

Moments and convex optimization for analysis and control of nonlinear partial differential equations

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Problem setting – analysis

$$\begin{aligned} F(x, y(x), \mathcal{D}y(x)) &= 0 & \text{for } x \in \Omega^\circ \\ G(x, y(x), \mathcal{D}y(x)) &= 0 & \text{for } x \in \partial\Omega, \end{aligned}$$

$\Omega \subset \mathbb{R}^n$ compact

$y : \mathbb{R}^n \rightarrow \mathbb{R}^k$

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Example: $L(x, y, z) = y^2, L_{\partial}(x, y, z) \Rightarrow J(y(\cdot)) = \int_{\Omega} y(x)^2 dx$

Problem setting – analysis

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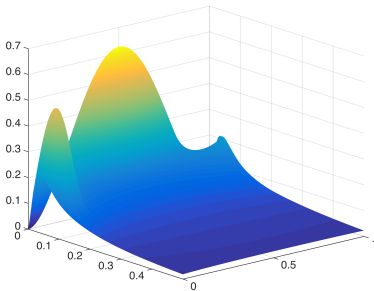
Goal: establish bounds on

inf / sup $J(y)$
subject to y solves the PDE

Infinite dimensional linear programming

$$\begin{aligned} \min_{\mu} \langle g, \mu \rangle \\ \mathcal{A}\mu = b \\ \mu \in \mathcal{M}^+ \end{aligned}$$

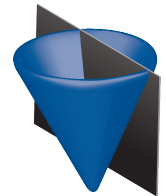
Infinite-dimensional LP



$\inf_{y} / \sup_{y} \quad J(y)$
 subject to y solves the PDE



$$\begin{aligned} \min_{y} \langle g_N, y \rangle \\ \mathcal{A}_N y = b_N \\ y \in \mathcal{M}_N^+ \end{aligned}$$

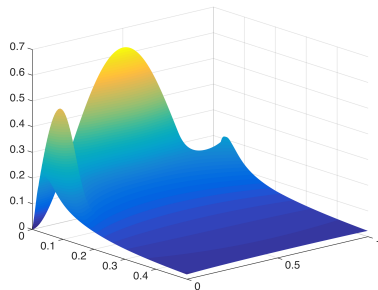


Convex semidefinite program

Infinite dimensional linear programming

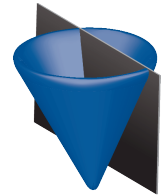
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Convex semidefinite program

Long history: Global optimization (Lasserre, Parrilo, Nesterov,...)

Stability of ODEs (Rantzer, Vaydia,...)

Optimal control of ODEs (Young, Vinter, Lasserre, Henrion, Gaitsgory,...)

⋮

Occupation and boundary measures

Occupation and boundary measures

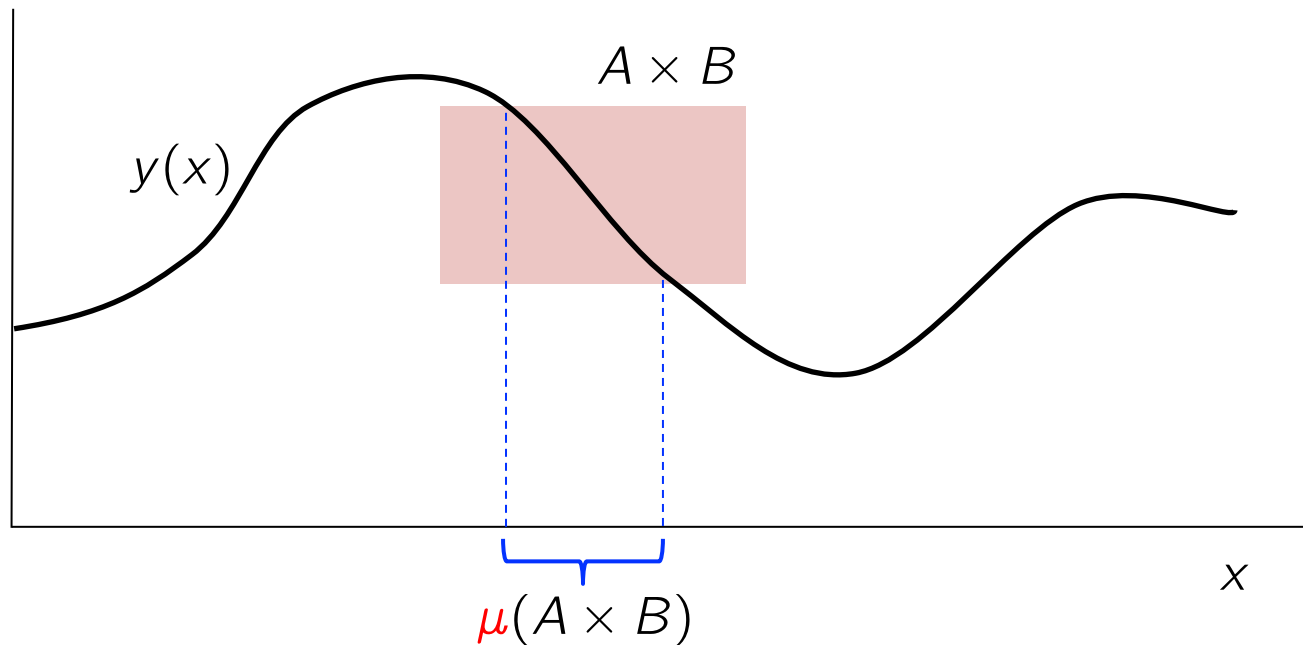
Occupation measure

$$\mu(A \times B \times C) = \int_{\Omega} \mathbb{I}_{A \times B \times C}(x, y(x), \mathcal{D}y(x)) dx$$

Occupation and boundary measures

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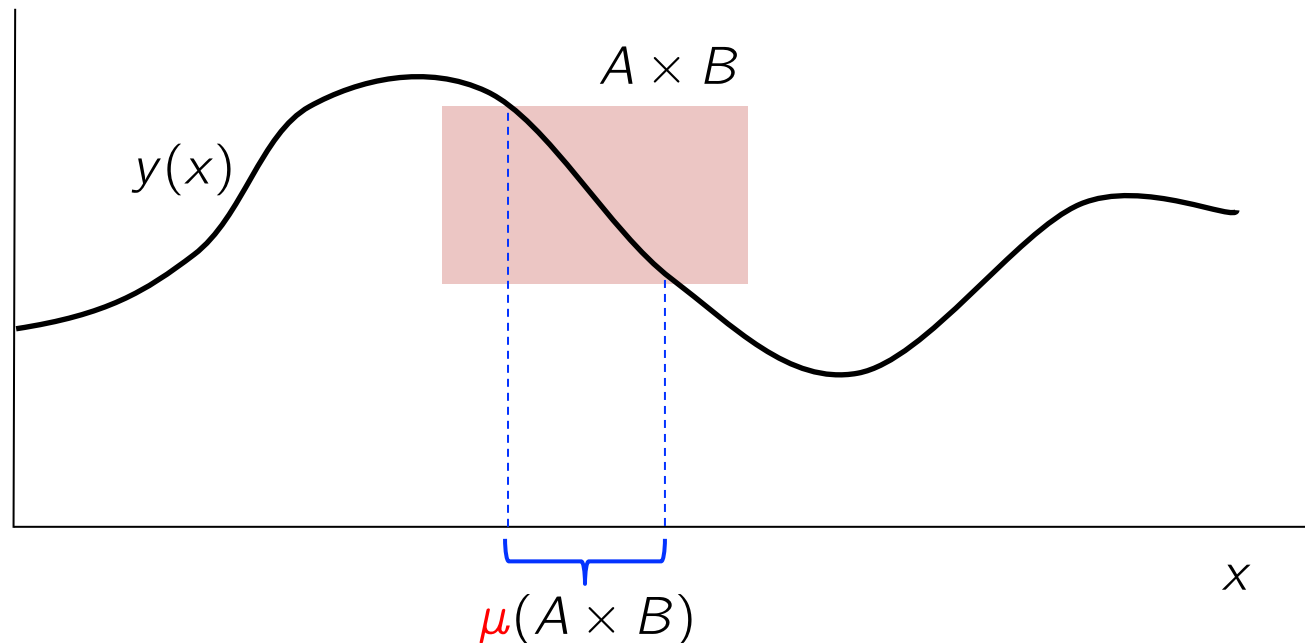
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Boundary measure

$$\mu_{\partial\Omega}(A \times B \times C) = \int_{\partial\Omega} \mathbb{I}_{A \times B \times C}(x, y(x), \mathcal{D}y(x)) d\sigma(x),$$



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Boundary measure

$$\mu_{\partial}(A \times B \times C) = \int_{\partial\Omega} \mathbb{I}_{A \times B \times C}(x, y(x), \mathcal{D}y(x)) d\sigma(x),$$

$$(\mu, \mu_{\partial}) \longleftrightarrow y(\cdot)$$

Occupation and boundary measures

Integration along solutions to the PDE \rightarrow spatial integration w.r.t. μ and μ_{∂}

$$\int_{\Omega} h(x, y(x), \mathcal{D}y(x)) dx = \int_{\Omega \times Y \times Z} h(x, y, z) d\mu(x, y, z)$$

for **all** $h \in L_{\infty}$

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$$\begin{aligned} \Rightarrow J(y(\cdot)) &= \int_{\Omega} L(x, y(x), \mathcal{D}y(x)) \, dx + \int_{\partial\Omega} L_{\partial}(x, y(x), \mathcal{D}y(x)) \, d\sigma(x) \\ &= \int_{\Omega} L(x, y, z) \, d\mu(x, y, z) + \int_{\partial\Omega} L_{\partial}(x, y, z) \, d\mu_{\partial}(x, y, z) \end{aligned}$$

When do μ and μ_{∂} come from our PDE?

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$$\int_{\Omega \times Y \times Z} \phi(x, y) F(x, y, z) d\mu(x, y, z) = 0$$

$$\int_{\partial\Omega \times Y \times Z} \phi(x, y) G(x, y, z) d\mu_{\partial}(x, y, z) = 0$$

$$\int_{\partial\Omega \times Y \times Z} \phi(x, y) \eta(x) d\mu_{\partial}(x, y, z) - \int_{\Omega \times Y \times Z} \frac{\partial\phi}{\partial x} + \frac{\partial\phi}{\partial y} z d\mu(x, y, z) = 0.$$

$$\int_{\partial\Omega \times Y \times Z} \psi(x) d\mu_{\partial}(x, y, z) = \int_{\partial\Omega} \psi(x) \sigma(x)$$

for **all** $\phi \in C^{\infty}(\Omega \times \mathbf{Y})$ and $\psi \in C(\Omega)$

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System of **linear** equations in μ, μ_{∂}

Infinite-dimensional LP

$$\begin{array}{ll} \inf / \sup & J(y(\cdot)) \\ & y(\cdot) \\ \text{subject to} & y(\cdot) \text{ solves the PDE} \end{array}$$



$$\inf / \sup_{\mu, \mu_{\partial}} \int_{\Omega} L(x, y, z) d\mu(x, y, z) + \int_{\partial\Omega} L_{\partial}(x, y, z) d\mu_{\partial}(x, y, z)$$

$$\int_{\Omega \times Y \times Z} \phi(x, y) F(x, y, z) d\mu(x, y, z) = 0 \quad \forall \phi \in C(\Omega \times Y)$$

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$$\int_{\partial\Omega \times Y \times Z} \psi(x) d\mu_{\partial}(x, y, z) = \int_{\partial\Omega} \psi(x) \sigma(x) \quad \forall \psi \in C(\Omega)$$

$$\mu \in \mathcal{M}(\Omega \times Y \times Z)_{+}, \quad \mu_{\partial} \in \mathcal{M}(\partial\Omega \times Y \times Z)_{+}$$

Infinite-dimensional LP

inf / sup $J(y(\cdot))$
 $y(\cdot)$
subject to $y(\cdot)$ solves the PDE



inf / sup $\langle (\mu, \mu_\partial), c \rangle$
 μ, μ_∂
s.t. $\mathcal{A}(\mu, \mu_\partial) = b$
 $(\mu, \mu_\partial) \in \mathcal{K}$

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optimal value p



$$\begin{array}{ll} \inf / \sup & \langle (\mu, \mu_{\partial}), c \rangle \\ & \mu, \mu_{\partial} \\ \text{s.t.} & \mathcal{A}(\mu, \mu_{\partial}) = b \\ & (\mu, \mu_{\partial}) \in \mathcal{K} \end{array}$$

optimal value p_{LP}

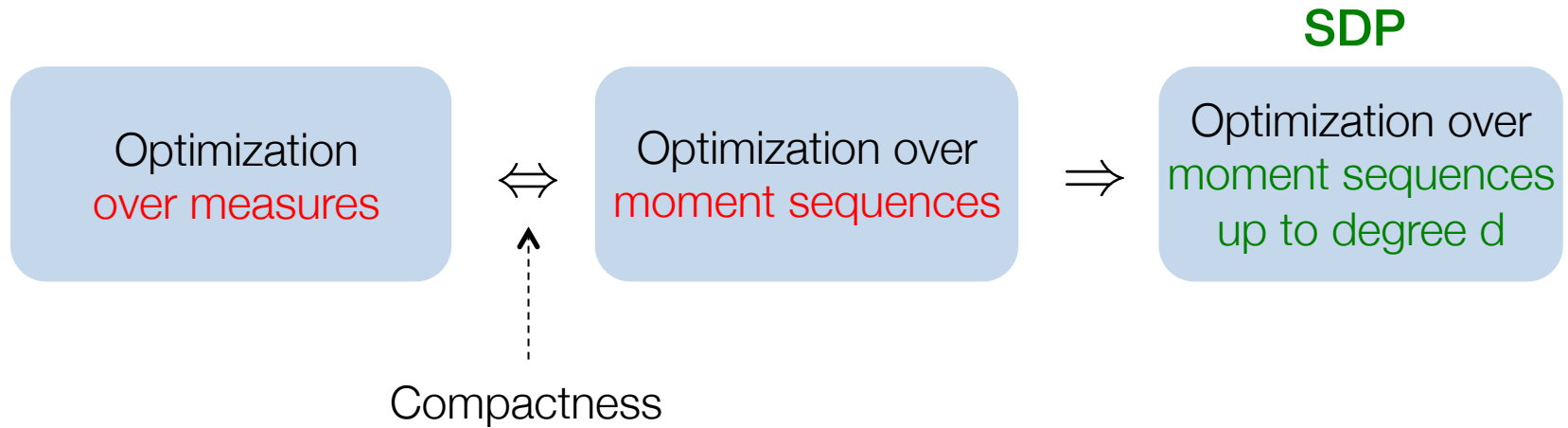
Lemma: p_{LP} is a lower/upper bound on p

Relaxation gap

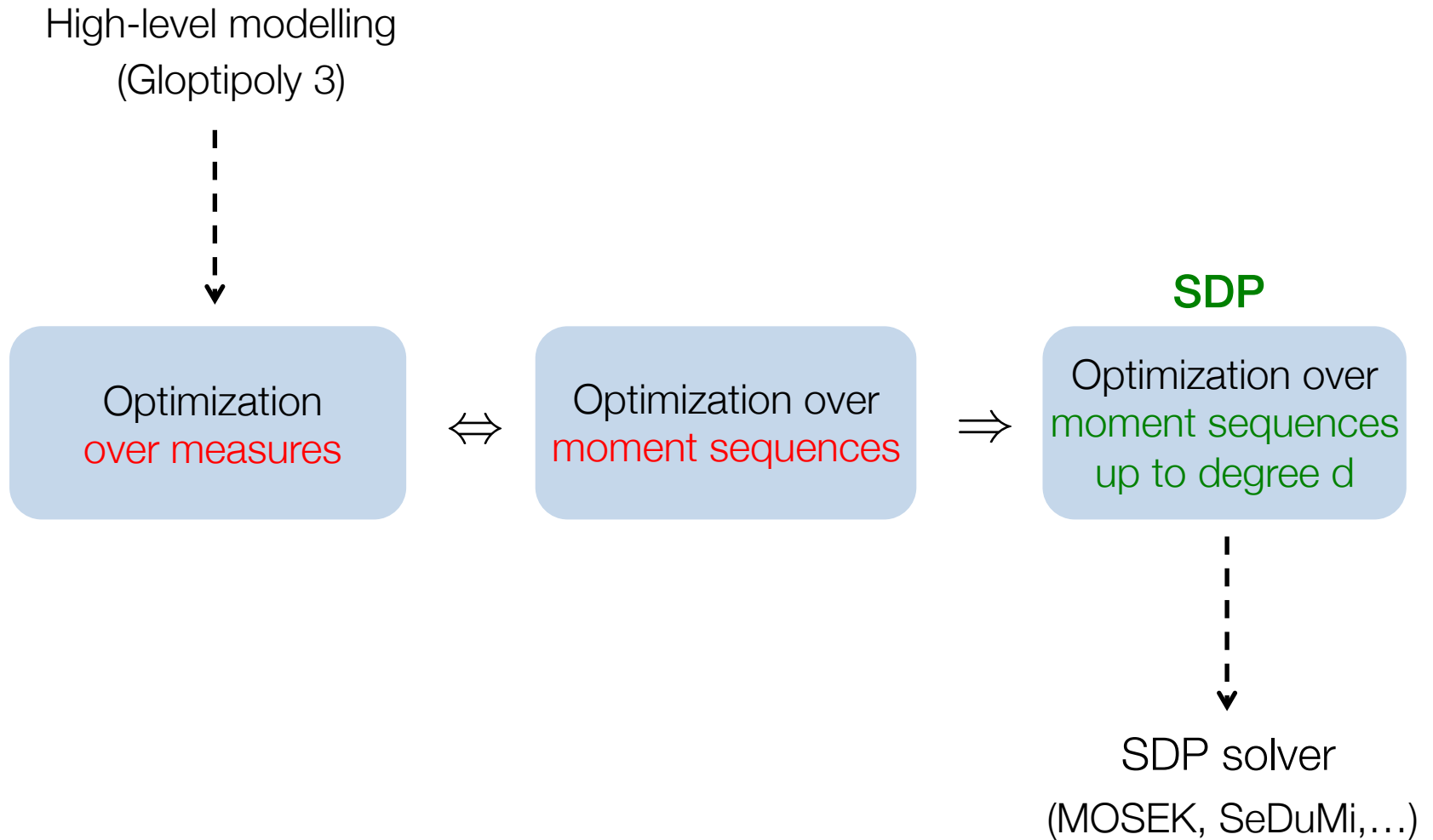
When do we have $p = p_{LP}$?

- Proven for ODEs
- Proven for scalar hyperbolic conservation laws in *[Marx et. al, 2018]*
→ additional constraints added to the LP - “entropy inequalities”
- General case **open**

Finite-dimensional approximation



Finite-dimensional approximation



Finite-dimensional approximation



Theorem: $p_k \leq p_{\text{LP}} \leq p$ and $\lim_{k \rightarrow \infty} p_k = p_{\text{LP}}$

Numerical examples – Burgers' equation

$$\frac{\partial y}{\partial x_1} + y \frac{\partial y}{\partial x_2} = 0 \quad \Omega = [0, 5] \times [0, 1]$$

- $y(0, x_2) = 10(x_2(1 - x_2))^2$
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Case 1: $J(y(\cdot)) = \int_0^5 \int_0^1 y(x_1, x_2)^2 dx_2 dx_1$

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Analytical solution: $J(y(\cdot)) = \frac{50}{63} \approx 0.79365079365$

$$\rho_{\text{LB}} \approx 0.79365079357$$

SDP bounds:
(d = 4)

$$\rho_{\text{UB}} \approx 0.79365080188$$

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Case 2: $J(y(\cdot)) = \int_0^5 \int_0^1 x_2^2 y(x_1, x_2)^2 dx_2 dx_1$

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Case 2: $J(y(\cdot)) = \int_0^5 \int_0^1 x_2^2 y(x_1, x_2)^2 dx_2 dx_1$

d	4	6	8
Lower bound (SeDuMi)	0.206	0.263	0.276
Upper bound (SeDuMi)	0.380	0.297	0.283
Parse time (Gloptipoly 3)	2.91s	3.41 s	6.23 s
SDP solve time (SeDuMi / MOSEK)	2.62 / 1.63 s	2.61 / 1.32 s	20.67 / 7.05 s

Control – problem setup

$$\begin{aligned} F(x, y(x), \mathcal{D}y(x)) &= C(x, y(x))u(x) && \text{for } x \in \Omega^\circ \\ G(x, y(x), \mathcal{D}y(x)) &= C_\partial(x, y(x))u_\partial(x) && \text{for } x \in \partial\Omega, \end{aligned}$$

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$$\begin{aligned} J(\mathbf{y}(\cdot)) &:= \int_{\Omega} L(x, \mathbf{y}(x), \mathcal{D}\mathbf{y}(x)) dx + \int_{\partial\Omega} L_\partial(x, \mathbf{y}(x), \mathcal{D}\mathbf{y}(x)) d\sigma(x) \\ &\quad + \int_{\Omega} L_u(x, \mathbf{y}(x)) u(x) dx + \int_{\partial\Omega} L_{u_\partial}(x, \mathbf{y}(x)) u_\partial d\sigma(x) \end{aligned}$$

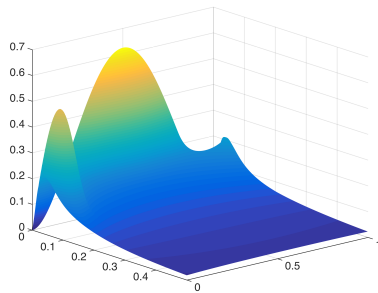
Goal: solve (at least approximately)

$$\begin{aligned} &\inf_{\mathbf{y}, u, u_\partial} && J(\mathbf{y}, u, u_\partial) \\ &\text{subject to} && \mathbf{y} \text{ solves the PDE}(u, u_\partial) \\ &&& 0 \leq u \leq 1 \text{ on } \Omega^\circ \\ &&& 0 \leq u_\partial \leq 1 \text{ on } \partial\Omega \end{aligned}$$

Infinite dimensional linear programming

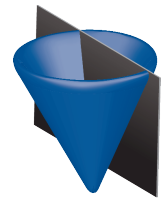
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Infinite-dimensional LP



Nonlinear PDE
with **control**

$$\begin{aligned} \min_{y} \langle g_N, y \rangle \\ \mathcal{A}_N y = b_N \\ y \in \mathcal{M}_N^+ \end{aligned}$$



Convex semidefinite program

Control measures

$$\nu(A \times B) := \int_{\Omega} \mathbb{I}_{A \times B}(x, y(x)) u(x) dx$$

$$\Leftrightarrow \nu \ll \bar{\mu} \text{ with density } u$$

Constraints easy to impose: $\nu \leq \bar{\mu} \Leftrightarrow u \in [0, 1]$

Control measures

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$$\nu_{\partial}(A \times B) := \int_{\partial\Omega} \mathbb{I}_{A \times B}(x, y(x)) u_{\partial}(x) dx$$

$$\Leftrightarrow \begin{aligned} \nu &\ll \bar{\mu} \text{ with density } u \\ \nu_{\partial} &\ll \bar{\mu}_{\partial} \text{ with density } u \end{aligned}$$

Constraints easy to impose: $\nu \leq \bar{\mu} \Leftrightarrow u \in [0, 1]$

$\nu_{\partial} \leq \bar{\mu}_{\partial} \Leftrightarrow u_{\partial} \in [0, 1]$

Infinite-dimensional LP – with control

$$\begin{array}{ll} \inf_{y, u, u_\partial} & J(y, u, u_\partial) \\ \text{subject to} & y \text{ solves the PDE}(u, u_\partial) \\ & 0 \leq u \leq 1 \text{ on } \Omega^\circ \\ & 0 \leq u_\partial \leq 1 \text{ on } \partial\Omega \end{array}$$



$$\begin{array}{ll} \inf / \sup_{\mu, \mu_\partial, \nu, \nu_\partial} & \langle (\mu, \mu_\partial, \nu, \nu_\partial), c \rangle \\ \text{s.t.} & \mathcal{A}(\mu, \mu_\partial, \nu, \nu_\partial) = b \\ & (\mu, \mu_\partial, \nu, \nu_\partial) \in \mathcal{K} \end{array}$$

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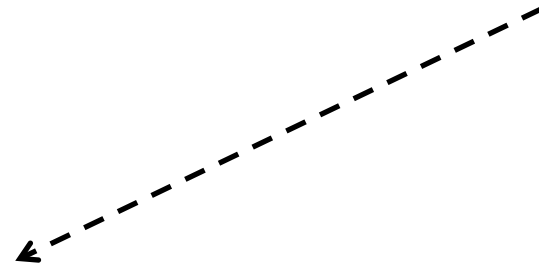


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optimal value p_{LP}

Lemma: p_{LP} is a lower bound on p

Controller extraction



Feedback controller

$$u(x_1, x_2) = \kappa(y(x_1, x_2), x_1, x_2)$$

$$u_{\partial}(x_1, x_2) = \kappa_{\partial}(y(x_1, x_2), x_1, x_2)$$

Numerical examples with control

$$\frac{\partial y}{\partial x_1} + y \frac{\partial y}{\partial x_2} = u(x_1, x_2) \quad \Omega = [0, 3] \times [0, 1]$$

- $y(0, x_2) = 10(x_2(1 - x_2))^2$
- $y(x_1, 0) = y(x_1, 1)$

Goal: minimize $\int_0^3 \int_0^1 y(x_1, x_2)^2 dx_2 dx_1$

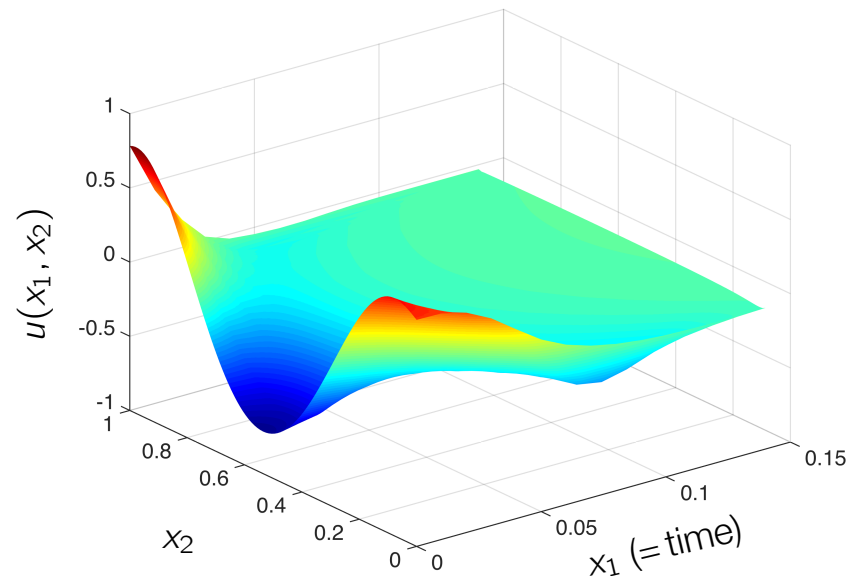
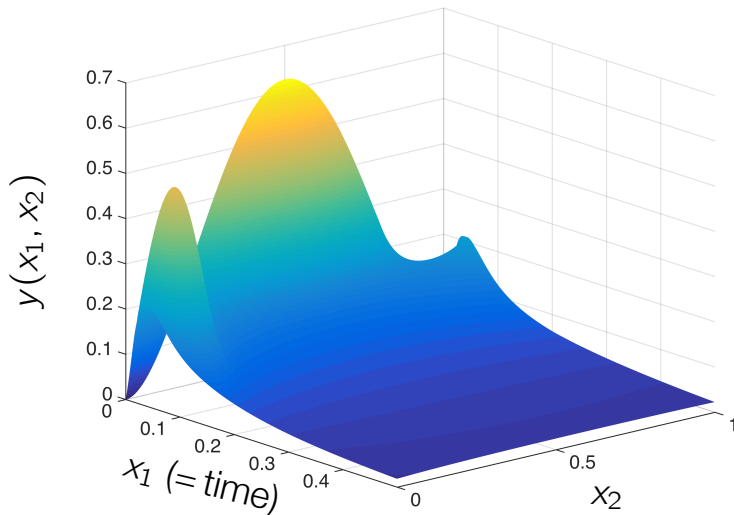
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SDP \rightarrow polynomial controller of degree 3



Computational complexity

Measures supported on subsets of \mathbb{R}^n of dimension

$$n = \dim(x) + \dim(y) + \# \text{ derivatives appearing nonlinearly}$$

Largest SDP block of size: $N = \binom{n+d/2}{n}$

n	4	6	8	10	12	17	21	24
$d = 4$	15	28	45	66	91	171	253	325
$d = 6$	35	84	165	286	455	1140	2024	2925
$d = 8$	70	210	495	1001	1820	5985	12650	20475

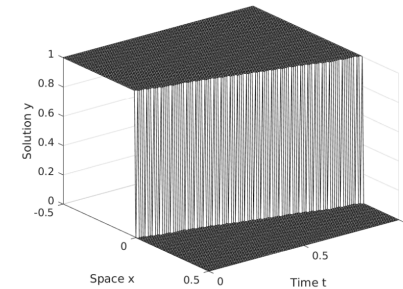
Complexity reduction: Sparsity

Degree bounding

Conclusion

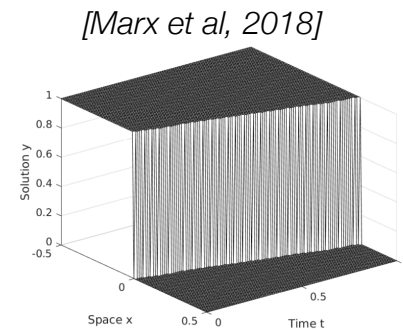
- **Convex** optimization based approach to analysis and control of PDEs
 - Off-the-shelf software available
- No spatio-temporal gridding
 - **Discontinuities** (e.g., shocks) well resolved
- Solutions represented by measures supported on their **graphs**

[Marx et al, 2018]



Conclusion

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Future directions

- Absence of relaxation gap
- More extensive numerical experiments

Preprint: <https://arxiv.org/abs/1804.07565>