

Relaxation Complexity: Algorithmic Possibilities and Limitations

joint work with Manuel Aprile, Gennadiy Averkov, Marco Di Summa, and Matthias Schymura

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Main Goal: find "good" linear representations of integer points *X* in polytopes *P*

Motivation: integer programming formulations

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- integer hull: LP = IP, but possibly high number of constraints
- extended formulations: allow additional variables for description



source: Extended Formulations for Polygons, Fiorini, Rothvoß, Tiwary. Discr. & Comp. Geom. 48, 2012

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Motivation: integer programming formulations

What does "good" mean?

- integer hull: LP = IP, but possibly high number of constraints
- extended formulations: allow additional variables for description
- relaxation complexity: minimal number of linear constraints



Relaxation Complexity—Definition

Let $P \subseteq \mathbb{R}^d$ be a polytope and let

 $X = P \cap \mathbb{Z}^d$.

Any such X is called lattice-convex, because

 $\operatorname{conv}(X) \cap \mathbb{Z}^d = X.$

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Definition (Weltge 2015, Kaibel & Weltge 2015)

Any polyhedron $Q \subseteq \mathbb{R}^d$ with $X = Q \cap \mathbb{Z}^d$ is called a relaxation of X. The relaxation complexity rc(X) is the minimal number of facets of a relaxation of X.

Relaxation Complexity—Examples

0/1 cube



cross-polytope

٠	٠	٠	٠	٠	٠	٠
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 $\operatorname{rc}(X) = d + 1$

Relaxation Complexity—Examples

0/1 cube



cross-polytope



 $\operatorname{rc}(X) = d + 1$

 $\operatorname{rc}(X) = \begin{cases} 4, & \text{if } d = 2, \\ d+1, & \text{otherwise} \end{cases}$

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Relaxation Complexity—Basic Properties

Let $P \subseteq \mathbb{R}^d$ be a polytope and let $X = P \cap \mathbb{Z}^d$

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Any polyhedron $Q \subseteq \mathbb{R}^d$ with $X = Q \cap \mathbb{Z}^d$ is called a relaxation of X. The relaxation complexity rc(X) is the minimal number of facets of a relaxation of X.

- ▶ rc(X) is the minimal number of inequalities needed to separate X from $\mathbb{Z}^d \setminus X$ (within aff(X))
- more generally, for $Y \subseteq \mathbb{Z}^d$, the minimal number of inequalities needed to separate X from $Y \setminus X$ is $rc(X, Y) \Rightarrow rc(X, Y) \leq rc(X)$
- ▶ $rc_Q(X)$ and $rc_Q(X, Y)$ mean restricting to rational polyhedra $\Rightarrow rc(X) \le rc_Q(X)$
- ▶ $rc(X) \le #facets of conv(X)$

Fundamental Questions

Let $X \subseteq \mathbb{Z}^d$ be lattice-convex.

Question Are rc(X) and $rc_{0}(X)$, and corresponding minimal relaxations, computable?

Let $\Delta_d = \{0, e^1, \ldots, e^d\}.$

Question (Kaibel & Weltge 2015)

Does $rc(X) = rc_Q(X)$ hold? In particular, is $rc(\Delta_d) = rc_Q(\Delta_d)$ true?

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Outline

Basic Concepts

Computability in Dimension 2

Computable Bounds

The Role of Rationality

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Main Tool—Observers



Definition (Observers)

Let $X \subseteq \mathbb{Z}^d$ be lattice-convex. A point $y \in \mathbb{Z}^d \setminus X$ is called an observer of X, if $\operatorname{conv}(X \cup \{y\}) \cap \mathbb{Z}^d = X \cup \{y\}$, that is, $X \cup \{y\}$ is also lattice-convex. We write $\operatorname{Obs}(X) := \left\{ y \in \mathbb{Z}^d \setminus X : y \text{ is an observer of } X \right\}.$

Observers

The observers are certifying the separation of *X* from $\mathbb{Z}^d \setminus X$!

Let $X \subseteq \mathbb{Z}^d$ be lattice-convex and let $Ax \leq b$ be a system of linear inequalities. The following are equivalent:

- The system $Ax \leq b$ separates X from $\mathbb{Z}^d \setminus X$.
- The system $Ax \leq b$ separates X from Obs(X).

 \implies rc(X) = rc(X, Obs(X))



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- \implies rc(X) = rc(X, Obs(X))



Observation on Computability (Averkov & Schymura 2021)

If Obs(X) is finite (and computable), then deciding $Is rc(X) \le k$? reduces to solving a MIP with binary integer variables.

Theorem (Averkov & Schymura 2021)

Let $X \subseteq \mathbb{Z}^d$ be lattice convex and full-dimensional. If

- 1. X is parity-complete, or
- 2. conv(X) contains an interior lattice point, or
- 3. the lattice width w(X) of X satisfies $w(X) > w^{\infty}(d)$, where $w^{\infty}(d)$ is the so-called finiteness threshold width,

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Computability in Dimension 2



Observers for d = 2

◦ let $X \subseteq \mathbb{Z}^2$ be finite and lattice convex with conv(X) = { $x \in \mathbb{R}^2$: $a_i x_1 + b_i x_2 \le c_i$, $i \in [m]$ } ◦ for each $i \in [m]$, assume a_i and b_i are co-prime

Proposition (Weltge 2015)

If $X \subseteq \mathbb{Z}^2$ is full-dimensional, finite, and lattice-convex, Obs(X) are the lattice points on the boundary of

 $\{x \in \mathbb{R}^2 : a_i x_1 + b_i x_2 \le c_i + 1, i \in [m]\}.$



Finding Relaxation Complexity for d = 2

Theorem (Averkov, H., & Schymura 2021)

Let $V \subseteq \mathbb{Z}^2$ be finite and 2-dimensional, let $X = \operatorname{conv}(V) \cap \mathbb{Z}^2$, and $Y = \operatorname{Obs}(X)$. Then, 1. $\operatorname{Obs}(X)$ can be computed in $O(|V| | \operatorname{conv}(V) \cap \mathbb{Z}^2)$ time:

1. Obs(X) can be computed in $O(|V| \log |V| + |Y| + \gamma |V|)$ time;

2. rc(X) can be computed in $O(|V| \log |V| + |V||Y| \log |Y| + \gamma |V|)$ time, where γ is an upper bound on the binary encoding size of any point in *V*.



Computable Bounds

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Strategy

$\operatorname{rc}(X) \leq \operatorname{rc}_{\mathbb{Q}}(X)$

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Approach Give up strict separation of *X* from $\mathbb{Z}^d \setminus X$ for the sake of robustness.

- $X \subseteq \mathbb{Z}^d$ full-dimensional and lattice-convex
- for $\varepsilon > 0$, let $X_{\varepsilon} \coloneqq X + \mathcal{B}_{\varepsilon}^{1}$, where $\mathcal{B}_{\varepsilon}^{1} = \{0, \pm \varepsilon e_{1}, \dots, \pm \varepsilon e_{d}\}$



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Definition (*ɛ***-relaxation complexity)**

A polyhedron $Q \subseteq \mathbb{R}^d$ is an ε -relaxation of X, if $X_{\varepsilon} \subseteq Q$ and $X = int(Q) \cap \mathbb{Z}^d$. We define $rc_{\varepsilon}(X)$ as the smallest number of facets of an ε -relaxation of X.

 $\blacktriangleright \ \varepsilon \geq \varepsilon' \implies \mathsf{rc}_{\varepsilon}(X) \geq \mathsf{rc}_{\varepsilon'}(X), \text{ since } \mathsf{conv}(X_{\varepsilon'}) \subseteq \mathsf{conv}(X_{\varepsilon})$

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Theorem (Averkov, H., & Schymura 2021)

1. For any $\varepsilon > 0$, there is a computable finite set $Y^{\varepsilon} \subseteq \mathbb{Z}^{d}$ with $\operatorname{rc}_{\varepsilon}(X) = \operatorname{rc}_{\varepsilon}(X, Y^{\varepsilon})$.

- 2. If $\varepsilon > 0$ is rational, then $rc_{\varepsilon}(X)$ can be computed in finite time.
- 3. $\operatorname{rc}_{\mathbb{Q}}(X) = \operatorname{rc}_{0}(X) := \min_{\varepsilon > 0} \operatorname{rc}_{\varepsilon}(X)$

Consequences

- \rightsquigarrow finite algorithm to compute (eventually tight) upper bounds on $rc_Q(X)$
- → we just don't know when to stop

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- 3. $\operatorname{rc}_{\mathbb{Q}}(X) = \operatorname{rc}_{0}(X) := \min_{\varepsilon > 0} \operatorname{rc}_{\varepsilon}(X)$

- **2.** computing $rc_{\varepsilon}(X, Y^{\varepsilon})$ for rational $\varepsilon > 0$ is a MILP with rational data
- 3. a rational relaxation of X is bounded and can be perturbed into an ε -relaxation

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- variant of Minkowski's first theorem (van der Corput 1936):
 if *q* is too far away from *C*, the red region contains more than |X| lattice points
- every ε -relaxation of X is contained in conv(X) + $c_{d,\varepsilon,X} \cdot \mathcal{B}_d^2$, for some computable $c_{d,\varepsilon,X} > 0$



Lower Bounds

Strategy for Answering " $rc(\Delta_d) = d + 1$?"

- derive a strong lower bound $\ell(X)$ on rc(X)
- If $\ell(\Delta_d) = d + 1$, we are done.


Kaibel & Weltge 2015:

- Let $X \subseteq \mathbb{Z}^d$ be lattice-convex and $H \subseteq \operatorname{aff}(X) \cap (\mathbb{Z}^d \setminus X)$
- ▶ *H* is a hiding set if, for any distinct $x, y \in H$, we have conv $({x, y}) \cap conv(X) \neq \emptyset$
- For any hiding set H, $rc(X) \ge |H|$.



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- $\blacktriangleright G(X) = (\mathbb{Z}^d \setminus X, E)$
- $E = \{\{x, y\} \in \binom{v}{2} : x, y \text{ form hiding set}\}$
- $\operatorname{rc}(X) \geq \chi(G(X))$



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Another Lower Bound

For any $Y \subseteq \mathbb{Z}^d$, we have

 $\operatorname{rc}(X, Y) \leq \operatorname{rc}(X) \leq \operatorname{rc}_{\mathbb{Q}}(X).$

Proposition (Averkov & Schymura 2020)

If $Y \subseteq \mathbb{Z}^d \setminus X$ is finite, rc(X, Y) can be computed by solving a bounded MIP.

Does there exist $Y \subseteq \mathbb{Z}^d$ finite with rc(X, Y) = rc(X)?

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Theorem (Averkov, H., & Schymura 2021)

Let $\Delta_d = \{0, e^1, \dots, e^d\}$ and $Y \subseteq \mathbb{Z}^d$ be finite. Then,

$$\operatorname{rc}(\Delta_d, Y) \leq \left\lceil \frac{d}{2} \right\rceil + 2.$$

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Consequences for Δ_d

Let $Y \subseteq \mathbb{Z}^d$ be finite.

► $\operatorname{rc}(\Delta_d, Y) \leq \lceil \frac{d}{2} \rceil + 2$

Consider restriction G' of hiding graph to nodes in Y.

• $\chi(G') \leq \lceil \frac{d}{2} \rceil + 2$

By the de Bruijn-Erdős theorem

► $\chi(G(\Delta_d)) \leq \lceil \frac{d}{2} \rceil + 2$

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In particular,

For Δ_4 , all lower bounds are at most 4, whereas $rc(\Delta_4) = 5$.

The Role of Rationality

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TU/e

The Simplex is Rebellious

For any finite $Y \subseteq \mathbb{Z}^d$,

 $\operatorname{rc}(\Delta_5, Y) \leq \operatorname{rc}(\Delta_5) \leq \operatorname{rc}_{\mathbb{Q}}(\Delta_5) = 6,$

and

 $\mathsf{rc}(\Delta_5, Y) \leq 5.$

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Question		
Is it really true that		
	$rc(\Delta_5) < rc_{\mathbb{Q}}(\Delta_5)$?	

Our results

Theorem (Aprile, Averkov, Di Summa, H. 2022+)

1. $5 = \operatorname{rc}(\Delta_5) < \operatorname{rc}_{\mathbb{Q}}(\Delta_5) = 6.$

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$$5 = \operatorname{rc}(\Delta_5) < \operatorname{rc}_{\mathbb{Q}}(\Delta_5) = 6.$$

2. We have $\operatorname{rc}(\Delta_d) \in O\left(\frac{d}{\sqrt{\log d}}\right)$.

Crucial Tool—Mixed Relaxation Complexity

- let $X \subseteq Y \subseteq \mathbb{R}^k$
- ▶ polyhedron $P \subseteq \mathbb{R}^k$ is relaxation of *X* within *Y* if $X = P \cap Y$
- ▶ rc(X, Y): minimum number of facets of relaxation
- $Y = \mathbb{Z}^d \times \mathbb{R}^1 \rightsquigarrow$ mixed relaxation complexity

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Interpretation: the continuous coordinate as height of a lifting

- $h: X \to \mathbb{R}$, where $X \subseteq \mathbb{Z}^d$
- ▶ lift_h(X) = {(x, h(x)) : x ∈ X}
- $\blacktriangleright \operatorname{clift}_h(X) = \operatorname{conv}(\operatorname{lift}_h(X))$



Proposition

Let $P \subseteq \mathbb{R}^{k+1}$ be a full-dimensional polytope, let $T \subseteq \mathbb{Z}^k$ be finite and non-empty, and let $h: T \to \mathbb{R}$. Then, *P* is a relaxation of $\operatorname{lift}_h(T)$ within $\mathbb{Z}^k \times \mathbb{R}$ iff

- every $p \in \text{lift}_h(T)$ is contained in an upper and lower facet of *P*, and
- the projection of *P* onto the first *k* components is a relaxation of *T* within \mathbb{Z}^k .



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- ucn and lcn: minimum size of up./low. covering

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- upper/lower covering: selection of upper/lower facets covering all (x, h(x)) for $x \in X$
- ucn and lcn: minimum size of up./low. covering
- ▶ $\operatorname{rc}((\operatorname{lift}_h(T), \mathbb{Z}^k \times \mathbb{R}) \leq \operatorname{rc}(T) + \operatorname{ucn}_h(T) + \operatorname{lcn}_h(T))$

The idea in dimension 5

consider

 $\Delta = \{0, e^1, e^2, e^3, (1, 0, 1, 1, 0), (0, 1, 1, 0, 1)\} \subset \mathbb{Z}^5,$

which is unimodularly equivalent to Δ_5

- let $\ell \subset \mathbb{R}^5$ be line spanned by $(0, 0, 0, 1, \sqrt{2})$
- ► Kaibel & Weltge 2015: $conv(\Delta) + \ell$ is unbounded relaxation of Δ (#facets \geq 6)

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Observation

Let $\pi \colon \mathbb{R}^5 \to \mathbb{R}^4$ be the projection

$$\pi(x_1, x_2, x_3, x_4, x_5) = (x_1, x_2, x_3, x_4 - \frac{1}{\sqrt{2}}x_5)$$

and $P \subseteq \mathbb{R}^4$ be a polyhedron with $P \cap (\mathbb{Z}^3 \times \mathbb{R}) = \pi(\Delta)$. Then, $Q := (P \times \{0\}) + \ell$ is a relaxation of Δ .

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Let $\pi \colon \mathbb{R}^5 \to \mathbb{R}^4$ be the projection

$$\pi(x_1, x_2, x_3, x_4, x_5) = (x_1, x_2, x_3, x_4 - \frac{1}{\sqrt{2}}x_5)$$

and $P \subseteq \mathbb{R}^4$ be a polyhedron with $P \cap (\mathbb{Z}^3 \times \mathbb{R}) = \pi(\Delta)$. Then, $Q := (P \times \{0\}) + \ell$ is a relaxation of Δ .

$$\Rightarrow \mathsf{rc}(\Delta, \mathbb{Z}^5) \leq \mathsf{rc}(\pi(\Delta), \mathbb{Z}^3 imes \mathbb{R})$$

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TU/e

A (3,1)-mixed relaxation

 $\mathsf{rc}(\Delta, \mathbb{Z}^5) \leq \mathsf{rc}(\pi(\Delta), \mathbb{Z}^3 \times \mathbb{R}) \rightsquigarrow it is sufficient to find mixed relaxation with 5 facets$

A (3,1)-mixed relaxation

 $\operatorname{rc}(\Delta, \mathbb{Z}^5) \leq \operatorname{rc}(\pi(\Delta), \mathbb{Z}^3 \times \mathbb{R}) \rightsquigarrow$ it is sufficient to find mixed relaxation with 5 facets A (3,1)-mixed relaxation of $\pi(\Delta)$ is given by the following inequalities with $\varepsilon = \frac{1}{8}$:

$$\begin{aligned} x_1 \geq x_4 \\ x_3 \geq x_4 \\ \varepsilon x_1 + x_2 + \frac{1-\varepsilon}{1+\sqrt{2}}x_3 + \frac{(1-\varepsilon)\sqrt{2}}{1+\sqrt{2}}x_4 \leq 1, \\ x_3 + \sqrt{2}x_4 \geq 0, \\ x_1 - (1+\varepsilon)x_2 + x_2 - x_4 \leq 1. \end{aligned}$$

Proof of $rc(\Delta_5) = 5$:

 $\mathsf{rc}(\Delta_5) = \mathsf{rc}(\Delta) \le \mathsf{rc}(\pi(\Delta), \mathbb{Z}^3 imes \mathbb{R})$

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Sublinear bound on relaxation complexity

- project (unimodular transformation of) Δ_5 onto \mathbb{R}^4
- find (3,1)-mixed relaxation of $\pi(\Delta_5)$



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We can interpret the continuous coordinate as a lifting from a 3-dimensional space!

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Summary of proof in dimension 5

- project (unimodular transformation of) Δ_5 onto \mathbb{R}^4
- find (3,1)-mixed relaxation of $\pi(\Delta_5)$

We can interpret the continuous coordinate as a lifting from a 3-dimensional space!



The proof idea

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Make calculations easier

▶ assume $d = 2^k - 1$.

Aim: find relaxation complexity of

$$\Delta_d = \left(\begin{array}{cccccccccc} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{array}\right)$$

Make calculations easier

▶ assume $d = 2^k - 1$.

Aim: find relaxation complexity of unimodularly equivalent

$$\Delta_d' = \begin{pmatrix} 0 & 1 & 0 & 0 & | & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & | & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & | & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Step 1: projection

▶ project $\Delta'_{k+(d-k)}$ on the first *k* coordinates via π :

$$\begin{pmatrix} 0 & 1 & 0 & 0 & | & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & | & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ \hline 0 & 0 & 0 & 0 & | & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \end{pmatrix} \mapsto \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 \\ \end{pmatrix}$$

• the projection yields $\{0, 1\}^k$

Step 2: lift and estimate

Lemma

Let $Y \subseteq \mathbb{Z}^k \setminus \Delta_k$ with $|Y| = \ell$. Let $h: \Delta_k \cup Y \to \mathbb{R}$ be a "suitable lifting function". Then,

 $\operatorname{\mathsf{rc}}(\Delta_{k+\ell}) \leq \operatorname{\mathsf{rc}}(\operatorname{lift}_h(\Delta_k \cup Y), \mathbb{Z}^k \times \mathbb{R}).$

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Consequently,

 $\mathsf{rc}(\Delta'_d) \leq \mathsf{rc}(\mathrm{lift}_h(\{0,1\}^k), \mathbb{Z}^k imes \mathbb{R})$

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Consequently,

 $\mathsf{rc}(\Delta_d') \leq \mathsf{rc}(\mathsf{lift}_\hbar(\{0,1\}^k), \mathbb{Z}^k \times \mathbb{R}) \leq \mathsf{rc}(\{0,1\}^k) + \mathrm{ucn}_\hbar(\{0,1\}^k) + \mathrm{lcn}_\hbar(\{0,1\}^k)$



Putting the pieces together

For a "suitable lifting" h:

 $\begin{aligned} \operatorname{rc}(\Delta_d) &= \operatorname{rc}(\Delta_{k+\ell}) \leq \operatorname{rc}(\{0,1\}^k) + \operatorname{ucn}_h(\{0,1\}^k) + \operatorname{lcn}_h(\{0,1\}^k) \\ &= (k+1) + O\Big(\frac{2^k}{\sqrt{k}}\Big) \\ &= O\Big(\frac{d}{\sqrt{\log(d)}}\Big) \end{aligned}$



Question

Are rc(X) and $rc_Q(X)$, and corresponding minimal relaxations, computable?

- ▶ yes, if *d* = 2
- ▶ yes, if there exists a finite $Y \subseteq \mathbb{Z}^d$ such that $rc(X, Y) = rc_Q(X)$

Question (Kaibel & Weltge 2015)

Does $rc(X) = rc_Q(X)$ hold? In particular, is $rc(\Delta_d) = rc_Q(\Delta_d)$ true?

• no, for every $d \ge 5$

Open questions

Computability Is rc(X) computable?

 \circ Averkov & Schymura 2020: yes, if $d \leq 3$ or X has special structure

Complexity How difficult is it to compute rc(X) if d = 3?

Finite Certificate Which *X* admit a finite $Y \subseteq \mathbb{Z}^d \setminus X$ with rc(X, Y) = rc(X)?



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Thank you for your attention!

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