

# Generalized Kernel Thinning



Raaz Divedi  
raaz@mit.edu  
MIT HARVARD UNIVERSITY



Lester Mackey  
lmackey@microsoft.com  
Microsoft Research

GitHub pip install goodpoints  
microsoft/goodpoints  
arXiv.org 2105.05842 Kernel Thinning, COLT 2021  
2110.01593 Generalized Kernel Thinning, ICLR 2022

## Motivation: Computational cardiology



- Modeling **digital twin heart** to predict therapy response in a *non-invasive* way requires single-cell modeling. Commonly used strategy:
- Estimate single cell model using Bayesian set-up: Use millions of Markov chain Monte Carlo (MCMC) points to approximate posterior  $\mathbb{P}^*$
- Feed these samples to whole-heart simulator

$$\mathbb{P}^* f \triangleq \int f(x) d\mathbb{P}^*(x) \approx \frac{1}{n} \sum_{i=1}^n f(x_i) \triangleq \mathbb{P}_{n,f}$$

$x_i$  = MCMC sample for single cell model parameters  
 $f$  = heart simulator

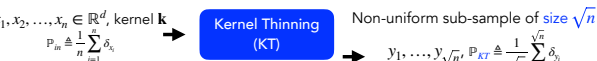
1 Million MCMC samples ~ 2 weeks  
Single evaluation of  $f$  ~ 5 weeks

Can NOT use all million samples....!

## Goal: Represent $\mathbb{P}^*$ using a few high quality points $(x_i)_{i=1}^n$

- I.I.D. sampling, and MCMC sampling** exhibit the **slow root-n Monte Carlo rate**  $|\mathbb{P}^* f - \mathbb{P}_{n,f}| = \Theta(n^{-1/2})$ , e.g.,  $\sim 10^6$  points for 0.1% error
- Computationally prohibitive for expensive  $f$  and common fixes uniform thinning, or **standard thinning**—choose every  $l$ -th point
- Accuracy degrades with such thinning**— $\Theta(\sqrt{t/n})$  worst-case error—same as the slow rate with  $n/t$  points, e.g.,  $n^{-1/4}$  rate with  $\sqrt{n}$  points

## Kernel Thinning: Better than Monte Carlo rate



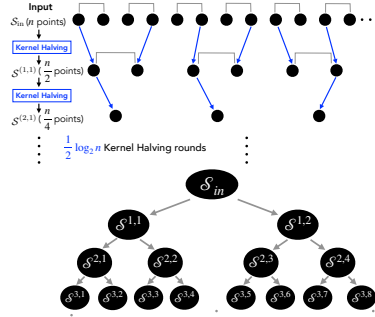
- With high probability, the **worst-case error**—MMD error—in the reproducing kernel Hilbert space (RKHS) satisfies

$$\sup_{\|g\|_{\mathcal{H}} \leq 1} |\mathbb{P}_n g - \mathbb{P}_{KT} g| \lesssim_d \begin{cases} n^{-1/2} \sqrt{\log n} & \text{(Compactly supported; e.g., B-spline } \mathbf{k}) \\ n^{-1/2} \sqrt{\log^{d+1} n \log \log n} & \text{(Sub-Gaussian tails; e.g., Gaussian } \mathbf{k}) \\ n^{-1/2} \sqrt{\log^{d+1} n \log \log n} & \text{(Sub-exponential tails; e.g., Matern } \mathbf{k}) \end{cases}$$

For output size  $s$ , the MMD error is  $\widetilde{O}(1/s)$

## KT: A two-stage algorithm

- KT-Split**: Repeated rounds of **non-uniform halving** (prefer diverse points based on kernel alignment) the parent coreset in two equal-sized children coresets



- KT-Swap**: Point-by-point refinement of the best child coreset by swapping with the best alternative in  $S_{in}^*$  if it improves the MMD error

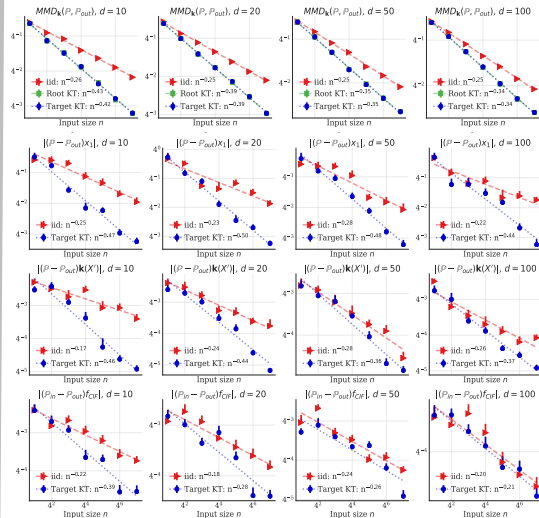
## Generalized kernel thinning

	Root KT [Original Algorithm]	Target KT	KT+ [Best of both worlds]
KT-Split kernel	$\mathbf{k}_{rt}$	$\mathbf{k}$	$\mathbf{k} + \mathbf{k}_{\alpha-rt}$
Single-function error	Same as MMD error	$\sqrt{\frac{\log n}{n}}$ For arbitrary $\mathbf{k}$ on arbitrary domain	$\sqrt{\frac{\log n}{n}}$
MMD error	See left panel	$\sqrt{\frac{\log^{ad+bn}}{n}}$ Analytic $\mathbf{k}$ $\sqrt{\frac{n^{dm}}{n^{(m-d)(2d-1)}}}$ $m$ -times differentiable $\mathbf{k}$	Min(Target KT Error, $\alpha$ -Root KT)

$$\mathbf{k}(x, y) = \left| \mathbf{k}_{rt}(x, z) \mathbf{k}_{rt}(z, y) d\mathbf{z} \right. \left. + \mathbf{k}_{\alpha-rt} = (\widehat{\mathbf{k}})^\alpha \right. \text{ where } \widehat{\cdot} \text{ denotes Fourier transform}$$

- Significantly superior to  $n^{-1/4}$  rates from Standard- $\sqrt{n}$  Thinning**
- In fact, nearly minimax integration error in many settings**
- Quasi Monte Carlo like guarantees, but KT guarantees apply to non-uniform targets with unbounded support**

## Good performance inside and outside of RKHS



## MMD error rates for popular kernels

Kernel $\mathbf{k}$	TARGET KT	ROOT KT	KT+
GAUSS( $\sigma$ )	$\frac{(\log n)^{\frac{d}{2}+1}}{\sqrt{n} \sigma^d}$	$\frac{(\log n)^{\frac{d}{2}+\frac{1}{2}}}{\sqrt{n} \sqrt{c_n}}$	$\frac{(\log n)^{\frac{d}{2}+\frac{1}{2}}}{\sqrt{n} \sqrt{c_n}}$
LAPLACE( $\sigma$ )	$n^{-\frac{1}{2}}$	N/A	$\frac{c_n (\log n)^{\frac{d}{2}+\frac{1}{2}}}{n}$
MATERN( $\nu, \gamma$ ) $\nu \in (\frac{1}{2}, d]$	$n^{-\frac{1}{2}}$	N/A	$\frac{c_n (\log n)^{\frac{d}{2}+\frac{1}{2}}}{n}$
MATERN( $\nu, \gamma$ ) $\nu > d$	$\min(n^{-\frac{1}{2}}, \frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n^{(m-d)(2d-1)}}})$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$
IMQ( $\nu, \gamma$ ) $\nu < \frac{d}{2}$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$	$\min(n^{-\frac{1}{2}}, \frac{\log n}{\sqrt{n^{1-d(2d-1)}}})$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$
IMQ( $\nu, \gamma$ ) $\nu \geq \frac{d}{2}$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n} \sqrt{c_n}}$	$\frac{(\log n)^{\frac{d+1}{2}}}{\sqrt{n}}$
SINC( $\theta$ )	$\frac{(\log n)^2}{\sqrt{n}}$	$n^{-\frac{1}{2}}$	$\frac{(\log n)^2}{\sqrt{n}}$
B-SPLINE( $2\beta + 1, \gamma$ ) $\beta \in 2\mathbb{N}$	$\sqrt{\frac{\log n}{n^{2\beta/(2\beta+1)}}}$	N/A	$\sqrt{\frac{\log n}{n}}$
B-SPLINE( $2\beta + 1, \gamma$ ) $\beta \in 2\mathbb{N}_0 + 1$	$\sqrt{\frac{\log n}{n^{2\beta/(2\beta+1)}}}$	$\sqrt{\frac{\log n}{n}}$	$\sqrt{\frac{\log n}{n}}$