

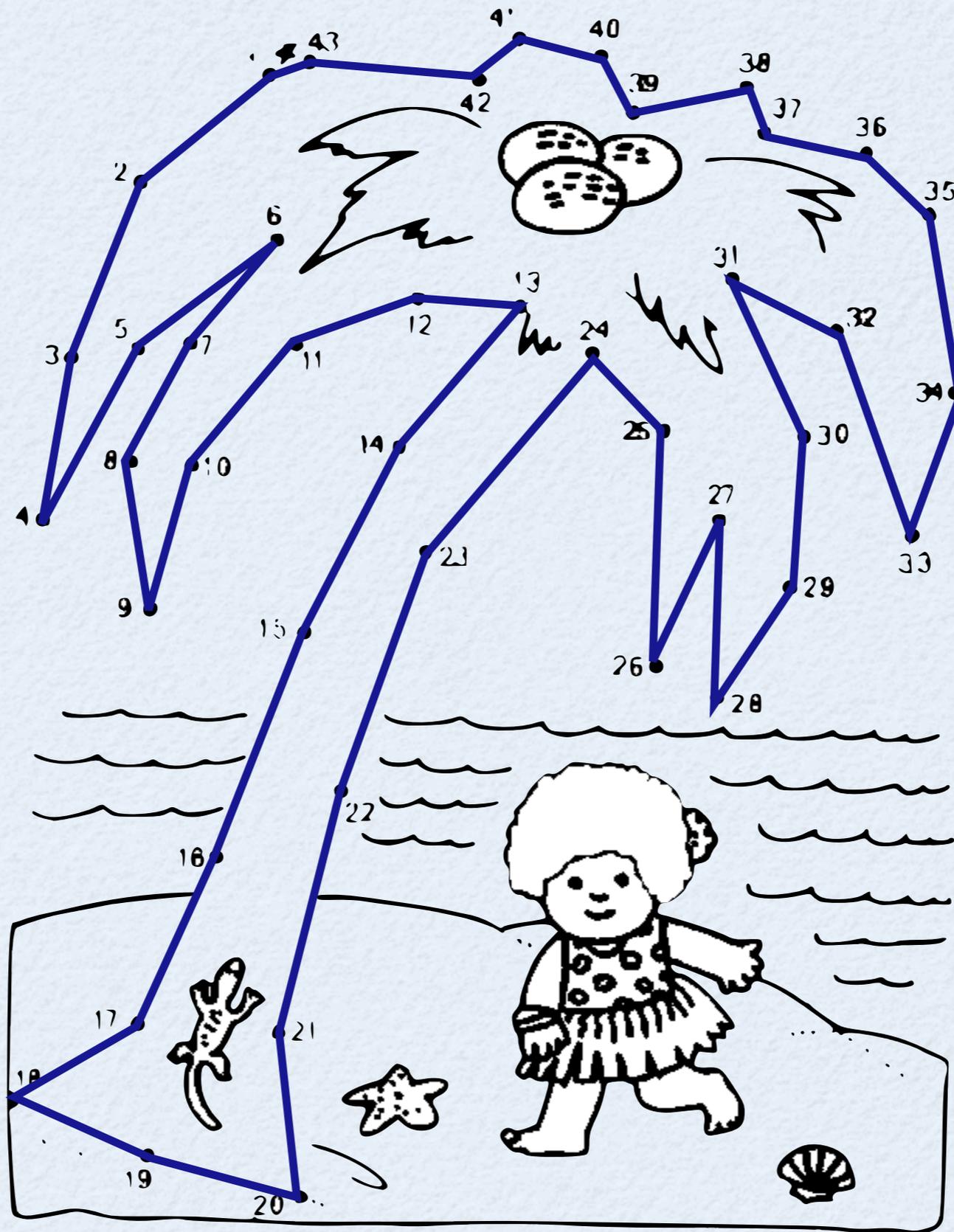
# Flow-Based Methods in Manifold Reconstruction

Bardia Sadri  
Duke University

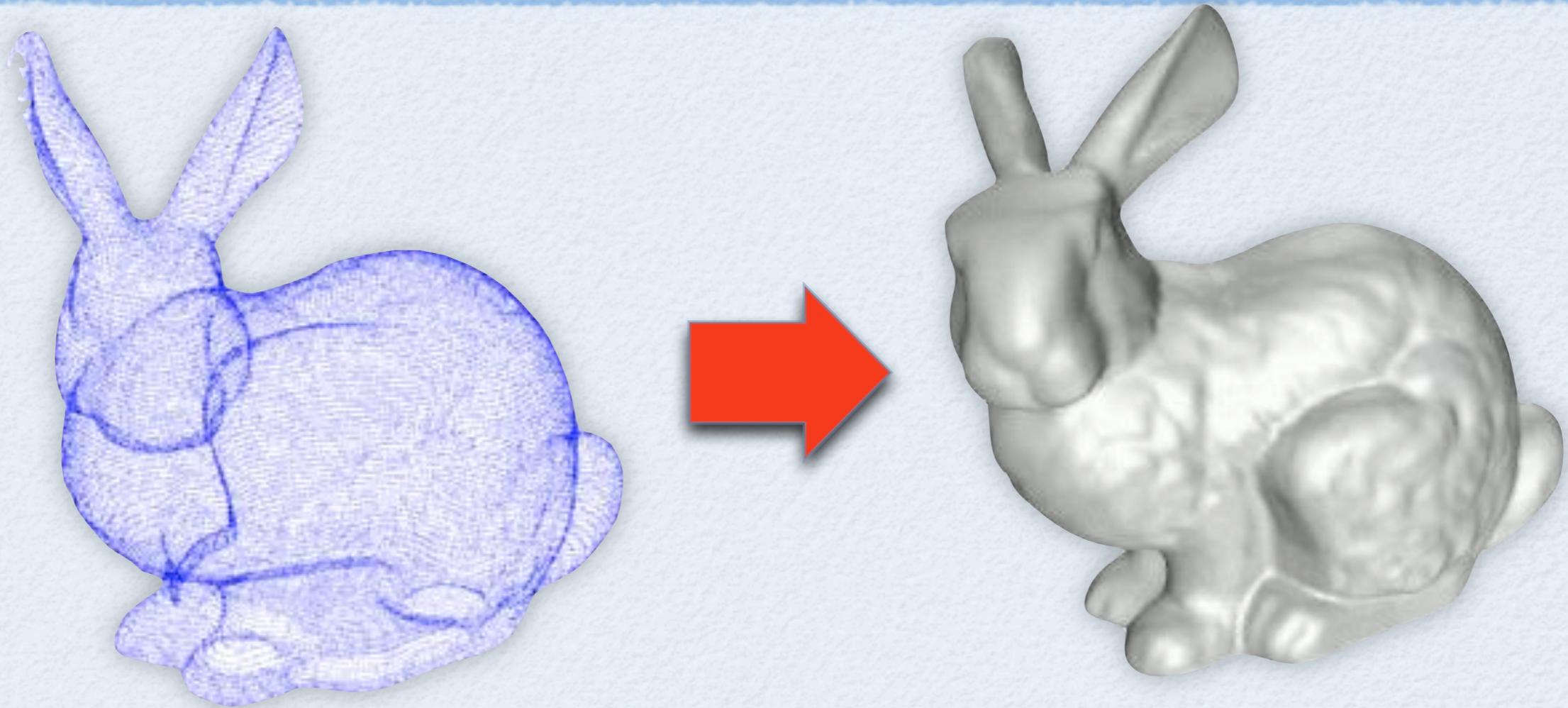
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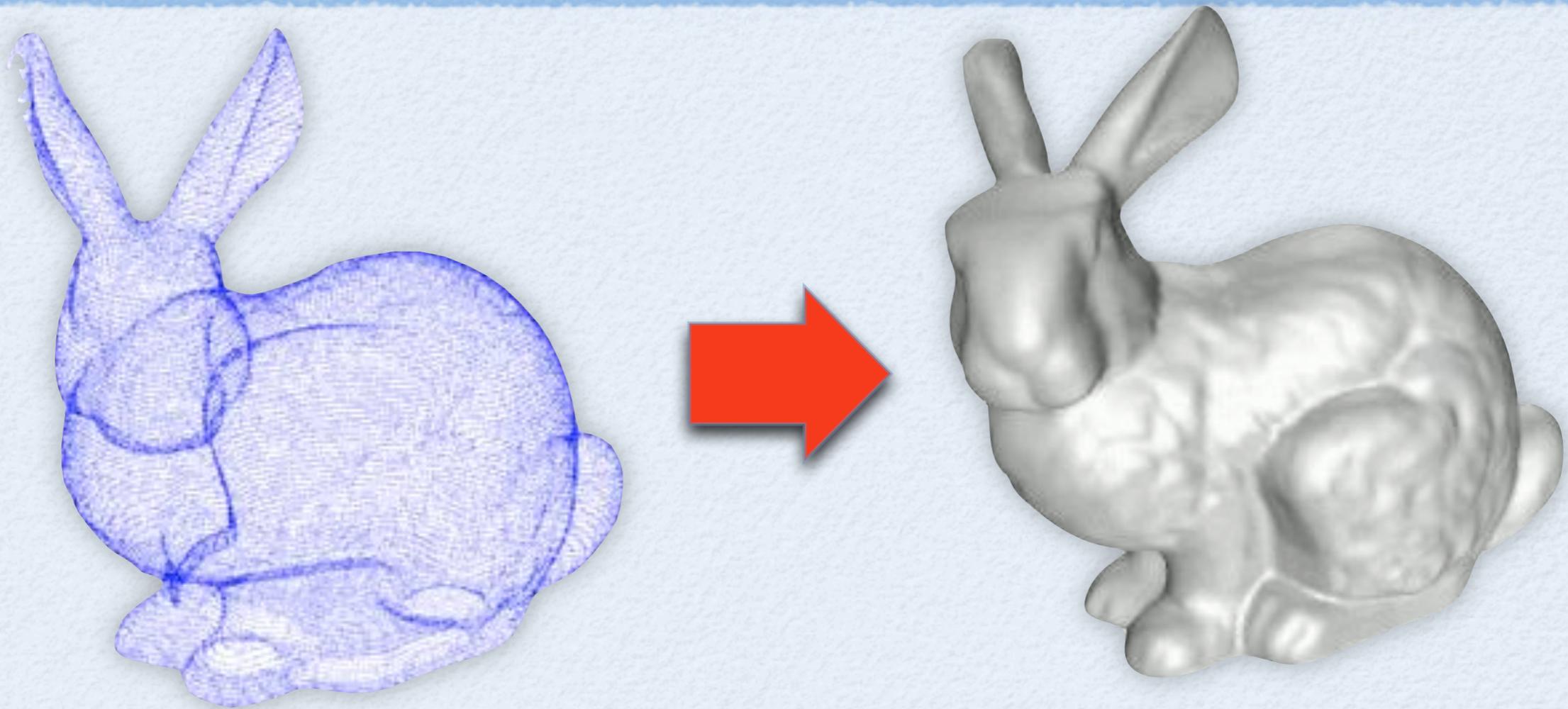


# Surface (manifold) reconstruction



Given a **point cloud** sampled from a **surface**  $\Sigma$ , we want to compute a surface  $\hat{\Sigma}$  that has the **same topology** as  $\Sigma$  and closely approximates it **geometrically**.

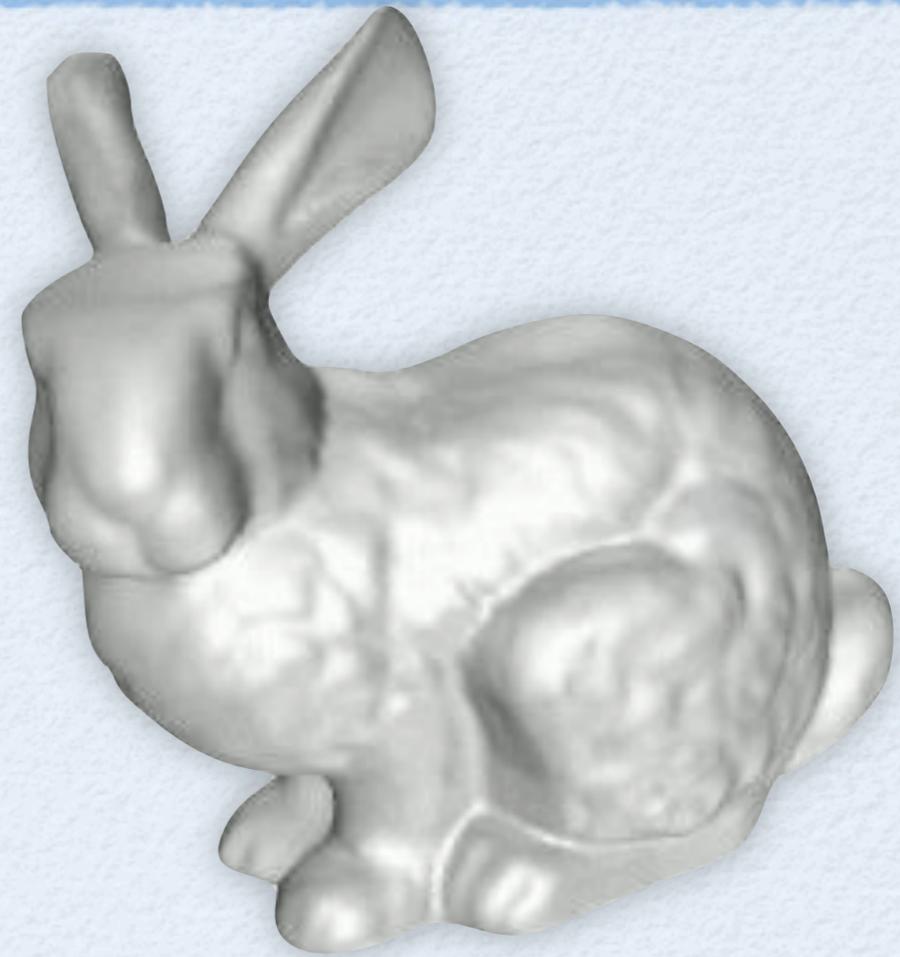
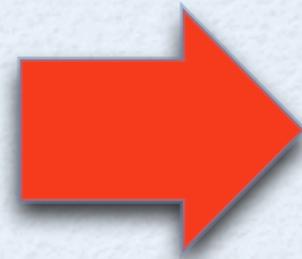
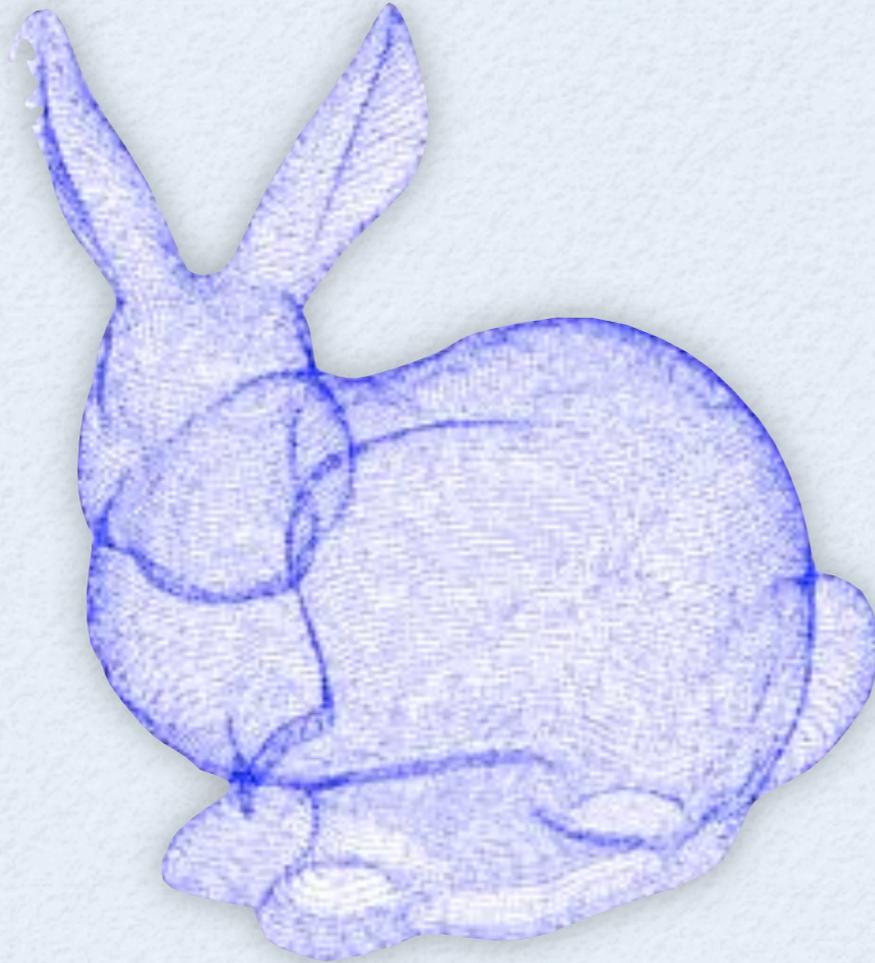
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co-dimension 1 submanifold of  $\mathbb{R}^n$

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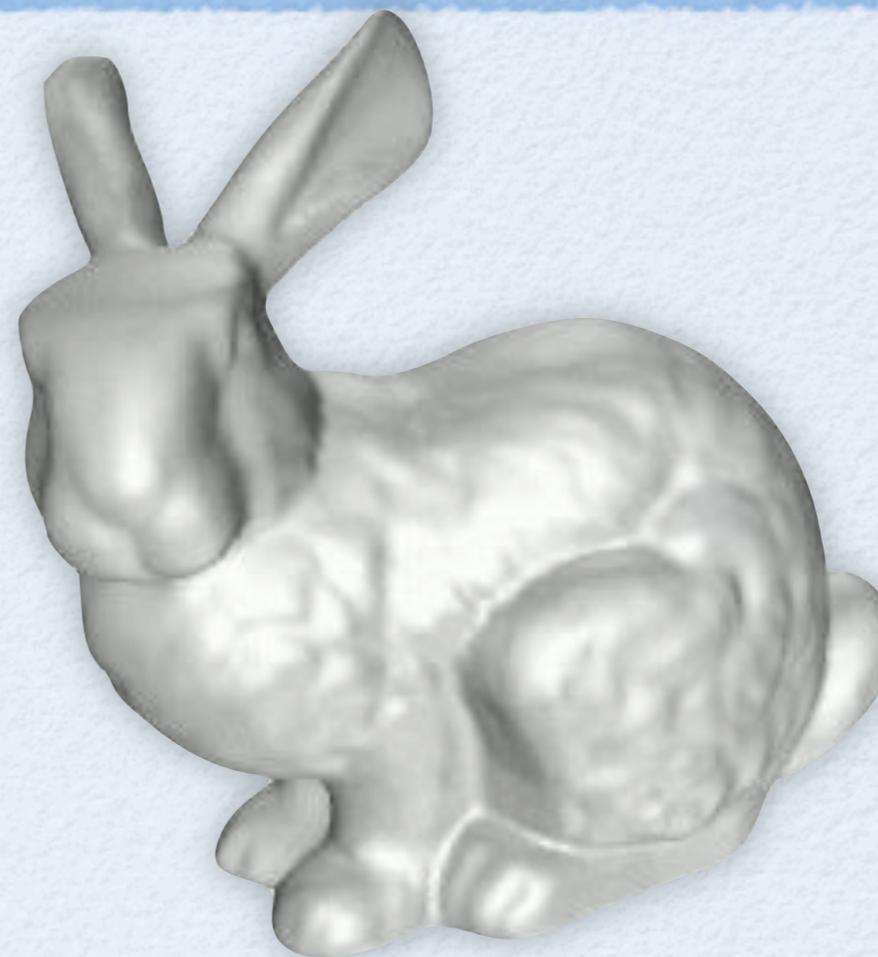
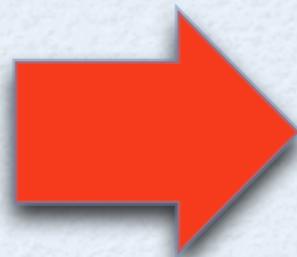
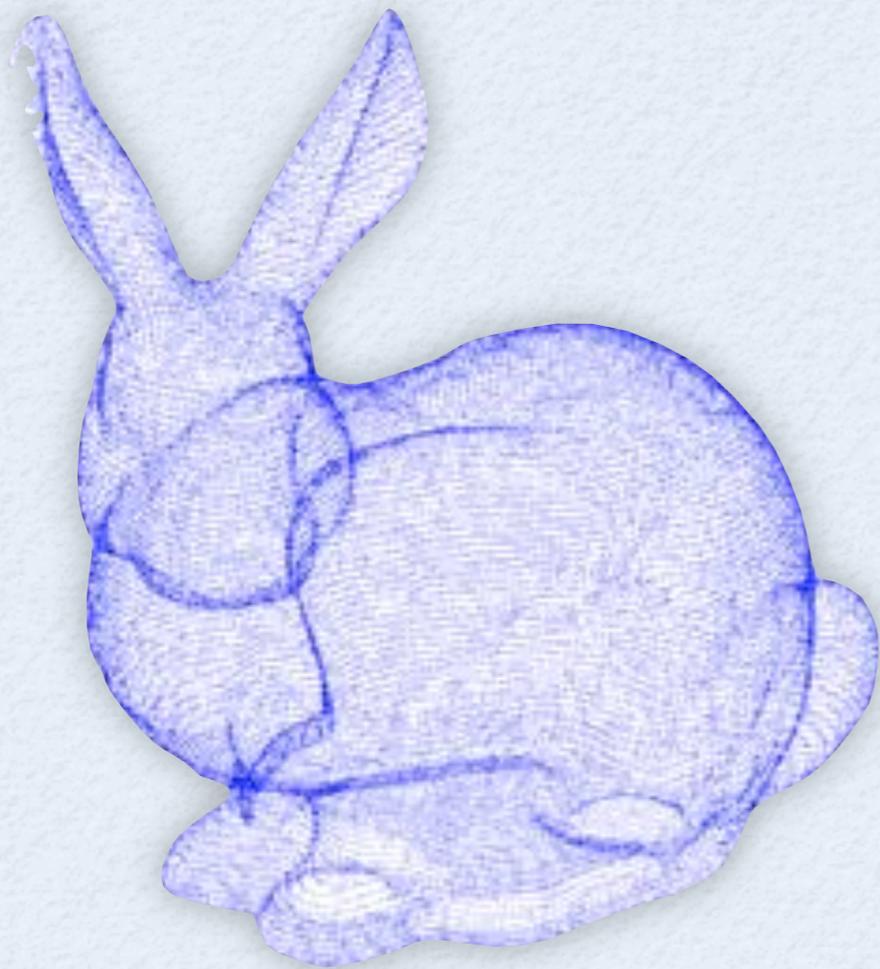


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homeomorphic  
ambient-isotopic

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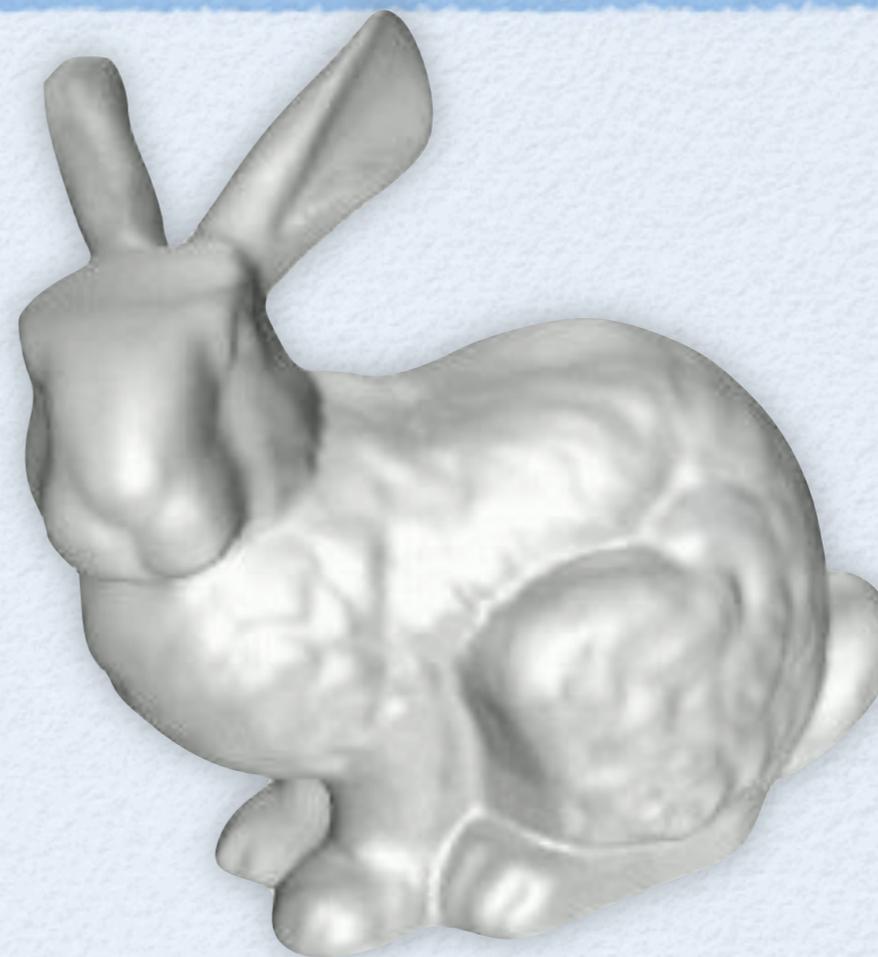
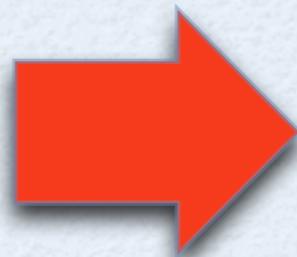
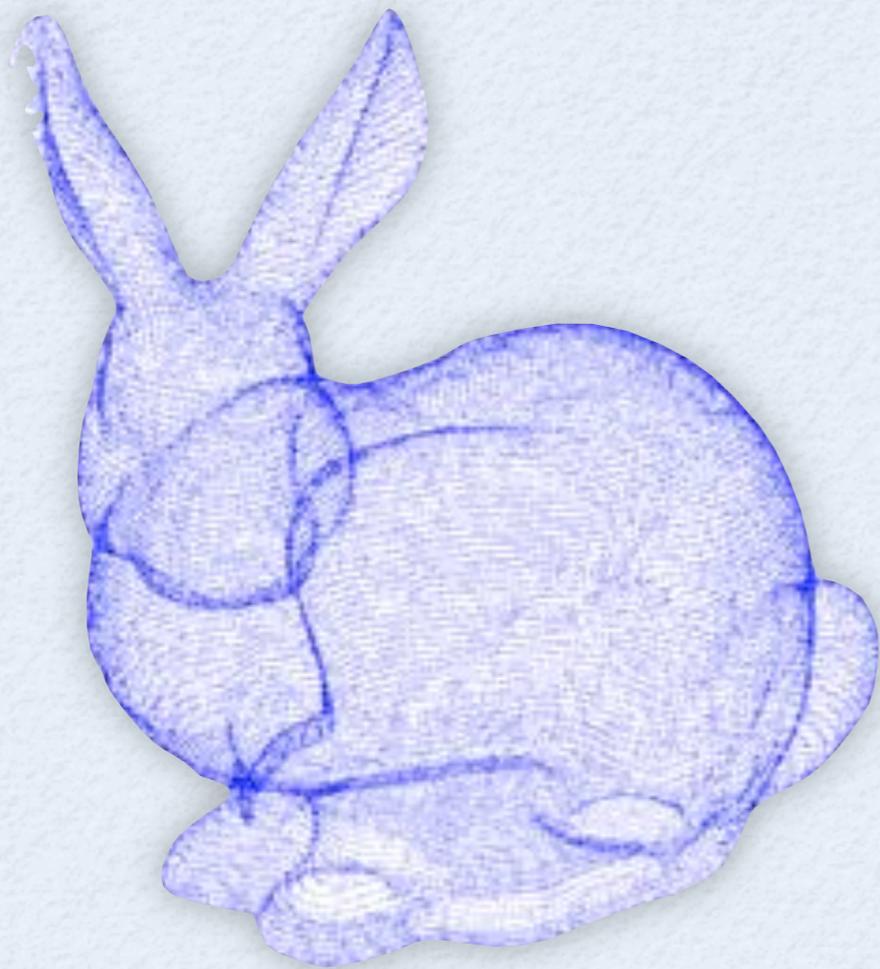
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**Hausdorff distance**  
relative to lfs

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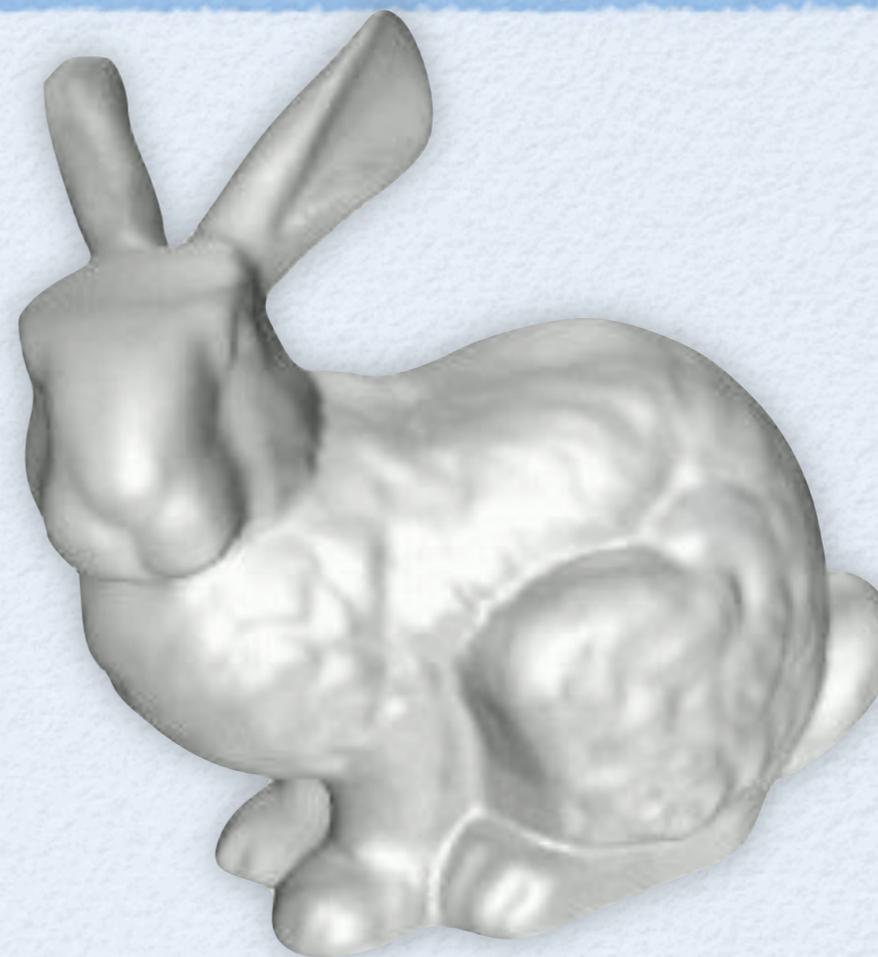
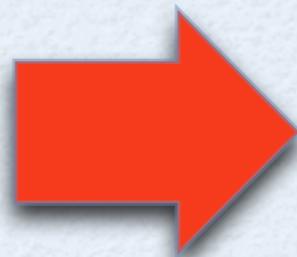
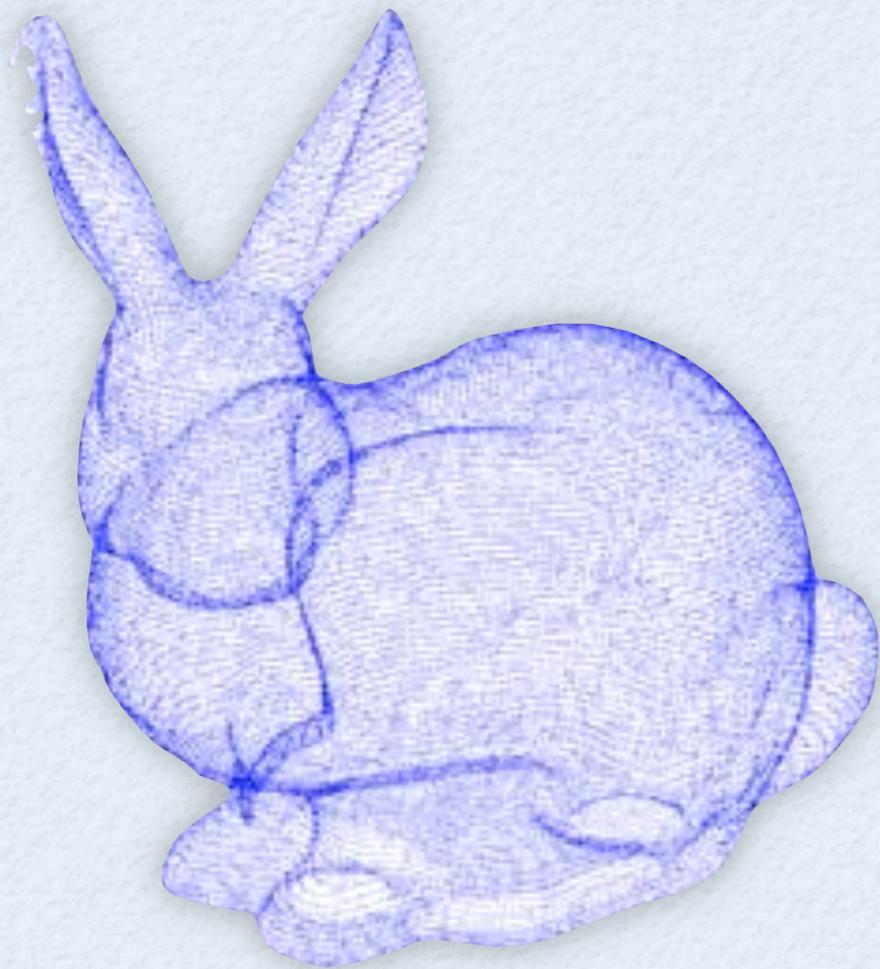
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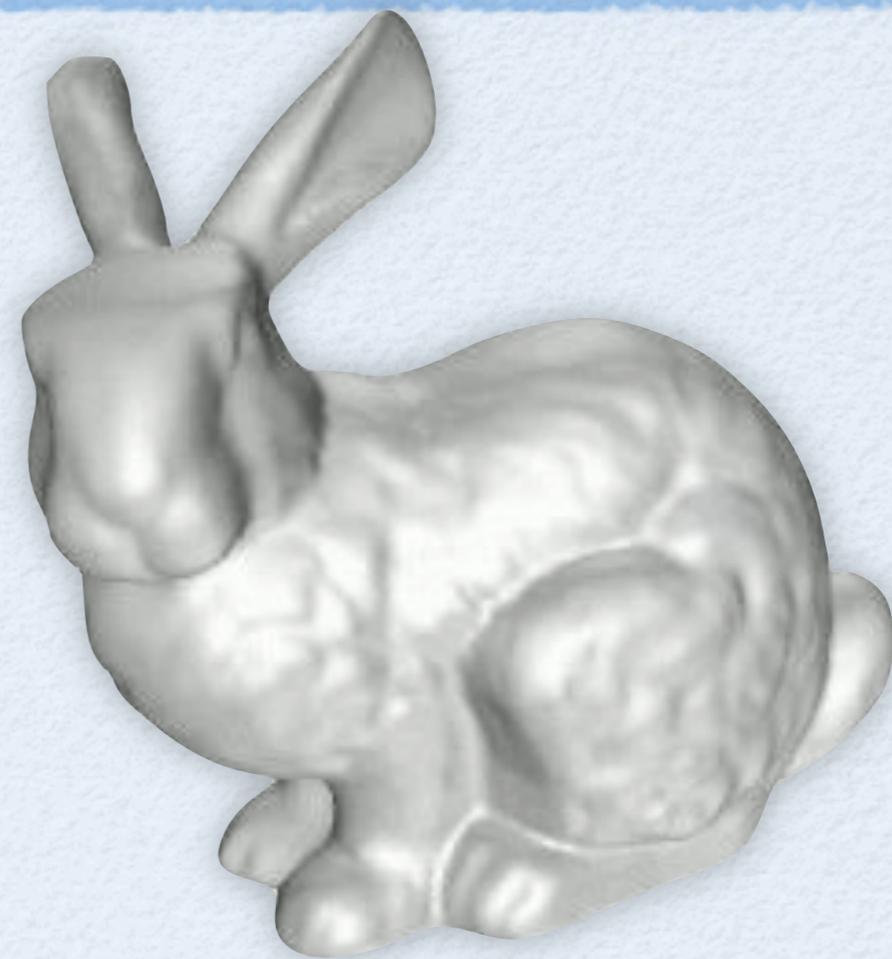
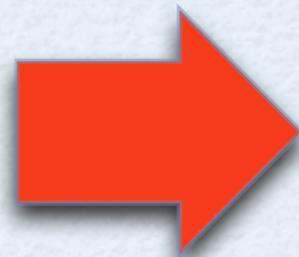
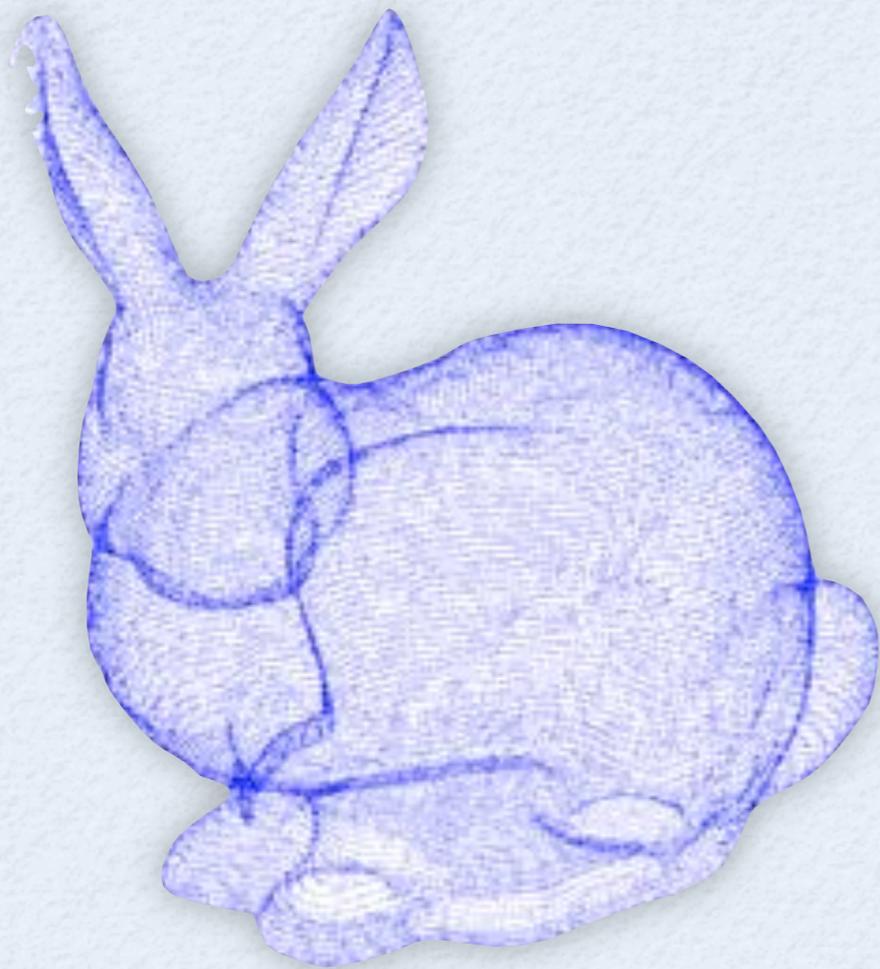
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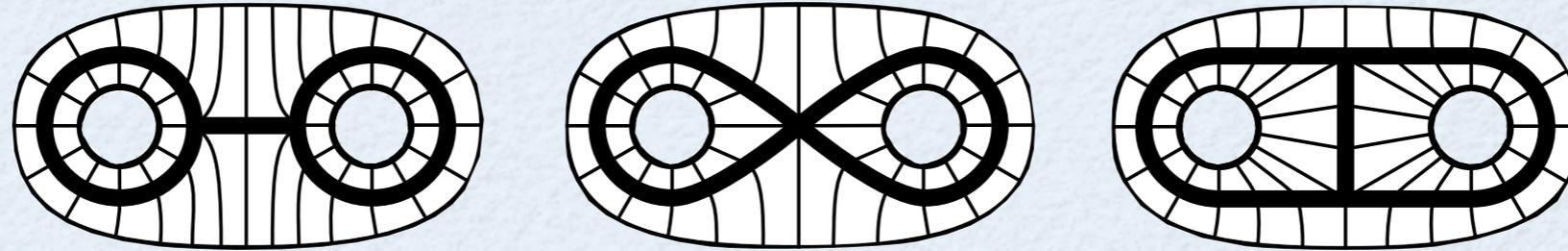
topological space

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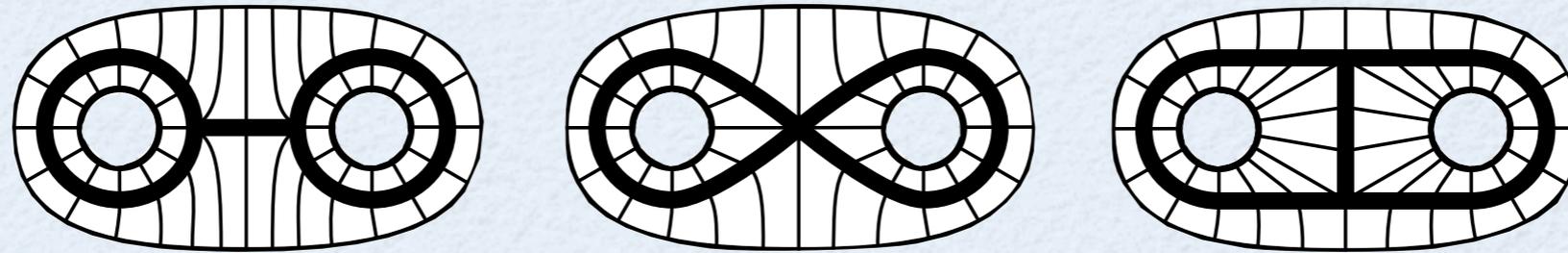
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Unlike homeomorphism, homotopy equivalence **does not preserve dimension**.

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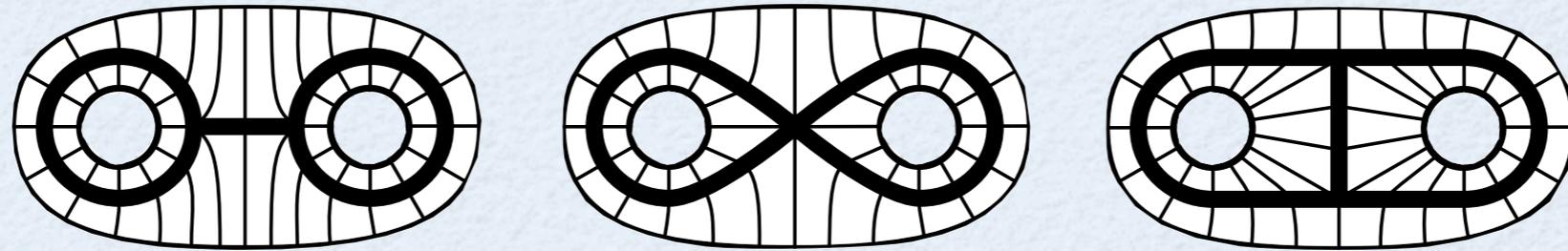


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All these knots have the **same homotopy type**, but **not their complements**.

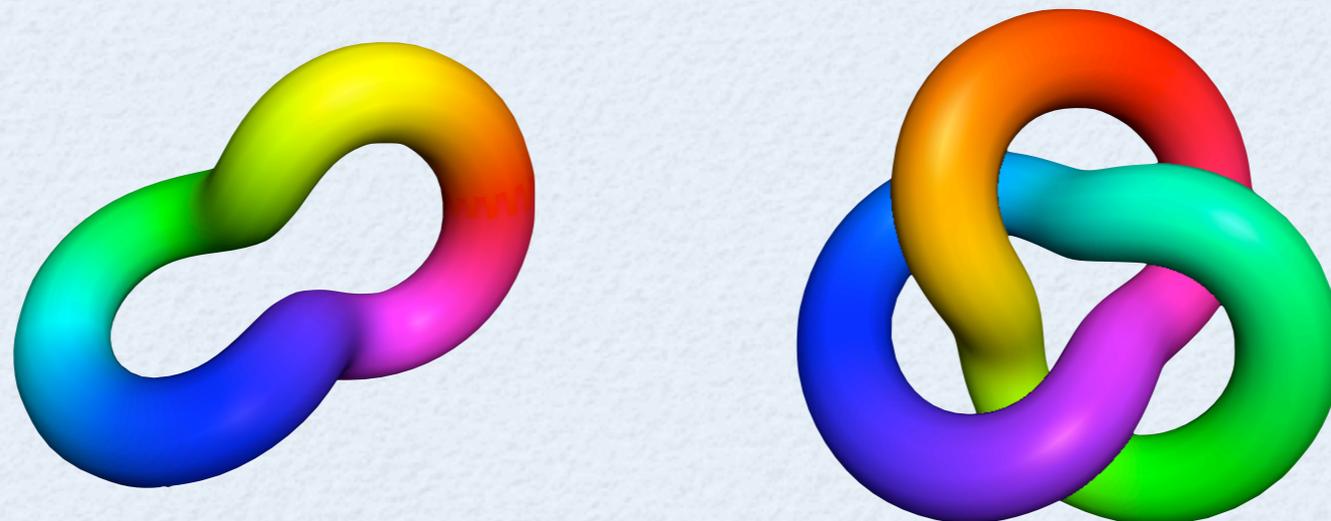
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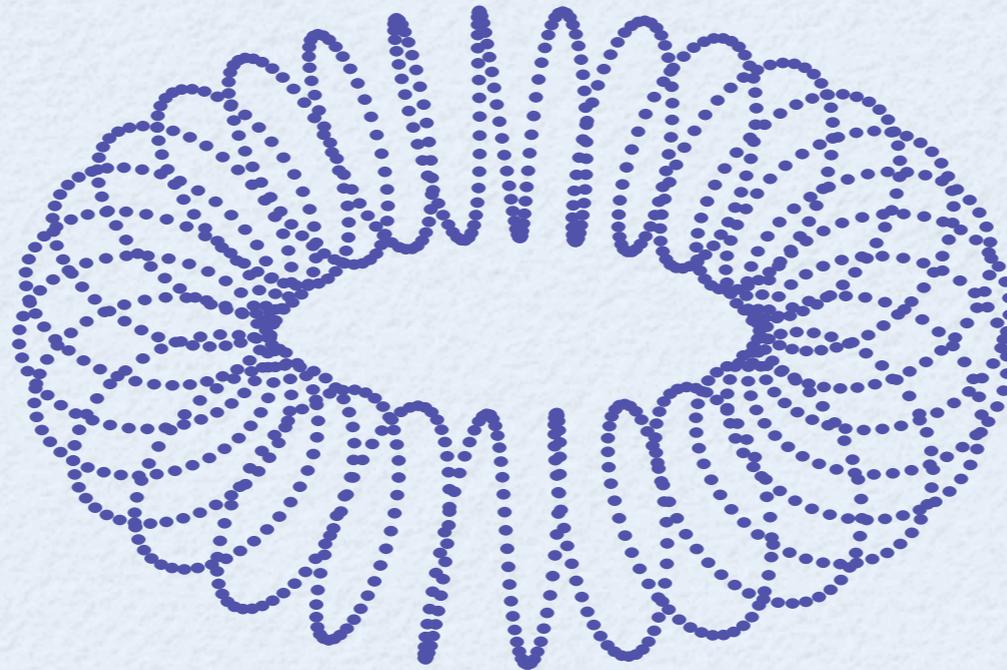


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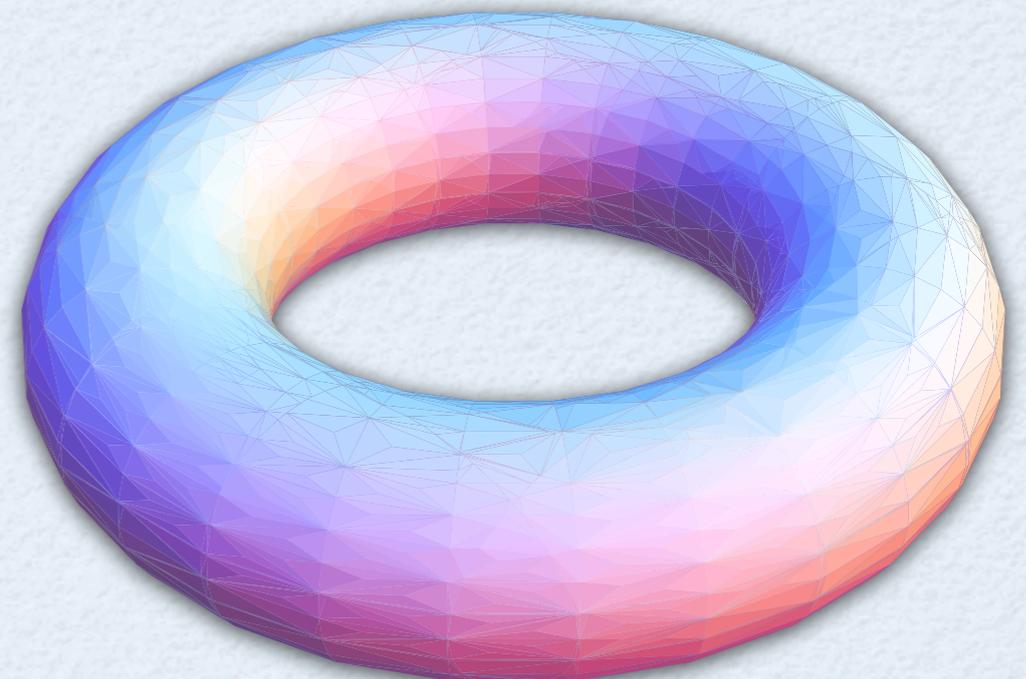
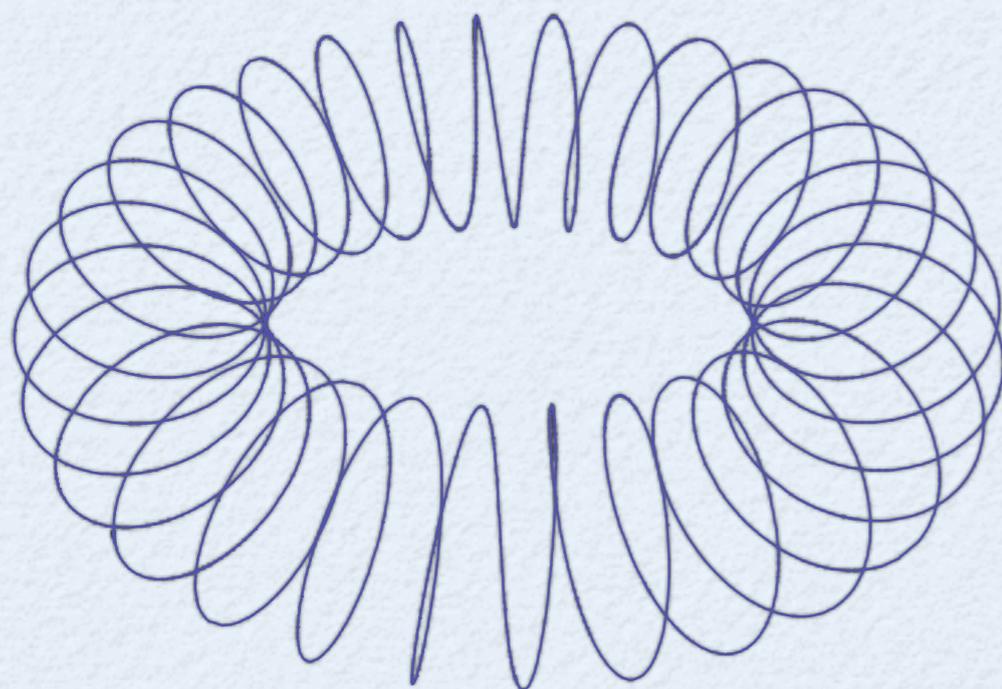
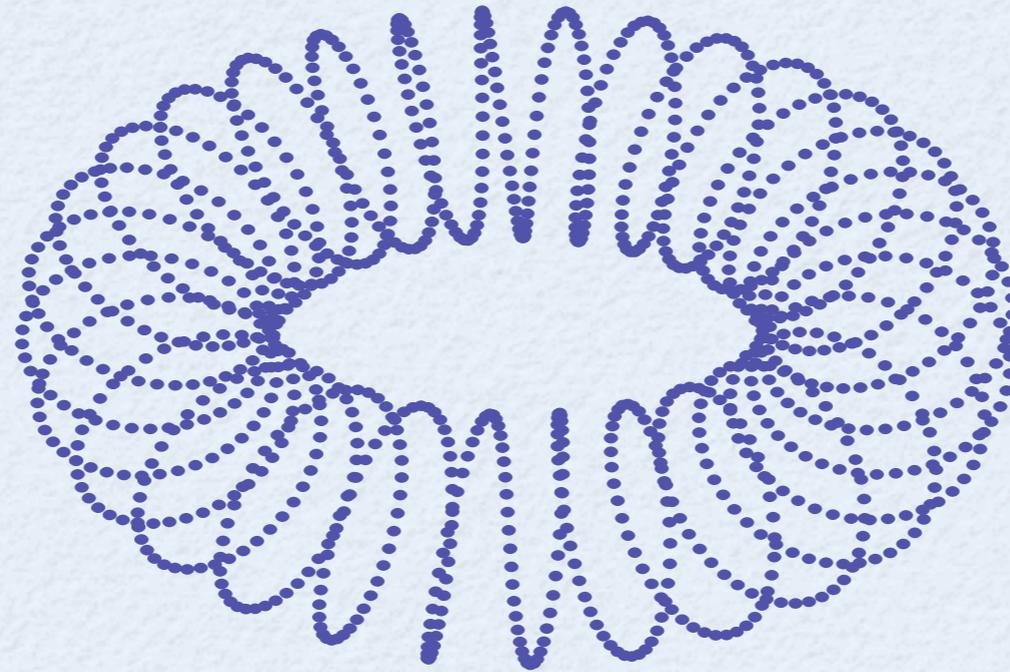
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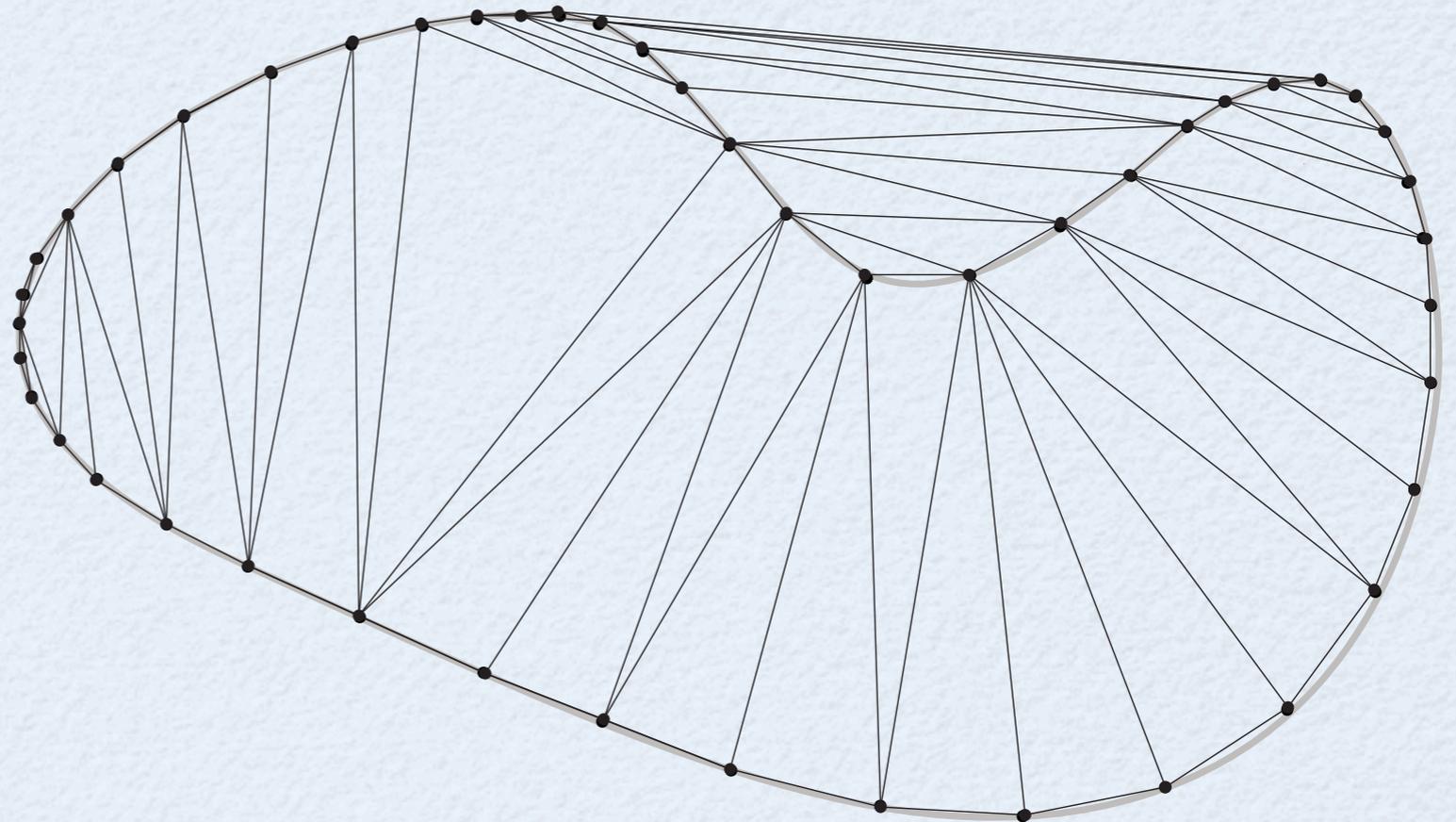
# Very rich area!

- Reconstruction as an **iso-surfaces**:
  - 0-set of signed dist functs [Hoppe et al'92, Curless et al'96]
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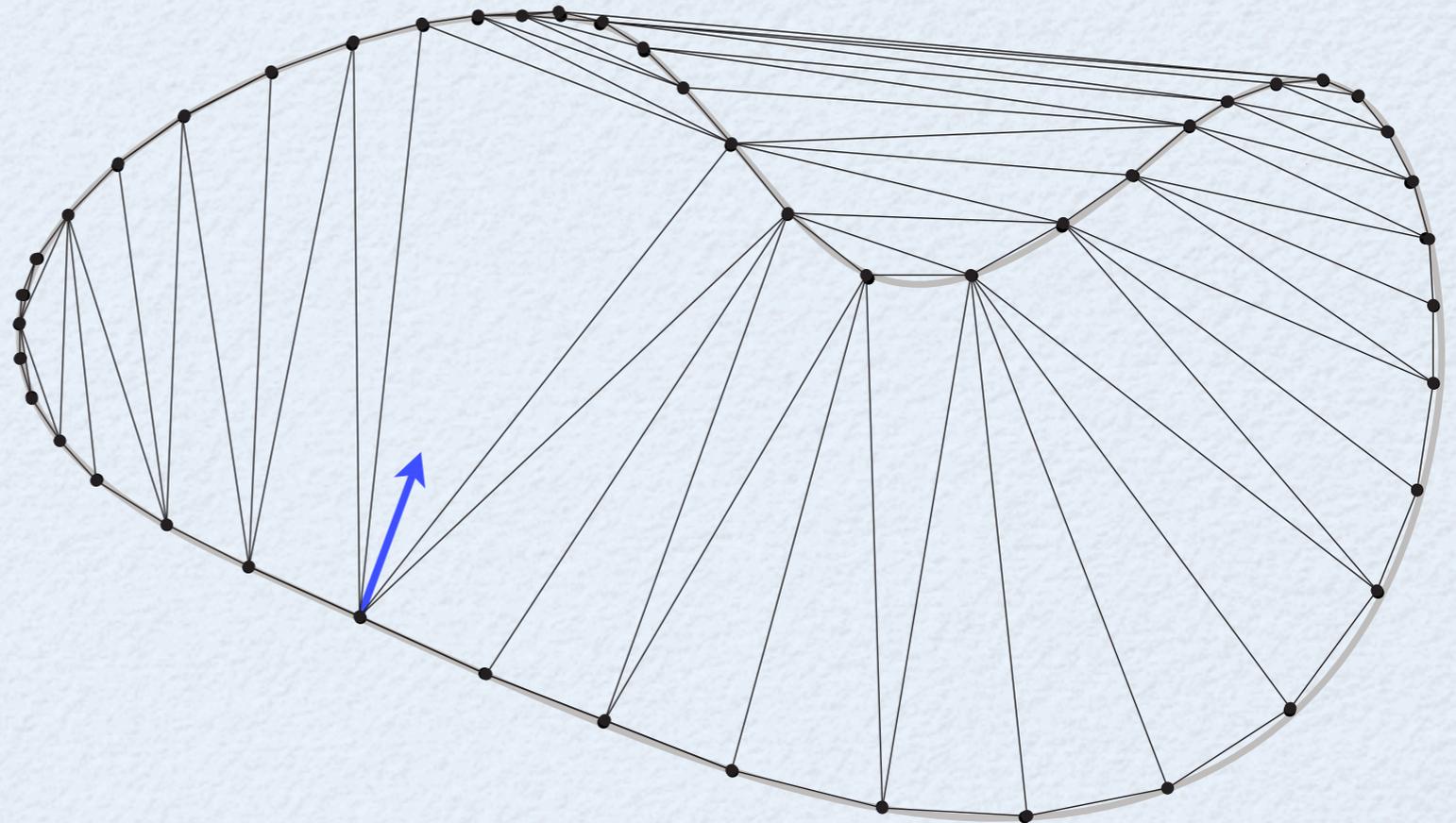
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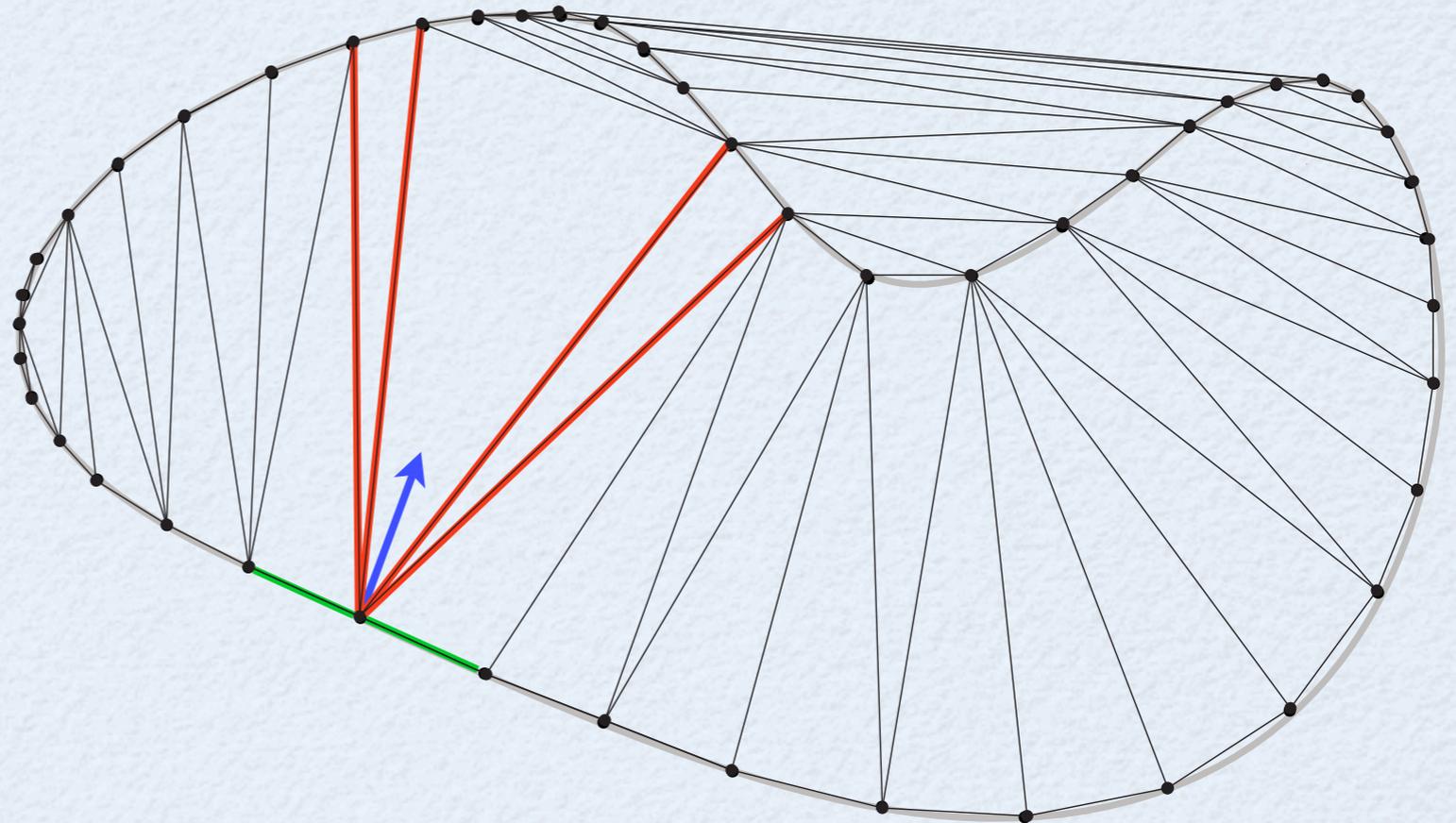
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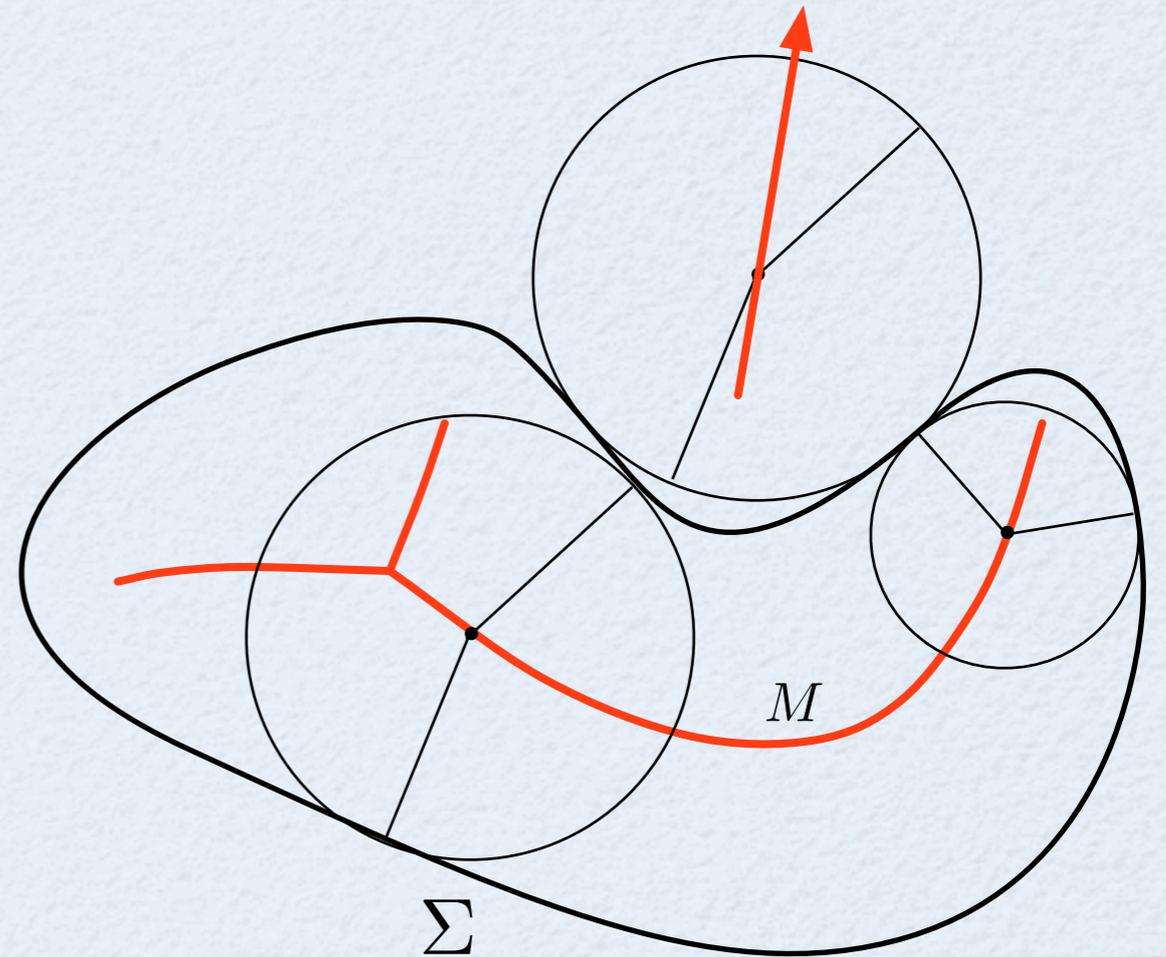
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The **medial axis (MA)** of  $\Sigma$  is the set of points  $M \subset \mathbb{R}^n$  that have  $\geq 2$  closest points in  $\Sigma$ .

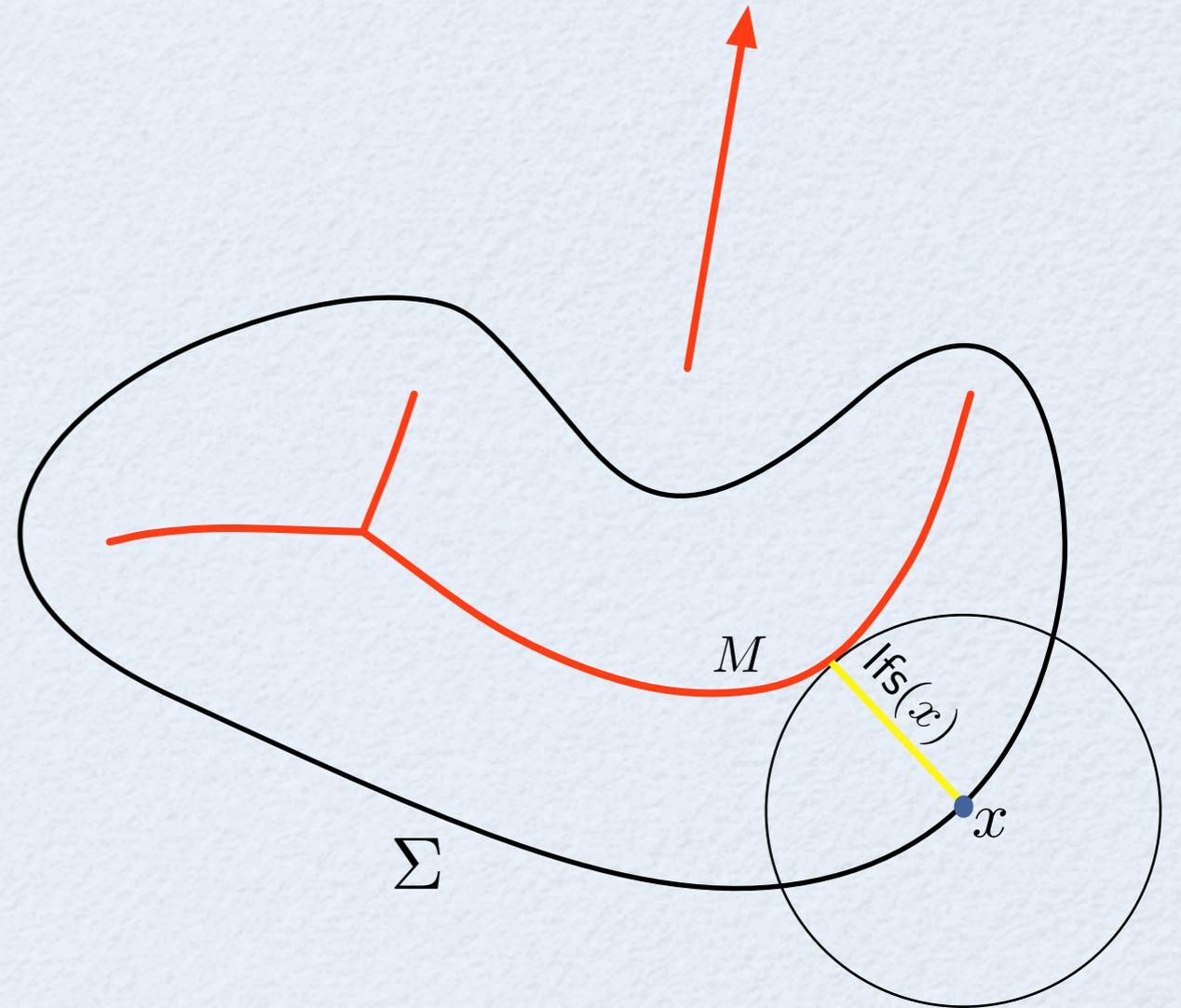


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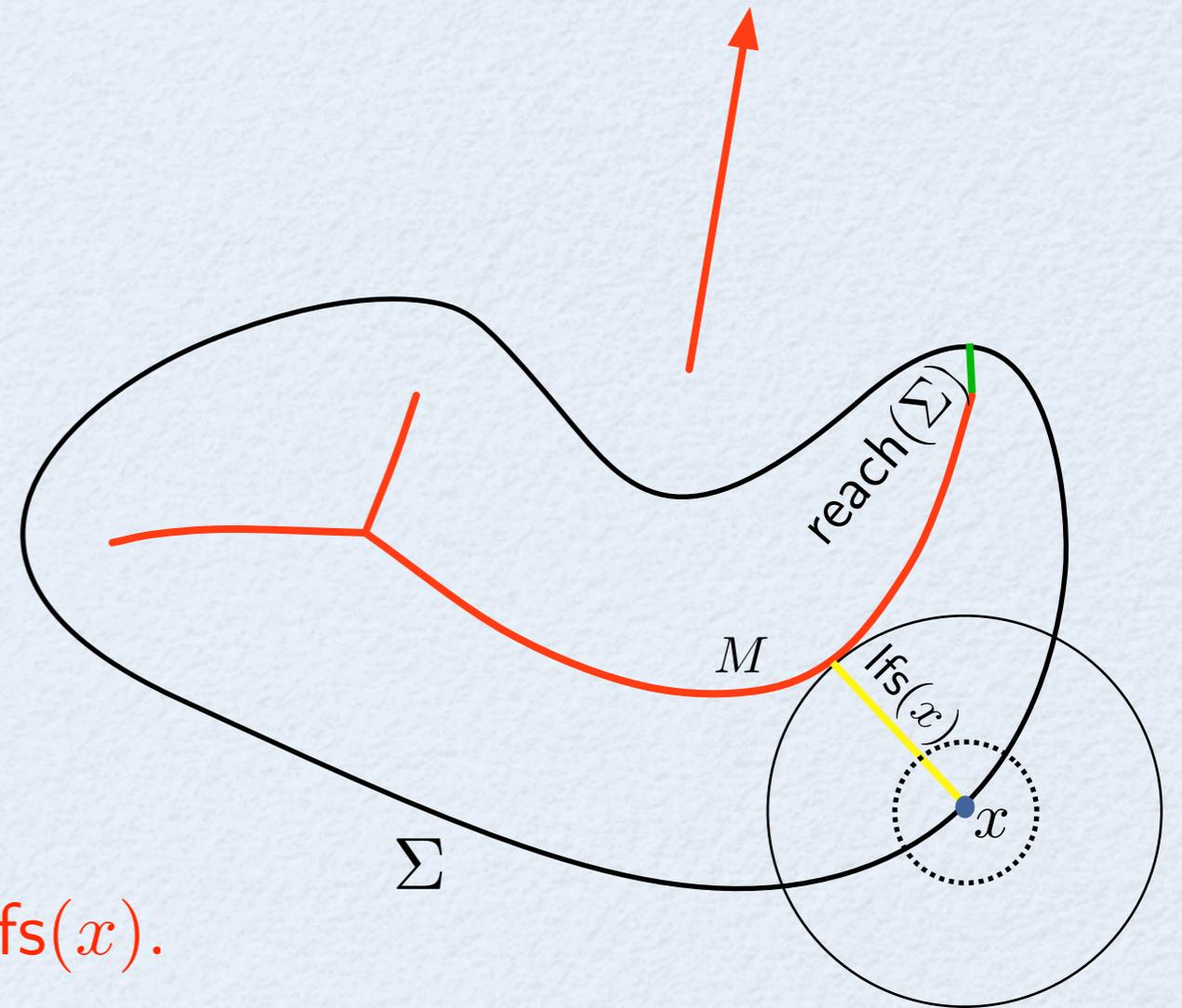
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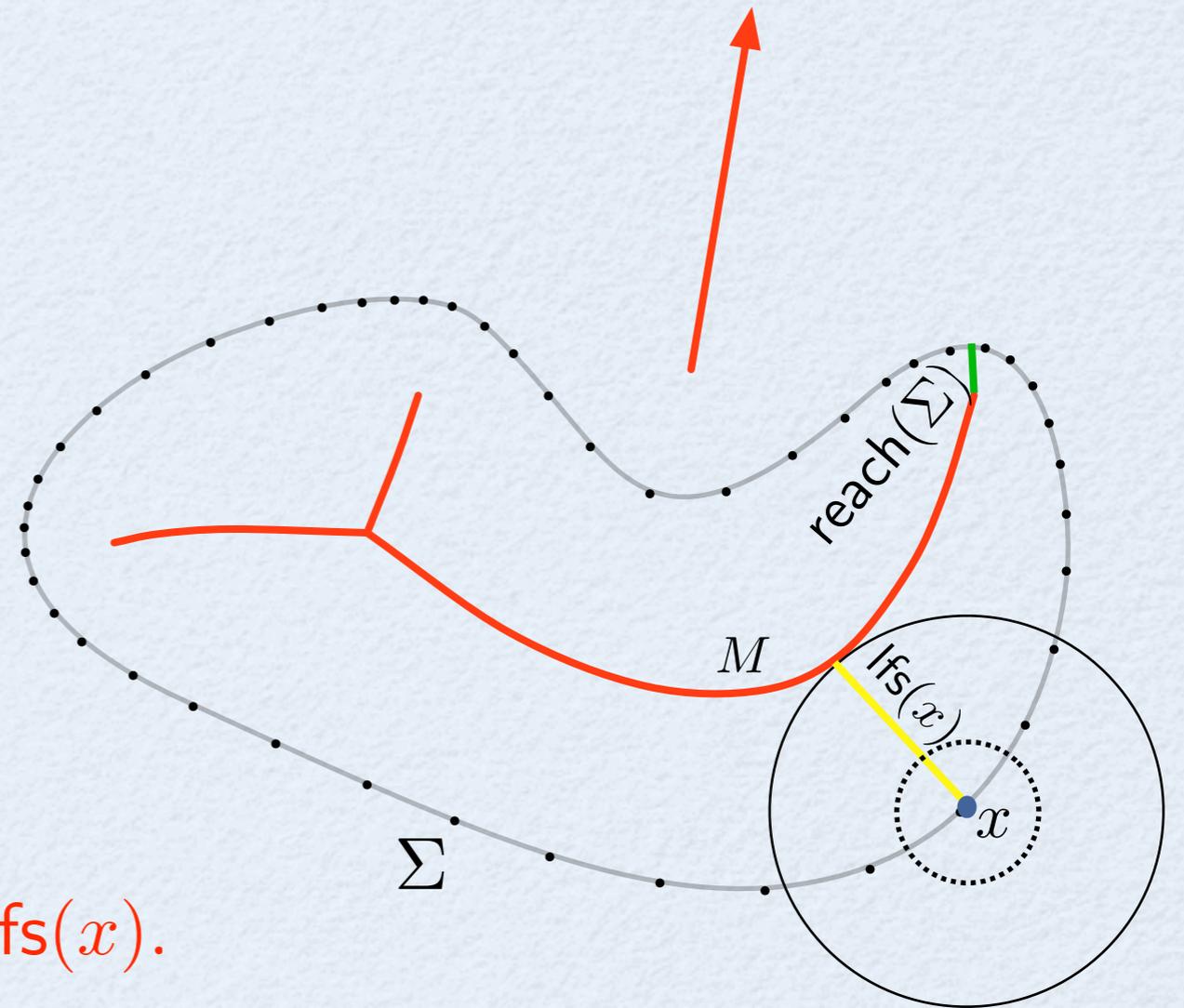
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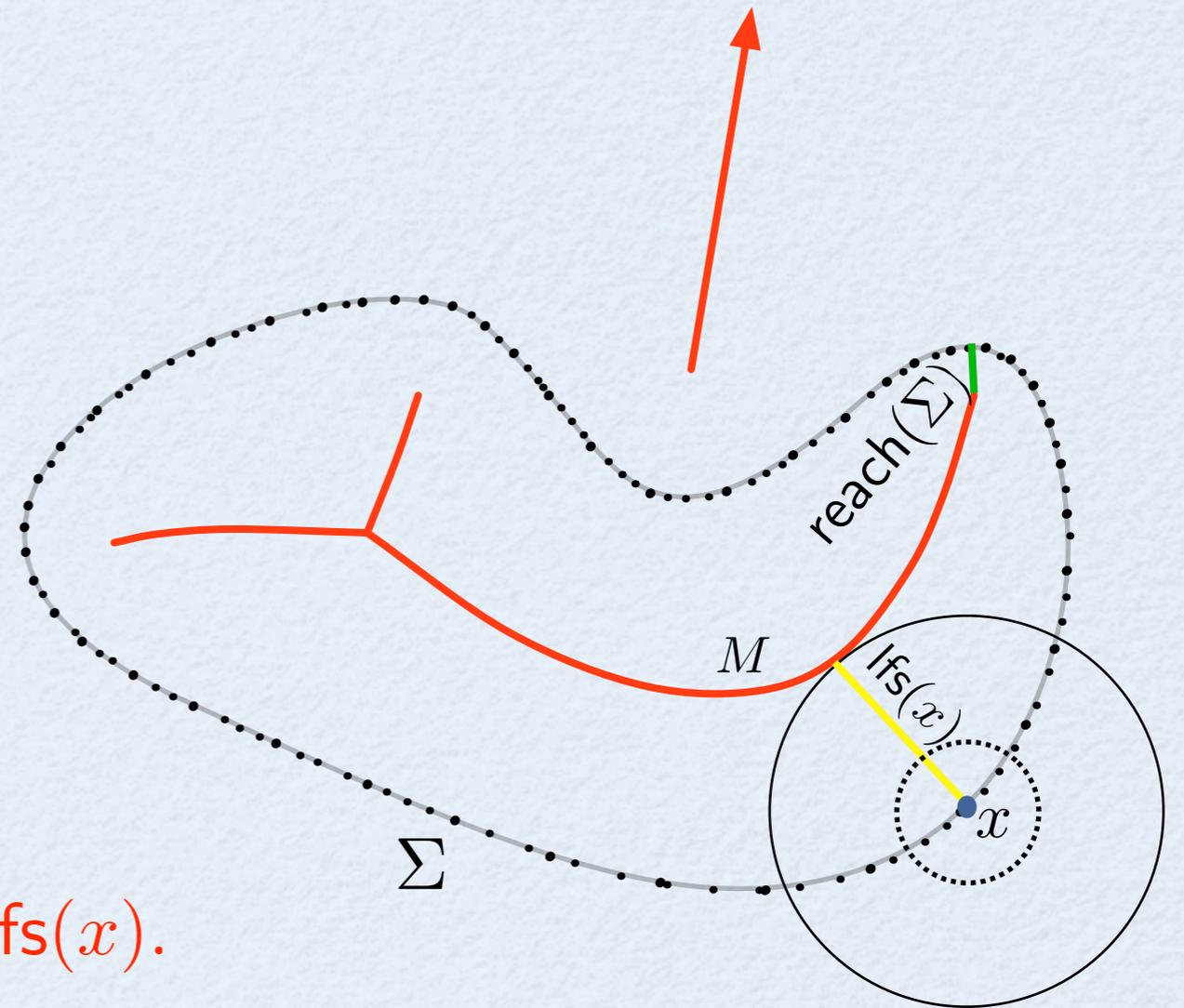
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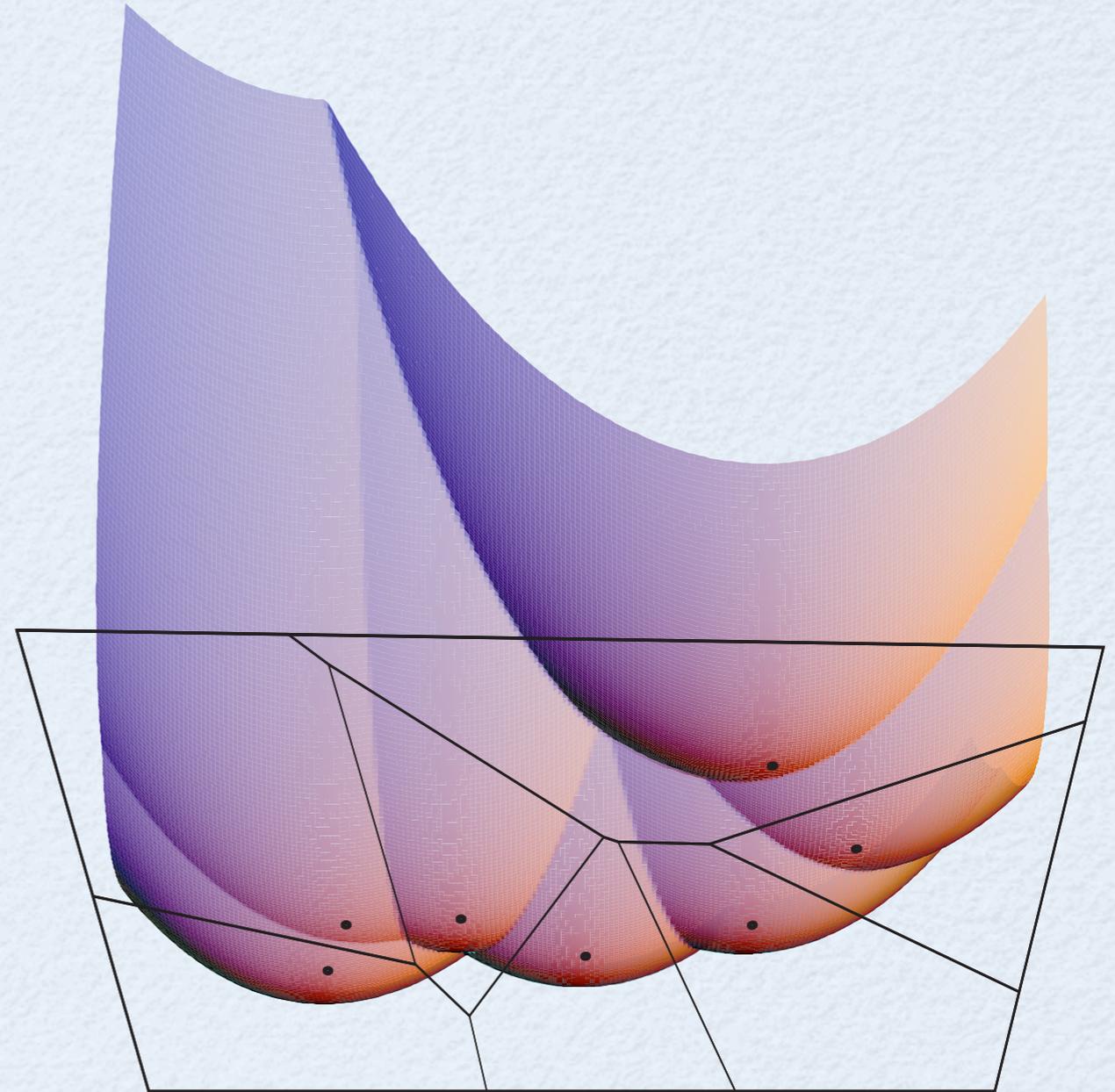
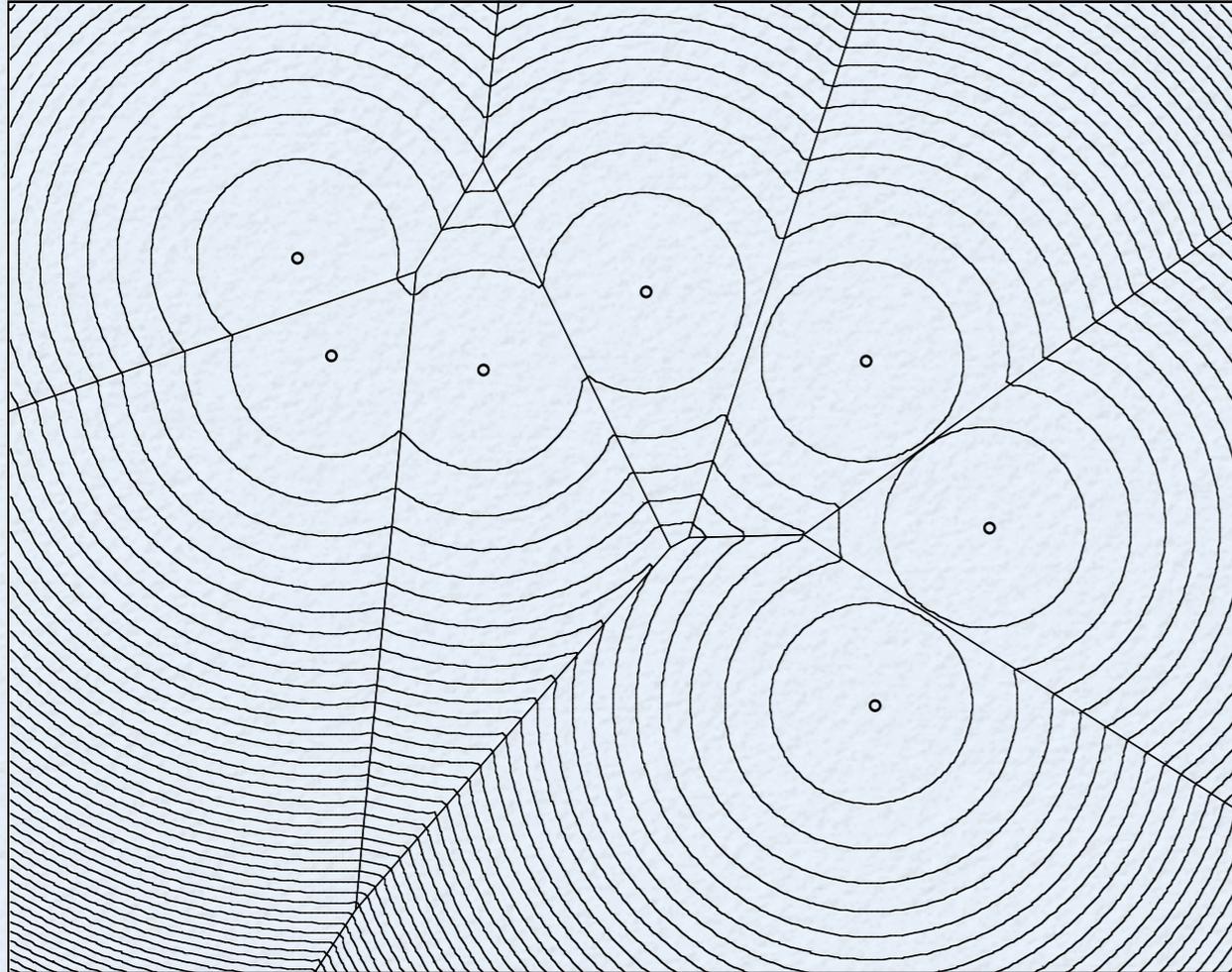
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# (Squared) distance function

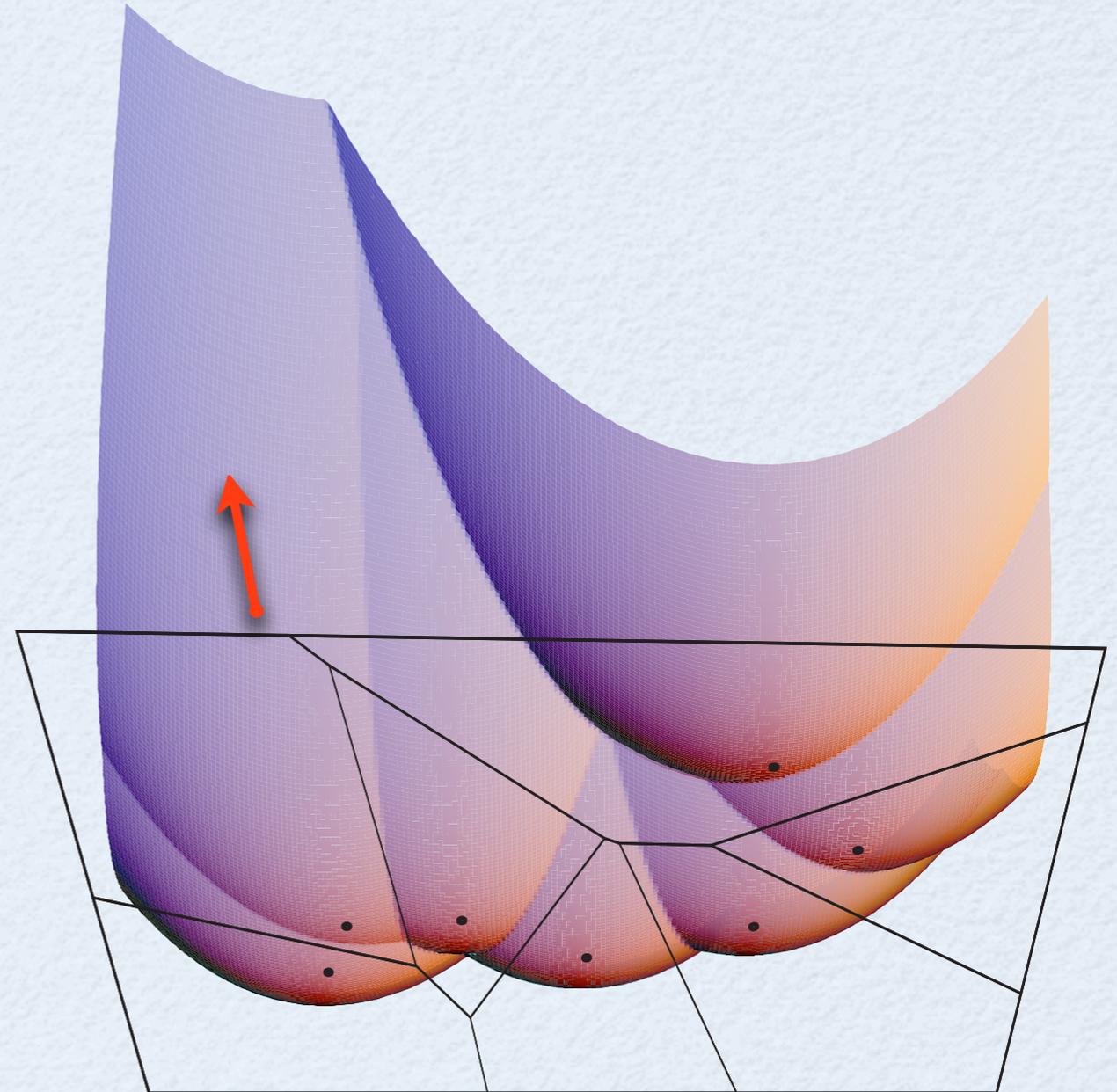
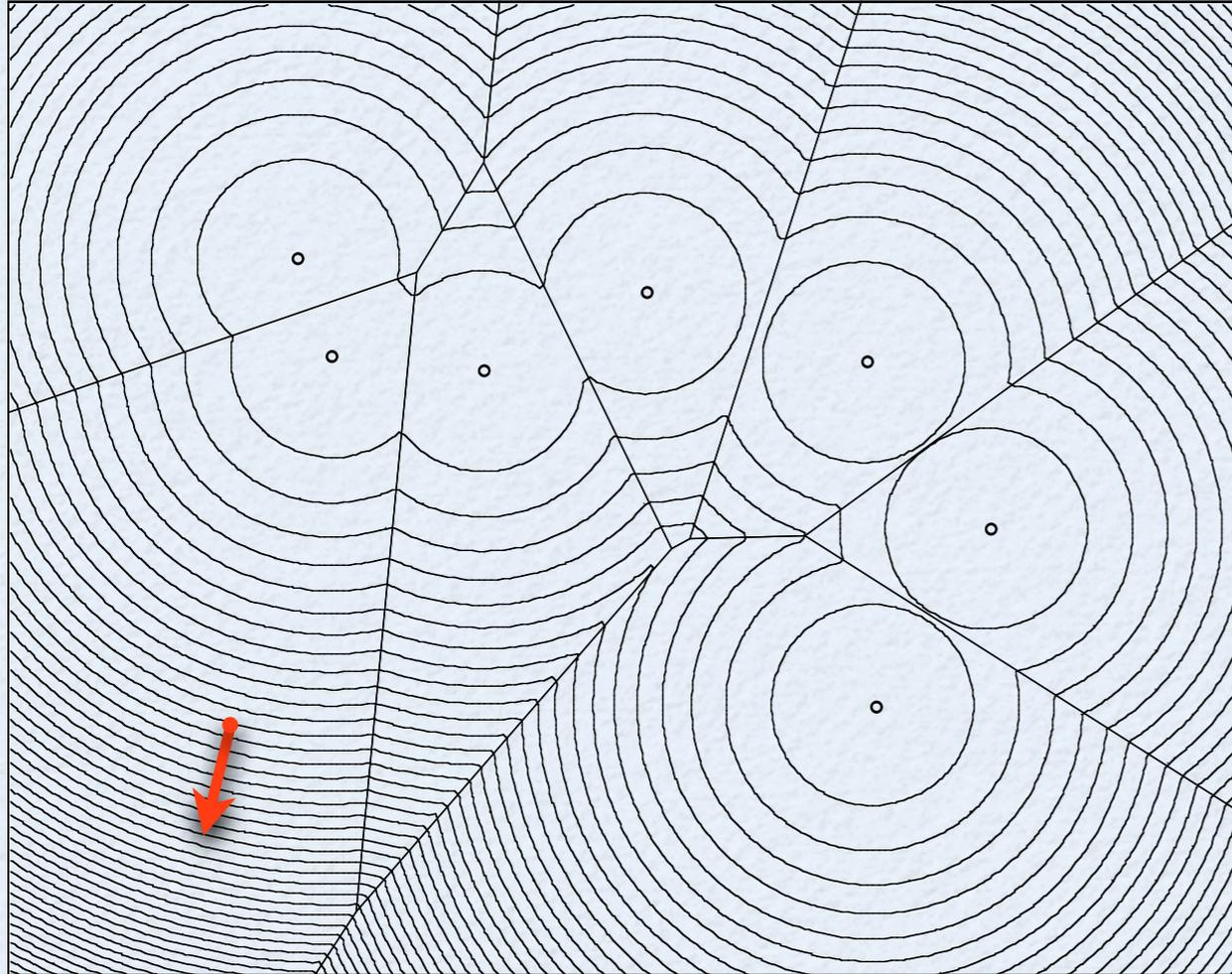


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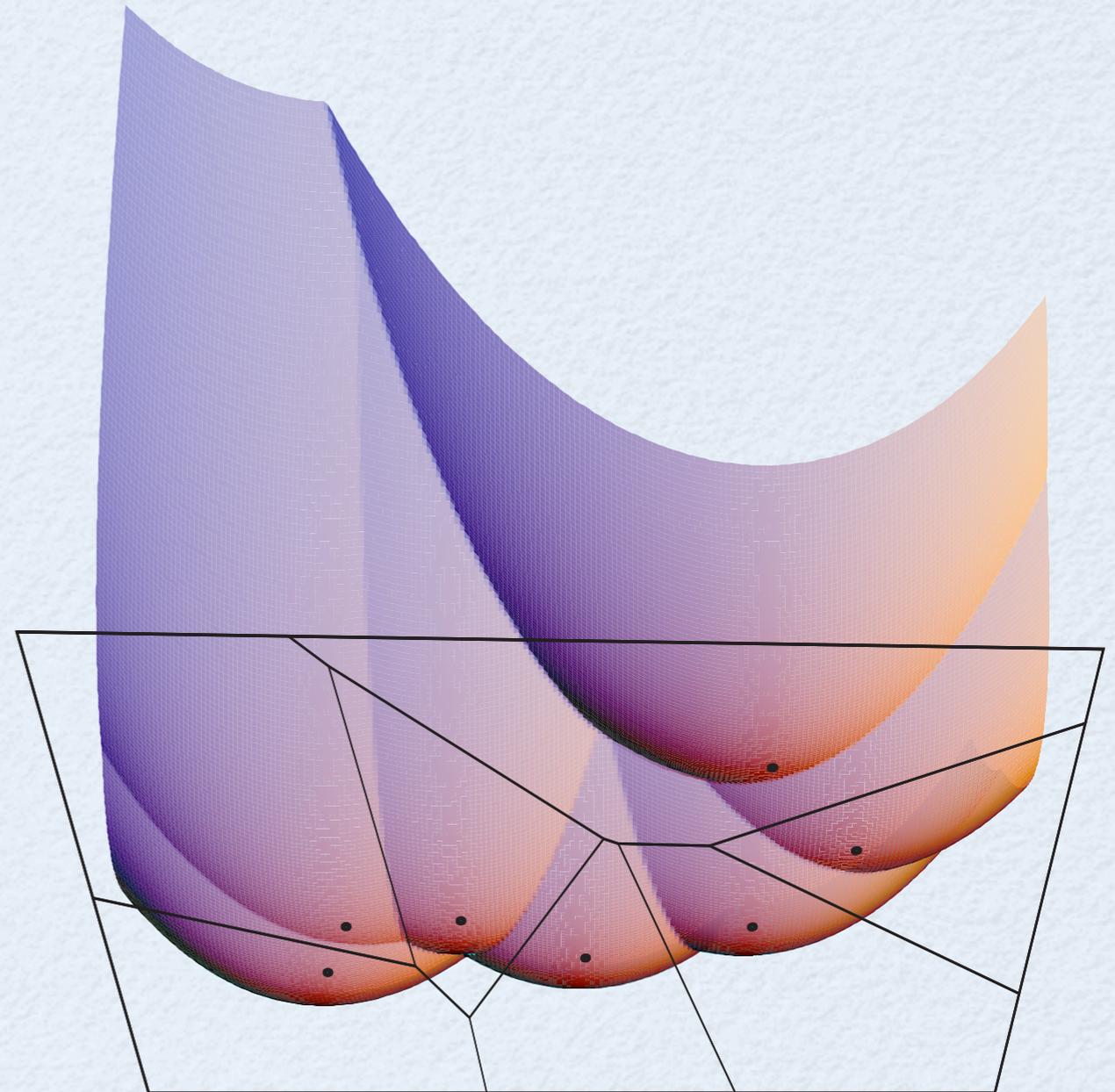
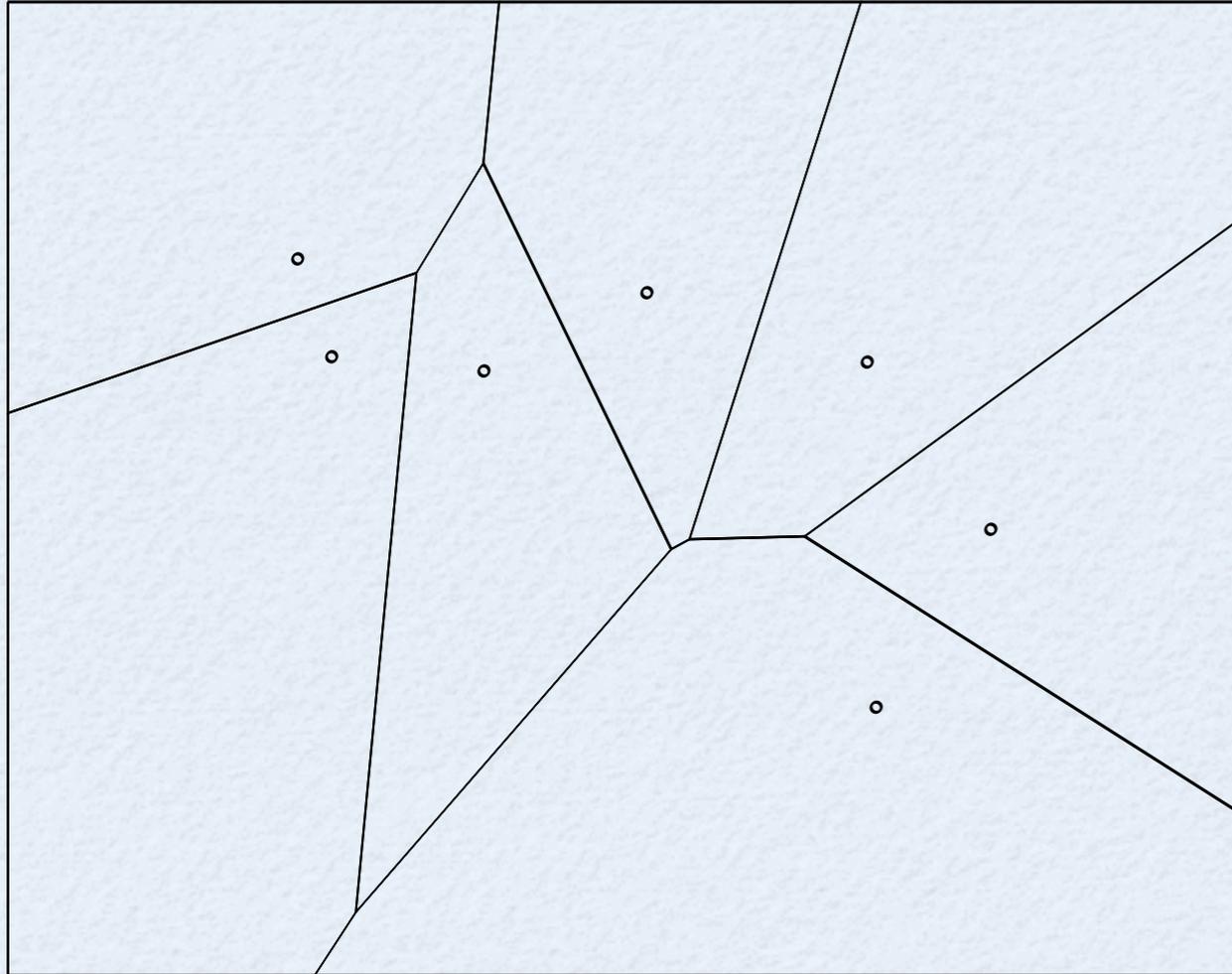


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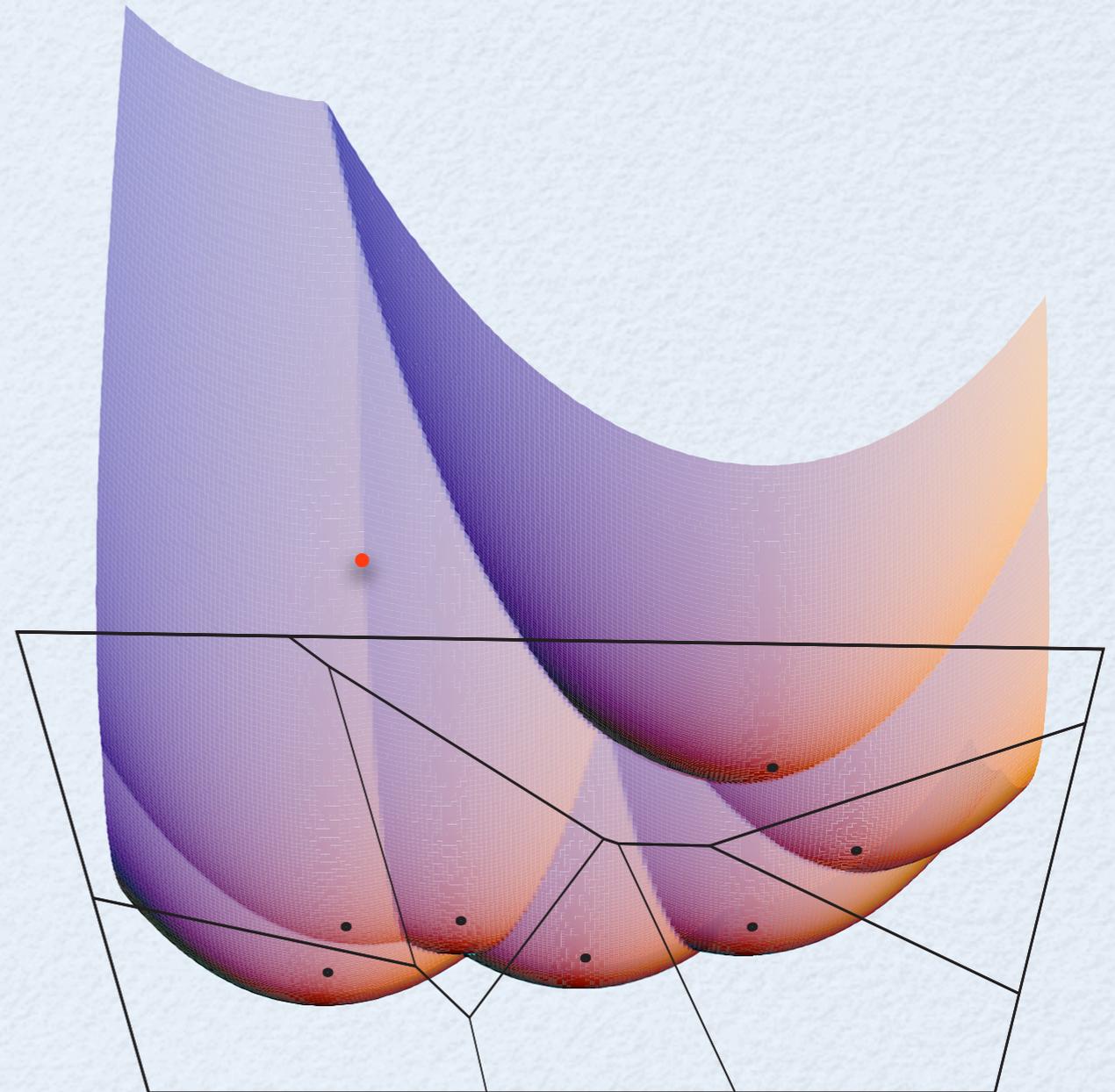
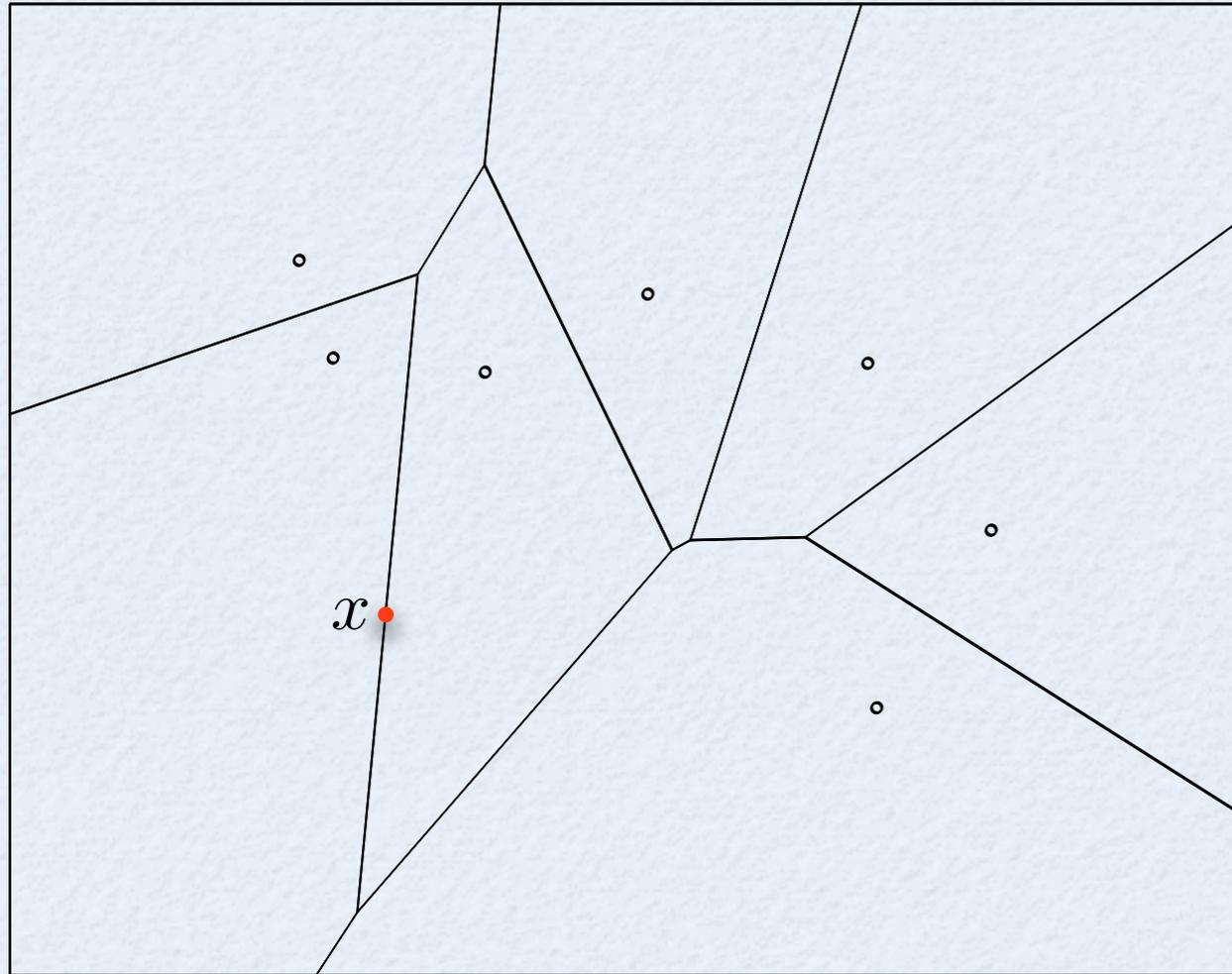
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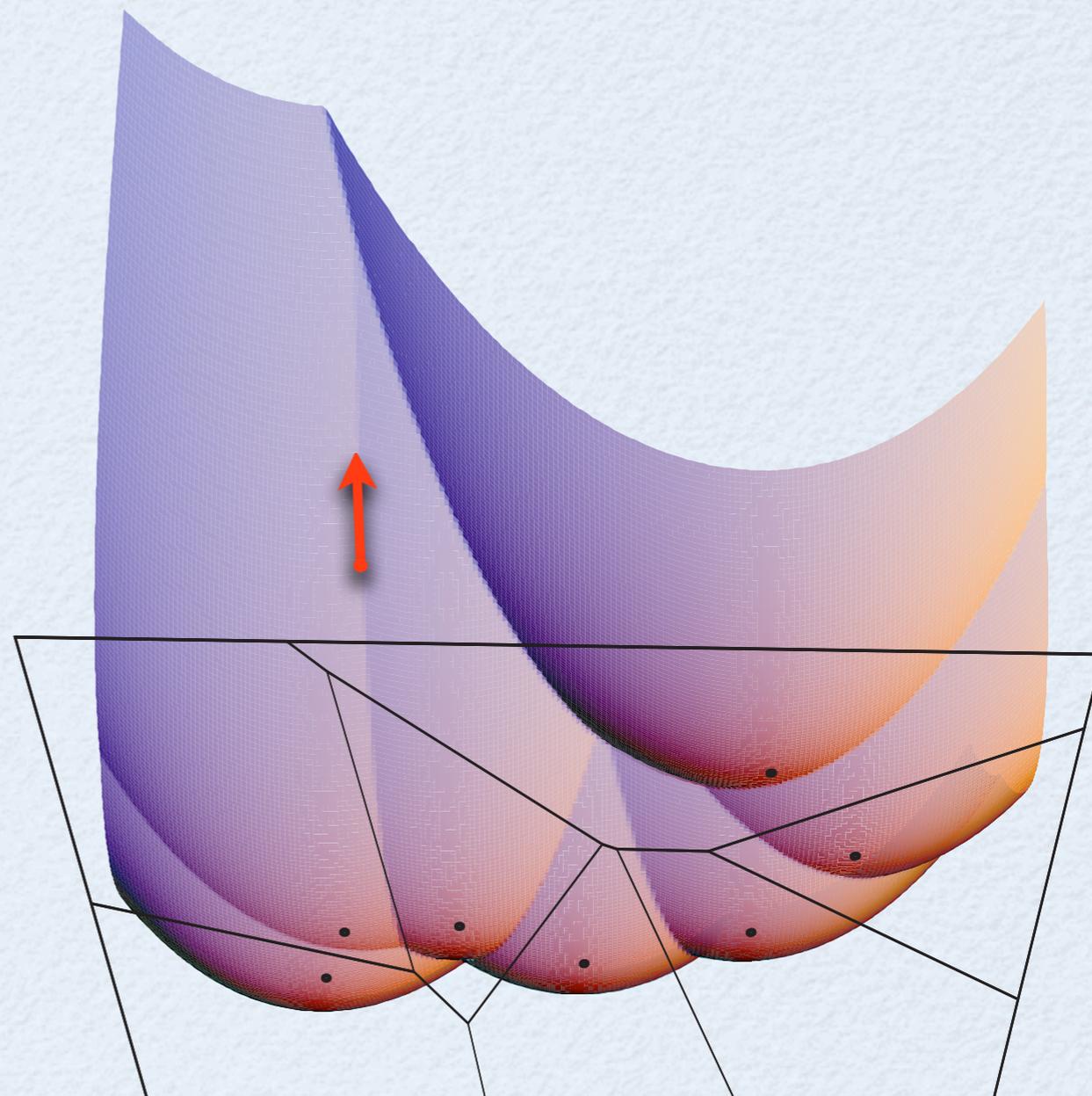
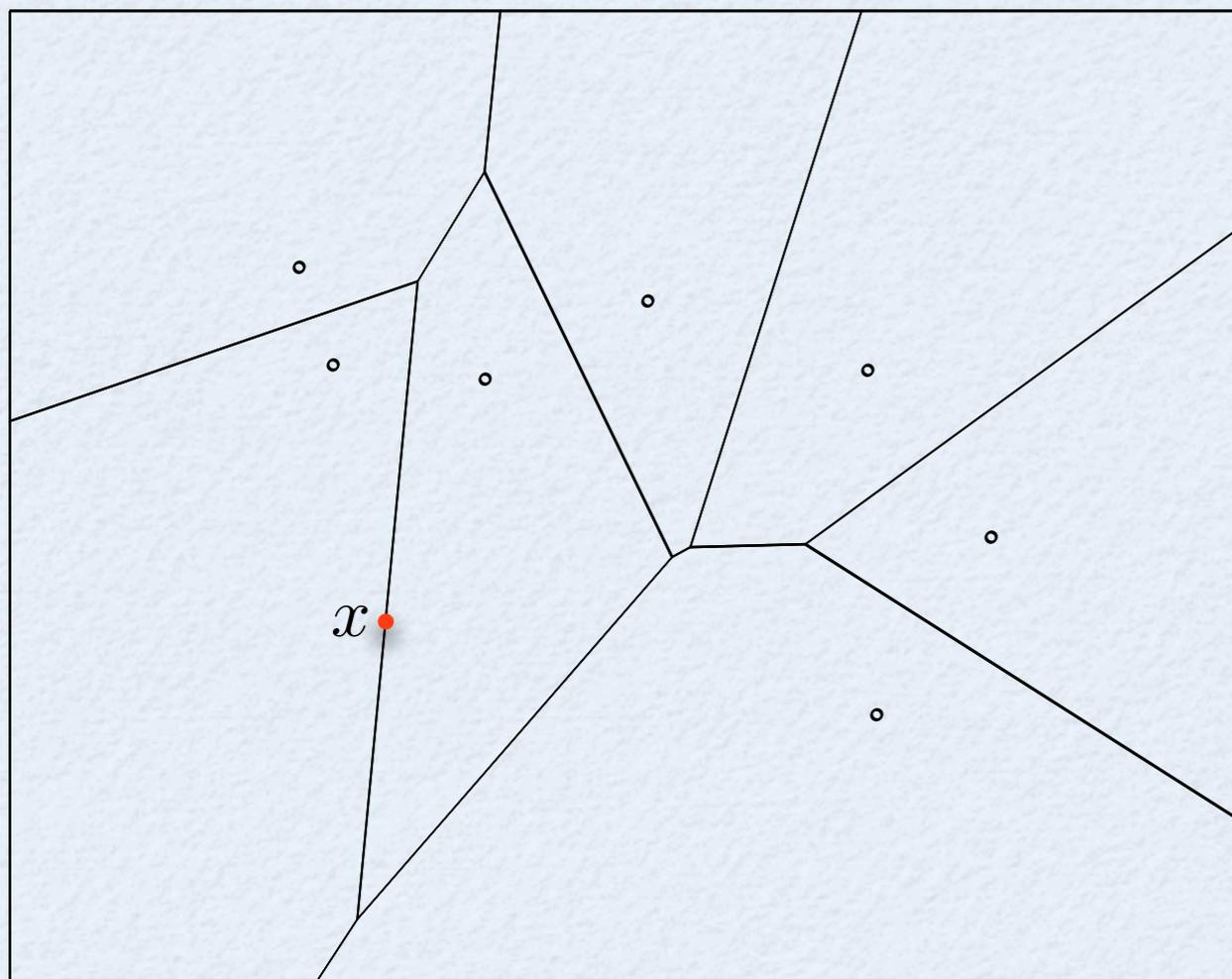
# Generalized gradient



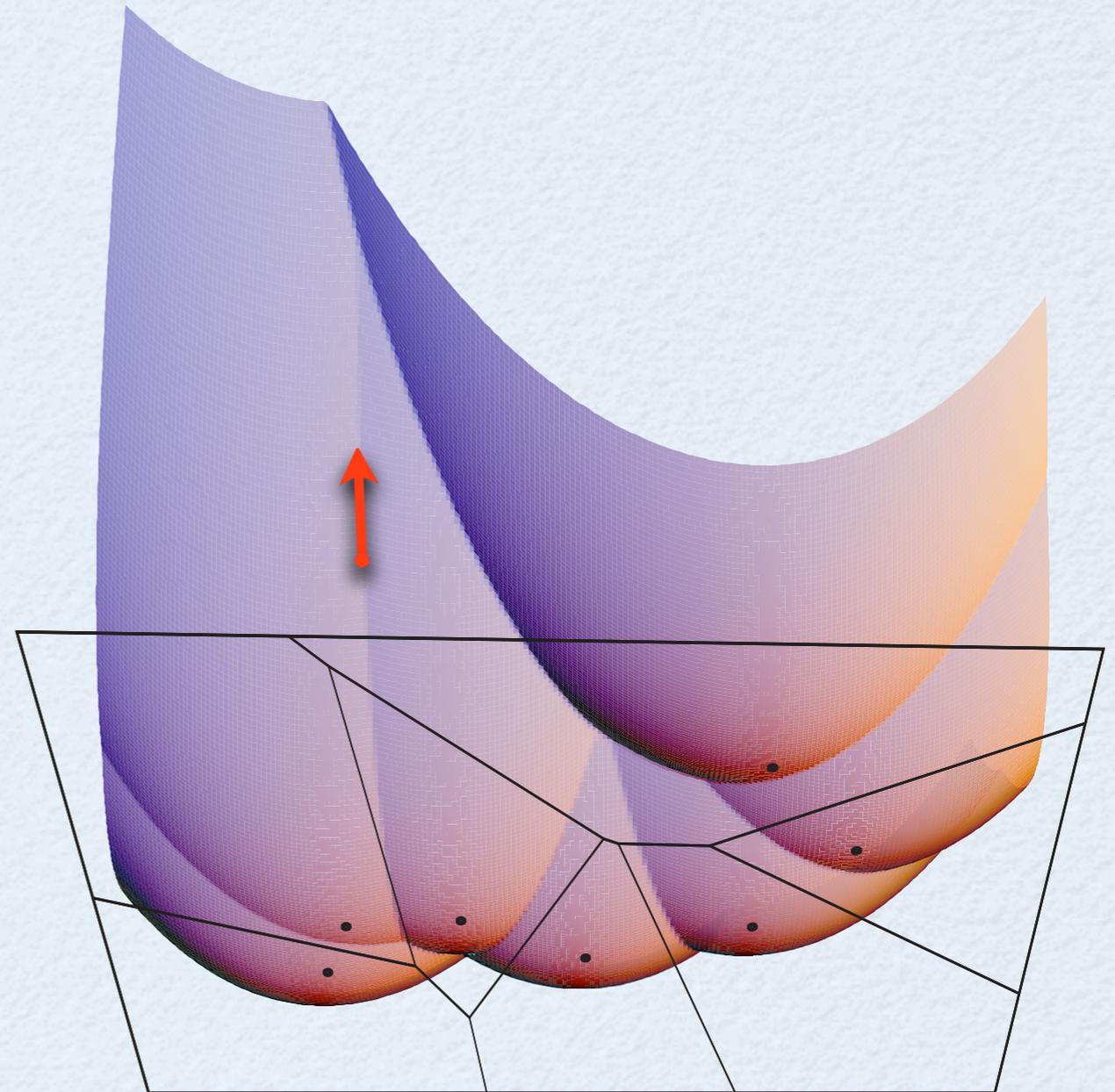
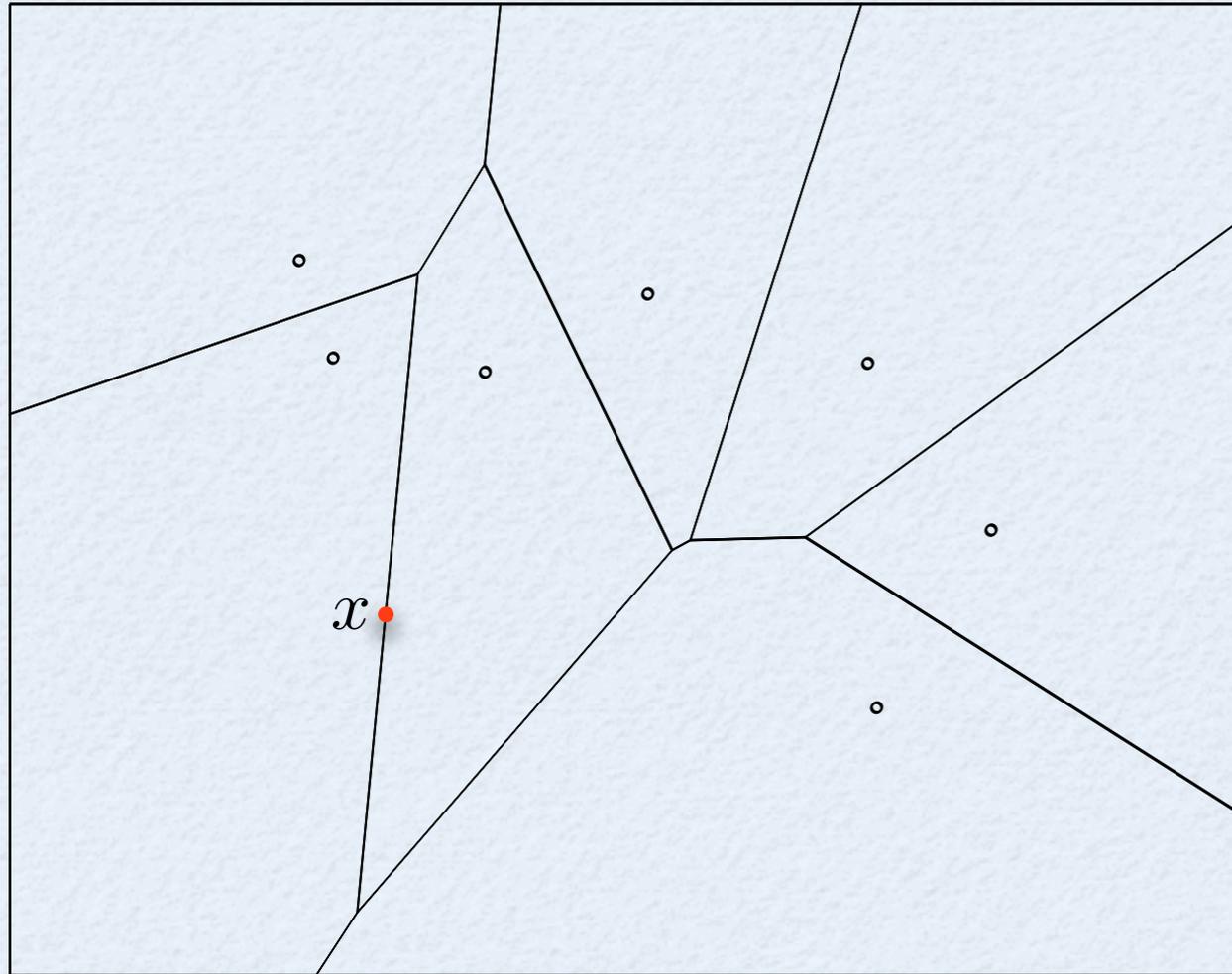
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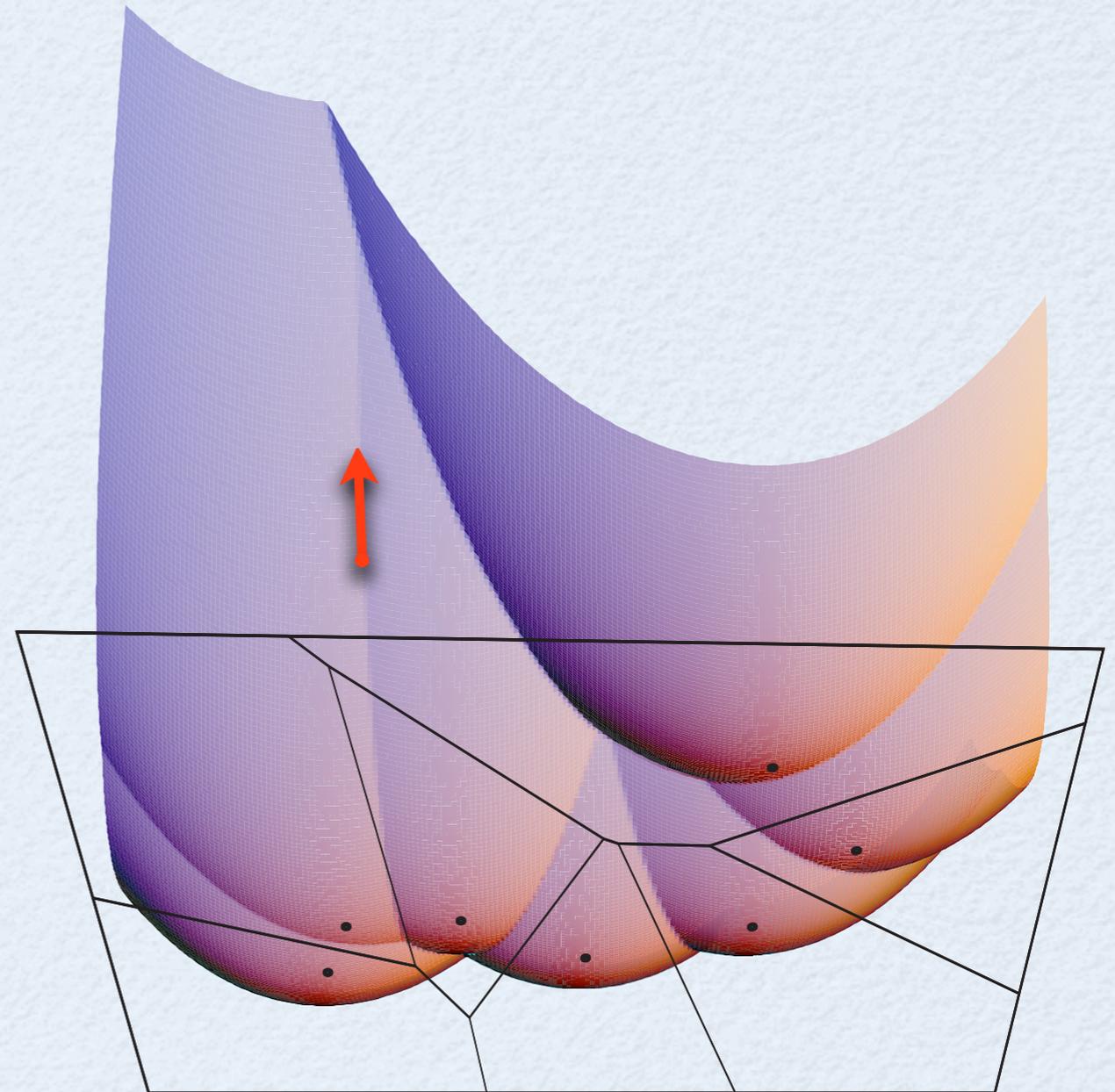
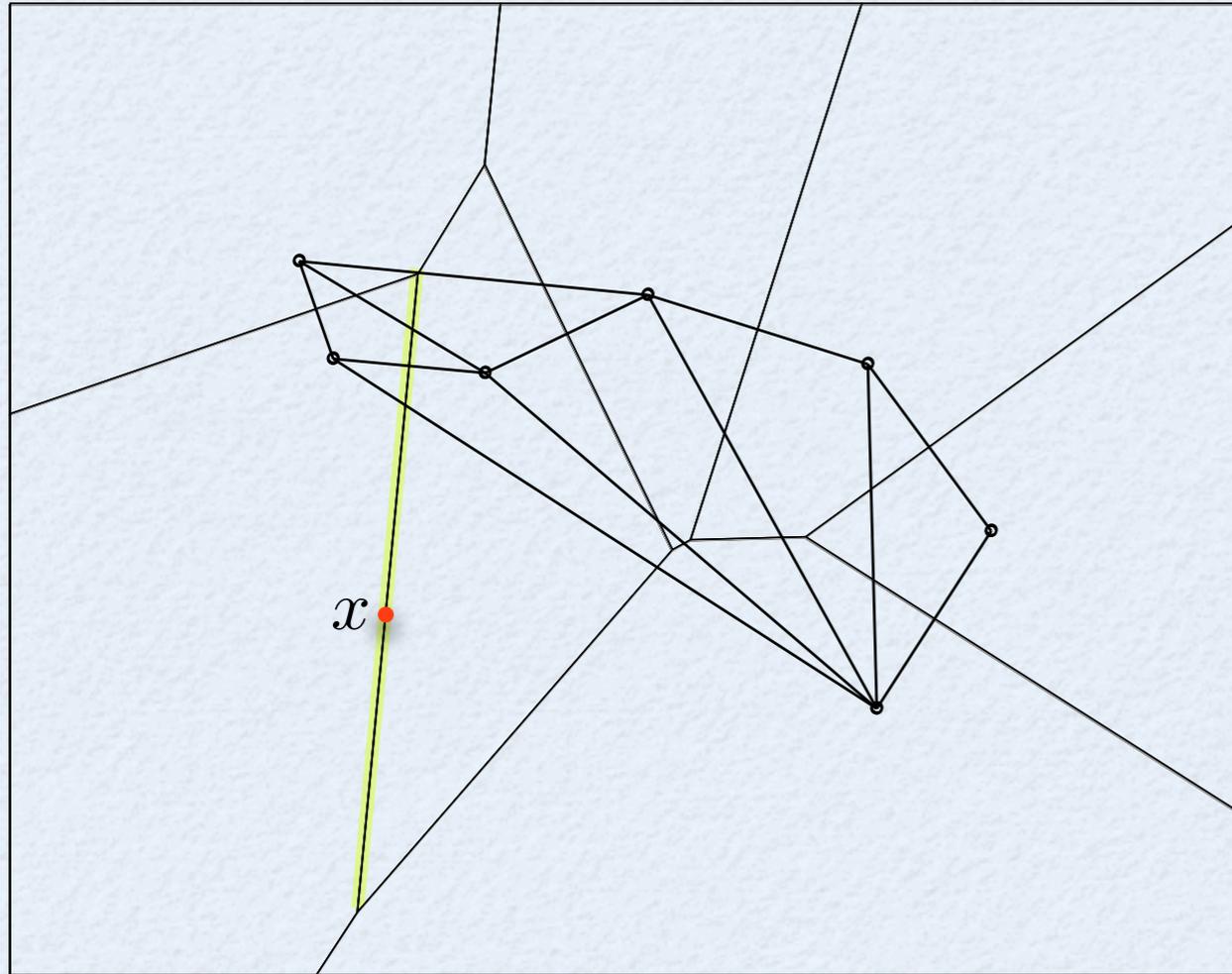


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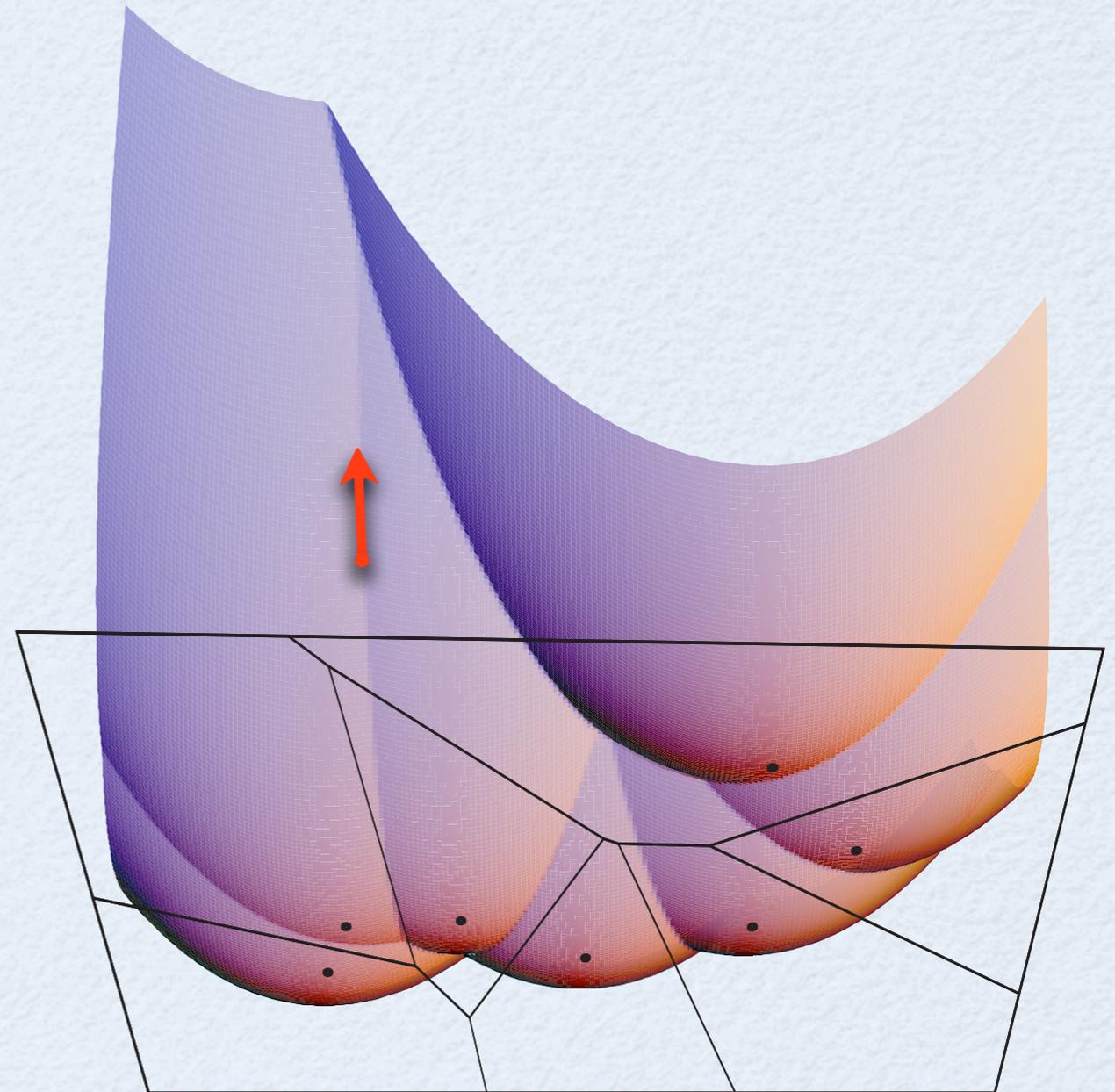
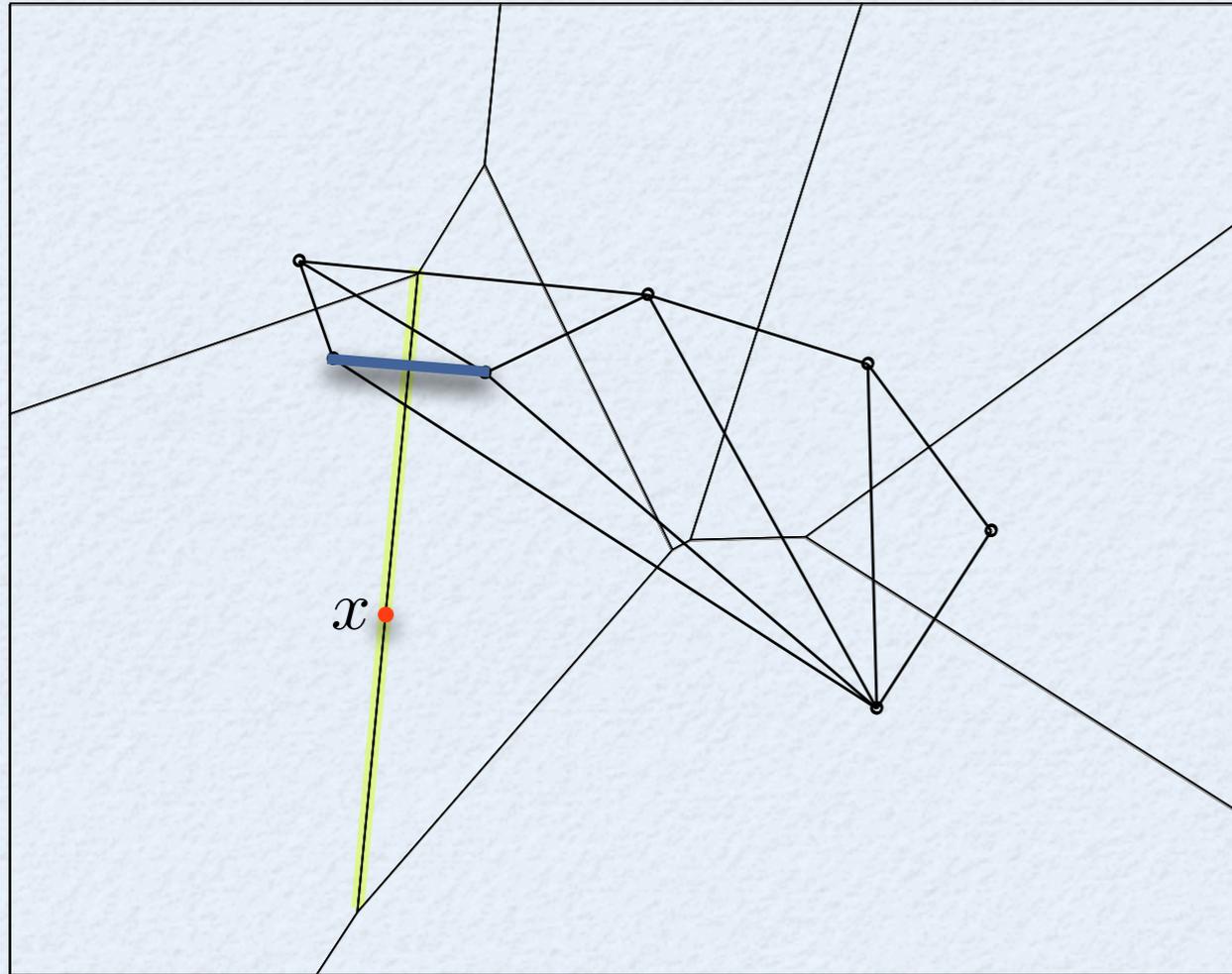
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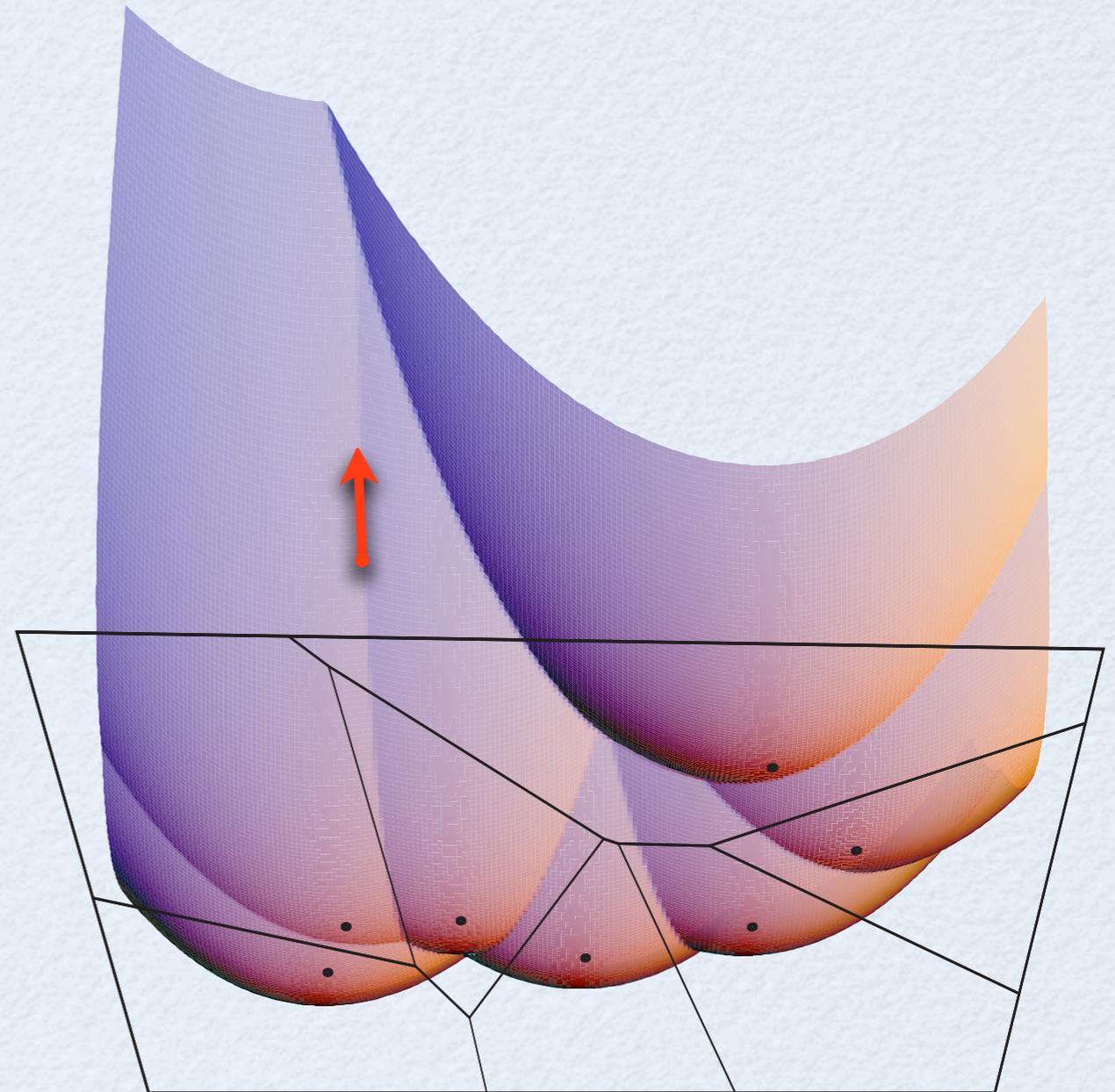
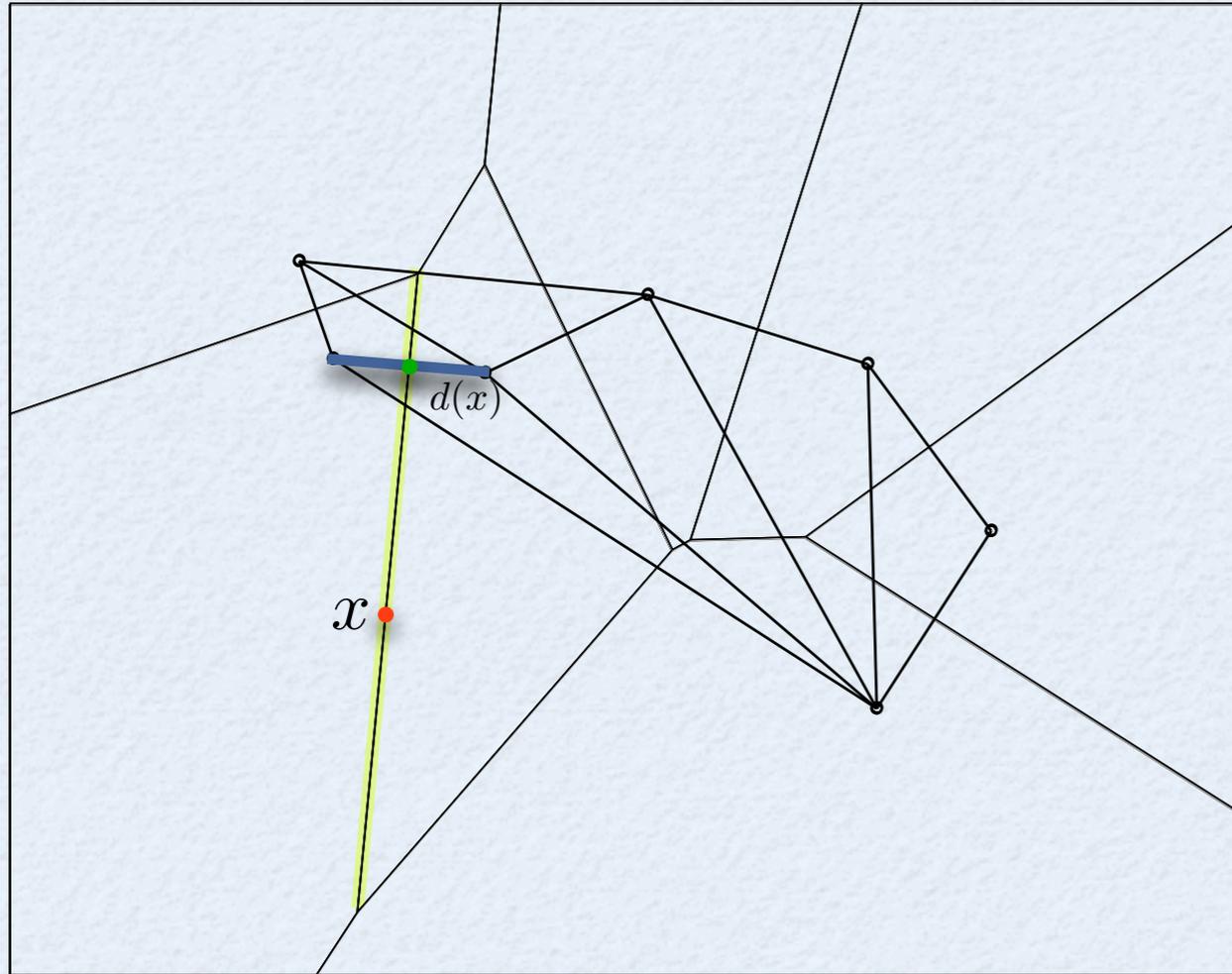
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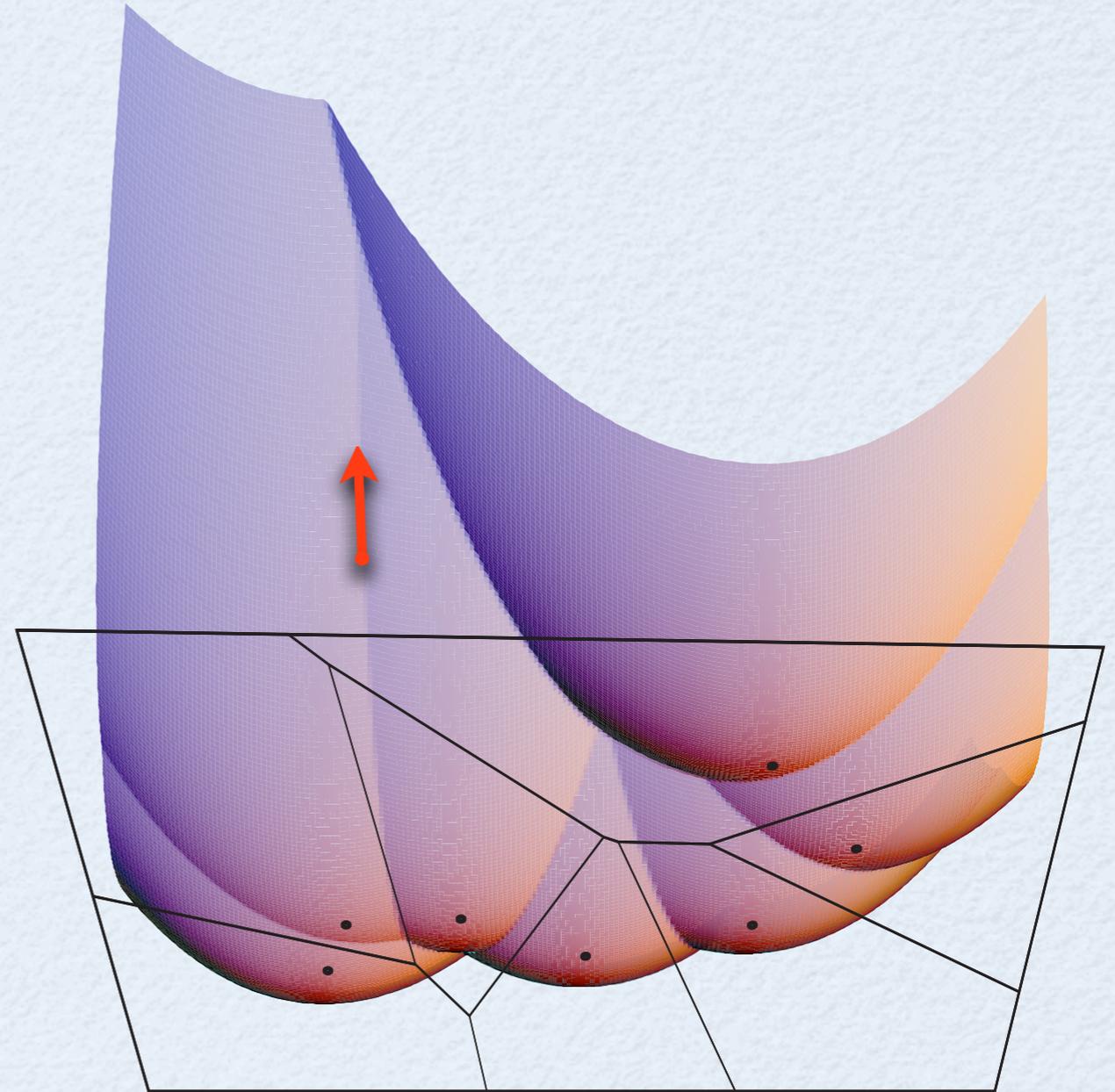
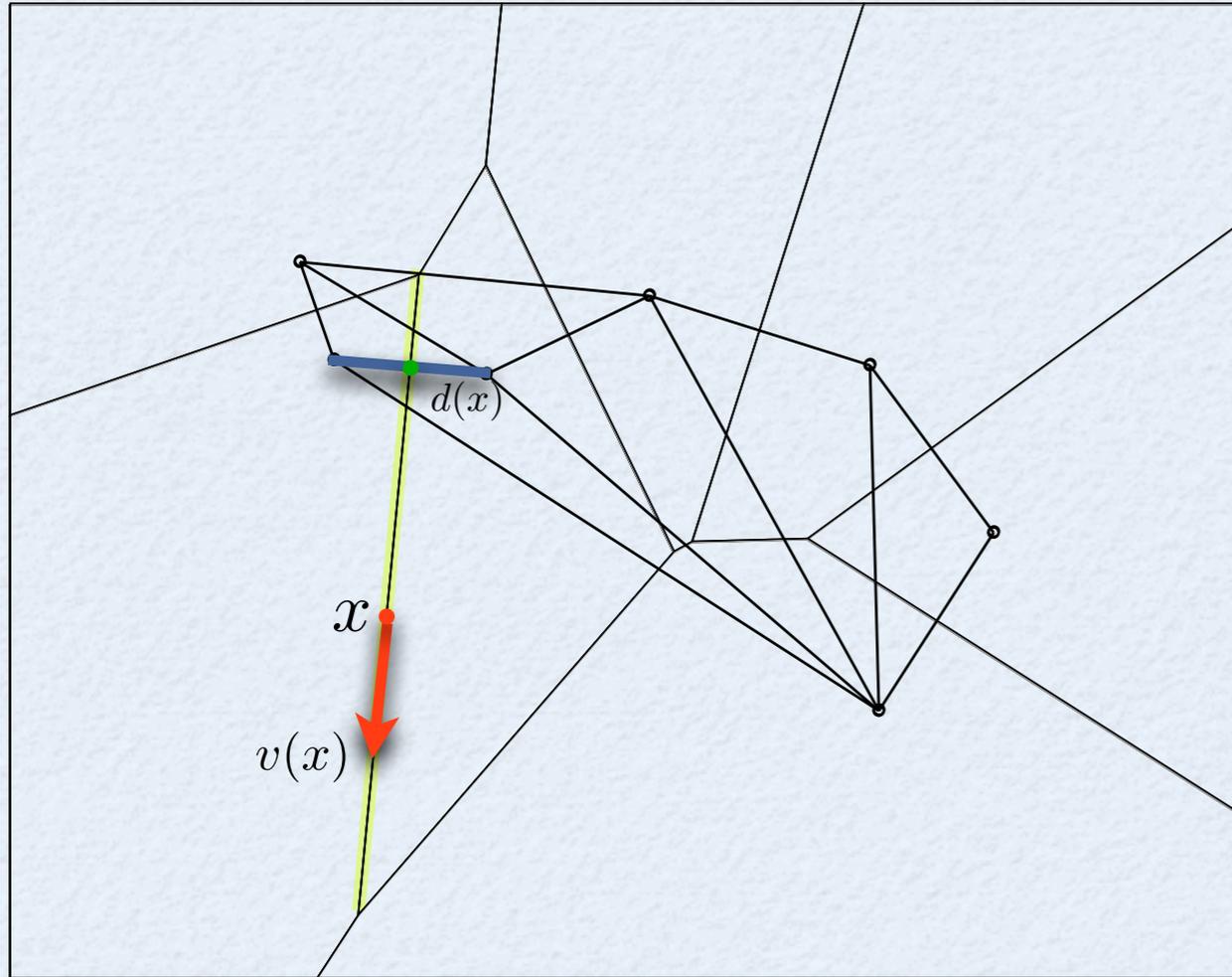
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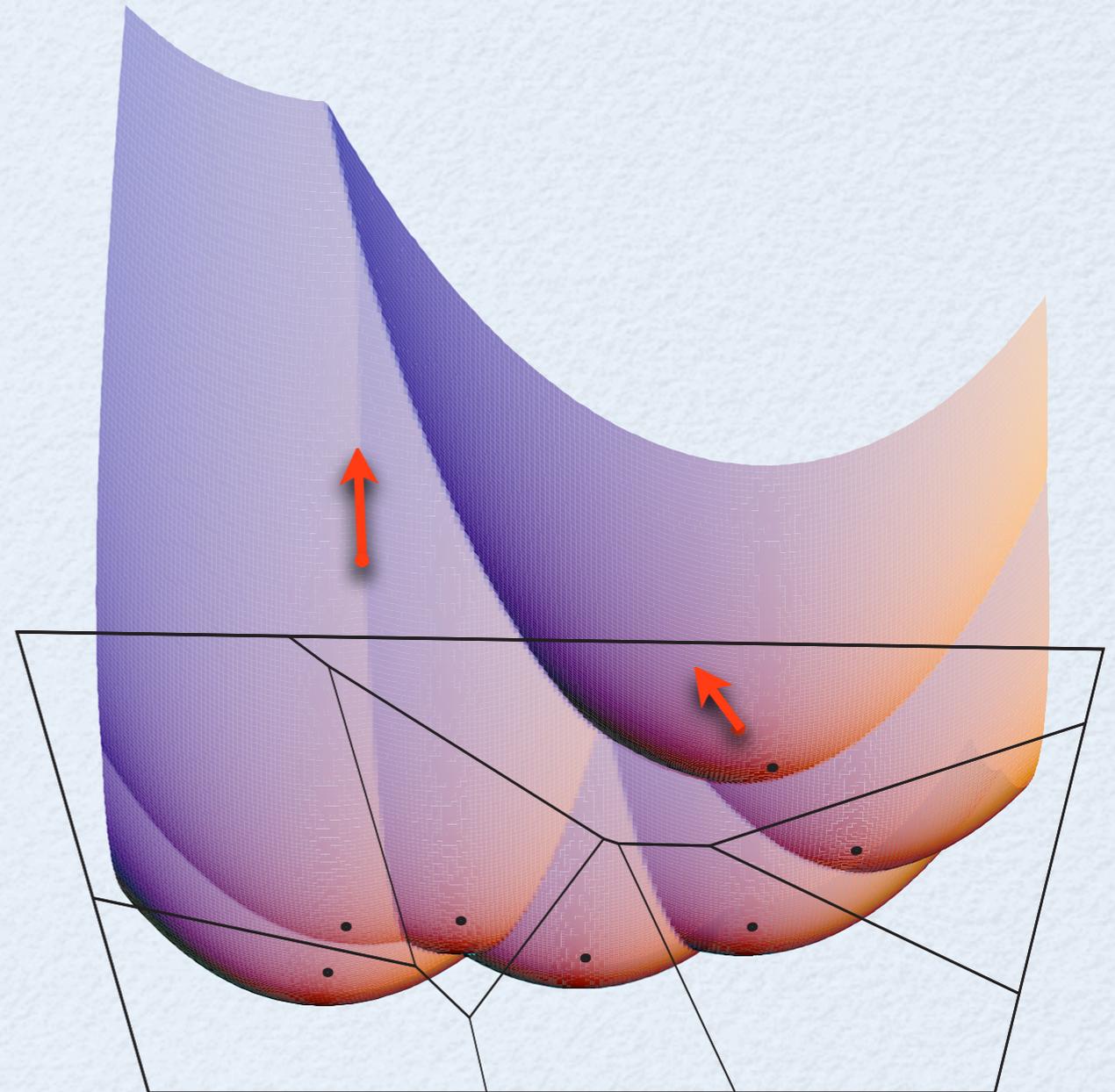
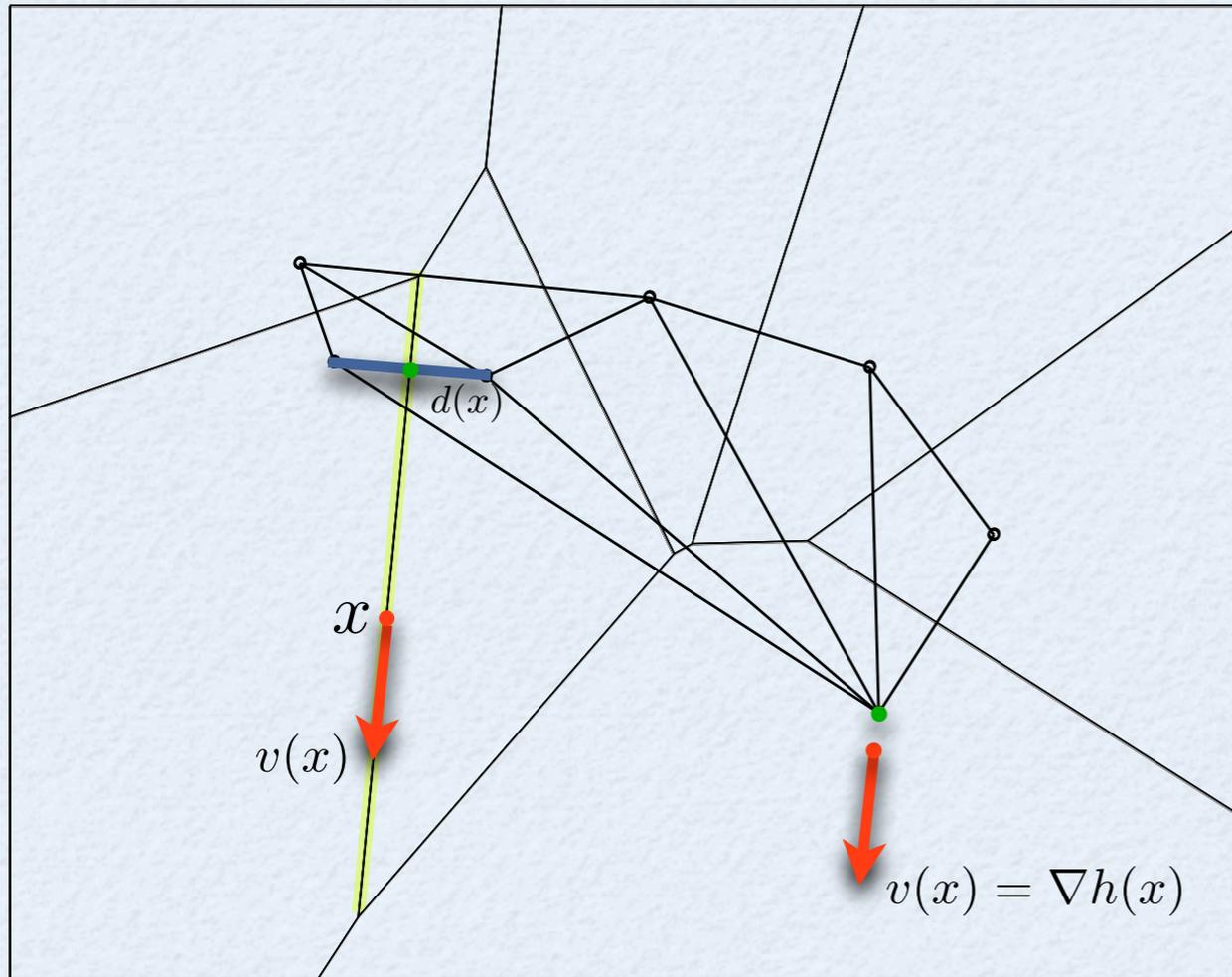
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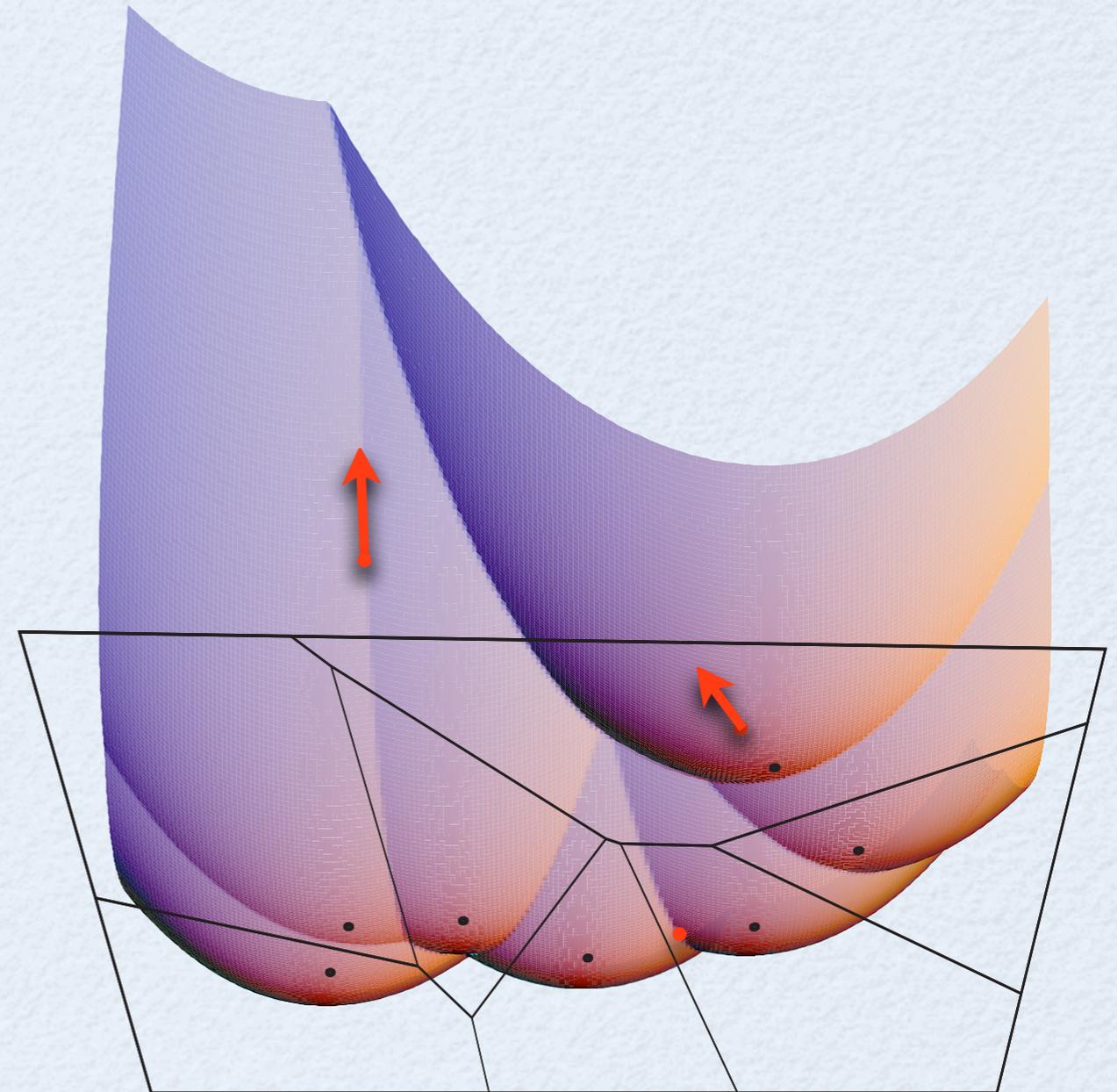
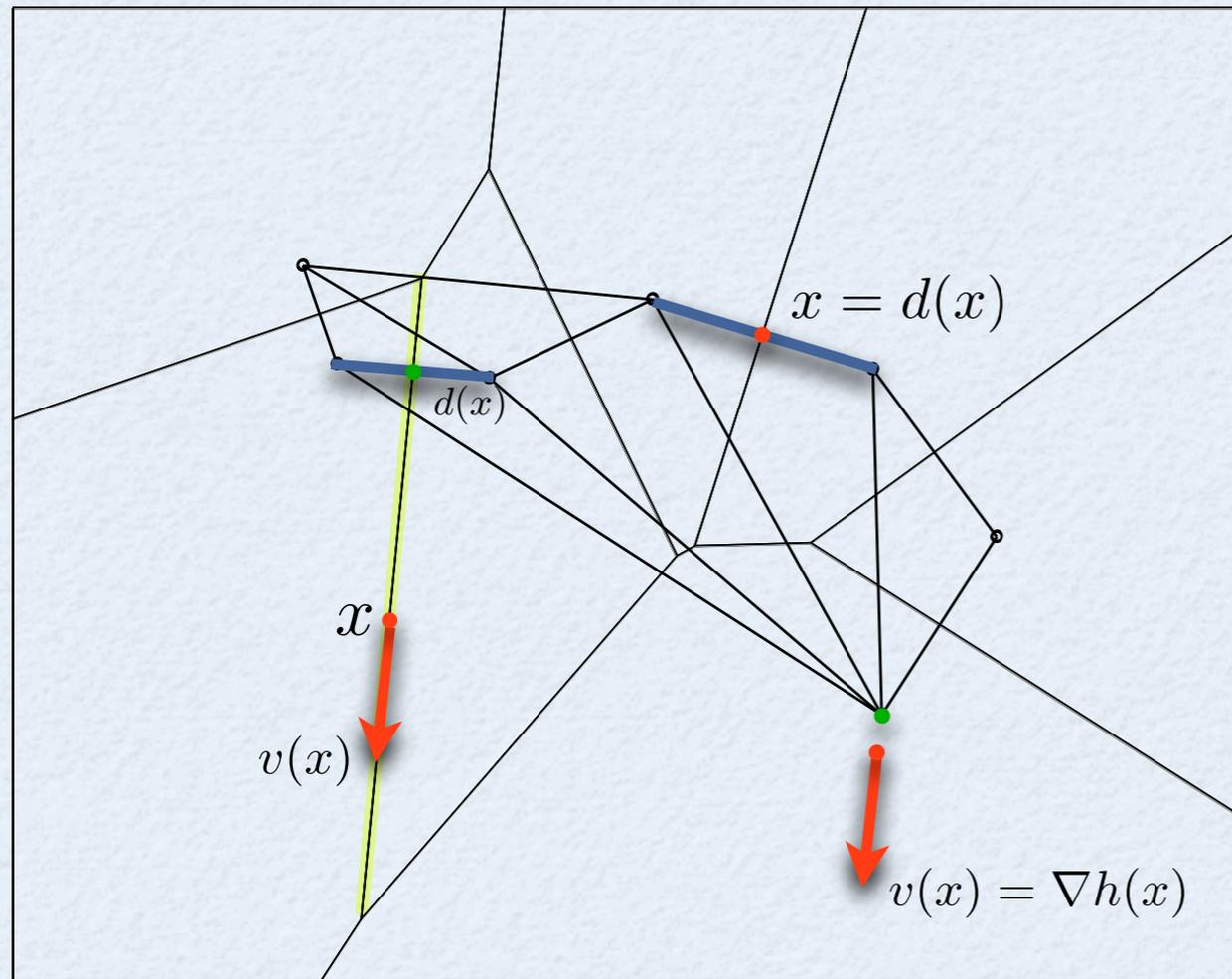
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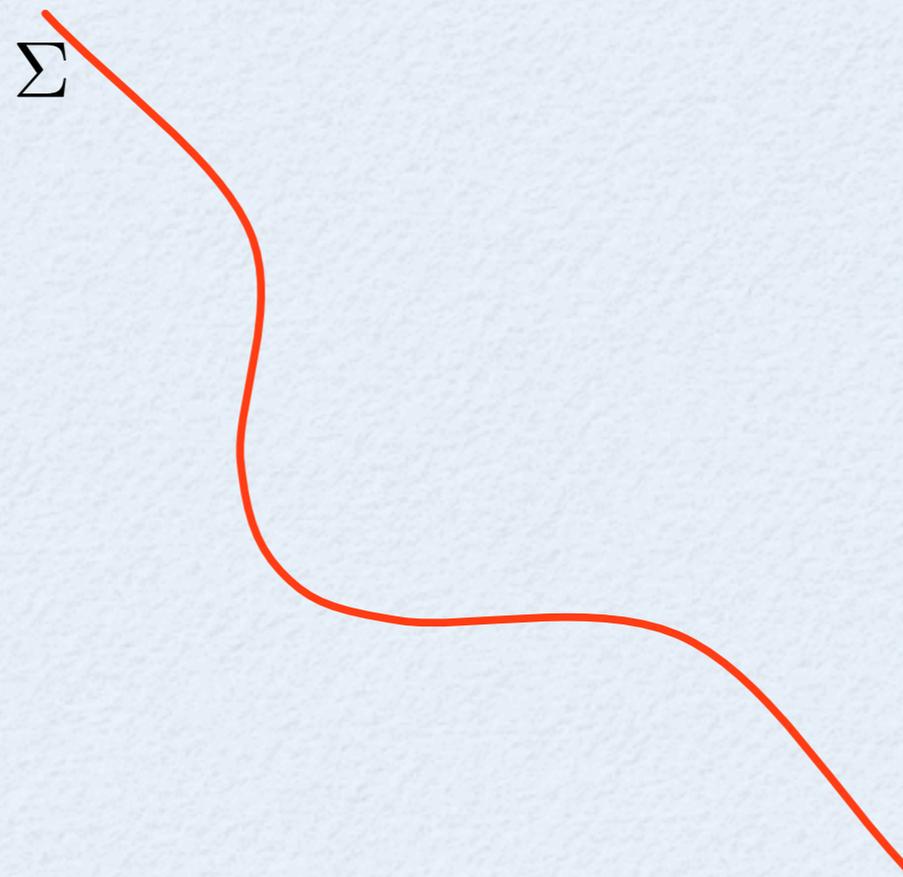
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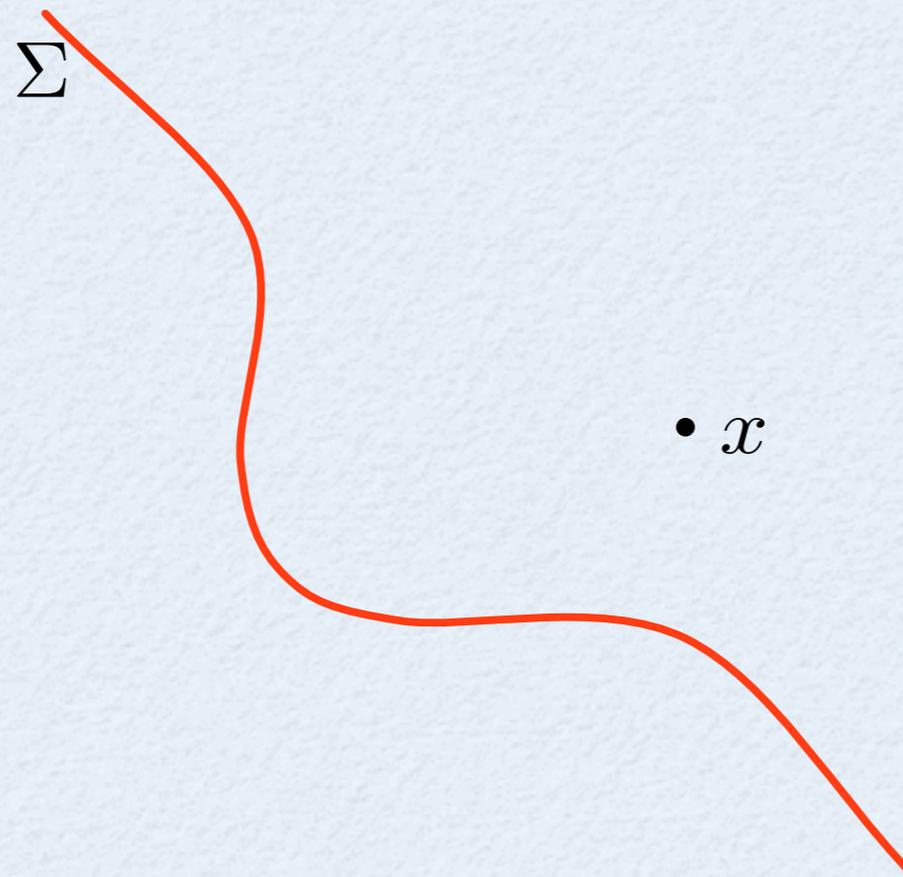
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Generalized gradients can be defined for distance to any **compact** set.



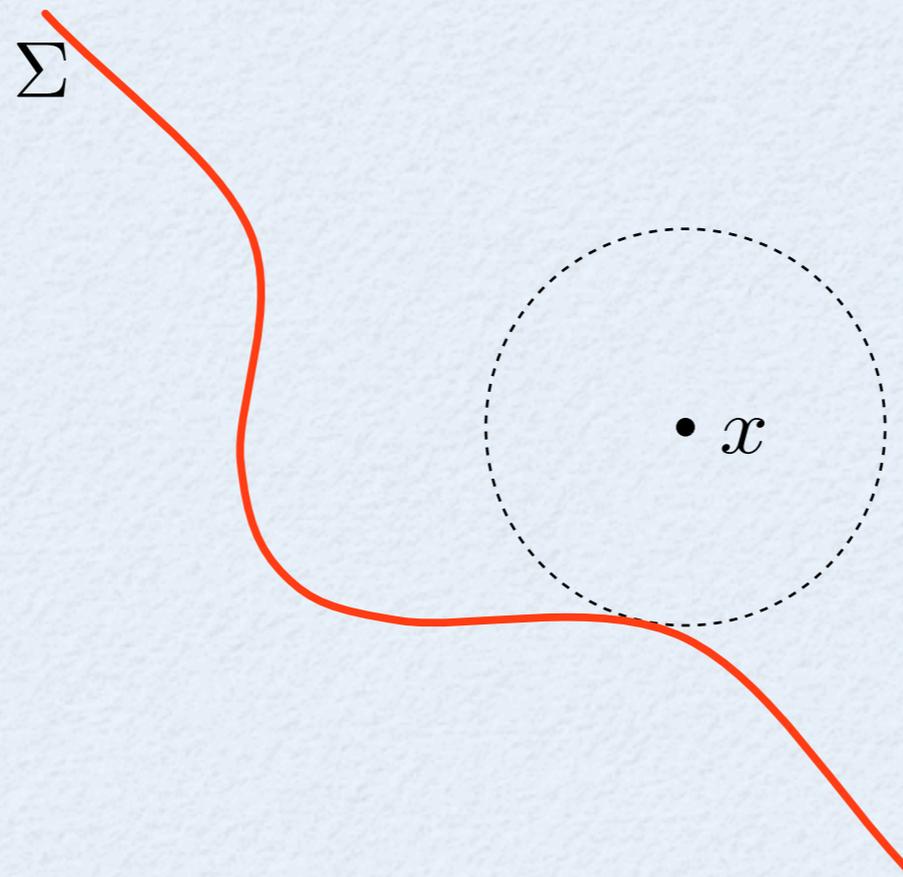
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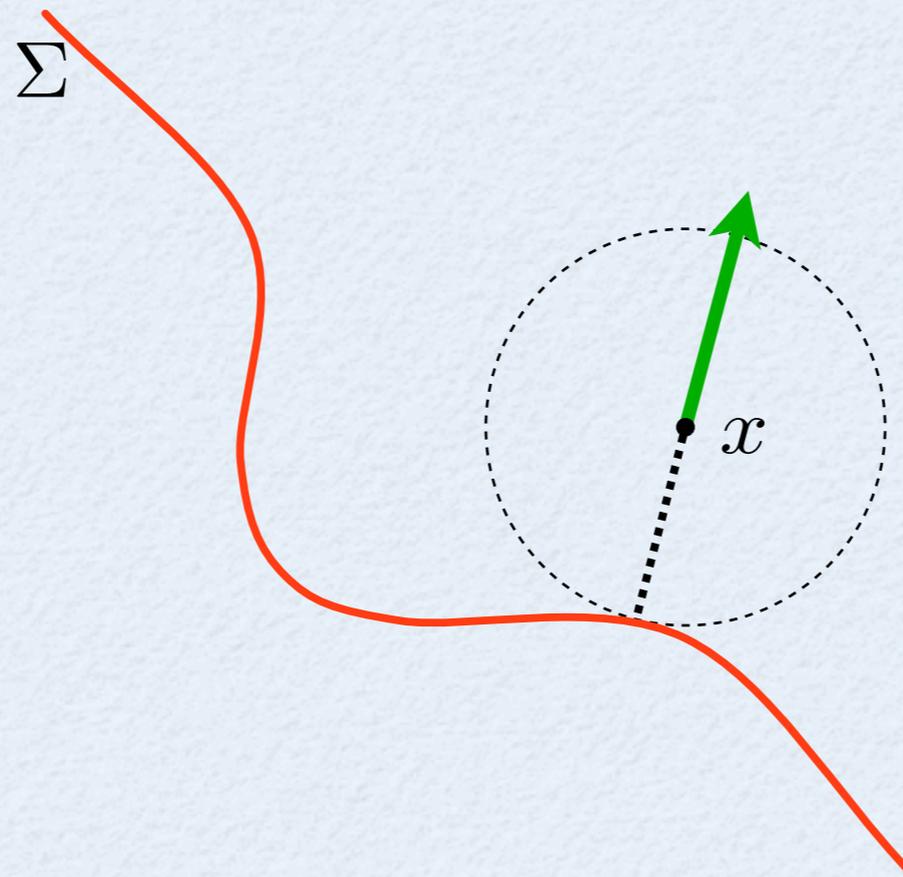
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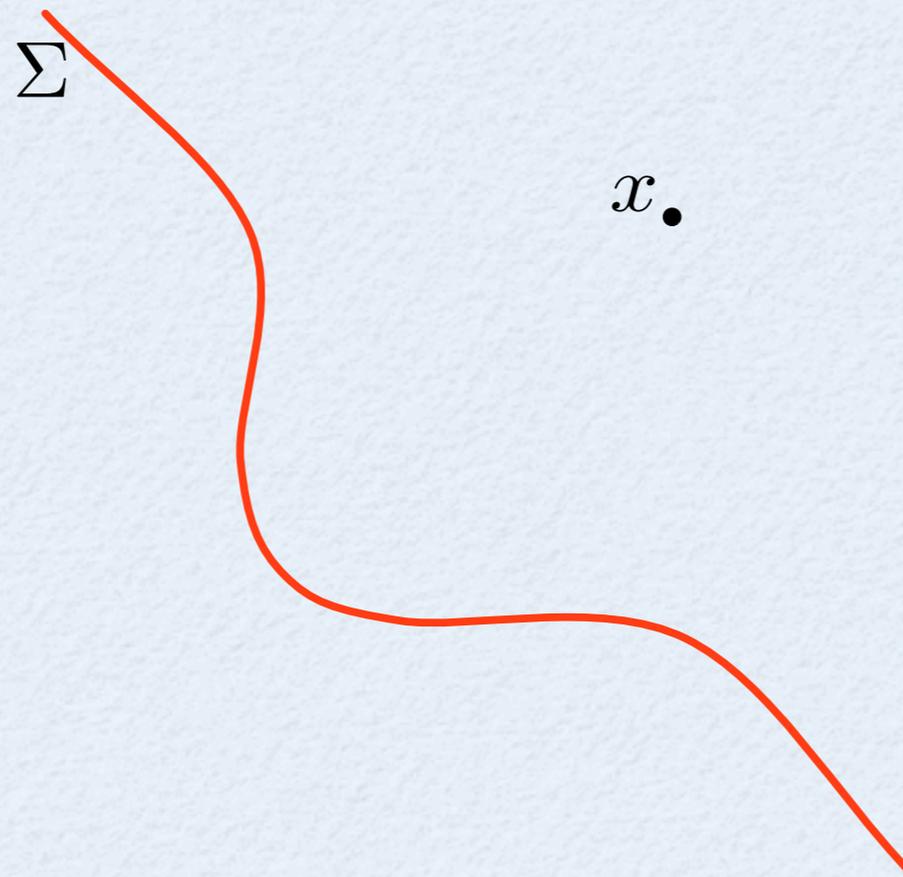
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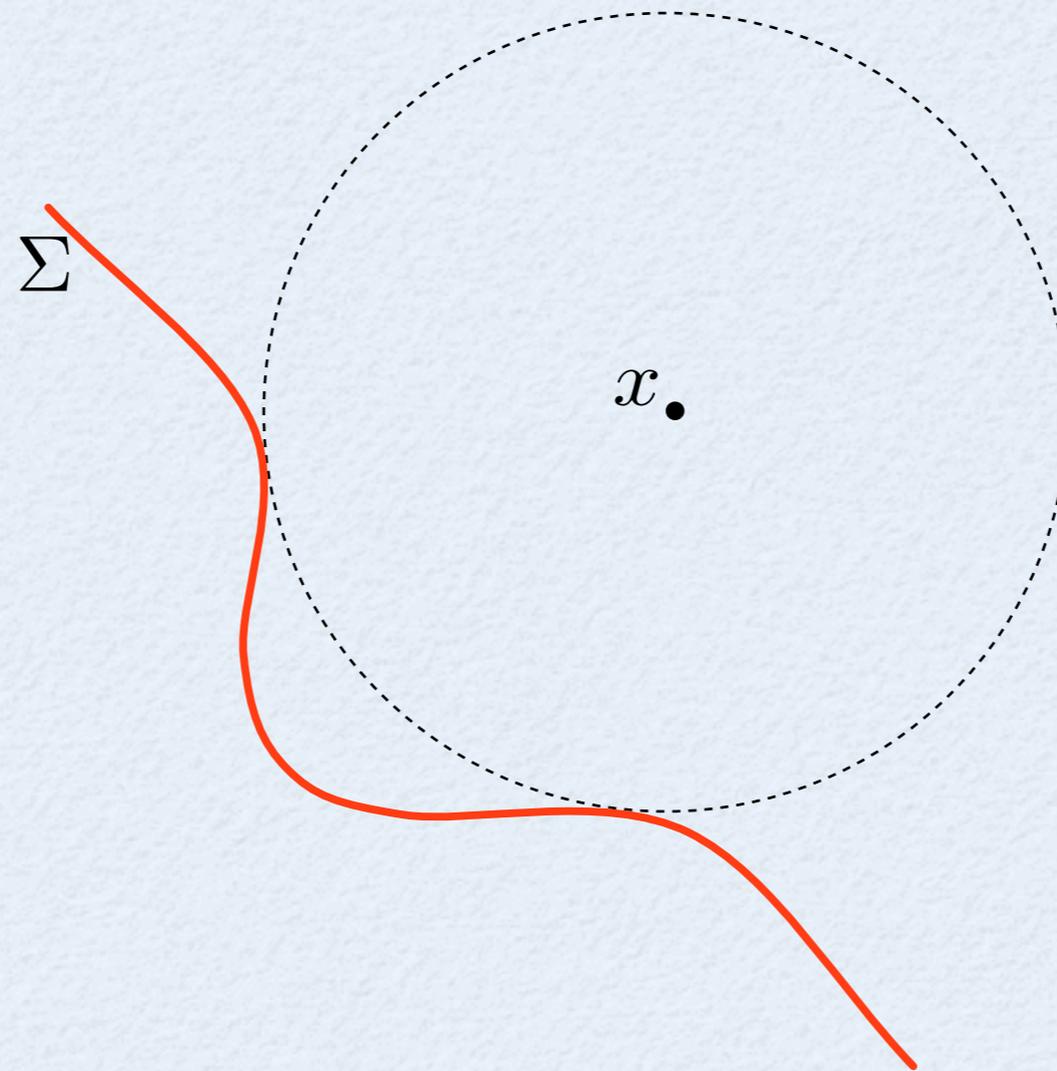
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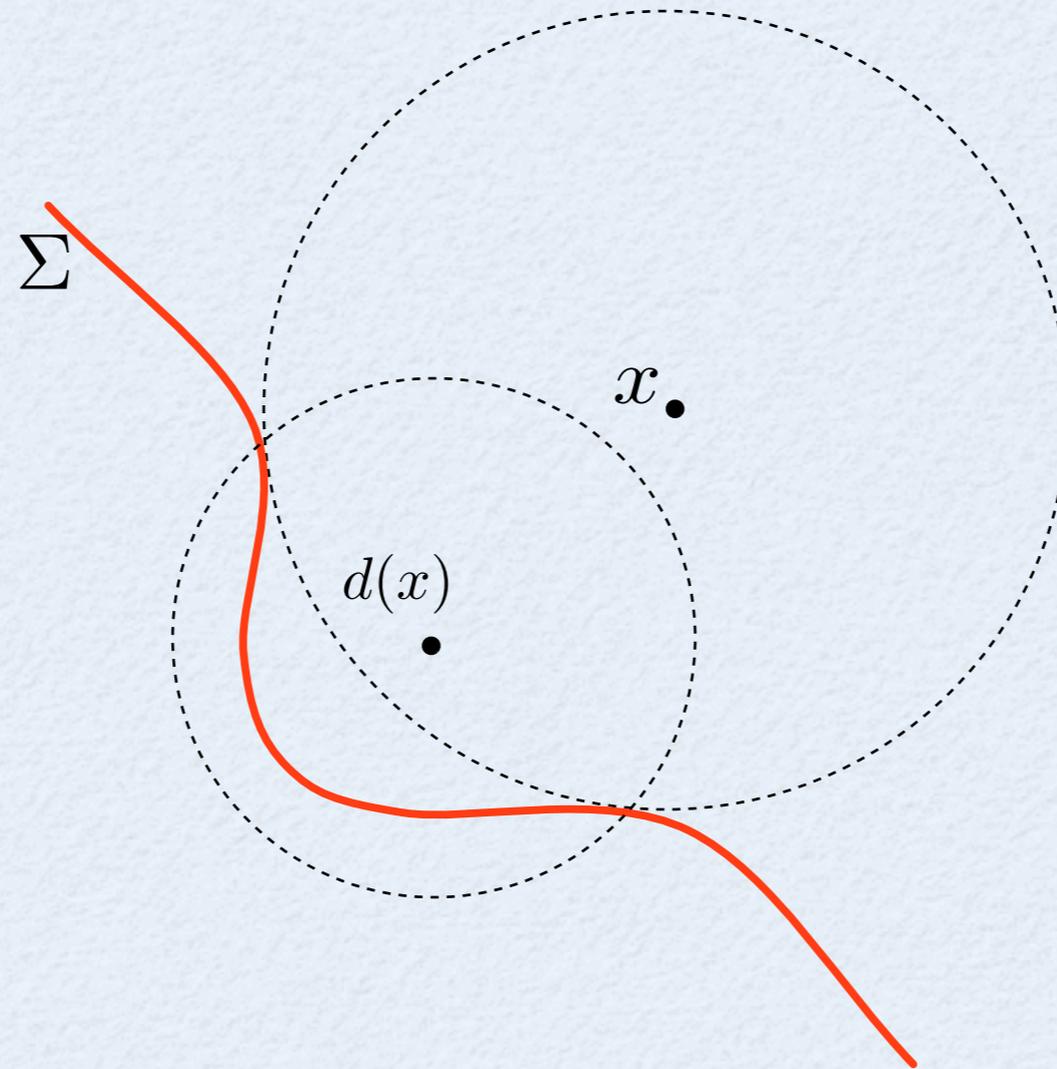
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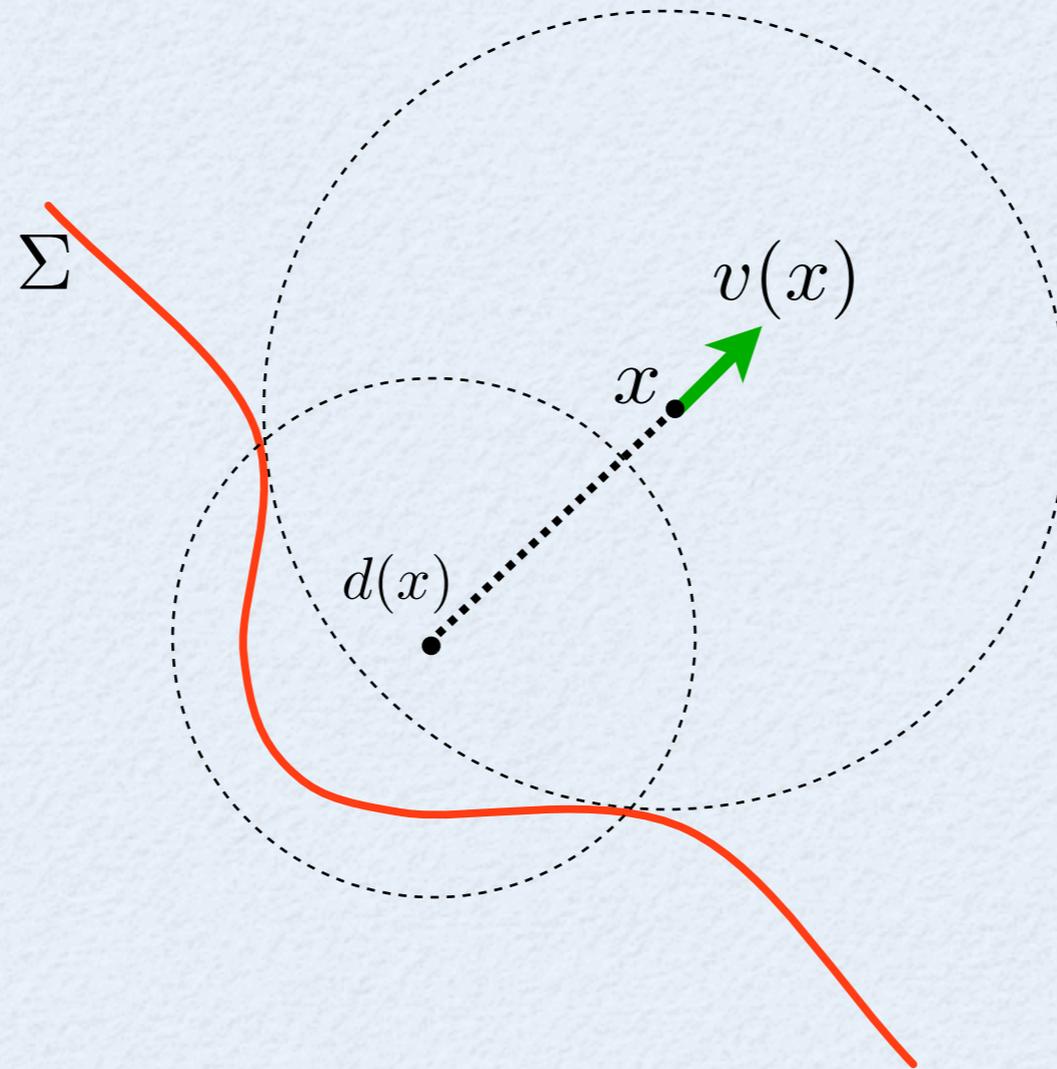
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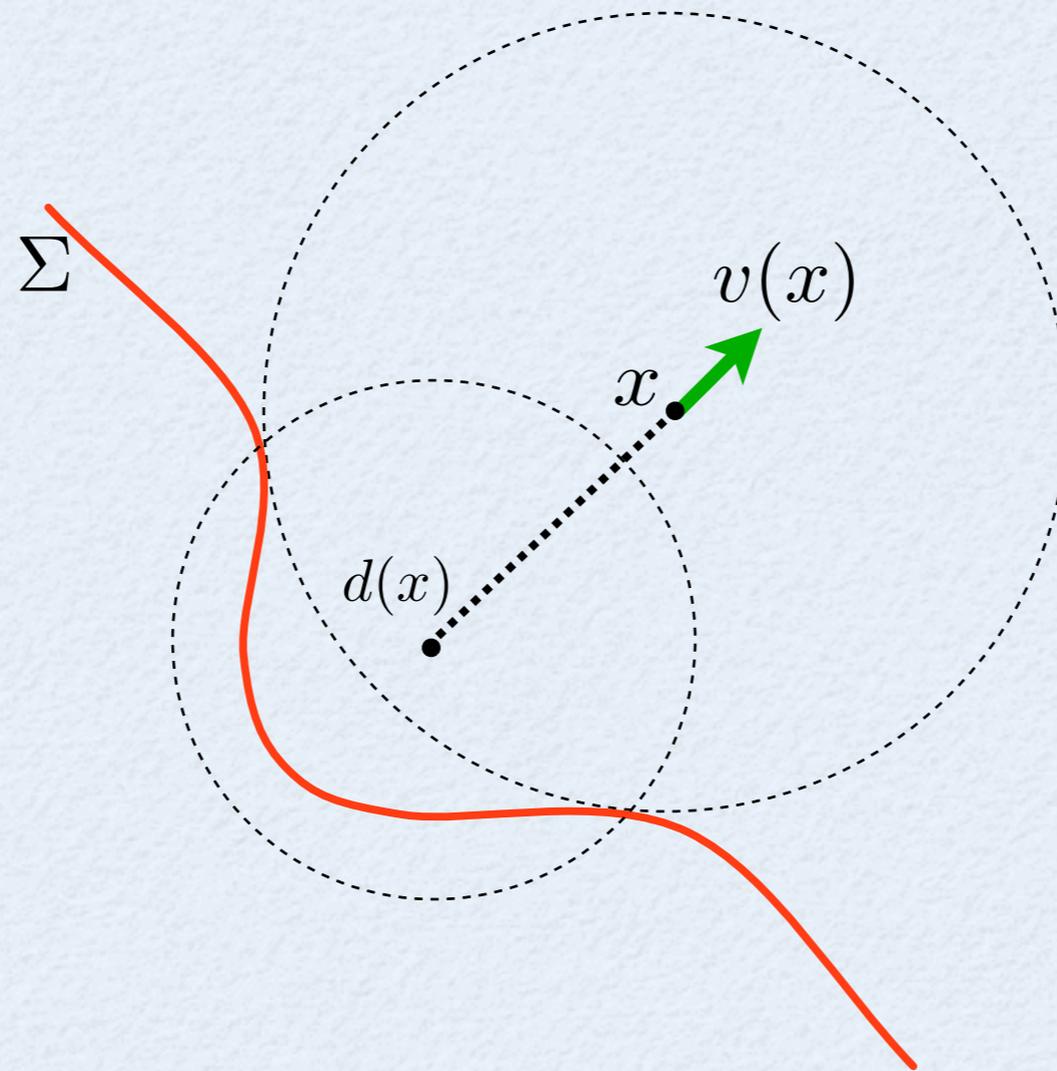
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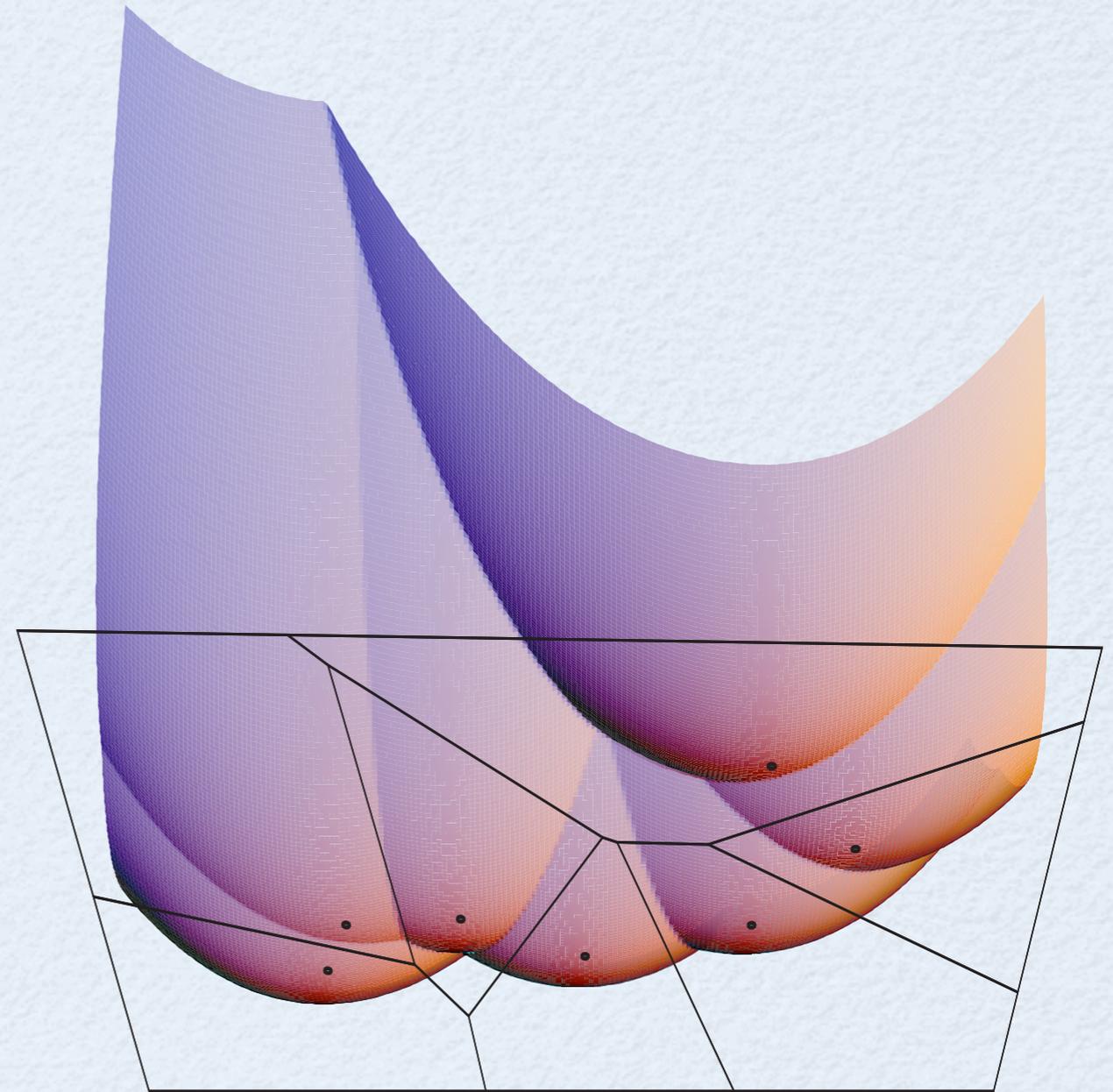
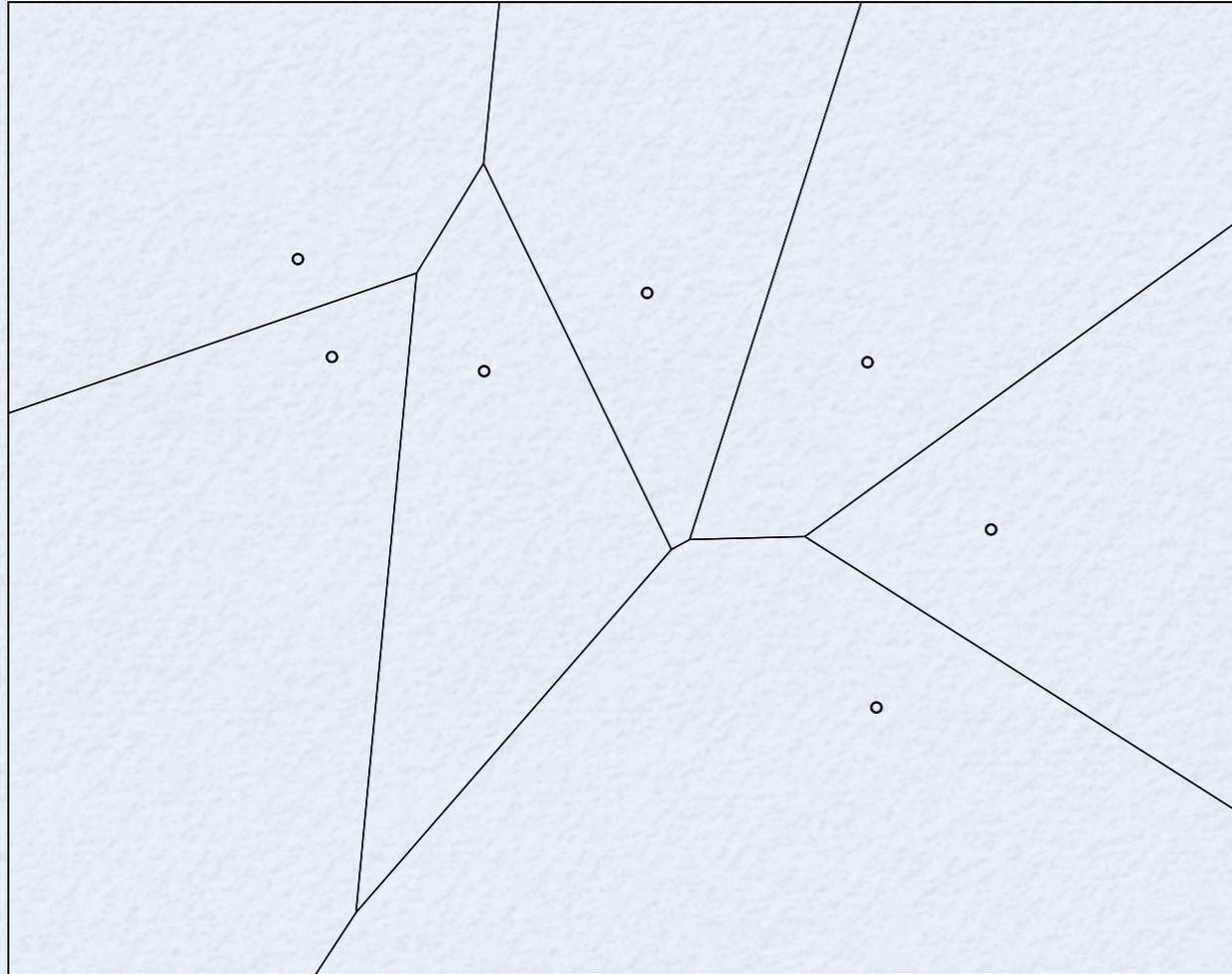
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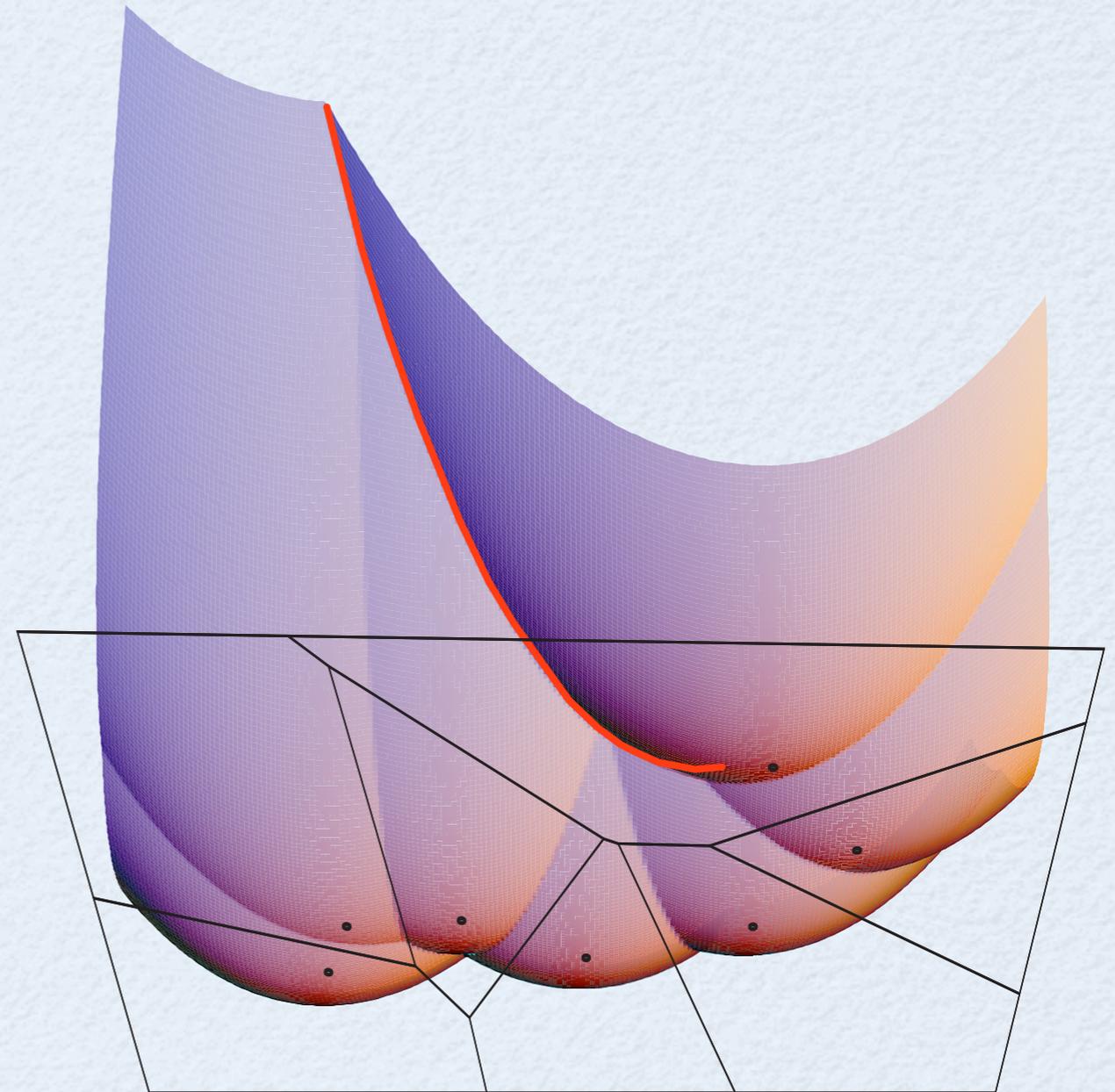
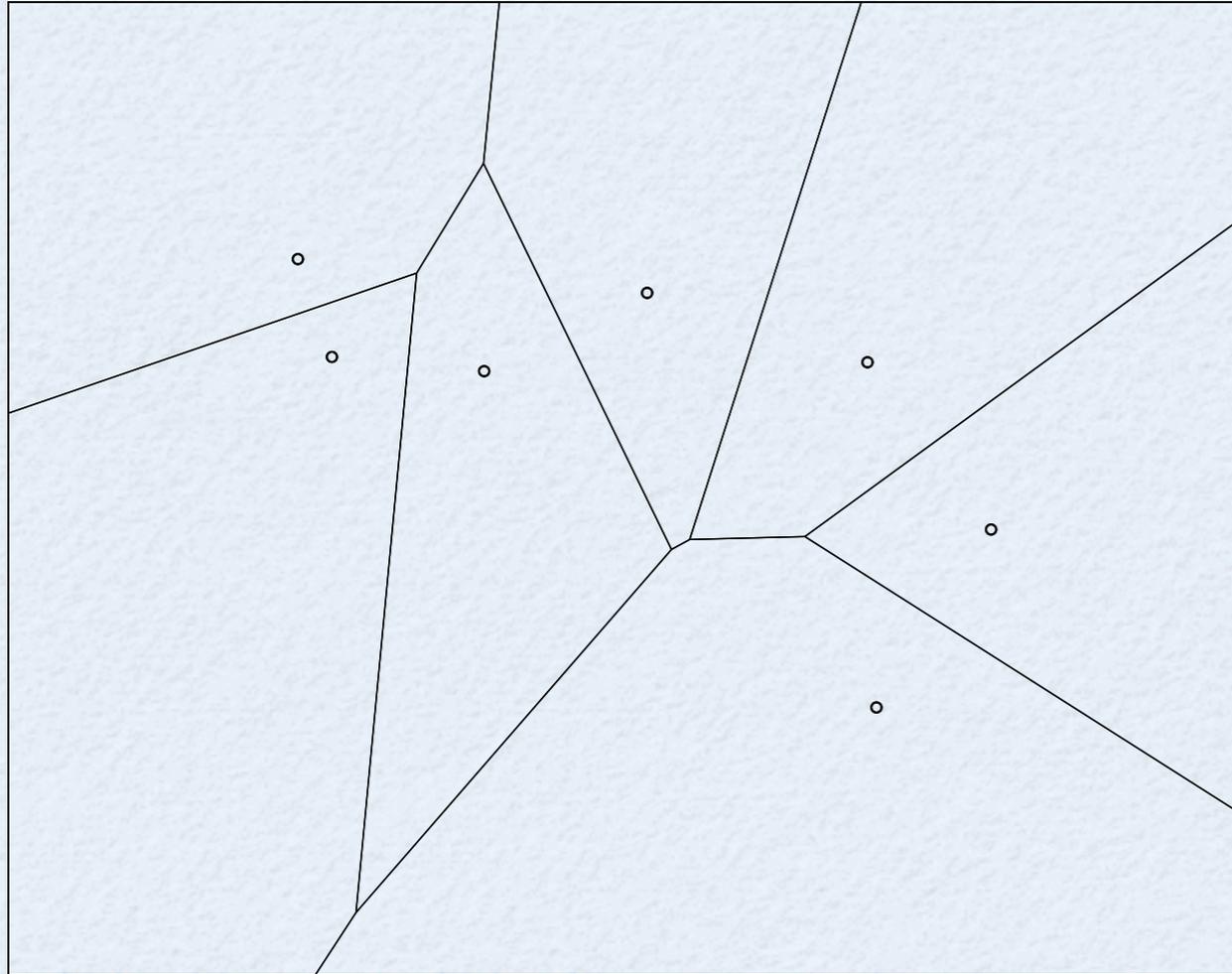
... or even for (geodesic) distances relative to a compact subset of a Riemannian manifold. [Grove' 93]

# Integrating $v$



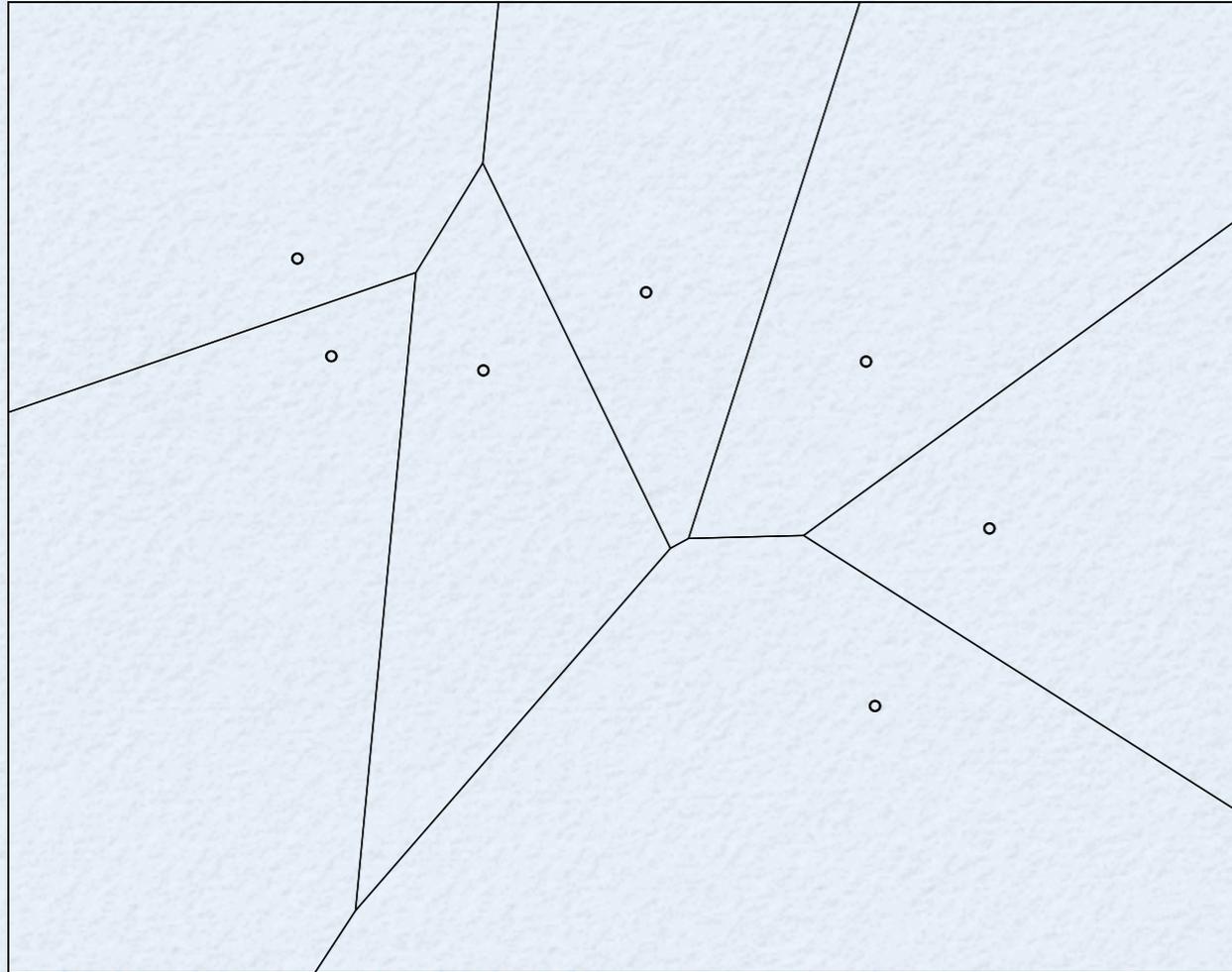
Moving at point  $x$  with speed  $v(x)$  results a flow map  $\phi : \mathbb{R}^+ \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ .

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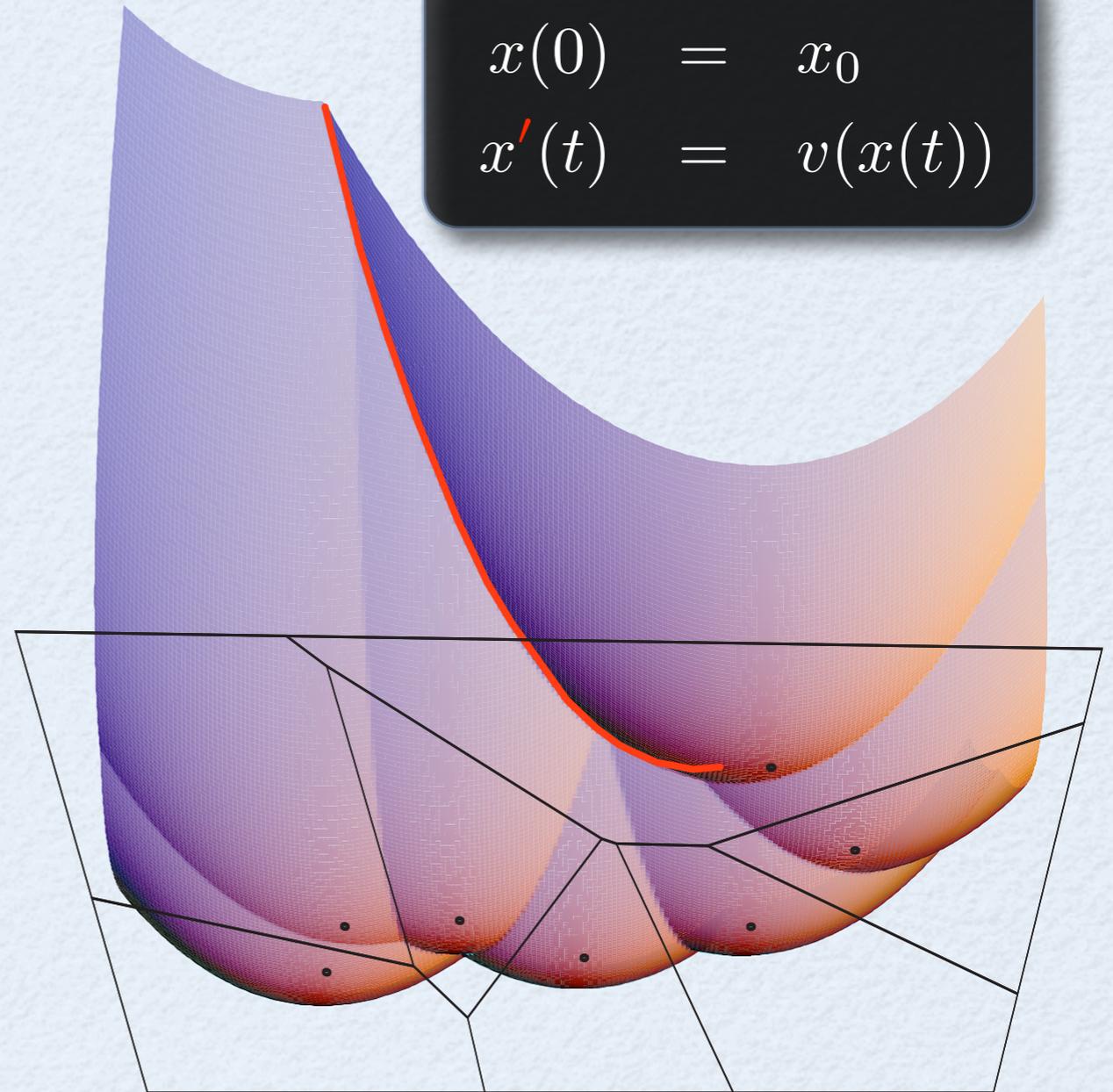


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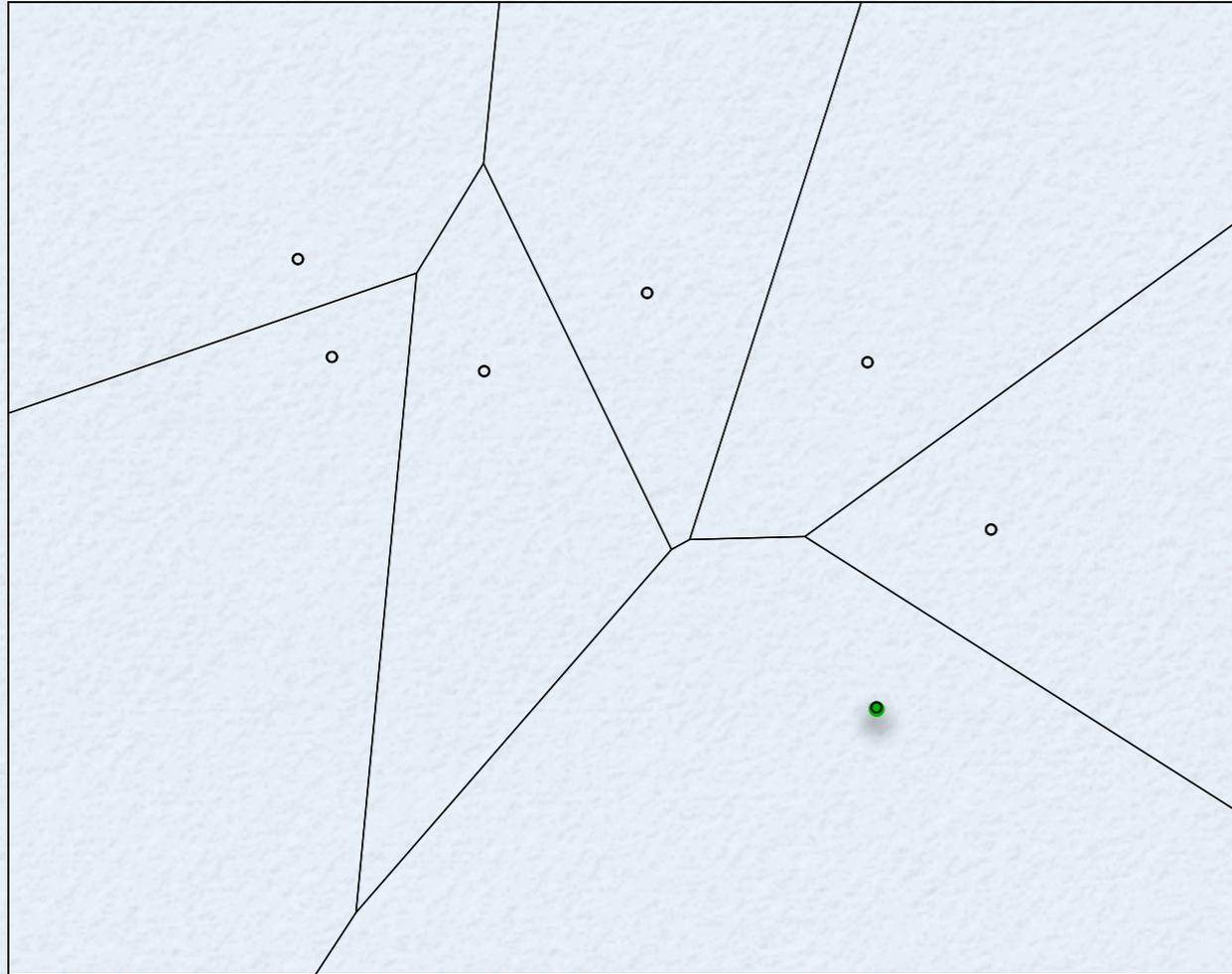


$$\begin{aligned}x(0) &= x_0 \\x'(t) &= v(x(t))\end{aligned}$$

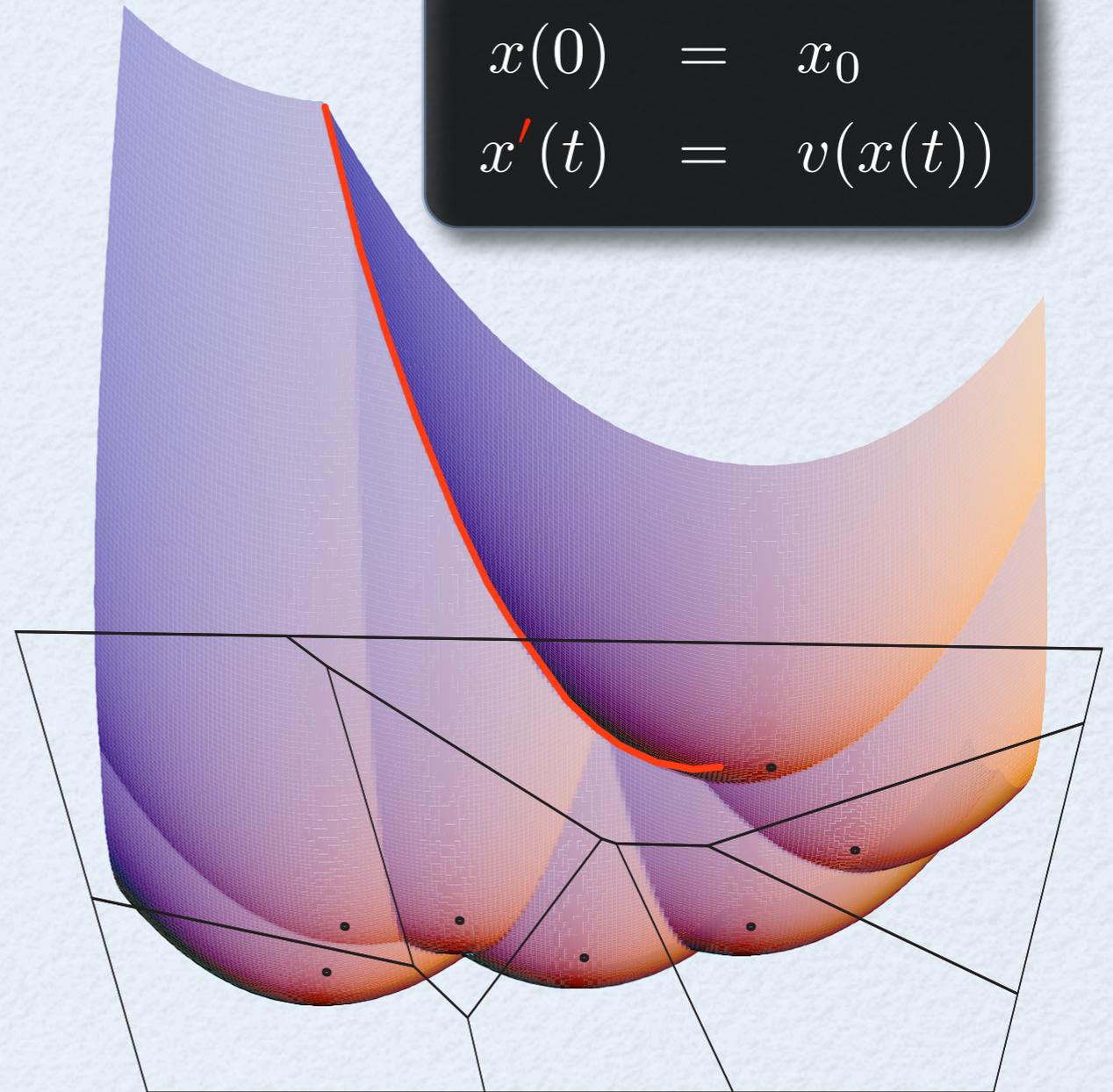


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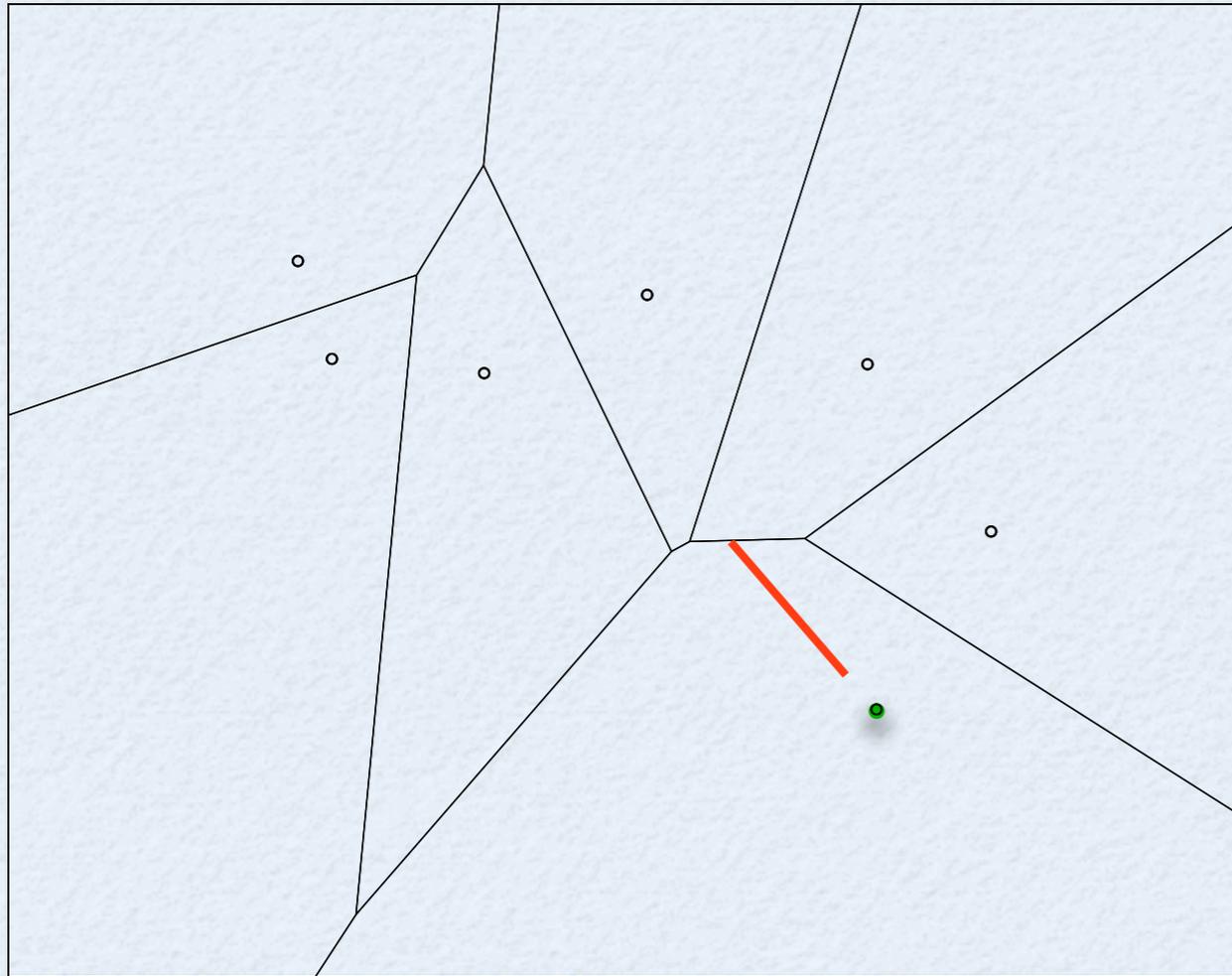


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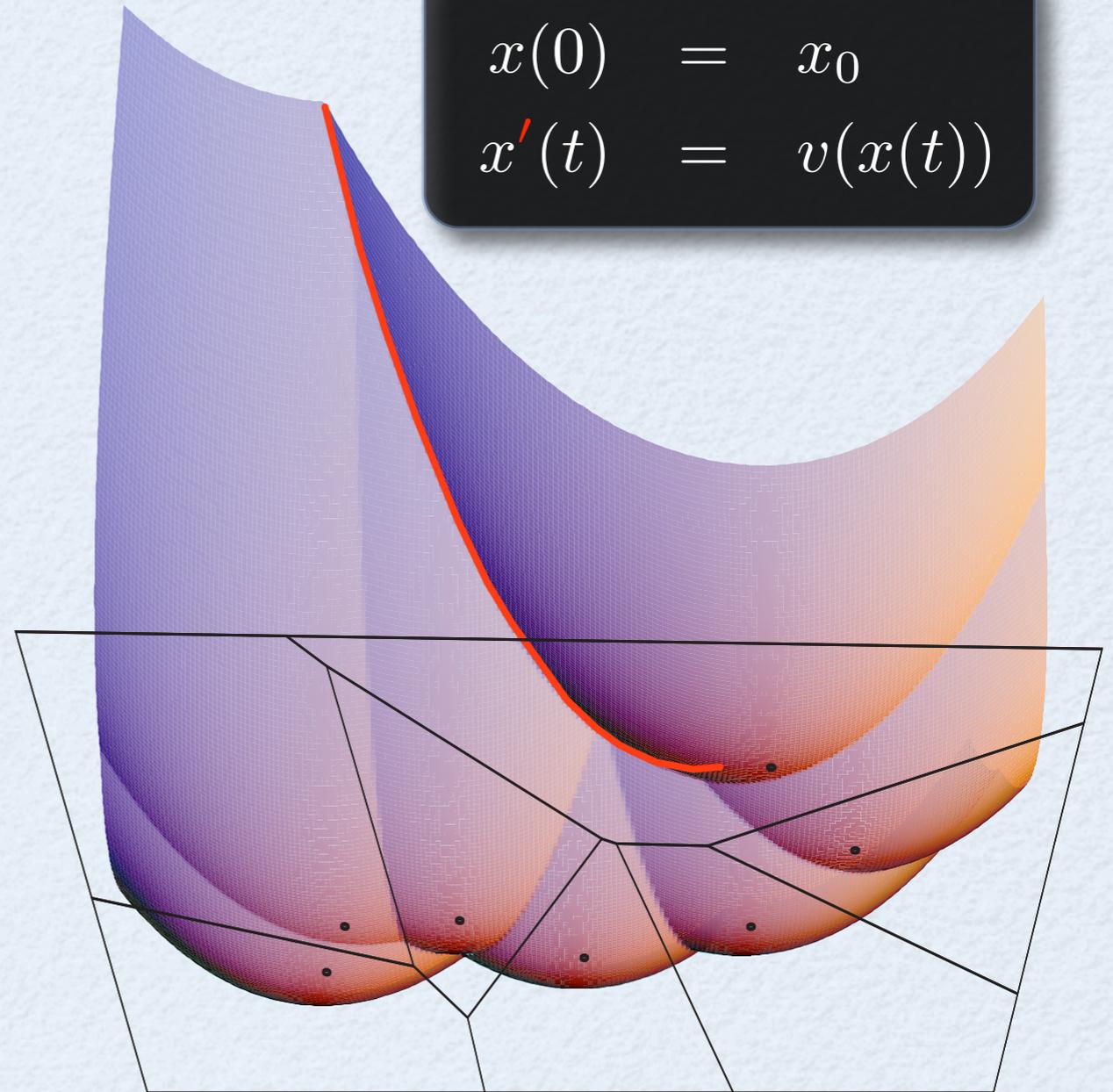


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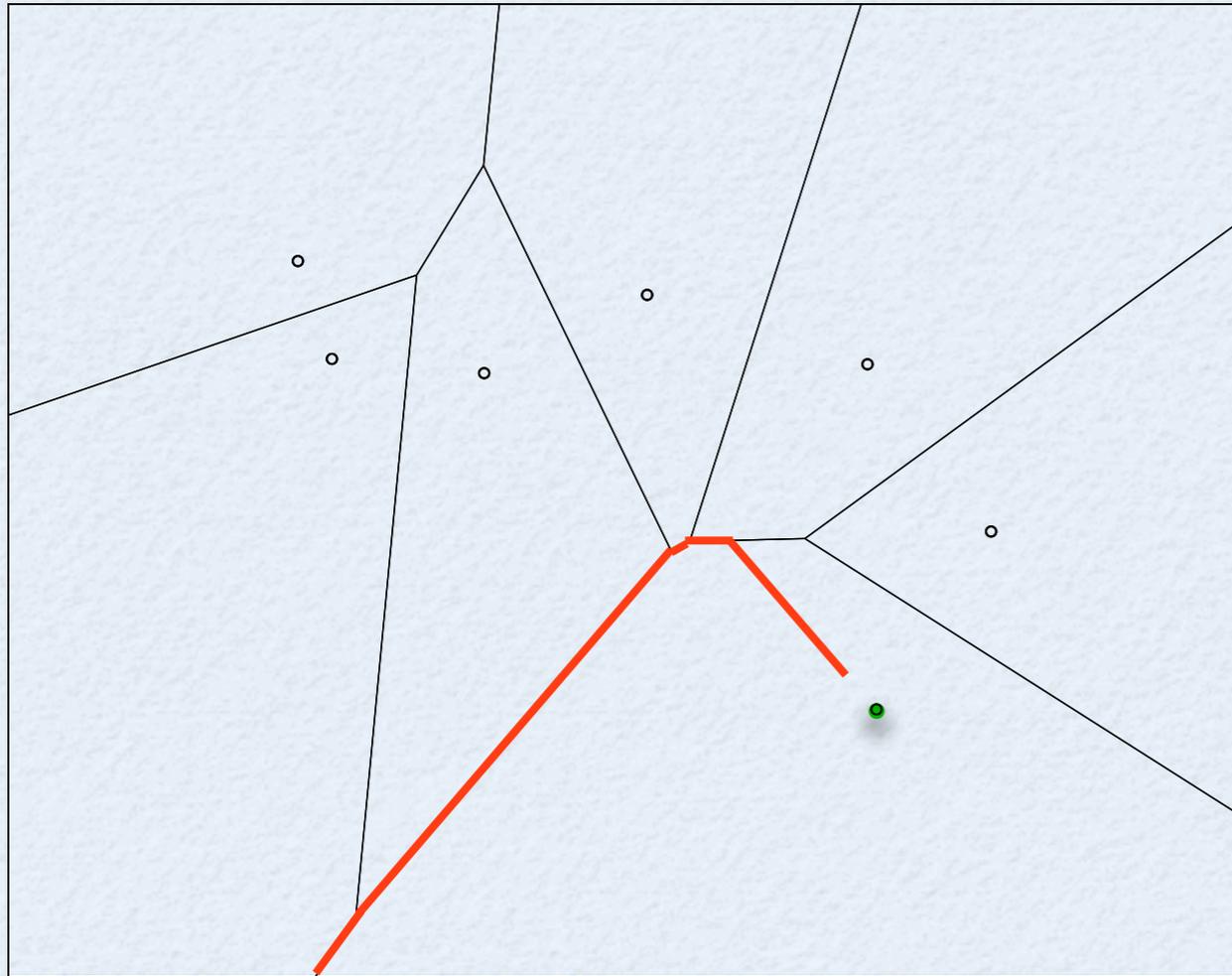


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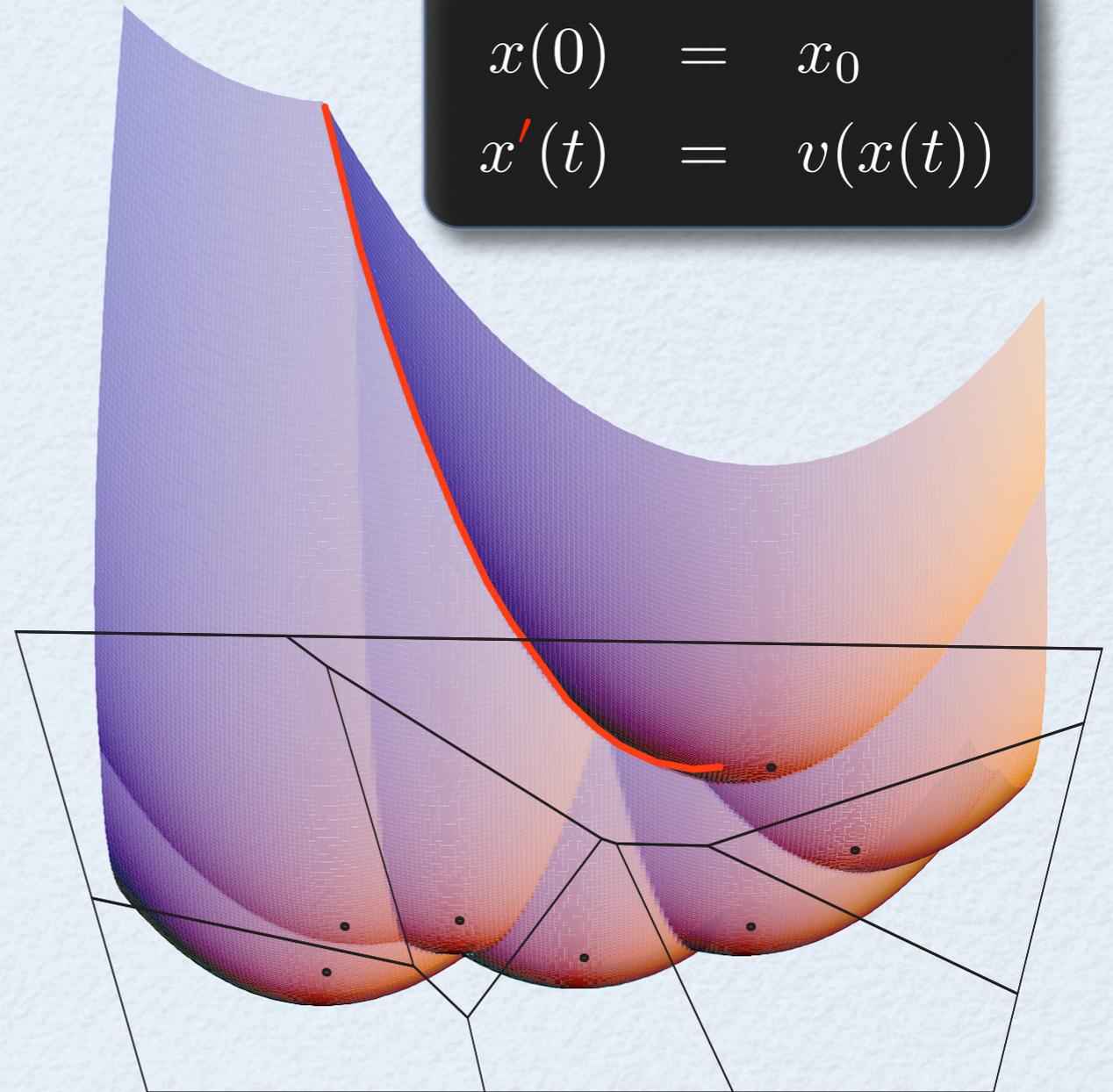


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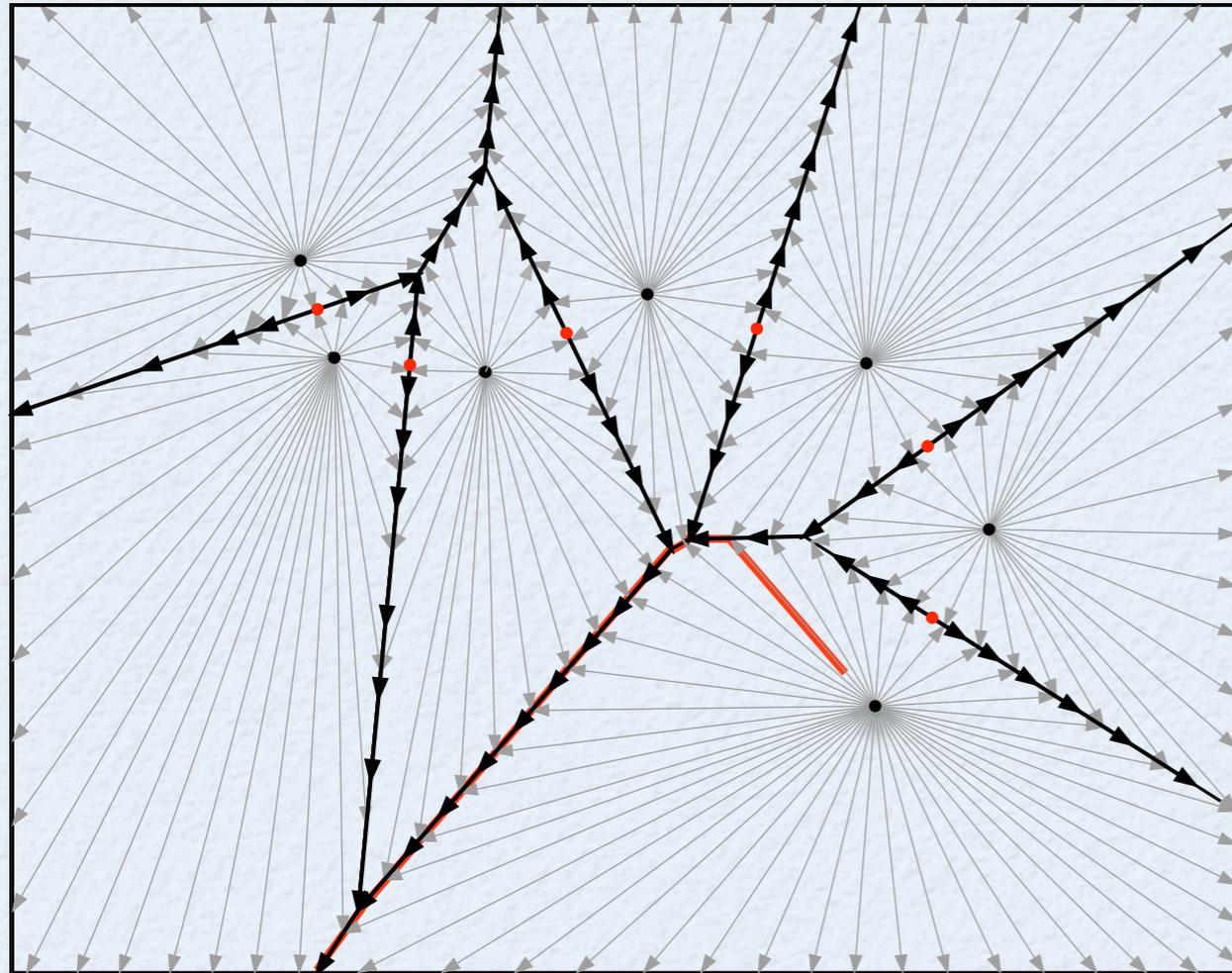


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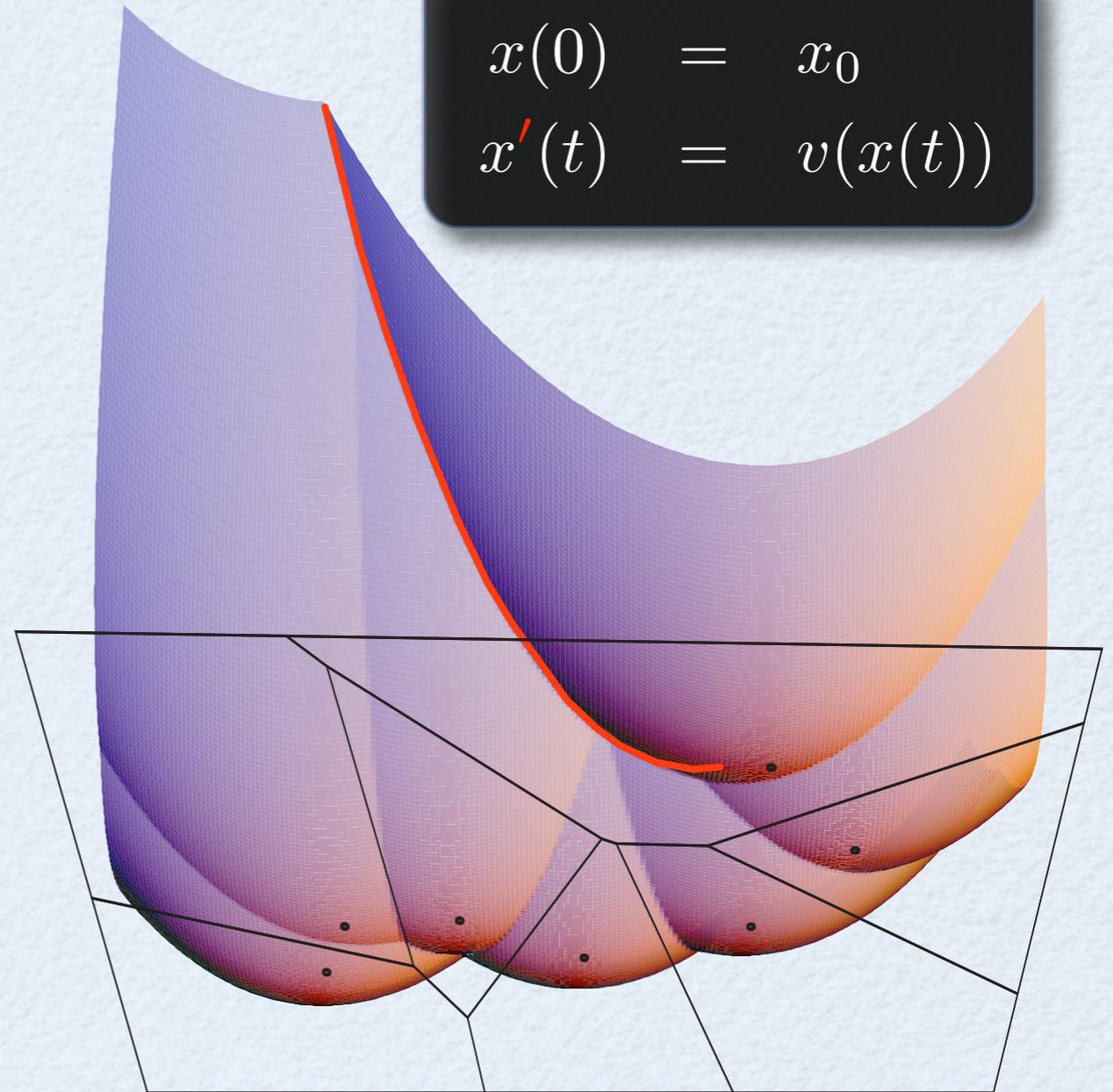


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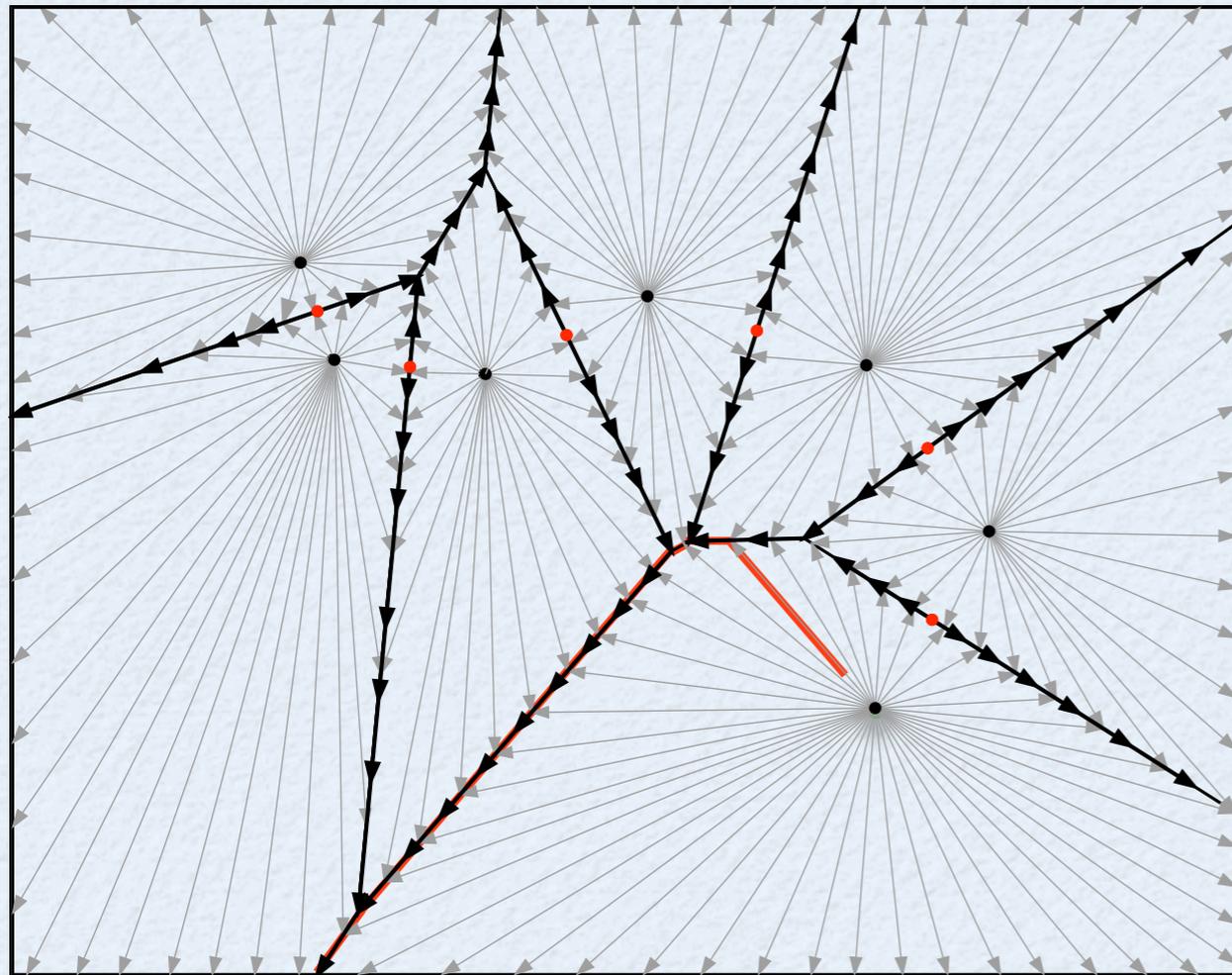


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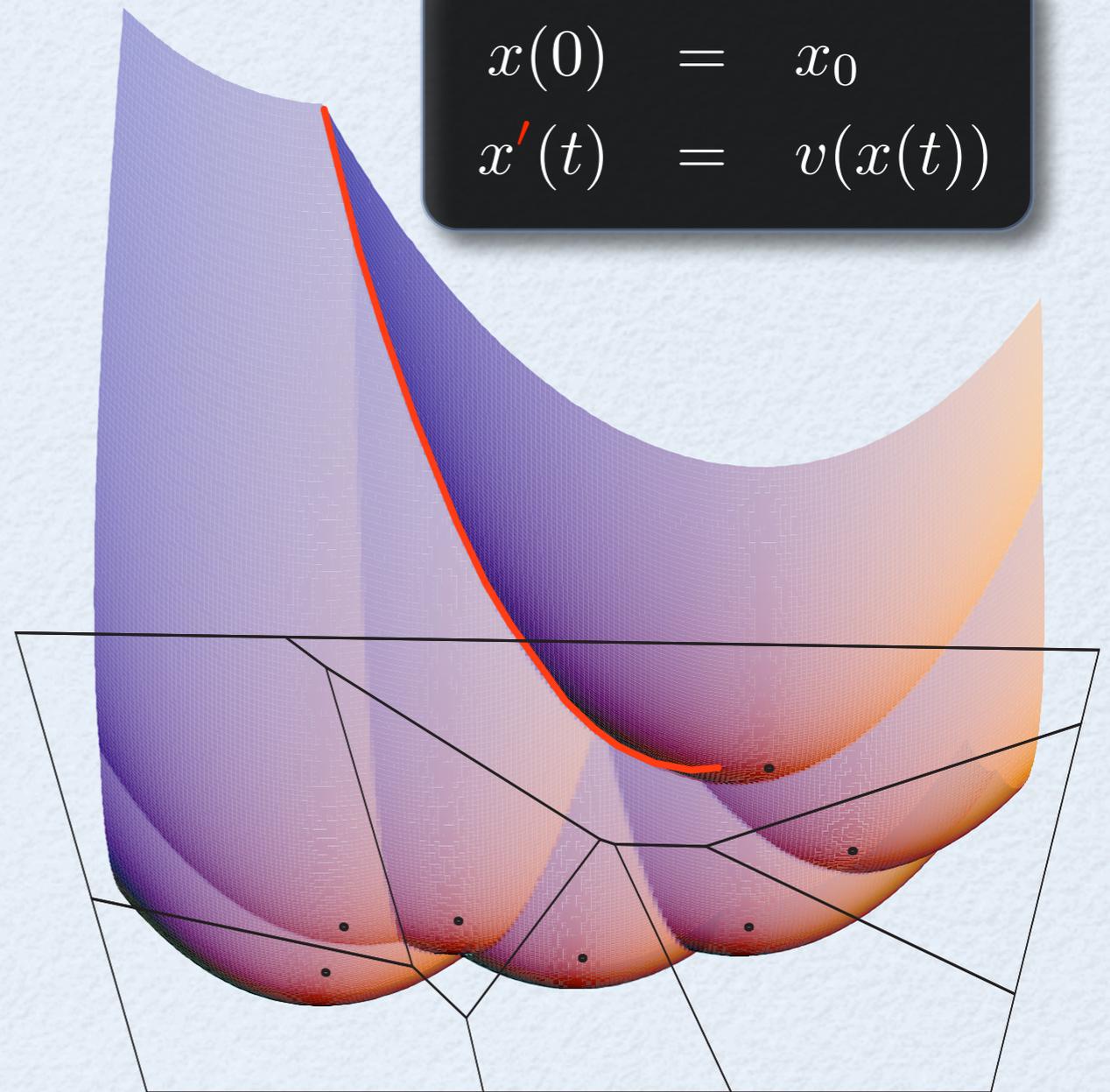


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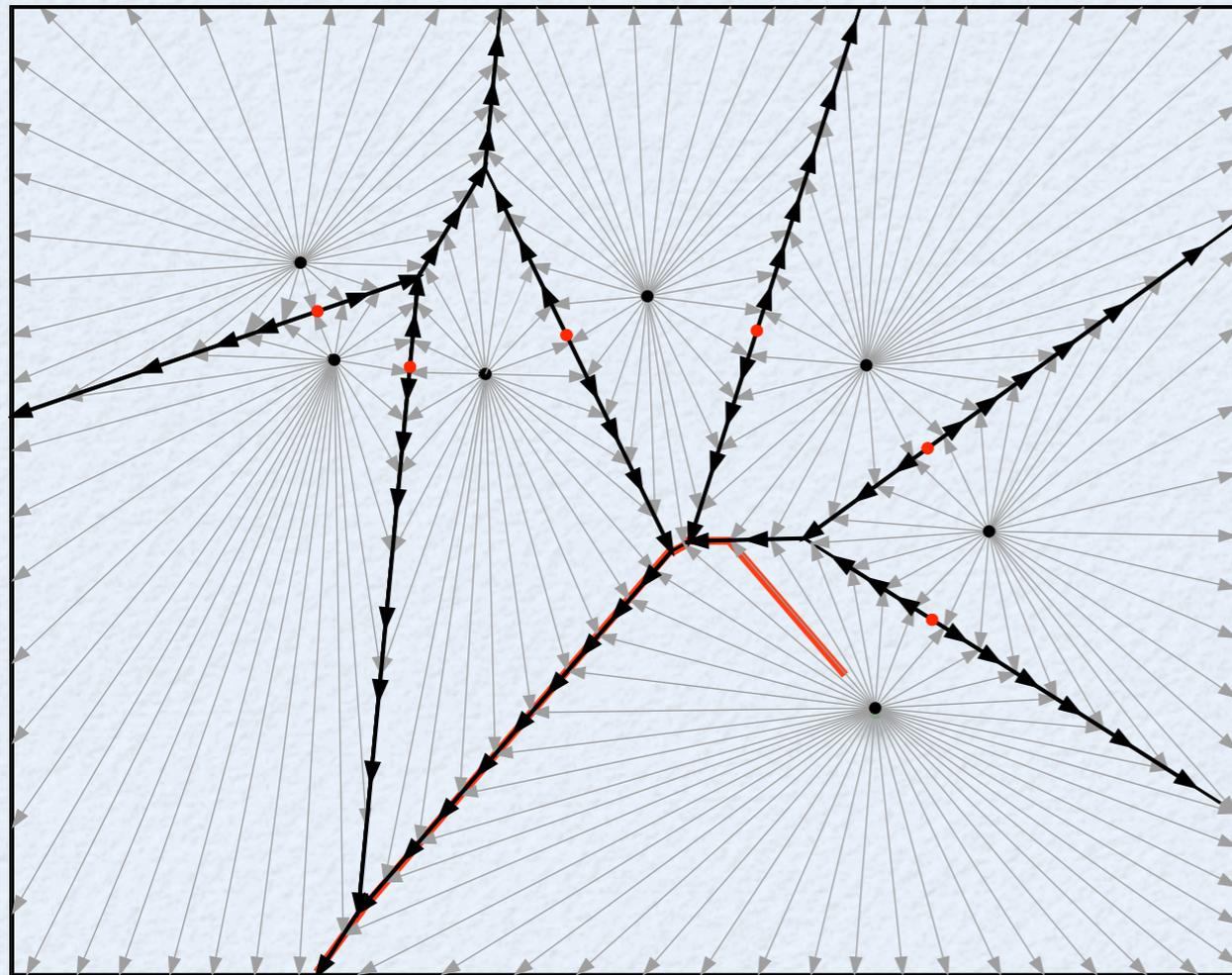
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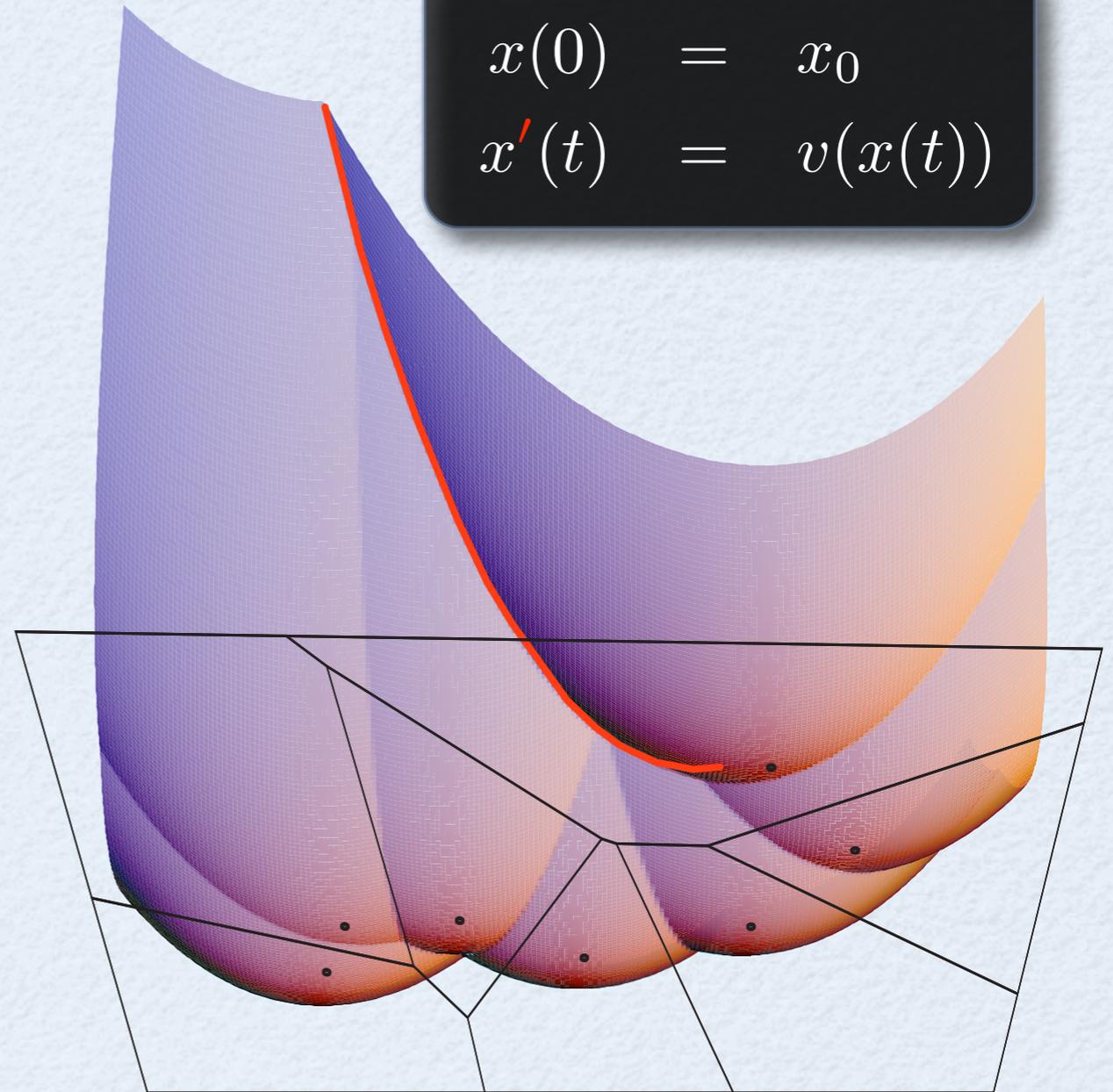
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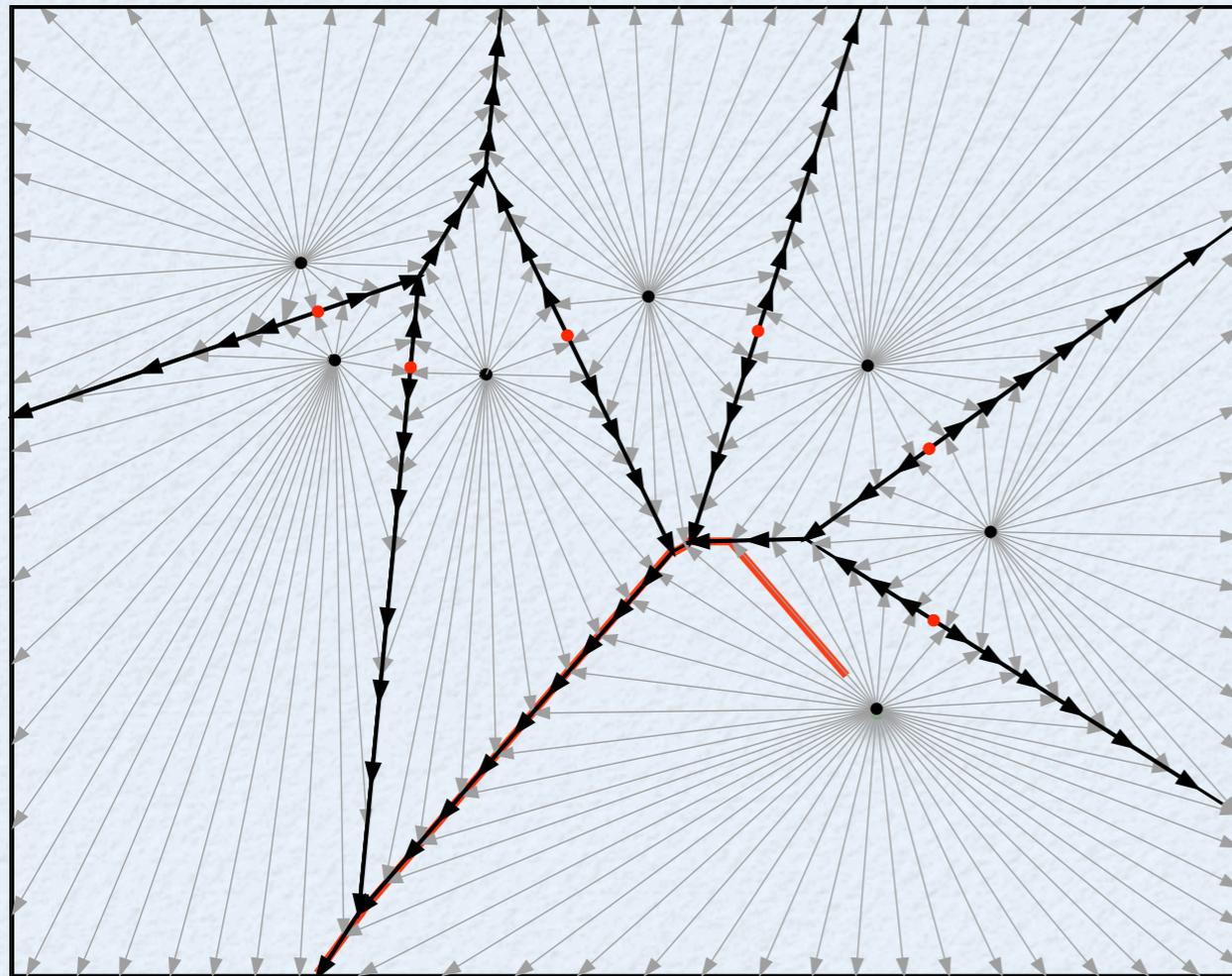


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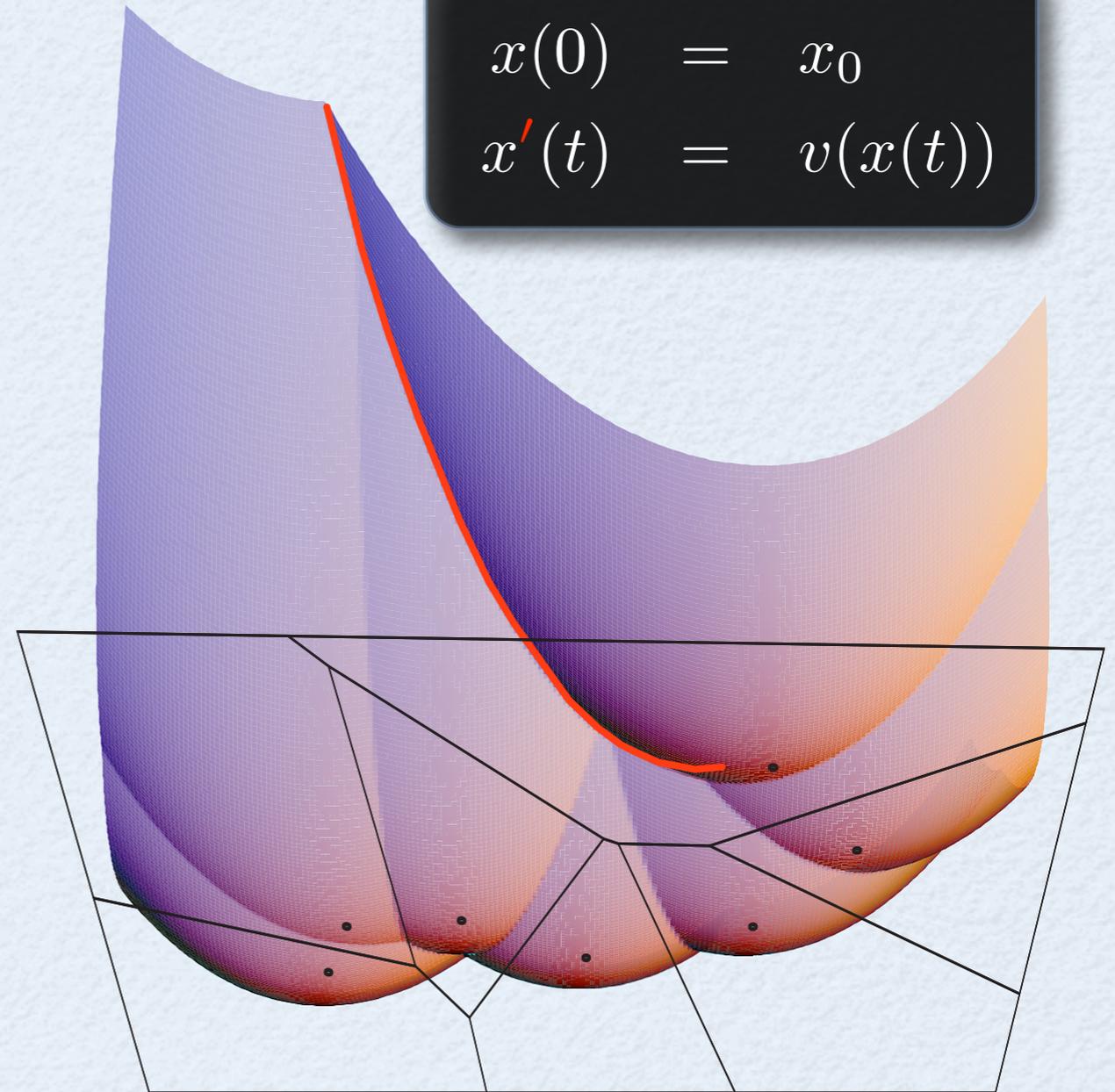
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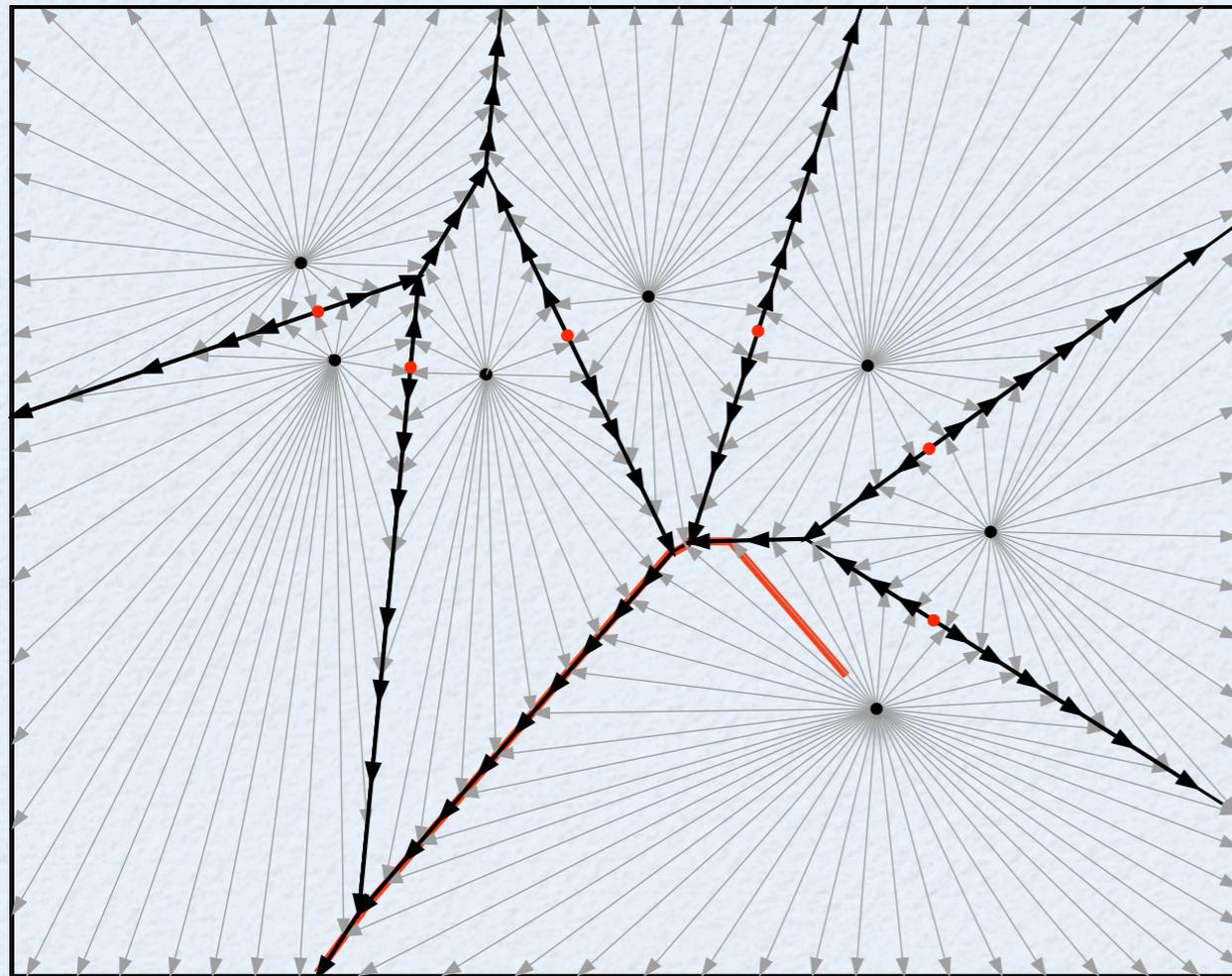
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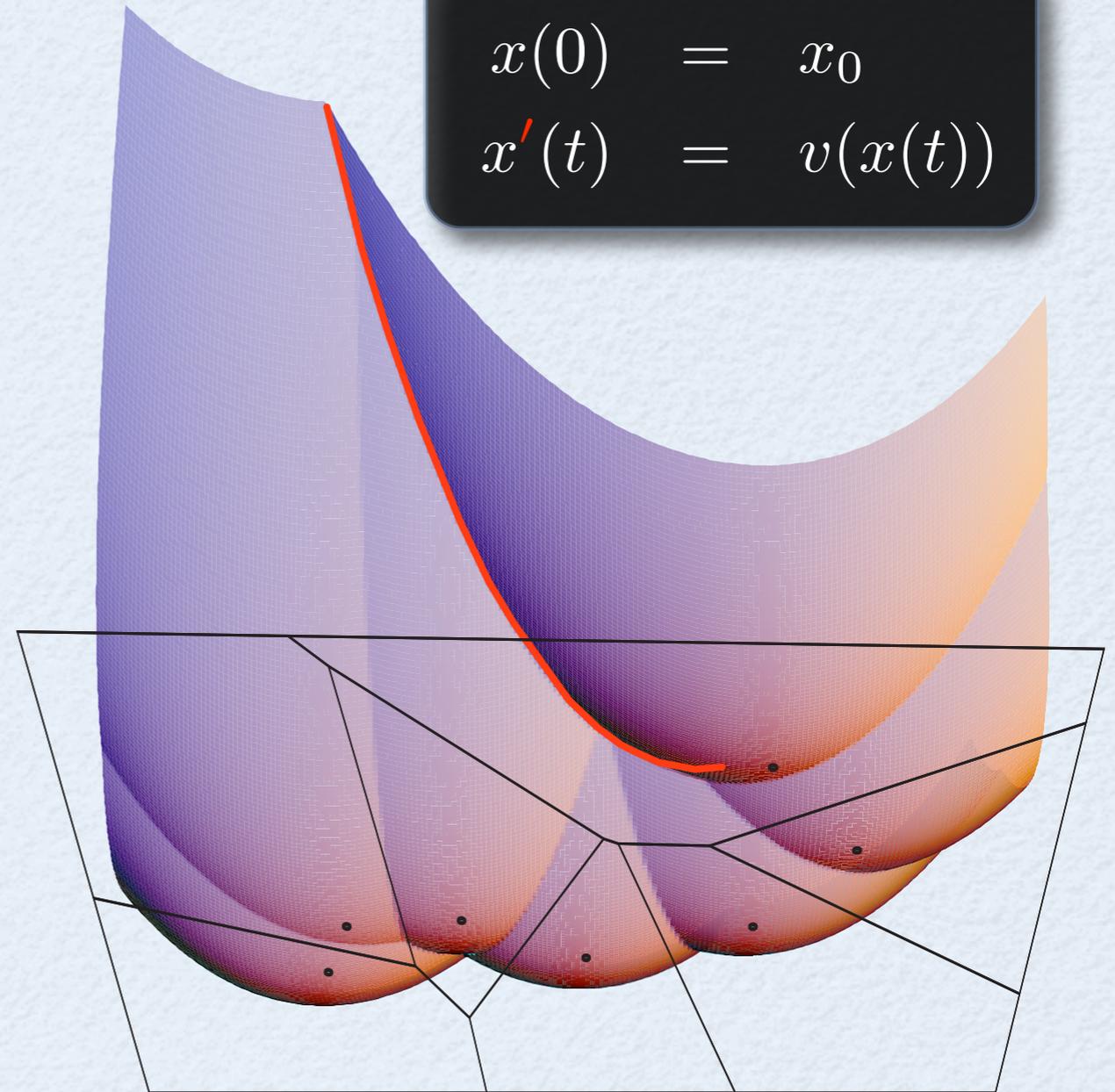
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**Theorem** [Lieutier'04].  $\phi$  is continuous.

# A criterion for homotopy equivalence

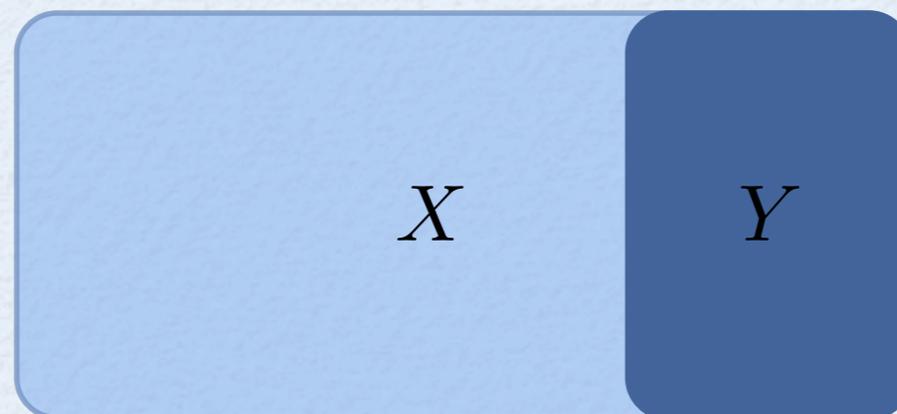
**Proposition.** Let  $X$  and  $Y \subseteq X$  be arbitrary sets and

$$H : [0, 1] \times X \rightarrow X$$

be a **continuous** function (on both variables) satisfying

1.  $\forall x \in X : H(0, x) = x$
2.  $\forall y \in Y, \forall t \in [0, 1] : H(t, y) \in Y$
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Then  $X$  and  $Y$  have the same homotopy type.



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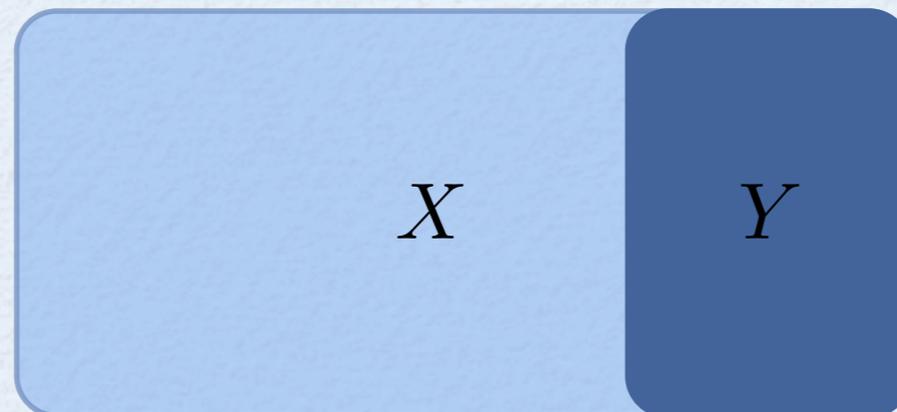
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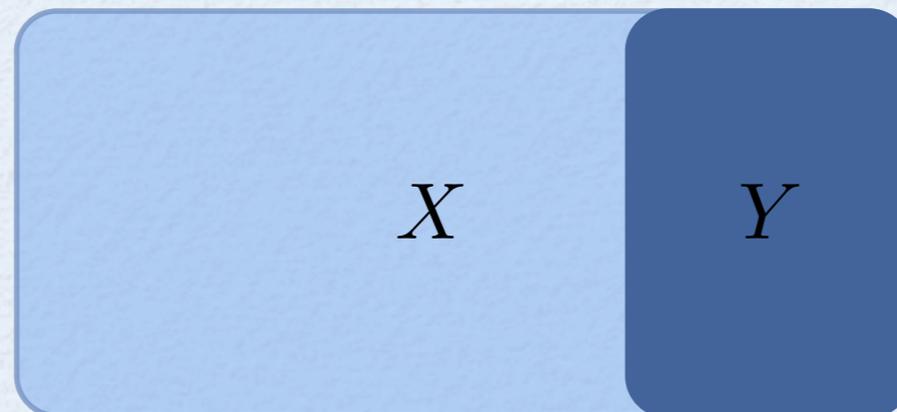
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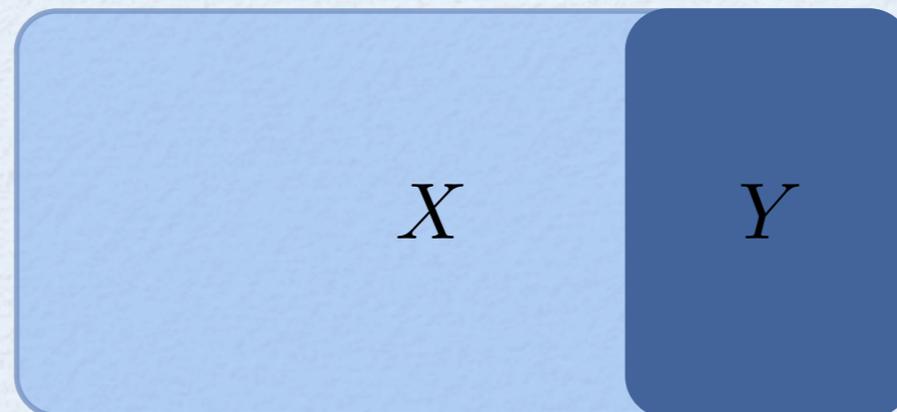
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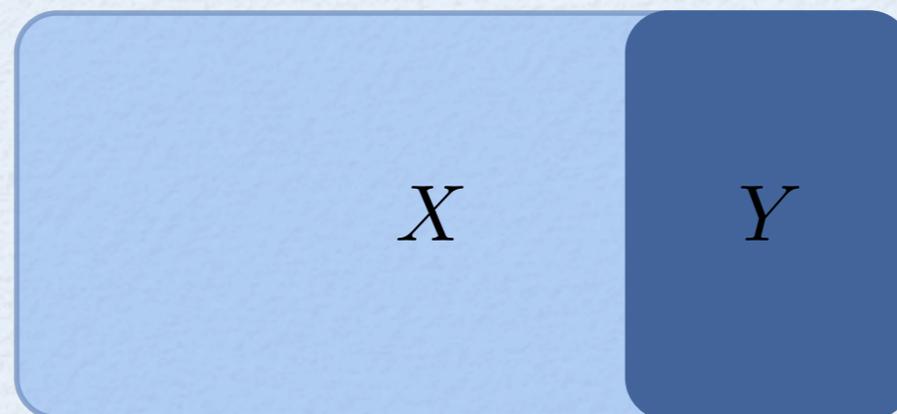
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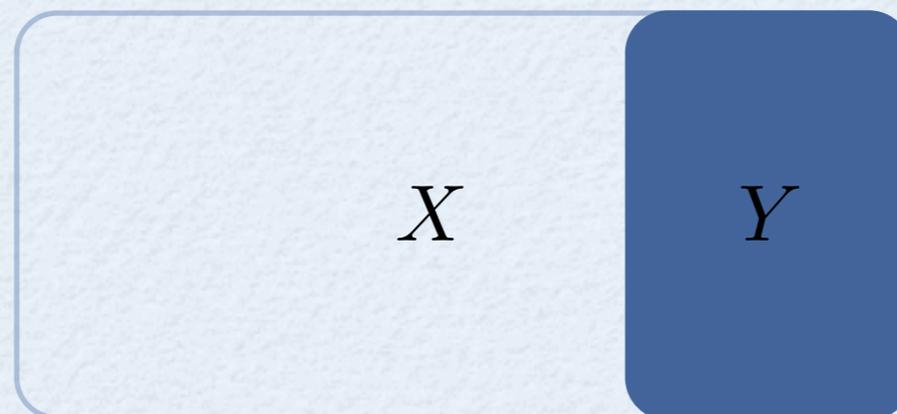
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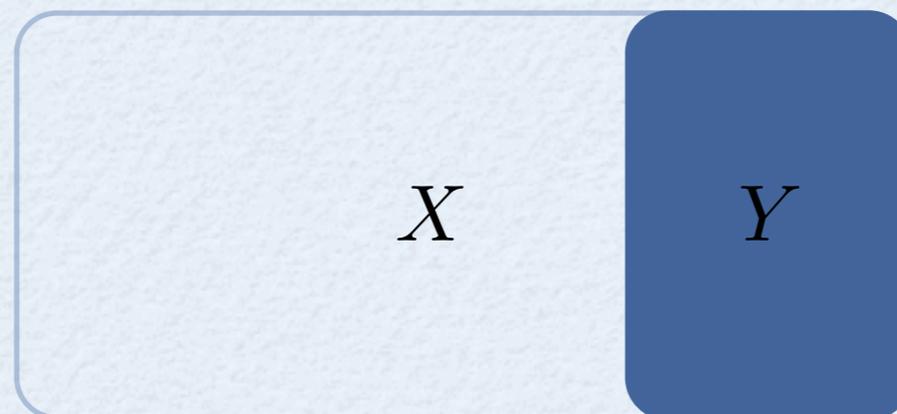
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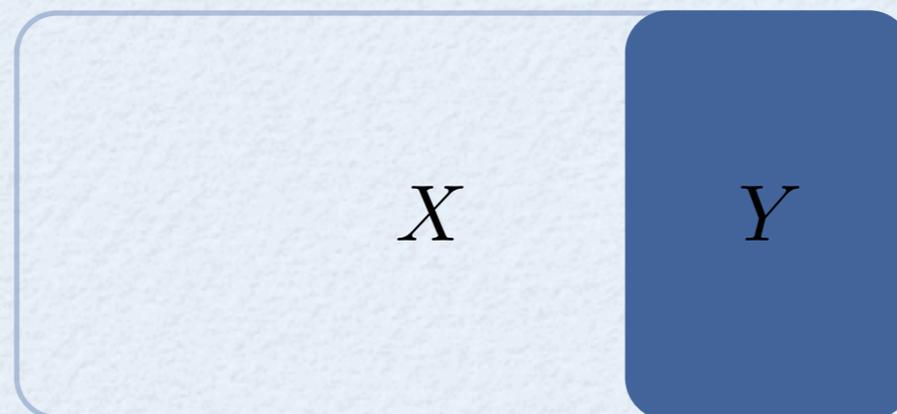
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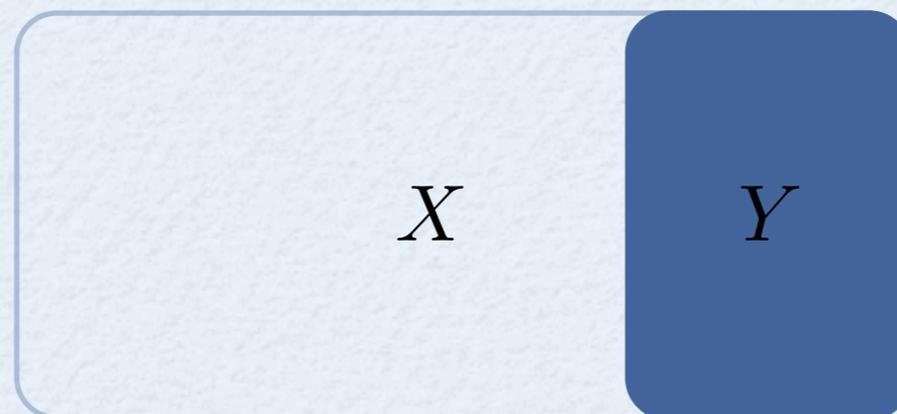
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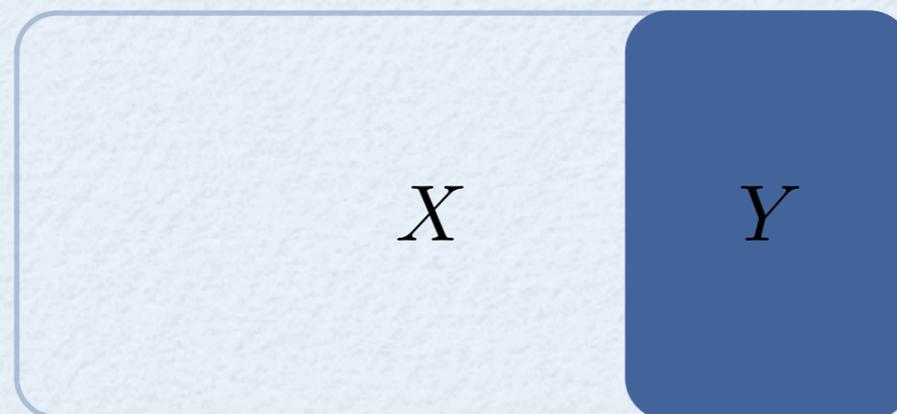
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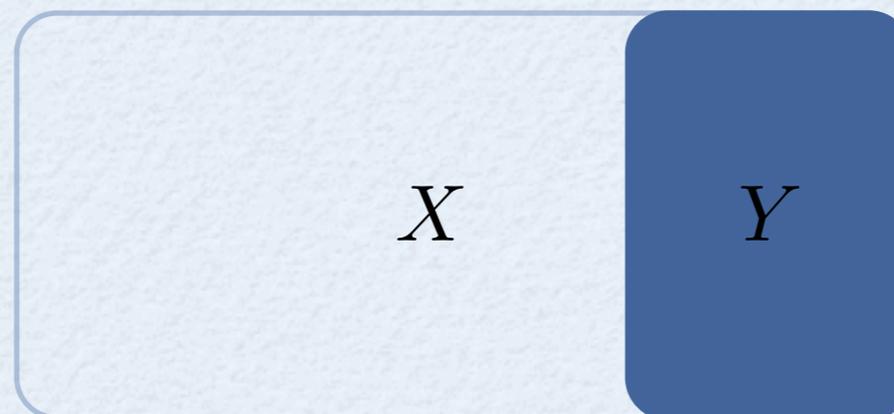
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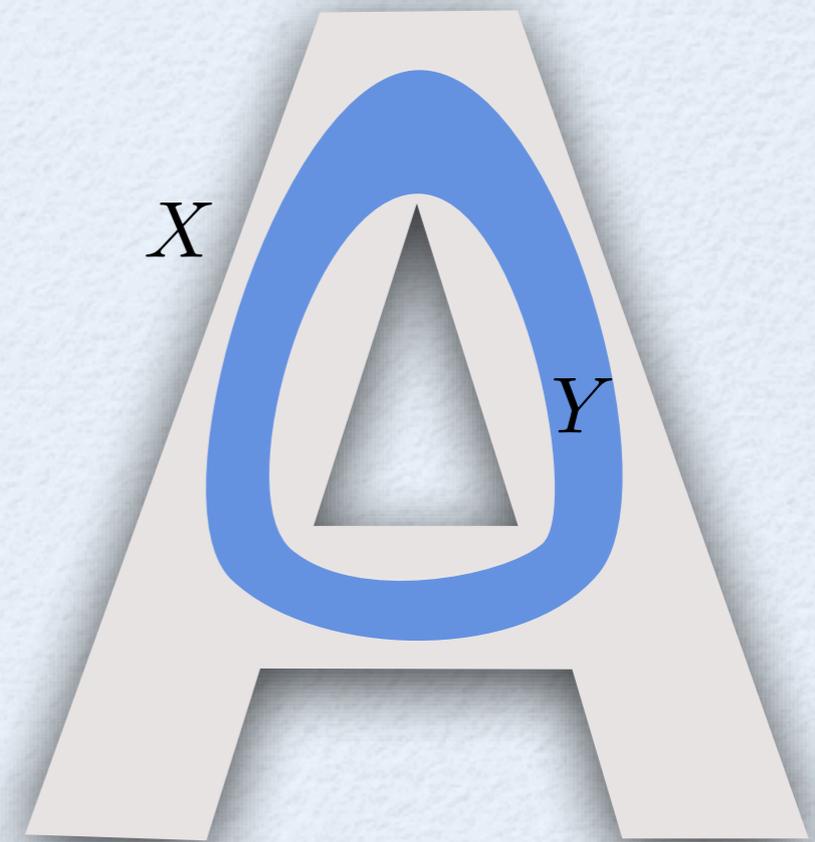


# Using flow for proving homotopy equivalence

**Lemma [Lieutier'04].** If  $Y \subset X$  are **bounded** and

1.  $\phi(X) = X$  and  $\phi(Y) = Y$ , and
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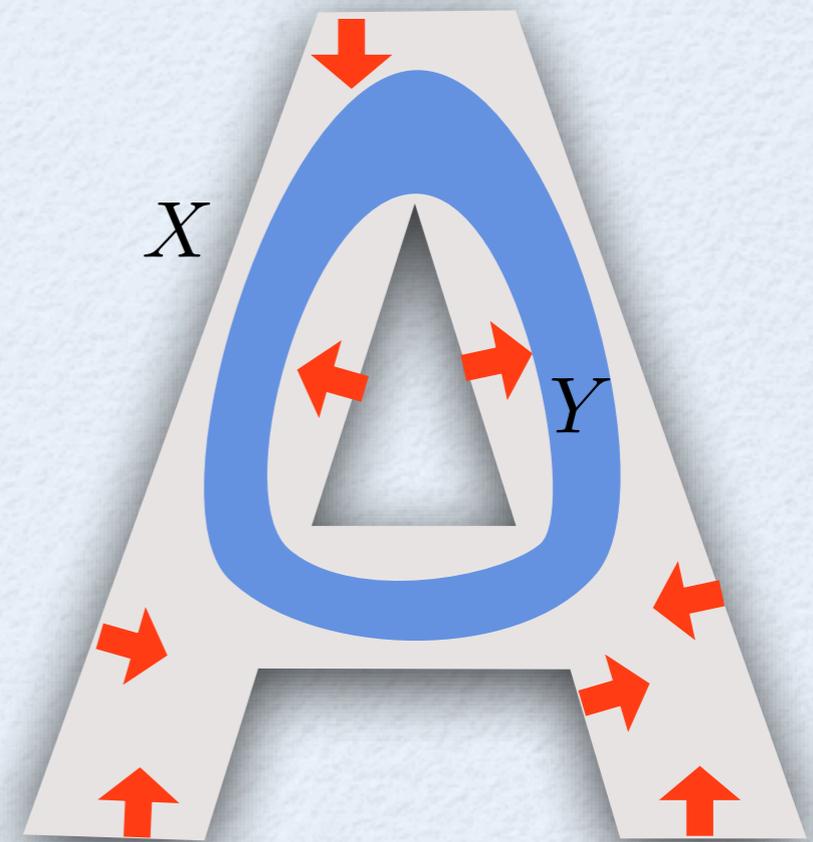


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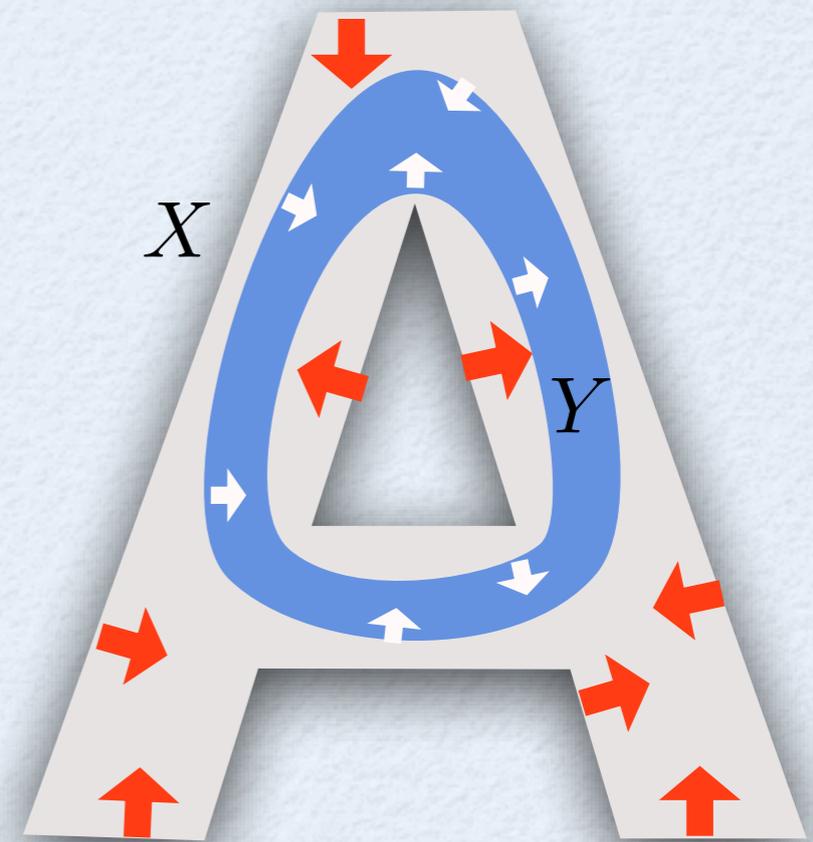


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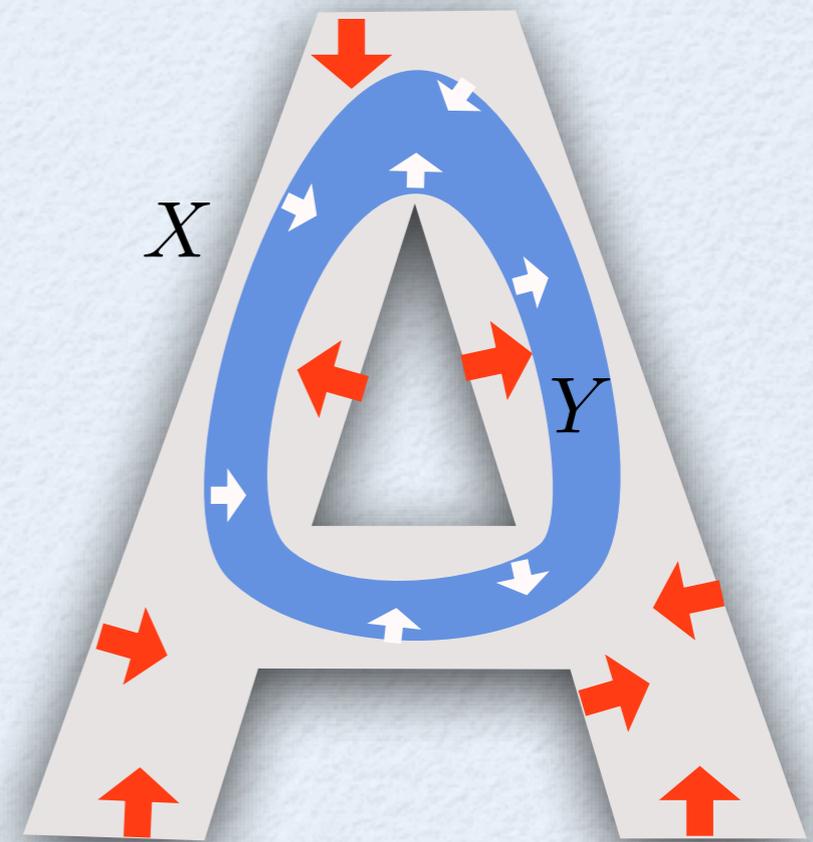


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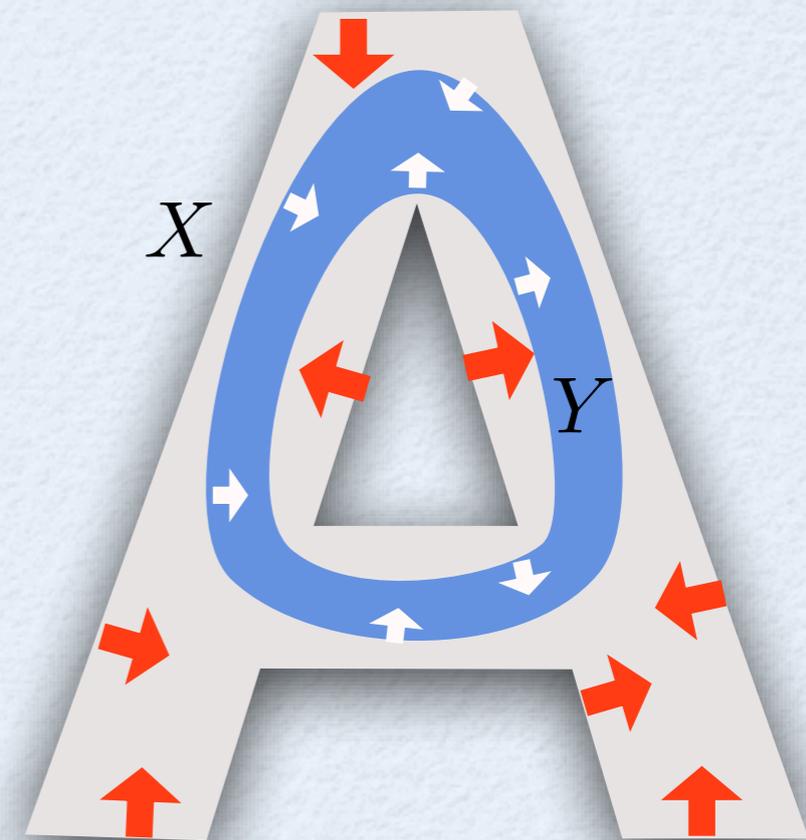
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**"speed"** lower bound

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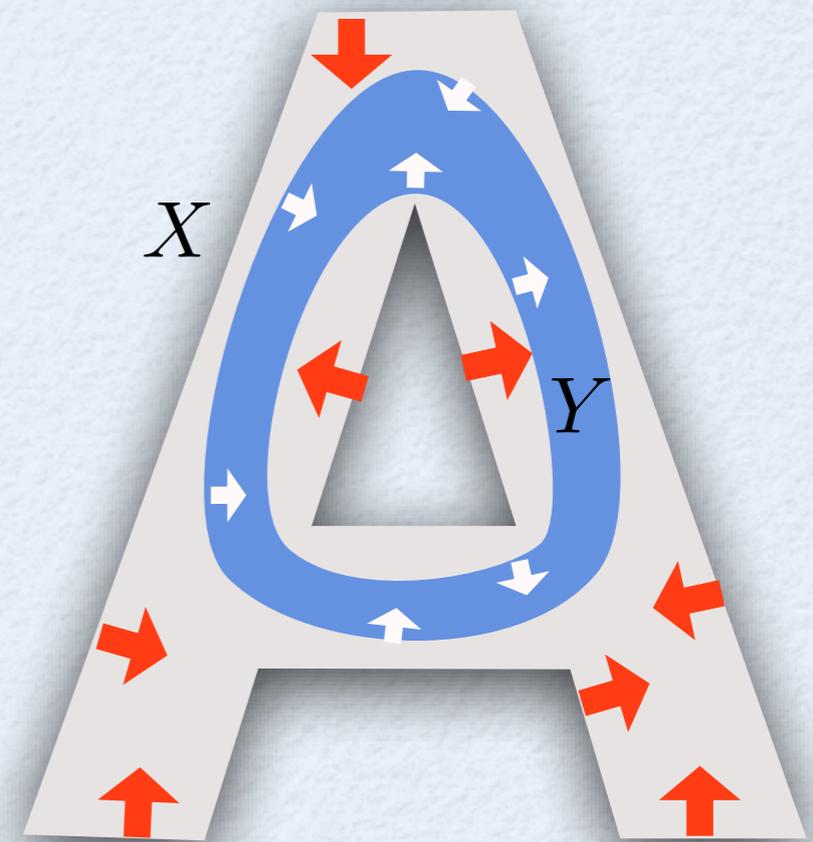
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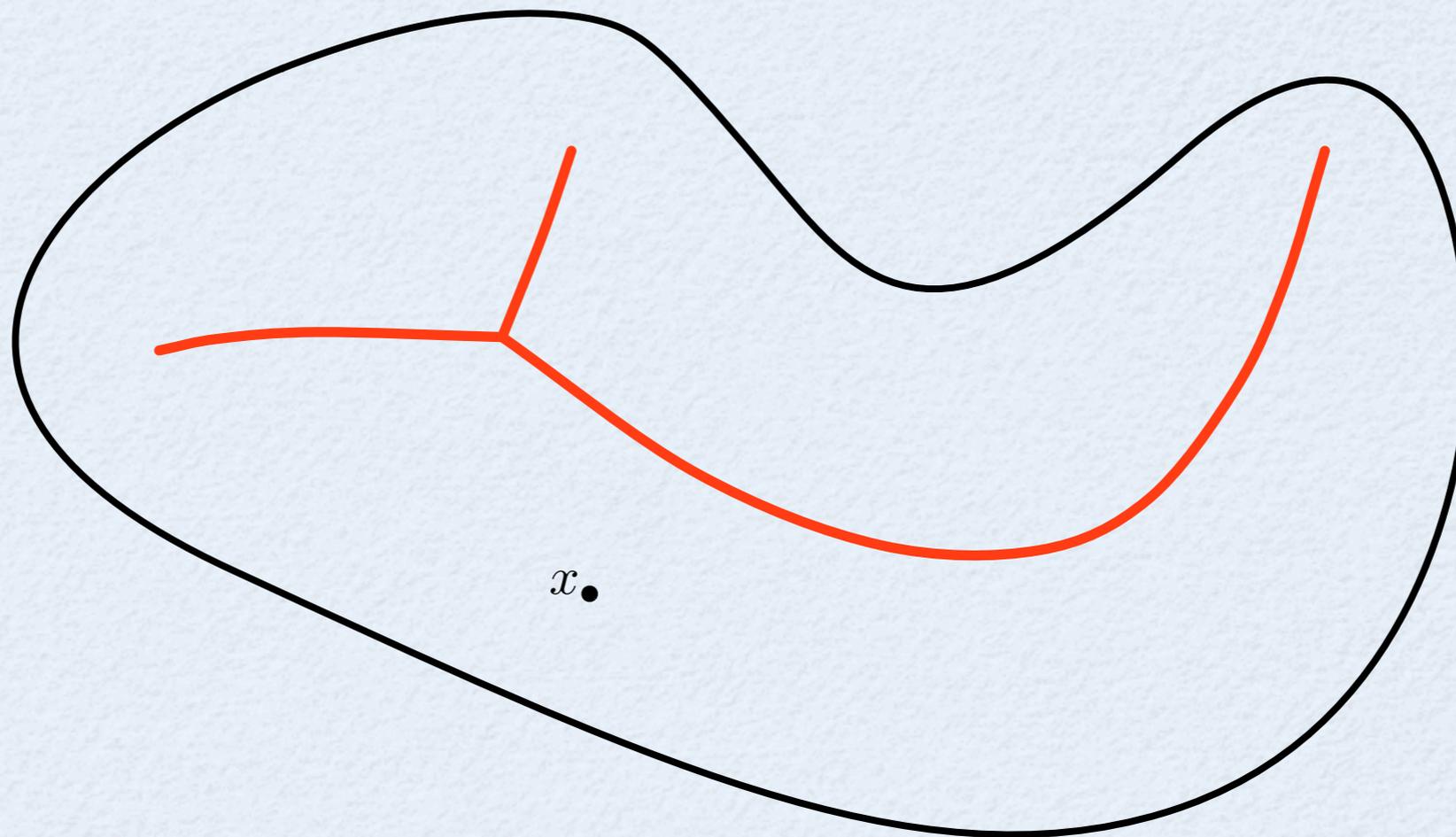
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So, we **"push  $X$  into  $Y$ "** at **speed  $> 0$** .



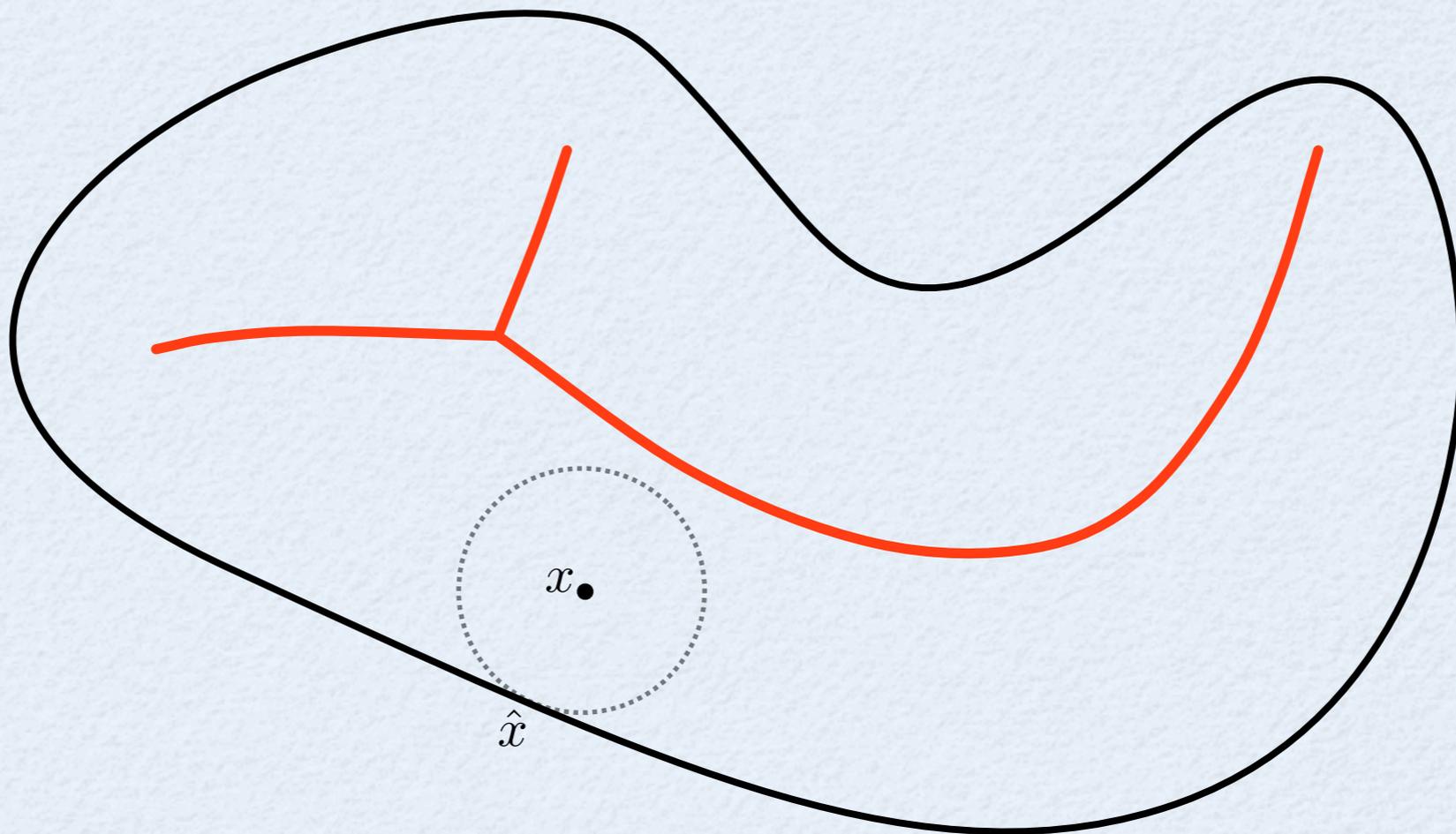
# Important flow-tight sets

complements of tubular neighborhoods of the manifold, and union of balls placed at samples are flow-tight, for the right range of parameters.



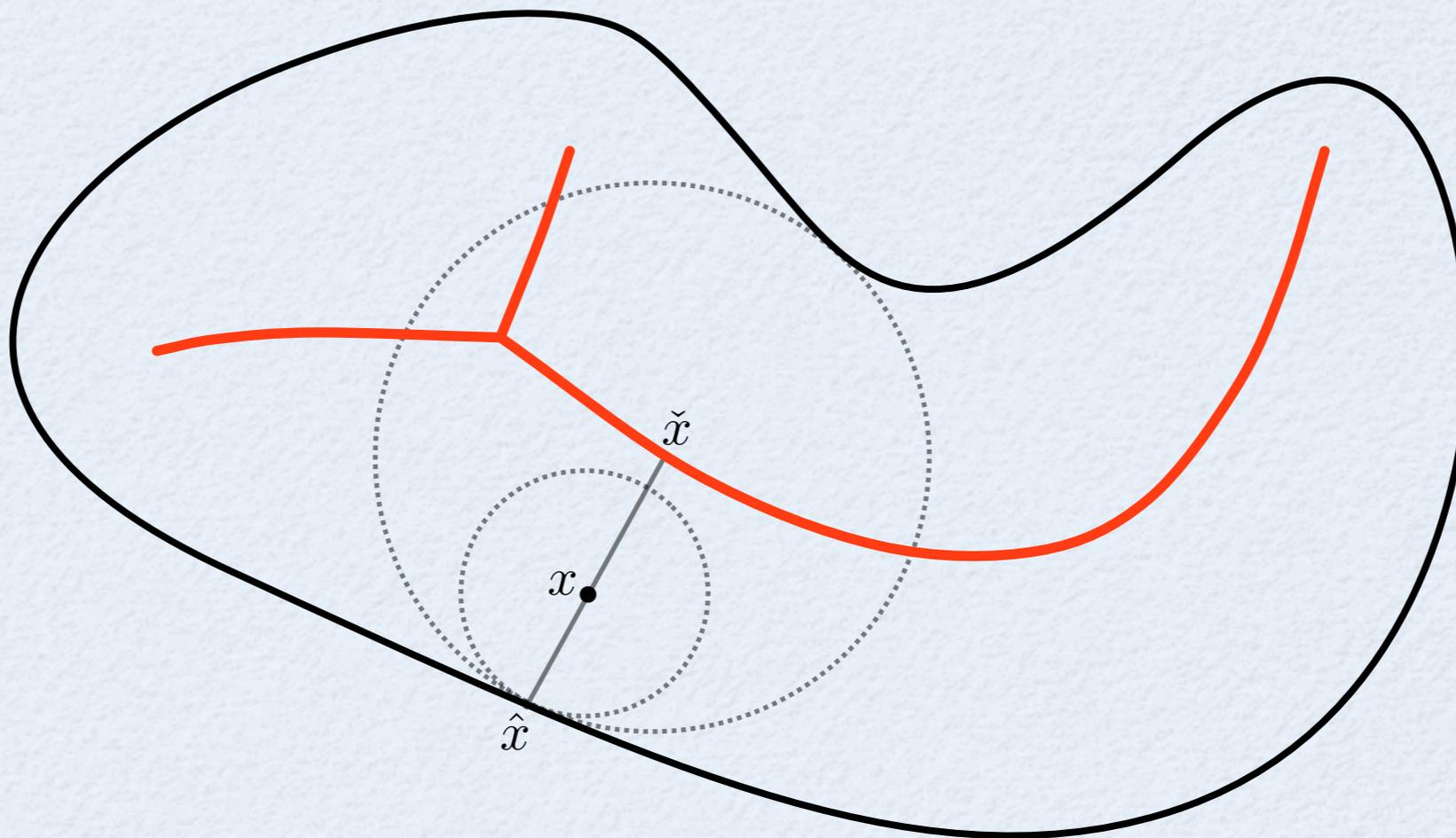
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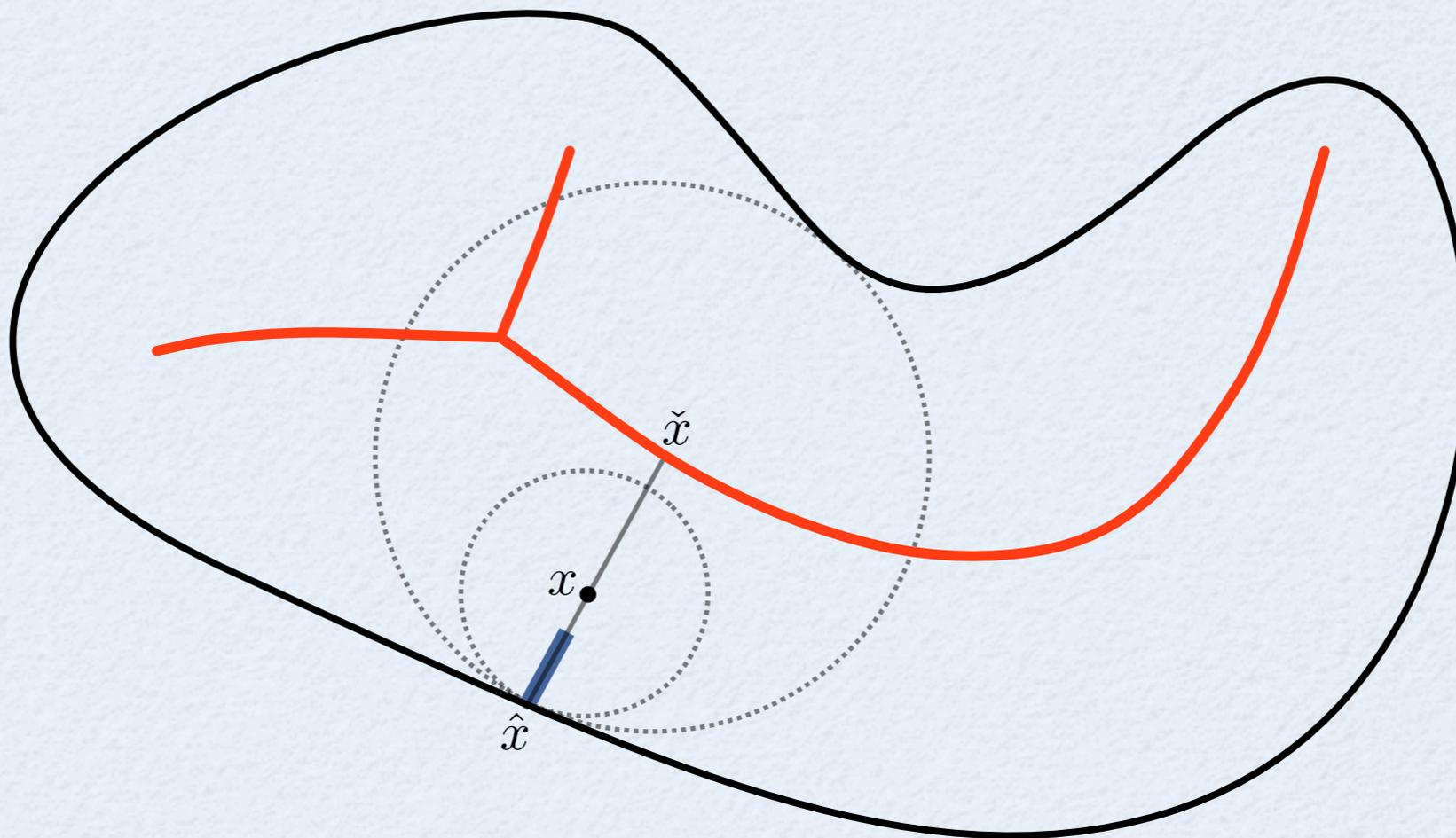
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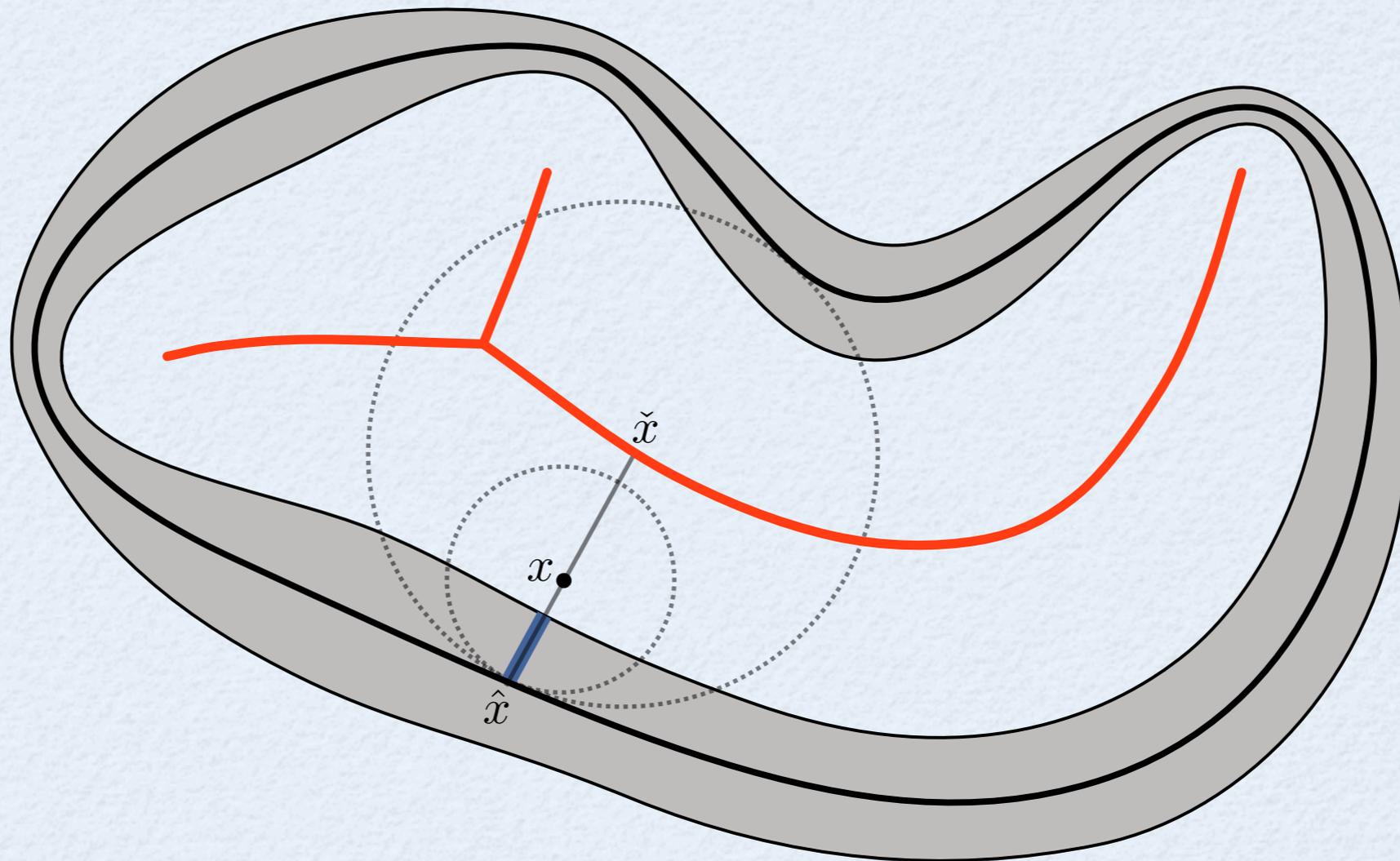
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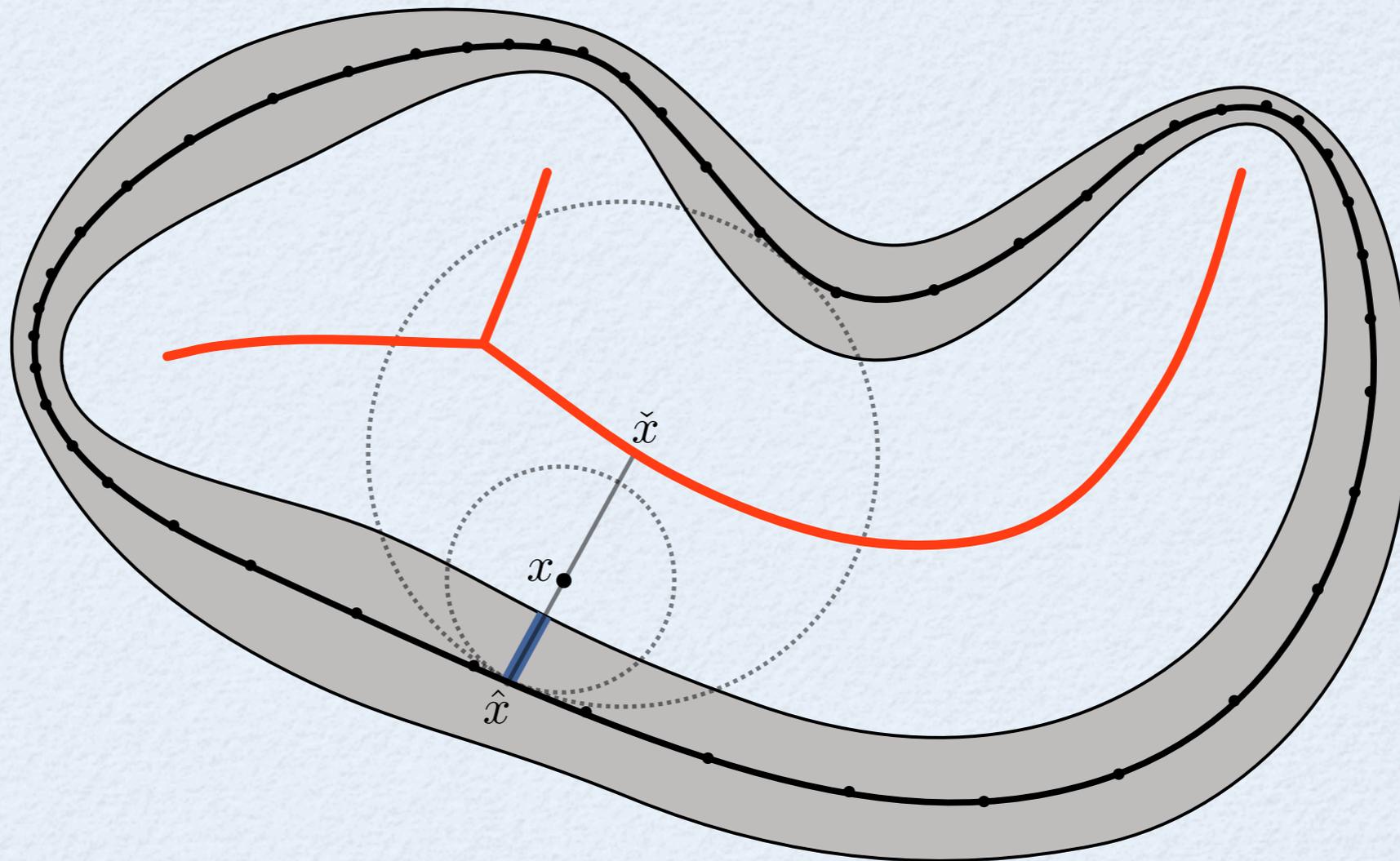
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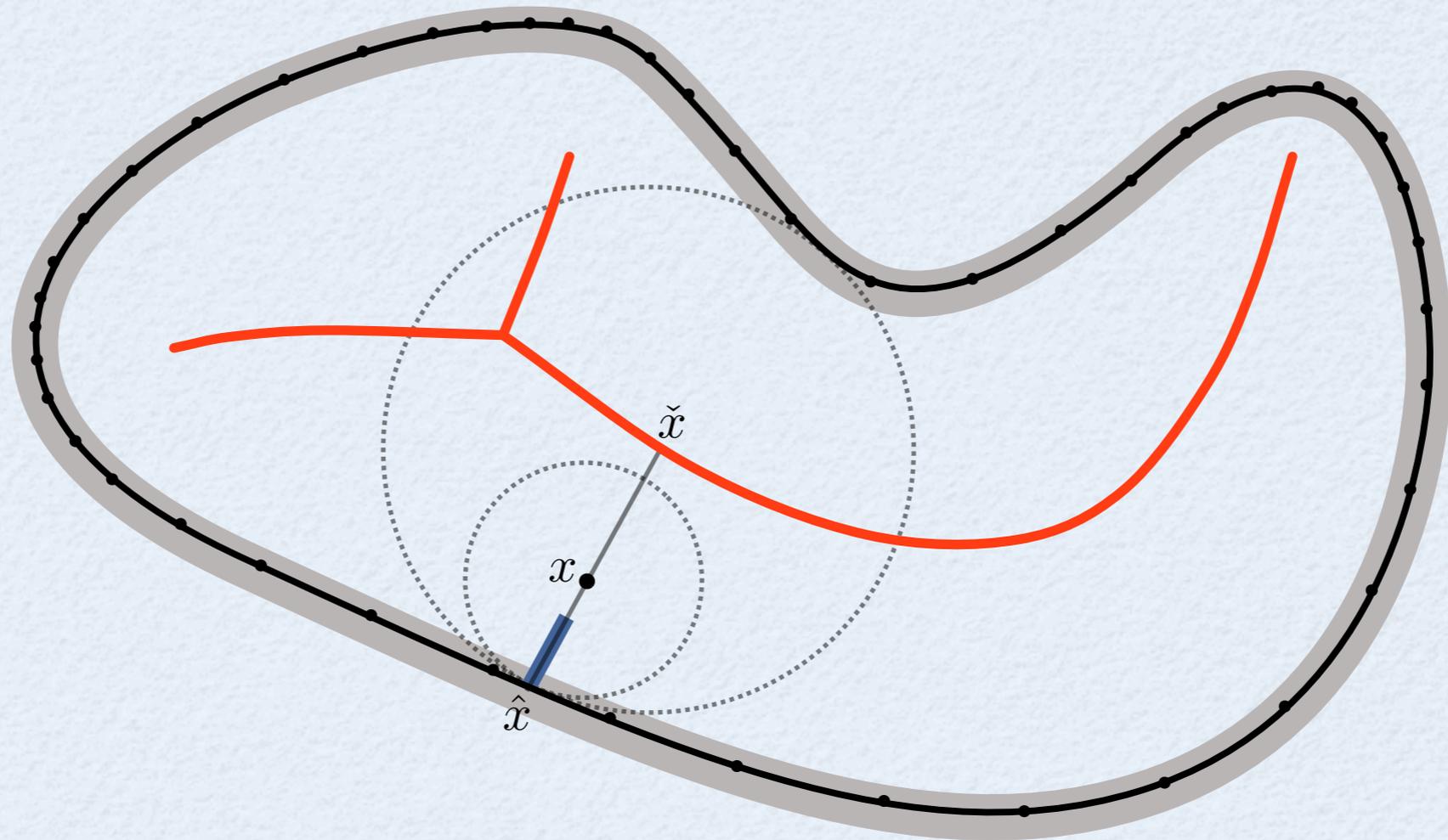
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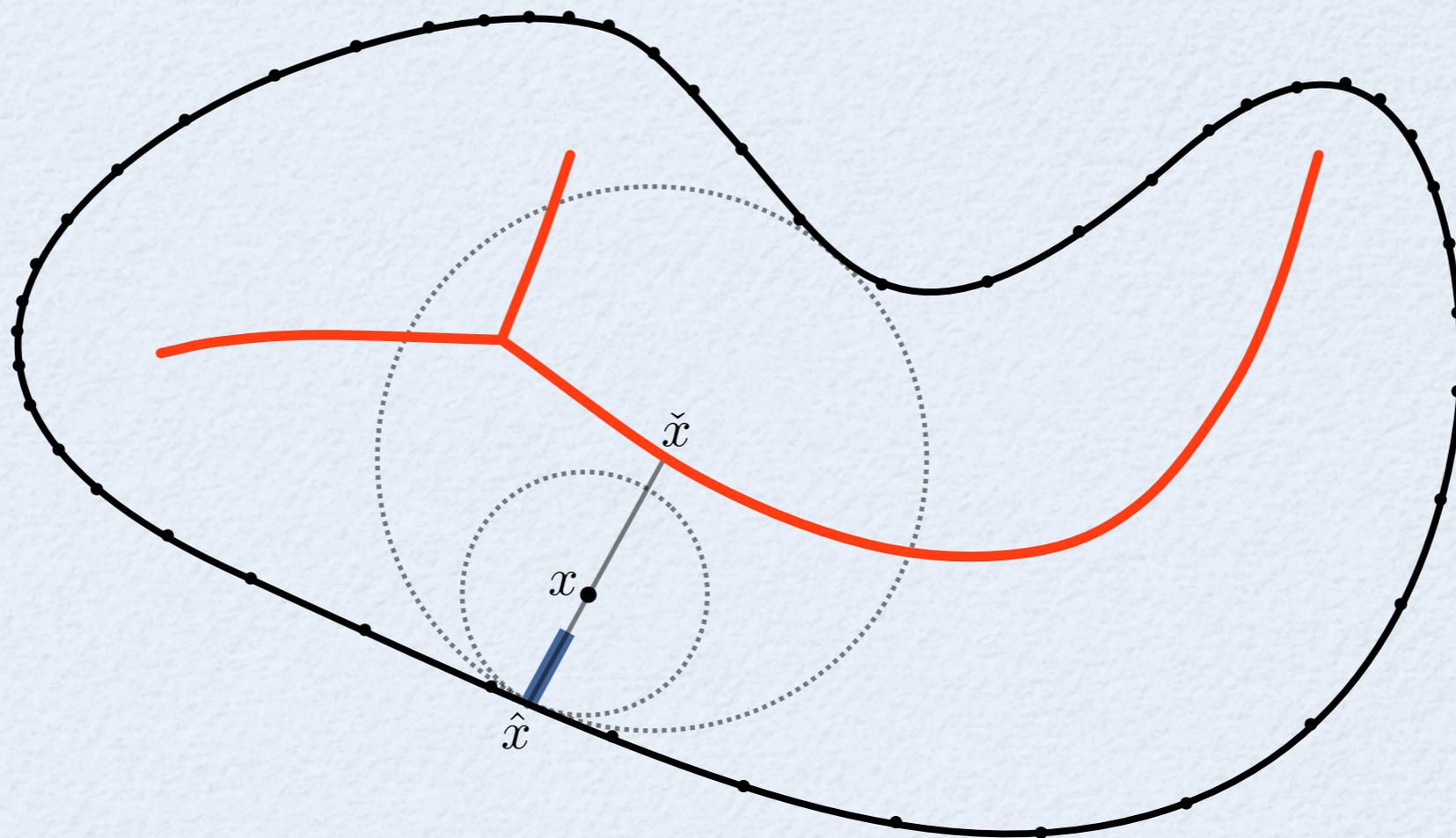
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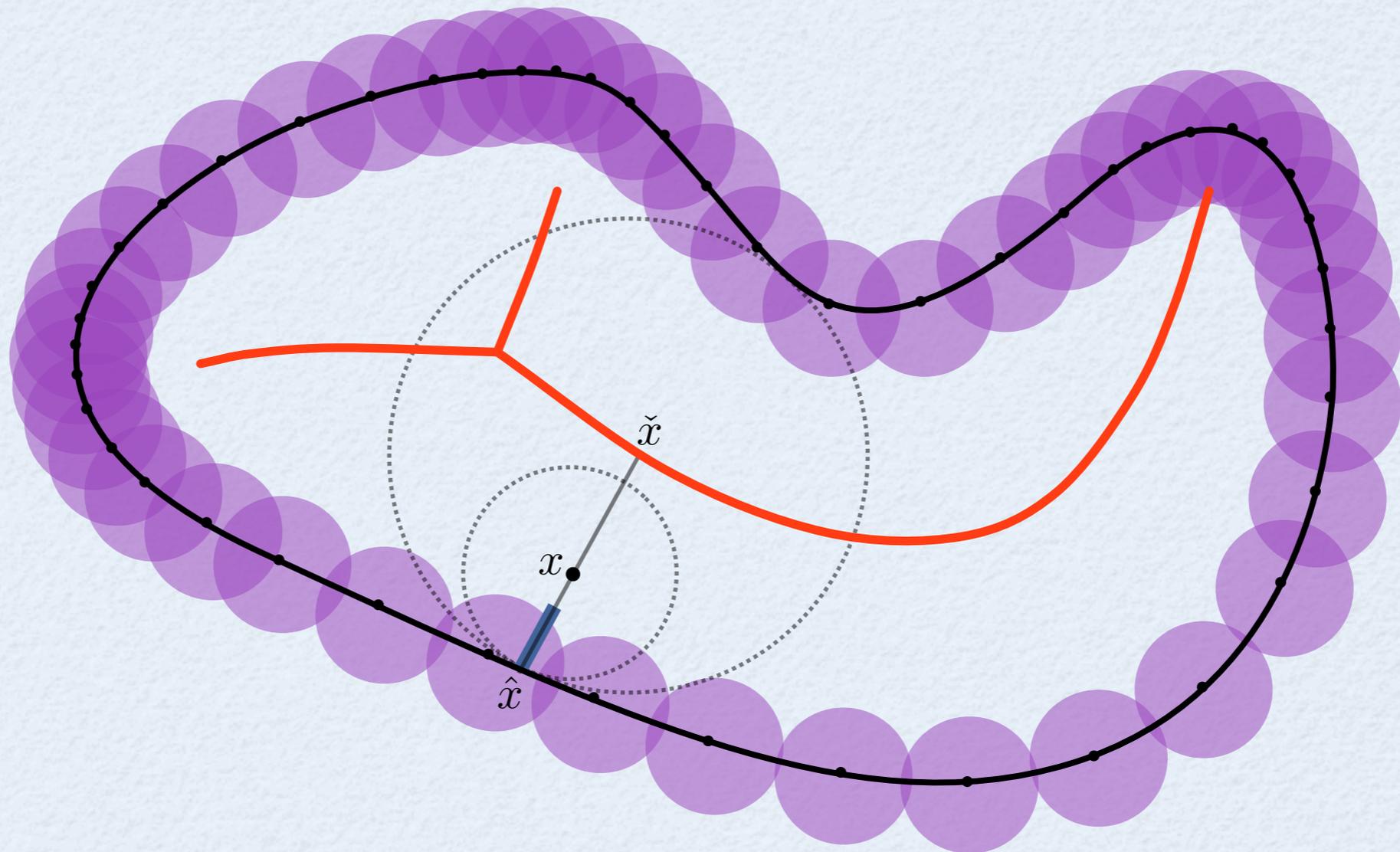
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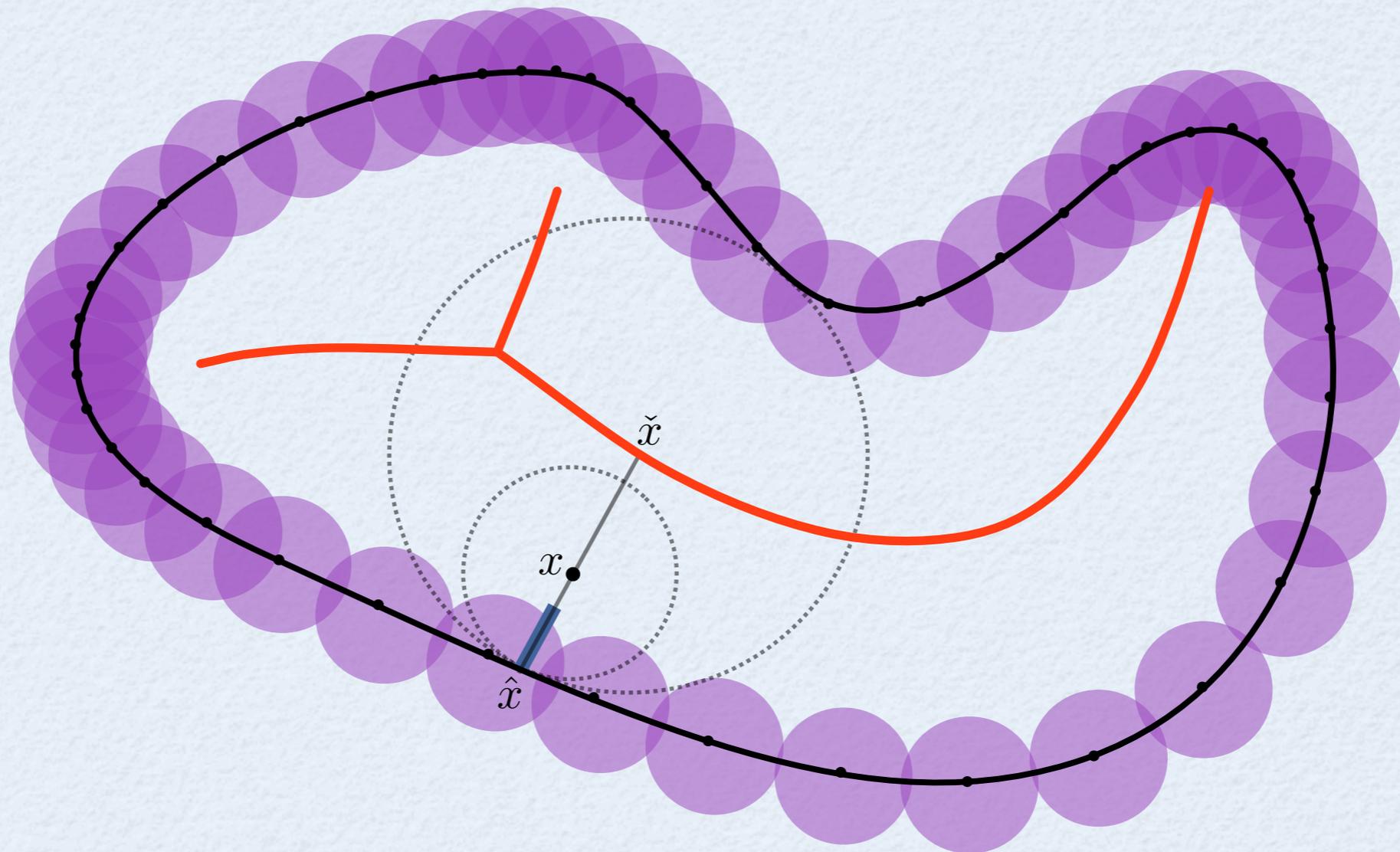
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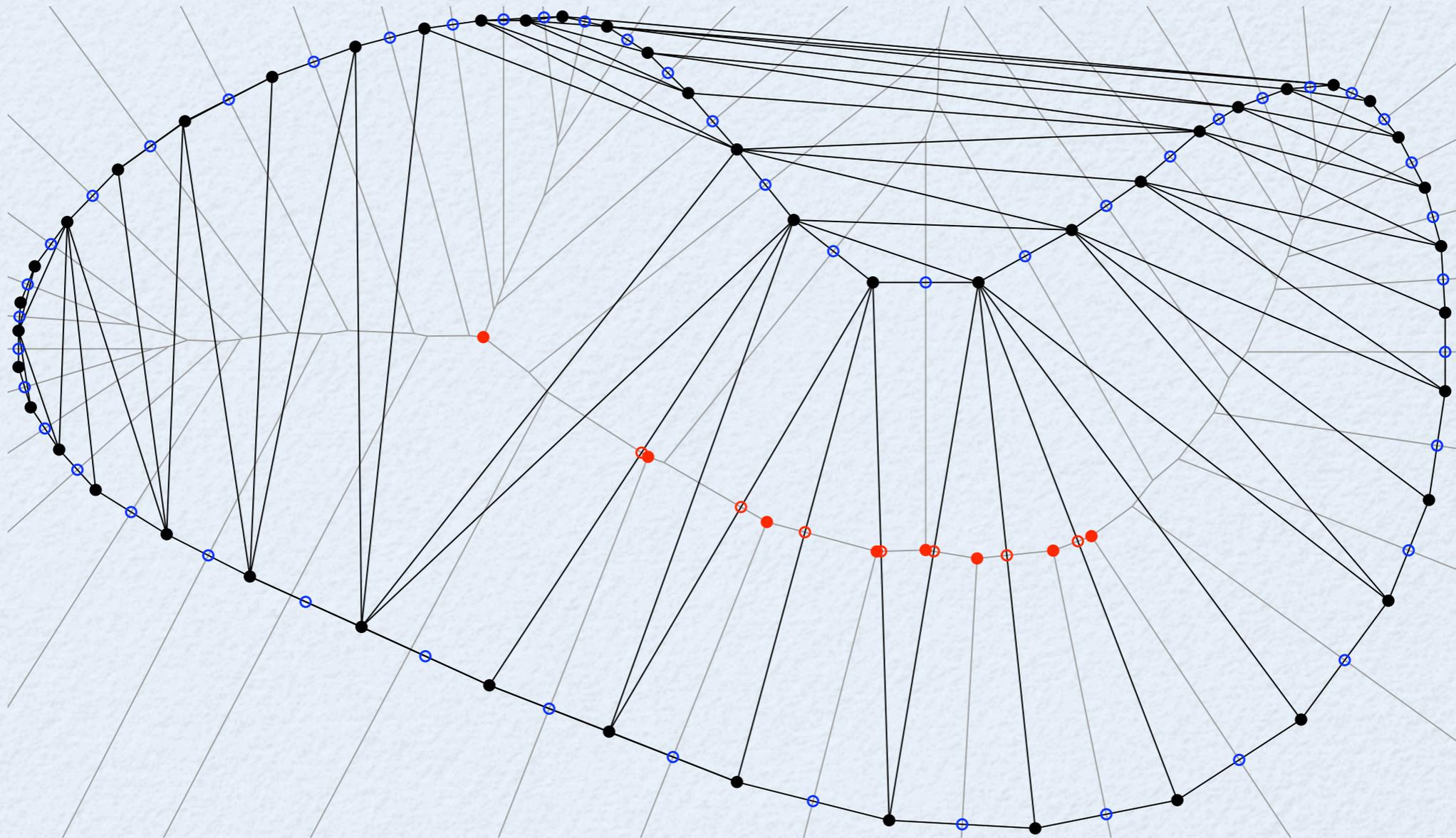
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Finite **unions** and **intersections** of flow-tight sets are flow-tight.

# Critical Points of Distance Function

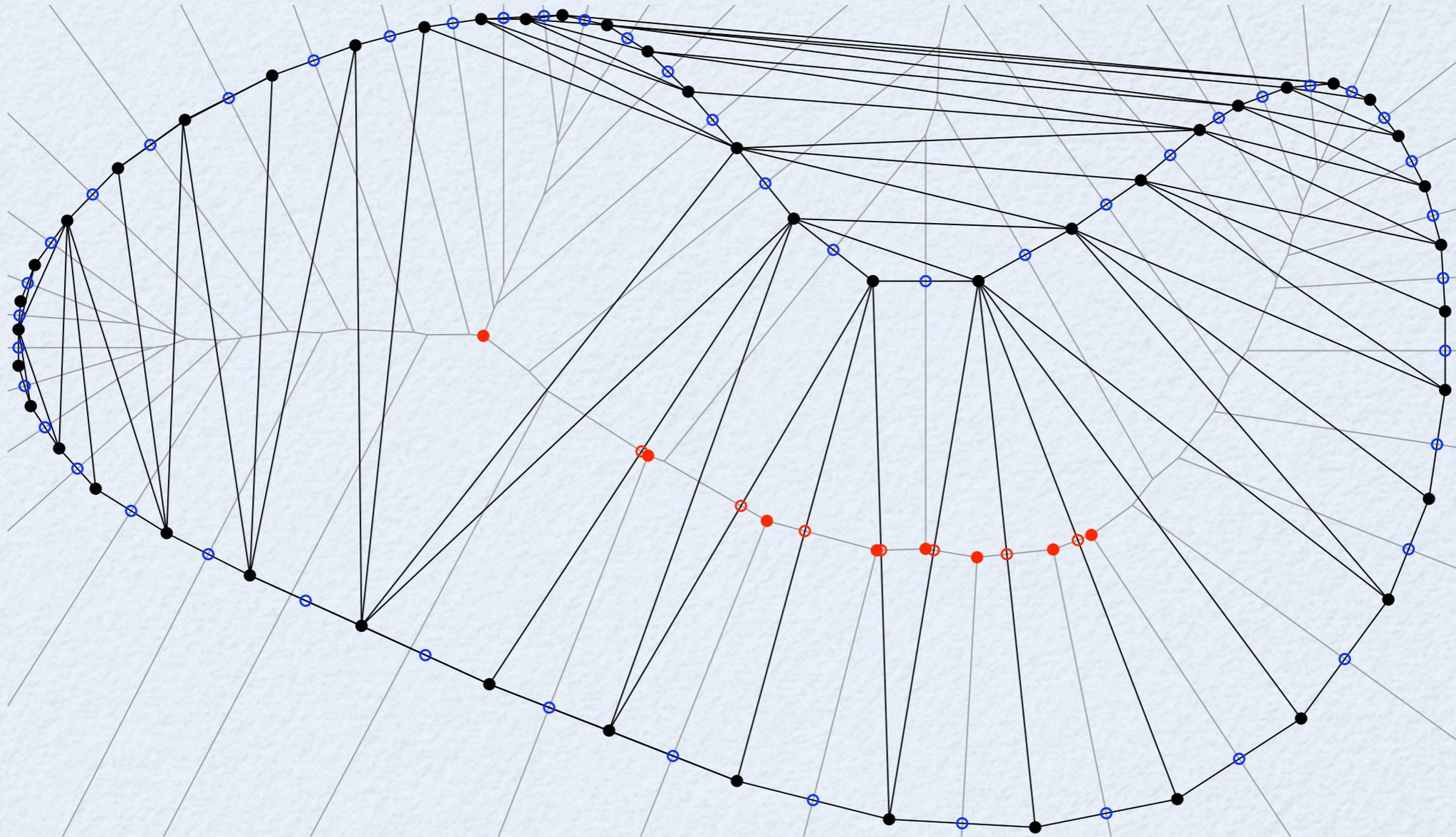
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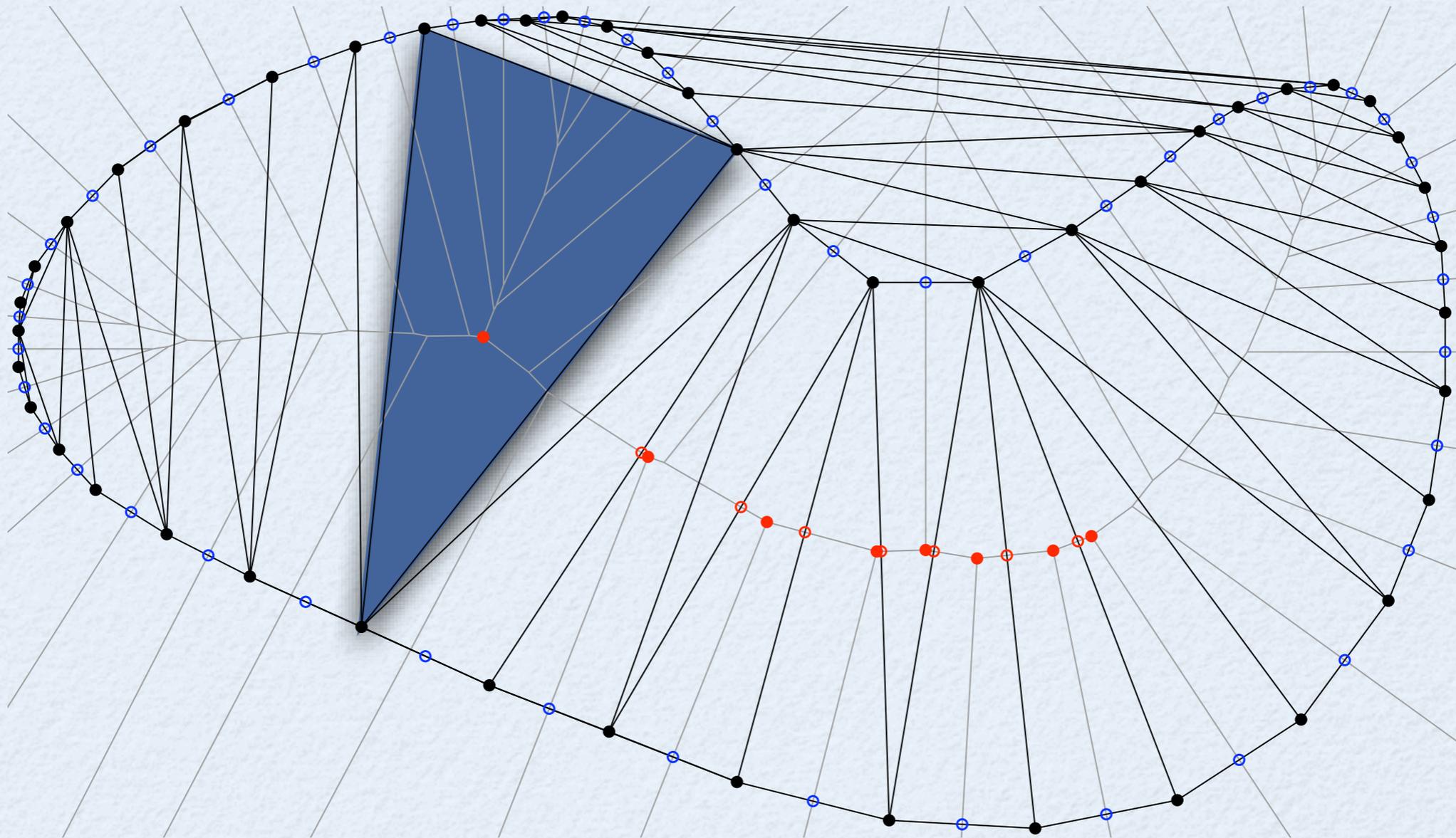
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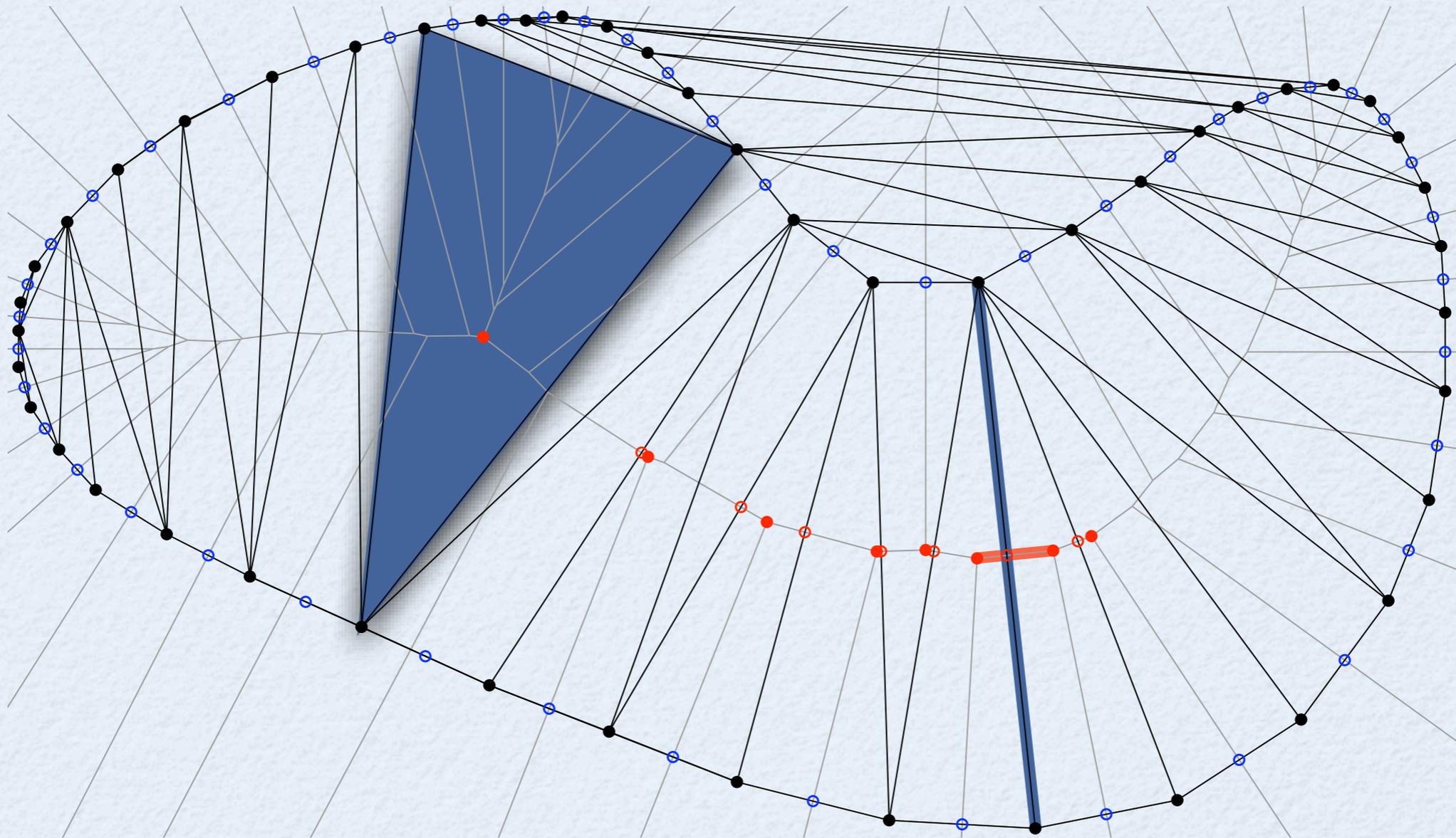
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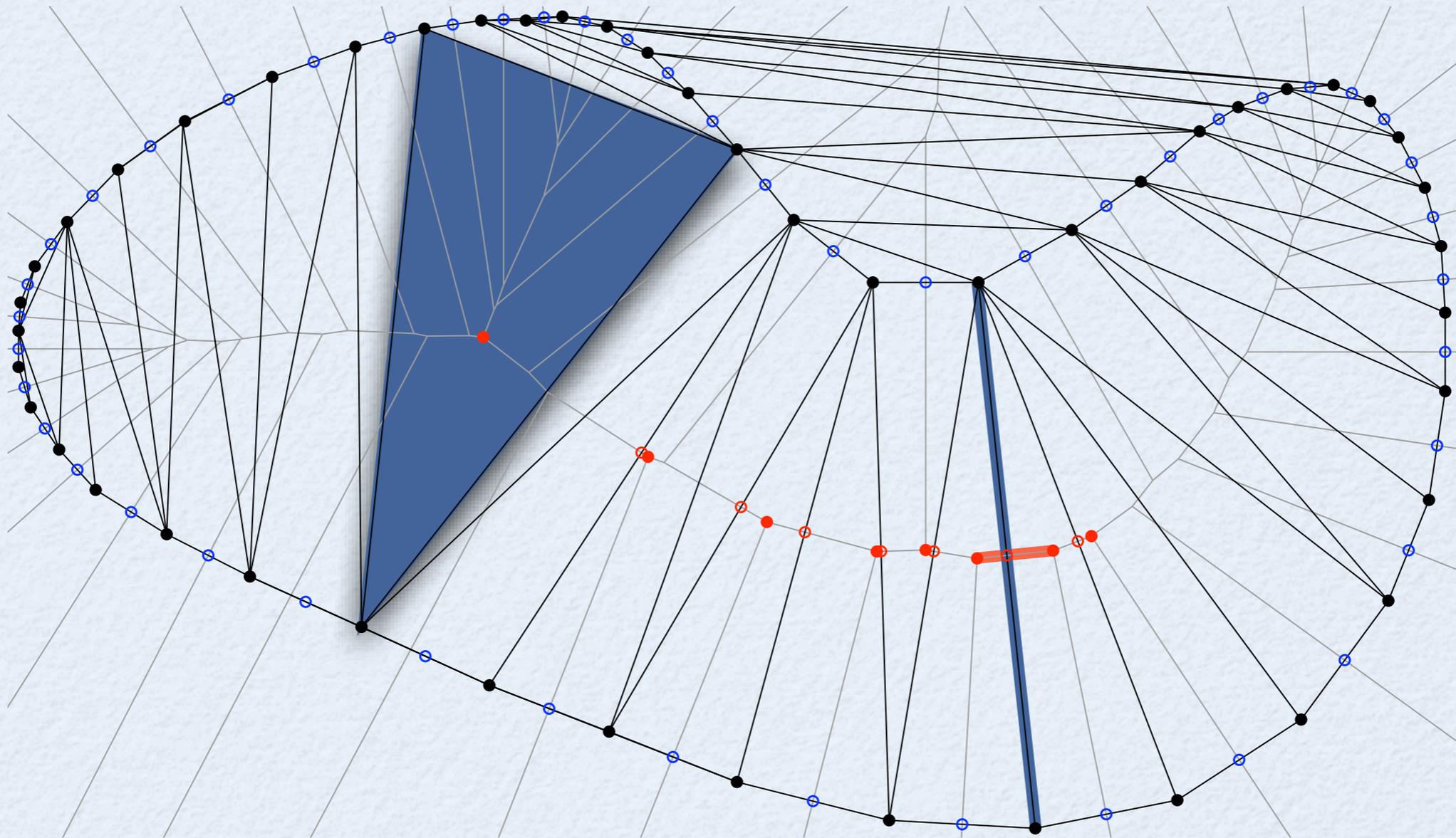
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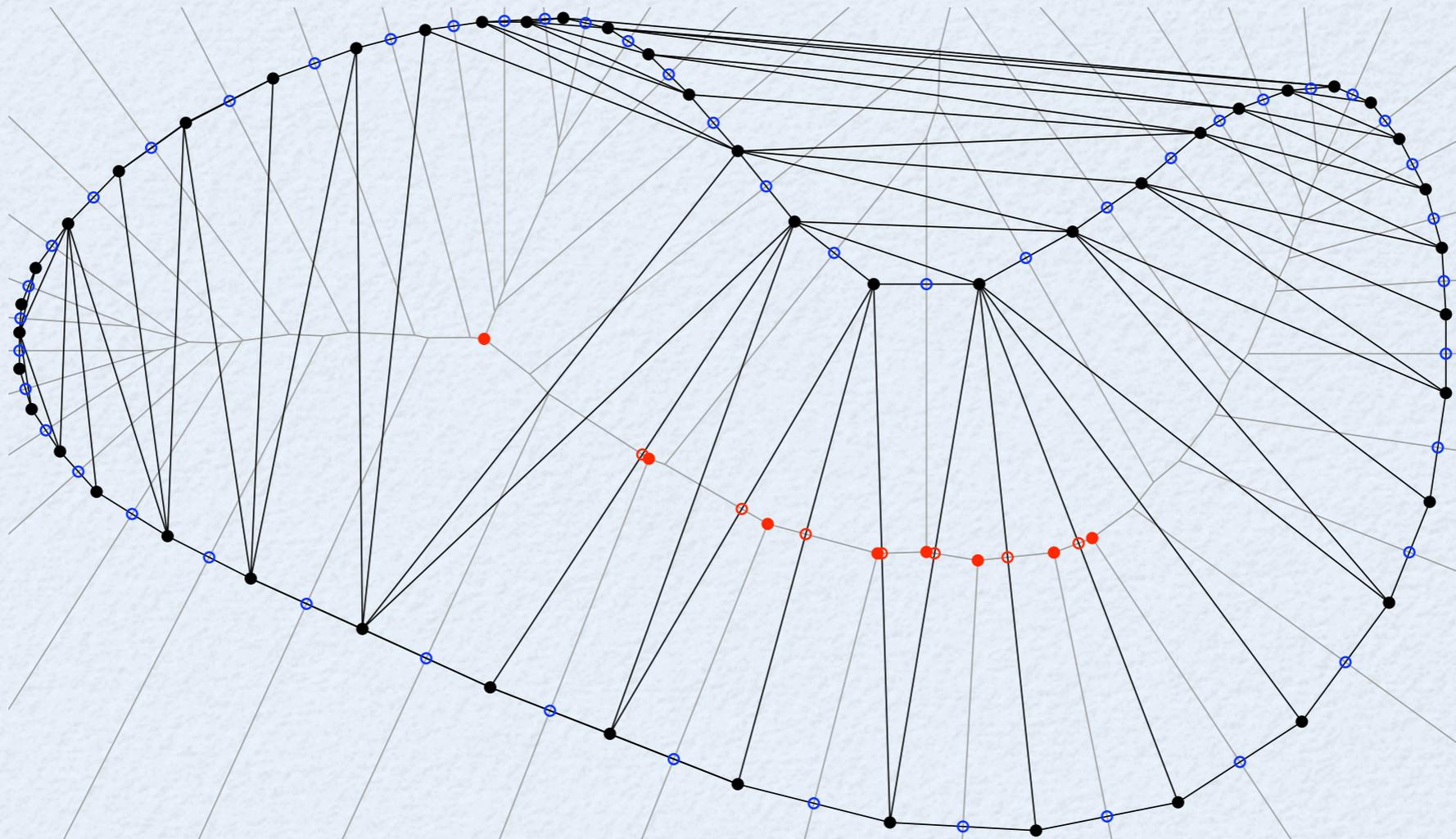


The **index** of  $c$  is the **dimension** of  $D(c)$ .

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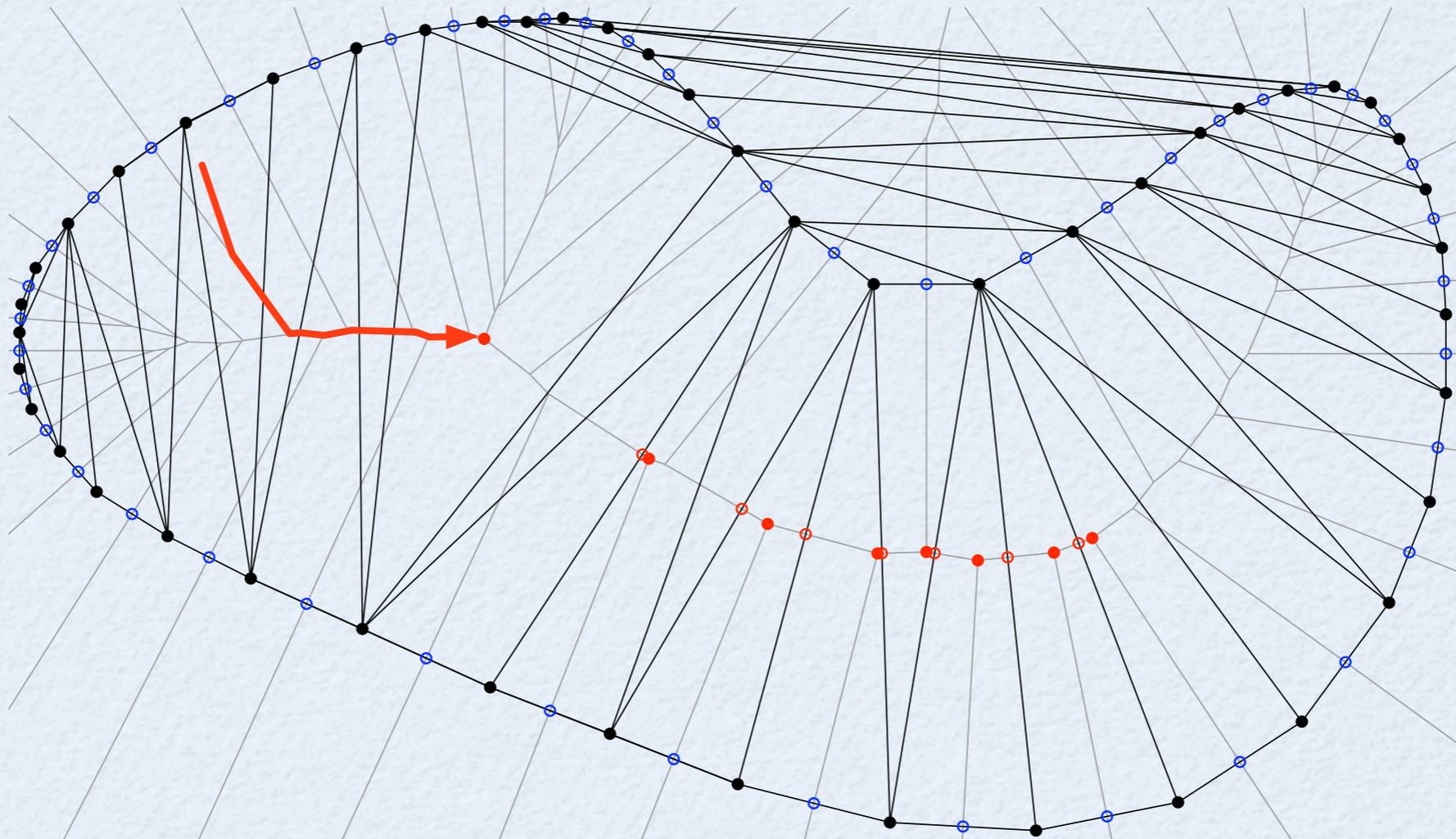
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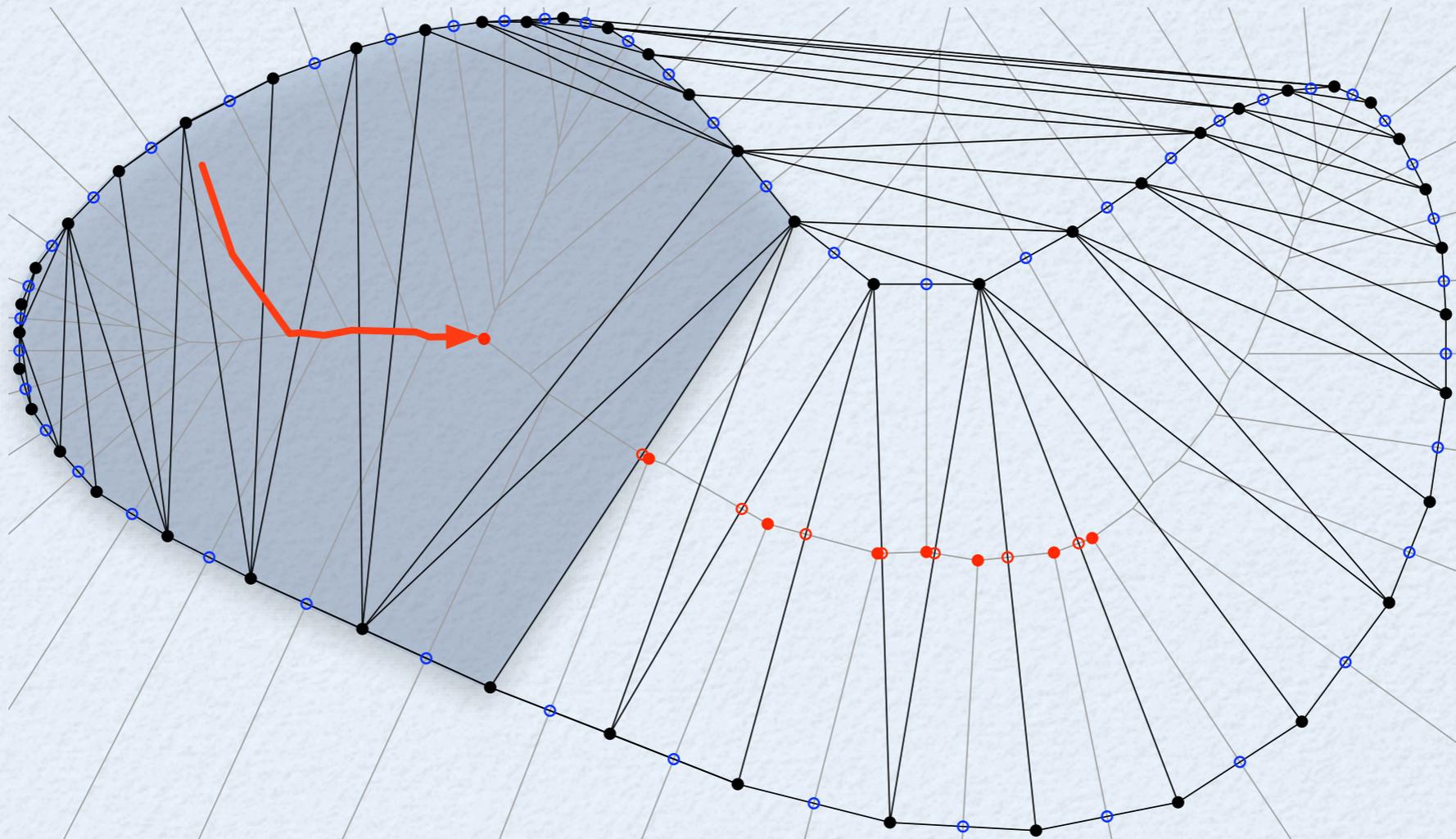
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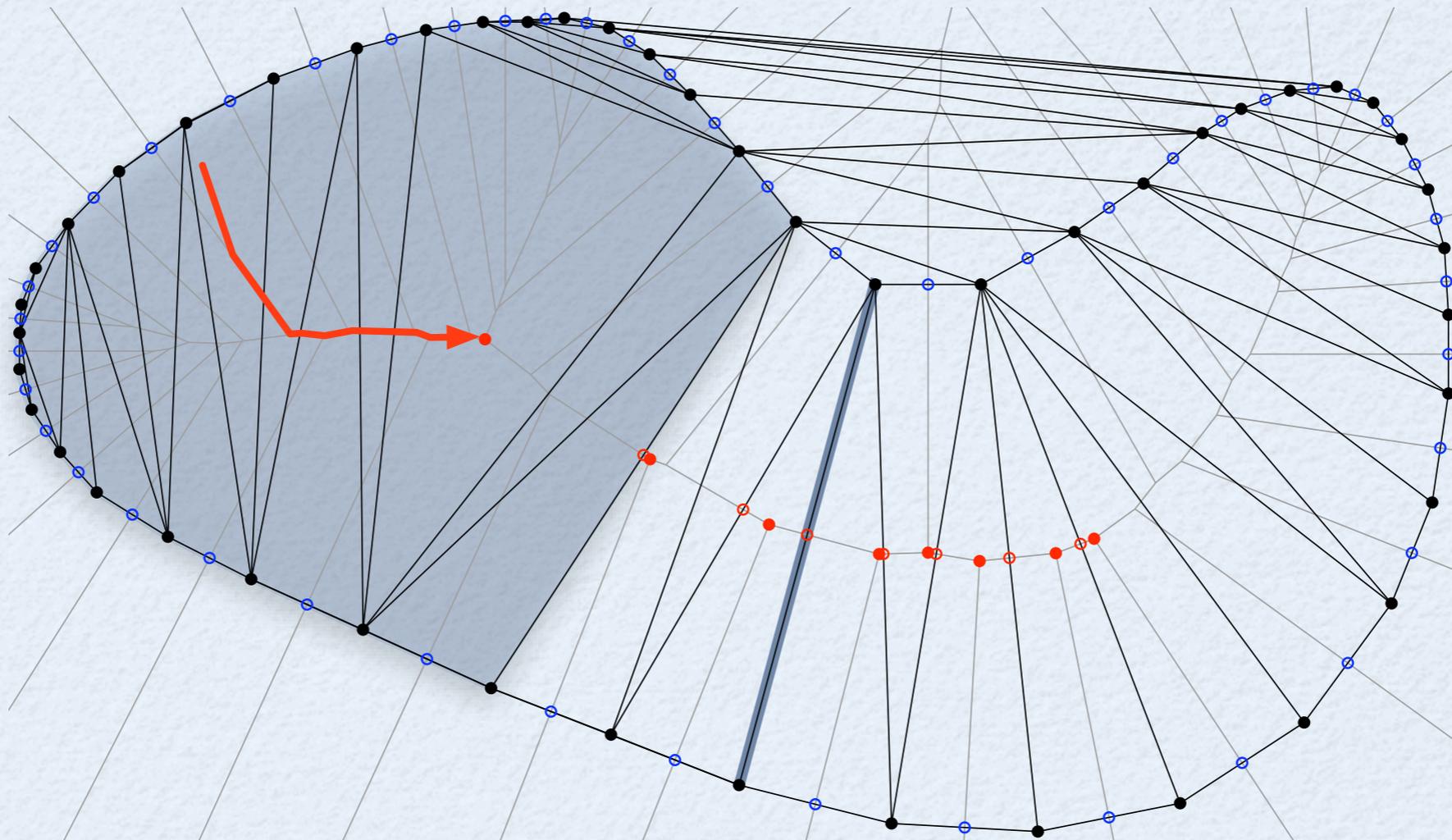
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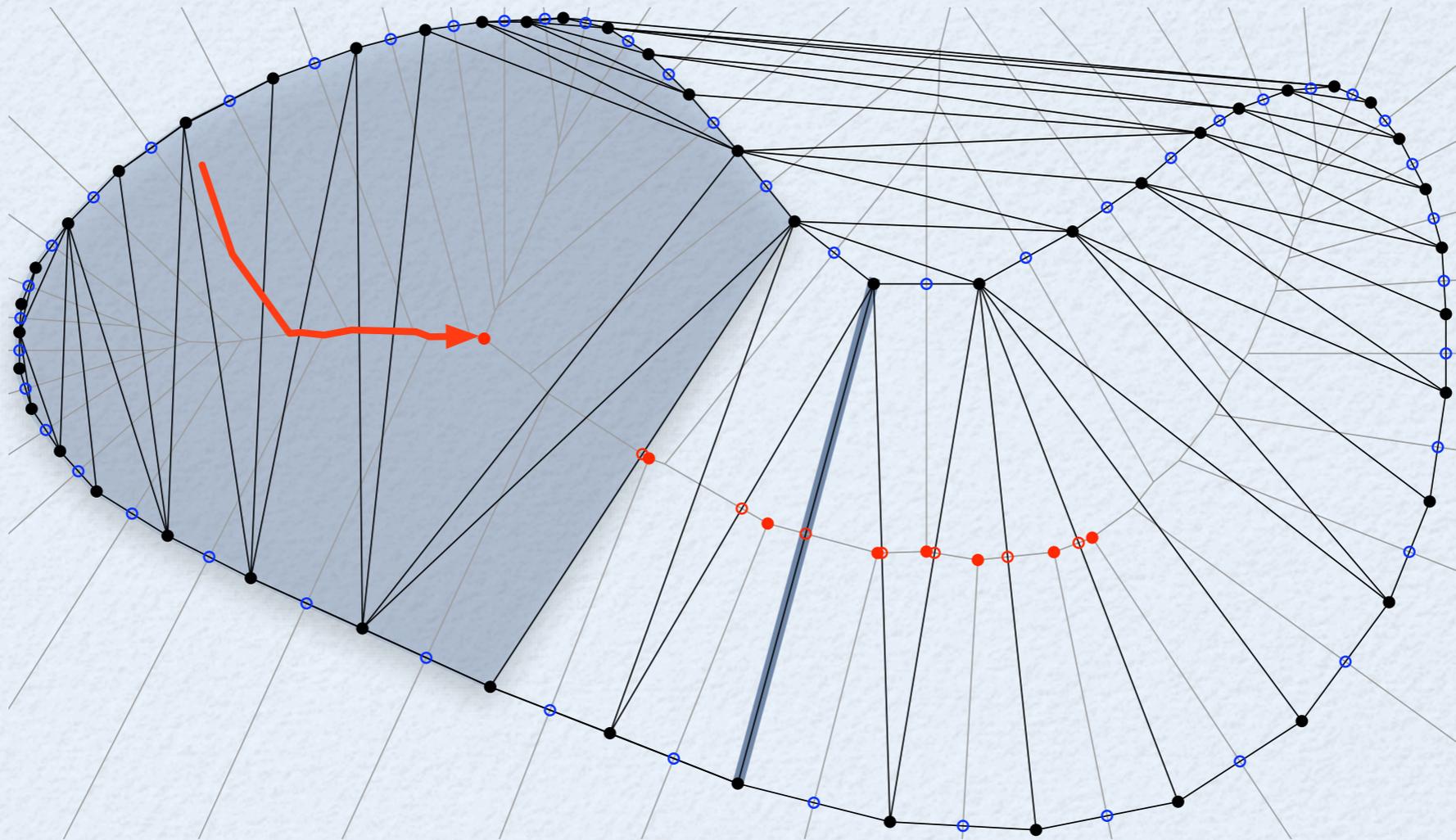
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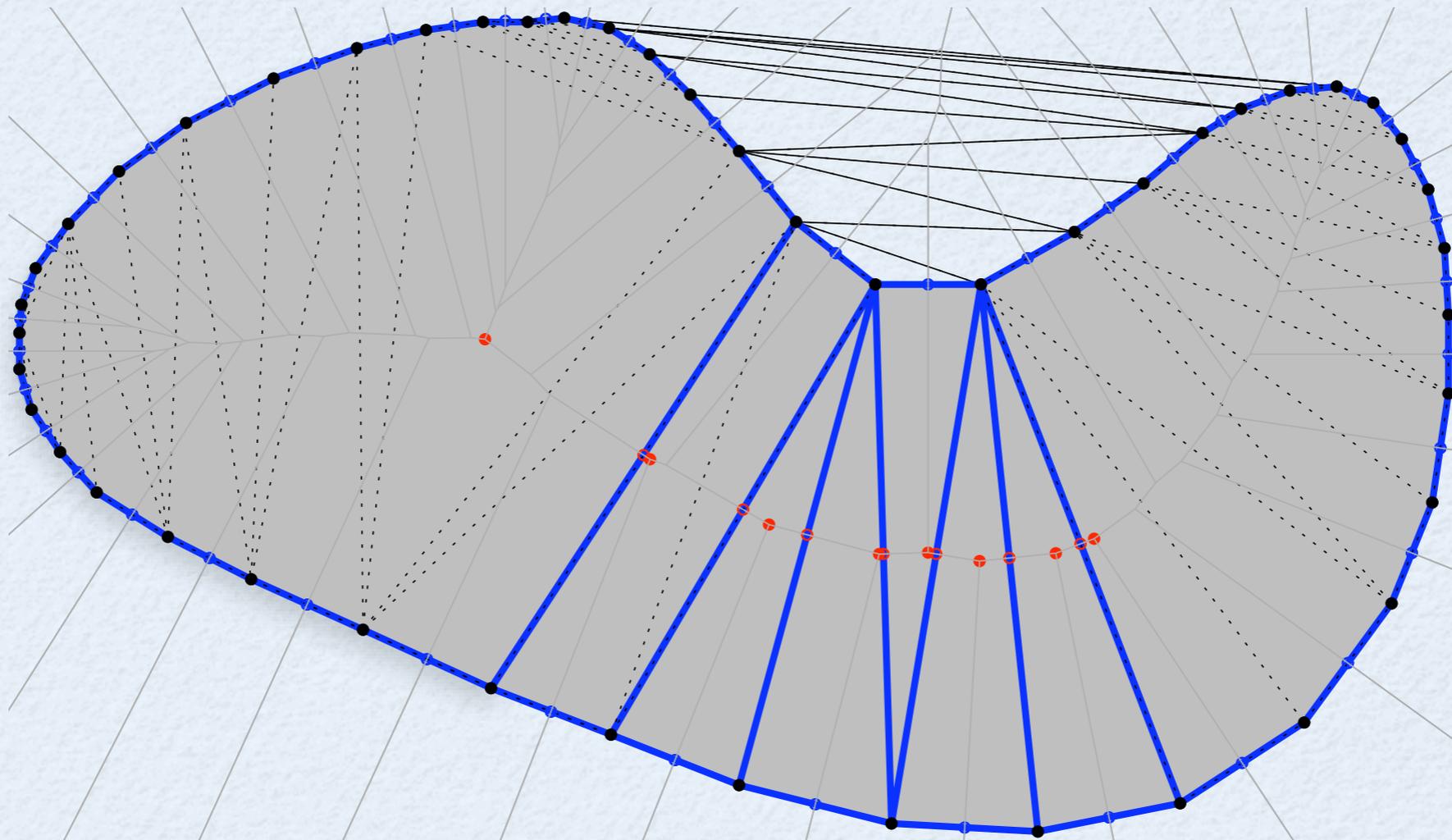


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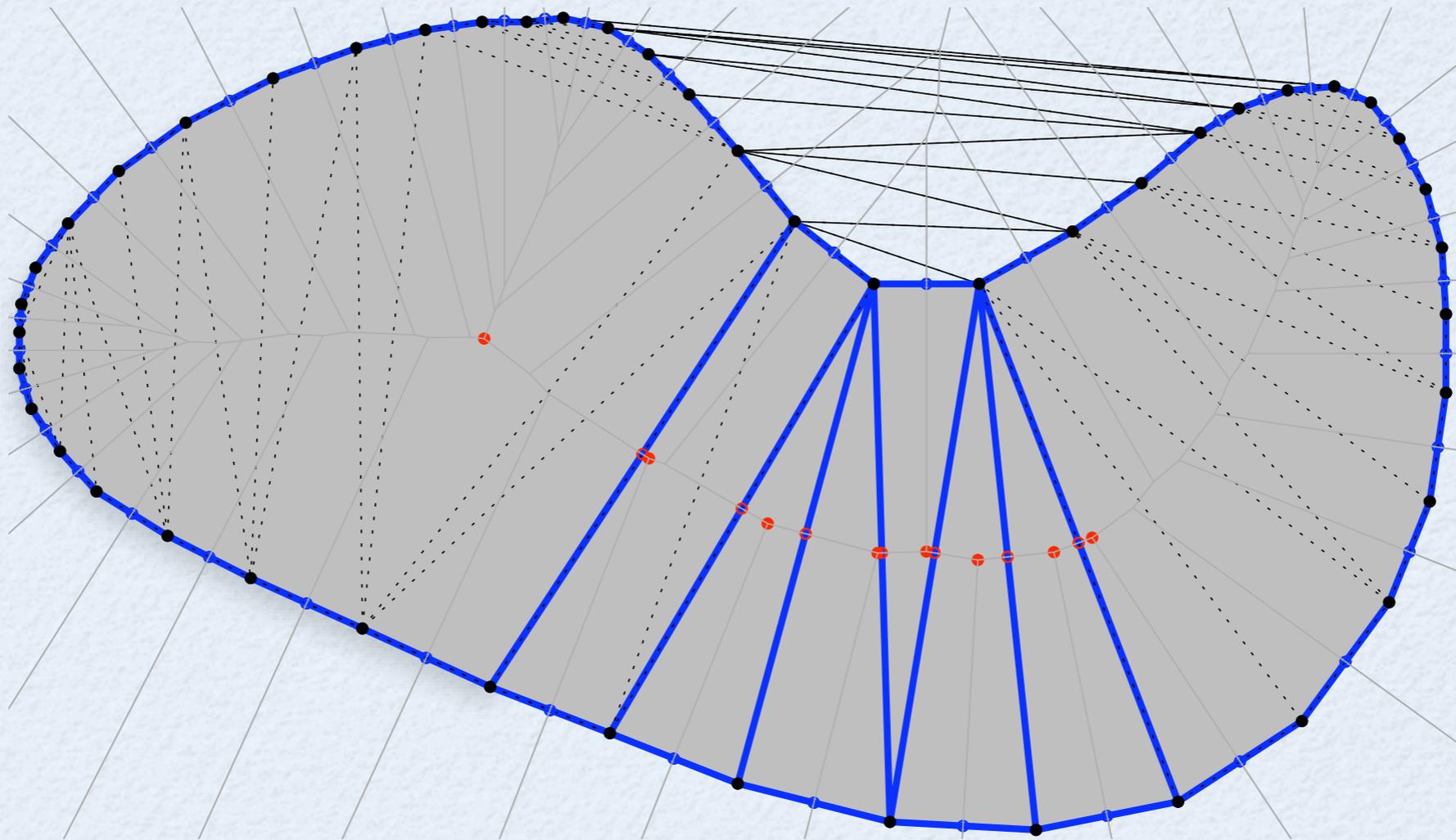


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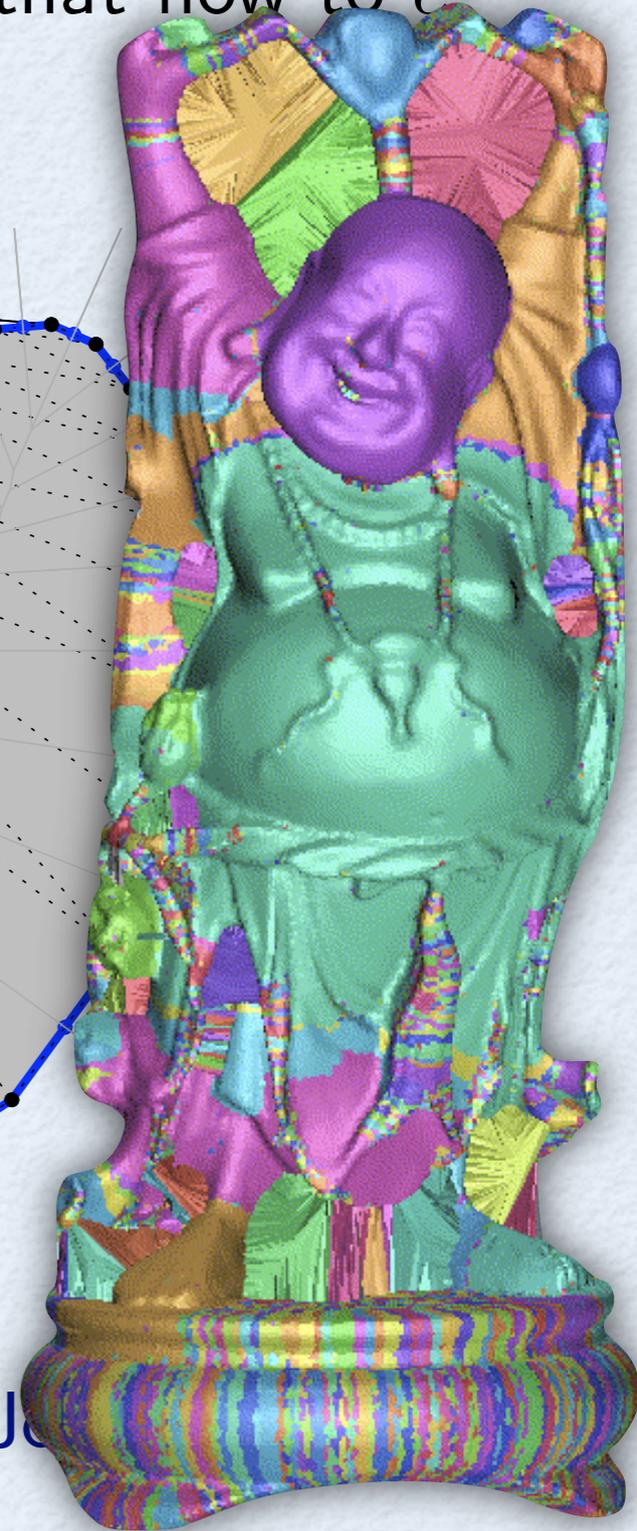
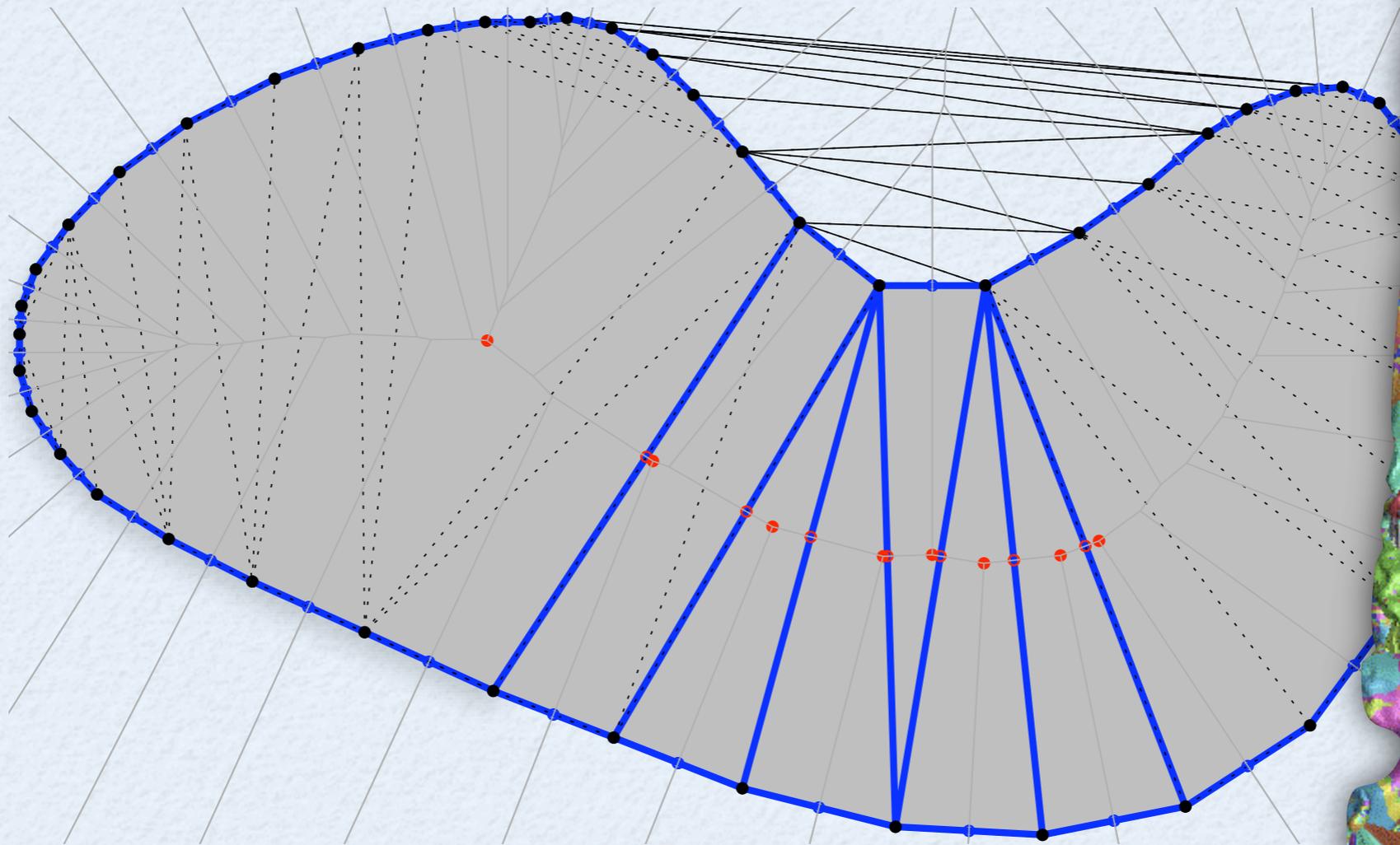
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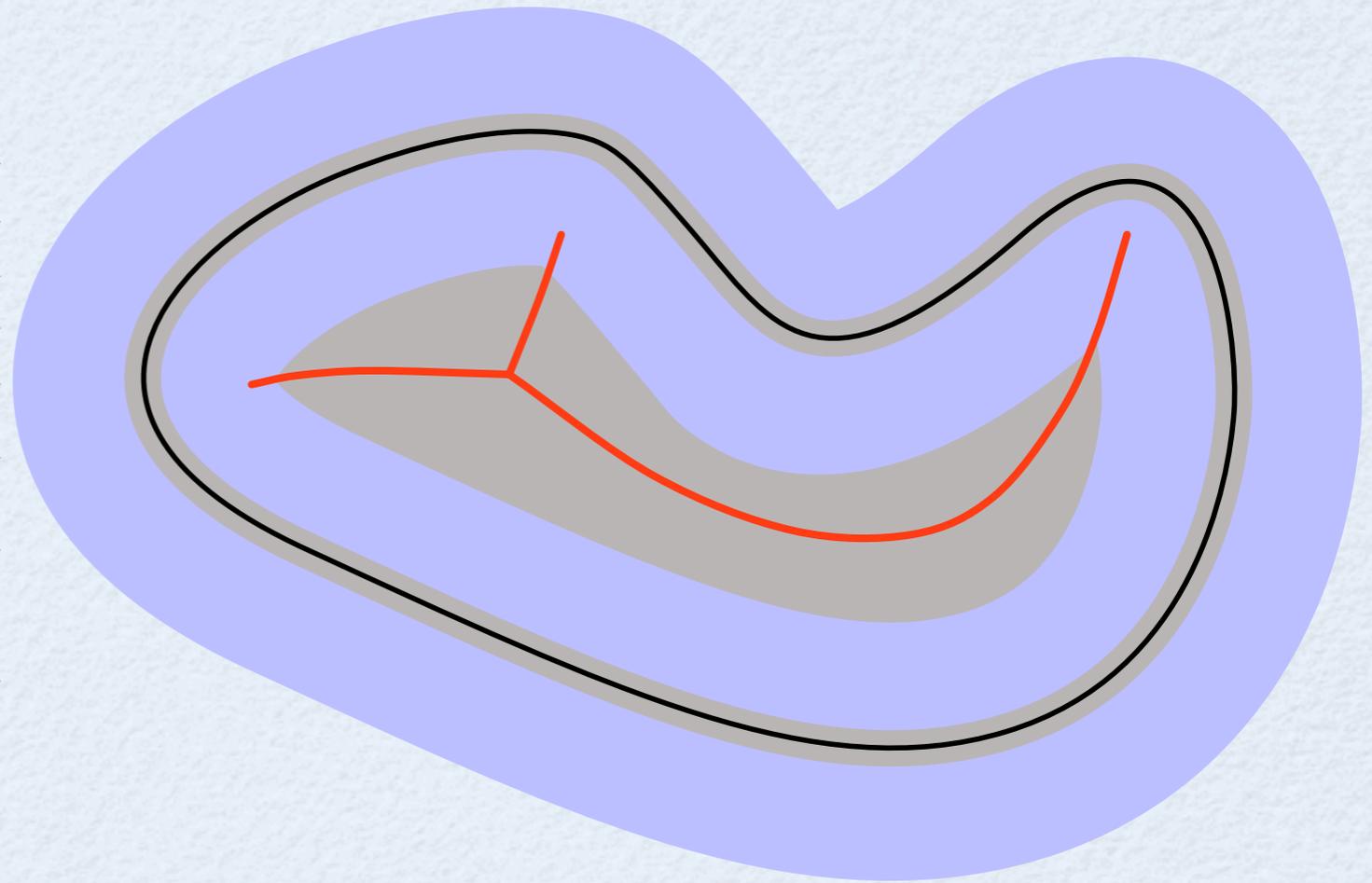
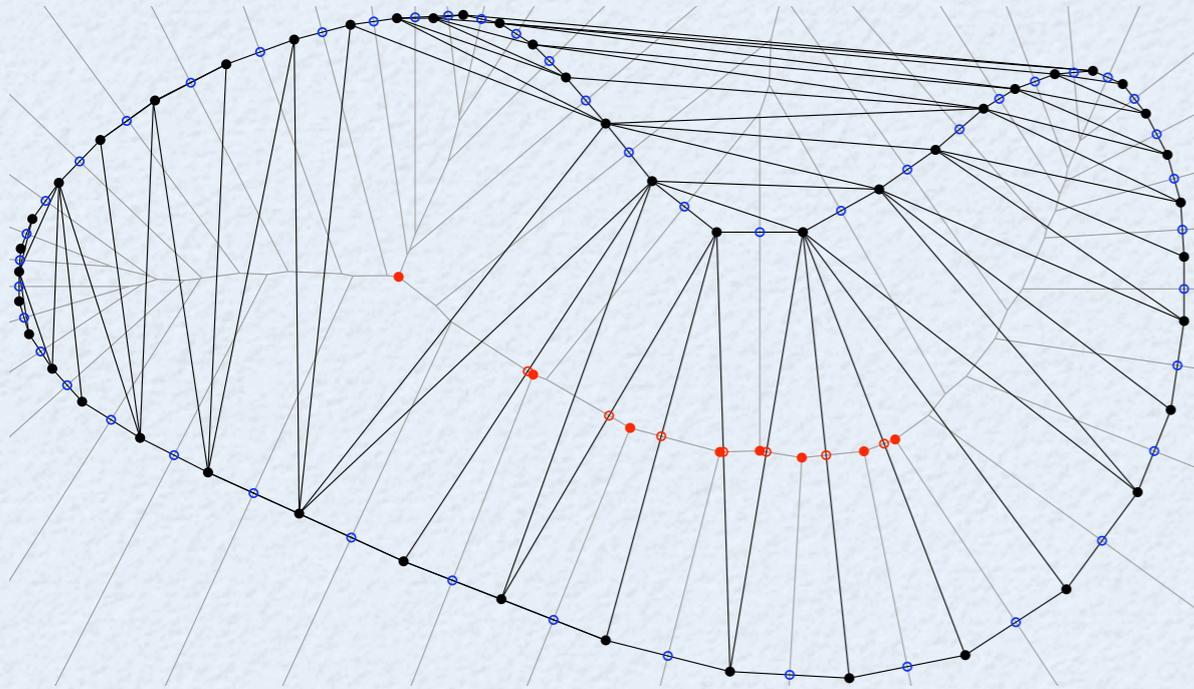
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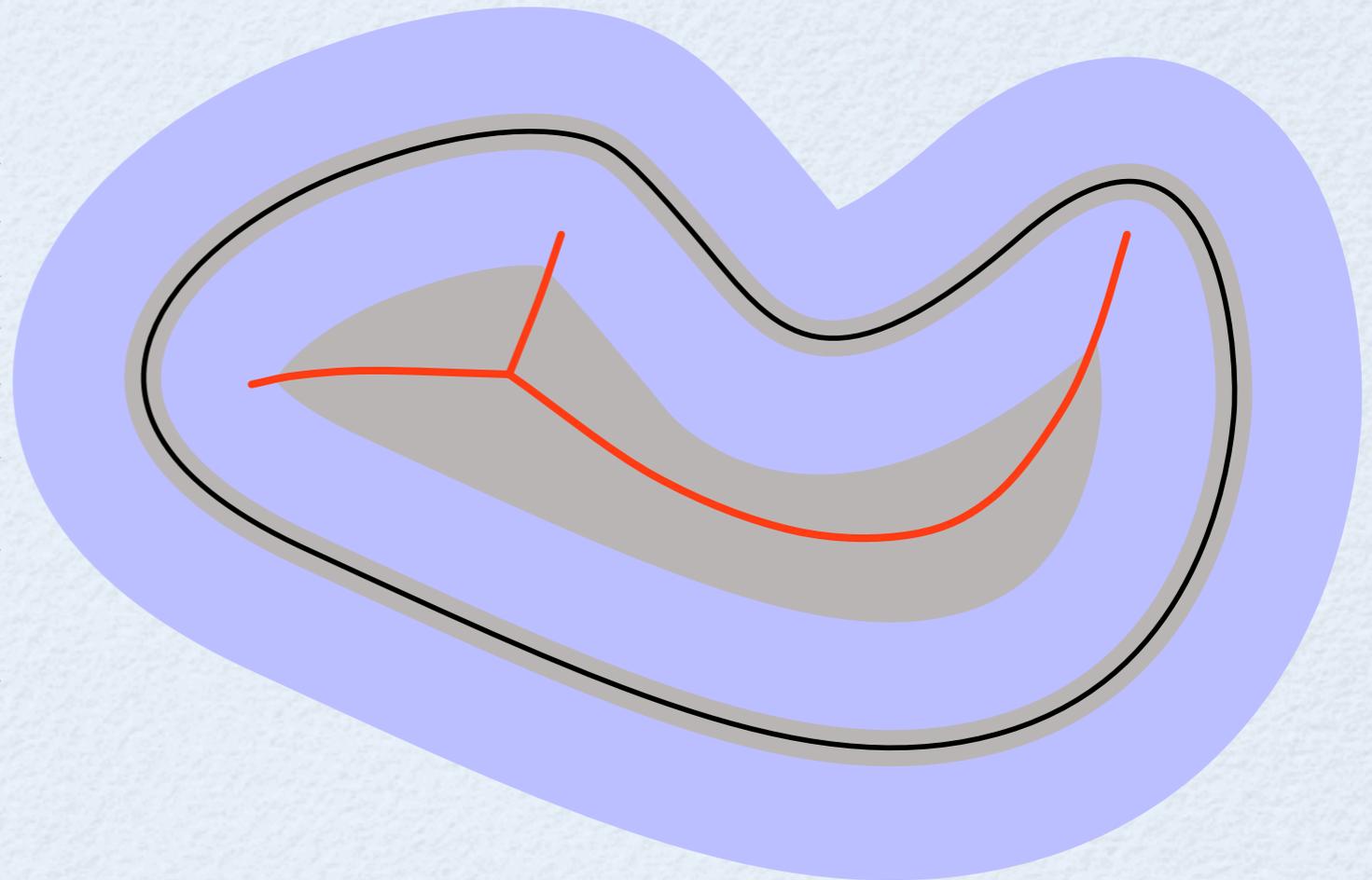
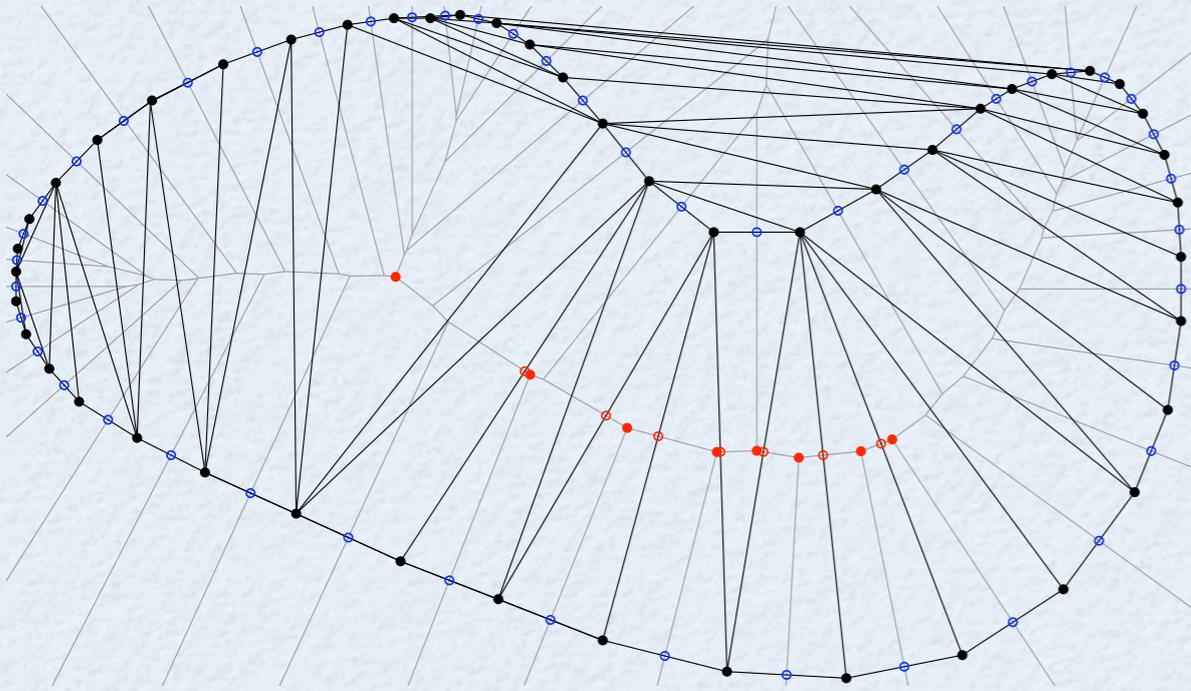
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# Separation of critical points

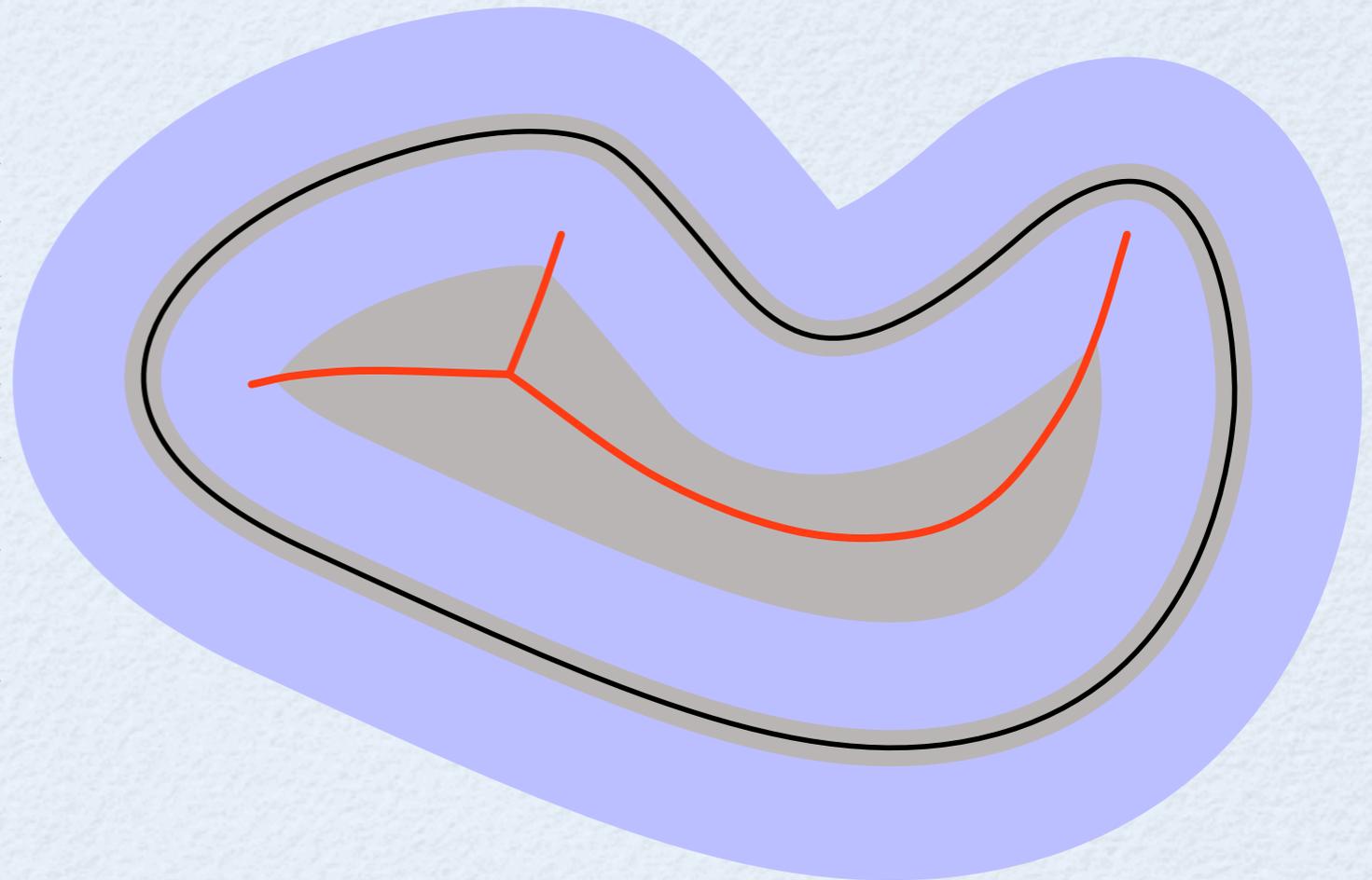
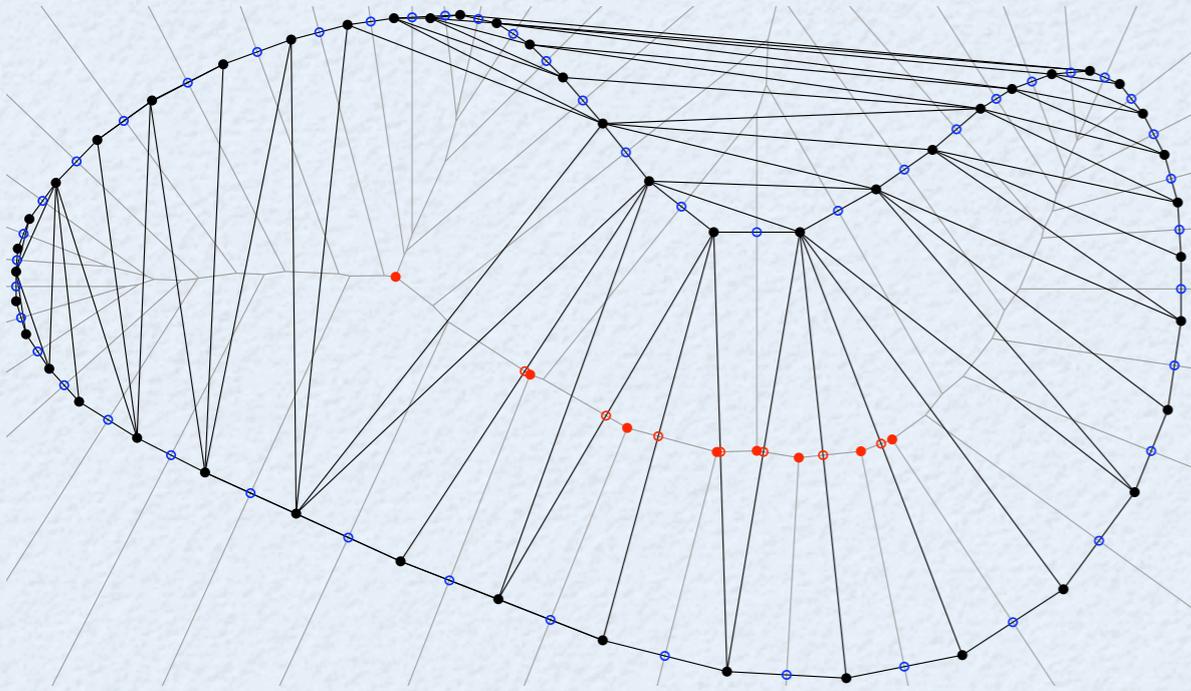


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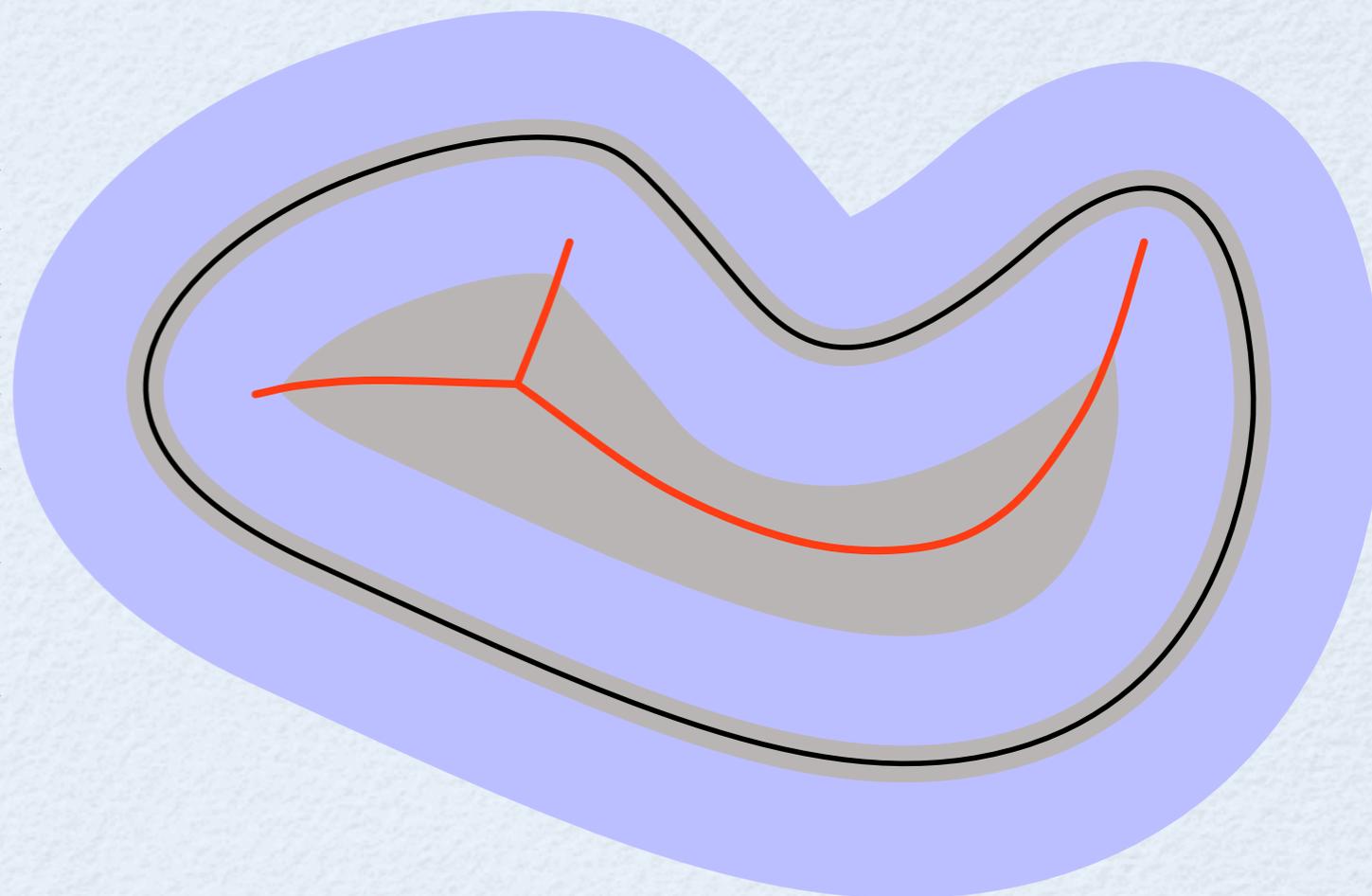
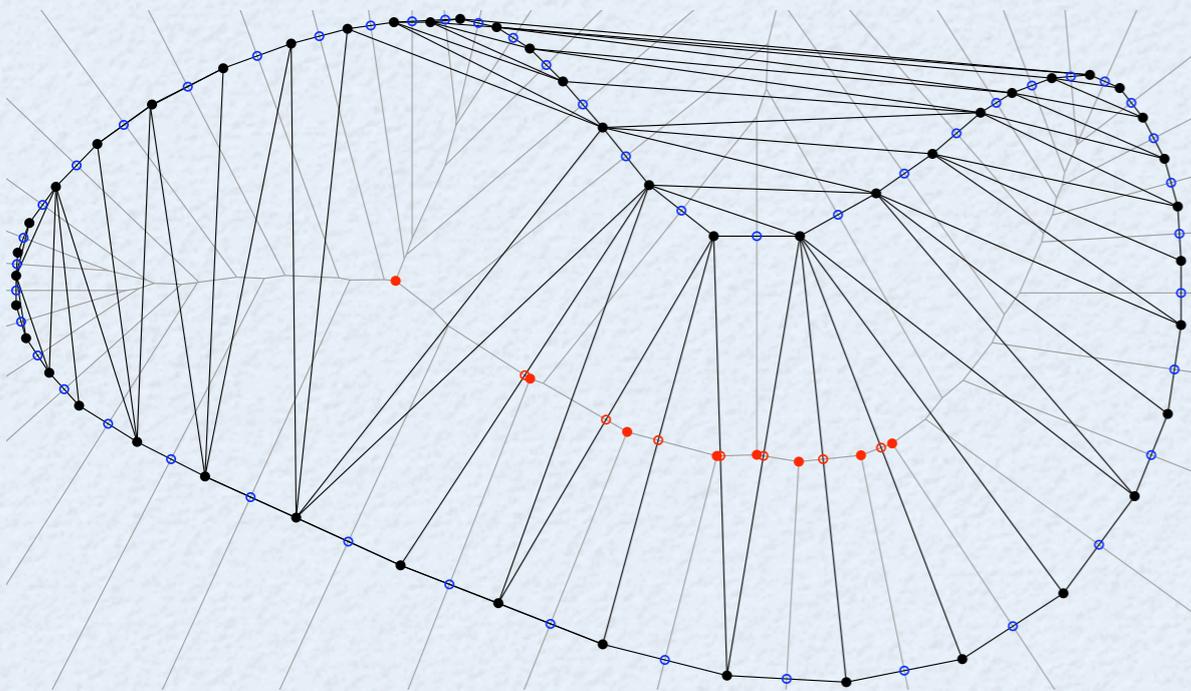
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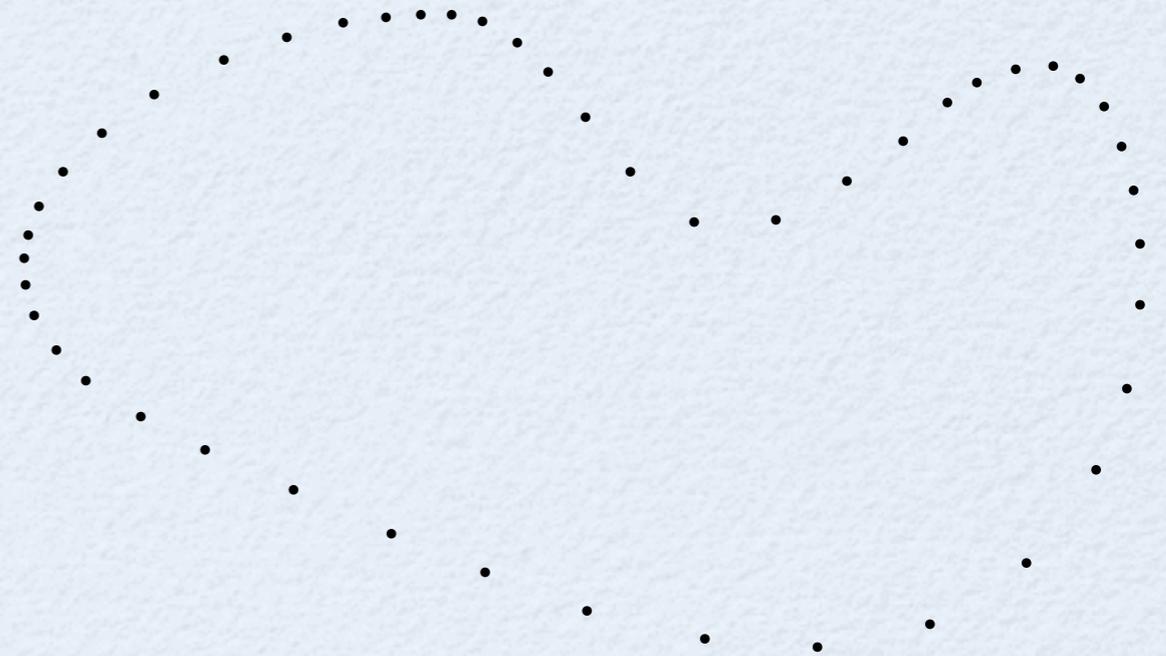


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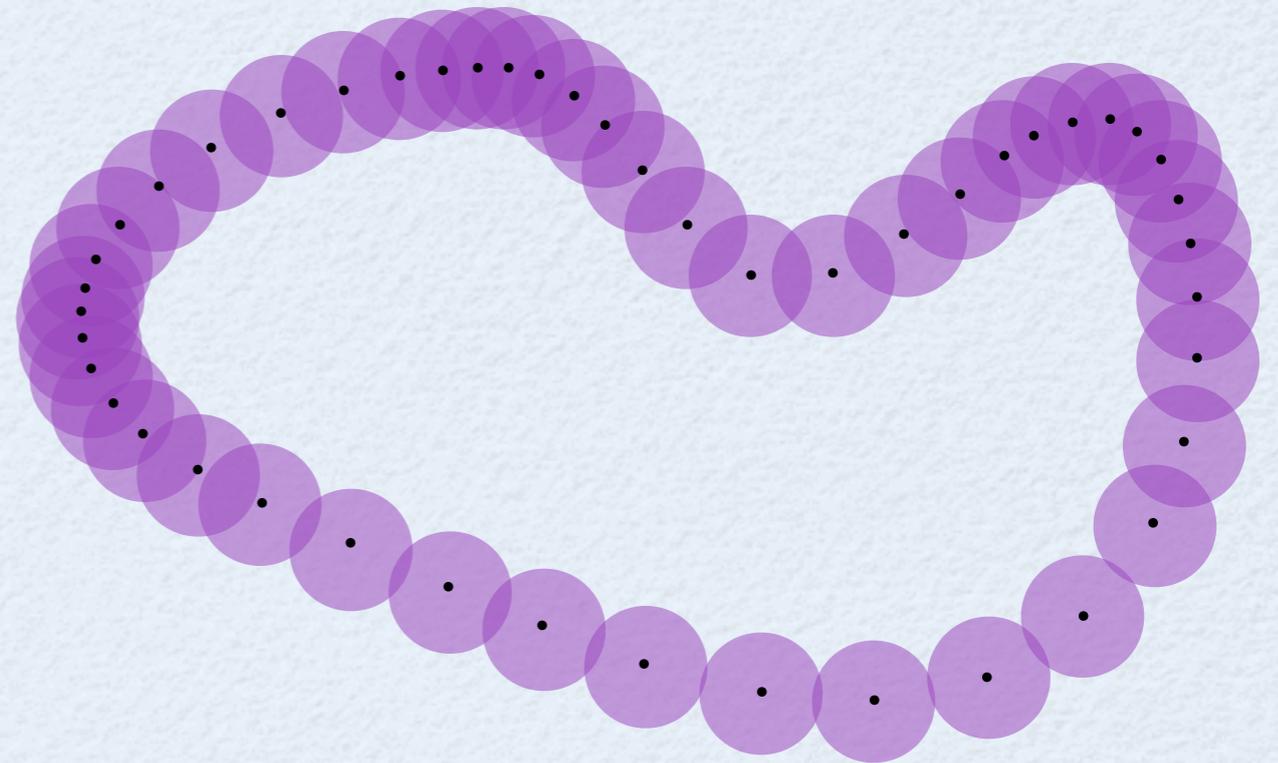
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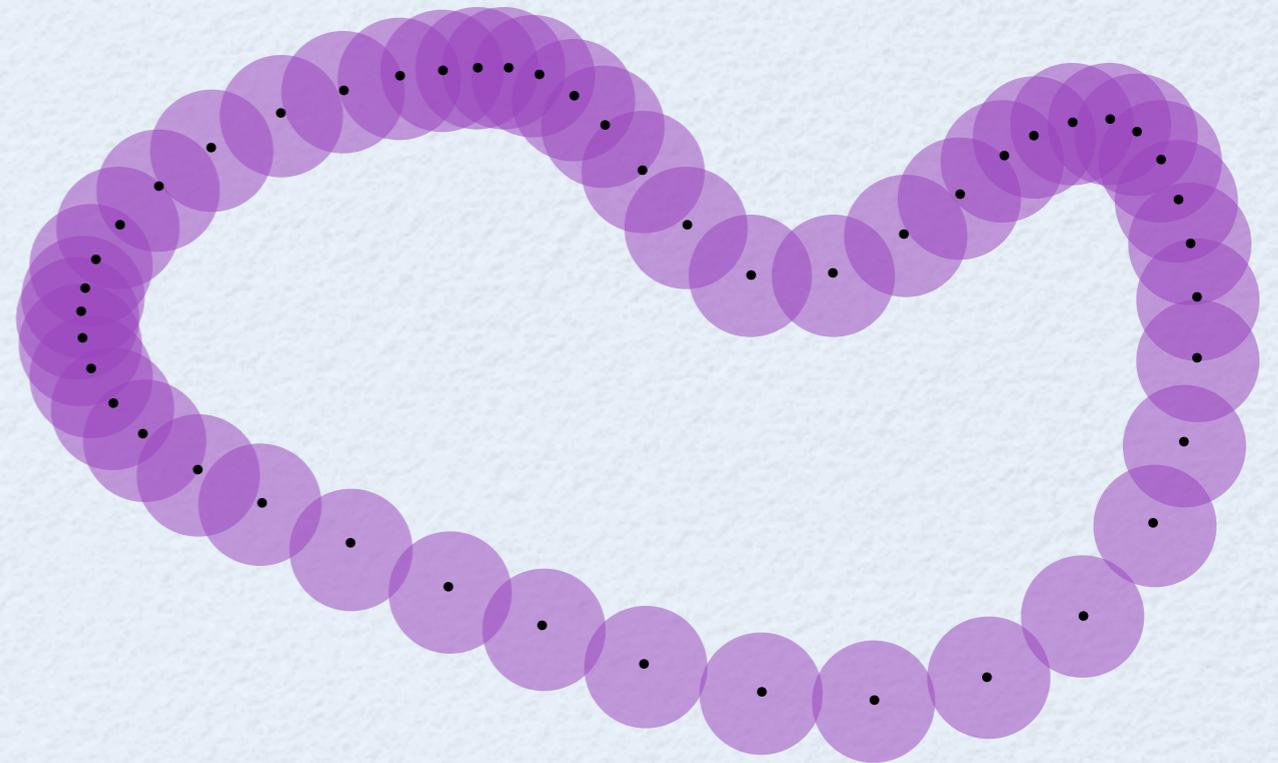
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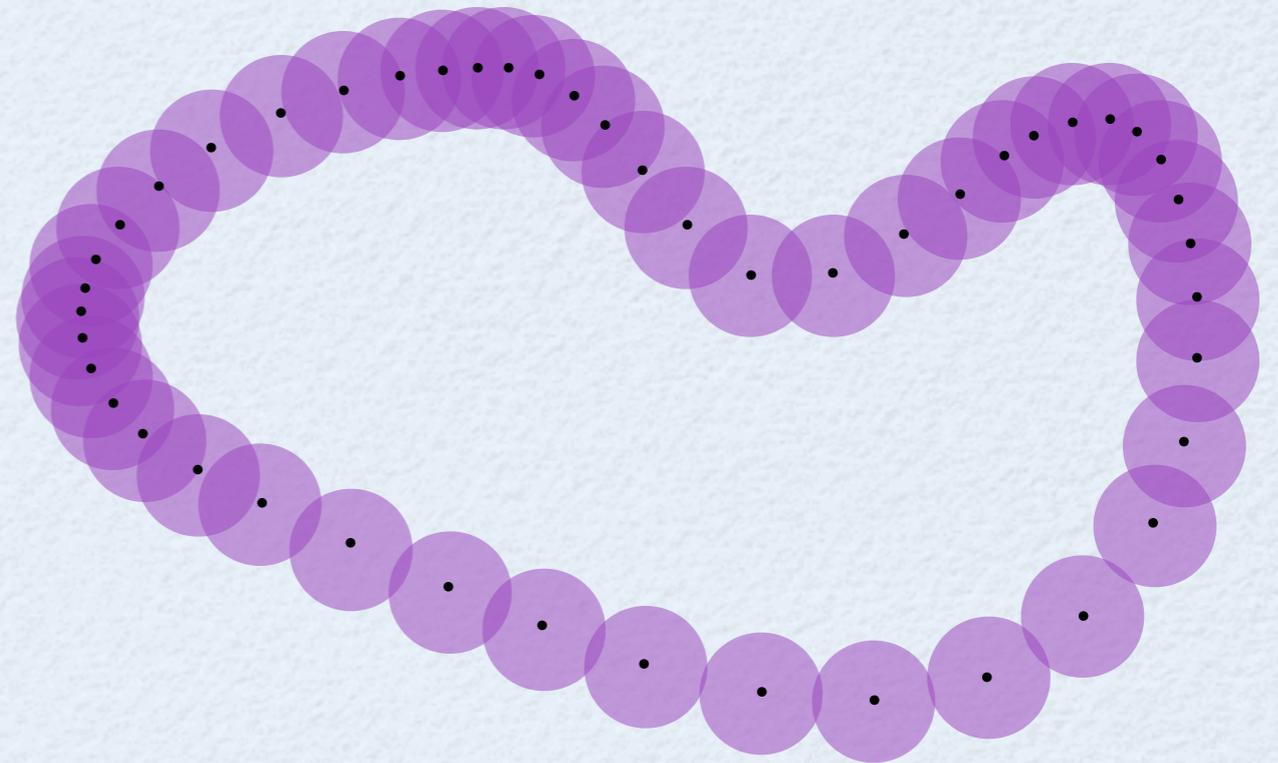
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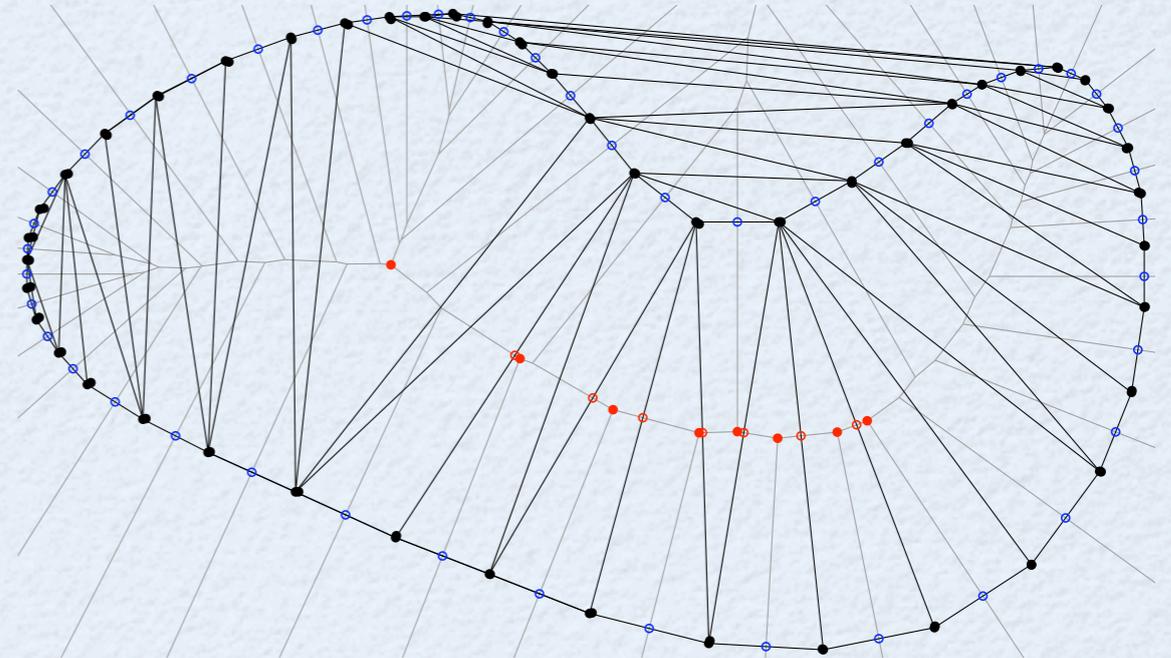


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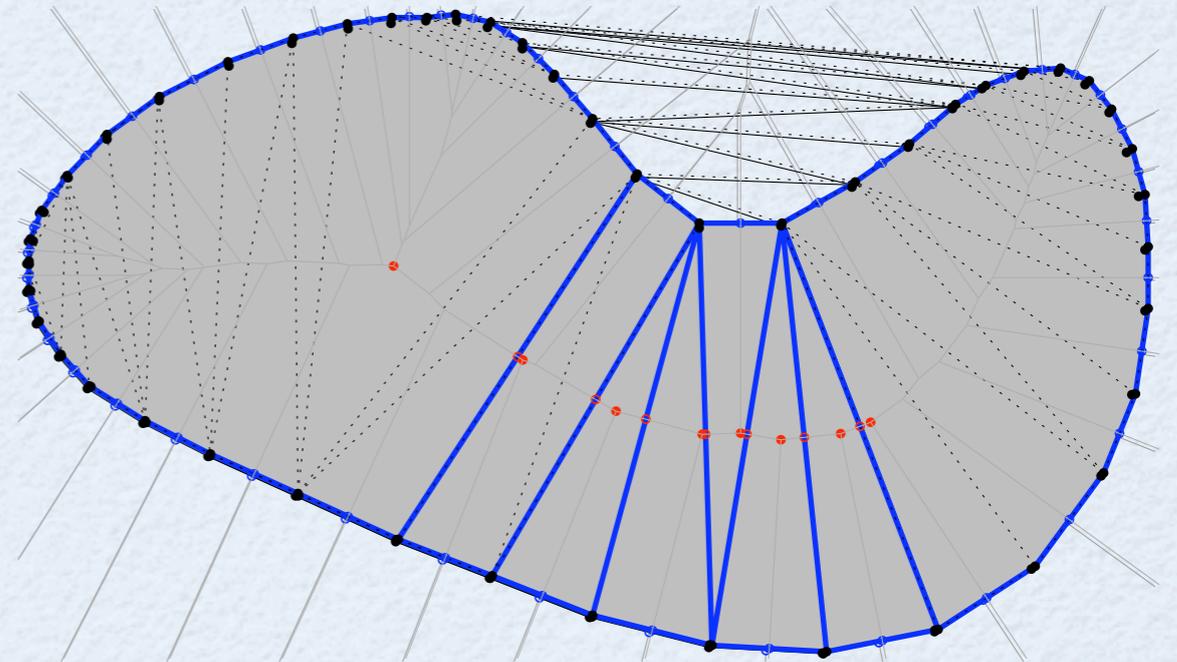


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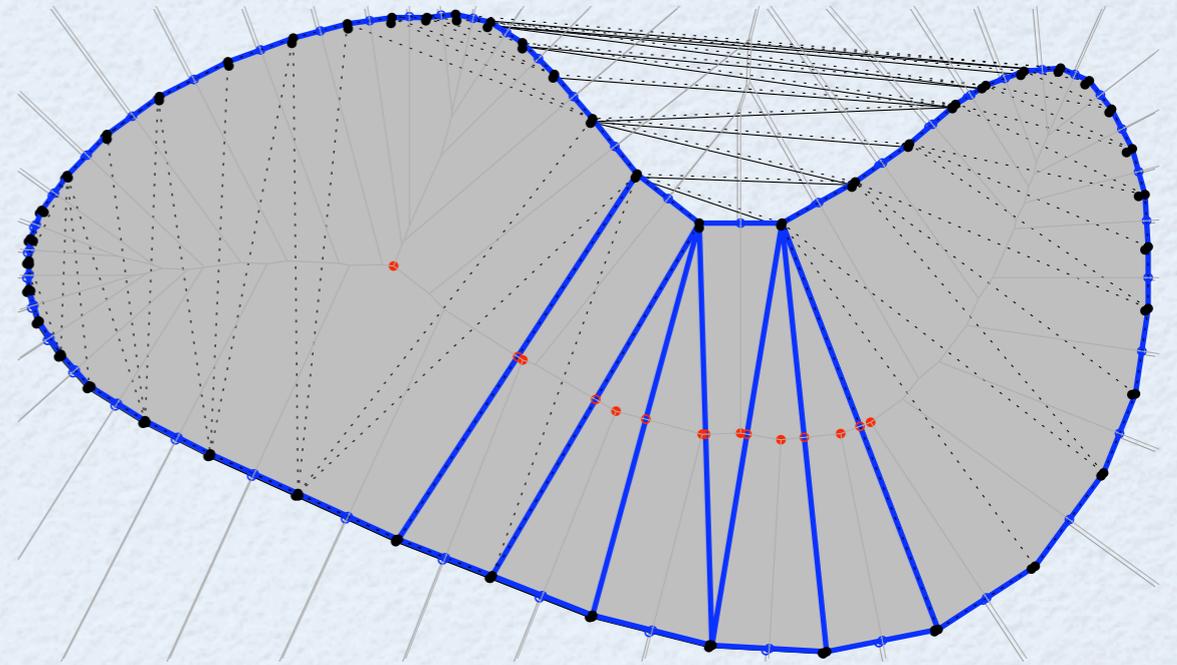


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4. [S'08] Under **uniform sampling**, union of  $S_m$ 's of **shallow** crit pts is homotopy equiv to the sampled manifold and that of **deep** ones is homotopy equiv to the complement of manifold.

# Filtering the flow complex

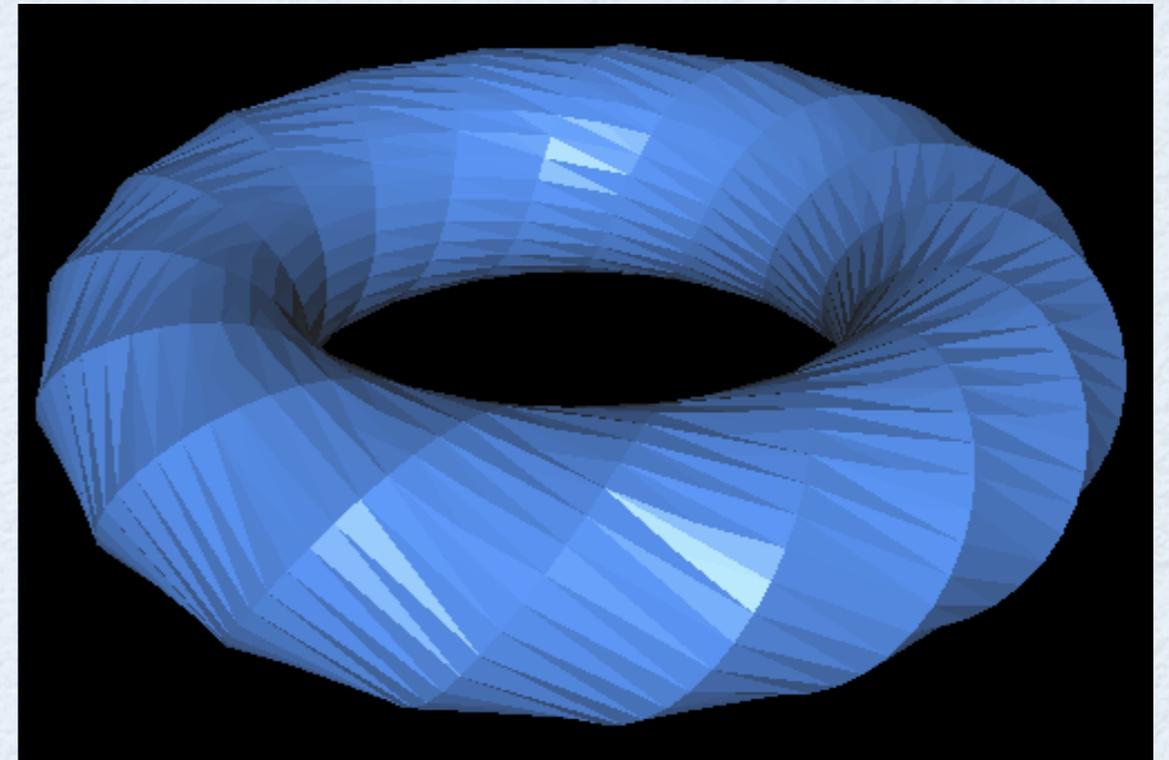
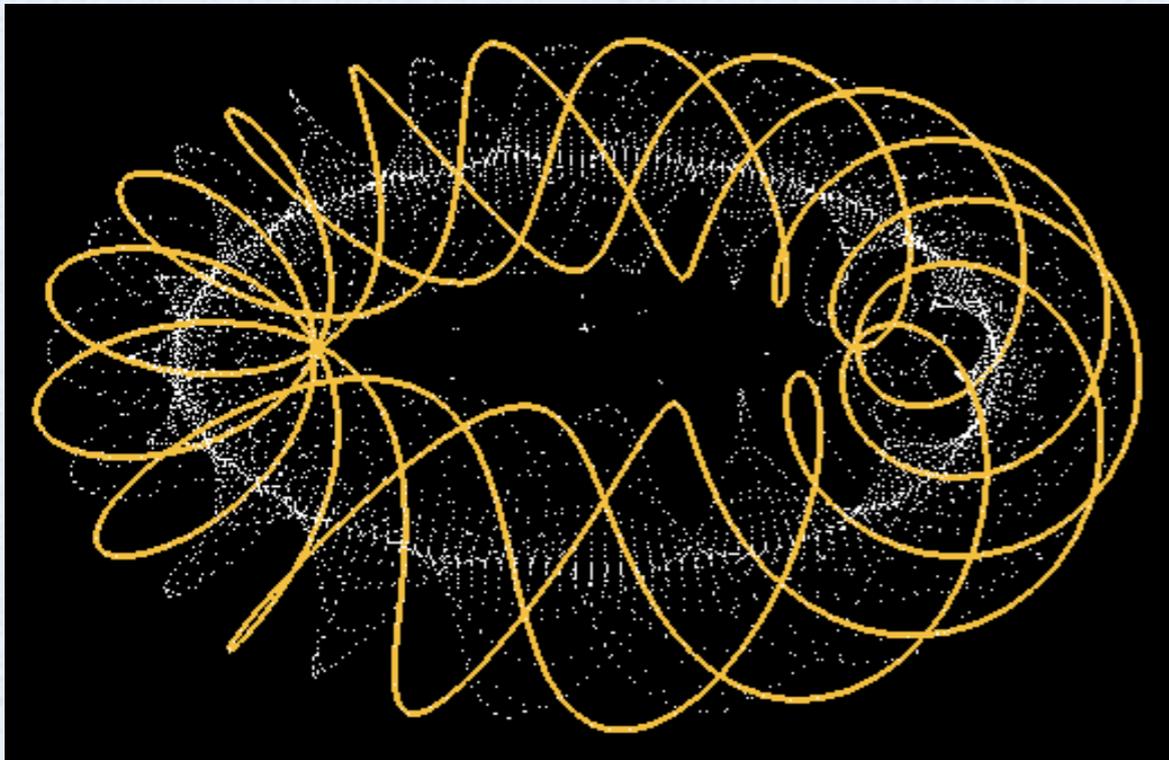
## Theorem.

Let  $P \subset \mathbb{R}^n$  and  $h$  be the induced distance function. If  $h(c_1) < \dots < h(c_k)$  are critical points of  $h$ , then for any submanifold  $\Sigma$  of  $\mathbb{R}^n$  densely sampled by  $P$ , there is a  $1 < j < k$ , such that:

$$\bigcup_{i=1}^j \text{Sm}(c_i) \simeq \Sigma$$

and

$$\bigcup_{i=j+1}^k \text{Sm}(c_i) \simeq \Sigma^c$$



# Other results using distance induced flows

[Lieutier'04] The **medial axis** of any bounded open subset of  $\mathbb{R}^n$  is homotopy equivalent to it.

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**Thank You!**