

# Lecture 4: SDP implementation of SOS

[Shor '87, Nesterov '00; Lasserre, Parrilo-early '00s]

## LOGISTICS:

- ✓ HW schedule
- ✓ Project ideas
- ✓ Switch to in-person

$$\text{OPT} := \begin{cases} \text{maximize} & p(x) \\ \text{subj. to} & x \in \mathbb{R}^n \\ & f_i(x) = 0 \text{ for } i=1, \dots, a \\ & g_j(x) \geq 0 \text{ for } j=1, \dots, b \end{cases}$$

≤ variables  
≤ data

Parrilo / "proof" relaxation:

$$\text{Parr}_D := \begin{cases} \text{minimize} & c \\ \text{subj. to} & c - p(x) \stackrel{!}{=} \sum_{i=1}^a f_i(x) q_i(x) + r_0(x) + \sum_{j=1}^b g_j(x) r_j(x) \\ & q_i(x) \in \mathbb{R}[x_1, \dots, x_n] \\ & \deg f_i q_i \leq D \\ & r_0, r_1, \dots, r_j \in \text{SOS} \\ & \deg r_0, \deg g_j r_j \leq D. \end{cases}$$

"degree D SOS proofs"

Def: (Multisets)  $\binom{[n]}{k} \stackrel{\subset \text{SET}}{=} \{\text{multisets size } k \text{ in } [n]\} \quad (= S: [n] \rightarrow \mathbb{N}, |S| = \sum_i S(i) = k)$

$\binom{[n]}{\leq k} = \{\text{multisets size between } 0 \text{ and } k\}$ . Natural ordering: by size, lex.

$$x^S = \prod_i x_i^{S(i)} = \prod_{i \in S} x_i$$

Def:  $x^{\otimes \leq d} = (x^S)_{S \in \binom{[n]}{\leq d}}$  (Ex:  $n=2, x^{\otimes \leq 3} =$

$$\begin{bmatrix} 1 \\ x_1 \\ x_2 \\ x_1^2 \\ x_1 x_2 \\ x_2^2 \\ x_1^3 \\ x_1^2 x_2 \\ x_1 x_2^2 \\ x_2^3 \end{bmatrix}$$

Def: (Coeff. vector)  $p \in \mathbb{R}[x]$   $\deg p \leq D$

$\rightarrow v^{(p,D)} \in \mathbb{R}^{\binom{[n]}{\leq D}}$  vec. of coeff., unique s.t.

$$p(x) \stackrel{!}{=} \langle v^{(p,D)}, x^{\otimes \leq D} \rangle$$

Prop:  $p \in \mathbb{R}[x], \deg p \leq D \rightarrow \exists M^{(p,D)}$  s.t.  $\forall q$  w/  $\deg pq \leq D$ ,  
 $M^{(p,D)} v^{(q, D-\deg p)} = v^{(pq, D)}$

$$c - p(x) = \sum_{i=1}^a f_i(x) q_i(x) + r_0(x) + \sum_{j=1}^b g_j(x) r_j(x)$$

$$\begin{aligned} \underline{v^{(c,D)}} - \underline{v^{(p,D)}} &= \sum_{i=1}^a \underline{M^{(f_i, D)}} \underline{v^{(q_i, D)}} + \sum_{j=1}^b \underline{M^{(g_j, D)}} \underline{v^{(r_j, D)}} \\ &= c e_1 \end{aligned}$$

Now, how to impose  $r_j \in \text{SOS}$  on  $v^{(r_j, D)}$ ?

Def:  $D \geq 2$  even,  $p \in \mathbb{R}[x]$ ,  $\deg p \leq D$ .  $S \in \mathbb{R}^{\binom{D+1}{\leq D/2} \times \binom{D+1}{\leq D/2}}$  represents  $p$  if  
 $p(x) \stackrel{(\dagger)}{=} x^{\otimes D/2 T} S x^{\otimes D/2}$

Rk: Not unique in general.



$$x^{\otimes \leq 1} = \begin{bmatrix} 1 \\ x \\ x \\ 1 \end{bmatrix}$$

$$p(x) = \sum_{i,j} A_{ij} x_i x_j + \sum_i B_i x_i + C$$



$$p(x) = x_1 x_2 x_3 x_4$$

$S$  represents  $p$  iff  $\sum_i \cdot = 1$ .

Lem:  $p \in \text{SOS} \iff \exists S$  representing  $p$  s.t.  $S \succ 0$ .

Pf:  $p \in \text{SOS} \iff p = \sum_i s_i(x)^2 = \sum_i \left\langle v^{(s_i, D/2)}, x^{\otimes D/2} \right\rangle^2$   
 $= x^{\otimes D/2 T} \left( \underbrace{\sum_i v^{(s_i, D/2)} v^{(s_i, D/2) T}}_S \right) x^{\otimes D/2}$

Def:  $\text{vec}(S) :=$  columns of  $S$  concatenated.

Prop:  $D \geq 2$  even  $\rightarrow \exists V^{(D)}$  s.t.  $\forall S \in \mathbb{R}_{\text{sym}}^{\binom{D+1}{\leq D/2} \times \binom{D+1}{\leq D/2}}$   
 $V^{(D)} \text{vec}(S) = v^{(p, D)}$  where  $S$  represents  $p$ .

Thm: (Perrillo SDP)

$$P_{\text{Perr}_D} = \begin{cases} \text{maximize} & c \\ \text{s.t.} & c e_1 - v^{(p, D)} = \sum_1^a M^{(f_i, D)} v^{(g_i, D - \deg f_i)} \\ & + v^{(D)} \text{vec}(R_0) \\ & + \sum_1^b M^{(g_j, D)} v^{(D)} \text{vec}(R_j) \\ & R_0, \dots, R_b \succ 0 \text{ "satisfiable"} \\ & v^{(g_i, D - \deg f_i)} \in \mathbb{R}^{\binom{D+1}{\leq D - \deg f_i}} \end{cases}$$

SDP!

Observation:

- ① Inequality constr.  $g_j(x) \geq 0$  very expensive
- ② Lin. constr.  $\rightarrow n^{O(D)}$  indep. of  $f_i$
- ③  $(a+b) n^{O(D)}$  variables,  $n^{O(D)}$  constraints,  $b$  psd constr.

Dual Lasserre relaxation:

Def:  $\tilde{E} : \mathbb{R}[x_1, \dots, x_n]_{\leq D} \rightarrow \mathbb{R}$  is deg.  $D$  pseudoexpectation if:

①  $\tilde{E}$  linear

②  $\tilde{E}[1] = 1$

$\rightarrow m_{\emptyset} = 1$

③  $\tilde{E}[f_i q_j] = 0 \quad \forall i \in [a] \text{ deg } f_i \leq D$

$\rightarrow 0 = \langle M^{(f_i, D)} v, m \rangle \quad \forall v$   
 $= \langle v, M^{(f_i, D)} \rangle \Leftrightarrow M^{(f_i, D)} \succeq 0$

④A  $\tilde{E}[s^2] \geq 0$  if  $\text{deg } s^2 \leq D$

$\rightarrow \text{mat}(m)_{S, T} = \tilde{E}[x^S x^T]$

④B  $\tilde{E}[g_j s^2] \geq 0 \quad \forall j \in [b] \text{ deg } g_j s^2 \leq D$

④A  $\Leftrightarrow \text{mat}(m) \succeq 0$

$K := \{x : f_i(x) = 0, g_j(x) \geq 0\}$

$$\text{OPT} = \left\{ \begin{array}{l} \max p(x) \\ \text{s.t. } x \in K \end{array} \right\} = \left\{ \begin{array}{l} \max \int p(x) d\mu \\ \text{s.t. } \mu \text{ prob. measure over } K \end{array} \right\} \leq \left\{ \begin{array}{l} \max \tilde{E} p(x) \\ \text{s.t. } \tilde{E} \text{ deg } D \text{ p.e.} \end{array} \right\} =: \text{Lass}_D$$

To implement: Linearity  $\rightarrow \tilde{E}$  specified by pseudomoments  $m = (\tilde{E} x^S)_{S \in \binom{[n]}{\leq D}} = \tilde{E} x^{\oplus \leq D}$

$\tilde{E} p(x) = \langle v^{(p, D)}, m \rangle$

Thm:  $\text{Lass}_D = (\text{some SDP})$

Prop:  $\text{Lass}_D$  and  $\text{Parr}_D$  are dual SDPs.

Thm: (Weak duality)  $\text{Lass}_D \leq \text{Parr}_D$

Pf: Feasible pt. for  $\text{Parr}_D$ :

$$\tilde{E} \left\{ c - p(x) \right\} = \underbrace{\tilde{E} \left[ \sum_1^a f_i(x) q_i(x) \right]}_{=0} + \underbrace{\tilde{E} [r_0(x)]}_{\geq 0} + \sum_1^b \underbrace{g_j(x) r_j(x)}_{\geq 0}$$

Feasible pt.  $\tilde{E}$  for  $\text{Lass}_D$

$\rightarrow c - \tilde{E} p(x) \geq 0 \rightarrow \tilde{E} p(x) \leq c$

Thm: (Strong duality) Archimedean (constraints "prox"  $\sum_1^r x_i^2 \leq R$ )  $\Rightarrow \text{Lass}_D = \text{Parr}_D =: \text{SOS}_D$

[Josa, Hermon 108]

Thm: (Convergence) Archimedean  $\Rightarrow \lim_{D \rightarrow \infty} \text{SOS}_D = \text{OPT}$

Pf:  $\epsilon > 0, \forall x \in K, p(x) < \text{OPT} + \epsilon$ . Archimedean + Putinar's Positivstellensatz  $\Rightarrow \exists \text{ SOS proof of deg } D(\epsilon) \text{ of } p(x) \leq \text{OPT} + \epsilon \rightarrow \text{SOS}_D \leq \text{OPT} + \epsilon$

Thm: (Finite convergence) Often,  $\exists D$  st.  $\text{SOS}_D = \text{OPT}$ .

Wie ~ '10  $\rightarrow$  Archimedean  $\Rightarrow$  finite conv. holds "generically" (for "most" problems).