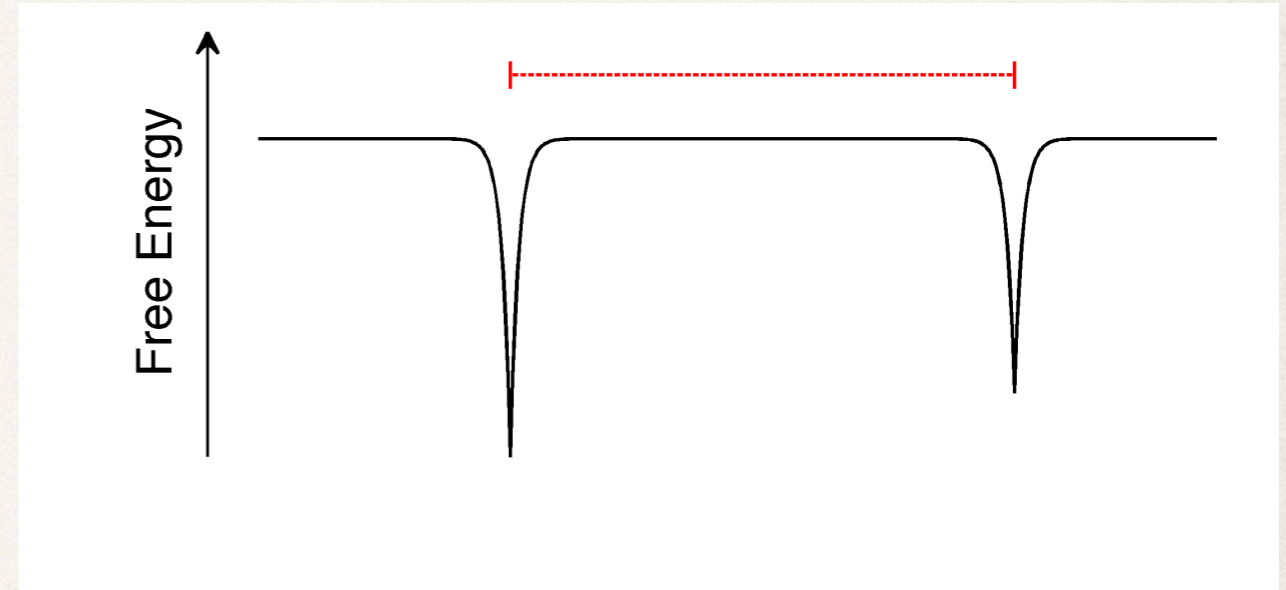
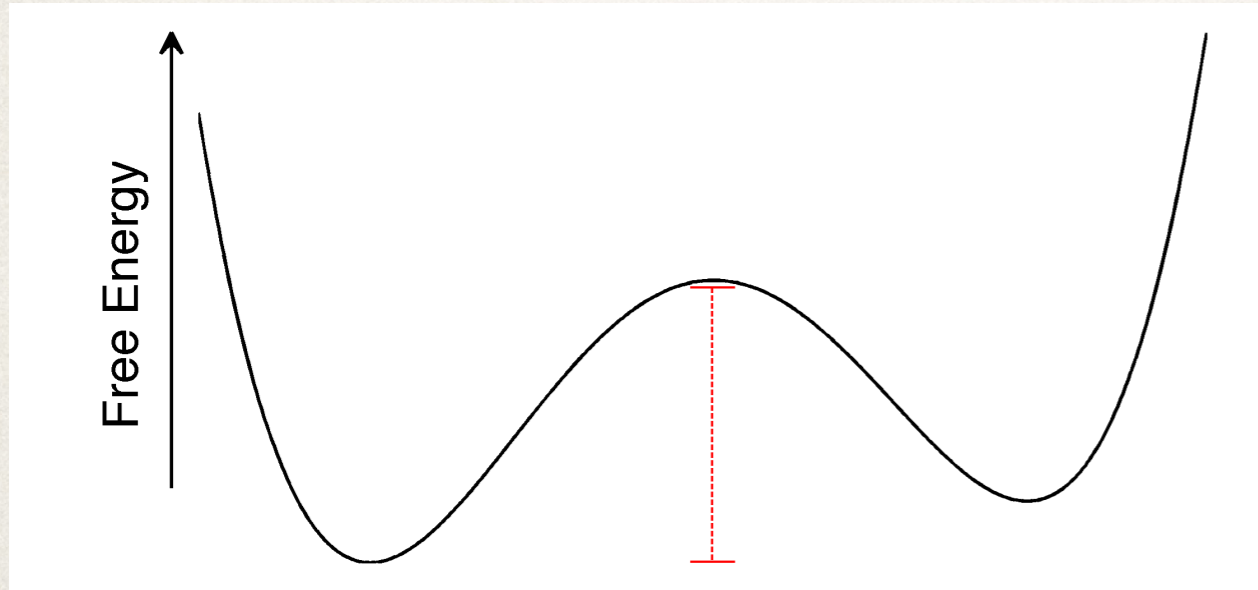
Wang et al, Nat. Comm, (2015)

Common feature = **short-ranged**  
(c.f. diameter of particles)

# Challenges of very short-ranged interactions

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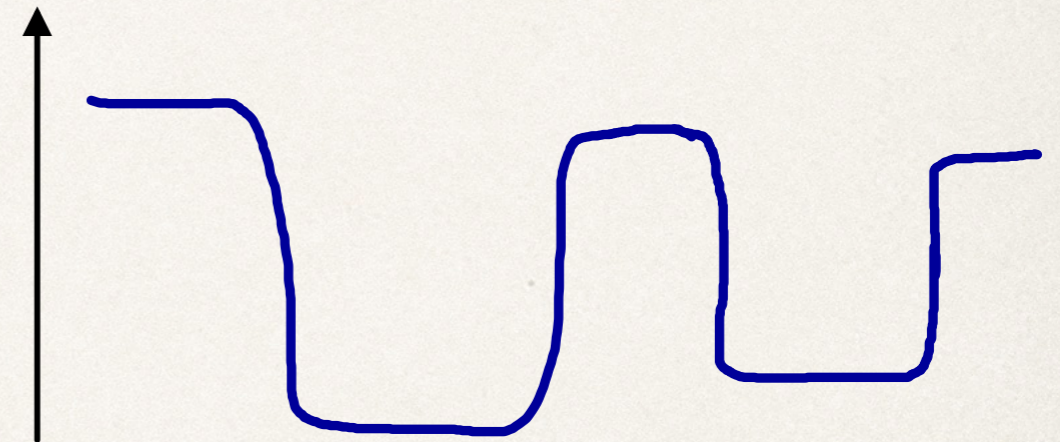
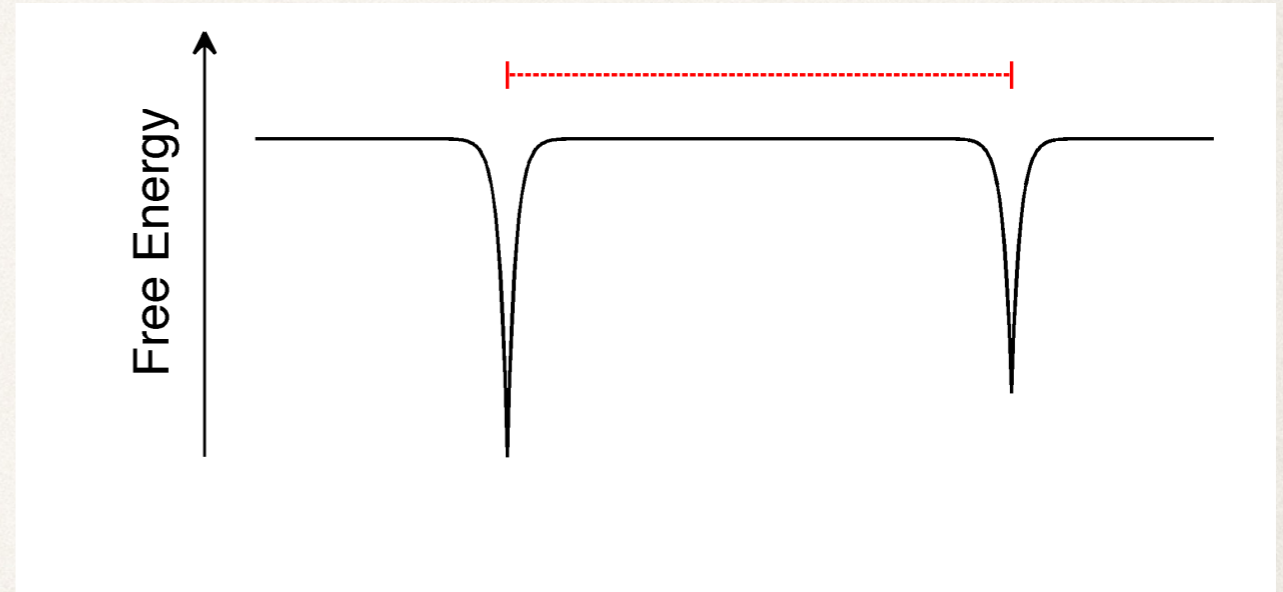
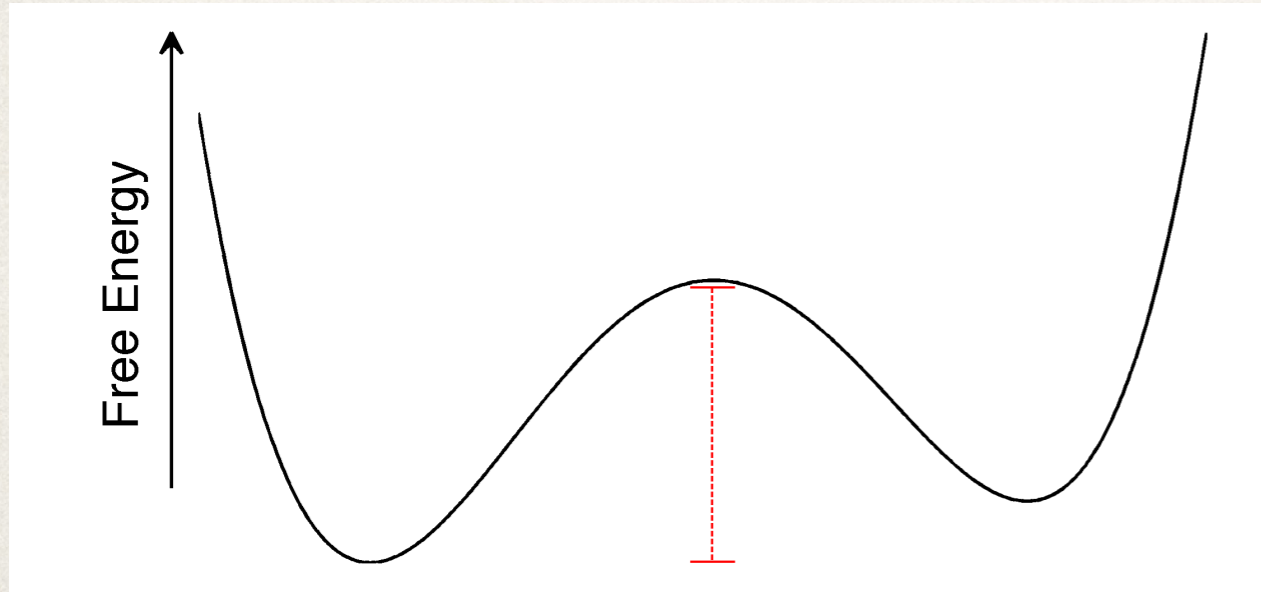
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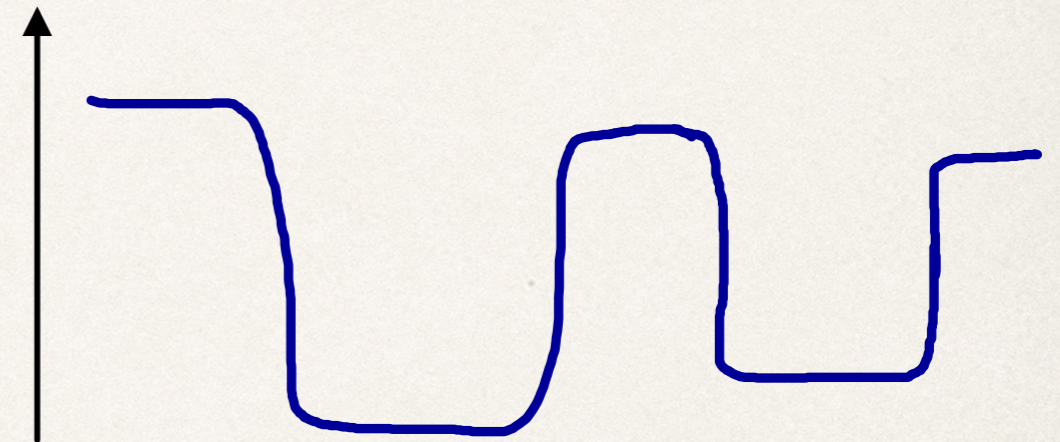
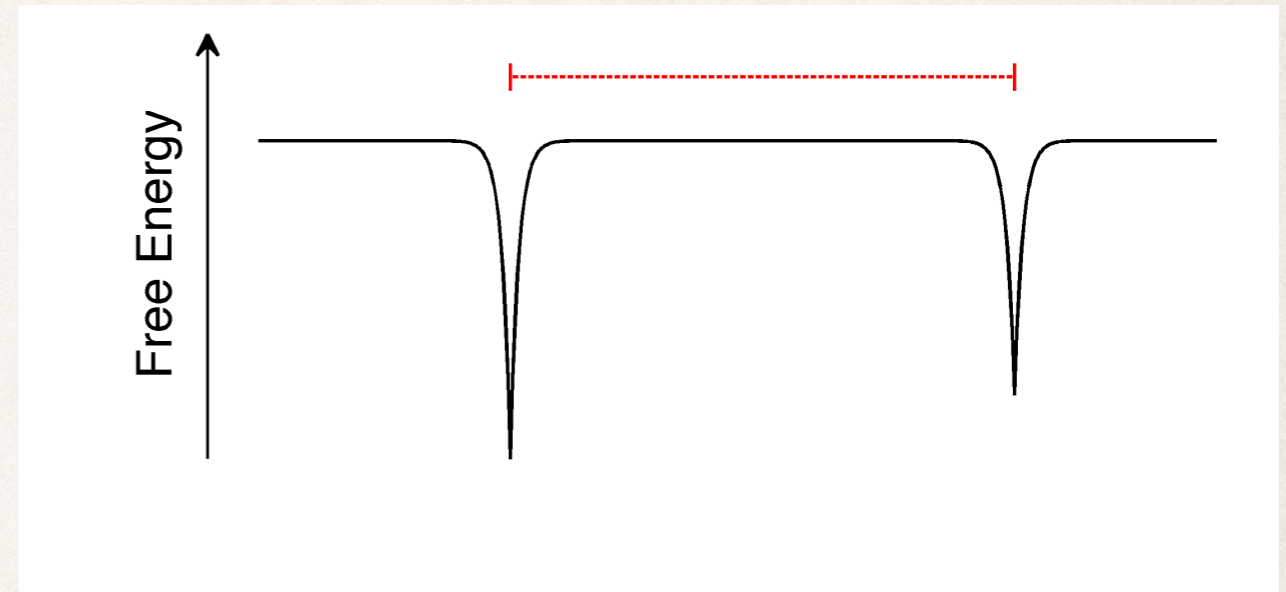
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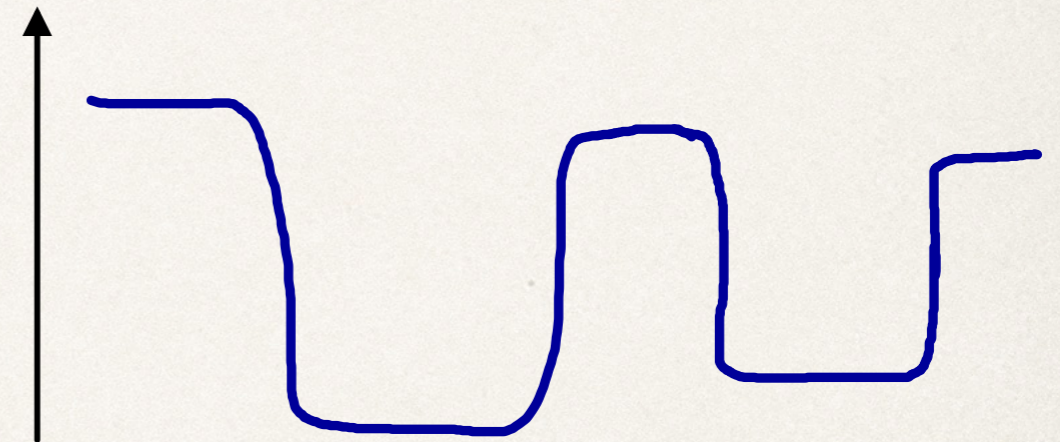
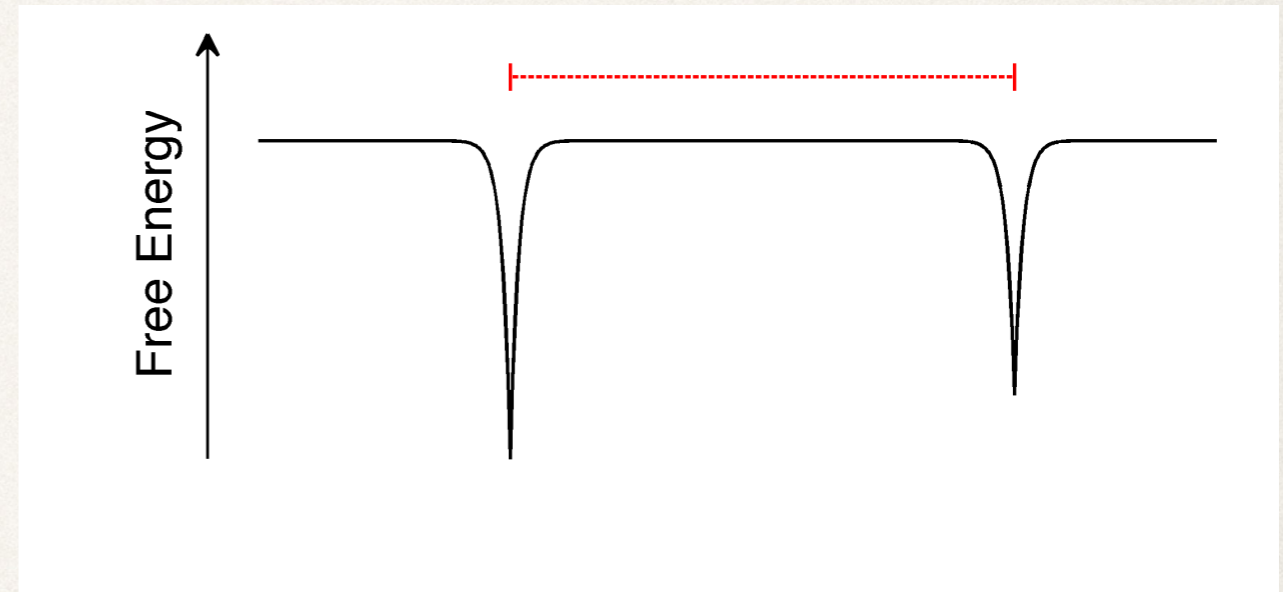
# Challenges of very short-ranged interactions

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## Challenges:

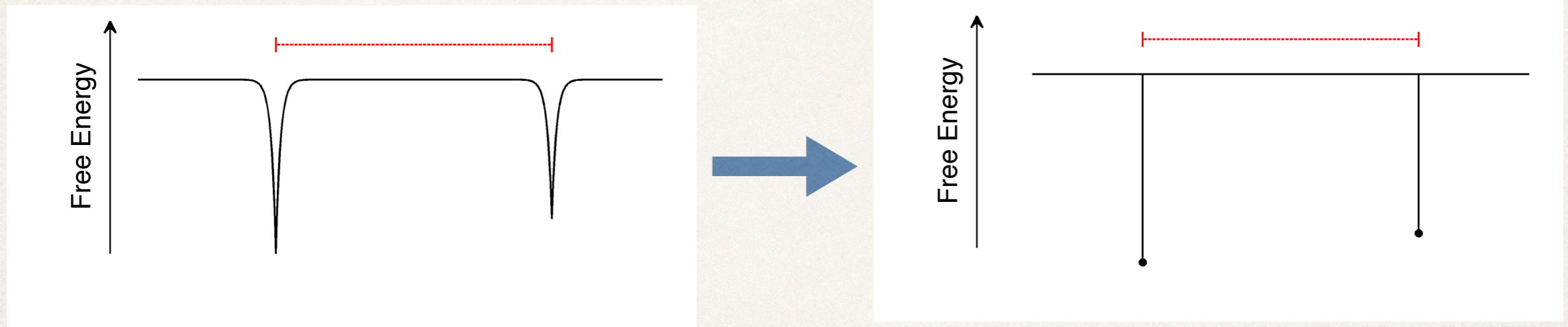
- **Numerical** — need a very small time step to simulate
- **Conceptual** — theories based on landscape smoothness (local minima, saddle points, etc) don't work as well



# Mitigating the challenge

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Shrink bonds to zero-range  $\longrightarrow$  they become constraints  $\delta(q)$



Need tools to:

- Sample particles with distance (or other) constraints (*this talk*) (to calculate volumes)
- Add & drop constraints via MCMC (*ask me later*) or in a way that is consistent with their dynamics (*work in progress with Nawaf Bou-Rabee*)
- Incorporate hydrodynamics (*e.g. Aleks Donev*) & DNA-induced dynamics
- Solve inverse problems involving their interactions (??)

Setup for sampling  $\rho(x) = Z^{-1} \delta(q(x))$

$$q(x) = (q_1(x), \dots, q_m(x)) : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

Strategy: sample measure on constraint manifold

$$M = \{x \in \mathbb{R}^n : q_1(x) = 0, q_2(x) = 0, \dots, q_m(x) = 0\}$$

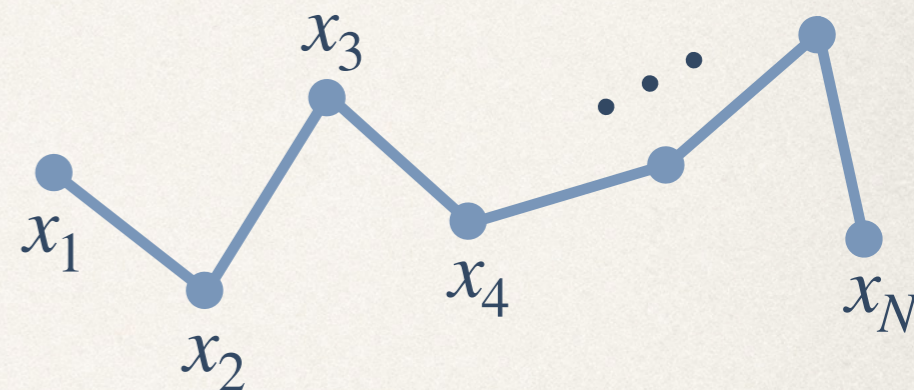
e.g.

$$q_1(x) = |x_1 - x_2|^2 - d_{12}^2$$

$$q_2(x) = |x_2 - x_3|^2 - d_{23}^2$$

$\vdots$   $\vdots$

$$q_{N-1}(x) = |x_{N-1} - x_N|^2 - d_{N-1N}^2$$



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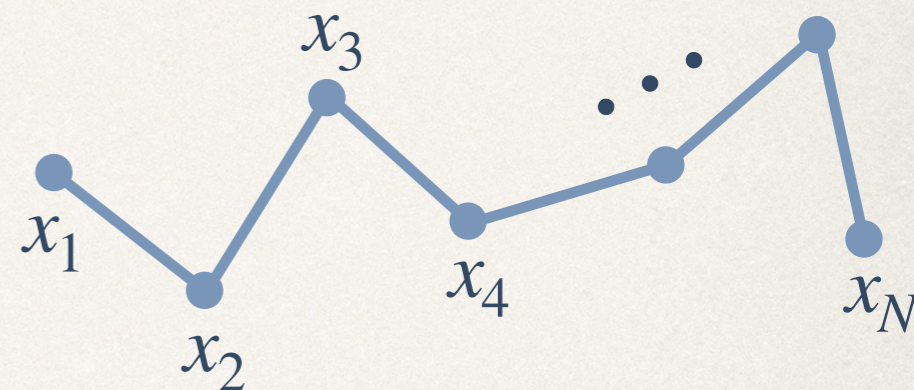
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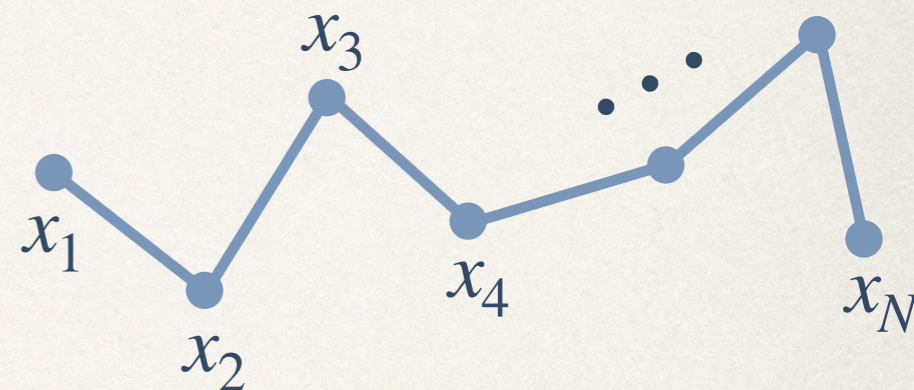
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- doesn't always have to hold!  
(and even when it does, won't necessarily hold  $\forall x$ )

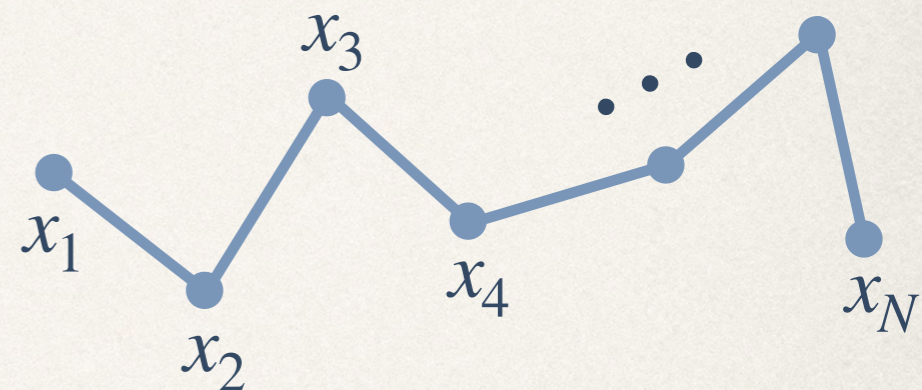
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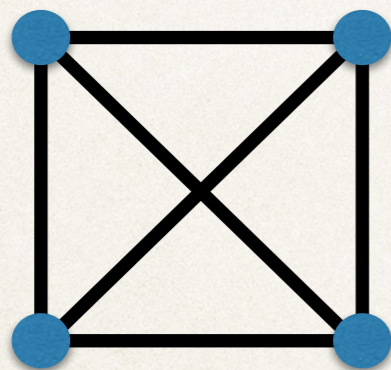
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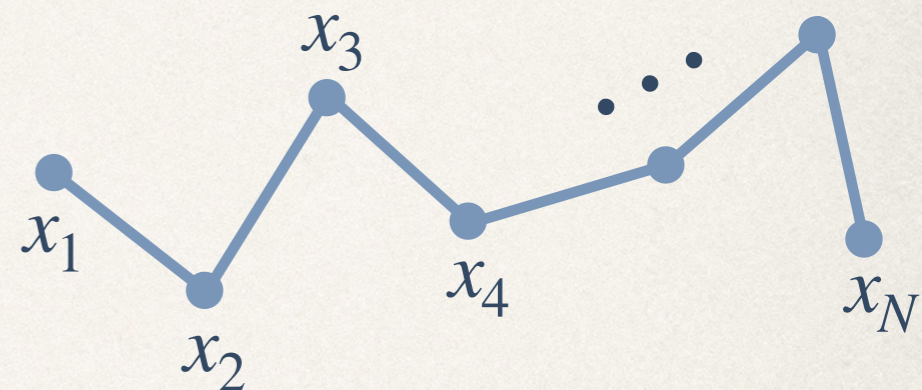
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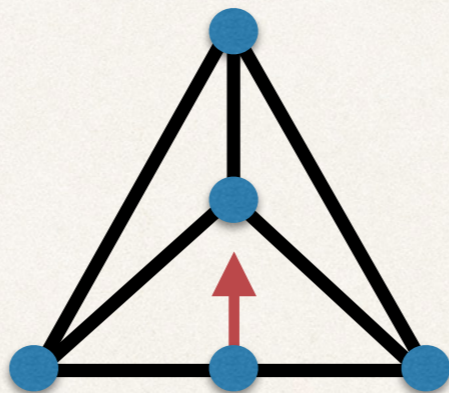
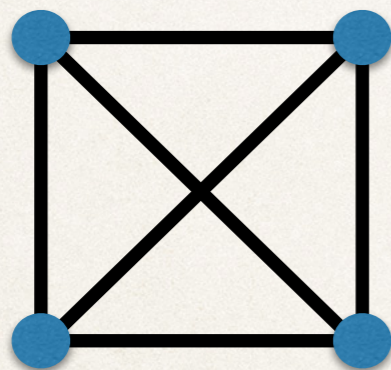
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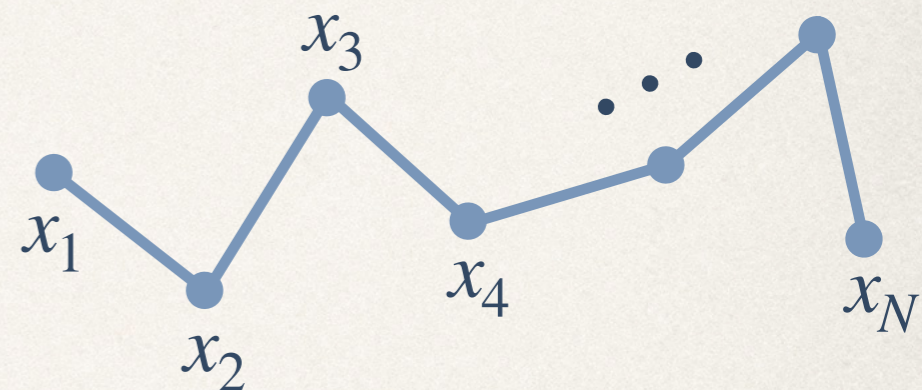
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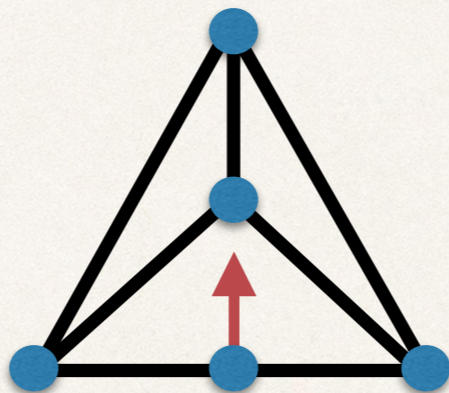
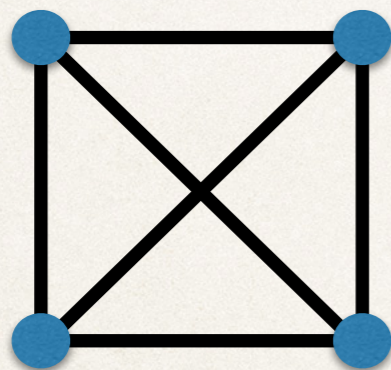
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**Assume**

$\{\nabla q_1(x), \dots, \nabla q_m(x)\}$  linearly independent  $\forall x \in M$ .

- implies  $M$  is a manifold (dimension  $d=n-m$ )
- doesn't always have to hold!  
(and even when it does, won't necessarily hold  $\forall x$ )



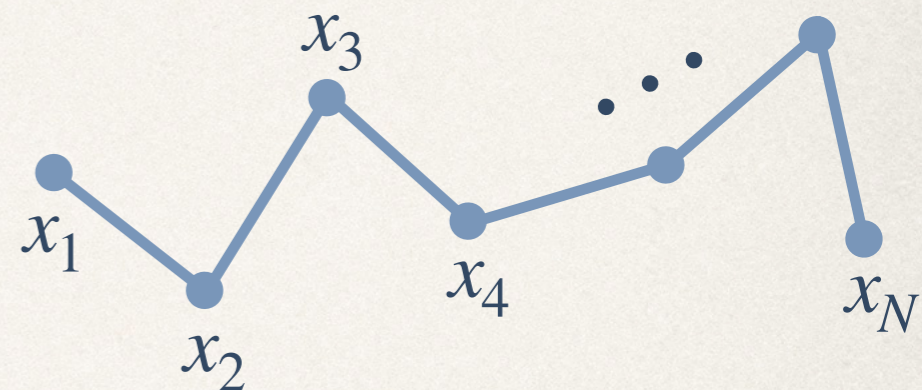
e.g.

$$q_1(x) = |x_1 - x_2|^2 - d_{12}^2$$

$$q_2(x) = |x_2 - x_3|^2 - d_{23}^2$$

$\vdots$

$$q_{N-1}(x) = |x_{N-1} - x_N|^2 - d_{N-1N}^2$$



**Given**  $\sigma(dx)$  = natural surface measure on  $M$  (=Hausdorff measure)



**Setup for sampling**  $\rho(x) = Z^{-1} \delta(q(x))$

$$q(x) = (q_1(x), \dots, q_m(x)) : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

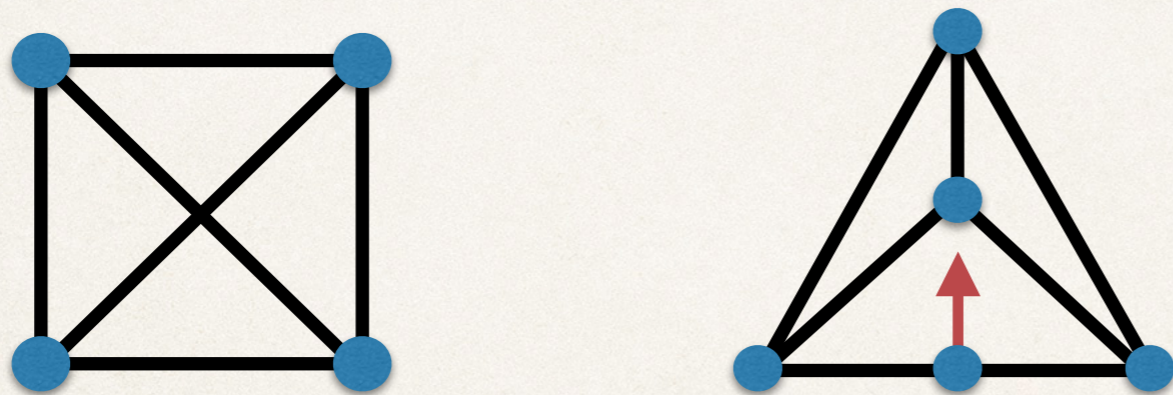
**Strategy:** sample measure on constraint manifold

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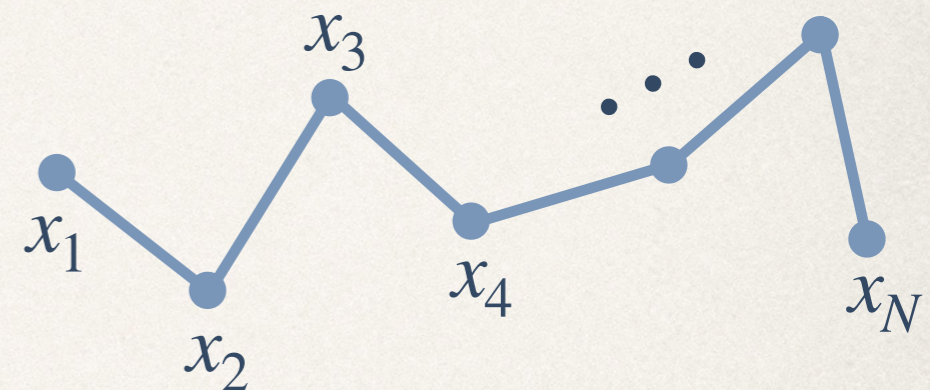
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**Given**  $\sigma(dx)$  = natural surface measure on  $M$  (=Hausdorff measure)

**Sample density**  $\rho(x) = f(x) \sigma(dx)$

s.t  $f(x) \sigma(dx) = \delta(q(x)) dx$

## Two questions for today:

---

- What is  $f(x)$  so that  $f(x)\sigma(dx) = \delta(q(x))dx$  ?
- How to sample the measure  $\rho(x) = Z^{-1}f(x)\sigma(dx)$  ?

*Then some examples!*

What is  $f(x)$  so that  $f(x)\sigma(dx) = \delta(q(x))dx$  ?

---

Fatten constraints by some amount  $\epsilon$  :

$$M^\epsilon = \{x \in \mathbb{R}^n : -\epsilon < q_i(x) < \epsilon, \quad i = 1, \dots, m\}$$

Sample  $M^\epsilon$  uniformly  $\longrightarrow$  density  $\rho^\epsilon(x)$

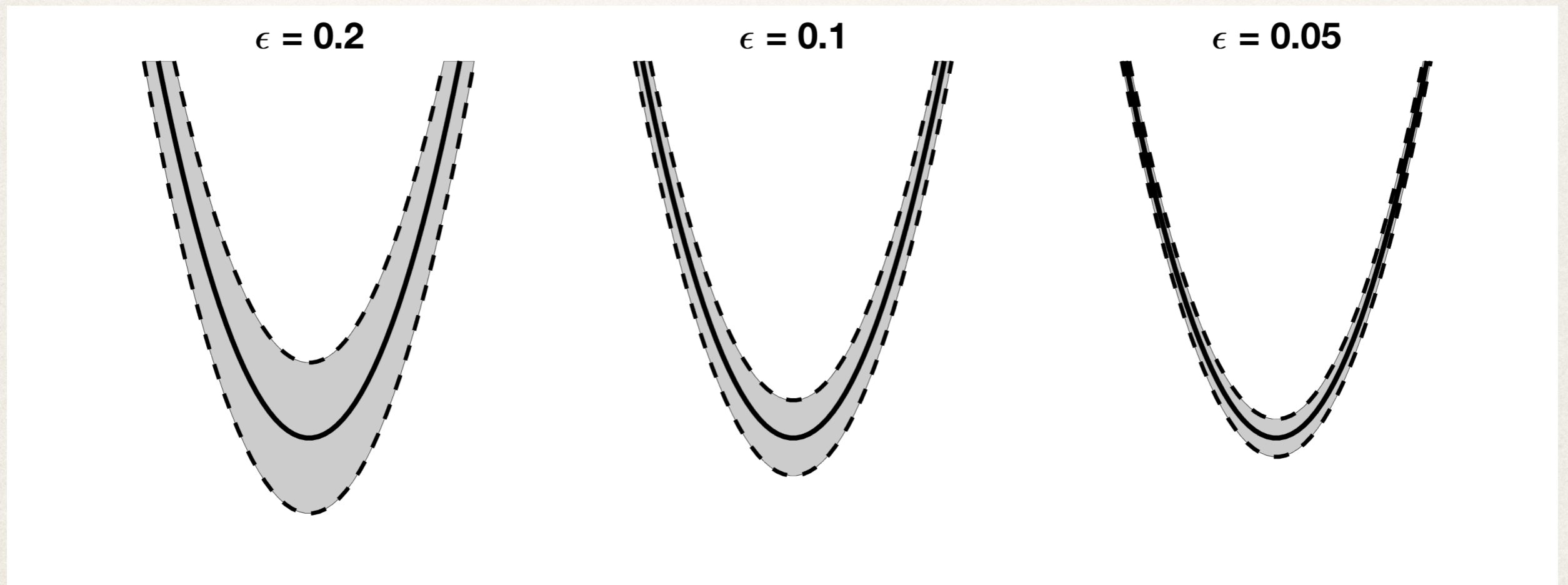
Then 
$$\delta(q(x)) = \lim_{\epsilon \rightarrow 0} \rho^\epsilon(x).$$

# Example

---

$$q(x, y) = y - x^2$$

$$M^\epsilon = \{(x, y) : -\epsilon < y - x^2 < \epsilon, y < 1\}$$

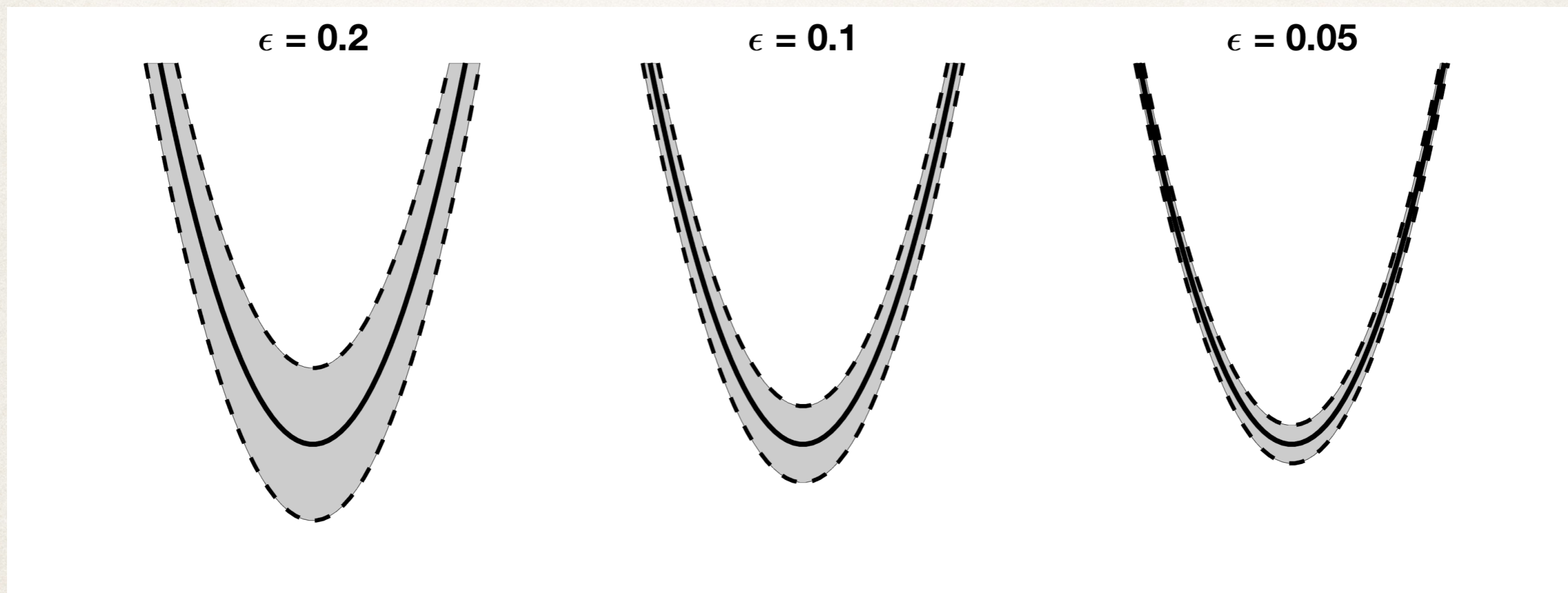


$(x(s), y(s)) =$  arc-length parameterization,  $\sigma(ds) = ds$

## Example

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$(x(s), y(s)) =$  arc-length parameterization,  $\sigma(ds) = ds$

$$\rho^\epsilon(s) \approx (Z^\epsilon)^{-1} \frac{\epsilon}{|\nabla q(s)|} \implies \rho(s) \propto |\nabla q(s)|^{-1}$$

## Coarea formula (formal)

---

e.g. Federer, (1959)

$$|\nabla q(x)|^{-1} \sigma(dx) = \delta(q(x)) dx$$

i.e.  $f(x) = |\nabla q(x)|^{-1}$

pseudo-determinant

$$|\nabla q| = |(\nabla q)^T \nabla q|^{1/2}, \quad \nabla q = (\nabla q_1 \quad \nabla q_2 \quad \cdots \quad \nabla q_m)$$

## How to sample the measure $\rho(x) = Z^{-1}f(x)\sigma(dx)$ ?

---

- Give simple algorithm here (Zappa, H.-C., Goodman, CPAM 2018)  
Not necessarily the most efficient.  
But, the most efficient to program!
- For a Hamiltonian-based method, see e.g. T. Lelièvre's talk
  - Lelièvre, Rousset, Stoltz , arxiv (2018)
- Also:
  - Diaconis, Holmes, Shashahani, (2013)
  - Byrne, Girolami, Scan. J. Stat. (2013)
  - Cicotti, Vanden-Eijnden, Chem Phys Chem (2006)

**Sampling algorithm.** Generate random variables  $X_1, X_2, \dots$  via a random walk on  $M$ .

---

- Suppose  $X_n = x$ .
- Let  $T_x =$  Tangent space to  $M$ , at  $x$   
 $N_x =$  Normal space to  $M$ , at  $x$

$$\mathbb{R}^n \cong T_x \oplus N_x$$

- Propose  $y = x + v + w$  with
  - $v \in T_x \rightarrow$  density  $p(v;x)$
  - $w \in N_x \rightarrow$  solve  $q(x+v+w) = 0$ .
- Metropolis-Hastings accept / Reject move:

Acceptance probability  $\min \left( 1, \frac{f(y)T(y \rightarrow x)}{f(x)T(x \rightarrow y)} \right)$

$T(x \rightarrow y)\sigma(dy) =$   
transition density on  $M$



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---

• Suppose  $X_n = x$ .

*Warning! Notation abuse!*

• Let  $T_x =$  Tangent space to  $M$ , at  $x$

$T_x$  is also orthonormal matrix

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How to compute:

$$QR(\nabla q) = (N_x \mid T_x) R$$

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- $v \in T_x \rightarrow$  density  $p(v;x)$

*There are other ways to find  $w$ ! (eg  $w \in N_y$ .)*

- $w \in N_x \rightarrow$  solve  $q(x+v+w) = 0$ .

*But this one has a lot of nice properties.*

$$\text{Solve } q\left(x + v + \sum_{i=1}^m a_i \nabla q_i\right) = 0 \text{ for } a=(a_1, \dots, a_m).$$

- Metropolis-Hastings accept / Reject move:

Acceptance probability  $\min \left( 1, \frac{f(y)T(y \rightarrow x)}{f(x)T(x \rightarrow y)} \right)$

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# Proposal Move

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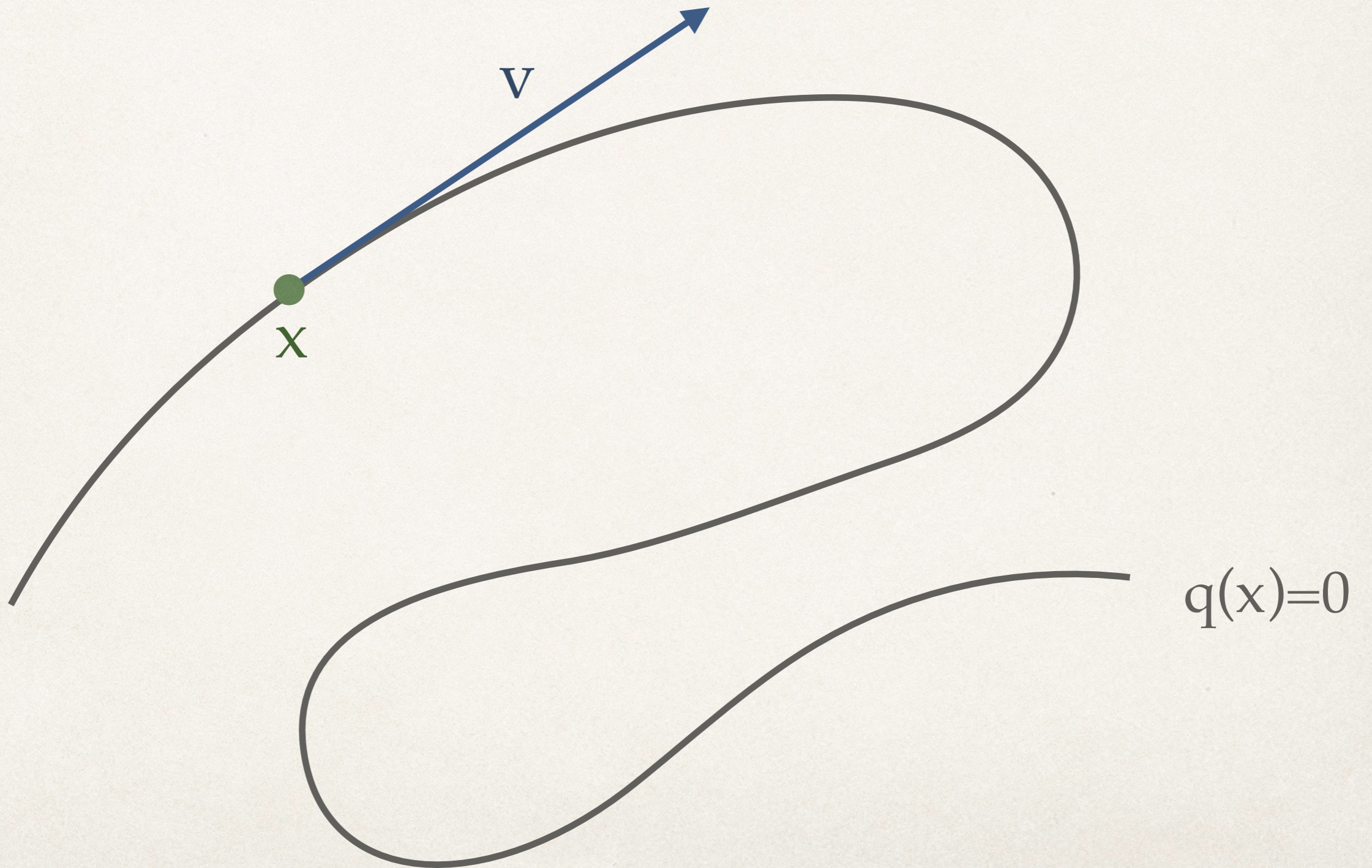
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# Proposal Move

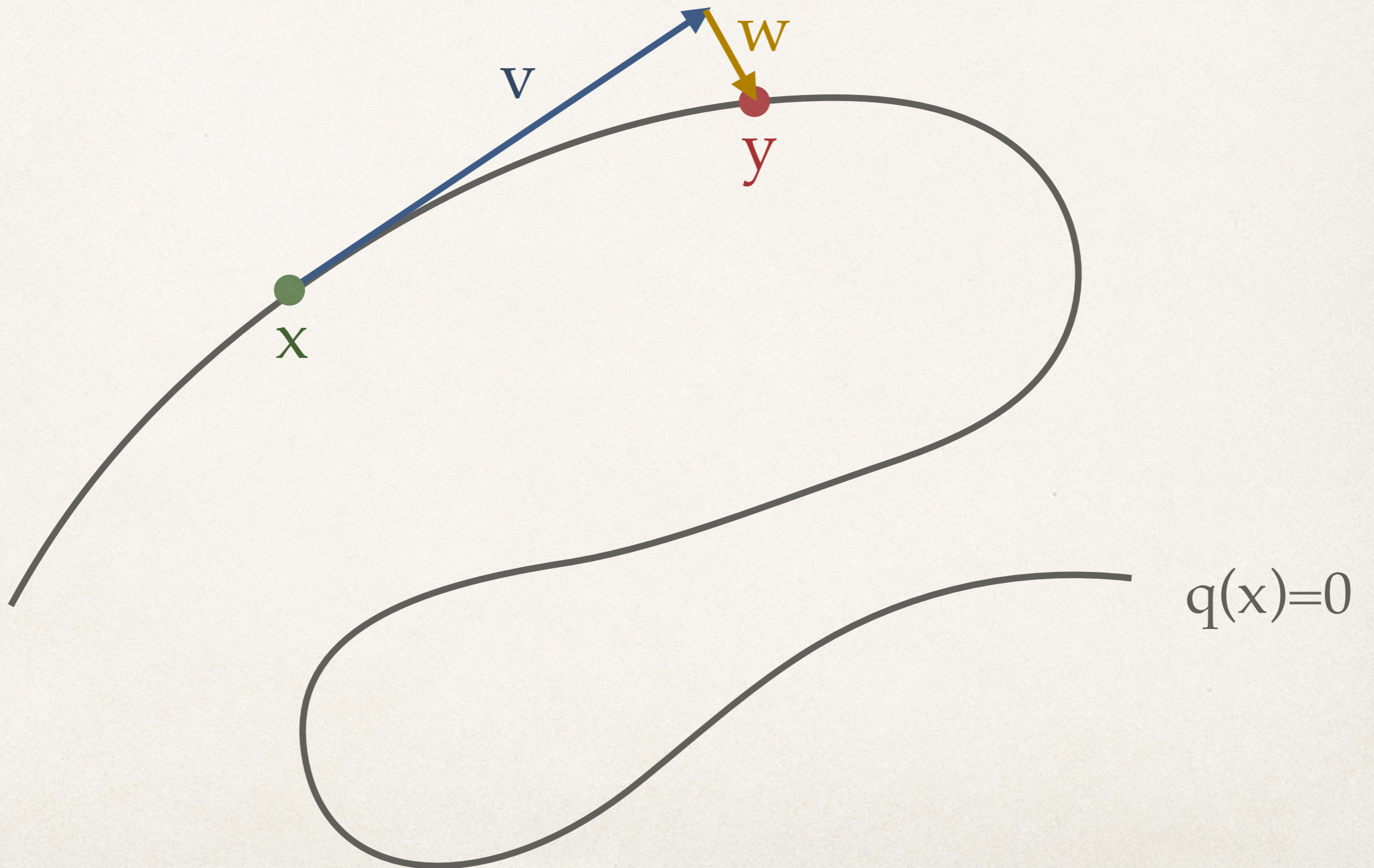
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# Proposal Move

---



Proposal densities  $T(x \rightarrow y)$ ,  $T(y \rightarrow x)$

---

$$T(x \rightarrow y) = p(v; x) \left| \frac{\partial y}{\partial v} \right|^{-1} 1_{A_x}(y) + \xi_x \delta(y - x)$$

$p(v; x)$  = density of  $v$  at  $x$

$\left| \frac{\partial y}{\partial v} \right|$  = volume element for transformation  $v \rightarrow y$

$A_x = \{y \in M \text{ such that } y \text{ can be reached from } x \text{ using numerical solver}\}$

$\xi_x$  = probability of numerical solver failing to find  $y$ , after choosing  $v$



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Reverse density

Proposal densities  $T(x \rightarrow y), T(y \rightarrow x)$

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density of  $v$  at  $x$

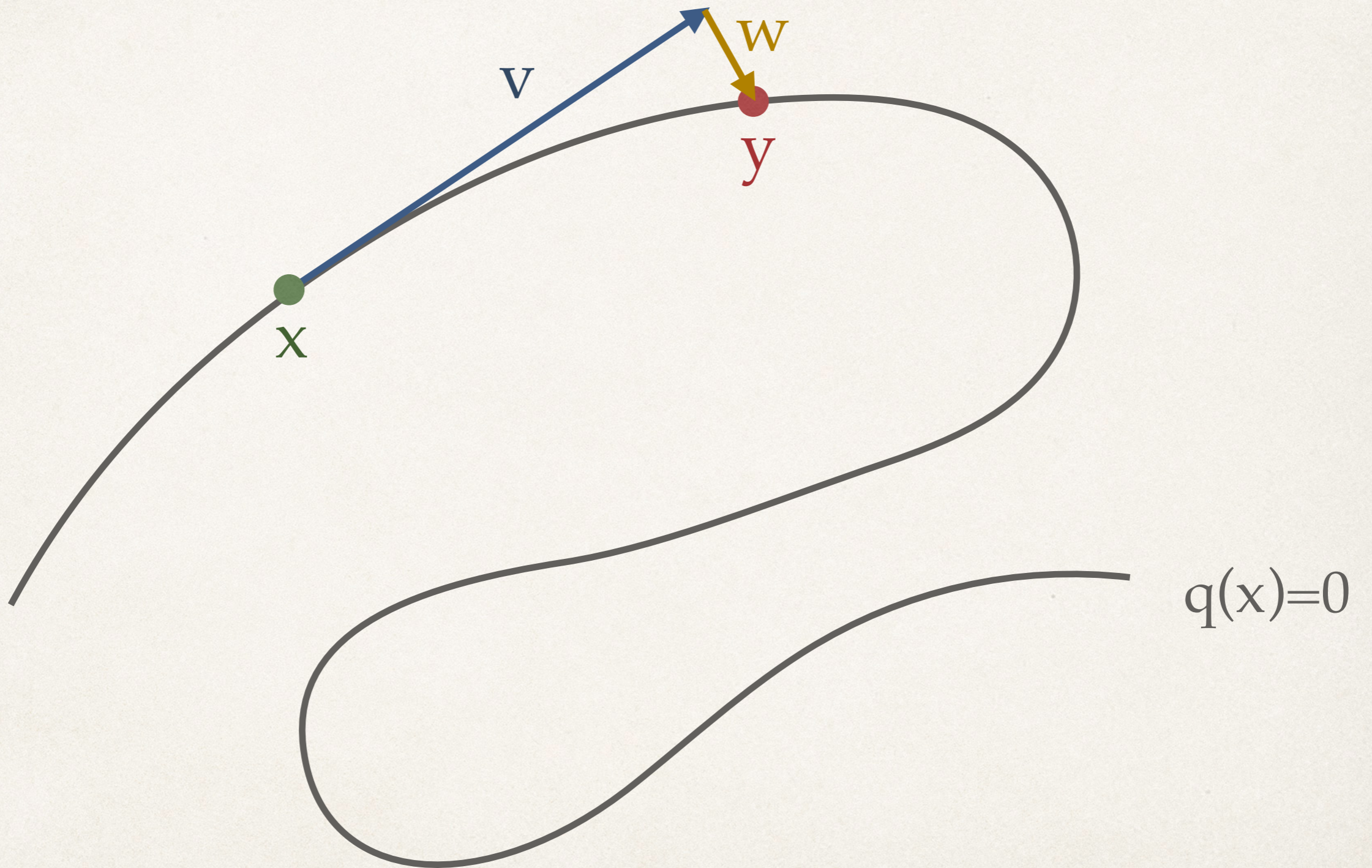
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Reverse density

$$T(y \rightarrow x) = p(v'; y) \left| \frac{\partial x}{\partial v'} \right|^{-1} 1_{A_y}(x) + \xi_y \delta(x - y)$$

# Proposal Move

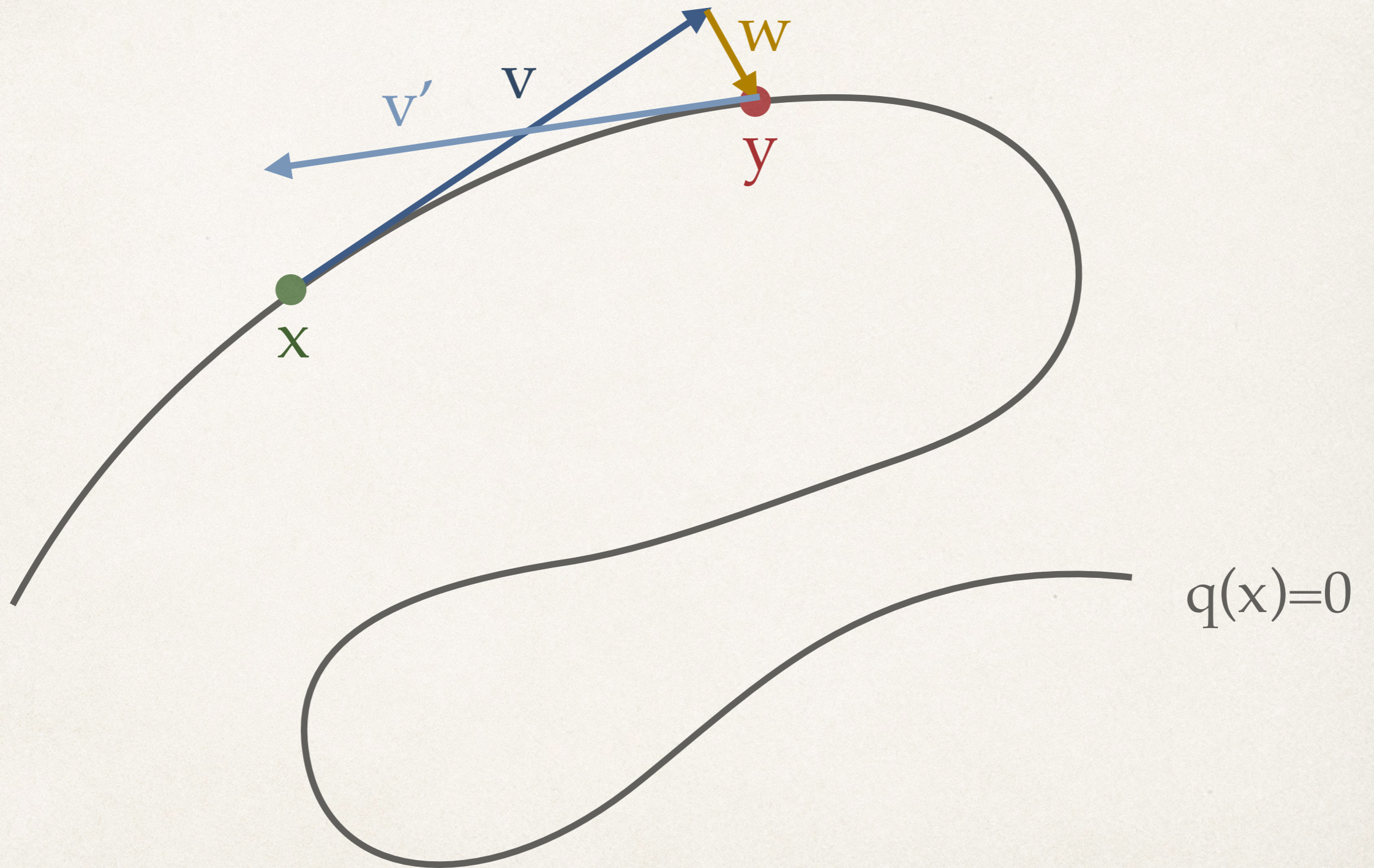
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# Proposal Move

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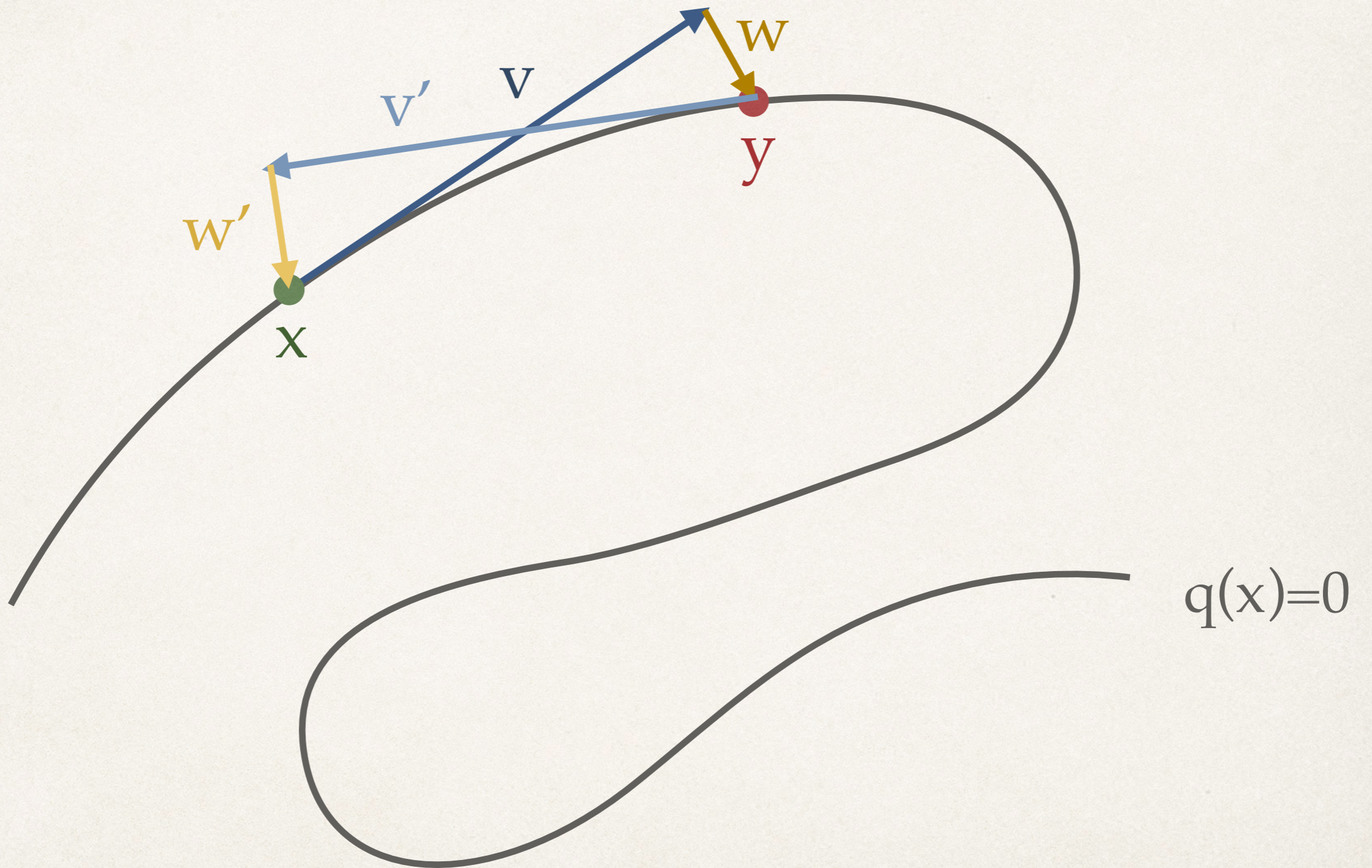
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# Proposal Move

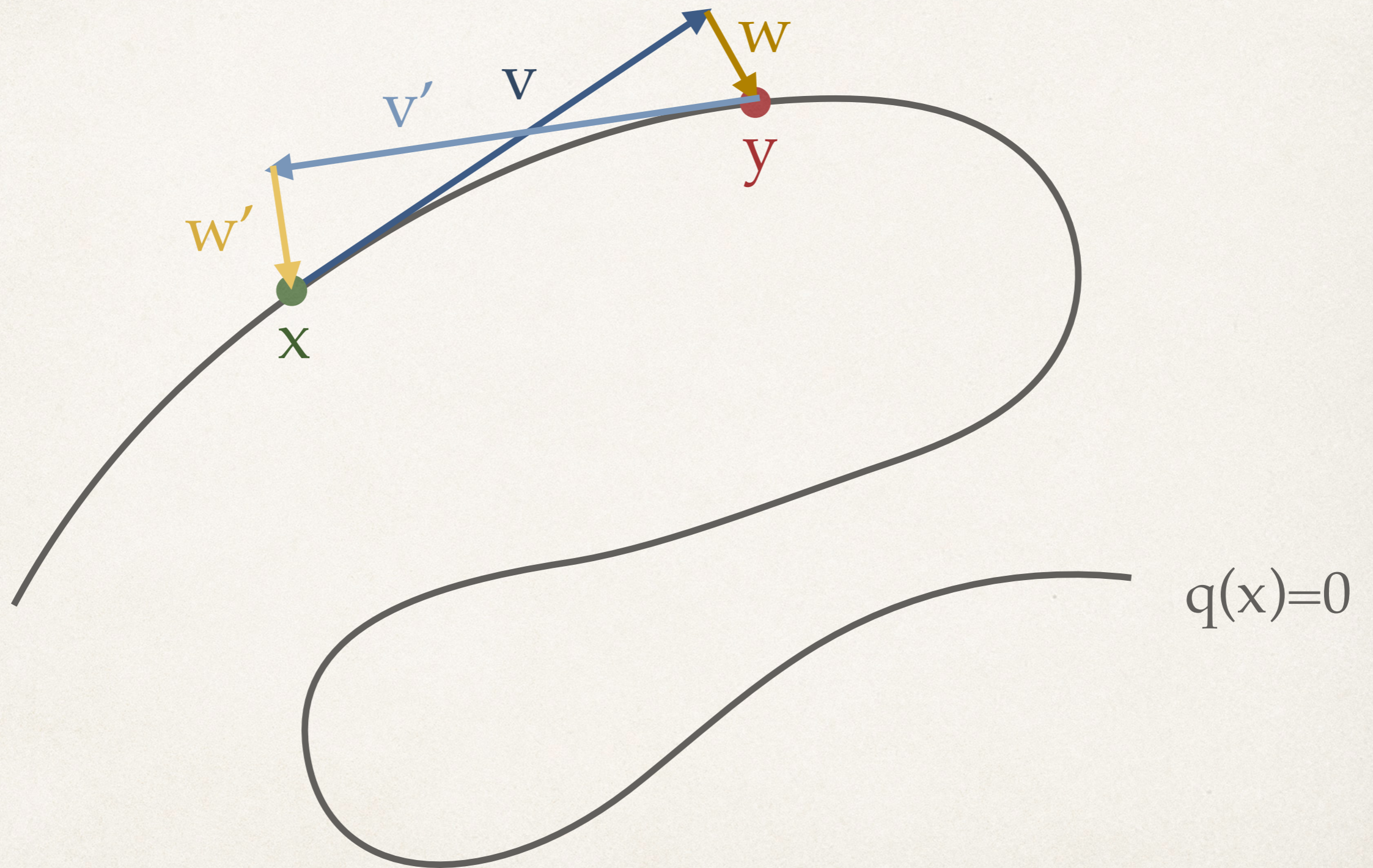
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# Proposal Move

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$$v' = T_y T_y^T (x - y) \implies p(v'; x) \text{ is known}$$



Proposal densities  $T(x \rightarrow y)$ ,  $T(y \rightarrow x)$

---

$$T(x \rightarrow y) = p(v; x) \left| \frac{\partial y}{\partial v} \right|^{-1} \mathbf{1}_{A_x}(y) + \xi_x \delta(y - x)$$

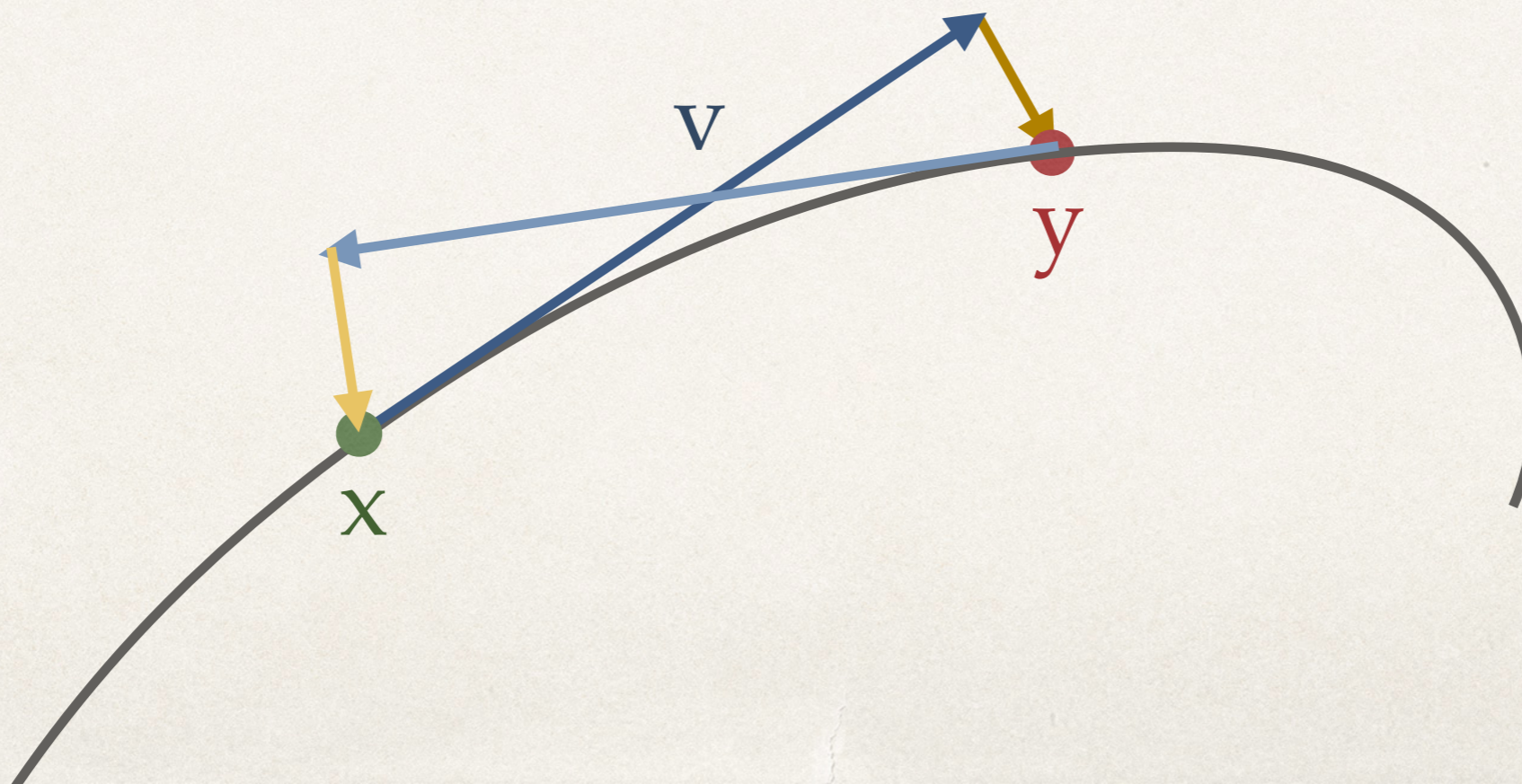
volume element for transformation  $v \rightarrow y$

Proposal densities  $T(x \rightarrow y)$ ,  $T(y \rightarrow x)$

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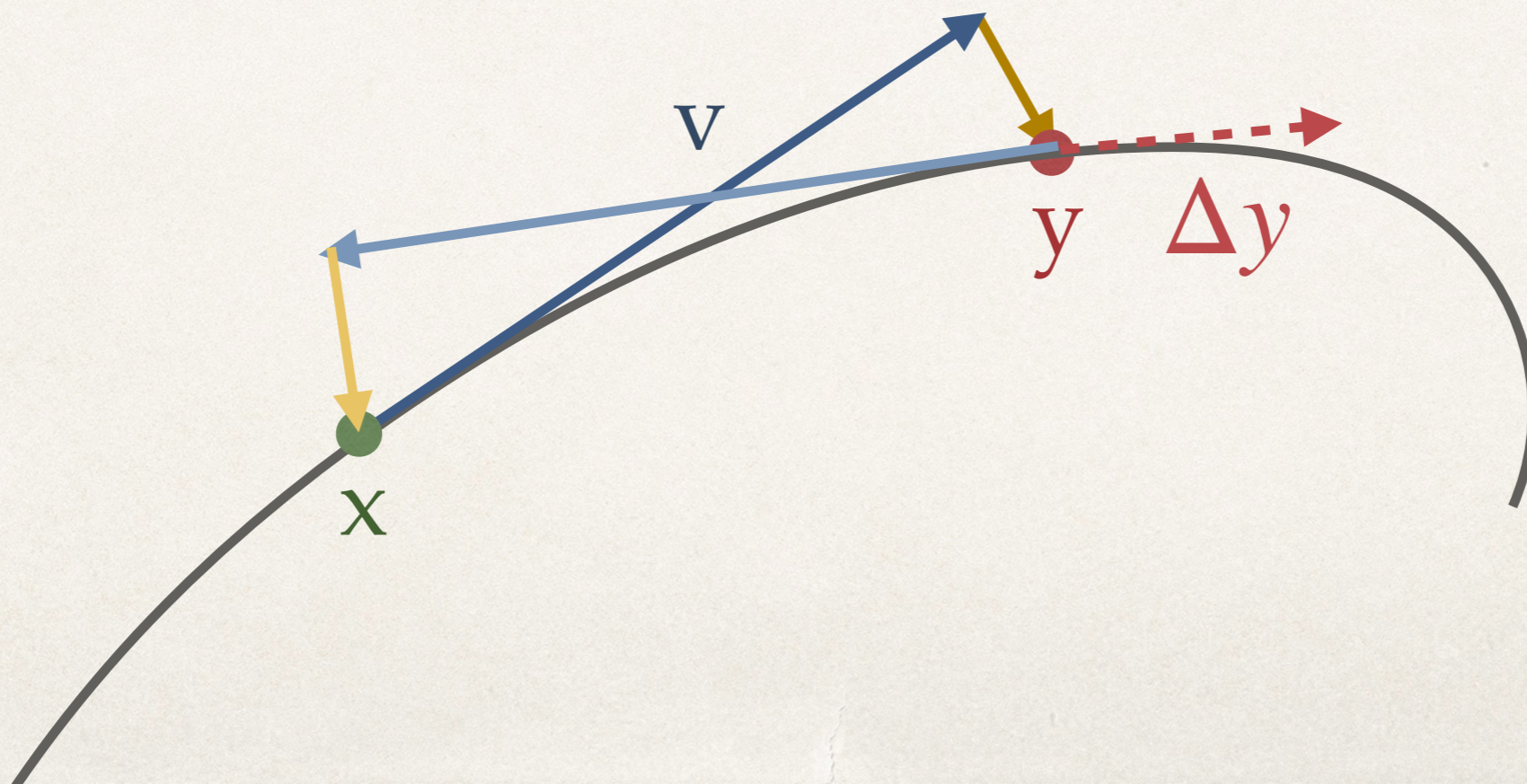


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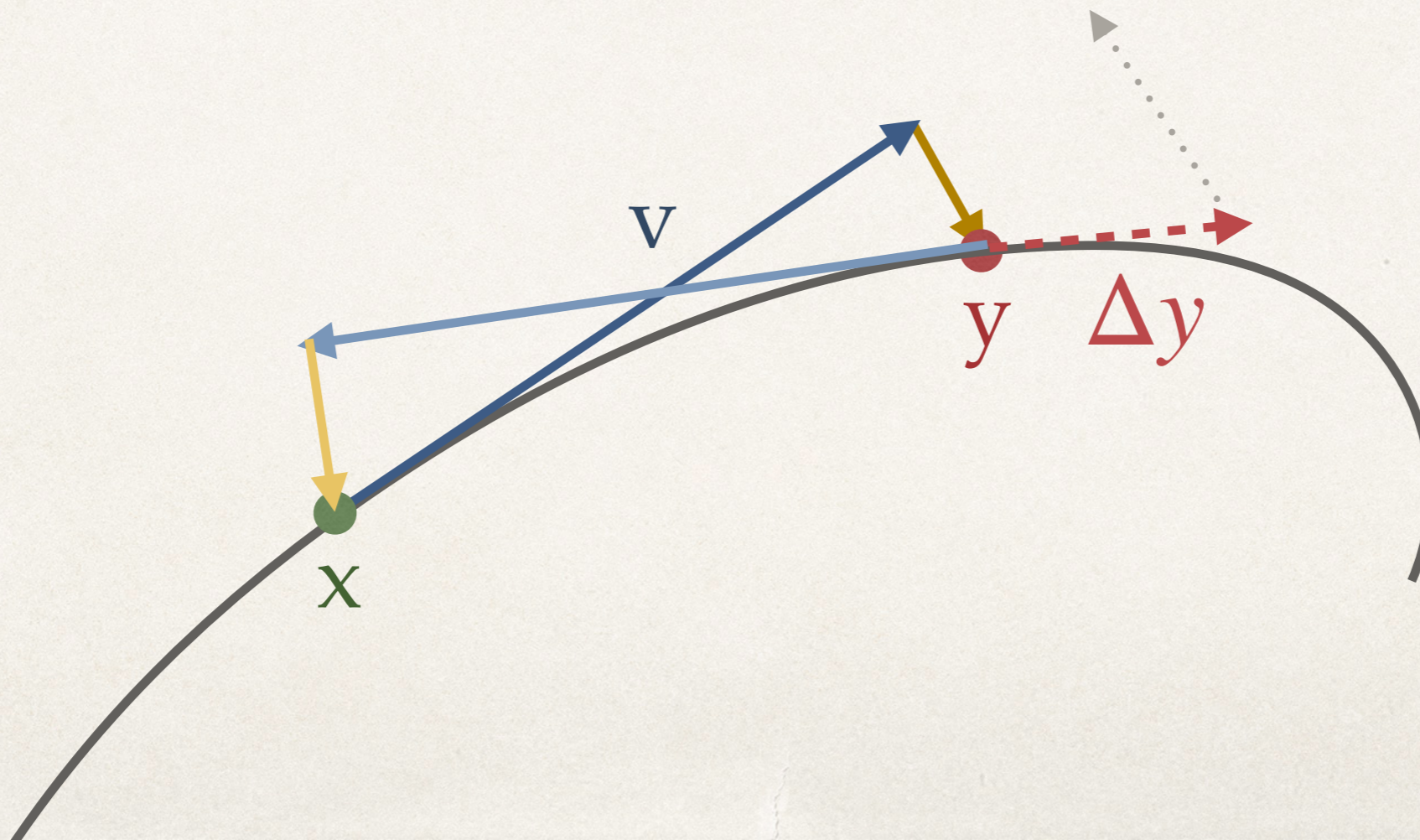


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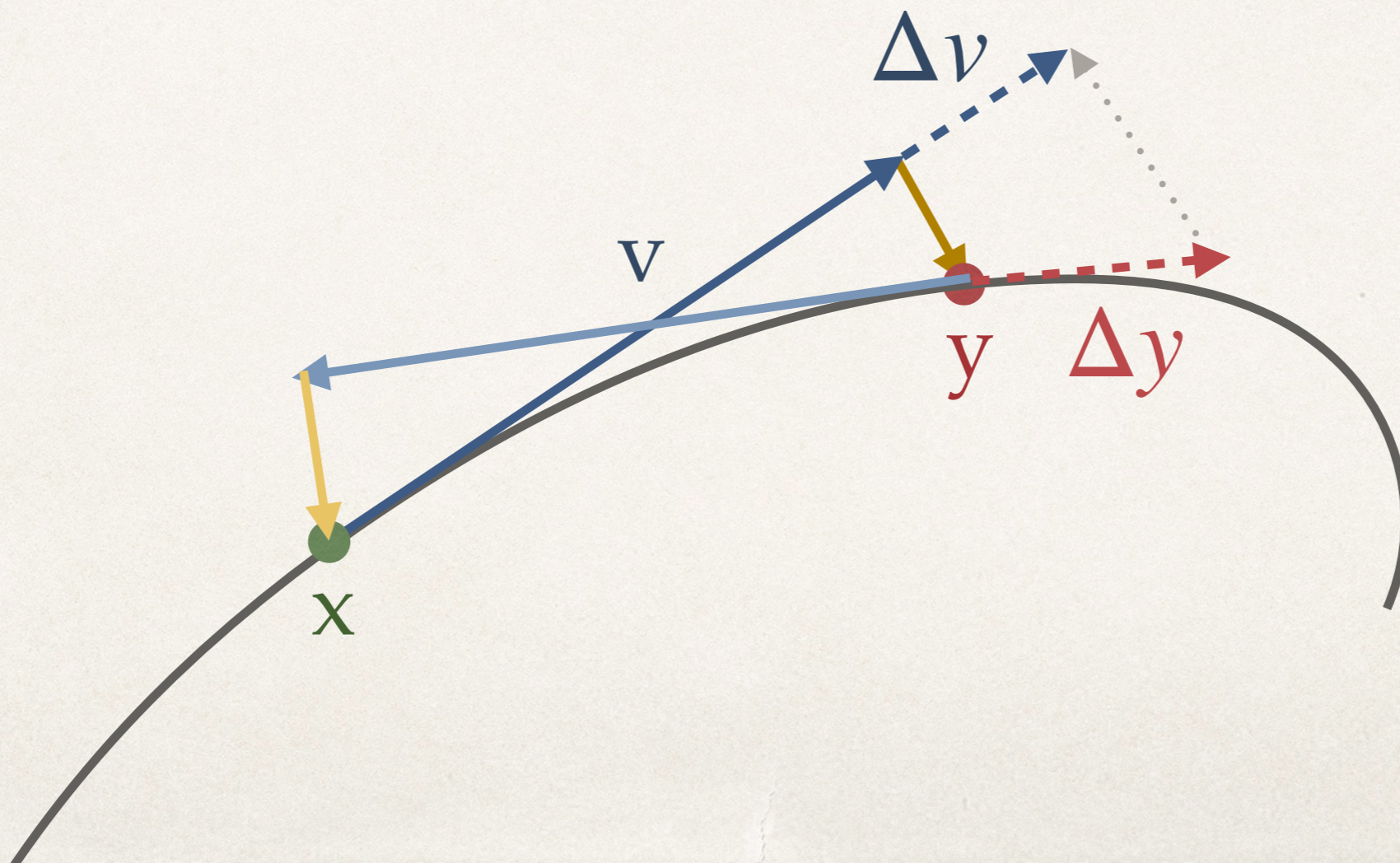


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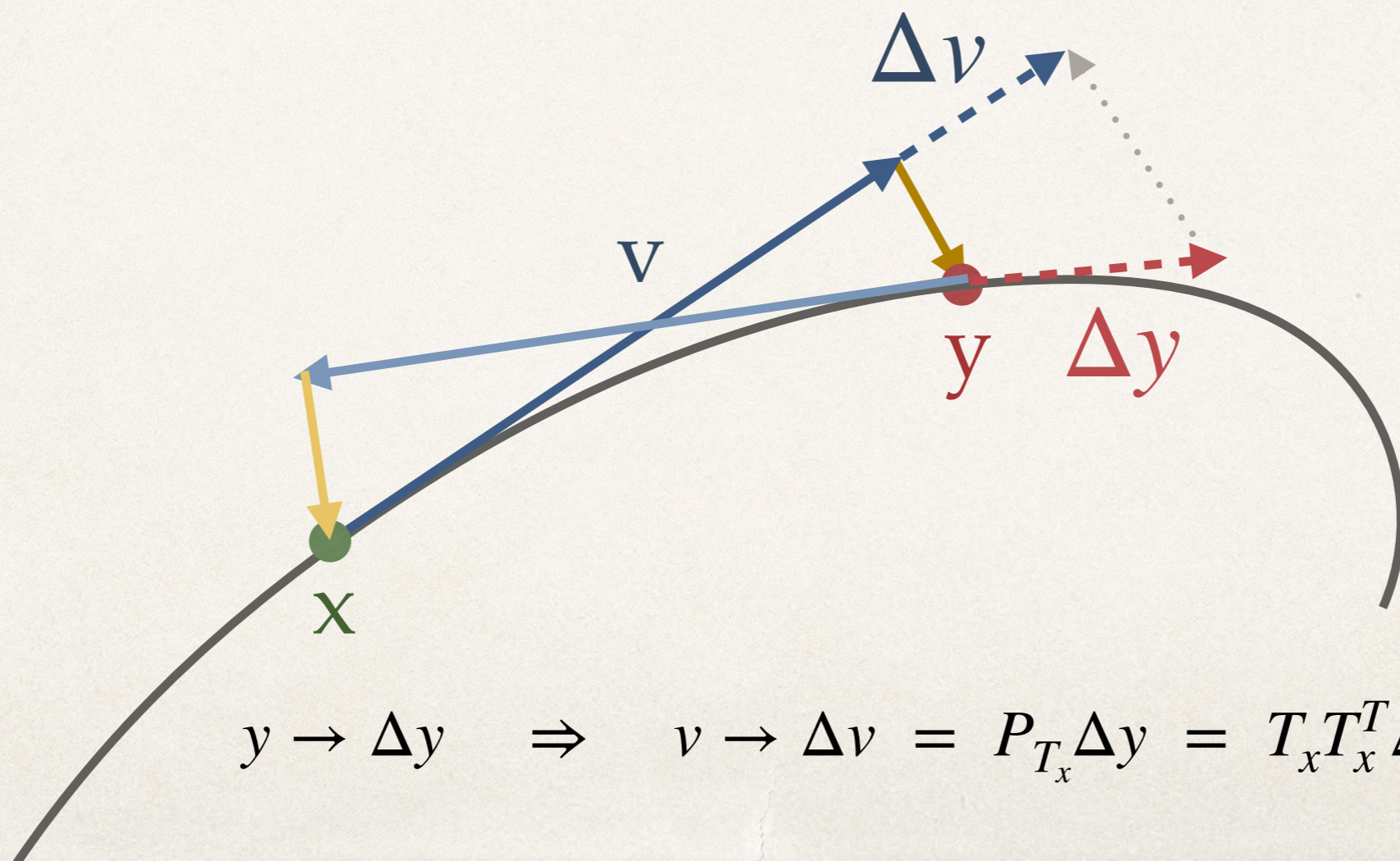


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volume element for transformation  $v \rightarrow y$



$$y \rightarrow \Delta y \quad \Rightarrow \quad v \rightarrow \Delta v = P_{T_x} \Delta y = T_x T_x^T \Delta y$$

$$\left| \frac{\partial y}{\partial v} \right|^{-1} = |T_x^T T_y|$$

$$\left| \frac{\partial y}{\partial v} \right|^{-1} = |T_x^T T_y|$$

...but...

$$\left| \frac{\partial x}{\partial v'} \right|^{-1} = |T_y^T T_x| = |T_x^T T_y| !$$

Therefore these factors cancel, and we don't need to calculate them.

(Not true for stratifications...)



$$\left| \frac{\partial y}{\partial v} \right|^{-1} = |T_x^T T_y|$$

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Therefore these factors cancel, and we don't need to calculate them.

(Not true for stratifications...)

*If  $w \in N_y$ . these factors are much more complicated (and don't cancel.)*

Proposal densities  $T(x \rightarrow y)$ ,  $T(y \rightarrow x)$

---

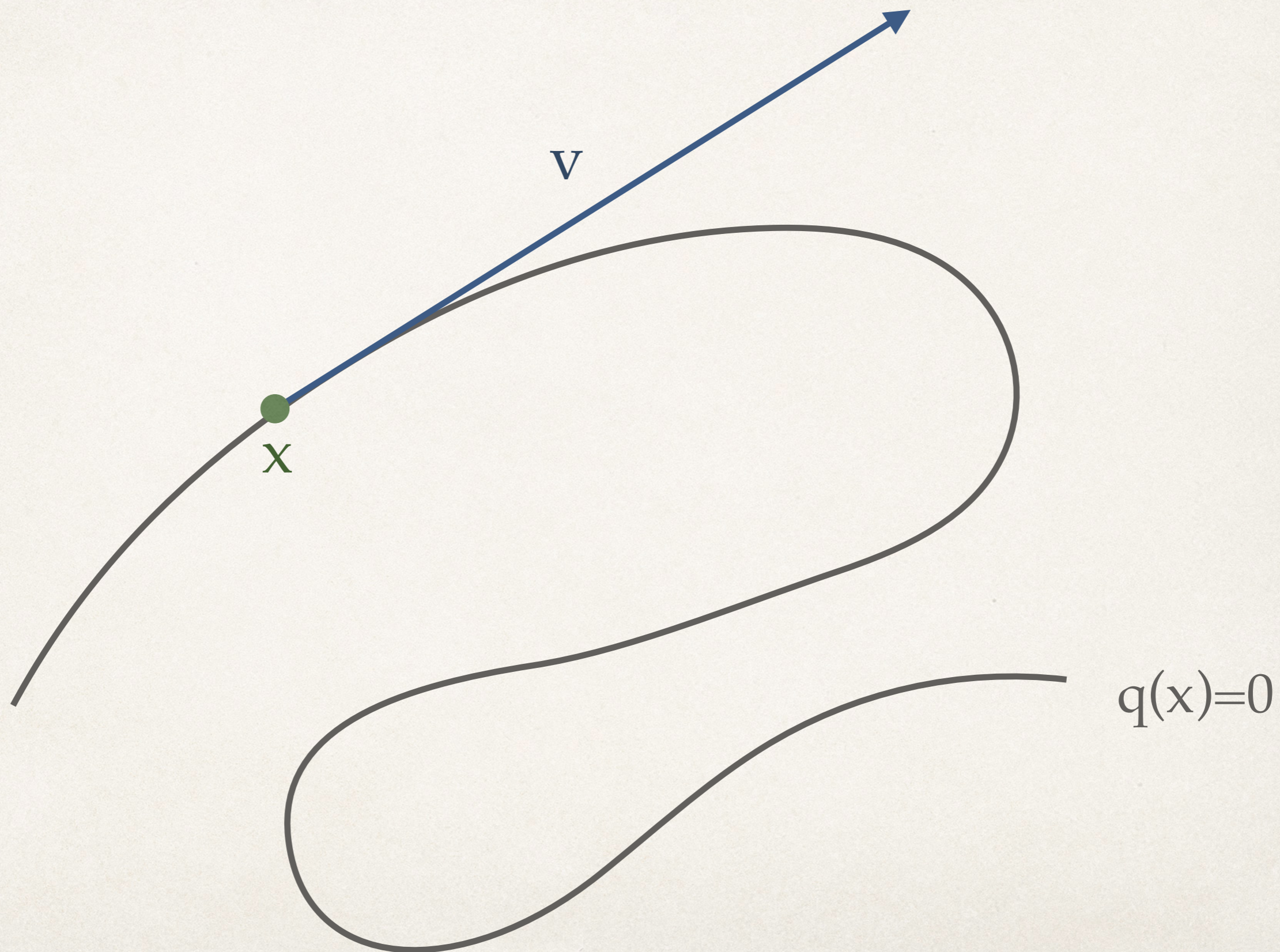
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$= 1$  if  $y$  can be reached from  $x$  using numerical solver  $= x$  if projection fails

What could go wrong?

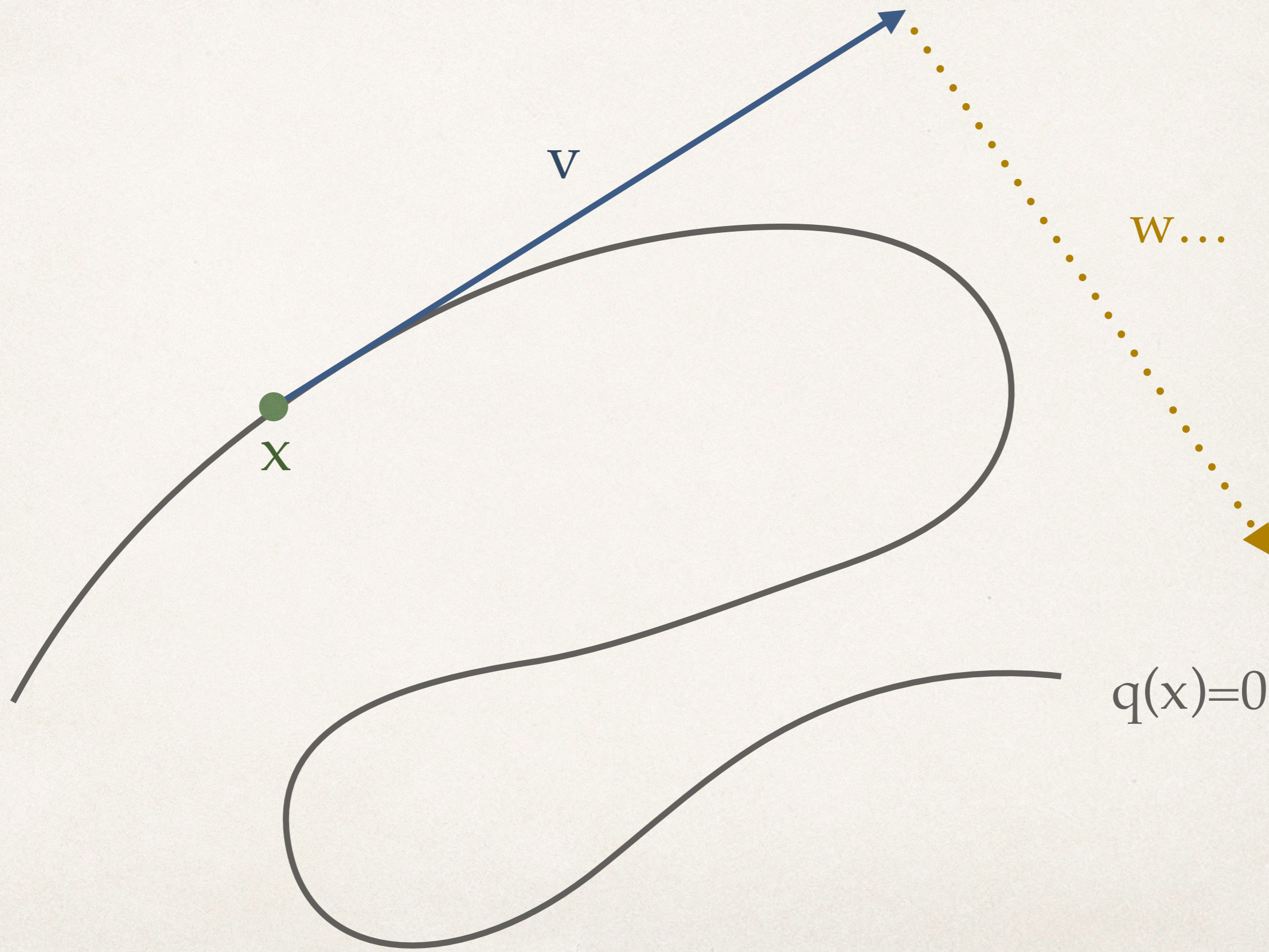
# Solution doesn't exist (forward move)

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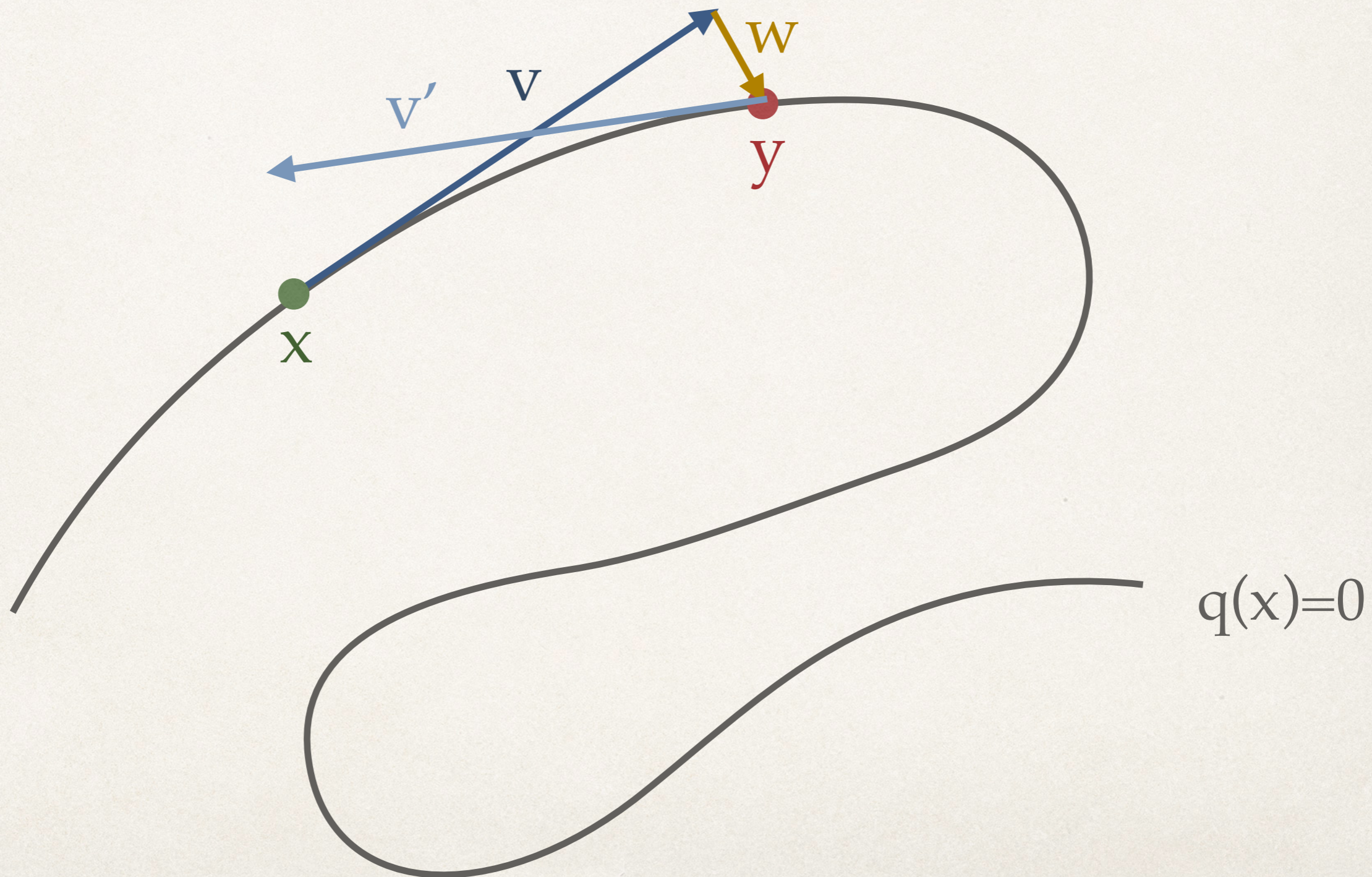
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# Numerical solver doesn't converge (forward & backward moves)

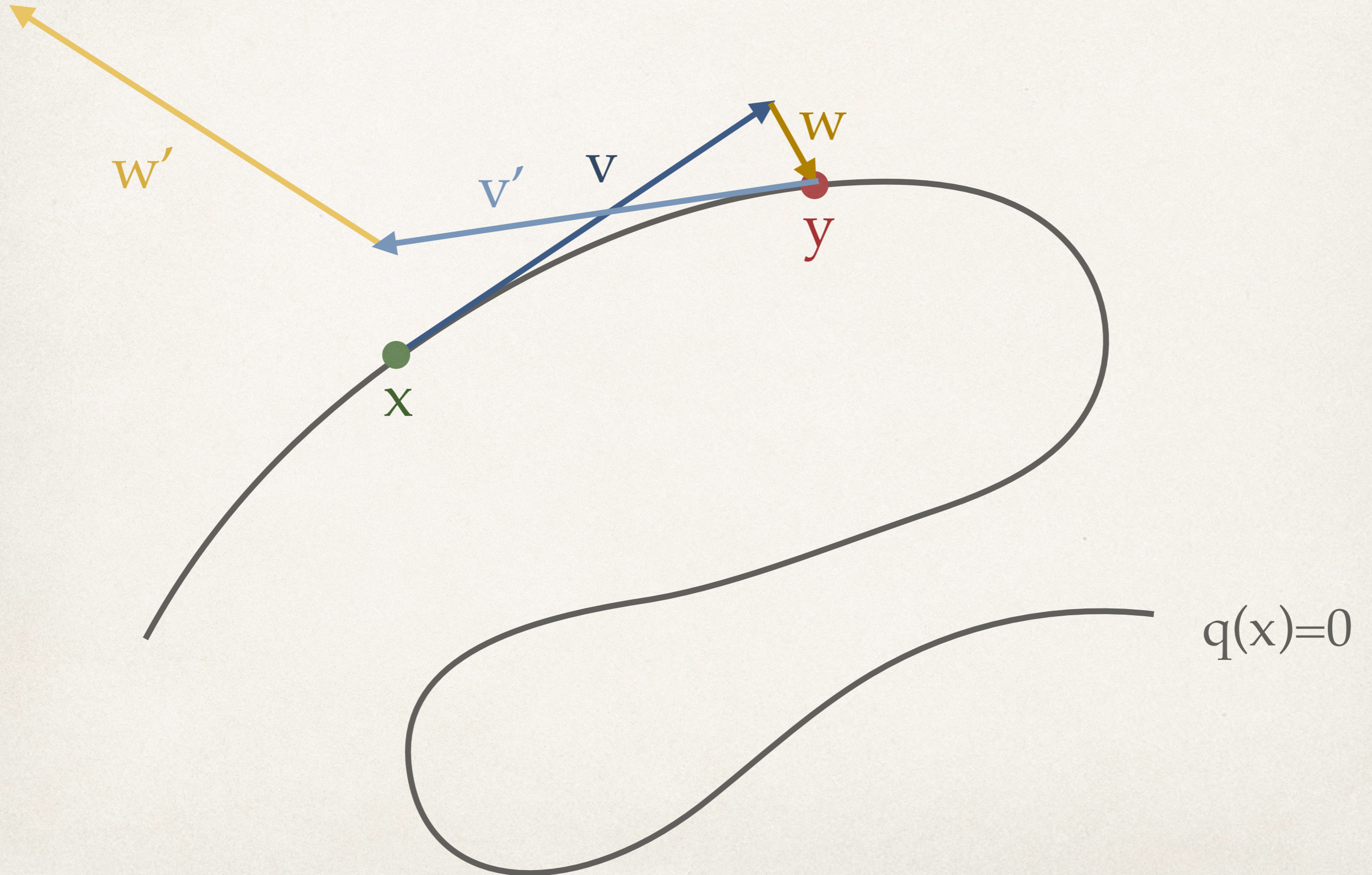
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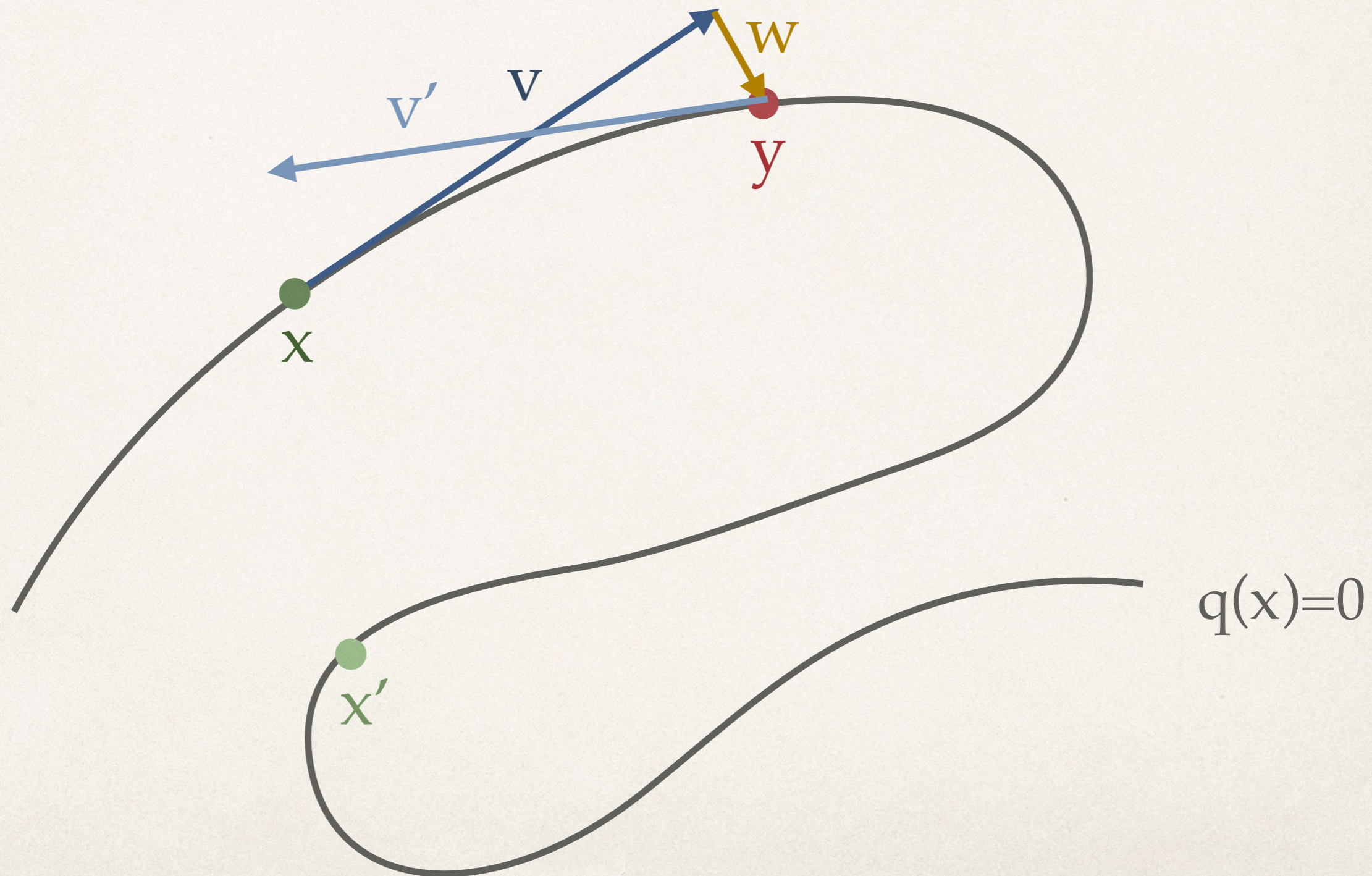
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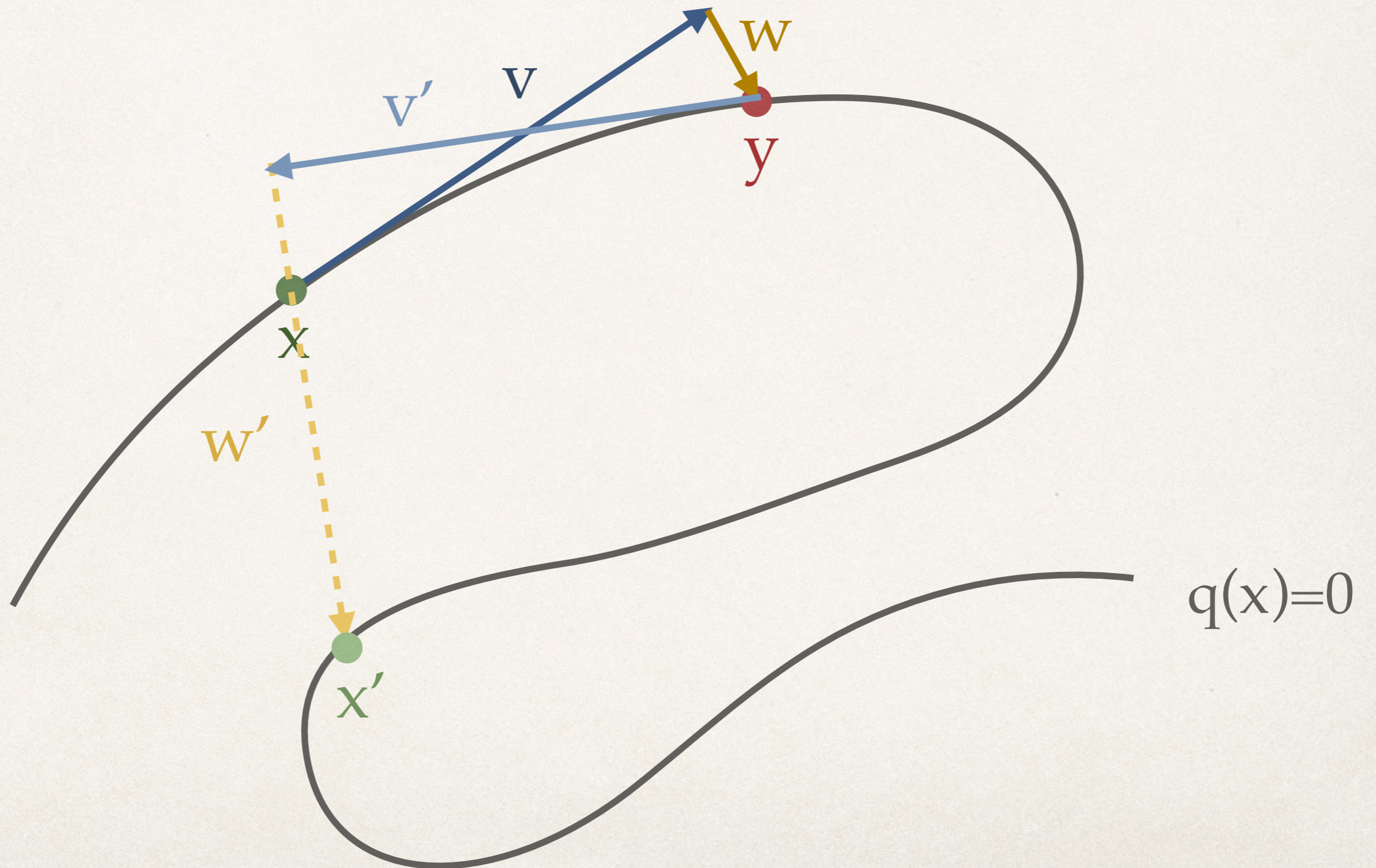
Solver converges, but gives a different point  $x' \neq x$  (reverse move)

---



Solver converges, but gives a different point  $x' \neq x$  (reverse move)

---





## Proposal densities $T(x \rightarrow y), T(y \rightarrow x)$

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=  $x$  if projection fails

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=  $y$  if projection fails

Given  $y \in A_x$ , we *don't know* if  $x \in A_y$

—> **we have to check reverse projection**

Check: (i) reverse projection converges, (ii) it converges to  $x$ .

*Code time!*

# Issues

---

- $|\nabla q| = 0 \rightarrow$  then what?
- Is this really worth it? Projections are costly...
- Numerical solver — better to be lazy. How lazy?
- Can we sample a density concentrated near, but not exactly on, a manifold, using a similar technique?
- Numerically we are never exactly on the manifold... so why do we get the right measure?
- Inequalities & highly nonconvex spaces (can we treat them like constraints?)