

More applications of the d -neighbor equivalence: acyclic and connectivity constraints

Benjamin Bergougnoux^{*}, Mamadou Kanté[†]

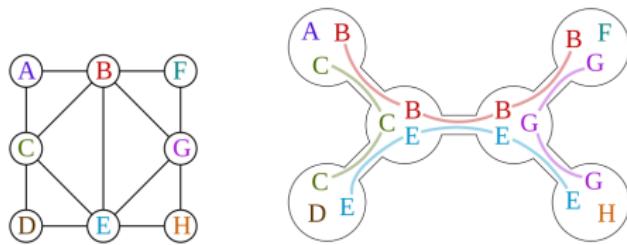
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IBS, Daejong, July 23 2019

The famous: tree-width

The most studied graph parameter.



- ▶ Measure how close a graph is to the structure of a tree.
- ▶ $2^{O(\text{tw})} \cdot n$ time algorithms for many NP-hard problems.
- ▶ Can be approximated in time $2^{O(\text{tw})} \cdot n$.

Limits and alternatives

Tree-width is unbounded in any **dense graph class**.

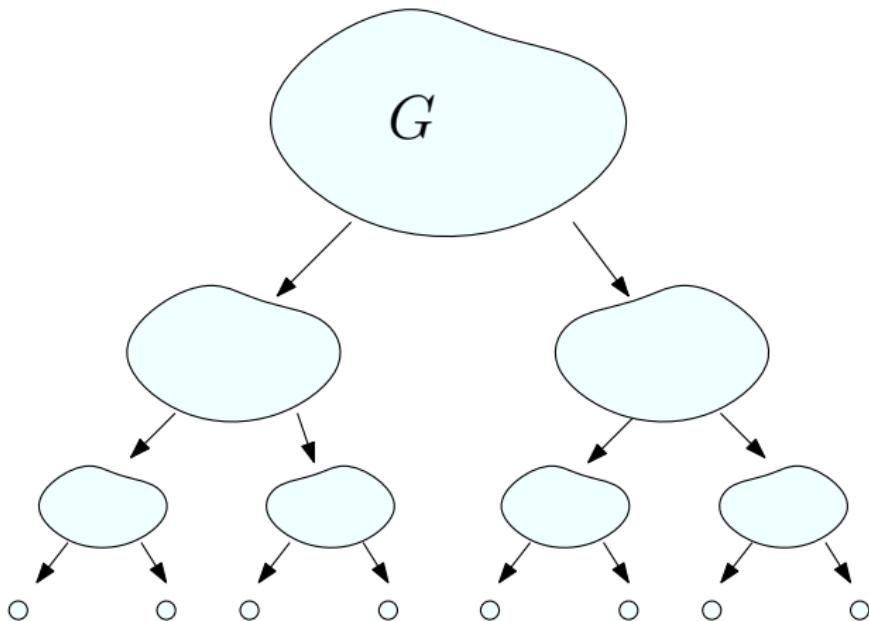
→ Tree-width of a clique = $n - 1$.

- ▶ Dense graphs can be simple.
- ▶ Many **NP-hard** problems are tractable in on some dense graph classes.
- ▶ We can explain this with other width measures.
 - clique-width, rank-width, mim width.

Divide a graph

Divide a graph

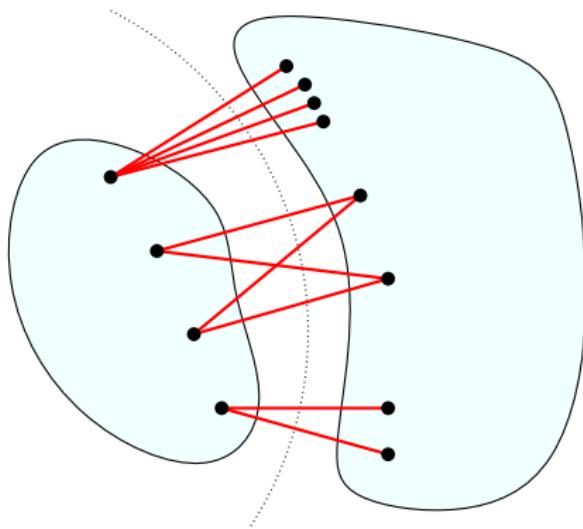
Recursively decompose your graph...



We recursively **cut** the vertex set in **two**

Divide a graph

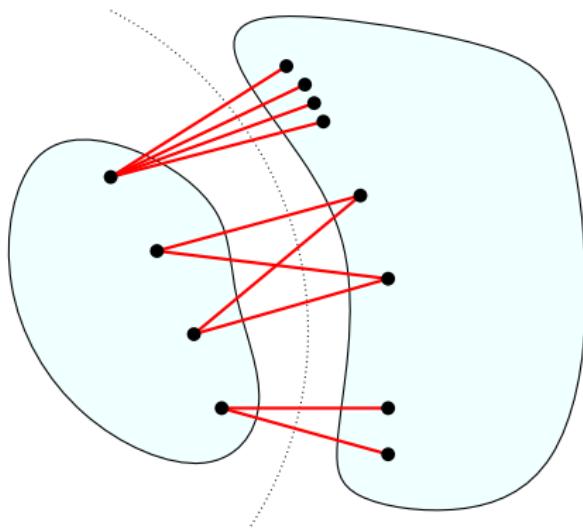
Recursively decompose your graph... into simple cuts.



Different notions of **simplicity** = different **width measures**.

Divide a graph

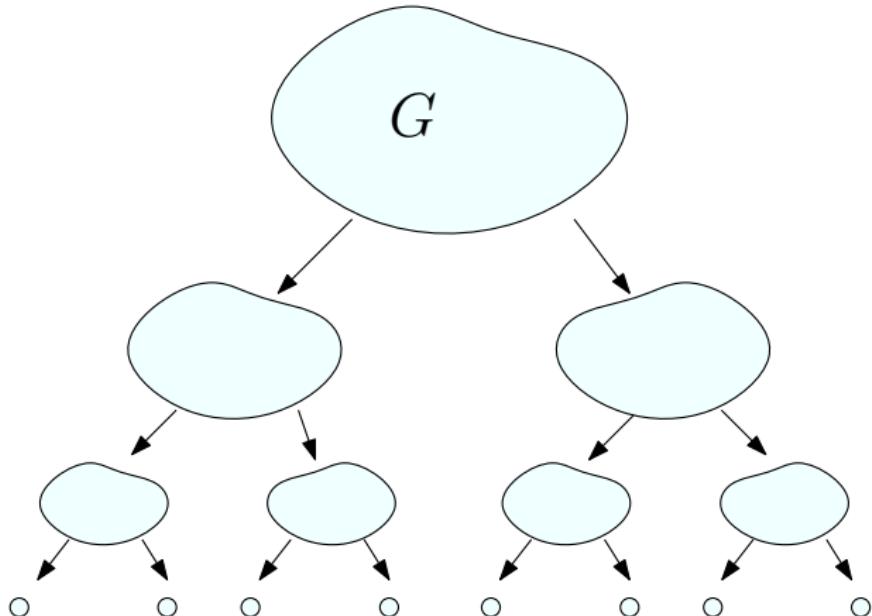
We describe the **simplicity** of a cut with a **function f** : $\text{cut} \rightarrow \mathbb{N}$.



Exemple: $f(\text{cut}) = \text{number of vertices}$ having at least one neighbor in the rest of the graph.

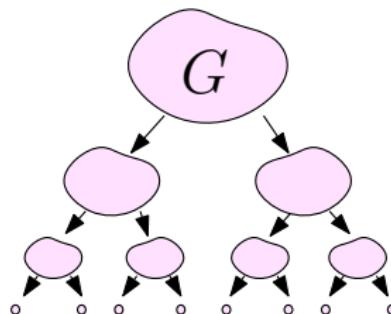
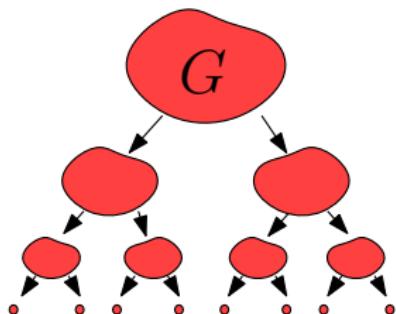
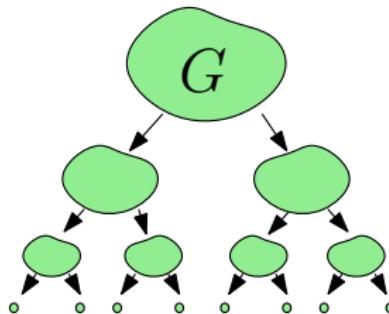
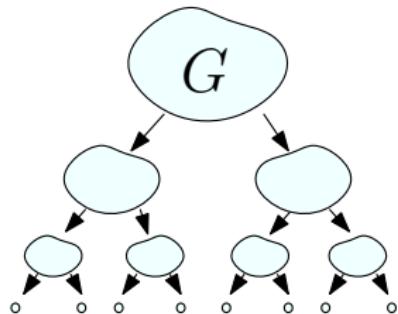
Divide a graph

Width of a decomposition $D := \max f(\text{cut})$ among the cuts of D .



Divide a graph

Width of a graph $G := \min$ width of the decompositions of G .

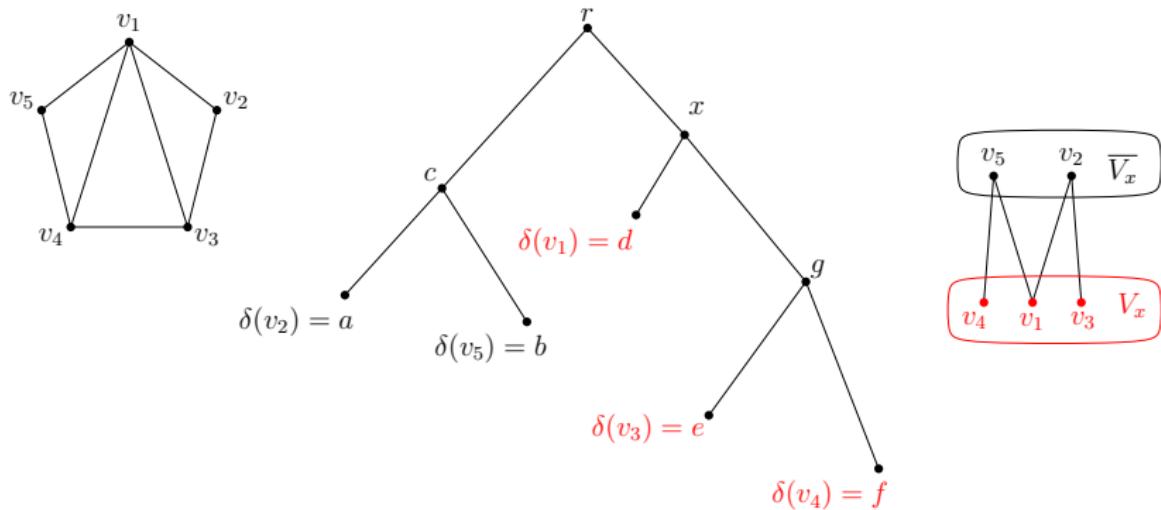


A formalism for dividing

A **rooted layout** of a graph G is a pair (T, δ) with

- ▶ T a binary tree,
- ▶ δ a bijection between the leaves of T and the **vertices** of G .

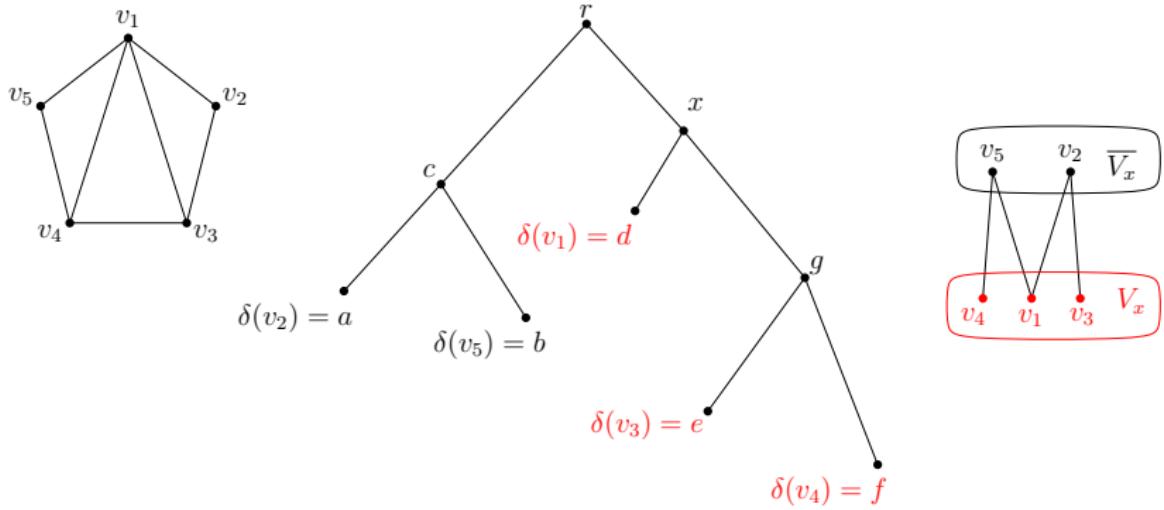
Each **node** x of T is associated with a vertex set $V_x \subseteq V(G)$:



f-width

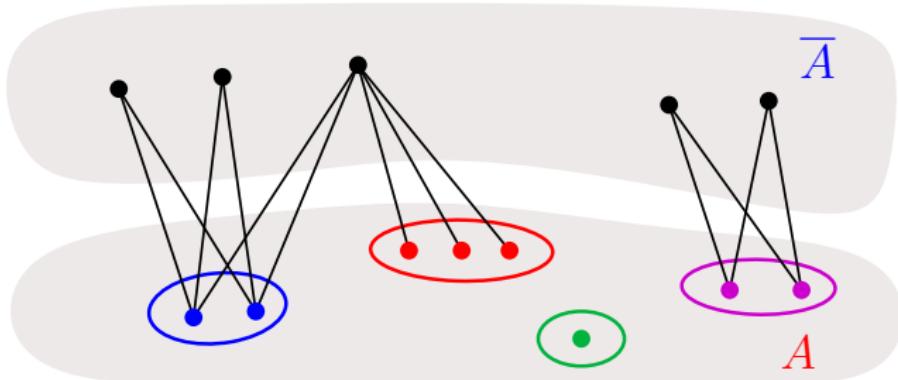
Given a function $f : 2^{V(G)} \rightarrow \mathbb{N}$, we define the **f-width** of

- ▶ a rooted layout (T, δ) : $f(T, \delta) := \max_{x \in V(T)} f(V_x)$,
- ▶ a graph G : $f(G) := \min f(\mathcal{L})$ among all rooted layouts \mathcal{L} of G .



Module-width

Defined from the function $\text{mw}(A) := |\{N(v) \cap \overline{A} : v \in A\}|$.



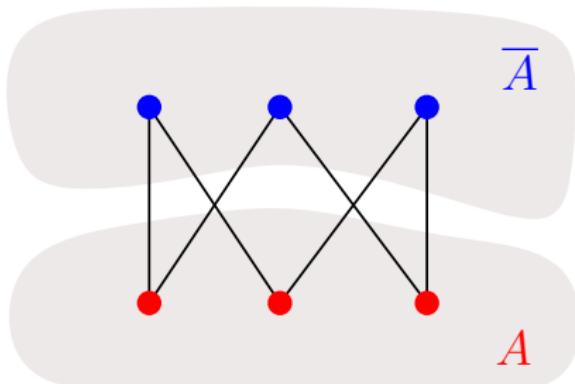
Linearly equivalent to clique-width:

[Rao 2006]

For all graphs G , we have $\text{mw}(G) \leq \text{cw}(G) \leq 2\text{mw}(G)$.

Rank-width

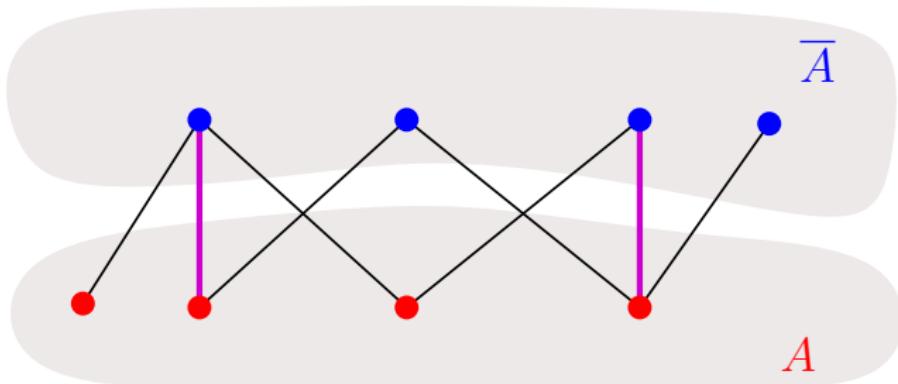
Defined from the function $\text{rw}(A) :=$ the rank of adjacency matrix between A and \overline{A} over $GF(2)$.



$$\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix}$$

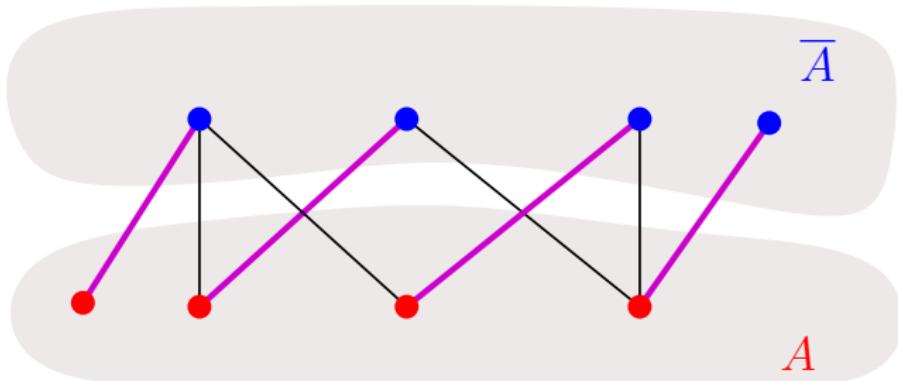
Maximum Induced Matching width (mim-width)

Defined from the function $\text{mim}(A) :=$ the size of a maximum induced matching in the bipartite graph between A and \overline{A} .



Maximum matching width

Defined from the function $\text{mmw}(A) := |\{N(v) \cap \overline{A} : v \in A\}|$.



Linearly equivalent to **tree-width**:

[Vatshelle 2012]

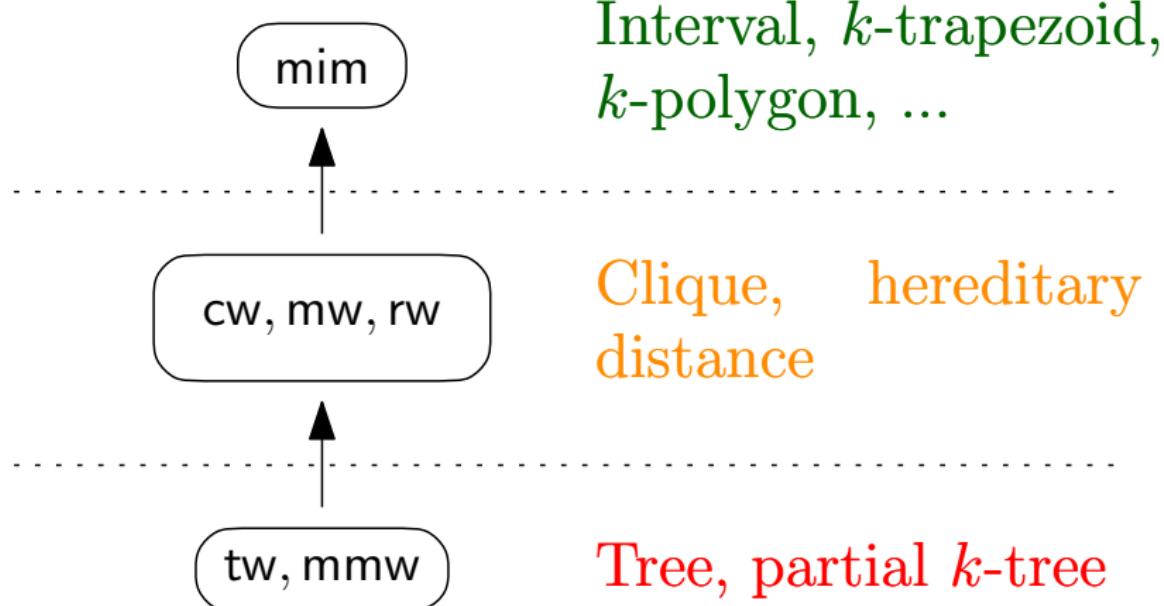
For all graphs G , we have $\frac{1}{3}\text{tw}(G) \leq \text{mmw}(G) \leq \text{tw}(G)$.

How to compare them?

There are **three aspects** to consider:

- ▶ The **generality**/modeling power.
- ▶ The **complexity of computing** a decomposition of optimal/approximated width.
- ▶ **Algorithmic applications.**

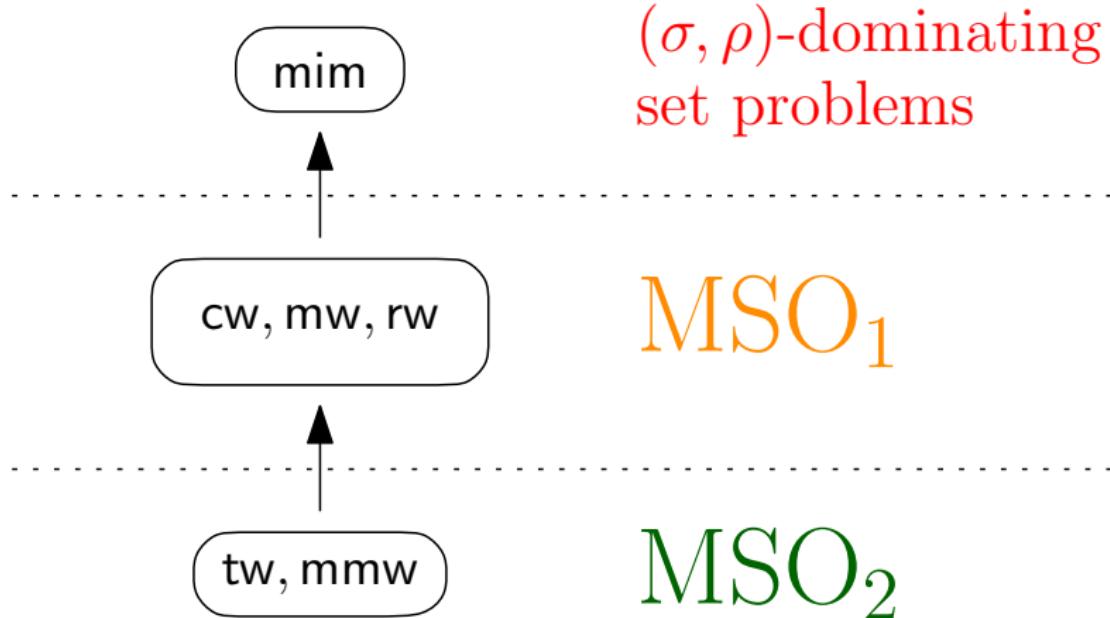
Generality



(B) Computation complexity

- ▶ NP-hard for all these widths measures.
- ▶ Efficient algorithms for tree-width and rank-width.
→ Running time: $2^{O(k)} \cdot n^{O(1)}$.
- ▶ Tough open questions for clique-width and mim-width.

(C) Algorithmic applications

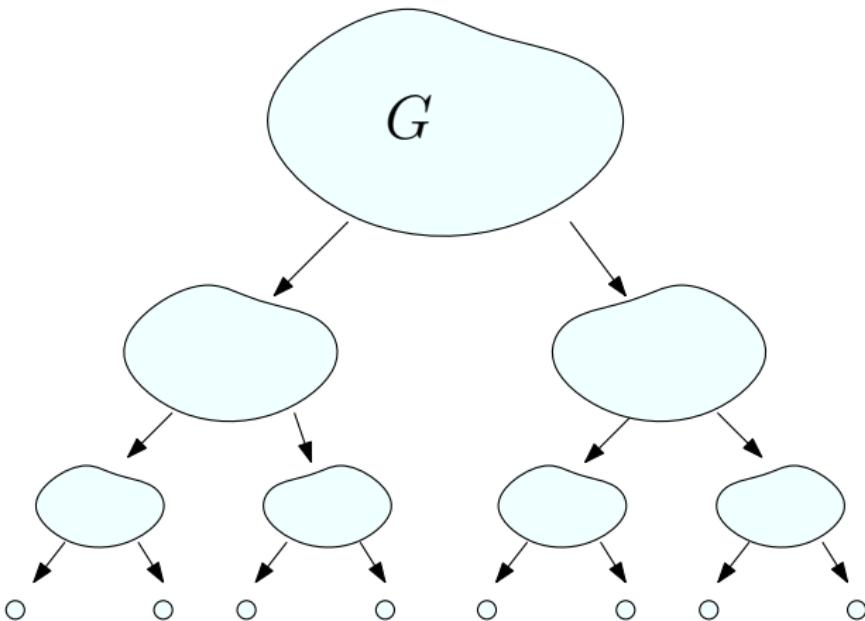


Conquer

Intuition: conquer

At each **encountered cut**: we solve a sub-problem.

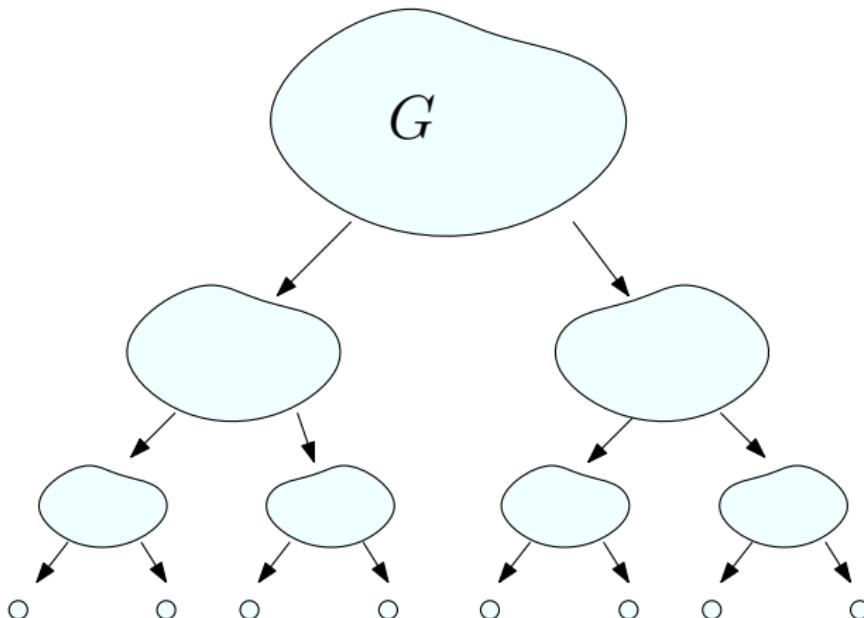
→ Computing a set of **partial solutions**.



Intuition: conquer

At each **encountered cut**: we solve a sub-problem.

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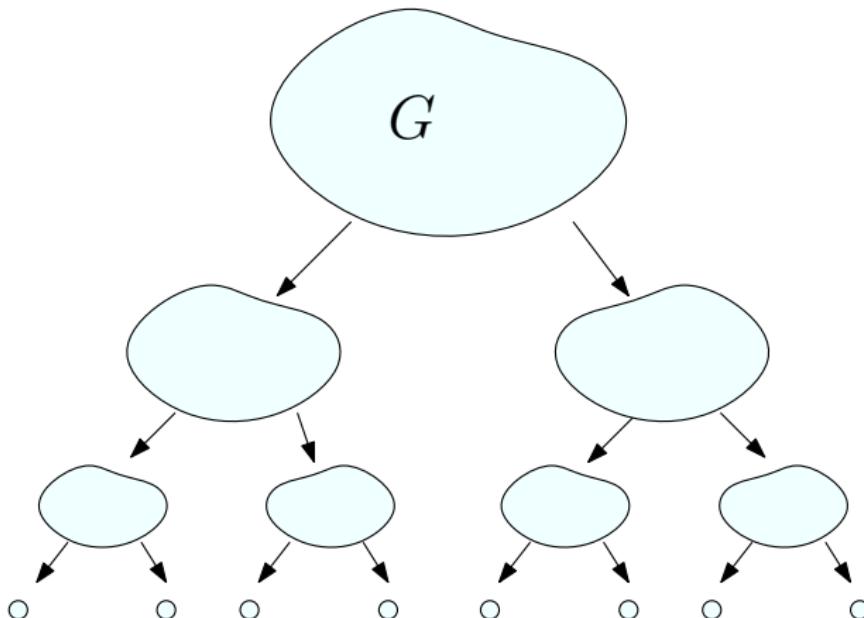


At the **root**: we obtain a **solution**.

Intuition: conquer

At each **encountered cut**: we solve a sub-problem.

→ Computing a set of **partial solutions**.

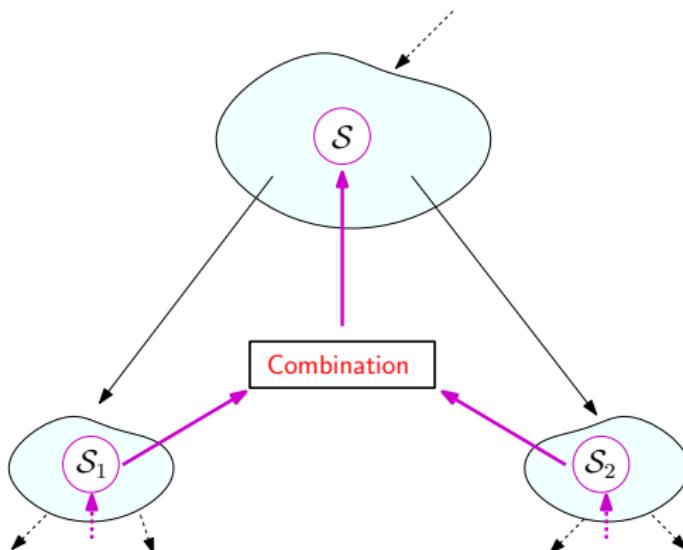


The computation is **trivial** for **leaves**.

Intuition: conquer

To compute a set of partial solutions of an internal cut:

→ We combine the sets of partial solutions of its children.

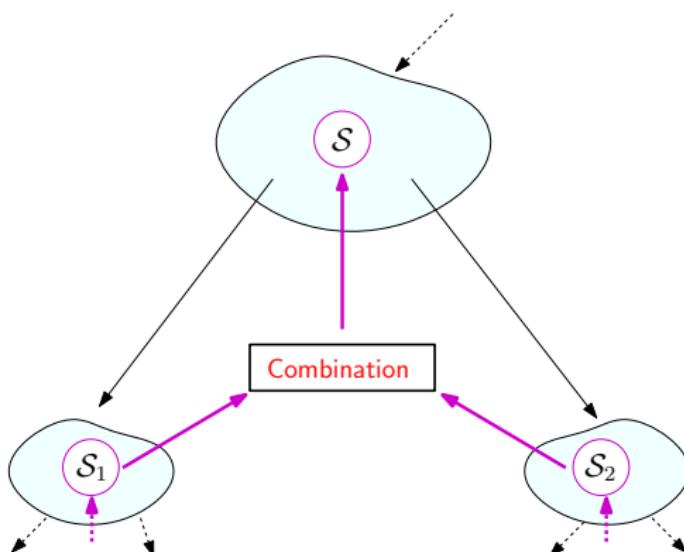


It is not trivial but rarely complicated.

Intuition: conquer

To compute a set of partial solutions of an internal cut:

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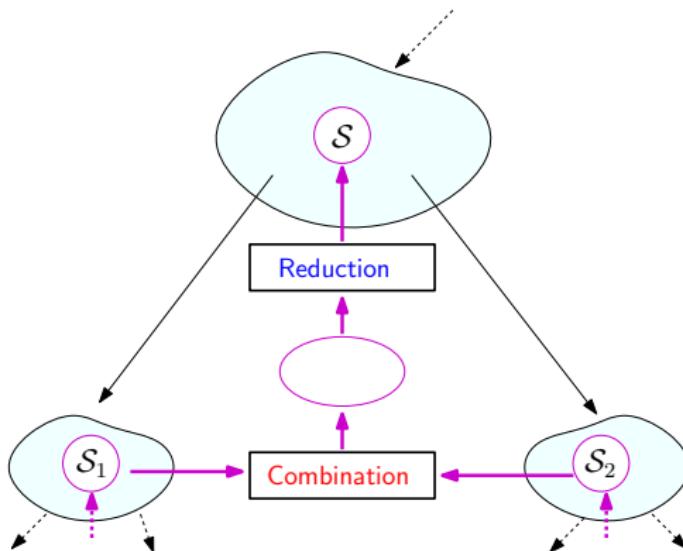


In general: running time = $O(|\mathcal{S}_1| \cdot |\mathcal{S}_2|)$.

Key step: reduction

Combining increase the size of the manipulated sets.

→ We need to reduce the size of the combination.



Key step: reduction

We need to **upper-bound** the **number of partial solutions** we need to keep.

- ▶ If the upper bound is $f(k) \cdot n^{g(k)}$ \Rightarrow an **XP** algorithm.
- ▶ If the upper bound is $f(k) \cdot n^{O(1)}$ \Rightarrow an **FPT** algorithm.

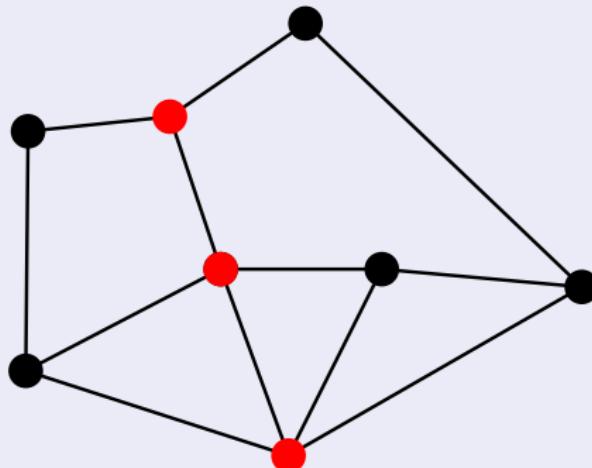


Connected Dominating set and 1-neighbor width

Connected Dominating set and 1-neighbor width

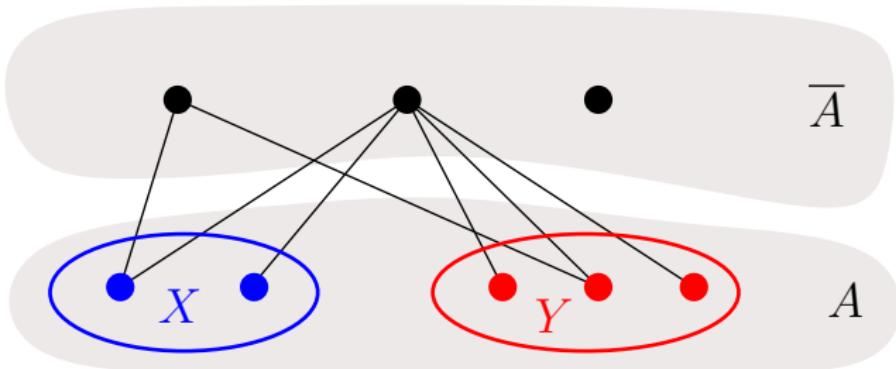
Connected dominating set

Finding a vertex set D of minimum weight which dominates all the vertices and which induces a connected graph.



1-neighbor equivalence relation

$X, Y \subseteq A$ are 1-neighbor equivalent in A if $N(X) \cap \overline{A} = N(Y) \cap \overline{A}$.



1-neighbor width

Defined from the function $\text{nec}_1(A) :=$ the number of equivalence classes.

Results

Theorem [Bui-Xuan, Telle and Vatshelle, 2013]

Dominating set is solvable in time $\text{nec}_1(\mathcal{L})^{O(1)} \cdot n^{O(1)}$.

Theorem [B. and Kanté 2018]

Connected dominating set is solvable in time $\text{nec}_1(\mathcal{L})^{O(1)} \cdot n^{O(1)}$.

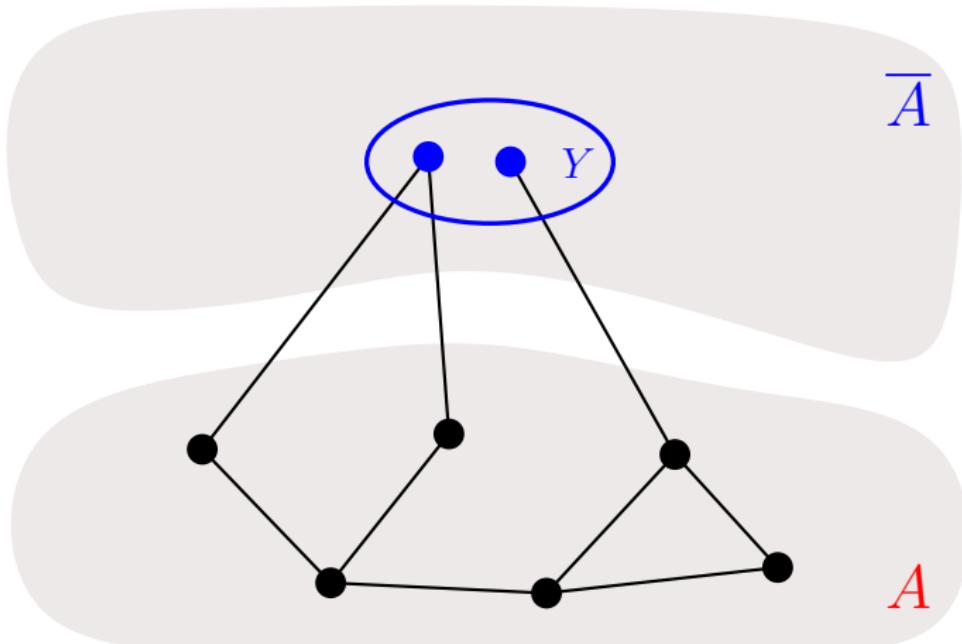
Consequences on the other width measures:

Lemme

A $\text{nec}_1(\mathcal{L})^{O(1)} \cdot n^{O(1)}$ time algorithm \Rightarrow we can solve the problem in time:
 $2^{O(\text{tw})} \cdot n^{O(1)}$, $2^{O(\text{cw})} \cdot n^{O(1)}$, $2^{O(\text{rw}^2)} \cdot n^{O(1)}$ and $n^{O(\text{mim})}$.

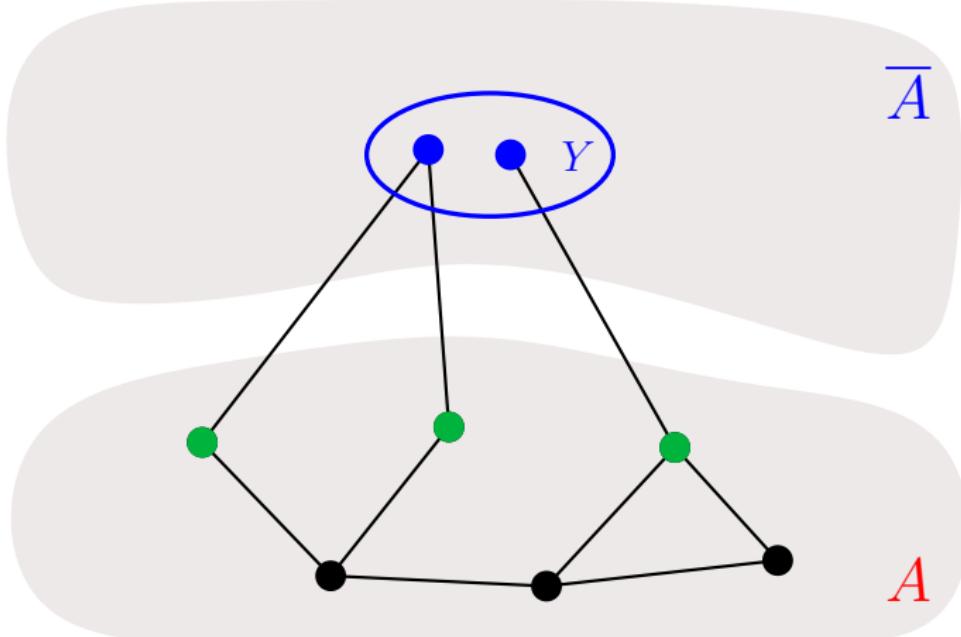
Dealing with domination

We compute a set of partial solutions for each equivalence class R' of the 1-neighbor equivalence over \overline{A} .



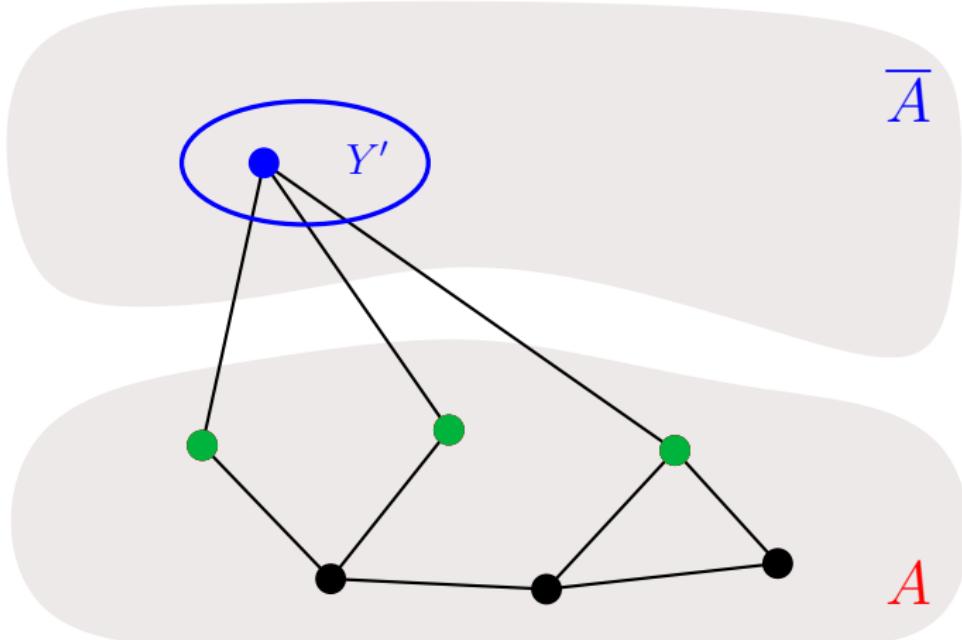
Dealing with domination

The sets $Y \in R'$ have the same neighborhood in A .
→ We know which vertices in A will be dominated.



Dealing with domination

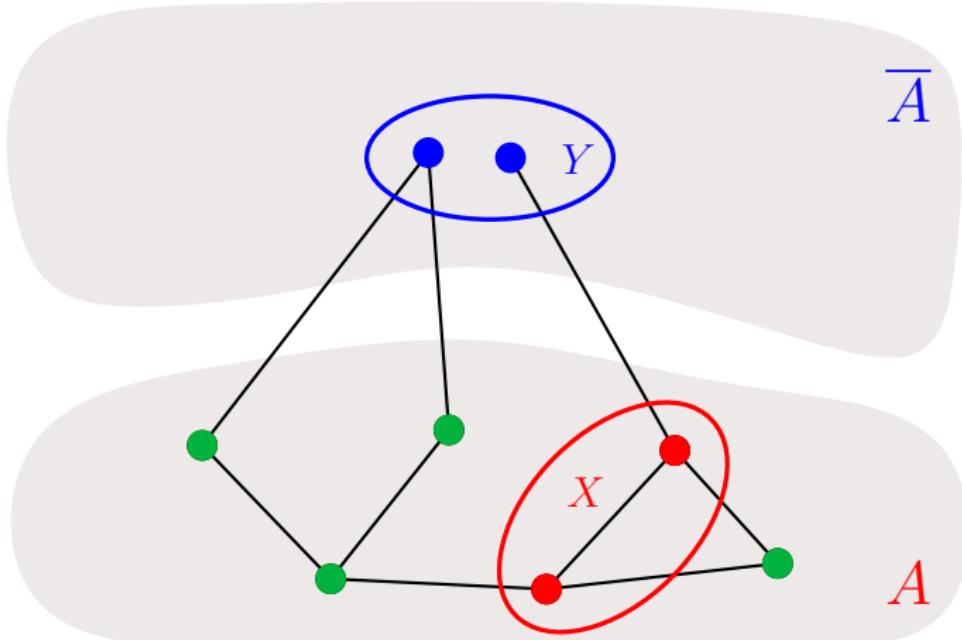
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Dealing with domination

Partial solutions associated with R' :

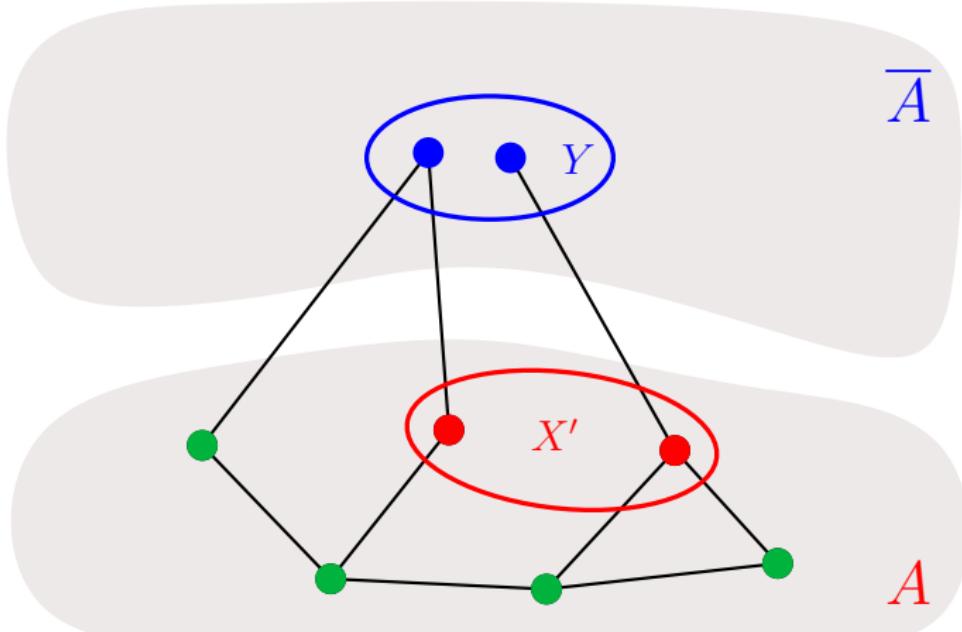
$\rightarrow X \subseteq A$ such that $X \cup Y$ dominates A , for (all) $Y \in R'$



Dealing with domination

Partial solutions associated with R' :

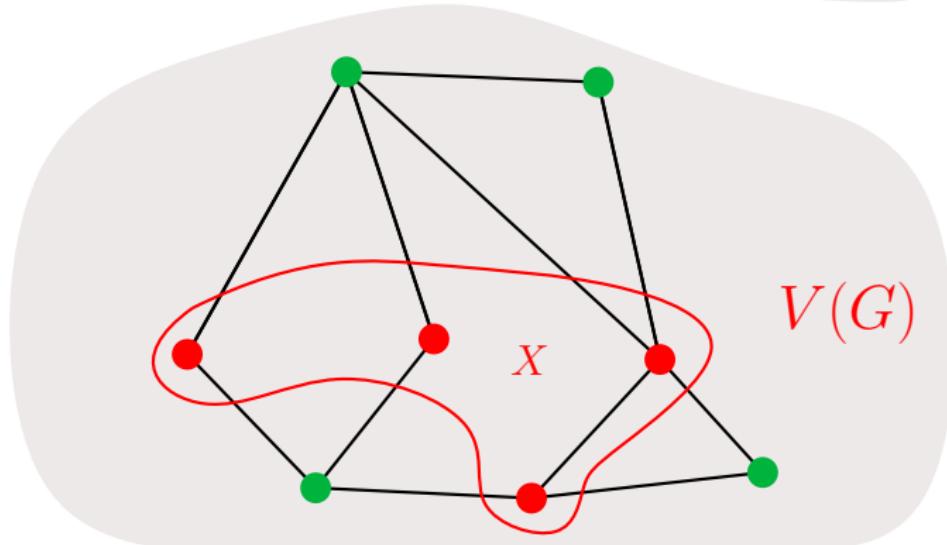
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Dealing with domination

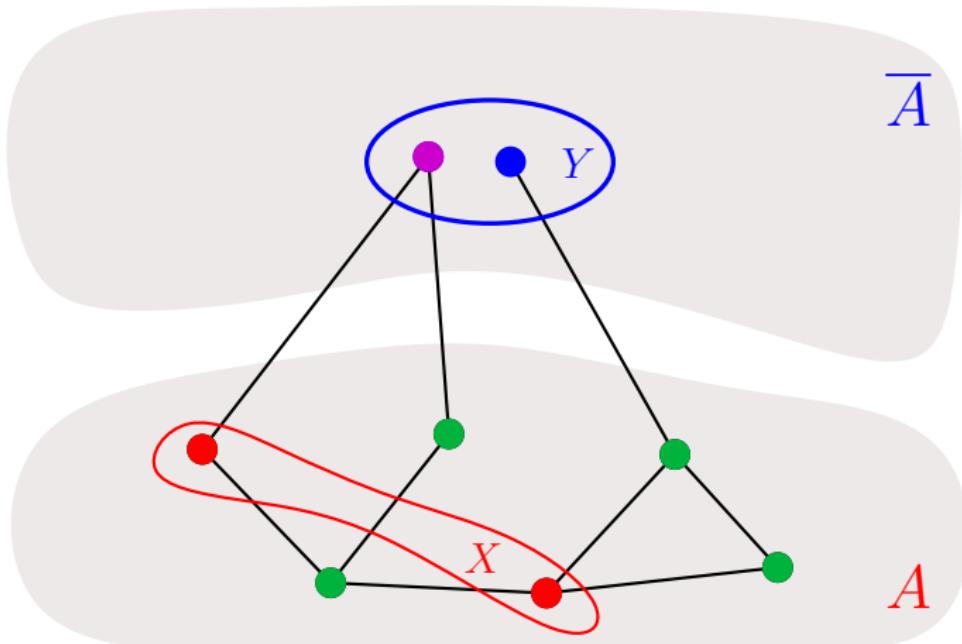
At the **root** of the decomposition, the cut is $(V(G), \emptyset)$:
→ A **partial solution** is a **dominating set**.

\emptyset



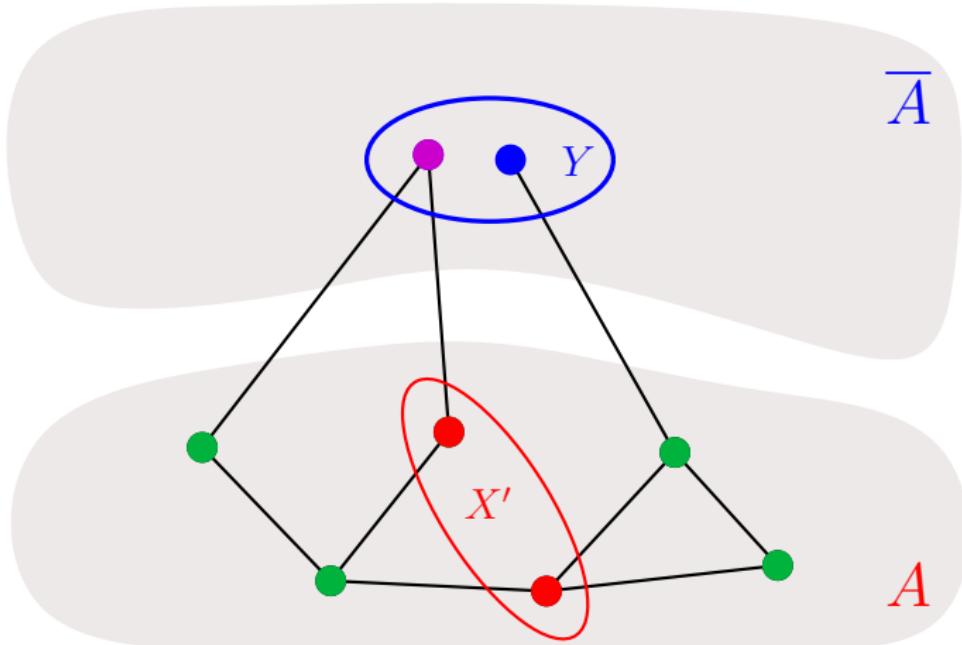
Dealing with domination

Two **partial solutions** associated with R' are **equivalent** for the **domination** if they are 1-neighbor equivalent!



Dealing with domination

Two **partial solutions** associated with R' are **equivalent** for the **domination** if they are 1-neighbor equivalent!



Lemma [Bui-Xuan, Telle and Vatshelle, 2013]

To solve Dominating set, it is enough to keep $\text{nec}_1(A)^2$ partial solutions at each step.

One partial solution:

- ▶ for each 1-neighbor equivalence class R' of \bar{A} , and
- ▶ for each 1-neighbor equivalence class R of A

Dealing with connectivity

- We need an equivalence relation between sets of partial solutions.

Dealing with connectivity

- We need an equivalence relation between sets of partial solutions.
- For all $Y \in R'$ and for all sets of partial solutions \mathcal{S} , we define:

$$\text{best}(\mathcal{S}, Y) := \min\{\text{weight}(X) : X \in \mathcal{S} \text{ and } G[X \cup Y] \text{ is connected}\}.$$

R' -representativity

We say that \mathcal{S}^* R' -represents \mathcal{S} if, for all $Y \in R'$, we have

$$\text{best}(\mathcal{S}, Y) = \text{best}(\mathcal{S}^*, Y).$$

Representative set

- ▶ At the root $(V(G), \emptyset)$: an $\{\emptyset\}$ -representative set of the set of all **partial solutions** must contain an **optimal solution**.
→ $\text{best}(\mathcal{S}, \emptyset) := \min\{\text{weight}(X) : X \in \mathcal{S} \text{ and } G[X] \text{ is connected}\}.$

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Theorem

There exists a function **reduce**:

- ▶ **Input:** a set of partial solutions \mathcal{S} .
- ▶ **Output:** $\mathcal{S}^* \subseteq \mathcal{S}$ such that $|\mathcal{S}^*| \leq \text{nec}_1(\mathcal{L})^2$ and \mathcal{S}^* R' -represents \mathcal{S} .
- ▶ **Running time:** $|\mathcal{S}| \cdot \text{nec}_1(\mathcal{L})^{O(1)} \cdot n^2$.

Sketch of proof

Inspiration [Bodlaender et al. 2013]

Rank based approach: technique to obtain $2^{O(\text{tw})} \cdot n$ time algorithms for many connectivity problems.

Let \mathcal{M} be the (\mathcal{S}, R') -matrix:

$$\mathcal{M}[\mathbf{X}, \mathbf{Y}] := \begin{cases} 1 & \text{if } G[\mathbf{X} \cup \mathbf{Y}] \text{ is connected,} \\ 0 & \text{otherwise.} \end{cases}$$

- ▶ In $GF(2)$: a basis of the row space of \mathcal{M} of minimum weight R' -represents \mathcal{S} .
- ▶ But \mathcal{M} is too big to be computed.

Sketch of proof

\mathcal{P} : the set of pairs (R'_1, R'_2) of 1-neighbor equivalence classes in \overline{A} .

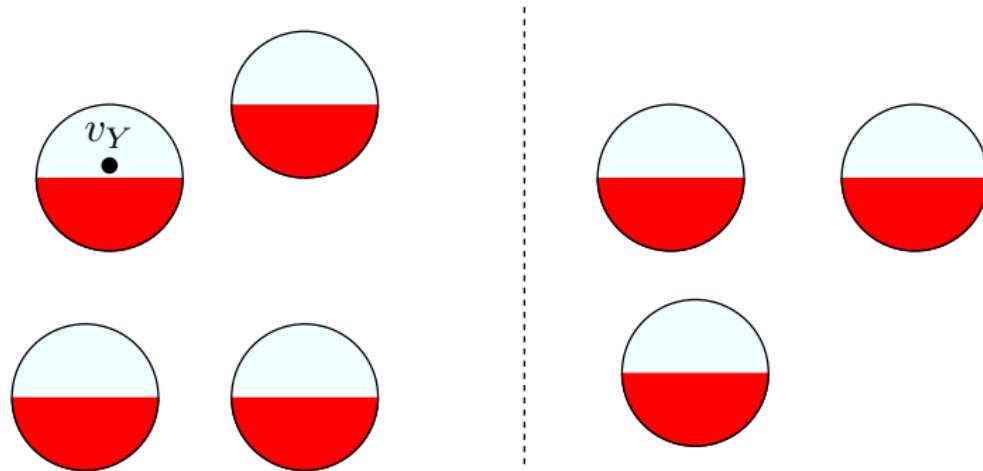
$$\mathcal{S} \left\{ \begin{array}{c} R' \\ \overbrace{\quad\quad\quad}^{\mathcal{M}} \end{array} \right\} = \mathcal{S} \left\{ \begin{array}{c} \mathcal{P} \\ \overbrace{\quad\quad\quad}^{\mathcal{C}} \end{array} \right\} \bullet \mathcal{P} \left\{ \begin{array}{c} R' \\ \overbrace{\quad\quad\quad}^{\overline{\mathcal{C}}} \end{array} \right\}$$

$GF(2)$

- ▶ A basis of \mathcal{C} is also a basis of \mathcal{M} .
- ▶ $|\mathcal{P}| = \text{nec}_1(A)^2$.
- ▶ \mathcal{C} is computable in time $|\mathcal{S}| \cdot |\mathcal{P}| \cdot n^2$.

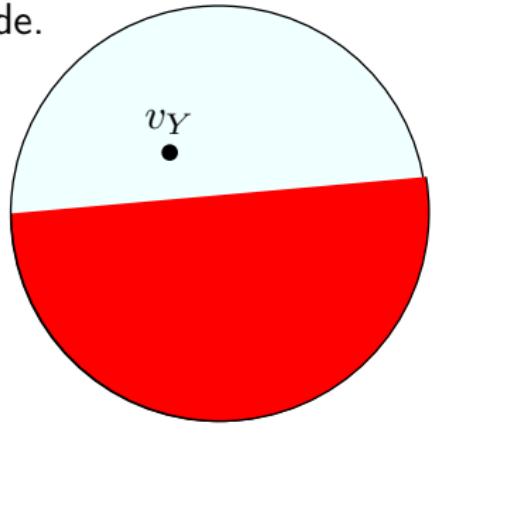
Trick

There is $2^{|CC(X \cup Y)|-1}$ ways of dividing $X \cup Y$ such that v_Y is on one side.



Trick

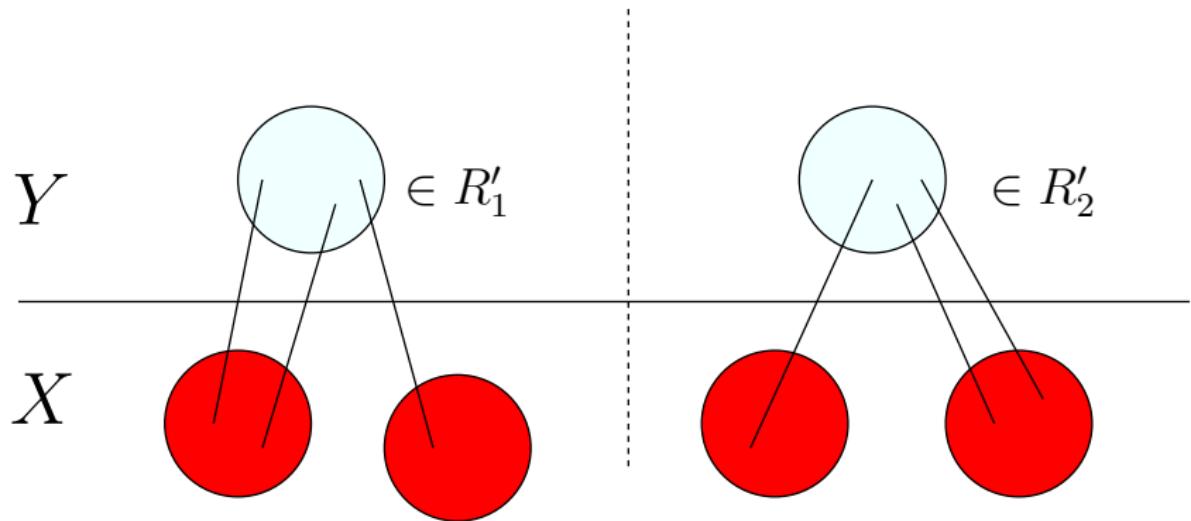
There is $2^{|CC(X \cup Y)|-1}$ ways of dividing $X \cup Y$ such that v_Y is on one side.



$$\mathcal{C} \cdot \bar{\mathcal{C}}[X, Y] = 2^{|CC(X \cup Y)|-1}$$

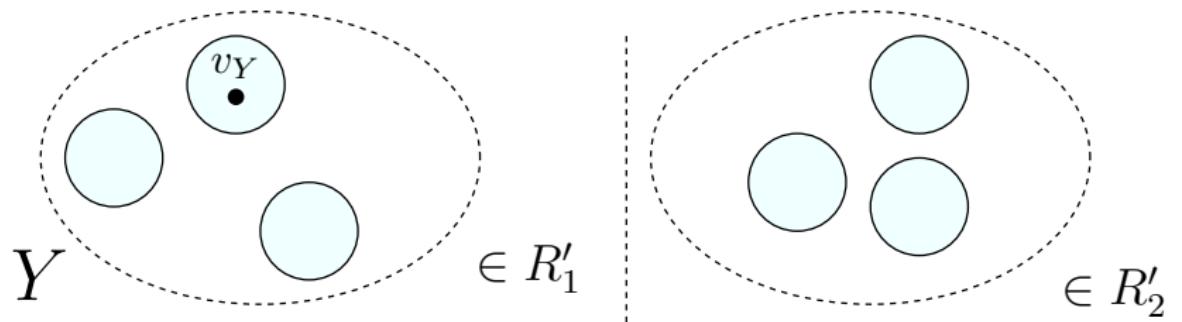
Trick

$\mathcal{C}[X, (R'_1, R'_2)] = 1$ if and only if



Trick

$\bar{\mathcal{C}}[(R'_1, R'_2), Y] = 1$ if and only if



Trick

$$\textcolor{red}{C} \cdot \overline{\mathcal{C}}[X, Y] = 2^{|CC(X \cup Y)| - 1}$$

$$\textcolor{red}{C} \cdot \overline{\mathcal{C}} \stackrel{GF(2)}{=} \mathcal{M}$$

Generalization

We can **generalize this** to other local constraints.

→ **d -neighbor equivalence**: nec_d with $d \in \mathbb{N}$.

Theorem [B. and Kanté 2018]

We can solve the **connected** variants of (σ, ρ) -Dominating Set problems in time $\text{nec}_d(\mathcal{L})^{O(1)} \cdot n^{O(1)}$.

→ Connected Vertex Cover, Node-Weighted Steiner Tree,....

Lemma

A $\text{nec}_d(\mathcal{L})^{O(1)} \cdot n^{O(1)}$ time algorithm ⇒ we can solve the problem in time $2^{O(\text{tw})} \cdot n$, $2^{O(\text{cw})} \cdot n$, $2^{O(\text{rw}^2)} \cdot n^3$ and $n^{O(\text{mim})}$.

Acyclicity

Theorem [B. and Kanté 2018]

We can solve in time: $2^{O(\text{tw})} \cdot n$, $2^{O(\text{cw})} \cdot n$, $2^{O(\text{rw}^2)} \cdot n^3$ and $n^{O(\text{mim})}$ the acyclic and the **acyclic \wedge connected** variants of any (σ, ρ) -Dominating Set problem

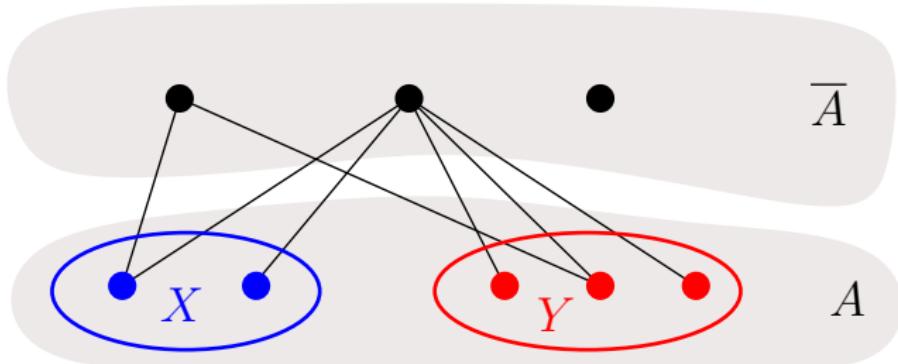
- Feedback Vertex Set, Maximum Induced Linear Forest,...
- Maximum Induced Tree, Longest Induced Path,...

- ▶ No $\text{nec}_d(\mathcal{L})^{O(1)} \cdot n^{O(1)}$ time algorithms (open question).
 - At some point, we had to use the **specificity** of the different width measures...

d -neighbor equivalence relation

$X, Y \subseteq A$ are d -neighbor equivalent in A if for all $v \in \overline{A}$, we have

$$\min(d, |N(v) \cap X|) = \min(d, |N(v) \cap Y|).$$

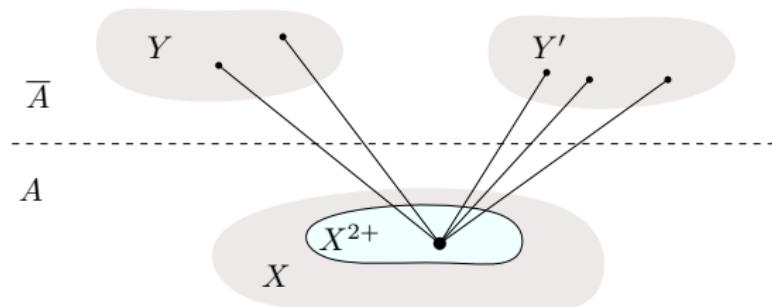


d -neighbor width

Defined from the function $\text{nec}_d(A) :=$ maximum between the number of equivalence classes of the d -neighbor equivalence over A and \overline{A} .

Maximum Induced Tree vs 2-neighbor equivalence

We compute a set of partial solutions for every 2-neighbor equivalence class R' .



We know the vertices that will have at least two neighbors.

Lemma

If X leads to a solutions, then $|X^{2+}|$ is upper bounded by $2\text{mim}(A)$, $2\text{rw}(A)$, $\text{mw}(A)$.

New notion of representativity

Let R' be a 2-neighbor equivalence class.

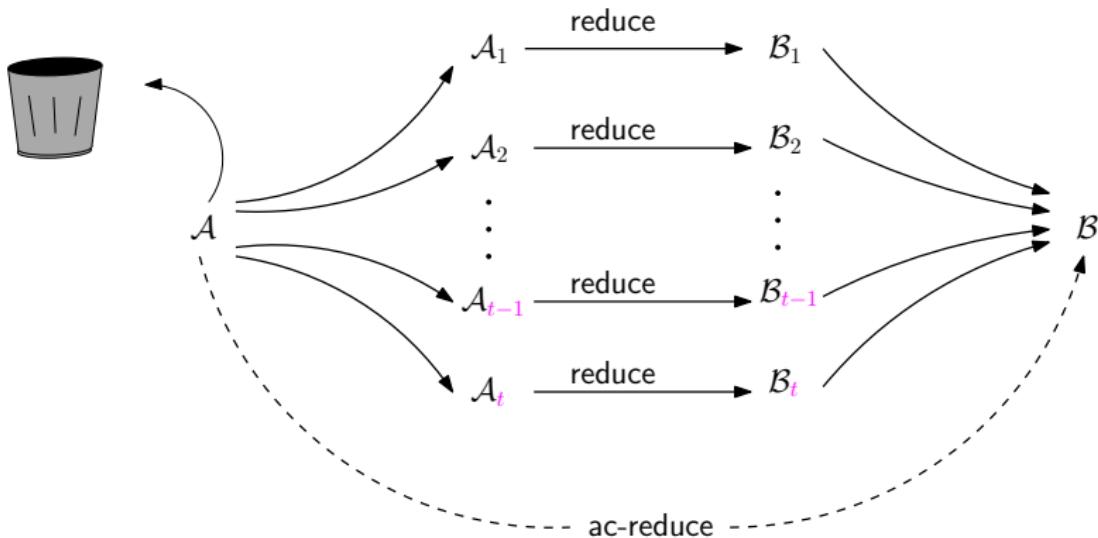
- For all $Y \in R'$ and for all sets of partial solutions \mathcal{S} , we define:
 $\text{ac-best}(\mathcal{S}, Y) := \min\{\text{weight}(X) : X \in \mathcal{S} \text{ and } G[X \cup Y] \text{ is a tree}\}.$

Definition R' -ac-representativity

We say that \mathcal{S}^* R' -ac-represents \mathcal{S} if for all $Y \in R'$, we have

$$\text{ac-best}(\mathcal{S}, Y) = \text{ac-best}(\mathcal{S}^*, Y).$$

Manage acyclicity



- With $t \leq 2^{\text{mw}+1} \cdot n$ or $2^{2\text{rw}^2+1} \cdot n$ or $2n^{2\text{mim}+1}$.

Overview

Thanks to the *d*-neighbor equivalence, we obtained the best algorithms:

- ▶ for many problems
 - (σ, ρ) -Dominating Set problems and their variants.
- ▶ for many width-measures.
 - clique-width, rank-width, mim-width, \mathbb{Q} -rank-width and tree-width...

The algorithms we get for clique-width and tree-width are optimal under ETH.

→ What about rank-width: $2^{O(rw^2)} \cdot n^{O(1)}$ is optimal?

Hamiltonian cycle, Max Cut and Edge Dominating Set

Can we use the d -neighbor equivalence for W[1]-hard problems parameterized by clique-width?

- ▶ We can solve these 3 problems in time $2^{O(\text{tw})} \cdot n$ and $n^{O(\text{cw})}$.
→ Optimal under ETH.
- ▶ Using the d -neighbor equivalence width d a constant is useless.

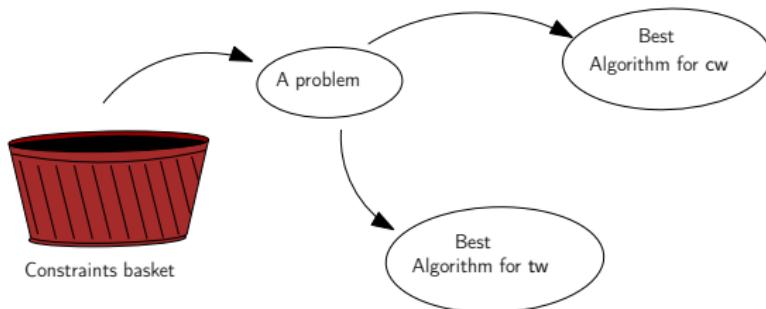
Lemma

If we can solve a problem in time $\text{nec}_n(\mathcal{L})^{O(1)} \cdot n^{O(1)}$, then we can solve it in time $n^{O(\text{cw})}$, $n^{O(\text{rw}_{\mathbb{Q}})}$ and $n^{2^{O(\text{rw})}}$.

- ▶ We can solve Max Cut in time $\text{nec}_n(\mathcal{L})^{O(1)} \cdot n^{O(1)}$.

The dream

Towards a “Courcelle’s theorem” which gives **efficient algorithms?**



Example:

We want a **set of vertices** X of **minimum weight** satisfying:

$$\text{DominatingSet}(X) \wedge \text{Acyclic}(X) \wedge \text{Connected}(X).$$

Thm \Rightarrow We can find one in time: $2^{O(\text{tw})} \cdot n$, $2^{O(\text{cw})} \cdot n$, $2^{O(\text{rw}^2)} \cdot n^3$.

