Math (P)Review Part II: Vector Calculus

Computer Graphics
CMU 15-462/662, Spring 2018

Assignment 0.5 (Out today!)

- Same story as last homework; second part on vector calculus.
- Slightly fewer questions

Andrew ID: kmcrane

1 Vector Calculus

1.1 Dot and Cross Product

In our study of linear algebra, we looked *inner products* in the abstract, *i.e.*, we said that an inner product $\langle\cdot,\cdot\rangle$ was *any* operation that is symmetric, bilinear, *etc.* In the context of vector calculus, we often work with one very special inner product called the **dot product**, which has a concrete geometric relationship to lengths and angles in $\mathbb{R}^n$. In particular, consider any two n-dimensional Euclidean vectors $\mathbf{u} = (u_1, \ldots, u_n)$ $\mathbf{v} = (v_1, \ldots, v_n)$ where the components u_i, v_i are expressed with respect to some orthonormal basis $\mathbf{e}_1, \ldots, \mathbf{e}_n$. The **dot product** is defined as

$$\mathbf{u} \cdot \mathbf{v} := \sum_{i=1}^{n} u_i v_i,$$

and satisfies the geometric relationship

$$\mathbf{u} \cdot \mathbf{v} := |\mathbf{u}||\mathbf{v}|\cos(\theta),$$

where $|\mathbf{u}|$ and $|\mathbf{v}|$ are the lengths of $\mathbf{u}$ and $\mathbf{v}$, respectively, and $\theta \geq 0$ is the (unsigned) angle between them.

Exercise 1. *Suppose we are working in $\mathbb{R}^2$ with the standard orthonormal basis $\mathbf{e}_1 := (1,0)$, $\mathbf{e}_2 := (0,1)$.*

(a) Compute the Cartesian coordinates of a vector $\mathbf{u}$ with length $\ell_1 := 6$ and counter-clockwise angle $\theta_1 :=$ 0.100 relative to the positive $\mathbf{e}_1$-axis. ***[Hint:*** *You may want to revisit our earlier discussion of polar coordinates.]*

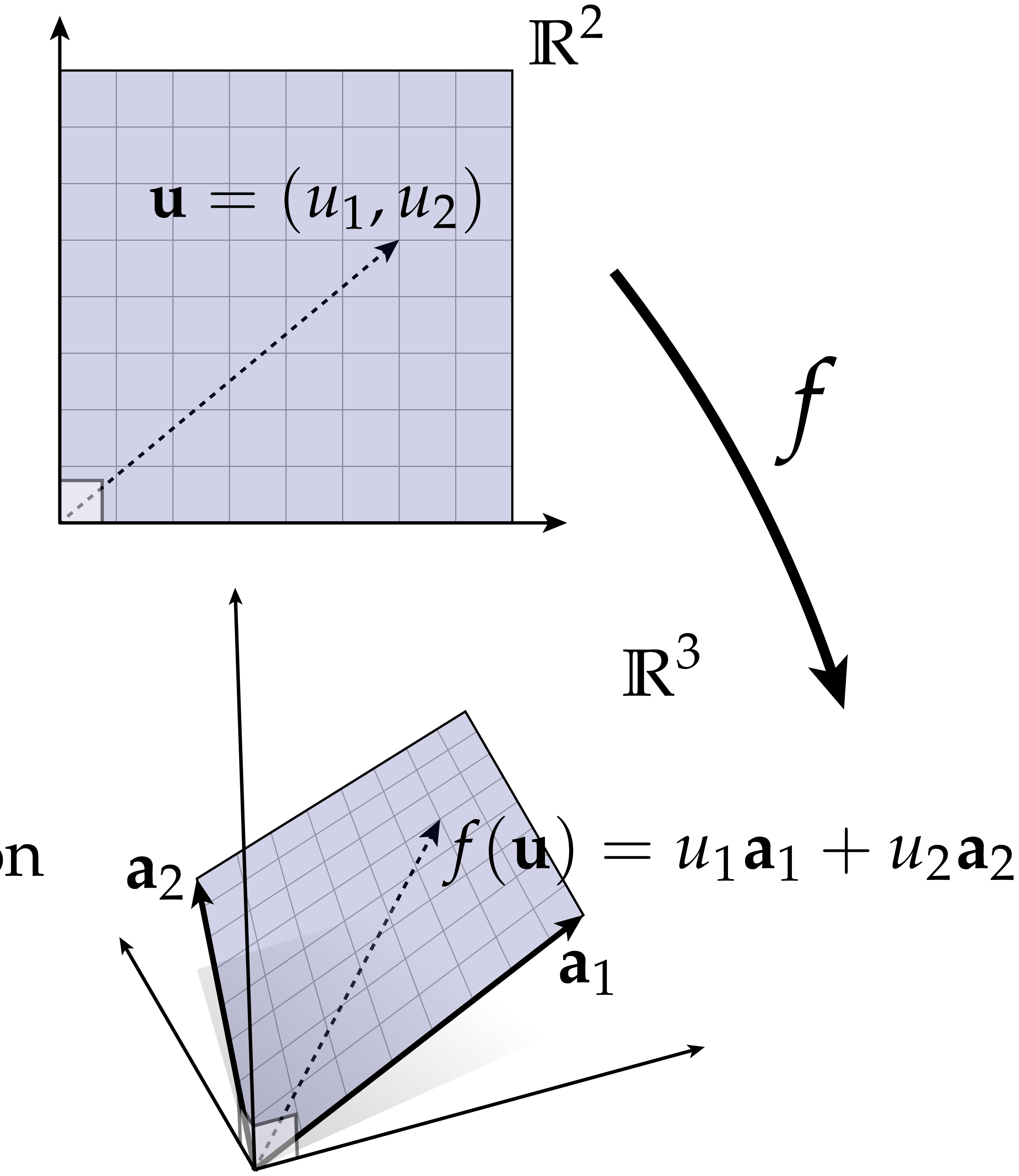
(b) Compute the Cartesian coordinates of a vector $\mathbf{v}$ with length $\ell_2 := 3$ and counter-clockwise angle $\theta_2 :=$

Last Time: Linear Algebra

- **Touched on a variety of topics:**

vectors & vector spaces
norm
L^2 norm/inner product
span
Gram-Schmidt
linear systems
quadratic forms
...

vectors as functions
inner product
linear maps
basis
frequency decomposition
bilinear forms
matrices
...



- **Don't have time to cover everything!**
- **But there are some fantastic lectures online:**

http://bit.ly/2bfjIlY

Vector Calculus in Computer Graphics

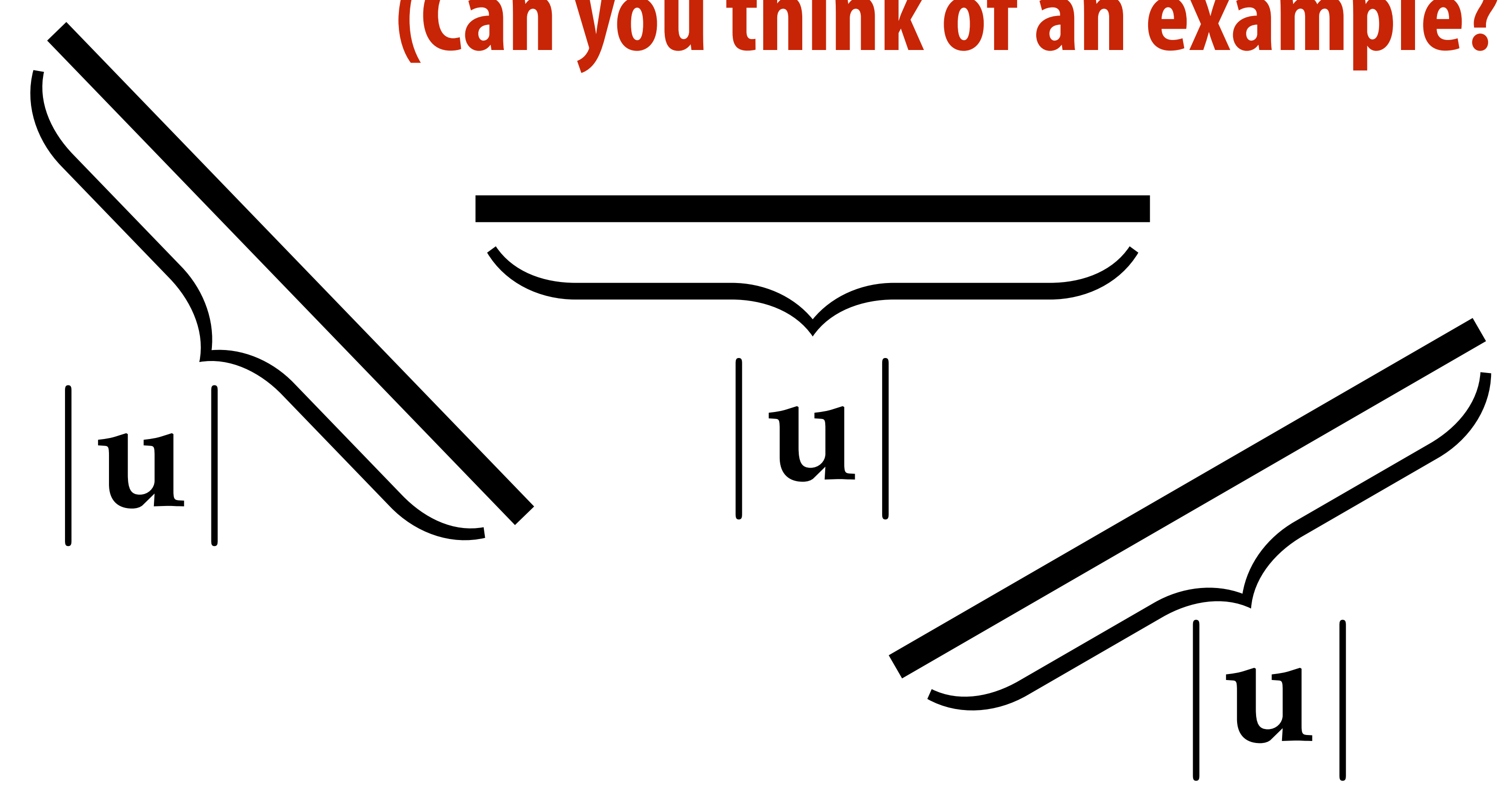
- Today's topic: vector calculus.
- Why is vector calculus important for computer graphics?
  - Basic language for talking about spatial relationships, transformations, etc.
  - Much of modern graphics (physically-based animation, geometry processing, etc.) formulated in terms of partial differential equations (PDEs) that use div, curl, Laplacian...
  - As we saw last time, vector-valued data is everywhere in graphics!


Euclidean Norm

- **Last time, developed idea of norm, which measures total size, length, volume, intensity, etc.**
- **For geometric calculations, the norm we most often care about is the Euclidean norm**
- **Euclidean norm is any notion of length preserved by rotations/translations/reflections of space.**
- **In orthonormal coordinates:**

Not true for all norms!
(Can you think of an example?)

$$|\mathbf{u}| := \sqrt{u_1^2 + \cdots + u_n^2}$$

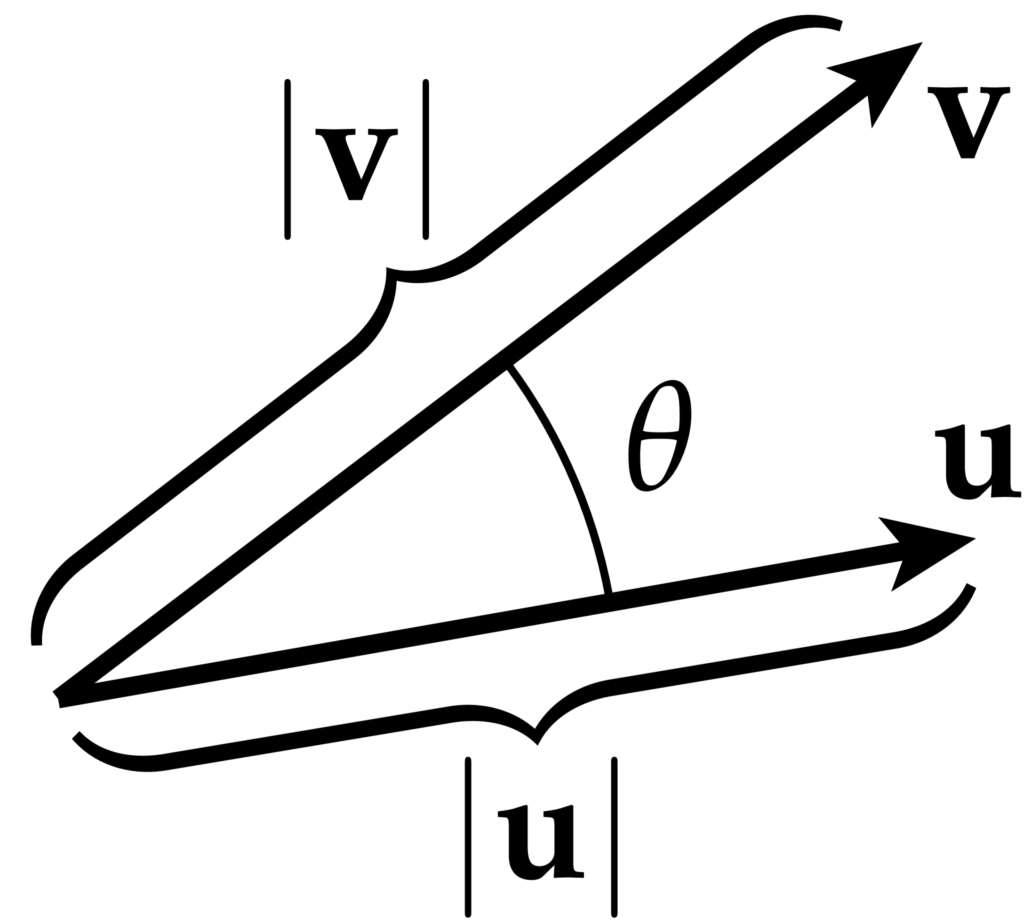


WARNING: This quantity does not encode geometric length unless vectors are encoded in an orthonormal basis. (Common source of bugs!)

Euclidean Inner Product / Dot Product

- Likewise, lots of possible inner products—intuitively, measure some notion of "alignment."
- For geometric calculations, want to use inner product that captures something about geometry!
- For n-dimensional vectors, Euclidean inner product defined as

$$\langle \mathbf{u}, \mathbf{v} \rangle := |\mathbf{u}||\mathbf{v}|\cos(\theta)$$



- In orthonormal Cartesian coordinates, can be represented via the dot product

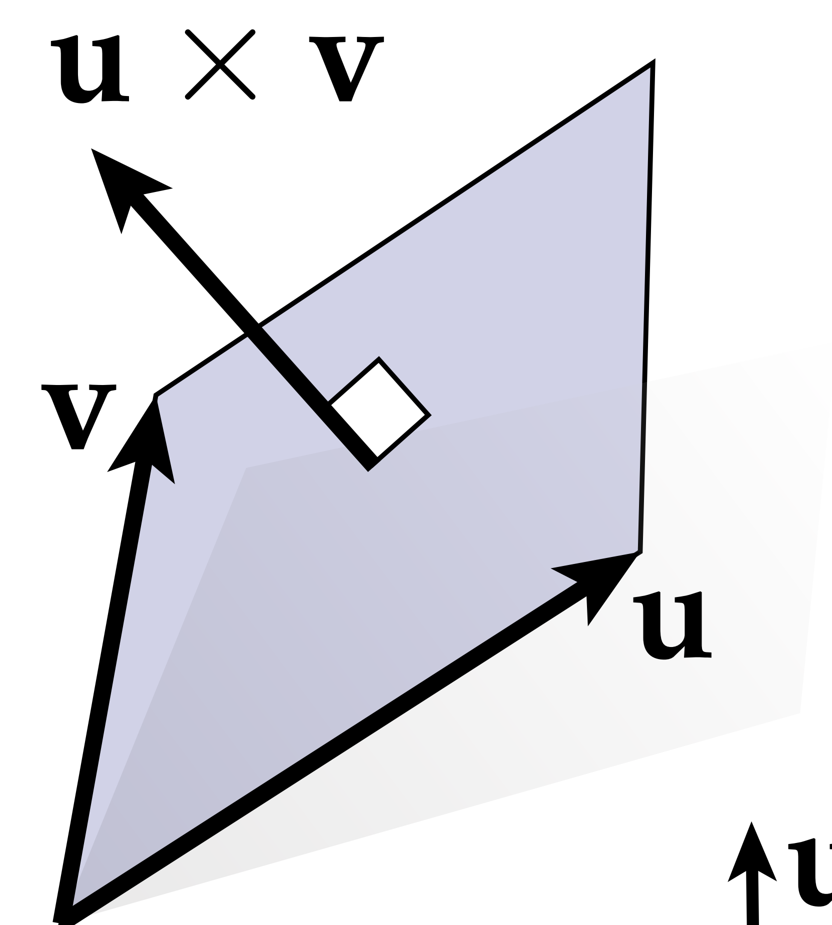
$$\mathbf{u} \cdot \mathbf{v} := u_1 v_1 + \cdots + u_n v_n$$

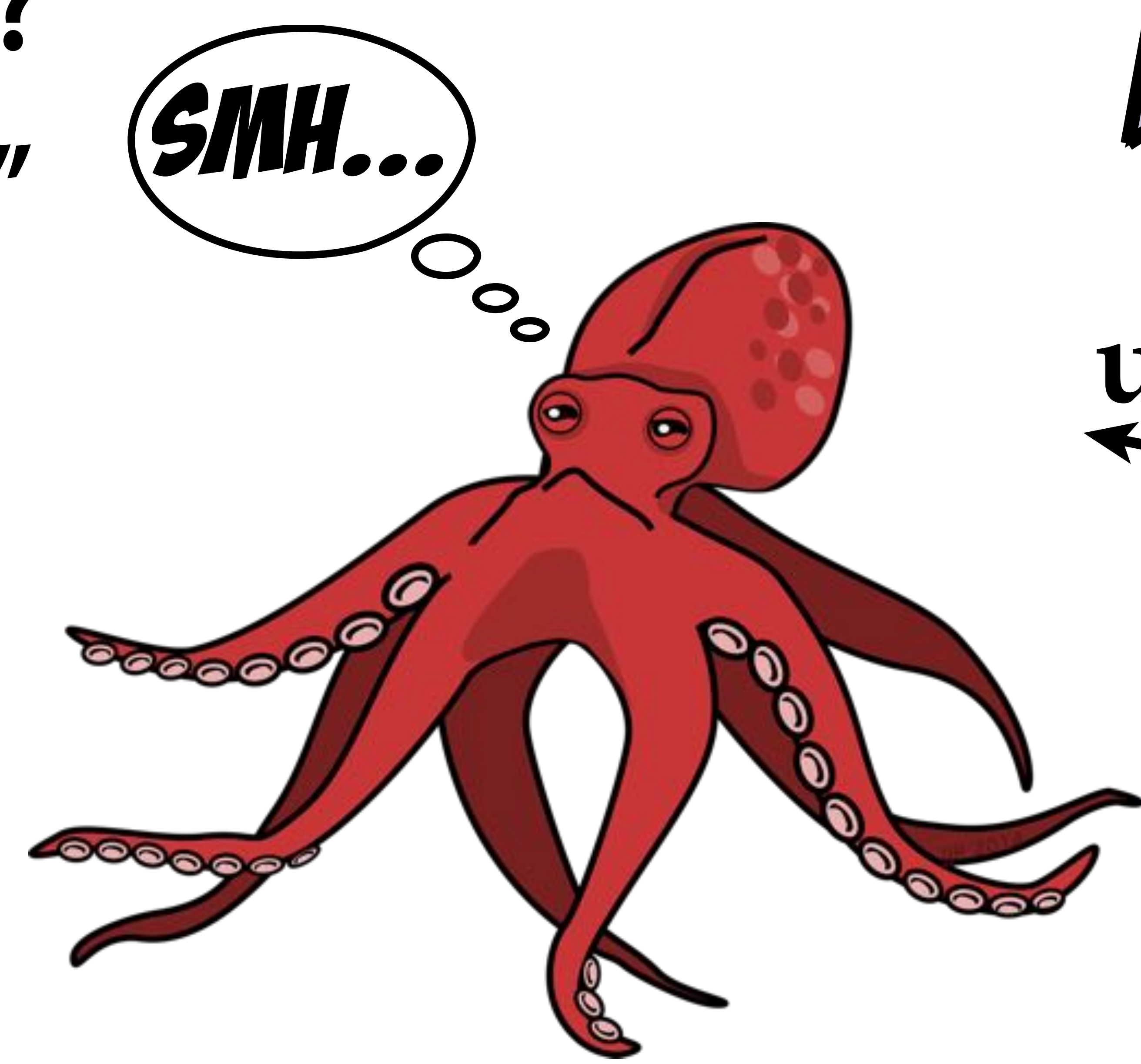
- WARNING: As with Euclidean norm, no geometric meaning unless coordinates come from an orthonormal basis.

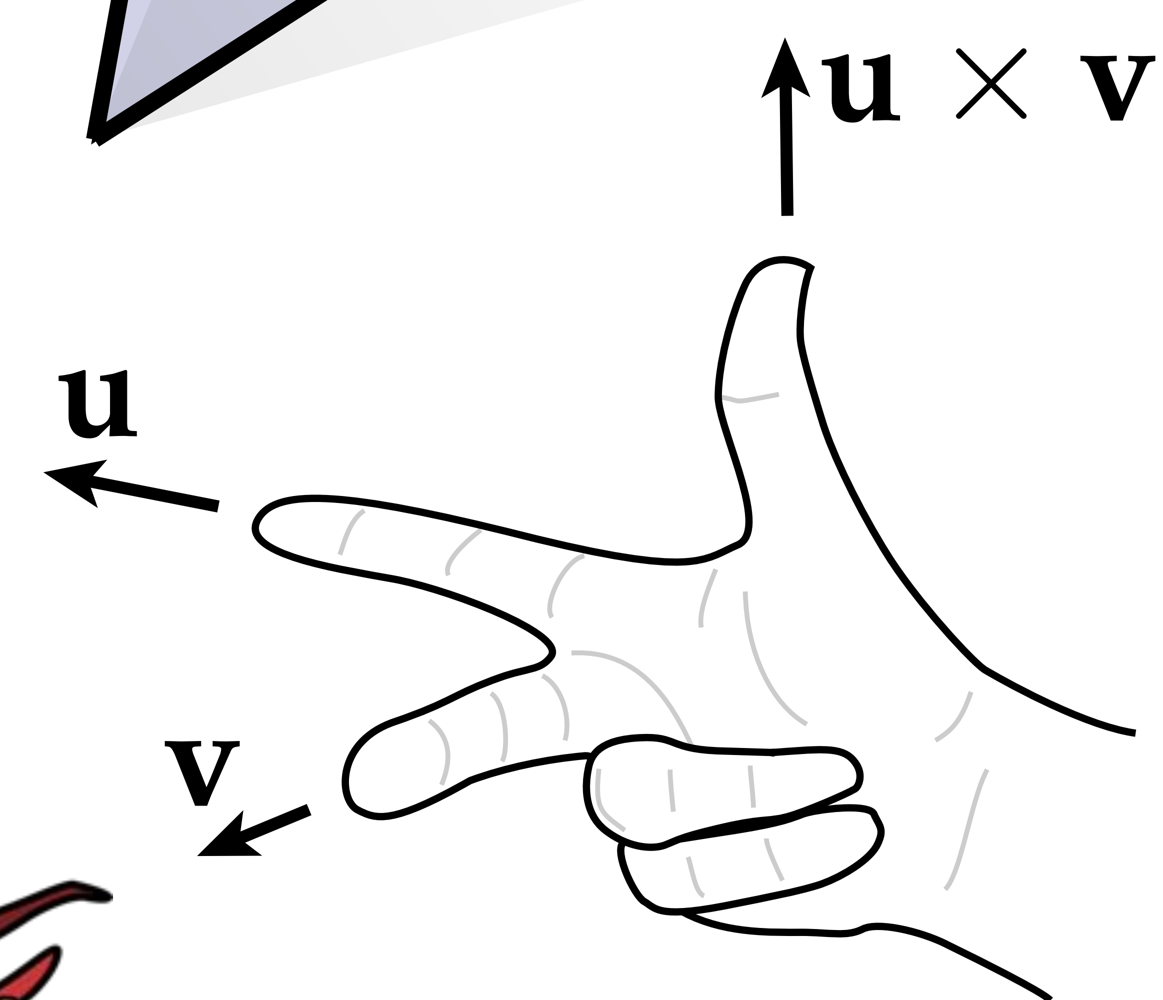
Q: How do you express the Euclidean inner product in an arbitrary basis?

Cross Product

- Inner product takes two vectors and produces a scalar
- In 3D, cross product is a natural way to take two vectors and get a vector, written as "u x v"
- Geometrically:
  - magnitude equal to parallelogram area
  - direction orthogonal to both vectors
  - …but which way?
- Use "right hand rule"





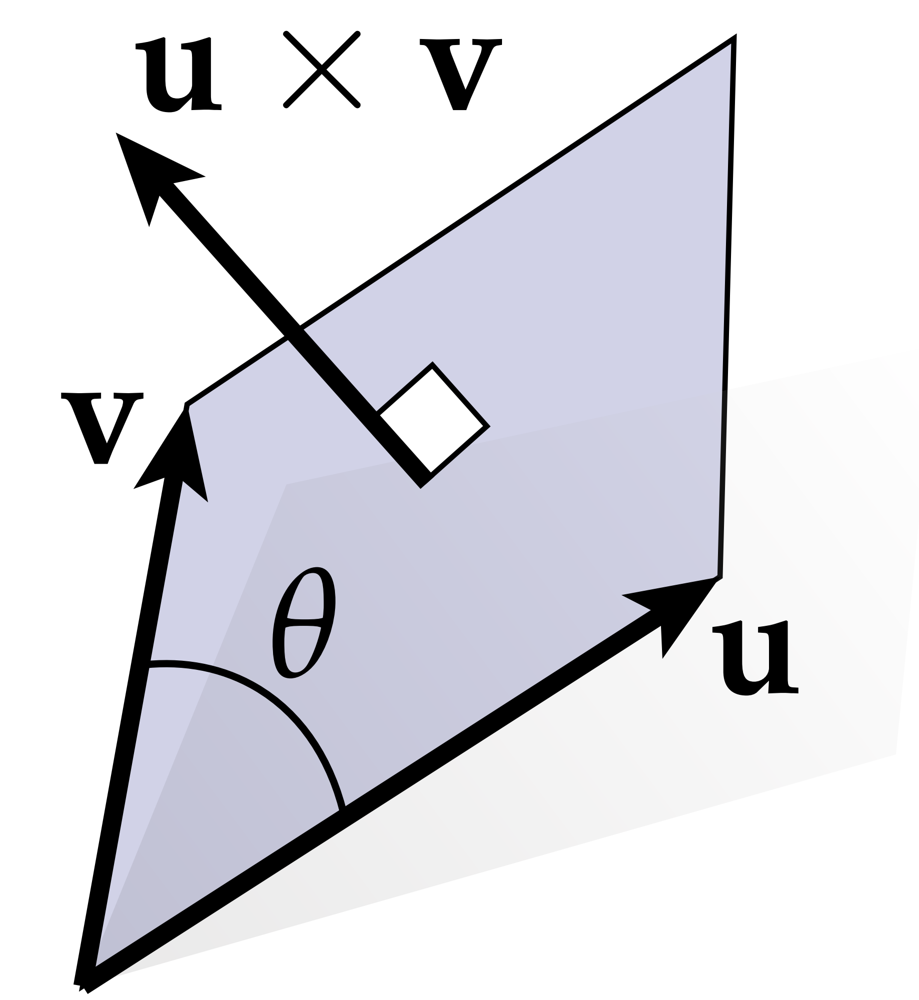


(Q: Why only 3D?)

Cross Product, Determinant, and Angle

- **More precise definition (that does not require hands):**

$$\sqrt{\det(\mathbf{u}, \mathbf{v}, \mathbf{u} \times \mathbf{v})} = |\mathbf{u}||\mathbf{v}|\sin(\theta)$$



- **θ is angle between u and v**
- **"det" is determinant of three column vectors**
- **Uniquely determines coordinate formula:**

$$\mathbf{u} \times \mathbf{v} := \begin{bmatrix} u_2 v_3 - u_3 v_2 \\ u_3 v_1 - u_1 v_3 \\ u_1 v_2 - u_2 v_1 \end{bmatrix}$$

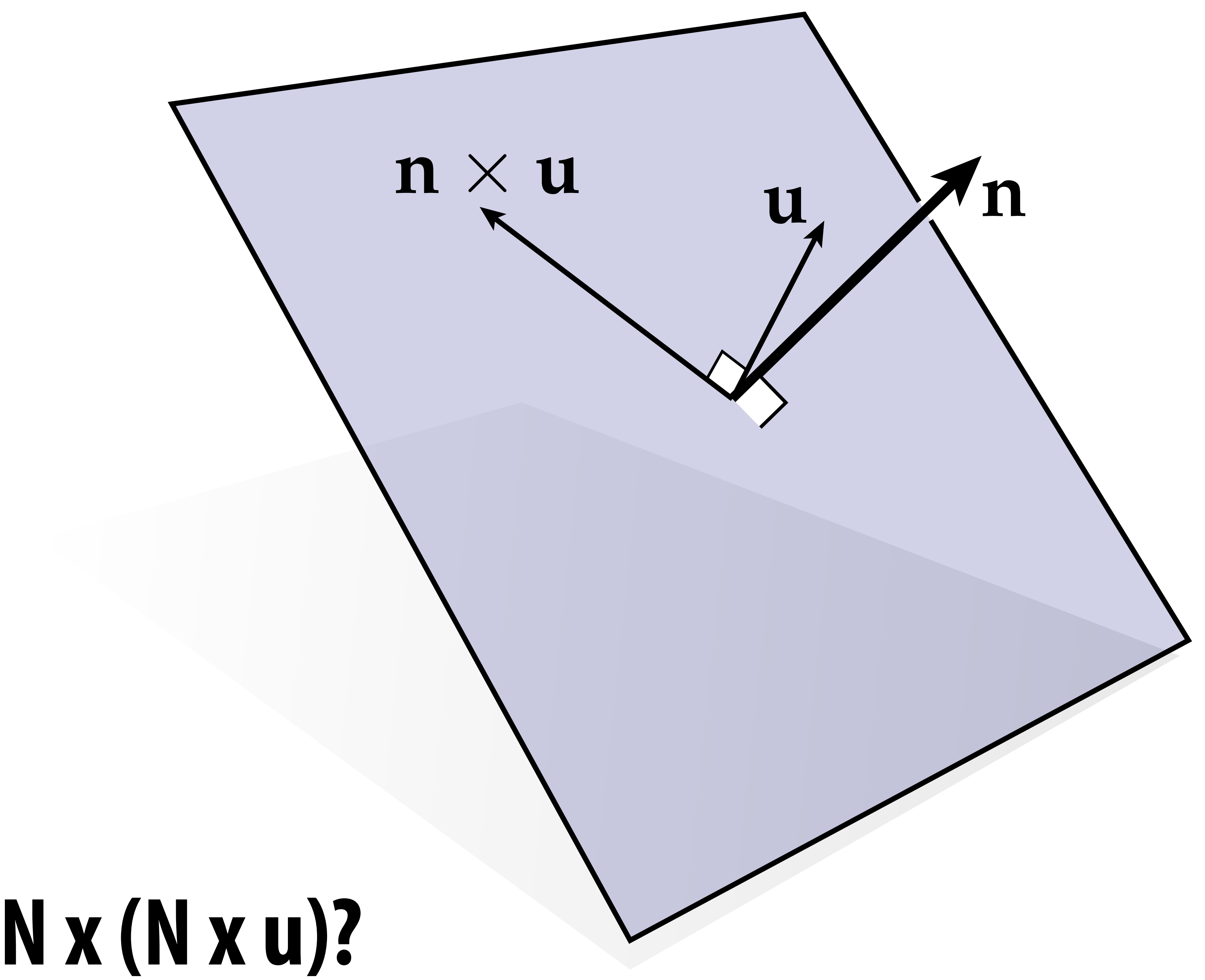
$$\begin{vmatrix} \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 \\ u_1 & u_2 & u_3 \\ v_1 & v_2 & v_3 \end{vmatrix}$$

(mnemonic)

- **Useful abuse of notation in 2D:** $\mathbf{u} \times \mathbf{v} := u_1 v_2 - u_2 v_1$

Cross Product as Quarter Rotation

- **Simple but useful observation for manipulating vectors in 3D: cross product with a unit vector N is equivalent to a quarter-rotation in the plane with normal N:**



- **Q: What is N x (N x u)?**
- **Q: If you have u and N x u, how do you get a rotation by some arbitrary angle θ?**

Matrix Representation of Dot Product

- **Often convenient to express dot product via matrix product:**

$$\mathbf{u}\cdot\mathbf{v} = \mathbf{u}^{\mathsf{T}}\mathbf{v} = \begin{bmatrix} u_1 & \cdots & u_n \end{bmatrix} \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix} = \sum_{i=1}^{n} u_i v_i$$

- **By the way, what about some other inner product?**
- **E.g., <u,v> := 2 u1 v1 + u1 v2 + u2 v1 + 3 u2 v2**

$$\underbrace{\begin{bmatrix} u_1 & u_2 \end{bmatrix}}_{\mathbf{u}^{\mathsf{T}}} \underbrace{\begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} v_1 \\ v_2 \end{bmatrix}}_{\mathbf{v}} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} 2v_1 + v_2 \\ v_1 + 3v_2 \end{bmatrix}$$

$$= (2u_1v_1 + u_1v_2) + (u_2v_1 + 3u_2v_2). \quad \checkmark$$

Q: Why is matrix representing inner product always symmetric (A^{T}=A)?

Matrix Representation of Cross Product

- **Can also represent cross product via matrix multiplication:**

$$\mathbf{u} := (u_1, u_2, u_3) \qquad \Rightarrow \hat{\mathbf{u}} := \begin{bmatrix} 0 & -u_3 & u_2 \\ u_3 & 0 & -u_1 \\ -u_2 & u_1 & 0 \end{bmatrix}$$

$$\mathbf{u} \times \mathbf{v} = \hat{\mathbf{u}}\mathbf{v} \;\; = \begin{bmatrix} 0 & -u_3 & u_2 \\ u_3 & 0 & -u_1 \\ -u_2 & u_1 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$$

(Did we get it right?)

- **Q: Without building a new matrix, how can we express v x u?**
- **A: Useful to notice that v x u = -u x v (why?). Hence,**

$$\mathbf{v} \times \mathbf{u} = -\hat{\mathbf{u}}\mathbf{v} \;\; = \hat{\mathbf{u}}^{\mathsf{T}}\mathbf{v}$$

Determinant

- **Q: How do you compute the determinant of a matrix?**

$$\mathbf{A} := \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

- **A: Apply some algorithm somebody told me once upon a time:**

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \quad \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \quad \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

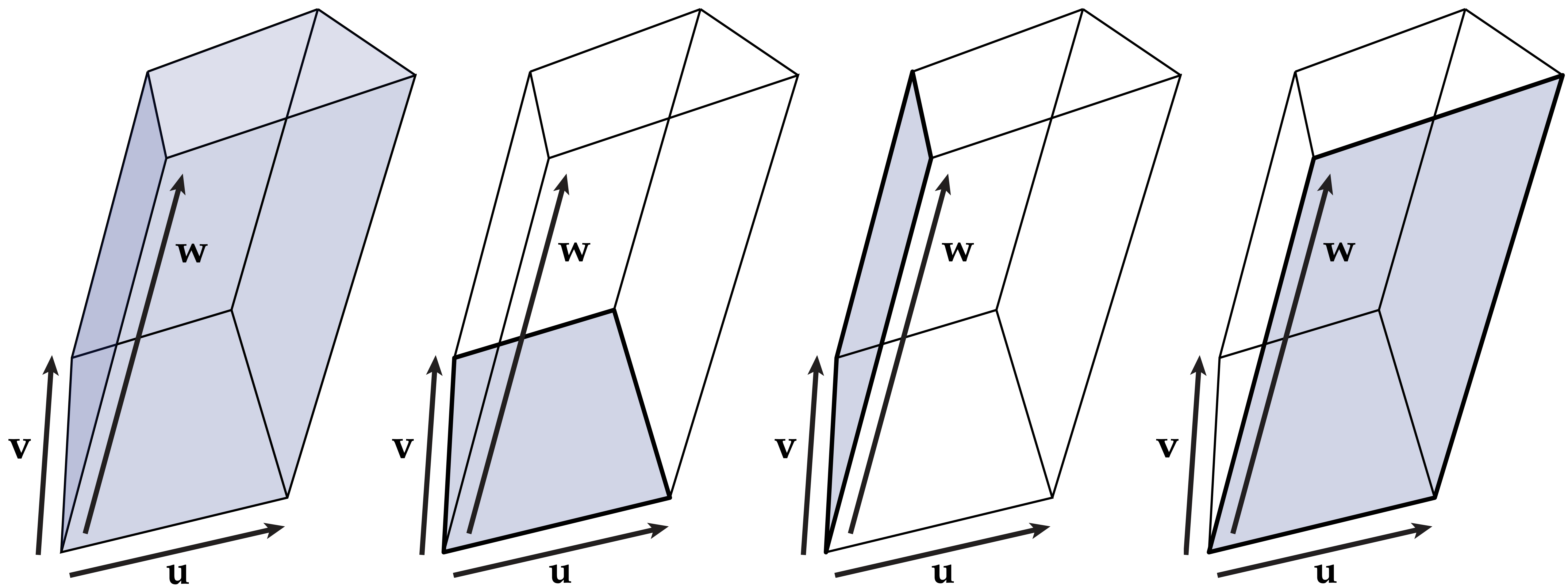
$$\det(\mathbf{A}) = a(ei - fh) + b(fg - di) + c(dh - eg)$$

Totally obvious… right?

- **Q: No! What the heck does this number mean?!**

Determinant, Volume and Triple Product

- **Better answer: det(u,v,w) encodes (signed) volume of parallelpiped with edge vectors u, v, w.**



$$\det(\mathbf{u},\mathbf{v},\mathbf{w}) \quad = \quad (\mathbf{u}\times\mathbf{v})\cdot\mathbf{w} \quad = \quad (\mathbf{v}\times\mathbf{w})\cdot\mathbf{u} \quad = \quad (\mathbf{w}\times\mathbf{u})\cdot\mathbf{v}$$

- **Relationship known as a "triple product formula"**
- **(Q: What happens if we reverse order of cross product?)**

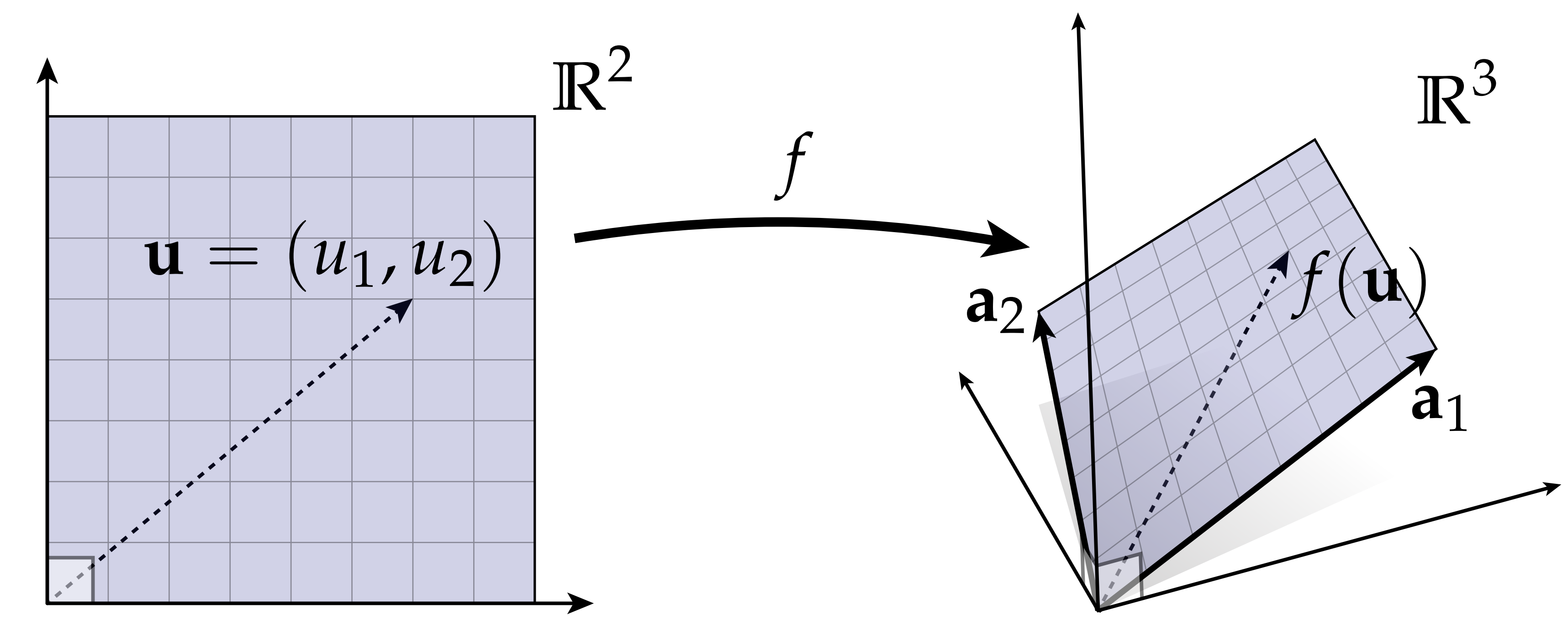
Determinant of a Linear Map

- **Q: If a matrix A encodes a linear map f, what does det(A) mean?**

Representing Linear Maps via Matrices

- **Key example: suppose I have a linear map**

$$f(\mathbf{u}) = u_1\mathbf{a}_1 + u_2\mathbf{a}_2$$



- **How do I encode as a matrix?**
- **Easy: “a” vectors become matrix columns:**

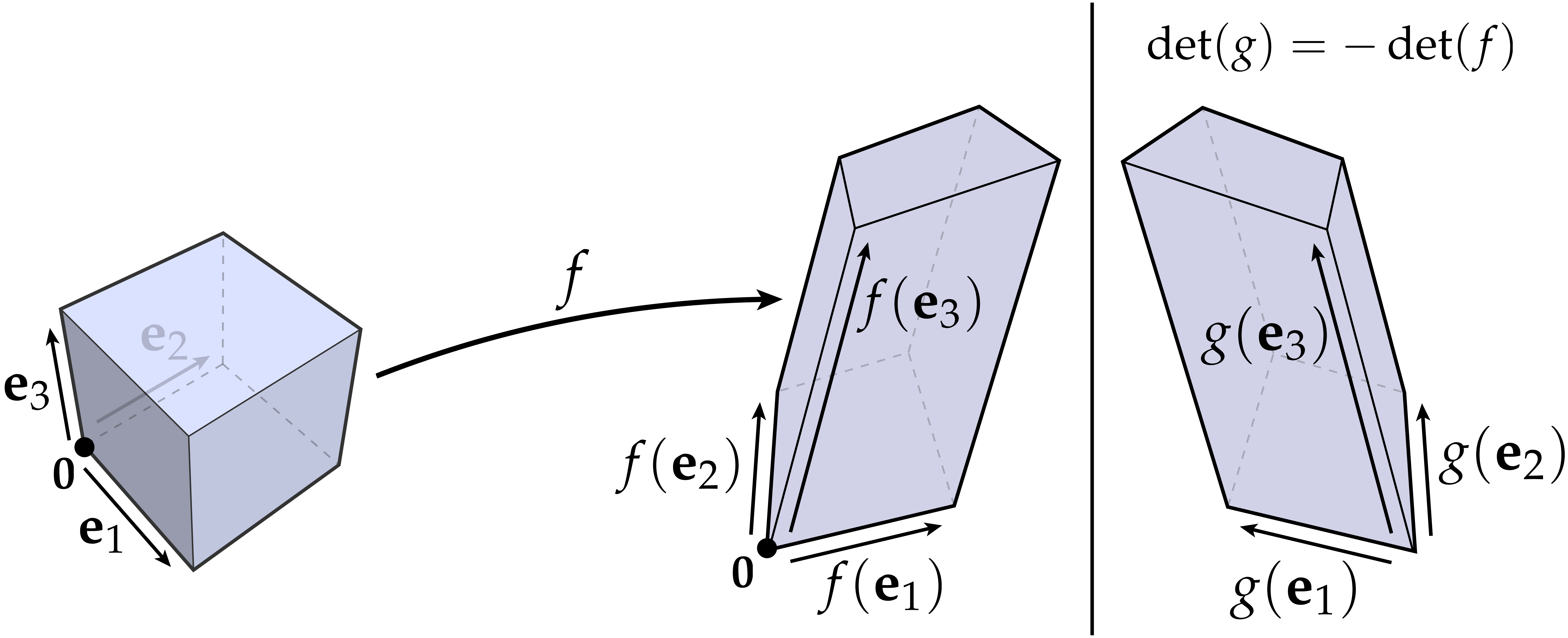
$$A := \begin{bmatrix} a_{1,x} & a_{2,x} \\ a_{1,y} & a_{2,y} \\ a_{1,z} & a_{2,z} \end{bmatrix}$$

- **Now, matrix-vector multiply recovers original map:**

$$\begin{bmatrix} a_{1,x} & a_{2,x} \\ a_{1,y} & a_{2,y} \\ a_{1,z} & a_{2,z} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} a_{1,x}u_1 + a_{2,x}u_2 \\ a_{1,y}u_1 + a_{2,y}u_2 \\ a_{1,z}u_1 + a_{2,x}u_2 \end{bmatrix} = u_1\mathbf{a}_1 + u_2\mathbf{a}_2$$

Determinant of a Linear Map

- **Q: If a matrix A encodes a linear map f, what does det(A) mean?**



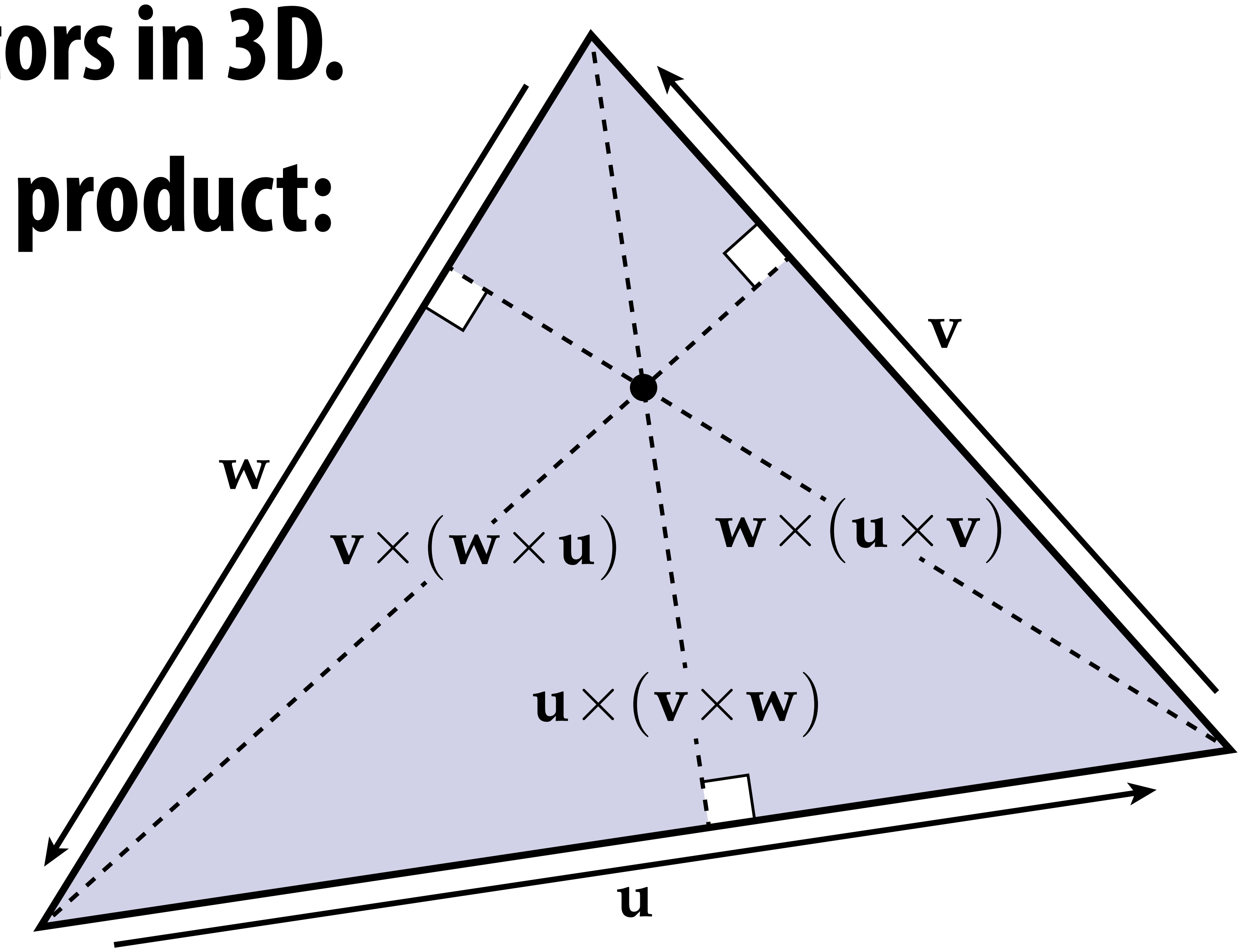
- **A: It measures the change in volume.**
- **Q: What does the sign of the determinant tell us, in this case?**
- **A: It tells us whether orientation was reversed (det(A) < 0)**

(Do we really need a matrix in order to talk about the determinant of a linear map?)

Other Triple Products

- Super useful for working w/ vectors in 3D.
- E.g., Jacobi identity for the cross product:

$$
\begin{aligned}
\mathbf{u} \times (\mathbf{v} \times \mathbf{w}) \quad &+ \\
\mathbf{v} \times (\mathbf{w} \times \mathbf{u}) \quad &+ \\
\mathbf{w} \times (\mathbf{u} \times \mathbf{v}) \quad &= \quad 0
\end{aligned}
$$



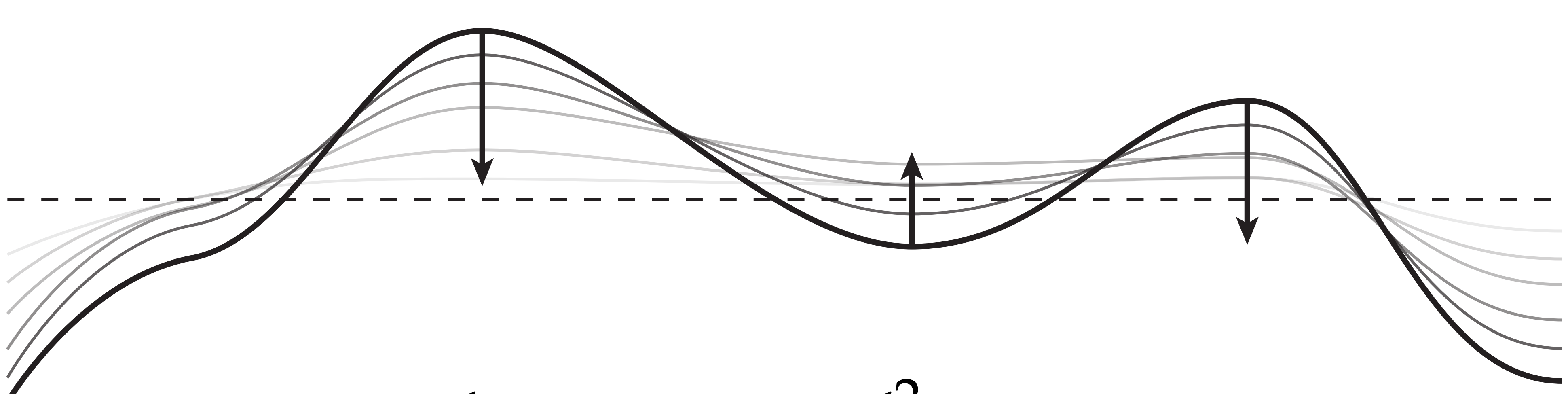
- Why is it true, geometrically?
- There is a geometric reason, but not nearly as obvious as det: has to do w/ fact that triangle's altitudes meet at a point.
- Yet another triple product: Lagrange's identity

$$\mathbf{u} \times (\mathbf{v} \times \mathbf{w}) = \mathbf{v}(\mathbf{u} \cdot \mathbf{w}) - \mathbf{w}(\mathbf{u} \cdot \mathbf{v})$$

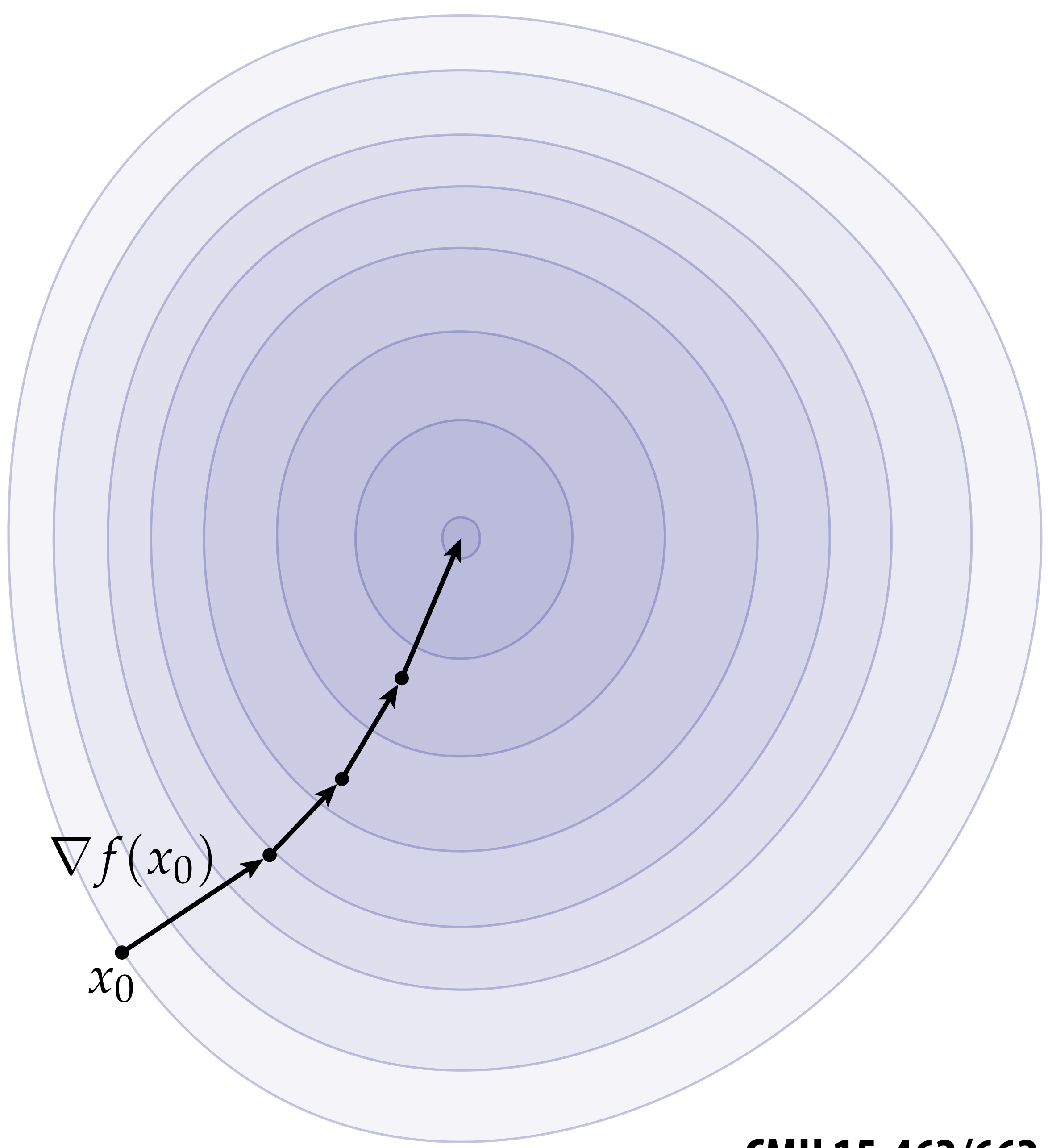
(Can you come up with a geometric interpretation?)

Differential Operators - Overview

- Next up: differential operators and vector fields.
- Why is this useful for computer graphics?
  - Many physical/geometric problems expressed in terms of relative rates of change (ODEs, PDEs).
  - These tools also provide foundation for numerical optimization—e.g., minimize cost by following the gradient of some objective.



$$\frac{d}{dt}\phi(x) = \frac{d^2}{dx^2}\phi(x)$$



Derivative as Slope

- **Consider a function f(x): R → R**
- **What does its derivative f' mean?**
- **One interpretation "rise over run"**
- **Leads to usual definition:**

$$f'(x_0) := \lim_{\varepsilon \to 0} \frac{f(x_0+\varepsilon) - f(x_0)}{\varepsilon}$$

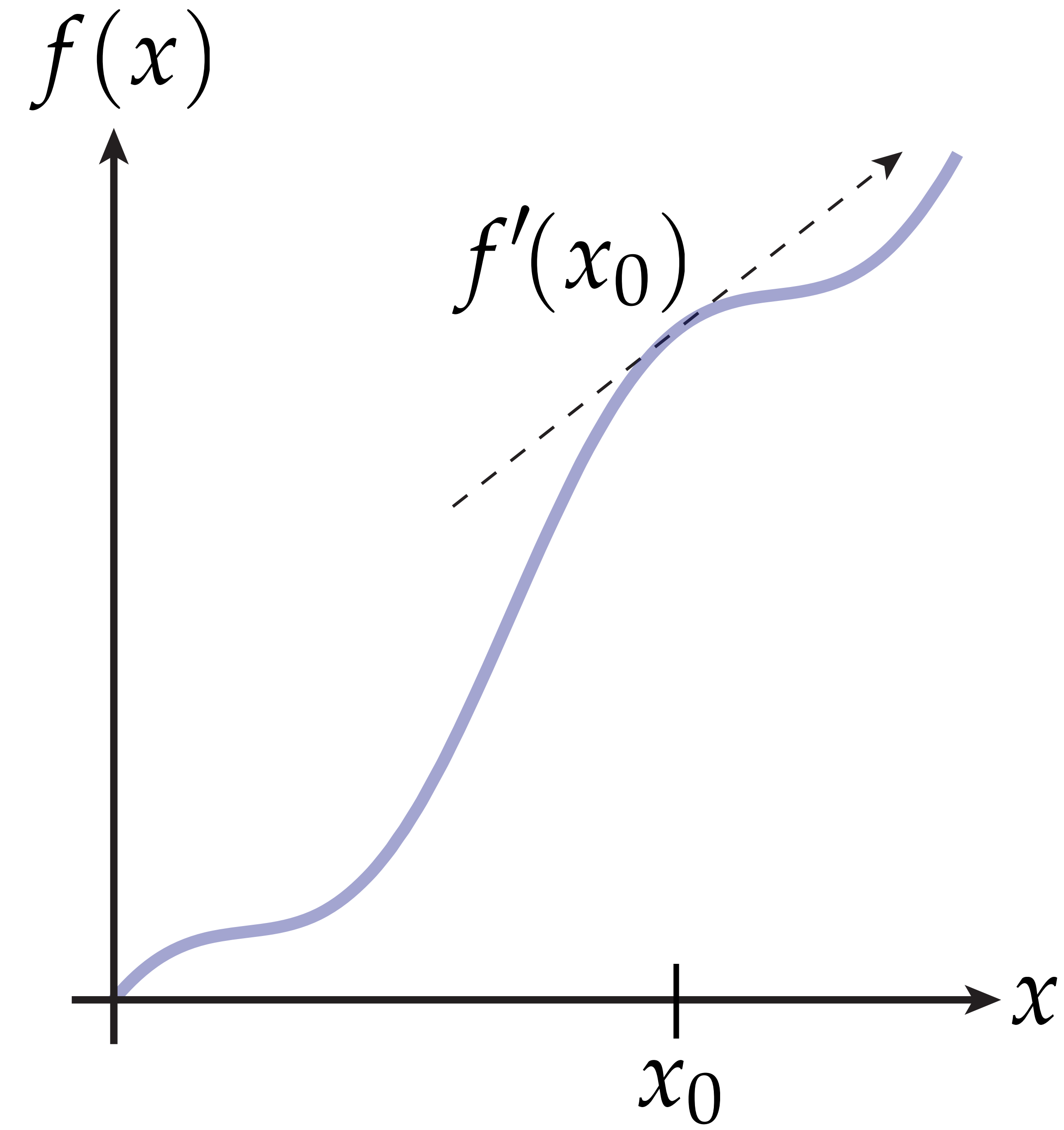
- **Careful! What if slope is different when we walk in opposite direction?**

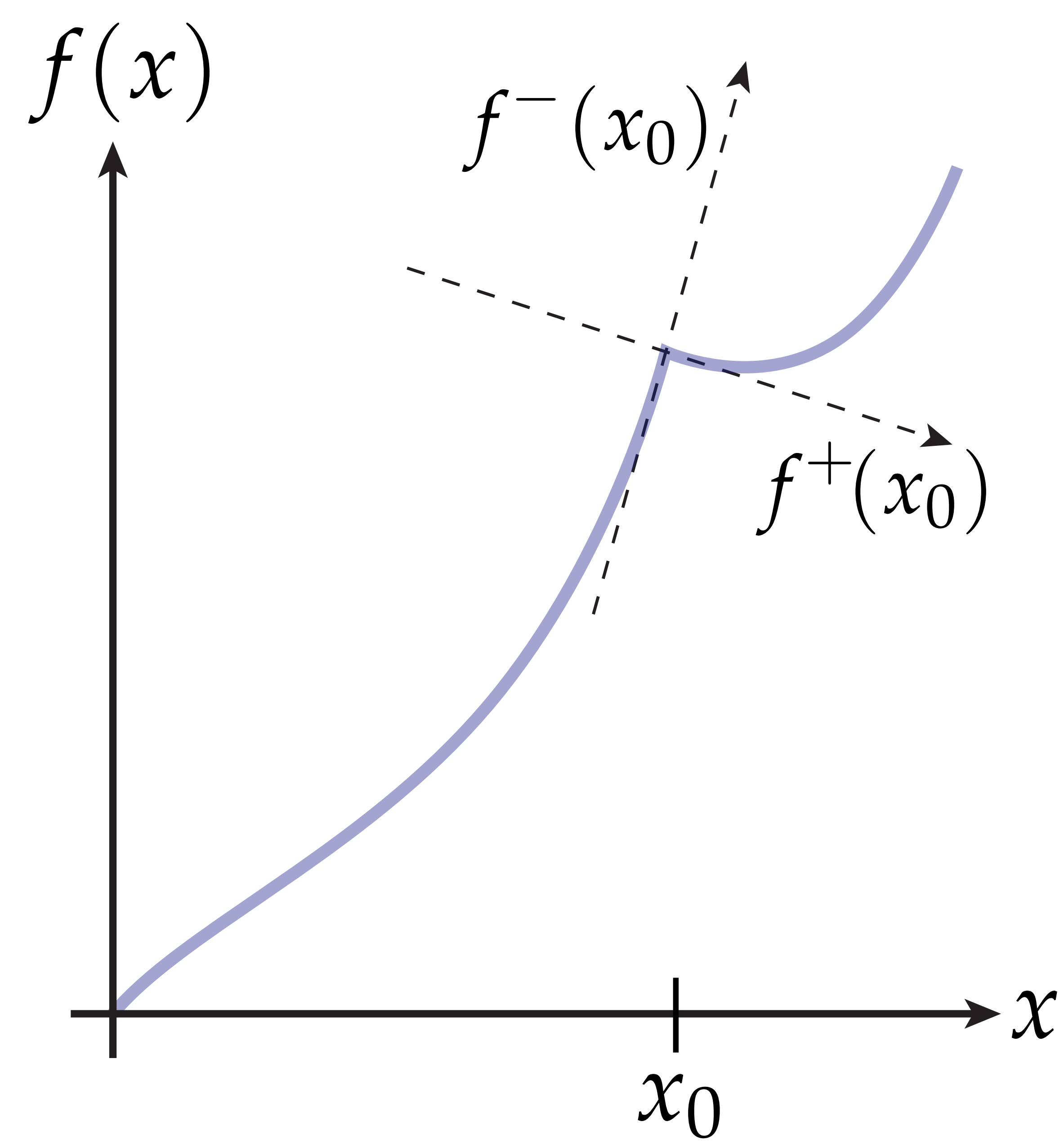
$$f^+(x_0) := \lim_{\varepsilon \to 0} \frac{f(x_0+\varepsilon) - f(x_0)}{\varepsilon}$$

$$f^-(x_0) := \lim_{\varepsilon \to 0} \frac{f(x_0) - f(x_0-\varepsilon)}{\varepsilon}$$

- **Differentiable at x0 if $f^+ = f^-$.**

Many functions in graphics are NOT differentiable!

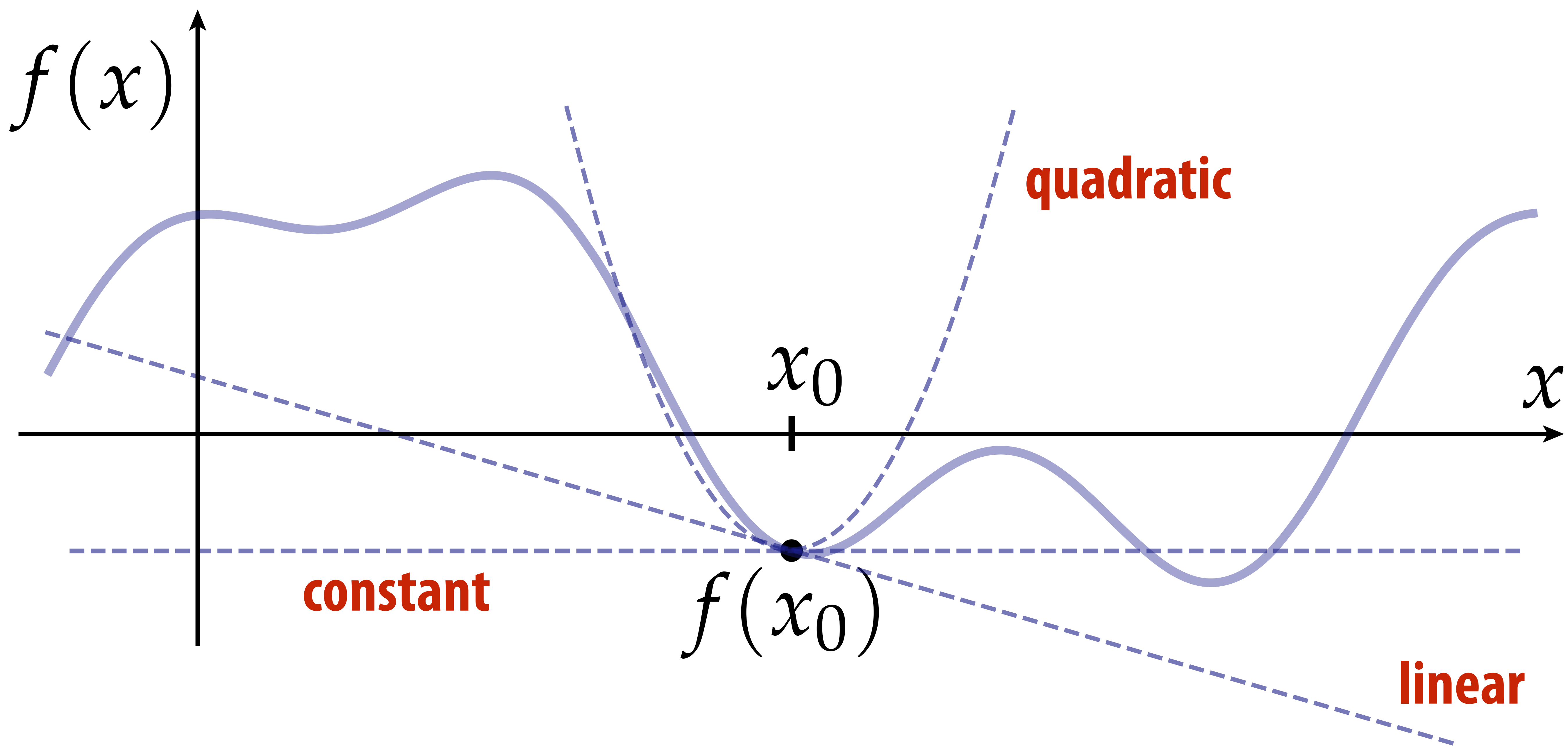




Derivative as Best Linear Approximation

- **Any smooth function f(x) can be expressed as a Taylor series:**

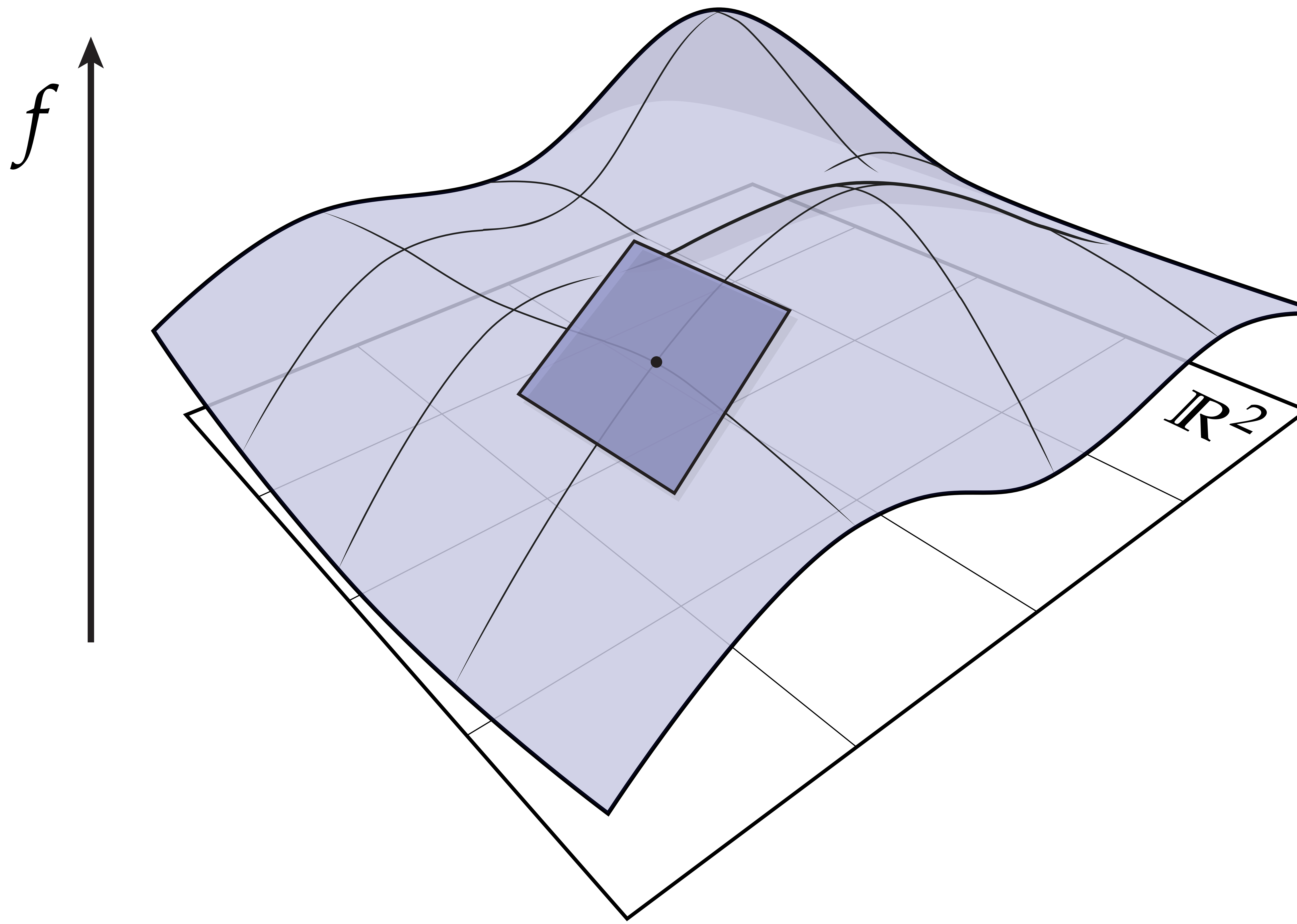
$$\underbrace{f(x) = f(x_0)}_{\text{constant}} + \underbrace{f'(x_0)(x - x_0)}_{\text{linear}} + \underbrace{\frac{(x-x_0)^2}{2!} f''(x_0)}_{\text{quadratic}} + \cdots$$



- **Replacing complicated functions with a linear (and sometimes quadratic) approximation is a favorite trick in graphics algorithms—we'll see many examples.**

Derivative as Best Linear Approximation

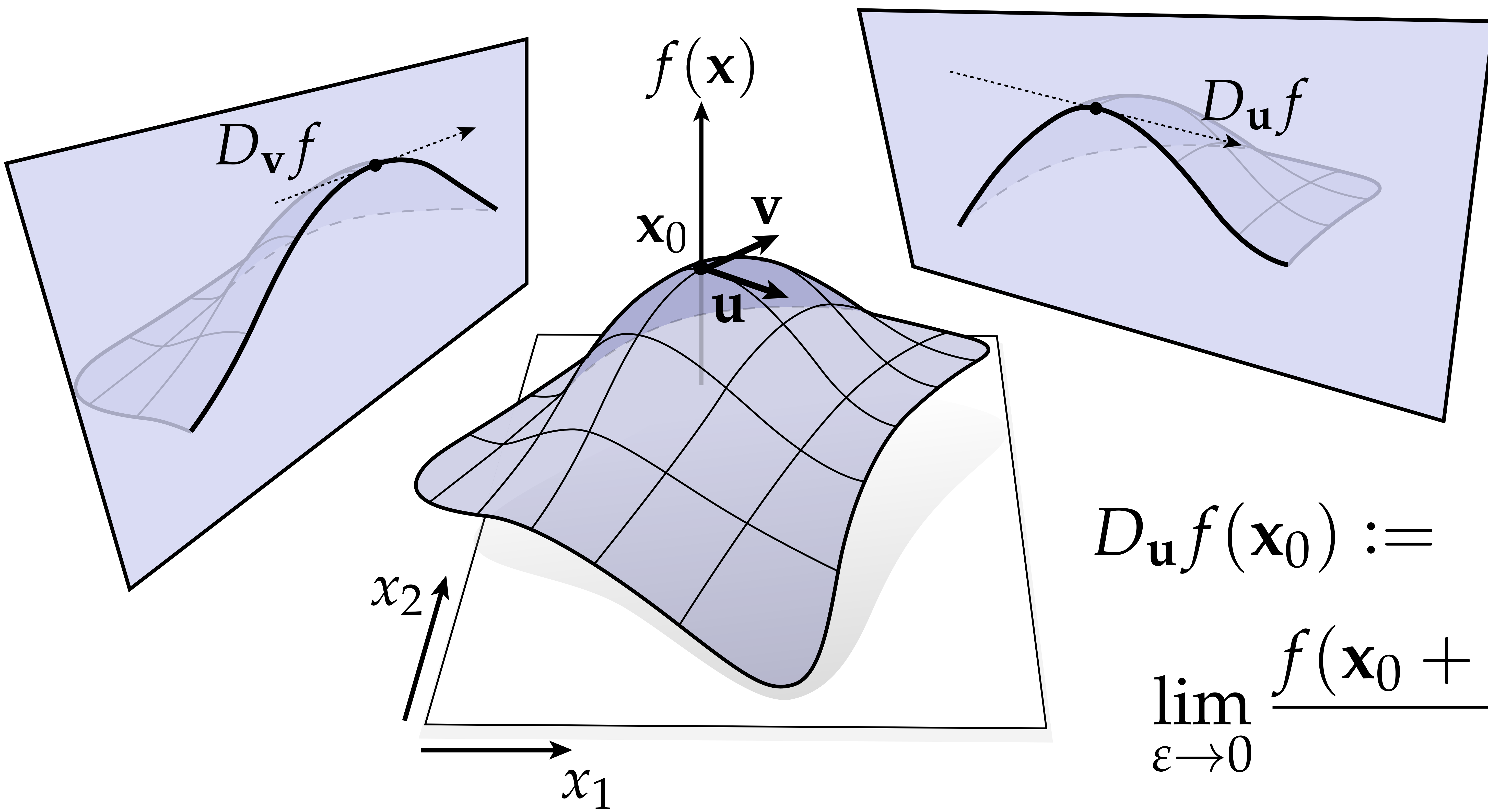
- **Intuitively, same idea applies for functions of multiple variables:**



How do we think about derivatives for a function that has multiple variables?

Directional Derivative

- One way: suppose we have a function f(x1,x2)
  - Take a "slice" through the function along some line
  - Then just apply the usual derivative!
  - Called the directional derivative



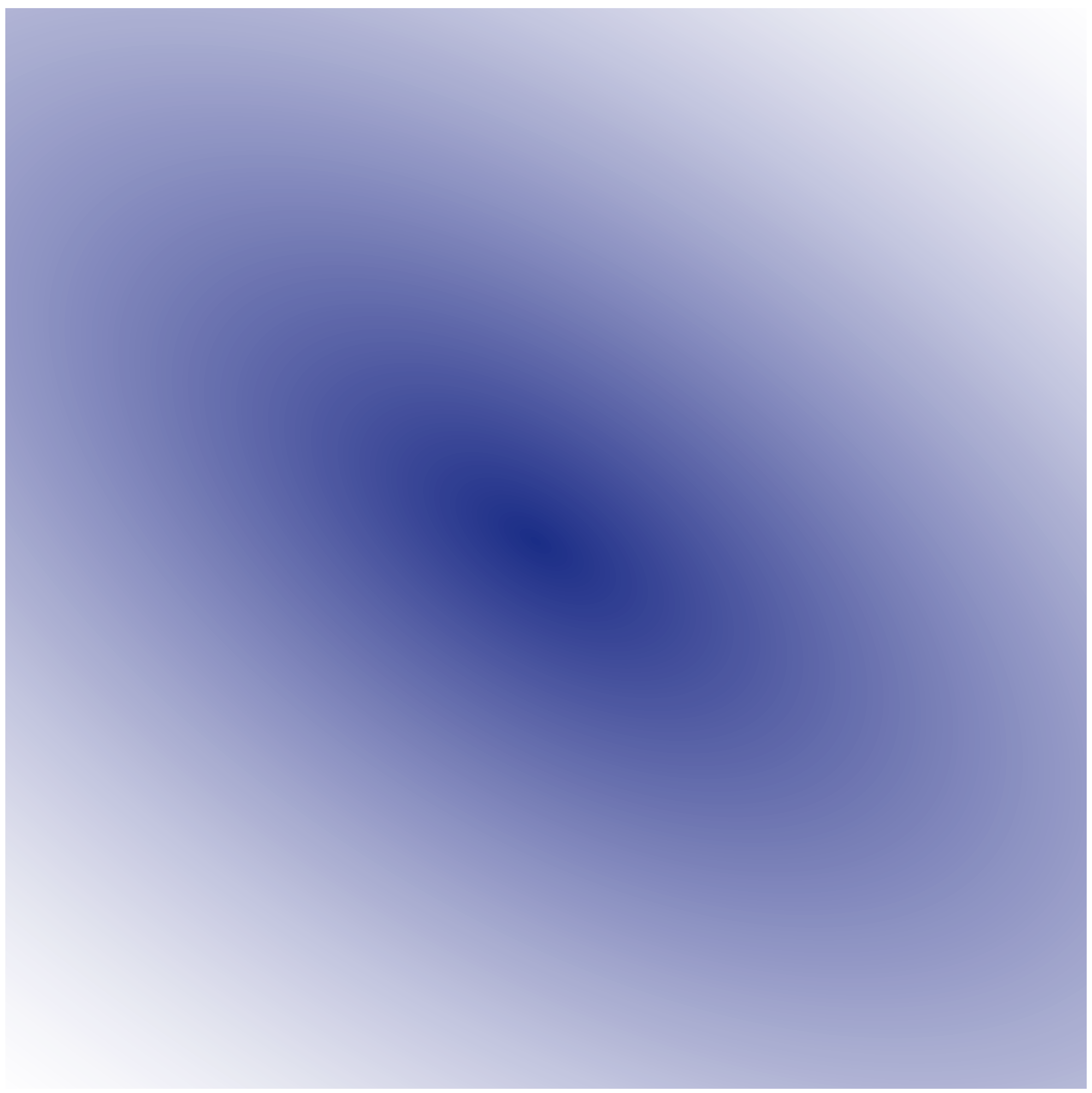
take a small step along u

$$D_{\mathbf{u}}f(\mathbf{x}_0) := \lim_{\varepsilon \to 0} \frac{f(\mathbf{x}_0 + \varepsilon\mathbf{u}) - f(\mathbf{x}_0)}{\varepsilon}$$

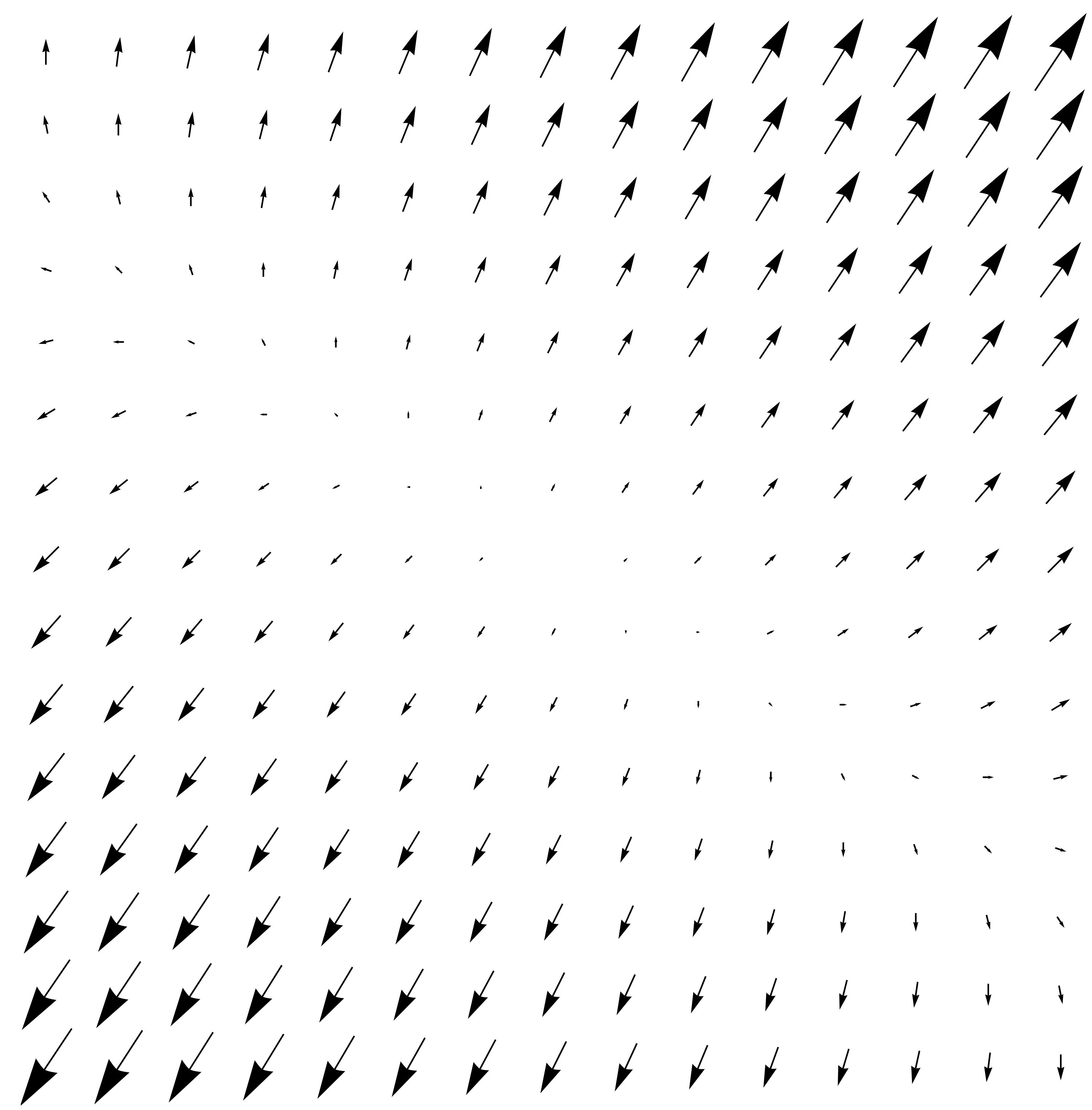
Gradient

"nabla"

- **Given a multivariable function $f(\mathbf{x})$, gradient $\nabla f(\mathbf{x})$ assigns a vector at each point:**



$f(\mathbf{x})$



$\nabla f(\mathbf{x})$

- **(Ok, but which vectors, exactly?)**

Gradient in Coordinates

- **Most familiar definition: list of partial derivatives**
- **I.e., imagine that all but one of the coordinates are just constant values, and take the usual derivative**

$$\nabla f = \begin{bmatrix} \partial f / \partial x_1 \\ \vdots \\ \partial f / \partial x_n \end{bmatrix}$$

- **Practically speaking, two potential drawbacks:**
  - **Role of inner product is not clear (more later!)**
  - **No way to differentiate functions of functions F(f) since we don't have a finite list of coordinates $x_1, \ldots, x_n$**
- **Still, extremely common way to calculate the gradient…**

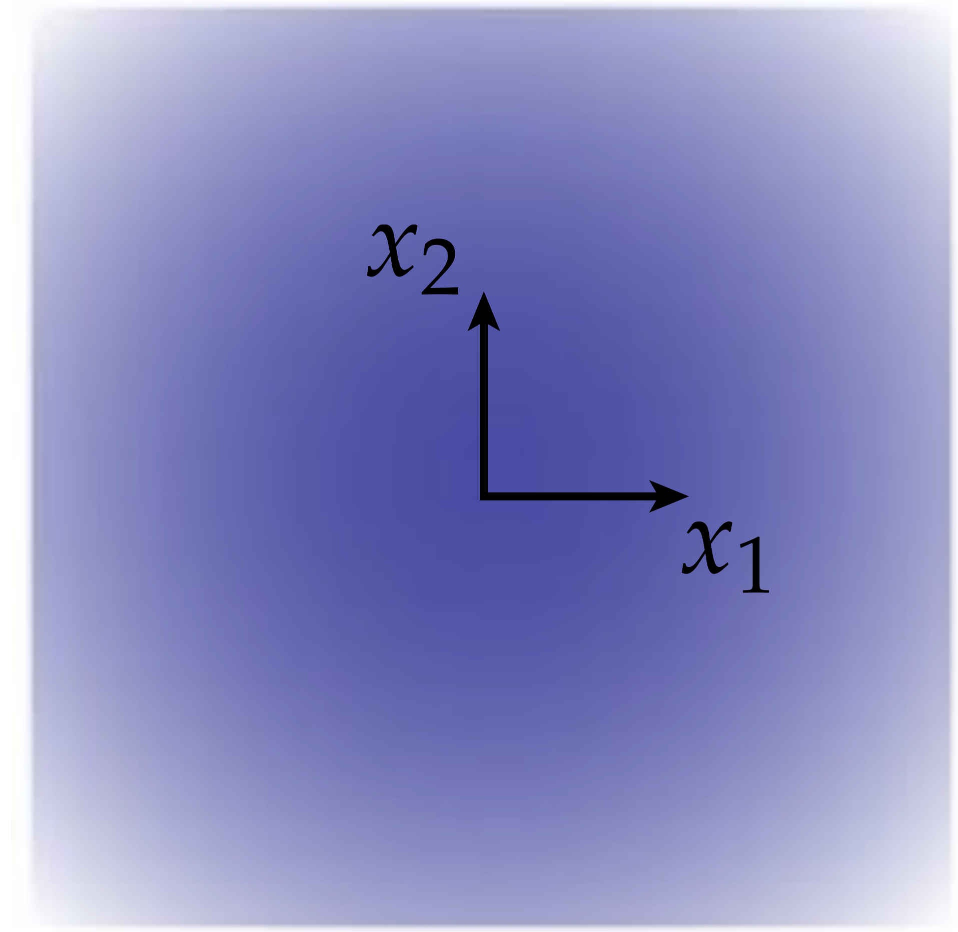
Example: Gradient in Coordinates

$$f(\mathbf{x}) := x_1^2 + x_2^2$$

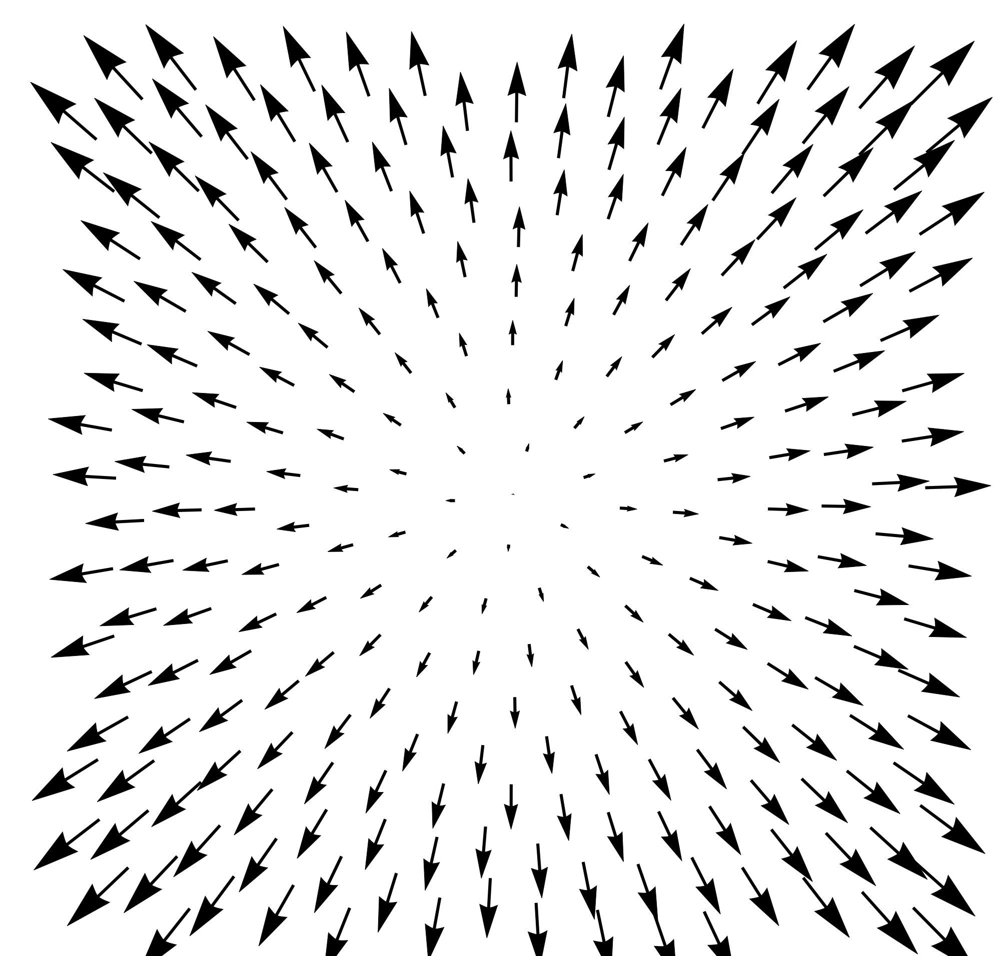
$$\frac{\partial f}{\partial x_1} = \frac{\partial}{\partial x_1} x_1^2 + \frac{\partial}{\partial x_1} x_2^2 = 2x_1 + 0$$

$$\frac{\partial f}{\partial x_2} = \frac{\partial}{\partial x_2} x_1^2 + \frac{\partial}{\partial x_2} x_2^2 = 0 + 2x_2$$

$$\nabla f(\mathbf{x}) = \begin{bmatrix} 2x_1 \\ 2x_2 \end{bmatrix} = 2\mathbf{x}$$



$f(\mathbf{x})$

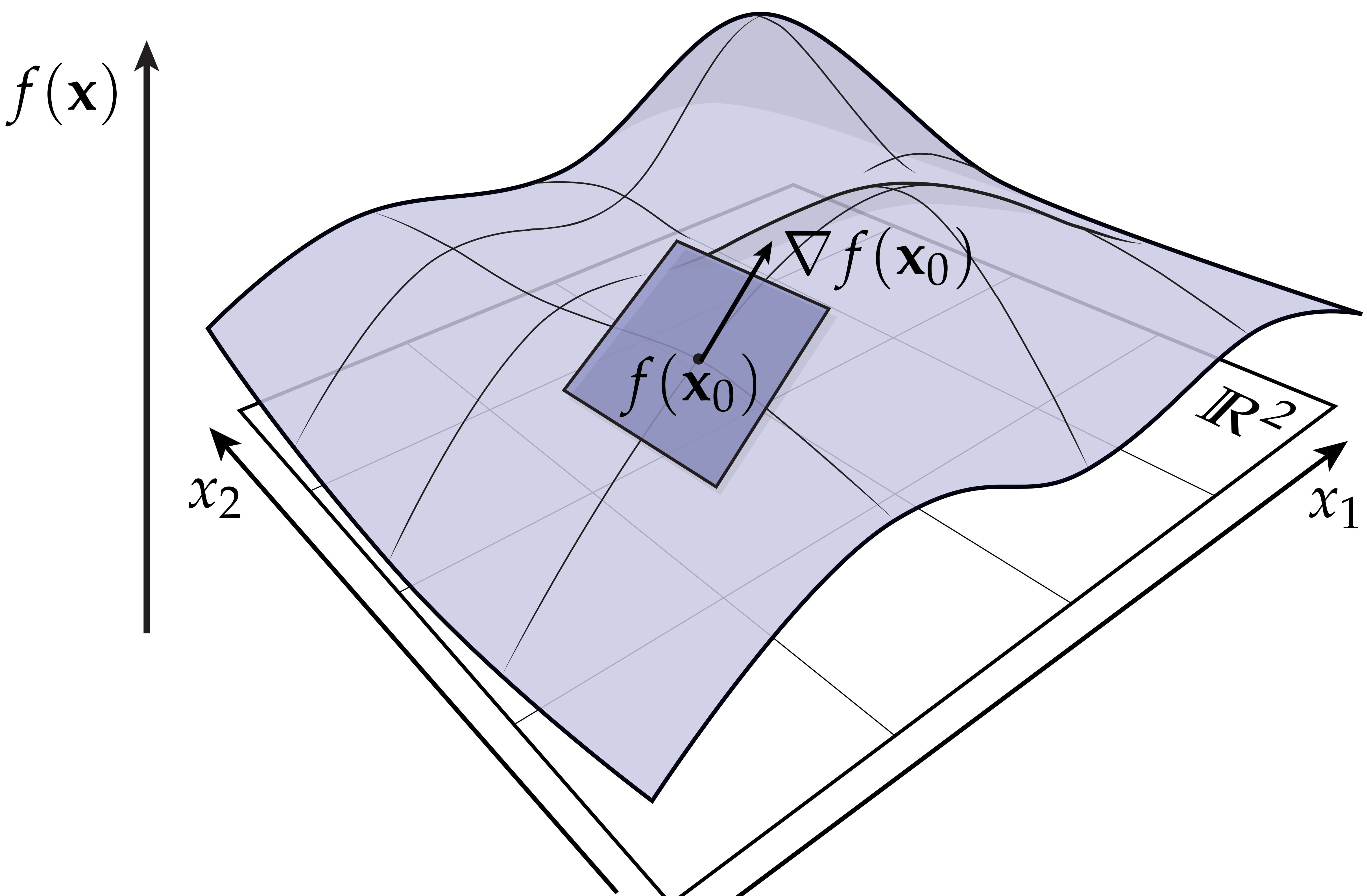


$\nabla f(\mathbf{x})$

Gradient as Best Linear Approximation

Another way to think about it: at each point x0, gradient is the vector $\nabla f(\mathbf{x}_0)$ that leads to the best possible approximation

$$f(\mathbf{x}) \approx f(\mathbf{x}_0) + \langle \nabla f(\mathbf{x}_0), \mathbf{x} - \mathbf{x}_0 \rangle$$

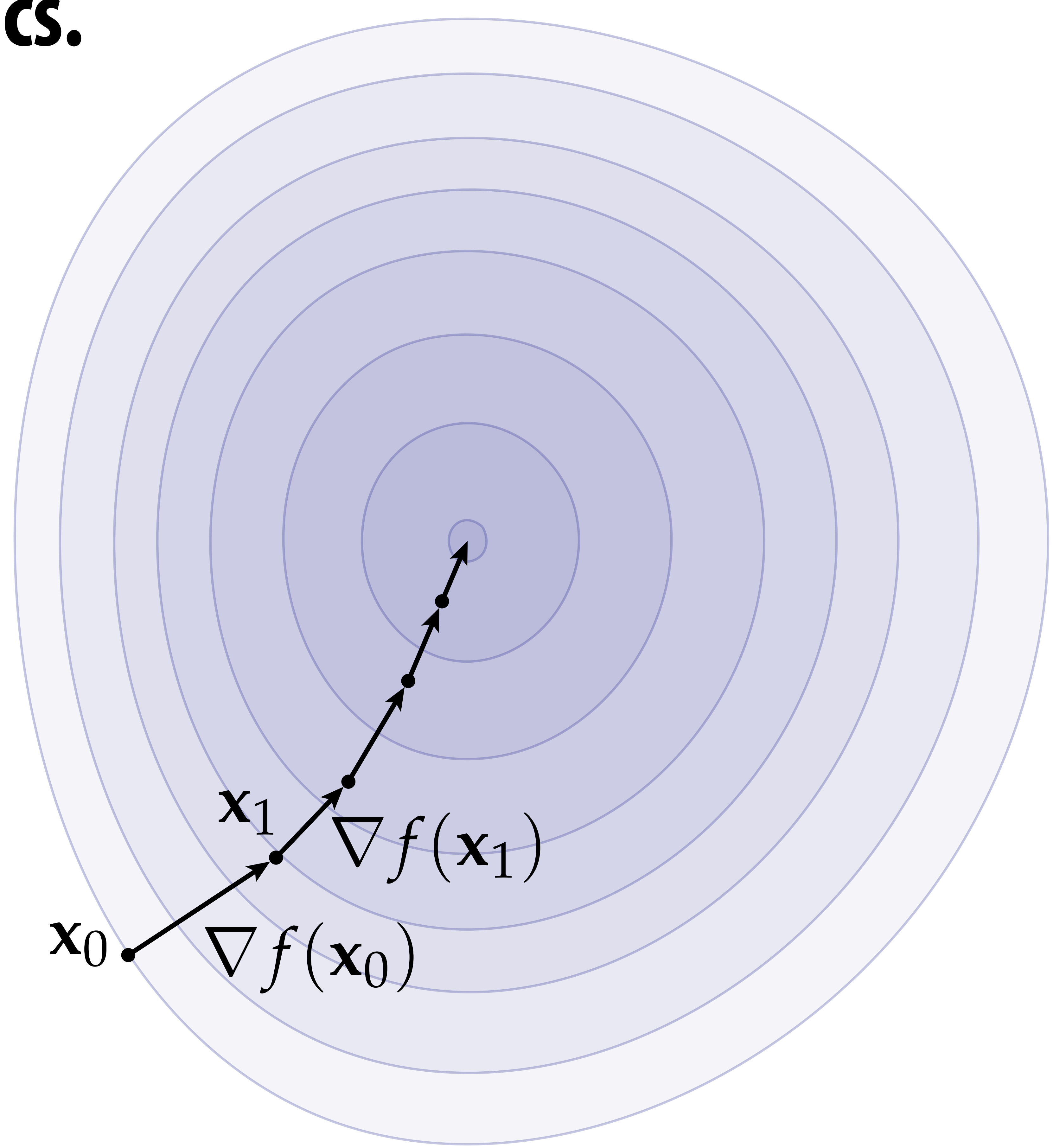


Starting at $\mathbf{x}_0$, this term gets:

- **bigger if we move in the direction of the gradient,**
- **smaller if we move in the opposite direction, and**
- **doesn't change if we move orthogonal to gradient.**

Gradient As Direction of Steepest Ascent

- Another way to think about it: direction of "steepest ascent"
- I.e., what direction should we travel to increase value of function as quickly as possible?
- This viewpoint leads to algorithms for optimization, commonly used in graphics.



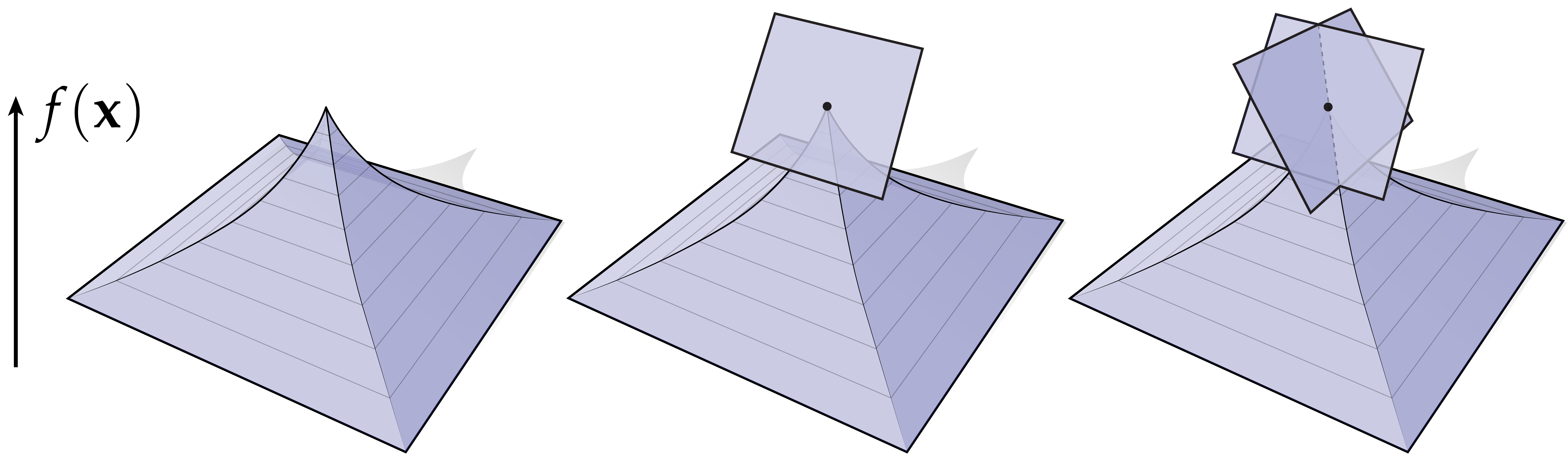
Gradient and Directional Derivative

At each point x, gradient is unique vector $\nabla f(\mathbf{x})$ such that

$$\langle \nabla f(x), \mathbf{u} \rangle = D_{\mathbf{u}} f(\mathbf{x})$$

for all u. In other words, such that taking the inner product w/ this vector gives you the directional derivative in any direction u.

Can't happen if function is not differentiable!



(Notice: gradient also depends on choice of inner product...)

Example: Gradient of Dot Product

- **Consider the dot product expressed in terms of matrices:**

$$f := \mathbf{u}^\mathsf{T}\mathbf{v}$$

- **What is gradient of f with respect to u?**
- **One way: write it out in coordinates:**

$$\mathbf{u}^\mathsf{T}\mathbf{v} = \sum_{i=1}^{n} u_i v_i$$

(equals zero unless i = k)

$$\frac{\partial}{\partial u_k}\sum_{i=1}^{n} u_i v_i = \sum_{i=1}^{n} \frac{\partial}{\partial u_k}(u_i v_i) = v_k$$

$$\Rightarrow \nabla_{\mathbf{u}} f = \begin{bmatrix} v_1 \\ \dots \\ v_n \end{bmatrix}$$

In other words:

$$\boxed{\nabla_{\mathbf{u}}(\mathbf{u}^\mathsf{T}\mathbf{v}) = \mathbf{v}}$$

Not so different from $\frac{d}{dx}(xy) = y$!

Gradients of Matrix-Valued Expressions

- **EXTREMELY useful in graphics to be able to differentiate matrix-valued expressions**
- **Ultimately, expressions look much like ordinary derivatives**

For any two vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ and **symmetric** matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$:

Matrix Derivative	Looks Like
$\nabla_{\mathbf{x}}(\mathbf{x}^T\mathbf{y}) = \mathbf{y}$	$\frac{d}{dx}xy = y$
$\nabla_{\mathbf{x}}(\mathbf{x}^T\mathbf{x}) = 2\mathbf{x}$	$\frac{d}{dx}x^2 = 2x$
$\nabla_{\mathbf{x}}(\mathbf{x}^T A\mathbf{y}) = A\mathbf{y}$	$\frac{d}{dx}axy = ay$
$\nabla_{\mathbf{x}}(\mathbf{x}^T A\mathbf{x}) = 2A\mathbf{x}$	$\frac{d}{dx}ax^2 = 2ax$
$\ldots$	$\ldots$

Excellent resource: Petersen & Pedersen, "The Matrix Cookbook"

- **At least once in your life, work these out meticulously in coordinates (to convince yourself they're true).**
- **Then… forget about coordinates altogether!**

Advanced*: L² Gradient

- Consider a function of a function $F(f)$
- What is the gradient of F with respect to f?
- Can't take partial derivatives anymore!
- Instead, look for function ∇F such that for all functions u,

$$\langle\langle \nabla F, u \rangle\rangle = D_u F$$

- What is directional derivative of a function of a function??
- Don't freak out—just return to good old-fashioned limit:

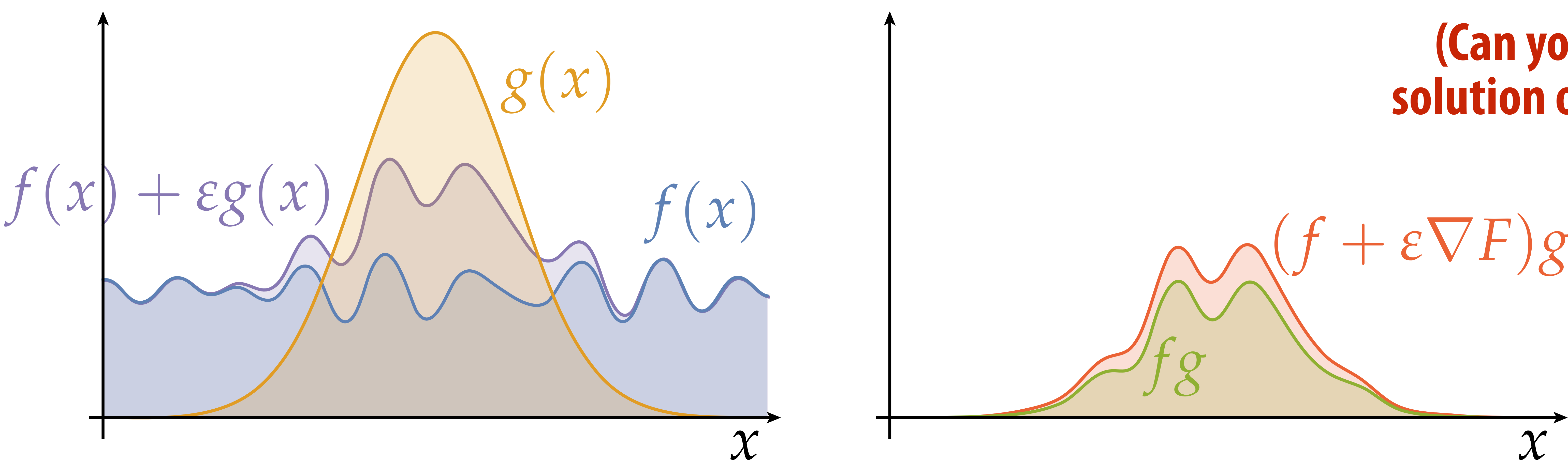
$$D_u F(f) = \lim_{\varepsilon \to 0} \frac{F(f + \varepsilon u) - F(f)}{\varepsilon}$$

- This strategy becomes much clearer w/ a concrete example...

*as in, NOT on the test! (But perhaps somewhere in the test of life…)

Advanced Visual Example: L^2 Gradient

- Consider function $F(f) := \langle\langle f, g \rangle\rangle$ for f: [0,1]→R
- I claim the gradient is: $\nabla F = g$
- Does this make sense intuitively? How can we increase inner product with g as quickly as possible?
  - inner product measures how well functions are "aligned"
  - g is definitely function best-aligned with g!
  - so to increase inner product, add a little bit of g to f



(Can you work this solution out formally?)

Advanced Example: L² Gradient

- Consider function $F(f) := ||f||^2$ for arguments f: [0,1]→R
- At each "point" f0, we want function ∇F such that for all functions u

$$\langle\langle \nabla F(f_0), u \rangle\rangle = \lim_{\varepsilon \to 0} \frac{F(f_0 + \varepsilon u) - F(f_0)}{\varepsilon}$$

- Expanding 1st term in numerator, we get

$$||f_0 + \varepsilon u||^2 = ||f_0||^2 + \varepsilon^2 ||u||^2 + 2\varepsilon \langle\langle f_0, u \rangle\rangle$$

- Hence, limit becomes

$$\lim_{\varepsilon \to 0} (\varepsilon ||u||^2 + 2\langle\langle f_0, u \rangle\rangle) = 2\langle\langle f_0, u \rangle\rangle$$

- The only solution to $\langle\langle \nabla F(f_0), u \rangle\rangle = 2\langle\langle f_0, u \rangle\rangle$ for all u is

$$\boxed{\nabla F(f_0) = 2f_0}$$

not much different from $\frac{d}{dx} x^2 = 2x$!

Key idea:

Once you get the hang of taking the gradient of ordinary functions, it's (superficially) not much harder for more exotic objects like matrices, functions of functions, . . .

Vector Fields

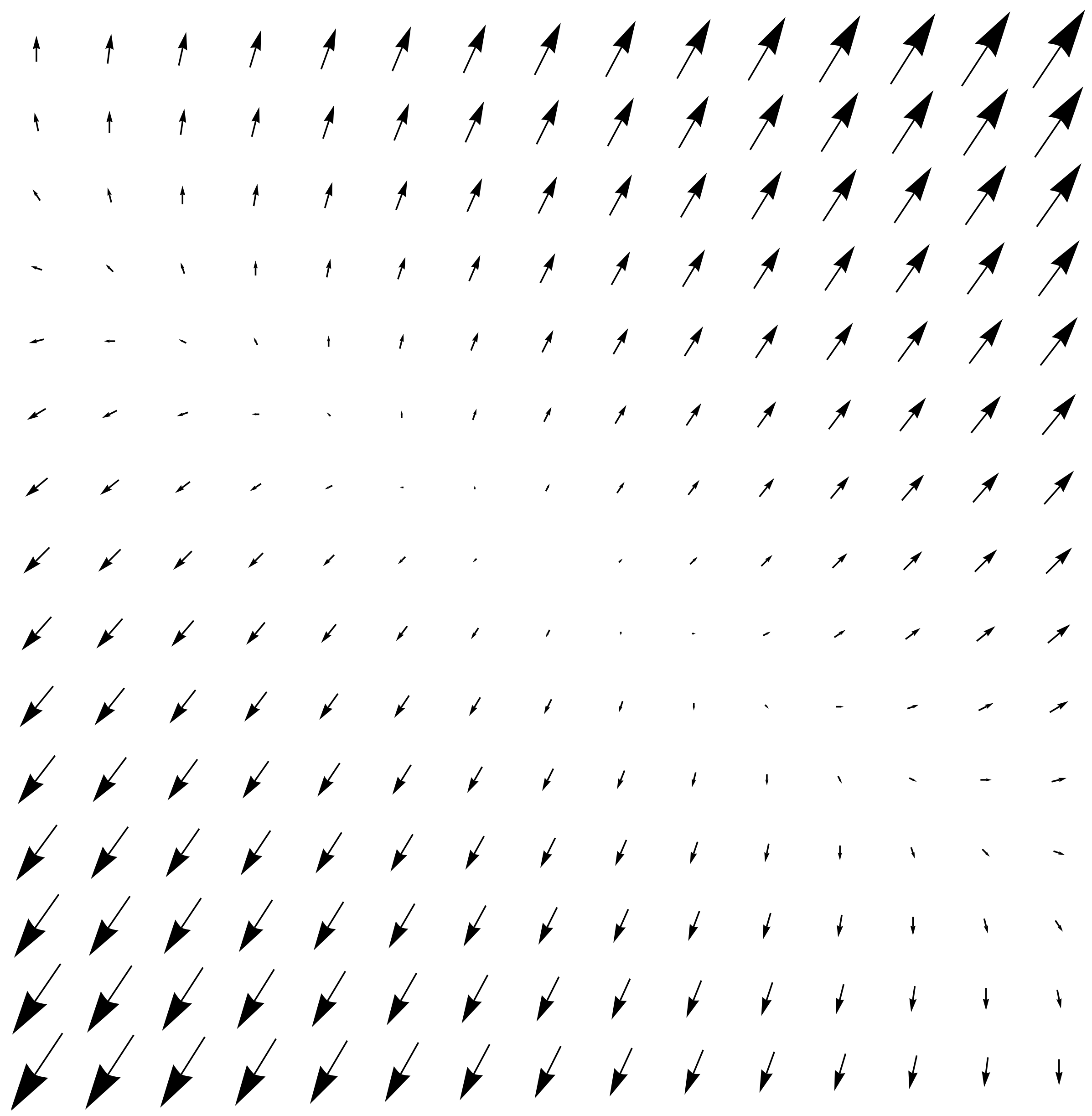
- Gradient was our first example of a vector field
- In general, a vector field assigns a vector to each point in space
- E.g., can think of a 2-vector field in the plane as a map

$$X : \mathbb{R}^2 \to \mathbb{R}^2$$

- For example, saw a gradient field

$$\nabla f(x, y) = (2x, 2y)$$

(for function $f(x,y) = x^2 + y^2$)



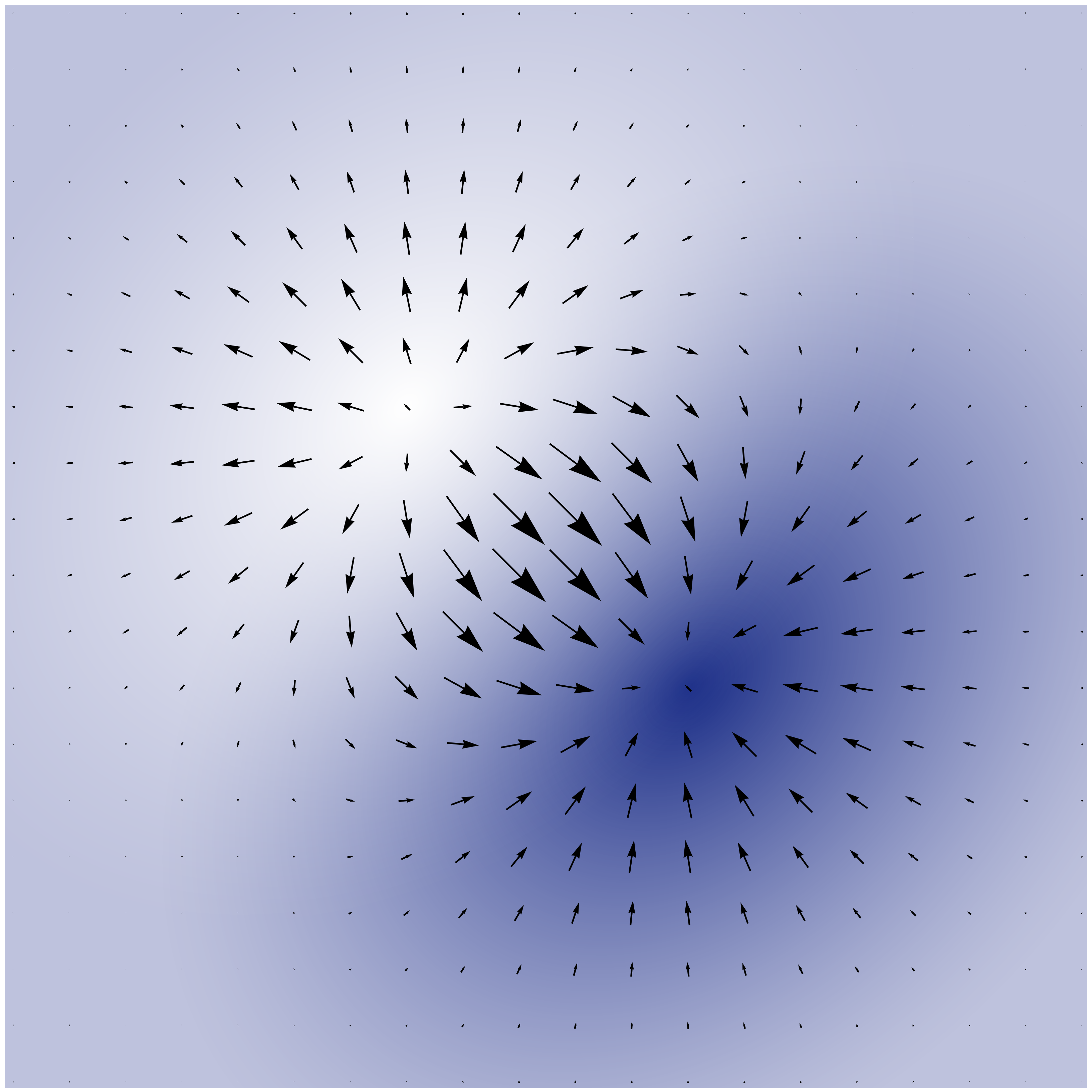
$\nabla f(\mathbf{x})$

Q: How do we measure the change in a vector field?

Divergence and Curl

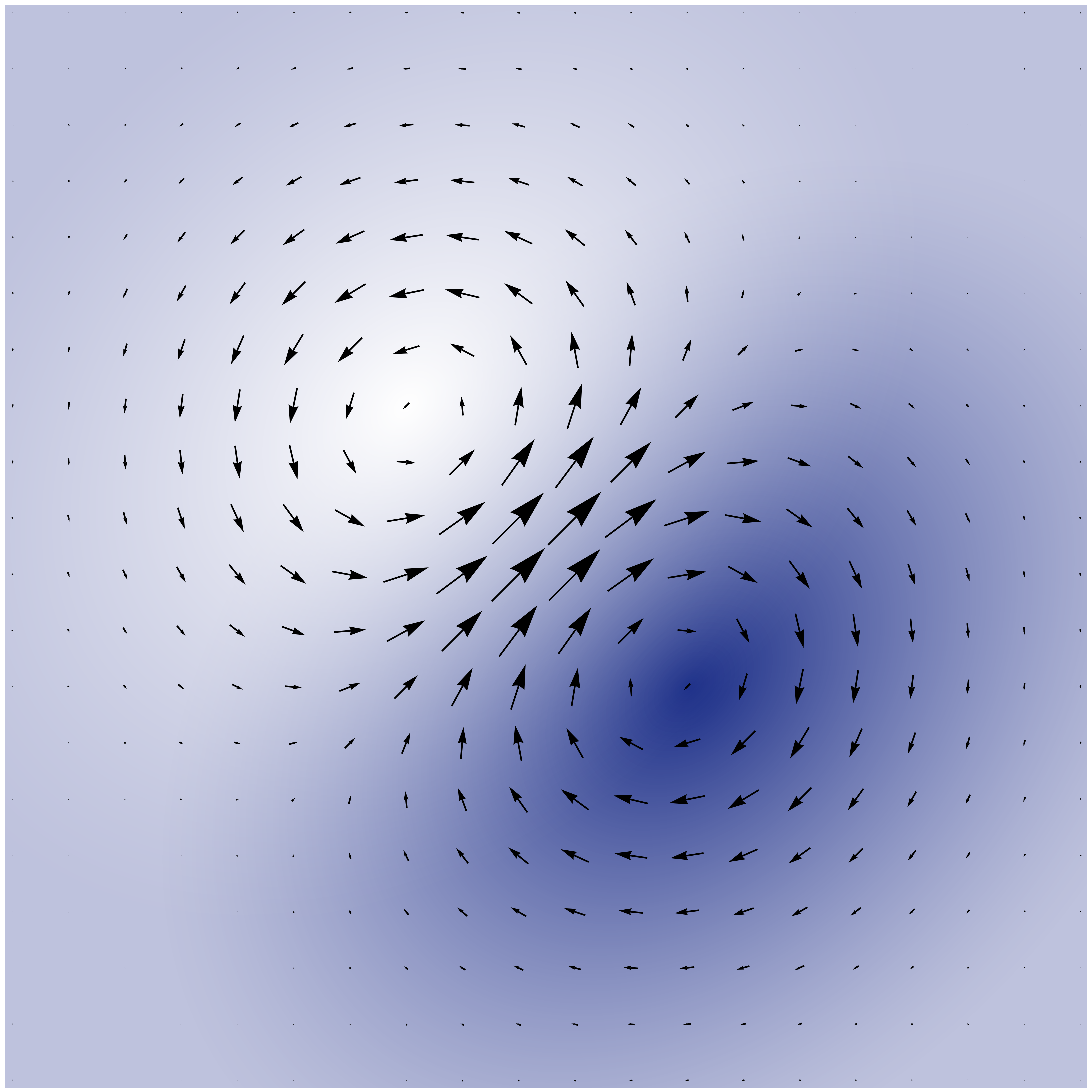
- **Two basic derivatives for vector fields:**

"How much is field shrinking/expanding?"



$\mathrm{div}\ X$

"How much is field spinning?"



$\mathrm{curl}\ Y$

Divergence

- Also commonly written as $\nabla \cdot X$
- Suggests a coordinate definition for divergence
- Think of ∇ as a "vector of derivatives"

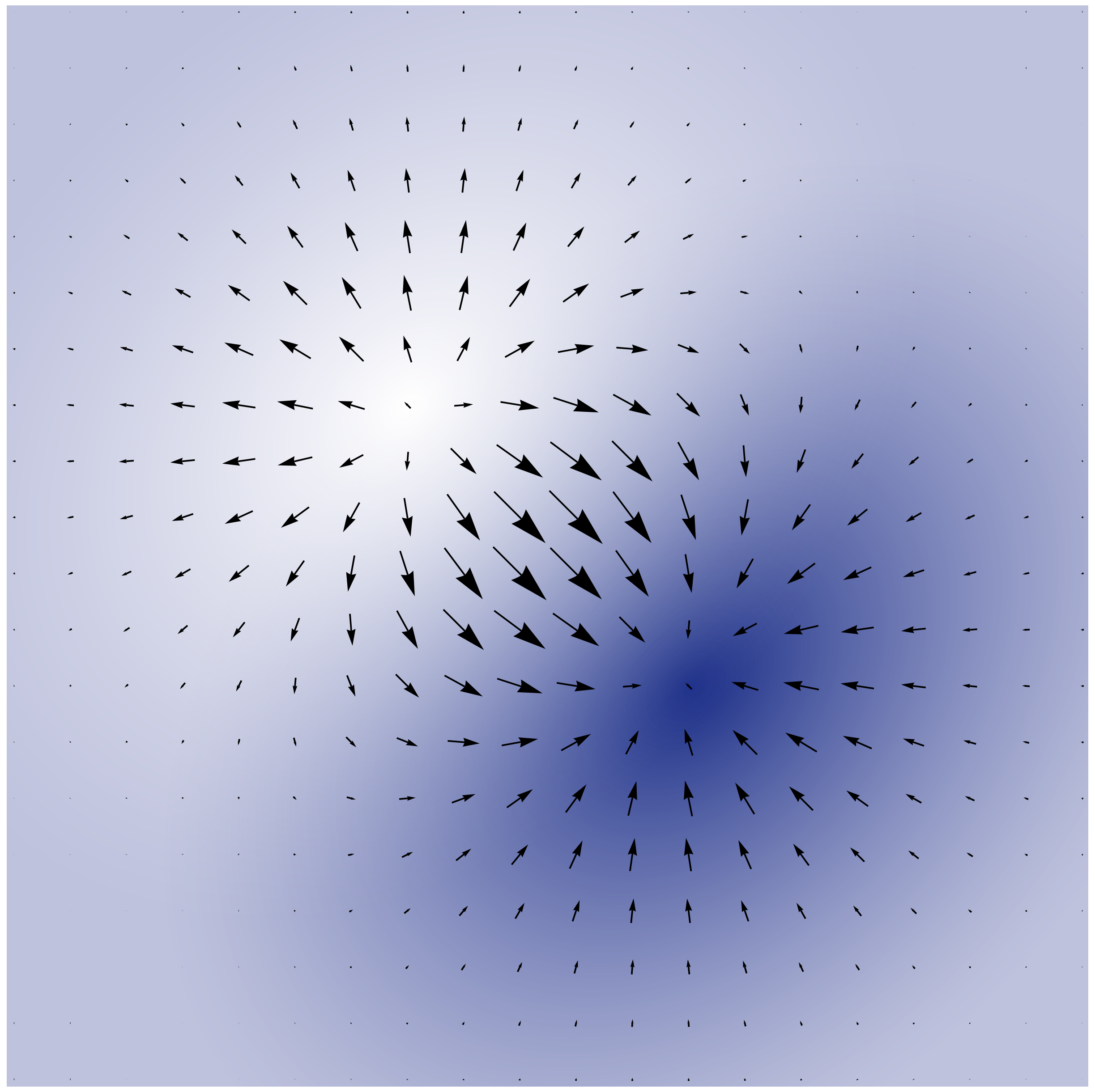
$$\nabla = \left(\frac{\partial}{\partial u_1}, \cdots, \frac{\partial}{\partial u_n} \right)$$

- Think of X as a "vector of functions"

$$X(\mathbf{u}) = (X_1(\mathbf{u}), \ldots, X_n(\mathbf{u}))$$

- Then divergence is

$$\nabla \cdot X := \sum_{i=1}^{n} \partial X_i / \partial u_i$$

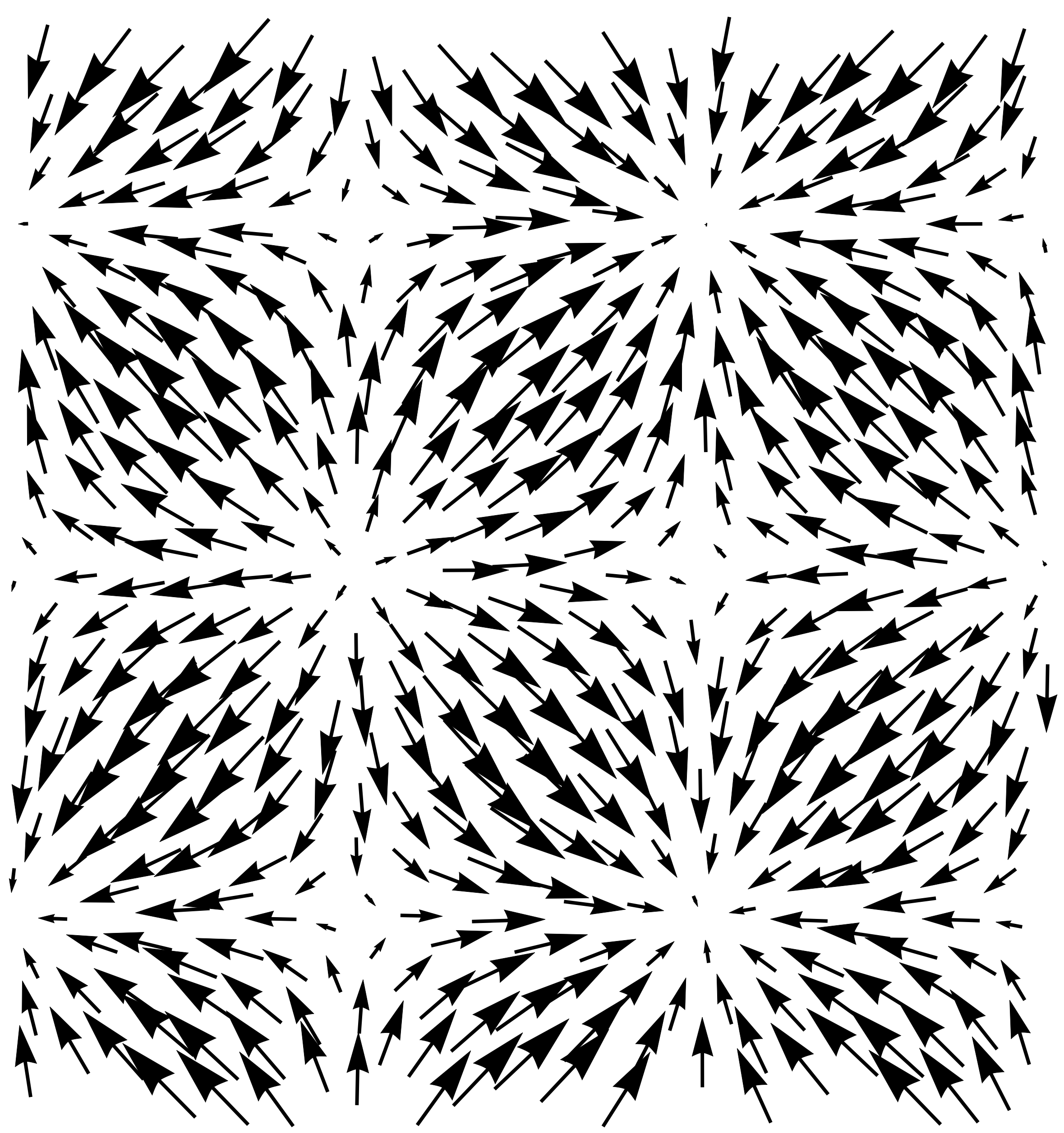


$\nabla \cdot X$

Divergence - Example

- **Consider the vector field** $X(u,v) := (\cos(u), \sin(v))$
- **Divergence is then**

$$\nabla \cdot X = \frac{\partial}{\partial u}\cos(u) + \frac{\partial}{\partial v}\sin(v) = -\sin(u) + \cos(v).$$



X

$\nabla \cdot X$

Curl

- **Also commonly written as** $\nabla \times X$
- **Suggests a coordinate definition for curl**
- **This time, think of ∇ as a vector of just three derivatives:**

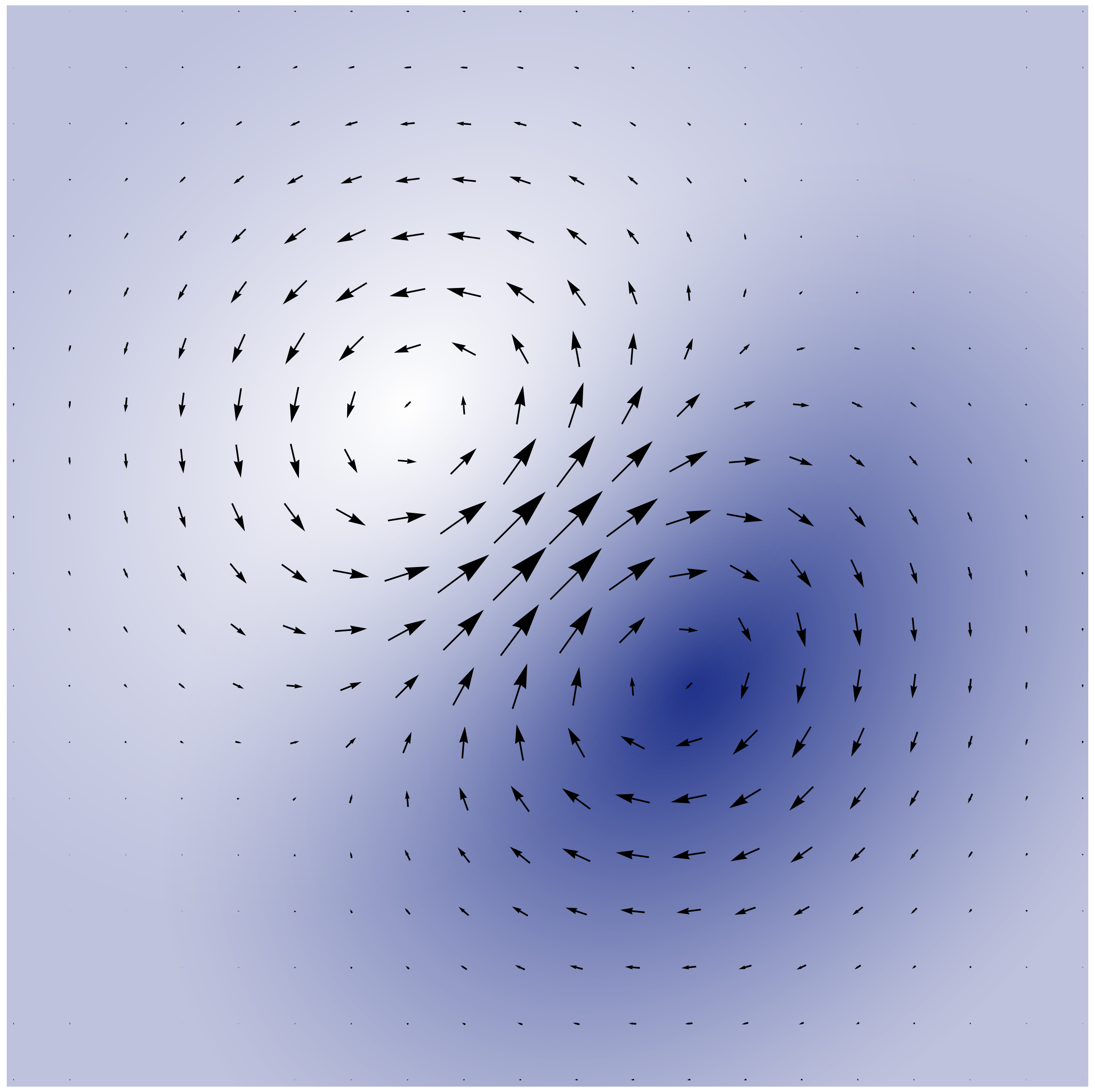
$$\nabla = \left(\frac{\partial}{\partial u_1}, \frac{\partial}{\partial u_2}, \frac{\partial}{\partial u_3} \right)$$

- **Think of X as vector of three functions:**

$$X(\mathbf{u}) = (X_1(\mathbf{u}), X_2(\mathbf{u}), X_3(\mathbf{u}))$$

- **Then curl is**

$$\nabla \times X := \left[\begin{array}{c} \partial X_3/\partial u_2 - \partial X_2/\partial u_3 \\ \partial X_1/\partial u_3 - \partial X_3/\partial u_1 \\ \partial X_2/\partial u_1 - \partial X_1/\partial u_2 \end{array} \right]$$



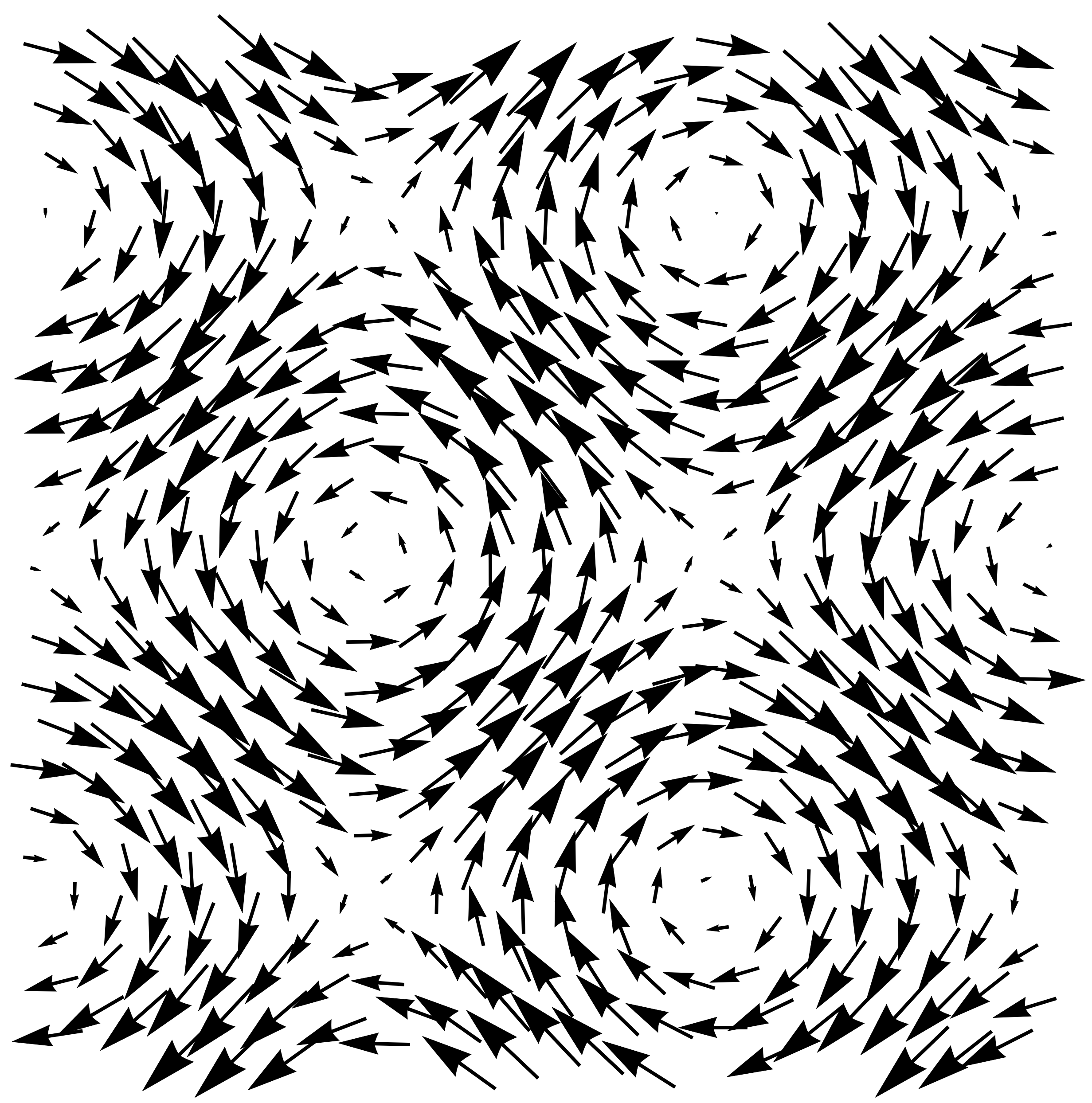
$\nabla \times X$

(2D "curl": $\nabla \times X := \partial X_2/\partial u_1 - \partial X_1/\partial u_2$**)**

Curl - Example

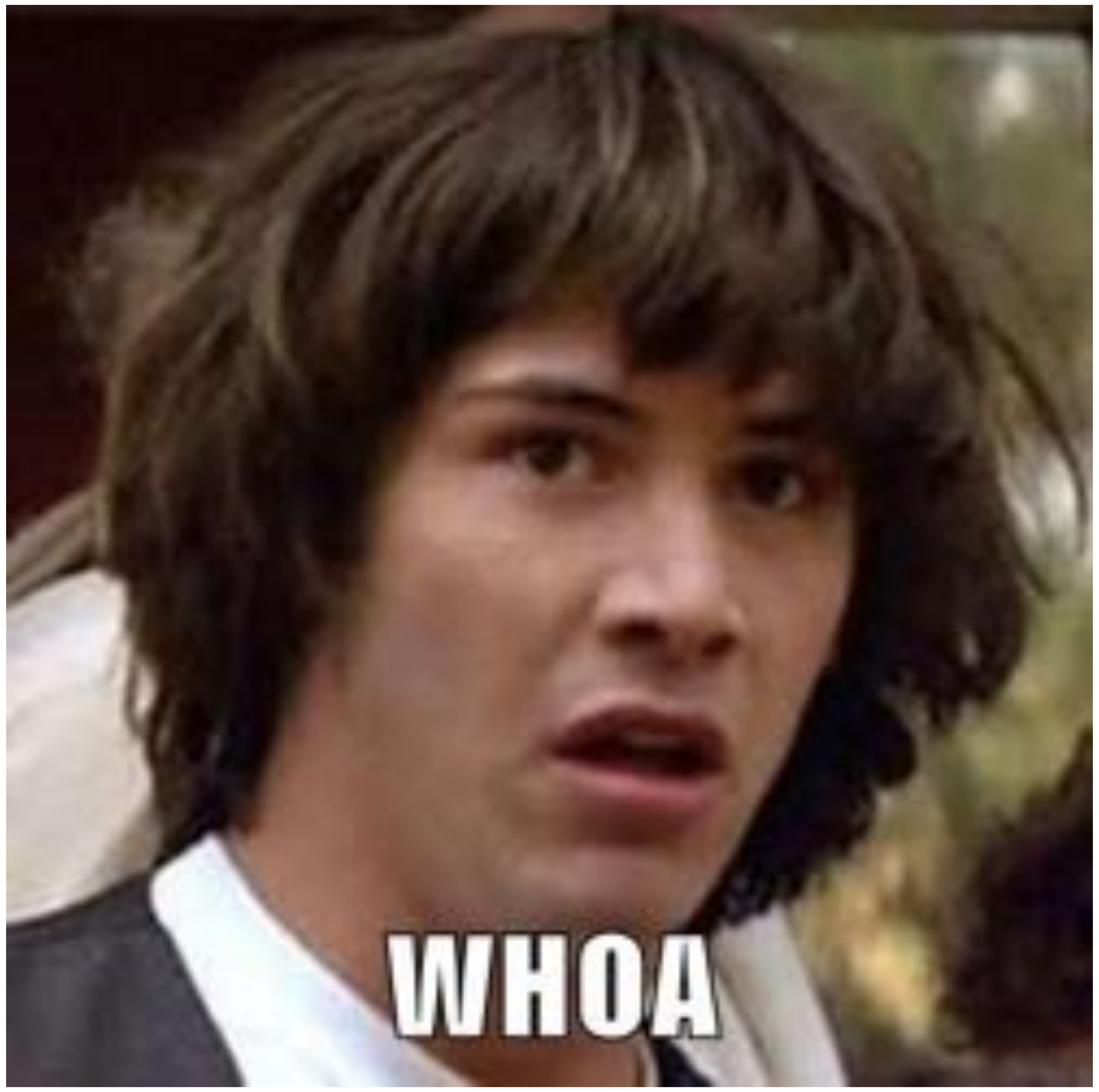
- **Consider the vector field** $X(u,v) := (-\sin(v), \cos(u))$
- **(2D) Curl is then**

$$\nabla \times X = \frac{\partial}{\partial u}\cos(u) - \frac{\partial}{\partial v}(-\sin(v)) = -\sin(u) + \cos(v).$$



X

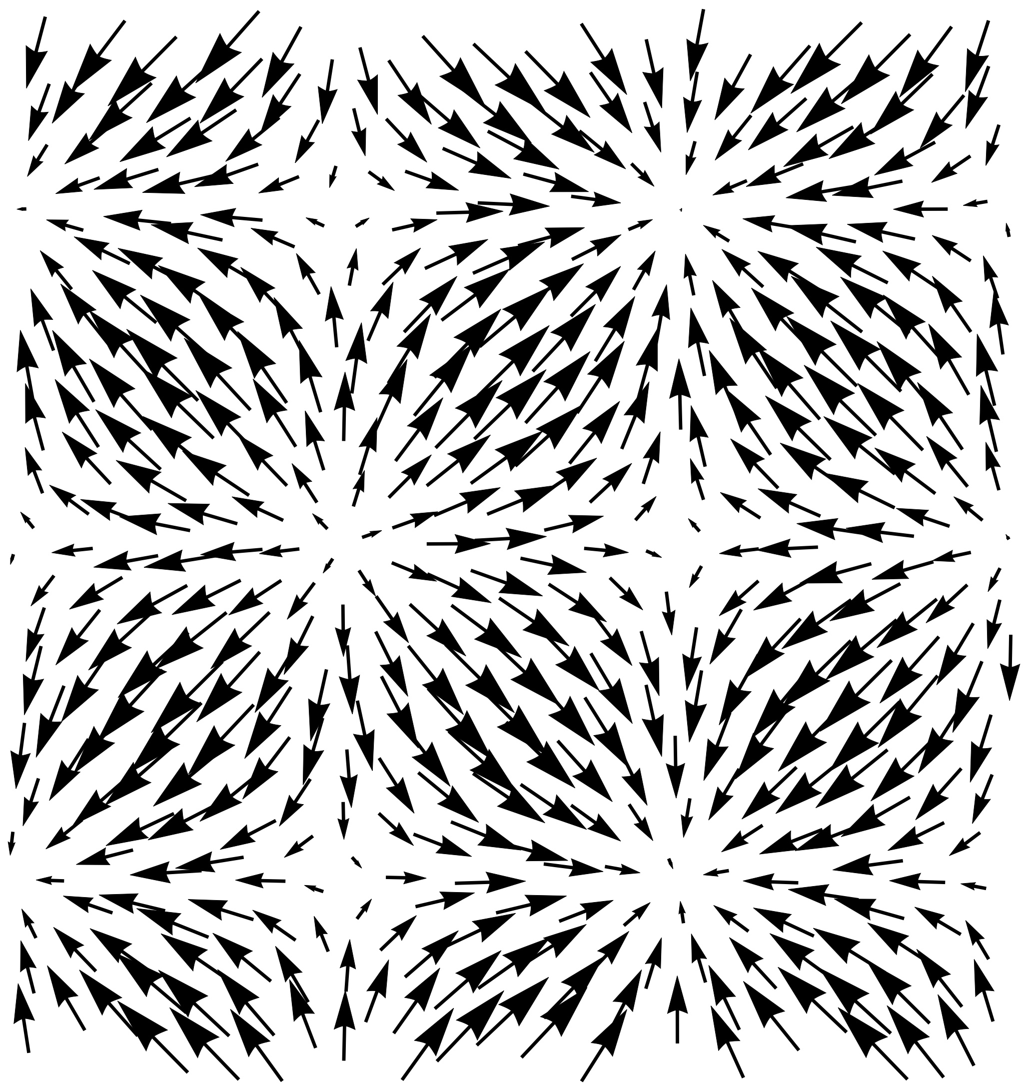
$\nabla \times X$



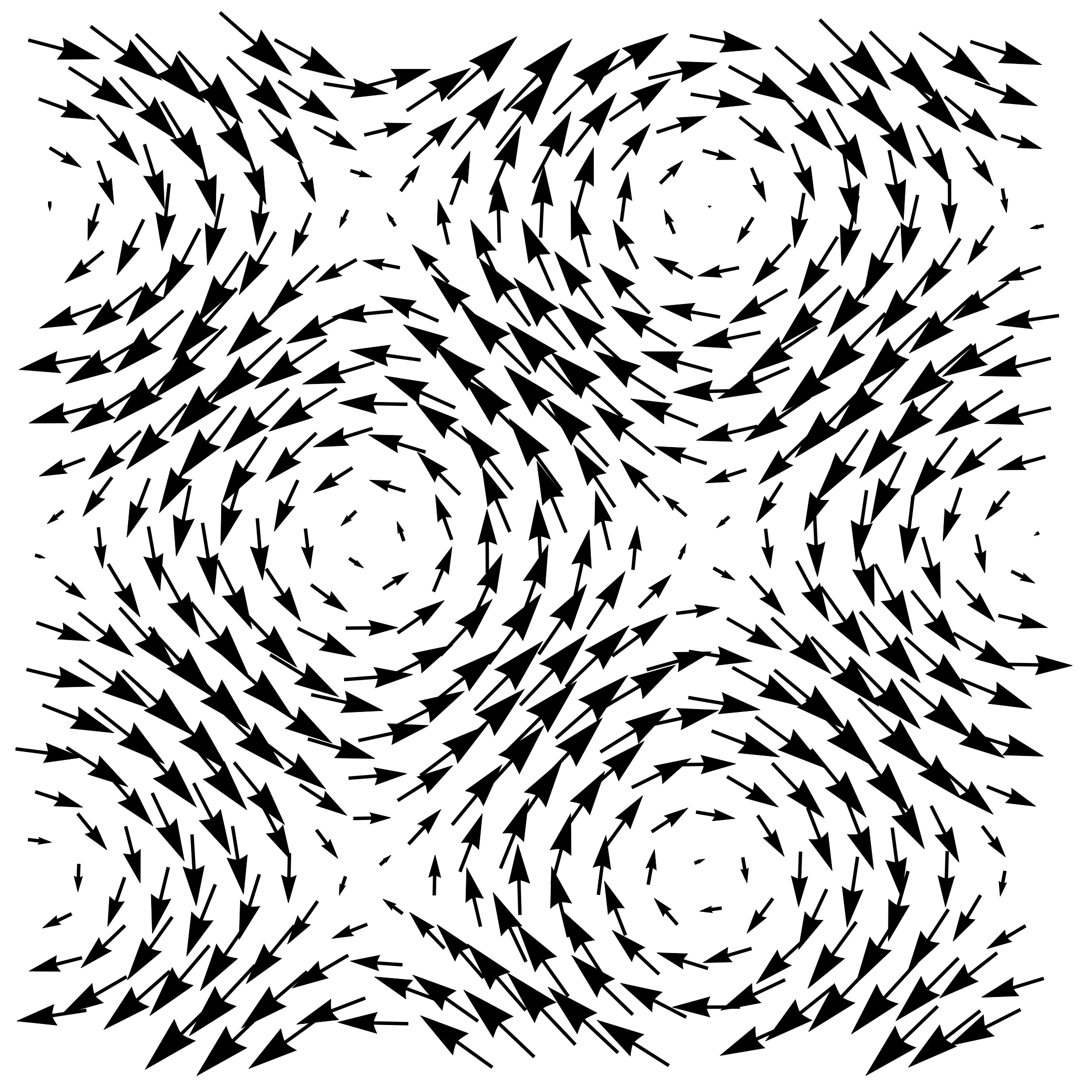
Notice anything about the relationship between curl and divergence?

Divergence vs. Curl (2D)

- Divergence of X is the same as curl of 90-degree rotation of X:



X



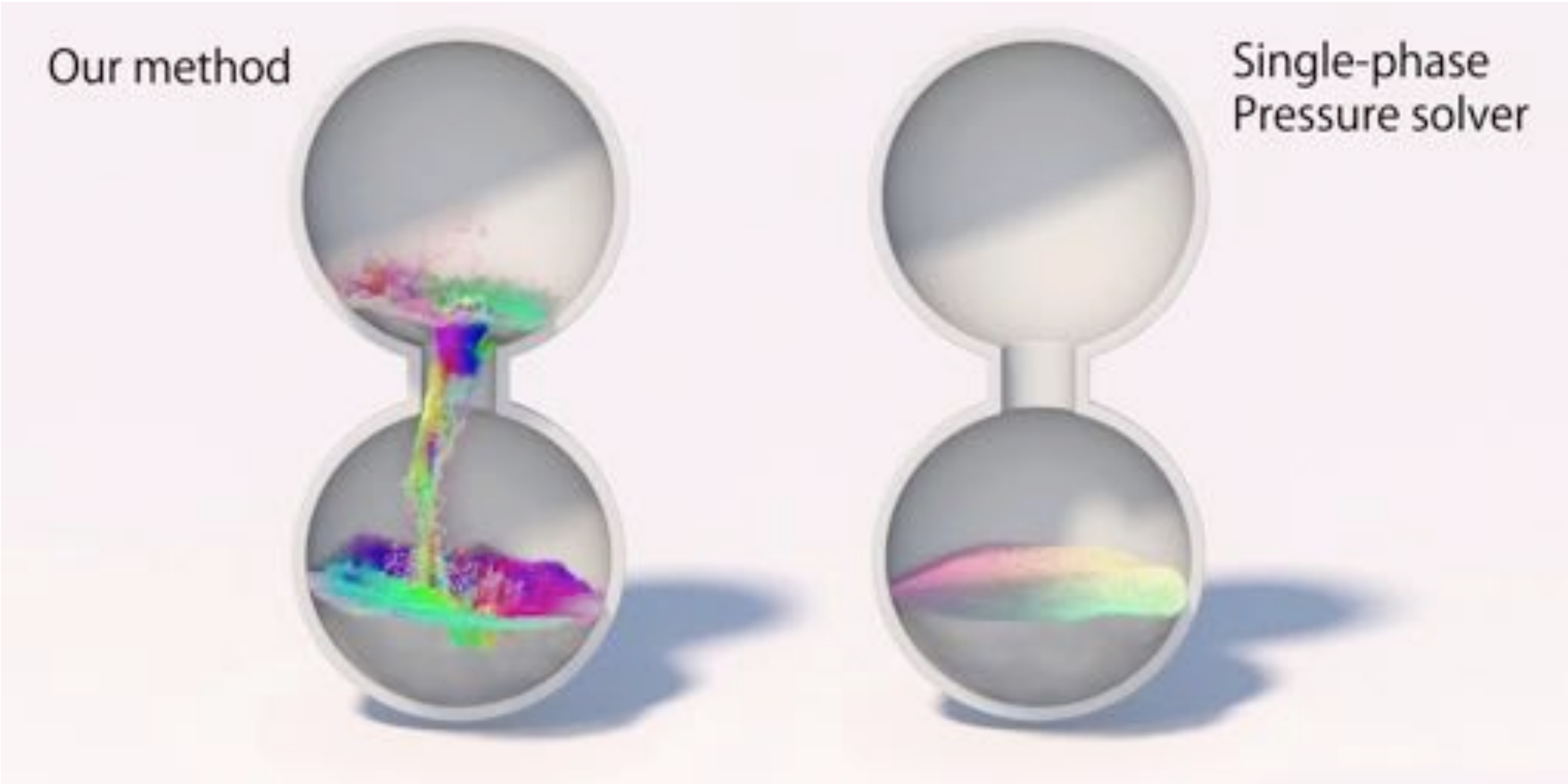
$X^{\perp}$

$\nabla \cdot X = \nabla \times X^{\perp}$

- Playing these kinds of games w/ vector fields plays an important role in algorithms (e.g., fluid simulation)

- (Q: Can you come up with an analogous relationship in 3D?)

Example: Fluids w/ Stream Function



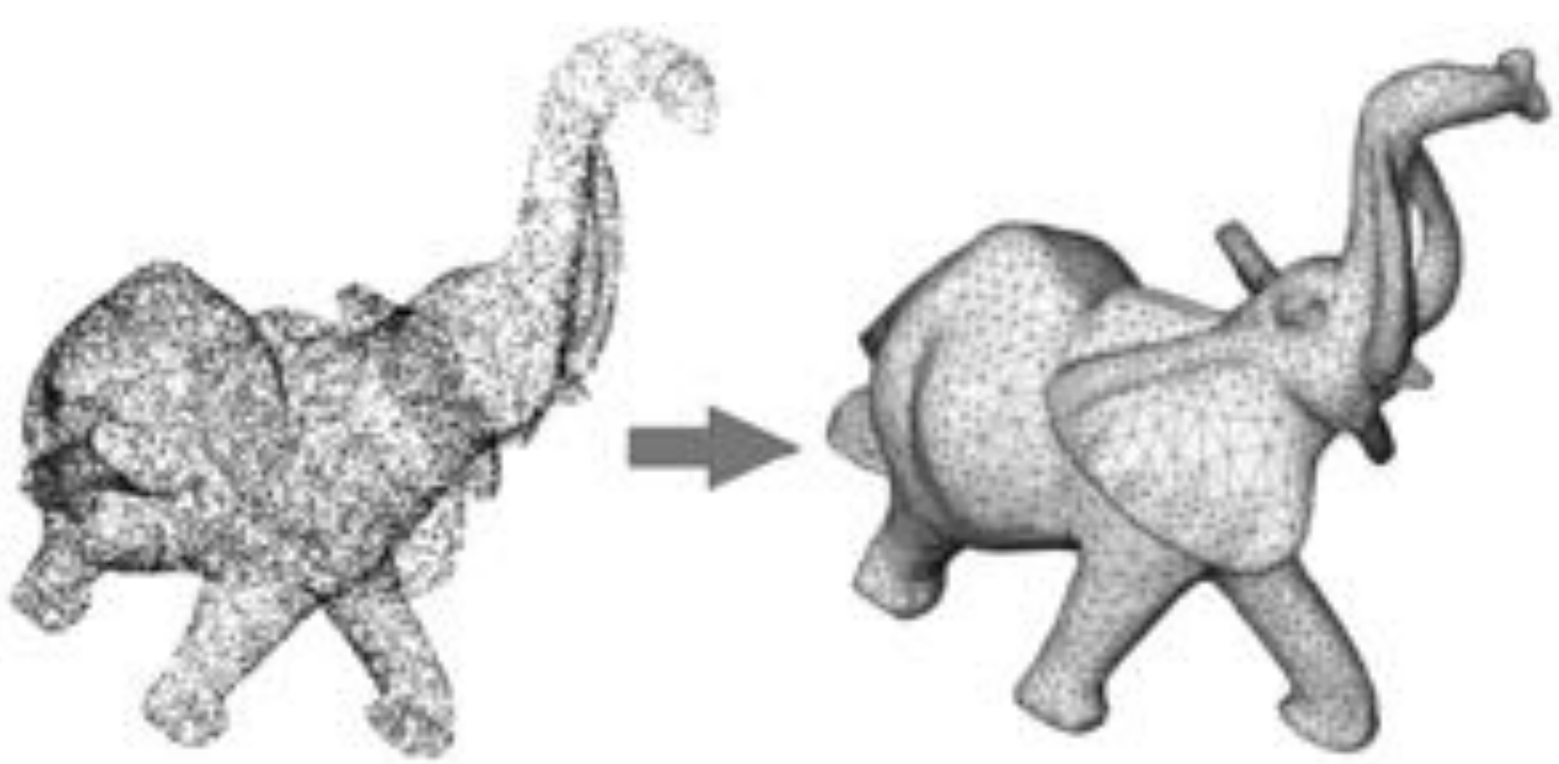
$$\min_{\Psi} ||u^* - \nabla \times \Psi||^2$$
$$u = \nabla \times \Psi$$

$$\Delta p = \nabla \cdot u^*$$
$$u = u^* - \nabla p$$

Ando et al, "A Stream Function Solver for Liquid Simulations" (SIGGRAPH 2015)

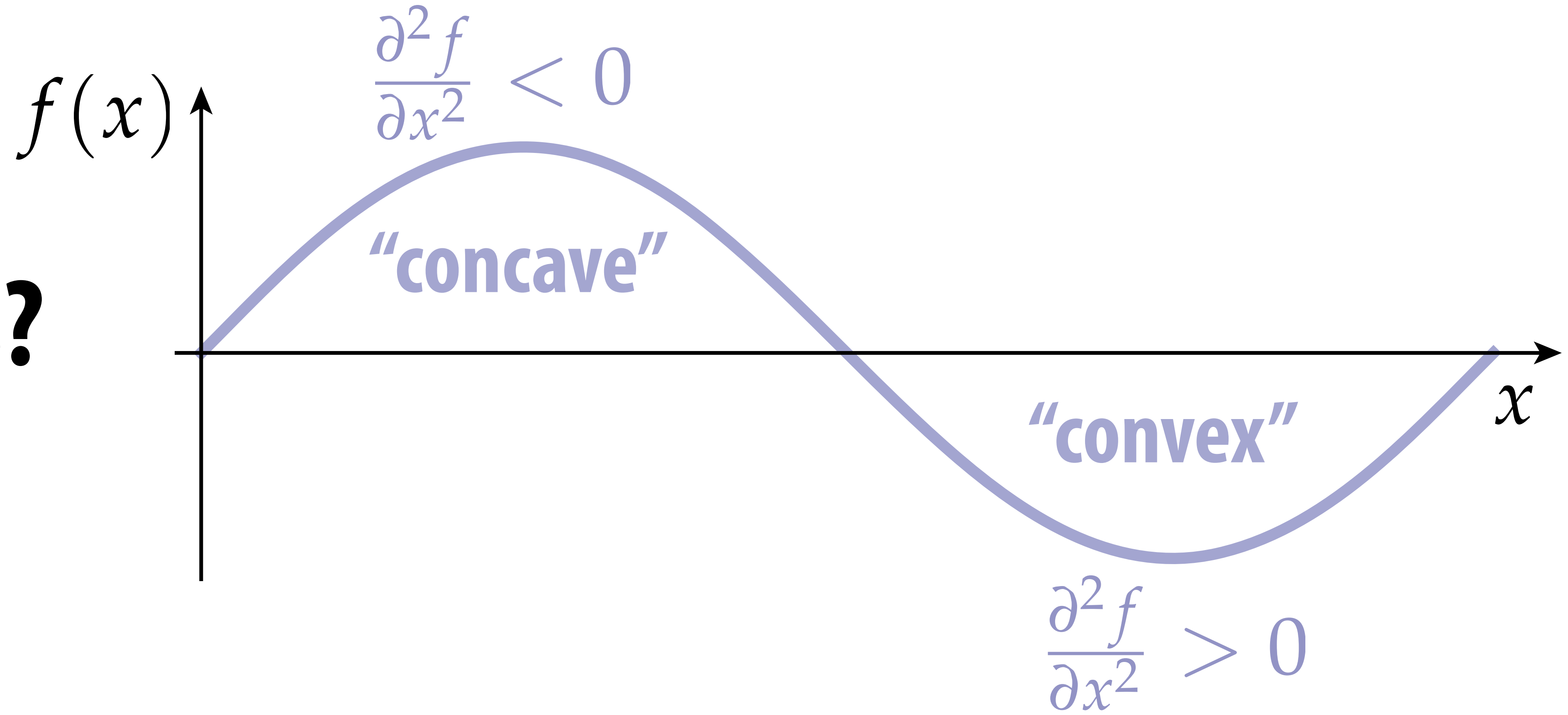
Laplacian

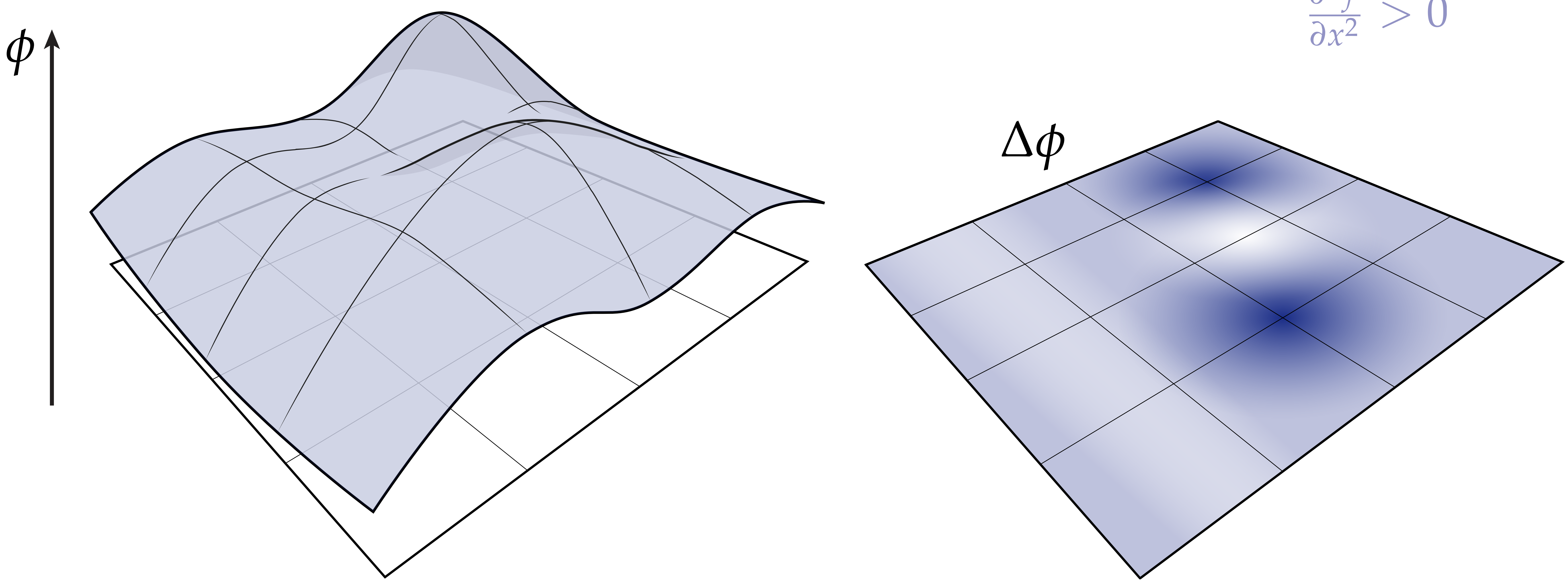
- One more operator we haven't seen yet: the Laplacian
- Unbelievably important object in graphics, showing up across geometry, rendering, simulation, imaging
  - basis for Fourier transform / frequency decomposition
  - used to define model PDEs (Laplace, heat, wave equations)
  - encodes rich information about geometry



Laplacian—Visual Intuition

Q: For ordinary function f(x), what does 2nd derivative tell us?





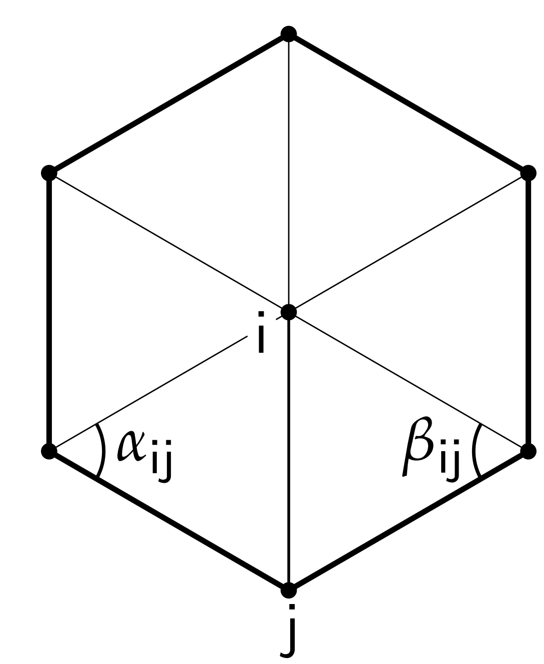
Likewise, Laplacian measures "curvature" of a function.

Laplacian—Many Definitions

- **Maps a scalar function to another scalar function (linearly!)**
- **Usually* denoted by** Δ ← **"Delta"**
- **Many starting points for Laplacian:**
  - **divergence of gradient** $\Delta f := \nabla \cdot \nabla f = \text{div}(\text{grad} f)$
  - **sum of 2nd partial derivatives** $\Delta f := \sum_{i=1}^{n} \partial^2 f / \partial x_i^2$
  - **gradient of Dirichlet energy** $\Delta f := -\nabla_f (\frac{1}{2} ||\nabla f||^2)$
  - **by analogy: graph Laplacian**
  - **variation of surface area**
  - **trace of Hessian …**

	1	
1	-4	1
	1	

$$\frac{4u_{ij} - u_{i+1,j} - u_{i-1,j} - u_{i,j+1} - u_{i,j-1}}{h^2}$$



$$\frac{1}{2}\sum_j (\cot \alpha_{ij} + \cot \beta_{ij})(u_j - u_i)$$

***Or by** ∇^2**, but we'll reserve this symbol for the Hessian**

Laplacian—Example

- **Let's use coordinate definition:** $\Delta f := \sum_i \partial^2 f / \partial x_i^2$
- **Consider the function** $f(x_1, x_2) := \cos(3x_1) + \sin(3x_2)$
- **We have**

$$\frac{\partial^2}{\partial x_1^2} f = \frac{\partial^2}{\partial x_1^2} \cos(3x_1) + \cancelto{0}{\frac{\partial^2}{\partial x_1^2} \sin(3x_2)} =$$

$$-3 \frac{\partial}{\partial x_1} \sin(3x_1) = -9\cos(3x_1).$$

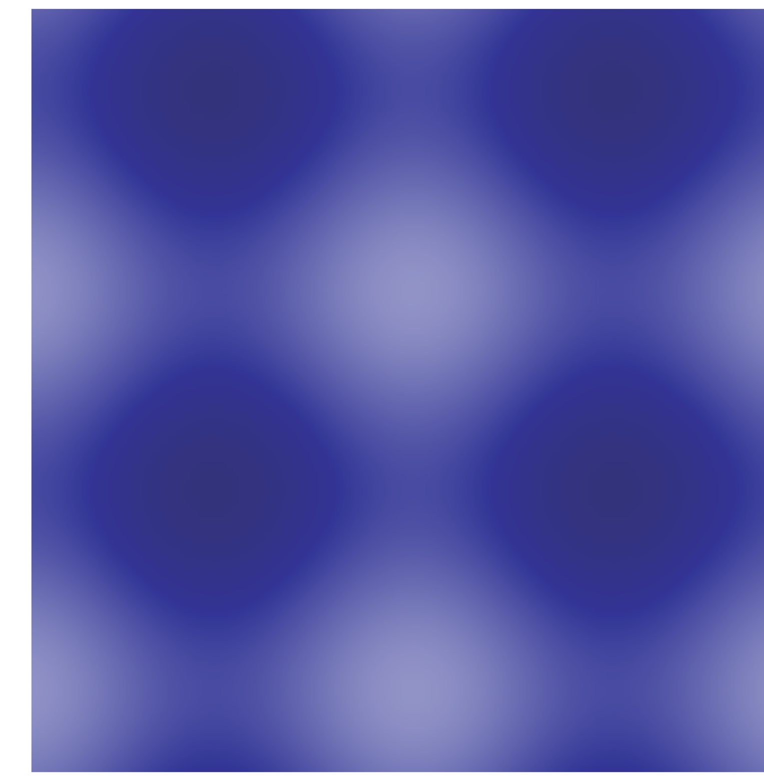
and

$$\frac{\partial^2}{\partial x_2^2} f = -9\sin(3x_2).$$

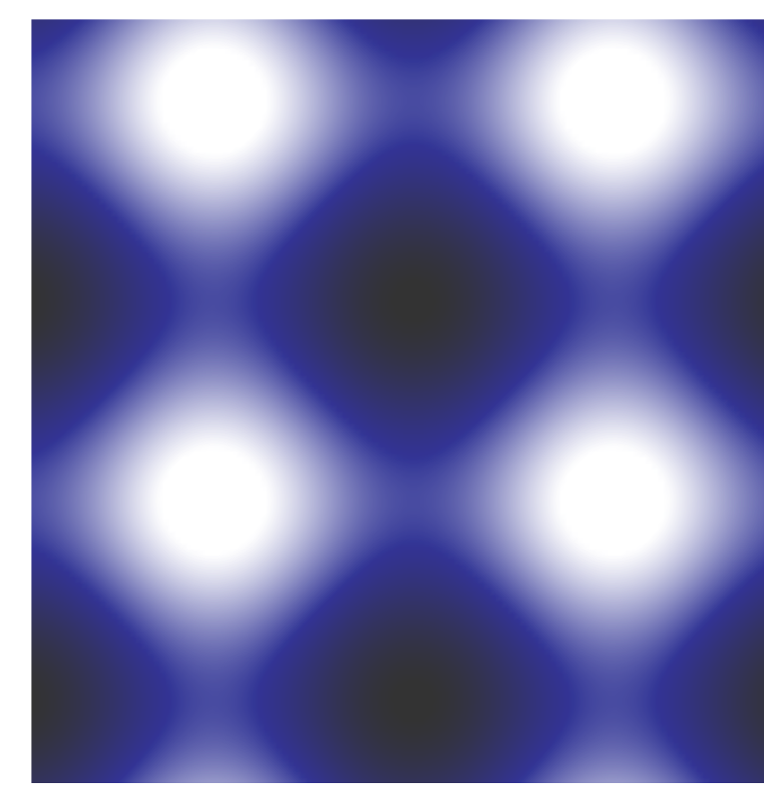
Hence,

$$\Delta f = -9(\cos(3x_1) + \sin(3x_2))$$
$$= -9f$$

Interesting! Does this always happen?



f

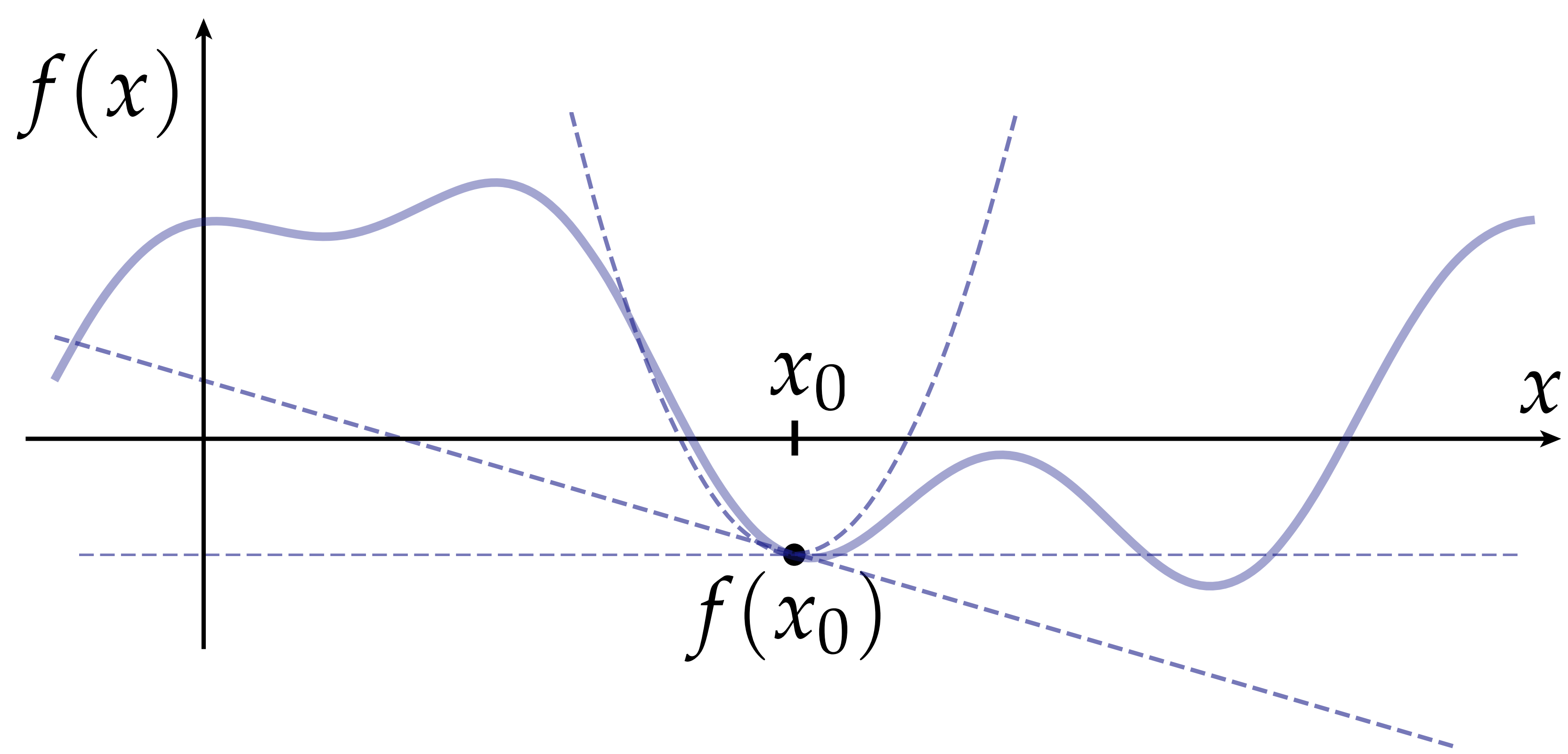


Δf

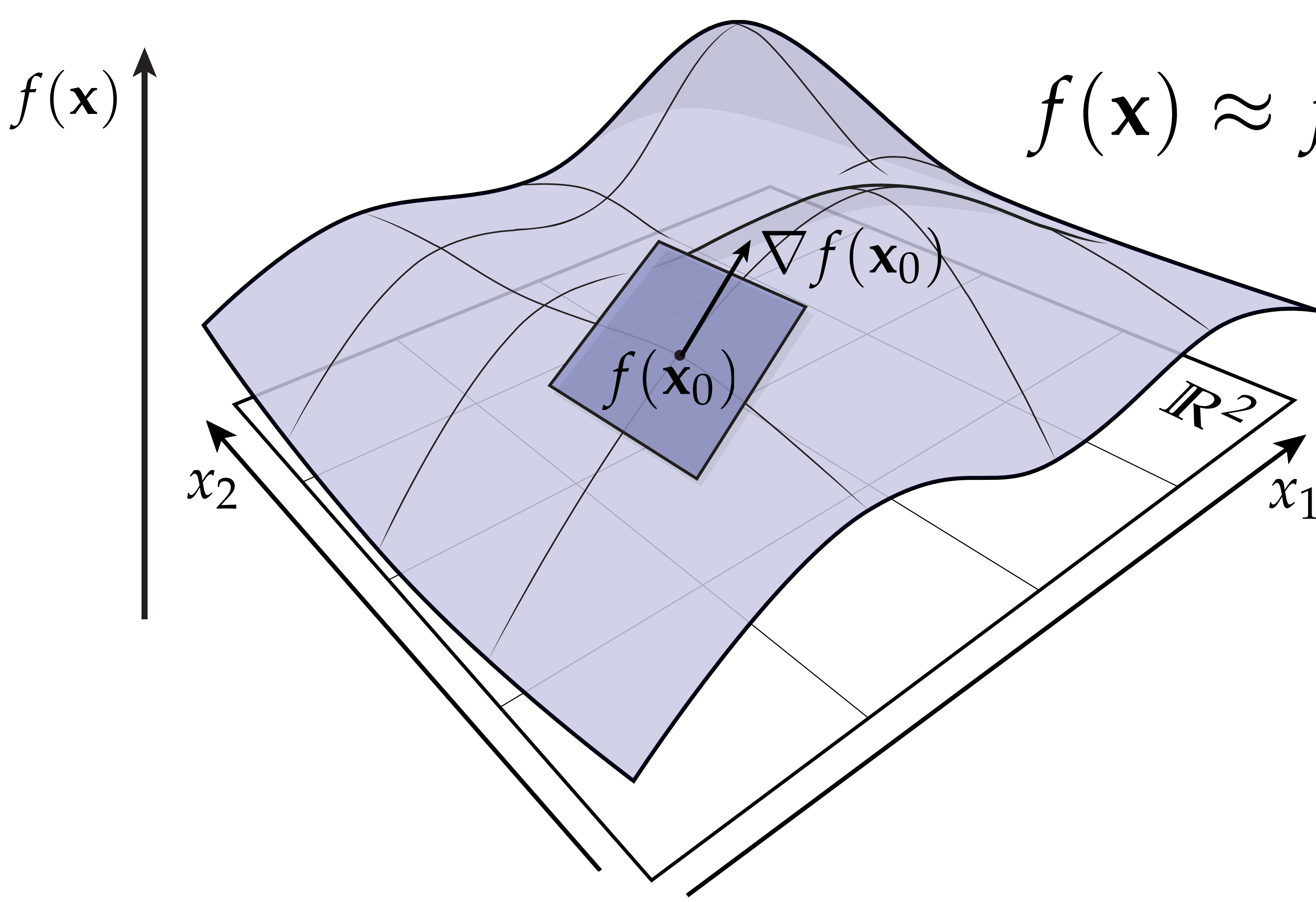
Hessian

- **Our final differential operator—Hessian will help us locally approximate complicated functions by a few simple terms**
- **Recall our Taylor series**

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{(x-x_0)^2}{2!} f''(x_0) + \cdots$$



- **How do we do this for multivariable functions?**
- **Already talked about best linear approximation, using gradient:**



$$f(\mathbf{x}) \approx f(\mathbf{x}_0) + \langle \nabla f(\mathbf{x}_0), \mathbf{x} - \mathbf{x}_0 \rangle$$

Hessian gives us next, "quadratic" term.

Hessian in Coordinates

- Typically denote Hessian by symbol
- Just as gradient was "vector that gives us partial derivatives of the function," Hessian is "operator that gives us partial derivatives of the gradient":

$$(\nabla^2 f)\mathbf{u} := D_{\mathbf{u}}(\nabla f)$$

- For a function f(x): $R^n \to R$, can be more explicit:

$$\nabla^2 f := \begin{bmatrix} \frac{\partial^2 f}{\partial x_1 \partial x_1} & \cdots & \frac{\partial^2}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2}{\partial x_n \partial x_n} \end{bmatrix}$$

Q: Why is this matrix always symmetric?

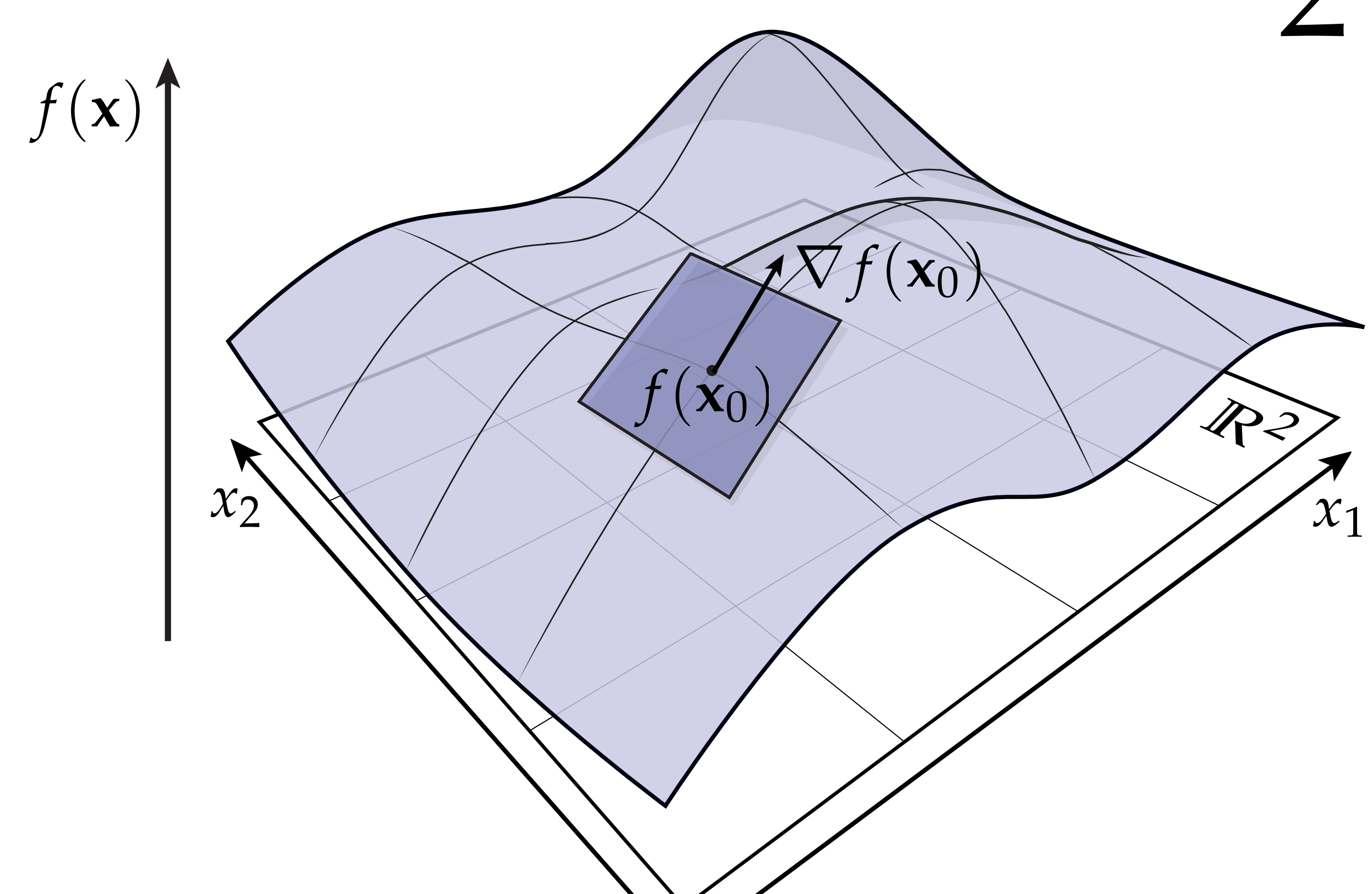
Taylor Series for Multivariable Functions

- Using Hessian, can now write 2nd-order approximation of any smooth, multivariable function f(x) around some point x_0:

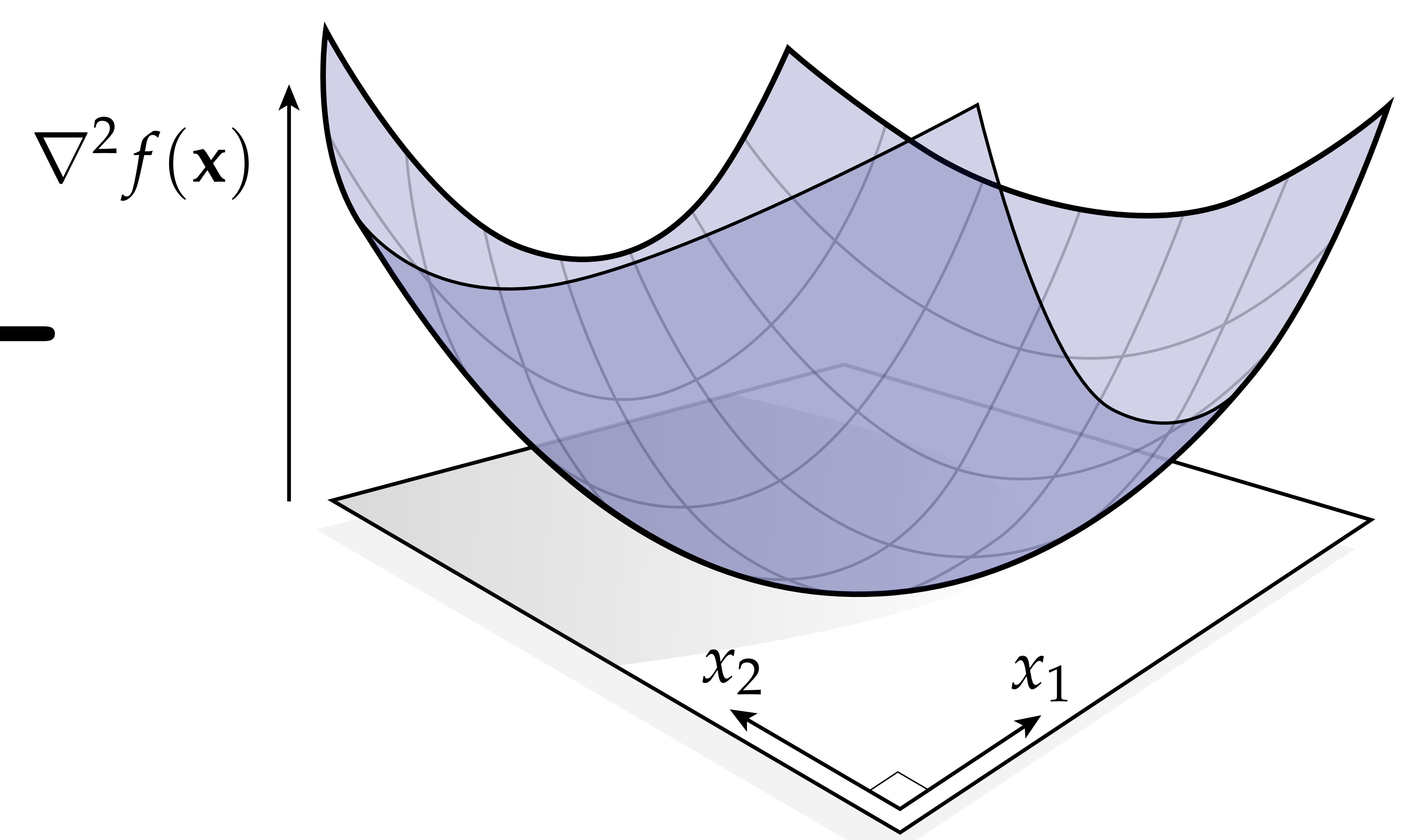
$$f(\mathbf{x}) \approx \underbrace{f(\mathbf{x}_0)}_{c\in\mathbb{R}}^{\text{constant}} + \langle \underbrace{\nabla f(\mathbf{x}_0)}_{\mathbf{b}\in\mathbb{R}^n}^{\text{linear}}, \mathbf{x}-\mathbf{x}_0\rangle + \langle \underbrace{\nabla^2 f(x_0)}_{\mathbf{A}\in\mathbb{R}^{n\times n}}^{\text{quadratic}}(\mathbf{x}-\mathbf{x}_0), \mathbf{x}-\mathbf{x}_0\rangle/2$$

- Can write this in matrix form as

$$f(\mathbf{x}) \approx \frac{1}{2}\mathbf{x}^{\mathsf{T}}\mathbf{A}\mathbf{x} + \mathbf{b}^{\mathsf{T}}\mathbf{x} + c$$



+



Will see later on how this approximation is very useful for optimization!

Next time: Rasterization

- Next time, we'll talk about drawing a triangle
- And it's a lot more interesting than it might seem…
- Also, what's up with these "jagged" lines?