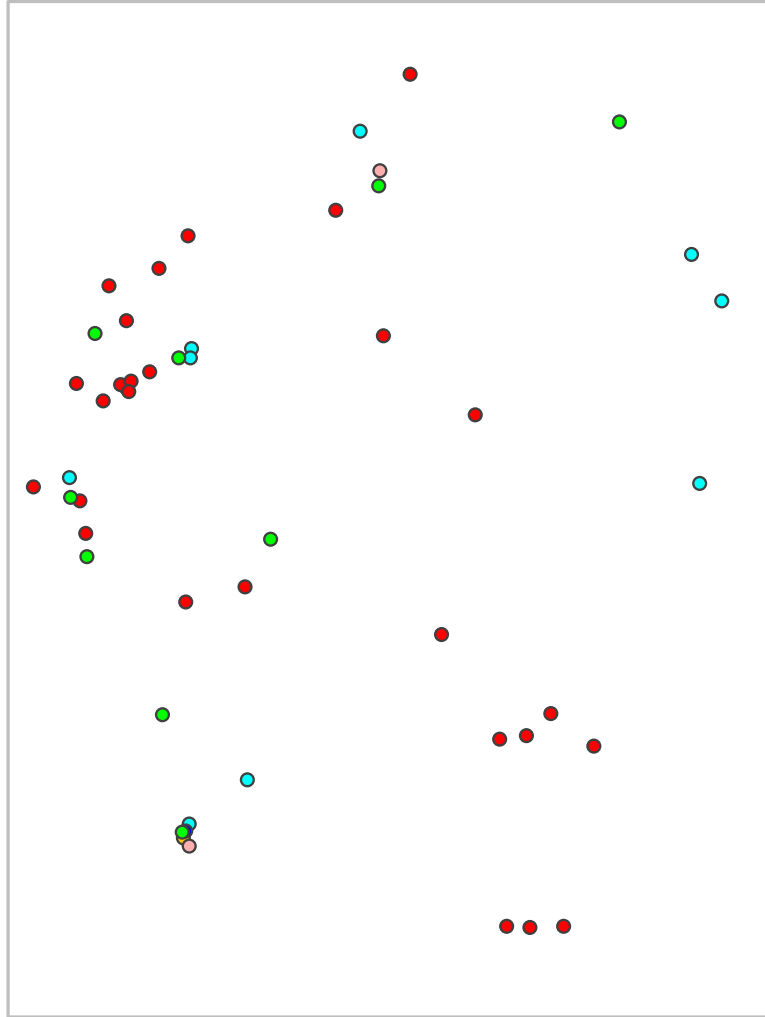


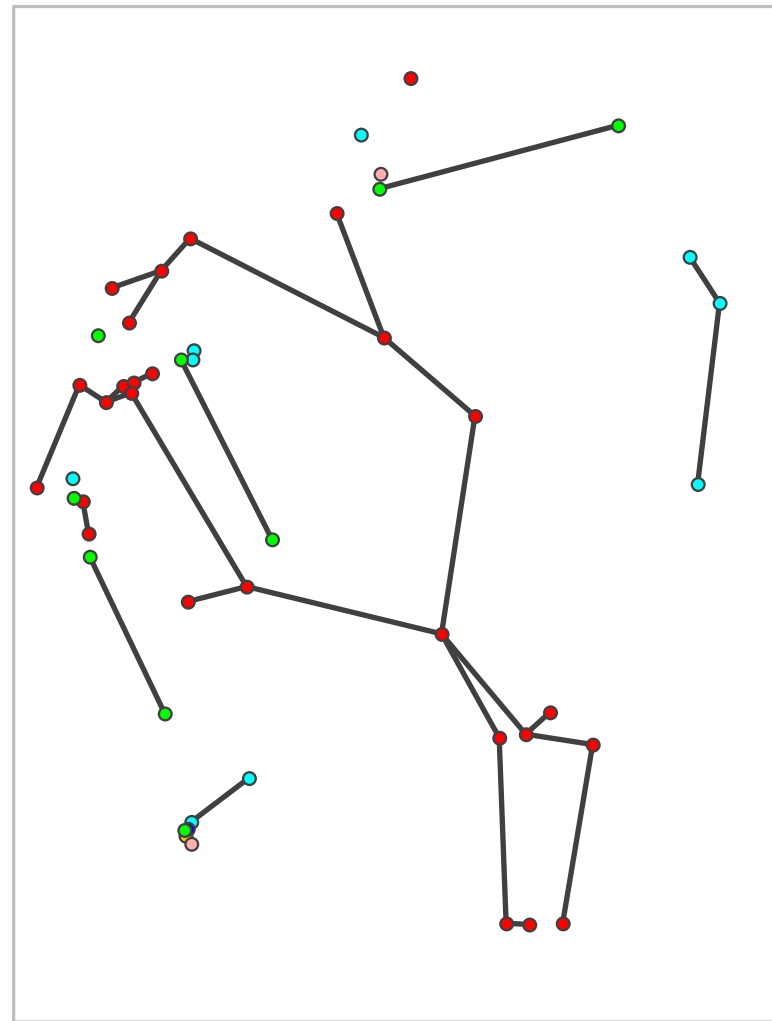
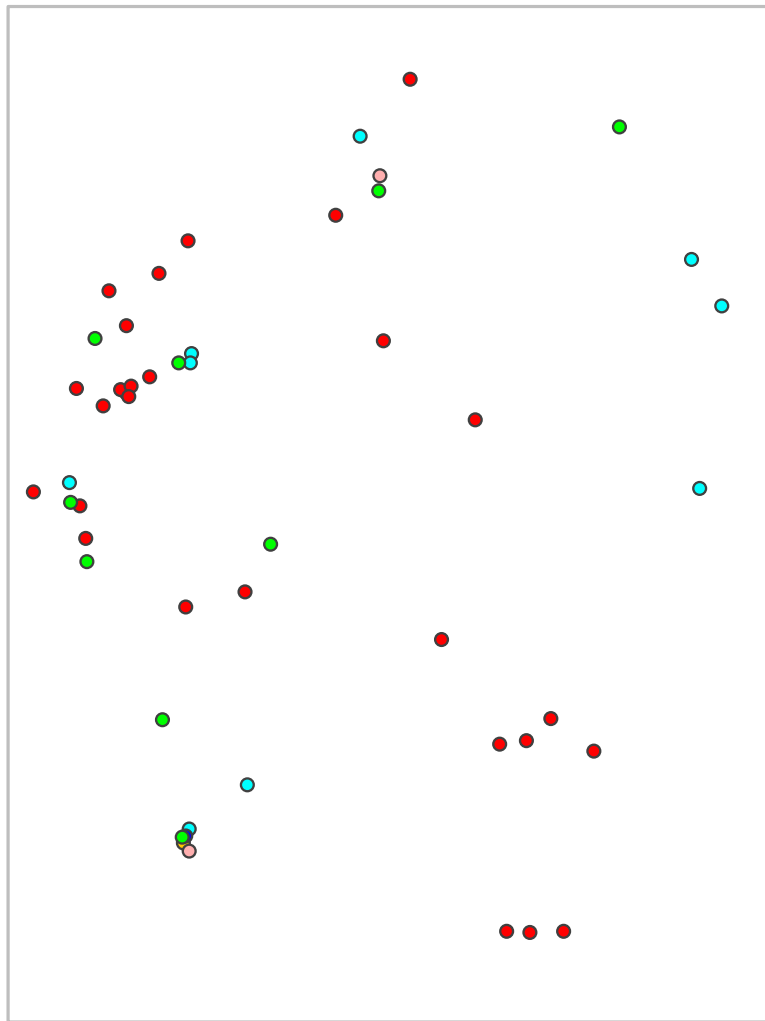
Cluster Minimization in Geometric Graphs

Jakob Geiger

Motivation

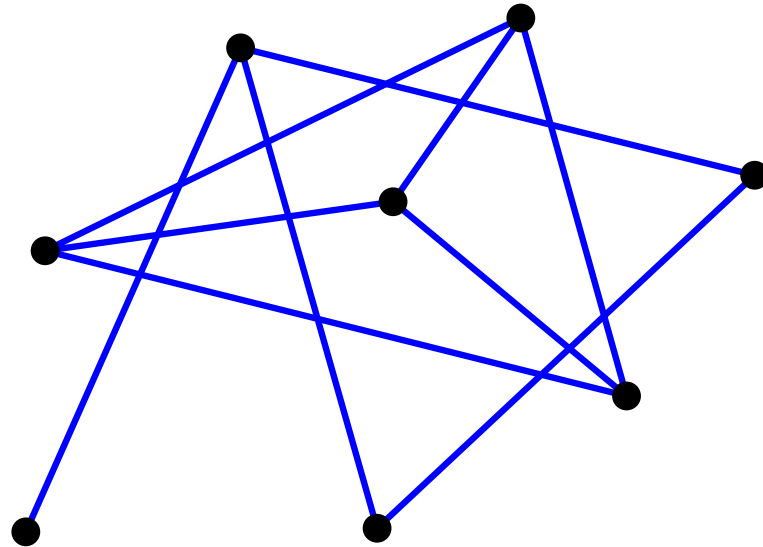


Motivation



Cluster Minimization

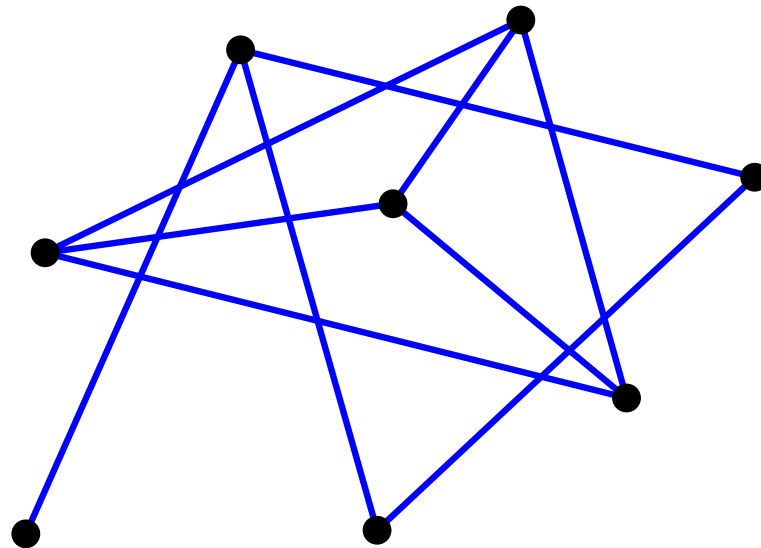
Given: Geometric graph $G = (V, E)$



Cluster Minimization

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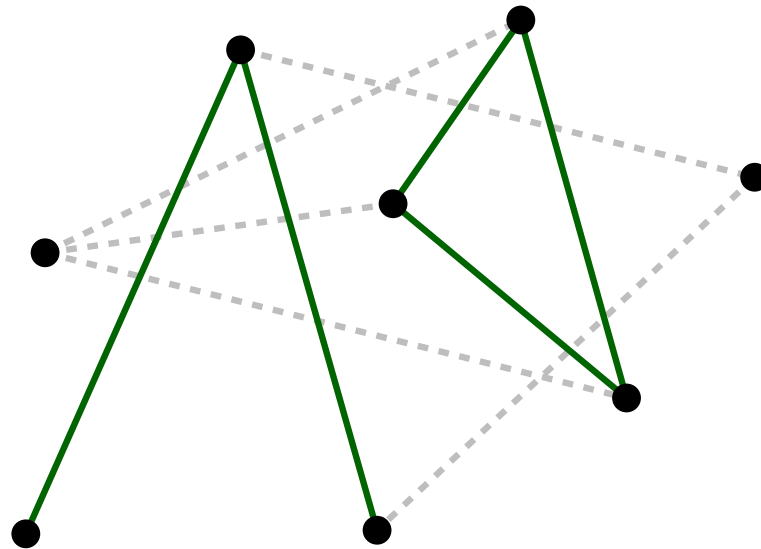
Goal: Find a subgraph $H = (V, E')$ of G such that no two edges in E' cross and the number of connected components in H is minimized.



Cluster Minimization

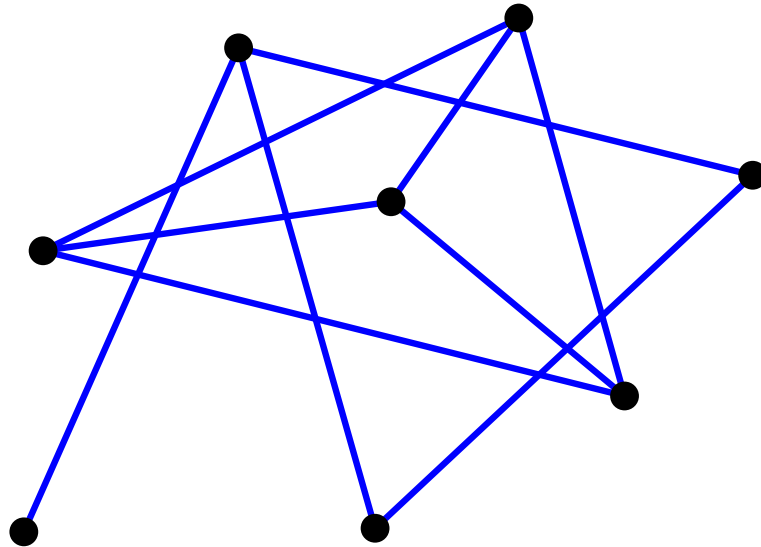
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Edge Maximization

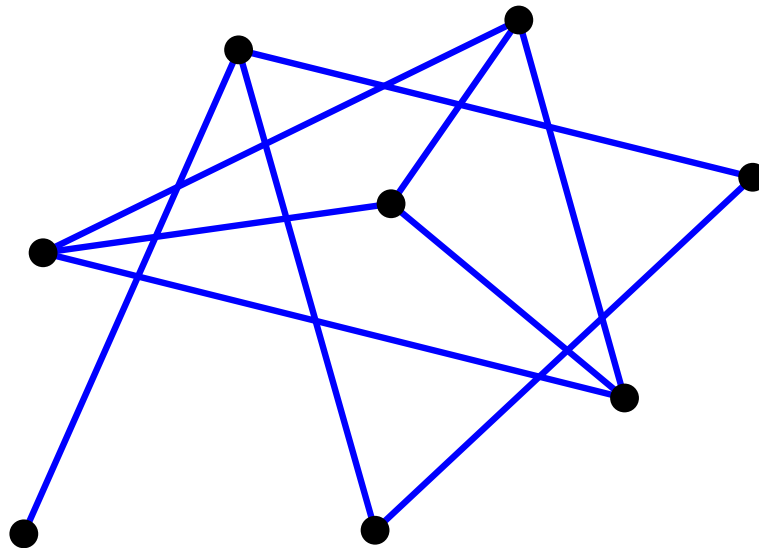
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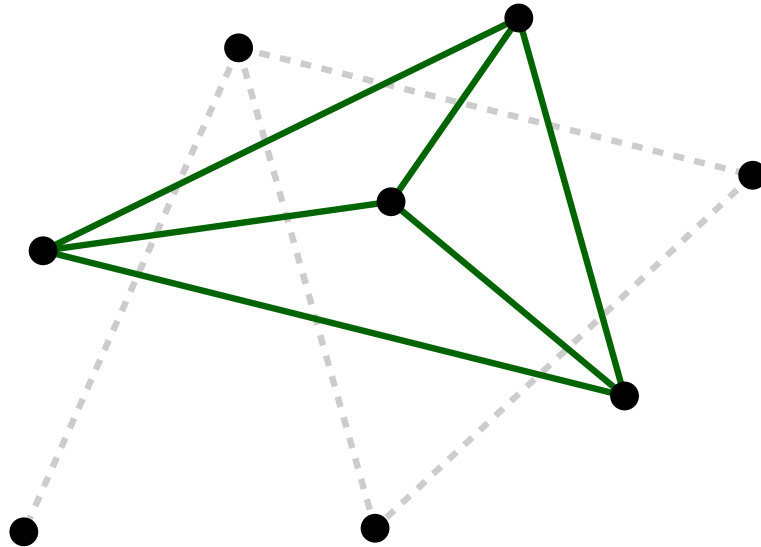
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Edge Maximization

Given: Geometric graph $G = (V, E)$

Goal: Find a subgraph $H = (V, E')$ of G such that no two edges in E' cross and $|E'|$ is maximized.



State of the art

Problem	Quality	Runtime
Cluster Minimization	exact	?
– Greedy	?	polynomial
– 1-plane graphs	exact	polynomial
Edge Maximization	exact	NP-hard

all results by [Akitaya et al. 2019]

My contribution

Problem	Quality	Complexity
Cluster Min.	exact	NP-hard
– Greedy	no const. factor	$n + k + m \log m$
– Rev. Greedy	no const. factor	$n + k \log k + m \log m$
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Edge Max.	exact	NP-hard

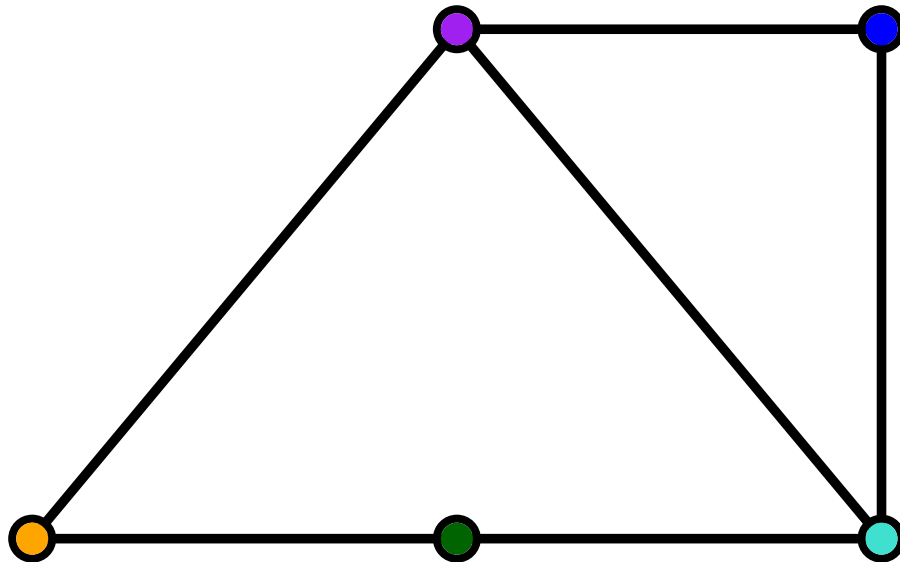
NP-Hardness

Independent Set \leq_p Cluster Minimization

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Independent Set \leq_p Cluster Minimization

- Given an instance of Independent Set,

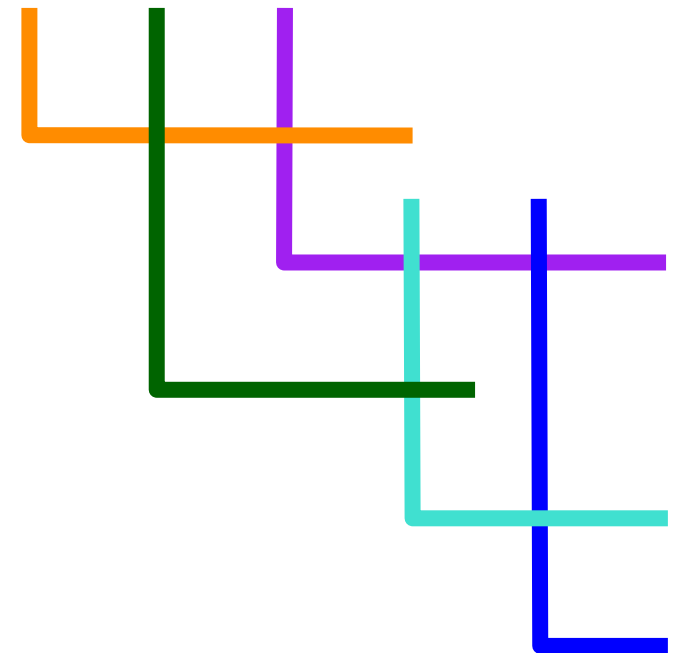
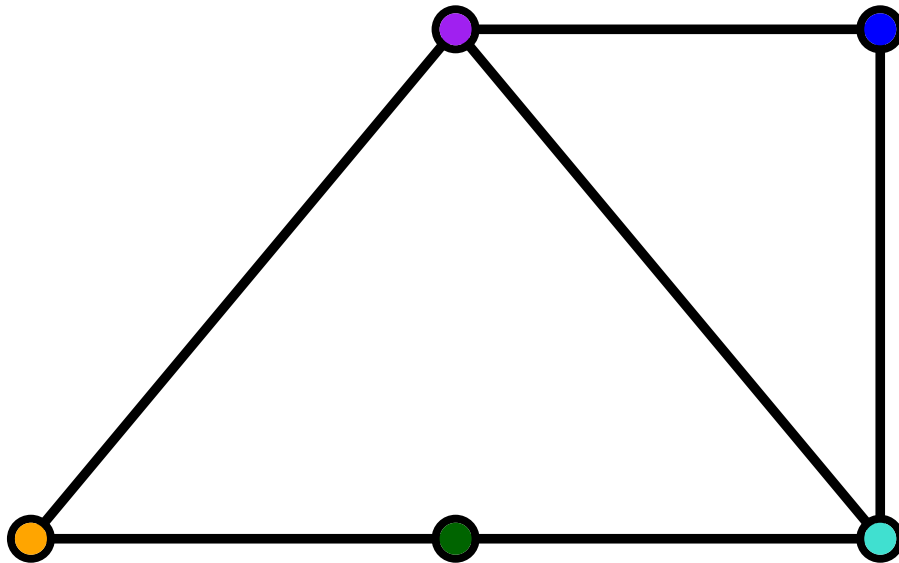


NP-Hardness

Independent Set \leq_p Cluster Minimization

- Given an instance of Independent Set,
- Construct an equivalent L-shape intersection graph...

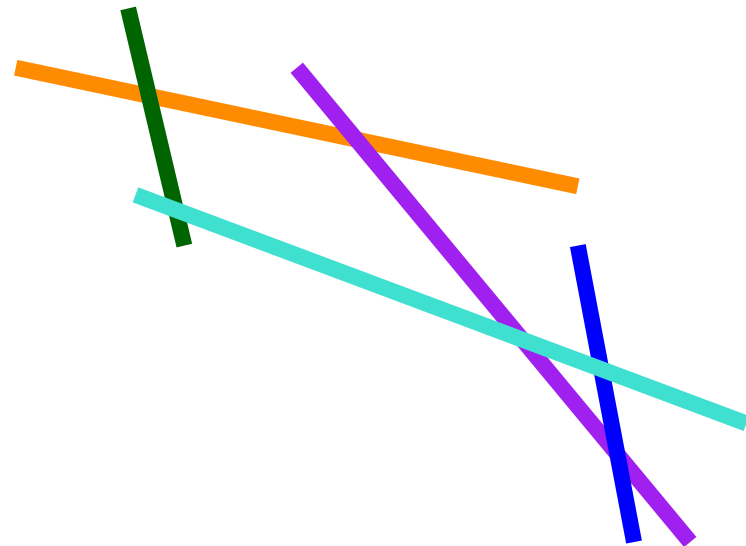
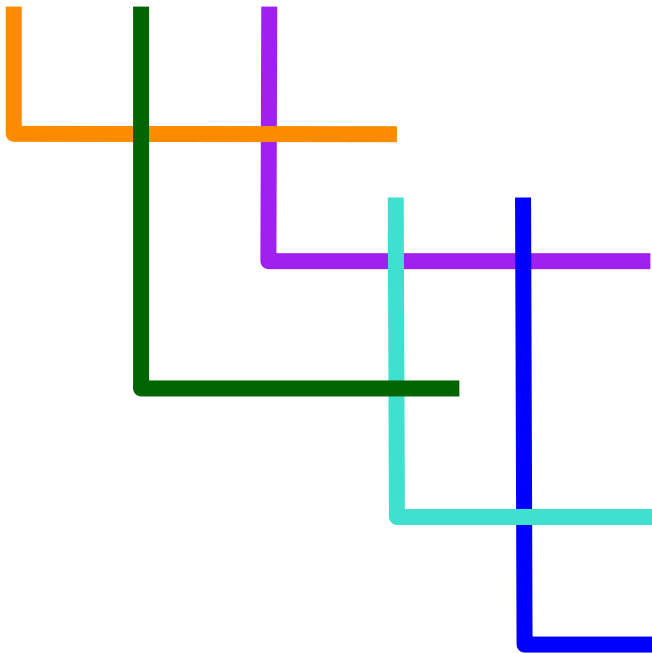
[Gonçalves et al. 2018]



NP-Hardness

Independent Set \leq_p Cluster Minimization

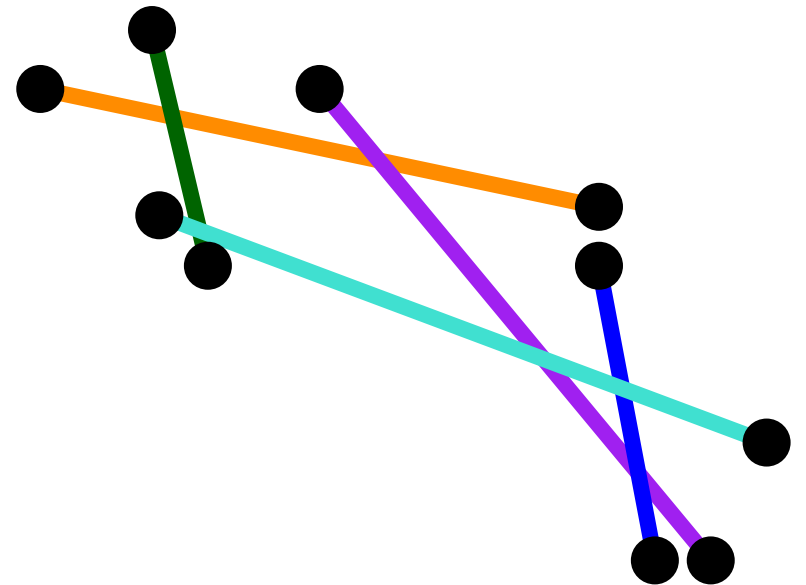
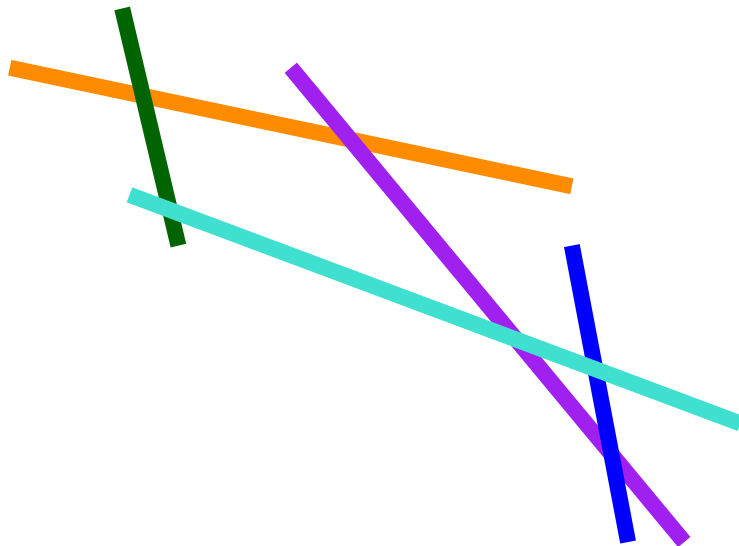
- Given an instance of Independent Set,
- Construct an equivalent L-shape intersection graph... [Biedl 2020]
- ... then construct an equivalent segment intersection graph.



NP-Hardness

Independent Set \leq_p Cluster Minimization

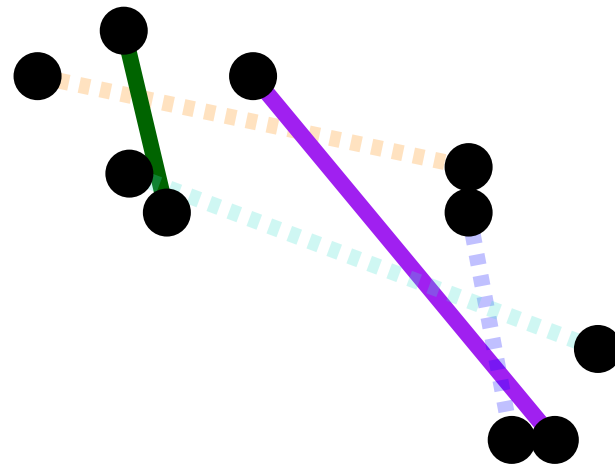
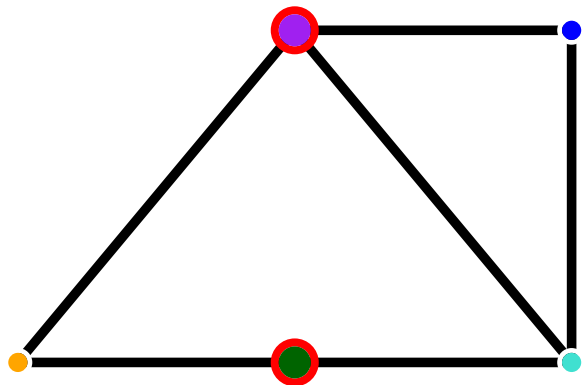
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- Use the segments as edges in a geometric graph and place vertices at each endpoint.



NP-Hardness

Independent Set \leq_p Cluster Minimization

- Given an instance of Independent Set,
- Construct an equivalent L-shape intersection graph...
- ... then construct an equivalent segment intersection graph.
- Use the segments as edges in a geometric graph and place vertices at each endpoint.
- In the resulting geometric graph, a solution with $2n - k$ clusters represents an independent set of size k .



Heuristics

Greedy: Iteratively select the least crossed edge

Heuristics

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Reverse Greedy: Iteratively delete the most crossed edge

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Preprocessing: compute all edge crossings

Heuristics

Greedy: Iteratively select the least crossed edge

Reverse Greedy: Iteratively delete the most crossed edge

Preprocessing: compute all edge crossings

$\Rightarrow O(k + m \log m)$ [Balaban 1995]

Greedy

Iteratively select the least crossed edge

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Use Union-Find to manage clusters

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Use Union-Find to manage clusters $\Rightarrow O(n + m\alpha(m))$

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\Rightarrow Fibonacci-Heap!

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REMOVE	$O(\log n)^*$
EXTRACTMIN	$O(\log n)^*$
DECREASEKEY	$O(1)^*$

*amortized

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1-plane graphs: $m, k \in O(n)$

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\Rightarrow Fibonacci-Heap! $\Rightarrow O(k + m \log m)$

Overall Runtime: $O(n + k + m \log m)$

1-plane graphs: $m, k \in O(n)$

\Rightarrow Overall runtime reduces to $O(n \log n)$!

Reverse Greedy

Iteratively delete the most crossed edge

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Reverse Greedy

Iteratively delete the most crossed edge

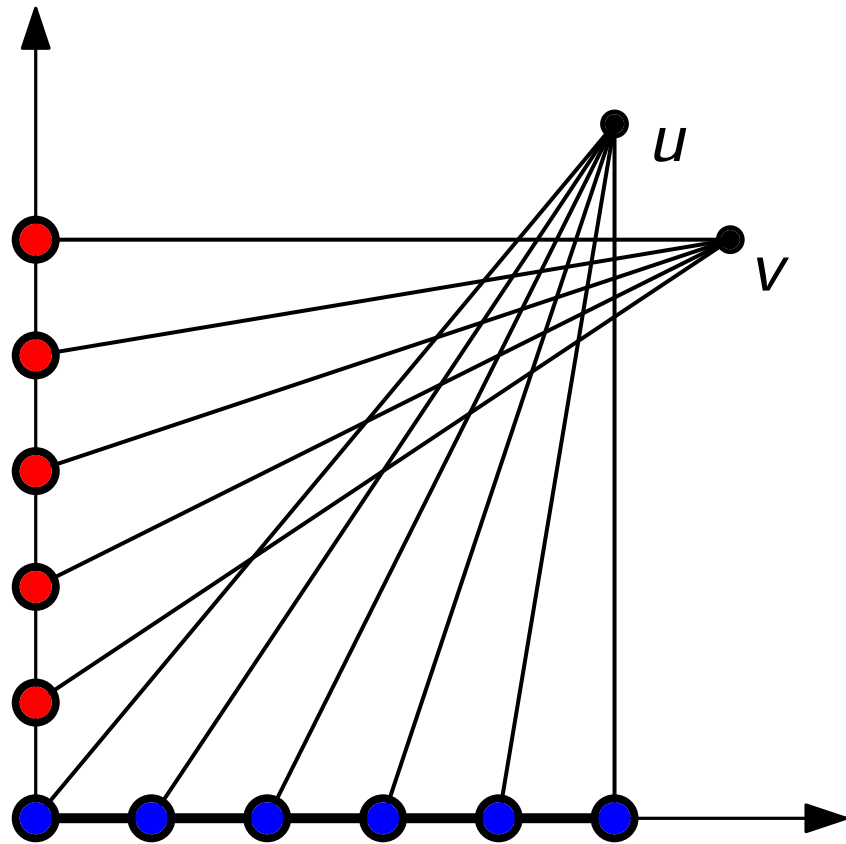
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Overall Runtime: $O(n + k \log k + m \log m)$

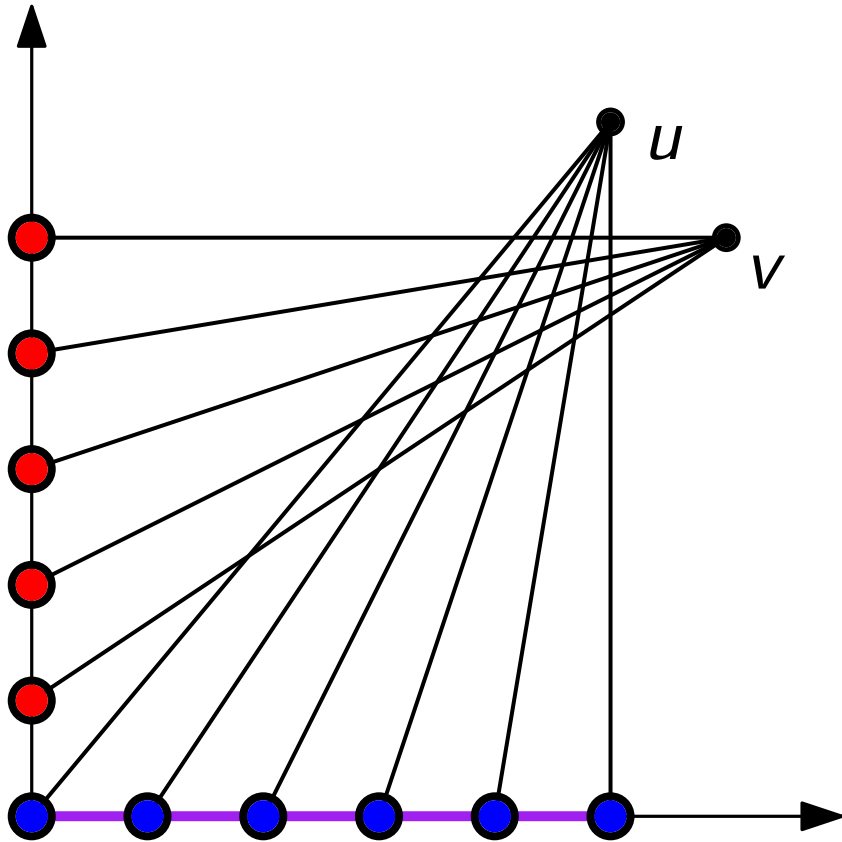
Performance Analysis – Theoretical



n red, $n + 1$ blue vertices

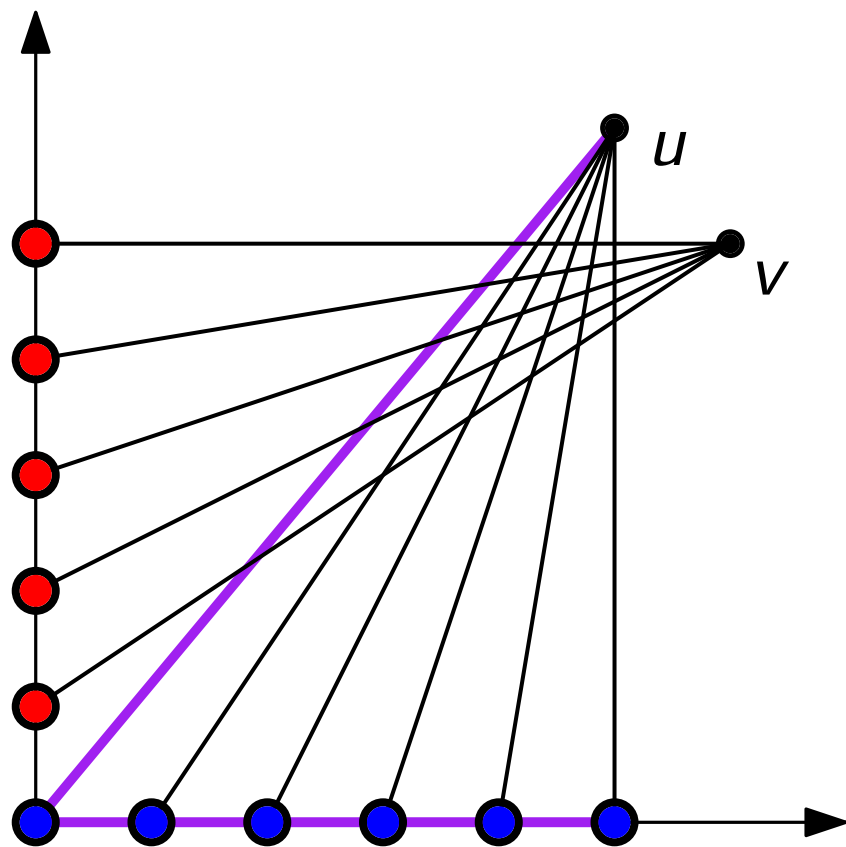
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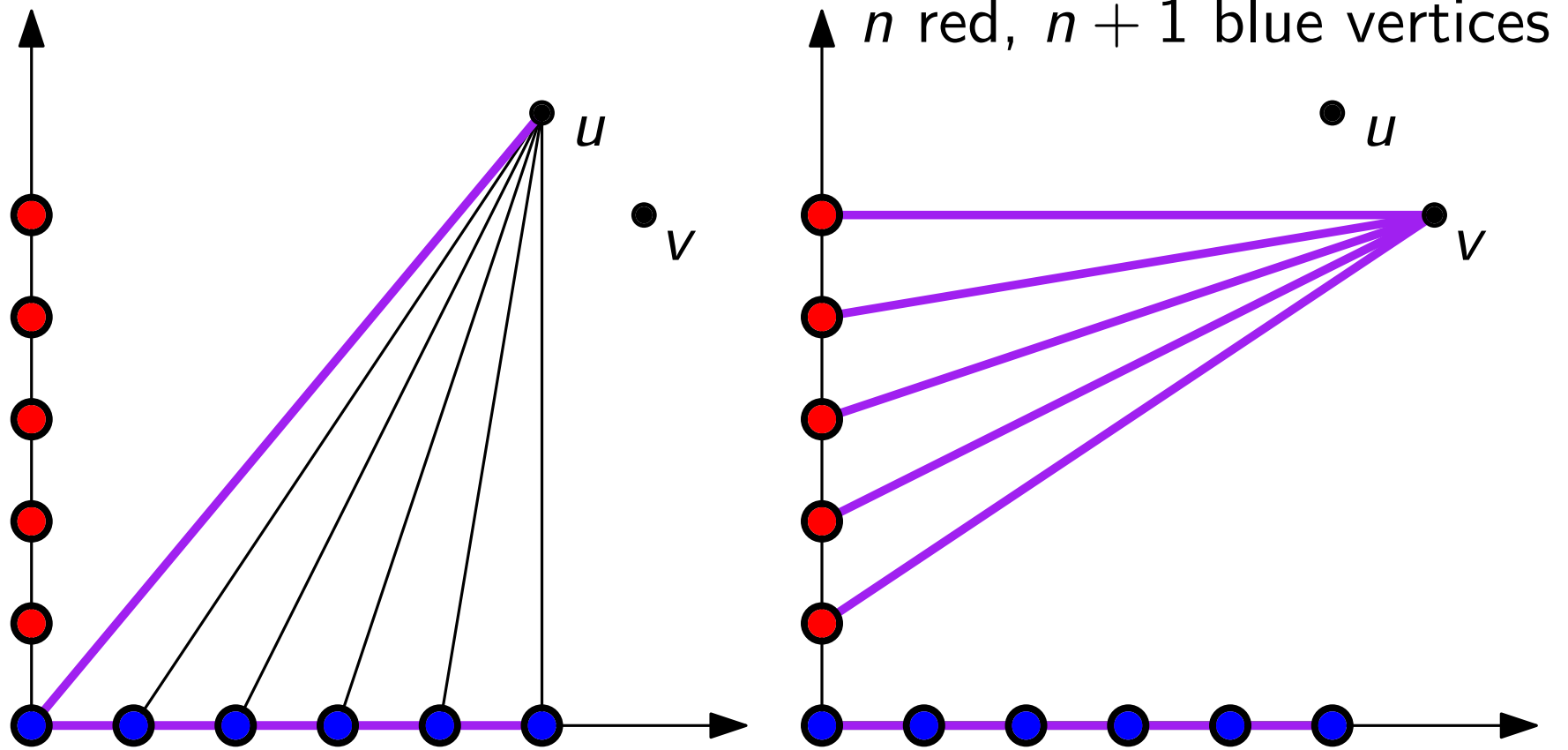


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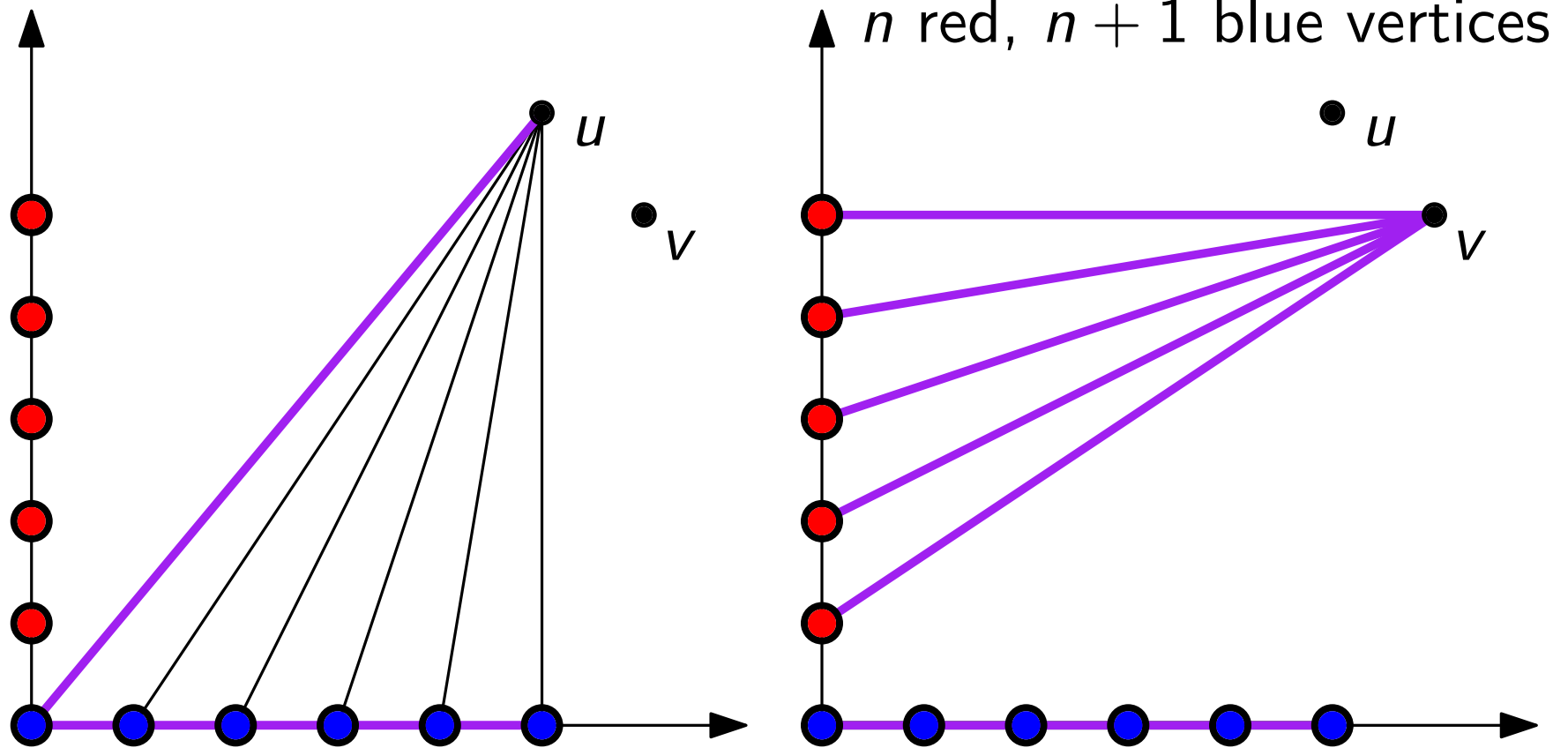


Performance Analysis – Theoretical



Greedy/Reverse Greedy: $n + 2$ clusters

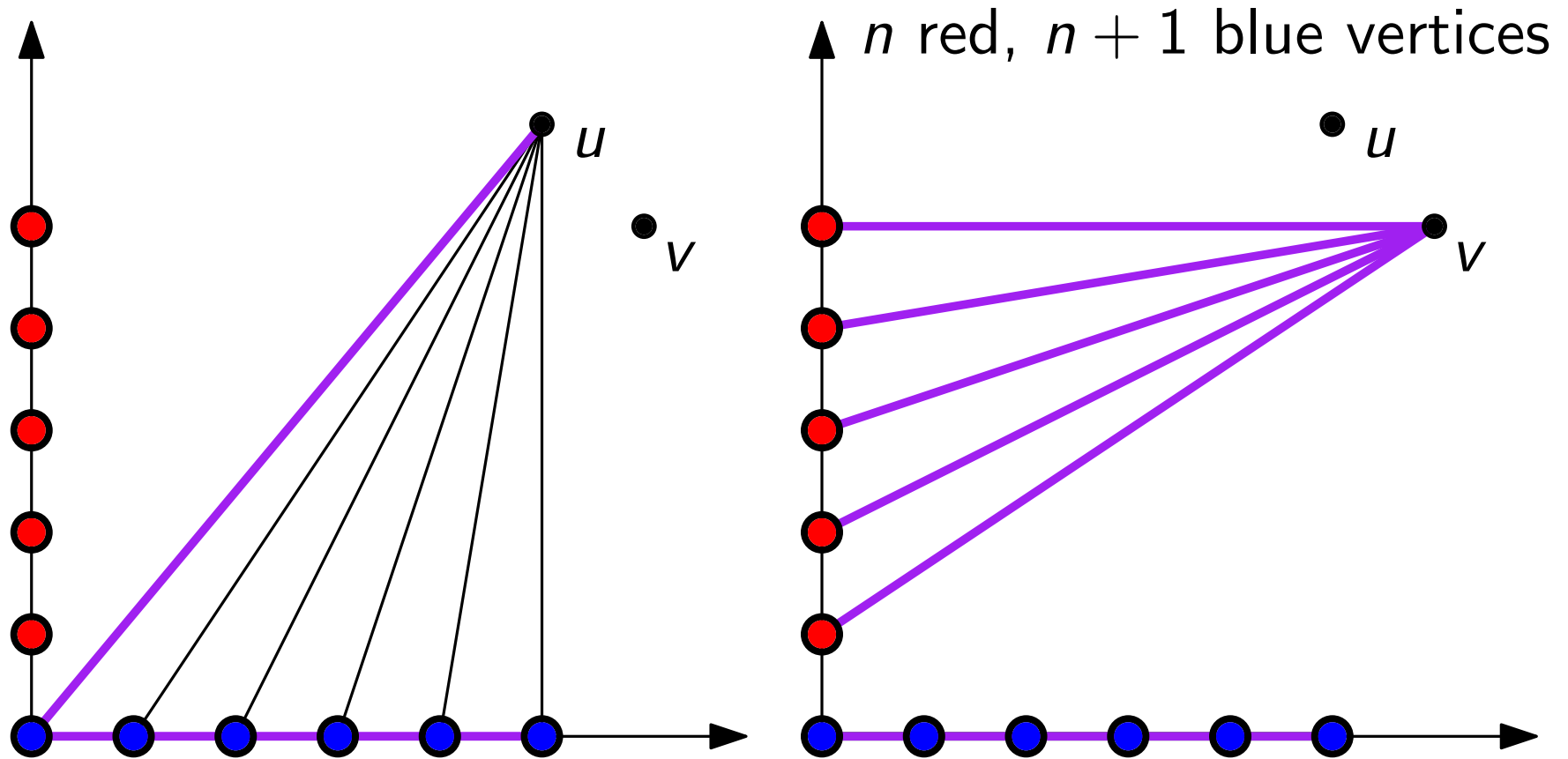
Performance Analysis – Theoretical



Greedy/Reverse Greedy: $n + 2$ clusters

Optimal solution:

Performance Analysis – Theoretical

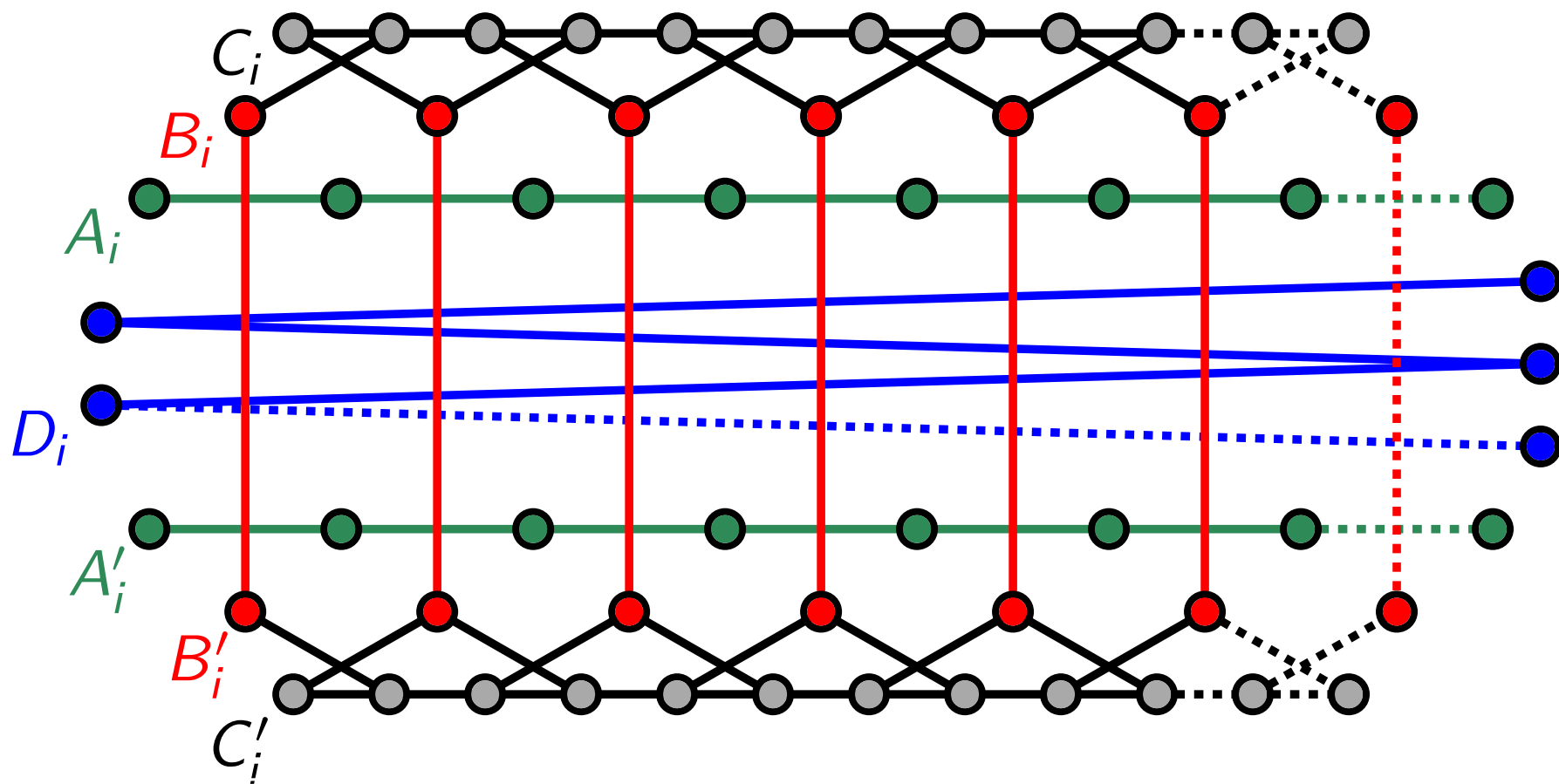


Greedy/Reverse Greedy: $n + 2$ clusters

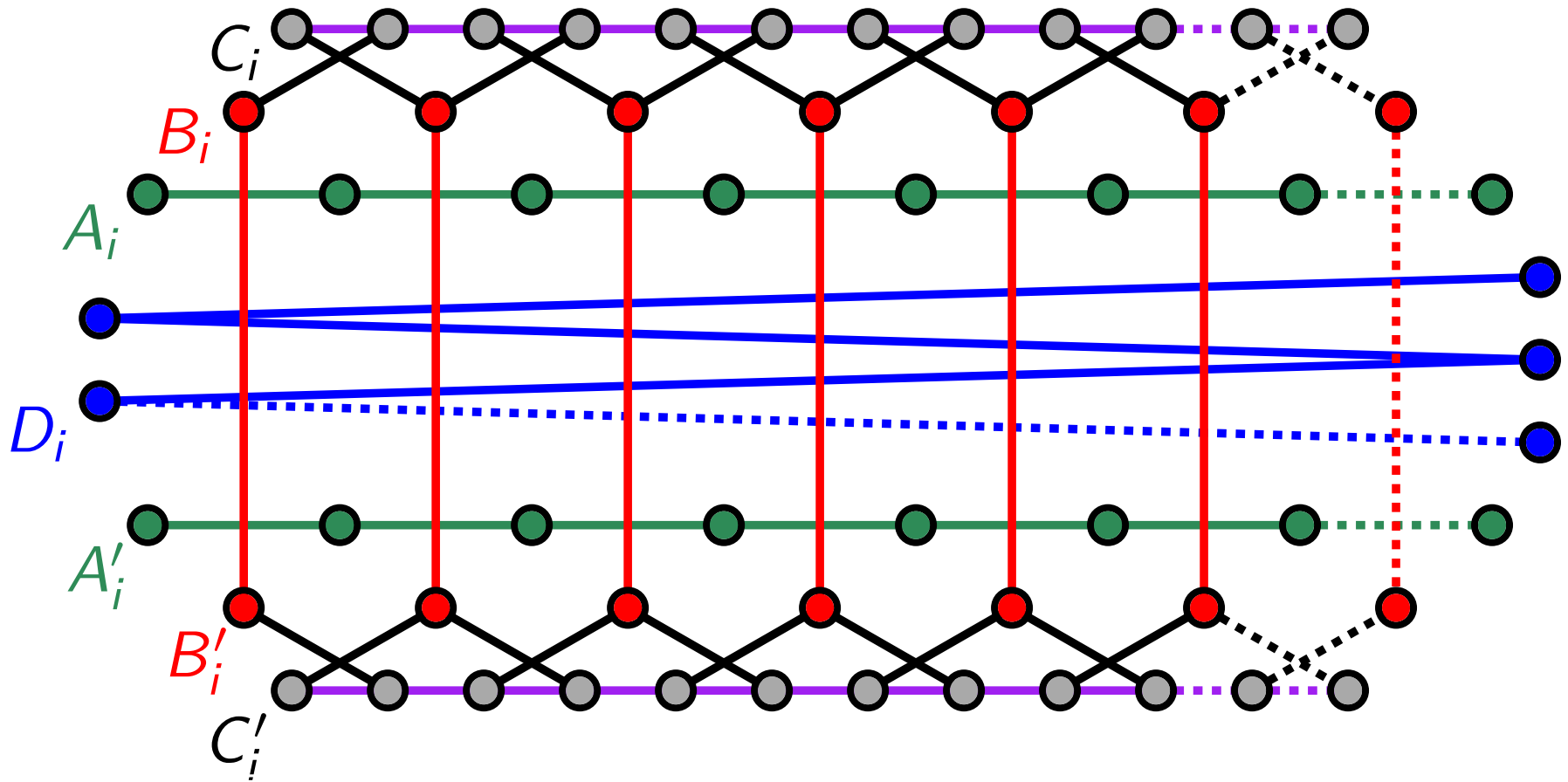
Optimal solution: 4 clusters

⇒ no constant approximation factor for both heuristics!

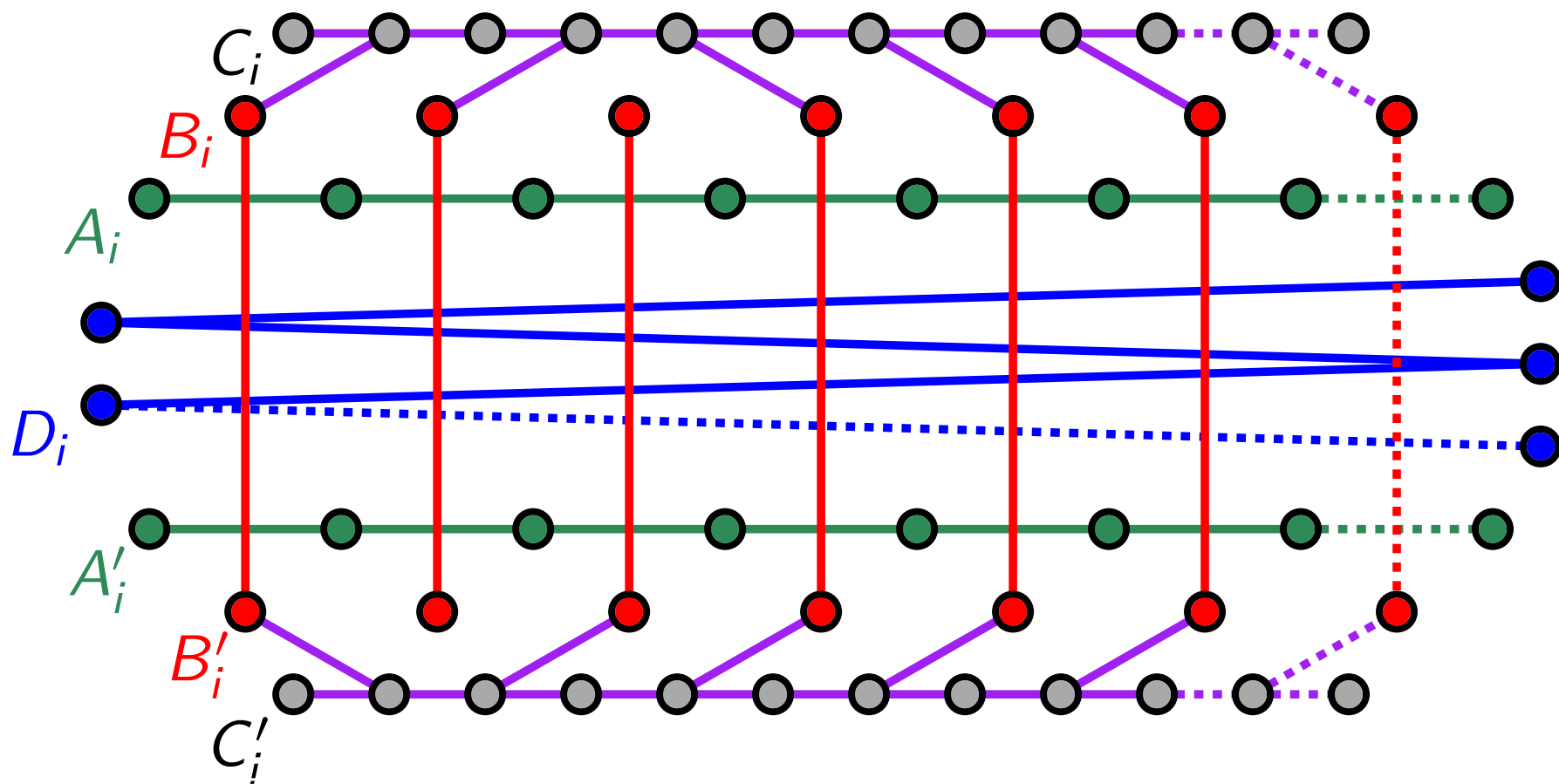
Performance – Greedy vs. Reverse Greedy



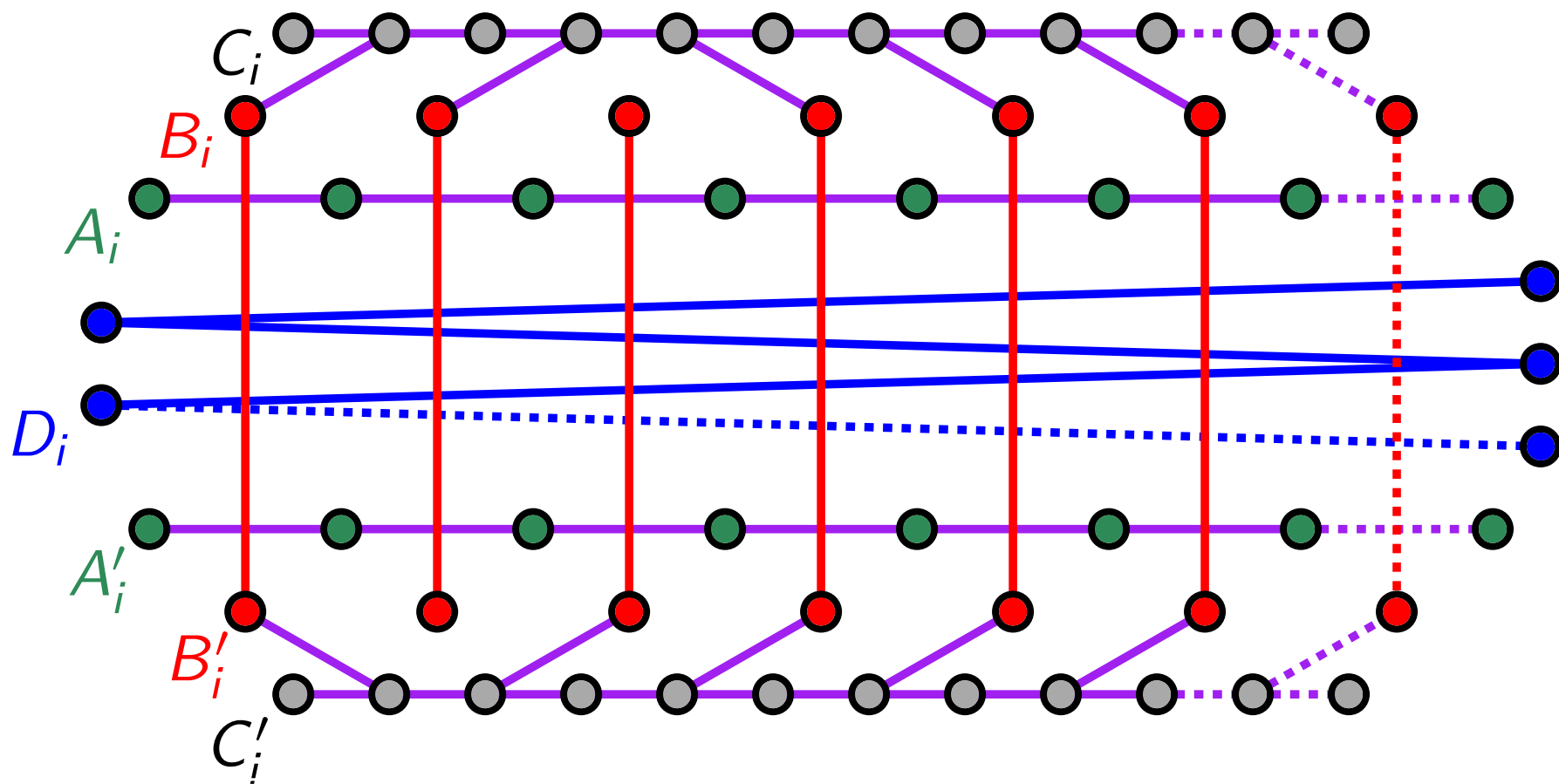
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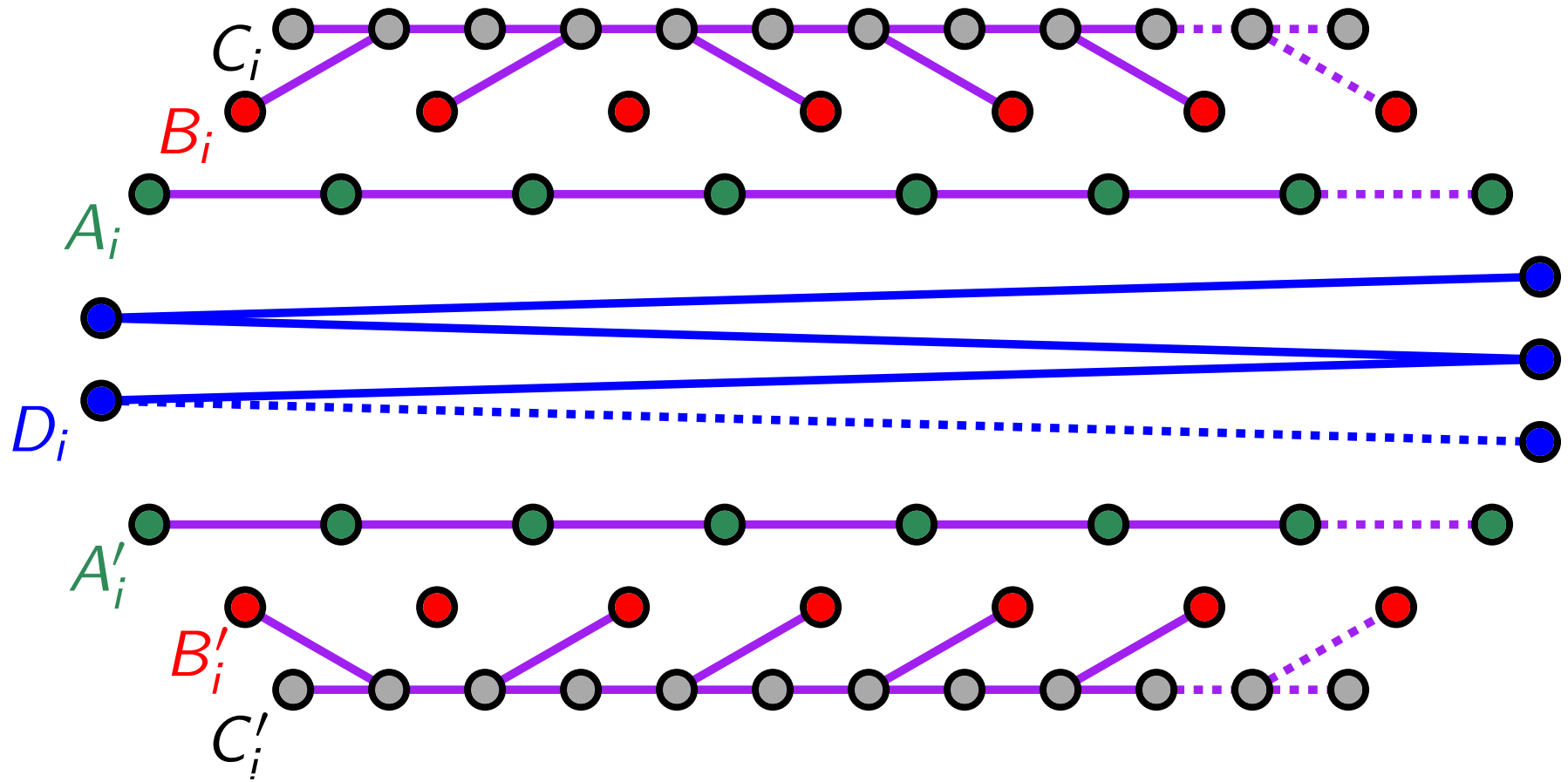
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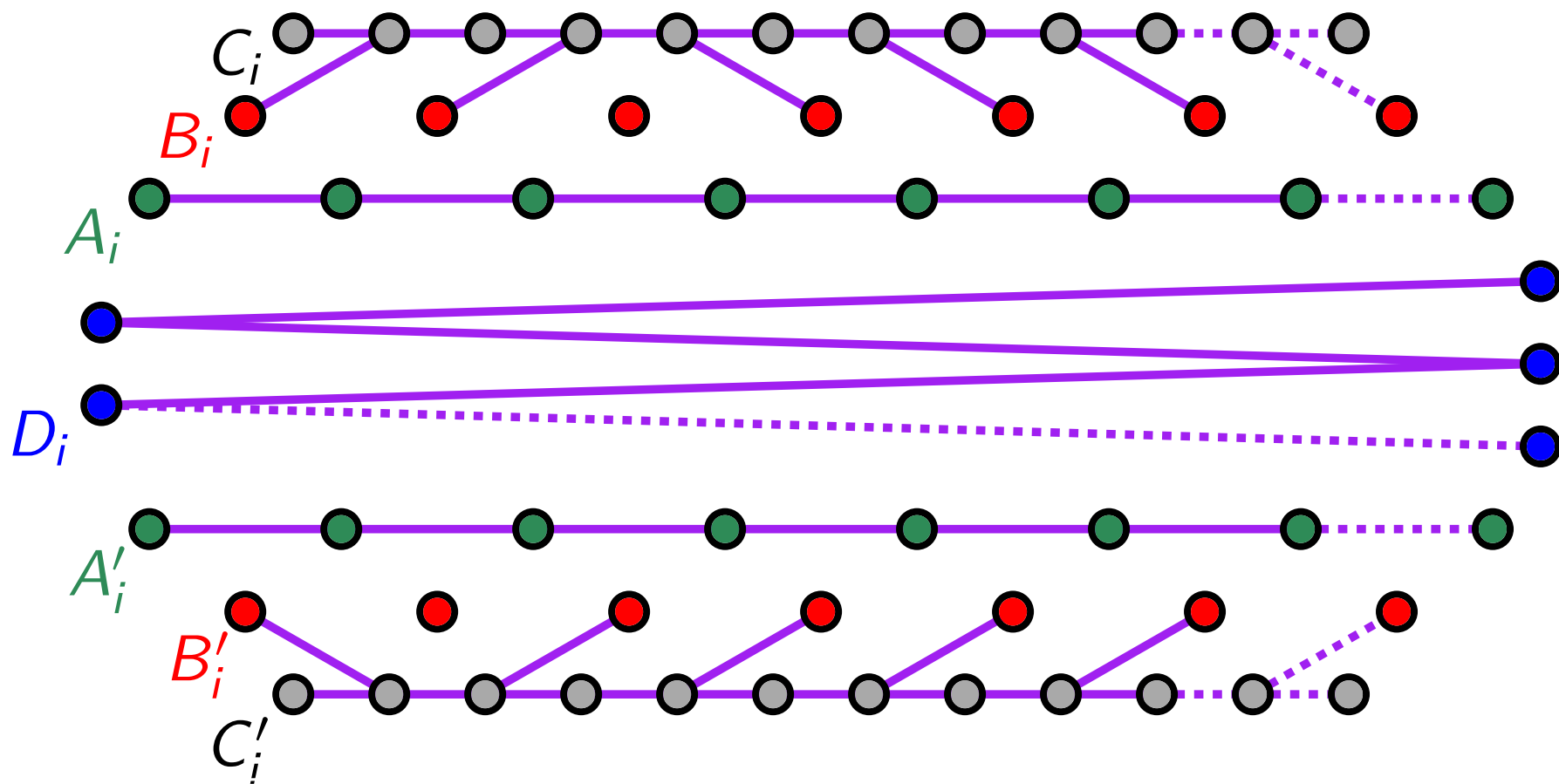
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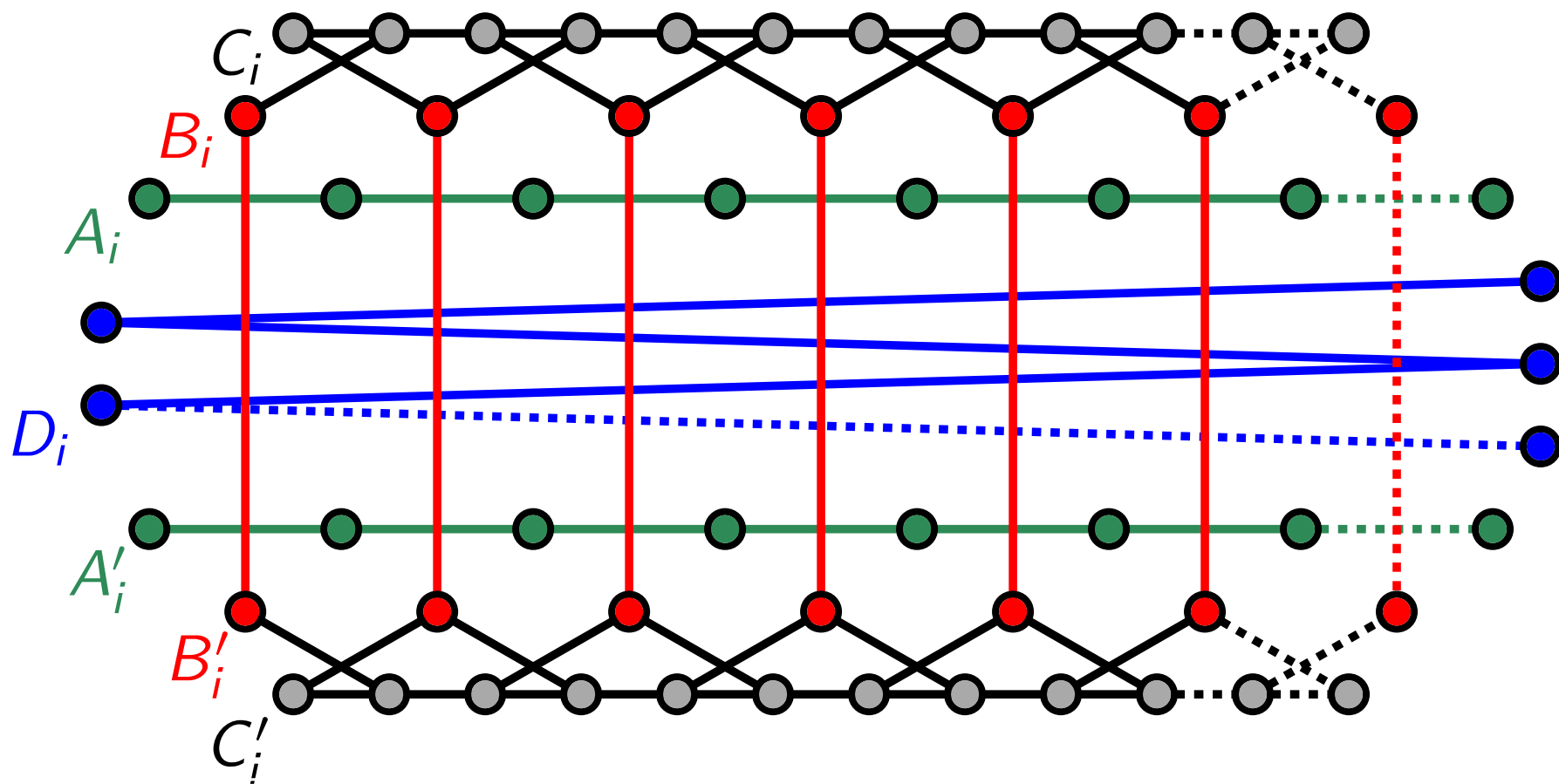
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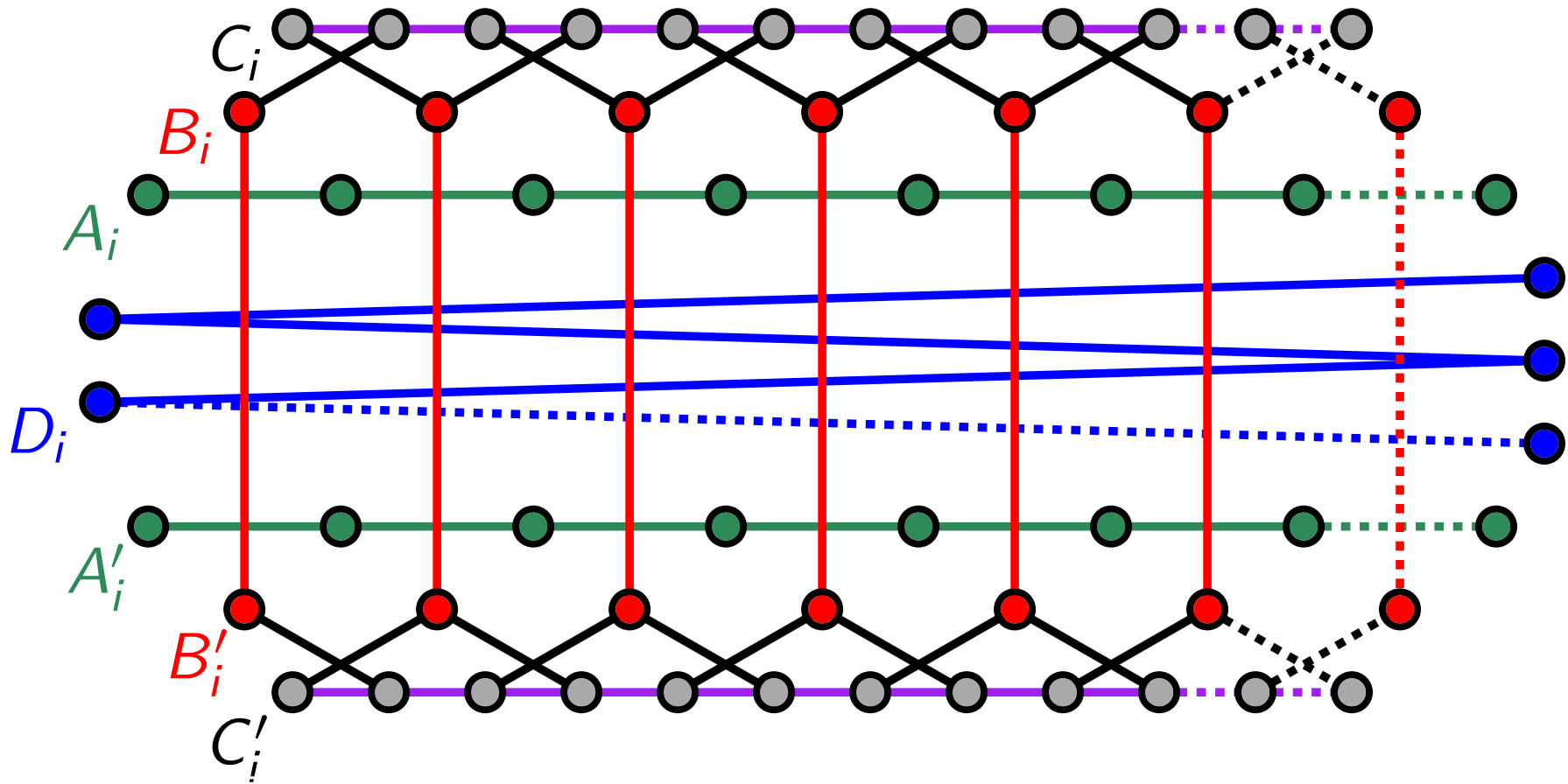
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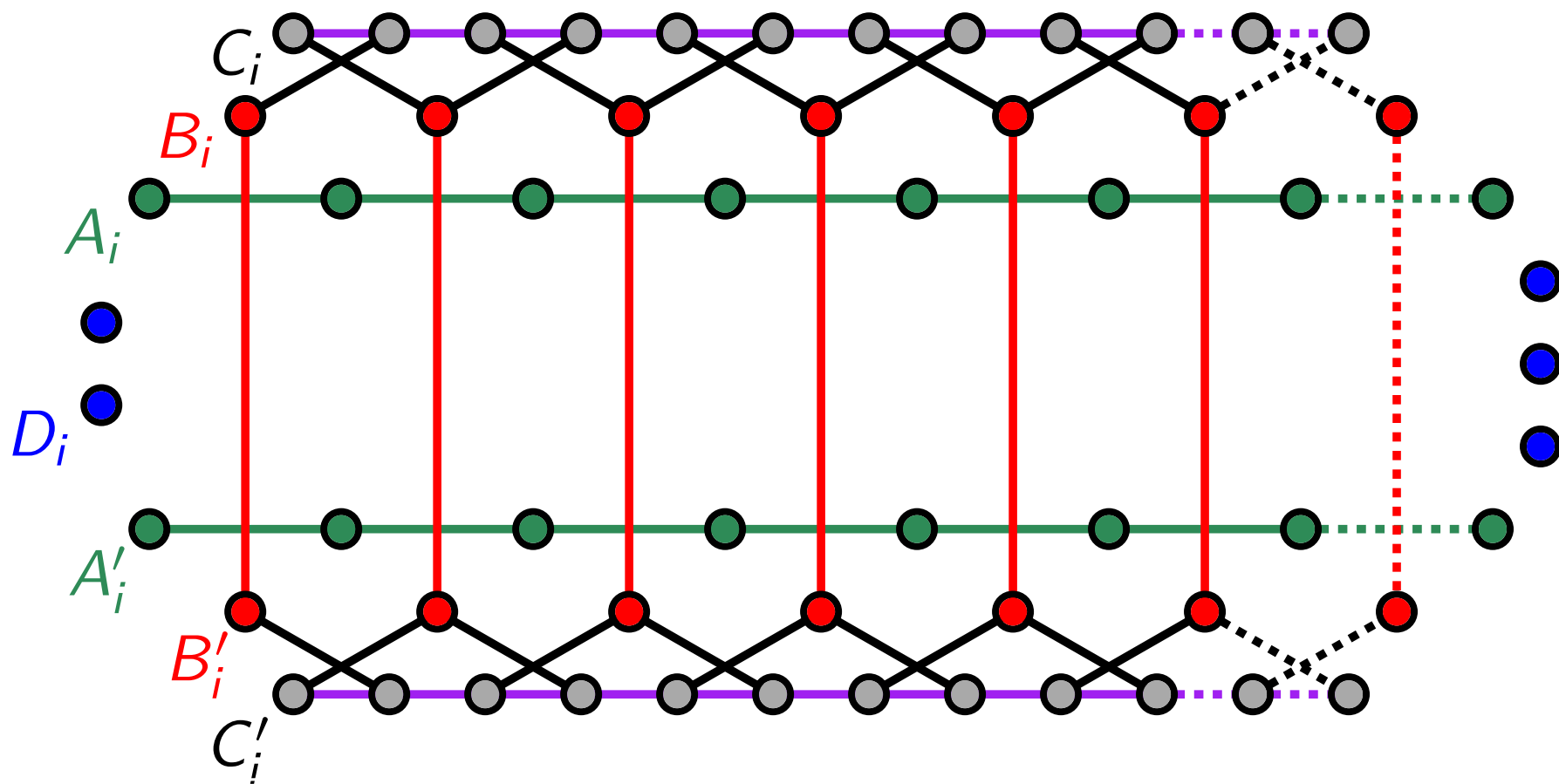
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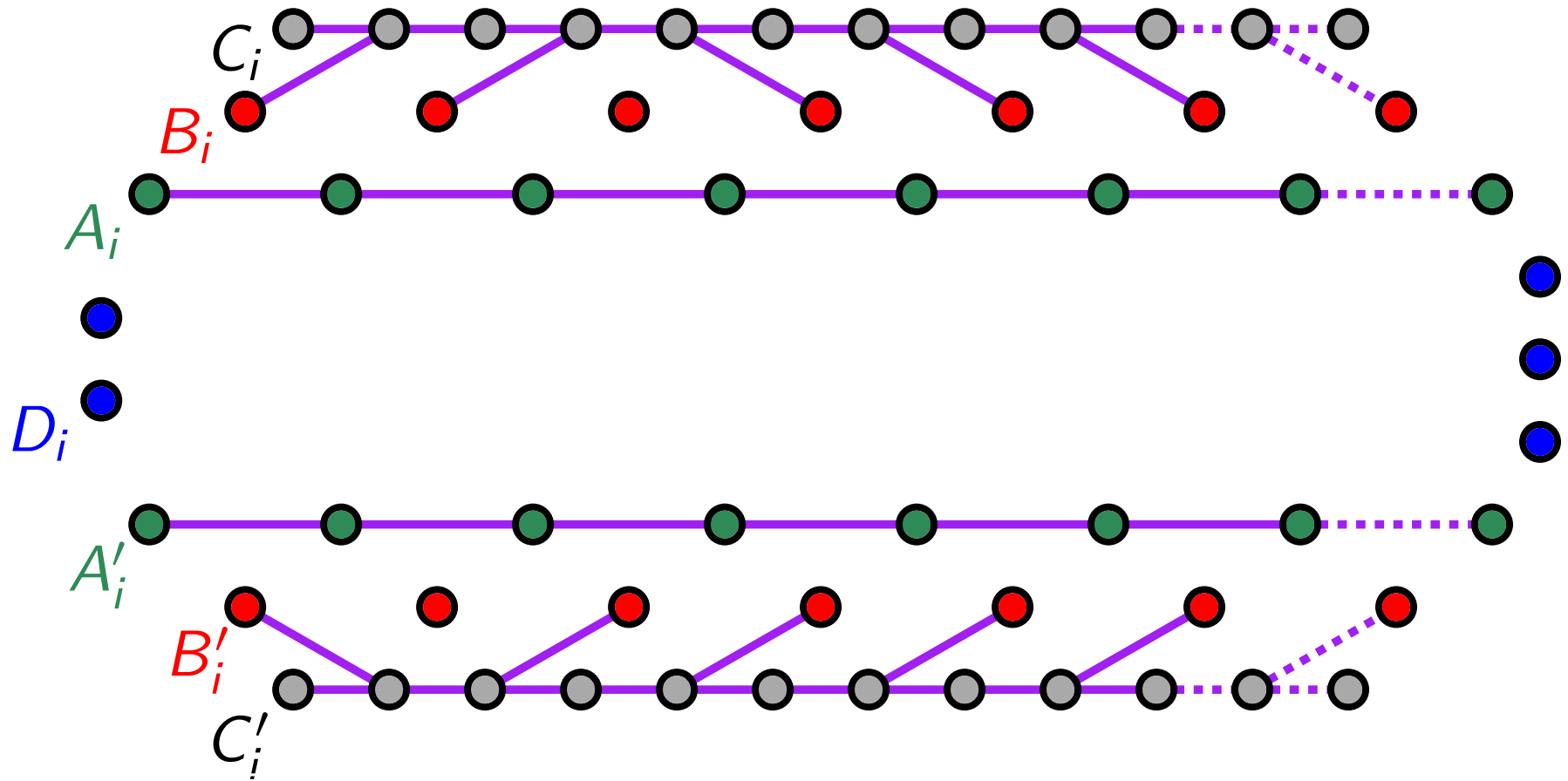
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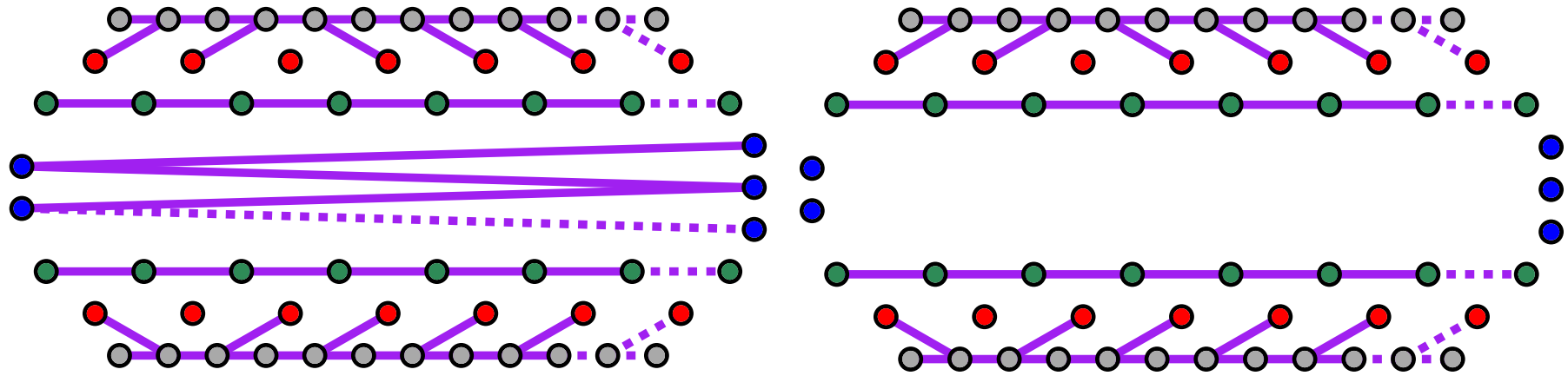
Performance – Greedy vs. Reverse Greedy



Performance – Greedy vs. Reverse Greedy



Performance – Greedy vs. Reverse Greedy



Greedy 7 clusters vs. Reverse Greedy $k+7$!

An ILP for Cluster Minimization

Sketch:

An ILP for Cluster Minimization

Sketch:

- Model Cluster Minimization as a flow network.

An ILP for Cluster Minimization

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- Each node is either a source or a sink.

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- ILP minimizes the number of sinks.

Experiment setup

- Use map of places of interest in a city.

Experiment setup

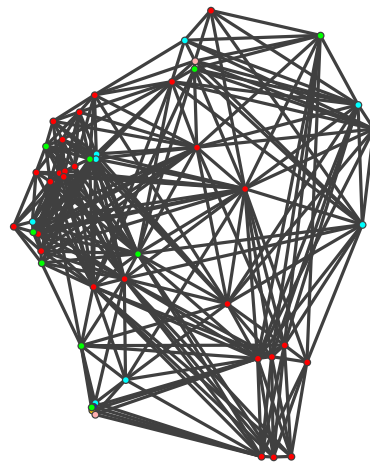
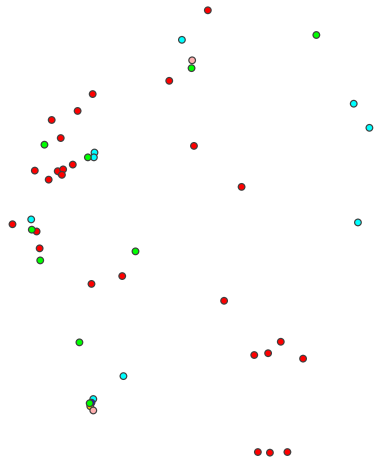
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- Divide the map in quadrants of varying sizes.

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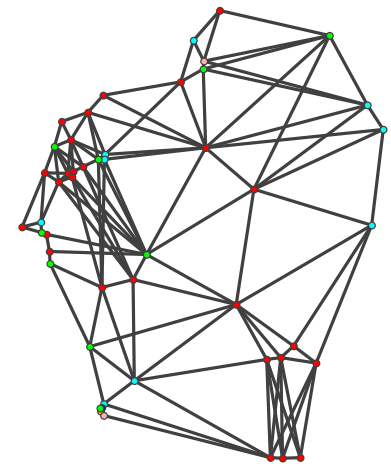
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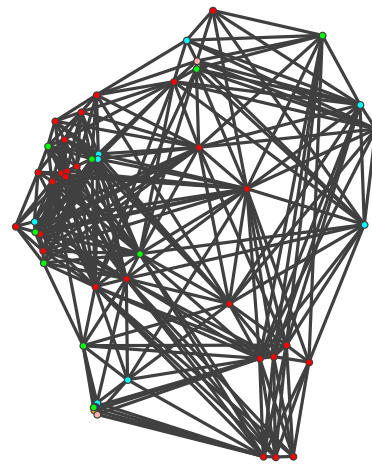
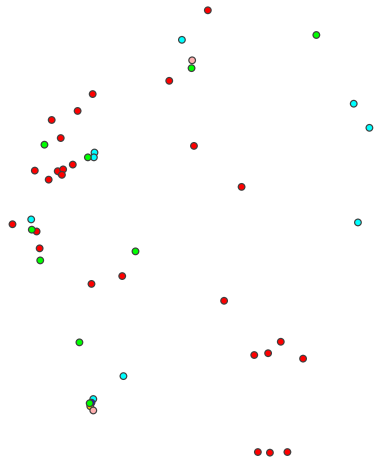
$$\beta = 0.5$$



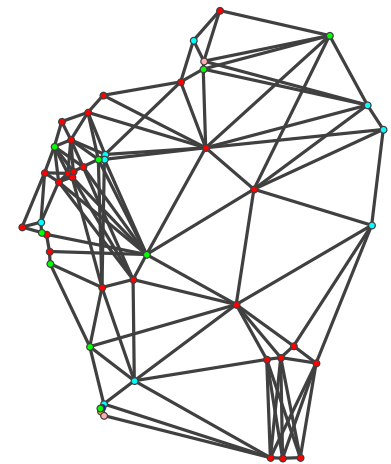
$$\beta = 0.9$$

Experiment setup

- Use map of places of interest in a city.
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- Run both heuristics, ILP where feasible.

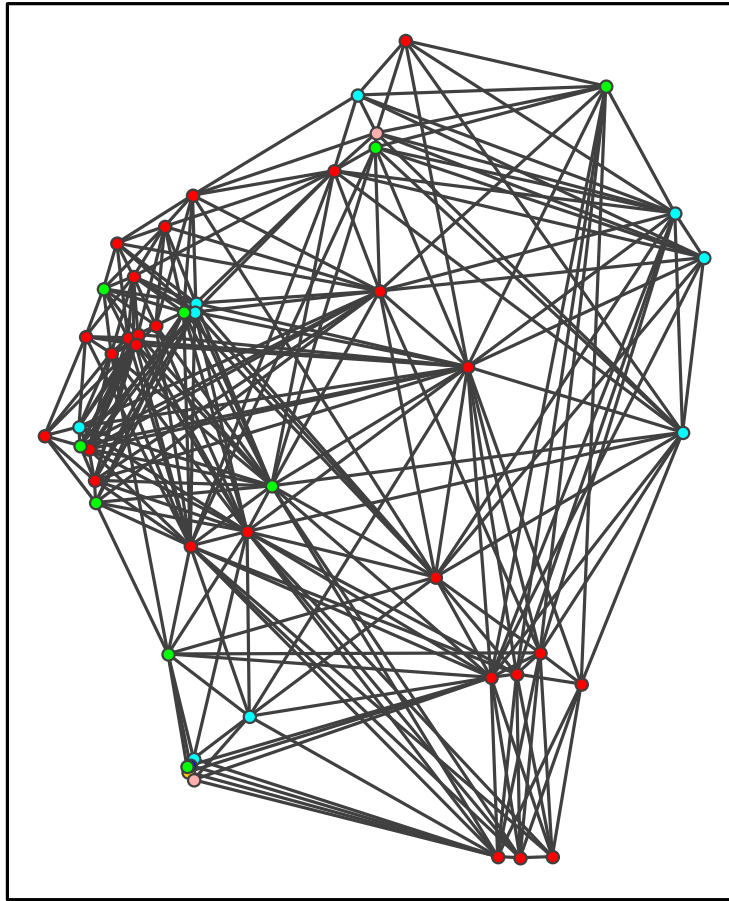


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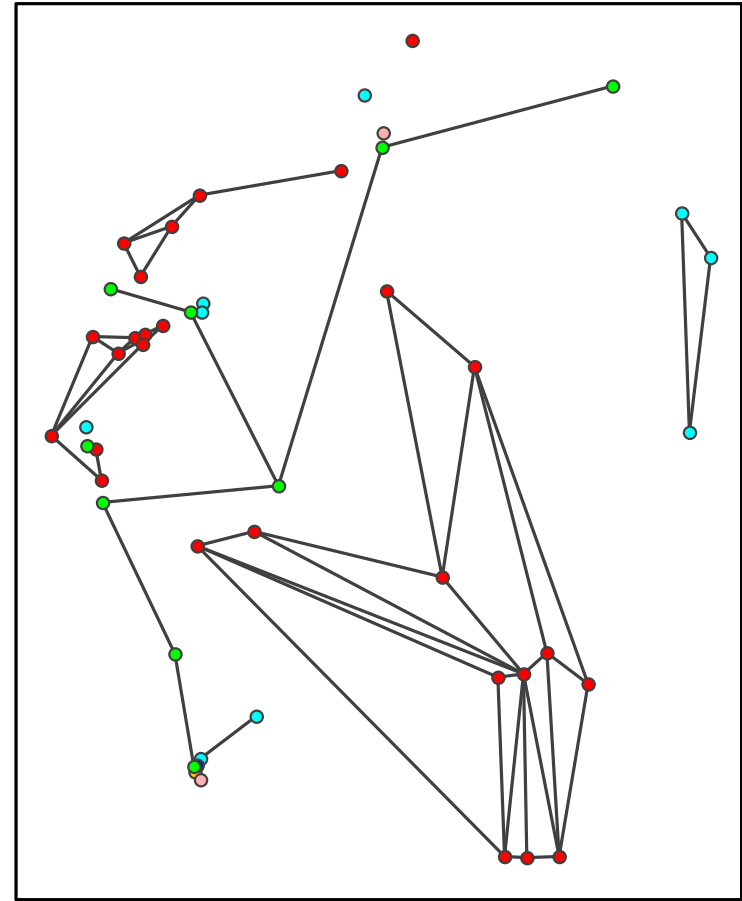


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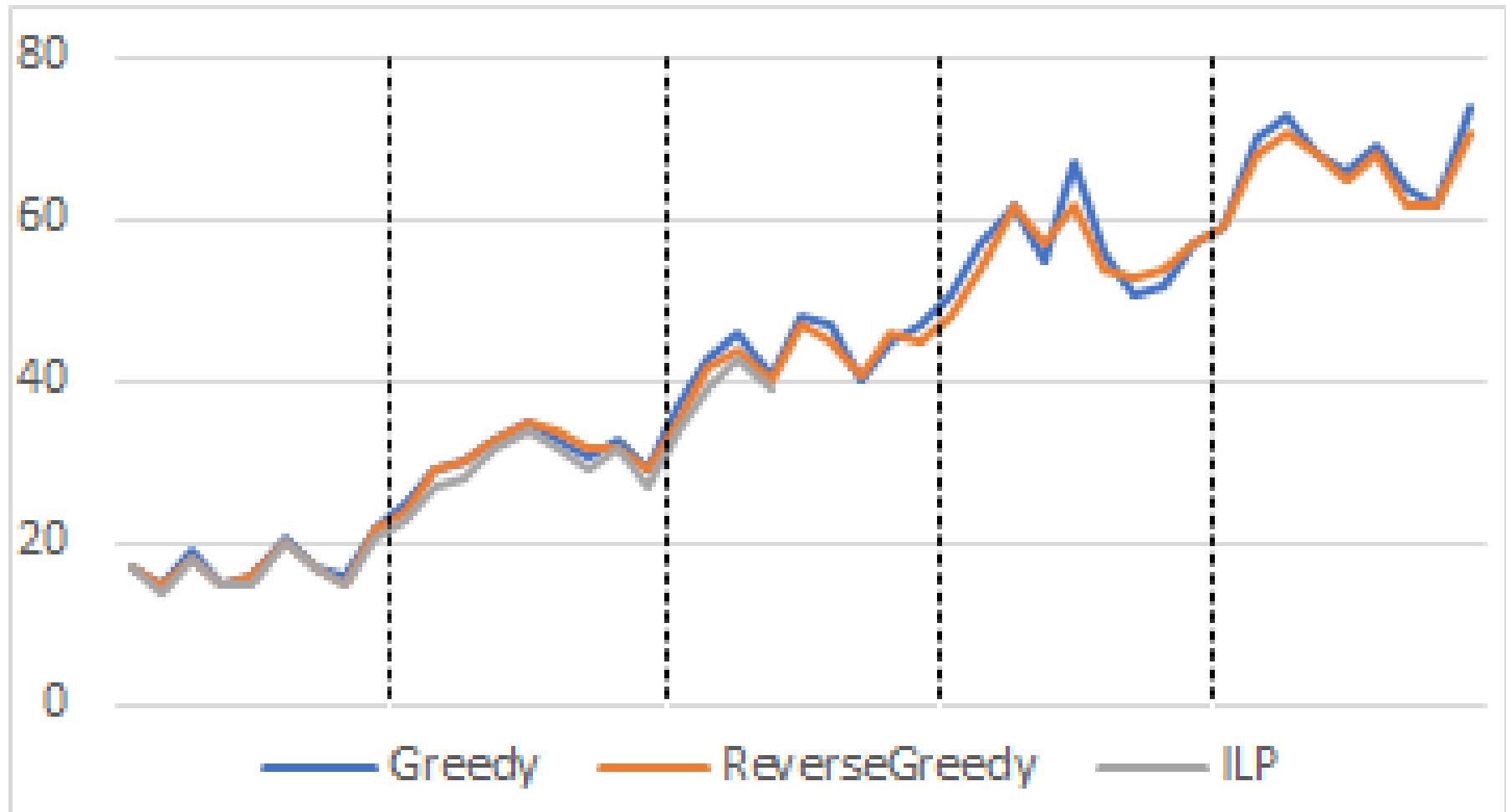


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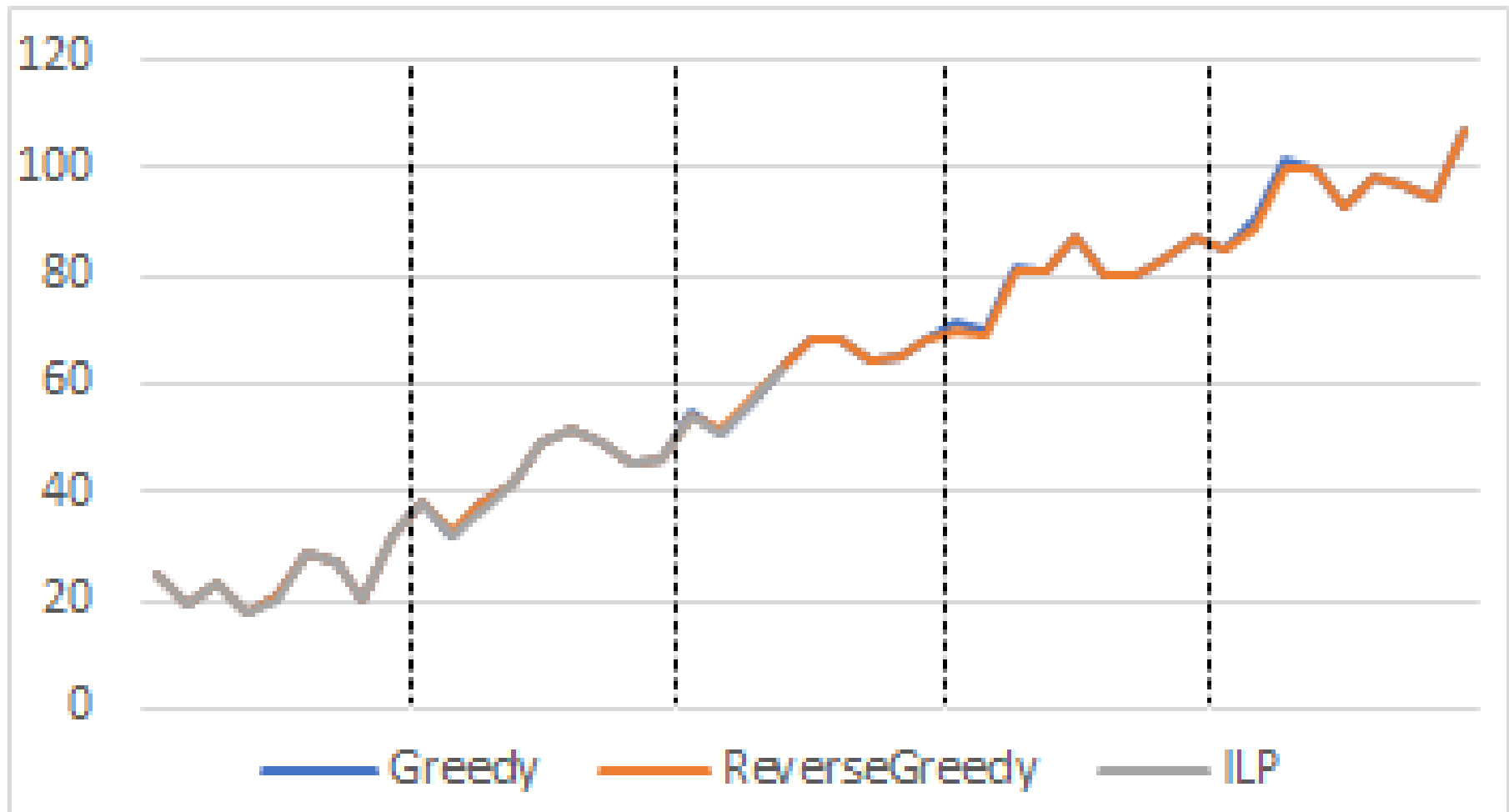
50 points, 15 clusters

Performance Analysis - Experiments



$$\beta = 0.5$$

Performance Analysis - Experiments



$$\beta = 0.9$$

Experiment Summary

Biggest difference: Greedy 37 clusters vs. ILP 34 clusters!

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Biggest difference: Greedy 37 clusters vs. ILP 34 clusters!

Reverse Greedy tends to perform better than Greedy, but differences are marginal

Summary and Future Work

Problem	Quality	Complexity
Cluster Min.	exact	NP-hard
– Greedy	no const. factor	$n + k + m \log m$
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- There is a graph family on which the Greedy algorithm is arbitrarily better than the Reverse Greedy algorithm.
- Is there a graph family where the opposite is true?
- Is there a constant factor approximation for Cluster Minimization?
- How does the problem change if we allow *some* crossings?

Summary and Future Work

- Can we enhance the Greedy algorithm somehow?

