# On a concept of a generic intersection cut callback 

## Liding Xu

OptimiX, LIX, École Polytechnique
November 4, 2022

## Table of Contents

# Introduction to Intersection Cuts 

Examples<br>Lattice<br>Nonlinear functions<br>Polynomials<br>Signomials

Generic Intersection Cut Callback

Discussions

## Intersection cuts

The goal of intersection cuts: convexify hard non-convex sets.

- Given a complex set $\mathcal{S}$, we want to tighten a polyhedral outer approximation $\mathcal{P}$ of $\mathcal{S}$;
- The polyhedral outer approximation (an LP relaxation) should be constructed a priori.
- Useful for LP-based solvers.


## History and recent development

History:

- Concave programs (Hoang 1964): $\mathcal{S}$ is the epigraph of a concave function;
- Integer programs (Balas 1971): $\mathcal{S}$ is a lattice:
- Linear complementary programs (Ibaraki 1973): $\mathcal{S}$ is a complementary condition $x_{i} x_{j}=0$.


## History and recent development

Recent development (in non-convex MINLPs):

- Bilevel programs (Fischetti 2018);
- Factorable Programs (Serrano 2019): $\mathcal{S}$ is a sublevel set of a difference of concave functions;


## History and recent development

Recent development (in non-convex MINLPs):

- Bilevel programs (Fischetti 2018);
- Factorable Programs (Serrano 2019): $\mathcal{S}$ is a sublevel set of a difference of concave functions;
- Extended formulation of quadratic/polynomial programs (Bienstock 2020): $\mathcal{S}$ is an outer product set (set of rank-1 matrices):
- Projected formulation of quadratic programs (Muñoz 2022): $\mathcal{S}$ is a sublevel set of a quadratic function (quadratic constraint).


## Cut construction methods: phase 1

Preparation phase:

- Assumption: a point $z^{\prime} \notin \mathcal{S}$, and a corner polyhedron (simplicial cone) $\mathcal{R}$ pointed at $z^{\prime}$.


## Cut construction methods: phase 1

Preparation phase:

- Assumption: a point $z^{\prime} \notin \mathcal{S}$, and a corner polyhedron (simplicial cone) $\mathcal{R}$ pointed at $z^{\prime}$.
- How to obtain?
- optimizing a relaxation problem over the polyhedral outer approximation $\mathcal{P}$.
- $z^{\prime}$ is the optimal solution at a vertex of $\mathcal{P}$.
- find edges of $\mathcal{P}$ adjacent to $z^{\prime}$, these edges' convex hull is $\mathcal{R}$.


## Visualization of preparation phase



Nonconvex S is enclosed by red border.
Polyheral outer approximation P is the outer polytope.

## Cut construction methods: phase 2

Set construction phase:
Definition
Given $\mathcal{S} \in \mathbb{R}^{p}$, a closed set $\mathcal{C}$ is called $\mathcal{S}$-free, if the following conditions are satisfied:

1. $\mathcal{C}$ is convex;
2. inter $(\mathcal{C}) \cap \mathcal{S}=\emptyset$.

Find an $\mathcal{S}$-free set $\mathcal{C}$ containing $z^{\prime}$.

## Visualization of set construction phase


$E$ is the relaxation point,
C is the circle containing it.

## Cut construction methods: phase 3

Separation phase:

- Intersect the corner polyhedron $\mathcal{R}$ with the set $\mathcal{C}$.
- Intersection points support a separating hyperplane (an intersection cut).


## Visualization of separation phase



## Separation problem reduction

- Phase 1 and 3 are standard procedures.
- The only non-standard (non-trivial) procedure is Phase 2.


## Separation problem reduction

- Phase 1 and 3 are standard procedures.
- The only non-standard (non-trivial) procedure is Phase 2.
- Larger $\mathcal{S}$-fee set gives rise to stronger cuts, so maximal $\mathcal{S}$-free set is good.
- We next review methods to construct $\mathcal{S}$-free sets in Phase 2 .


## Lattice sets

- Integer Programming: $\mathcal{S}$ is a lattice (the set of integer points).
- Maximal lattice-free sets in $\mathbb{R}^{2}$ :
- Splits;
- Triangles;
- Quadrilaterals;
- Gomory's Mixed Integer Cuts are split intersection cuts.


## Visualization of lattice-free sets



## Sublevel set of difference of concave (convex) forms

Theorem (Khamisov 1999,Serrano 2019)
Assume $\mathcal{S}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}(z) \leq 0\right\}$, where $f_{1}, f_{2}$ are concave functions. Then, for $z^{\prime} \in \operatorname{dom}\left(f_{2}\right)$,
$\mathcal{C}_{z^{\prime}}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}\left(z^{\prime}\right)-\nabla f_{2}\left(z^{\prime}\right)^{\top}\left(z-z^{\prime}\right) \geq 0\right\}$ is a $\mathcal{S}$-free set.

## Sublevel set of difference of concave (convex) forms

Theorem (Khamisov 1999,Serrano 2019)
Assume $\mathcal{S}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}(z) \leq 0\right\}$, where $f_{1}, f_{2}$ are concave functions. Then, for $z^{\prime} \in \operatorname{dom}\left(f_{2}\right)$,
$\mathcal{C}_{z^{\prime}}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}\left(z^{\prime}\right)-\nabla f_{2}\left(z^{\prime}\right)^{\top}\left(z-z^{\prime}\right) \geq 0\right\}$ is a $\mathcal{S}$-free set.

Theorem (Serrano 2021)
Assume $\mathcal{S}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}(z) \leq 0\right\}$, where $f_{1}, f_{2}$ are concave functions and positive-homogeneous of degree-1. Then, for
$z^{\prime} \in \operatorname{dom}\left(f_{2}\right)$,
$\mathcal{C}_{z^{\prime}}:=\left\{z \in \mathbb{R}^{p}: f_{1}(z)-f_{2}\left(z^{\prime}\right)-\nabla f_{2}\left(z^{\prime}\right)^{\top}\left(z-z^{\prime}\right) \geq 0\right\}$ is a maximal $\mathcal{S}$-free set.
Remark: for some case, positive-homogeneity of one concave function can be relaxed.

## Visualization of a sublevel-free set



## Polynomial/signomial programming

$$
\begin{align*}
\max & \sum_{k \in \mathcal{K}_{0}} a_{i k} \prod_{j \in[n]} x_{j}^{\alpha_{k j}}  \tag{1a}\\
\forall i \in[m] & \sum_{k \in \mathcal{K}_{i}} a_{i k} \prod_{j \in[n]} x_{j}^{\alpha_{k j}} \leq 0 \tag{1b}
\end{align*}
$$

where $\mathcal{K}$ is the index set for the whole monomial terms
$\left\{\prod_{j \in[n]} x_{j}^{\alpha_{k j}}\right\}_{k \in \mathcal{K}}, \mathcal{K}_{0}$ and $\mathcal{K}_{i}$ are its subsets.

- Polynomial programming: $\alpha_{k j} \in \mathbb{Z}_{+}$(nonegative integer);
- Signomial programming: $\alpha_{k j} \in \mathbb{R}$ (real);


## Examples: extended formulation of polynomial programming

Dense lifting: a polynomial program can be lifted to an LP + rank-1 condition on a matrix $X$ (Bienstock 2020).

- $X_{i j}$ represents a product of two monomial terms.
- Theorem: if $X$ is rank one, then the determinants of its 2-by-2 minors are zeros;
- Example of a principle minor: $X_{i i} X_{j j}-X_{i j}^{2}=0$.


## Examples: extended formulation of polynomial programming

Dense lifting: a polynomial program can be lifted to an LP + rank-1 condition on a matrix $X$ (Bienstock 2020).

- $X_{i j}$ represents a product of two monomial terms.
- Theorem: if $X$ is rank one, then the determinants of its 2 -by- 2 minors are zeros;
- Example of a principle minor: $X_{i i} X_{j j}-X_{i j}^{2}=0$.
- Reformulation: $\left(X_{i i}+X_{j j}\right)^{2}-\left(X_{i i}-X_{j j}\right)^{2}=4 X_{i j}^{2}$;
- DCC equivalence: $\left(X_{i i}+X_{j j}\right)^{2}-\left(X_{i i}-X_{j j}\right)^{2}-4 X_{i j}^{2} \leq 0$ and $\left(X_{i i}+X_{j j}\right)^{2}-\left(X_{i i}-X_{j j}\right)^{2}-4 X_{i j}^{2} \geq 0$;


## Examples: extended formulation of signomial programming

Sparse lifting: a signomial program can be lifted to an LP + condition $y=x^{\alpha}$ (our working paper).

- Signomial-term-set $\mathcal{S}=\left\{(x, y) \in \mathbb{R}_{+}^{n} \times \mathbb{R}_{+}: y \leq x^{\alpha}\right\}$, where $\alpha$ is an exponent vector with negative and/or positive entries;


## Examples: extended formulation of signomial programming

Sparse lifting: a signomial program can be lifted to an LP + condition $y=x^{\alpha}$ (our working paper).

- Signomial-term-set $\mathcal{S}=\left\{(x, y) \in \mathbb{R}_{+}^{n} \times \mathbb{R}_{+}: y \leq x^{\alpha}\right\}$, where $\alpha$ is an exponent vector with negative and/or positive entries;
- After some transformation,

$$
\begin{aligned}
& \mathcal{S}=\left\{(u, v) \in \mathbb{R}_{+}^{h} \times \mathbb{R}_{+}^{\prime}: u^{\beta}-v^{\gamma} \leq 0\right\}, \text { where } \\
& \max \left(\|\beta\|_{1},\|\gamma\|_{1}\right)=1 \text { and } \beta, \gamma \geq 0 .
\end{aligned}
$$

## Examples: extended formulation of signomial programming

Sparse lifting: a signomial program can be lifted to an LP + condition $y=x^{\alpha}$ (our working paper).

- Signomial-term-set $\mathcal{S}=\left\{(x, y) \in \mathbb{R}_{+}^{n} \times \mathbb{R}_{+}: y \leq x^{\alpha}\right\}$, where $\alpha$ is an exponent vector with negative and/or positive entries;
- After some transformation, $\mathcal{S}=\left\{(u, v) \in \mathbb{R}_{+}^{h} \times \mathbb{R}_{+}^{\prime}: u^{\beta}-v^{\gamma} \leq 0\right\}$, where $\max \left(\|\beta\|_{1},\|\gamma\|_{1}\right)=1$ and $\beta, \gamma \geq 0$.
- Intersection cuts: $u^{\beta}, v^{\gamma}$ are power functions (whose hypograph are power cone representable) and concave, $\mathcal{S}$ now is in the difference of concave form;


## Examples: extended formulation of signomial programming

- Factorable programming: $u^{\beta}$ is concave, so it under-estimators can be constructed by factorization. For instance, $u_{1}^{0.5} u_{2}^{0.3} u_{3}^{0.2} \leq t$ is reverse convex.
- (conventional) multilinear factorization:
$u_{1}^{0.5} \leq t_{1}, u_{2}^{0.3} \leq t_{2}, u_{3}^{0.2} \leq t_{3}, t_{1} t_{2} t_{3} \leq t$.
- (new) power factorization: $u_{2}^{0.6} u_{3}^{0.4} \leq t_{1}, u_{1}^{0.5} t_{1}^{0.5} \leq t$. We can give convex envelopes of $u_{2}^{0.6} u_{3}^{0.4}, u_{1}^{0.5} t_{1}^{0.5}$.


## Supporting intersection cuts

- In the future, we will find more families of $\mathcal{S}$-free sets.
- Users want to quickly know the performance of cuts from their $\mathcal{S}$-free sets in a real solver, rather than manually constructing polyhedral outer approximation.
- A callback-based solution.


## Pipeline of intersection cuts

- Phase 1 deals with simplex tableau and construct corner polyhedron (standard).
- Phase 3 finds intersection points (standard).
- Non-standard: phase 2, defining an $\mathcal{S}$-free set.


## Defining $\mathcal{S}$-free set

An $\mathcal{S}$-free set is $\mathcal{C}:=\{z \in \mathcal{D}: g(z) \geq 0\}, \mathcal{D}$ is a domain, and $g\left(z^{\prime}\right) \geq 0$.

- $g$ is concave over $\mathcal{D}$.
- A sublevel-free set $\mathcal{C}:=\{z \in \mathcal{D}: g(z) \geq 0\}$.
- Arbitrary set $\mathcal{C}$ (like lattice-free): $g(z)= \begin{cases}1, & z \in \mathcal{D} \cap \mathcal{C} \\ -\infty, & \text { otherwise }\end{cases}$ is an indicator function.
Interface: the user needs to register the defining-variables of $\mathcal{C}$ and domain $\mathcal{D}$.


## Oracle access and separation

Defining $\mathcal{C}$ is equivalent to defining 0th-order (function value) access to $g(z)$, optional: 1th-order (gradient value) oracle access to $g(z)$.

- The separation problem: find intersection point of ray $z^{\prime}+t r$ $(t \geq 0)$ with $\mathcal{C}$, where $r$ is an extreme ray of the corner polyhedron $\mathcal{R}$;
- Equivalently, find root of the 1d function $g\left(z^{\prime}+t r\right)$;


## Oracle access and separation

Defining $\mathcal{C}$ is equivalent to defining 0th-order (function value) access to $g(z)$, optional: 1th-order (gradient value) oracle access to $g(z)$.

- The separation problem: find intersection point of ray $z^{\prime}+t r$ $(t \geq 0)$ with $\mathcal{C}$, where $r$ is an extreme ray of the corner polyhedron $\mathcal{R}$;
- Equivalently, find root of the 1d function $g\left(z^{\prime}+t r\right)$;
- Bisection root finding: 0th-order oracle access.
- Newton root finding: Oth-order and 1th-order oracle access. Interface: user provides 0th-order and 1th-order oracle access.


## Root finding



## Abstract functions of the callback

Setting:

- BisectionOrNewtion: TRUE or FALSE.

Minimal interface functions

- Register(): register variables and domain for an S-free set.
- ZeroOrderOracle(): Oth-order access.
- FirstOrderOracle(): 1st-order access.

The callback automatically extracts corner polyhedron, finds roots, and checks numerical stability.

## Limitations

Intersection cuts can be dense and thus numerically dangerous.

## Strengthenning methods

We can at best approximate $\operatorname{conv}\left(\mathcal{C}^{c} \cap \mathcal{R}\right)$, and $\mathcal{R}$ is a loose relaxation of $\mathcal{P}$. Balas's original (generalized) intersection cuts definition: $\mathcal{R}$ is $\mathcal{P}$.

- Consider variables' bounds: Chielma 2022.
- Consider bounded simplex paths from a relaxation point, more edges of $\mathcal{P}$ are considered: Balas 2022.


## Comparing lift-and-project

When $\mathcal{C}$ is a polyhedron,

- Intersection cuts for $\left(\operatorname{conv}\left(\mathcal{C}^{c} \cap \mathcal{R}\right)\right)$ is weaker than lift-project cuts $\left(\operatorname{conv}\left(\mathcal{C}^{c} \cap \mathcal{P}\right)\right)$.
- Assume $\mathcal{P}=\mathcal{R}$, intersection cuts are then equivalent to lift-and-project cuts
When $\mathcal{C}$ is not polyhedron
- Only Intersection cuts works.

