A Linear-Time Kernel Goodness-of-Fit Test

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Kenji Fukumizu[3] Arthur Gretton[1]

NIPS 2017
Best paper!





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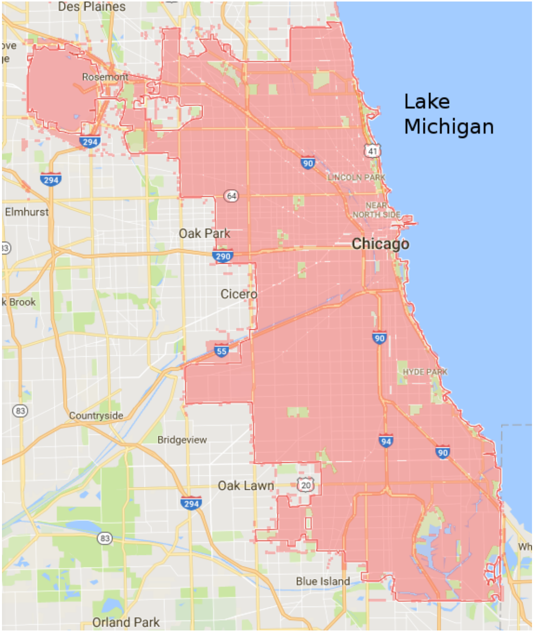
Workshop on Functional Inference and Machine Intelligence, Tokyo
20 February 2018

Model Criticism



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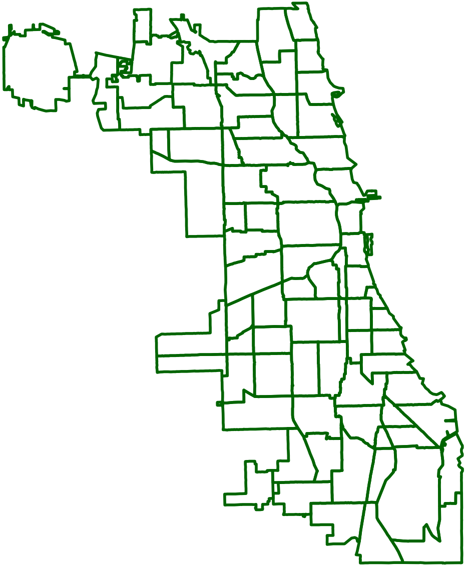

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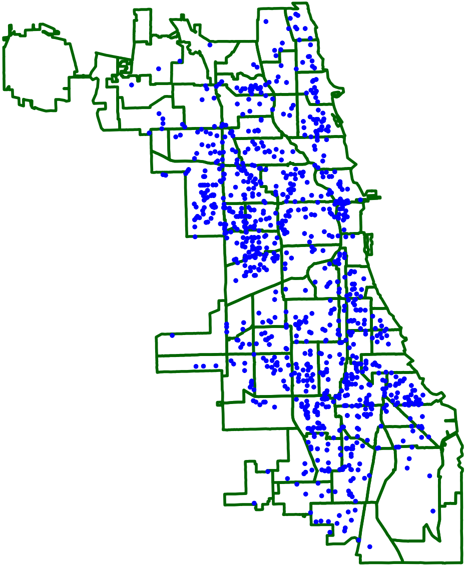
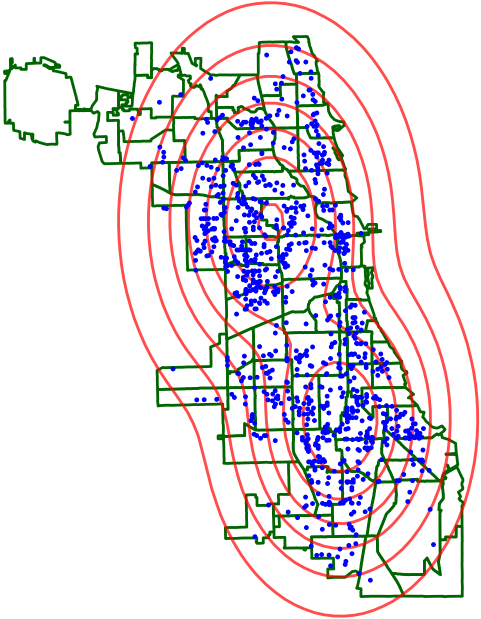


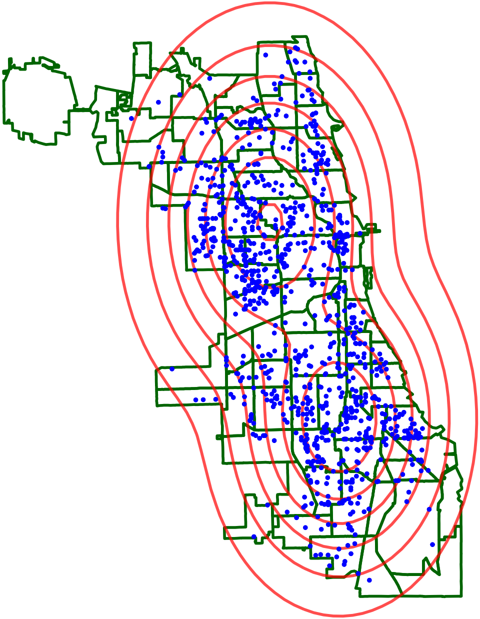
Data = robbery events in Chicago in 2016.

Model Criticism



Is this a good model?

Model Criticism



Goals:

1. Test if a (complicated) model fits the data.
2. If it does not, show a location where it fails.

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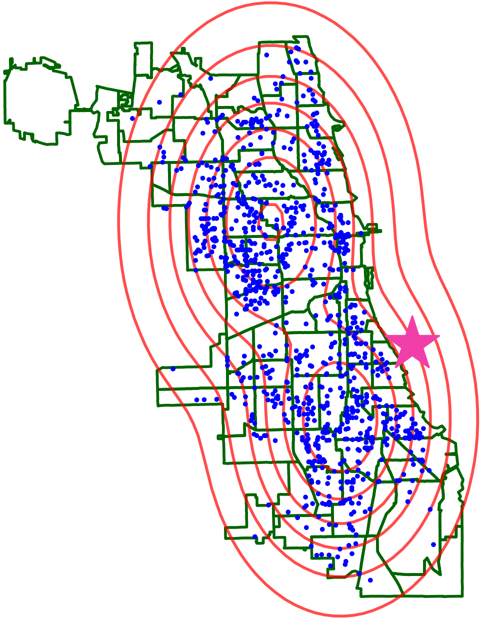

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Goodness-of-fit Testing

Given:

1. Sample $\{\mathbf{x}_i\}_{i=1}^{n} \overset{i.i.d.}{\sim} q$ (unknown) on $\mathbb{R}^d$,
2. Unnormalized density p (known model).

$$H_0 : p = q$$
$$H_1 : p \neq q$$

Want a test . . .

1. Nonparametric.
2. Linear-time. Runtime is $\mathcal{O}(n)$. Fast.
3. Interpretable. Model criticism by finding ★.

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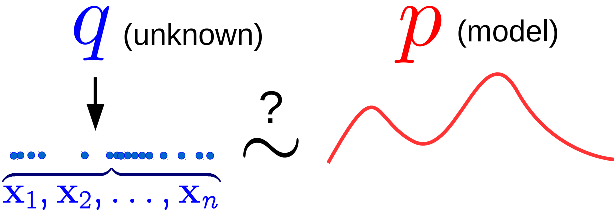

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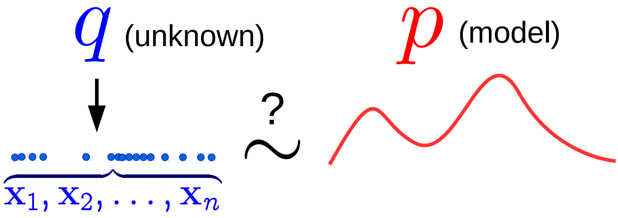

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Maximum Mean Discrepancy (MMD) Witness Function (Gretton et al., 2012)

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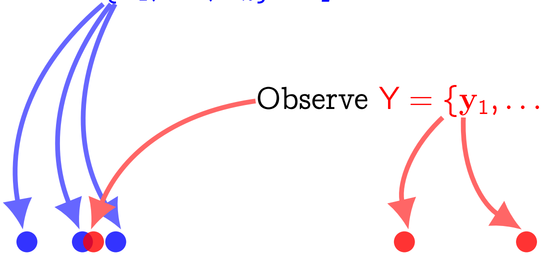
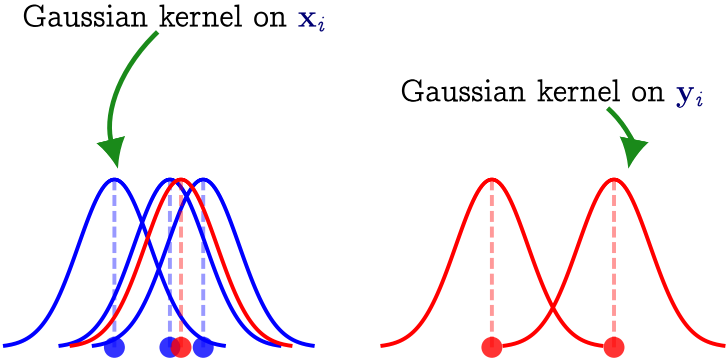
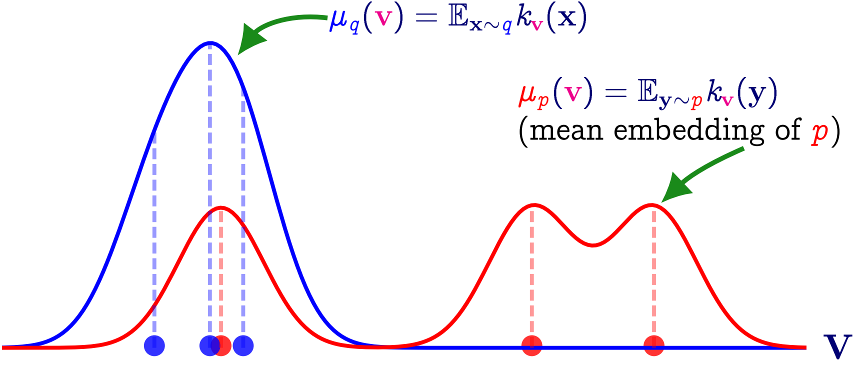
Observe $\mathsf{X} = \{\mathbf{x}_1, \ldots, \mathbf{x}_n\} \sim q$

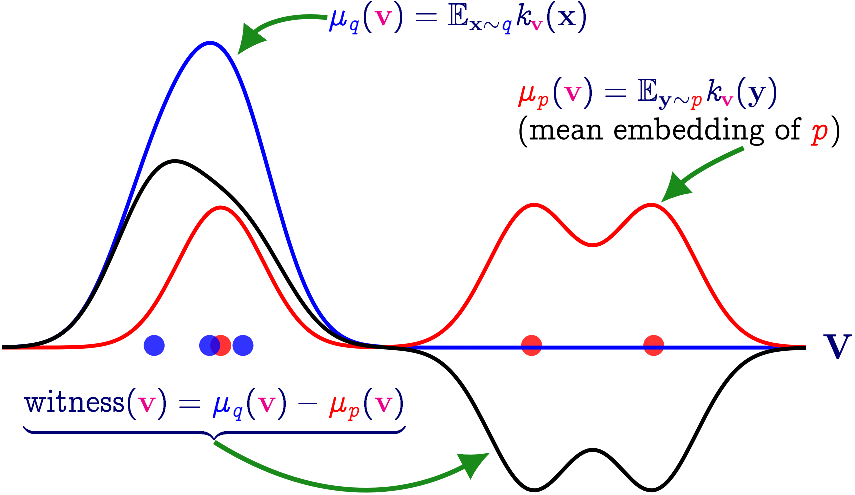
Observe $\mathsf{Y} = \{\mathbf{y}_1, \ldots, \mathbf{y}_n\} \sim p$




Gaussian kernel on $\mathbf{x}_i$
Gaussian kernel on $\mathbf{y}_i$


$\mu_q(\mathbf{v}) = \mathbb{E}_{\mathbf{x}\sim q} k_{\mathbf{v}}(\mathbf{x})$
$\mu_p(\mathbf{v}) = \mathbb{E}_{\mathbf{y}\sim p} k_{\mathbf{v}}(\mathbf{y})$
(mean embedding of p)
$\mathbf{V}$

Maximum Mean Discrepancy (MMD) Witness Function (Gretton et al., 2012)



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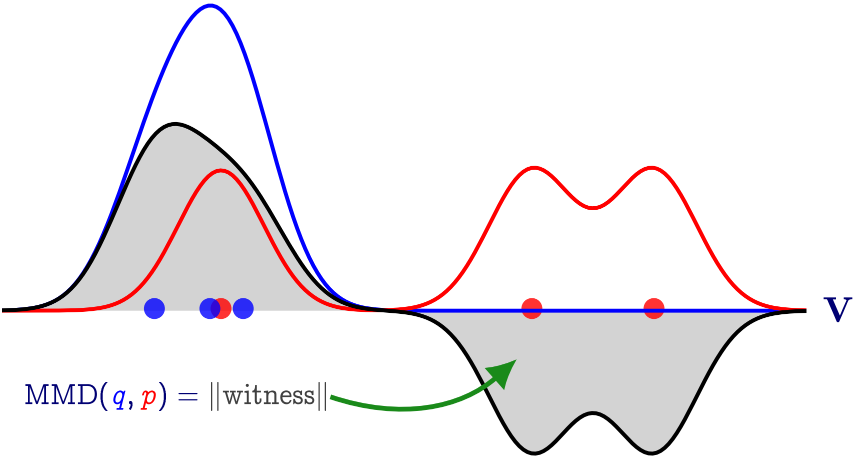

$\text{MMD}(q, p) = ||\text{witness}||$

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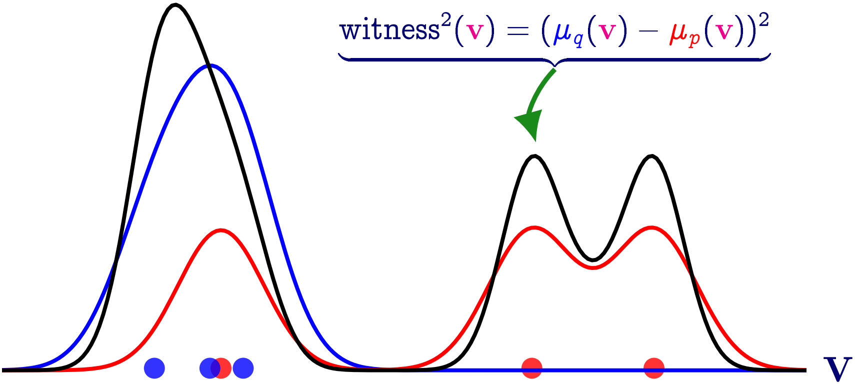

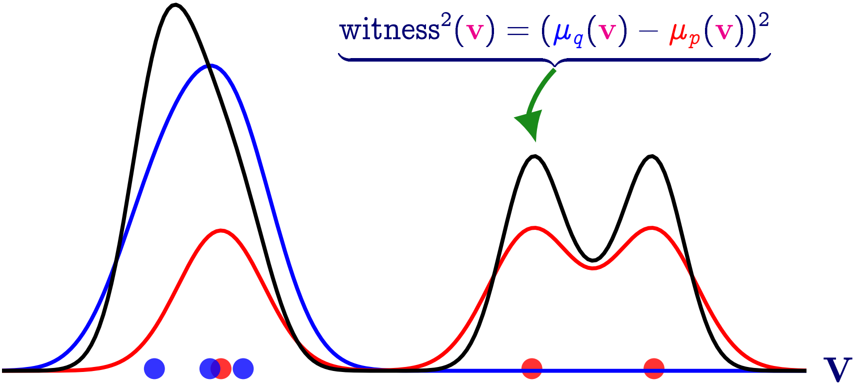

- $\text{witness}^2(\mathbf{v})$ can be used to find a good test location $\mathbf{v}^* =$ ★ .

Model Criticism by the MMD Witness

- Find a location $\mathbf{v}$ at which q and p differ most (ME test) [Jitkrittum et al., 2016].

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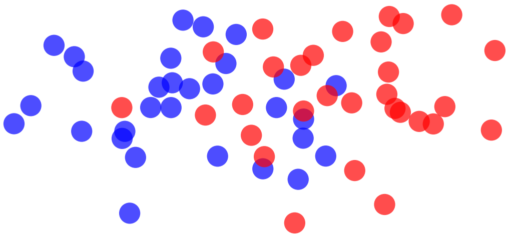

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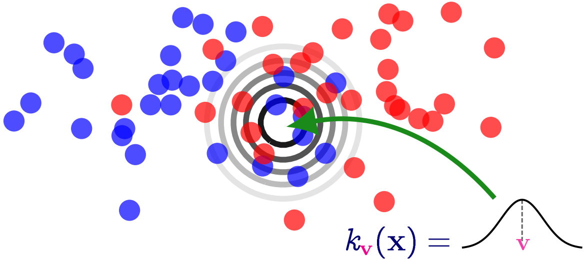
score: 0.008



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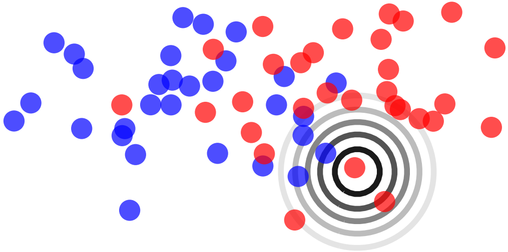
score: 1.6



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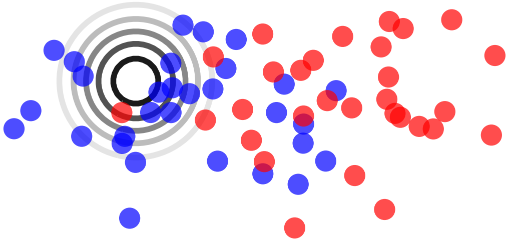
score: 13



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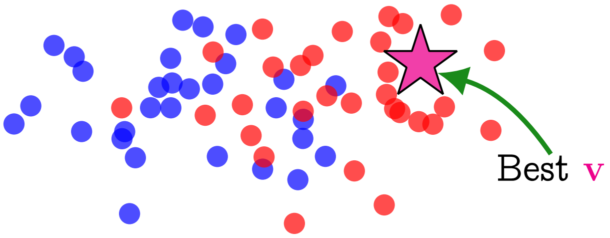

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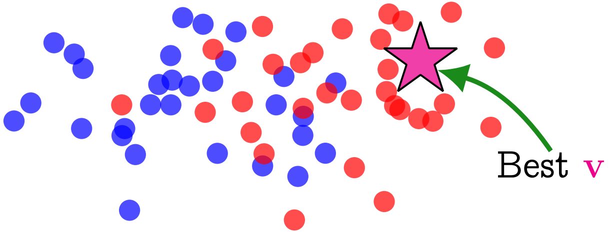

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No sample from p.
Difficult to generate.

The Stein Witness Function [Liu et al., 2016, Chwialkowski et al., 2016]

Problem: No sample from p. Cannot estimate $\mathbb{E}_{\mathbf{y}\sim p}[k_{\mathbf{v}}(\mathbf{y})]$.

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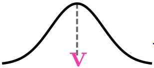
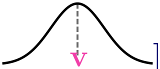
(Stein) witness($\mathbf{v}$) $= \mathbb{E}_{\mathbf{x}\sim q}[\, T_p$ 

$] - \mathbb{E}_{\mathbf{y}\sim p}[\, T_p$ 

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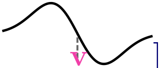
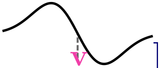
(Stein) witness($\mathbf{v}$) $= \mathbb{E}_{\mathbf{x}\sim q}[$ 

$] - \mathbb{E}_{\mathbf{y}\sim p}[$ 

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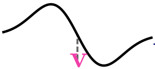
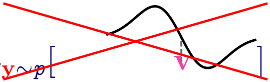
(Stein) witness($\mathbf{v}$) $= \mathbb{E}_{\mathbf{x}\sim q}[$ 

$] - \mathbb{E}_{\mathbf{y}\sim p}[$ 

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Idea: Define T_p such that $\mathbb{E}_{\mathbf{y}\sim p}(T_p k_{\mathbf{v}})(\mathbf{y}) = 0$, for any $\mathbf{v}$.

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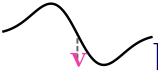
(Stein) witness($\mathbf{v}$) $= \mathbb{E}_{\mathbf{x}\sim q}[$ 

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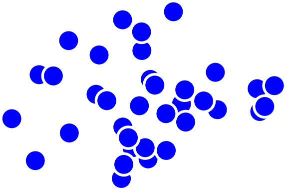
Goodness-of-fit test:

1. Find $\mathbf{v}^* = \arg\max_{\mathbf{v}} \text{score}(\mathbf{v})$.
2. Reject H_0 if $\text{witness}^2(\mathbf{v}^*) > \text{threshold}$.

Proposal: Model Criticism with the Stein Witness



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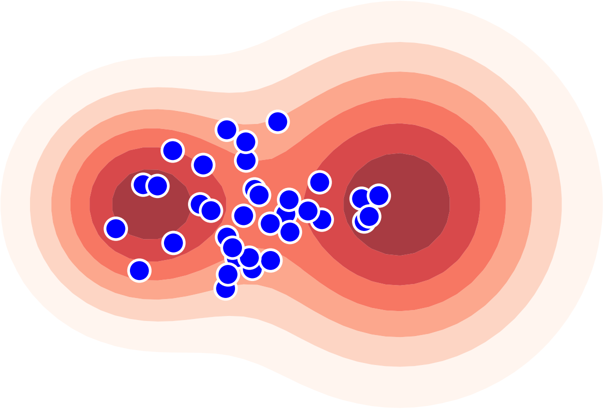

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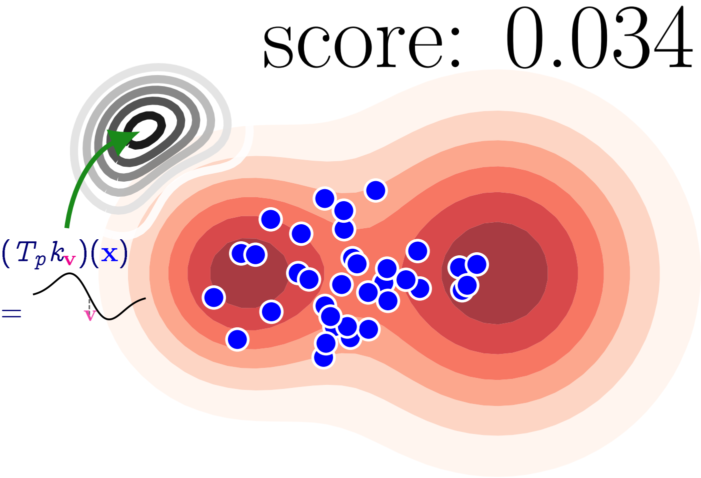

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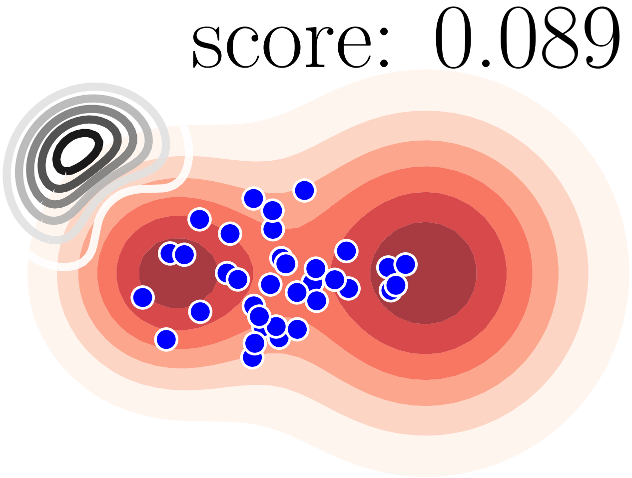

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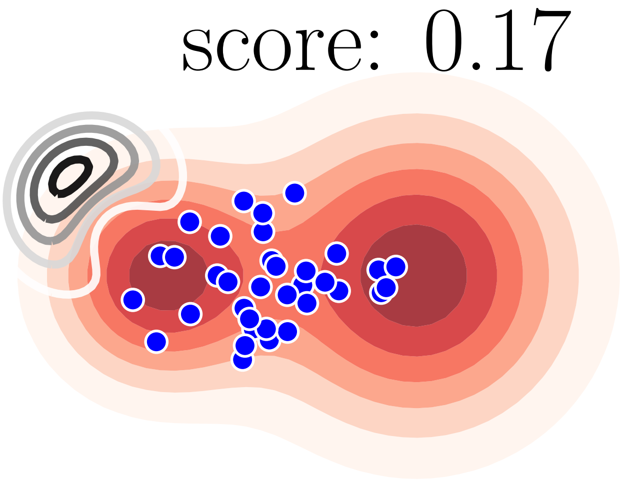

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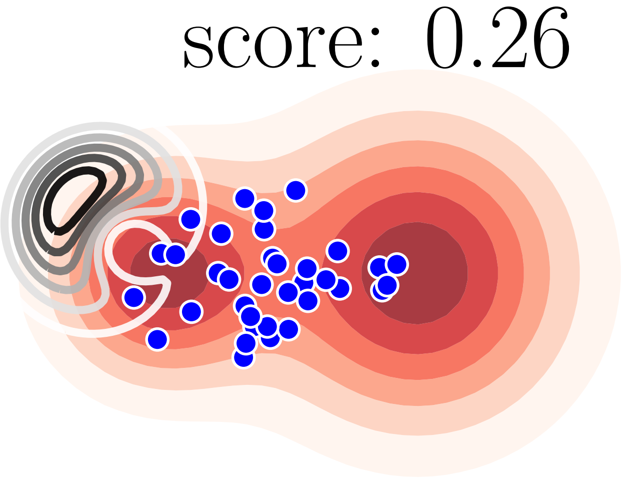

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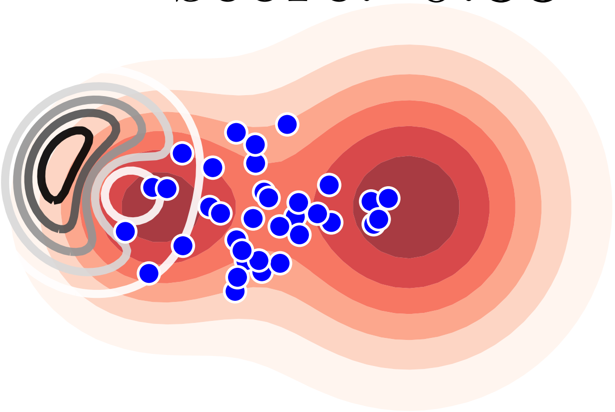
Proposal: Model Criticism with the Stein Witness

score: 0.33



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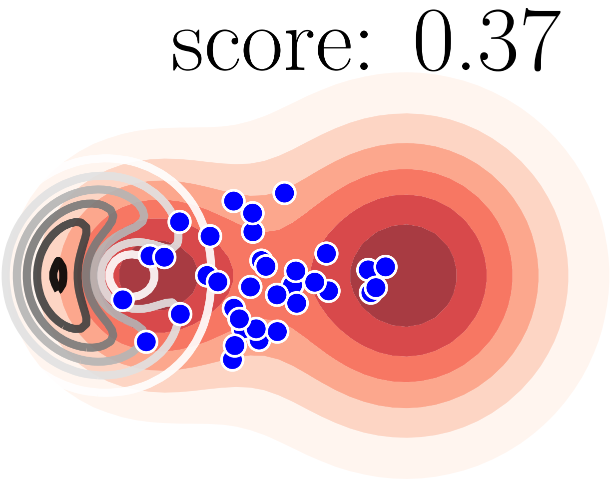

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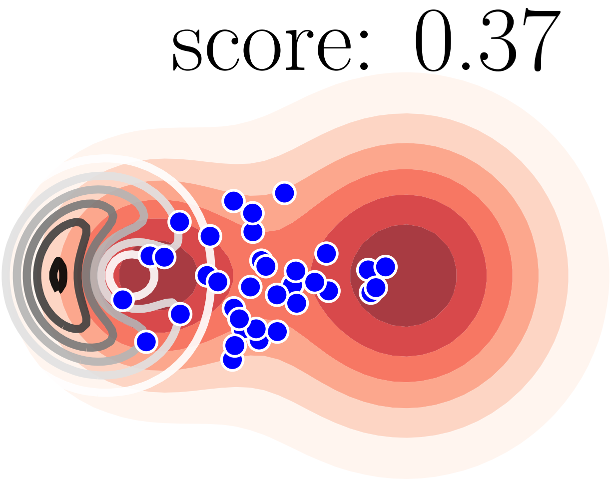

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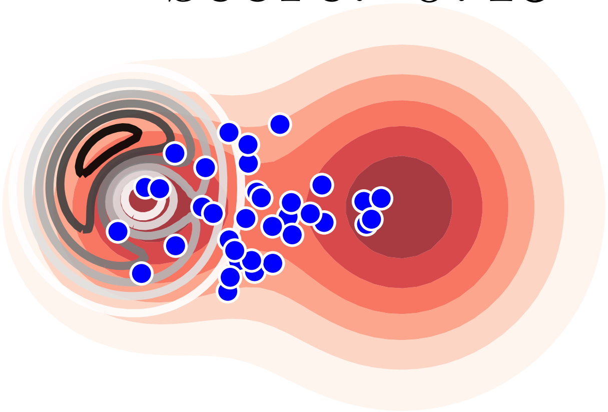
Proposal: Model Criticism with the Stein Witness

score: 0.45



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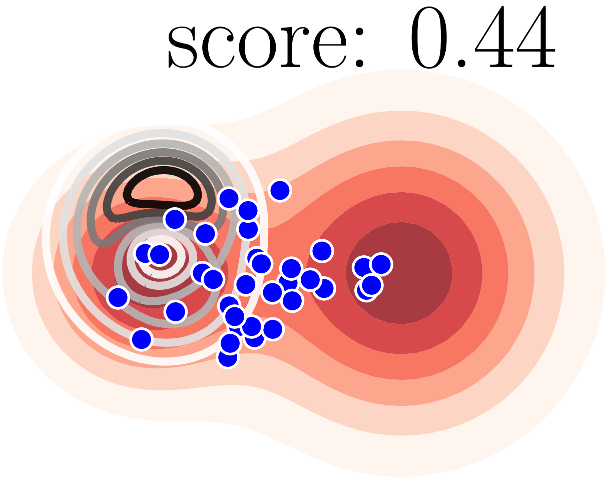
Proposal: Model Criticism with the Stein Witness



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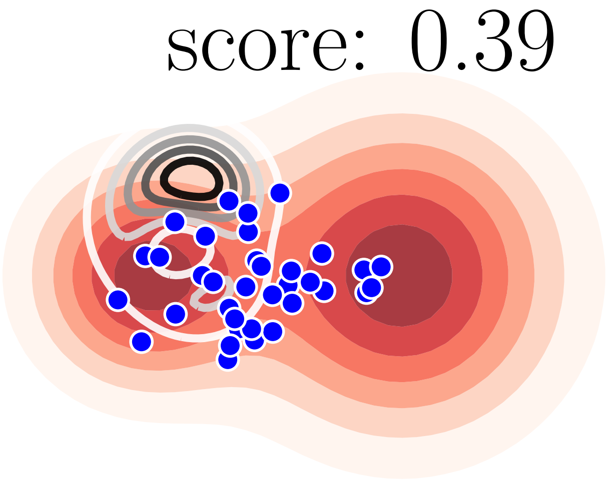

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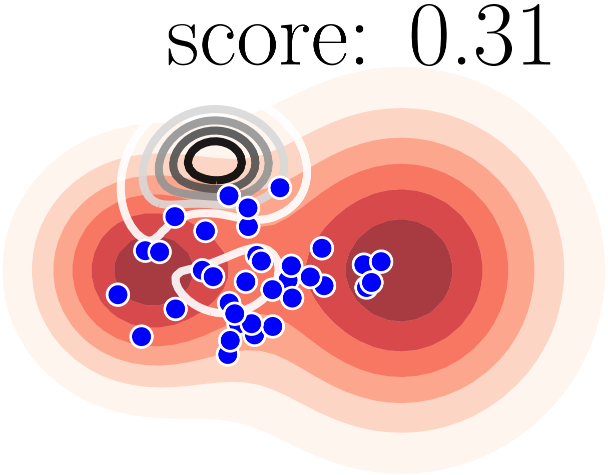

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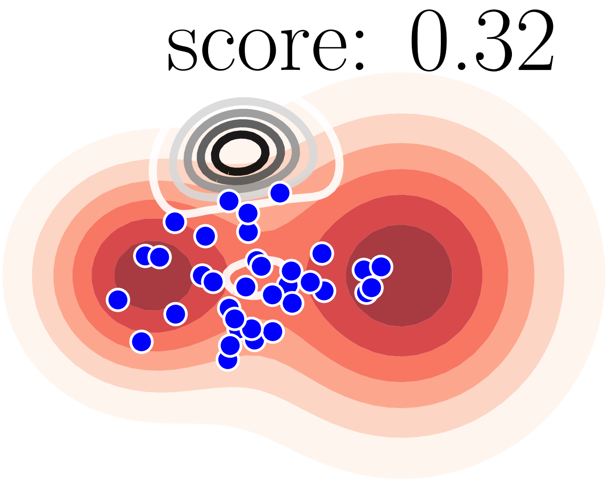

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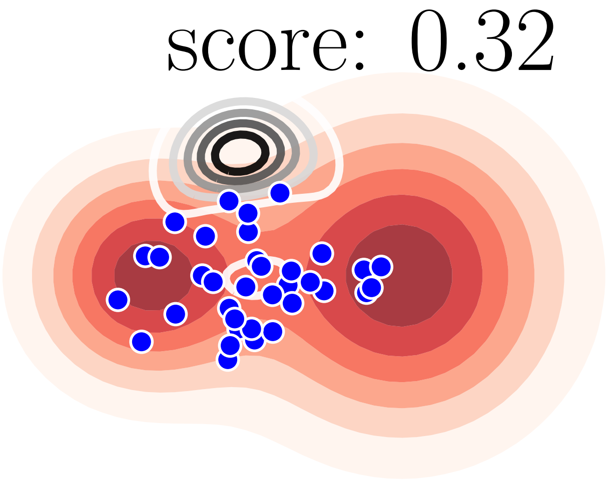

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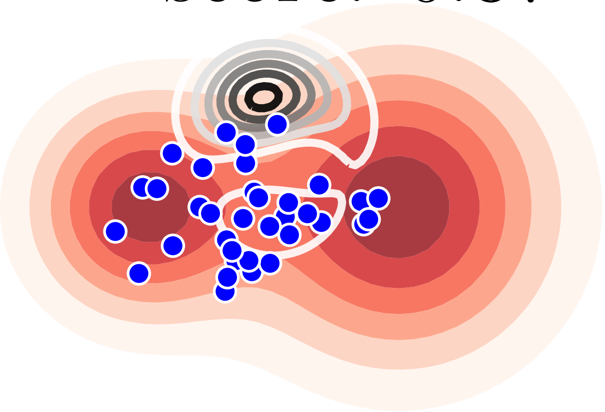
Proposal: Model Criticism with the Stein Witness

score: 0.37



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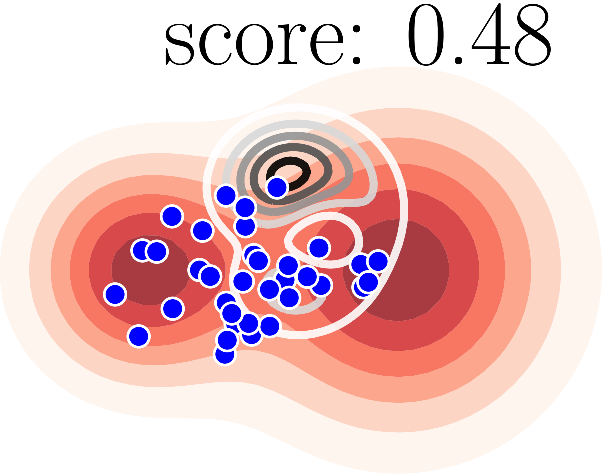

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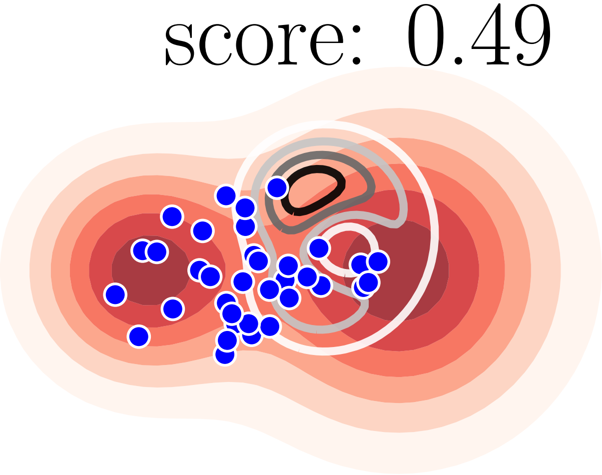

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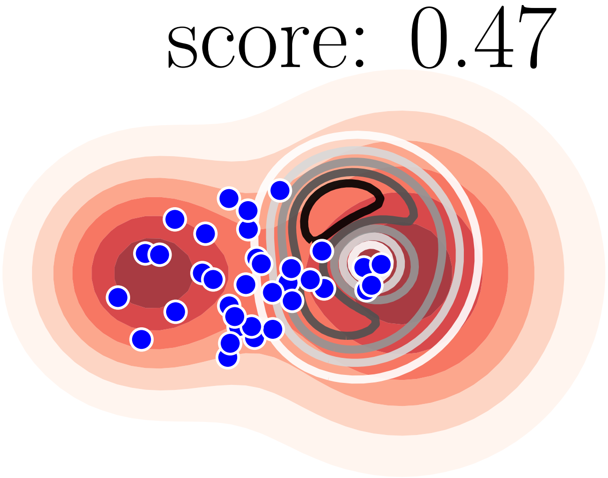

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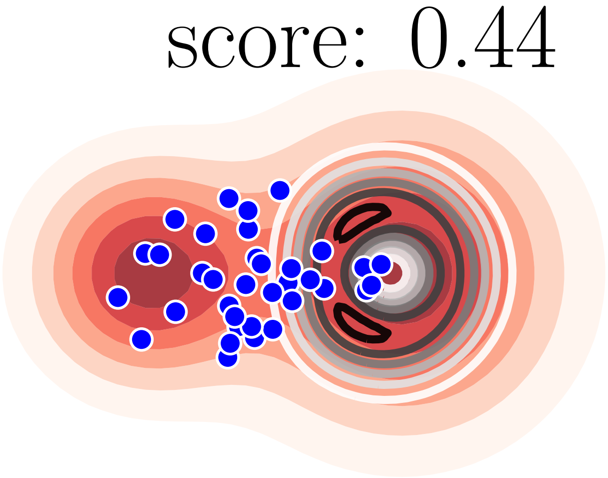

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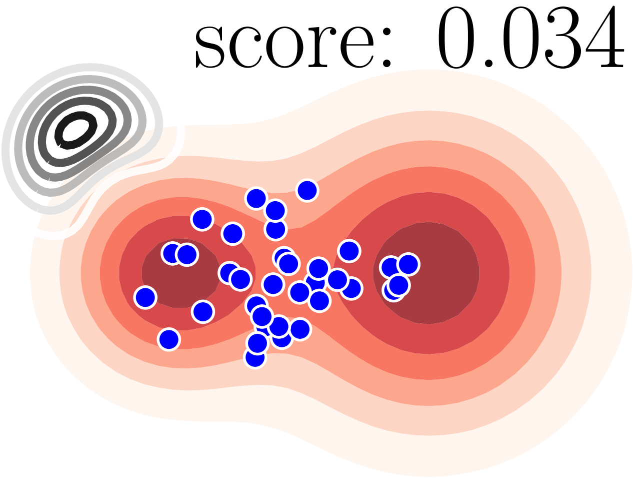

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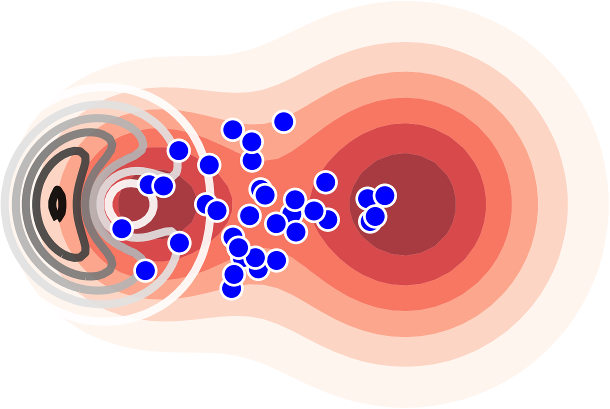

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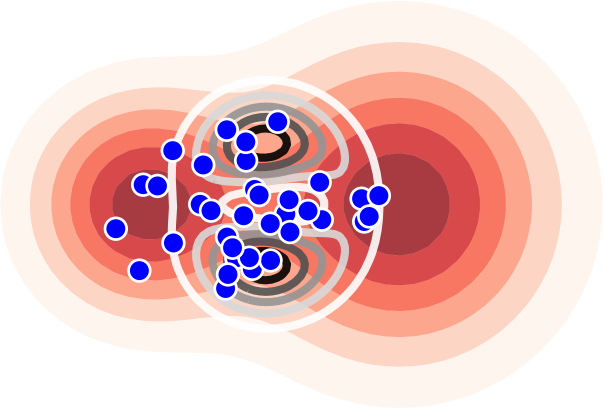
Proposal: Model Criticism with the Stein Witness

score: 0.16



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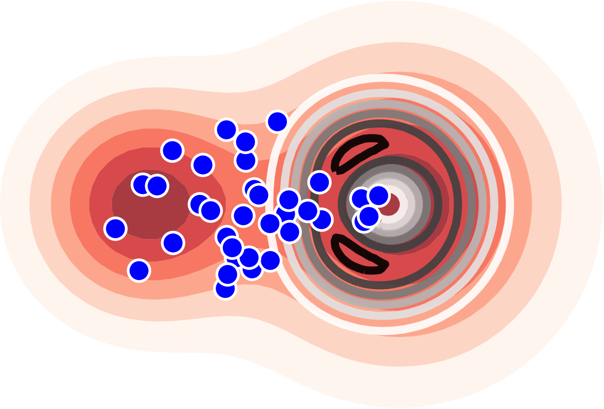
Proposal: Model Criticism with the Stein Witness

score: 0.44



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Theory

1. What is $T_p k_{\mathbf{v}}$?
2. Test statistic
3. Distributions of the test statistic, test threshold.
4. What does $\mathbf{v}^* = \arg\max_{\mathbf{v}} \mathrm{score}(\mathbf{v})$ do theoretically?

(1) What is $T_p k_{\mathbf{v}}$?

Recall $\text{witness}(\mathbf{v}) = \mathbb{E}_{\mathbf{x}\sim q}(T_p k_{\mathbf{v}})(\mathbf{x}) - \cancel{\mathbb{E}_{\mathbf{y}\sim p}(T_p k_{\mathbf{v}})(\mathbf{y})}$

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$$(T_p k_{\mathbf{v}})(\mathbf{y}) = \frac{1}{p(\mathbf{y})}\frac{d}{d\mathbf{y}}[k_{\mathbf{v}}(\mathbf{y})p(\mathbf{y})].$$

Then, $\mathbb{E}_{\mathbf{y}\sim p}(T_p k_{\mathbf{v}})(\mathbf{y}) = 0$.

[Liu et al., 2016, Chwialkowski et al., 2016]

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Proof:

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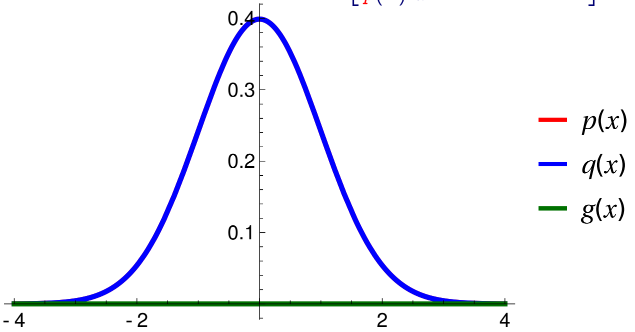
&= 0
\end{aligned}$$

(assume $\lim_{|\mathbf{y}|\to\infty} k_{\mathbf{v}}(\mathbf{y}) p(\mathbf{y})$)

(2) Proposal: The Finite Set Stein Discrepancy (FSSD)

- Recall Stein witness: $\mathbf{g}(\mathbf{v}) := \mathbb{E}_{\mathbf{x}\sim q}\left[\frac{1}{p(\mathbf{x})}\frac{d}{d\mathbf{x}}[k_{\mathbf{v}}(\mathbf{x})p(\mathbf{x})]\right]$.



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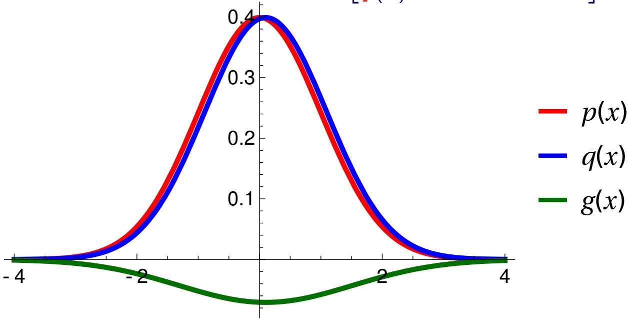

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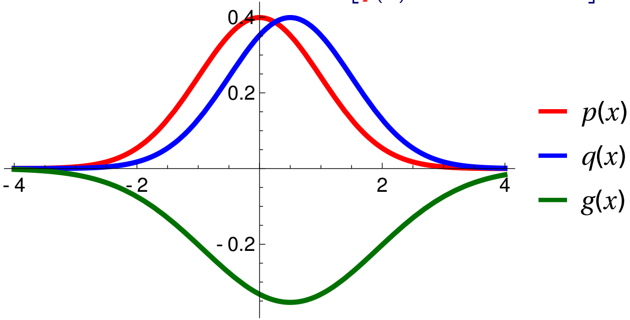

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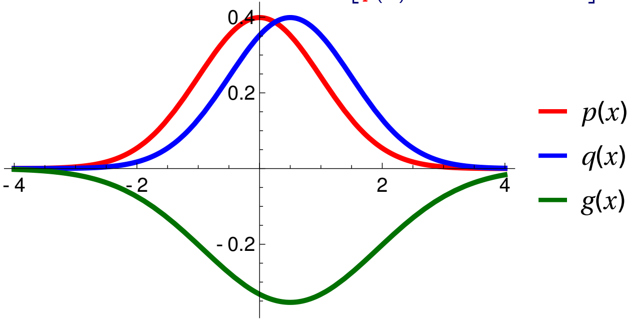

- **FSSD statistic**: Evaluate g^2 at J test locations $V = \{\mathbf{v}_1, \ldots, \mathbf{v}_J\}$.
- Population FSSD

$$\mathrm{FSSD}^2 = \frac{1}{dJ}\sum_{j=1}^{J}\|\mathbf{g}(\mathbf{v}_j)\|_2^2.$$

- Unbiased estimator $\widehat{\mathrm{FSSD}^2}$ computable in $\mathcal{O}(d^2 Jn)$ time. (d = input dimension)

(2) FSSD is a Discrepancy Measure

- $\mathrm{FSSD}^2 = \frac{1}{dJ}\sum_{j=1}^{J} \|\mathbf{g}(\mathbf{v}_j)\|_2^2$.

Theorem 1 (FSSD is a discrepancy measure).

Main conditions:

1. *(Nice kernel) Kernel k is C_0-universal, and real analytic e.g., Gaussian kernel.*
2. *(Vanishing boundary)* $\lim_{\|\mathbf{x}\|\to\infty} p(\mathbf{x}) k_{\mathbf{v}}(\mathbf{x}) = \mathbf{0}$.
3. *(Avoid "blind spots") Locations $\mathbf{v}_1, \ldots, \mathbf{v}_J \sim \eta$ which has a density.*

Then, for any $J \geq 1$, η-almost surely,

$$\mathrm{FSSD}^2 = 0 \iff p = q.$$

Summary: Evaluating the witness at random locations is sufficient to detect the discrepancy between p, q.

(2) What Are "Blind Spots"?

$$\text{Recall } \mathbf{g}(\mathbf{v}) := \mathbb{E}_{\mathbf{x}\sim q}\left[\frac{1}{p(\mathbf{x})}\frac{d}{d\mathbf{x}}[k_{\mathbf{v}}(\mathbf{x})p(\mathbf{x})]\right].$$

Consider $p = \mathcal{N}(0,1)$ and $q = \mathcal{N}(0,\sigma_q^2)$. Use unit-width Gaussian kernel.

$$g(v) = \frac{v \exp\left(-\frac{v^2}{2+2\sigma_q^2}\right)\left(\sigma_q^2 - 1\right)}{\left(1+\sigma_q^2\right)^{3/2}}$$

- If $v = 0$, then $\text{FSSD}^2 = g^2(v) = 0$ regardless of σ_q^2.
- If $g \neq 0$, and k is real analytic, $R = \{v \mid g(v) = 0\}$ (blind spots) has 0 Lebesgue measure.
- So, if $v \sim$ a distribution with a density, then $v \notin R$.

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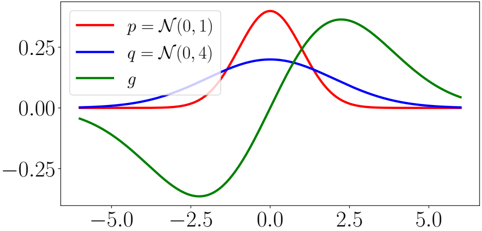

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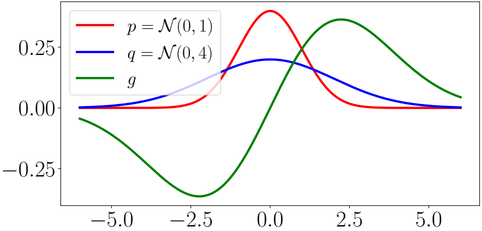

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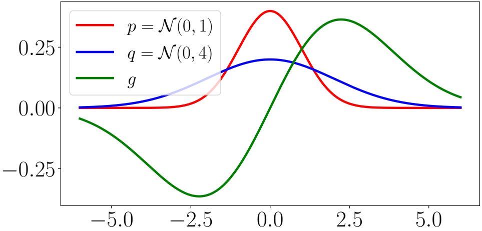

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- So, if $v \sim$ a distribution with a density, then $v \notin R$.

(2) What Are "Blind Spots"?

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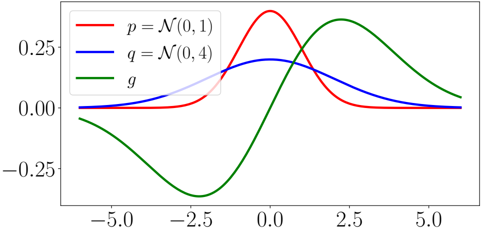

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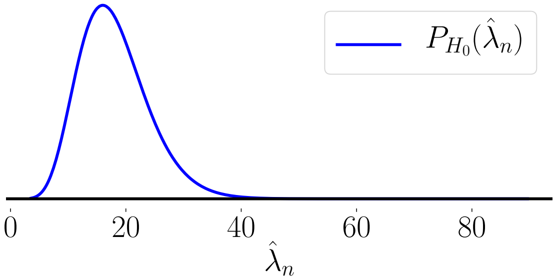

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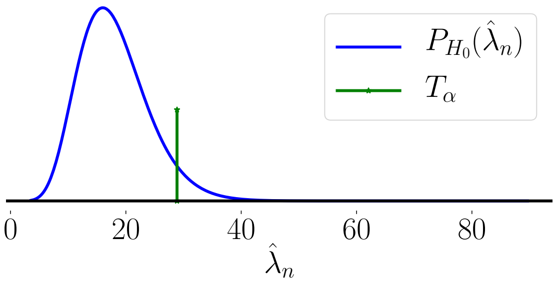

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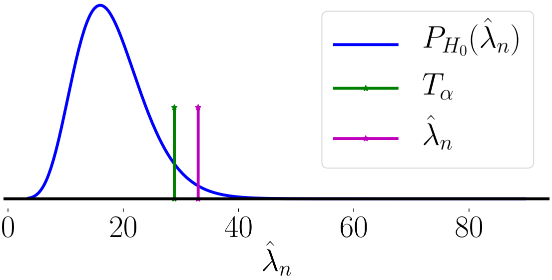

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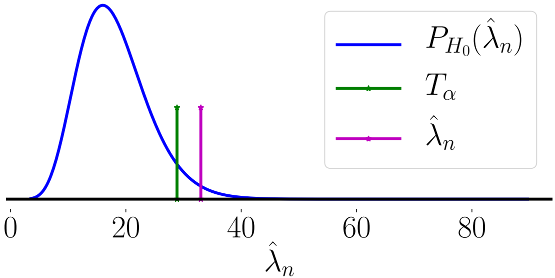

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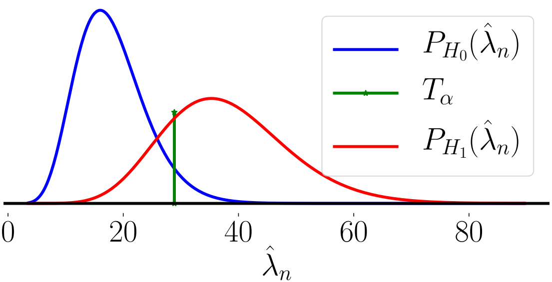

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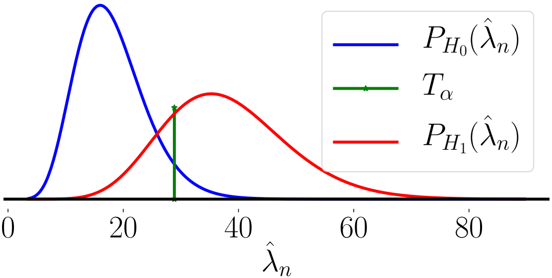

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witness$^2(V)$ → noise(V)

(4) What Does $\arg\max_{\mathbf{v}} \mathrm{score}(\mathbf{v})$ Do?

Proposition 1 (Asymptotic test power).

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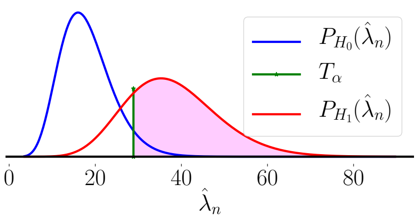

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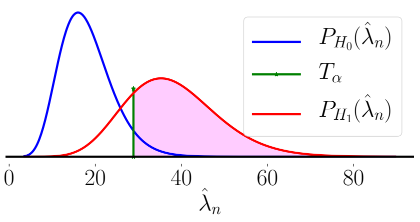

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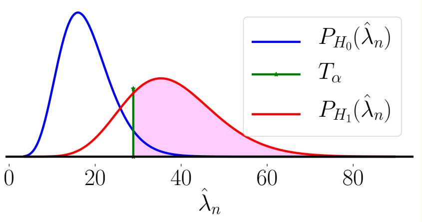

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Related Works

Kernel Stein Discrepancy (KSD) [Liu et al., 2016, Chwialkowski et al., 2016]

- Recall Stein witness:
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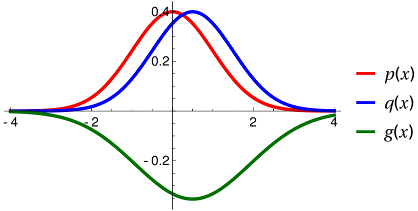

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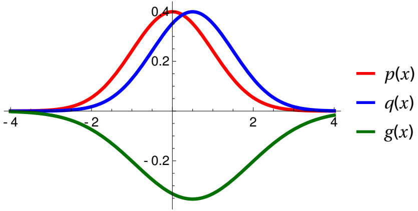

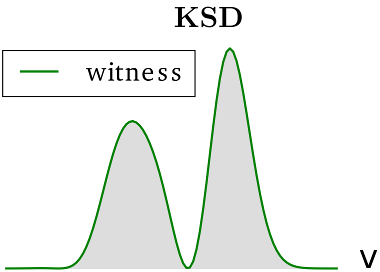

$\text{KSD}^2 = ||\mathbf{g}||^2_{\text{RKHS}}$ (RKHS norm).

Good when the difference between p, q is spatially diffuse.

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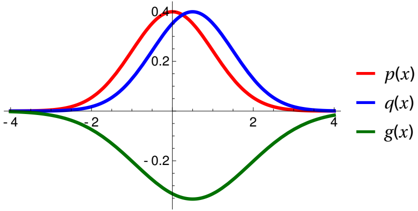

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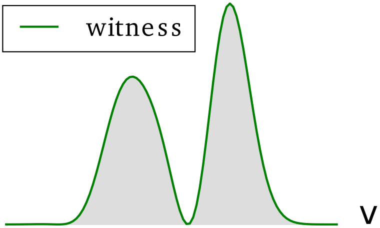

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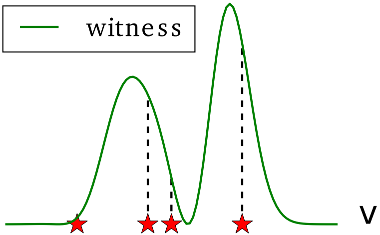
Proposed FSSD



$\mathrm{FSSD}^2 = \frac{1}{dJ}\sum_{j=1}^{J}\|\mathbf{g}(\mathbf{v}_j)\|_2^2.$

Good when the difference between p, q is local.

Kernel Stein Discrepancy (KSD)

Closed-form expression for KSD: [Liu et al., 2016, Chwialkowski et al., 2016]

$$\mathrm{KSD}^2 = \|\mathbf{g}\|^2_{\mathrm{RKHS}} = \overbrace{\mathbb{E}_{\mathbf{x}\sim q}\mathbb{E}_{\mathbf{y}\sim q}}^{\text{double sums}} h_p(\mathbf{x}, \mathbf{y})$$

where

$$\begin{aligned} h_p(\mathrm{x}, \mathrm{y}) := & \left[\partial_{\mathrm{x}} \log p(\mathrm{x})\right] k(\mathrm{x}, \mathrm{y}) \left[\partial_{\mathrm{y}} \log p(\mathrm{y})\right] \\ & + \left[\partial_{\mathrm{y}} \log p(\mathrm{y})\right] \partial_{\mathrm{x}} k(\mathrm{x}, \mathrm{y}) \\ & + \left[\partial_{\mathrm{x}} \log p(\mathrm{x})\right] \partial_{\mathrm{y}} k(\mathrm{x}, \mathrm{y}) \\ & + \partial_{\mathrm{x}} \partial_{\mathrm{y}} k(\mathrm{x}, \mathrm{y}) \end{aligned}$$

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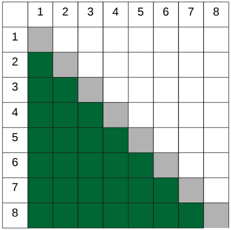
Linear-Time Kernel Stein Discrepancy (LKS)

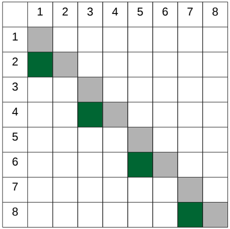
- [Liu et al., 2016] also proposed a linear version of KSD.
- For $\{\mathbf{x}_i\}_{i=1}^n \sim q$, KSD test statistic is

$$\frac{2}{n(n-1)} \sum_{i<j} h_p(\mathbf{x}_i, \mathbf{x}_j).$$



- LKS test statistic is a "running average"

$$\frac{2}{n} \sum_{i=1}^{n/2} h_p(\mathbf{x}_{2i-1}, \mathbf{x}_{2i}).$$



- Both unbiased. LKS has $\mathcal{O}(d^2 n)$ runtime. Same as proposed FSSD.
- ✗ LKS has high variance. Poor test power.

Simulation Settings

- Gaussian kernel $k(\mathbf{x}, \mathbf{v}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{v}\|_2^2}{2\sigma_k^2}\right)$

	Method	Description
1	**FSSD-opt**	Proposed. With optimization. $J = 5$.
2	FSSD-rand	Proposed. Random test locations.
3	**KSD**	Quadratic-time kernel Stein discrepancy [Liu et al., 2016, Chwialkowski et al., 2016]
4	LKS	Linear-time running average version of KSD.
5	MMD-opt	MMD two-sample test [Gretton et al., 2012]. With optimization.
6	ME-test	Mean Embeddings two-sample test [Jitkrittum et al., 2016]. With optimization.

- Two-sample tests need to draw sample from p.
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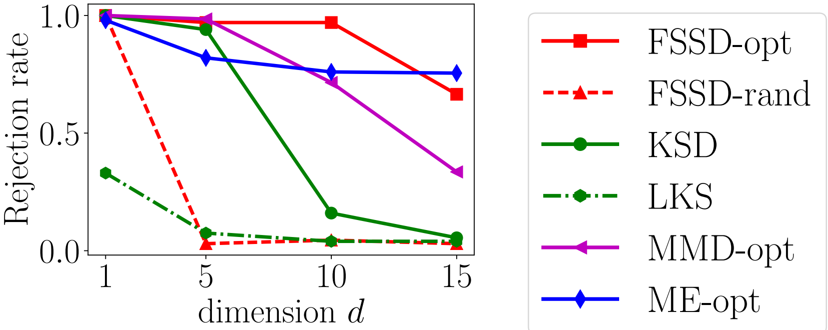
Gaussian Vs. Laplace

- p = Gaussian. q = Laplace. Same mean and variance. High-order moments differ.
- Sample size $n = 1000$.



- Optimization increases the power.
- Two-sample tests can perform well in this case (p, q clearly differ).

Gaussian-Bernoulli Restricted Boltzmann Machine (RBM)

- $p(\mathbf{x})$ is the marginal of

$$p(\mathbf{x}, \mathbf{h}) = \frac{1}{Z} \exp\left(\mathbf{x}^\top \mathbf{B}\mathbf{h} + \mathbf{b}^\top \mathbf{x} + \mathbf{c}^\top \mathbf{x} - \frac{1}{2}\|\mathbf{x}\|^2\right),$$

  where $\mathbf{x} \in \mathbb{R}^{50}$, $\mathbf{h} \in \{\pm 1\}^{40}$ is latent. Randomly pick $\mathbf{B}, \mathbf{b}, \mathbf{c}$.
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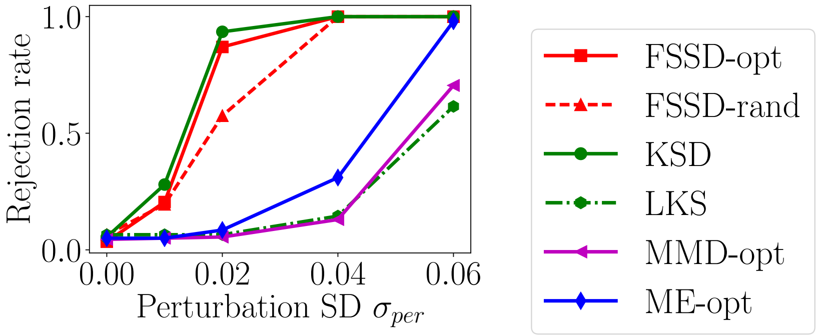
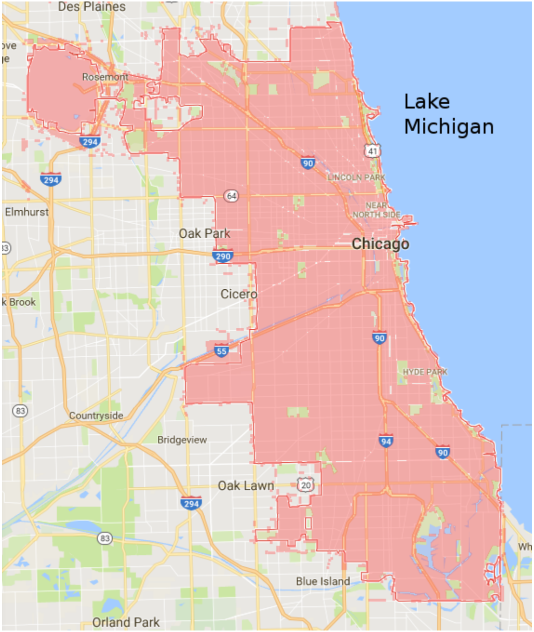


KSD ($\mathcal{O}(n^2)$), FSSD-opt ($\mathcal{O}(n)$) comparable. LKS has low power.

Interpretable Test Locations: Chicago Crime



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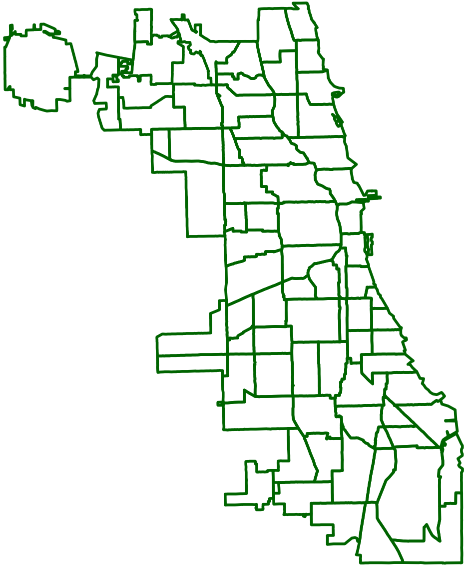

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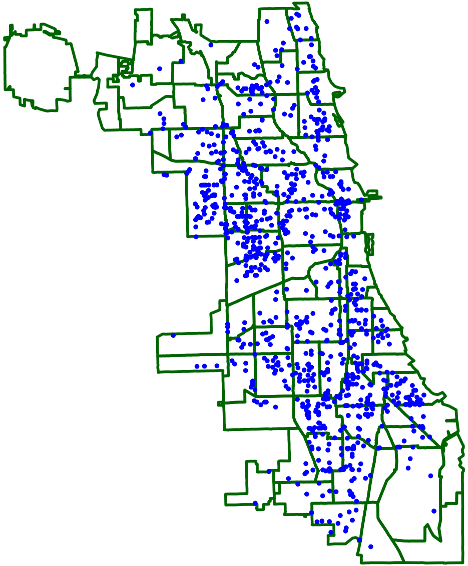
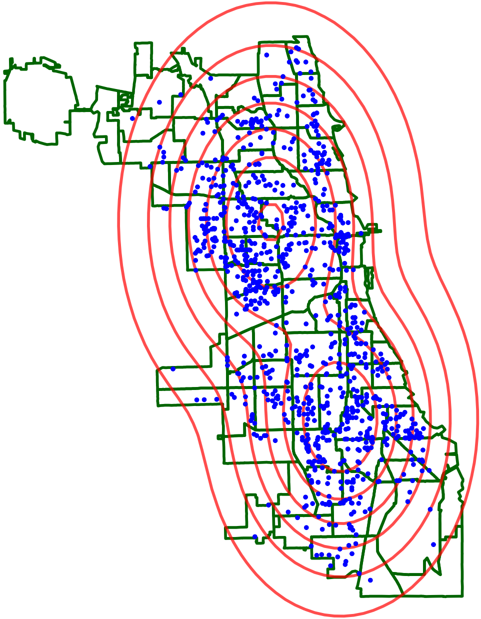


- $n = 11957$ robbery events in Chicago in 2016.
  - lat/long coordinates = sample from q.
- Model spatial density with Gaussian mixtures.

Interpretable Test Locations: Chicago Crime



Model p = 2-component Gaussian mixture.

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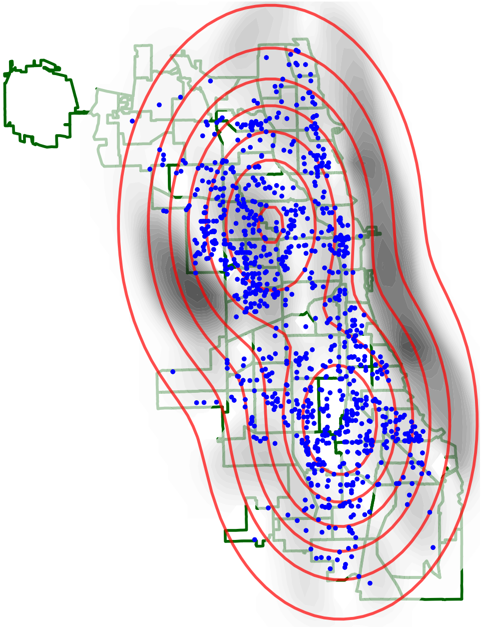
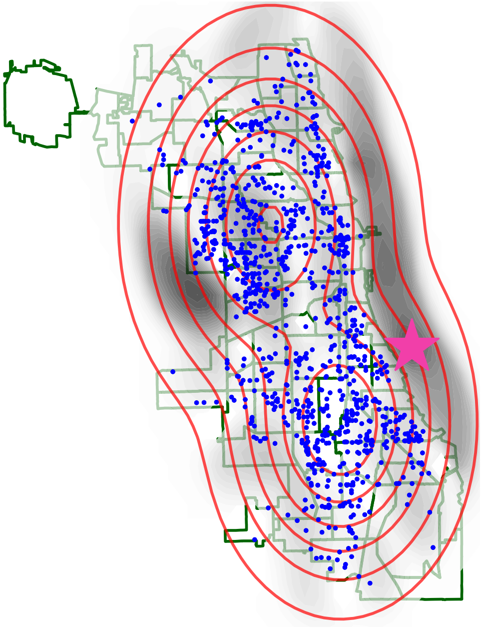


Score surface

Interpretable Test Locations: Chicago Crime



★ = optimized **v**.

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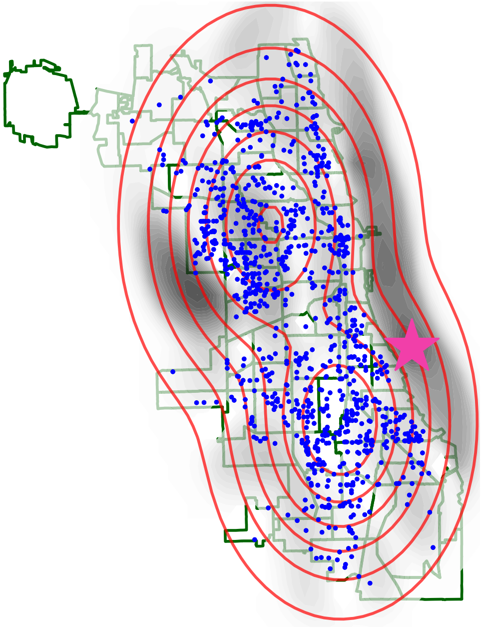

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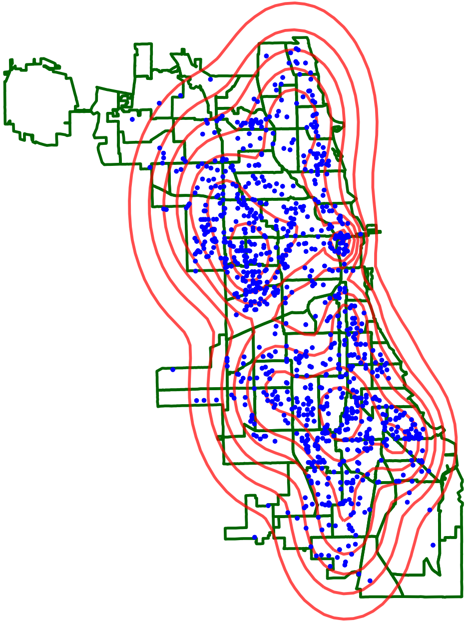
No robbery in Lake Michigan.

Interpretable Test Locations: Chicago Crime



Model p = 10-component Gaussian mixture.

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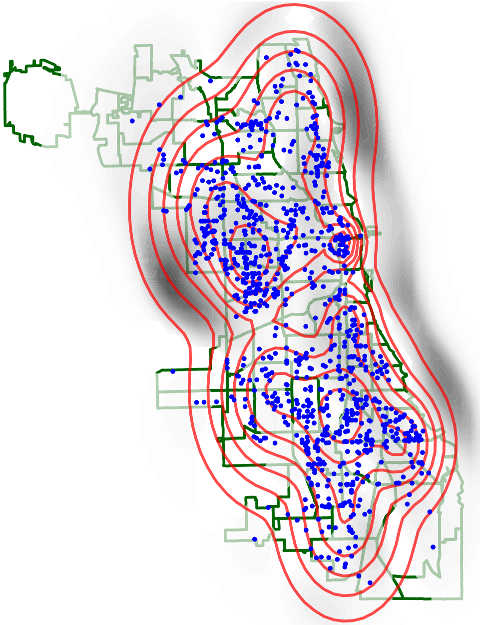
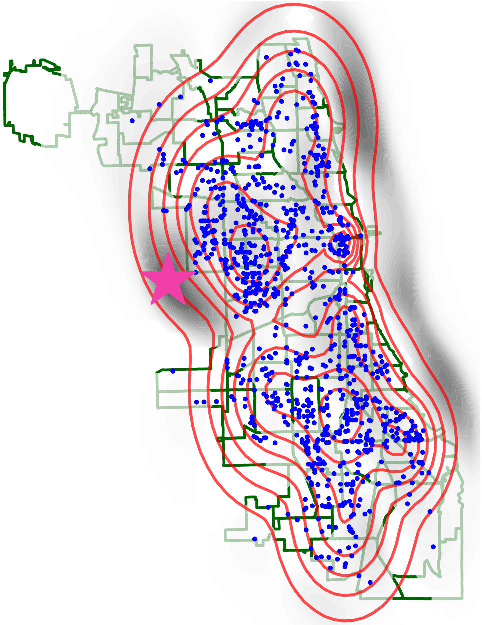


Capture the right tail better.

Interpretable Test Locations: Chicago Crime



Still, does not capture the left tail.

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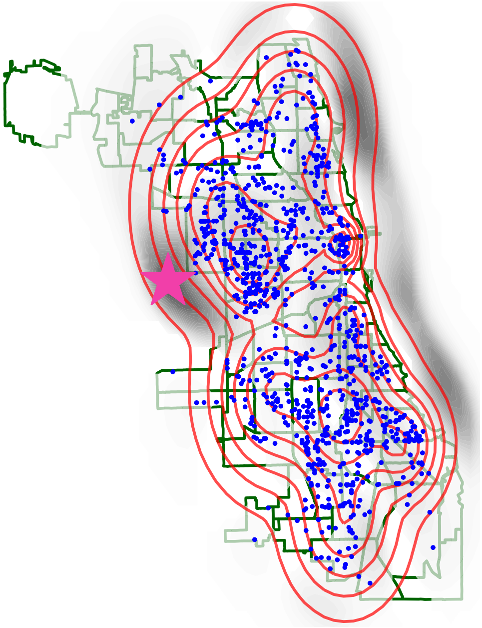

Still, does not capture the left tail.

Learned test locations are interpretable.

Bahadur Slope and Bahadur Efficiency

- Bahadur slope $\approxeq$ rate of p-value $\to 0$ under H_1 as $n \to \infty$.
- Measure a test's sensitivity to the departure from H_0.

$$H_0 \colon \theta = \mathbf{0},$$
$$H_1 \colon \theta \neq \mathbf{0}.$$

- Typically $\mathrm{pval}_n \approx \exp\left(-\frac{1}{2} c(\theta) n\right)$ where $c(\theta) > 0$ under H_1, and $c(\mathbf{0}) = 0$ [Bahadur, 1960].
- $c(\theta)$ higher $\implies$ more sensitive. Good.

Bahadur slope

$$c(\theta) := -2 \operatorname*{plim}_{n\to\infty} \frac{\log\left(1 - F(T_n)\right)}{n},$$

where $F(t) =$ CDF of T_n under H_0.

- Bahadur efficiency = ratio of slopes of two tests.

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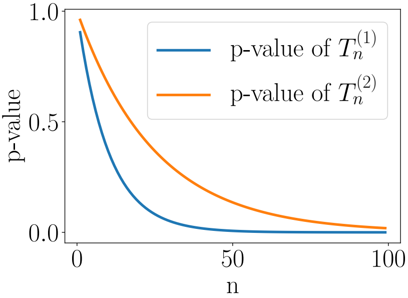

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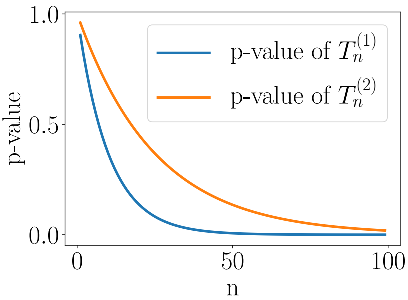

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Gaussian Mean Shift Problem

Consider $p = \mathcal{N}(0,1)$ and $q = \mathcal{N}(\mu_q, 1)$.

- Assume $J = 1$ location for $n\widehat{\mathrm{FSSD}^2}$. Gaussian kernel (bandwidth $= \sigma_k^2$)

$$c^{(\mathrm{FSSD})}(\mu_q, v, \sigma_k^2) = \frac{\sigma_k^2 \left(\sigma_k^2 + 2\right)^3 \mu_q^2 e^{\frac{v^2}{\sigma_k^2+2} - \frac{(v-\mu_q)^2}{\sigma_k^2+1}}}{\sqrt{\frac{2}{\sigma_k^2} + 1}\left(\sigma_k^2 + 1\right)\left(\sigma_k^6 + 4\sigma_k^4 + \left(v^2 + 5\right)\sigma_k^2 + 2\right)}.$$

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$$c^{(\mathrm{LKS})}(\mu_q, \kappa^2) = \frac{\left(\kappa^2\right)^{5/2}\left(\kappa^2 + 4\right)^{5/2} \mu_q^4}{2\left(\kappa^2 + 2\right)\left(\kappa^8 + 8\kappa^6 + 21\kappa^4 + 20\kappa^2 + 12\right)}.$$

Theorem 2 (FSSD is at least two times more efficient).

Fix $\sigma_k^2 = 1$ for $n\widehat{\mathrm{FSSD}^2}$. Then, $\forall \mu_q \neq 0$, $\exists v \in \mathbb{R}$, $\forall \kappa^2 > 0$, we have Bahadur efficiency

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Conclusion

- Proposed The Finite Set Stein Discrepancy (**FSSD**).
- Goodness-of-fit test based on FSSD is
  1. nonparametric,
  2. linear-time,
  3. tunable (parameters automatically tuned).
  4. interpretable.

A Linear-Time Kernel Goodness-of-Fit Test
Wittawat Jitkrittum, Wenkai Xu, Zoltán Szabó, Kenji Fukumizu, Arthur Gretton
NIPS 2017 (best paper award)
Python code: `https://github.com/wittawatj/kgof`

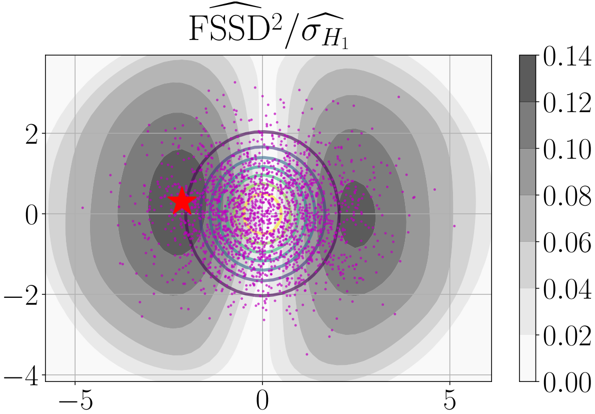
Questions?

Thank you

Illustration: Score Surface

- Consider $J = 1$ location.
- $\text{score}(\mathbf{v}) = \frac{\widehat{\text{FSSD}^2}(\mathbf{v})}{\widehat{\sigma_{H_1}}(\mathbf{v})}$ (gray), p in wireframe, $\{\mathbf{x}_i\}_{i=1}^n \sim q$ in purple, ★ = best $\mathbf{v}$.

$$p = \mathcal{N}\left(\mathbf{0}, \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right) \text{ vs. } q = \mathcal{N}\left(\mathbf{0}, \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix}\right).$$



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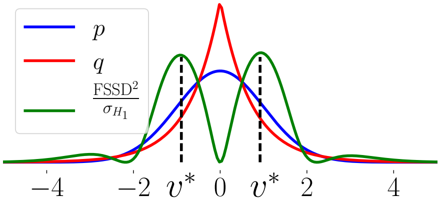
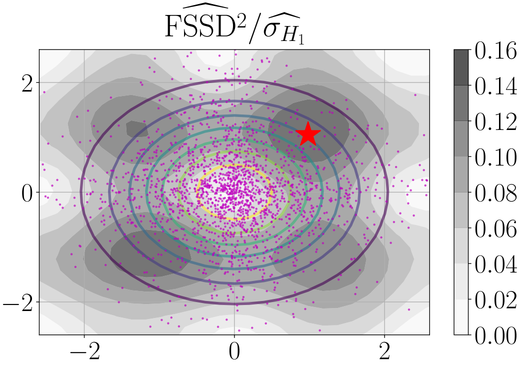
$$p = \mathcal{N}(\mathbf{0}, \mathbf{I}) \text{ vs. } q = \text{Laplace with same mean \& variance.}$$





FSSD and KSD in 1D Gaussian Case

Consider $p = \mathcal{N}(0,1)$ and $q = \mathcal{N}(\mu_q, \sigma_q^2)$.

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$$\mathrm{FSSD}^2 = \frac{\sigma_k^2 e^{-\frac{(v-\mu_q)^2}{\sigma_k^2+\sigma_q^2}} \left(\left(\sigma_k^2 + 1\right) \mu_q + v \left(\sigma_q^2 - 1\right) \right)^2}{\left(\sigma_k^2 + \sigma_q^2\right)^3}.$$

- If $\mu_q \neq 0, \sigma_q^2 \neq 1$, and $v = -\frac{(\sigma_k^2+1)\mu_q}{(\sigma_q^2-1)}$, then $\mathrm{FSSD}^2 = 0$!
  - This is why v should be drawn from a distribution with a density.
- For KSD, Gaussian kernel (bandwidth $= \kappa^2$).

$$S^2 = \frac{\mu_q^2 \left(\kappa^2 + 2\sigma_q^2\right) + \left(\sigma_q^2 - 1\right)^2}{\left(\kappa^2 + 2\sigma_q^2\right) \sqrt{\frac{2\sigma_q^2}{\kappa^2} + 1}}.$$

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FSSD is a Discrepancy Measure

Theorem 3.

Let $V = \{\mathbf{v}_1, \ldots, \mathbf{v}_J\} \subset \mathbb{R}^d$ be drawn i.i.d. from a distribution η which has a density. Let $\mathcal{X}$ be a connected open set in $\mathbb{R}^d$. Assume

1. *(Nice RKHS) Kernel $k : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ is C_0-universal, and real analytic.*
2. *(Stein witness not too rough) $\|g\|_{\mathcal{F}}^2 < \infty$.*
3. *(Finite Fisher divergence) $\mathbb{E}_{\mathbf{x}\sim q}\|\nabla_{\mathbf{x}} \log \frac{p(\mathbf{x})}{q(\mathbf{x})}\|^2 < \infty$.*
4. *(Vanishing boundary) $\lim_{\|\mathbf{x}\|\to\infty} p(\mathbf{x})\mathbf{g}(\mathbf{x}) = \mathbf{0}$.*

Then, for any $J \geq 1$, η-almost surely

$$\mathrm{FSSD}^2 = 0 \text{ if and only if } p = q.$$

- Gaussian kernel $k(\mathbf{x}, \mathbf{v}) = \exp\left(-\frac{\|\mathbf{x}-\mathbf{v}\|_2^2}{2\sigma_k^2}\right)$ works.
- In practice, $J = 1$ or $J = 5$.

Asymptotic Distributions of $\widehat{\mathrm{FSSD}^2}$

- Recall $\xi(\mathbf{x}, \mathbf{v}) := \frac{1}{p(\mathbf{x})}\partial_{\mathbf{x}}[k(\mathbf{x}, \mathbf{v})p(\mathbf{x})] \in \mathbb{R}^d$.
- $\tau(\mathbf{x}) :=$ vertically stack $\xi(\mathbf{x}, \mathbf{v}_1), \ldots \xi(\mathbf{x}, \mathbf{v}_J) \in \mathbb{R}^{dJ}$. Feature vector of $\mathbf{x}$.
- Mean feature: $\mu := \mathbb{E}_{\mathbf{x}\sim q}[\tau(\mathbf{x})]$.
- $\Sigma_r := \mathrm{cov}_{\mathbf{x}\sim r}[\tau(\mathbf{x})] \in \mathbb{R}^{dJ\times dJ}$ for $r \in \{p, q\}$

Proposition 2 (Asymptotic distributions).

Let $Z_1, \ldots, Z_{dJ} \overset{i.i.d.}{\sim} \mathcal{N}(0, 1)$, and $\{\omega_i\}_{i=1}^{dJ}$ be the eigenvalues of Σ_p.

1. *Under $H_0 : p = q$, asymptotically $n\widehat{\mathrm{FSSD}^2} \xrightarrow{d} \sum_{i=1}^{dJ}(Z_i^2 - 1)\omega_i$.*
   - *Easy to simulate to get p-value.*
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2. *Under $H_1 : p \neq q$, we have $\sqrt{n}(\widehat{\mathrm{FSSD}^2} - \mathrm{FSSD}^2) \xrightarrow{d} \mathcal{N}(0, \sigma^2_{H_1})$ where $\sigma^2_{H_1} := 4\mu^\top\Sigma_q\mu$. Implies $\mathbb{P}$(reject H_0) $\to 1$ as $n \to \infty$.*

But, how to estimate Σ_p? No sample from p!

- Theorem: Using $\hat{\Sigma}_q$ (computed with $\{\mathbf{x}_i\}_{i=1}^n \sim q$) still leads to a consistent test.

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Bahadur Slopes of FSSD and LKS

Theorem 4.

The Bahadur slope of $n\widehat{\mathrm{FSSD}^2}$ *is*

$$c^{(\mathrm{FSSD})} := \mathrm{FSSD}^2/\omega_1,$$

where ω_1 *is the maximum eigenvalue of* $\Sigma_p := \mathrm{cov}_{\mathbf{x}\sim p}[\tau(\mathbf{x})]$.

Theorem 5.

The Bahadur slope of the linear-time kernel Stein (LKS) statistic $\sqrt{n}\widehat{S_l^2}$ *is*

$$c^{(\mathrm{LKS})} = \frac{1}{2}\frac{\left[\mathbb{E}_q h_p(\mathbf{x},\mathbf{x}')\right]^2}{\mathbb{E}_p\left[h_p^2(\mathbf{x},\mathbf{x}')\right]},$$

where h_p *is the U-statistic kernel of the KSD statistic.*

Bahadur Slopes of FSSD and LKS

Theorem 4.

The Bahadur slope of $n\widehat{\mathrm{FSSD}^2}$ *is*

$$c^{(\mathrm{FSSD})} := \mathrm{FSSD}^2/\omega_1,$$

where ω_1 *is the maximum eigenvalue of* $\Sigma_p := \mathrm{cov}_{\mathbf{x}\sim p}[\tau(\mathbf{x})]$.

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Harder RBM Problem

- Perturb only one entry of $\mathbf{B} \in \mathbb{R}^{50\times 40}$ (in the RBM).
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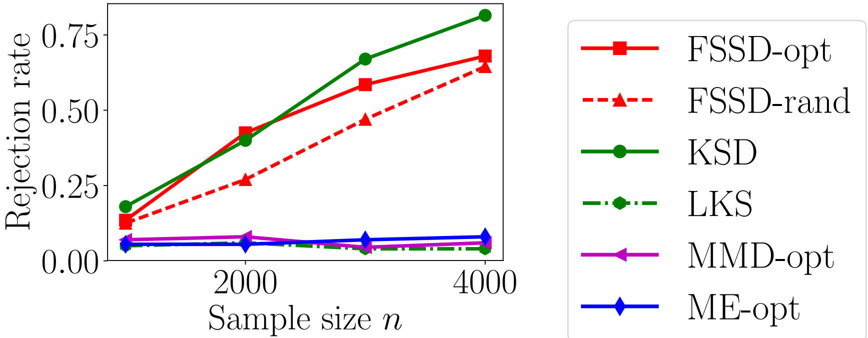

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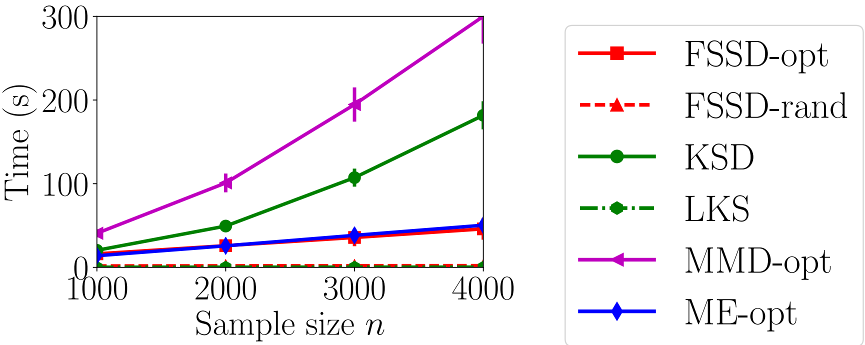

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