

Complexity of parameterized problems

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Lecture #3
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Lower bounds

So far we have seen positive results: basic algorithmic techniques for fixed-parameter tractability.

What kind of negative results we have?

- Can we show that a problem (e.g., **CLIQUE**) is **not** FPT?
- Can we show that a problem (e.g., **VERTEX COVER**) has **no** algorithm with running time, say, $2^{o(k)} \cdot n^{O(1)}$?

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This would require showing that $P \neq NP$: if $P = NP$, then, e.g., k -**CLIQUE** is polynomial-time solvable, hence FPT.

Can we give some evidence for negative results?

Classical complexity — reminder

NP:

- The class of all languages that can be recognized by a polynomial-time NTM.
- The class of all languages with a witness of polynomial size

Nondeterministic Turing Machine (NTM): single tape, finite alphabet, finite state, head can move left/right only one cell. In each step, the machine can branch into an arbitrary number of directions. Run is successful if at least one branch is successful.

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Polynomial-time reduction from problem P to problem Q : a function ϕ with the following properties:

- $\phi(x)$ is a yes-instance of $Q \iff x$ is a yes-instance of P ,
- $\phi(x)$ can be computed in time $|x|^{O(1)}$.

Definition: Problem Q is **NP-hard** if any problem in **NP** can be reduced to Q .

If an **NP-hard** problem can be solved in polynomial time, then every problem in **NP** can be solved in polynomial time (i.e., $P = NP$).

Parameterized complexity

To build a complexity theory for parameterized problems, we need two concepts:

- An appropriate notion of reduction.
- An appropriate hypothesis.

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Fact: Graph G has an independent set $k \Leftrightarrow G$ has a vertex cover of size $n - k$.



- This is a correct polynomial-time reduction.
- However, **VERTEX COVER** is FPT, but **INDEPENDENT SET** is not known to be FPT.

Parameterized reductions

Definition

Parameterized reduction from problem A to problem B : a function ϕ with the following properties:

- $\phi(x)$ is a yes-instance of $B \iff x$ is a yes-instance of A ,
- $\phi(x)$ can be computed in time $f(k) \cdot |x|^{O(1)}$, where k is the parameter of x ,
- If k is the parameter of x and k' is the parameter of $\phi(x)$, then $k' \leq g(k)$ for some function g .

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Theorem

If there is a parameterized reduction from problem A to problem B and B is FPT, then A is also FPT.

Intuitively: Reduction $A \rightarrow B$ + algorithm for B gives an algorithm for A .

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Non-example: Transforming an **INDEPENDENT SET** instance (G, k) into a **VERTEX COVER** instance $(G, n - k)$ is **not** a parameterized reduction.

Example: Transforming an **INDEPENDENT SET** instance (G, k) into a **CLIQUE** instance (\overline{G}, k) is a parameterized reduction.

Parameterized reductions

Theorem

If there is a parameterized reduction from problem A to problem B and B is FPT, then A is also FPT.

Proof: Suppose that

- the reduction has running time $f(k)n^{c_1}$,
- the reduction creates an instance with parameter at most $g(k)$, and
- B can be solved in time $h(k)n^{c_2}$.

Then running the reduction and solving the created instance of B gives an algorithm for A with running time

$$f(k)n^{c_1} + h(g(k)) \cdot (f(k)n^{c_1})^{c_2} \leq f'(k)n^{c_1 c_2}$$

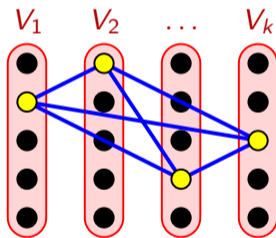
for some function f' .

MULTICOLORED CLIQUE

A useful variant of **CLIQUE**:

MULTICOLORED CLIQUE: The vertices of the input graph G are colored with k colors and we have to find a clique containing one vertex from each color.

(or **PARTITIONED CLIQUE**)



Theorem

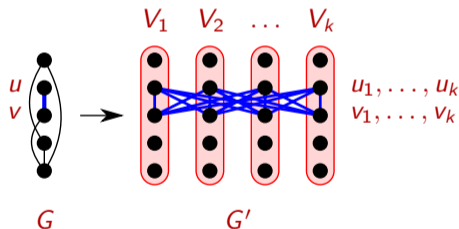
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MULTICOLORED CLIQUE

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Create G' by replacing each vertex v with k vertices, one in each color class. If u and v are adjacent in the original graph, connect all copies of u with all copies of v .



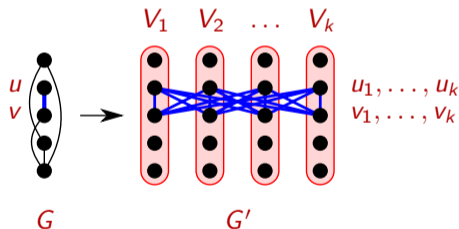
k -clique in $G \iff$ multicolored k -clique in G' .

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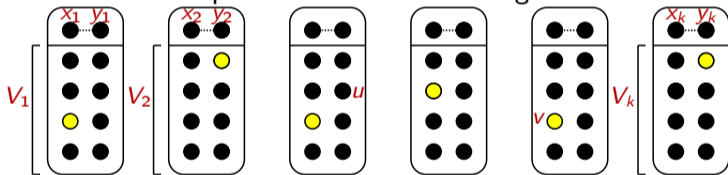
Similarly: reduction to **MULTICOLORED INDEPENDENT SET**.

DOMINATING SET

Theorem

There is a parameterized reduction from **MULTICOLORED INDEPENDENT SET** to **DOMINATING SET**.

Proof: Let G be a graph with color classes V_1, \dots, V_k . We construct a graph H such that G has a multicolored k -clique iff H has a dominating set of size k .



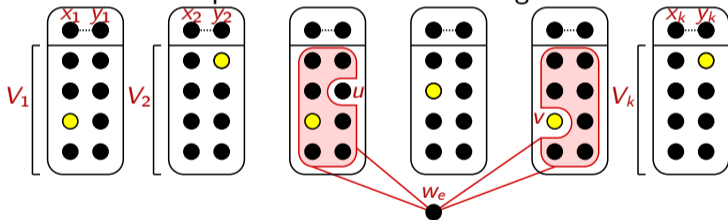
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- The dominating set has to contain one vertex from each of the k cliques V_1, \dots, V_k to dominate every x_i and y_i .
- For every edge $e = uv$, an additional vertex w_e ensures that these selections describe an independent set.

Variants of DOMINATING SET

- **DOMINATING SET**: Given a graph, find k vertices that dominate every vertex.
- **RED-BLUE DOMINATING SET**: Given a bipartite graph, find k vertices on the red side that dominate the blue side.
- **SET COVER**: Given a set system, find k sets whose union covers the universe.
- **HITTING SET**: Given a set system, find k elements that intersect every set in the system.

All of these problems are equivalent under parameterized reductions, hence at least as hard as **CLIQUE**.

Basic hypotheses

It seems that parameterized complexity theory cannot be built on assuming $P \neq NP$ – we have to assume something stronger.

Engineers' Hypothesis

k -CLIQUE cannot be solved in time $f(k) \cdot n^{O(1)}$.

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k -STEP HALTING PROBLEM (is there a path of the given NTM that stops in k steps?) cannot be solved in time $f(k) \cdot n^{O(1)}$.

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Exponential Time Hypothesis (ETH)

n -variable 3SAT cannot be solved in time $2^{o(n)}$.

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Summary

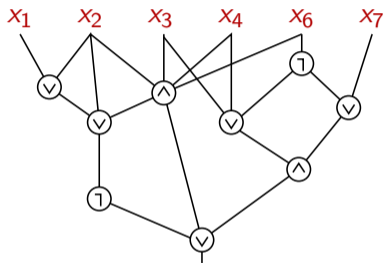
- INDEPENDENT SET and k -STEP HALTING PROBLEM can be reduced to each other \Rightarrow Engineers' Hypothesis and Theorists' Hypothesis are equivalent!
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Summary

- INDEPENDENT SET and k -STEP HALTING PROBLEM can be reduced to each other \Rightarrow Engineers' Hypothesis and Theorists' Hypothesis are equivalent!
- INDEPENDENT SET and k -STEP HALTING PROBLEM can be reduced to DOMINATING SET.
- Is there a parameterized reduction from DOMINATING SET to INDEPENDENT SET?
- Probably not. Unlike in NP-completeness, where most problems are equivalent, here we have a hierarchy of hard problems.
 - INDEPENDENT SET is $W[1]$ -complete.
 - DOMINATING SET is $W[2]$ -complete.
- Does not matter if we only care about whether a problem is FPT or not!

Boolean circuit

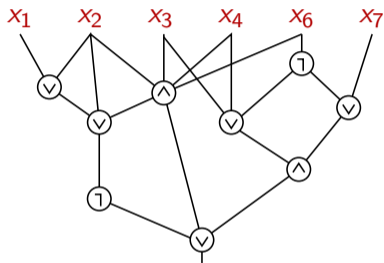
A **Boolean circuit** consists of input gates, negation gates, AND gates, OR gates, and a single output gate.



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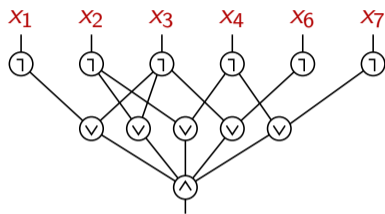
CIRCUIT SATISFIABILITY: Given a Boolean circuit C , decide if there is an assignment on the inputs of C making the output true.

Weight of an assignment: number of true values.

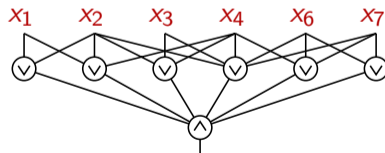
WEIGHTED CIRCUIT SATISFIABILITY: Given a Boolean circuit C and an integer k , decide if there is an assignment of weight k making the output true.

WEIGHTED CIRCUIT SATISFIABILITY

INDEPENDENT SET can be reduced to WEIGHTED CIRCUIT SATISFIABILITY:

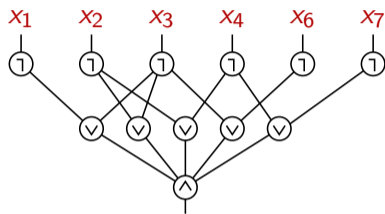


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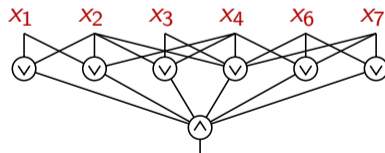


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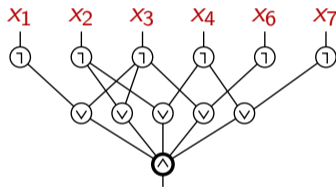


To express DOMINATING SET, we need more complicated circuits.

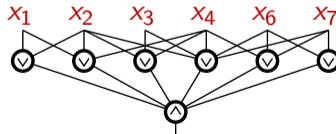
Depth and weft

The **depth** of a circuit is the maximum length of a path from an input to the output.
A gate is **large** if it has more than 2 inputs. The **weft** of a circuit is the maximum number of large gates on a path from an input to the output.

INDEPENDENT SET: weft 1, depth 3



DOMINATING SET: weft 2, depth 2



The W-hierarchy

Let $C[t, d]$ be the set of all circuits having weft at most t and depth at most d .

Definition

A problem P is in the class $W[t]$ if there is a constant d and a parameterized reduction from P to **WEIGHTED CIRCUIT SATISFIABILITY** of $C[t, d]$.

We have seen that **INDEPENDENT SET** is in $W[1]$ and **DOMINATING SET** is in $W[2]$.

Fact: **INDEPENDENT SET** is $W[1]$ -complete.

Fact: **DOMINATING SET** is $W[2]$ -complete.

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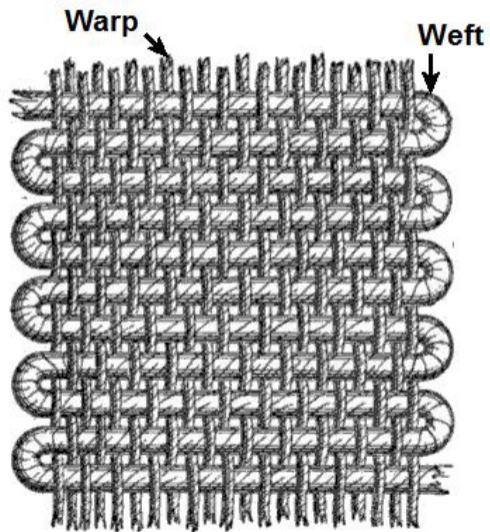
Fact: **DOMINATING SET** is $W[2]$ -complete.

If any $W[1]$ -complete problem is FPT, then $FPT = W[1]$ and every problem in $W[1]$ is FPT.

If any $W[2]$ -complete problem is in $W[1]$, then $W[1] = W[2]$.

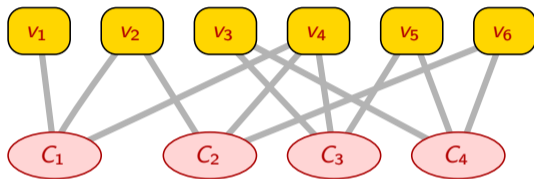
\Rightarrow If there is a parameterized reduction from **DOMINATING SET** to **INDEPENDENT SET**, then $W[1] = W[2]$.

Weft



Parameterized reductions

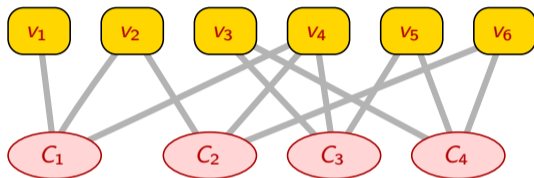
Typical **NP**-hardness proofs: reduction from e.g., **CLIQUE** or **3SAT**, representing each vertex/edge/variable/clause with a gadget.



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Types of parameterized reductions:

- Reductions keeping the structure of the graph.
 - **CLIQUE** \Rightarrow **INDEPENDENT SET**
- Reductions with vertex representations.
 - **MULTICOLORED INDEPENDENT SET** \Rightarrow **DOMINATING SET**
- Reductions with vertex and edge representations.

ODD SET

ODD SET: Given a set system \mathcal{F} over a universe U and an integer k , find a set S of at most k elements such that $|S \cap F|$ is odd for every $F \in \mathcal{F}$.

Theorem

ODD SET is $W[1]$ -hard parameterized by k .

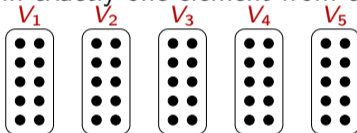
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First try: Reduction from MULTICOLORED INDEPENDENT SET. Let $U = V_1 \cup \dots \cup V_k$ and introduce each set V_i into \mathcal{F} .

\Rightarrow The solution has to contain exactly one element from each V_i .



If $xy \in E(G)$, how can we express that $x \in V_i$ and $y \in V_j$ cannot be selected simultaneously?

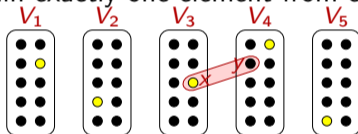
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- introducing $\{x, y\}$ into \mathcal{F} forces that **exactly one** of x and y appears in the solution,

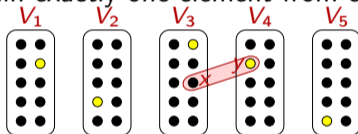
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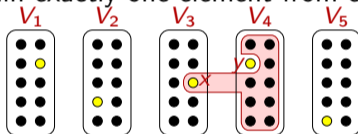
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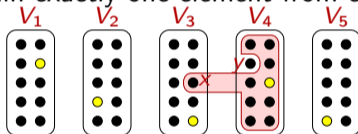
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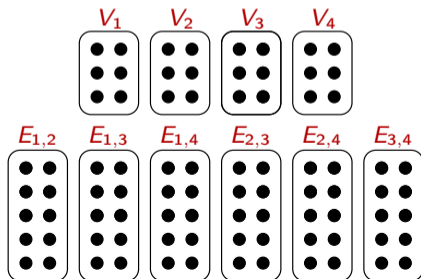
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Reduction from **MULTICOLORED CLIQUE**.

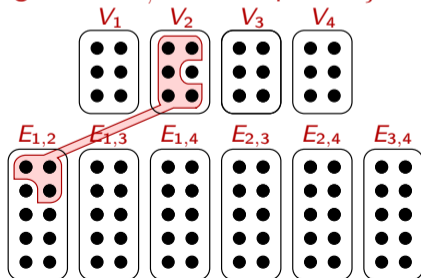
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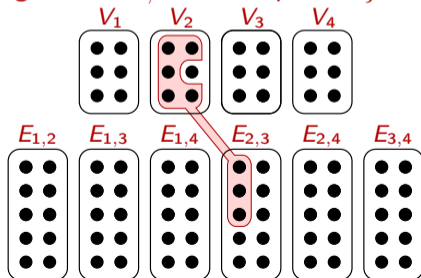
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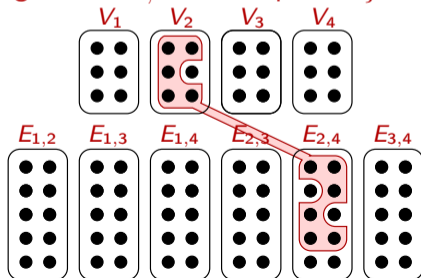
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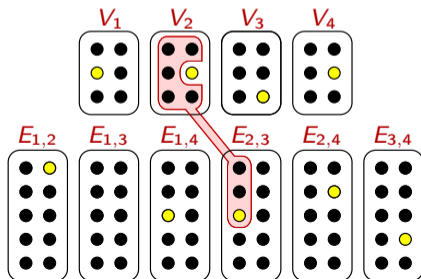
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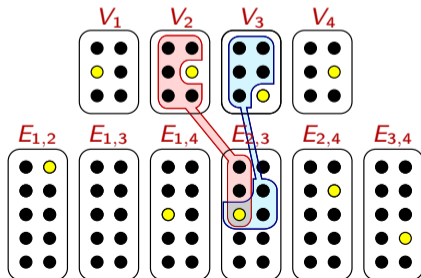
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- $v \in V_i$ selected \iff edges with endpoint v are selected from $E_{i,x}$ and $E_{x,i}$



ODD SET

Reduction from **MULTICOLORED CLIQUE**.

- For every $v \in V_i$ and $x \neq i$, we introduce the sets:
 $(V_i \setminus \{v\}) \cup \{\text{every edge from } E_{i,x} \text{ with endpoint } v\}$
 $(V_i \setminus \{v\}) \cup \{\text{every edge from } E_{x,i} \text{ with endpoint } v\}$
- $v \in V_i$ selected \iff edges with endpoint v are selected from $E_{i,x}$ and $E_{x,i}$
- $v_i \in V_i$ selected \iff edge $v_i v_j$ is selected in $E_{i,x}$
- $v_j \in V_j$ selected



Vertex and edge representation

Key idea

- Represent the vertices of the clique by k gadgets.
- Represent the edges of the clique by $\binom{k}{2}$ gadgets.
- Connect edge gadget $E_{i,j}$ to vertex gadgets V_i and V_j such that if $E_{i,j}$ represents the edge between $x \in V_i$ and $y \in V_j$, then it forces V_i to x and V_j to y .

Variants of HITTING SET

The following problems are $W[1]$ -hard, with very similar proofs:

- ODD SET
- EXACT ODD SET (find a set of size exactly k . . .)
- EXACT EVEN SET
- UNIQUE HITTING SET
(at most k elements that hit each set exactly once)
- EXACT UNIQUE HITTING SET
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(exactly k elements that hit each set exactly once)

A problem that is also $W[1]$ -hard, but requires very different techniques:

- EVEN SET: Given a set system \mathcal{F} and an integer k , find a **nonempty** set S of at most k elements such $|F \cap S|$ is even for every $F \in \mathcal{F}$.

Summary

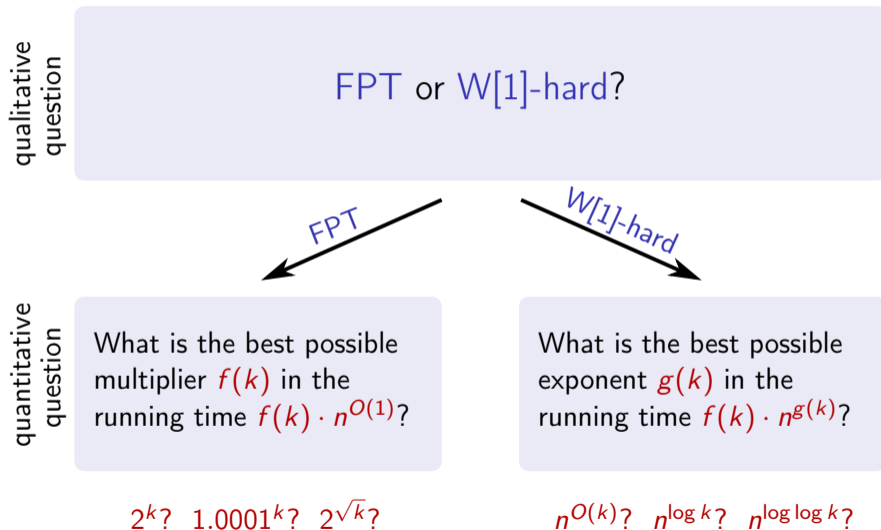
- By parameterized reductions, we can show that lots of parameterized problems are at least as hard as **CLIQUE**, hence unlikely to be fixed-parameter tractable.
- Connection with Turing machines gives some supporting evidence for hardness (only of theoretical interest).
- The **W**-hierarchy classifies the problems according to hardness (only of theoretical interest).
- Important trick in **W[1]**-hardness proofs: vertex and edge representations.

Shift of focus

qualitative
question

FPT or $W[1]$ -hard?

Shift of focus



Better algorithms for VERTEX COVER

- We have seen a $2^k \cdot n^{O(1)}$ time algorithm.
- Easy to improve to, e.g., $1.618^k \cdot n^{O(1)}$.
- Current best $f(k)$: $1.2738^k \cdot n^{O(1)}$.
- Lower bounds?
 - Is, say, $1.001^k \cdot n^{O(1)}$ time possible?
 - Is $2^{k/\log k} \cdot n^{O(1)}$ time possible?

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Of course, for all we know, it is possible that $P = NP$ and VERTEX COVER is polynomial-time solvable.

⇒ We can hope only for conditional lower bounds.

Exponential Time Hypothesis (ETH)

3CNF: ϕ is a conjunction of clauses, where each clause is a disjunction of at most 3 literals (= a variable or its negation), e.g., $(x_1 \vee x_3 \vee \bar{x}_4) \wedge (\bar{x}_2 \vee \bar{x}_3) \vee (x_1 \vee x_2 \vee x_4)$.

3SAT: given a 3CNF formula ϕ with n variables and m clauses, decide whether ϕ is satisfiable.

- Current best algorithm is 1.30704^n [Hertli 2011].
- Can we do **significantly** better, e.g, $2^{O(n/\log n)}$?

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Hypothesis introduced by Impagliazzo, Paturi, and Zane in 2001:

Exponential Time Hypothesis (ETH) [consequence of]

There is no $2^{o(n)}$ -time algorithm for n -variable 3SAT.

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Hypothesis introduced by Impagliazzo, Paturi, and Zane in 2001:

Exponential Time Hypothesis (ETH) [real statement]

There is a constant $\delta > 0$ such that there is no $O(2^{\delta n})$ time algorithm for 3SAT.

Sparsification

Exponential Time Hypothesis (ETH) [consequence of]

There is no $2^{o(n)}$ -time algorithm for n -variable 3SAT.

Observe: an n -variable 3SAT formula can have $m = \Omega(n^3)$ clauses.

Are there algorithms that are subexponential in the size $n + m$ of the 3SAT formula?

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Sparsification Lemma

There is a $2^{o(n)}$ -time algorithm for n -variable 3SAT.



There is a $2^{o(n+m)}$ -time algorithm for n -variable m -clause 3SAT.

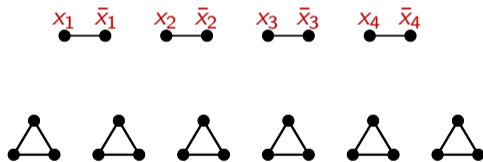
Intuitively: When considering a hard 3SAT instance, we can assume that it has $m = O(n)$ clauses.

Lower bounds based on ETH

Exponential Time Hypothesis (ETH) + Sparsification Lemma

There is no $2^{o(n+m)}$ -time algorithm for n -variable m -clause 3SAT.

The textbook reduction from 3SAT to VERTEX COVER:



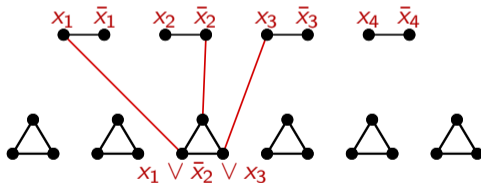
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formula is satisfiable \Leftrightarrow there is a vertex cover of size $n + 2m$

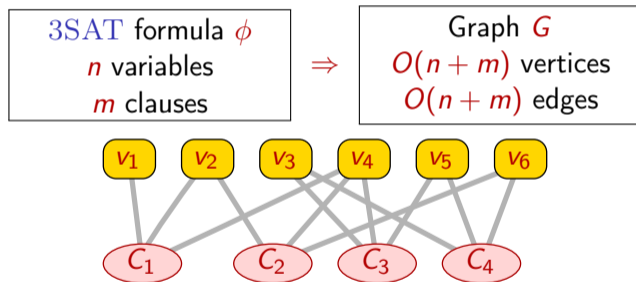


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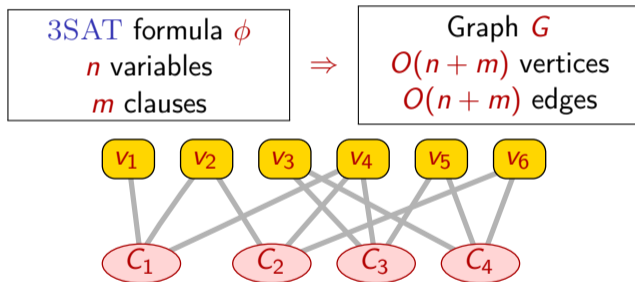


Lower bounds based on ETH

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Corollary

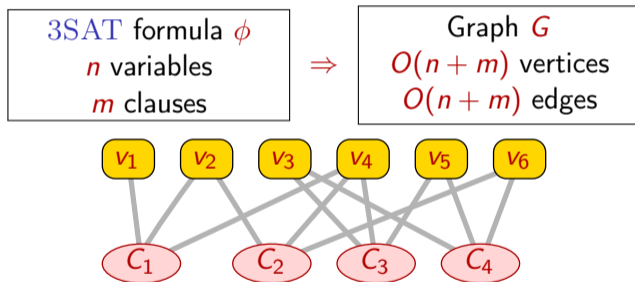
Assuming ETH, there is no $2^{o(n)}$ algorithm for VERTEX COVER on an n -vertex graph.

Lower bounds based on ETH

Exponential Time Hypothesis (ETH) + Sparsification Lemma

There is no $2^{o(n+m)}$ -time algorithm for n -variable m -clause 3SAT.

The textbook reduction from 3SAT to VERTEX COVER:



Corollary

Assuming ETH, there is no $2^{o(k)} \cdot n^{O(1)}$ algorithm for VERTEX COVER.

Other problems

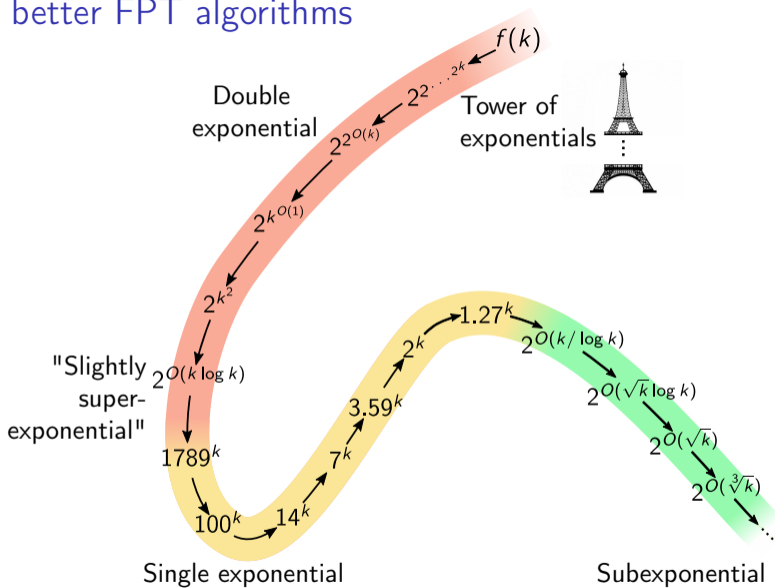
There are polytime reductions from **3SAT** to many problems such that the reduction creates a graph with $O(n + m)$ vertices/edges.

Consequence: Assuming ETH, the following problems cannot be solved in time $2^{o(n)}$ and hence in time $2^{o(k)} \cdot n^{O(1)}$ (but $2^{O(k)} \cdot n^{O(1)}$ time algorithms are known):

- VERTEX COVER
- LONGEST CYCLE
- FEEDBACK VERTEX SET
- MULTIWAY CUT
- ODD CYCLE TRANSVERSAL
- STEINER TREE
- ...

Seems to be the natural behavior of FPT problems?

The race for better FPT algorithms

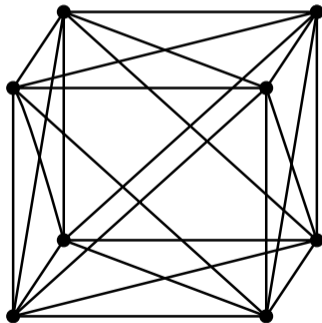


EDGE CLIQUE COVER

EDGE CLIQUE COVER: Given a graph G and an integer k , cover the edges of G with at most k cliques.

(the cliques need not be edge disjoint)

Equivalently: can G be represented as an intersection graph over a k element universe?

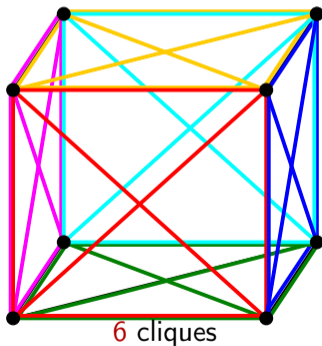


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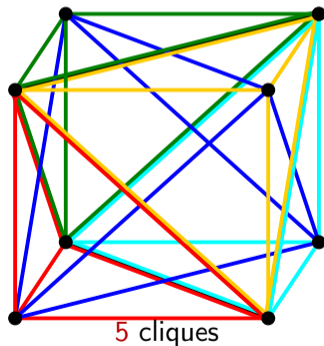


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EDGE CLIQUE COVER

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Simple algorithm (sketch)

- If two adjacent vertices have the same neighborhood (“twins”), then remove one of them.
- If there are no twins and isolated vertices, then $|V(G)| > 2^k$ implies that there is no solution.
- Use brute force.

Running time: $2^{2^{O(k)}} \cdot n^{O(1)}$ — double exponential dependence on k !

EDGE CLIQUE COVER

EDGE CLIQUE COVER: Given a graph G and an integer k , cover the edges of G with at most k cliques.

(the cliques need not be edge disjoint)

Double-exponential dependence on k cannot be avoided!

Theorem

Assuming ETH, there is no $2^{2^{o(k)}} \cdot n^{O(1)}$ time algorithm for **EDGE CLIQUE COVER**.

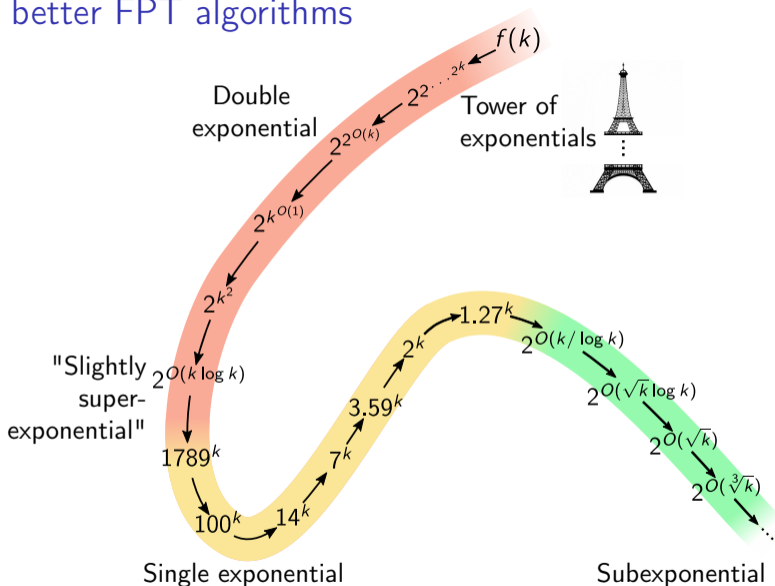
Proof:

3SAT
 n variables



EDGE CLIQUE COVER
 $k = O(\log n)$

The race for better FPT algorithms



Slightly superexponential algorithms

Running time of the form $2^{O(k \log k)} \cdot n^{O(1)}$ appear naturally in parameterized algorithms usually because of one of two reasons:

- 1 Branching into k directions at most k times explores a search tree of size $k^k = 2^{O(k \log k)}$.

Example: FEEDBACK VERTEX SET in the first lecture.

- 2 Trying $k! = 2^{O(k \log k)}$ permutations of k elements (or partitions, matchings, ...)

Can we avoid these steps and obtain $2^{O(k)} \cdot n^{O(1)}$ time algorithms?

CLOSEST STRING

CLOSEST STRING

Given strings s_1, \dots, s_k of length L over alphabet Σ , and an integer d , find a string s (of length L) such that Hamming distance $d(s, s_i) \leq d$ for every $1 \leq i \leq k$.

(Hamming distance: number of differing positions)

s_1	C	B	D	C	C	A	C	B	B
s_2	A	B	D	B	C	A	B	D	B
s_3	C	D	D	B	A	C	C	B	D
s_4	D	D	A	B	A	C	C	B	D
s_5	A	C	D	B	D	D	C	B	C

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Different parameters:

- Number k of strings.
- Length L of strings
- Maximum distance d .
- Alphabet size $|\Sigma|$.

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Different parameters:

- Number k of strings.
- Length L of strings
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- Alphabet size $|\Sigma|$.

We can ask for running time for example

- $f(d)n^{O(1)}$: FPT parameterized by d
- $f(k, |\Sigma|)n^{O(1)}$: FPT with combined parameters k and $|\Sigma|$

CLOSEST STRING

Theorem

CLOSEST STRING can be solved in time $2^{O(d \log d)} n^{O(1)}$.

- **Main idea:** Given a string y at Hamming distance ℓ from some solution, we use branching to find a string at distance at most $\ell - 1$ from some solution.
- Initially, $y = x_1$ is at distance at most d from some solution.

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- **Main idea:** Given a string y at Hamming distance ℓ from some solution, we use branching to find a string at distance at most $\ell - 1$ from some solution.
- Initially, $y = x_1$ is at distance at most d from some solution.
- If y is not a solution, then there is an x_i with $d(y, x_i) \geq d + 1$.
 - Look at the first $d + 1$ positions p where $x_i[p] \neq y[p]$. For every solution z , it is true for one such p that $x_i[p] = z[p]$.
 - Branch on choosing one of these $d + 1$ positions and replace $y[p]$ with $x_i[p]$: distance of y from solution z decreases to $\ell - 1$.
- Running time $(d + 1)^d \cdot n^{O(1)} = 2^{O(d \log d)} n^{O(1)}$.

CLOSEST STRING

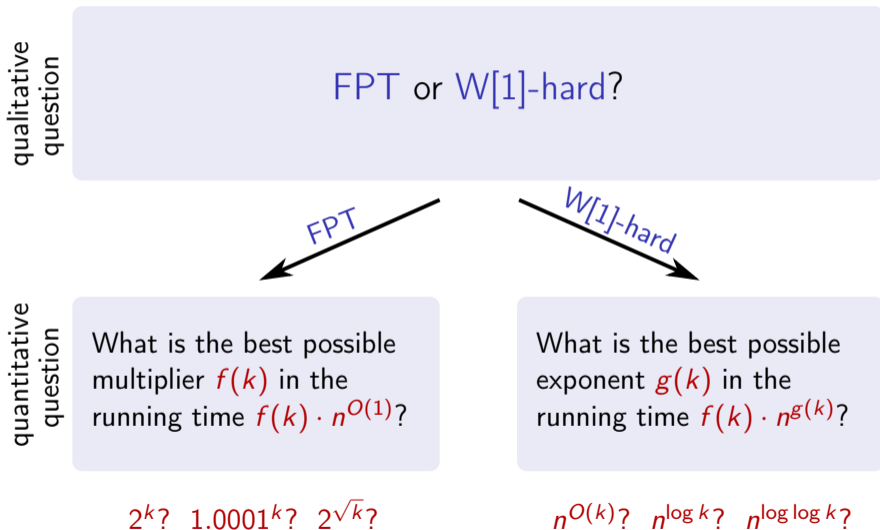
Theorem

Assuming ETH, CLOSEST STRING has no $2^{o(d \log d)} n^{O(1)}$ algorithm.

Proof:



Shift of focus



Better algorithms for W[1]-hard problems

- $O(n^k)$ algorithm for k -CLIQUE by brute force.
- $O(n^{0.79k})$ algorithms using fast matrix multiplication.
- W[1]-hardness of k -CLIQUE gives evidence that there is no $f(k) \cdot n^{O(1)}$ time algorithm.
- But what about improvements of the exponent $O(k)$?

$$\begin{array}{l} n^{\sqrt{k}} \\ n^{\log k} \quad n^{k/\log \log k} \\ 2^{2^k} \cdot n^{\log \log \log k} \quad n^{\sqrt{k}} \end{array}$$

Better algorithms for $W[1]$ -hard problems

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Theorem

Assuming ETH, k -CLIQUE has no $f(k) \cdot n^{o(k)}$ algorithm for any computable function f .

In particular, ETH implies that k -CLIQUE is not FPT.

Basic hypotheses

Engineers' Hypothesis

k -CLIQUE cannot be solved in time $f(k) \cdot n^{O(1)}$.



Theorists' Hypothesis

k -STEP HALTING PROBLEM (is there a path of the given NTM that stops in k steps?) cannot be solved in time $f(k) \cdot n^{O(1)}$.



Exponential Time Hypothesis (ETH)

n -variable 3SAT cannot be solved in time $2^{o(n)}$.

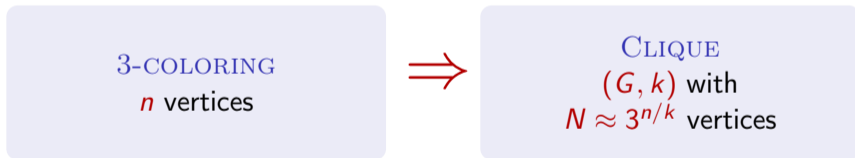
Lower bound for k -CLIQUE

Theorem

Assuming ETH, k -CLIQUE has no $f(k) \cdot N^{o(k)}$ algorithm for any computable function f .

Proof:

Textbook reduction from 3SAT to 3-COLORING shows that, assuming ETH, there is no $2^{o(n)}$ time algorithm for 3-COLORING on an n -vertex graph. Then



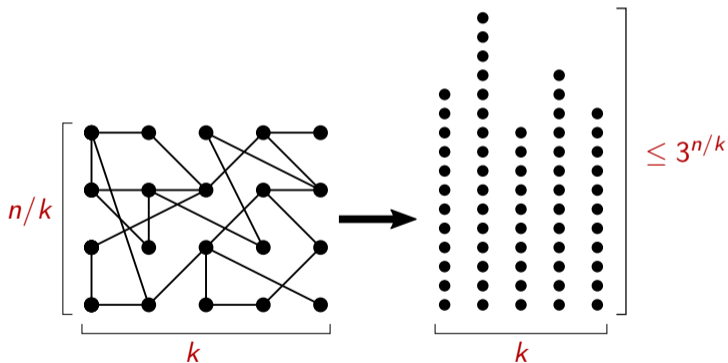
$N^{o(k)}$ algorithm for CLIQUE $\Rightarrow (3^{n/k})^{o(k)} = 3^{o(n)}$ algorithm for 3-COLORING

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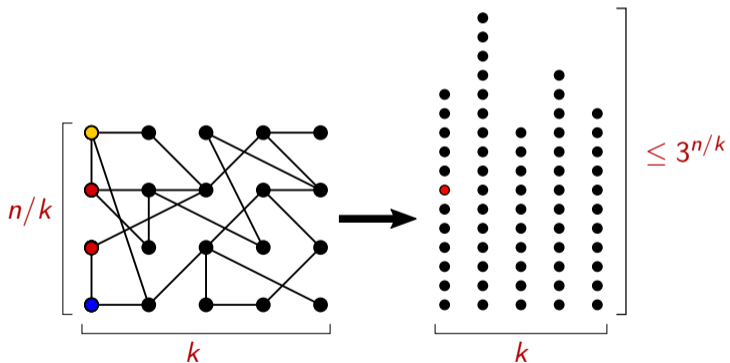
Create a vertex per each consistent coloring of each group.

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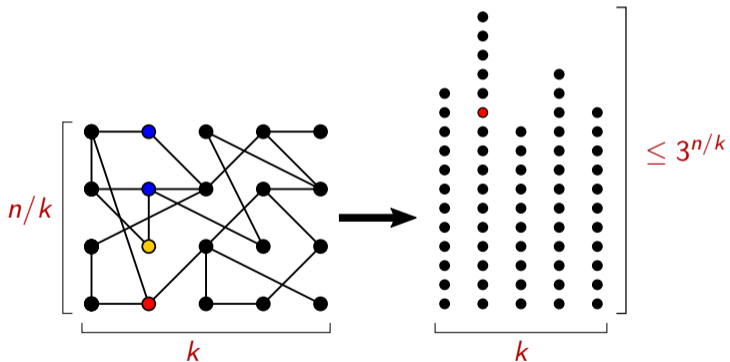
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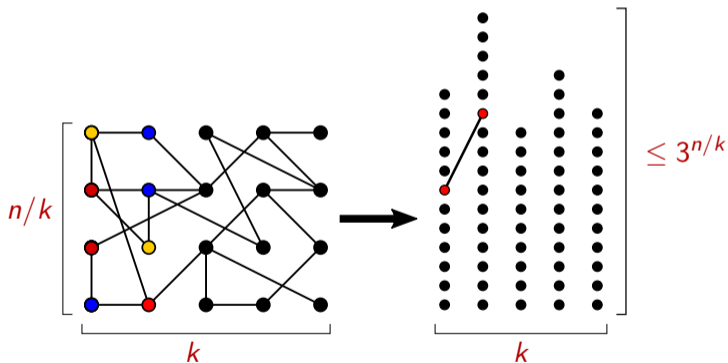
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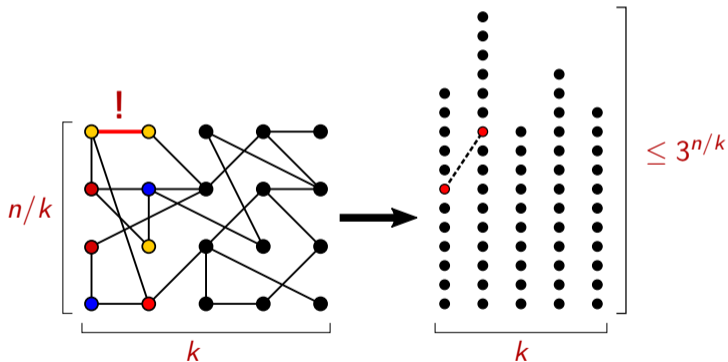
Connect two vertices if they represent colorings that are consistent together.

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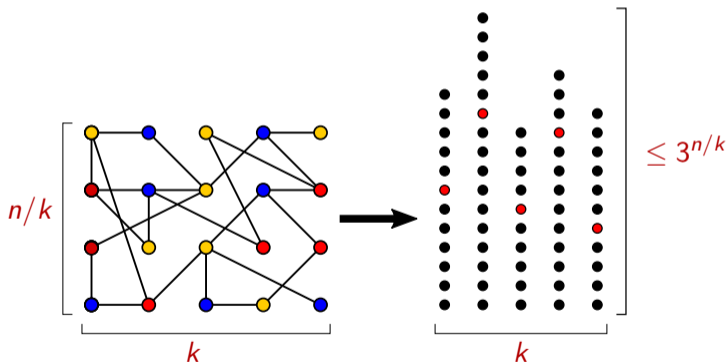
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Left graph has a 3-coloring \Leftrightarrow Right graph contains a k -clique

Lower bound for k -CLIQUE

Theorem

Assuming ETH, k -CLIQUE has no $f(k) \cdot N^{o(k)}$ algorithm for any computable function f .

Proof:

- We have constructed a new graph with $N = k \cdot 3^{n/k}$ vertices that has a k -clique if and only if the original graph is 3-colorable.
- Suppose that k -CLIQUE has a $2^k \cdot N^{o(k)}$ time algorithm.
- Doing the reduction with $k := \log n$ gives us an algorithm for 3-COLORING with running time

$$2^k \cdot N^{o(k)} = n \cdot (\log n)^{o(\log n)} \cdot 3^{n \cdot o(\log n) / \log n} = 2^{o(n)}.$$

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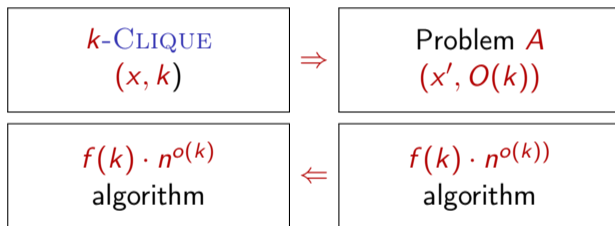
- Choosing $k := \log \log n$ would rule out a $2^{2^k} \cdot N^{o(k)}$ algorithm etc.
- In general, we need to choose roughly $k := f^{-1}(n)$ groups (technicalities omitted).

Tight bounds

Theorem

Assuming ETH, k -CLIQUE has no $f(k) \cdot n^{o(k)}$ algorithm for any computable function f .

Transferring to other problems:

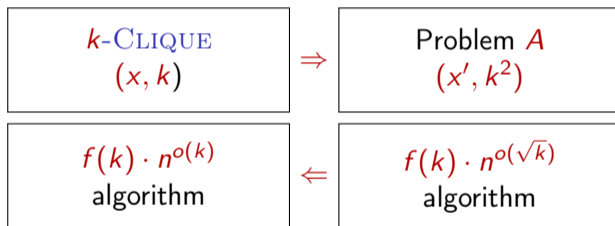


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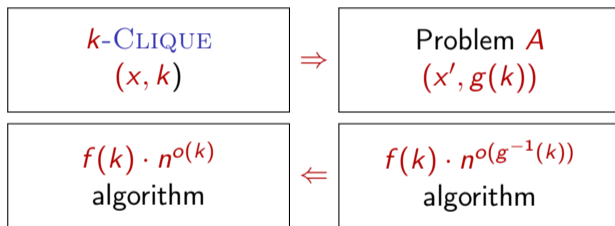


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Assuming ETH, k -CLIQUE has no $f(k) \cdot n^{o(k)}$ algorithm for any computable function f .

Transferring to other problems:

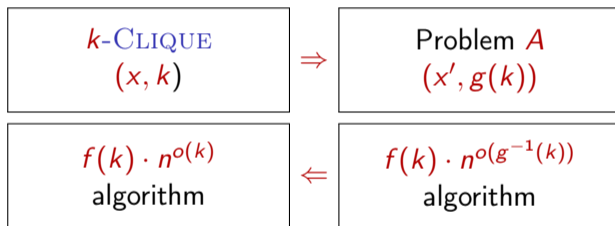


Tight bounds

Theorem

Assuming ETH, k -CLIQUE has no $f(k) \cdot n^{o(k)}$ algorithm for any computable function f .

Transferring to other problems:



Bottom line:

- To rule out $f(k) \cdot n^{o(k)}$ algorithms, we need a parameterized reduction that blows up the parameter at most *linearly*.
- To rule out $f(k) \cdot n^{o(\sqrt{k})}$ algorithms, we need a parameterized reduction that blows up the parameter at most *quadratically*.

Tight bounds

Assuming ETH, there is no $f(k)n^{o(k)}$ time algorithms for

- SET COVER
- HITTING SET
- CONNECTED DOMINATING SET
- INDEPENDENT DOMINATING SET
- PARTIAL VERTEX COVER
- DOMINATING SET in bipartite graphs
- ...

Summary

- Parameterized reductions from **CLIQUE** or **INDEPENDENT SET** can give evidence that a problem is not FPT.
- ETH can give tight bounds on the $f(k)$ for FPT problems.
- ETH can give tight bounds on the exponent of n for $W[1]$ -hard problems.