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# A Semidefinite Approach for the Single Row Facility Layout Problem

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# Outline

- **Master's thesis:** "Solution Approaches for the Single Row Facility Layout Problem based on Semidefinite Programming"
- TU Dortmund
- Supervisor: Prof. Dr. [Anja Fischer](#)

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- 1 Single Row Facility Layout Problem
- 2 Best Exact Approaches in the Literature
- 3 A New Semidefinite Approach
- 4 Results

# Single Row Facility Layout Problem (SRFLP)

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- $n$  one-dimensional facilities  $[n] := \{1, \dots, n\}$
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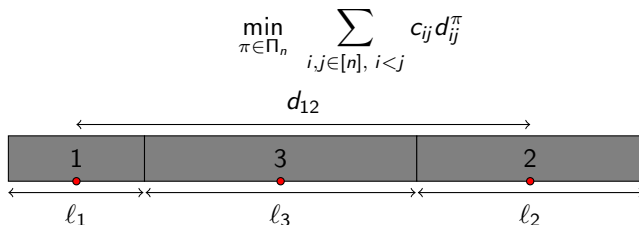
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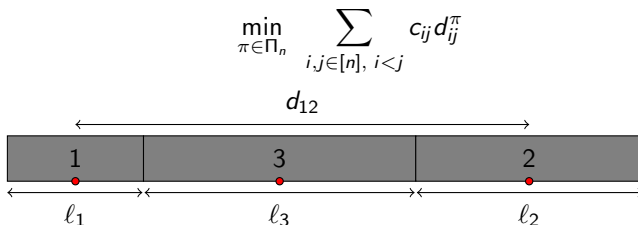
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- strongly  $\mathcal{NP}$ -hard
- many applications (e.g., in manufacturing systems)

# Betweenness Approach (Amaral, 2009)

## Betweenness variables:

$$b_{ikj} = \begin{cases} 1, & \text{if } k \text{ lies between } i \text{ and } j \\ 0, & \text{otherwise} \end{cases}, \quad k \neq i < j \neq k$$



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- simplex method impractical

# Semidefinite Formulation

**Ordering variables:**  $x_{ij} = \begin{cases} +1, & \text{if } i \text{ left of } j \\ -1, & \text{otherwise} \end{cases}, \quad i, j \in [n], i < j$

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Up to a constant, (SRFLP) is **equivalent** to (see Anjos et al., 2005)

$$\begin{aligned} \min \quad & \sum_{\substack{i, j \in [n] \\ i < j}} \frac{c_{ij}}{2} \left( - \sum_{\substack{k \in [n] \\ k < i}} \ell_k x_{ki} x_{kj} - \sum_{\substack{k \in [n] \\ i < k < j}} \ell_k x_{ik} x_{kj} + \sum_{\substack{k \in [n] \\ k > j}} \ell_k x_{ik} x_{jk} \right) \\ \text{s.t.} \quad & x_{ij} x_{jk} - x_{ij} x_{ik} - x_{ik} x_{jk} = -1, \quad i, j, k \in [n], i < j < k, \quad (*) \\ & x_{ij} \in \{-1, 1\}, \quad i, j \in [n], i < j. \end{aligned}$$

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**Semidefinite** lifting up to the symmetric **matrix space**:

$$\min \{ \langle C, X \rangle : X \text{ satisfies } (*), \text{diag}(X) = e, X \succeq 0, \text{rank}(X) = 1 \},$$

where  $X = xx^\top$  with entries  $X_{ij,kl} = x_{ij} x_{kl}$ .

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$$\min \{ \langle C, X \rangle : X \text{ satisfies } (*), \text{ diag}(X) = e, X \succeq 0 \} \quad (\text{SDP}_0)$$

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- $\mathcal{O}(n^6)$  triangle inequalities can be added as cutting planes:

$$\begin{aligned} X_{i,j} + X_{i,k} + X_{j,k} &\geq -1, & 1 \leq i < j < k \leq \binom{n}{2} \\ X_{i,j} - X_{i,k} - X_{j,k} &\geq -1, & 1 \leq i < j < k \leq \binom{n}{2} \\ -X_{i,j} + X_{i,k} - X_{j,k} &\geq -1, & 1 \leq i < j < k \leq \binom{n}{2} \\ -X_{i,j} - X_{i,k} + X_{j,k} &\geq -1, & 1 \leq i < j < k \leq \binom{n}{2} \end{aligned}$$

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- interior-point methods (IPMs) require  $\mathcal{O}(n^9)$  time to solve  $(\text{SDP}_0)$
- Hungerländer & Rendl (2012, 2013):
  - additional 'matrix cuts'
  - partial Lagrangian approach
  - IPMs + bundle method  $\hookrightarrow$  nonsmooth optimization
  - instances with  $n \leq 42$  solved

# Strengthened Relaxation

- $\mathcal{O}(n^{10})$  pentagonal inequalities  $\sum_{1 \leq i < j \leq 5} \delta_i \delta_j X_{p_i, p_j} \geq -2, \quad \delta_k \in \{\pm 1\}$

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## Proposition

*The semidefinite relaxation ( $\text{SDP}_{\mathcal{P}^*}$ ) is at least as strong as the linear relaxation of the betweenness approach.*

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- heuristic separation for general pentagonal, hexagonal, and heptagonal inequalities



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$$\begin{aligned} \sup \quad & \left\{ -e^\top \lambda - e^\top \mu - \frac{\alpha}{2} \binom{n}{2}^2 - \frac{1}{2\alpha} \left\| [C + \mathcal{A}^\top(\lambda) + \mathcal{B}^\top(\mu)]_- \right\|_F^2 \right\} \\ \text{s.t.} \quad & \lambda \geq 0, \mu \text{ free} \end{aligned} \quad (\text{DSDP}_\alpha)$$

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- $[\cdot]_-$ : projection onto the cone of negative semidefinite matrices
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- $[\cdot]_-$ : projection onto the cone of negative semidefinite matrices
- $\|\cdot\|_F$ : Frobenius norm
- $(\text{DSDP}_\alpha)$  **convex** optimization problem with bound constraints
- objective function **differentiable**  $\hookrightarrow$  L-BFGS-B method
- usual SDP bound can be approximated with **arbitrary precision**

# Algorithmic Approach II

## Cutting plane approach:

- L-BFGS-B method can be warm-started
- $X_{\text{approx}} = -\frac{1}{\alpha} [C + \mathcal{A}^\top(\lambda) + \mathcal{B}^\top(\mu)]_-$

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## Implementation:

- C implementation
- BiqCrunch as template

# Results and Future Work

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  - solves **almost all** benchmark instances with up to  $n = 81$
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## Future work:

- branch-and-bound approach

# References

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