

S²: Efficient Graph Based Active Learning

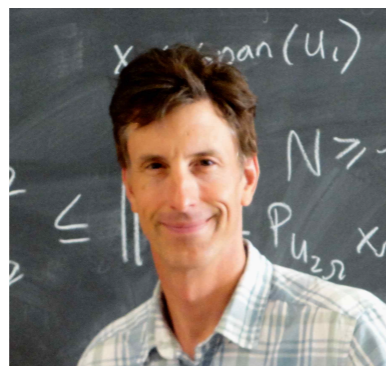
Gautam Dasarathy

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Carnegie Mellon University

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<http://gautamdasarathy.com>

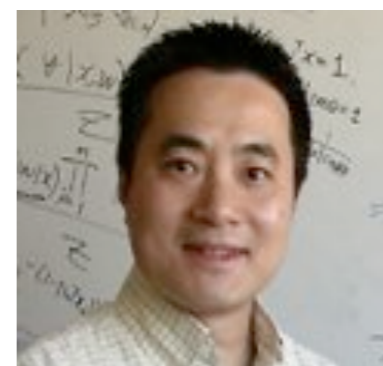
joint work with



Rob Nowak

ECE

UW - Madison



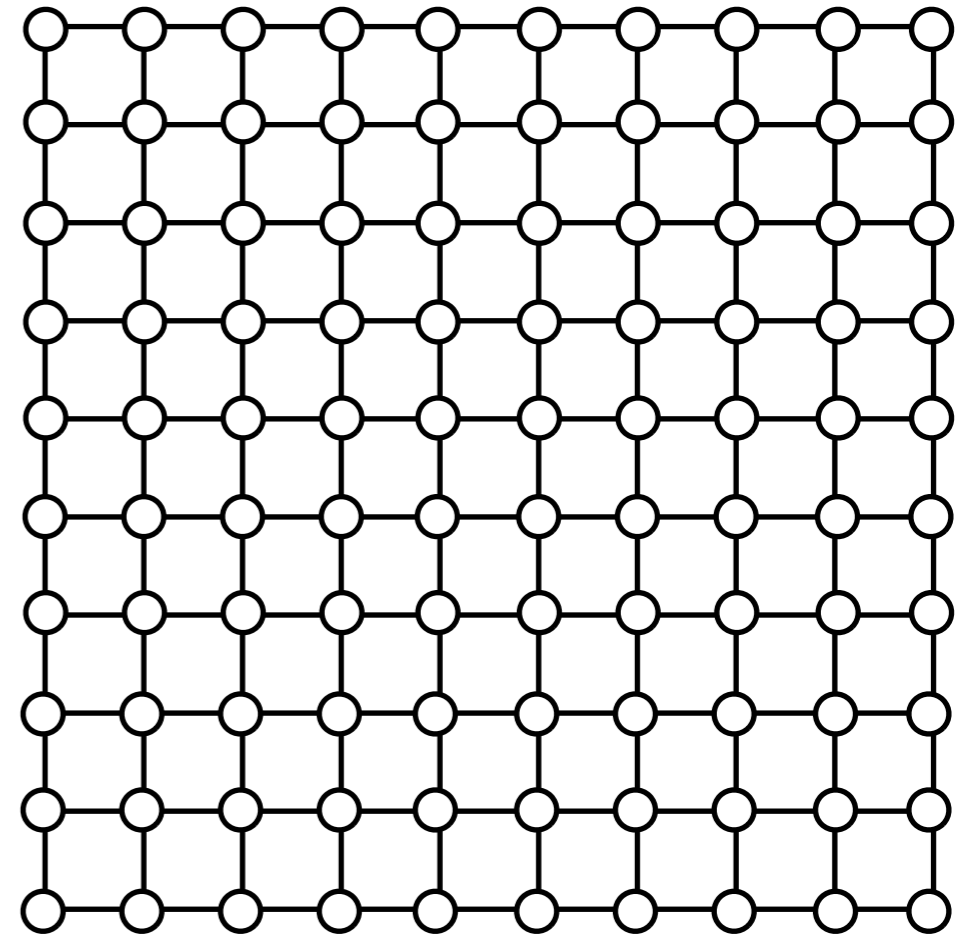
Xiaojin (Jerry) Zhu

Computer Sciences

UW - Madison

The Problem

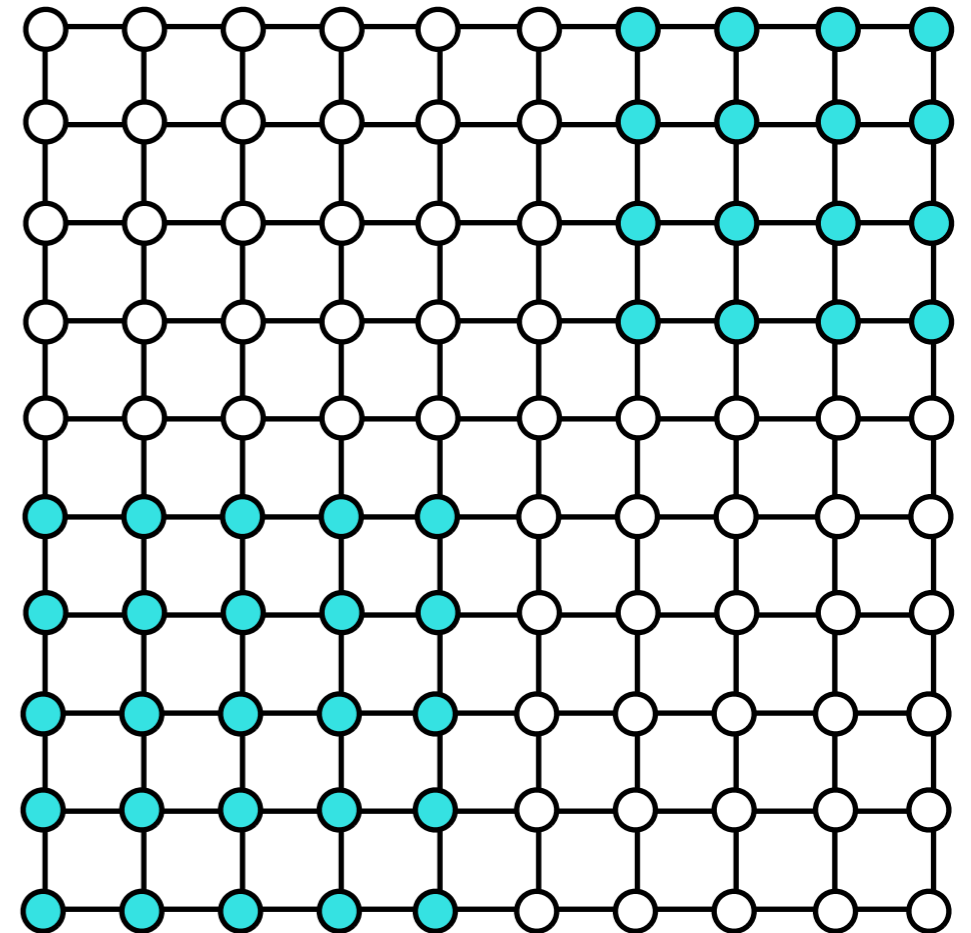
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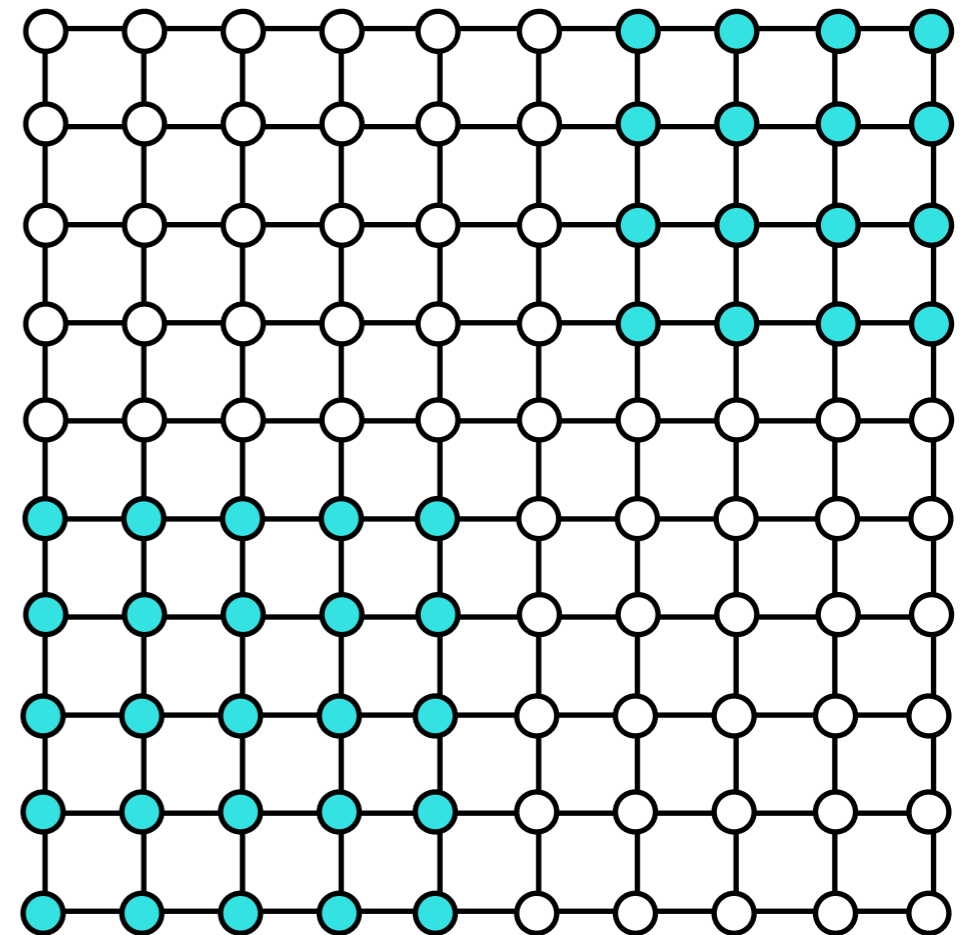
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Goal: **Sequentially** and **actively** select a subset $L \subset [n]$ to be labeled.

Predict $\{f(i) : i \notin L\}$.



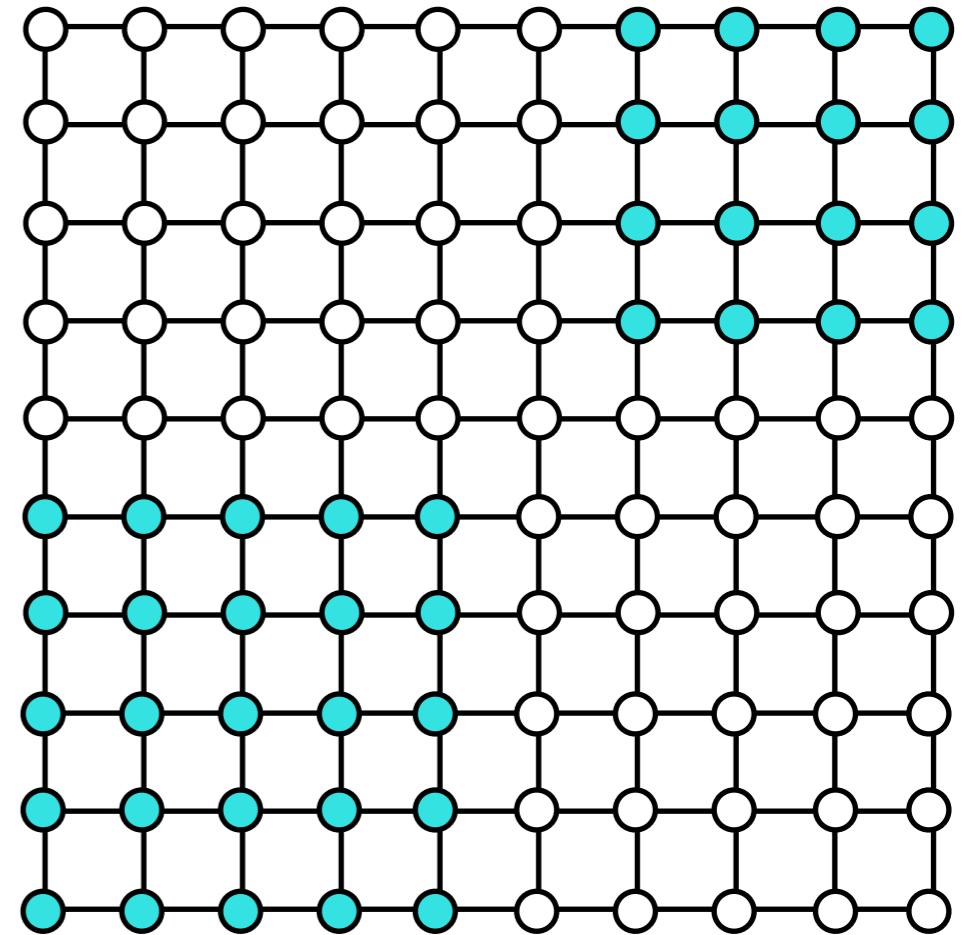
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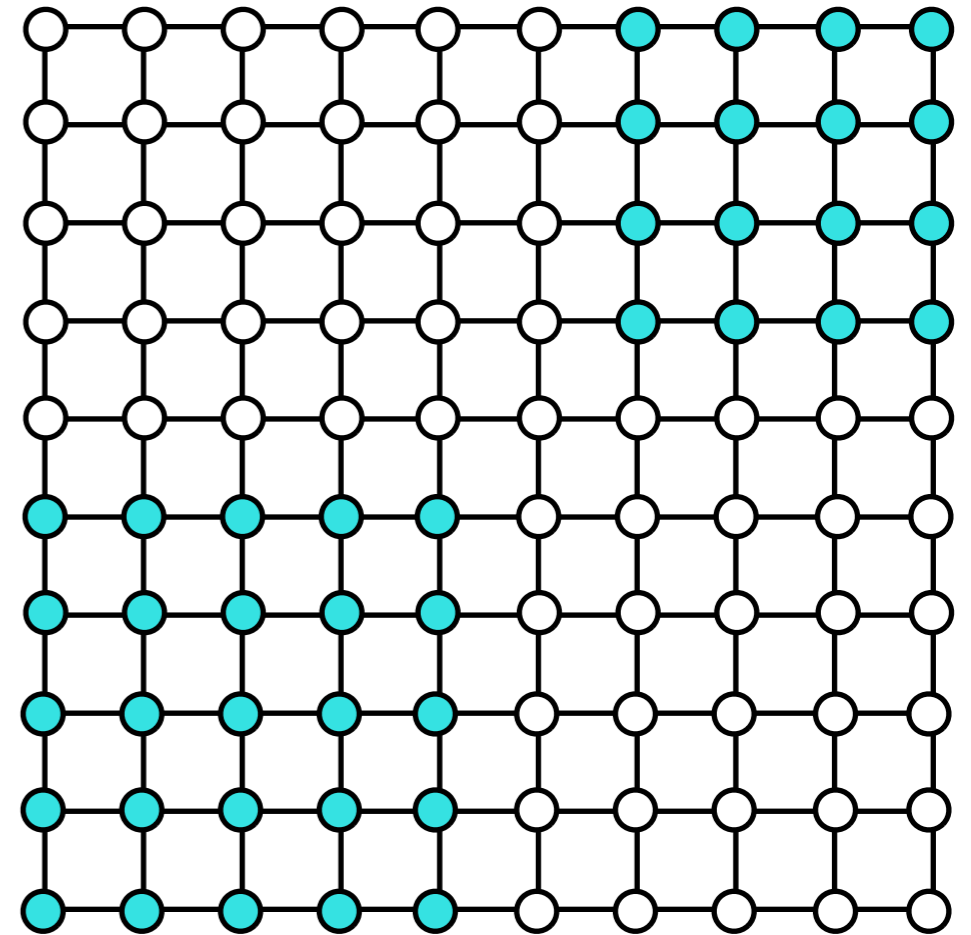


We are naturally interested in questions like:

- How to **choose** L (**efficiently**) ?
- How **big** does L have to be ?
- How does the **interaction between f and G** affect these things?

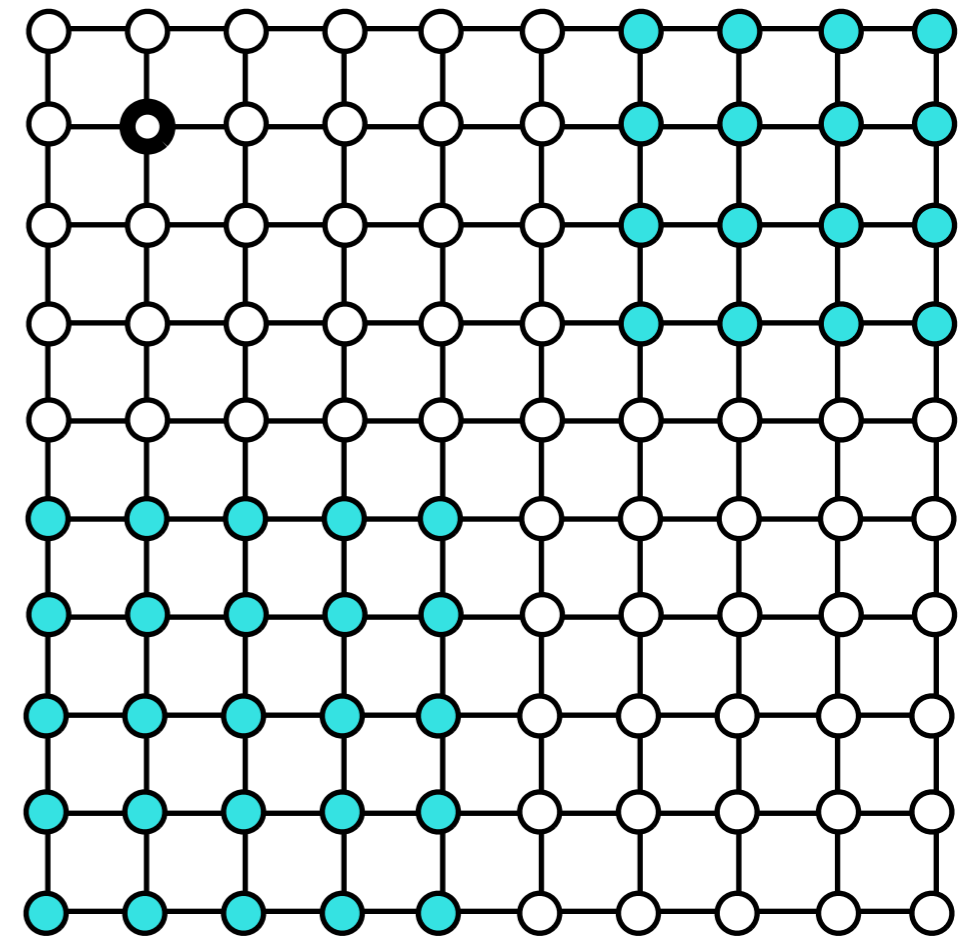
The S^2 Algorithm

- **Randomly query** vertices till you find a pair with opposite labels.
- Among all shortest paths connecting oppositely labeled vertices, **pick the shortest** one and query the vertex at its **mid-point**.
 - If you find a “cut” edge, remove it and proceed.
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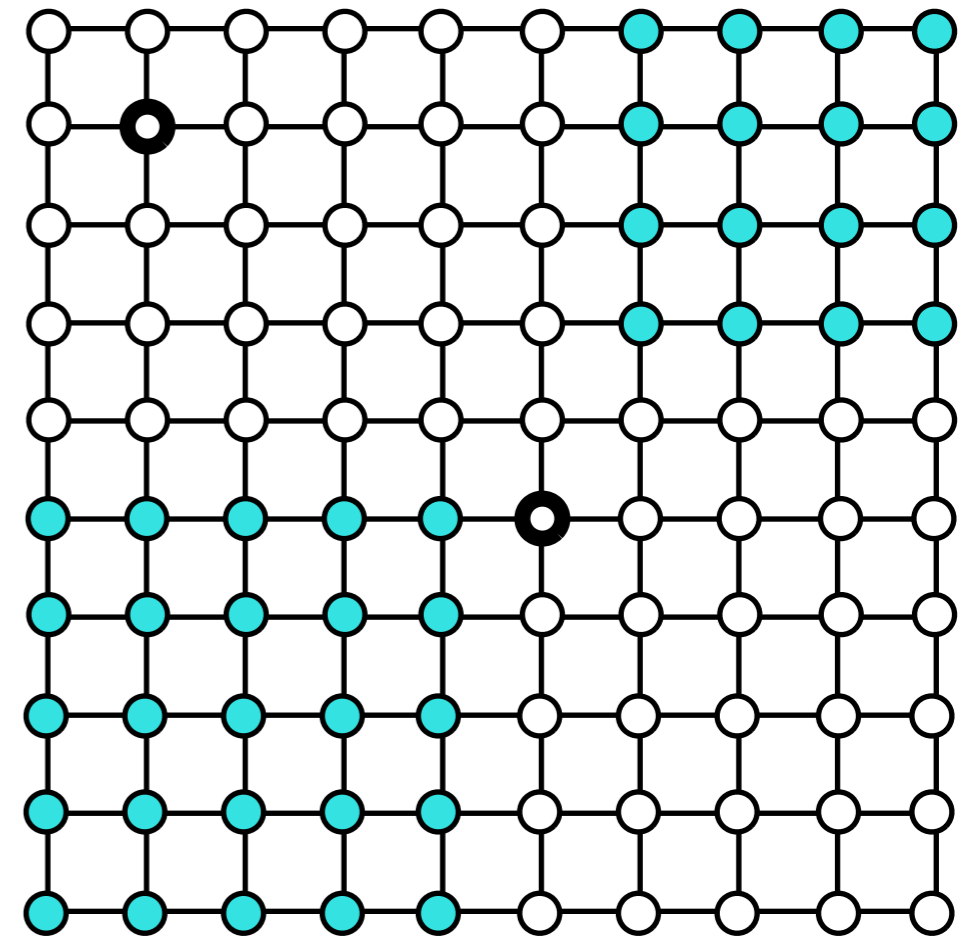
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Randomly query

The S^2 Algorithm

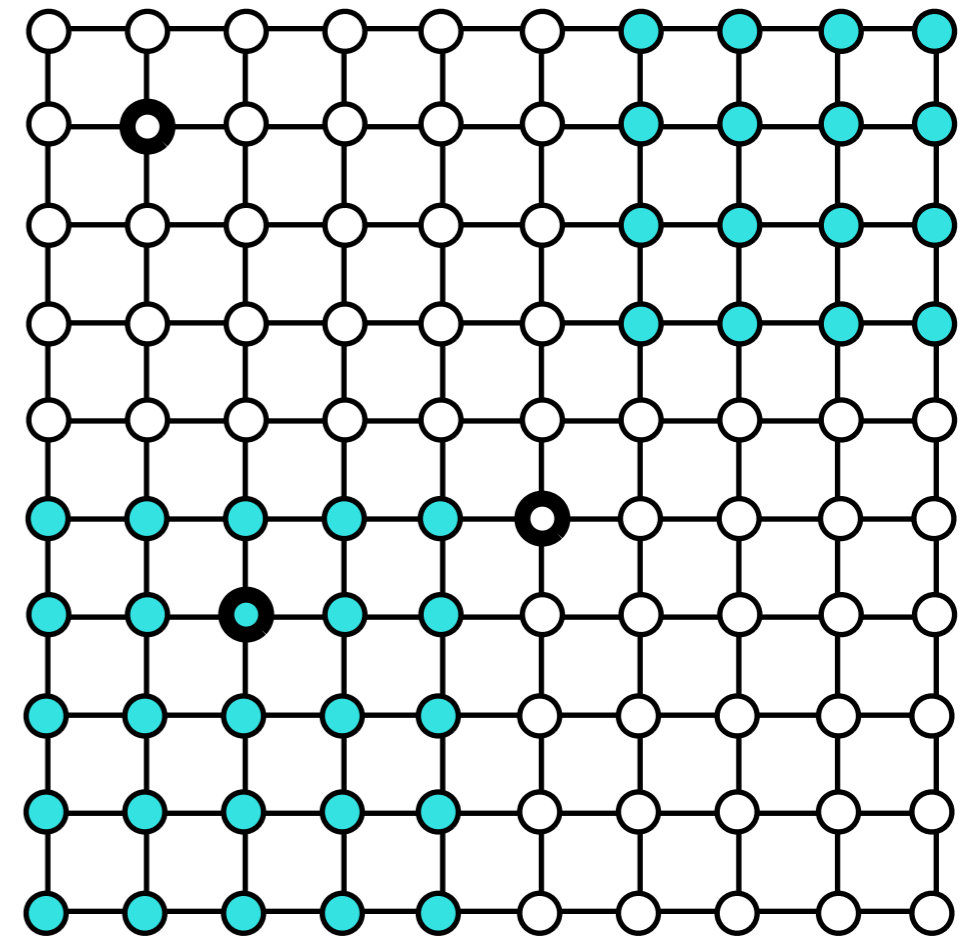
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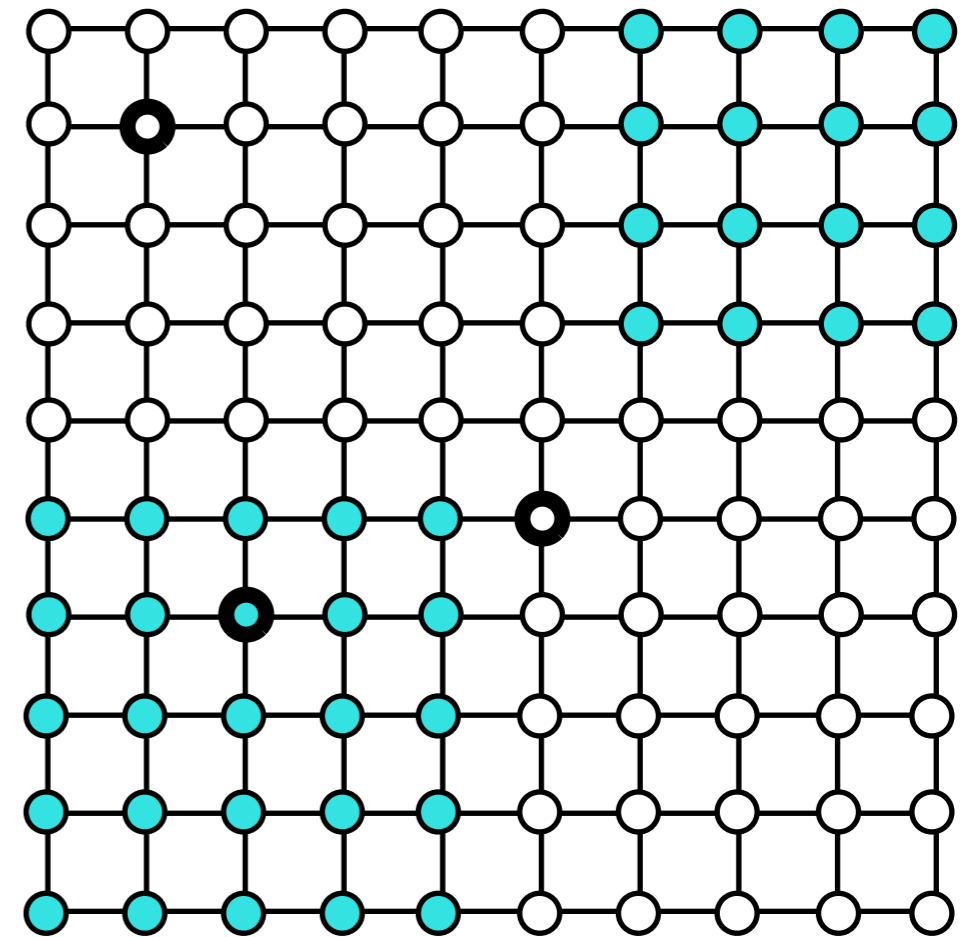
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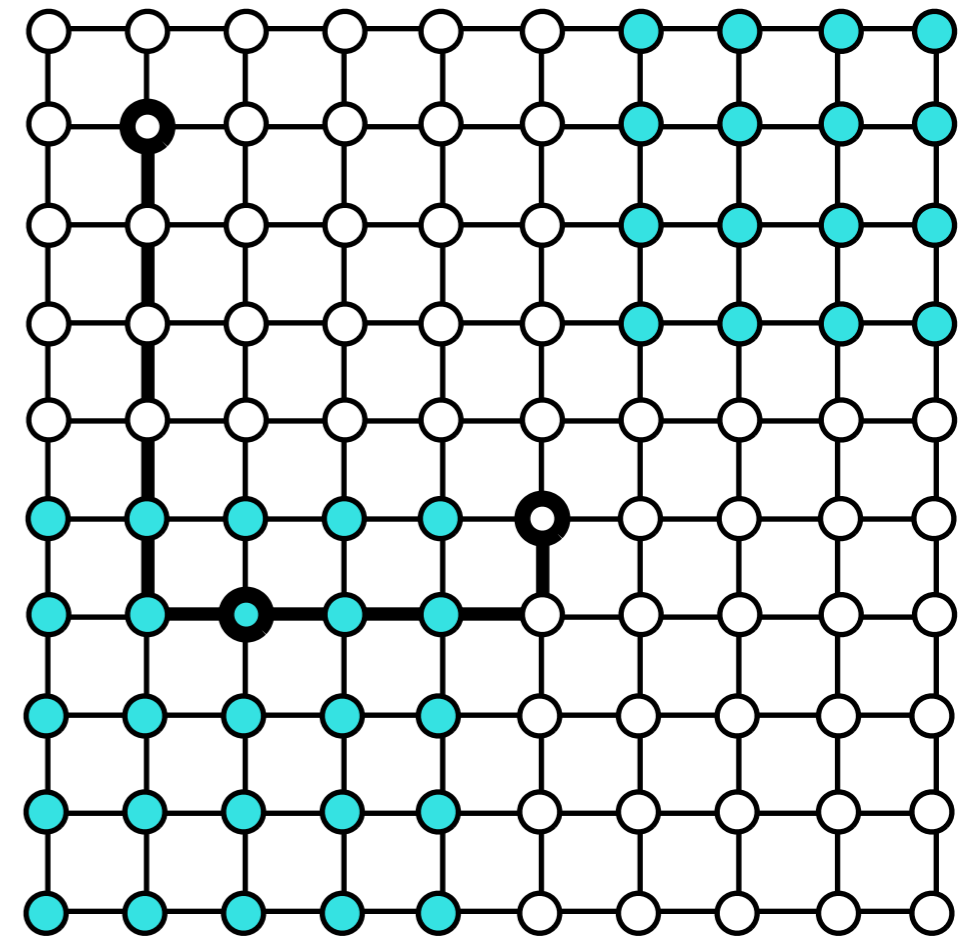
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Found oppositely labeled vertices

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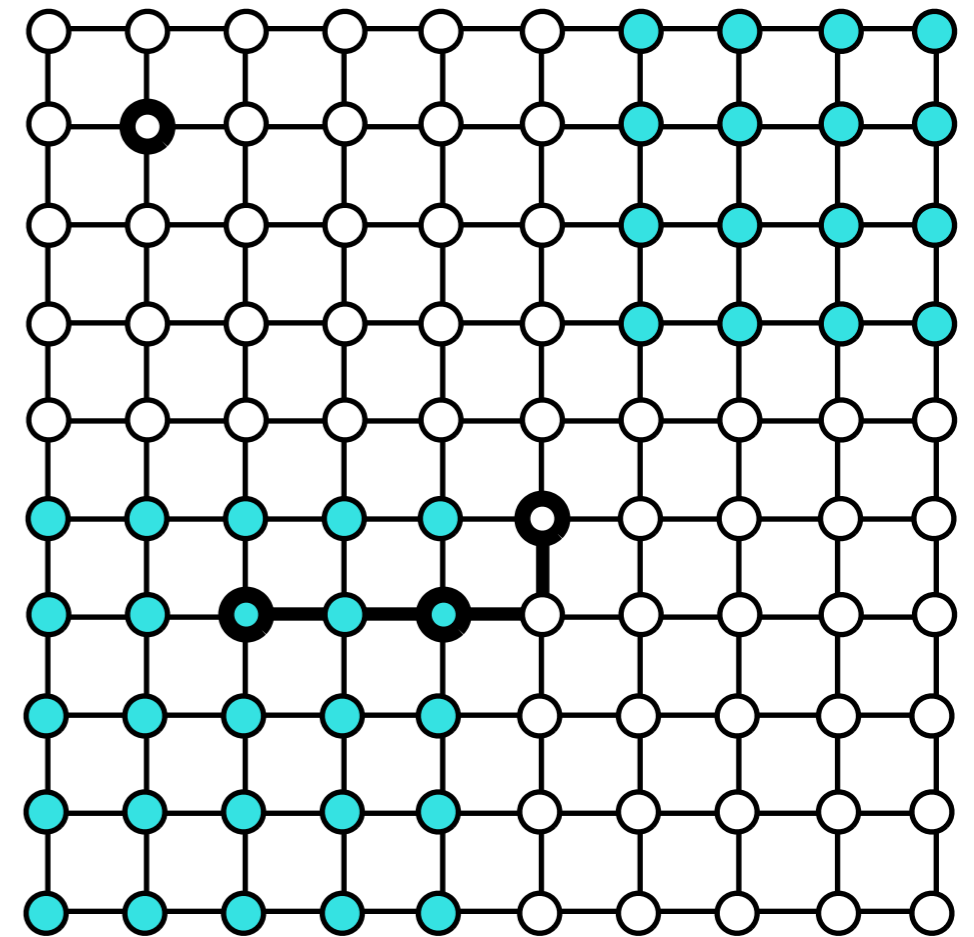
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There are 2 shortest paths connecting oppositely labeled vertices.

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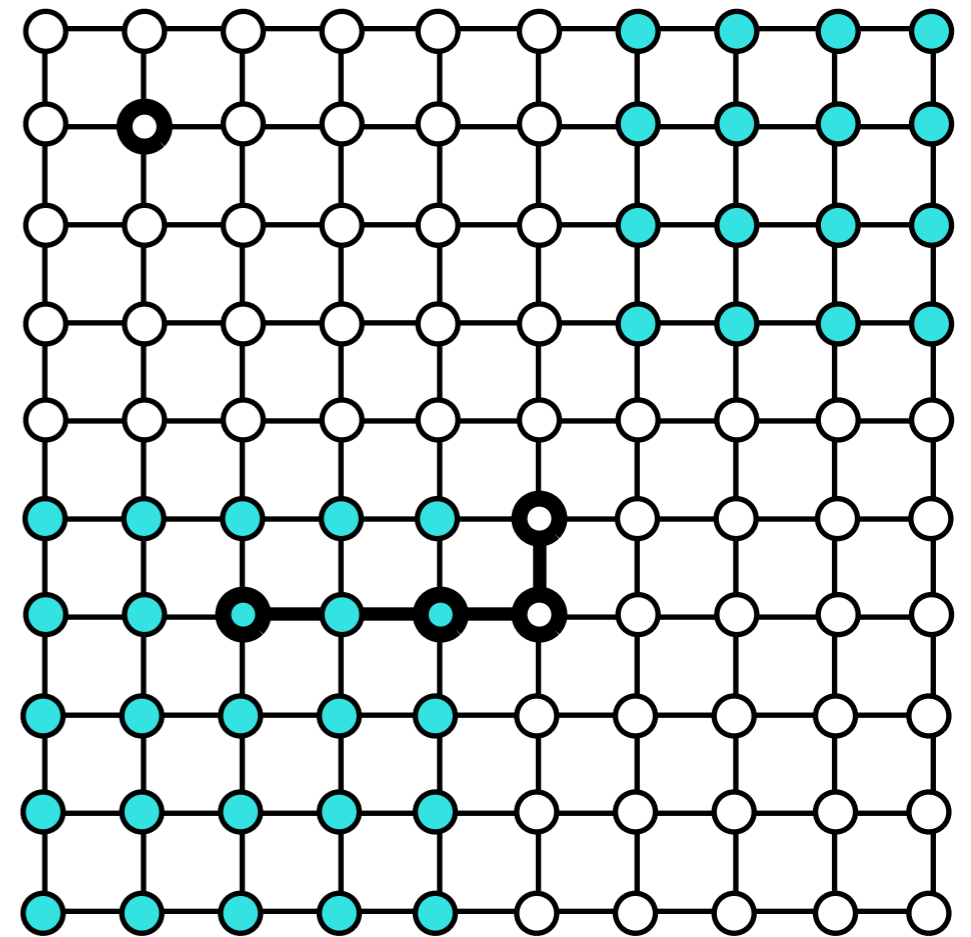
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Pick the shortest shortest path and query at midpoint.

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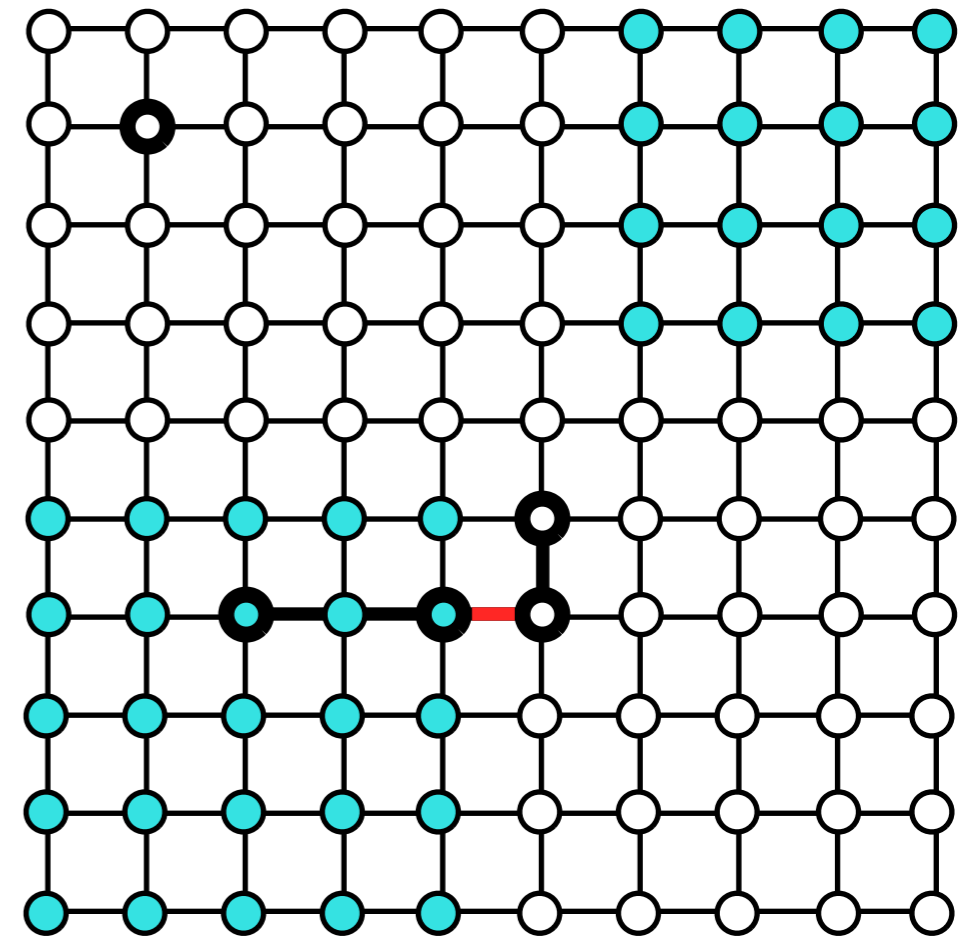
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Continue this and remove any cut edges found

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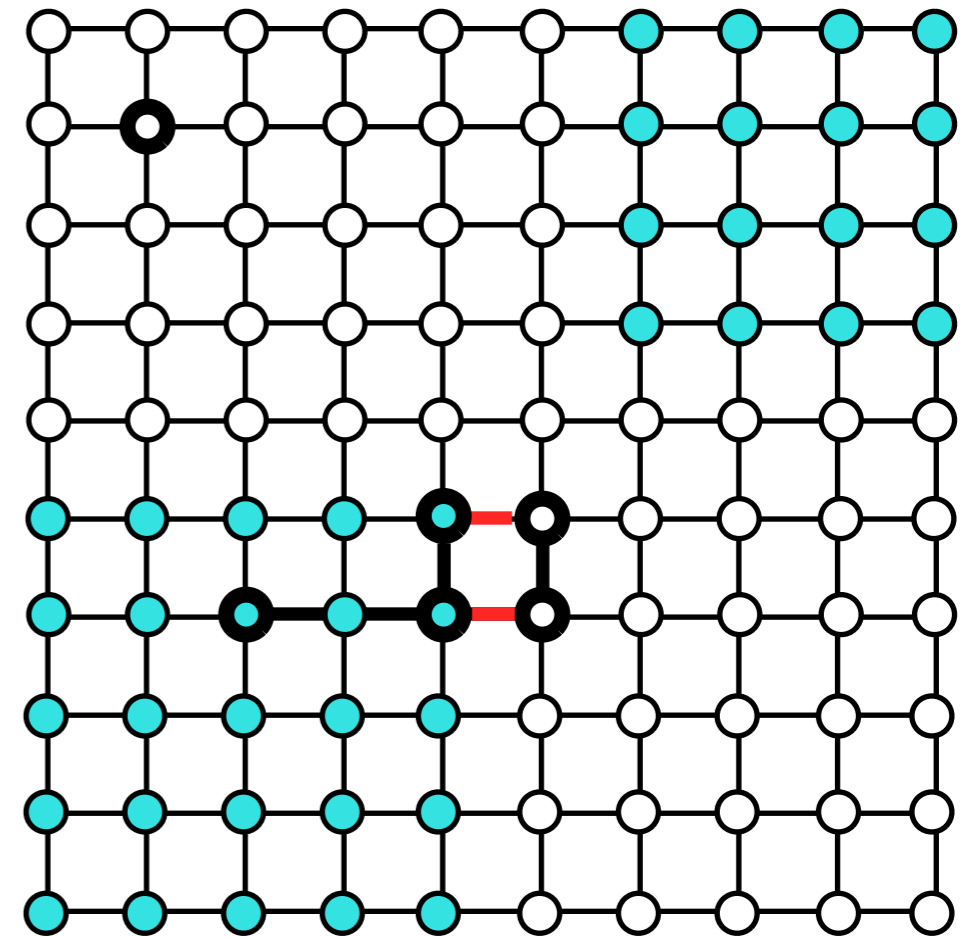
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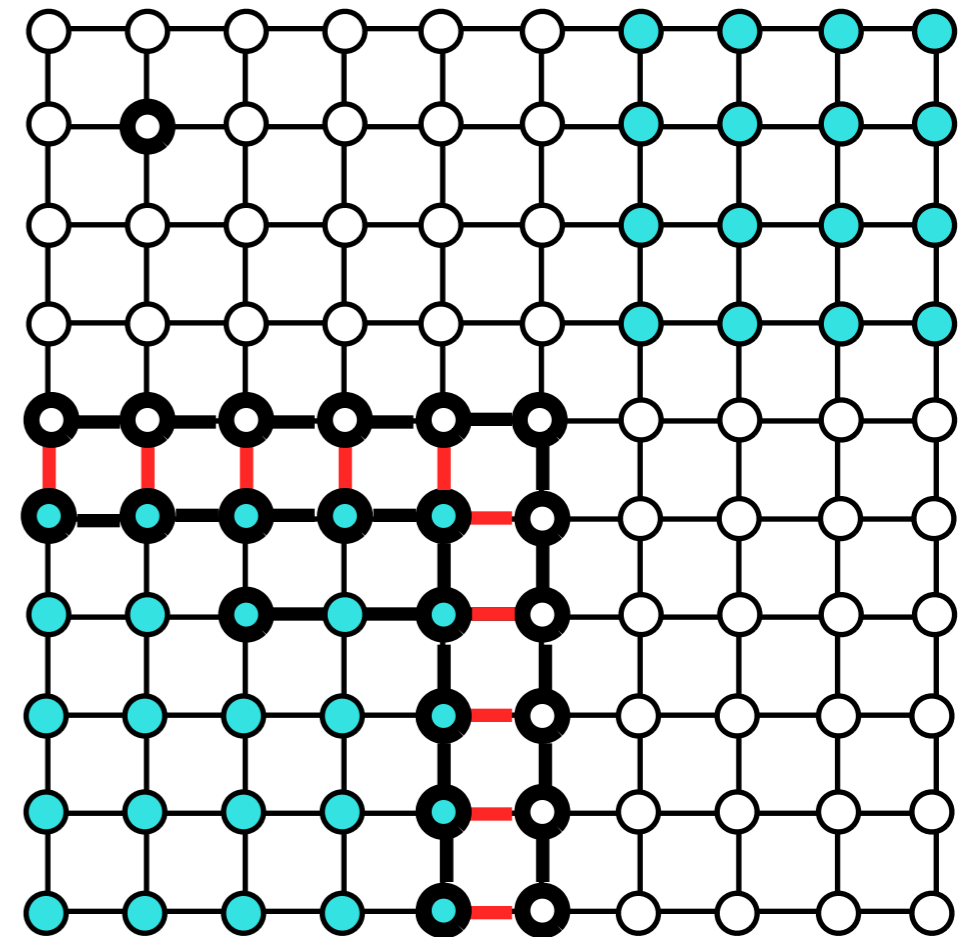
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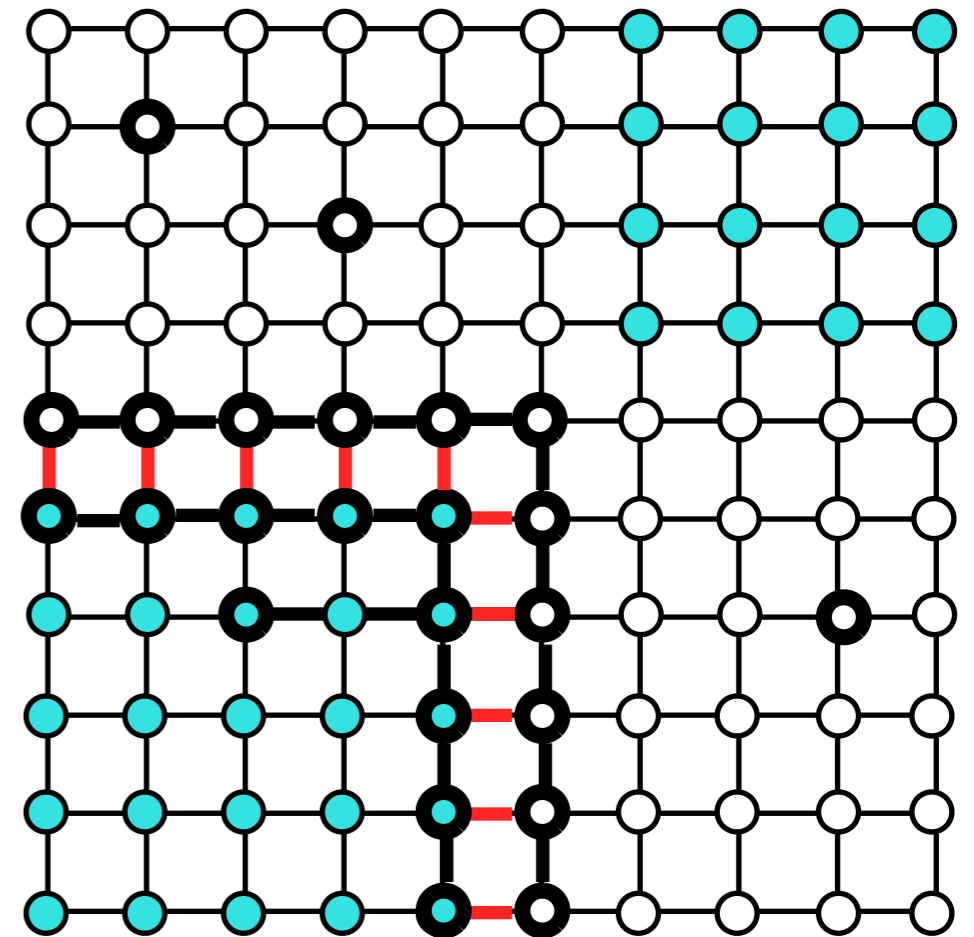
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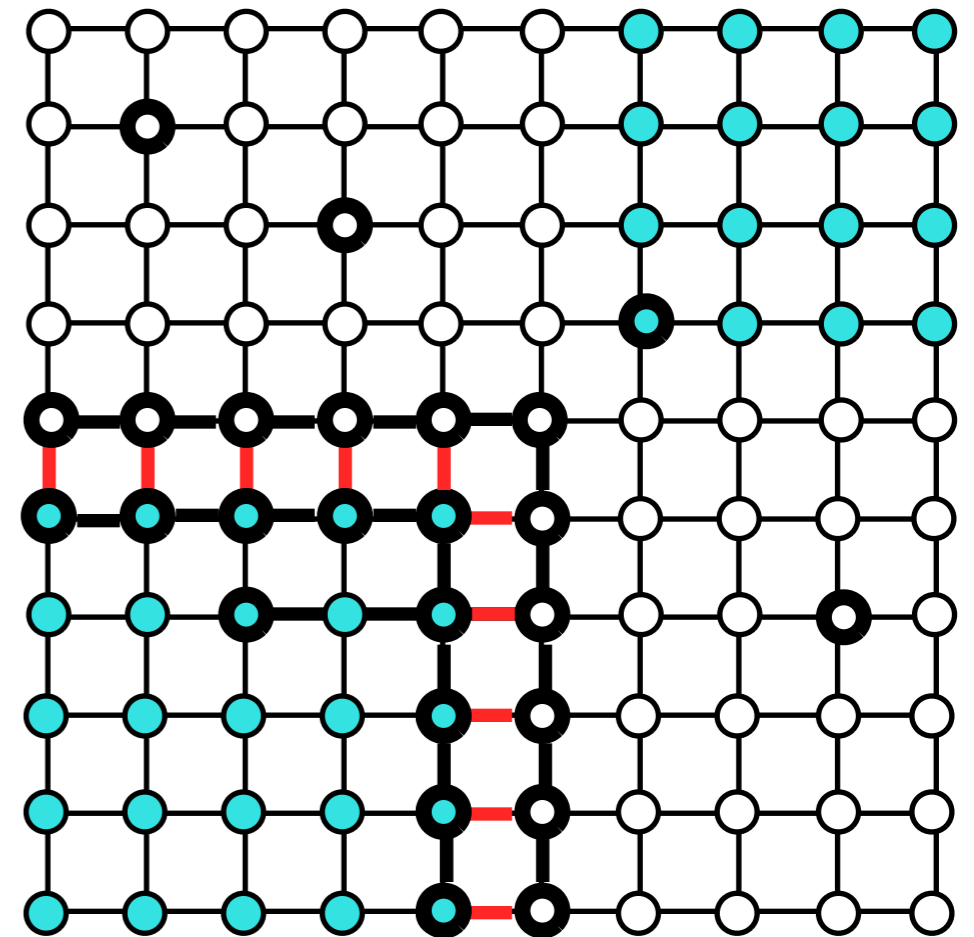
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Randomly query again till we find connected pairs of oppositely labeled vertices

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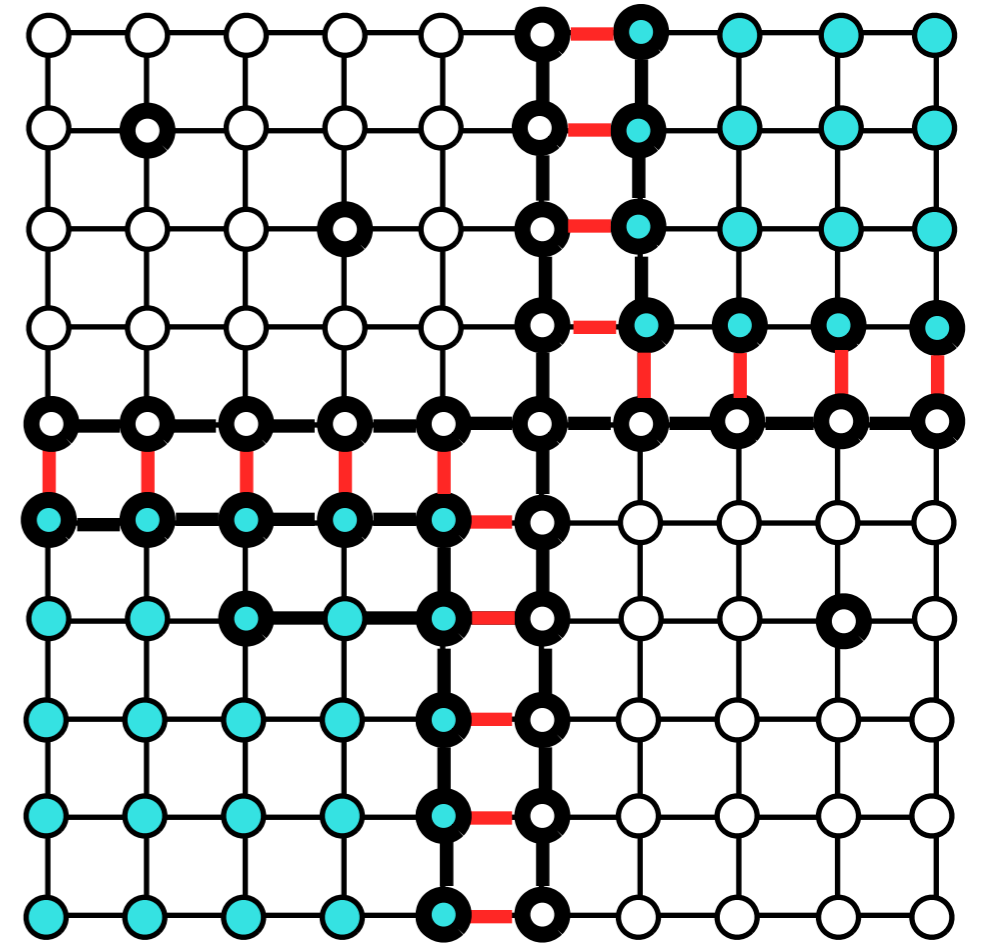
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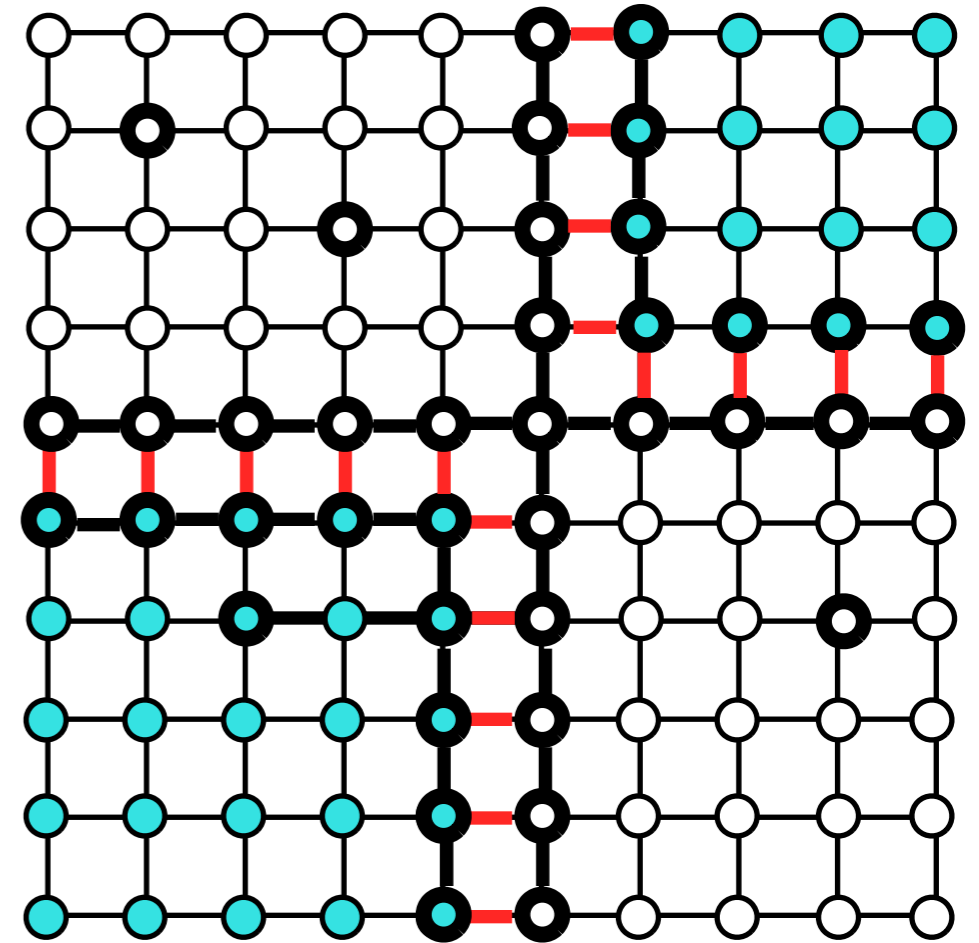
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Back to bisecting shortest shortest paths

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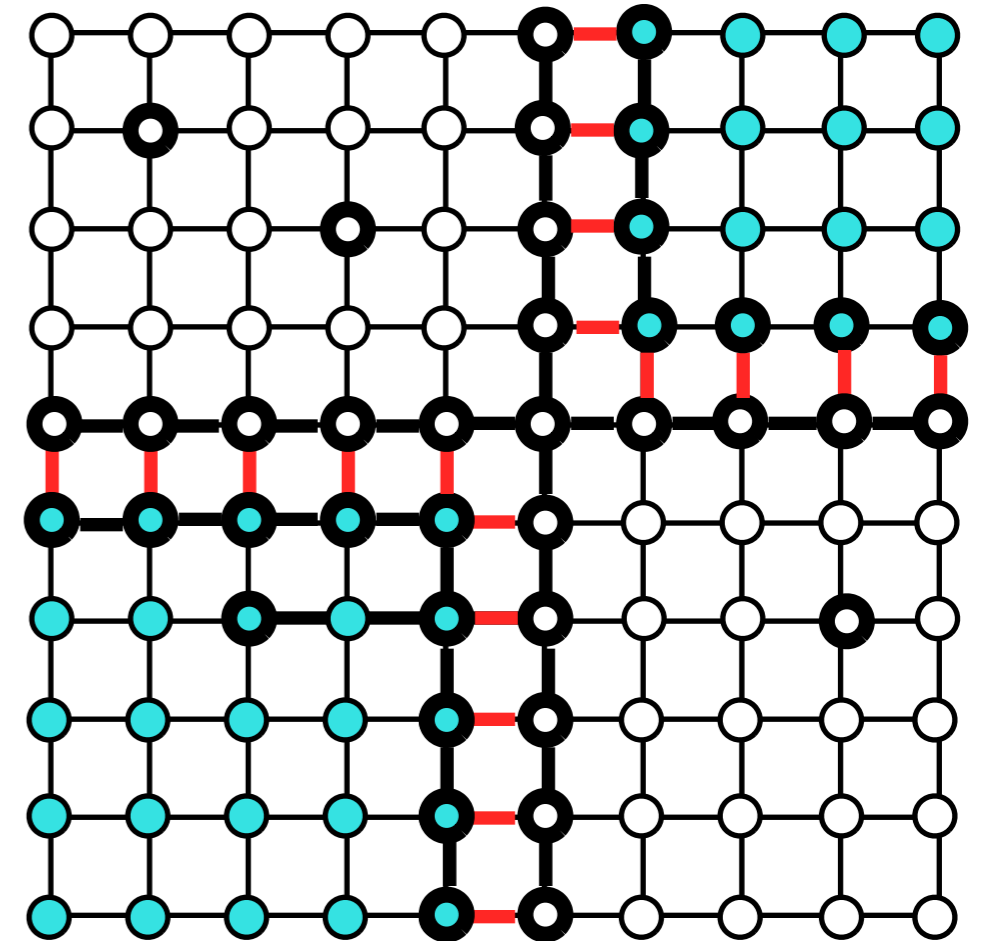
Back to bisecting shortest shortest paths

S^2 thereby very efficiently finds the cut-edges

Visit the poster!

Please visit the poster to:

- Find out about our **novel parametrization of the complexity** of a binary function with respect to the graph.
 - Size of the cut set (boundary) $|\partial C|$
 - Class balancedness β
 - Cut set composed of m sets of cut edges such that each set is κ clustered.



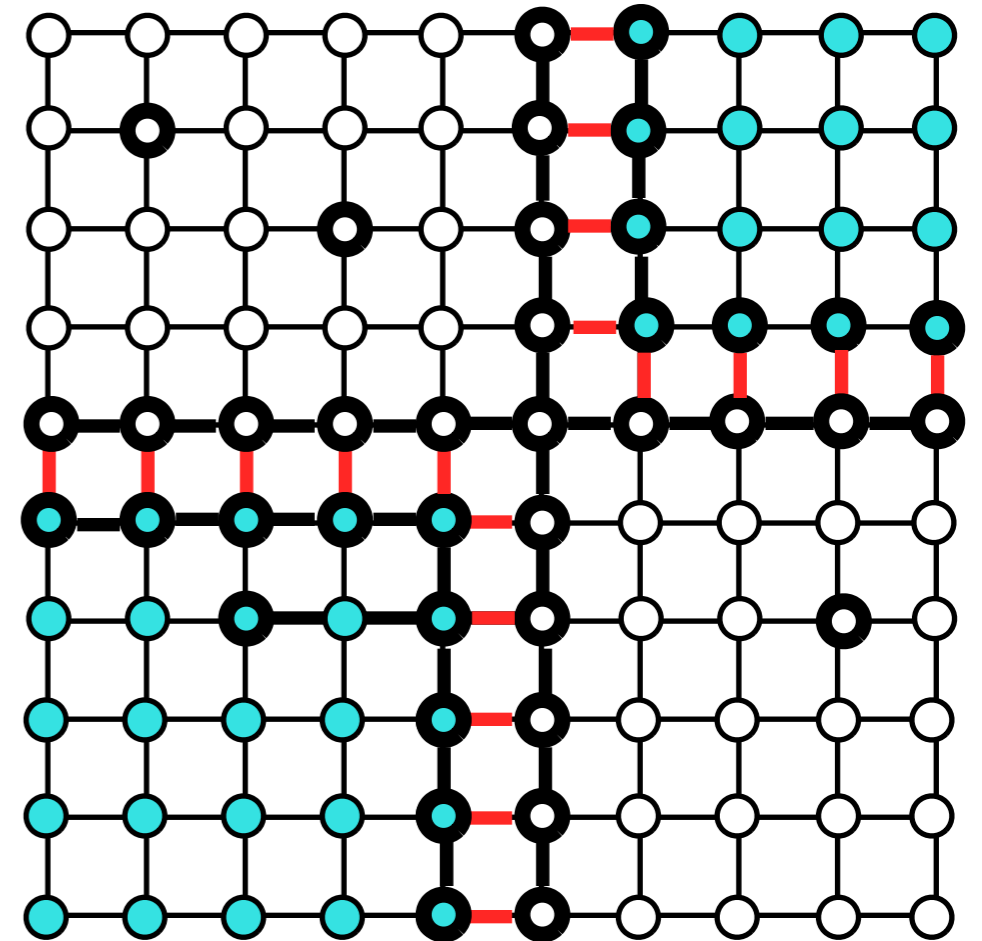
[arXiv : 1506.08760](https://arxiv.org/abs/1506.08760)

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$$\text{Query complexity} \sim \frac{\log(1/\beta\epsilon)}{\log(1/(1-\beta))} + m \log n + |\partial C| \log \kappa$$



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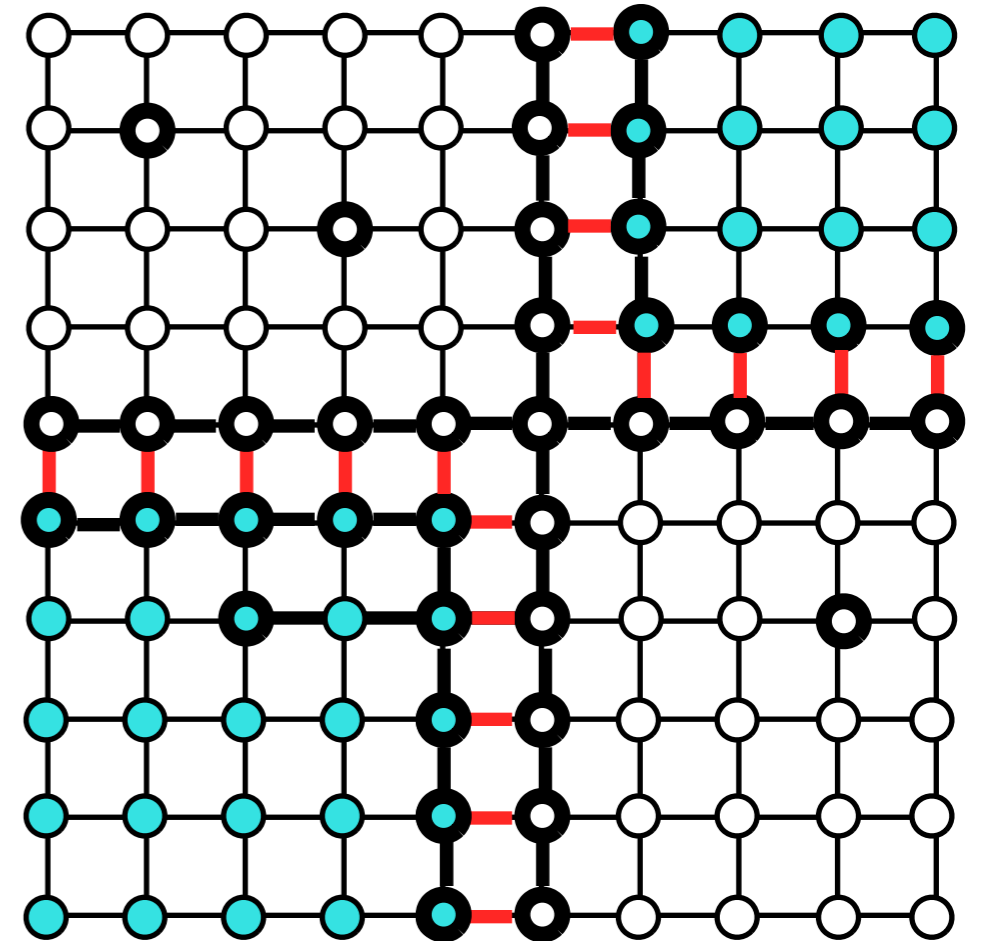
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- Learn how S^2 achieves near minimax optimal sample complexity for **nonparametric active classification.**
 - Consider the lattice graph and run S^2
 - For a broad class of problems (Bayes decision boundary satisfies some regularity condition), sample complexity is

$$\mathcal{O}\left(\left(\frac{\log n}{n}\right)^{1/d-1}\right)$$



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