

# 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:**  $L(x, y, z) = y^2$ ,  $L_{\partial}(x, y, z) = 0 \quad \Rightarrow \quad J(y(\cdot)) = \int_{\Omega} y(x)^2 \, dx$

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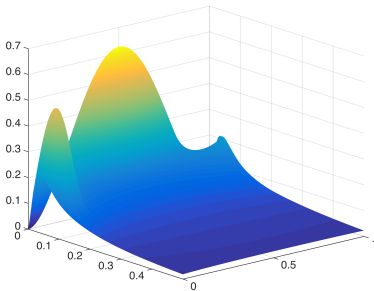
**Goal:** establish bounds on

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

# Infinite dimensional linear programming

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

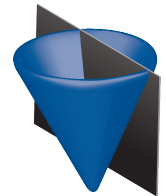
**Infinite**-dimensional LP



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



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

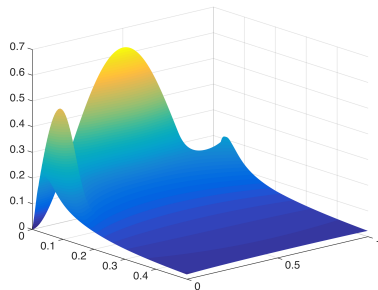


**Convex** semidefinite program

# Infinite dimensional linear programming

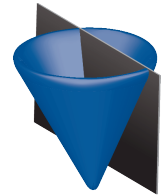
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**Convex** semidefinite program

**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

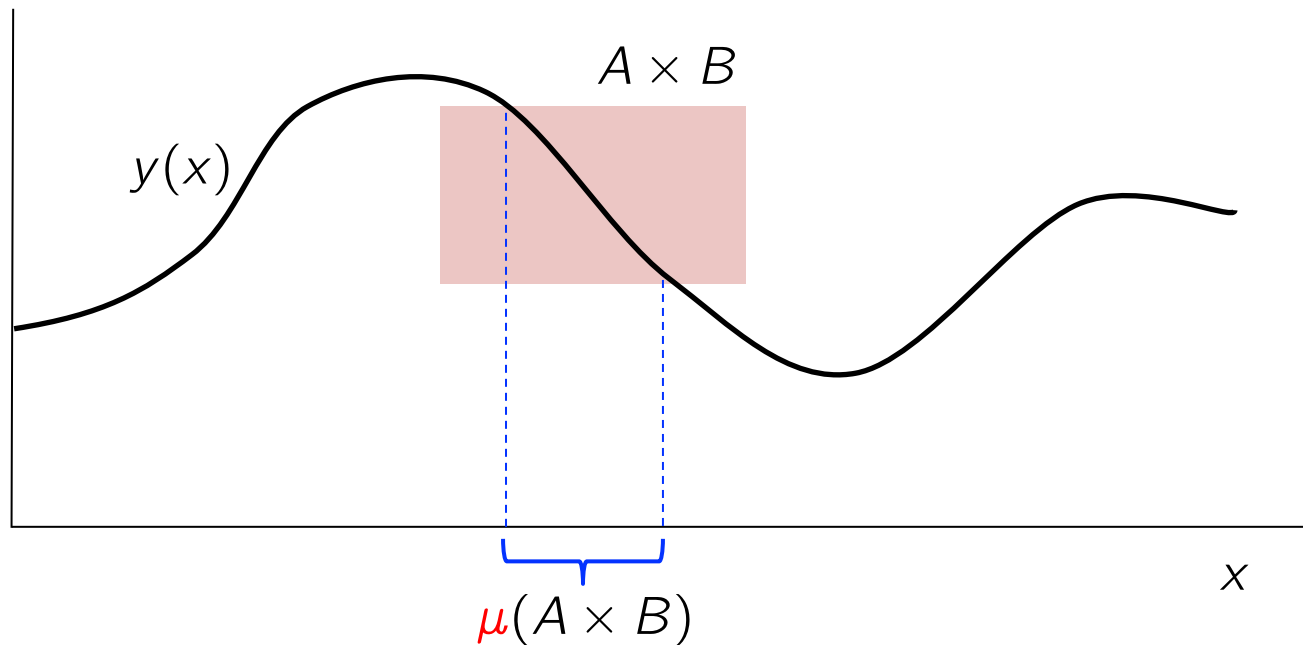
## Occupation measure

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

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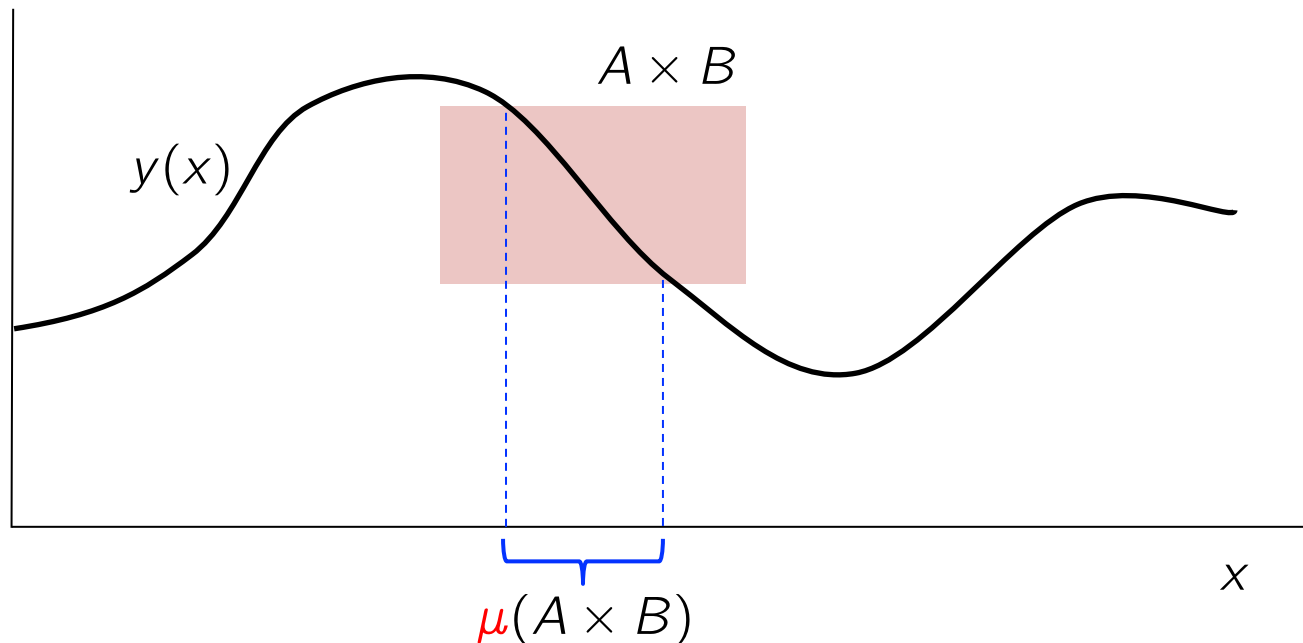
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## Boundary measure

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



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

# Occupation and boundary measures

Integration along solutions to the PDE  $\rightarrow$  spatial integration w.r.t.  $\mu$  and  $\mu_{\partial}$

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

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

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

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

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

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

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

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

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System of **linear** equations in  $\mu, \mu_{\partial}$

# Infinite-dimensional LP

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



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

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

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

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

# Infinite-dimensional LP

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



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

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

optimal value  $p$



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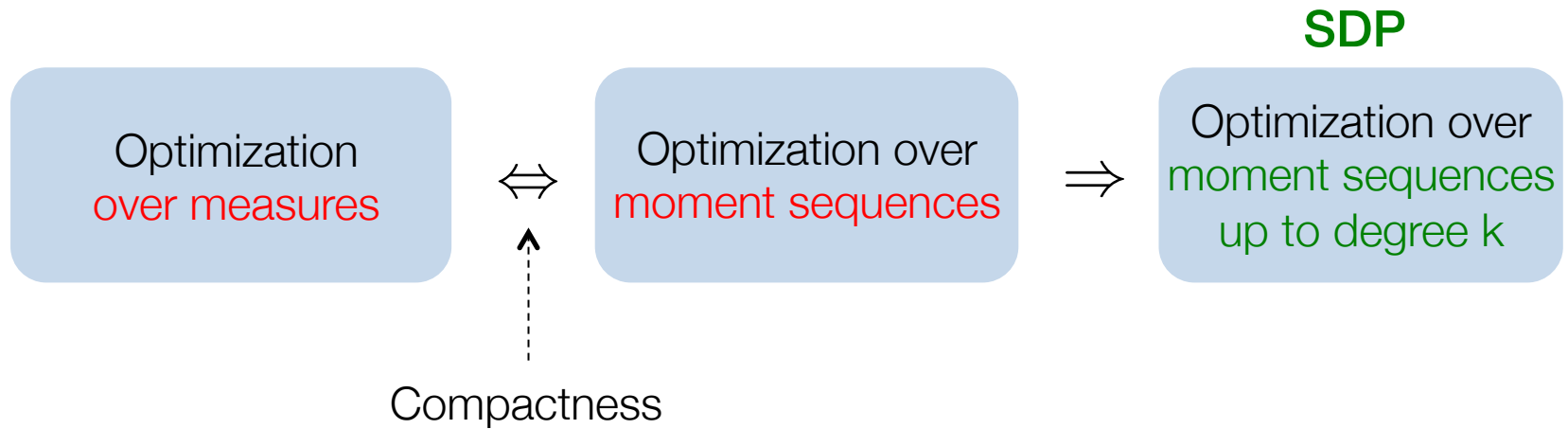
**Lemma:**  $p_{\text{LP}}$  is a lower/upper bound on  $p$

# Relaxation gap

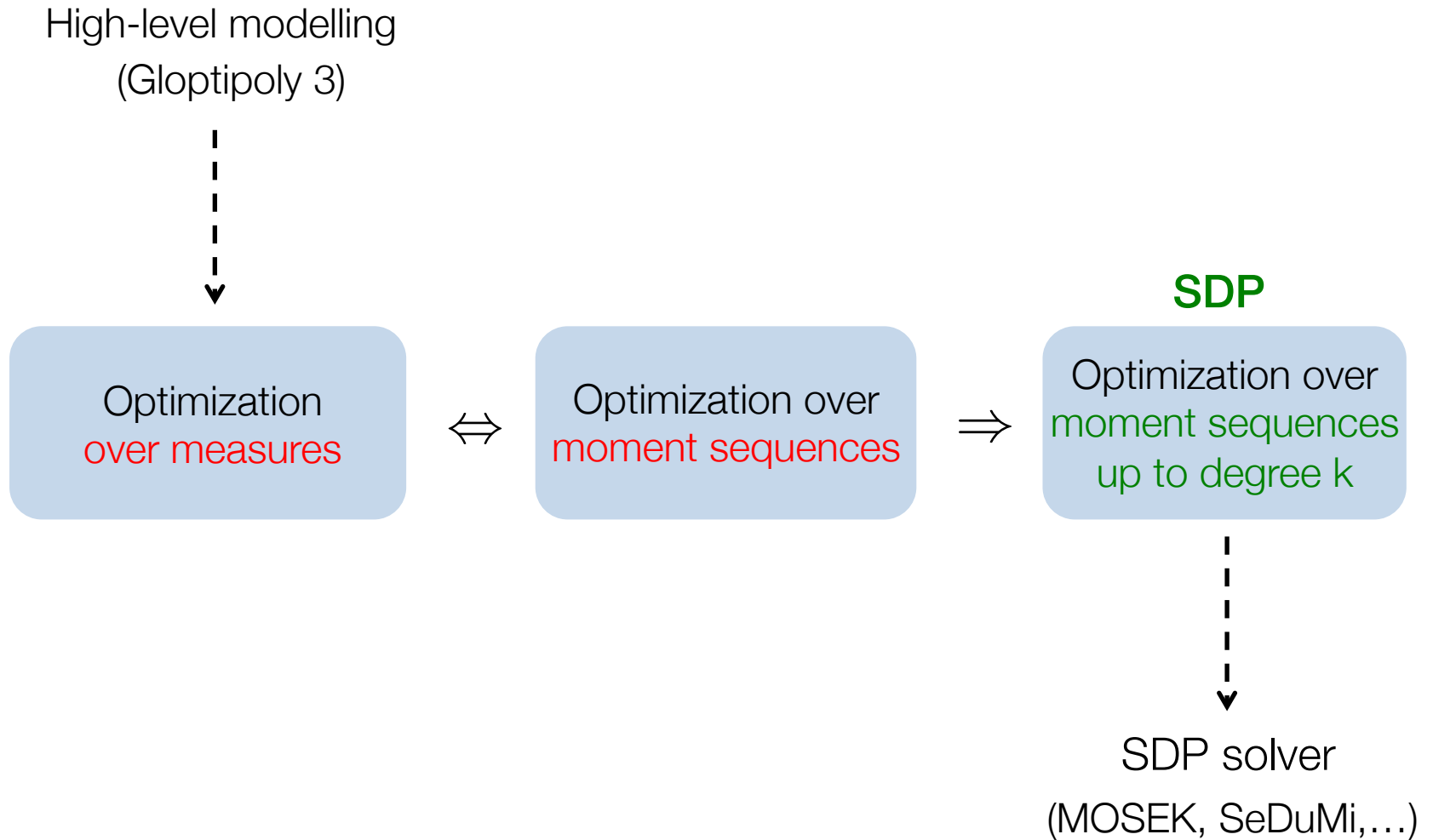
When do we have  $p = p_{LP}$ ?

- 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



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# 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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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)

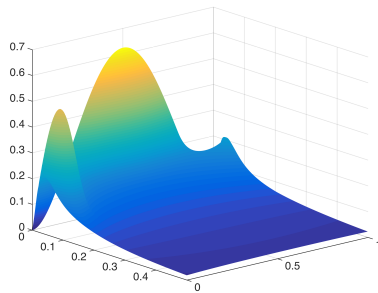
$$\begin{aligned} \inf_{\mathbf{y}, u, u_\partial} & J(\mathbf{y}, u, u_\partial) \\ \text{subject to } & \mathbf{y} \text{ solves the PDE}(u, u_\partial) \\ & 0 \leq u \leq 1 \text{ on } \Omega^\circ \\ & 0 \leq u_\partial \leq 1 \text{ on } \partial\Omega \end{aligned}$$



# Infinite dimensional linear programming

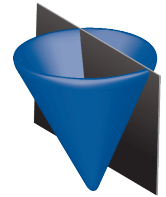
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**Infinite**-dimensional LP



**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:  $\nu \leq \bar{\mu} \Leftrightarrow u \in [0, 1]$

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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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optimal value  $p$

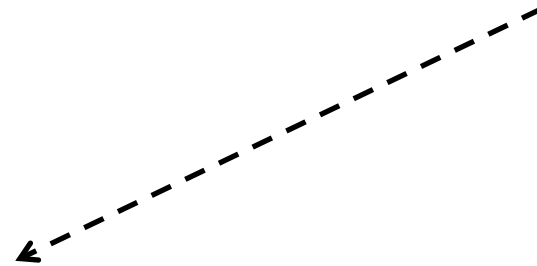


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optimal value  $p_{\text{LP}}$

**Lemma:**  $p_{\text{LP}}$  is a lower bound on  $p$

# Controller extraction



**Feedback** controller

$$u(x) = \kappa(y(x), x)$$

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

# Numerical examples with control

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

- $y(0, x_2) = 10(x_2(1 - x_2))^2$
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**Goal:** minimize  $\int_0^3 \int_0^1 y(x_1, x_2)^2 dx_2 dx_1$

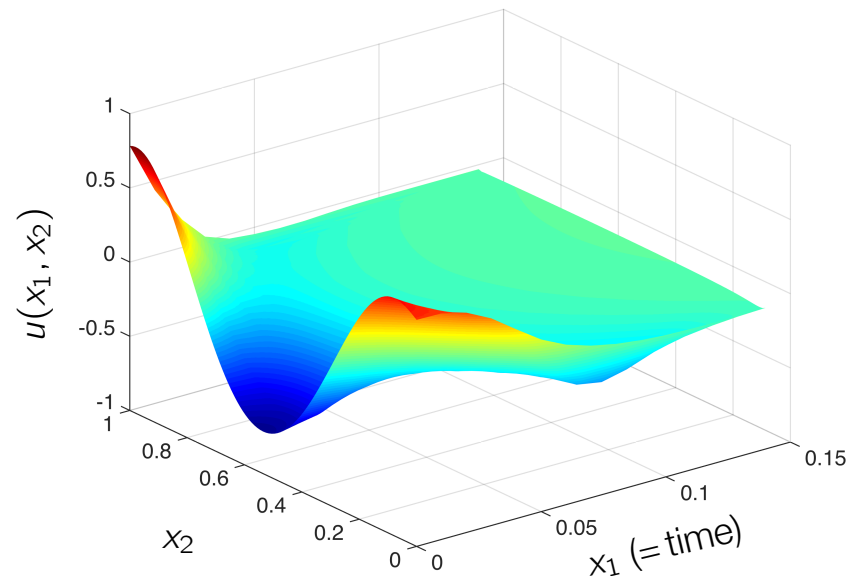
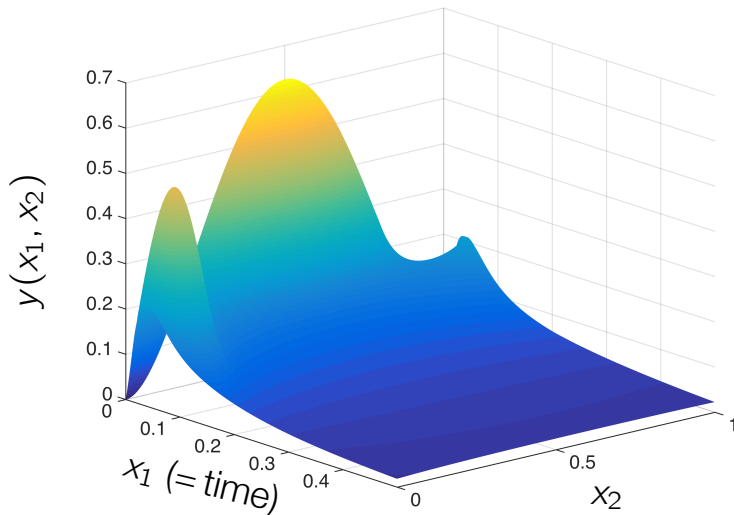
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SDP  $\rightarrow$  polynomial controller of degree 3





# 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:  $N = \binom{n+d/2}{n}$

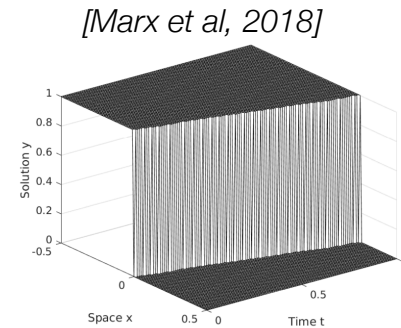
$n$	4	6	8	10	12	17	21	24
$d = 4$	15	28	45	66	91	171	253	325
$d = 6$	35	84	165	286	455	1140	2024	2925
$d = 8$	70	210	495	1001	1820	5985	12650	20475

**Complexity reduction:** Sparsity

Degree bounding

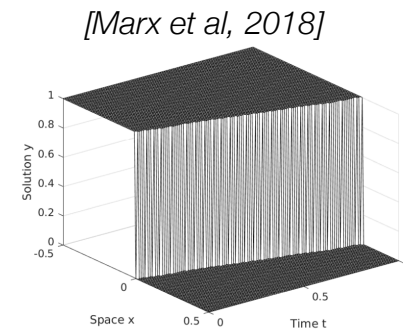
# Conclusion

- **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**



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# Future directions

- Absence of relaxation gap
- More extensive numerical experiments

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