# Lower bounds for polynomial kernelization 

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## Kernelization - recap

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- Unparameterized variant: $k$ is appended to $x$ in unary.
- Kernelization algorithm takes on input an instance ( $x, k$ ), and outputs an instance ( $x^{\prime}, k^{\prime}$ ) such that

$$
(x, k) \in L \Leftrightarrow\left(x^{\prime}, k^{\prime}\right) \in L \quad \text { and } \quad\left|x^{\prime}\right|+k^{\prime} \leqslant f(k)
$$

for some computable function $f$.

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- We are interested in polynomial kernels, where $f$ is a polynomial.
- Before 2008, no tool to classify FPT problems wrt. whether they have polykernels or not.


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- Take $t=k^{7}$ instances $\left(G_{1}, k\right),\left(G_{2}, k\right), \ldots,\left(G_{t}, k\right)$.
- Let $H$ be a disjoint union of $G_{1}, G_{2}, \ldots, G_{t}$. Then the answer to $(H, k)$ is YES if and only if the answer to any $\left(G_{i}, k\right)$ is YES.


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## Intuition

The final number of bits is much less than the number input instances. Most of the instances have to be discarded completely.

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- For instance, when $R \in \mathbf{N P}$ and $L$ is $\mathbf{N P}$-hard.
- Note: There are examples when a poly-compression is known but a poly-kernel is not known, because it is unclear whether $R$ is in NP.


## OR-distillation

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## OR-distillation of $L$ into $R$

Input: Words $x_{1}, x_{2}, \ldots, x_{t}$, each of length at most $k$.
Time: $\quad \operatorname{poly}\left(t+\sum_{i=1}^{t}\left|x_{i}\right|\right)$.
Output: One word $y$ such that
(a) $|y|=\operatorname{poly}(k)$, and
(b) $y \in R$ if and only if $x_{i} \in L$ for at least one $i$.

## OR-distillation on picture

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$t$ instances


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Intuition: Necessary loss of information $\rightsquigarrow$ Contradiction for an NP-hard $L$ Define OR- $L=\left\{x_{1} \# x_{2} \# \ldots \# x_{t}: x_{i} \in L\right.$ for at least one $\left.i\right\}$. OR-distillation $L \rightarrow R$ is a polynomial compression OR-L/max $\left|x_{i}\right| \rightarrow R$

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- NP $\subseteq$ coNP/poly implies $\mathrm{PH}=\Sigma_{3}^{\mathrm{P}}$.
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- The proof is very short, but very tricky.


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Output: One instance $\left(y, k^{\star}\right)$ such that
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## OR-composition theorem

Suppose a parameterized problem $L$ admits an OR-composition algorithm, and the unparameterized version of $L$ is NP-hard. Then $L$ does not admit a polynomial kernel unless NP $\subseteq$ coNP/poly.

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- Composition:

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- A graph admits a $k$-path iff any of its connected components does.
- Same for $k$-Cycle and many other problems.
- Today, investigating the existence of a polynomial kernel is often a secondary goal after showing that a problem is FPT.


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- Observed also earlier via different arguments.
(Dom, Lokshtanov, and Saurabh; 2009)


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- Most of the works use a subset of mentioned features.
- Later: a new formalism cross-composition gathers all the features. (Bodlaender, Jansen, and Kratsch; 2011)


## Polynomial equivalence relation

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Equivalence relation $\sim$ on $\Sigma^{\star}$ is a polynomial equivalence relation if:

- checking whether two words $x, y \in \Sigma^{\star}$ are $\sim$-equivalent can be done in poly $(|x|+|y|)$ time; and
- $\sim$ partitions words of length $\leqslant n$ into poly $(n)$ equivalence classes.


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- Examples, supposing some reasonable graph encoding:
- partitioning with respect to the number of vertices of the graph;
- or with respect to (i) the number of vertices, (ii) the number of edges, (iii) size of the maximum matching, (iv) budget.


## Cross-composition

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An unparameterized problem $Q$ cross-composes into a parameterized problem $L$, if there exists a polynomial equivalence relation $\sim$ and an algorithm that, given $\sim$-equivalent strings $x_{1}, x_{2}, \ldots, x_{t}$, in time poly $\left(t+\sum_{i=1}^{t}\left|x_{i}\right|\right)$ produces one instance $\left(y, k^{\star}\right)$ such that

- $\left(y, k^{\star}\right) \in L$ iff $x_{i} \in Q$ for at least one $i=1,2, \ldots, t$,
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## Cross-composition theorem

If some NP-hard problem $Q$ cross-composes into $L$, then $L$ has no polynomial compression into any language $R$, unless NP $\subseteq$ coNP/poly.

## Proof

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$$
\begin{aligned}
& k=\max \left|x_{i}\right|, \quad \log t=\mathcal{O}(k)
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- In fact, cross-composition is a good framework to express also all the previous results.
- Plan for now: show some non-trivial cross-composition to give an intuition about basic tricks.


## Application 1: Set Splitting

## SET Splitting

I: Universe $U$ and family of subsets $\mathcal{F} \subseteq 2^{U}$
P: $\quad|U|$
Q: Is there a coloring $\mathcal{C}: U \rightarrow\{\mathbf{B}, \mathbf{W}\}$ such that every set $X \in \mathcal{F}$ is split, i.e., contains a black and a white element?

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- We show a cross-composition of Set Splitting into itself.
- We may assume that the universes are of the same size, hence we think of them as of one, common universe.


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P: $|U|$
Q: Is there a coloring $\mathcal{C}: U \rightarrow\{\mathbf{B}, \mathbf{W}\}$ such that every set $X \in \mathcal{F}$ is split, i.e., contains a black and a white element?

- We show a cross-composition of Set Splitting into itself.
- We may assume that the universes are of the same size, hence we think of them as of one, common universe.
- Assume that $t$ is a power of 2 (by copying the instances).


## Cross-composing into SET Splitting

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$1+\log t$ pairs of vertices
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PLAYGROUND
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## Cross-composing into SET Splitting

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Input: Instances (U, \mathcal{F}}\mp@subsup{}{}{i}
Output: Instance ( }\mp@subsup{U}{}{*},\mp@subsup{\mathcal{F}}{}{*}
|U*| = |U| +2 log}t+
    \mathcal{F}}\mp@subsup{}{}{*}\mathrm{ consists of:
```



PLAYGROUND
joint universe $U$

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$(\Leftarrow):$
$(\Rightarrow): \quad \mathcal{C}$ on IS defines, which instance must be solved in PL

If $\left(U, \mathcal{F}^{i}\right)$ is solvable, we set IS accordingly, and solve this instance in PL.

Remaining sets are split for free.


## PLAYGROUND

joint universe $U$

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- Main lesson:
- Model the choice of the instance to be solved.
- Idea: choose $\log t$ bits of its index on an appropriate gadget.
- Choice of the index makes the instance active, while the other instances are "switched off".


## PPTs

- Idea: Hardness of kernelization can be transferred via reductions, similarly to NP-hardness.
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## Polynomial parameter transformation (PPT)

A polynomial parameter transformation from a parameterized problem $P$ to a parameterized problem $Q$ is a polynomial-time algorithm that transforms a given instance ( $x, k$ ) of $P$ into an equivalent instance $\left(x^{\prime}, k^{\prime}\right)$ of $Q$ such that $k^{\prime}=\operatorname{poly}(k)$.

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## Observation

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- Proof:

Compose the PPT with the assumed compression for $Q$.

## Application 2: Steiner Tree

## Steiner Tree

I: Graph $G$ with terminals $T \subseteq V(G), k \in \mathbb{N}$
P: $\quad k+|T|$
Q: Is there a set $X \subseteq V(G) \backslash T$, such that $|X| \leqslant k$ and $G[T \cup X]$ is connected?


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- We show that Steiner Tree has no polykernel (unless...) using a PPT from a auxiliary problem.


The auxiliary problem technique

- Introduce a simpler problem $P$, which is almost trivially compositional.
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- High level: Extract the essence of the original problem into the auxiliary problem.


## Colorful Graph Motif

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- Now: PPT from CGM to ST.


## From CGM to ST




Attach a terminal to every color class.
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- Note: Composition for CGM is far simpler than trying to do this directly for Steiner Tree.


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A weak cross-composition of dimension $d$ from an unpar. problem $Q$ to a par. problem $L$, is an algorithm that, given $\sim$-equivalent strings $x_{1}, x_{2}, \ldots, x_{t}$ for some polynomial equivalence relation $\sim$, in time poly $\left(t+\sum_{i=1}^{t}\left|x_{i}\right|\right)$ produces one instance $\left(y, k^{\star}\right)$ such that

- $\left(y, k^{\star}\right) \in L$ iff $x_{i} \in Q$ for at least one $i=1,2, \ldots, t$,
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Suppose NP $\nsubseteq$ coNP/poly. If some NP-hard problem $Q$ has a cross-composition of dimension $d$ into $L$, then $L$ does not admit a compression into any language $R$ with bitsize $\mathcal{O}\left(k^{d-\varepsilon}\right)$ for any $\varepsilon>0$.

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- Note: The $2 k$-kernel for VC needs $\mathcal{O}\left(k^{2}\right)$ bits for the encoding.


## Conclusions

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- Thank you for your attention!

Tikz faces based on a code by Raoul Kessels, http://www.texample.net/tikz/examples/emoticons/,
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