

Towards the Extremes:

The Best Scenario of an Interval Linear Program

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Interval Uncertainty

Interval-valued uncertainty stems from rounding, estimations, measurement errors, discretization, etc.

Definition

Given two matrices $\underline{A}, \bar{A} \in \mathbb{R}^{m \times n}$ with $\underline{A} \leq \bar{A}$, we define an interval matrix $[A] = [\underline{A}, \bar{A}]$ as the set

$$\{A \in \mathbb{R}^{m \times n} : \underline{A} \leq A \leq \bar{A}\}.$$

For example $[A] = \begin{pmatrix} [0, 1] & 2 \\ [3, 5] & [-1, 1] \end{pmatrix}$ or $[b] = \begin{pmatrix} [1, 2] \\ [0, 3] \\ [1, 2] \end{pmatrix}$.

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(interval box)

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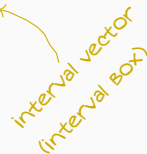
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Given $[A] \in \mathbb{IR}^{m \times n}$, $[b] \in \mathbb{IR}^m$, we define an **interval linear system** of inequalities

$$[A]x \leq [b]$$

as the set of all systems $Ax \leq b$ with $A \in [A]$, $b \in [b]$.

Usually, we consider **weakly feasible solutions**, i.e. solutions that are feasible for at least one scenario $Ax \leq b$ of the interval system.

The weakly feasible set is not convex in general!
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Interval Linear System: An Example

For example, consider the interval linear system of equations:

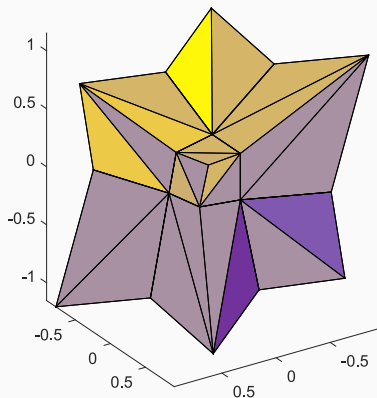
$$\begin{pmatrix} 5 & [1, 2] & 1 \\ [1, 2] & 5 & [0, 2] \\ [1, 4] & [0, 2] & 5 \end{pmatrix} x = \begin{pmatrix} [-2, 2] \\ [-2, 2] \\ [-2, 2] \end{pmatrix}$$

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...and its weakly feasible set.



Definition

Given $[A] \in \mathbb{IR}^{m \times n}$, $[b] \in \mathbb{IR}^m$, $[c] \in \mathbb{IR}^n$, we define an **interval linear program** (in the standard form)

$$\text{minimize } [c]^T x \text{ subject to } [A]x = [b], x \geq 0$$

as the set of all linear programs in the form minimize $c^T x$ subject to $Ax = b, x \geq 0$ with $A \in [A]$, $b \in [b]$, $c \in [c]$.

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Optimal Value Range

An interval linear program can have different “optimal” values

$$f(A, b, c) = \inf \{c^T x : Ax = b, x \geq 0\}$$

we allow infinite values

throughout the different scenarios with $A \in [A]$, $b \in [b]$, $c \in [c]$.

We are usually interested in the **optimal value range**, which is the interval $[\underline{f}, \bar{f}]$ with the extremal optimal values

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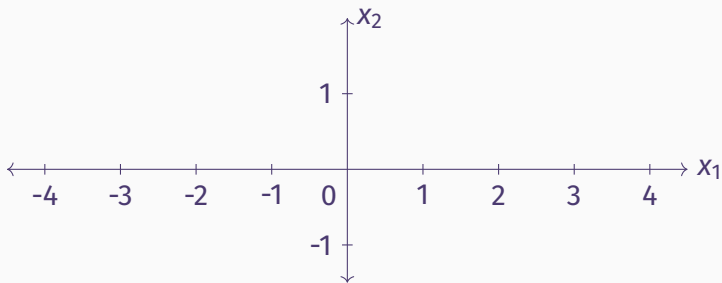
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$$\begin{array}{ll} \text{maximize} & x_2 \\ \text{subject to} & [-1, 1]x_1 + x_2 \leq 0 \\ & x_2 \leq 1 \end{array}$$

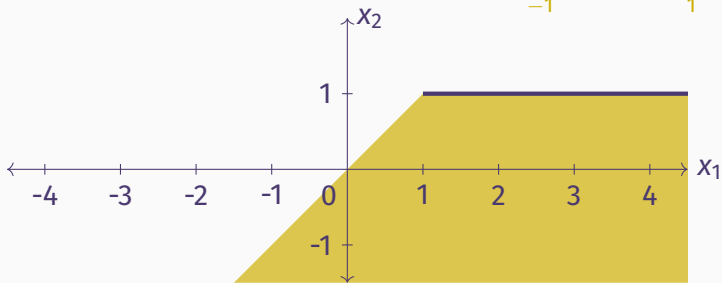


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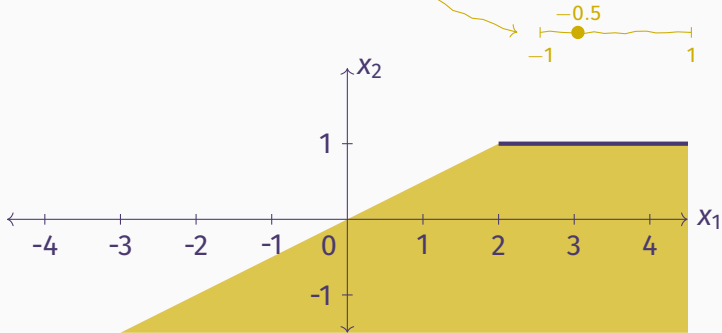
Let's traverse through this!



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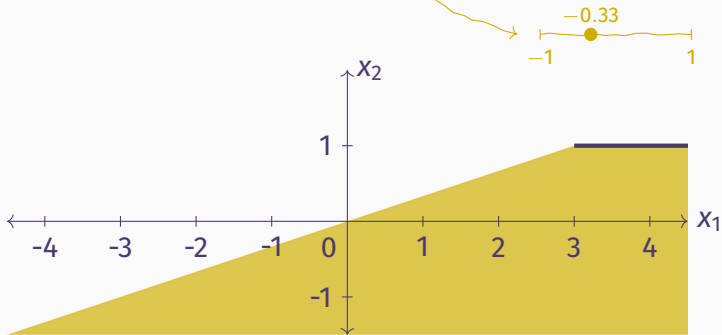
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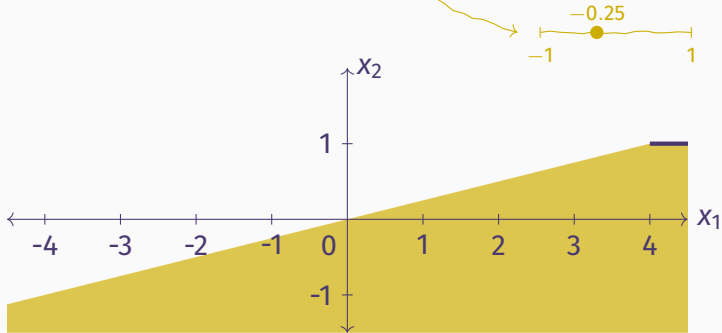
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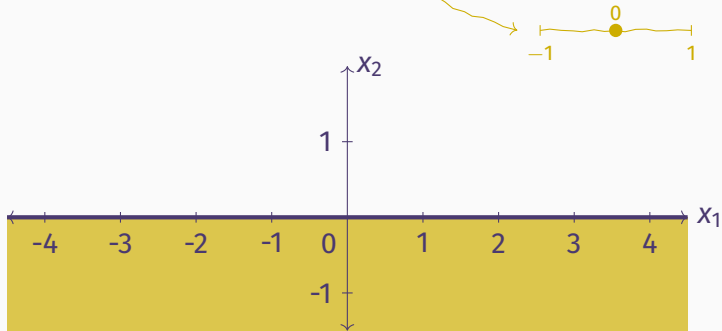
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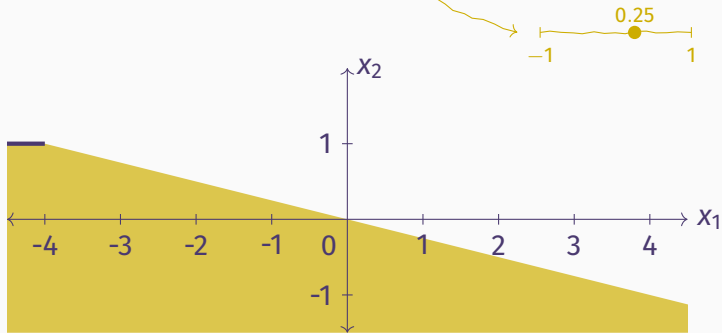
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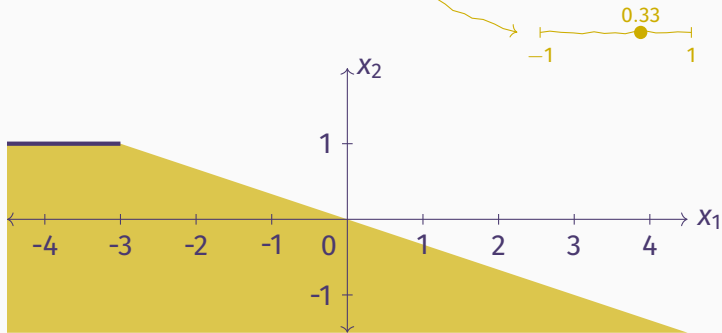
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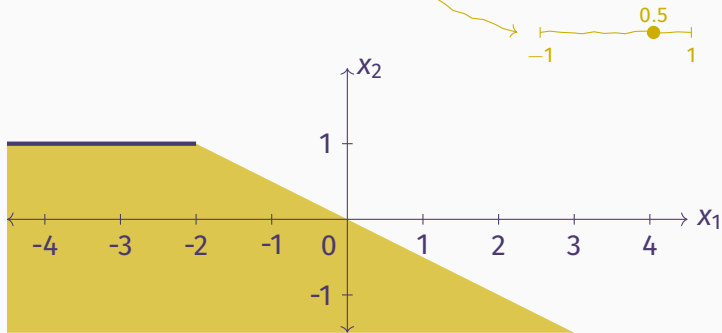
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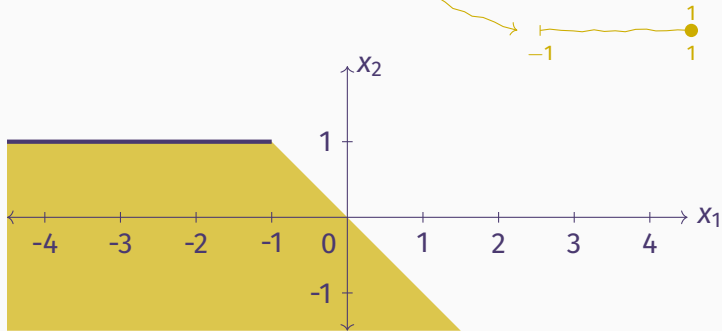
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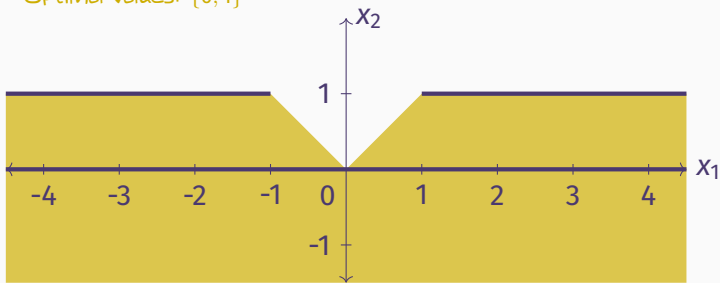
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Optimal values: $\{0, 1\}$



Theorem (Rohn, 1984; Mráz, 1998)

The upper bound \bar{f} on the optimal value range (i.e. the worst optimal value) can be computed as

$$\bar{f} = \sup_{s \in \{\pm 1\}^m} f(A_c - \text{diag}(s)A_\Delta, b_c + \text{diag}(s)b_\Delta, \bar{c}),$$

where $A_c = \frac{1}{2}(\bar{A} + \underline{A})$ and $A_\Delta = \frac{1}{2}(\bar{A} - \underline{A})$.

extremal scenarios



We also obtain the corresponding worst scenario:

$$A_c - \text{diag}(s)A_\Delta \in [A]$$

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The best optimal value \underline{f} can be found by optimizing over the set of all weakly feasible solutions.

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This is not a scenario of $[A]x = [b], x \geq 0$.

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Let $f([A], [b], [c])$ be finite and let x^* be an optimal solution of the problem $\min \underline{c}^T x : \underline{A}x \leq \bar{b}, \bar{A}x \geq \underline{b}, x \geq 0$. Then, we have

$$\underline{f}([A], [b], [c]) = f(A_c - \text{diag}(s)A_\Delta, b_c + \text{diag}(s)b_\Delta, \underline{c}),$$

where

$$s_i = \begin{cases} \frac{(A_c x^* - b_c)_i}{(A_\Delta x^* + b_\Delta)_i}, & \text{if } (A_\Delta x^* + b_\Delta)_i > 0, \\ 1, & \text{if } (A_\Delta x^* + b_\Delta)_i = 0. \end{cases}$$

Since $s \notin \{\pm 1\}^m$, in general, this is not an extremal scenario.
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Let the problem

$$\max \underline{b}^T p_1 - \bar{b}^T p_2 : \bar{A}^T p_1 - \underline{A}^T p_2 \leq \underline{c}, p_1 \geq 0, p_2 \geq 0$$

have an optimal solution p_1^*, p_2^* satisfying $p_1^* + p_2^* > 0$. Then $f([A], [b], [c]) = f(A_c - \text{diag}(s)A_\Delta, b_c + \text{diag}(s)b_\Delta, \underline{c})$, where

$$s_i = \begin{cases} 1 & \text{if } (p_2^*)_i > 0, \\ -1 & \text{if } (p_2^*)_i = 0. \end{cases}$$

In this case, we have an extremal Best scenario.

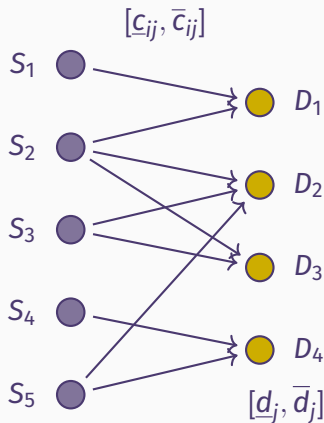
Interval Transportation Problem (ITP)

$$\text{minimize } \sum_{i,j} [c_{ij}, \bar{c}_{ij}] x_{ij}$$

$$\text{subject to } \sum_j x_{ij} = [\underline{s}_i, \bar{s}_i] \quad \forall i$$

$$\sum_i x_{ij} = [\underline{d}_j, \bar{d}_j] \quad \forall j$$

$$x_{ij} \geq 0 \quad \forall i, j$$



m supply nodes

n demand nodes

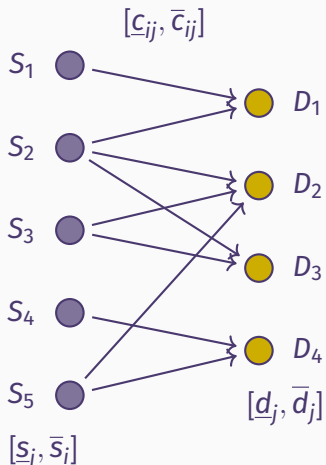
For the best scenario, we can fix $c = \underline{c}$, since we have $x \geq 0$.

We can also rewrite the interval problem as a linear program:

$$\begin{array}{ll}
 \text{minimize} & \sum_{i,j} \underline{c}_{ij} x_{ij} \\
 \text{subject to} & \underline{s}_i \leq \sum_j x_{ij} \leq \bar{s}_i, \quad \forall i, \\
 & \underline{d}_j \leq \sum_i x_{ij} \leq \bar{d}_j, \quad \forall j, \\
 & x_{ij} \geq 0, \quad \forall i, j.
 \end{array}$$

$\sum_j x_{ij} = [\underline{s}_i, \bar{s}_i]$
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Assume we have $\underline{s}, \underline{d} > 0$.

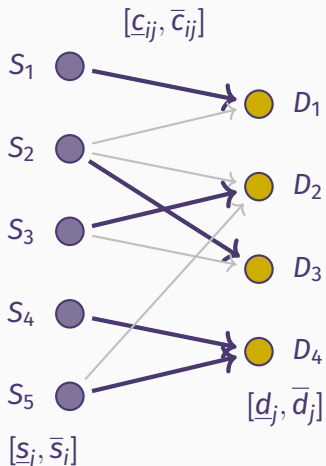


Then $x_{ij} > 0$ holds for at least $\max\{m, n\}$ variables x_{ij} , since we have to satisfy all suppliers and customers.

\Rightarrow At most $2m + 2n - \max\{m, n\}$ slacks of the inequalities are non-zero in a (basic) solution, and at least $\max\{m, n\}$ slacks are zero.

Thus, we have at least $\max\{m, n\}$ extremal values s_i, d_i in the best scenario of ITP.

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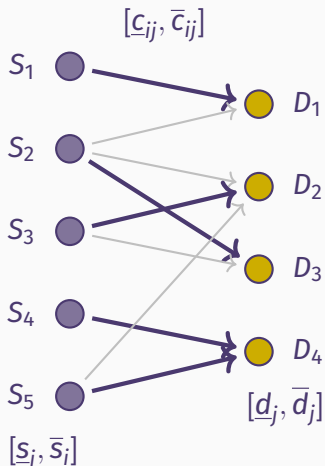


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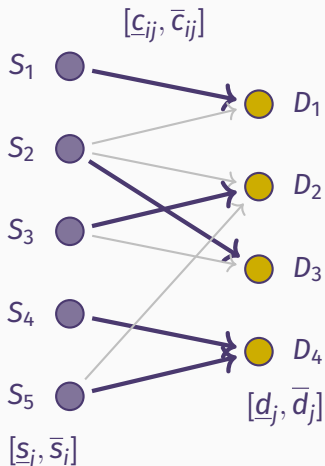


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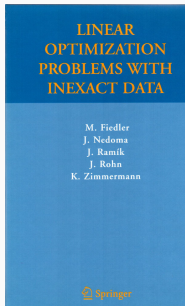
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- We considered the interval linear programming problem of computing the **optimal value range** and the corresponding **best and worst scenarios**.
- For interval programs in standard form, we can find an **extremal worst-case scenario**, in which all coefficients are set to their respective bounds.
- For the **best case**, this is not true, in general. Therefore, we study the extremal structure of the best scenario. For the special case of an **interval transportation problem**, we have derived a bound on the number of extremal coefficients.

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in Theory and Applications.

Chapter 2

INTERVAL LINEAR PROGRAMMING: A SURVEY

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Abstract

Interval linear programming is presented. This is equivalent either to set based integer programming or to linear programming with interval data. Using interval arithmetic, the dual feasibility theory, in particular, may be done efficiently. Duality may be handled in various ways, e.g. by weakly programming, interval analysis or basic analysis, and of course by simple and dual. In this paper, we report on the progress and open issues in the field and the questions that remain independent and unsatisfactory within this branch. In this field we investigate the problems of optimization theory, how solving regular set based problems, duality etc. Completely new are discussed, how can we use an algorithmically weak model and so on.

This approach is more general and powerful than the standard optimization analysis, in integer analysis, we consider systems of only one parameter, which is very common. In the other hand, interval analysis, based approach makes it harder understanding of integer problems. We present a brief overview of the latest results with new insights and directions for some challenging problems.

MSC: 90C45, 52B15, 90C30. **Keywords:** Interval linear programming.

Keywords: Linear interval analysis, linear programming, interval analysis, optimal value range, interval matrix, basic feasibility, AMS Subject Classification: 90C45, 90C30, 52B15.

1. Introduction

Many practical problems are solved by linear programming. Since real life problems are subject to some fluctuations in terms, measurements and estimations, we have to include in it

