

Algorithmes paramétrés efficaces

Ignasi Sau

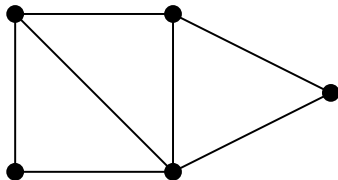
Équipe **AIGCo**
Algorithmes, **G**raphes et **C**ombinatoire

CIEL

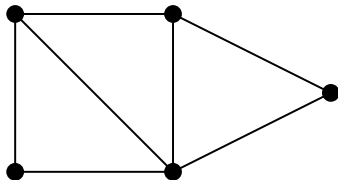
13 mai 2019



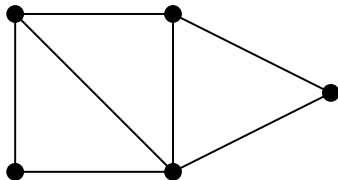
Graph theory



Graph theory  Graph algorithms



Graph theory  Graph algorithms  Parameterized complexity



Outline of the talk

- 1 Introduction
 - Parameterized complexity
 - Treewidth
- 2 FPT algorithms parameterized by treewidth
- 3 The $\mathcal{F}$ -DELETION problem
- 4 Further research

Next section is...

1 Introduction

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- Treewidth

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Crucial notion in complexity theory: NP-completeness

- Cook-Levin Theorem (1971): the SAT problem is NP-complete.
- Karp (1972): list of 21 *important* NP-complete problems.
- Nowadays, literally thousands of problems are known to be NP-hard: unless $P = NP$, they cannot be solved in polynomial time.

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- Nowadays, literally thousands of problems are known to be NP-hard: unless $P = NP$, they cannot be solved in polynomial time.
- But what does it mean for a problem to be NP-hard?

No algorithm solves all instances optimally in polynomial time.

Are all instances really hard to solve?

Maybe there are relevant **subsets of instances** that can be solved **efficiently**.

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- **VLSI design**: the number of circuit layers is usually ≤ 10 .
- **Computational biology**: Real instances of DNA chain reconstruction usually have treewidth ≤ 11 .
- **Robotics**: Number of degrees of freedom in motion planning problems ≤ 10 .
- **Compilers**: Checking compatibility of type declarations is hard, but usually the depth of type declarations is ≤ 10 .

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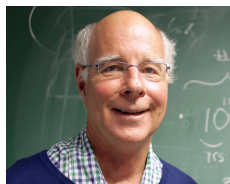
Message

In many applications, not only the **total size** of the instance matters, but also the value of an **additional parameter**.

The area of parameterized complexity

Idea Measure the complexity of an algorithm in terms of the **input size** and an **additional parameter**.

This theory started in the late 80's, by **Downey** and **Fellows**:



Today, it is a well-established area with **hundreds** of articles published every year in the most prestigious TCS journals and conferences.

Parameterized problems

A **parameterized problem** is a language $L \subseteq \Sigma^* \times \mathbb{N}$,
where Σ is a fixed, finite alphabet.

For an instance $(x, k) \in \Sigma^* \times \mathbb{N}$, k is called the **parameter**.

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These three problems are **NP-hard**, but are they **equally** hard?

They behave quite differently...

- k -VERTEX COVER: Solvable in time $\mathcal{O}(2^k \cdot (m + n))$
- k -CLIQUE: Solvable in time $\mathcal{O}(k^2 \cdot n^k)$
- VERTEX k -COLORING: NP-hard for fixed $k = 3$.

They behave quite differently...

- k -VERTEX COVER: Solvable in time $\mathcal{O}(2^k \cdot (m + n)) = f(k) \cdot n^{\mathcal{O}(1)}$.
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The problem is **para-NP-hard**

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Working hypothesis of parameterized complexity: k -CLIQUE is not FPT

(in classical complexity: 3-SAT cannot be solved in poly-time)

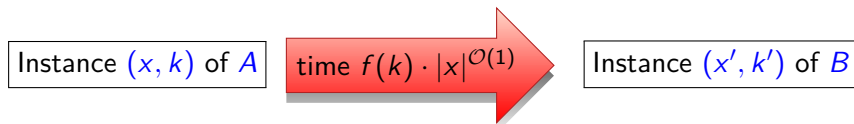
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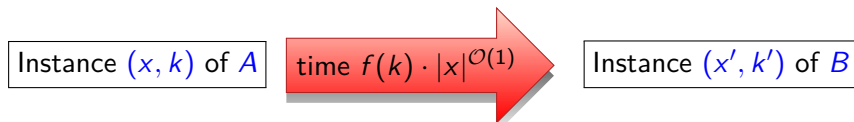
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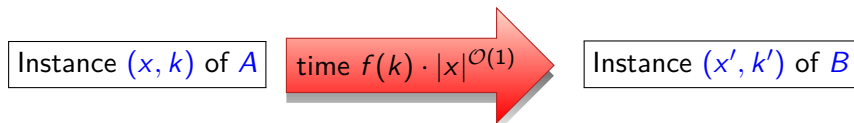


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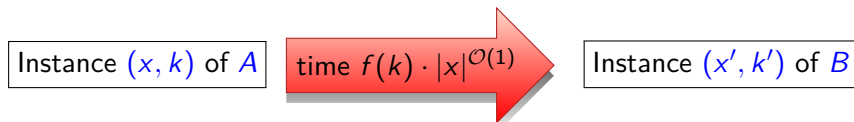
W[1]-hard problem: $\exists$ parameterized reduction from k -CLIQUE to it.

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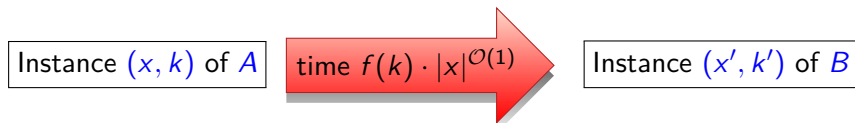
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W[i]-hard: strong evidence of **not** being **FPT**. Hypothesis: $\text{FPT} \neq \text{W}[1]$

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Do all FPT problems admit polynomial kernels?

NO!

Theorem (Bodlaender, Downey, Fellows, Hermelin. 2009)

*Deciding whether a graph has a PATH with $\geq k$ vertices is FPT but **does not admit a polynomial kernel**, unless $\text{NP} \subseteq \text{coNP}/\text{poly}$.*

Typical approach to deal with a parameterized problem

Parameterized problem L

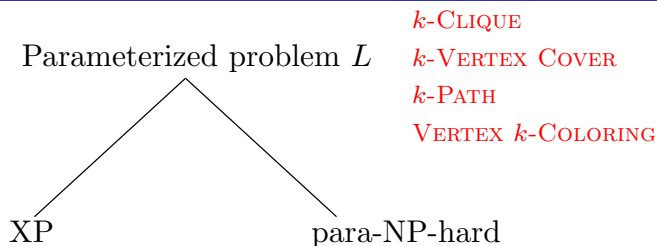
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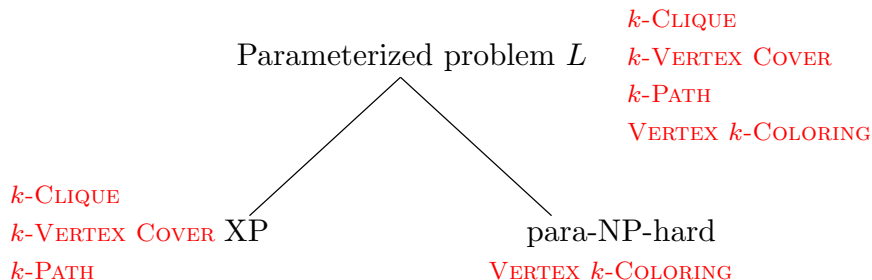
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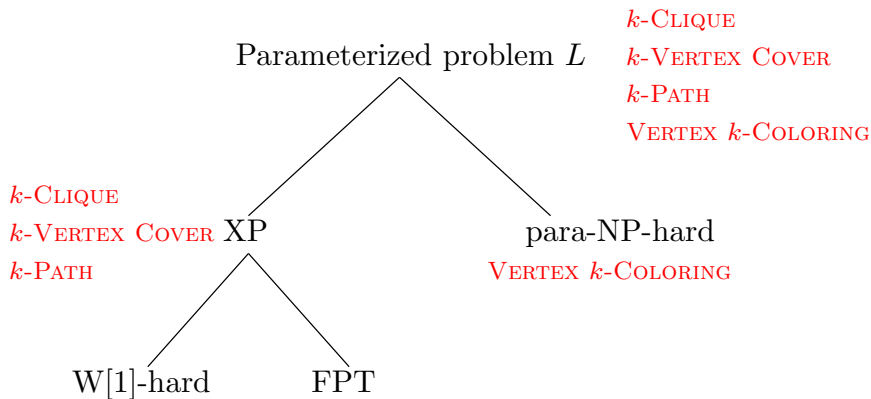
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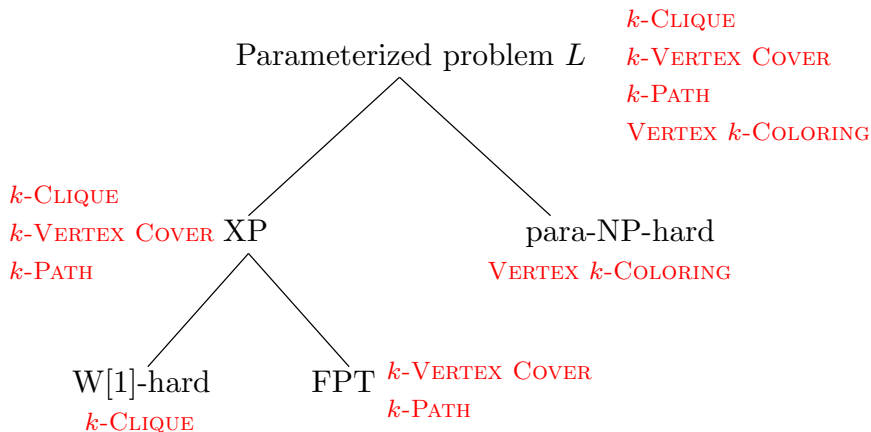
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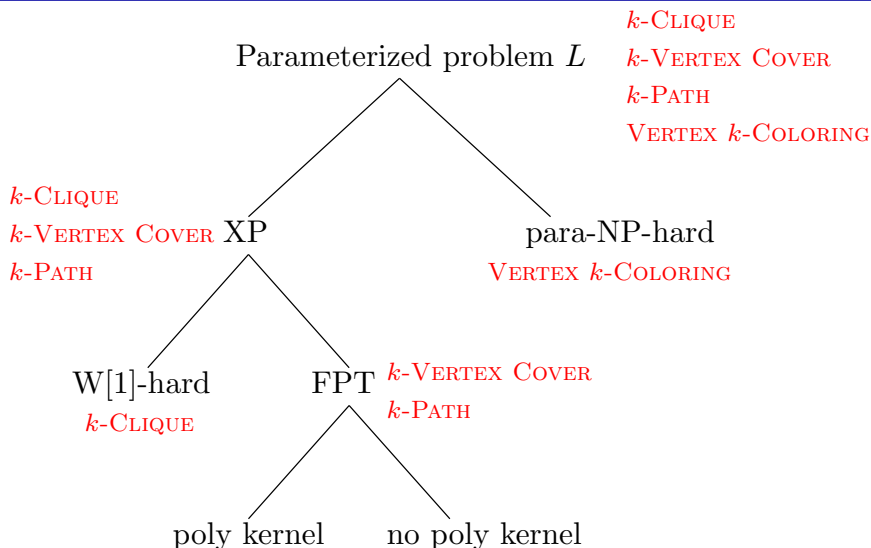
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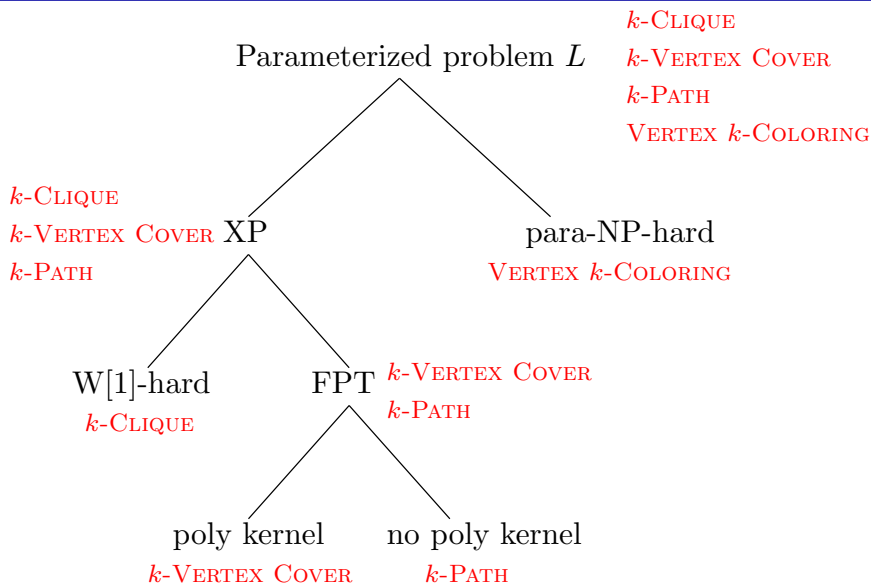
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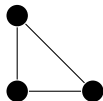


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Treewidth via k -trees

Example of a 2-tree:

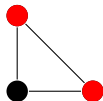


[Figure by Julien Baste]

A k -tree is a graph that can be built starting from a $(k + 1)$ -clique and then **iteratively** adding a vertex connected to a k -clique.

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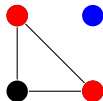


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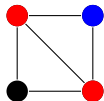


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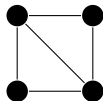


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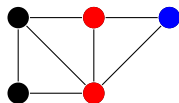


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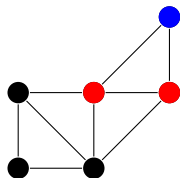


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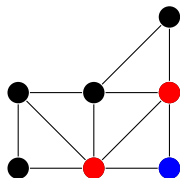


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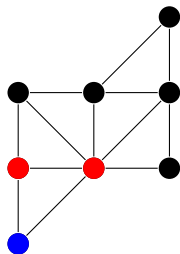


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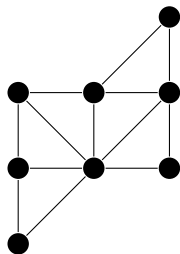


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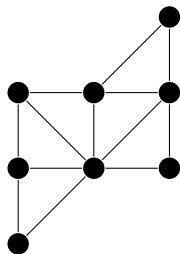


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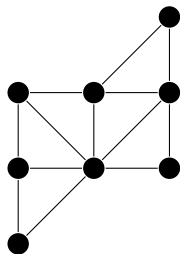
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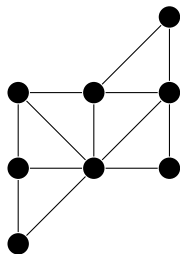
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smallest integer k such that G is a partial k -tree.

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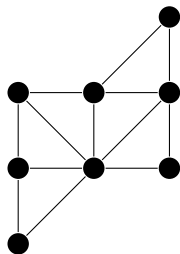
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Construction suggests the notion of **tree decomposition**: **small separators**.

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- ② Treewidth behaves very well **algorithmically**, and algorithms parameterized by treewidth appear **very often** in FPT algorithms.
- ③ In many **practical scenarios**, it turns out that the **treewidth** of the associated graph is **small** (programming languages, road networks, ...).

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Graph logic that allows quantification over sets of vertices and edges.

Example: $\text{DomSet}(S) : [\forall v \in V(G) \setminus S, \exists u \in S : \{u, v\} \in E(G)]$

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- ② For the problems that are **FPT** parameterized by **treewidth**, what about the existence of **polynomial kernels**?

Most natural problems (VERTEX COVER, DOMINATING SET, ...) do **not** admit **polynomial kernels** parameterized by **treewidth**.

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Remark: Algorithms parameterized by treewidth appear very often as a “black box” in all kinds of parameterized algorithms.

Lower bounds on the running times of FPT algorithms

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ETH: The 3-SAT problem on n variables cannot be solved in time $2^{\mathcal{O}(n)}$

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Typical statements:

ETH $\Rightarrow$ k -VERTEX COVER cannot be solved in time $2^{o(k)} \cdot n^{O(1)}$.

ETH $\Rightarrow$ PLANAR k -VERTEX COVER cannot in time $2^{o(\sqrt{k})} \cdot n^{O(1)}$.

Dynamic programming on tree decompositions

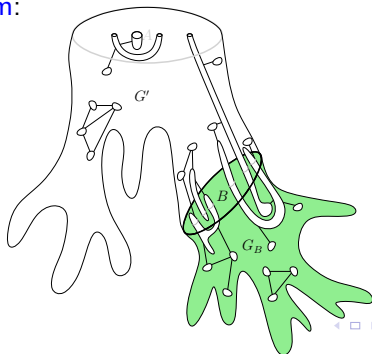
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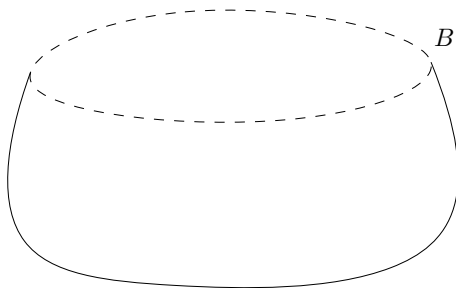
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- Starting from the **leaves** of the tree decomposition, a set of appropriately defined **partial solutions** is computed recursively until the **root**, where a **global solution** is obtained.
- The way that these **partial solutions** are defined depends on each **particular problem**:



Two behaviors for problems parameterized by treewidth

Local problems

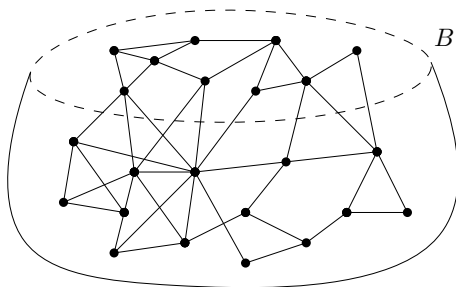
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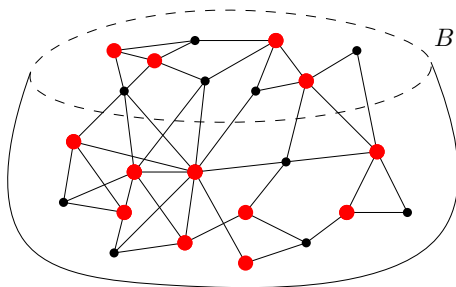
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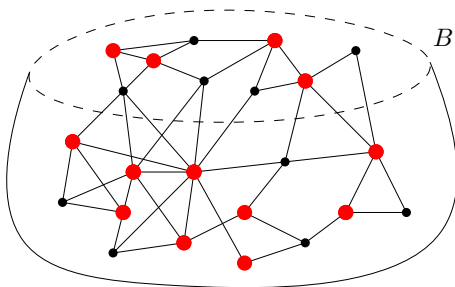
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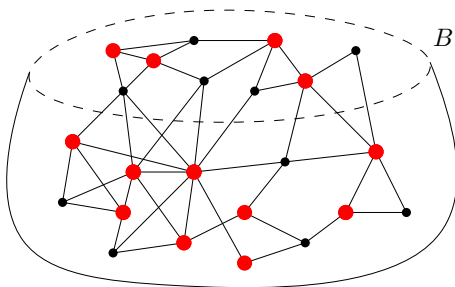
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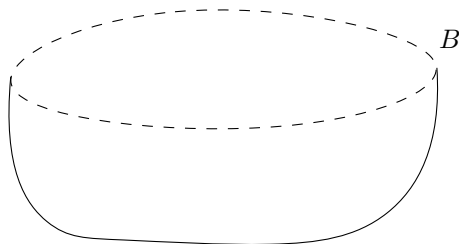


- It is sufficient to store, for each bag B , the subset of vertices of B that belong to a partial solution: 2^{tw} choices
- The “natural” DP algorithms lead to (optimal) single-exponential algorithms:

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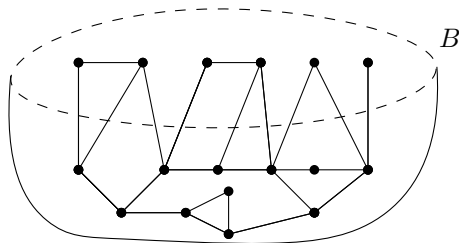
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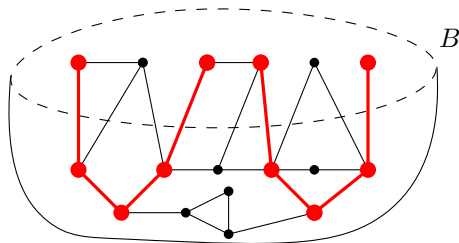
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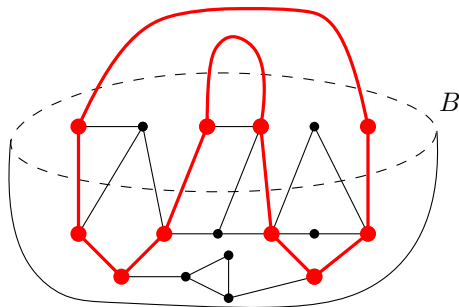
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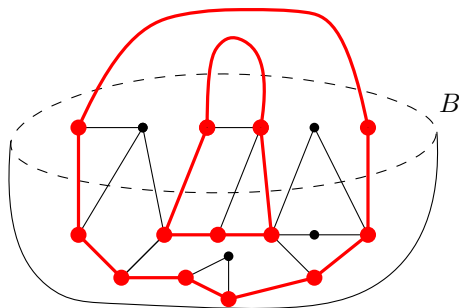
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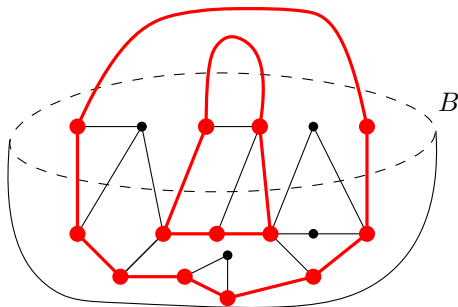
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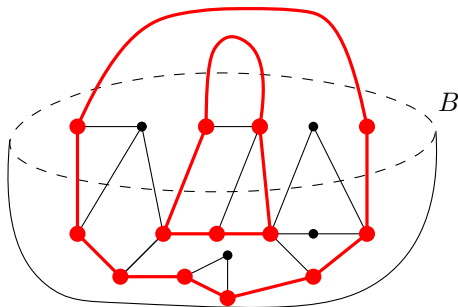
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Two types of behavior

There seem to be **two behaviors** for problems parameterized by treewidth:

- **Local problems:**

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VERTEX COVER, DOMINATING SET, ...

- **Connectivity problems:**

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It was believed that, except on **sparse graphs** (**planar**, **surfaces**), algorithms in time $2^{\mathcal{O}(\text{tw} \cdot \log \text{tw})} \cdot n^{\mathcal{O}(1)}$ were **optimal** for **connectivity problems**.

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Deterministic algorithms with algebraic tricks:

[Bodlaender, Cygan, Kratsch, Nederlof. 2013]

Representative sets in matroids:

[Fomin, Lokshtanov, Saurabh. 2014]

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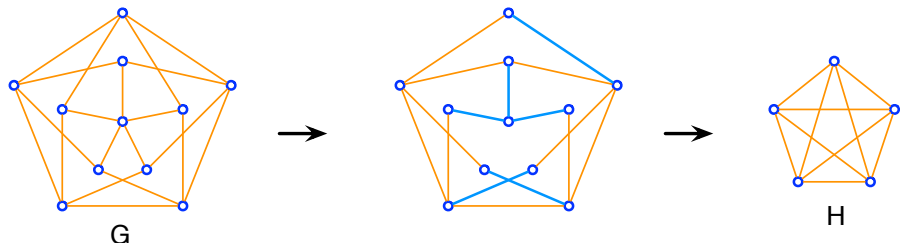
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There are **other examples** of such problems...

Next section is...

- 1 Introduction
 - Parameterized complexity
 - Treewidth
- 2 FPT algorithms parameterized by treewidth
- 3 The $\mathcal{F}$ -DELETION problem
- 4 Further research

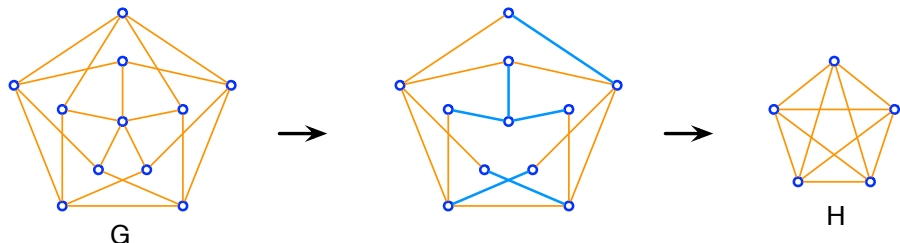
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[Figure by Gwenaël Joret]

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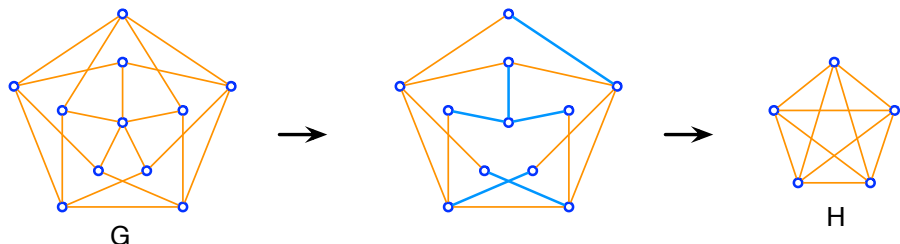
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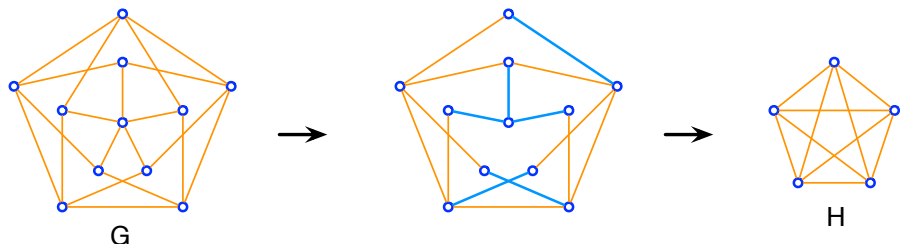
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- $\mathcal{F} = \{K_2\}$: VERTEX COVER.

Easily solvable in time $2^{\Theta(\text{tw})} \cdot n^{\mathcal{O}(1)}$.

- $\mathcal{F} = \{C_3\}$: FEEDBACK VERTEX SET.

“Hardly” solvable in time $2^{\Theta(\text{tw})} \cdot n^{\mathcal{O}(1)}$.

[Cut&Count. 2011]

- $\mathcal{F} = \{K_5, K_{3,3}\}$: VERTEX PLANARIZATION.

Solvable in time $2^{\Theta(\text{tw} \cdot \log \text{tw})} \cdot n^{\mathcal{O}(1)}$.

[Jansen, Lokshantov, Saurabh. 2014 + Pilipczuk. 2015]

Covering topological minors

Let $\mathcal{F}$ be a fixed finite collection of graphs.

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[Lewis, Yannakakis. 1980]

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[Lewis, Yannakakis. 1980]

FPT by Courcelle's Theorem.

Objective

Determine, for every fixed $\mathcal{F}$, the (asymptotically) smallest function $f_{\mathcal{F}}$ such that $\mathcal{F}$ -M-DELETION/ $\mathcal{F}$ -TM-DELETION can be solved in time

$$f_{\mathcal{F}}(\text{tw}) \cdot n^{\mathcal{O}(1)}$$

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- We do not want to optimize the degree of the polynomial factor.
- We do not want to optimize the constants.
- Our hardness results hold under the ETH.

Summary of our results

¹Connected collection $\mathcal{F}$: all the graphs are connected.

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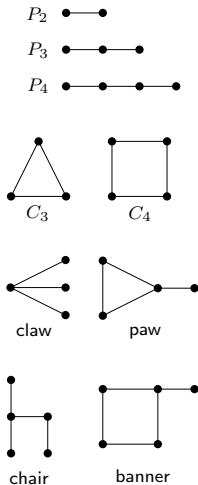
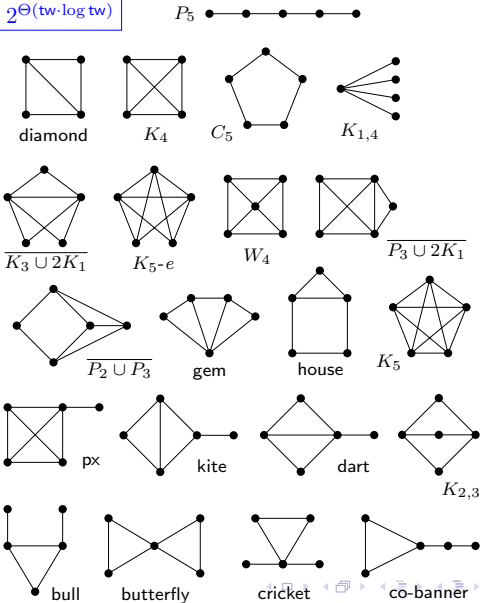
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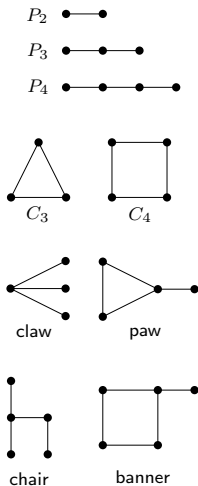
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Complexity of hitting a single connected minor H

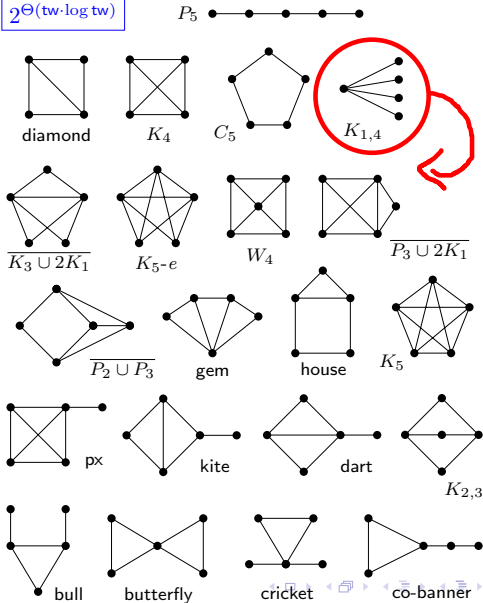
 $2^{\Theta(\text{tw})}$

 $2^{\Theta(\text{tw} \cdot \log \text{tw})}$


For topological minors, there is (at least) one change

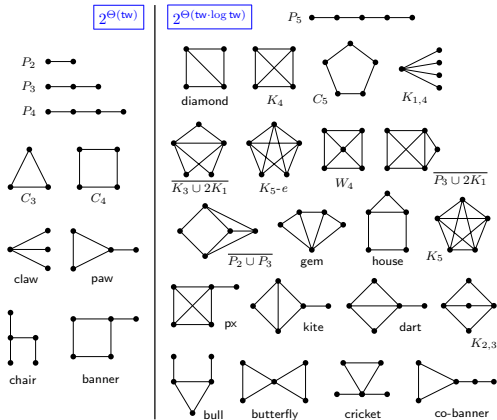
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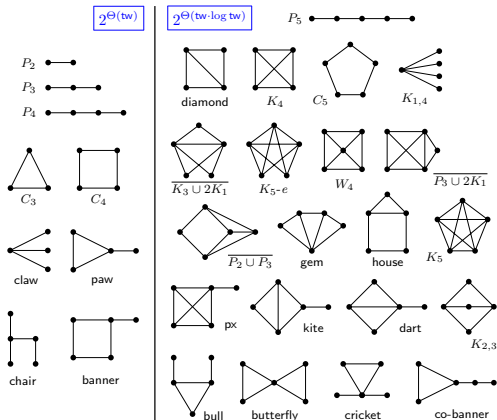


A compact statement for a single connected graph



All these cases can be succinctly described as follows:

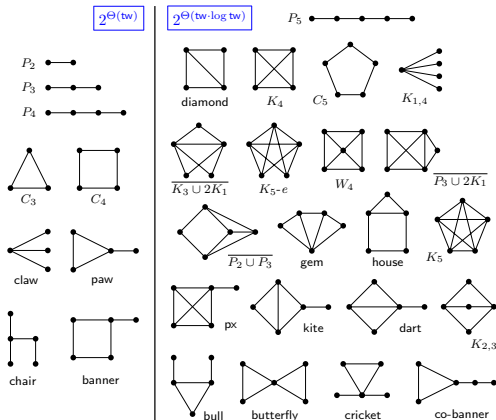
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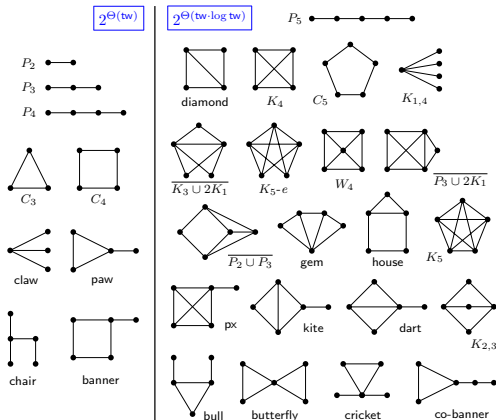
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All these cases can be succinctly described as follows:

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A dichotomy for hitting connected minors

We can prove that any **connected** H with $|V(H)| \geq 6$ is **hard**:
 $\{H\}$ -M-DELETION cannot be solved in time $2^{o(\text{tw} \cdot \log \text{tw})} \cdot n^{\mathcal{O}(1)}$ under the ETH.

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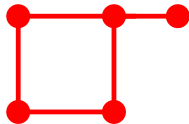
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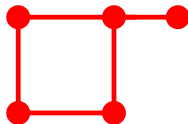
In both cases, the running time is asymptotically **optimal** under the ETH.

» skip

Why the banner??

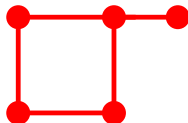


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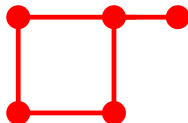
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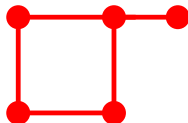
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- Both such types of components can be maintained by a dynamic programming algorithm in **single-exponential** time.
- If the characterization of the allowed connected components is **enriched** in some way, such as restricting the length of the allowed cycles or forbidding certain degrees, the problem becomes harder.

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- For every $\mathcal{F}$: time $2^{2^{\mathcal{O}(\text{tw} \cdot \log \text{tw})}} \cdot n^{\mathcal{O}(1)}$.
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3 Lower bounds under the ETH

- $2^{o(\text{tw})}$ is “easy”.
- $2^{o(\text{tw} \cdot \log \text{tw})}$ is much more involved and we get ideas from:

[Lokshtanov, Marx, Saurabh. 2011]

[Marcin Pilipczuk. 2017]

[Bonnet, Brettell, Kwon, Marx. 2017]

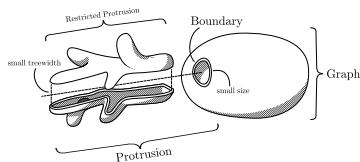
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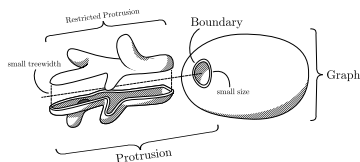
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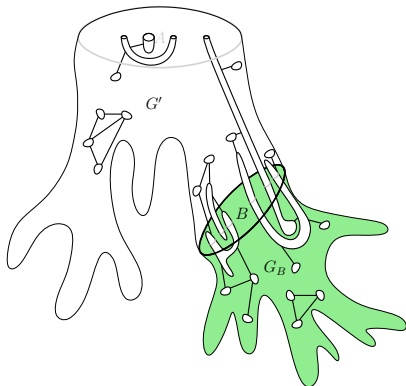
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Extra: Bidimensionality, irrelevant vertices, protrusion decomposition...

» skip

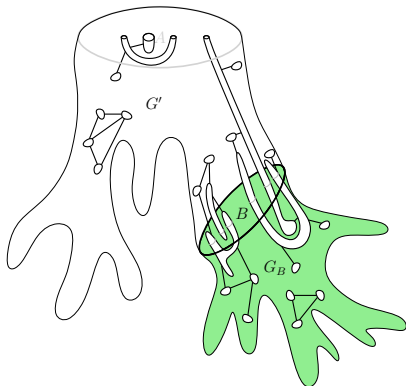
Algorithm for a general collection $\mathcal{F}$

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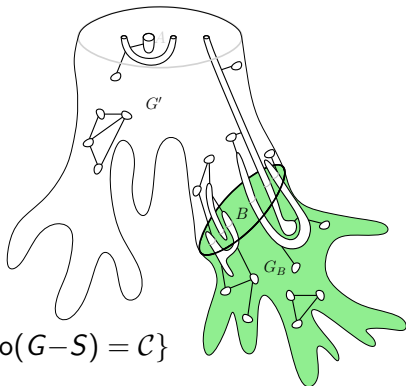
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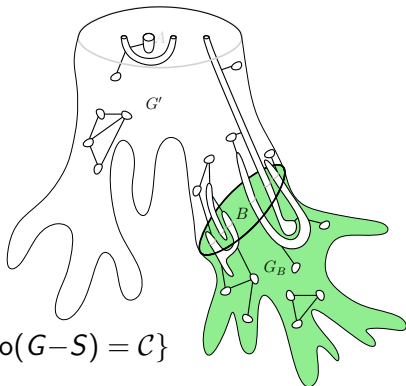


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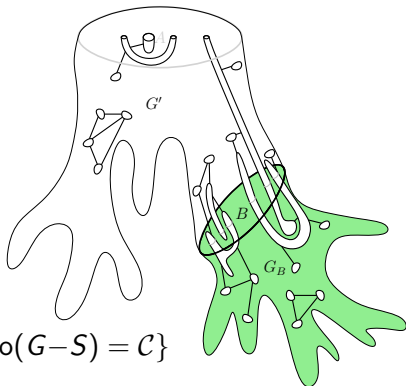


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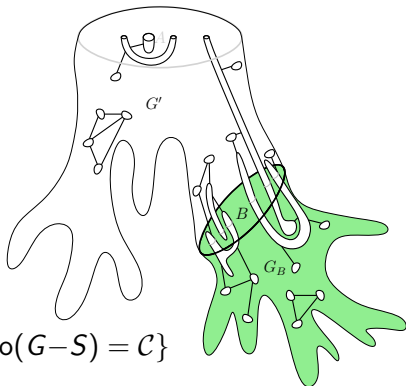
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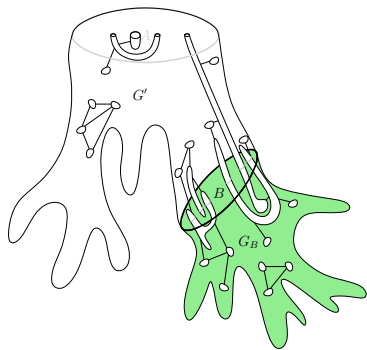
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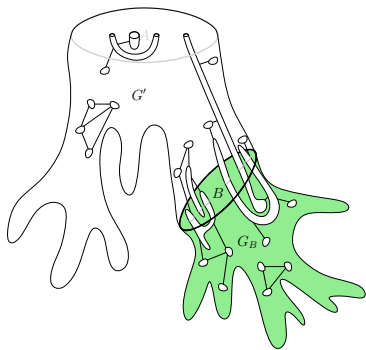
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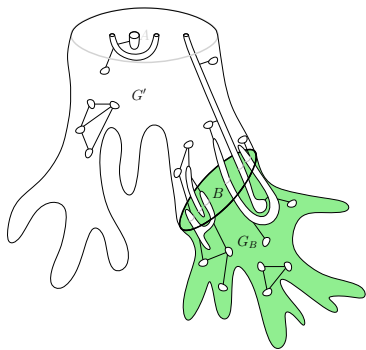


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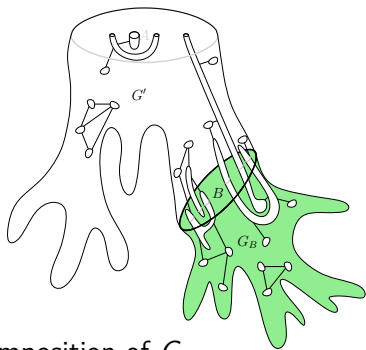
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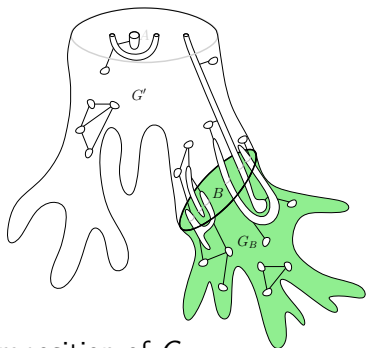
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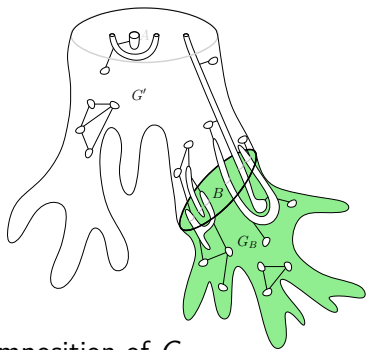


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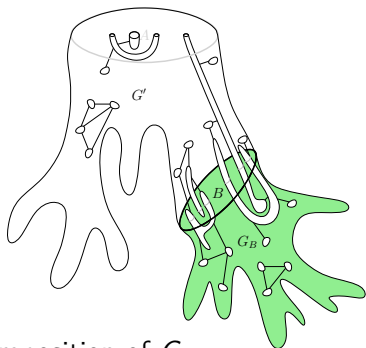
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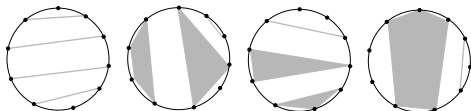
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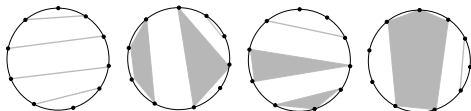
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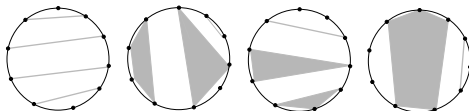
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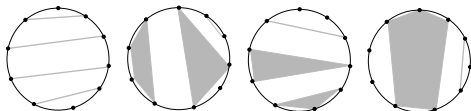


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- We can extend this algorithm to input graphs G embedded in **arbitrary surfaces** by using **surface-cut decompositions**. [Rué, S., Thilikos. 2014]

Next section is...

- 1 Introduction
 - Parameterized complexity
 - Treewidth
- 2 FPT algorithms parameterized by treewidth
- 3 The $\mathcal{F}$ -DELETION problem
- 4 Further research

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Gràcies!

