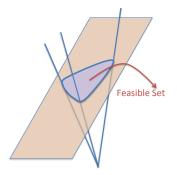
Decomposed Structured Subsets for Semidefinite Optimization

Jared Miller¹, Yang Zheng², Mario Sznaier¹, Antonis Papachristodoulou³ Virtual Sessions, July 13-17, 2020

¹Northeastern University, ²Harvard University, ³Oxford University

Modern control problems require solutions of large scale SDPs

$$\min_{X} \langle C, X \rangle$$
$$b_{i} = \langle A_{i}, X \rangle \mid_{i=1}^{m}$$
$$X \in \mathbb{S}_{+}^{n}$$



Scales polynomially with *n* and *m*

Approximations of SDPs

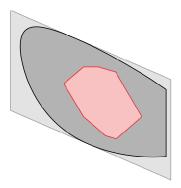
Approximate large SDPs Structured (simpler) subset of PSD

Diagonal Dominance $(\mathcal{D}\mathcal{D})$:

 $X_{ii} \geq \sum_{i \neq j} |X_{ij}|$

bounds by Linear Programming

Generalizes to Factor Width

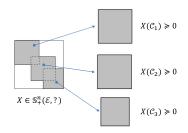


 $\mathcal{DD} \subset \mathbb{S}_+ \subset \mathcal{DD}^*$

Use structure to simplify problem

- Sparsity
- Symmetry
- Algebraic

Large PSD cone \rightarrow smaller cones Often renders problems tractable

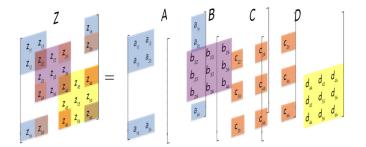


Blocks agree on overlap

Example of Chordal Sparsity

 $Z \succeq 0 \iff \exists A, B, C, D$ such that

A+B+C+D=Z, $A, B, C, D \succeq 0$



Large sparse PSD \leftrightarrow sum of smaller PSD

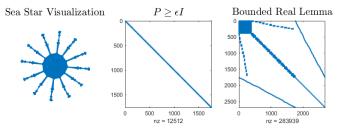
Network H-infinity Estimation

Small Gain theorem: G robustly stable if $\|G\|_\infty < 1$

Bounded Real Lemma: $\|G\|_{\infty} < \gamma$ iff $\exists P \succ 0$

$$\begin{bmatrix} PA + A^{\mathsf{T}}P + C^{\mathsf{T}}C & P^{\mathsf{T}}B + C^{\mathsf{T}}D \\ B^{\mathsf{T}}P + D^{\mathsf{T}}C & -\gamma^{2}I \end{bmatrix} \prec 0.$$

Block-diagonal P inherits sparsity of network



Sea Star network topology and LMI sparsity

Sea Star

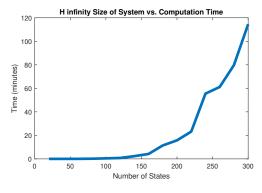


Inspiration for Sea Star Network

H-infinity Optimization

No structure: \approx 2 hours for 300 states

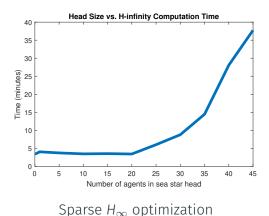
Out of memory: \geq 400 states (64 GB RAM)



Dense H_{∞} optimization

Sea Star structure with chordal decomposition Head sizes 0...45, largest clique 242

Out of memory: Head Size \geq 50



For what values of (a, b) is M(a, b) PSD-completable?

$$M(a,b) = \begin{bmatrix} 1 & \frac{1}{2} + a & ? & ? \\ \frac{1}{2} + a & 2 - b & -2a & a + b \\ ? & -2a & 5 & b/2 \\ ? & a + b & b/2 & 2 \end{bmatrix}$$

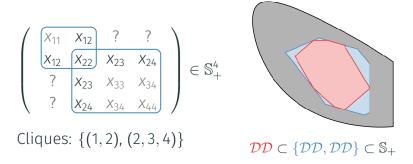
Cliques are $C_1 = (1, 2)$ $C_2 = (2, 3, 4)$

Decomposed Structured Subsets

Structured Subsets destroy problem properties

Decompose, then approximate

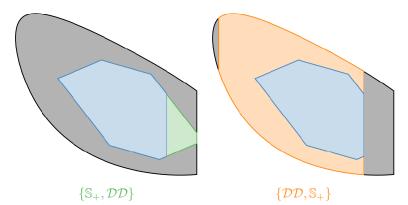
Blocks are \mathcal{DD} vs. Matrix is \mathcal{DD}



Preserving structure yields tighter approximations

Mixing Cones

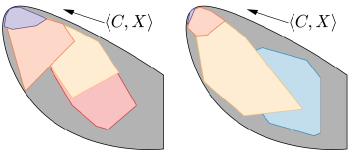
Adds flexibility in optimization



Useful if problem has few large cliques, bottleneck

Change of Basis

Iteratively refine approximations (Ahmadi, Hall 2015)



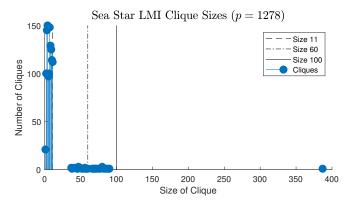
Start from $\mathcal{D}\mathcal{D}$

Start from $\{\mathcal{DD}, \mathcal{DD}\}$

Standard vs. Decomposed Change of Basis

Improved solution quality with structure

310 agents, each a random linear system of order \leq 10 70 in 'head', 20 in each of the 12 'arms' in 2 'knuckles'

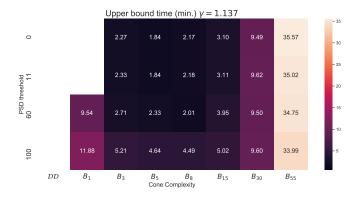


Single clique sized 387, rest have size < 90

Sea Star Upper Bounds

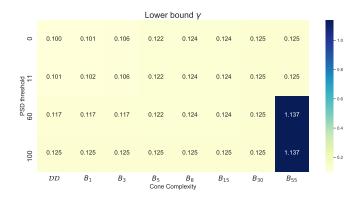
Cliques larger than threshold remain PSD

B_k: Block-factor-width 2 matrices, k-sized blocks



Time to find γ by upper bound K (minutes)

Dual decomposed structured subsets for lower bounds Can verify if approximation = SDP solution (KKT)



 γ found by lower bound $\mathit{K^*}$

- Structure in SDPs is powerful
- Decompositions allow for tractable programs
- Preserve structure while approximating
- Increased performance and tighter bounds with structure

https://github.com/zhengy09/SDPfw