

Algorithms for the Metric Dimension problem on directed graphs

Antoine Dailly, Florent Foucaud, Anni Hakanen
LIMOS, Clermont-Ferrand

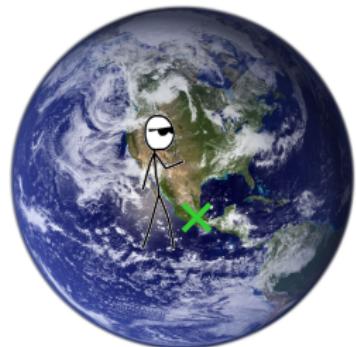
Séminaire Algo du GREYC
February 28, 2023



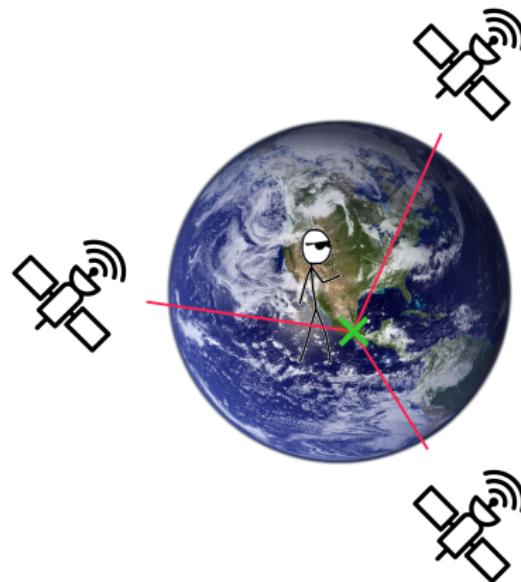
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Question

How can we transpose this approach to graphs?

Metric Dimension

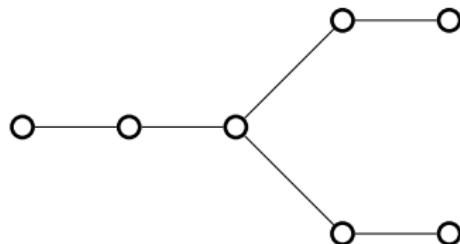
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b **resolves** u and v if $\text{dist}(b, u) \neq \text{dist}(b, v)$

Metric Dimension

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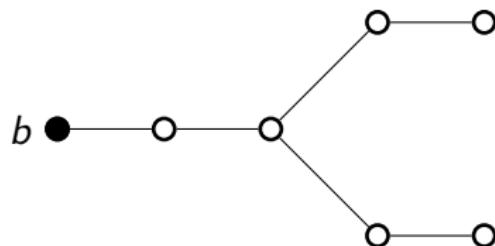
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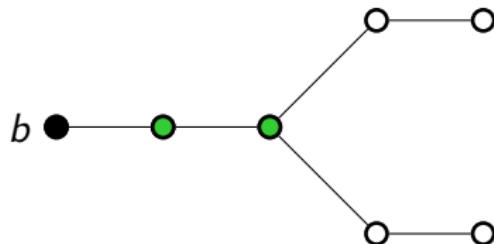
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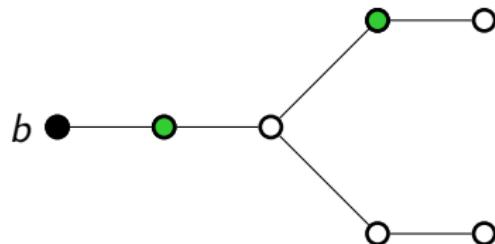
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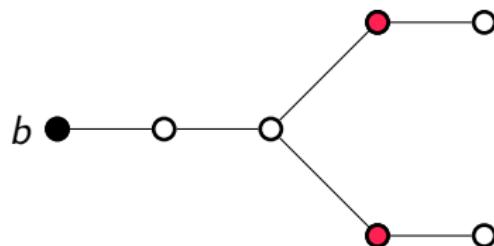
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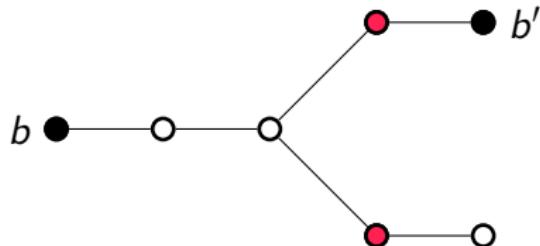
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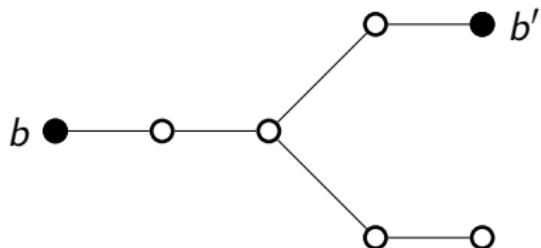
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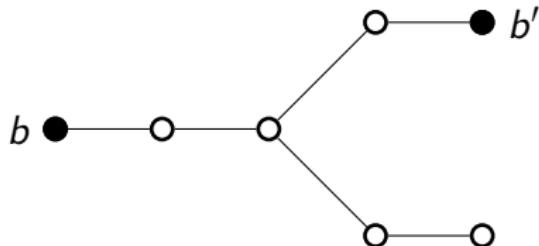
Resolving Set [Slater, 1975] [Harary & Melter, 1976]

$R \subseteq V(G)$ is a **resolving set** of G iff for every pair $\{u, v\}$, there is $b \in R$ that resolves u and v

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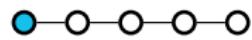
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Metric Dimension

$\text{MD}(G)$ = minimum size of a resolving set of G

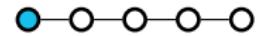
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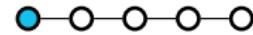


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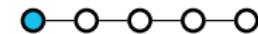


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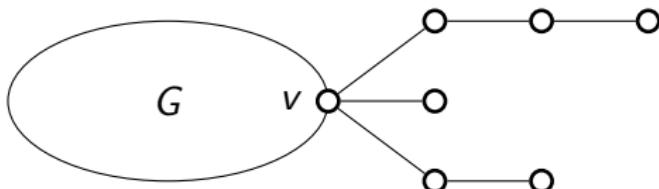
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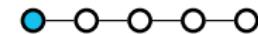
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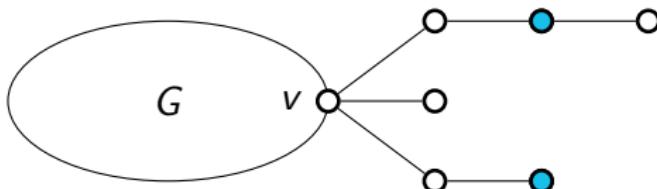


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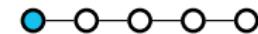
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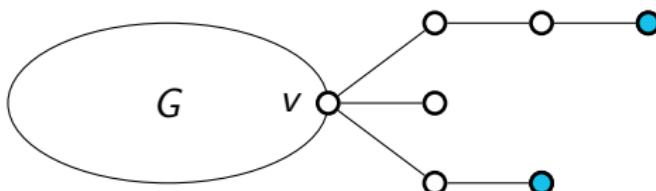
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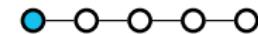
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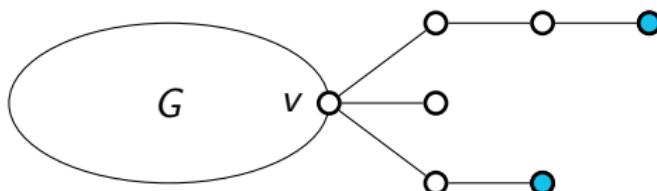


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3. Trees? The simple leg rule gives an optimal resolving set [Slater, 1975]

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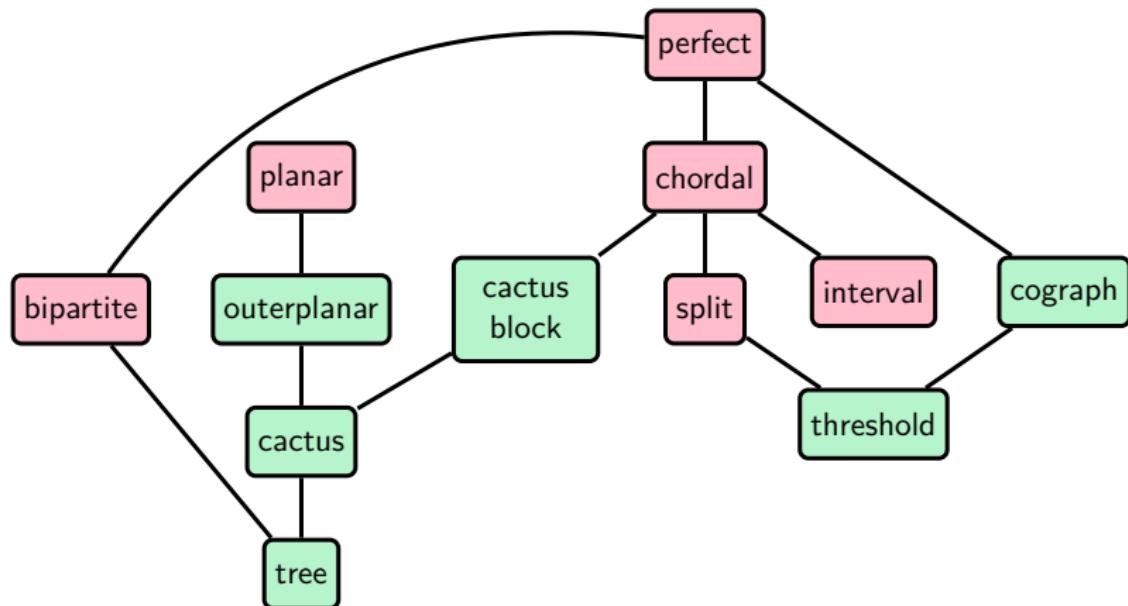
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A few positive results...

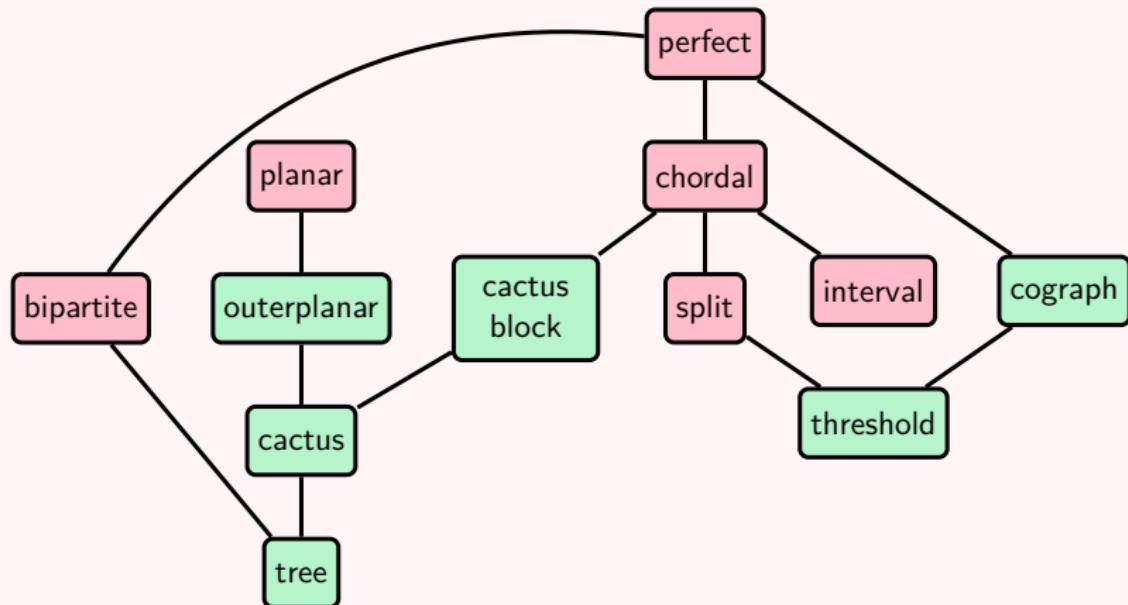
- ▶ Linear-time: cographs [Epstein *et al.*, 2012], cactus block graphs [Hoffmann *et al.*, 2016]
- ▶ Polynomial-time: outerplanar graphs [Díaz *et al.*, 2012]
- ▶ FPT for bounded treelength [Belmonte *et al.*, 2015]

Inclusion diagram

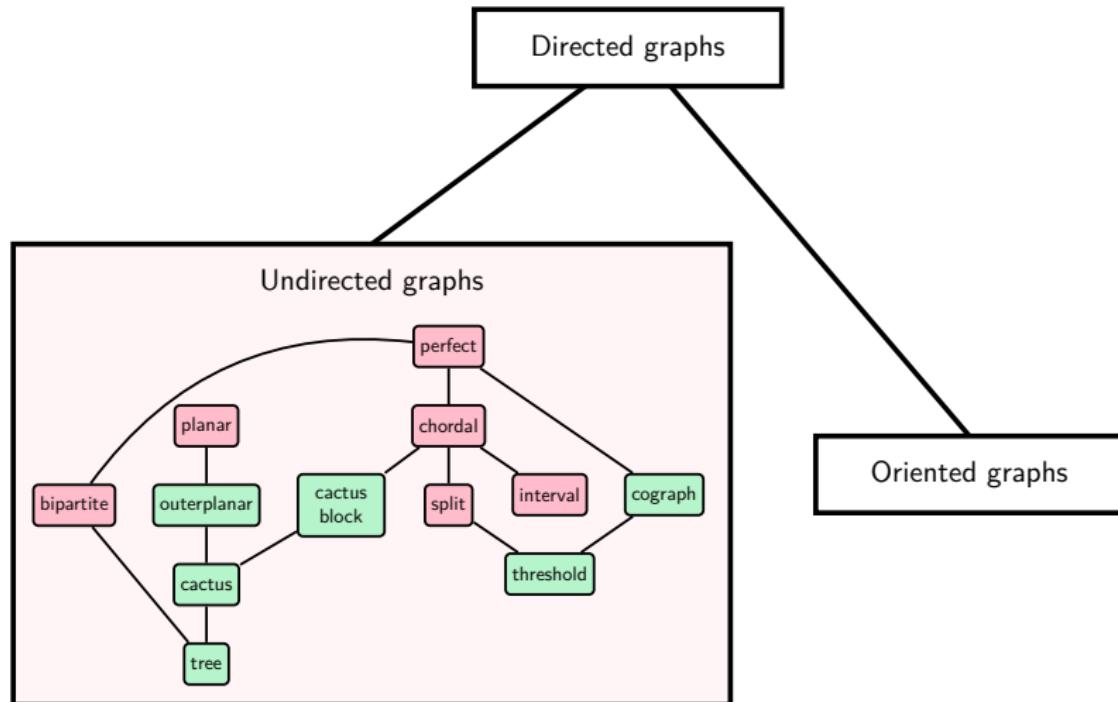


Inclusion diagram

Undirected graphs

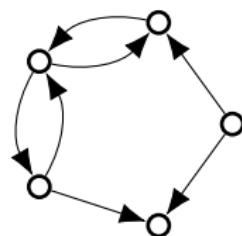


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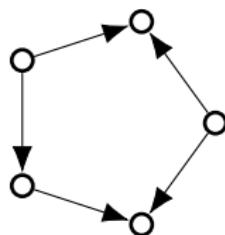
Definitions

- A **directed graph** may contain 2-cycles



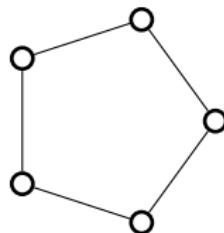
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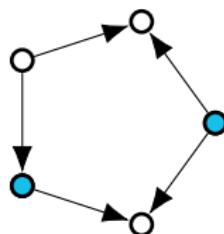
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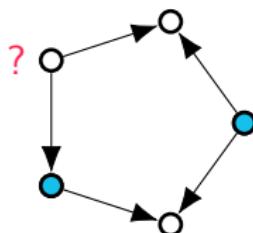


The definitions for Metric Dimension do not change:

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But there will be **reachability** problems!

Previous work

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- ▶ Linear-time algorithm for orientations of trees [Araujo *et al.*, 2023+]

Algorithm for orientations of trees

Theorem [Araujo et al., 2023+]

A minimum-size resolving set R of an orientation of a tree can be computed in **linear** time.

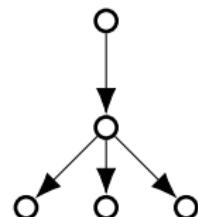
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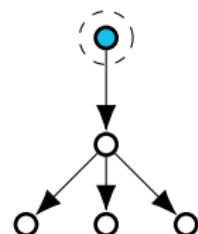
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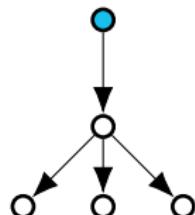
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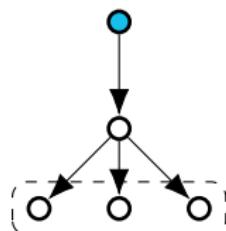
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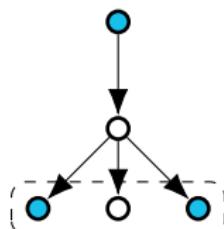
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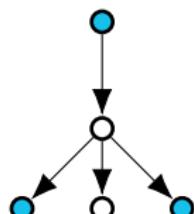
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Holds for all directed graphs!

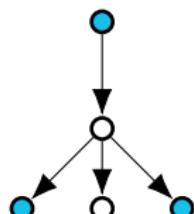
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- 3 The set R constructed this way is a resolving set

Our results

Theorem [D., Foucaud & Hakanen, 2023+]

Linear-time algorithms for minimum-size resolving sets of directed trees and orientations of unicyclic graphs.

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FPT algorithm parameterized by directed modular width.

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There is a **linear-time** algorithm computing a minimum-size resolving set of a **directed tree**.

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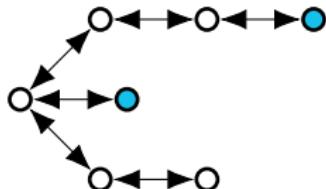
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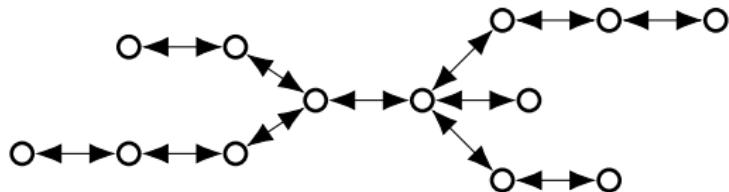
- ▶ Sources + resolving sets of in-twins
- ▶ Resolving legs of strongly connected components



Directed trees (2) Dummy vertices

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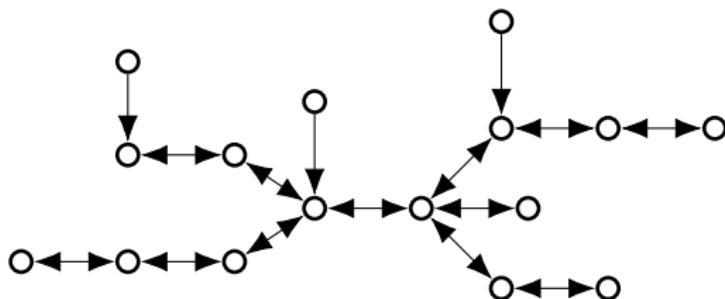
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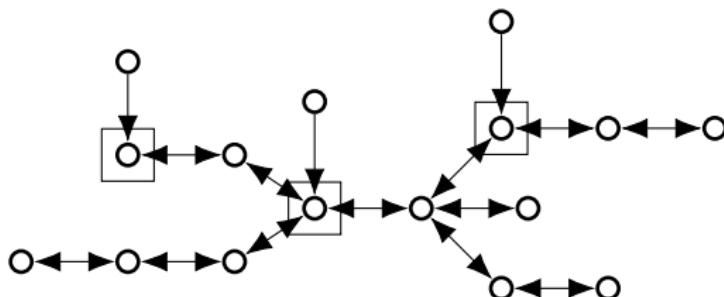
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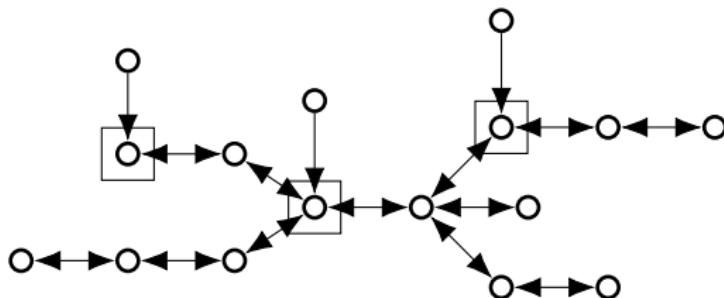
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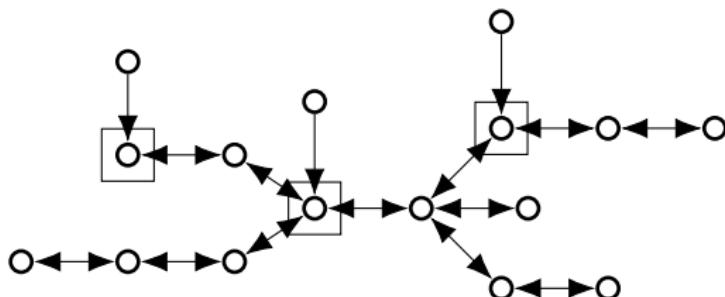


Every dummy vertex is a **representative** of the vertices in the resolving set behind the in-arc

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Definition

In a strongly connected component C , every $v \in C$ such that an arc \overrightarrow{uv} with $u \notin C$ exists is a **dummy vertex**.



Every dummy vertex is a **representative** of the vertices in the resolving set behind the in-arc

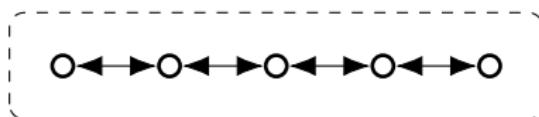
They act like degree ≥ 3 vertices for the purpose of legs

Directed trees (3) First problem: escalators

Definition

An **escalator** is a strongly connected component with:

- ▶ a path as an underlying graph

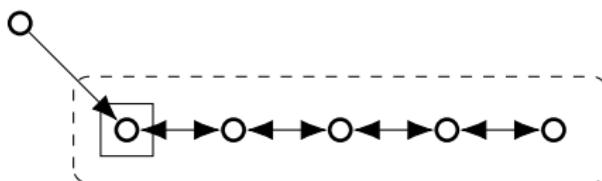


Directed trees (3) First problem: escalators

Definition

An **escalator** is a strongly connected component with:

- ▶ a path as an underlying graph
- ▶ only one in-arc from outside, at one end

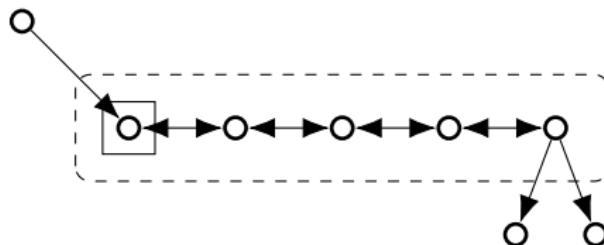


Directed trees (3) First problem: escalators

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An **escalator** is a strongly connected component with:

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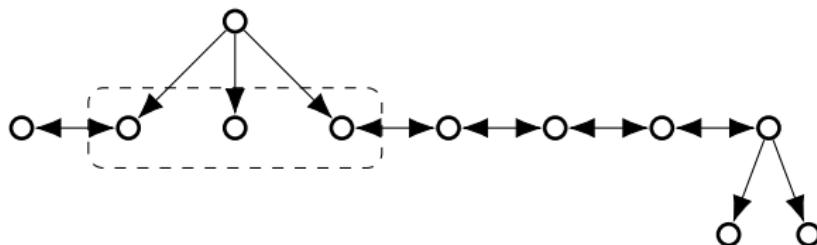


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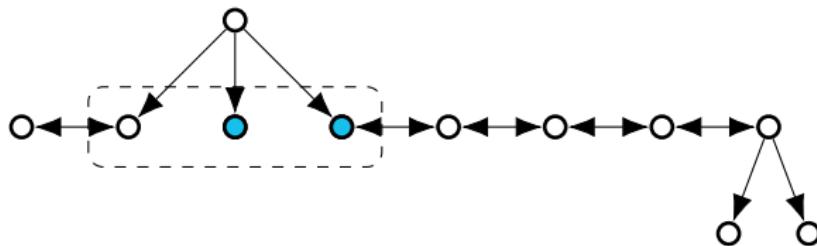
→ These are almost-in-twins

Directed trees (3) First problem: escalators

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→ These are **almost-in-twins**

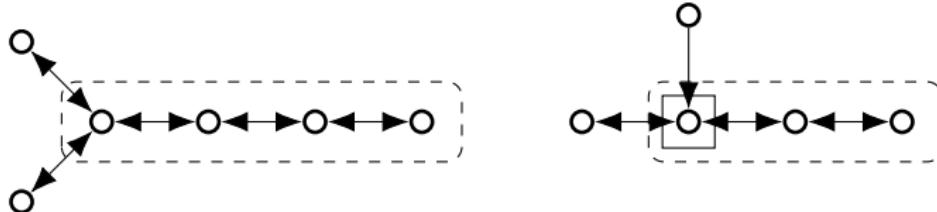
- ▶ For each set of k almost-in-twins, take $k - 1$ in the resolving set

Directed trees (4) Second problem: special legs

Definition

In a strongly connected component, a **special leg** is a leg that:

- ▶ spans from a dummy or degree ≥ 3 (in the component) vertex

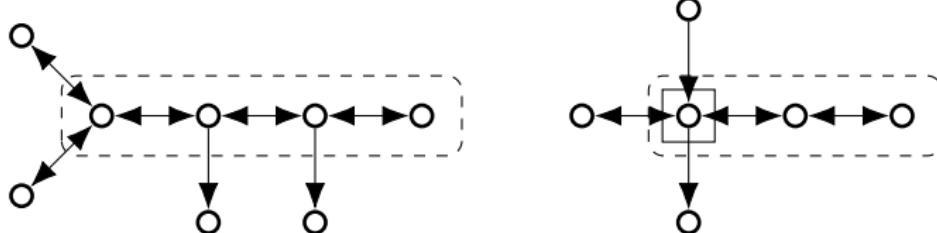


Directed trees (4) Second problem: special legs

Definition

In a strongly connected component, a **special leg** is a leg that:

- ▶ spans from a dummy or degree ≥ 3 (in the component) vertex
- ▶ has at least one out-arc from a vertex other than its endpoint

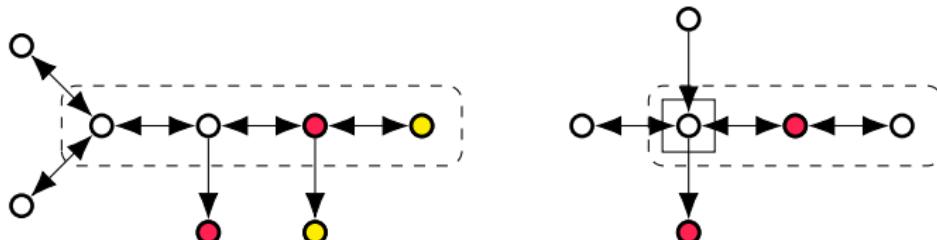


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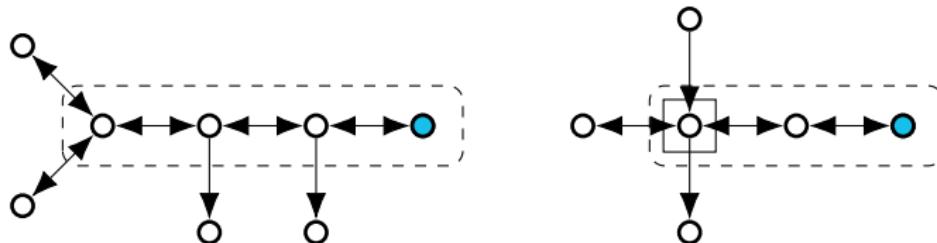
→ Conflict between pairs!

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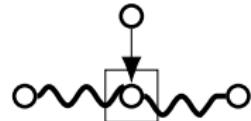
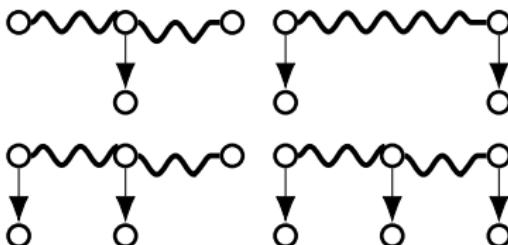
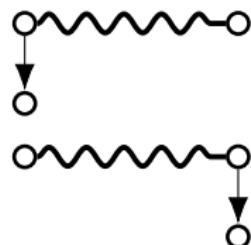


→ Conflict between pairs!

- ▶ Take the endpoint of each special leg

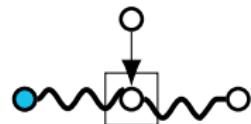
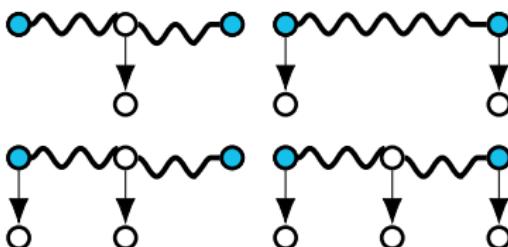
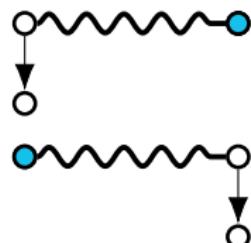
Directed trees (5) Third problem: some paths...

The strongly connected components whose underlying graph is a path (snake = any positive length) with the following patterns:



Directed trees (5) Third problem: some paths...

The strongly connected components whose underlying graph is a path (snake = any positive length) with the following patterns:



... require one or two endpoints.

Directed trees (6) The final algorithm

Theorem [D., Foucaud & Hakanen, 2023+]

There is a **linear-time** algorithm computing a minimum-size resolving set of a **directed tree**.

Directed trees (6) The final algorithm

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There is a **linear-time** algorithm computing a minimum-size resolving set of a **directed tree**.

Algorithm

1. Take every source, resolve each set of almost-in-twins

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2. For each strongly connected component
 - 2.1 Mark the dummy vertices

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 - 2.2 Solve the special paths cases (previous slide)

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This gives a resolving set... which we prove is minimum-size!

Orientations of unicyclic graphs

Theorem [D., Foucaud & Hakanen, 2023+]

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Orientations of unicyclic graphs

Theorem [D., Foucaud & Hakanen, 2023+]

There is a **linear-time** algorithm computing a minimum-size resolving set of the orientation of a unicyclic graph.

Algorithm

1. Take every source
2. Orient edges
3. Resolve each set of in-twins with some priority

Orientations of unicyclic graphs

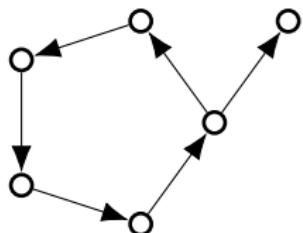
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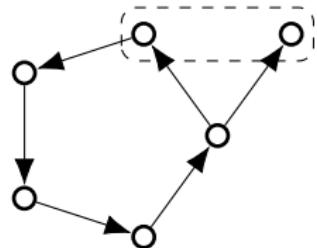
Algorithm

1. Take every source
2. Manage a few special cases (at most one more vertex)
3. Resolve each set of in-twins with some priority

No sink in the cycle

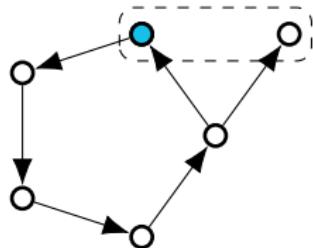


No sink in the cycle



Which in-twin?

No sink in the cycle

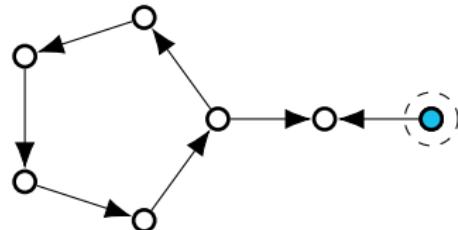
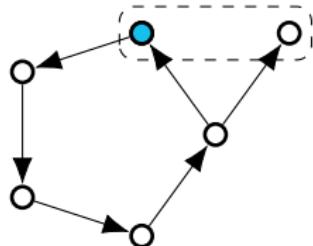


Which in-twin?

Priority

Give priority to in-twins **in
the cycle**

No sink in the cycle



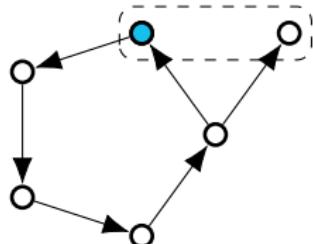
⚠ Special case (Reachability)

Which in-twin?

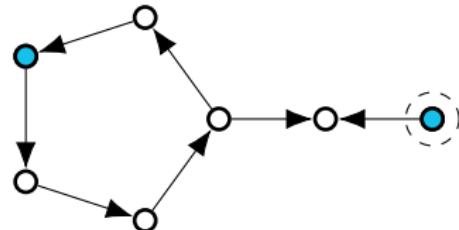
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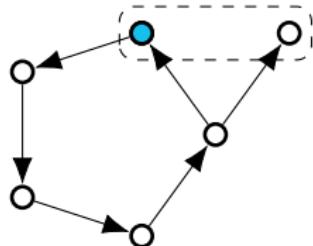


⚠ Special case (Reachability)
⇒ Take one vertex from the cycle

Priority

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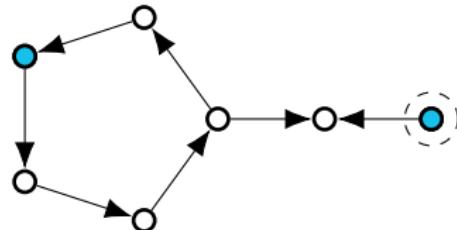
No sink in the cycle



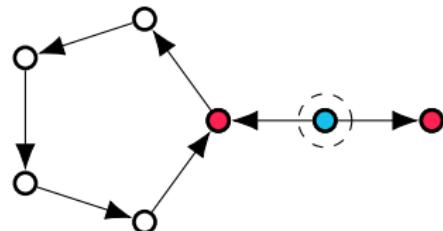
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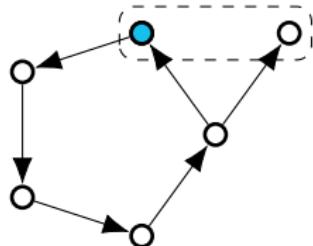


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⚠ Special case (Unresolved pair)

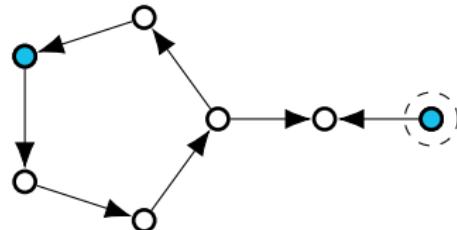
No sink in the cycle



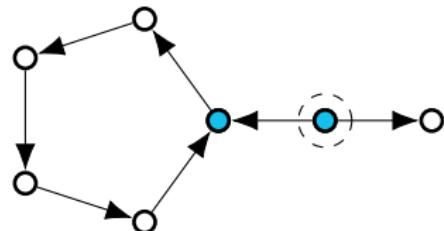
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Priority

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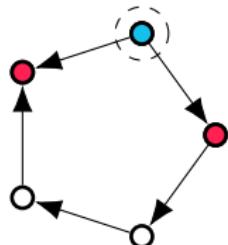


⚠ Special case (Reachability)
⇒ Take one vertex from the cycle



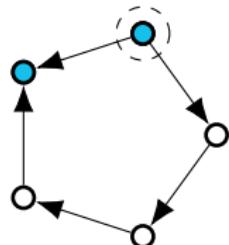
⚠ Special case (Unresolved pair)
⇒ Take one unresolved vertex

One sink in the cycle



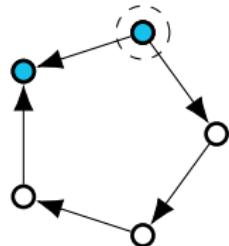
⚠ **Special case**
(Unresolved pair)

One sink in the cycle

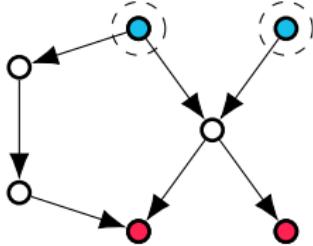


⚠ **Special case**
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⇒ Take one
unresolved vertex

One sink in the cycle

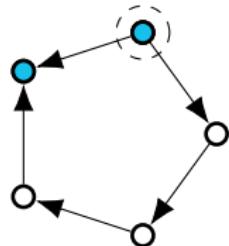


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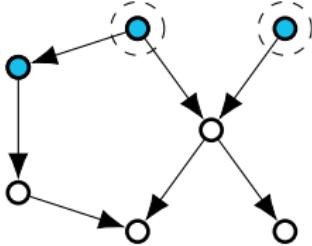


⚠ Special case
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One sink in the cycle

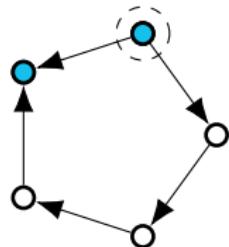


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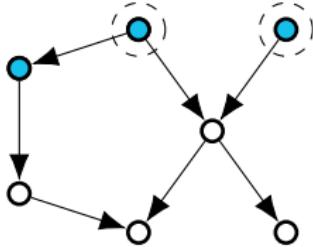


⚠ Special case
(Unresolved pair)
⇒ Take one vertex
along the long path

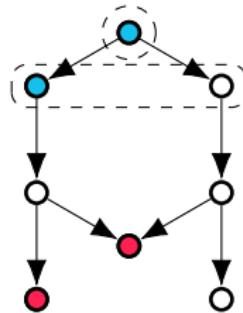
One sink in the cycle



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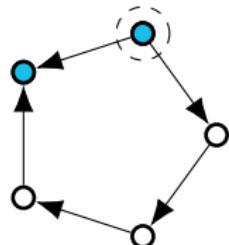


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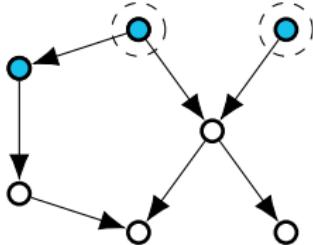


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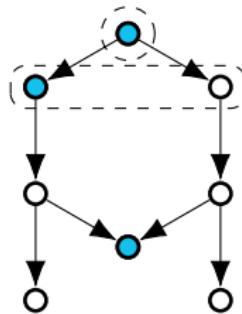
One sink in the cycle



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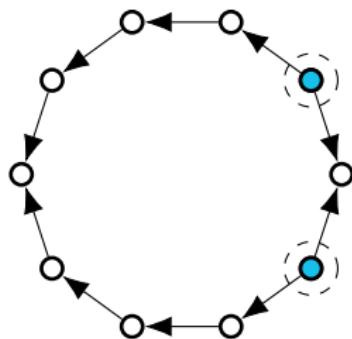


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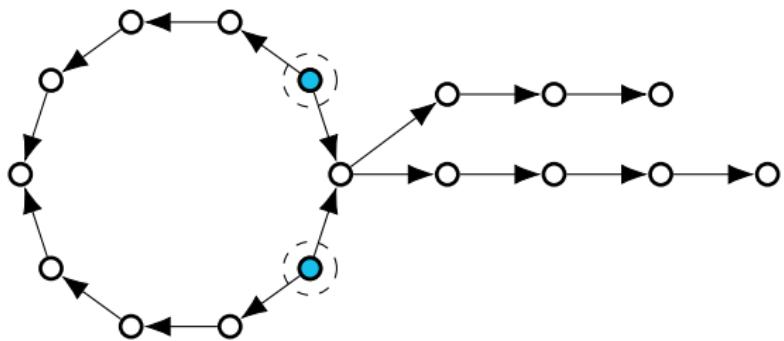


⚠ Special case
(Unresolved pair)
⇒ Take the sink of
the cycle

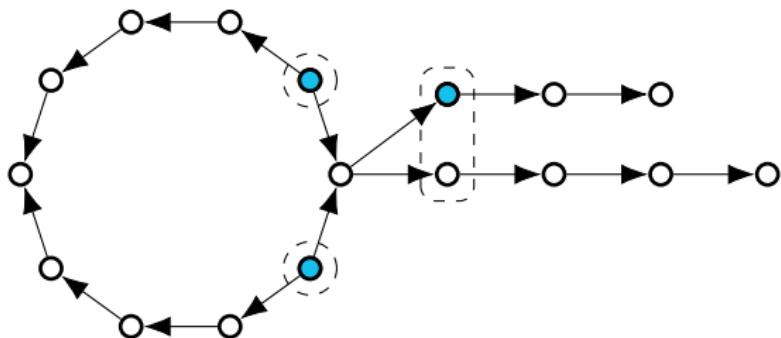
Two sinks in the cycle



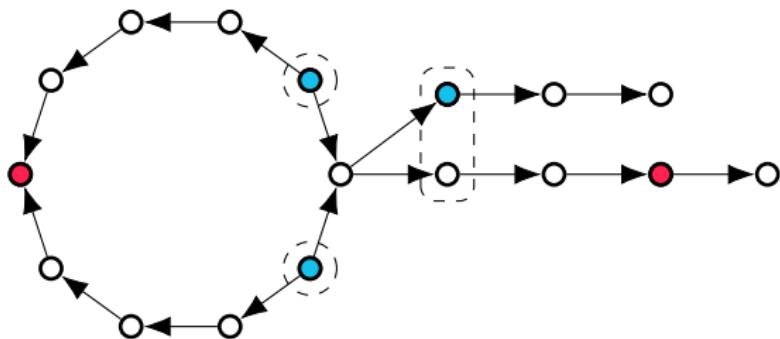
Two sinks in the cycle



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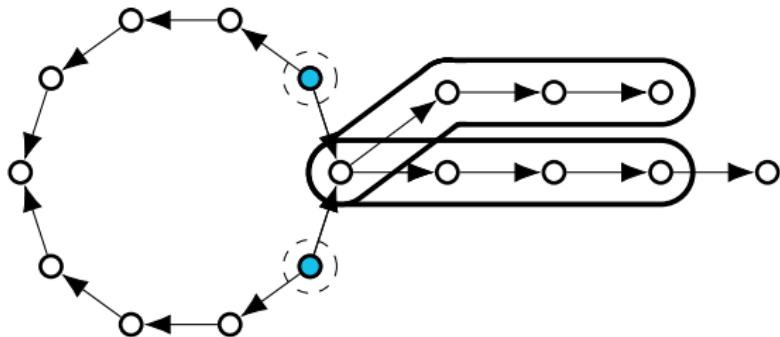


Two sinks in the cycle



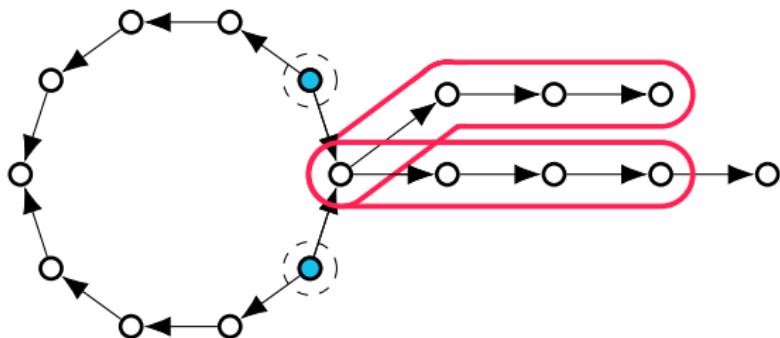
⚠ Special case (Unresolved pair)

Two sinks in the cycle



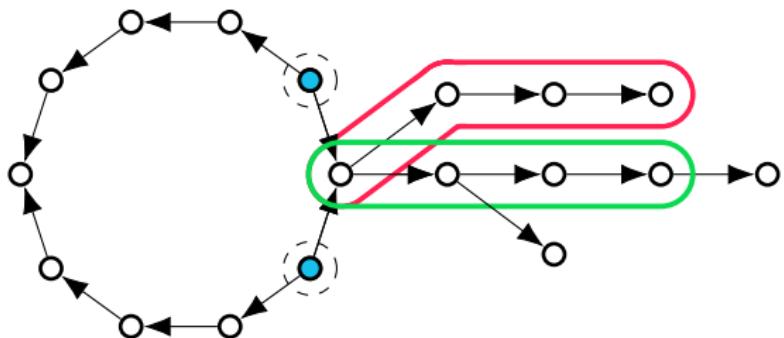
Those are **concerning paths**,

Two sinks in the cycle



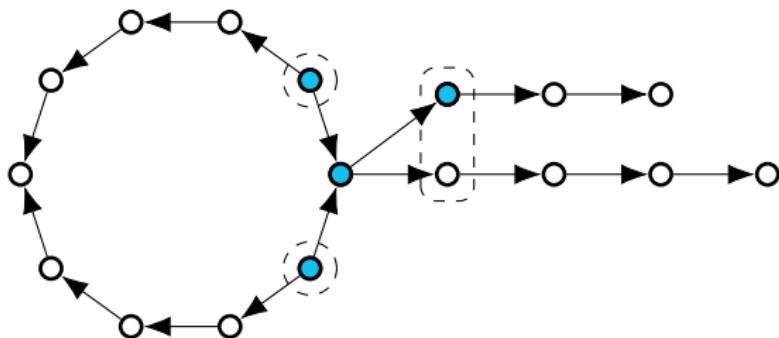
Those are **concerning paths**,
which can be either **unfixable**

Two sinks in the cycle



Those are **concerning paths**,
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Two sinks in the cycle

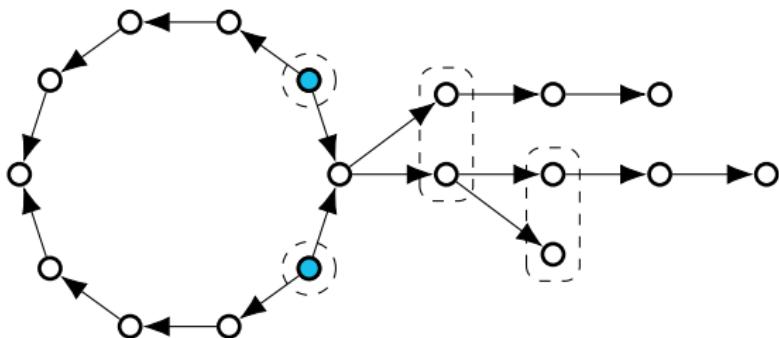


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Special case & Priority

- If all the concerning paths are unfixable, then, take the sink

Two sinks in the cycle

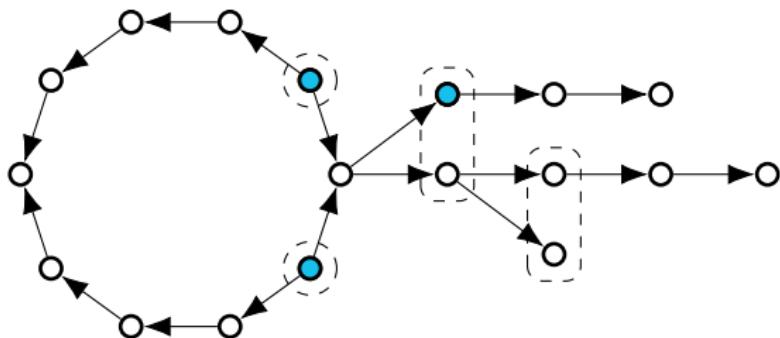


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- Otherwise,

Two sinks in the cycle

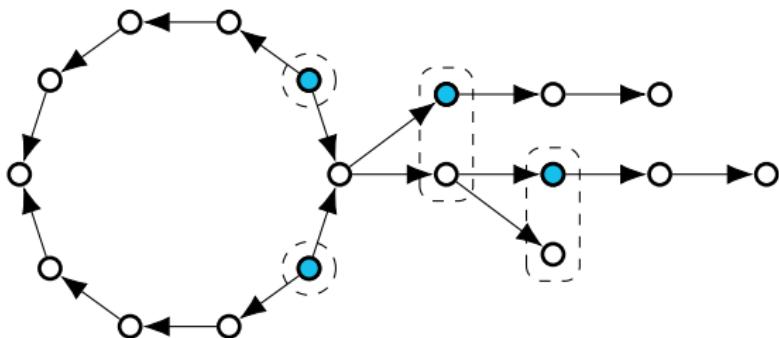


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- If all the concerning paths are unfixable, then, take the sink
- Otherwise, **priority** to in-twins in unfixable paths

Two sinks in the cycle



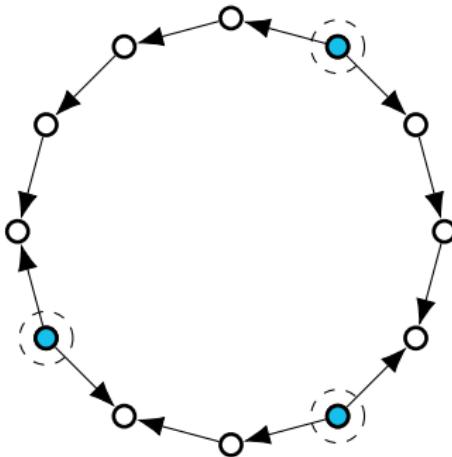
Those are **concerning paths**,
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Special case & Priority

- If all the concerning paths are unfixable, then, take the sink
- Otherwise, **priority** to in-twins in unfixable paths, then concerning paths

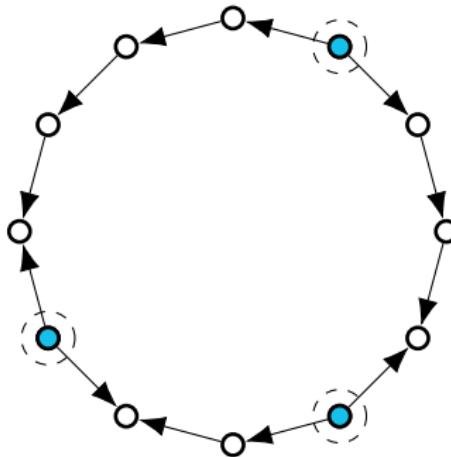
More than two sinks in the cycle

More than two sinks in the cycle



→ No problem!

More than two sinks in the cycle



→ No problem!

Linear-time algorithm

1. Take every source
2. Manage the special cases
3. Resolve each set of in-twins with some priority

NP-hardness (1) The gadgets

Theorem [D., Foucaud & Hakanen, 2023+]

DIRECTED METRIC DIMENSION is NP-complete for **planar triangle-free DAGs of maximum degree 6**.

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Proof

Reduction from VERTEX COVER on planar cubic biconnected undirected graphs [Mohar, 2001]

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In particular, such graphs have a perfect matching [Petersen, 1891].

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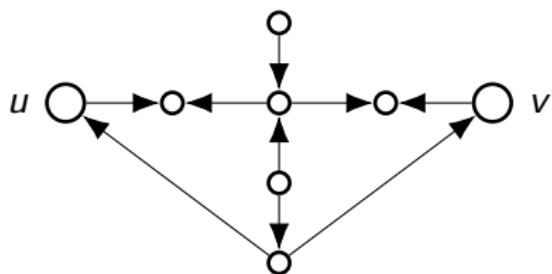
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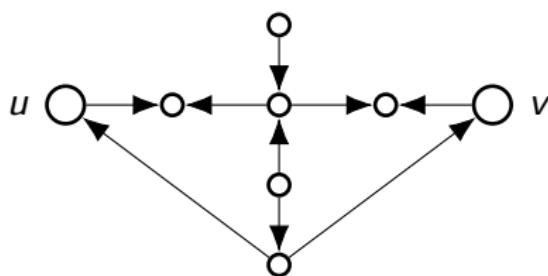
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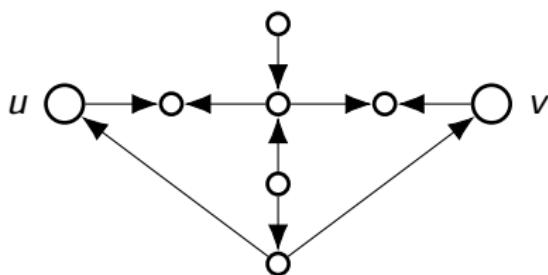
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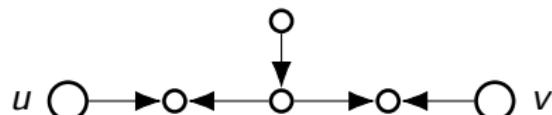
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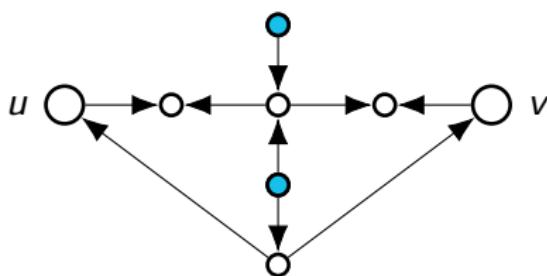
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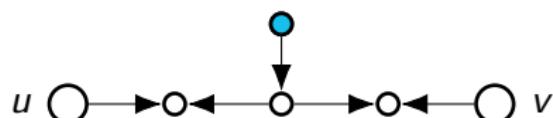
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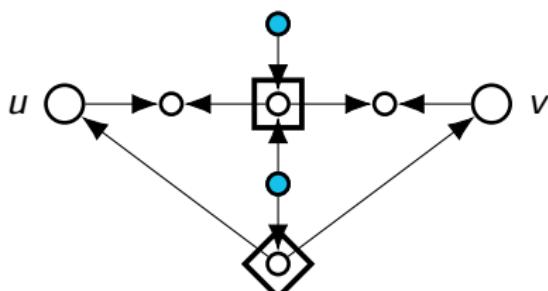
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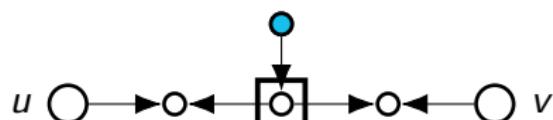
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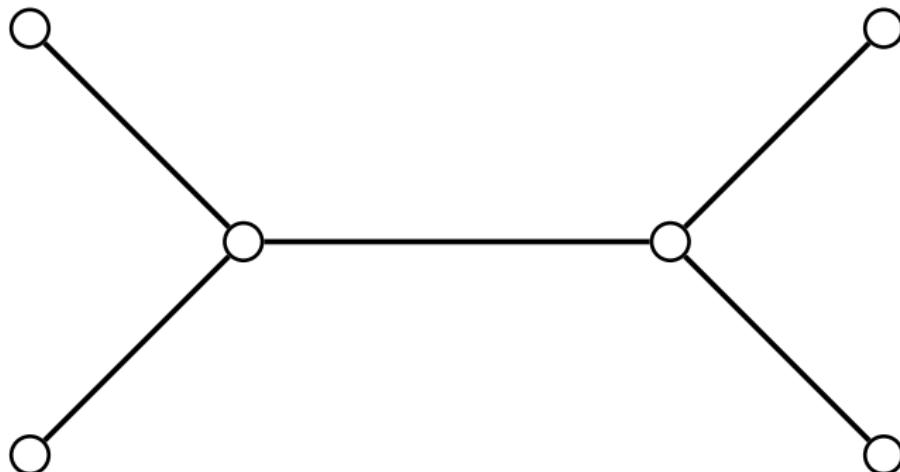


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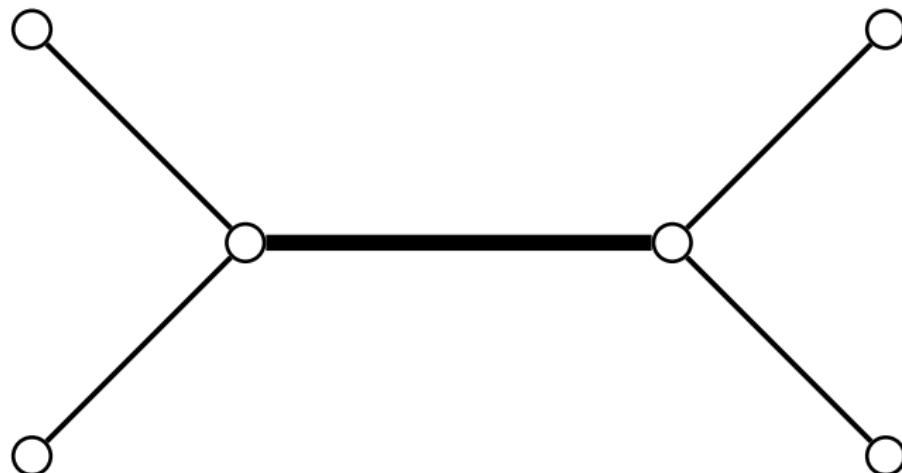
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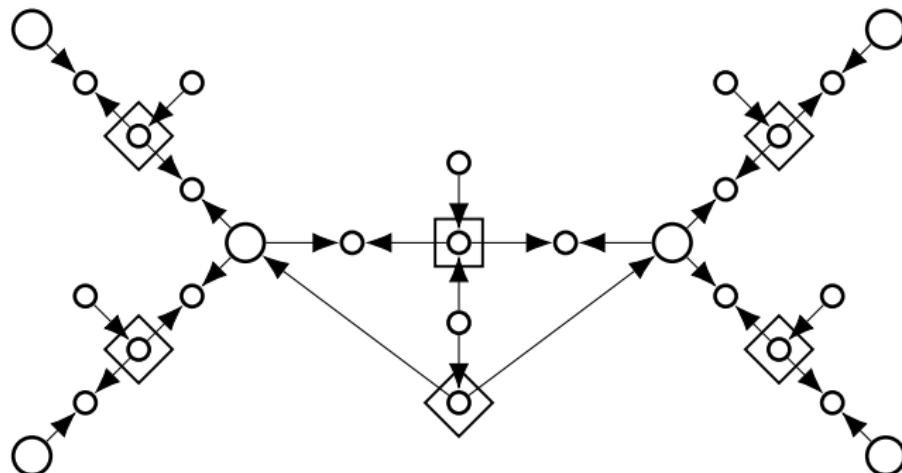
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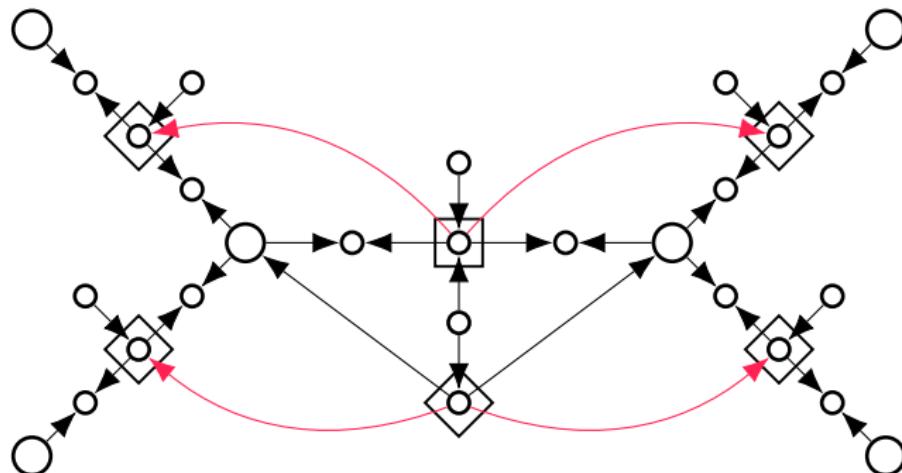
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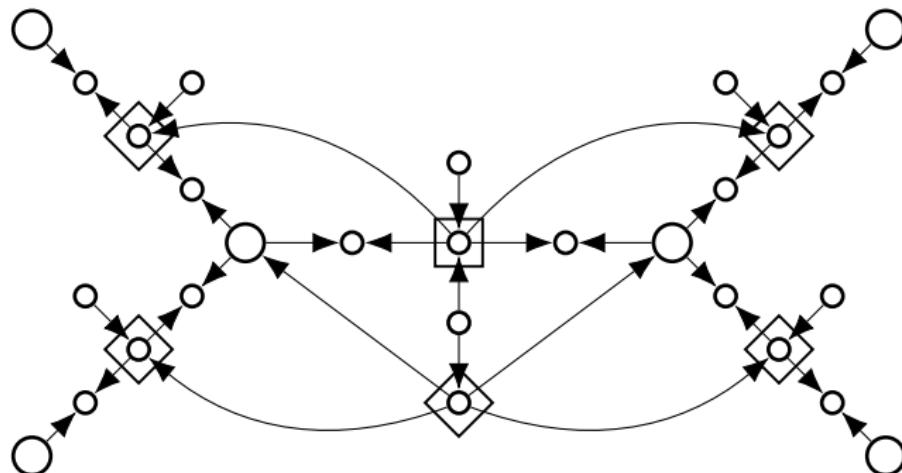
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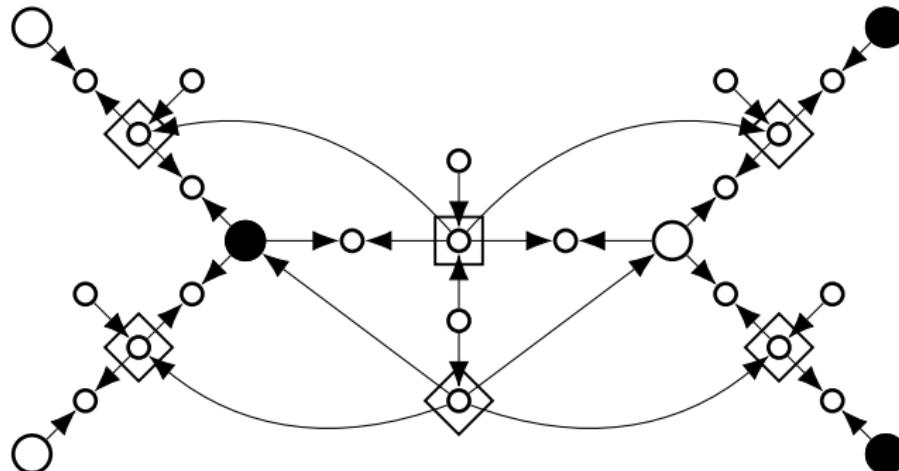


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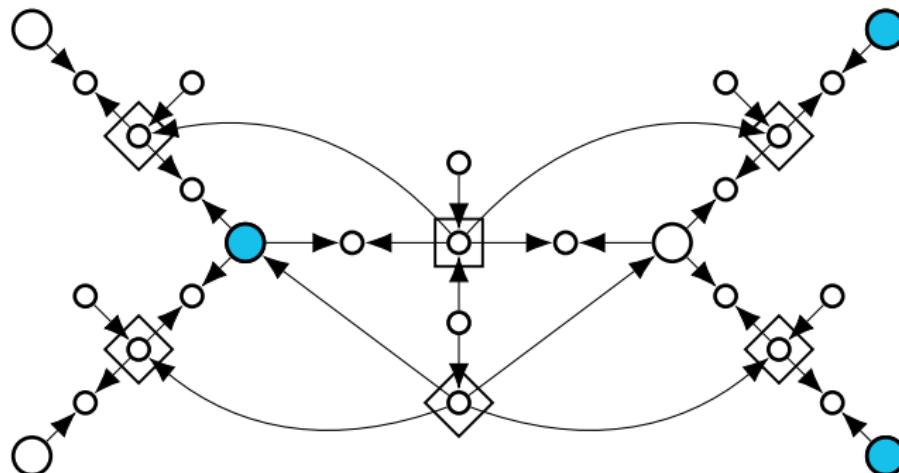
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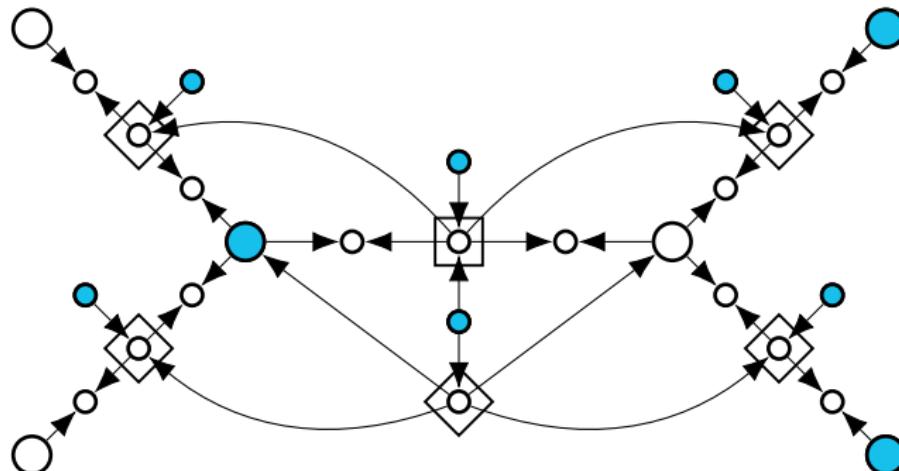


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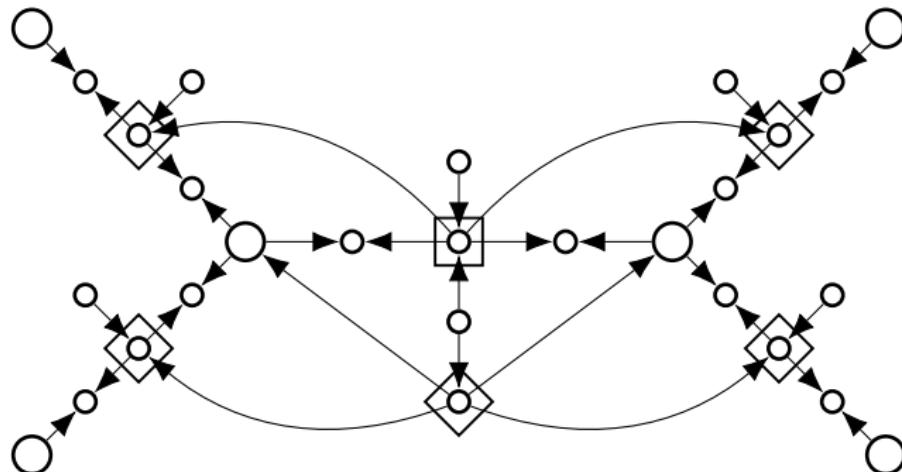


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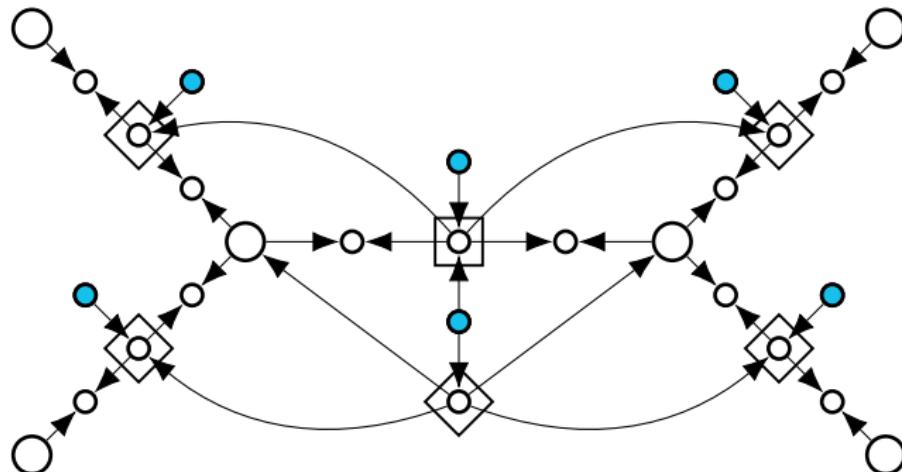


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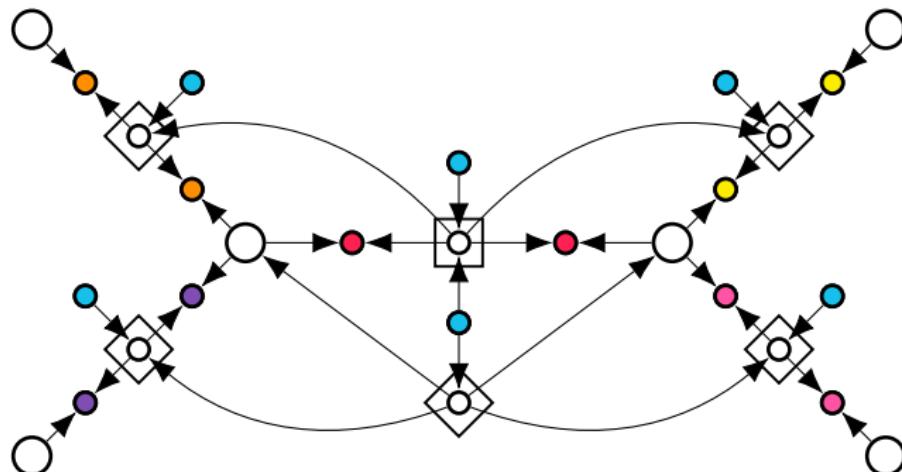


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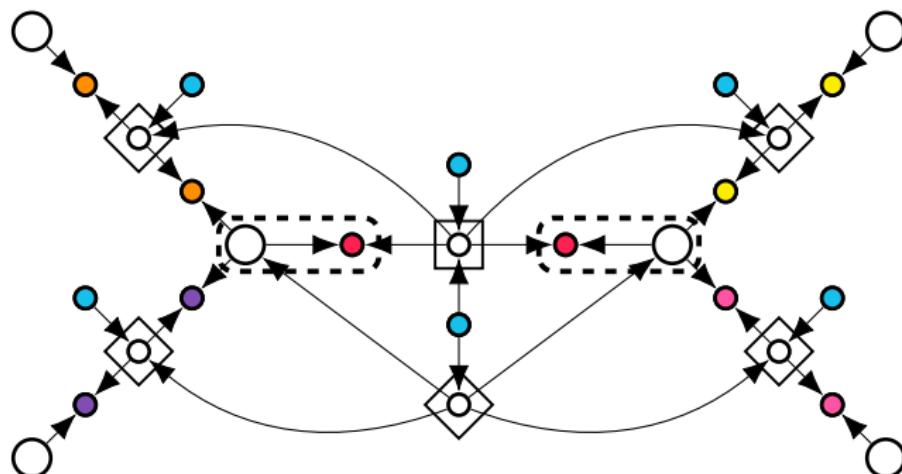
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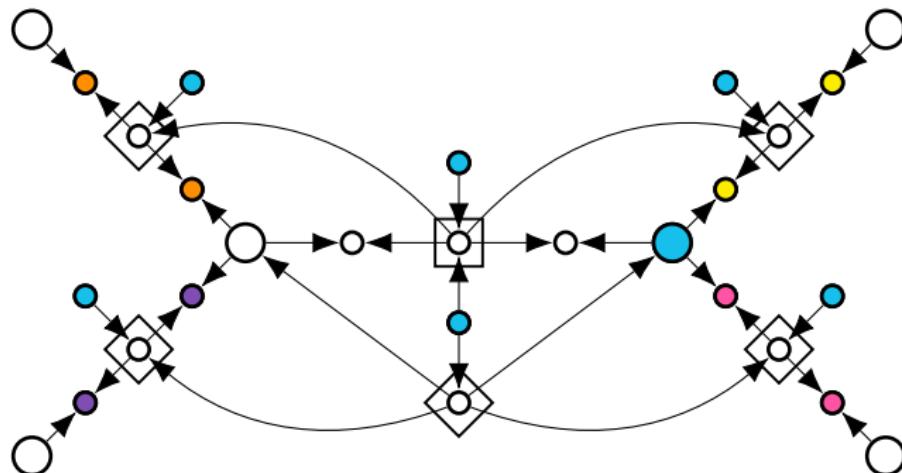


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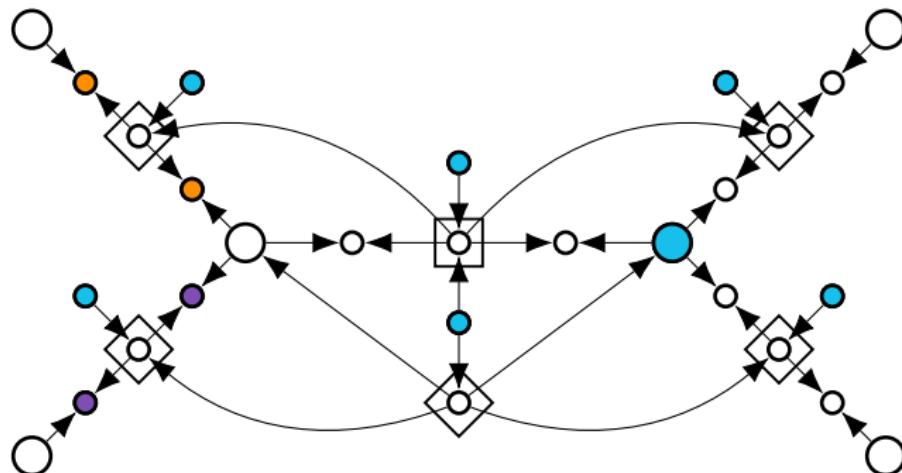
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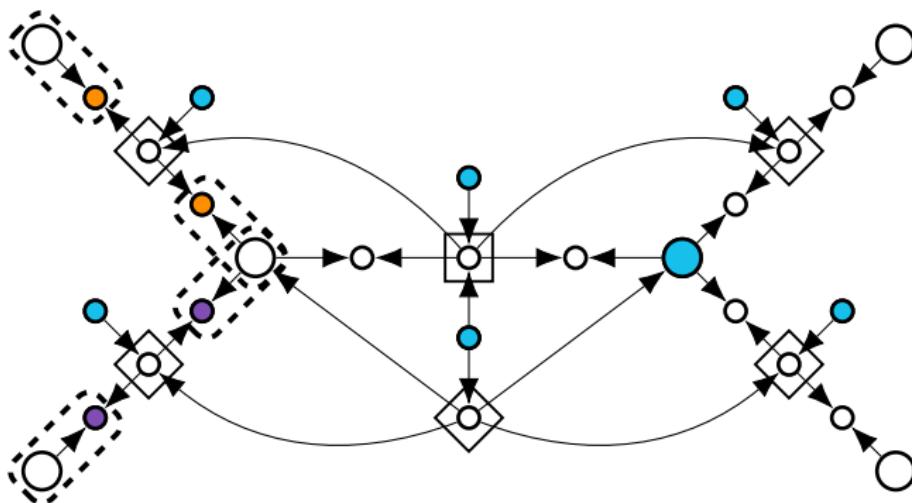
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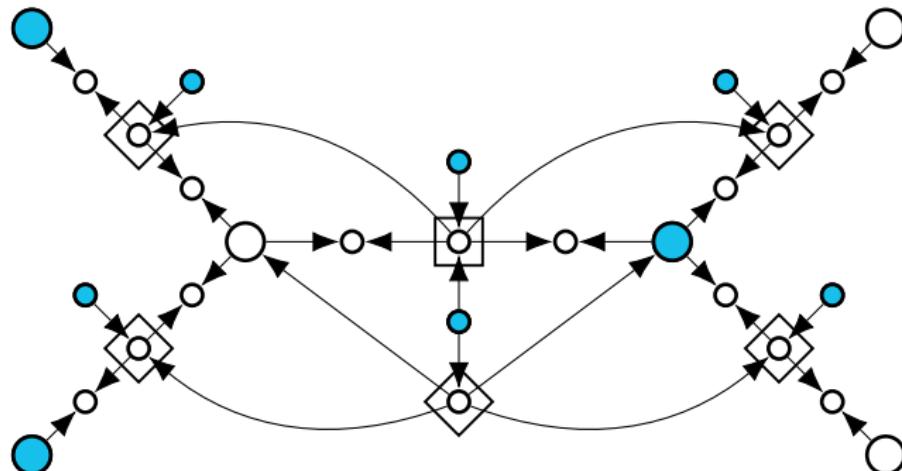


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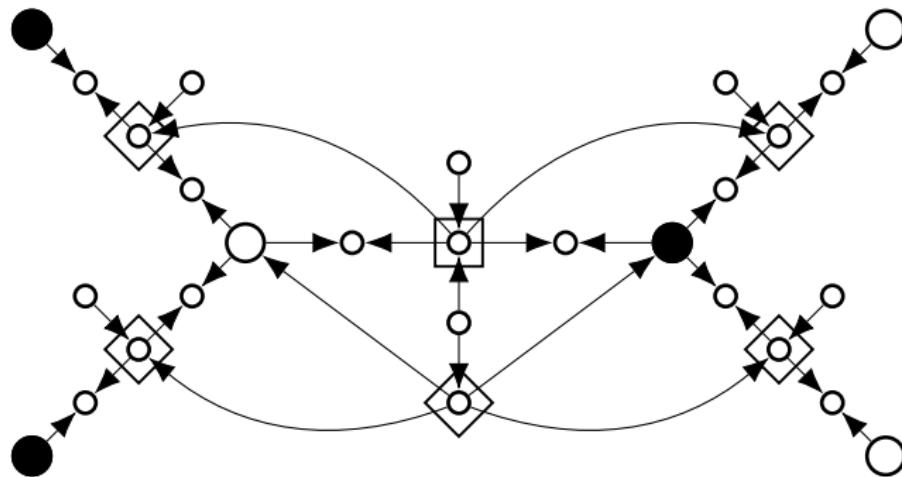
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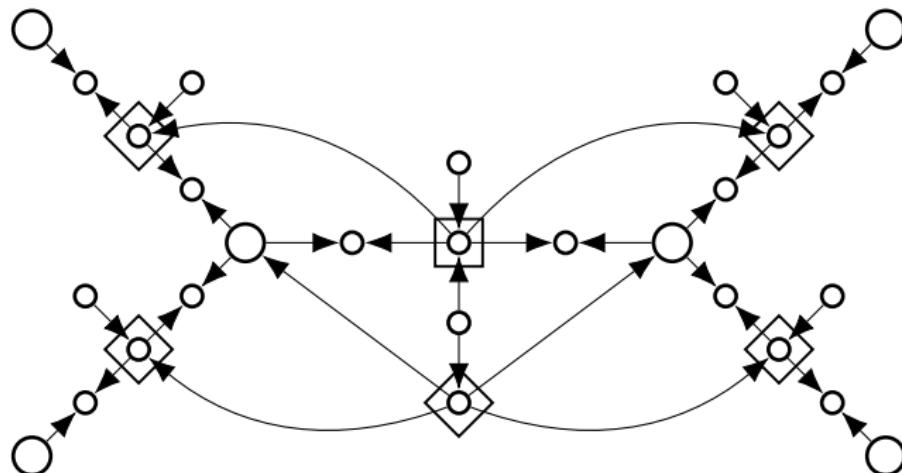


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Theorem [D., Foucaud & Hakanen, 2023+]

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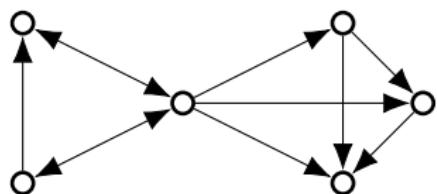
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Modular decompositions

Definition [Gallai, 1967] (and many others)

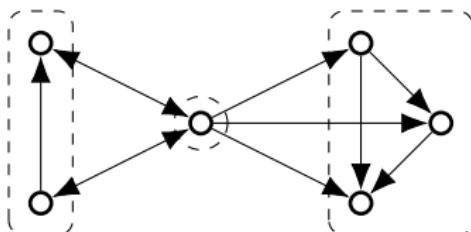
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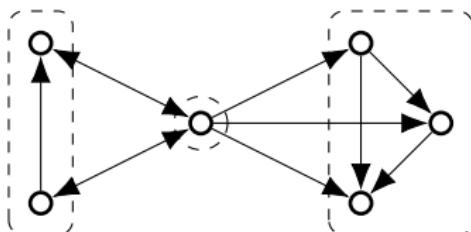


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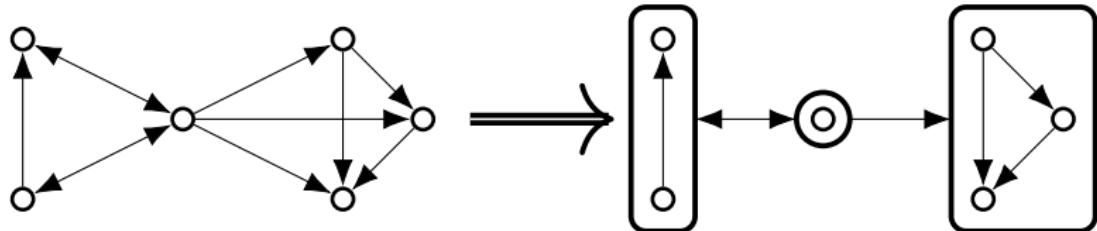


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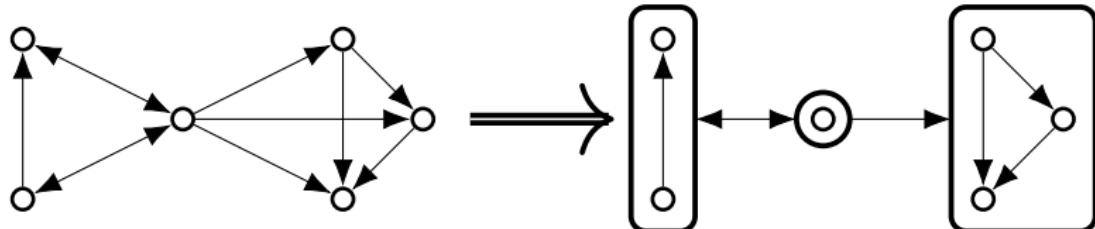
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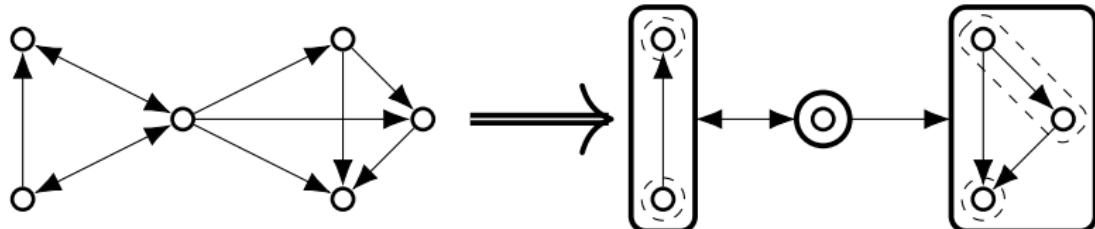
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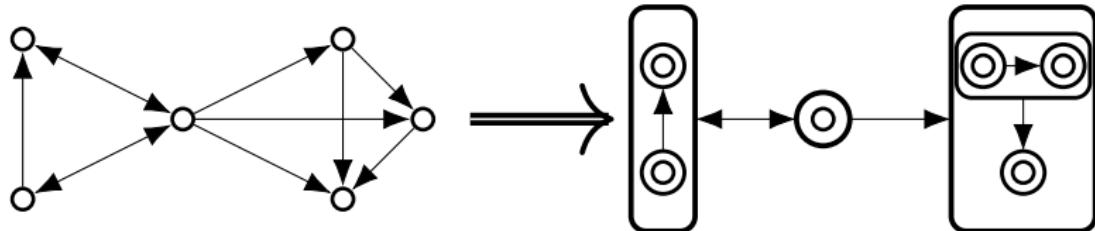
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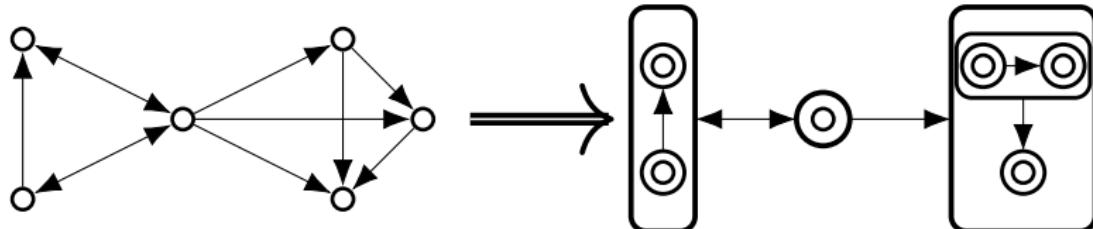
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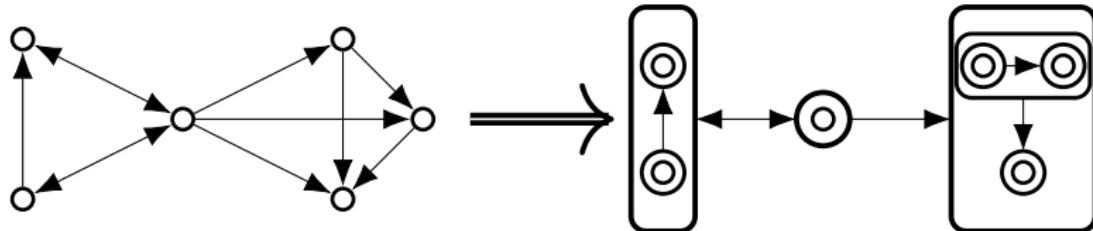
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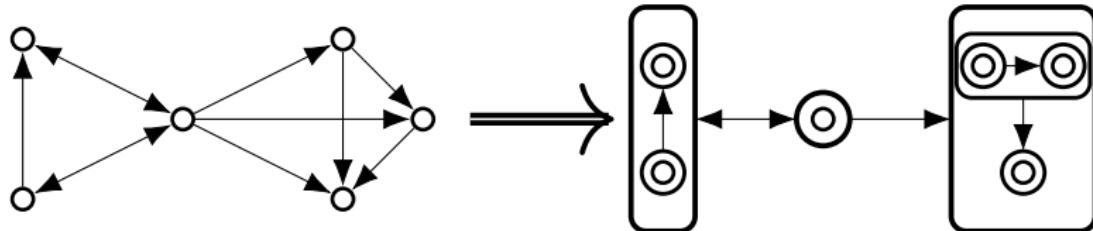
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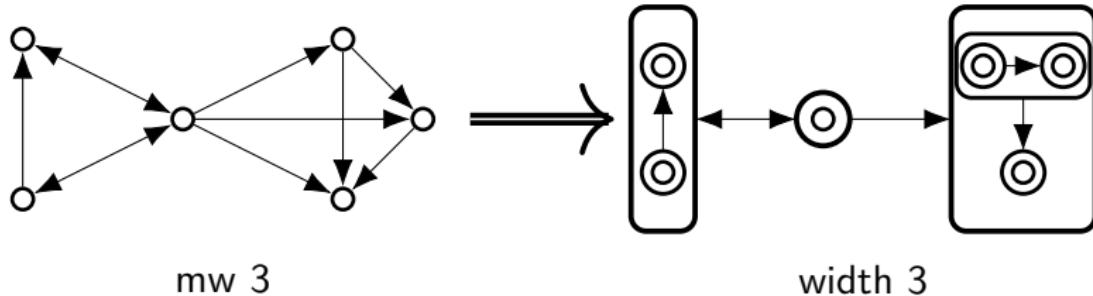
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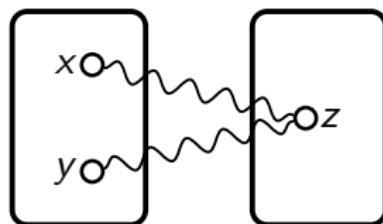
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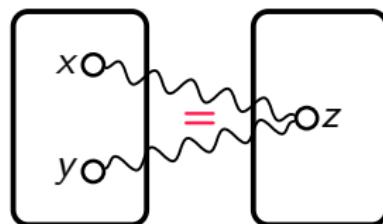
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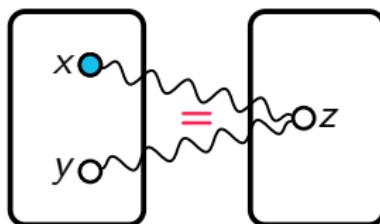
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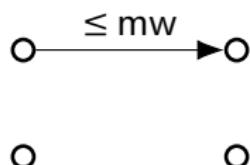
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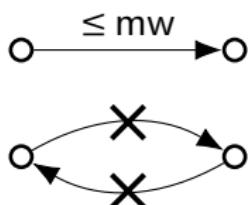
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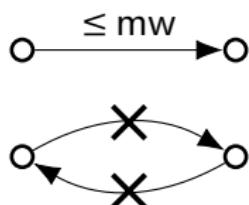
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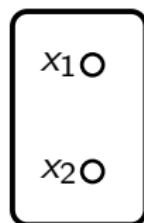
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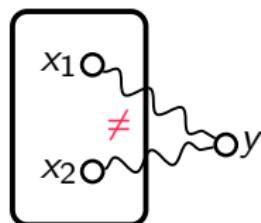
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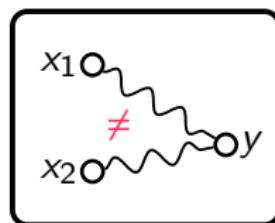
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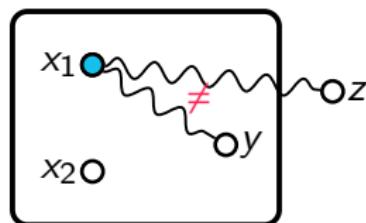
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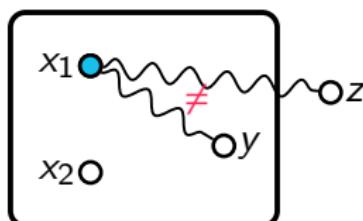
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Properties of the modular decomposition

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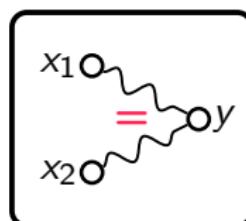
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But what if, for some $y \in M_i$,
 $\text{dist}(x_1, y) = \text{dist}(x_2, y)$ for every $x_1, x_2 \in M_i$?

d -constant vertices

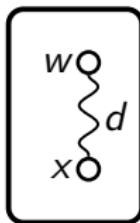
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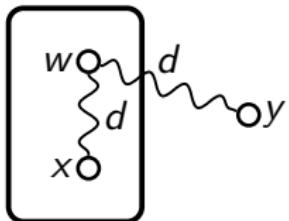
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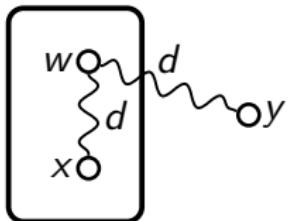


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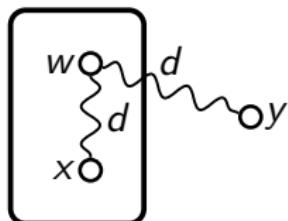
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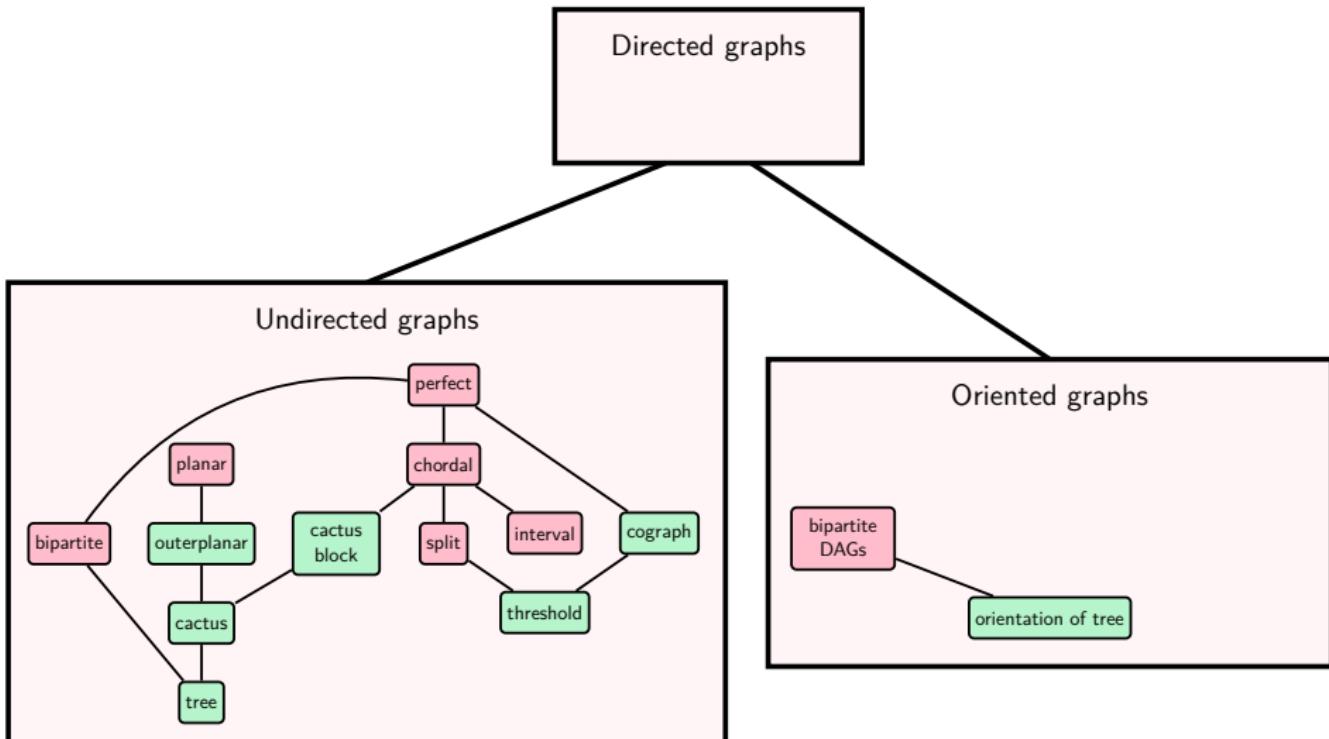
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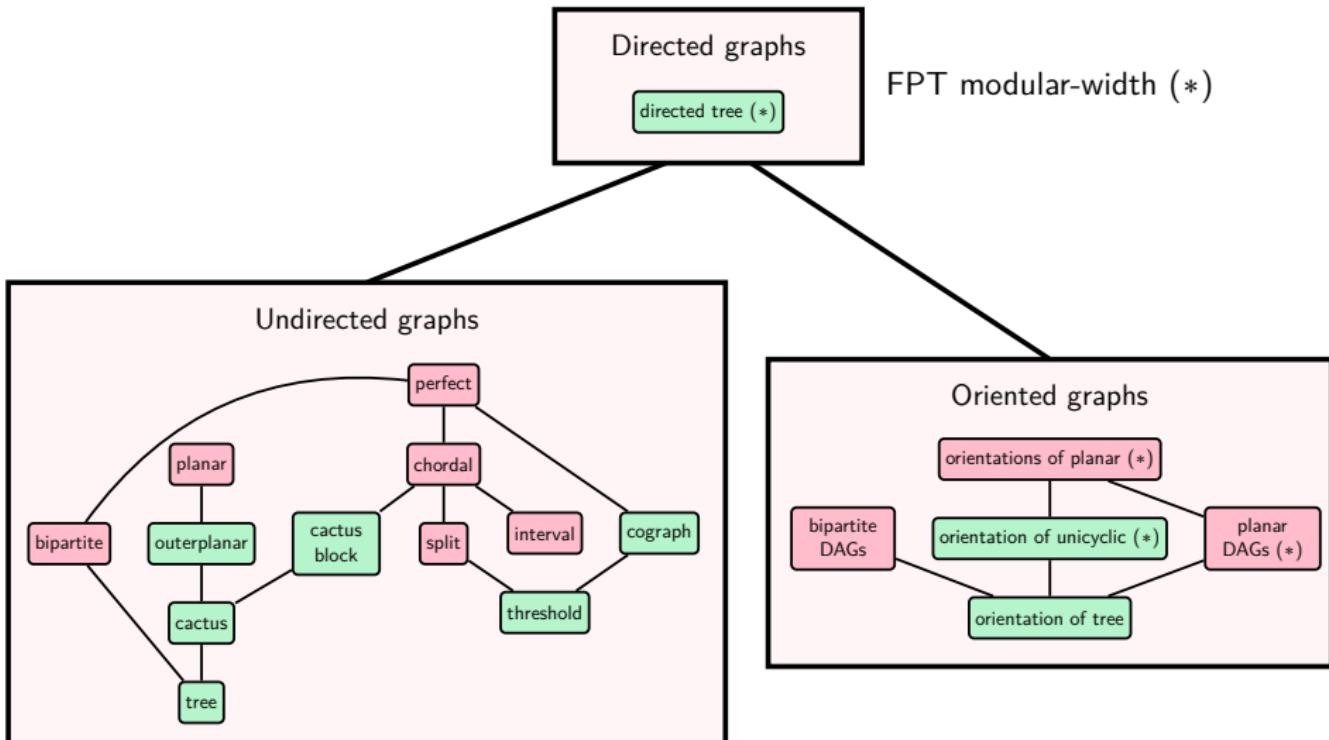
... but $d \in \{1, \dots, mw, \infty\}$ so their number is **bounded by** $mw + 1$ for each factor!

⇒ We can brute-force them when combining local solutions.

New inclusion diagram:



New inclusion diagram: (*) = our results



Final words

Our contribution to Metric Dimension on directed graphs

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- ▶ Linear-time algorithms (directed trees, orientations of unicyclic)
- ▶ FPT algorithm using modular decomposition

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