

Recent Advances on the Complexity of Parameterized Counting Problems

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Counting problems

Instead of **finding** one solution, we need to **count** the number of solutions.

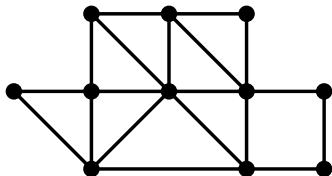
Applications: probability, statistical physics, pattern frequency. . .

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RELIABILITY: If each edge fails with probability $\frac{1}{2}$ independently, what is the probability that the graph remains connected?



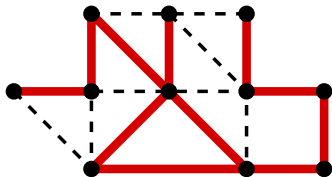
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= counting the number of connected subgraphs

Finding vs. counting

Finding a perfect matching in a bipartite graph is polynomial-time solvable.

[Ford and Fulkerson 1956]

vs.

Counting the number of perfect matchings in a bipartite graph is $\#P$ -hard.

[Valiant 1979]

This talk

Counting problems in the area of parameterized algorithms.

- Quick intro to parameterized algorithms.
- Connection between counting homomorphisms and subgraphs.
- Algorithmic applications.
- Complexity applications.

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Main message

Parameterized subgraph counting problems can be understood via homomorphism counting problems.

...and this connection gives both algorithmic and complexity results!

Parameterized problems

Main idea

Instead of expressing the running time as a function $T(n)$ of n , we express it as a function $T(n, k)$ of the input size n and some parameter k of the input.

In other words: we do not want to be efficient on all inputs of size n , only for those where k is small.

Parameterized problems

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In other words: we do not want to be efficient on all inputs of size n , only for those where k is small.

What can be the parameter k ?

- The size k of the solution we are looking for.
- The maximum degree of the input graph.
- The dimension of the point set in the input.
- The length of the strings in the input.
- The length of clauses in the input Boolean formula.
- ...

Parameterized complexity

Problem:

VERTEX COVER

INDEPENDENT SET

Input:

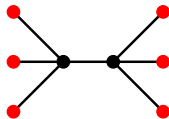
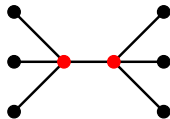
Graph G , integer k

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Question:

Is it possible to cover the edges with k vertices?

Is it possible to find k independent vertices?



Complexity:

NP-complete

NP-complete

Parameterized complexity

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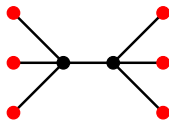
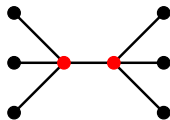
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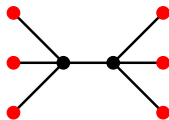
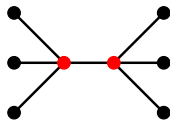
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$O(2^k n^2)$ algorithm

No $n^{o(k)}$ algorithm

exists 😊

known 😞

Example: Bounded search tree method

Algorithm for VERTEX COVER:

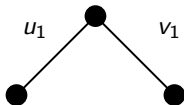
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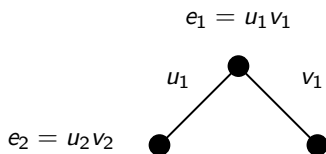
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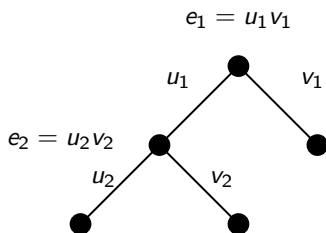
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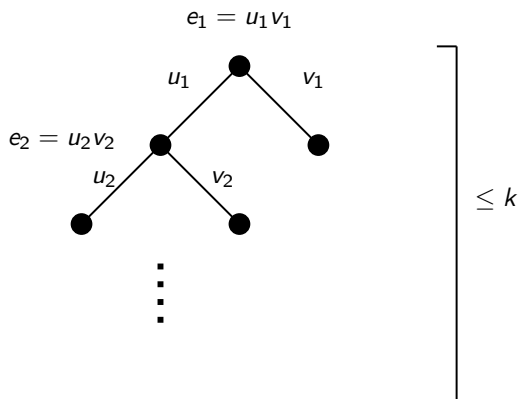
Example: Bounded search tree method

Algorithm for VERTEX COVER:



Example: Bounded search tree method

Algorithm for VERTEX COVER:



Height of the search tree $\leq k \Rightarrow$ at most 2^k leaves $\Rightarrow 2^k \cdot n^{O(1)}$ time algorithm.

Fixed-parameter tractability

Main definition

A parameterized problem is **fixed-parameter tractable (FPT)** if there is an $f(k)n^c$ time algorithm for some constant c .

Fixed-parameter tractability

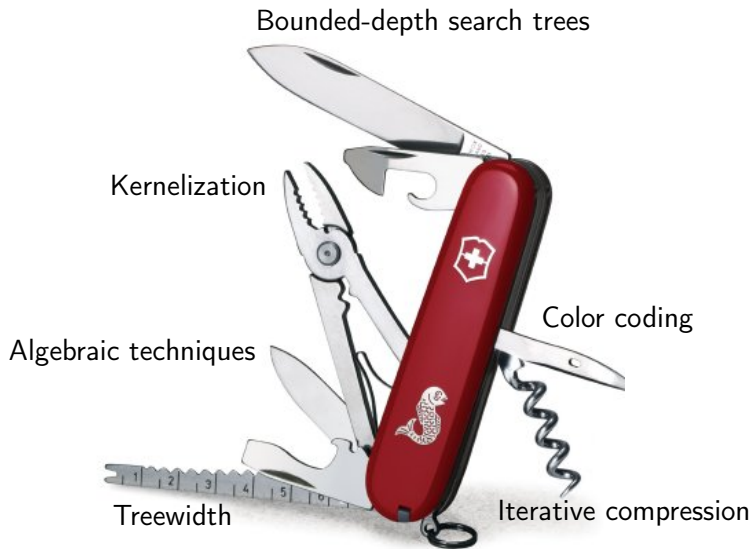
Main definition

A parameterized problem is **fixed-parameter tractable (FPT)** if there is an $f(k)n^c$ time algorithm for some constant c .

Examples of NP-hard problems that are FPT:

- Finding a vertex cover of size k .
- Finding a path of length k .
- Finding k disjoint triangles.
- Drawing the graph in the plane with k edge crossings.
- Finding disjoint paths that connect k pairs of points.
- ...

FPT techniques



W[1]-hardness

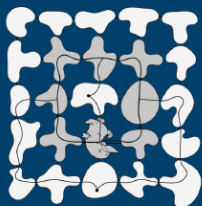
Negative evidence similar to NP-completeness. If a problem is **W[1]-hard**, then the problem is not FPT unless $FPT=W[1]$.

Some W[1]-hard problems:

- Finding a clique/independent set of size k .
- Finding a dominating set of size k .
- Finding k pairwise disjoint sets.
- ...

Marek Cygan · Fedor V. Fomin
Łukasz Kowalik · Daniel Lokshtanov
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Michał Pilipczuk · Saket Saurabh

Parameterized Algorithms



 Springer

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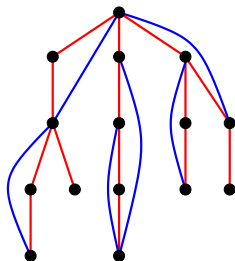
Springer 2015



Example: Win/Win for k -PATH

Simple $2^{O(k)} \cdot n^{O(1)}$ time algorithm for finding a path of length k .

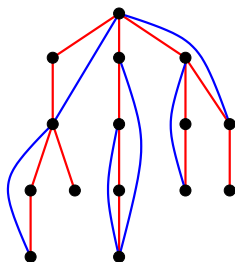
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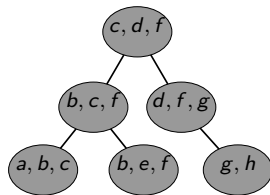
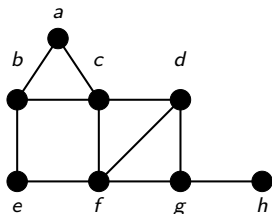


- 2 If DFS tree has height $> k$:
we can find a k -path.
- 3 If DFS tree has height $\leq k$:
treewidth is $\leq k \Rightarrow$ Use an algorithm with running time
 $2^{O(\text{tw})} \cdot n^{O(1)}$ for finding the longest path.

Treewidth — a measure of “tree-likeness”

Tree decomposition: Vertices are arranged in a tree structure satisfying the following properties:

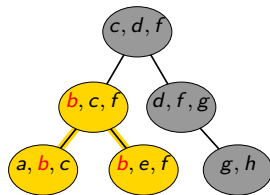
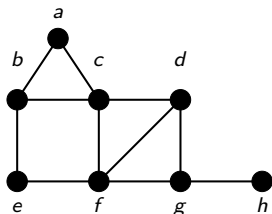
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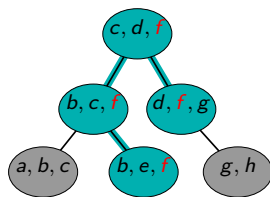
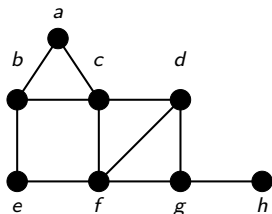
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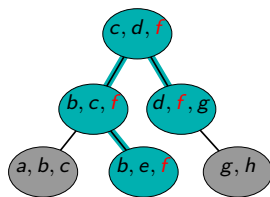
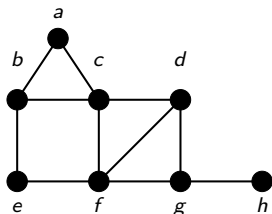
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Width of the decomposition: largest bag size -1 .

treewidth: width of the best decomposition.



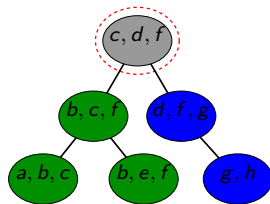
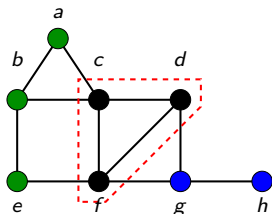
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Each bag is a separator.

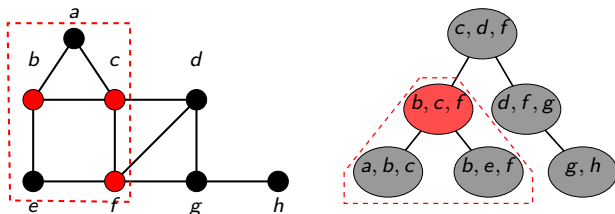
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A subtree communicates with the outside world only via the root of the subtree.

Counting complexity

- $W[1]$ -hardness: “as hard as finding a k -clique”
- $\#W[1]$ -hardness: “as hard as counting k -cliques”

What can happen to the counting version of an FPT problem?

- 1 (easy) The same algorithmic technique shows that the counting problem is FPT.
- 2 (easy, but different) New algorithmic techniques are needed to show that the counting version is FPT.
- 3 (hard) New lower bound techniques are needed to show that the counting version is $\#W[1]$ -hard.

Finding vs. counting

Generalization to counting:

- **WORKS** for the **VERTEX COVER** branching algorithm
 \Rightarrow **#VERTEX COVER** is FPT.
- **DOES NOT WORK** for the **# k -PATH** win/win algorithm

What is the parameterized complexity of **# k -PATH**?

Finding vs. counting

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What is the parameterized complexity of **#k-PATH**?

Even more troubling question:

What is the parameterized complexity of
the (even simpler) **#k-MATCHING**?

#k-MATCHING

\Rightarrow

#k-PATH

Counting k -paths and k -matchings

Colorful history:

- $\#k\text{-PATH}$ is $\#W[1]$ -hard
[Flum and Grohe, FOCS 2002]

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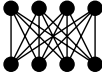
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[Curticapean, Dell, and M, STOC 2017] — *tells the real story.*

Counting patterns

Main question

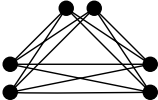
Which type of subgraph patterns are easy to count?



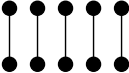
biclique



clique complete



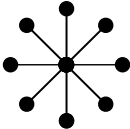
multipartite graph



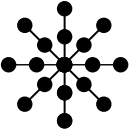
matching



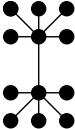
path



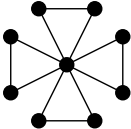
star



subdivided star



double star

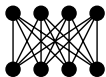


windmill

Counting patterns

Main question

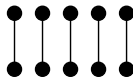
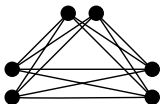
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biclique



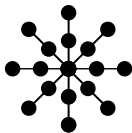
clique complete multipartite graph



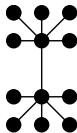
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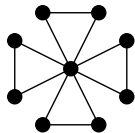
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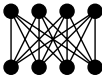


windmill

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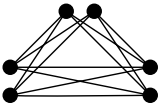
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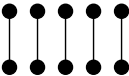
biclique



clique



complete multipartite graph



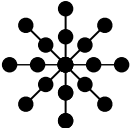
matching



path



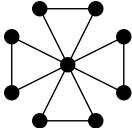
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windmill

Counting patterns

Patterns with small vertex cover number are is easy to count:

Theorem [multiple references]

$\#\text{SUB}(H)$ can be solved in time $n^{\text{vc}(H)+O(1)}$.

But what about patterns with large vertex cover number?

Counting patterns

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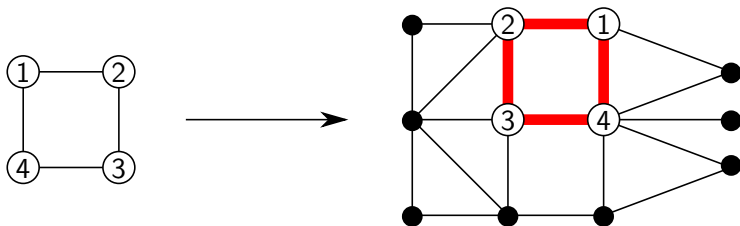
We will understand the complexity of counting any class of patterns, not just paths or matchings!

Main message

Parameterized subgraph counting problems can be understood via homomorphism counting problems.

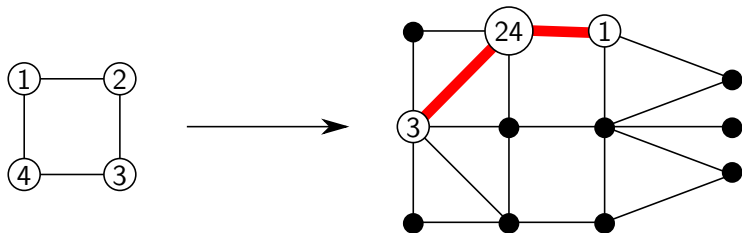
Homomorphisms

A **homomorphism** from H to G is a mapping $f: V(H) \rightarrow V(G)$ such that if ab is an edge of H , then $f(a)f(b)$ is an edge of G .



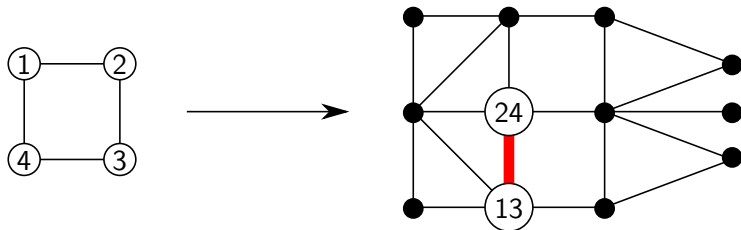
Homomorphisms

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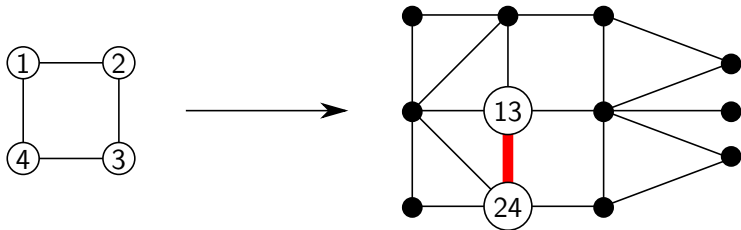
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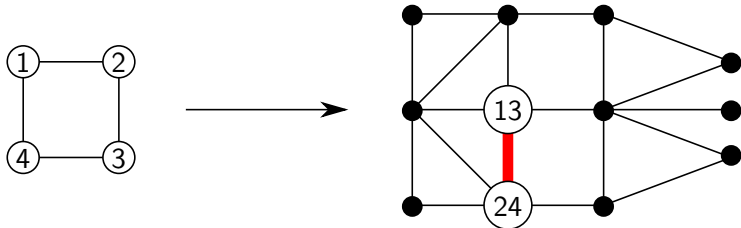
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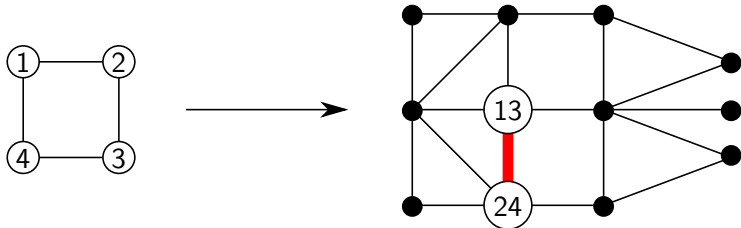
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Which pattern graphs H are easy for counting homomorphisms?

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Which pattern graphs H are easy for counting homomorphisms?

Theorem (trivial)

For every fixed H , the problem $\#\text{HOM}(H)$ (count homomorphisms from H to the given graph G) is polynomial-time solvable.

... because we can try all $|V(G)|^{|V(H)|}$ possible mappings $f: V(H) \rightarrow V(G)$.

Counting homomorphisms

Better questions:

- Which classes \mathcal{H} (e.g., paths, stars, matchings) of patterns can be counted in polynomial time?
- What is the best exponent for $\text{HOM}(H)$?

Fact

$\#\text{HOM}(H)$ can be solved in time $O(n^{\text{tw}(H)+1})$.

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Difference between finding and counting:

Finding:
 $\text{HOM}(K_{k,k})$ is trivial

vs.

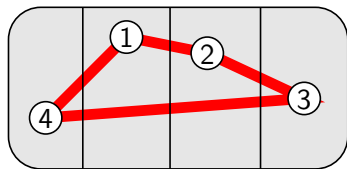
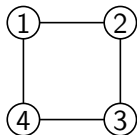
Counting:
 $\#\text{HOM}(K_{k,k})$ is W[1]-hard

Partitioned homomorphism

PARTITIONED HOMOMORPHISM

Input: H , G , and partition Π of $V(G)$ into $|V(H)|$ classes.

Task: Find a homomorphism ϕ that maps the vertices of H to different classes.



Theorem [M 2010]

There is a universal constant $\gamma > 0$ such that if for some H there is an $O(n^{\gamma \cdot \text{tw}(H)} / \log \text{tw}(H))$ time algorithm for $\text{PARTHOM}(H)$, then ETH fails.

Counting partitioned homomorphisms

$$\# \text{PARTHOM}(H) \Rightarrow \# \text{HOM}(H)$$

G_P for $P \subseteq \text{class}(\Pi)$: subgraph of G induced by the classes P .

Simple application of the inclusion-exclusion principle:

$$\# \text{part-hom}(H, G) = \sum_{P \subseteq \text{class}(\Pi)} (-1)^{|\text{class}(P)| - |P|} \cdot \# \text{hom}(H, G_P)$$

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Theorem [Dalmau and Jonsson 2004][M 2010]

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Counting homomorphisms — summary

Treewidth of H determines the complexity of the problem:

- $O(n^{\text{tw}(H)+1})$ upper bound.
- $\Omega(n^{\gamma \cdot \text{tw}(H) / \log \text{tw}(H)})$ lower bound (assuming ETH).

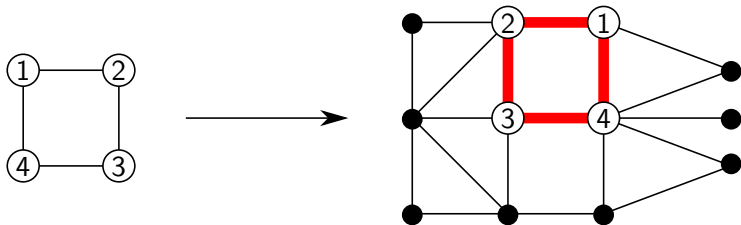
If we restrict the problem to a class \mathcal{H} of patterns:

- If \mathcal{H} has bounded treewidth (e.g, stars, paths, ...), then the problem is polynomial-time solvable.
- If \mathcal{H} has unbounded treewidth (e.g, cliques, bicliques, grids, ...), then the problem is **not** polynomial-time solvable (assuming ETH).

Subgraphs \Leftrightarrow homomorphisms

Easy to check:

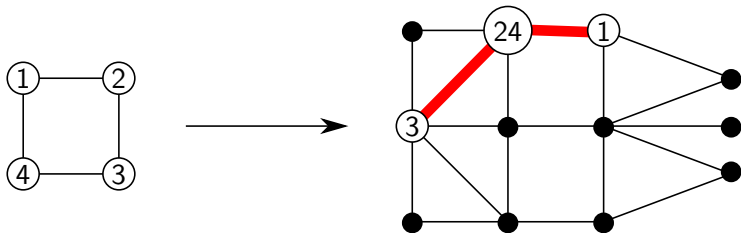
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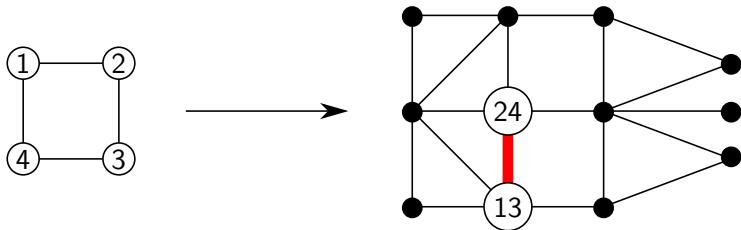
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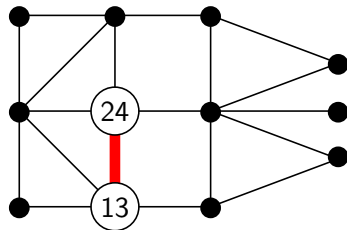
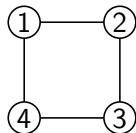
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Not completely obvious:

The formula can be reversed by inclusion-exclusion.

$$\text{sub}(\square, G) = \frac{1}{8}\text{hom}(\square, G) - \frac{1}{4}\text{hom}(\text{---}, G) + \frac{1}{8}\text{hom}(\text{---}, G)$$

Subgraphs \Leftrightarrow homomorphisms

Definition

$\text{surj}(H, G)$: number of surjective homomorphisms from H to G (every vertex and edge of G appears in the image).

Homomorphisms can be counted by classifying according to the image F :

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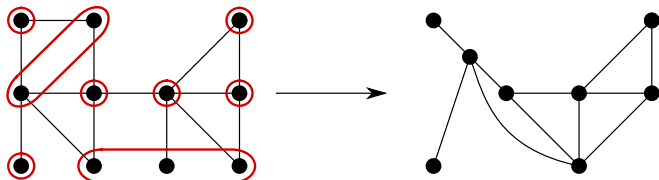
Homomorphisms can be counted by classifying according to the image F :

$$\begin{aligned} \text{hom}(\square, G) &= 8\text{sub}(\square, G) + 4\text{sub}(\text{---}, G) + 2\text{sub}(\text{---}, G) \\ &\quad \downarrow \\ \text{hom}(H, G) &= \sum_F \text{surj}(H, F)\text{sub}(F, G) \end{aligned}$$

Which of the terms can be nonzero?

Spasm

- $\text{Part}_0(H)$: set of partitions of $V(H)$ where each class is an independent set.
- For $\Pi \in \text{Part}_0(H)$, $H_{|\Pi}$ is obtained by contracting each class of Π to a single vertex.



- $\text{Spasm} = \{H_{|\Pi} \mid \Pi \in \text{Part}_0(H)\}$

$$\text{Spasm}(\text{---}) = \left\{ \text{---}, \text{---}, \triangle \text{---}, \square, \text{---}, \triangle, \text{---}, \text{---} \right\}$$

Subgraphs \Leftrightarrow homomorphisms

From subgraphs to homomorphisms:

$$\text{hom}(H, G) = \sum_F \text{surj}(H, F) \text{sub}(F, G)$$

where $\text{surj}(H, F) \neq 0$ if and only if $F \in \text{Spasm}(H)$.

From homomorphisms to subgraphs: [Lovász 1967]

$$\text{sub}(H, G) = \sum_F \beta_F \cdot \text{hom}(F, G)$$

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Extremely useful for applications in algorithms and complexity!

Algorithmic applications

$$\text{sub}(H, G) = \sum_{F \in \text{Spasm}(H)} \beta_F \cdot \text{hom}(F, G)$$



Max. treewidth in $\text{Spasm}(H)$ gives an upper bound on complexity:

Corollary

If every graph in $\text{Spasm}(H)$ has treewidth at most c , then $\text{sub}(H, G)$ can be computed in time $O(n^{c+1})$.

Algorithmic applications

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Observe: If H has k edges, then every graph in $\text{Spasm}(H)$ has at most k edges.

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Observe: If H has k edges, then every graph in $\text{Spasm}(H)$ has at most k edges.

Theorem [Scott and Sorkin 2007]

Every graph with $\leq k$ edges has treewidth at most $0.174k + O(1)$.

Corollary

If H has k edges, then $\text{sub}(H, G)$ can be computed in time $n^{0.174k+O(1)}$.

Counting k -paths

Corollary

If H has k edges, then $\text{sub}(H, G)$ can be computed in time $n^{0.174k+O(1)}$.

Example: Counting k -paths

- Brute force: $O(n^k)$.
- Meet in the middle: $O(n^{0.5k})$
[Björklund et al., ESA 2009],[Koutis and Williams, ICALP 2009]
- [Björklund et al., SODA 2014]: $n^{0.455k+O(1)}$.
- **New!** by counting homomorphisms in the spasm: $n^{0.174k+O(1)}$.

Counting small cycles

Counting triangles using matrix multiplication:

$$\text{sub}(C_3, G) = \frac{1}{6} \text{tr Adj}^3(G)$$

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For $k \leq 7$, we can compute $\text{sub}(C_k, G)$ in time n^ω (where $\omega < 2.373$ is the matrix-multiplication exponent).

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We can recover this result:

- Check: if $k \leq 7$, then every graph in $\text{Spasm}(C_k, G)$ has treewidth at most 2.
- For treewidth 2, the $O(n^{2+1})$ homomorphism algorithm can be improved to $O(n^\omega)$ with fast matrix multiplication.
- $\Rightarrow O(n^\omega)$ algorithm for $\text{sub}(C_k, G)$ if $k \leq 7$.

Complexity applications

$$\text{sub}(H, G) = \sum_{F \in \text{Spasm}(H)} \beta_F \cdot \text{hom}(F, G)$$

Note: Every β_F is nonzero.

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- **Obvious:**

if we can compute $\text{hom}(F, G)$ for any $F \in \text{Spasm}(H)$

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Complexity of $\text{hom}(F, G)$ for any $F \in \text{Spasm}(H)$ is a **lower bound** on the complexity of $\text{sub}(H, G)$.

Matrices

Fix an enumeration of graphs with $\leq k$ edges with nondecreasing number of edges.

- **Hom** matrix: row i , column j is $\text{hom}(H_i, H_j)$.
- **Sub** matrix: row i , column j is $\text{sub}(H_i, H_j)$.
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Hom	=	Surj	·	Sub
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Matrices

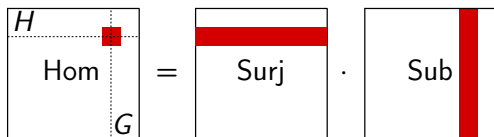
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The **Hom** matrix is invertible!

Categorical product

One of the standard graph products:

Definition

$G_1 \times G_2$ has vertex set $V(G_1) \times V(G_2)$ and (v_1, v_2) and (v'_1, v'_2) adjacent in $G_1 \times G_2 \iff v_1 v'_1 \in E(G_1)$ and $v_2 v'_2 \in E(G_2)$.

[missing figure]

Exercise:

$$\text{hom}(H, G_1 \times G_2) = \text{hom}(H, G_1) \cdot \text{hom}(H, G_2)$$

Extracting a term

Lemma

Given an algorithm for $\text{sub}(H, G) = \sum_{F \in \text{Spasm}(H)} \beta_F \cdot \text{hom}(F, G)$ (with $\beta_F \neq 0$), we can compute $\text{hom}(F, G)$ for any $F \in \text{Spasm}(H)$.

Use the algorithm on $Z \times G$ for every Z with $\leq k = |E(H)|$ edges.

$$\text{sub}(H, Z \times G) = b_Z$$

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	\vdots		\vdots
	$\beta_{F_t} \cdot \text{hom}(F_t, G)$		b_{Z_t}

The **Hom** matrix is invertible, so we can solve this system of equations!

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Bottom line:

complexity of
 $\#\text{SUB}(H)$

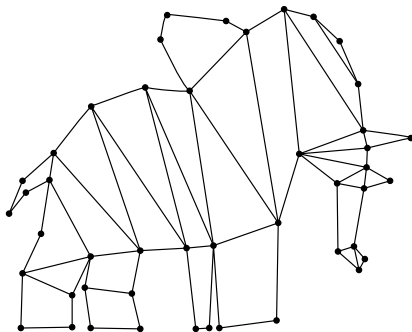
=

hardest $\#\text{HOM}(F)$ for
 $F \in \text{Spasm}(H)$

Complexity depends on the maximum treewidth in $\text{Spasm}(H)$!

Complexity of counting patterns

What is the best exponent for counting occurrences of this 46-vertex graph H ?



Answer: Compute $\text{Spasm}(H)$ and find the best exponent for each of the resulting homomorphism problems!

Hardness results for $\#k$ -MATCHING

Not FPT:

Theorem

Counting k -matchings is $\#W[1]$ -hard.

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More precise bound:

$\text{Spasm}(M_k)$ contains every graph with k edges



$\text{Spasm}(M_k)$ contains graphs with treewidth $\Omega(k)$



no $f(k)n^{o(k/\log k)}$ time algorithm for $\#k$ -MATCHING,
assuming ETH.

Role of vertex cover number

What property of H determines the max. treewidth in $\text{Spasm}(H)$?

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The vertex cover number of H :

- **Upper bound:**

For every $F \in \text{Spasm}(H)$, we have $\text{tw}(F) \leq \text{vc}(F) \leq \text{vc}(H)$.

- **Lower bound:**

H contains a matching of size $\text{vc}(H)/2$. We can show that for any F with at most $\text{vc}(H)/2$ edges, there is a graph in $\text{Spasm}(H)$ that contains F as a minor \Rightarrow there is a graph in $\text{Spasm}(H)$ with treewidth $\Omega(\text{vc}(H))$.

Counting subgraphs — summary

Vertex cover number of H determines the complexity of $\text{SUB}(H)$:

- $n^{\text{vc}(H)+O(1)}$ upper bound.
- $\Omega(n^{\gamma \cdot \text{vc}(H)/\log \text{vc}(H)})$ lower bound.

If we restrict the problem to a class \mathcal{H} of patterns:

- If \mathcal{H} has bounded vertex cover number (e.g, stars, double stars, ...), then the problem is polynomial-time solvable.
- If \mathcal{H} has unbounded vertex cover number (e.g, cliques, paths, matchings, disjoint triangles, ...), then the problem is **not** polynomial-time solvable (assuming ETH).

Conclusions

Main message

Parameterized subgraph counting problems can be understood via homomorphism counting problems.

...and this connection gives both algorithmic and complexity results!

Working on counting problems is fun:

- You can revisit fundamental, “well-understood” problems.
- Requires a new set of lower bound techniques.
- Requires new algorithmic techniques.