## Aggregation of Bilinear Bipartite Equality Constraints and Application to FEM Update Problem

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#### 1

#### Background

Consider a set with two bilinear bipartite equality constraints.

$$S := \left\{ x \in [0,1]^{n_1}, y \in [0,1]^{n_2} \mid x^\top Q_i y + a_i^\top x + b_i^\top y + c_i = 0, \quad i \in [2] \right\}$$

Let us aggregate constraints with weights  $\lambda = (\lambda_1, \lambda_2) \in \mathbb{R}^2$ .

$$S_{f \lambda} := \left\{ x \in [0,1]^{n_1}, y \in [0,1]^{n_2} \left| egin{array}{c} \lambda_1 \cdot \left( x^ op Q_1 y + a_1^ op x + b_1^ op y + c_1 
ight) \ + \lambda_2 \cdot \left( x^ op Q_2 y + a_2^ op x + b_2^ op y + c_2 
ight) \end{array} 
ight. = 0 
ight. 
ight\}$$

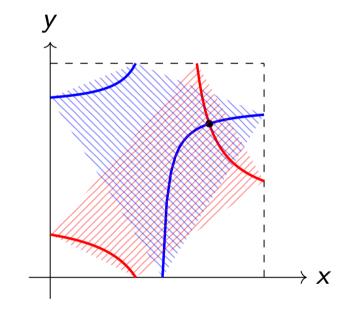
Remark  $S_{\lambda} \subset S$  for any  $\lambda \in \mathbb{R}^2$ , hence  $conv(S) \subset \bigcap_{\lambda \in \mathbb{R}^2} conv(S_{\lambda})$ .

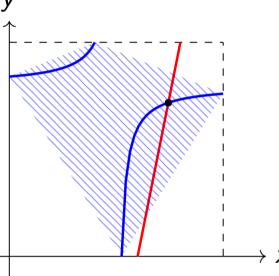
#### 2

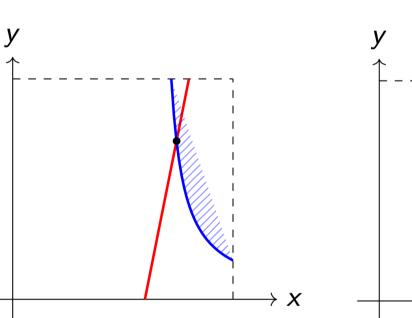
# Can conv(S) be represented with intersection of finite number of conv( $S_{\lambda}$ )'s?

**Proposition 1:** Yes, for  $n_1 = 1$  and  $n_2 = 1$ . There is  $T \subseteq \mathbb{R}^2$  where  $|T| \le 3$  such that  $conv(S) = \bigcap_{\lambda \in T} conv(S_{\lambda})$ .

#### Proof sketch:







(a)  $S_1$  (blue),  $S_2$  (red), their convex (b) Find a line representation L which (c) Find  $\tilde{S}_1$  intersecting with  $[0,1]^2$  (d) Find  $\tilde{S}_2$  with conv $(\tilde{S}_2) \cap L$  is hulls, and feasible region (black) gives a same feasible region with  $S_1$  box by only one branch on the opposite side of conv $(\tilde{S}_1) \cap L$ 

**Proposition 2:** No, for  $n_1 = 1$  and  $n_2 = 2$ , finite number of intersections does not give a convex hull. In other words, for  $T \subseteq \mathbb{R}^2$ , where  $|T| < \infty$ ,

$$\operatorname{conv}(S) \subsetneq \bigcap_{\lambda \in T} \operatorname{conv}(S_{\lambda}).$$

**Proof sketch:** Consider a counterexample:

$$S = \left\{ x, y_1, y_2 \in [0, 1]^3 \, \middle| \, \begin{array}{l} xy_1 = 0.5 \\ xy_2 = 0.5 \end{array} \right\}.$$

- 1. Note that  $y_1 = y_2$  for all  $(x, y_1, y_2) \in S$ , so  $conv(S) \subseteq \{x, y_1, y_2 \in [0, 1]^3 \mid y_1 = y_2\}$ .
- 2.  $\left(\frac{3}{4}, \frac{17}{24}, \frac{17}{24}\right) \in \text{conv}(S)$
- 3. For any  $\lambda \in \mathbb{R}^2$ , we can find  $\hat{\epsilon}(\lambda) > 0$  such that:  $(\frac{3}{4}, \frac{17}{24} + \epsilon, \frac{17}{24} \epsilon) \in \text{conv}(S_{\lambda})$ , for all  $0 \le \epsilon \le \hat{\epsilon}(\lambda)$ .
- 4. Let  $\epsilon_0 = \min_{\lambda \in \mathbb{R}^2} {\{\hat{\epsilon}(\lambda)\}}$ , then we found a point that is in all conv $(S_\lambda)$  but does not satisfy  $y_1 = y_2$ ; hence not in conv(S).

#### 3

# Can conv(S) be represented with intersection of infinite number of conv( $S_{\lambda}$ )'s?

**Proposition 3:** Even an infinite number of intersections does not give a convex hull. In other words,

$$\operatorname{\mathsf{conv}}(S) \subsetneq \bigcap_{\lambda \in \mathbb{R}^2} \operatorname{\mathsf{conv}}(S_\lambda).$$

**Proof sketch:** Consider a counterexample:

$$S = \left\{ x_1, x_2, y_1, y_2 \in [0, 1] \middle| \begin{array}{rrr} x_1 y_1 - 5x_1 y_2 - 2x_2 y_1 + 9x_2 y_2 & = & 0 \\ 3x_1 y_1 + 3x_1 y_2 + 5x_2 y_1 & = & 6 \end{array} \right\}.$$

- 1. Note that  $\hat{p} = (1, \frac{7}{10}, \frac{7}{8}, \frac{1}{6}) \notin \text{conv}(S)$ .
- 2. When we let  $\lambda = (1, \theta)$ , for all  $\theta \in \mathbb{R}$ , we can find  $p_1, ..., p_4 \in S_{\lambda}$  and weights  $w_1, ..., w_4$  such that  $\hat{p} = \sum w_i p_i$  and  $\sum w_i = 1$ .

e.g

$$\begin{array}{ll} p_1 = \left(1,0,\frac{3\theta+5}{3\theta+1},1\right), & p_2 = \left(1,1,\frac{6\theta}{8\theta-1},0\right), & p_3 = \left(1,1,\frac{3\theta-4}{8\theta-1},1\right), & p_4 = \left(1,\frac{3\theta-1}{5\theta-2},1,0\right), \\ w_1 = \frac{47(1+3\theta)}{120(1+47\theta)}, & w_2 = \frac{122+1343\theta-1645\theta^2}{120(1+47\theta)(1-2\theta)}, & w_3 = \frac{799\theta-27}{120(1+47\theta)}, & w_4 = \frac{-11(1-141\theta)(2-5\theta)}{120(1+47\theta)(1-2\theta)}. \end{array}$$

#### 4

### Can aggregations still be useful?

**Remark:** Despite results so far, aggregated equalities can provide a tight approximation of conv(S). Random shooting experiment for  $n_1 = n_2 = 2$  and minimizing over a random objective function shows significant reduction in gap.

Relative Gap	$\operatorname{conv}(S_1) \cap \operatorname{conv}(S_2)$	$igcap_{\lambda \in [-2,2]^2} \operatorname{conv}(\mathcal{S}_\lambda)$	$igcap_{\lambda \in [-10,10]^2} \operatorname{conv}(\mathcal{S}_\lambda)$
Average	5.25%	1.38%	0.56%
Maximum	96.14%	26.38%	22.22%
No. < 0.5%	57%	71%	87%

# How can we find some "nice" aggregation weights that will give a tight approximation of conv(S)?

**Heuristic:** When we have a relaxed solution  $(\hat{x}, \hat{y})$ , let's try to find an aggregation weights that may separate  $(\hat{x}, \hat{y})$ .

- 1. Fix y to  $\hat{y}$  in  $S_{\lambda}$ 
  - $\Longrightarrow S_{\lambda}|_{y=\hat{y}}$  is a hyperplane in the x space with parameters defined by  $\lambda \in \mathbb{R}^2$ .
- 2. Find  $\lambda \in \mathbb{R}^2$  such that the distance between  $S_{\lambda}|_{y=\hat{y}}$  and  $\hat{x}$  is maximized.

  (This is a convex problem and can be solved efficiently.)

  conv $(S_{\lambda})$  separating  $(\hat{x}, \hat{y})$
- 3. Go to step 1 and now fix x to  $\hat{x}$ .

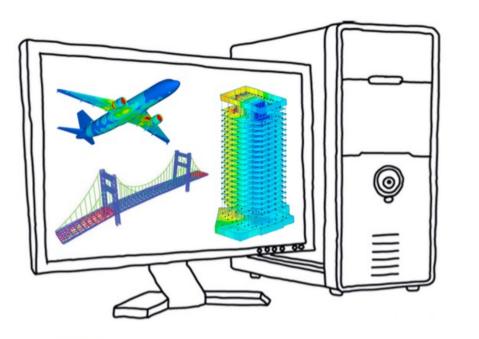
### 4. Choose among $\lambda$ 's that have maximum distance.

#### 6

#### Application to FEM Update Problem

**FEM Update**: The finite element (FE) model update problem in structural engineering seeks to minimize the differences between the predicted and actual behaviors of a built structure. This boils down to solving a generalized eigenvalue problem with eigenvalues, eigenvectors and matrix weights being variables, which can then be reformulated as a bilinear bipartite problem.

$$\begin{aligned} & \underset{\delta,x,y}{\text{min}} & \delta \\ & s.t. & & x^\top Q_i y + a_i^\top x + b_i^\top y + c_i = 0 \\ & \dots & \text{other linear constraints w.r.t. } \delta, x, y \end{aligned} \qquad \forall i \in [n]$$





(a) Mathematical Models

(b) As-built Structures

### Aggregations can improve branch and bound convergence!

(a) Convergence of Example Instance

0.01475 0.01450 0.01425 0.01400 0 1000 2000 3000 time (sec)

Lower Bound (BARON commercial solver)

Lower Bound (Branch and Bound with aggregation

12story 16story  $(n_1 = 14, n_2 = 24)$   $(n_1 = 19, n_2 = 48)$ 

(b) Average Relative Improvements

Root Node against
Branch and Bound w/o aggregation
3.08%
6.65%

Branch and Bound w/o aggregation
8.33% 2.60%
Final Gap against

Final Gap against

BARON commercial solver
82.45% 51.18%

**Remark:** There is a trade-off between making aggregations and making the convex hull tighter, so we limit the number of aggregations to add.

#### Refenreces

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- Santanu S Dey, Gonzalo Munoz, and Felipe Serrano. On obtaining the convex hull of quadratic inequalities via aggregations. SIAM Journal on Optimization, 32(2):659–686, 2022
- 72.00%
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