

# CS5643

## 04 ODEs and procedural turbulence

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Spring 2023

# Towards higher order

**Let's try expanding around  $t = (t_k + t_{k+1})/2$ ; call this time  $t_m$  for "midpoint"**

- $\mathbf{y}(t) = \mathbf{y}(t_m) + \dot{\mathbf{y}}(t_m)(t - t_m) + \frac{1}{2}\ddot{\mathbf{y}}(t_m)(t - t_m)^2 + O((t - t_m)^3)$

**evaluate at  $t_k$  and  $t_{k+1}$  to compute the step increment**

- $\mathbf{y}(t_{k+1}) - \mathbf{y}(t_k) = h\dot{\mathbf{y}}(t_m) + O(h^3)$  (try it yourself to see the canceling  $h^2$  term)

**...if only we knew  $\mathbf{y}(t_m)$ ! But we can use Forward Euler to estimate it**

- $\mathbf{y}(t_m) = \mathbf{y}(t_k) + \frac{h}{2}\dot{\mathbf{y}}(t_k) + O(h^2)$ , so let  $\mathbf{y}_m = \mathbf{y}_k + \frac{h}{2}\mathbf{f}(\mathbf{y}_k)$

- $\mathbf{f}(\mathbf{y} + O(h^2)) = \mathbf{f}(\mathbf{y}) + \mathbf{f}'(\mathbf{y})O(h^2) + O(h^2) = \mathbf{f}(\mathbf{y}) + O(h^2)$ , so  $\mathbf{f}(\mathbf{y}_m) = \dot{\mathbf{y}}(t_m) + O(h^2)$

- then  $\mathbf{y}(t_{k+1}) = \mathbf{y}(t_k) + h(\mathbf{f}(\mathbf{y}_m) + O(h^2)) + O(h^3) = \mathbf{y}(t_k) + h\mathbf{f}(\mathbf{y}_m) + O(h^3)$

- so let  $\mathbf{y}_{k+1} = \mathbf{y}_k + h\mathbf{f}(\mathbf{y}_m)$  and  $\mathbf{y}_{k+1}$  is a second-order estimate of  $\mathbf{y}(t_{k+1})$

# Midpoint method

## Timestep equations

$$\mathbf{y}_m = \mathbf{y}_k + \frac{h}{2}\mathbf{f}(\mathbf{y}_k)$$

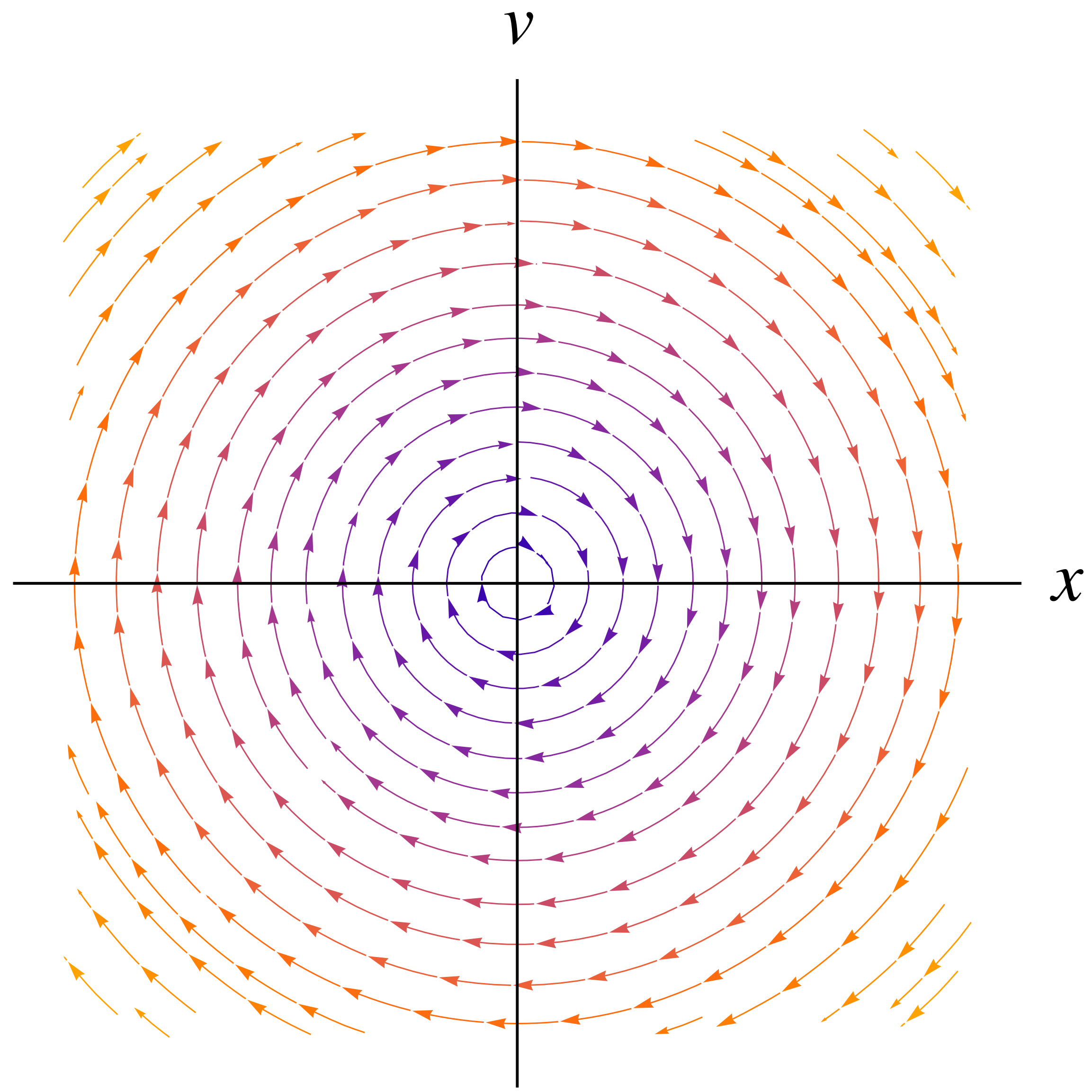
$$\mathbf{y}_{k+1} = \mathbf{y}_k + h\mathbf{f}(\mathbf{y}_m)$$

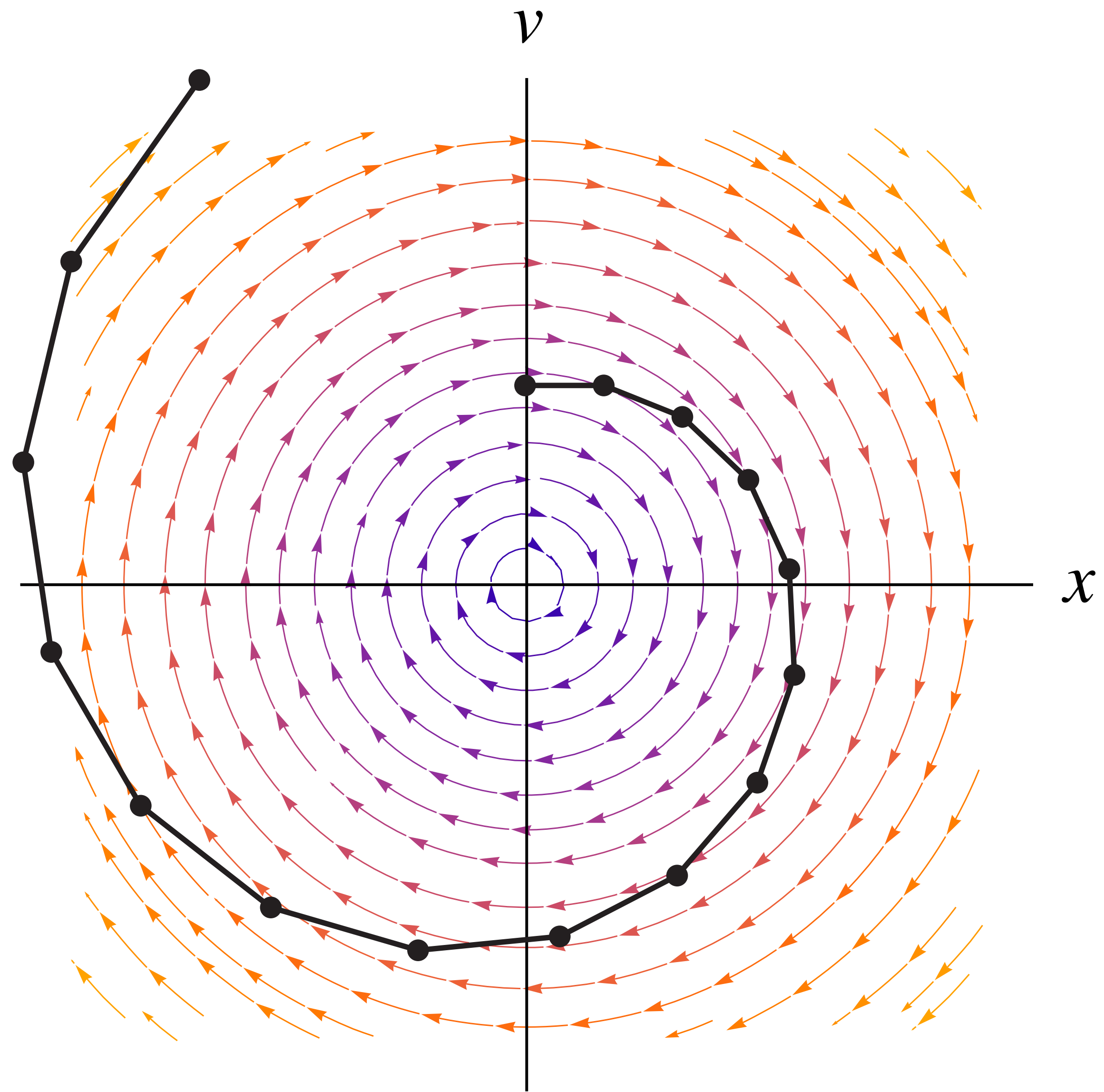
## This is

- an explicit integrator
- a *two-step* integrator (requires two evaluations of  $\mathbf{f}$ )
- accurate to second order

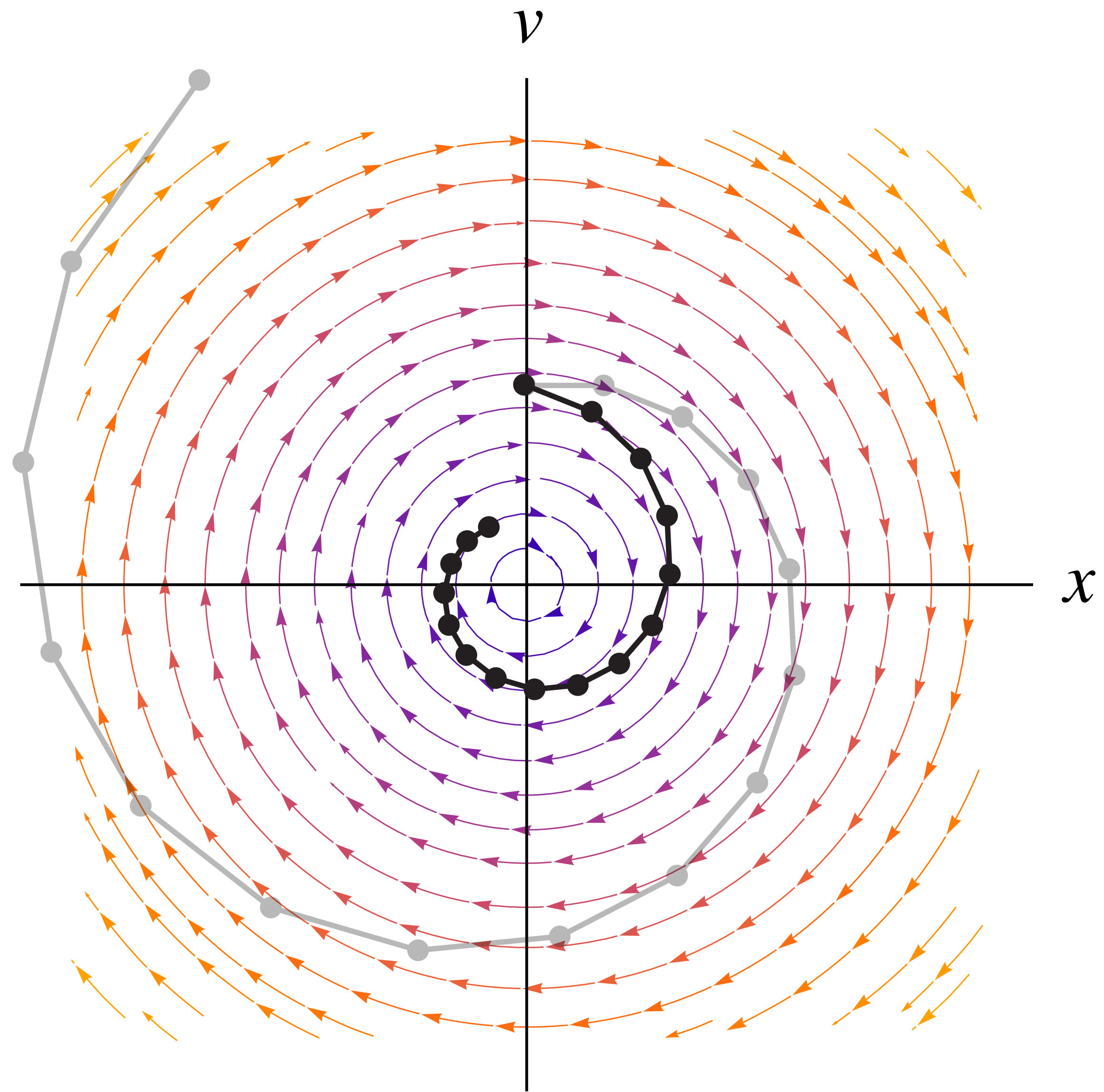
## It's also the first in a family of higher order integrators

- Runge-Kutta methods achieve order  $p$  accuracy with at least  $p$  function evaluations
- RK4 is a popular fourth-order scheme, good for smooth problems requiring high accuracy
- animation = not-so-smooth problems requiring low accuracy, hence we rarely go past second order

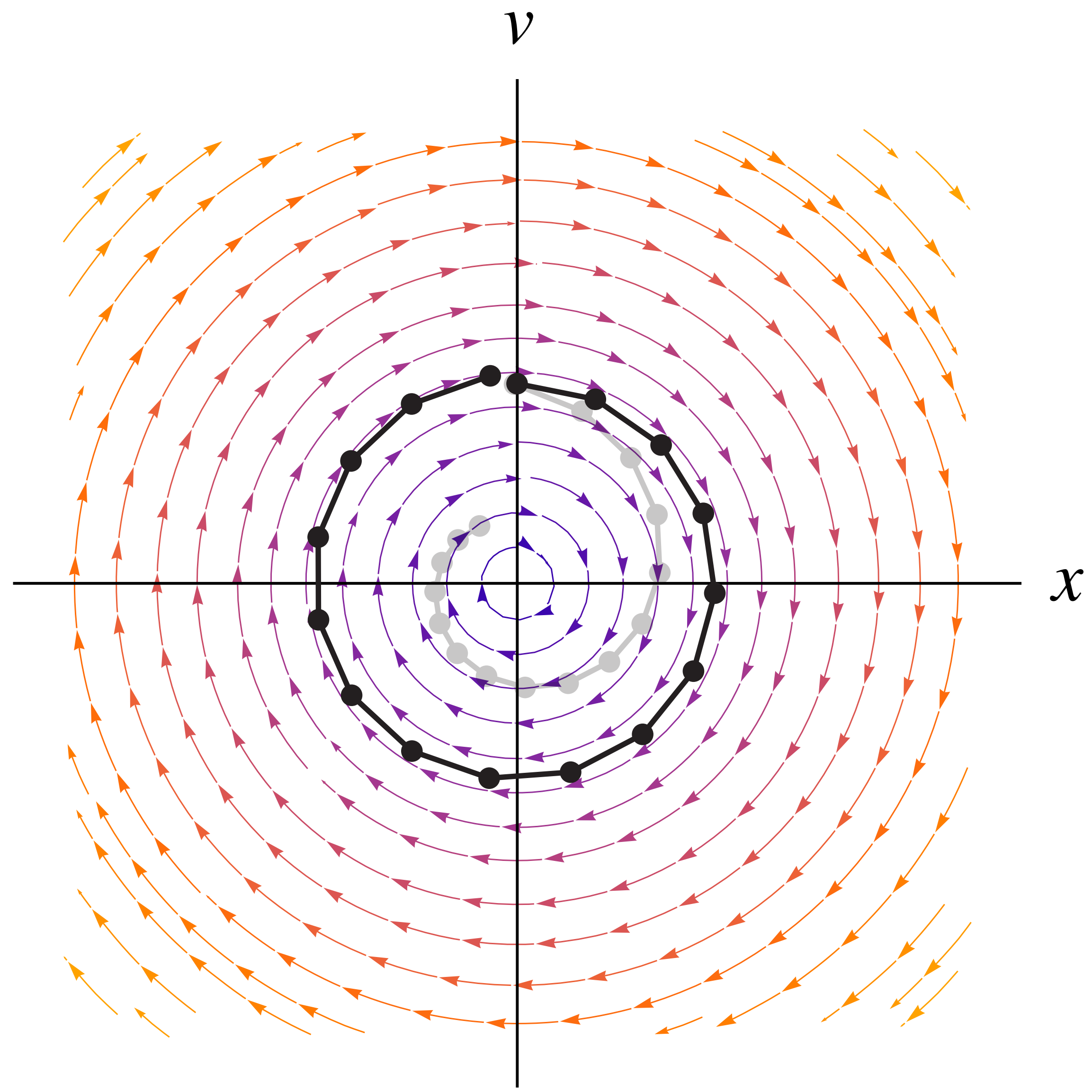




**forward Euler**



**backward Euler**



**midpoint method**

# Demo!

## **accuracy of integration along circular paths**

- Euler vs. midpoint



# Integrators for second-order systems

**Many useful systems have the form  $\ddot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t))$**

- note this equation skips over  $\dot{\mathbf{x}}$ ; acceleration does not depend on velocity, only position.

**Look at what the second step of the midpoint method does**

- $\mathbf{y}_{k+1} = \mathbf{y}_k + h\mathbf{f}(\mathbf{y}_m)$  translates to (naming  $\mathbf{y}_m$  as  $\mathbf{y}_{k+0.5}$ )

$$\mathbf{x}_{k+1} = \mathbf{x}_k + h\mathbf{v}_{k+0.5}$$

$$\mathbf{v}_{k+1} = \mathbf{v}_k + h\mathbf{f}(\mathbf{x}_{k+0.5})$$

← updating  $\mathbf{x}$  only requires  $\mathbf{v}_{k+0.5}$ ,  
and updating  $\mathbf{v}$  only requires  $\mathbf{x}_{k+0.5}$

- if we stagger the grids then we can have these values already!

$$\mathbf{x}_{k+1} = \mathbf{x}_k + h\mathbf{v}_{k+0.5}$$

$$\mathbf{v}_{k+1.5} = \mathbf{v}_{k+0.5} + h\mathbf{f}(\mathbf{x}_{k+1})$$

- this is an explicit method, and it's second order accurate for both position and velocity
- known as the Leapfrog integrator — elegant but prohibits velocity dependent forces

# Symplectic Euler's method (aka. semi-implicit)

## Leapfrog is nice but doesn't work for $\ddot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{v})$

- practical problem: can't evaluate  $\mathbf{f}$  without knowing  $\mathbf{x}$  and  $\mathbf{v}$  at the same time
- a practical solution: give up the interleaved steps but keep the timestep equations

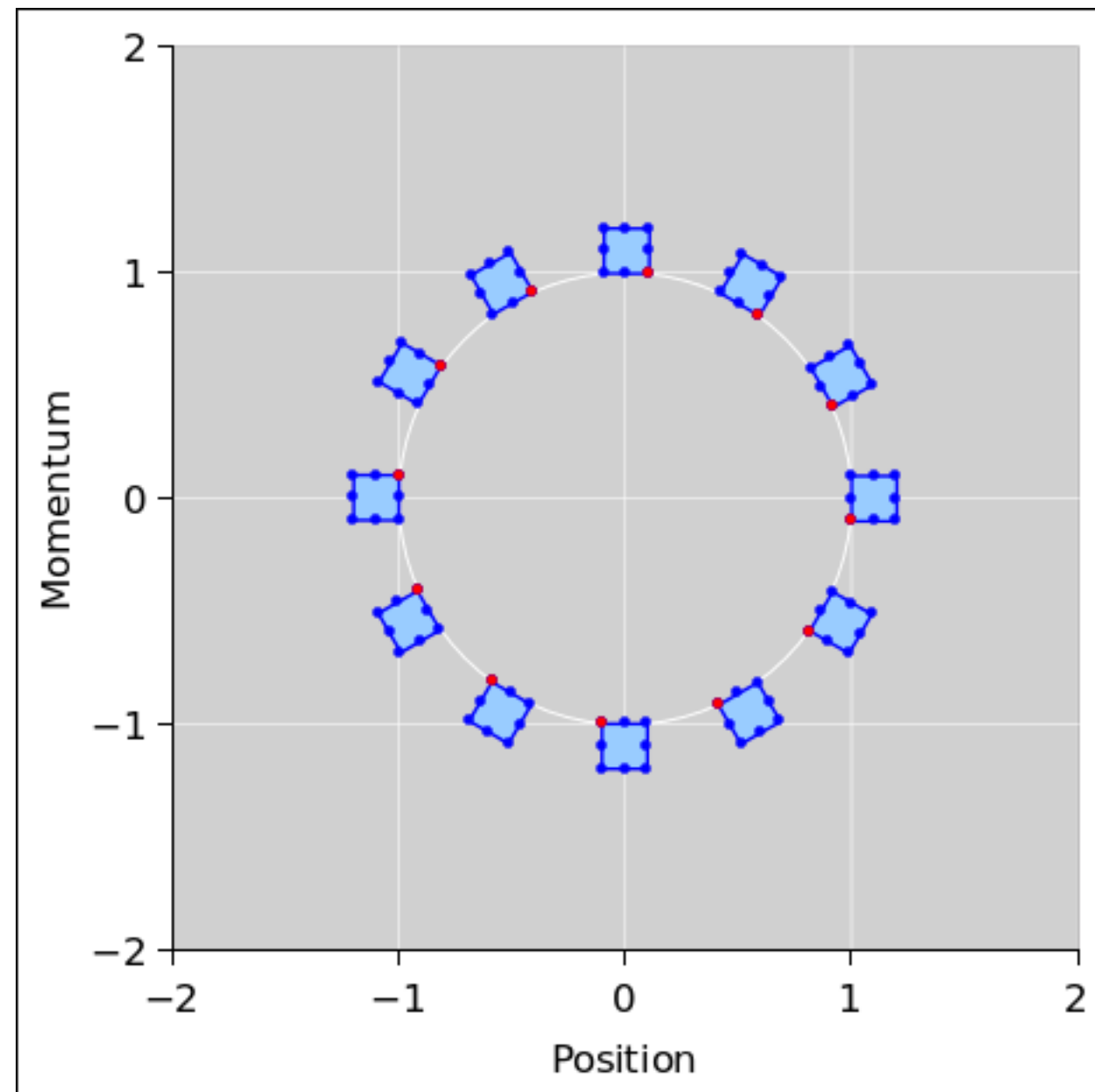
$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{x}_k + h\mathbf{v}_k \\ \mathbf{v}_{k+1} &= \mathbf{v}_k + h\mathbf{f}(\mathbf{x}_{k+1})\end{aligned}$$

this looks just like Forward Euler except for the last +1

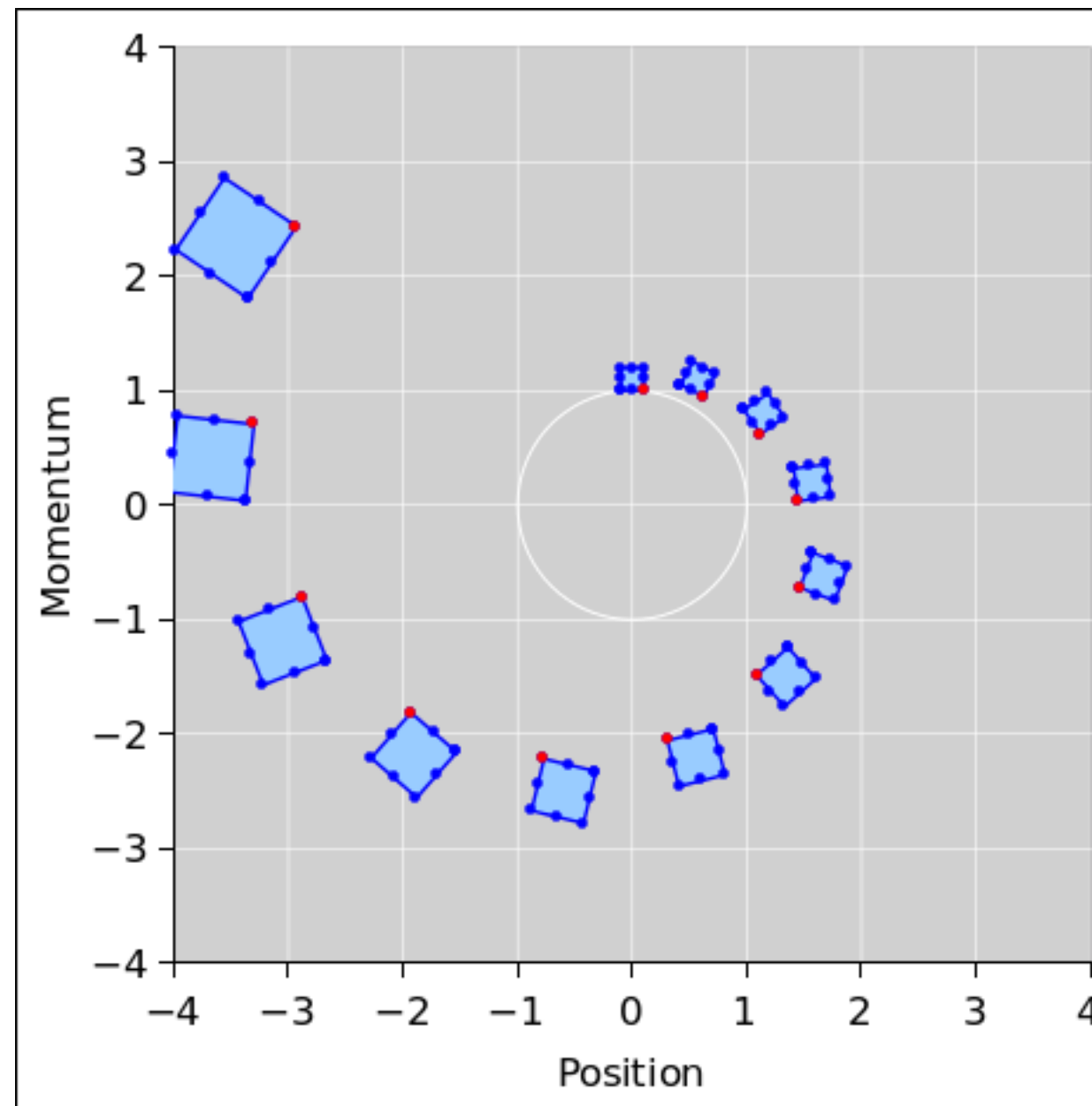
- or: use the position update from Forward Euler and the velocity update from Backward Euler
- this integrator shares a very nice property with Leapfrog: each timestep preserves area in the  $(\mathbf{x}, \mathbf{v})$  picture (really in position–momentum space)

$$\begin{bmatrix} \mathbf{x}_{k+1} \\ \mathbf{v}_{k+1} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & h \\ -h & 1 - h^2 \end{bmatrix}}_{\det = 1} \begin{bmatrix} \mathbf{x}_k \\ \mathbf{v}_k \end{bmatrix}$$

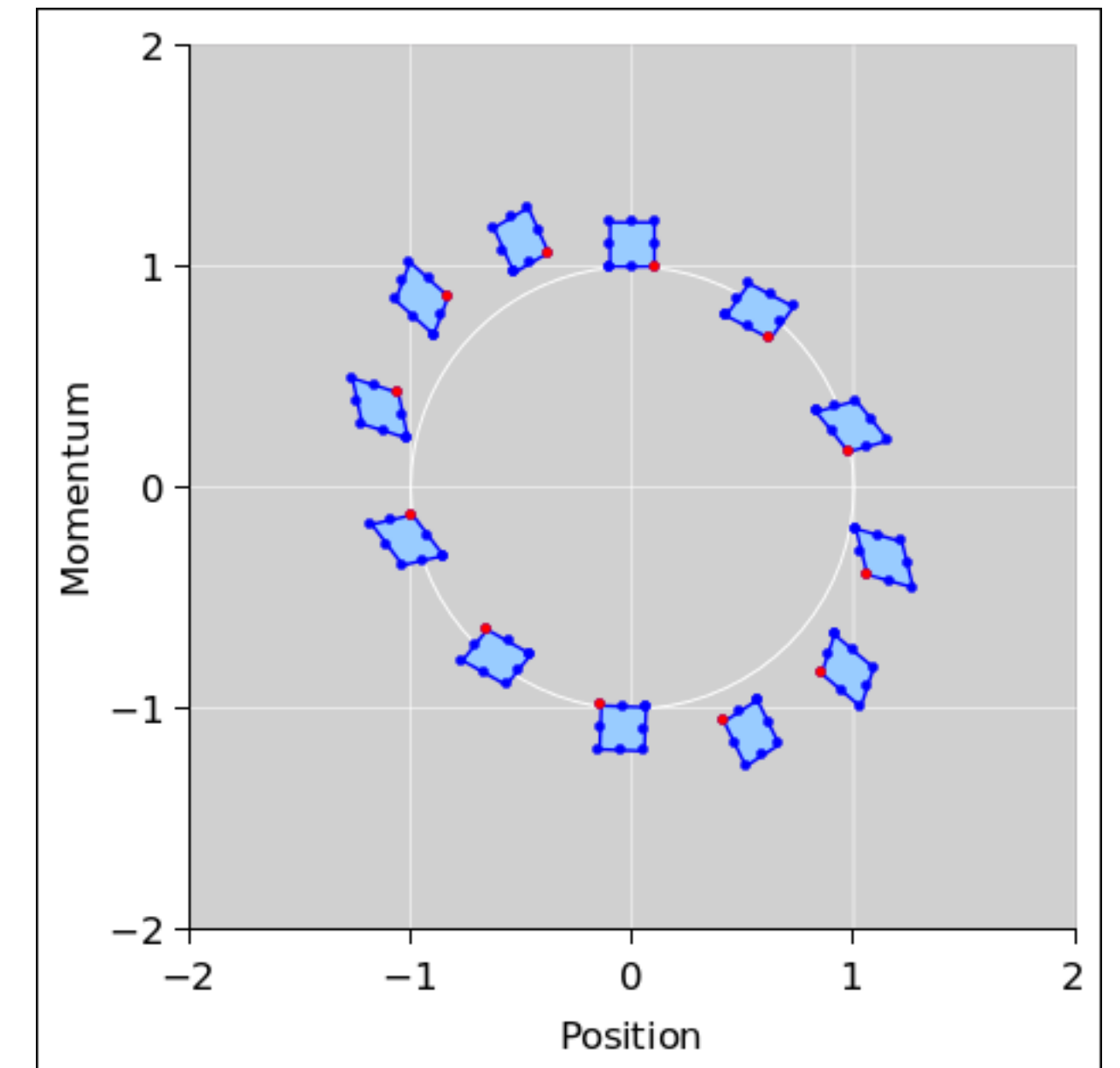
- this property holds for any Hamiltonian (roughly, energy conserving) system



exact

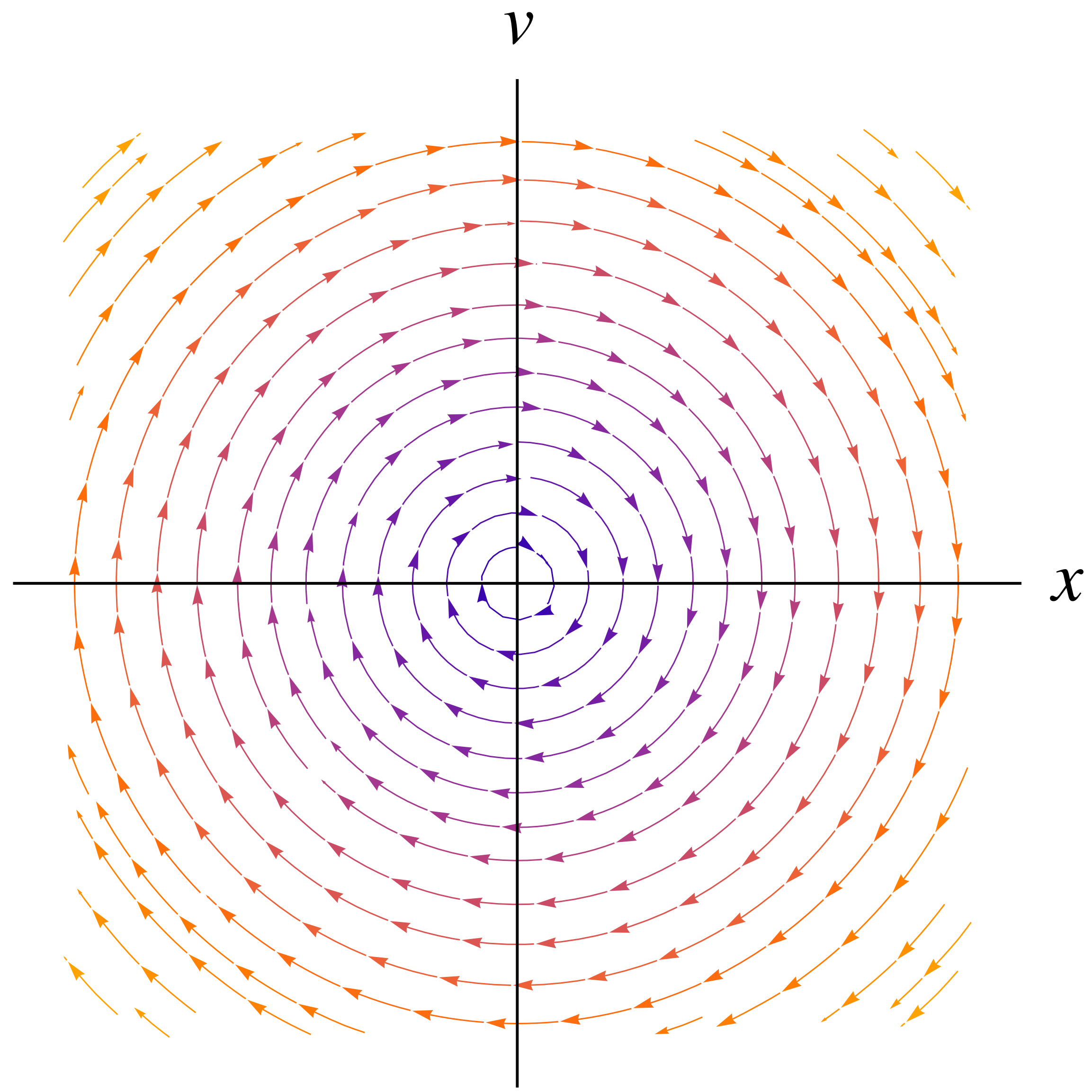


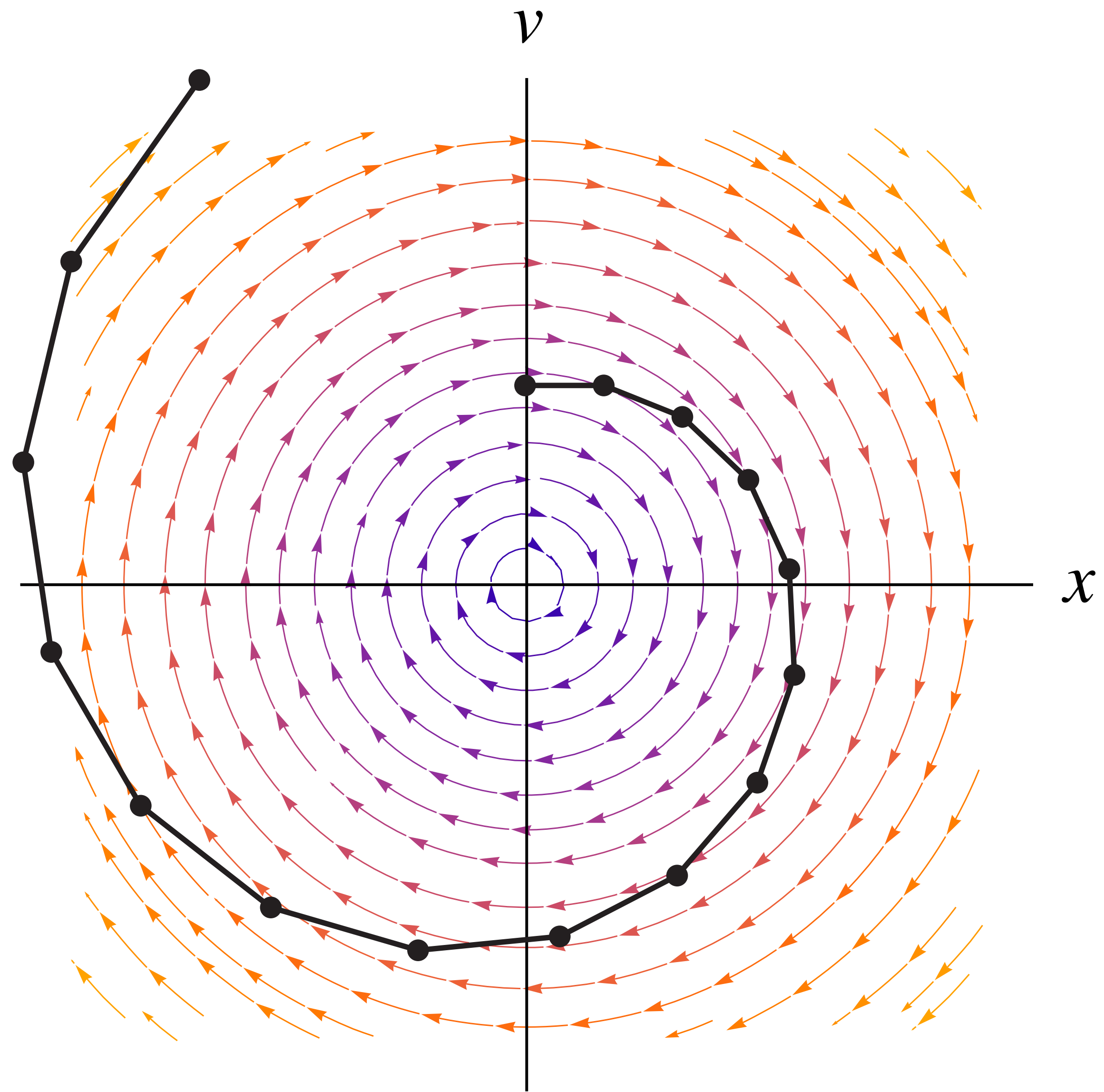
forward Euler



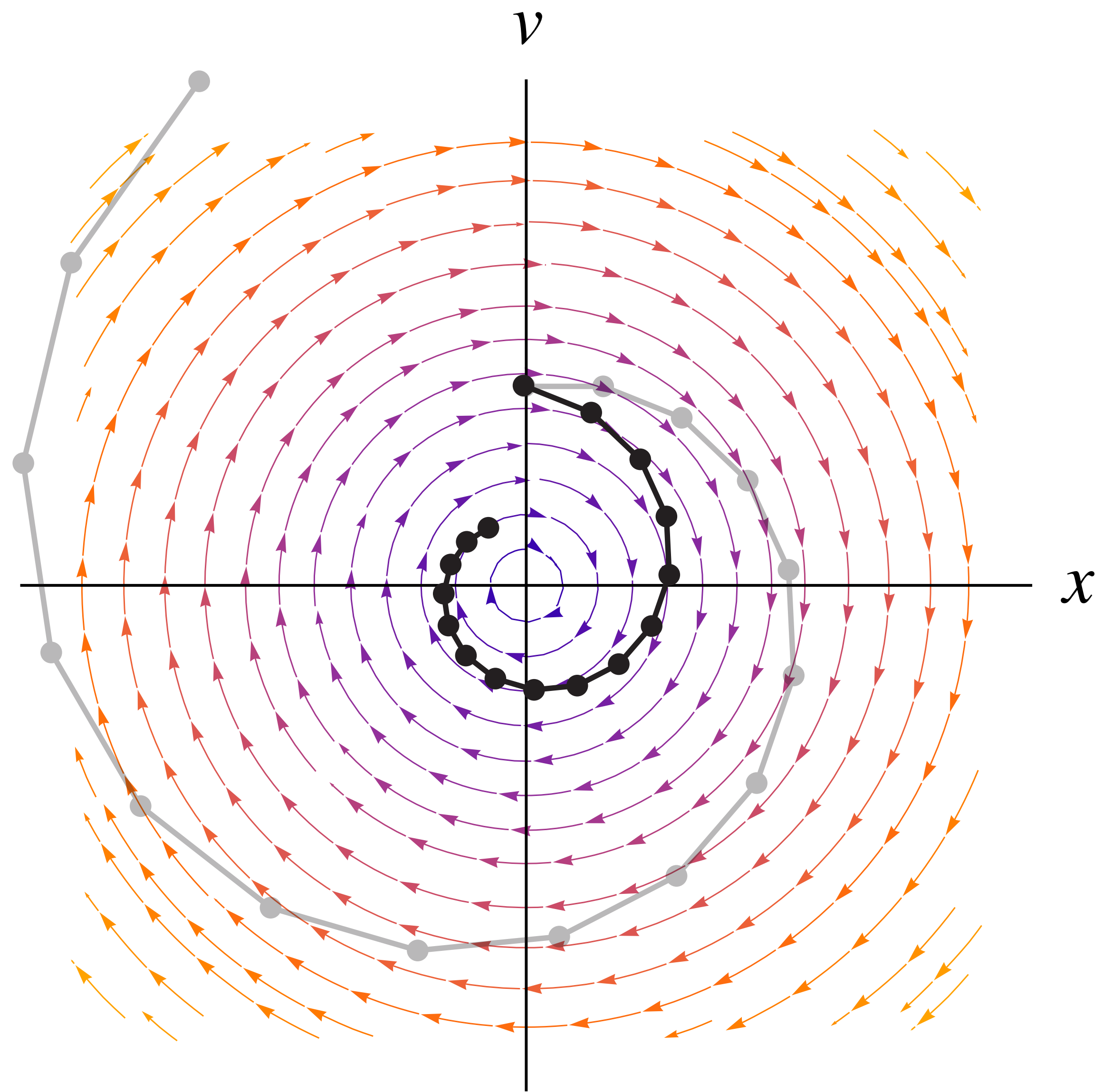
symplectic Euler

<https://www.av8n.com/physics/symplectic-integrator.htm>



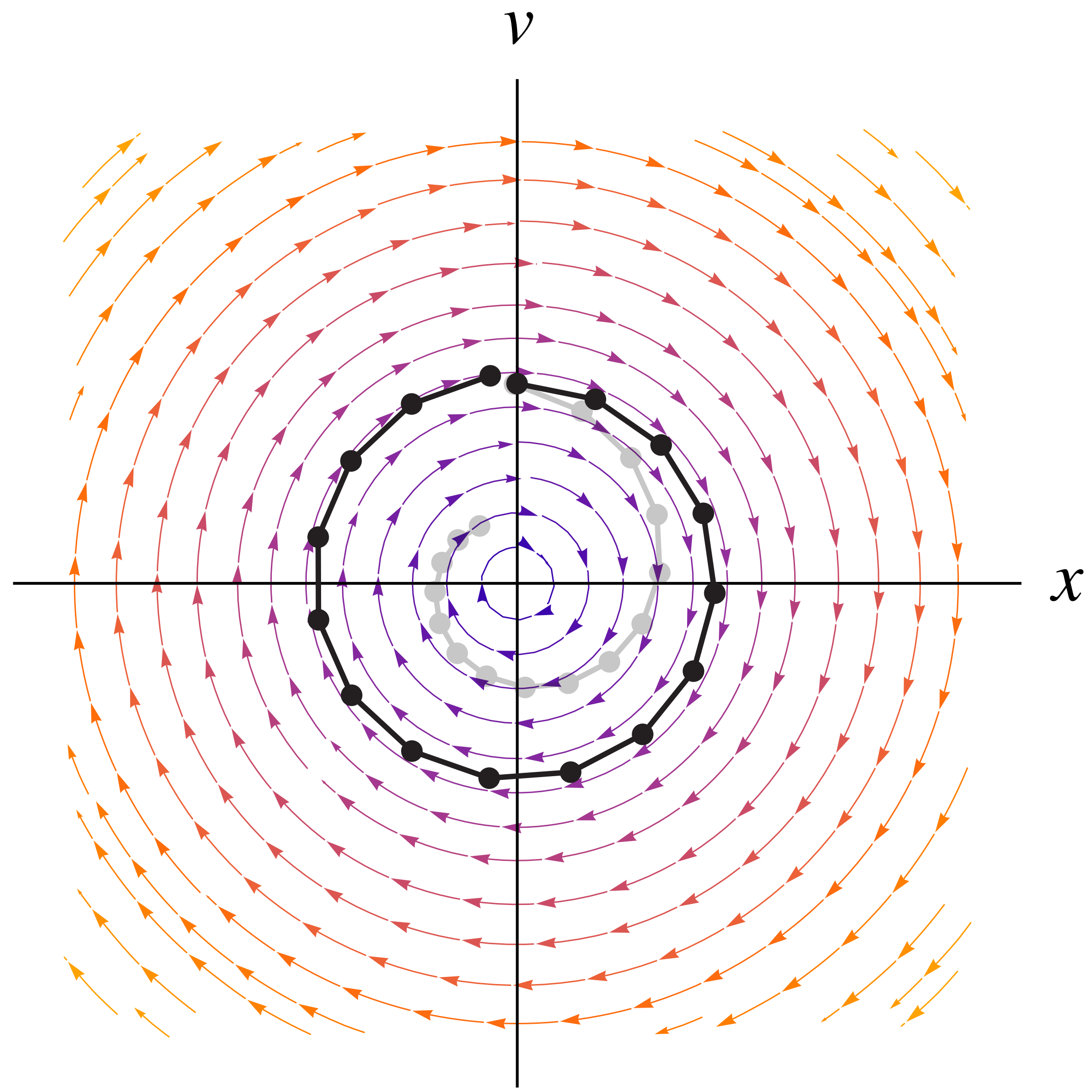


**forward Euler**

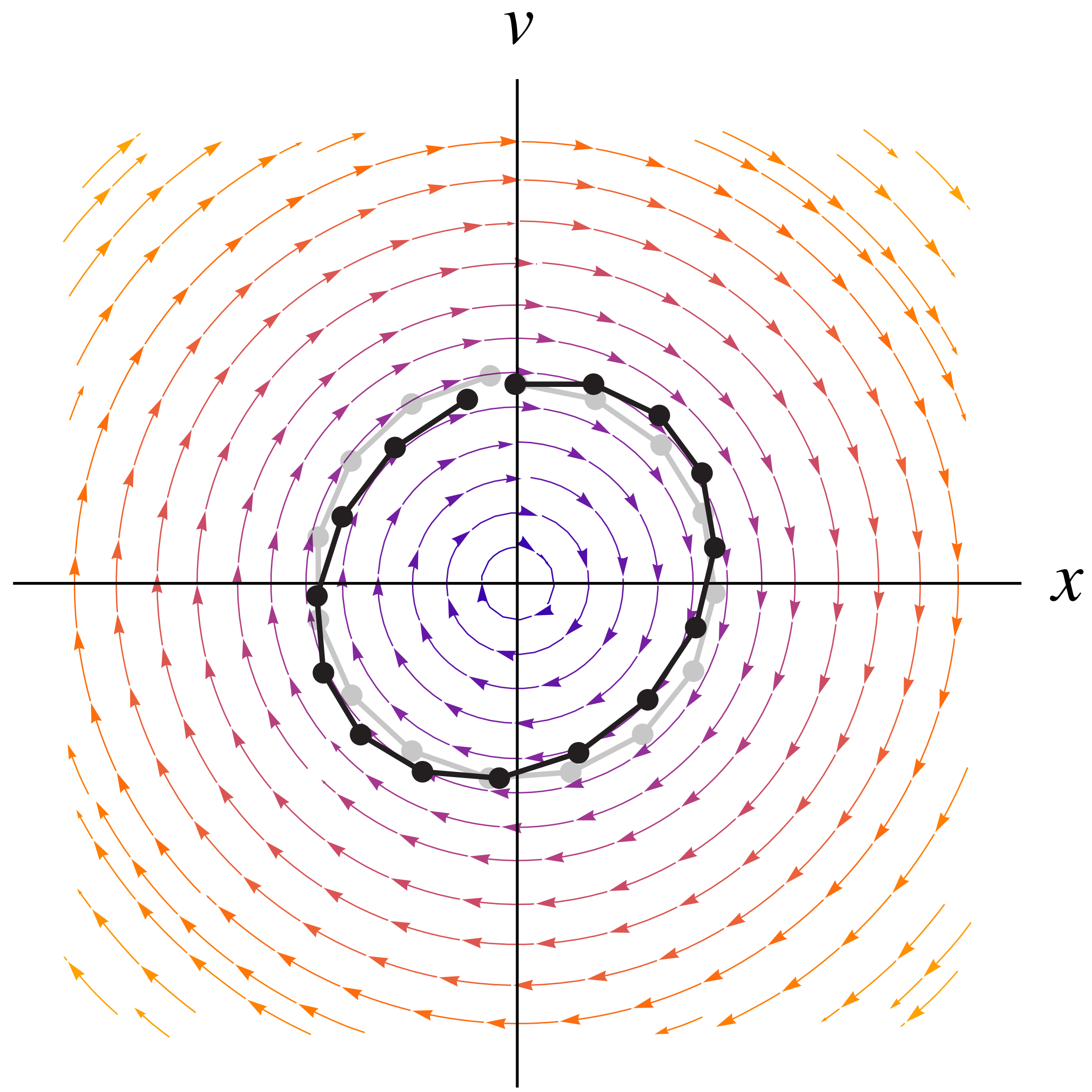


**backward Euler**



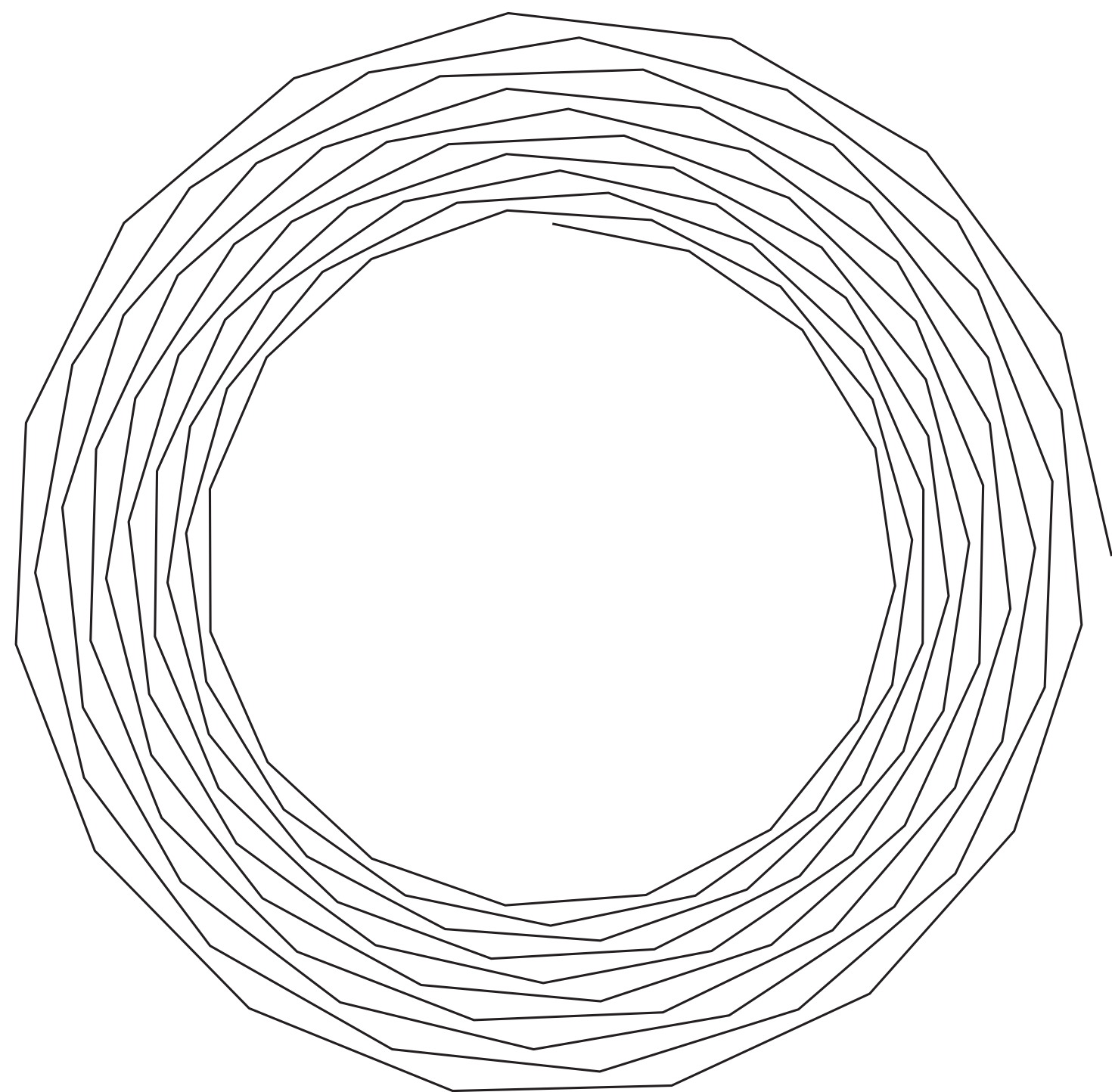


**midpoint method**

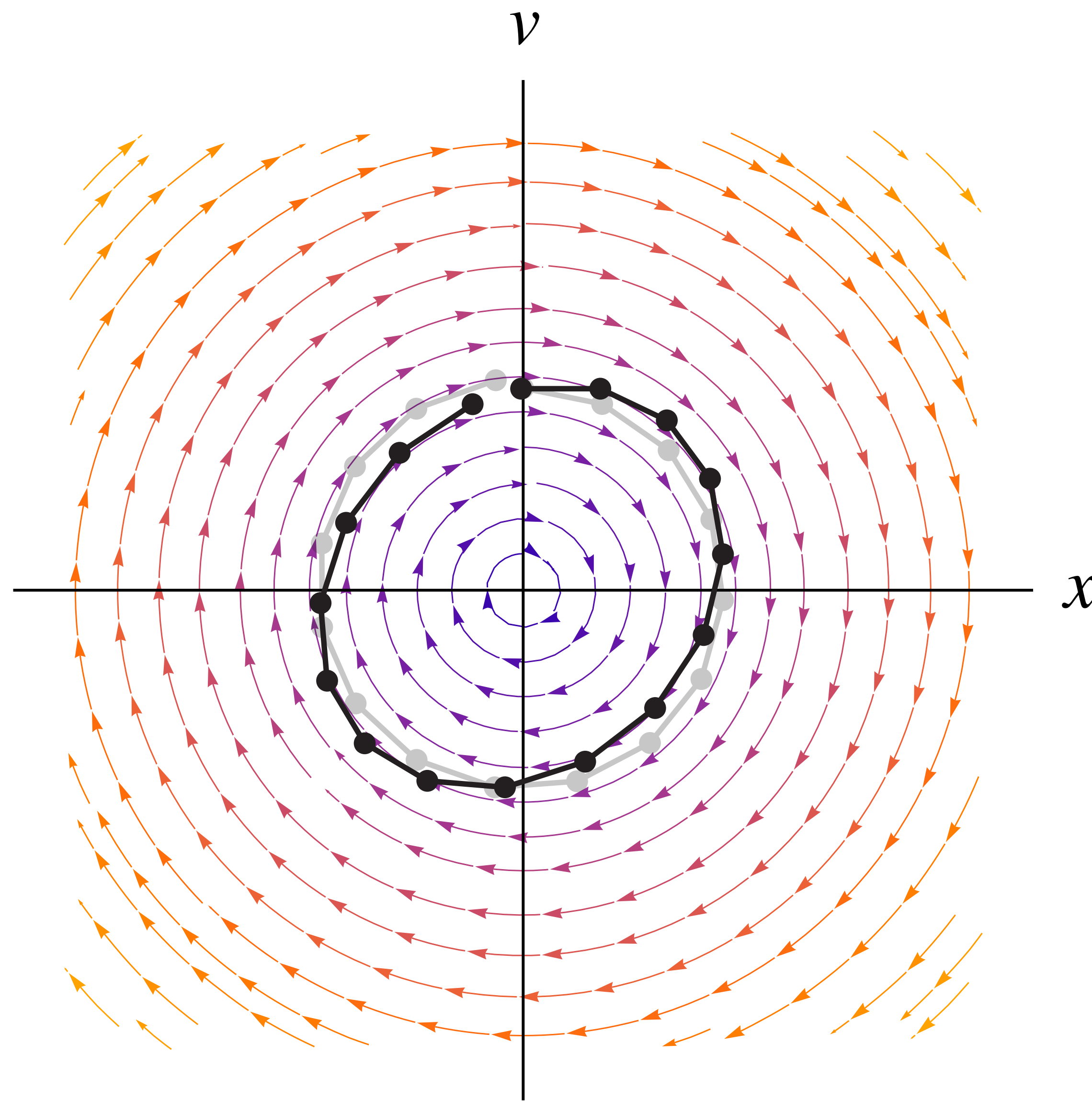


**symplectic Euler**

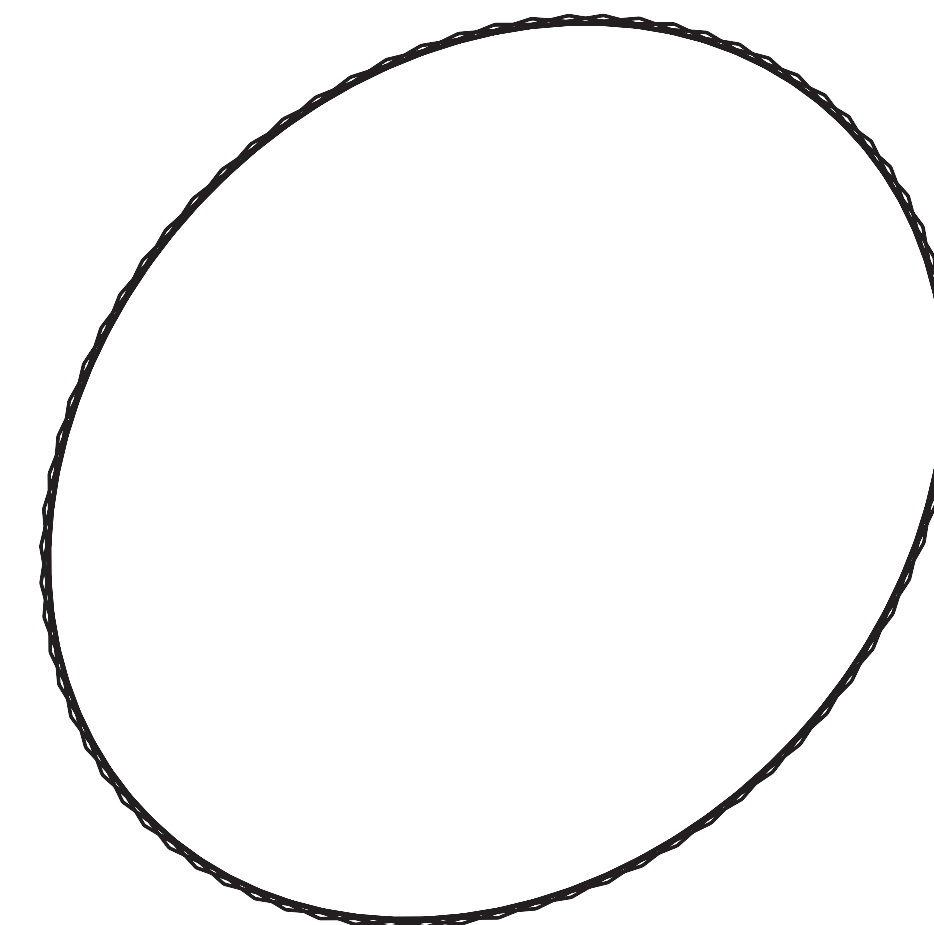




**midpoint  
for 10 laps**



**symplectic Euler**



**symplectic Euler  
for 10 laps**

# Procedural noise for animation

**for moving particles around we want irregular flow fields**

**graphics has a long tradition of defining nice looking “random” functions**

- this is procedural noise

**groundbreaking 1985 work of Ken Perlin established the basic approach:**

- start with random values on a grid
- interpolate to get functions that are smooth locally but vary at the grid scale
- combine noise functions of different scales to get nice results

**(newer methods make slightly better results)**

**this kind of noise can be leveraged into fake turbulence fields**

Side by side comparison:  
Coarse, underlying simulation

Large, synthesized one  
(7x higher resolution)



Wavelet Turbulence (Kim et al. SIGGRAPH 2008; Technical Oscar 2012)



Side by side comparison:  
Coarse, underlying simulation

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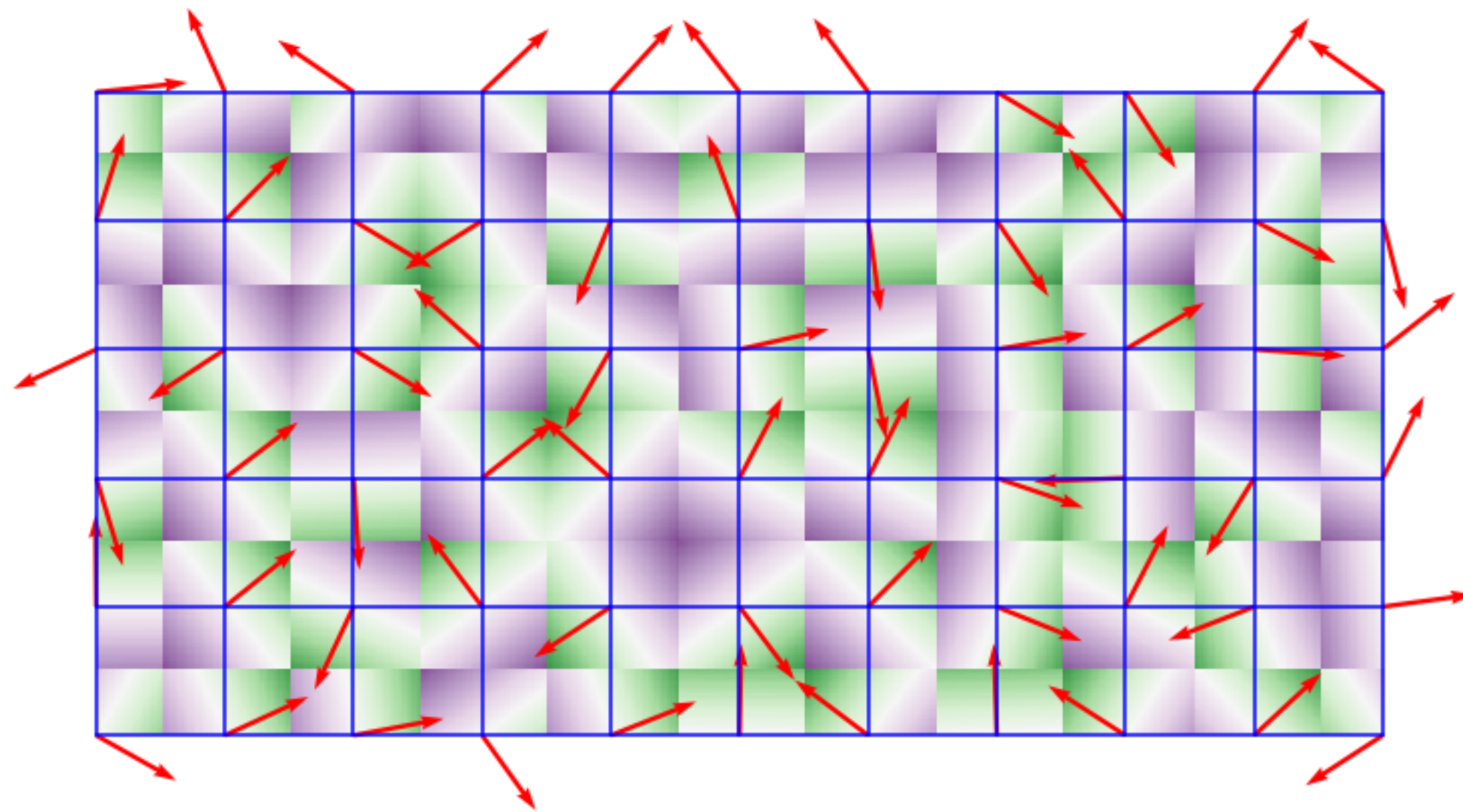


Wavelet Turbulence (Kim et al. SIGGRAPH 2008; Technical Oscar 2012)

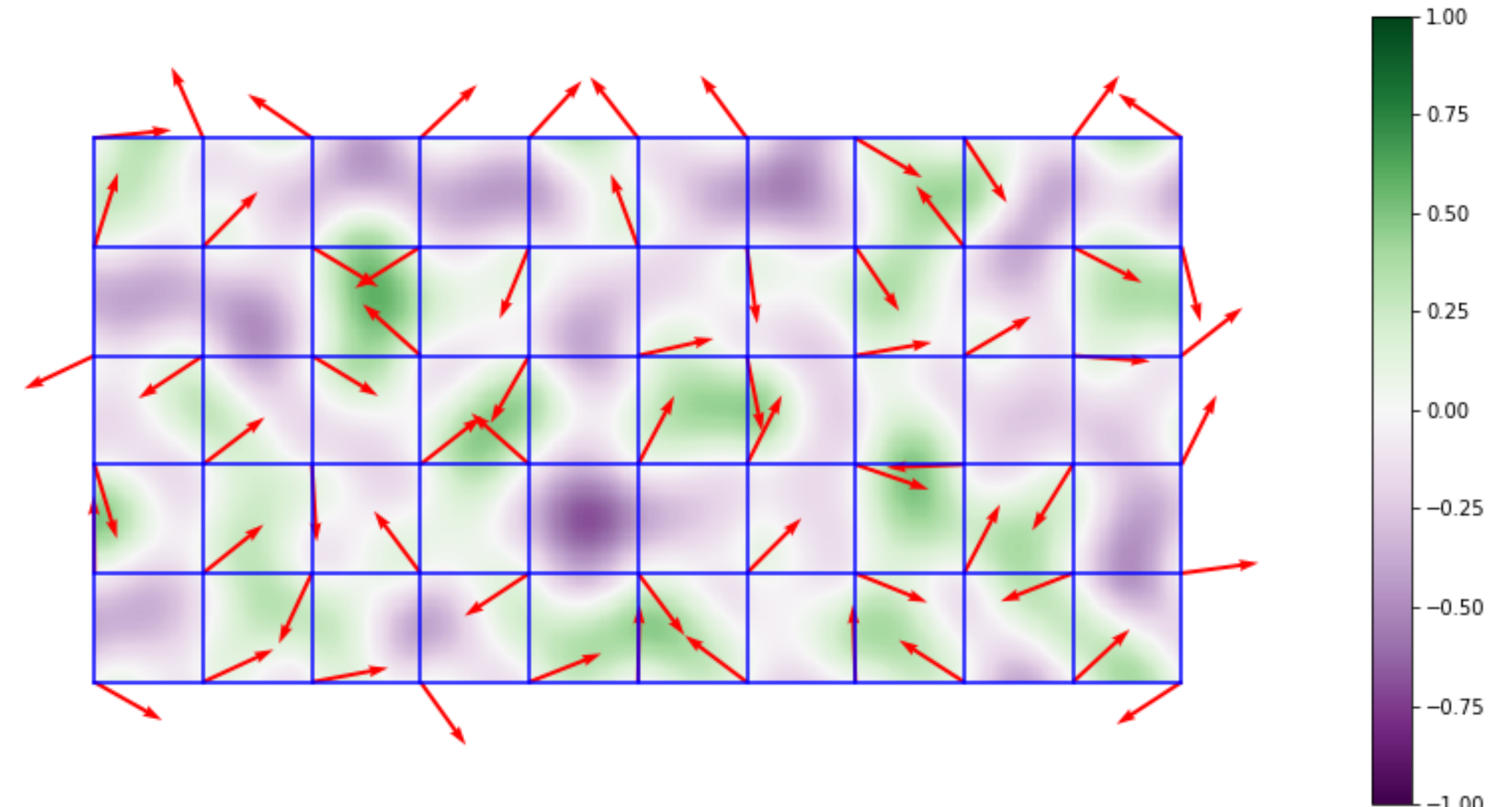
# Constructing Perlin noise in 2D

**1. define randomly oriented unit-slope gradients at integer points**

**2. interpolate between points using cubic smoothstep function  $3u^2 - 2u^3$**



nearest-neighbor linear gradients



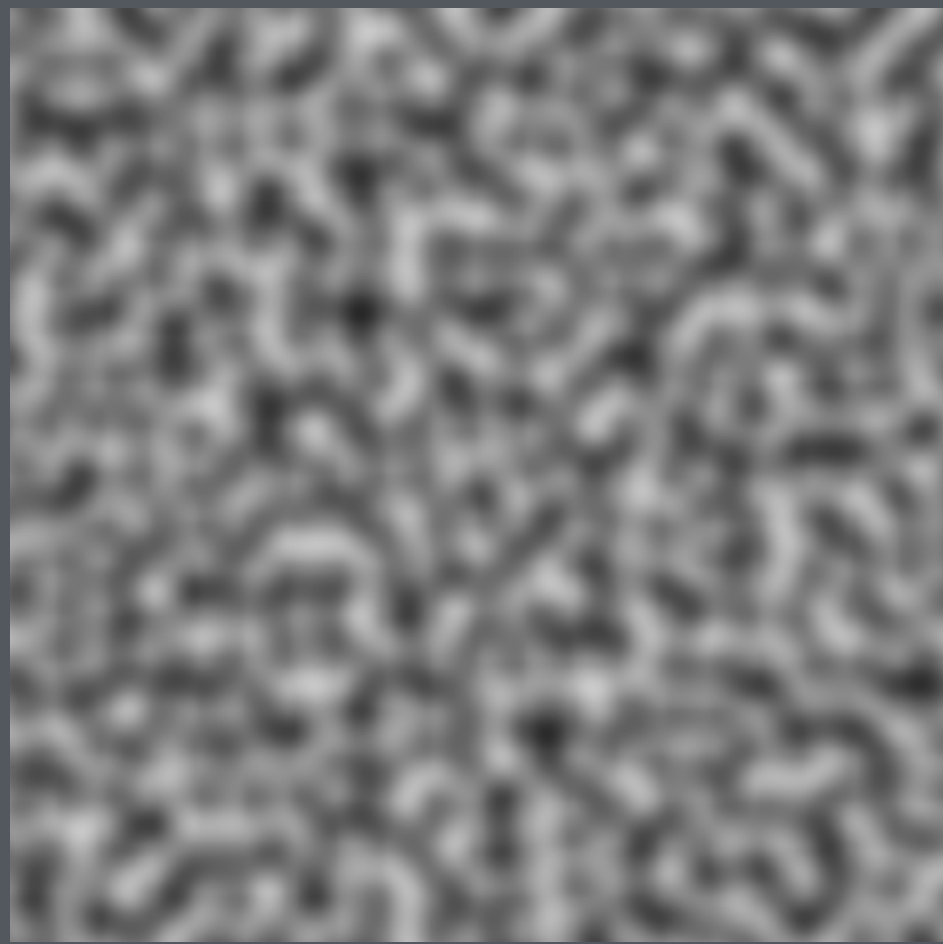
interpolated with smoothstep





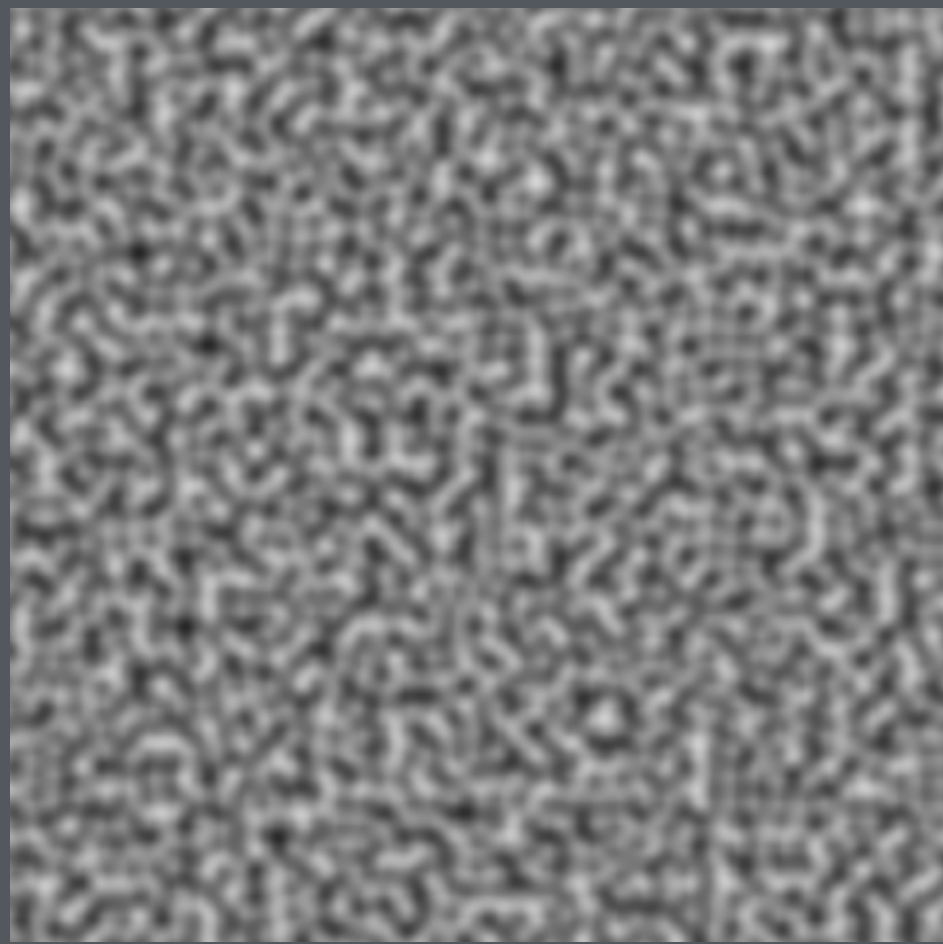
$\times 1$

+



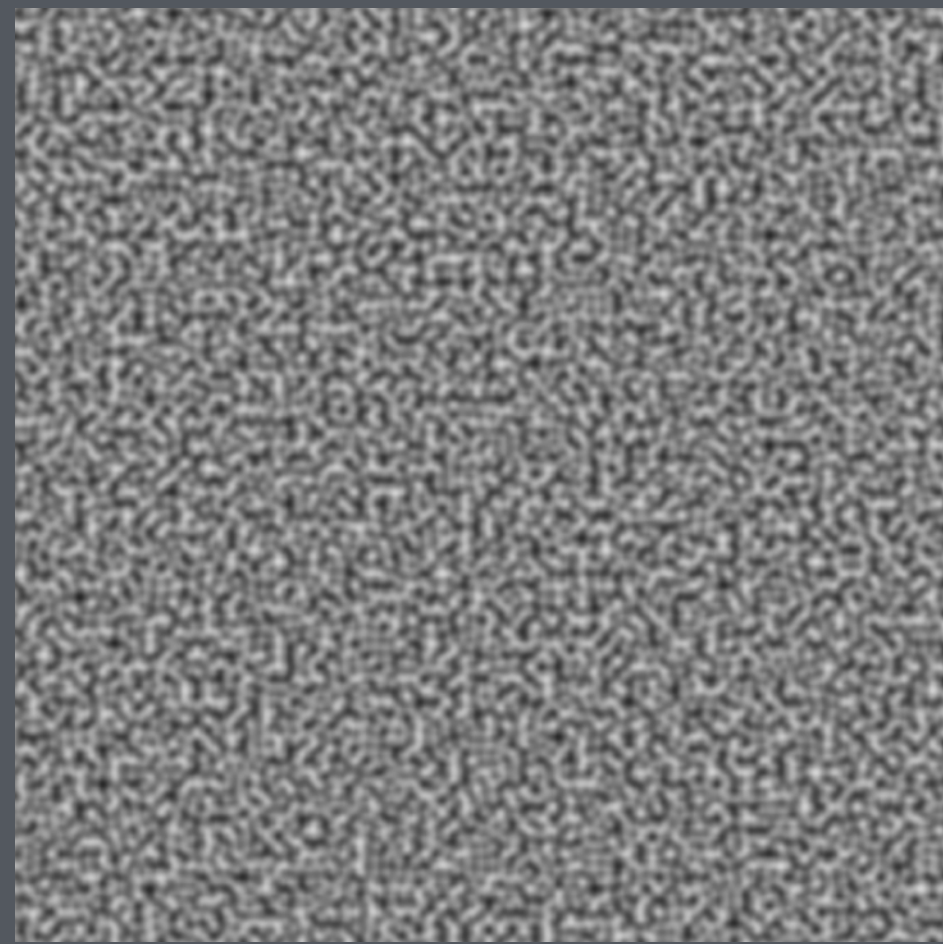
$\times \frac{1}{2}$

+



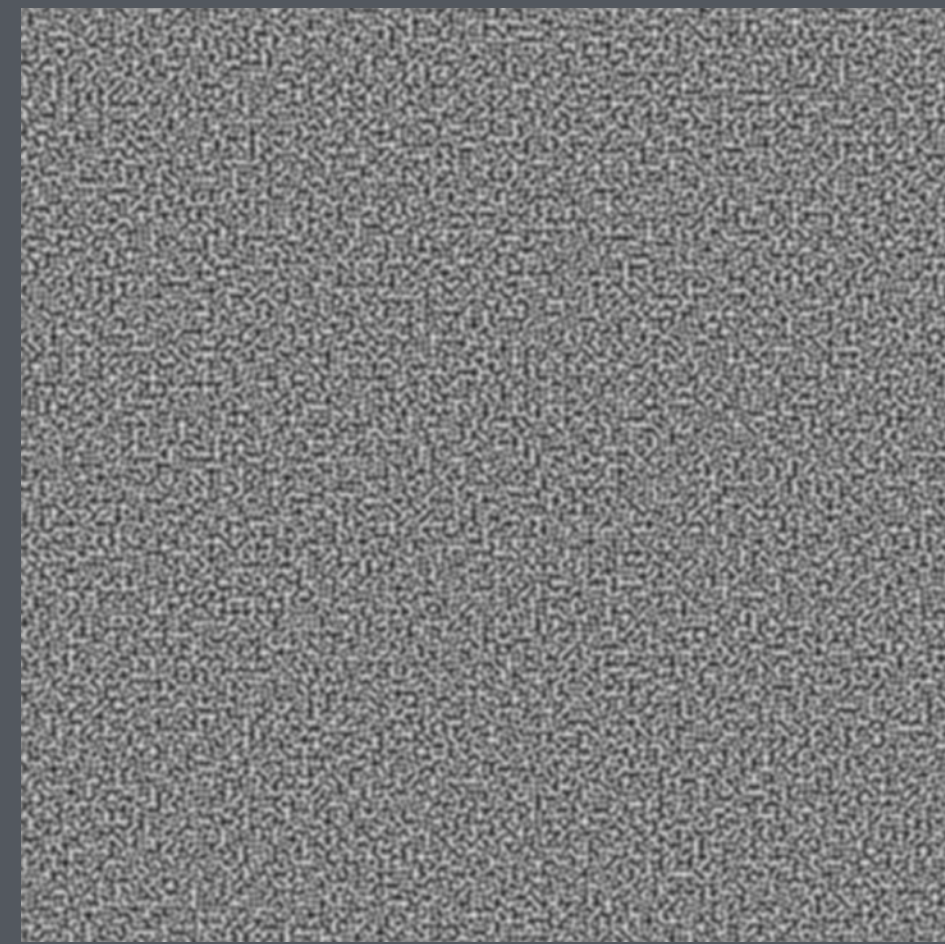
$\times \frac{1}{4}$

+



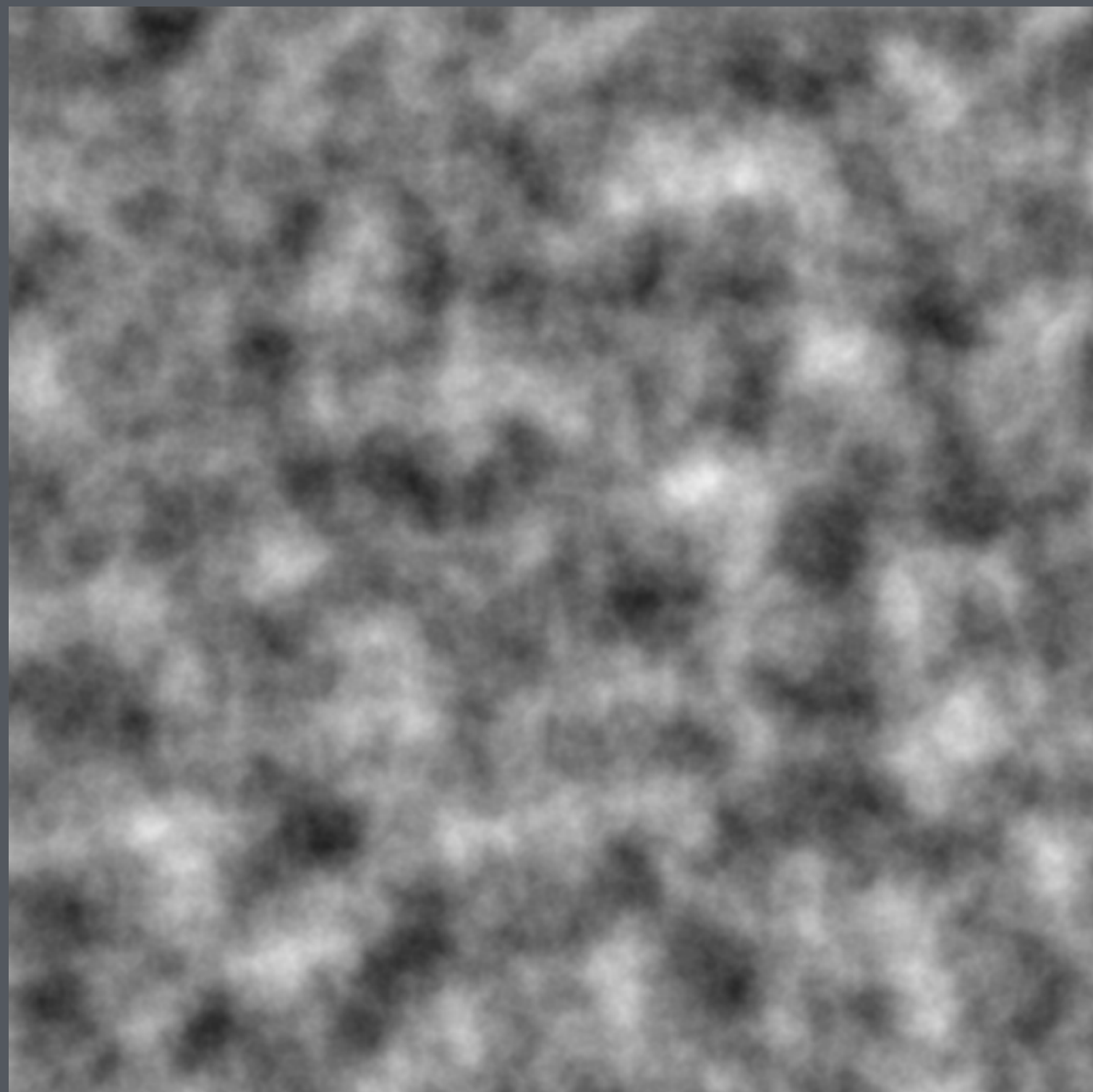
$\times \frac{1}{8}$

+



$\times \frac{1}{16}$

=



# Curl noise

## can use Perlin or other noise to make vector fields

- but try advecting particles through them — doesn't work so well
- want divergence-free fields
- define them as the curl of a vector potential!

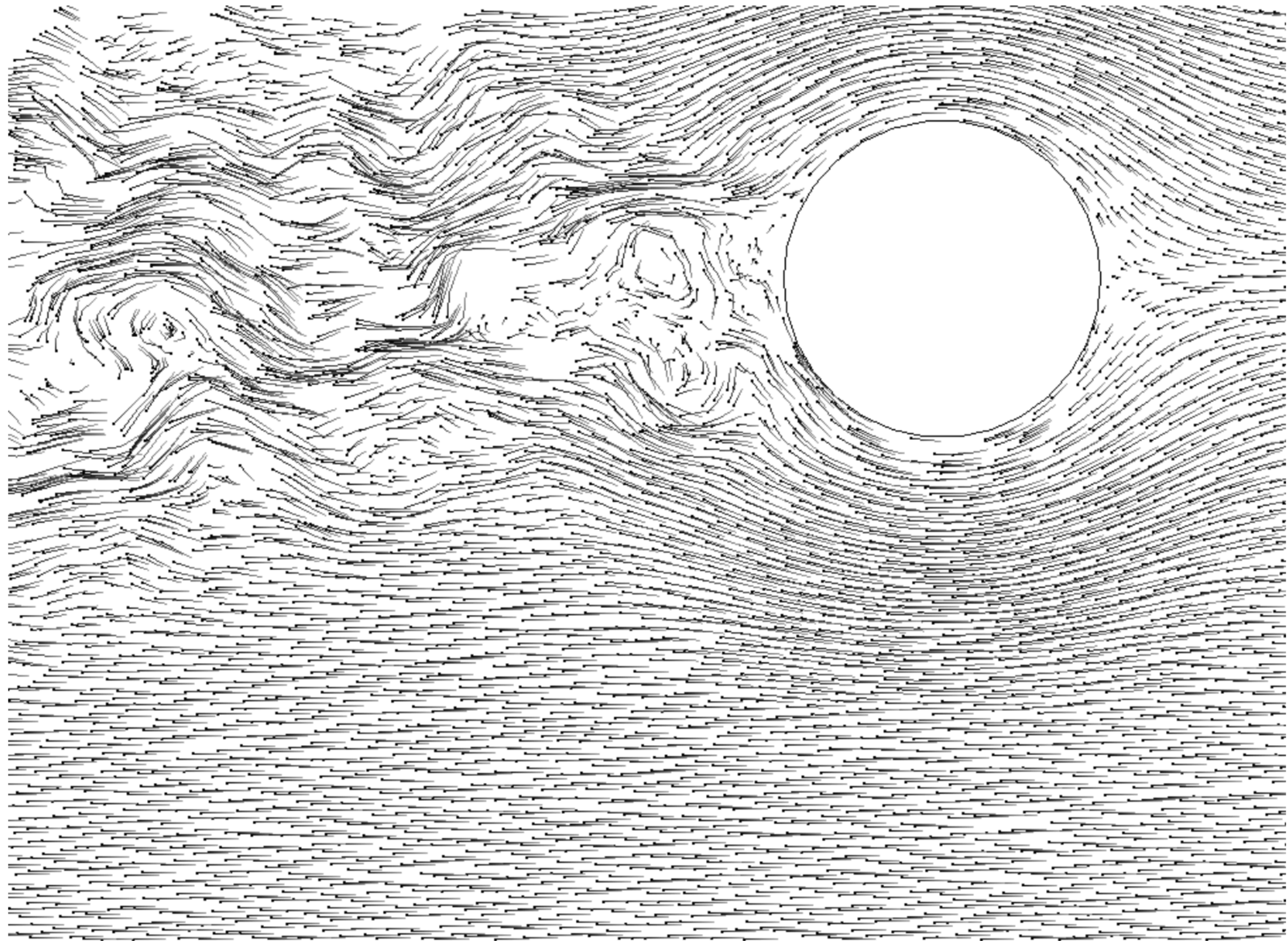
## add up multiple bands just like with regular Perlin noise

- the “Kolmogorov spectrum” is a result about low-viscosity turbulent fluids: velocity at frequency  $f$  is proportional to  $f^{-\frac{5}{6}}$
- close enough to  $f^{-1}$  that we might not worry about it...

## additional ways to control the flow

- spatially varying weights for the different bands to make stronger turbulence in some areas
- spatial modulation of the potential to make velocities avoid obstacles





Bridson et al. 2007



# Demos!

## **procedural noise**

- Perlin noise

## **line integral convolution**

- quick and easy way to visualize 2D vector fields

## **particle advection in fake turbulence fields**

- first order advection
- random vector fields using curl noise