

Tim Roith, Leon Bungert

Applied Mathematics, FAU Erlangen–Nürnberg

# Continuum Limit of Lipschitz Learning on Graphs

$\Gamma$ -Convergence and Compactness of Supremal Graph Functionals

## Semi-Supervised Learning on Graphs

### Semi-supervised Learning

Given a finite set of points  $\Omega_n \subset \Omega \subset \mathbb{R}^d$  with labels  $g : \mathcal{O}_n \subset \Omega_n \rightarrow \mathbb{R}$ , find a function

$$u_n : \Omega_n \rightarrow \mathbb{R}, \quad \text{s.t. } u = g \text{ on } \mathcal{O}_n.$$

**Smoothness assumption:** Points that are close to each other are more likely to share a label.

**$p$ -Laplacian Learning:** The objective of  $p$ -Laplacian learning [ST19] for  $p < \infty$  is to find  $u : \Omega_n \rightarrow \mathbb{R}$  that solves

$$\min_{u : \Omega_n \rightarrow \mathbb{R}} \sum_{x, y \in \Omega_n} w(x, y) |u(y) - u(x)|^p, \quad \text{s.t. } u = g \text{ on } \mathcal{O}_n.$$

### Lipschitz Learning

We want to find a function  $u : \Omega_n \rightarrow \mathbb{R}$  that solves the following minimization problem,

$$\min_{u : \Omega_n \rightarrow \mathbb{R}} \max_{x, y \in \Omega_n} w_n(x, y) |u(y) - u(x)|, \quad \text{s.t. } u = g \text{ on } \mathcal{O}_n,$$

$n \rightarrow \infty$

$$\min_{u \in W^{1,\infty}(\Omega)} \|\nabla u\|_{L^\infty(\Omega)}, \quad \text{s.t. } u = g \text{ on } \mathcal{O}.$$

Our convergence result [RB21] states that discrete minimizers convergence towards minimizers of the continuum problem above in  $L^\infty(\Omega)$ .

### Weighted Graphs

We model the data as a **weighted graph**  $(\Omega_n, w_n)$  with edge weights given by

$$w_n(x, y) := \eta(|x - y| / s_n), \quad x, y \in \Omega_n.$$

Here  $s_n > 0$  is a **scaling parameter** and

$$\eta : [0, \infty) \rightarrow [0, \infty)$$

is a kernel function.

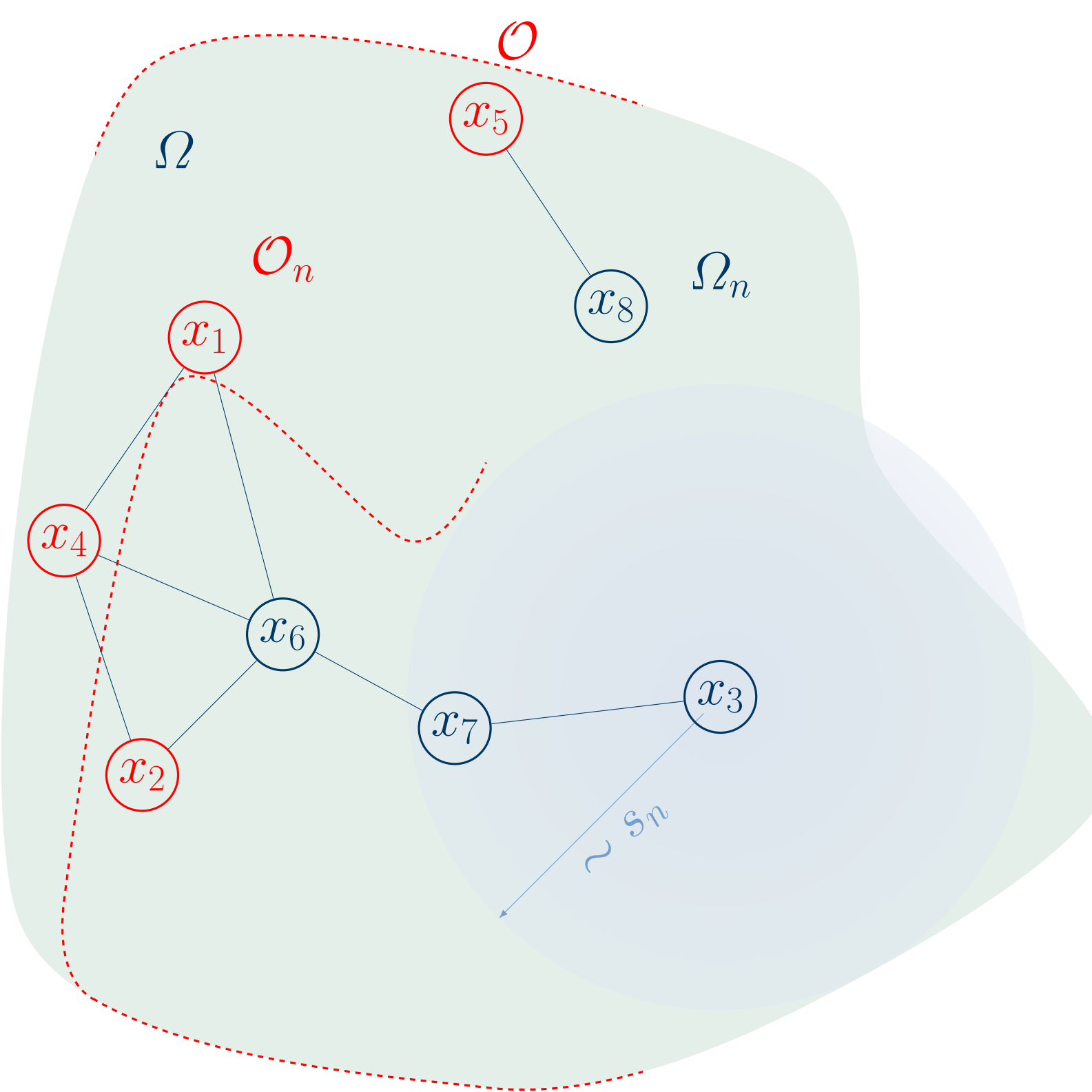
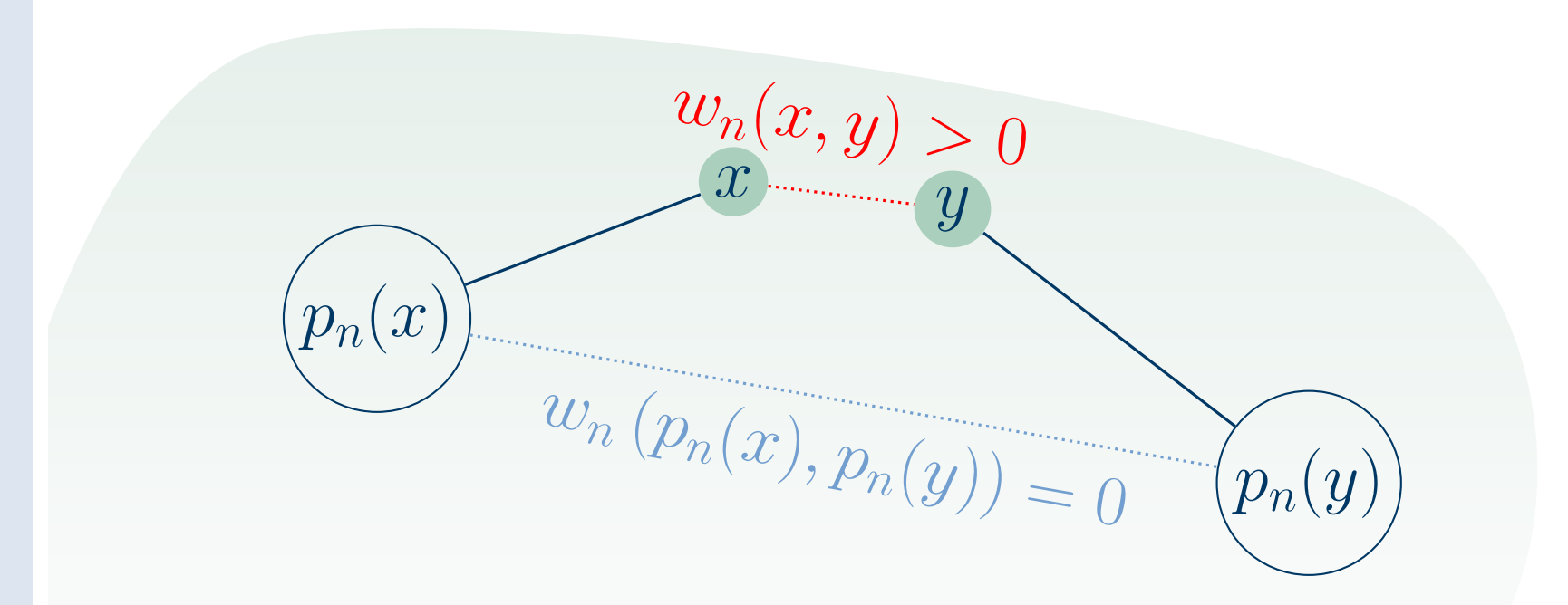


Figure: Visualization of the graph design.

### Scaling and Domain

For the continuum limit one has to avoid situations, where points  $x, y \in \Omega$  have significant weight while their closest vertices  $p_n(x), p_n(y) \in \Omega_n$  do not.

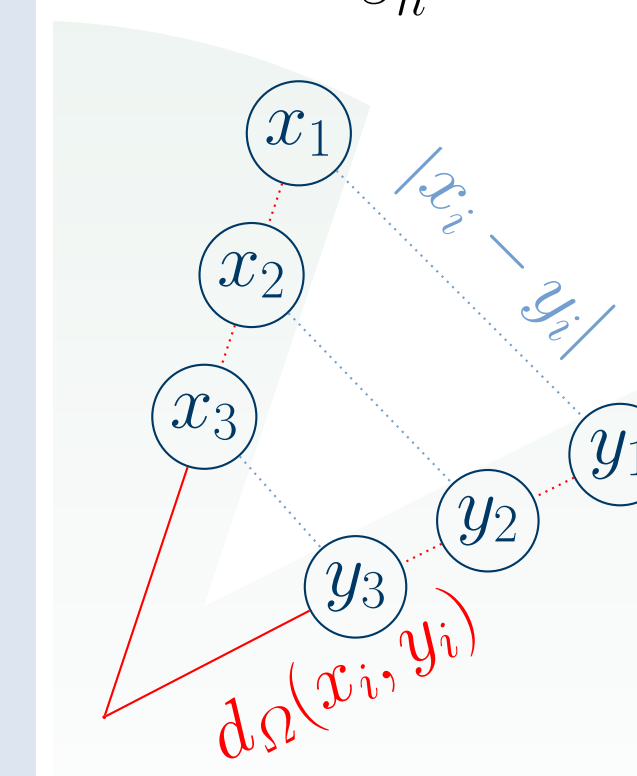


Using the Hausdorff distance

$$d_H(A, B) = \sup_{x \in A} \text{dist}(x, B) \vee \sup_{x \in B} \text{dist}(x, A)$$

we require the **weakest scaling** for asymptotic connectedness:

$$\frac{r_n}{s_n} := \frac{d_H(\Omega_n, \Omega) \vee d_H(\mathcal{O}_n, \mathcal{O})}{s_n} \rightarrow 0.$$



We also need **local convexity** of the domain, expressed via the geodesic distance

$$\lim_{\delta \downarrow 0} \sup_{|x - y| \leq \delta} \frac{d_\Omega(x, y)}{|x - y|} = 1.$$

This prevents sharp internal corners as displayed on the left.

## Continuum limit via $\Gamma$ -Convergence

### Graph and Continuum Functional

► The mapping  $p_n : \Omega \rightarrow \Omega_n$  denotes a **closest point projection**.

► The **graph functional** is extended to  $L^\infty(\Omega)$  via

$$\text{dom}(E_n) := \{u \in L^\infty(\Omega) : \exists \bar{u} : \Omega_n \rightarrow \mathbb{R}, u = \bar{u} \circ p_n, \bar{u}|_{\mathcal{O}_n} = g\},$$

$$E_n(u) := \frac{1}{s_n} \max_{x, y \in \Omega_n} w_n(x, y) |\bar{u}(x) - \bar{u}(y)|.$$

► The **continuum functional** is defined as

$$\text{dom}(\mathcal{E}) := \{u \in W^{1,\infty}(\Omega) : u = g \text{ on } \mathcal{O}\},$$

$$\mathcal{E}(u) := \|\nabla u\|_{L^\infty(\Omega)}.$$

### $\Gamma$ -Convergence and Compactness

Let  $\Omega$  be weakly convex and  $s_n$  a null sequence with

$$\frac{r_n}{s_n} \rightarrow 0.$$

Then it holds in the topology of  $L^\infty(\Omega)$ :

- $E_n \xrightarrow{\Gamma} \sigma_\eta \mathcal{E}$ ,
- $\sup_{n \in \mathbb{N}} E_n(u_n) < \infty$  implies that  $(u_n)_{n \in \mathbb{N}}$  is **relatively compact**.

### Minimizers and Ground States

Using  $\Gamma$ -convergence and compactness:

**Minimizers / ground states** of  $E_{n,\text{cons}}$  converge to minimizers / ground states of  $\mathcal{E}_{\text{cons}}$ .

Ground states of  $E_n$  and  $\mathcal{E}$  are solutions of

$$\min_{u \in L^\infty(\Omega)} \frac{F(u)}{\|u\|_{L^p(\Omega)}}, \quad F \in \{E_n, \mathcal{E}\},$$

and are **geodesic distance functions** [BKB20].

## Numerics

### Lipschitz Learning and Ground States

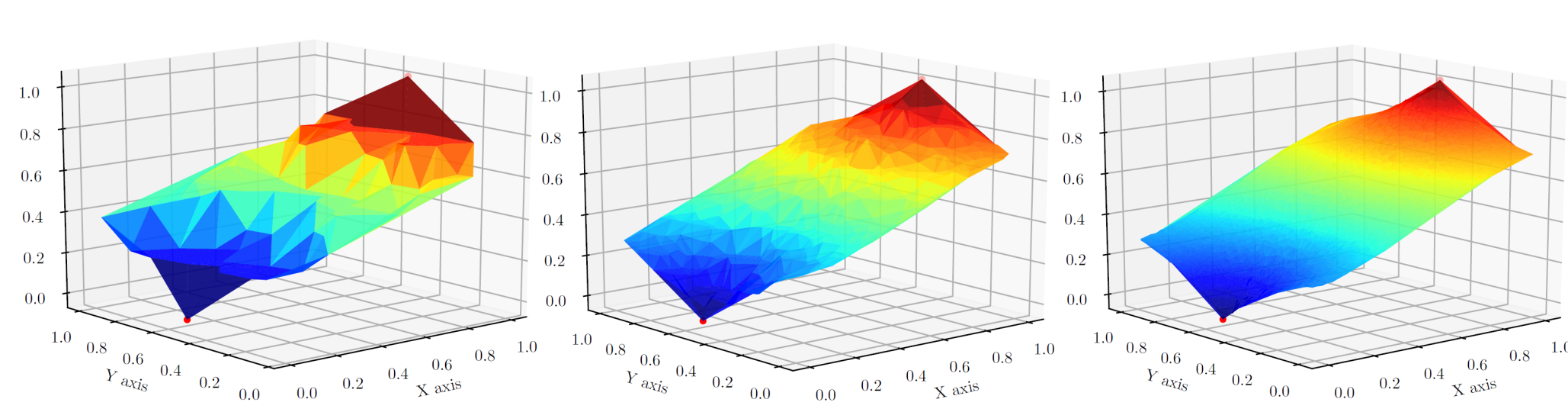


Figure: Continuum limit of Lipschitz Learning on the square with two fixed labels.

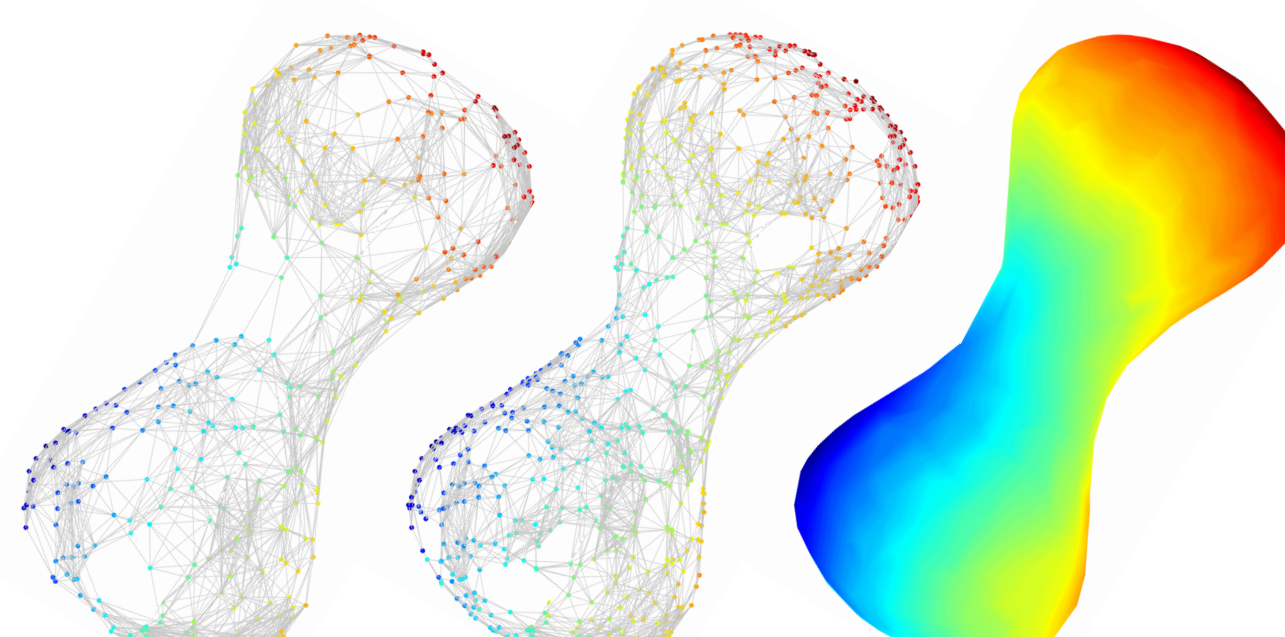


Figure: Continuum limit of ground states on a manifold with one fixed label.

### References

- [RB21] T. Roith and L. Bungert. *Continuum Limit of Lipschitz Learning on Graphs*. 2021. arXiv: 2012.03772 [cs.LG].
- [BKB20] L. Bungert, Y. Korolev, and M. Burger. “Structural analysis of an  $L$ -infinity variational problem and relations to distance functions”. In: *Pure and Applied Analysis* 2.3 (2020).
- [ST19] D. Slepcev and M. Thorpe. “Analysis of  $p$ -Laplacian regularization in semisupervised learning”. In: *SIAM J. Math. Anal.* 51.3 (2019).