

TMA4115 Matematikk 3

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Lecture 25: The Best of All Possible Worlds

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Key Points

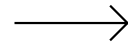
- ▶ Orthogonality + Diagonalisation = Symmetry
- ▶ Comes from Calculus
- ▶ Leads to Topology

Recap

- ▶ Basis of eigenvectors reveals structure
- ▶ Eigenvectors “natural” directions
- ▶ Partial information of eigenvalues classifies behaviour of system

Orthogonal Eigenvectors

ODE + Matrices + Orthogonality



Orthogonal Eigenvectors!

Question

When does A have a basis of orthogonal eigenvectors?

Spectral Theorem

Answer

A has a basis of orthogonal eigenvectors

$$\begin{aligned} &\iff \\ &A^T = A. \end{aligned}$$

Definition

$$\begin{aligned} &A^T = A \\ &\iff \\ &A \text{ is} \\ &\textit{symmetric} \end{aligned}$$

Quick Check in 2D: \implies

$$\left\{ \begin{bmatrix} a \\ b \end{bmatrix}, \begin{bmatrix} -b \\ a \end{bmatrix} \right\}, \quad a^2 + b^2 = 1$$

$$A \begin{bmatrix} a \\ b \end{bmatrix} = \lambda \begin{bmatrix} a \\ b \end{bmatrix}, \quad A \begin{bmatrix} -b \\ a \end{bmatrix} = \mu \begin{bmatrix} -b \\ a \end{bmatrix}$$

$$A \begin{bmatrix} 1 \\ 0 \end{bmatrix} = aA \begin{bmatrix} a \\ b \end{bmatrix} - bA \begin{bmatrix} -b \\ a \end{bmatrix} = \begin{bmatrix} \lambda a^2 + \mu b^2 \\ (\lambda - \mu)ab \end{bmatrix}$$

$$A \begin{bmatrix} 0 \\ 1 \end{bmatrix} = bA \begin{bmatrix} a \\ b \end{bmatrix} + aA \begin{bmatrix} -b \\ a \end{bmatrix} = \begin{bmatrix} (\lambda - \mu)ab \\ \mu a^2 + \lambda b^2 \end{bmatrix}$$

Quick Check in 2D: \Leftarrow

$$A = \begin{bmatrix} a & b \\ b & d \end{bmatrix}$$

$$c(\lambda) = \lambda^2 - (a + d)\lambda + (ad - b^2)$$

$$\frac{(a + d) \pm \sqrt{a^2 + 2ad + d^2 - 4ad + 4b^2}}{2}$$

Conclusion: Always at least one **real** eigenvalue

Quick Check in 2D: \Leftarrow

Suppose

$$\begin{bmatrix} a & b \\ b & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \lambda \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} ax + by \\ bx + dy \end{bmatrix}$$

$$-ayx + bx^2 - by^2 + dxy = \begin{bmatrix} x \\ y \end{bmatrix} \cdot \alpha \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} x \\ y \end{bmatrix} \cdot \beta \begin{bmatrix} -y \\ x \end{bmatrix} = \alpha$$

Conclusion:

$$\begin{bmatrix} a & b \\ b & d \end{bmatrix} \begin{bmatrix} -y \\ x \end{bmatrix} = 0 \begin{bmatrix} x \\ y \end{bmatrix} + \beta \begin{bmatrix} -y \\ x \end{bmatrix}$$

Symmetric Matrices from Functions

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}, \quad f(x, y)$$

Partial derivatives

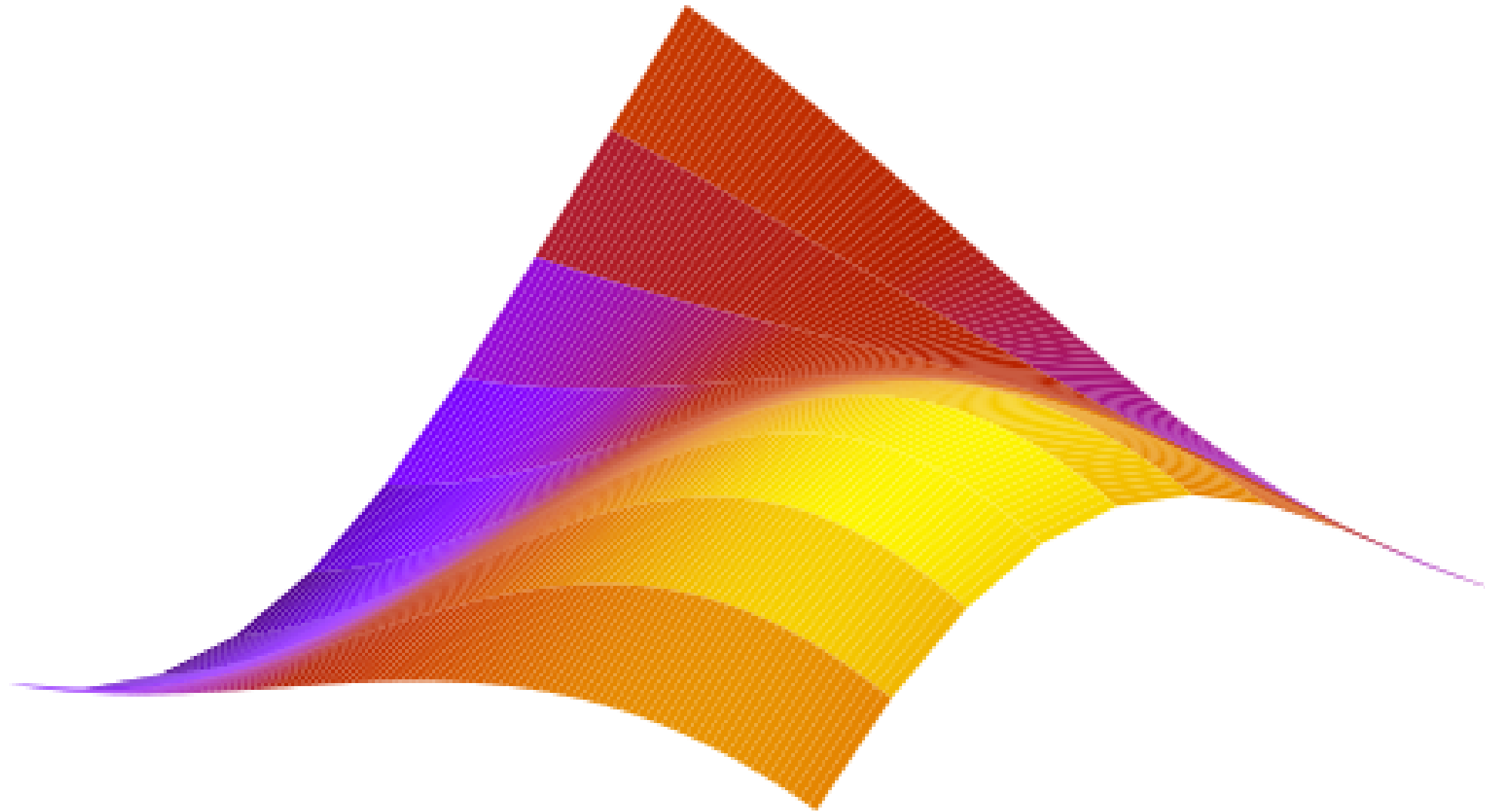
$$\frac{\partial f}{\partial x}(x, y) := \lim_{h \rightarrow 0} \frac{1}{h} (f(x + h, y) - f(x, y))$$

Gradient

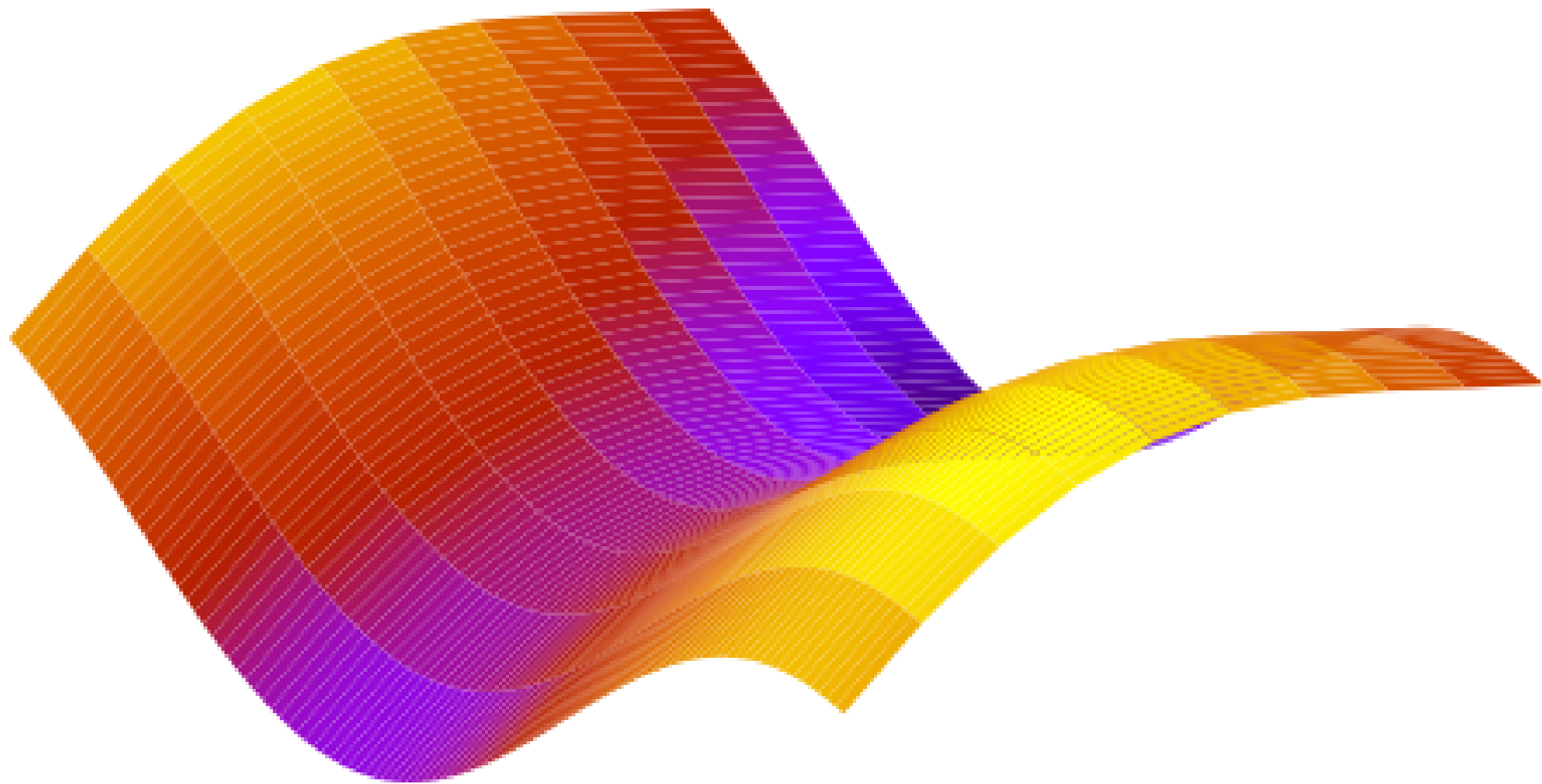
$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Points in the direction of greatest change in f

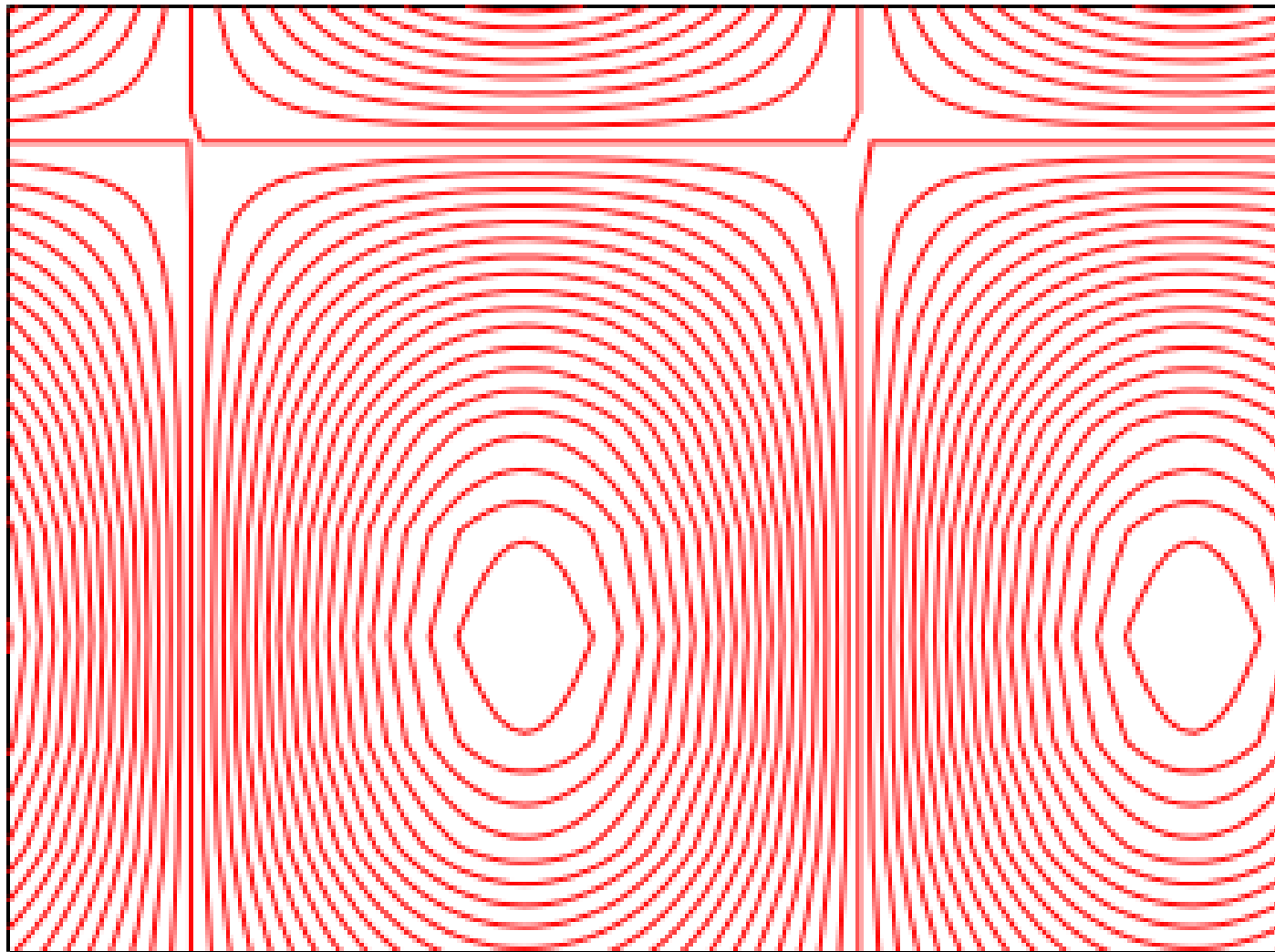
Some Examples



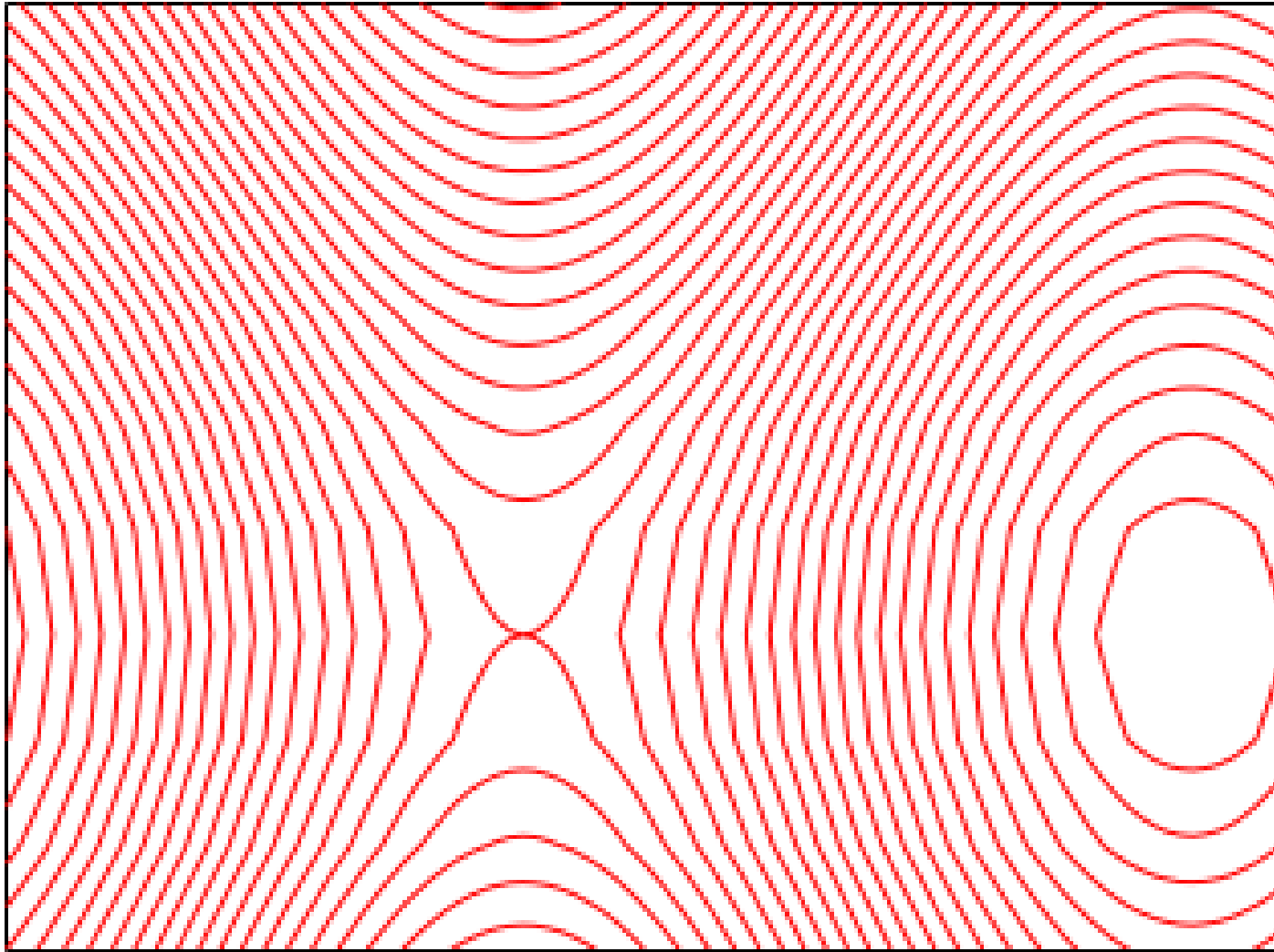
Some Examples



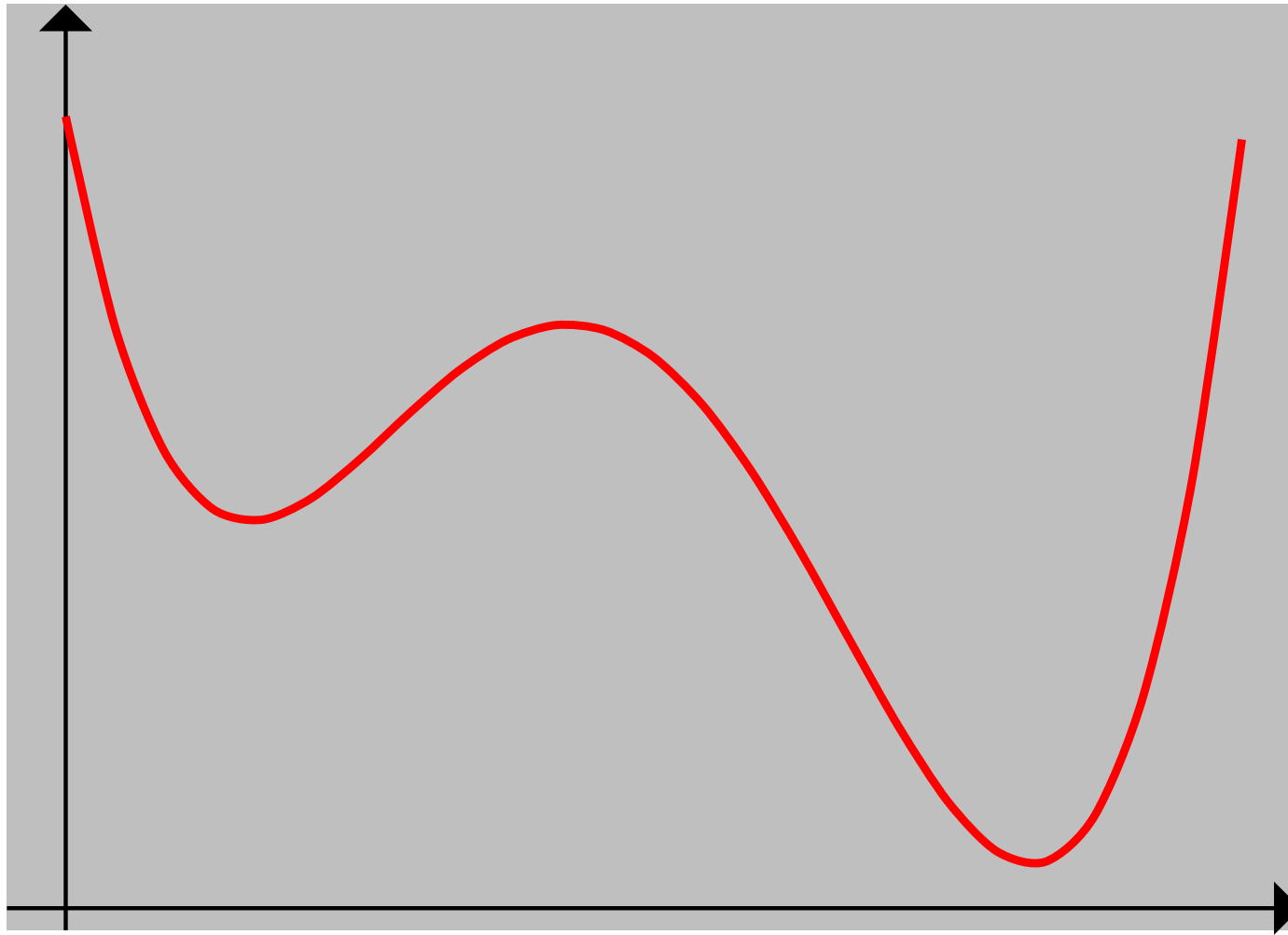
Some Examples



Some Examples



Interesting In Parts



View from Far Away

Remark

The **interesting** parts of a function are where it changes direction.

Reminder

$g: \mathbb{R} \rightarrow \mathbb{R}$

- ▶ Critical Point: $g'(t_0) = 0$
- ▶ $g''(t_0) > 0 \implies$ minimum
- ▶ $g''(t_0) < 0 \implies$ maximum
- ▶ $g''(t_0) = 0 \implies$ need more information

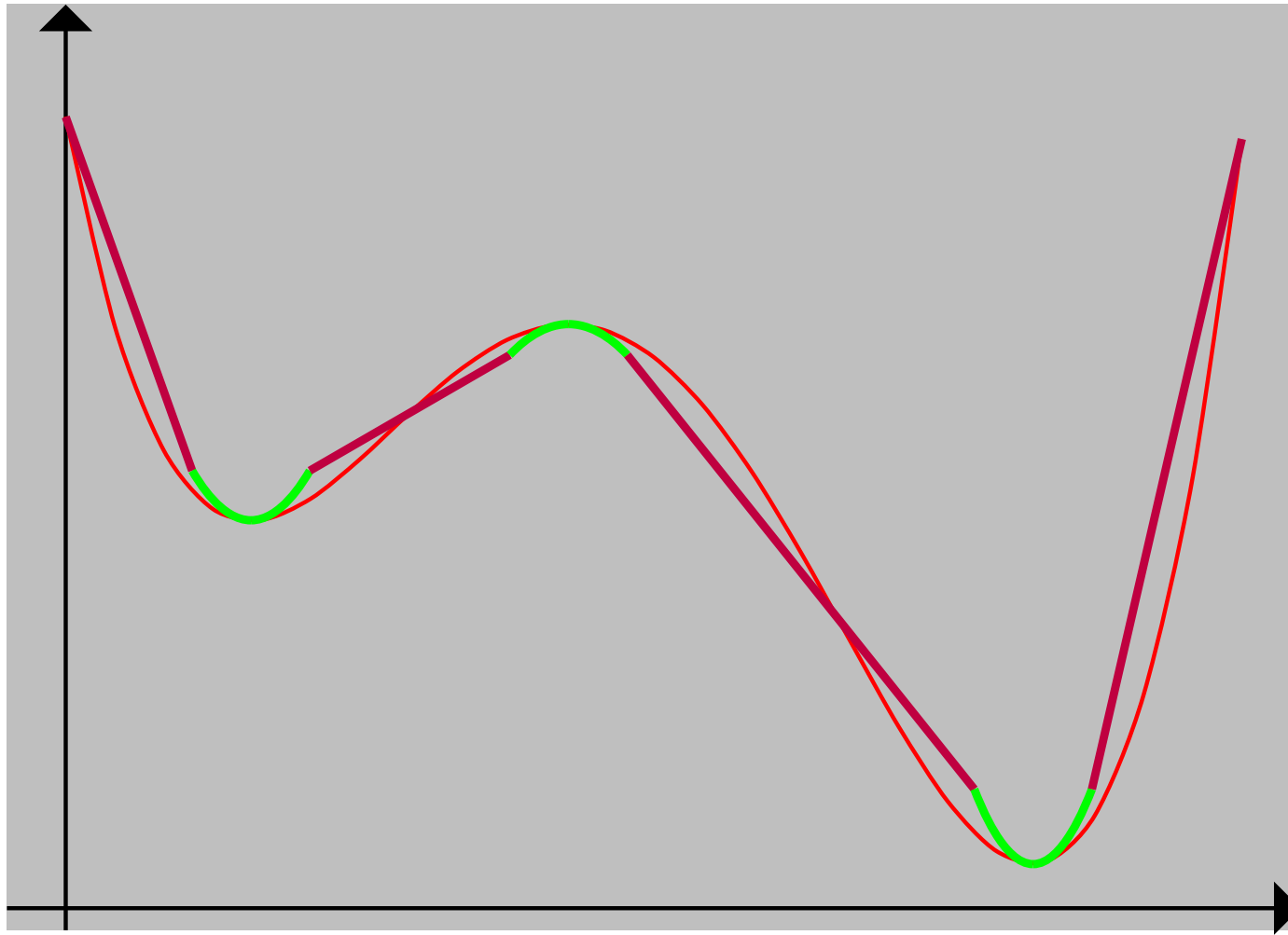
In Close-Up

$$g'(t_0) = 0 \implies$$

$$g(t_0 + h) \simeq g(t_0) + h^2 g''(t)$$

If g is “good”, put a quadratic at each critical point and join up via straight lines.

Joined-Up Functions



Higher Dimensions

First Approximation

$$f(x + h, y + k) \simeq f(x, y) + h \frac{\partial f}{\partial x}(x, y) + k \frac{\partial f}{\partial y}(x, y)$$

Second Approximation

$$\text{From: } \frac{\partial f}{\partial x}(x + h, y + k) \simeq \frac{\partial f}{\partial x} + h \frac{\partial^2 f}{\partial x^2} + k \frac{\partial^2 f}{\partial y \partial x}$$

$$\begin{aligned} \text{Get: } f(x + h, y + k) &\simeq f + h \frac{\partial f}{\partial x} + k \frac{\partial f}{\partial y} \\ &+ h^2 \frac{\partial^2 f}{\partial x^2} + hk \frac{\partial^2 f}{\partial y \partial x} \\ &+ k^2 \frac{\partial^2 f}{\partial y^2} + kh \frac{\partial^2 f}{\partial y \partial x} \end{aligned}$$

Critical Points

If $\nabla f(x, y) = \mathbf{0}$

$$f \simeq f(x, y) + h^2 \frac{\partial^2 f}{\partial x^2} + 2hk \frac{\partial^2 f}{\partial x \partial y} + k^2 \frac{\partial^2 f}{\partial y^2}$$

Connection with matrices

$$h \frac{\partial f}{\partial x} + k \frac{\partial f}{\partial y} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \cdot \begin{bmatrix} h \\ k \end{bmatrix}$$

$$h^2 \frac{\partial^2 f}{\partial x^2} + 2hk \frac{\partial^2 f}{\partial x \partial y} + k^2 \frac{\partial^2 f}{\partial y^2} = \begin{bmatrix} h \\ k \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \begin{bmatrix} h \\ k \end{bmatrix}$$

Quadratic Forms

Near a “good” **critical point**, $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ behaves like:

$$\begin{bmatrix} x \\ y \end{bmatrix} \cdot \begin{bmatrix} a & b \\ b & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = ax^2 + 2bxy + dy^2$$

Definition

$$ax^2 + 2bxy + dy^2$$

is a **quadratic form**

Orthogonal Diagonalisation

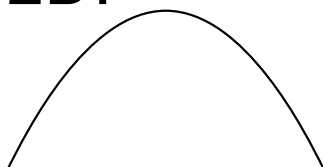
$$A = A^T, A\mathbf{u} = \mu\mathbf{u}, A\mathbf{v} = \nu\mathbf{v}, \mathbf{u} \bullet \mathbf{v} = 0$$

$$(\alpha\mathbf{u}) \bullet A(\alpha\mathbf{u}) = (\alpha\mathbf{u}) \bullet \mu(\alpha\mathbf{u}) = \mu\alpha^2$$

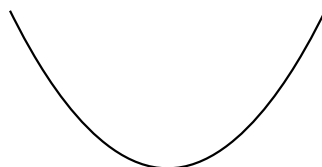
$$(\alpha\mathbf{u} + \beta\mathbf{v}) \bullet A(\alpha\mathbf{u} + \beta\mathbf{v}) = \mu\alpha^2 + \nu\beta^2$$

Possibilities

▶ 2D:

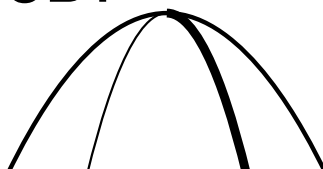


$$-x^2$$

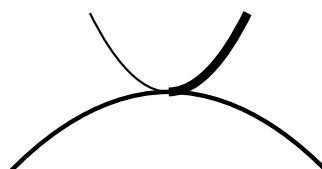


$$x^2$$

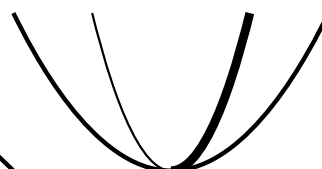
▶ 3D:



$$-x^2 - y^2$$

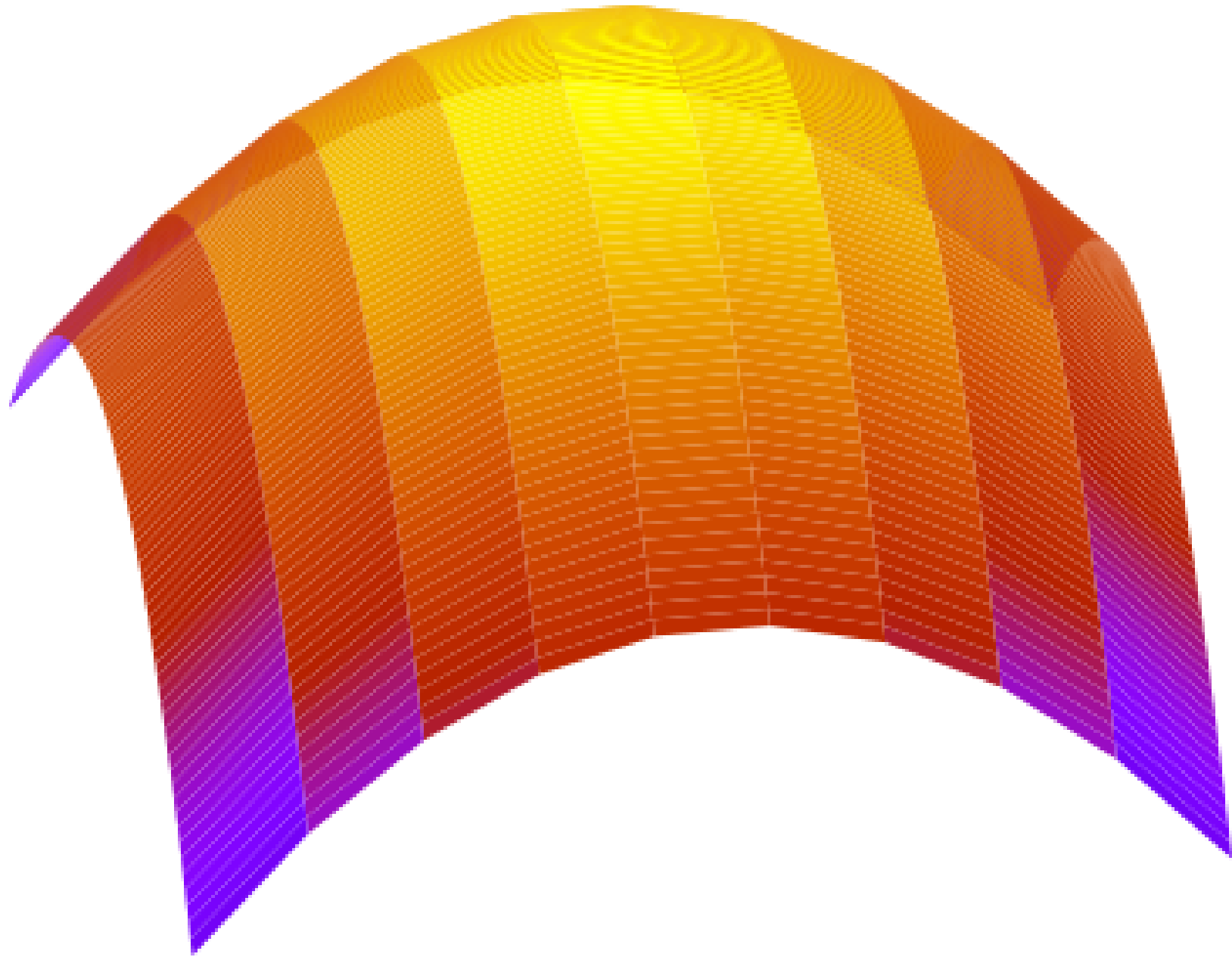


$$-x^2 + y^2$$

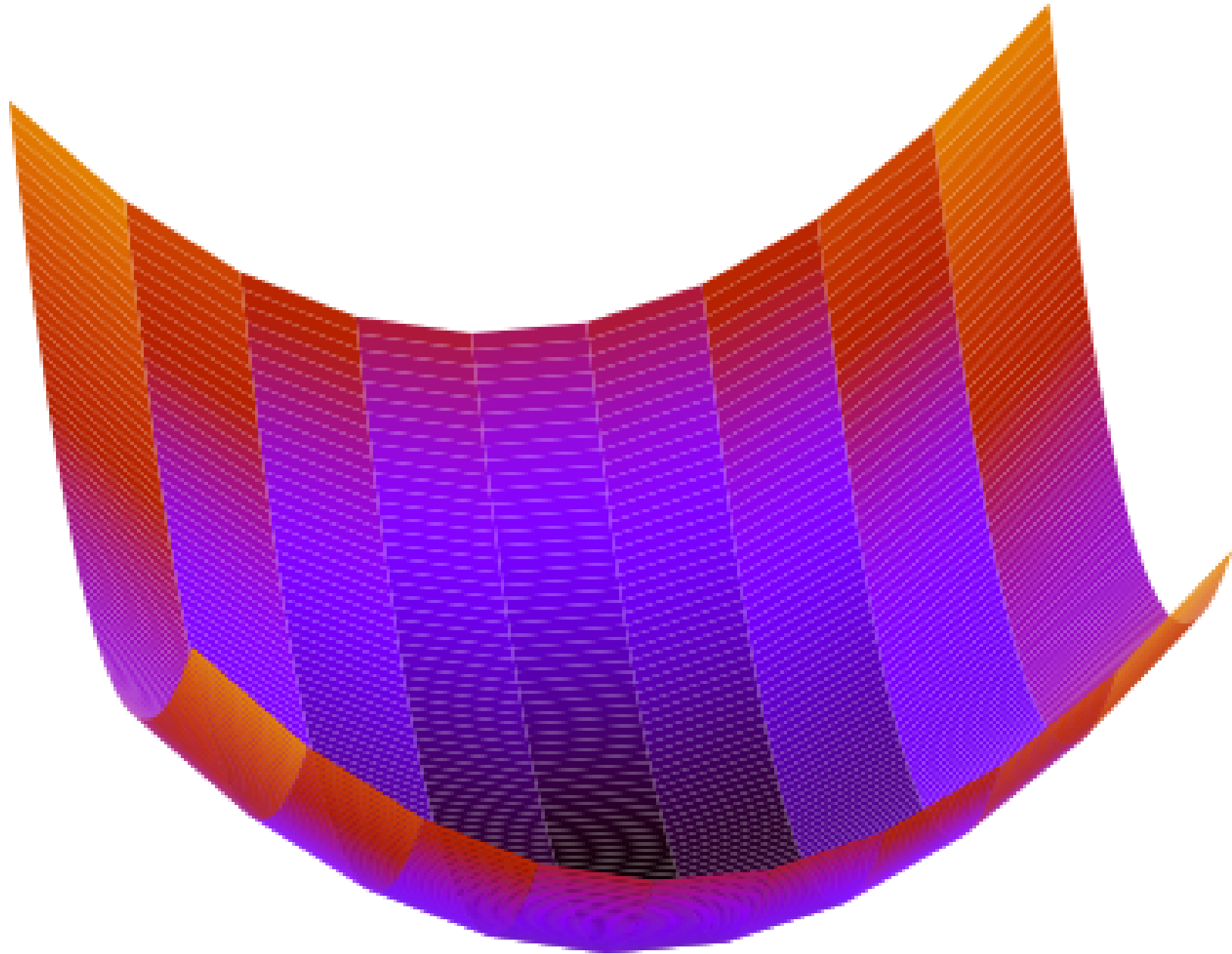


$$x^2 + y^2$$

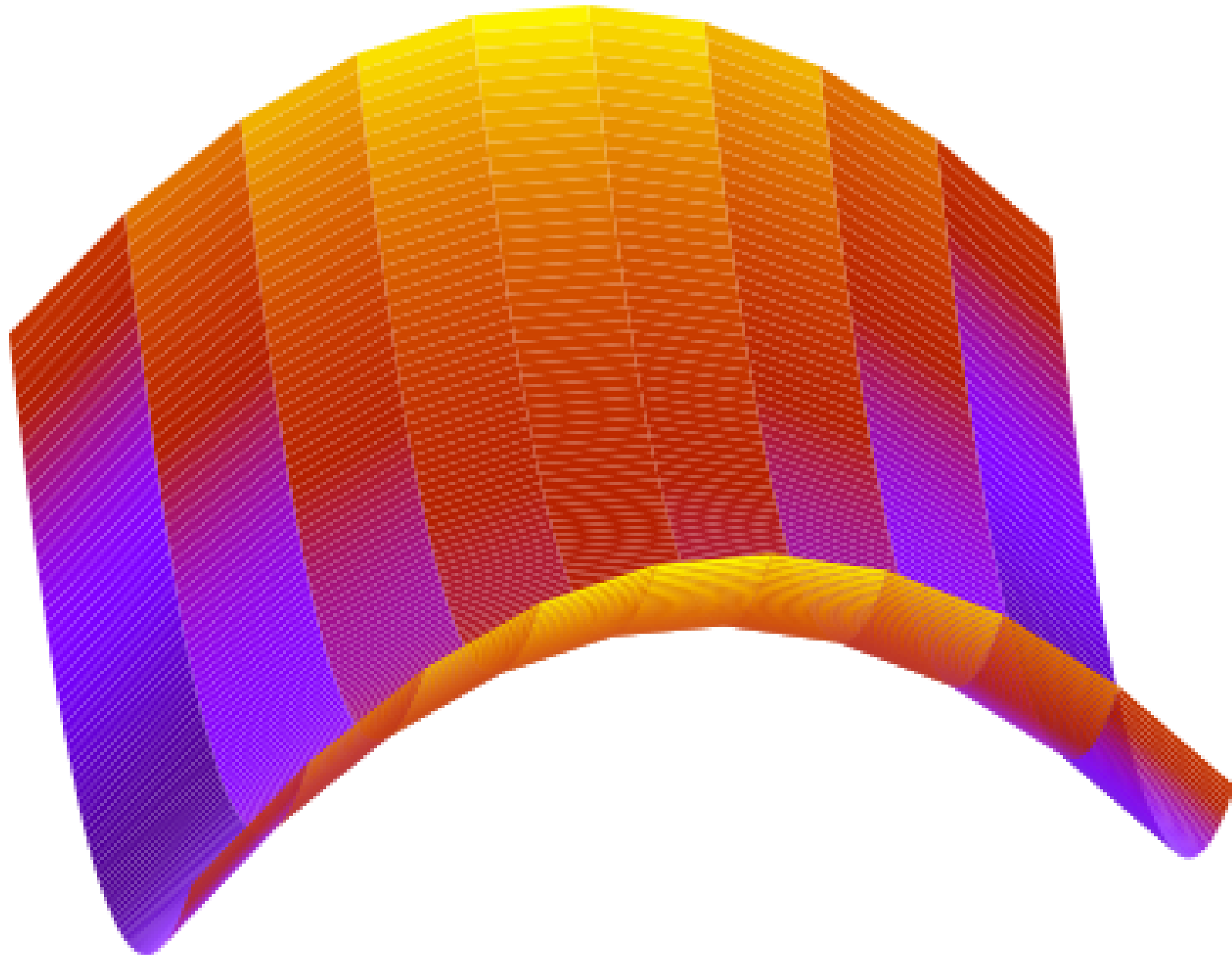
Maximum



Minimum



Saddle Point

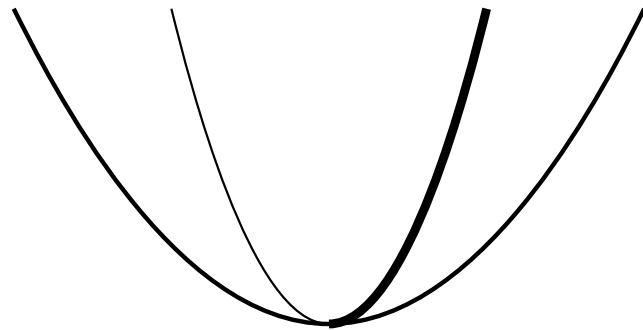
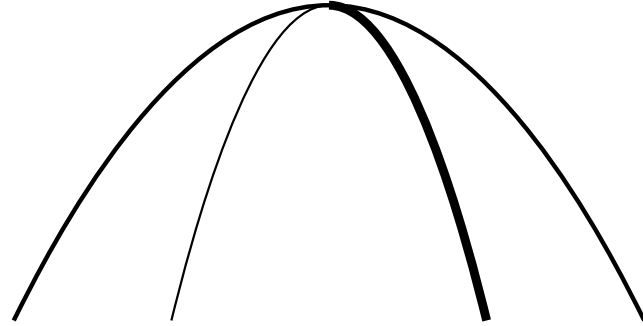


Reconstructing Surfaces

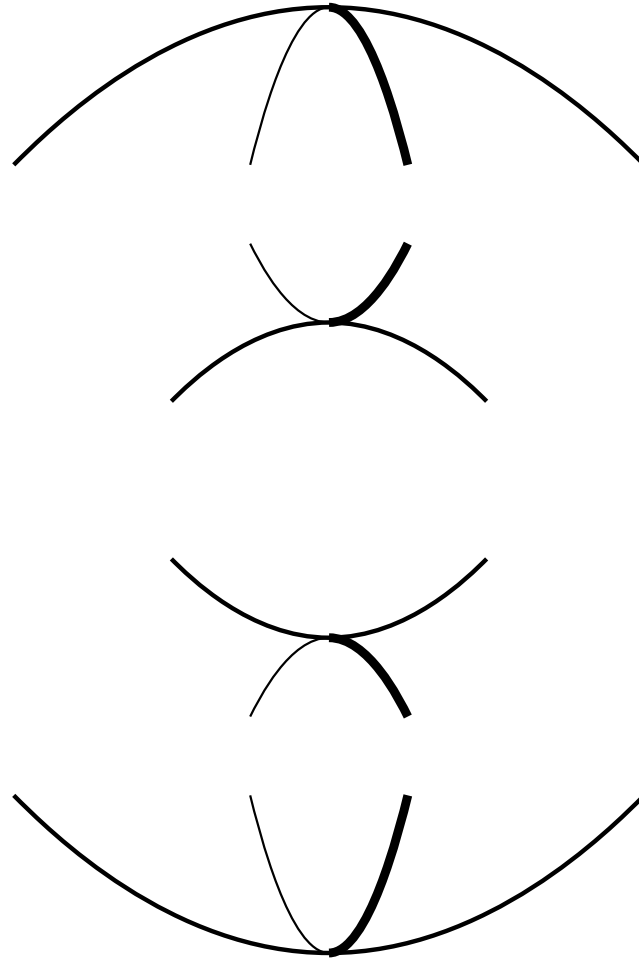
$$S \subseteq \mathbb{R}^3 \xrightarrow{f} \mathbb{R}$$

- ▶ Look at points where $\nabla f = \mathbf{0}$
- ▶ Classify by number of negative eigenvalues of $[\partial^2 f]$
- ▶ Stick together

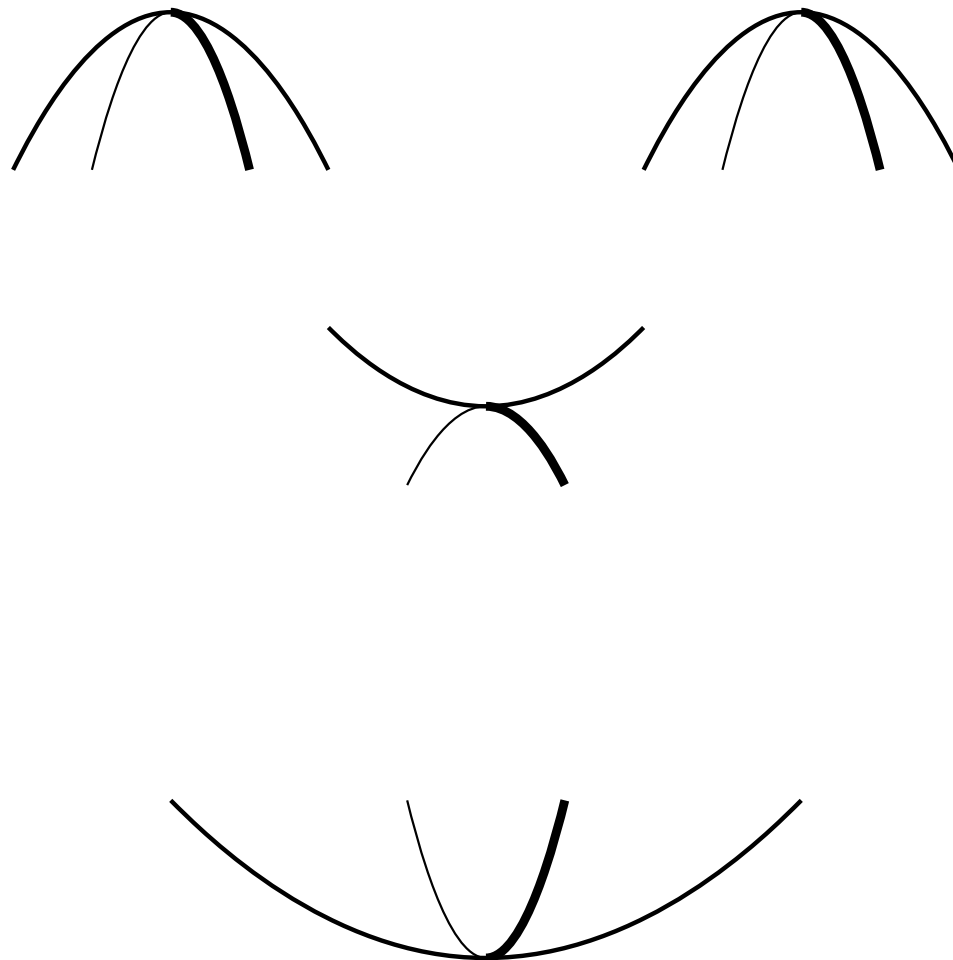
Sphere



Torus



Deformed Sphere



Which is Which

$$S \subseteq \mathbb{R}^3 \xrightarrow{f} \mathbb{R}$$

- ▶ Look at points where $\nabla f = \mathbf{0}$
- ▶ Classify by number of negative eigenvalues of $[\partial^2 f]$
- ▶ Count: $\#2 - \#1 + \#0$
 - ▶ Sphere: $1 - 0 + 1 = 2$
 - ▶ Torus: $1 - 2 + 1 = 0$
 - ▶ Deformed Sphere: $2 - 1 + 1 = 2$
 - ▶ Two-Holed Torus: $1 - 4 + 1 = -2$

Classification

This number **classifies** (certain) surfaces completely!

And ...

That's what I do!

Summary

- ▶ Symmetric \iff orthogonally diagonalisable
- ▶ Symmetric from differentiation
- ▶ Leads to . . . Topology!