

Topologically Stable Hough Transform

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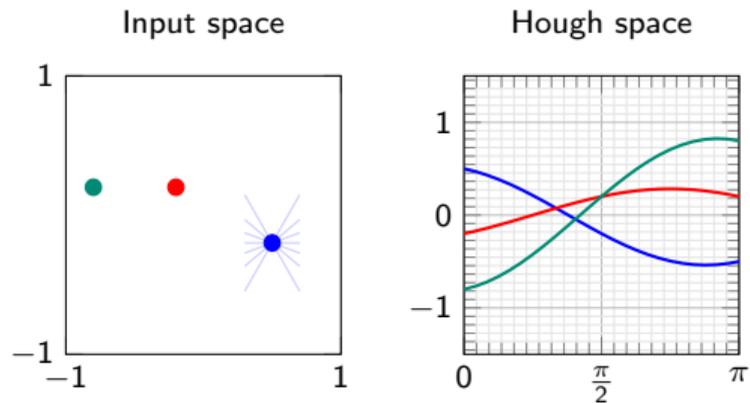
²Institute of Geometry
Graz University of Technology



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Line detection – a classic task in computer vision

Revisiting Hough transform



- ▶ Hough space = parameterization space of lines
line in input space $\hat{=}$ point in Hough space
- ▶ Blue curve in Hough space: the set of lines through the blue input point.
 - ▶ Intersection point of curves \rightarrow common line in input space \rightarrow to be detected
- ▶ Line detection: Discretize Hough space in bins, count votes (no. of curves through bin), find bins with many votes

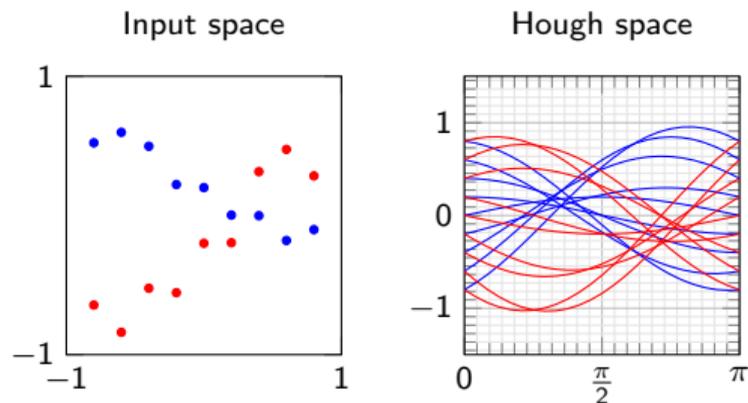
- ▶ Classic method in CV, dates back to 1960s [MC15]
- ▶ Implemented in standard libraries like OpenCV
- ▶ Generalized to other shapes, like circles and “general” shapes
- ▶ Can be mathematically understood as Radon transform (1910s)

Limitations of classic approach

Classic approach: Threshold on the number of votes to identify peaks.

Inherent limitation:

- ▶ Prone to noise: Cleanup heuristics to eliminate false positives
- ▶ Bin discretization hurts stability and accuracy. Making discretization finer \rightarrow bad for noise sensitivity and runtime



Rationale

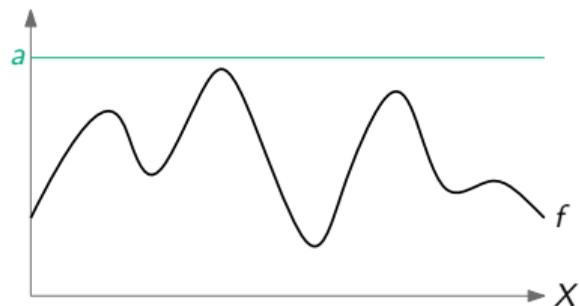
Robust identification of peaks is where persistent homology (PH) shines.

PH for peak detection

Idea of watershed in CV

Tracking the evolution of subspaces:

- ▶ Given a real-valued function $f: X \rightarrow \mathbb{R}$ over some topological space X
- ▶ We can look at the super-levelsets $f^{\geq a} = \{x \in X \mid f(x) \geq a\}$
- ▶ As a decreases from ∞ , $f^{\geq a}$ grows and “sweeps out” X



0-dimensional PH:

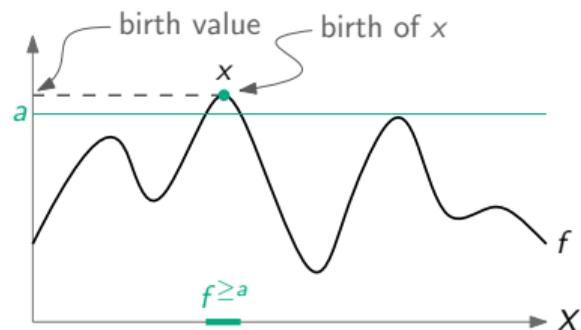
- ▶ Assume local maxima are isolated, with different f -values.
- ▶ Point x is **dominant** in $f^{\geq a}$ if x is f -maximal within its connected component.
 - ▶ If x is a local maximum, let $h = f(x)$, then x is dominant in $f^{\geq h}$. We call h the **birth** level of x .
- ▶ The **persistence** of x is the sup of $t \geq 0$ such that x is dominant in $f^{\geq h-t}$. We call $h - t$ the **death** level of x .
 - ▶ The global maximum has infinite persistence.

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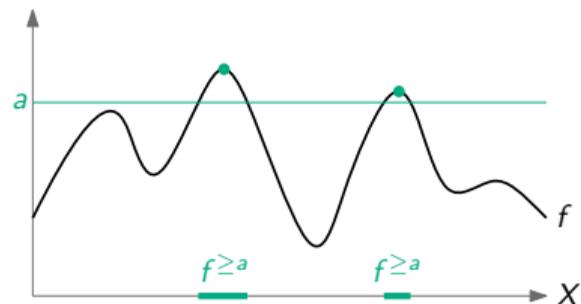
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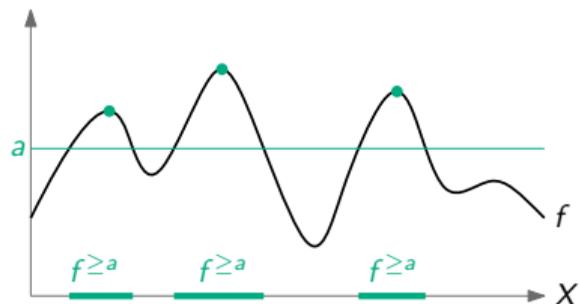
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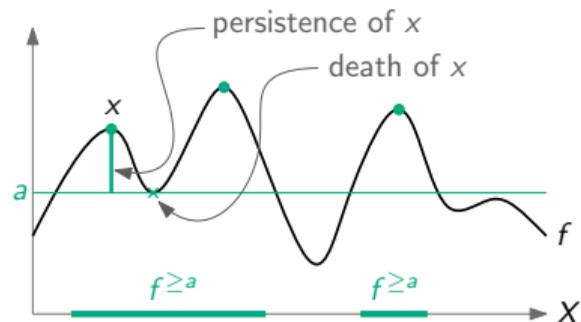
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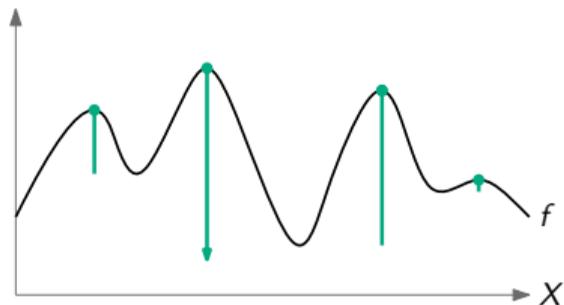
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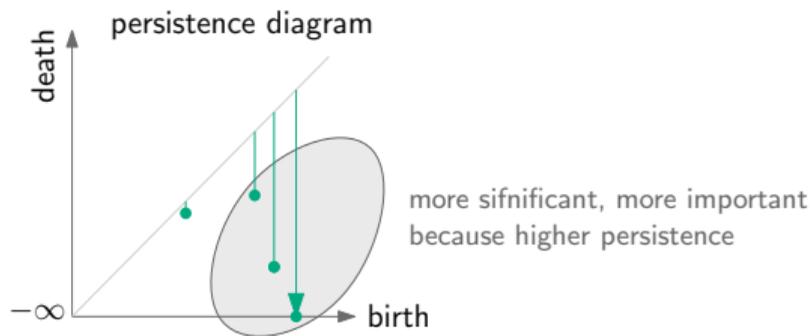
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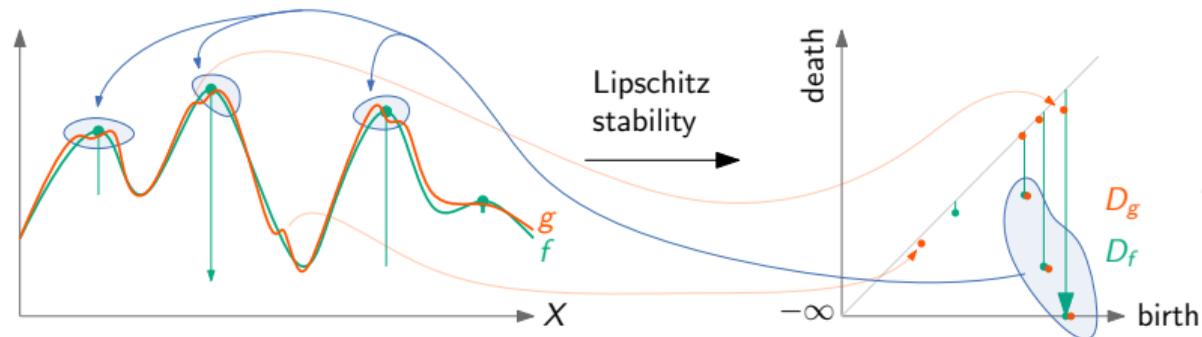
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PH is about stability

If we change f a little (e.g., noise) then also persistence (diagrams) changes only a little.



If f, g are close then the Diagram points are close. (Points close to diagonal are insignificant.)

Distance on persistence diagrams:

- ▶ D_f is the persistence diagram of f . (Formally a multiset, with ∞ -multiplicity at each diagonal point.)
- ▶ $d_B(D_f, D_g)$ is the bottleneck distance. (Which is $\inf_{\gamma: D_f \leftrightarrow D_g} \sup_{x \in D_f} \|x - \gamma(x)\|_\infty$.)

Theorem (Cohen-Steiner, Edelsbrunner, Harer 2007 [CEH07])

For any two (tame) functions $f, g: X \rightarrow \mathbb{R}$,

$$d_B(D_f, D_g) \leq \|f - g\|_\infty.$$

Why PH for Hough transform?

1

Understanding:

- ▶ As a tool to understand the limitations of the heuristics to identify noisy peaks.

2

Algorithm construction:

- ▶ Replace heuristics to robustly identify noisy peaks by Lipschitz-stable mathematical methods.

Programme

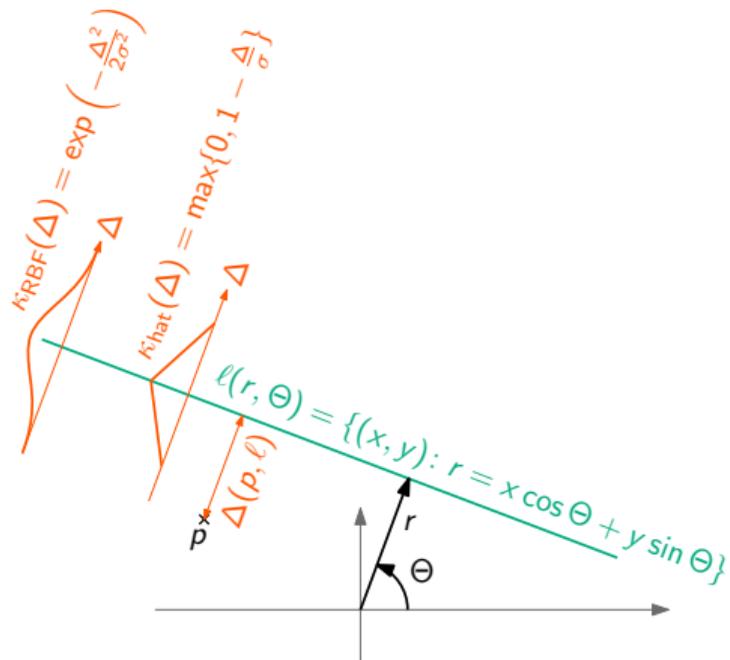
Lipschitz-stable sequence

input point cloud \mapsto Hough image \mapsto persistence diagram (persistent points $\hat{=}$ peaks $\hat{=}$ input lines)

For the first map to be continuous, we look for a continuous Hough image, not votes on a discrete bin grid.

Hough space

As the point-line dual space with Möbius topology



Hough space:

- ▶ $M = \mathbb{R} \times [0, \pi]$, where $(r, \Theta) \in M$ parametrizes a line $l(r, \Theta)$
- ▶ Note that $l(r, \Theta) = l(-r, \Theta + \pi)$, leading to well-known open Möbius strip topology¹ of M

Each point p spends a vote $S(p, \ell)$ to a line ℓ :

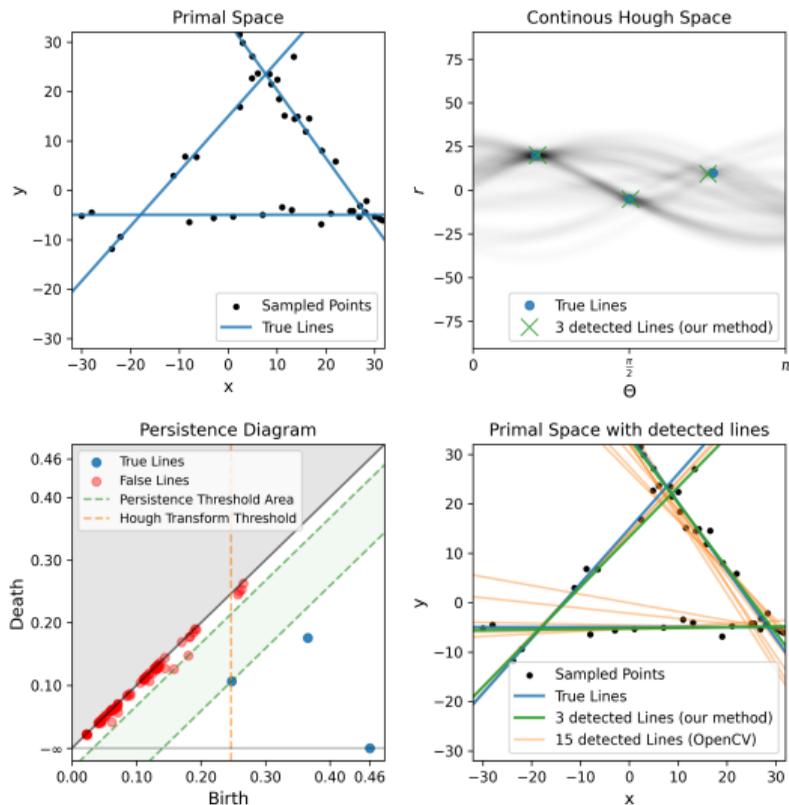
- ▶ $S(p, \ell) = \kappa(\Delta(p, \ell))$. Examples for κ are κ_{hat} or κ_{RBF}
- ▶ Require $\kappa: [0, \infty) \rightarrow [0, 1]$ with $\kappa(0) = 1$, monotonously decreasing, $\kappa(x) \rightarrow 0$ as $x \rightarrow \infty$

The score function $S: M \rightarrow [0, 1]$ collects all such votes for an input point set P :

- ▶ $S_P(\ell) = \frac{1}{|P|} \sum_{p \in P} S(p, \ell)$.
- ▶ Goal: Detecting peaks in S_P .

¹ Defining $(r, \Theta) \equiv (-r, \Theta + \pi)$ then M / \equiv is homeomorphic to the open Möbius strip.

Persistence-based selection of peaks



Theory for persistence-based peak computation:

- ▶ **Stability:** Let κ be λ -Lipschitz and P' be an ε -perturbation of P . Then $\|S_P - S_{P'}\|_\infty \leq \lambda\varepsilon$.
- ▶ **Matching maxima:** Let $\|S_P - S_{P'}\| = \varepsilon$ then there is a (partial) matching between local maxima (if persistence at least ε) and persistence differs by at most 2ε .
- ▶ **Location of matching maxima:** Let x be local maximum of S_P with birth level h and persistence α . Let $S_{P'}$ with $\|S_P - S_{P'}\| = \varepsilon < \alpha/2$. Then $S_{P'}$ contains local maximum x' with persistence $\geq \alpha - 2\varepsilon$, $|S_P(x') - h| \leq 2\varepsilon$ and x' in connected component of x in $S_P^{\geq h-\alpha}$.

Algorithm sketch:

- ▶ Discretize Hough space, with grid size by above theorems.
- ▶ Compute persistence diagram, e.g., cubical complexes, but respect the Möbius topology of M .
- ▶ Pick local maxima by thresholding persistence. (Classic methods pick by birth level.)

Faster computation

Approximate S_P based on a quad-tree subdivision that yields \tilde{S}_P

- ▶ with $\|S_P - \tilde{S}_P\|_\infty \leq \varepsilon$ and
- ▶ is **constant** on each quad-tree cell.

Subdivide cell B if

- ▶ $\lambda \cdot \text{diam}(B)/2\varepsilon$.
- ▶ Trivial λ is (global) $\lambda_{\kappa}\sqrt{2}$, but we show how to improve by a localized version.

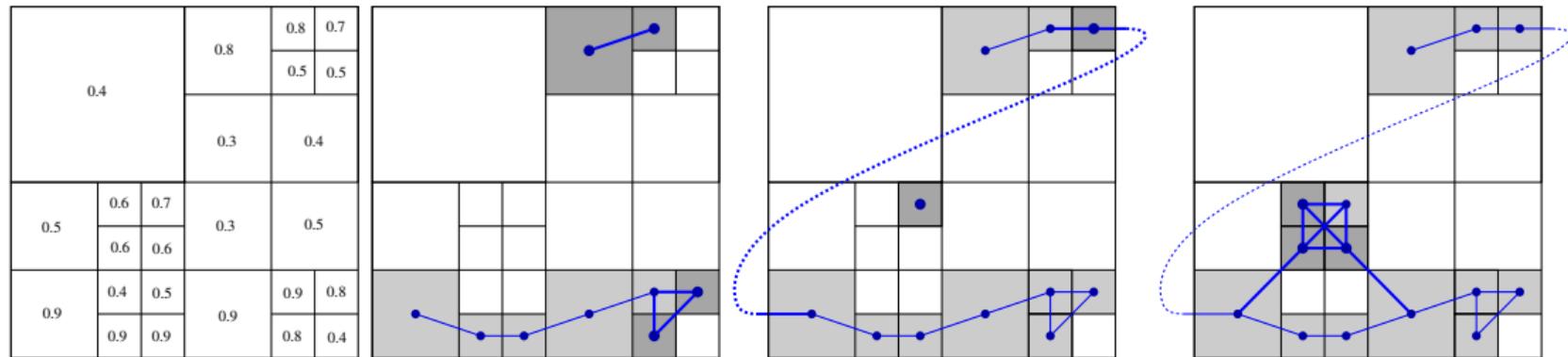


Figure: Sequence of super-levelsets and the nerve (blue) of the quad-tree subdivision, with Möbius topology, yielding persistence diagram.

Why the problem is nice:

- ▶ Tools from **computational topology** to methodologically revisit and improve a classic algorithm in CV.
- ▶ Tools from **computational geometry** with a grain of topology to improve runtime performance.
- ▶ A **nice application setting for PH** that is
 - ▶ not about point clouds,
 - ▶ not in “standard” Euclidean \mathbb{R}^n ,
 - ▶ in a dual space of the original problem.

What's next:

- ▶ Method: General shapes
- ▶ Theory: Improving on stability of locus of lines
- ▶ Experiments: Extensive evaluation (toy examples for now)

arXiv paper



GitHub code repository

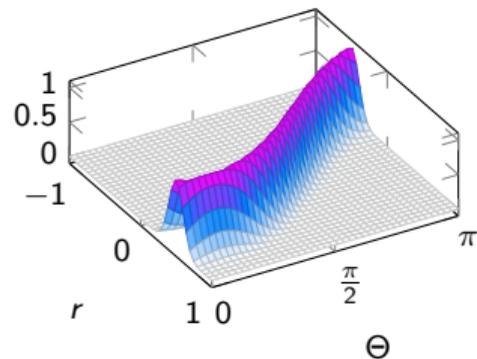


Thank you

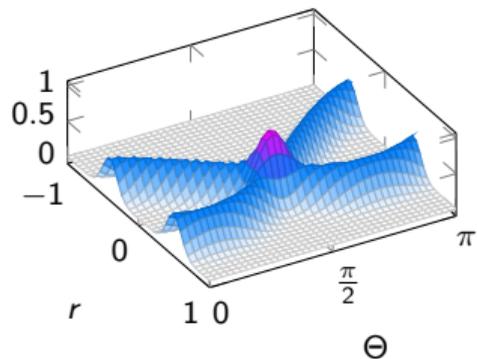
Strudel pictures

For $P = \{p\}$, the function graph of S_p has a **strudel**² shape: the kernel κ slides along the sinusoidal curve for p .

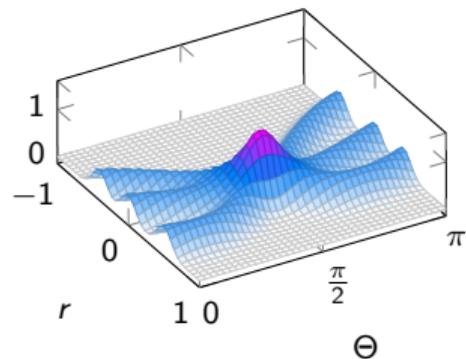
$$P = \{(0.5, 0.2)\}, \kappa = \kappa_{\text{RBF}}, \sigma = 0.1$$



$$\{(0.5, 0.2), (-0.4, 0.3)\}$$



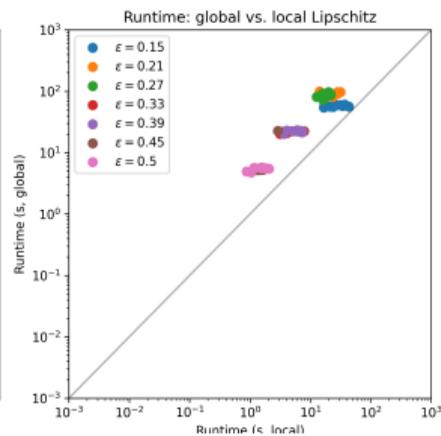
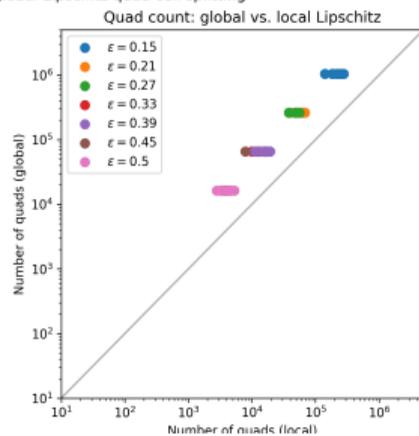
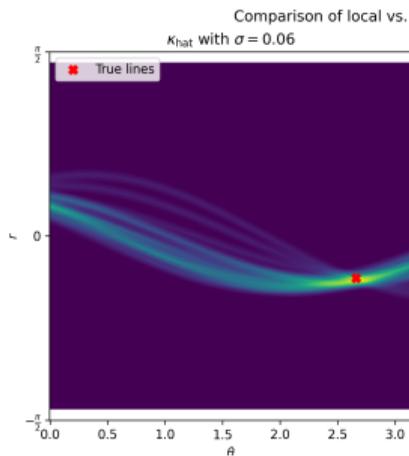
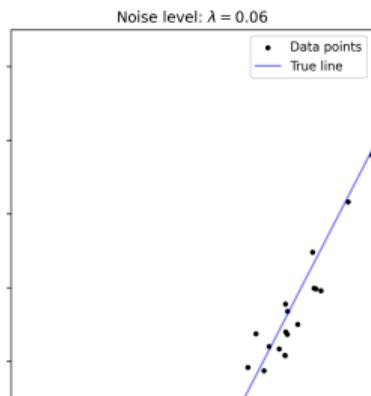
$$\{(0.5, 0.2), (-0.4, 0.3), (0.2, 0.25)\}$$



² <https://en.wikipedia.org/wiki/Strudel>

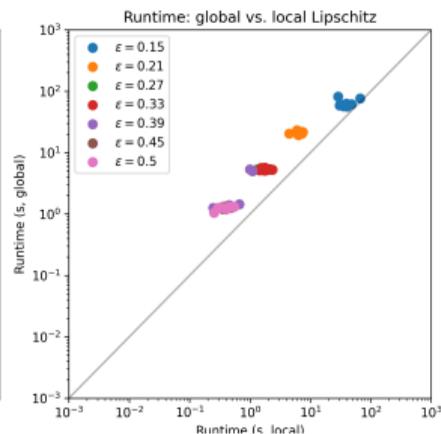
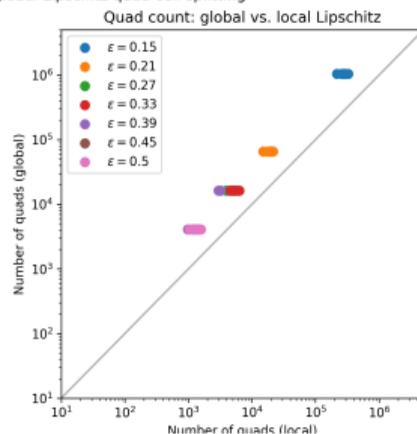
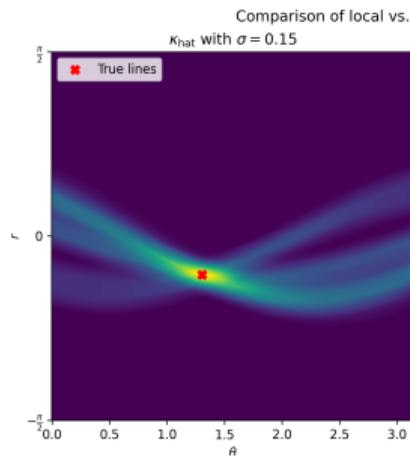
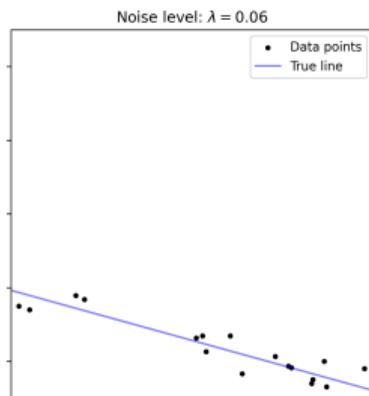
Quadtree cell splitting: Local versus global Lipschitz constant

Input in square of side-length 1.



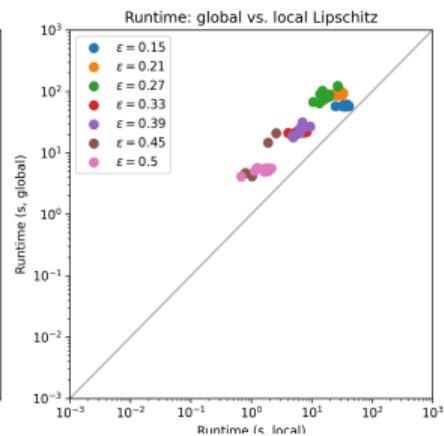
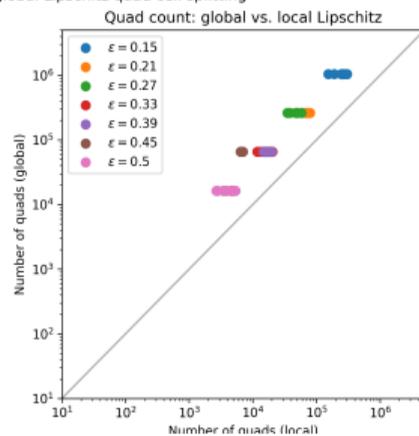
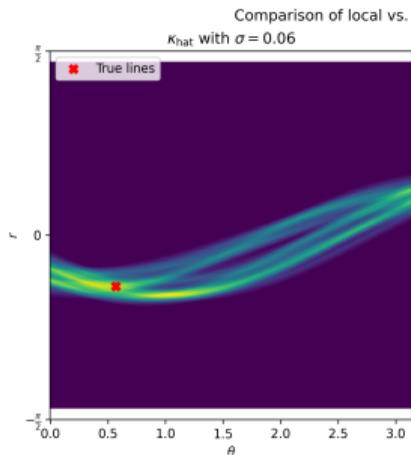
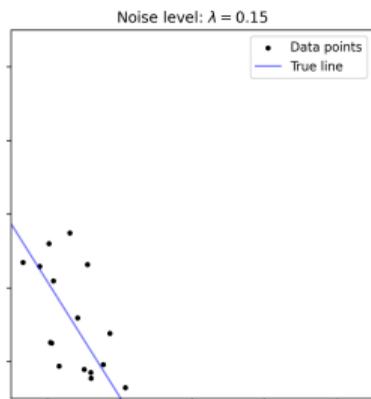
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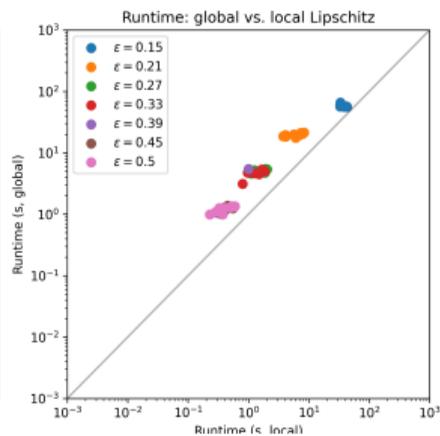
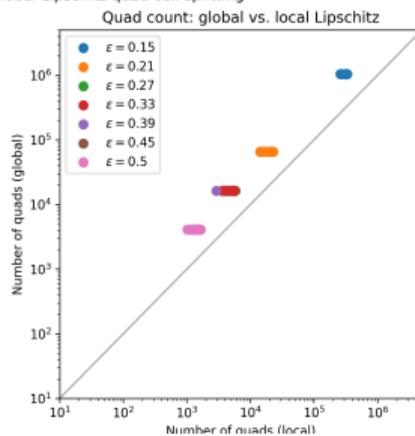
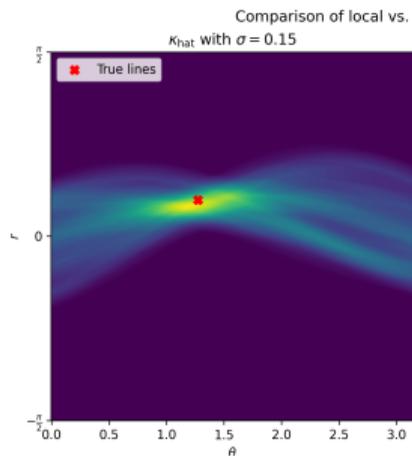
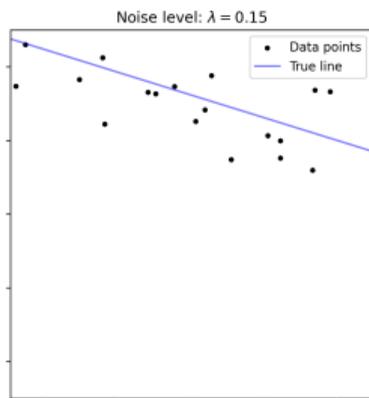
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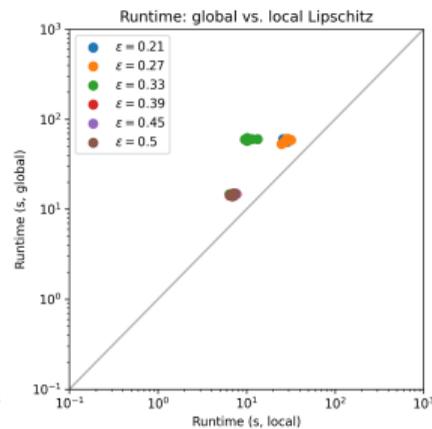
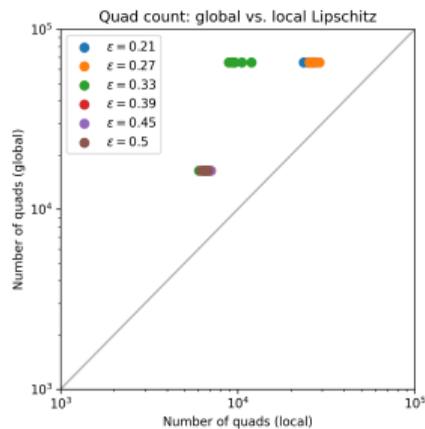
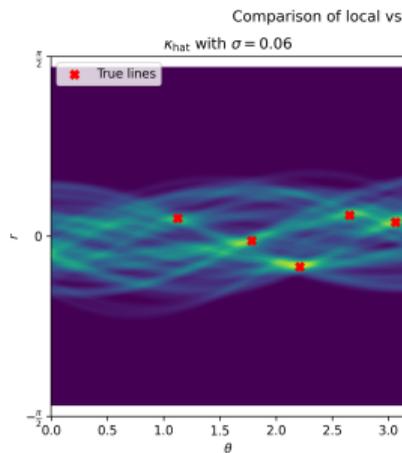
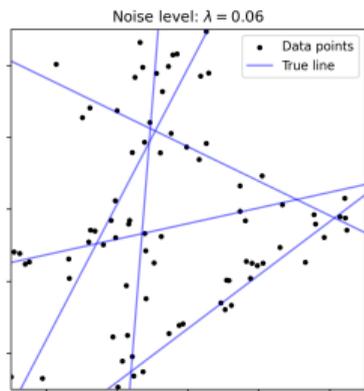
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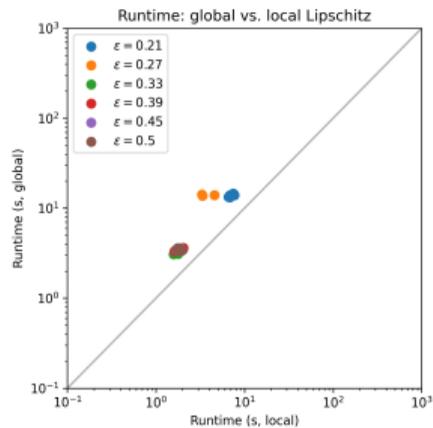
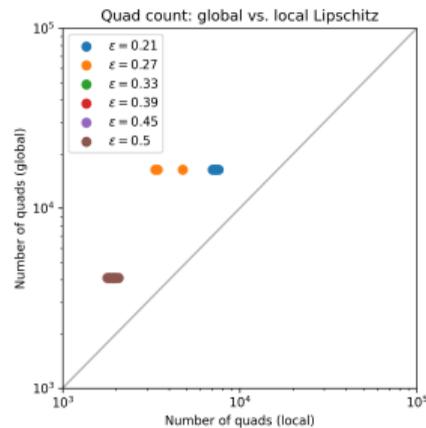
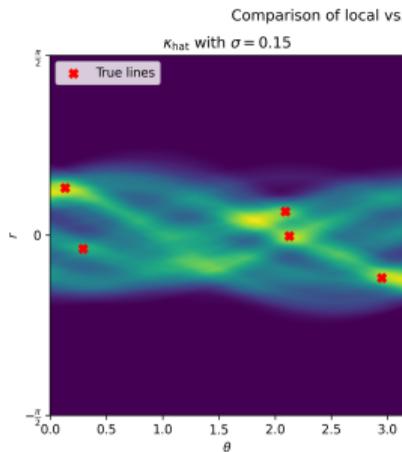
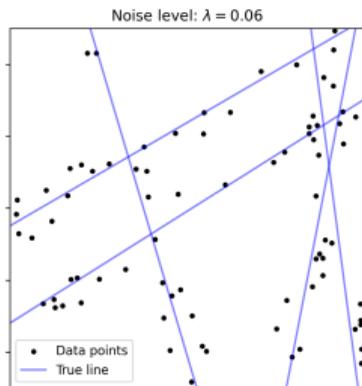
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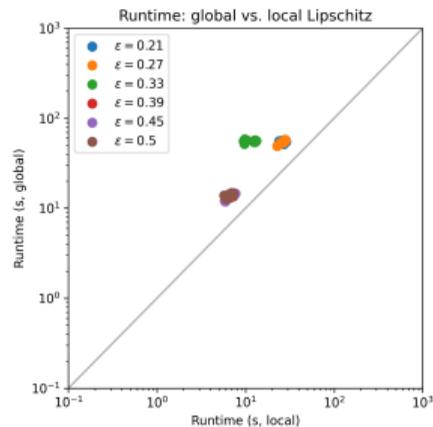
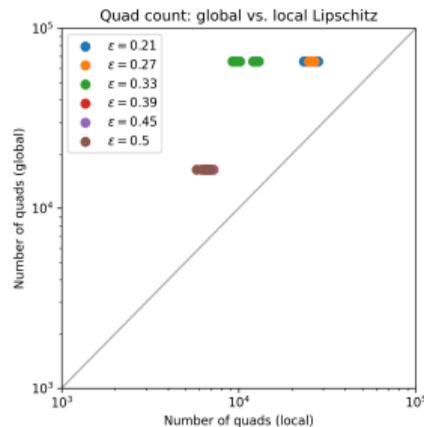
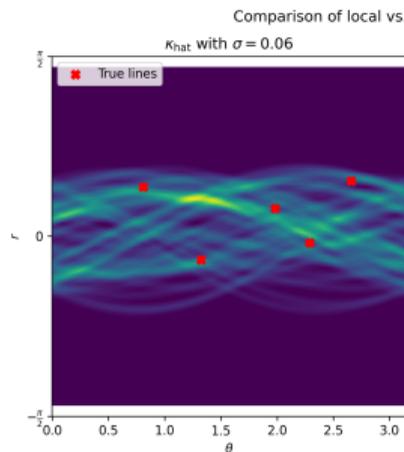
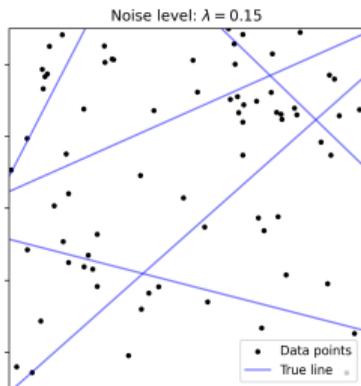
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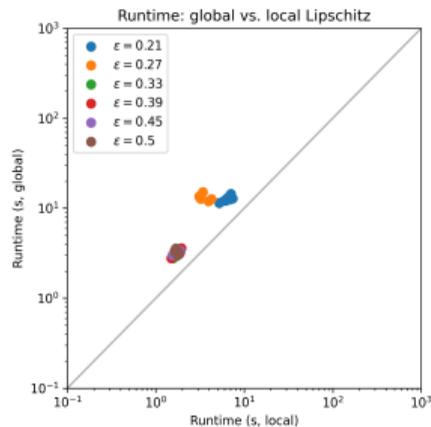
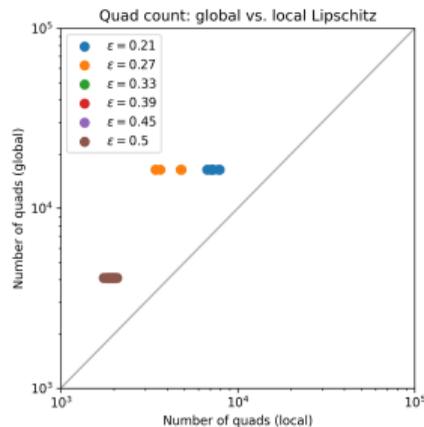
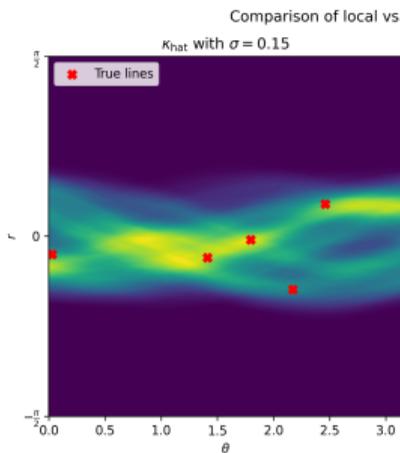
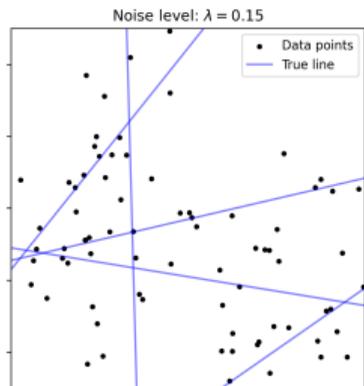
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Input in square of side-length 1.



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