

Graphs in Machine Learning SSL Learnability

When Does Graph-Based SSL Provably Help

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Partially based on material by: Branislav Kveton, Mikhail Belkin, Jerry Zhu

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- SSL: perfect knowledge of \mathcal{M} \equiv humongous amounts of \mathbf{x}_i

http://people.cs.uchicago.edu/~niyogi/papersps/ssminimax2.pdf

Set of learning problems - collections ${\mathcal P}$ of probability distributions:

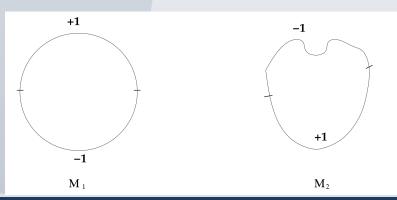
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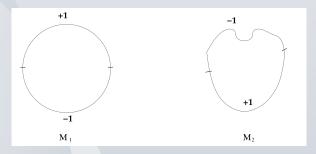
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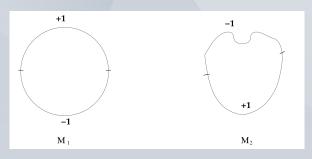
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In which cases there is a gap between $Q(n_l, \mathcal{P})$ and $R(n_l, \mathcal{P})$?

Hypothesis space \mathcal{H} : half of the circle as +1 and the rest as -1

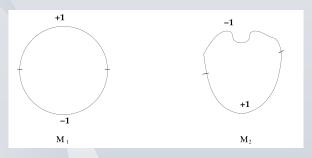


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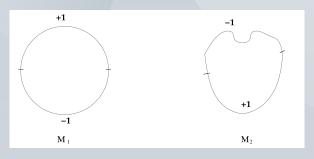
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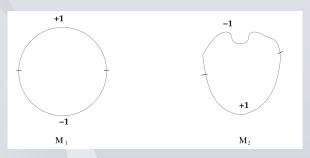
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Optimal rate
$$Q(n, \mathcal{P}) \leq 2\sqrt{\frac{3 \log n_l}{n_l}}$$

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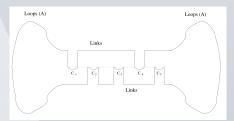
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We consider 2^d manifolds of the form

$$\mathcal{M} = \mathsf{Loops} \cup \mathsf{Links} \cup \mathit{C} \text{ where } \mathit{C} = \cup_{i=1}^{\mathit{d}} \mathit{C}_i$$

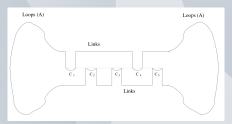


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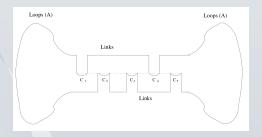
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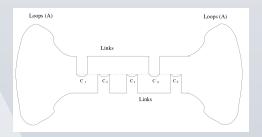
Main idea: d segments in C, d-I with no data, 2^I possible choices for labels, which helps us to lower bound

$$||A(\bar{z}) - m_n||_{L^2(\mathbf{p}_n)}$$



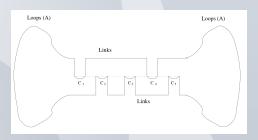
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• C_1 and C_4 are close



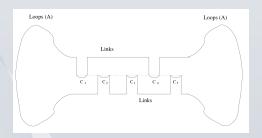
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- C_1 and C_3 are far
- we also need: target function varies smoothly
- altogether: closeness on manifold → similarity in labels

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Different degrees of knowing ${\mathcal M}$

- set membership oracle: $\mathbf{x} \overset{?}{\in} \mathcal{M}$
- approximate oracle
- knowing the harmonic functions on \mathcal{M}
- knowing the Laplacian $\mathcal{L}_{\mathcal{M}}$
- knowing eigenvalues and eigenfunctions
- topological invariants, e.g., dimension
- metric information: geodesic distance

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https://misovalko.github.io/mva-ml-graphs