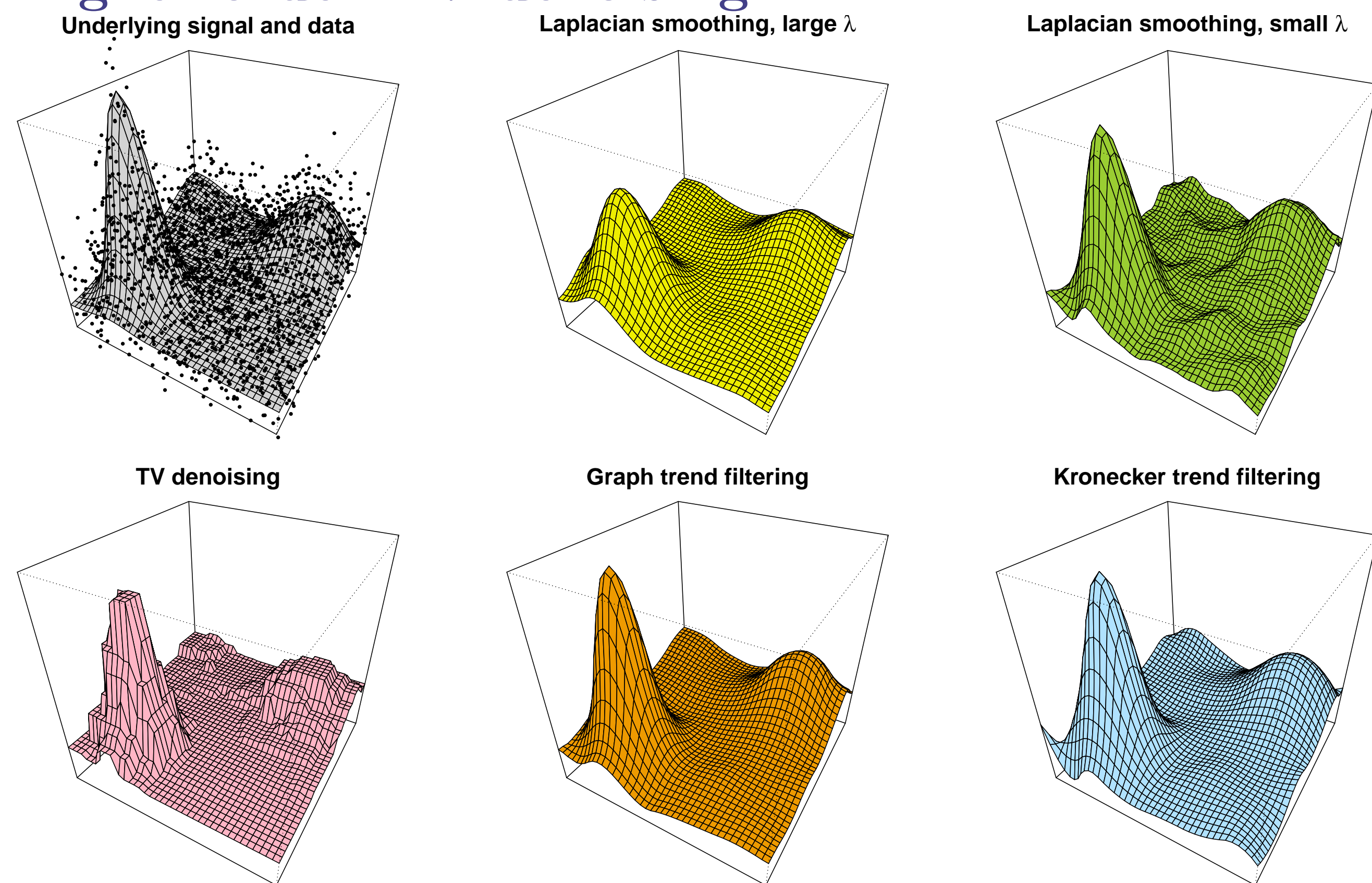


## INTRODUCTION AND OBJECTIVE

### Higher-order TV denoising



Higher-order TV-denoising recovers a better estimate

$$\hat{\theta} = \operatorname{argmin}_{\theta} \|\theta - y\|^2 + \lambda \|D\theta\|_1 \text{ — not a linear smoother}$$

### Nonparametric Regression on Graphs (d-dim grids)

$$y_i \sim N(\theta_{0,i}, \sigma^2), \text{ i.i.d., for } i = 1, \dots, n,$$

- $y$  is observed on every vertex of a graph.
- Estimate  $\theta_0$  using noisy observation  $y$ .

### Optimal rates (d-dim grids, $k$ th order TV)

	$k = 0$	$k \geq 1$
$d = 1$	$n^{-(2k+2)/(2k+3)}$ (Trend Filter)	
$d > 1$	$C_n/n$ (TV-denoising)	??

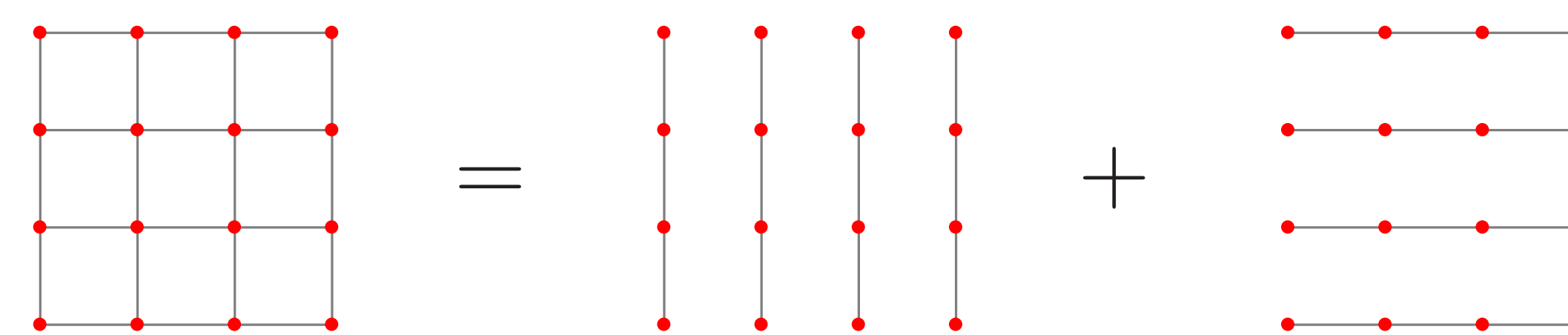
### Questions of interest

1. What is the discrete analog of  $k$ th order TV on grids ( $d > 1$ )?
2. Theoretically quantifying the denoising performance
  - How fast does MSE converge to 0 as we get more pixels?
3. Information-theoretic limit
  - How fast does it get for any method?

## KRONECKER TF AND GRAPH TF

◇ **Kronecker Trend Filtering (KTF)** Penalty is the sum of univariate penalties along rows and columns

$$\|\Delta_K^{(k+1)}\theta\|_1 = \sum_{j=1}^N \|D_{1d}^{(k+1)}\theta_{\cdot j}\|_1 + \sum_{i=1}^N \|D_{1d}^{(k+1)}\theta_{i\cdot}\|_1$$



◇ **Graph Trend Filtering (GTF)** (Wang et al., 2014):

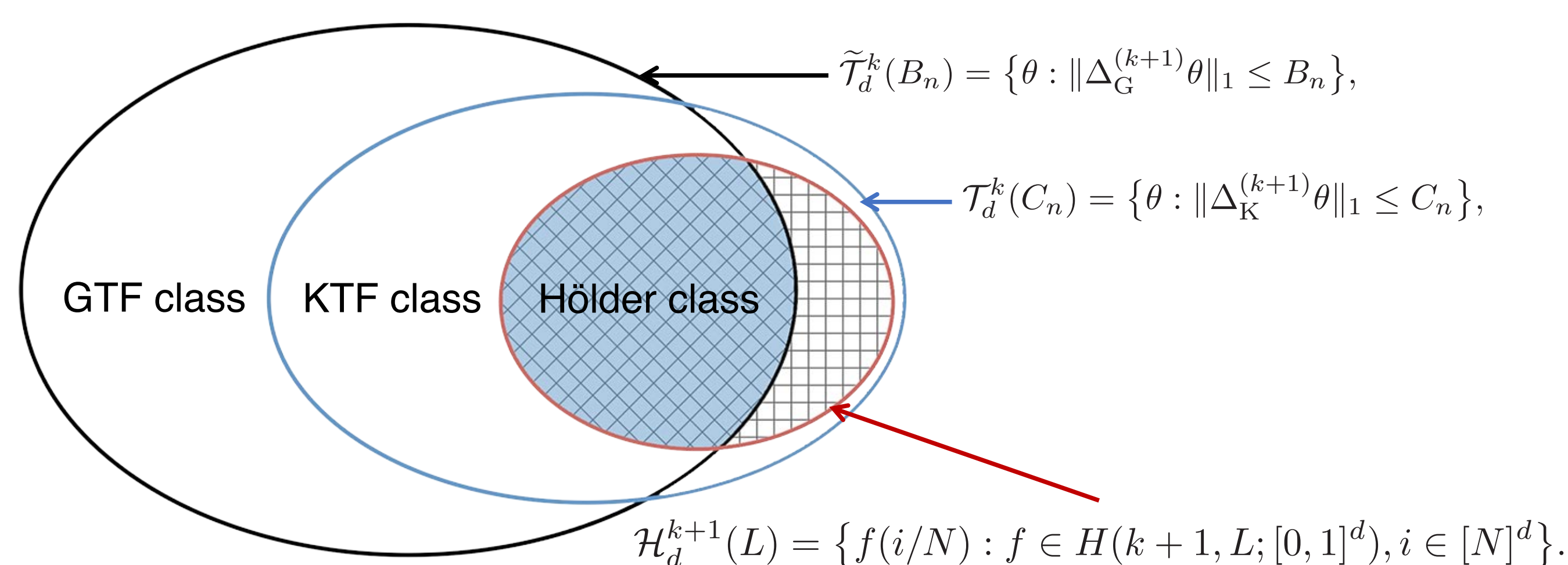
$$\Delta_G^{(1)}, \Delta_G^{(2)}, \Delta_G^{(3)}, \Delta_G^{(4)}, \dots = D, L, DL, L^2, \dots$$

where  $L = D^T D$  is the Laplacian of the grid. For  $k = 1$ ,

$$\begin{aligned} \text{GTF: } & |(\theta_1 - 2\theta_0 + \theta_2) + (\theta_3 - 2\theta_0 + \theta_4)| \\ \text{KTF: } & |\theta_1 - 2\theta_0 + \theta_2| + |\theta_3 - 2\theta_0 + \theta_4| \end{aligned}$$

- $\text{null}(\Delta_K^{(k+1)})$ :  $p \otimes q$  where  $p, q$  polynomials of degree  $\leq k$
- $\text{null}(\Delta_G^{(k+1)})$  is  $\mathbb{1}$ : constant function.

## FUNCTION CLASSES / SMOOTHNESS



- Hölder class  $\mathcal{H}_d^{k+1}(L) \subseteq$  KTF class  $\mathcal{T}_d^k(C_n)$  if  $C_n = cn^{1-(k+1)/d}$  (canonical scaling). **This delivers a lower bound for KTF class.**
- No such embedding for GTF class due to boundary artifacts! Embed an ellipsoid and apply classic results from Donoho, Liu & McGibbon (1990)

## OUR RESULTS

◇ **Upper bounds:** ( $d = 2, k \geq 1$ ) if  $\|\Delta_K\theta_0\|_1 \leq C_n, \|\Delta_G\theta_0\|_1 \leq B_n$

$$\text{MSE}(\hat{\theta}_K, \theta_0) = \tilde{O}_{\mathbb{P}}\left(\frac{C_n}{n}\right)^{2/(k+2)}, \quad \text{MSE}(\hat{\theta}_G, \theta_0) = \tilde{O}_{\mathbb{P}}\left(\frac{B_n}{n}\right)^{2/(k+2)}$$

◇ **Lower bounds:** For all  $d, k$

$$\text{Risk}(\tilde{\mathcal{T}}_d(C_n)) = \Omega\left(\left(\frac{C_n}{n}\right)^{\frac{2d}{2k+2+d}}\right), \quad \text{Risk}(\mathcal{T}_d(B_n)) = \Omega\left(\left(\frac{B_n}{n}\right)^{\frac{2d}{2k+2+d}}\right)$$

Matching rates for  $d = 2, k \geq 1$  up to log factors

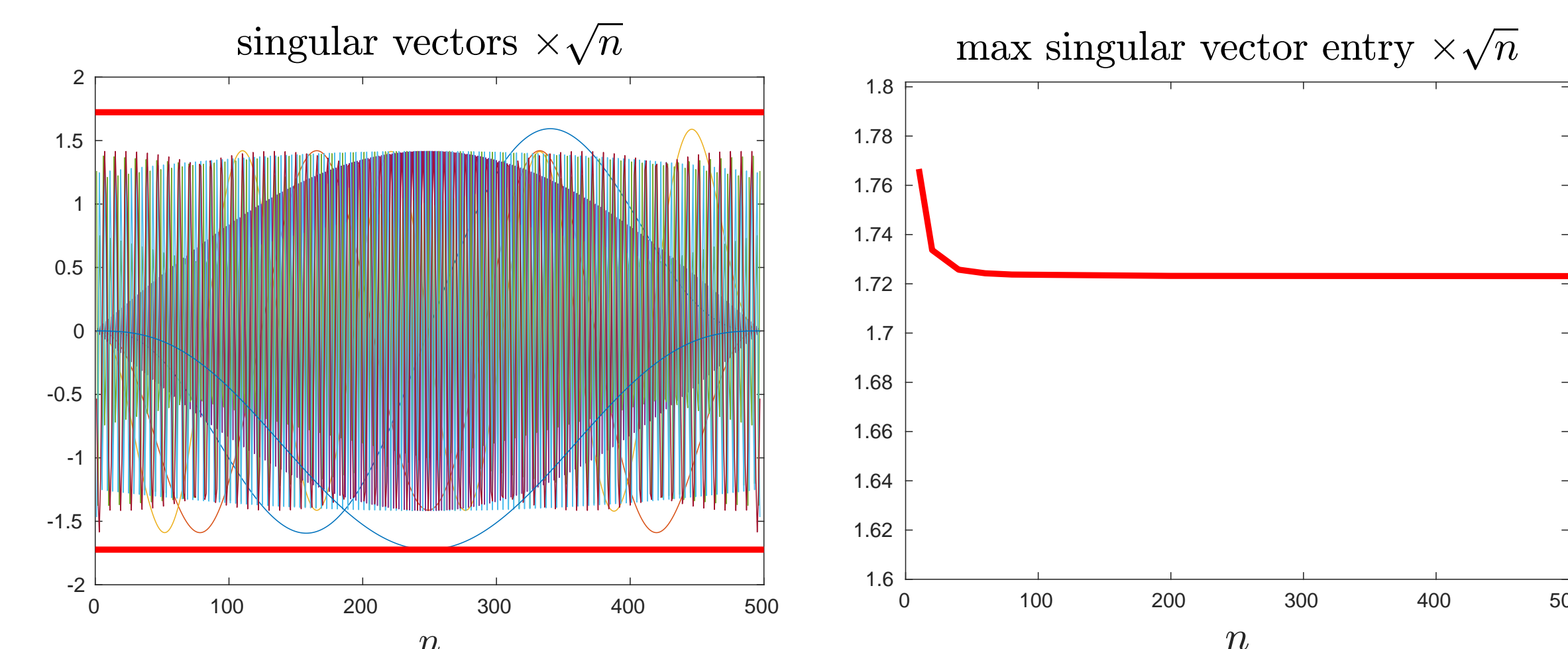
◇ **Minimax rates under canonical scaling:**

	d=1	d=2	d>2
Univariate TF (Tibshirani, 2014) (Mammen & Van De Geer, 2001)	k=0: $n^{-2/3}$	$n^{-2/4}$	$n^{-1/d}$
(This paper!)	k=1: $n^{-4/5}$	$n^{-4/6}$	?
	k>1: $n^{-\frac{2k+2}{2k+3}}$	$n^{-\frac{2k+2}{2k+4}}$	?

(Sadhanala, Wang, Tibshirani, 2016)  
Open problem: Minimax rate for  $d>2, k>1$

◇ **Upper bound proof ideas:**

- Use Theorem 6 of (Wang, Sharpnack, Smola, Tibshirani, 2016).
- $\Delta_K, \Delta_G$  have Kronecker product structure
- Singular vectors are nearly-sinusoidal (**challenging to prove!**)



- Singular values do not decay too fast

## REFERENCES

- [1] Donoho, Liu, and MacGibbon. Minimax Risk Over Hyperrectangles, and Implications. *Annals of Statistics*, 18(3):1416–1437, 1990.
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- [3] Bogoya, Bottcher, Grudsky, and Maximenko. Eigenvectors of Hermitian Toeplitz matrices with smooth simple-loop symbols. *Linear Algebra and its Applications*, 2016.