

Time-Varying LPs and SDPs

Joint work with Amirali Ahmadi

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Princeton University

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Outline

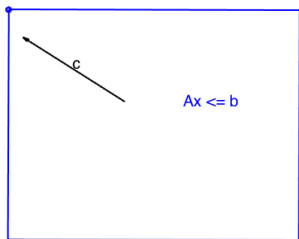
- 1 Introduction
- 2 Motivation for Polynomial Solutions
- 3 Geometry of a TV-LP
- 4 Continuous Solutions and Polynomials
- 5 TV-SDPs

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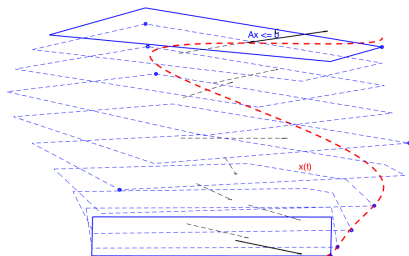
TV-LP

$$\begin{array}{ll} \underset{x}{\text{maximize}} & \langle c, x \rangle \\ \text{subject to} & Ax \leq b \end{array} \quad (\text{LP})$$

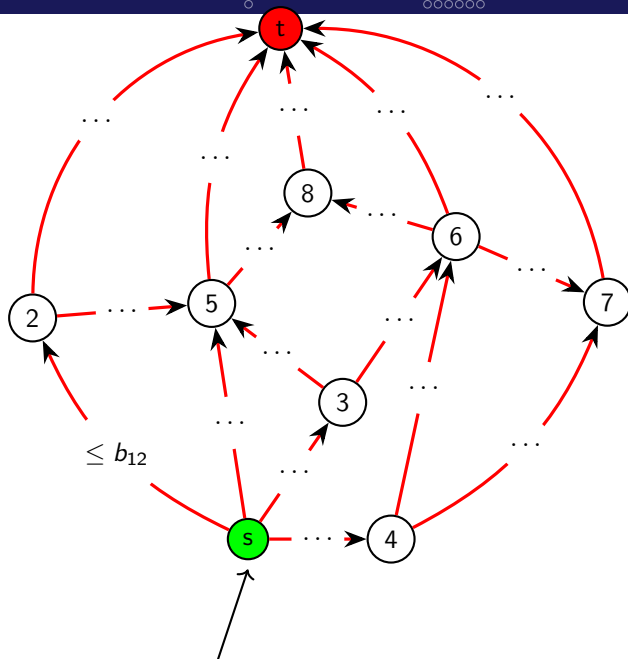


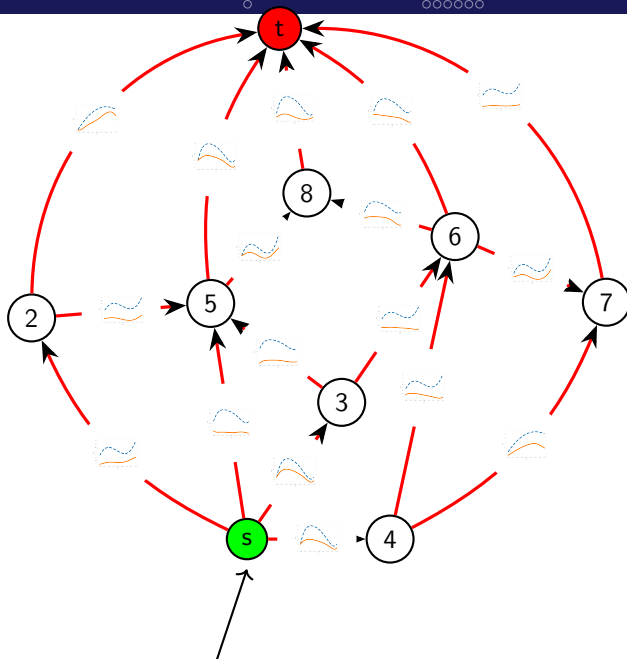
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$$\begin{aligned}
 & \underset{x(t)}{\text{maximize}} && \int_{-1}^1 \langle c(t), x(t) \rangle dt \\
 & \text{subject to} && A(t)x(t) \leq b(t) \quad \forall t \in [-1, 1]
 \end{aligned}
 \tag{TV-LP}$$



- A, b, c polynomials.
- Polynomials are general enough.





Contributions

- Study existence and optimality of polynomial solutions.
- Find the best polynomial solution of a given degree to a TV-LP / TV-SDP using a (non time-varying) SDP.

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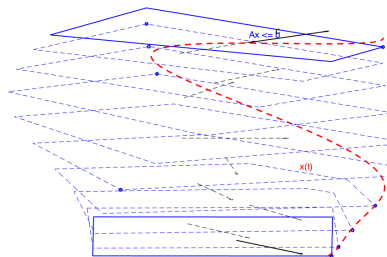
Are polynomials optimal to a TV-LP or TV-SDP?

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Are polynomials optimal to a TV-LP or TV-SDP?

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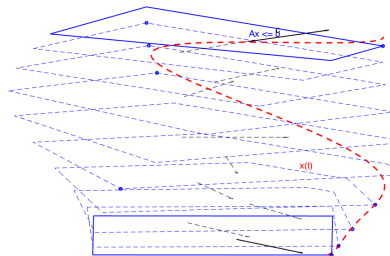
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- **Generally no!**

Near Optimality

$\forall \varepsilon > 0, \exists x(t) \in \mathbb{R}^n[t]$ such that:

- $A(t)x(t) \leq b(t)$
- $opt - \int_{-1}^1 \langle c(t), x(t) \rangle dt \leq \varepsilon.$



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We are interested in continuous solutions

Problems in practice:

- Deciding the transmission power of a cell tower during the day.
- Choosing the optimal control of a robotic arm.
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We want smooth solutions!

Positivstellensatz for TV-LPs (Polya-Szego, 1976)

Every nonnegative univariate polynomial $p(t)$ on $[-1, 1]$ can be written as

$$p = \sigma_0 + (1 - t)\sigma_1 + (1 + t)\sigma_2 + (1 - t^2)\sigma_3,$$

where $\sigma_i \in \text{SOS}$, $i = 0, \dots, 3$, with degree bounded by $\deg(p)$.

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In our case

- Constraint $A_i(t)x(t) \leq b_i(t) \quad \forall t \in [-1, 1]$

- Becomes

$$b_i(t) - A_i(t)x(t) = \sigma_0(t) + (1 - t)\sigma_1(t) + (1 + t)\sigma_2(t) + (1 - t^2)\sigma_3(t)$$

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That's a (non time-varying) SDP

$$\sigma(t) \in \text{SOS} \iff \exists Q \succeq 0, \sigma(t) = \begin{pmatrix} 1 \\ t \\ \vdots \\ t^{\frac{n}{2}} \end{pmatrix}^T Q \begin{pmatrix} 1 \\ t \\ \vdots \\ t^{\frac{n}{2}} \end{pmatrix}$$

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Geometry of a TV-LP

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Assumptions

The feasible set \mathcal{P}_t at time $t \in [-1, 1]$ is:

- nonempty
- bounded.

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Theorem (Geometry of the Feasible Set)

• *There exist:*

- N break points $-1 = t_1 < \dots < t_N = 1$,
- $N - 1$ finite sets of rational functions $\mathcal{V}_1, \dots, \mathcal{V}_{N-1} \subset \mathbb{R}^n(t)$,

such that:

$$\mathcal{P}_t = \text{conv}\{v(t), v \in \mathcal{V}_i\}$$

for every $i \in [N - 1], t \in (t_i, t_{i+1})$.

- *Every $v \in \mathcal{V}_i$ has the form $v(t) = A_{B_v}(t)^{-1} b_{B_v}(t)$.*

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Continuous Solutions: What could go wrong?

Good news

Continuous Feasibility \implies Continuous Optimality.

Continuous Solutions: What could go wrong?

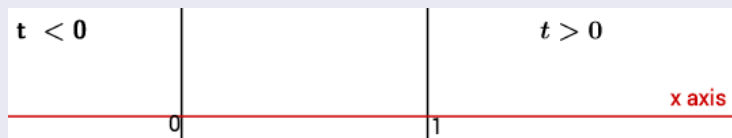
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Example (What could go wrong?)

A “discontinuous” TV-LP $\mathcal{P}_t := \{x \in \mathbb{R}, tx \geq 0, t(x-1) \geq 0\}$.

- $\mathcal{P}_t = [1, \infty)$ when $t > 0$.
- $\mathcal{P}_t = (-\infty, 0]$ when $t < 0$. No continuous solution!

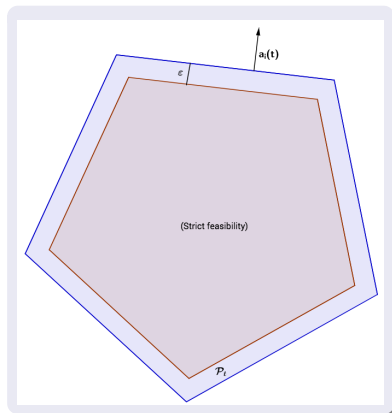


Strict Feasibility

Definition (Strict Feasibility)

A TV-LP is *strictly feasible* if there exists a (not necessarily continuous) function $x^s : [-1, 1] \rightarrow \mathbb{R}^n$ and a scalar $\varepsilon > 0$ such that

$$A(t)x^s(t) \leq b(t) - \varepsilon \mathbf{1}, \quad \forall t \in [-1, 1].$$



Theorem (Strict feasibility \implies Continuous solutions)

If a TV-LP is strictly feasible, then it has a continuous near optimal solution. Furthermore, the continuous solution can be chosen to be strictly feasible.

Polynomials: What could go wrong?

Optimality of continuous functions \implies Optimality of polynomials?

Example (No! A “Tight” TV-LP)

- $(1 + t^2)x(t) = 1$
- Only one solution $x(t) = \frac{1}{1+t^2}$. Not polynomial.

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Definition (Continuous Full-Dimensionality)

TV-LP is *continuously full-dimensional* if there exists a **constant** $\delta > 0$ and a **continuous** function $x^c : [-1, 1] \rightarrow \mathbb{R}^n$ such that $B(x^c(t), \delta) \subset \mathcal{P}_t, \forall t \in [-1, 1]$.

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Full-Dimensionality \implies Optimality of Polynomials

- Approximate $x^c(t)$ by a polynomial.

Strict Feasibility vs Continuous Full-dimensionality

- **Strict Feasibility** provides slackness in the space of the constraints.
- **Continuous full-dimensionality** provides slackness in the space of the variables.

Full-dimensionality \implies Strict feasibility?

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$t^2x \geq 0$ is continuously full-dimensional but **not** strictly feasible.

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Theorem (Strict feasibility \implies Optimality of Polynomial Solutions)

Strict feasibility \implies Full dimensionality \implies Optimality of Polynomial Solutions.

Application: MinCut

Maxflow (Primal)

$$\begin{aligned} \max_{f_{ij}} \sum_{j \sim 1} f_{1j} \\ \sum_{j \sim i} f_{ij} - f_{ji} &= 0, \quad i \in V \\ 0 \leq f_{ij} &\leq b_{ij}, \quad i \sim j \end{aligned}$$

► Live simulation.

Mincut (Dual)

$$\begin{aligned} \min_{d_{ij}, p_i} \sum_{i \sim j} b_{ij} d_{ij} \\ d_{ij} - p_i + p_j &\geq 0, \quad i \sim j \\ p_1 - p_n &\geq 1 \\ p_i &\geq 0, \quad i \in V \\ d_{ij} &\geq 0, \quad i \sim j \end{aligned}$$

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$$\begin{aligned} \max_{f_{ij}} & \int_{-1}^1 \sum_{j \sim i} f_{ij}(t) dt \\ \sum_{j \sim i} f_{ij}(t) - f_{ji}(t) &= 0, \quad i \in V \\ 0 \leq f_{ij}(t) &\leq b_{ij}(t), \quad i \sim j \end{aligned}$$

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Simulation

- Mincut is strictly feasible.
- Find best polynomial solution to both of degree 9.
- $85.42 \leq \text{opt} \leq 85.52$.

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TV-SDPs

$$\begin{array}{ll}
 \underset{X}{\text{maximize}} & \langle C, X \rangle \\
 \text{subject to} & \langle A_i, X \rangle \leq b_i \quad \forall i \in [m], \\
 & X \succeq 0
 \end{array} \quad (\text{TV-SDP})$$

- Generalisation of TV-LPs where we allow psd constraints

$$X \succeq 0.$$

TV-SDPs

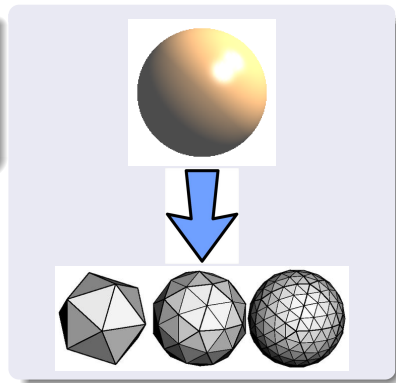
$$\begin{aligned}
 & \underset{X(t)}{\text{maximize}} && \int_{-1}^1 \langle C(t), X(t) \rangle dt \\
 & \text{subject to} && \langle A_i(t), X(t) \rangle \leq b_i(t) \quad \forall i \in [m], \forall t \in [-1, 1] \\
 & && X(t) \succeq 0 \quad \forall t \in [-1, 1]
 \end{aligned} \tag{TV-SDP}$$

- Generalisation of TV-LPs where we allow psd constraints

$$X(t) \succeq 0 \quad \forall t \in [-1, 1].$$

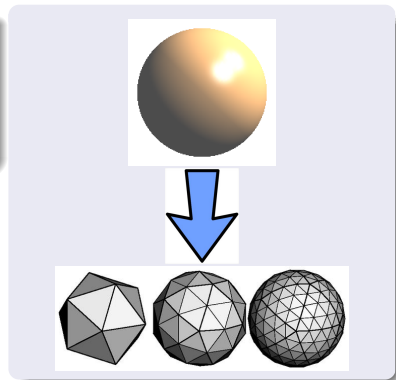
Approximating a spectrahedron by a polyhedron

- $N(\varepsilon)$ a ε -covering of $\{X \succeq 0, \|X\| = 1\}$.
- Replace $X(t) \succeq 0$ by $\sum_{Y \in N(\varepsilon)} \underbrace{\alpha_Y(t)}_{\geq 0} Y$.

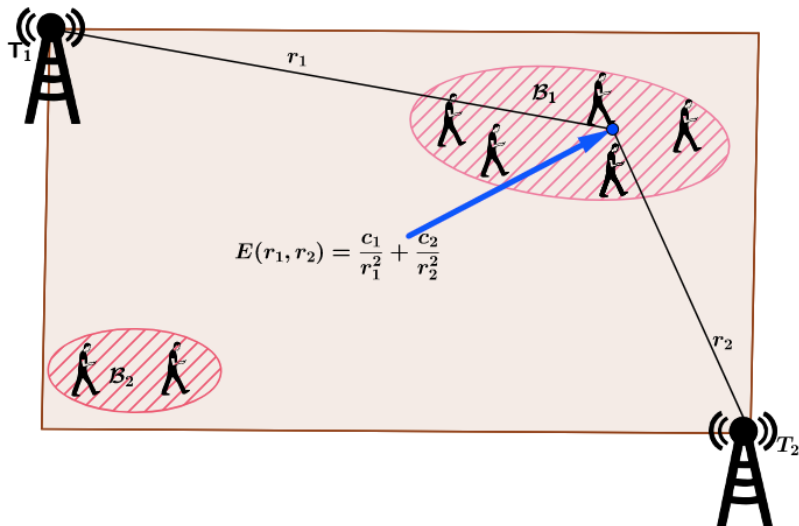


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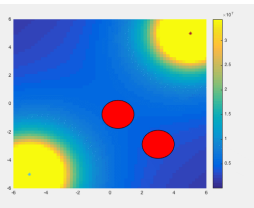
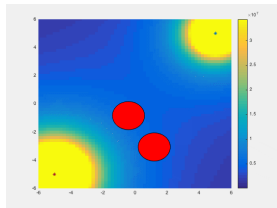
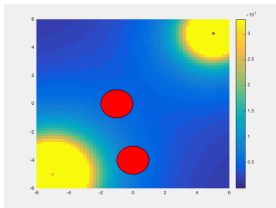
If a TV-SDP is strictly feasible, then polynomials are near optimal.



$$r_i^2 = (x - \bar{x}_i)^2 + (y - \bar{y}_i)^2, i = 1, 2$$

Results

d	$c_1(t)$	$c_2(t)$	$\int_{-1}^1 (c_1(t) + c_2(t)) dt$
0	31.96	21.63	107.19
1	$28.97 + 4.07t$	$24.23 - 3.7t$	106.38
2	$26.67 + 6.1t + 0.47t^2$	$25.78 - 5.82t + 0.44t^2$	105.49
7	$26.21 + 7.49t + 0.43t^2$ $- 3.27t^3 + 2.95t^4 - 0.15t^5$ $- 0.63t^6$	$26.18 + 7.16t + 0.81t^2$ $3.02t^3 - 3.38t^4 + 0.44t^5$ $0.63t^6$	105.42



Conclusion and Future Work

- Algorithms to optimize over polynomial solutions to TV-LPs / TV-SDPs using SOS optimization.
- Sufficient conditions under which polynomial solutions are optimal.

Possible improvements

- Strict feasibility excludes equality constraints.
- Except for TV-LPs, SOS optimization scales poorly. What about SOCP? QCQP?
- Add new dimension.