

# Untangling Knots Through Curve Repulsion

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# What the curious folks ponder about

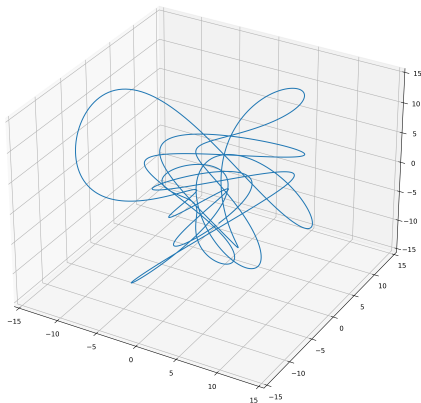
1 Introduction

2 Tangent-Point Energy

3 Gradient Flow

# Introduction

# A Cool Knot



**Figure:** Imagine your earphones getting tangled like this...

- Finding a “homotopy” from a knot to an unknot.

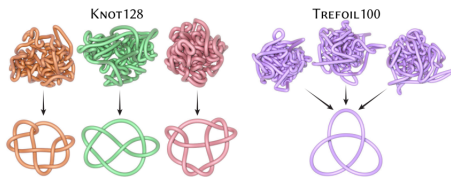


Figure: Unknots of test knots.[3]

- Finding a “homotopy” from a knot to an unknot.

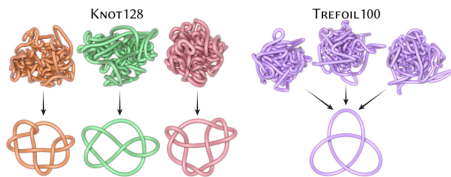


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- “Avoiding self-intersection”

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  - We evolve the curve according to the gradient flow equation.
  - There is a freedom in choosing the “gradient” here.



# General Strategy

- ① Define curve energy; penalizing the closeness of points on a curve.
  - Extreme-closeness of points on curve is a natural characteristic of a tangled curve.
- ② Attempt to decrease the curve energy by continuously deforming the curve.
  - We evolve the curve according to the gradient flow equation.
  - There is a freedom in choosing the “gradient” here.
- ③ We expect the stationary state to be the “unknot”
  - Or at least a simpler state...

# Tangent-Point Energy

# Defining Curve Energy

Given an (arc-length parameterised) curve  $\gamma : M \rightarrow \mathbb{R}^3$ , we wish to assign energy of the form:

$$\mathcal{E}(\gamma) := \iint_{M^2} k(\gamma_x, \gamma_y) \, d\gamma_x \, d\gamma_y \quad (1)$$

such that

- $\mathcal{E}$  is very high when two non-neighbouring points are very close.

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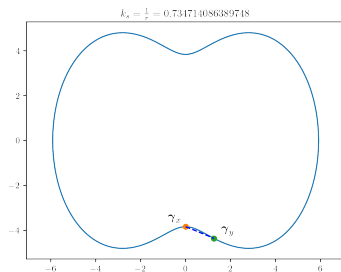
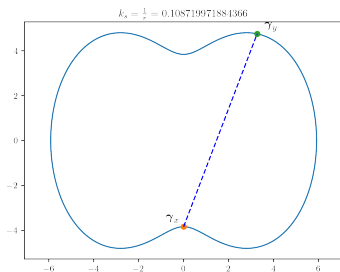
such that

- $\mathcal{E}$  is very high when two non-neighbouring points are very close.

A naïve choice is  $k(\gamma_x, \gamma_y) := \frac{1}{\|\gamma_x - \gamma_y\|}$

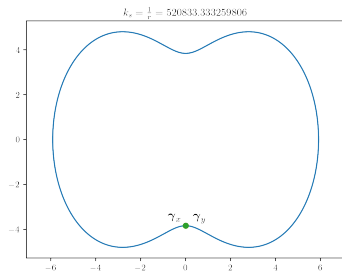
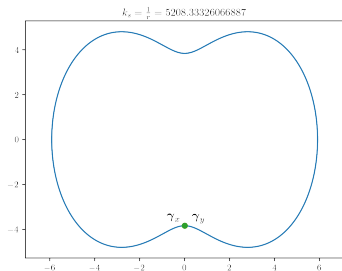
# Pitfall of the “Simple Energy”

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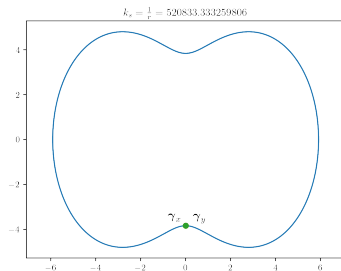
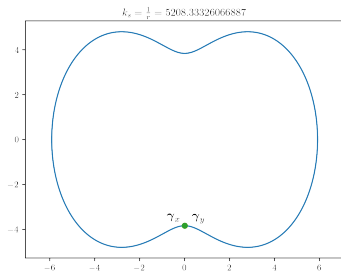
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This energy is not well-defined for a lot of curves!

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# Buck-Orloff Tangent-Point Energy

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## Definition (Buck-Orloff Tangent-Point Energy)

For a smooth curve  $\gamma$ , define

$$\mathcal{E}(\gamma) := \iint_{M^2} k_4^2(\gamma_x, \gamma_y, \mathbf{T}_x) \, d\gamma_x \, d\gamma_y$$

where  $\mathbf{T}_x$  is the unit tangent vector at  $\gamma_x$ , with the kernel defined as

$$k_4^2(\mathbf{p}, \mathbf{q}, \mathbf{T}) := \frac{\|\mathbf{T} \wedge (\mathbf{p} - \mathbf{q})\|^2}{\|\mathbf{p} - \mathbf{q}\|^4}$$

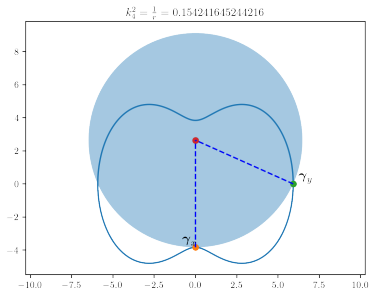
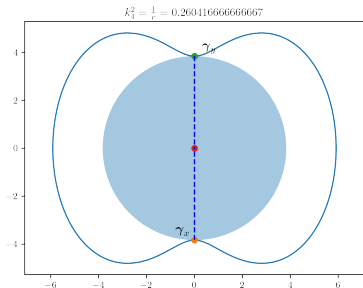
as **Buck-Orloff Tangent-Point Energy**. [1]

# Intuition

What is the intuition behind the kernel  $k_4^2(\mathbf{p}, \mathbf{q}, \mathbf{T}) := \frac{\|\mathbf{T} \wedge (\mathbf{p} - \mathbf{q})\|^2}{\|\mathbf{p} - \mathbf{q}\|^4}$ ?

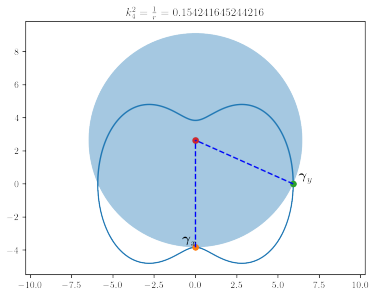
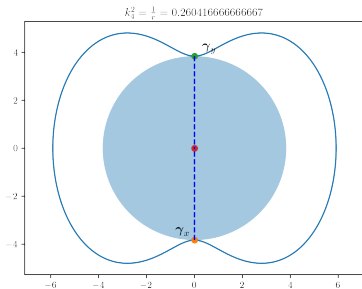
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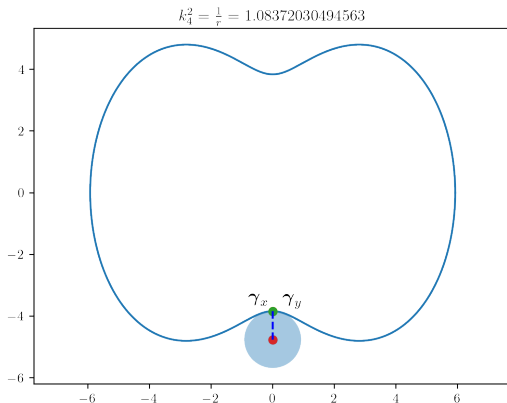
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## Remark

Note that closer does not necessarily mean the kernel is larger.

# Intuition



**Figure:** When two points are very close, the kernel converges to the curvature of the curve.

# Example: Buck-Orloff Tangent-Point Energy of a Circle

## Example

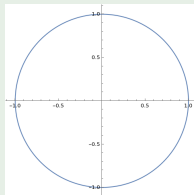
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$$\gamma(t) = (\cos t, \sin t, 0)$$

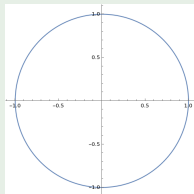


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Then write:

$$\begin{cases} \gamma_x(\theta) = (\cos \theta, \sin \theta, 0) \\ \gamma_y(\phi) = (\cos \phi, \sin \phi, 0) \\ \mathbf{T}_x(\theta) = (-\sin \theta, \cos \theta, 0) \end{cases}$$



## Example (Cont.)

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Substituting to Buck-Orloff Tangent-Point energy formula:

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Using a few identities:

$$\mathcal{E}(\gamma) = \int_{\theta=0}^{2\pi} \int_{\phi=0}^{2\pi} \frac{\|\mathbf{T}_x\|^2 \|\gamma_x - \gamma_y\|^2 - (\mathbf{T}_x \cdot (\gamma_x - \gamma_y))^2}{\|\gamma_x - \gamma_y\|^4} d\theta d\phi$$

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$$= \int_{\theta=0}^{2\pi} \int_{\phi=0}^{2\pi} \frac{\sin^2 \frac{\theta-\phi}{2}}{(-1 + \cos(\theta - \phi))^2} d\theta d\phi \quad (3)$$

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## Remark

Note that (4) suggests the order at “singularity” is inverse-square.

# General Tangent-Point Energy

A more general form of tangent-point energy comes from Yu, Schumacher, and Crane [3]:

## Definition (Generalised Tangent-Point Energy)

$$\mathcal{E}_\beta^\alpha(\gamma) := \iint_{M^2} \frac{\|\mathbf{T}_x \wedge (\gamma_x - \gamma_y)\|^\alpha}{\|\gamma_x - \gamma_y\|^\beta} d\gamma_x d\gamma_y$$

where  $\alpha > 1$  and  $\beta \in [\alpha + 2, 2\alpha + 1)$

## Remark

When  $\alpha = 2$  and  $\beta = 4$ , we are back to Buck-Orloff.

# Gradient Flow

# Motivating Gradient Flow

A simple method of minimising a (differentiable) function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is the steepest descent [2]

$$\mathbf{x}^{k+1} = \mathbf{x}^k - \alpha_k \nabla f(\mathbf{x}^k) \quad (6)$$

where  $\alpha^k > 0$ .

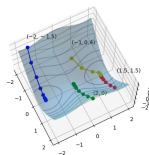


Figure: Steepest Descent

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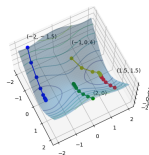


Figure: Steepest Descent

For motivation, take  $\alpha^k = \alpha \equiv \text{const.}$



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In the case of functional  $\mathcal{E} : X \rightarrow \mathbb{R}$ , analogously write steepest descent step:

$$f^{k+1} = f^k - \alpha \operatorname{grad}_X f$$

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Take limit as  $\Delta t \rightarrow 0$ , then scale time variable to nondimensionalise to get the gradient flow equation.

### Definition (Gradient Flow Equation)

$$\frac{\partial f}{\partial t} = -\operatorname{grad}_X f$$

But what is  $\operatorname{grad}_X f$ ?

# Gradient in Space of Function?

(Gradient of Function)

$\nabla f(\mathbf{x})$  is such that for all  $\mathbf{y} \in \mathbb{R}^n$

$$\nabla f(\mathbf{x}) \cdot \mathbf{y} = \left. \frac{\partial}{\partial \epsilon} f(\mathbf{x} + \epsilon \mathbf{y}) \right|_{\epsilon=0}$$

(Gradient of Functional)

$\text{grad}_X E(f)$  is such that for all  $g \in X$ ,

$$\langle \langle \text{grad}_X E, g \rangle \rangle_X = \left. \frac{\partial}{\partial \epsilon} E(f + \epsilon g) \right|_{\epsilon=0}$$

- [1] Gregory Buck and Jeremey Orloff. “A simple energy function for knots”. In: *Topology and its Applications* 61.3 (Feb. 1995), pp. 205–214. DOI: [10.1016/0166-8641\(94\)00024-w](https://doi.org/10.1016/0166-8641(94)00024-w).
- [2] “Chapter 8: Primal and Dual Projected Subgradient Methods”. In: *First-Order Methods in Optimization*, pp. 195–245. DOI: [10.1137/1.9781611974997.ch8](https://doi.org/10.1137/1.9781611974997.ch8). eprint: <https://epubs.siam.org/doi/pdf/10.1137/1.9781611974997.ch8>. URL: <https://epubs.siam.org/doi/abs/10.1137/1.9781611974997.ch8>.
- [3] Chris Yu, Henrik Schumacher, and Keenan Crane. “Repulsive Curves”. In: *ACM Transactions on Graphics* 40.2 (Apr. 2021), pp. 1–21. DOI: [10.1145/3439429](https://doi.org/10.1145/3439429).