# A Short Tour of Tractability Hunting <br> With a special focus on Parameterized Complexity 

Martin Berglund<br>Umeå University

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## On Guest Lectures

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Course only starting: lot of fundamentals remain. Yet I want to say something aspirational

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Course only starting: lot of fundamentals remain. Yet I want to say something aspirational

As such I will give a short tour of some complexity theory concepts ahead of their time

I will assume:

- Propositional logic
- A basic idea of what complexity, P and NP, means
- Some minor math and $\mathcal{O}$-notation

Will hopefully explain the rest

## Part I: Complexity Background and Tractability

## Classical complexity



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Objection 2: We simply cannot afford to consider all NP-hard problems intractable.

Still, we cannot just consider NP tractable: Cook was right!

## Vertex Cover

## Vertex Cover

Input: A graph $G=(V, E)$, a constant $k \in N$. Output: "Yes" if and only if there exists some $V^{\prime} \subseteq V,\left|V^{\prime}\right| \leq k$ such that every edge in $E$ touches a vertex in $V^{\prime}$.

Vertex Cover: Example


Vertex Cover: Example


## Vertex Cover: NP-complete

Vertex Cover is known to be NP-complete.

It is one of Karp's original 21 problems. Reduction from Chromatic Number (graph coloring).

It is easy to bring back to SAtisfiability however, or at least 3-SATISFIABILITY.

$$
\left[\begin{array}{c}
20-20 \\
20
\end{array}\right.
$$

## Practical solvability

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However, for Clique we have no practical algorithms for large instances

LTL Model Checking is PSPACE-complete, but used in practice to verify hardware design

## Confronting intractability

(1) Approximation
(2) Randomization
(3) "Islands of tractability"
(4) Parallelization
(5) Parameterization

## 1. Approximation

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Vertex Cover has a 2-approximation in polynomial time.
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PTAS: Polynomial time approximation schemes are the centerpiece.

## 2. Randomization

Randomized algorithms are algorithms permitted to flip coins

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The zoo is quite complex:


Randomized is faster for many problems in $P$, but $P \stackrel{?}{=} B P P$

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Fixing constants: SATISFIABILITY is in P if no clause has more than 2 literals.

Slicing: For every constant $k$ the $k$-Clique problem is in P .

Easy but clumsy: parameterized complexity picks up from here

## 4. Parallelization

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The complexity theory is quite interesting, the NC (Nick's Class after Nick Pippenger) hierarchy defines how problems may be split, within $P$
in general parallelization operates within $P$ to an even greater extent than randomization:

- Most complex problems actually resist parallelization
- Even if an NP-complete problem can be parallelized this entails increasing the amount of hardware exponentially (unless $\mathrm{P}=\mathrm{NP}$ )


## 5. Parameterization

## Part II: Fixed Parameter Tractability

## Solving 3-Vertex Cover



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## Solving 3-VERTEX COVER

?

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## Solving 3-VERTEX COVER

$$
c^{c}
$$

## Solving 3-VERTEX COVER

$$
\left.0^{4}\right)^{(3)}
$$

## Solving 3-VERTEX COVER

(6)

## Solving 3-VERTEX COVER

(b)

## Solving 3-VERTEX COVER

(b) (d)

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$$
\text { (b) (a) } 0^{4} 0^{b} b^{d} \sigma^{c} \sigma^{5}
$$

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$$

## Solving 3-Vertex Cover

$$
\begin{aligned}
& \text { (a) (b) (a) }
\end{aligned}
$$

## Solving 3-Vertex Cover

$$
\text { (b) (a) } 0_{0}^{4} 0^{b} b^{d} 0^{a} 0^{a}
$$

## Solving 3-VERTEX COVER

$$
\begin{aligned}
& \text { (e) } \\
& \text { (b) }
\end{aligned}
$$

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## Solving 3-Vertex Cover



## k-Vertex Cover

Given an instance ( $G, k$ ) of Vertex Cover, this bounded branching algorithm can solve it in time

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2^{k} \cdot \mathcal{O}(|G|)
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We say that Vertex Cover parameterized by $k$ is fixed-parameter tractable.

## Parameterizations

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Example. We can parameterize Vertex Cover by setting

$$
\kappa(G, k)=k
$$

## Parameterized problems

Definition. Let $\Sigma$ be a finite alphabet. A parameterized problem over $\Sigma$ is a pair $(Q, \kappa)$ consisting of

- a set $Q \subseteq \Sigma^{*}$ of strings over $\Sigma$, and
- a parameterization $\kappa$ of $\Sigma^{*}$.


## FPT algorithms

Definition. Let $\Sigma$ be a finite alphabet and $\kappa$ a parameterization of $\Sigma^{*}$.

- An algorithm is FPT w.r.t. $\kappa$ if there is a computable function $f: \mathbb{N} \rightarrow \mathbb{N}$ and a polynomial $p$ such that for every $x \in \Sigma^{*}$, the algorithm, when given $x$, has running time at most

$$
f(\kappa(x)) \cdot p(|x|) .
$$

## Parameterized tractability

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A parameterized problem $(Q, \kappa)$ over $\Sigma$ is fixed-parameter tractable if there is an FPT-algorithm w.r.t. $\kappa$ that decides $Q$.

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FPT is the class of all fixed-parameter tractable problems.

## Kernelization

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## Solving 4-Vertex Cover

$k=4$


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$\operatorname{deg}(c)>4$

## Solving 4-Vertex Cover

$$
k=3
$$



## Solving 4-Vertex Cover

$$
k=3
$$


$\operatorname{deg}(f)>3$

## Solving 4-Vertex Cover

$$
k=2
$$


(a)
(b)
(h)

## Solving 4-Vertex Cover

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$|E|<2^{2}$

## Solving $k$-Vertex Cover

More generally: exhaustively applying the 3 reduction rules transforms any VERTEX COVER instance into one where every vertex has a degree $2 \leq d \leq k$

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## Solving k-VERTEX Cover

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It does so in polynomial time in $|G|$

Combinatorics show that a $k$-coverable graph where all vertices have degree $2 \leq d \leq k$ cannot have more than $k^{2}$ vertices

A polynomial procedure making the whole problem work in terms of $k$ !

Applying the bounded branching algorithm to a reduced graph gives us $\mathcal{O}\left(1.2738^{k}\right) k^{2}$

## Kernelizations

Let $(Q, \kappa)$ be a parameterized problem over $\Sigma$. A kernelization of $(Q, \kappa)$ is a mapping

$$
K: \Sigma^{*} \rightarrow \Sigma^{*}
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such that

- $x \in Q \Leftrightarrow K(x) \in Q$,
- there is a computable function $g$ such that $|K(x)|<g(\kappa(x))$.


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## Theorem

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Theorem (!)
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FPT and XP



The parameterized hierarchy


## Parameterized Hardness

## Part III: Proving Limited Parameterizability

## Reductions

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(2) $p$ can't be too much larger than $p^{\prime}$ (or $p$ becomes easy in in terms of its size!)
- For P and NP: any reduction which runs in P solves both
- For parameterized complexity more care is needed


## Parameterized Reductions

Definition. Let $(Q, \kappa)$ and $\left(Q^{\prime}, \kappa^{\prime}\right)$ be two parameterized problems over $\Sigma$ and $\Gamma$.

An FPT-reduction from $(Q, \kappa)$ to ( $Q^{\prime}, \kappa^{\prime}$ ) is a mapping $R: \Sigma^{*} \rightarrow \Gamma^{*}$ such that
(1) $x \in Q \Leftrightarrow R(x) \in Q^{\prime}$, for all $x \in \Sigma^{*}$,
(2) $R$ is FPT-computable w.r.t. $\kappa$, and
(3) there is a computable function $g$ such that $\kappa^{\prime}(R(x)) \leq g(\kappa(x))$ for all $x \in \Sigma^{*}$.

## Demonstrating a Reduction

Unfortunately demonstrating a reduction gets complex

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The top of the hierarchy, XP, is also interesting

The class XP

## The class XP

Definition. Let $(Q, \kappa)$ be a parameterized problem over $\Sigma$. Then $(Q, \kappa)$ belongs to $X P$ if there is a function $f: \mathbb{N} \rightarrow \mathbb{N}$ and an algorithm that decides $Q$ and runs on input $x \in \Sigma^{*}$ in time

$$
|x|^{f(\kappa(x))}+f(\kappa(x)) .
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Recall slicing as an island of tractability technique

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This should illustrate why it can be viewed as crude compared to parameterized complexity: it is the worst case of the hierarchy

## Conclusion

This completes the small tour of tractability hunting

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An excellent treatment of the central concepts in computational complexity.

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A standard text on parameterized complexity theory.

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For now: Thanks for listening and enjoy the rest of the course!

