Approximation Algorithms

Lecture 4:
Linear Programming and LP-Duality

Part I:
Introduction to Linear Programming

Philipp Kindermann

Summer Semester 2020

Maximizing Profits

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Which choice of (x_1, x_2) maximizes the profit?

Solution

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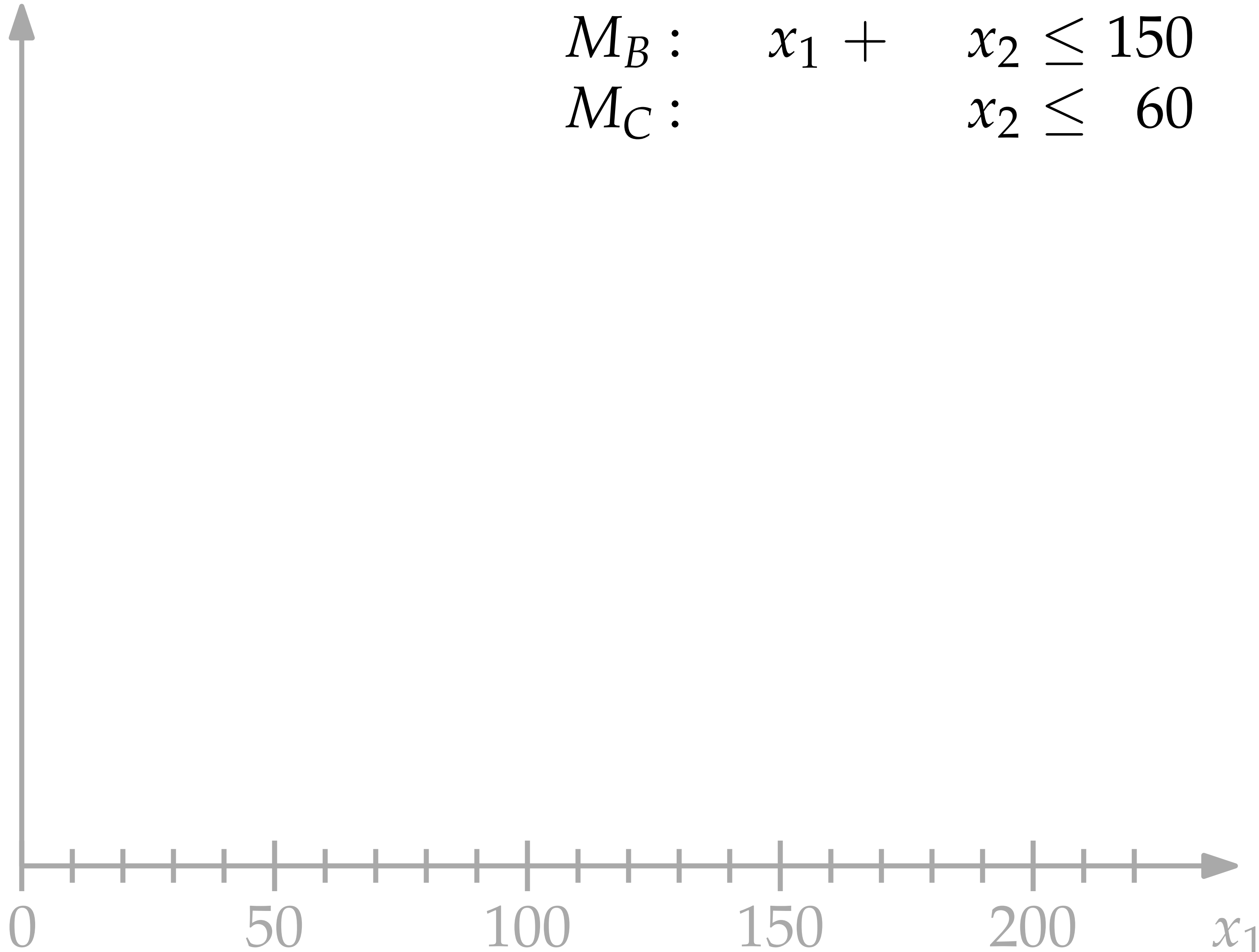

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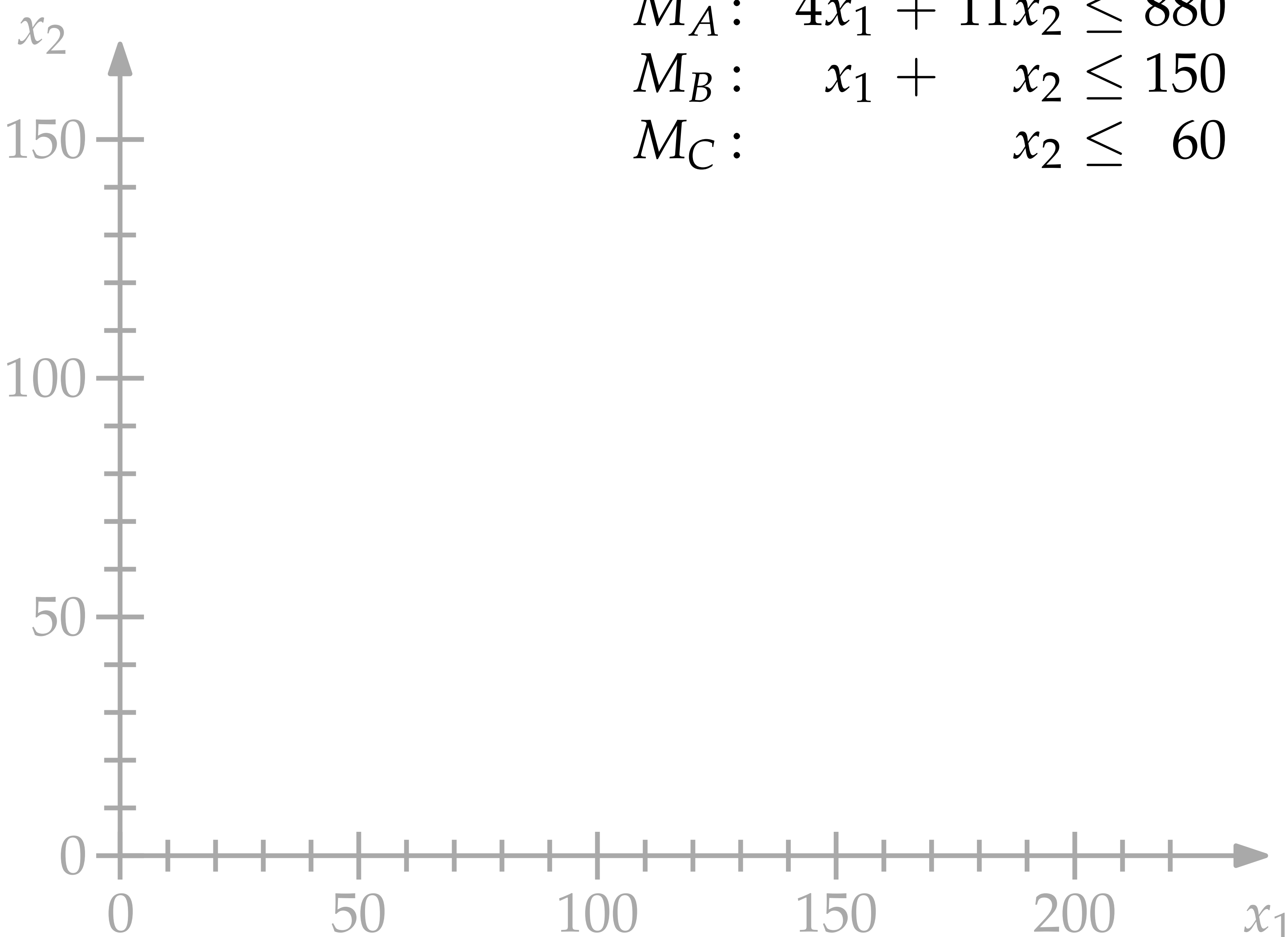

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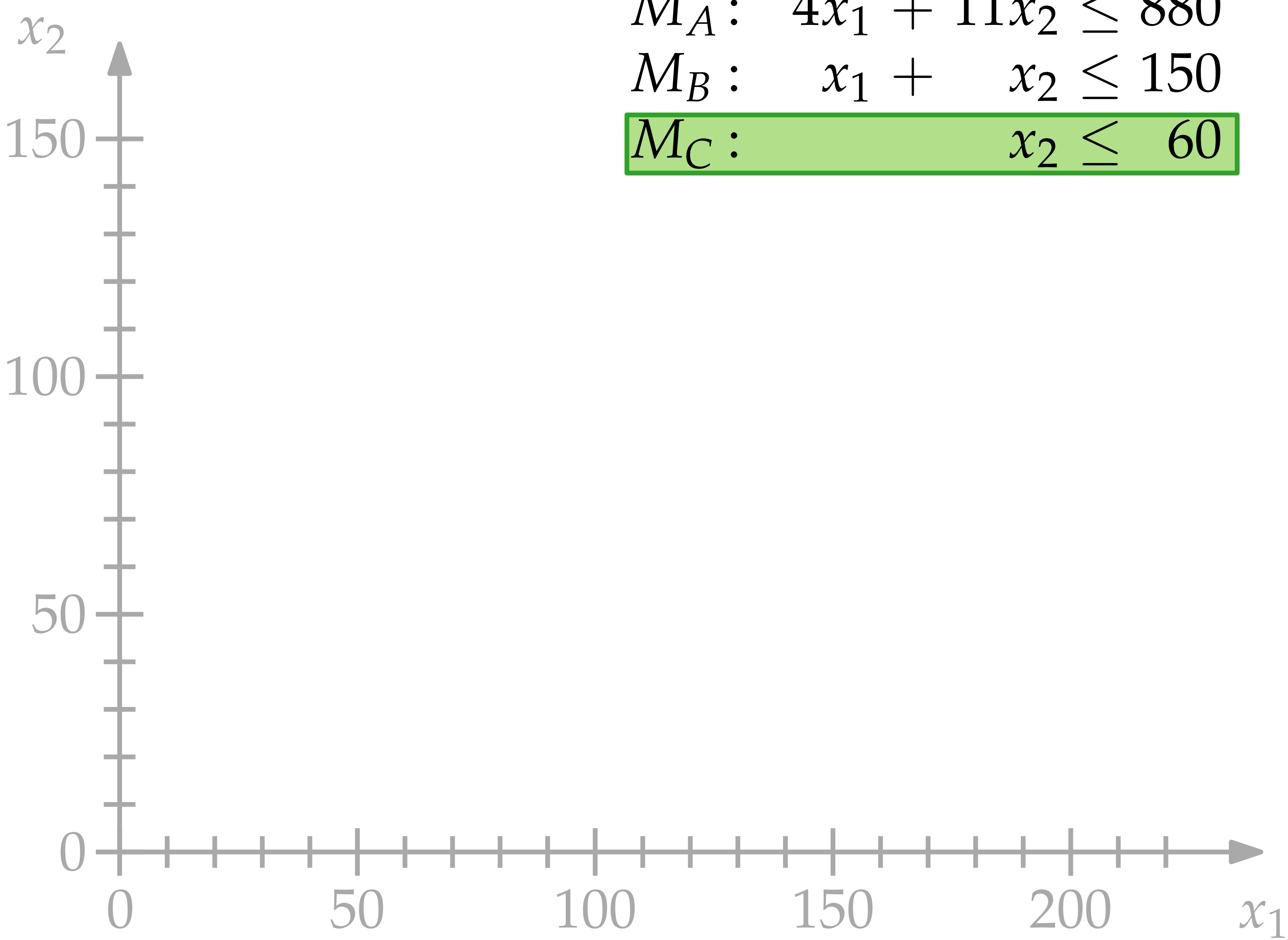

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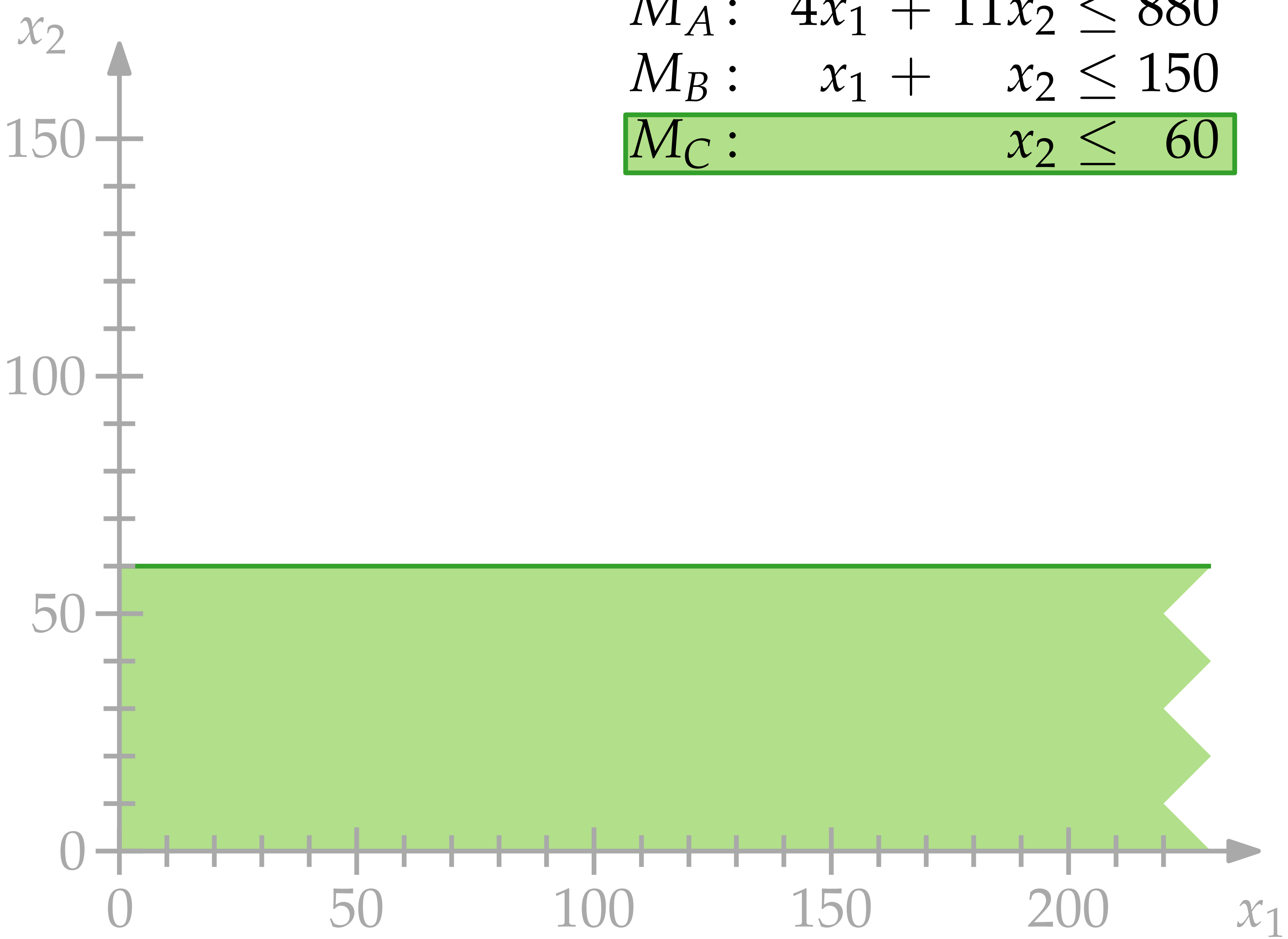

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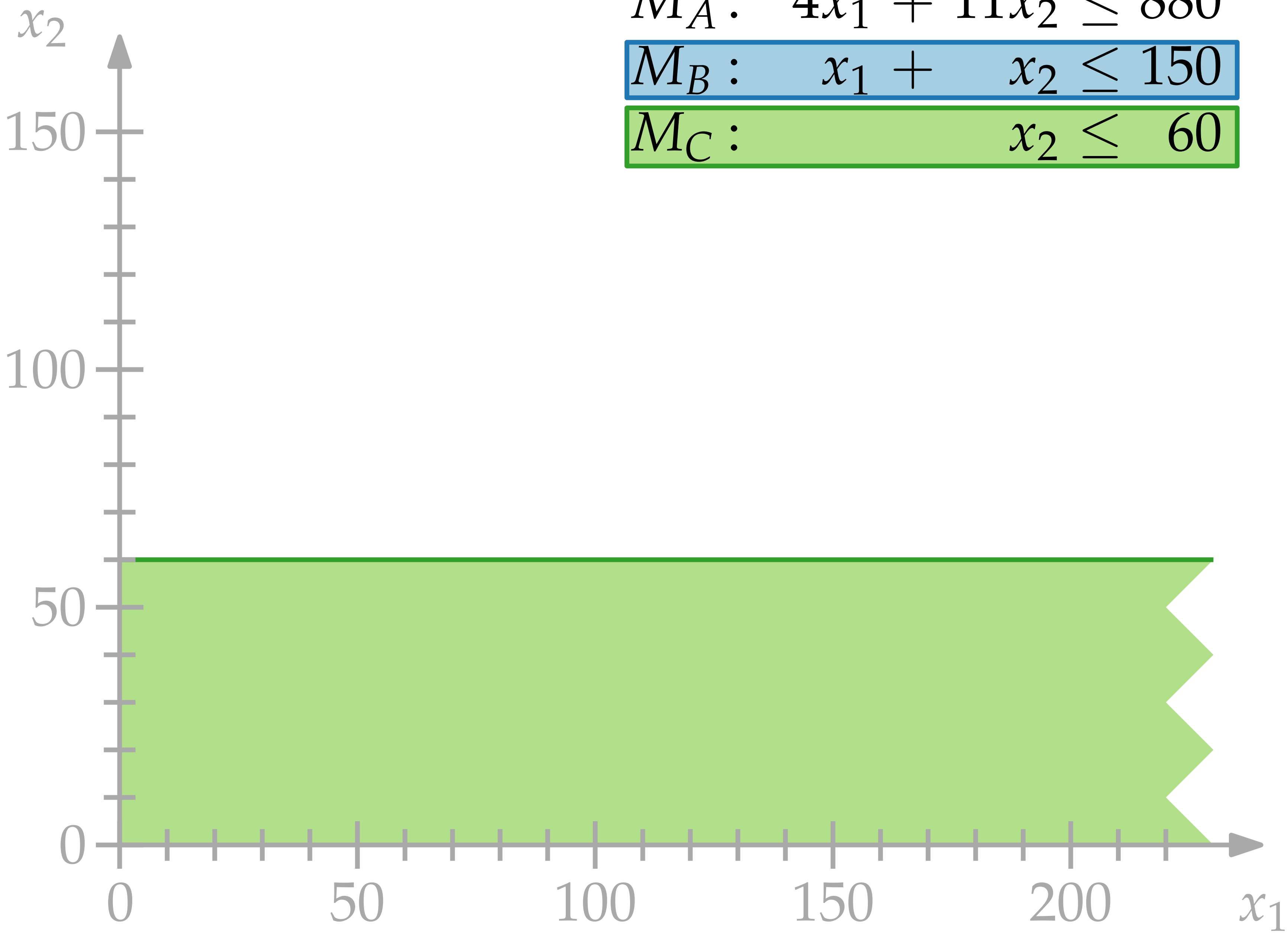

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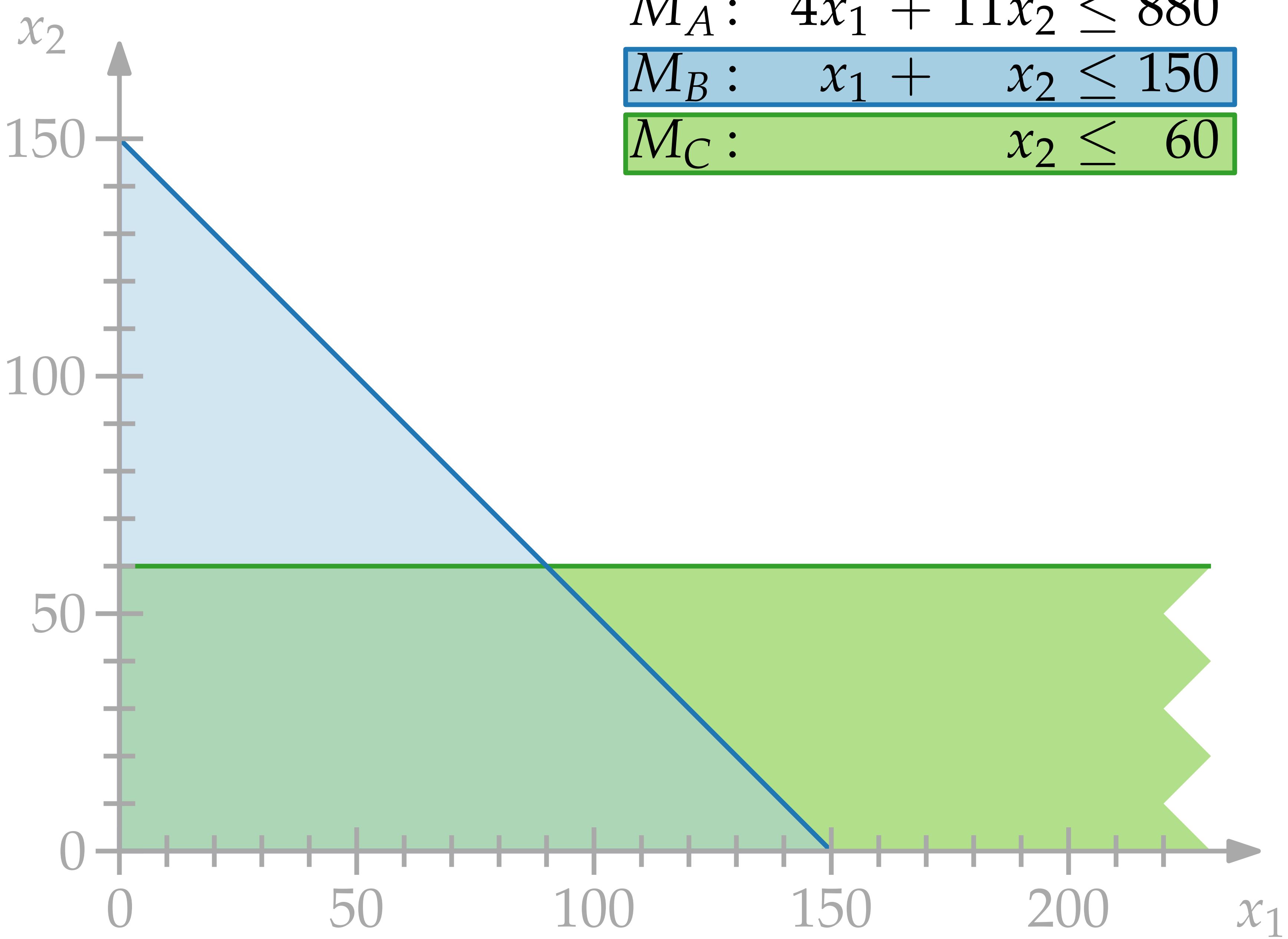

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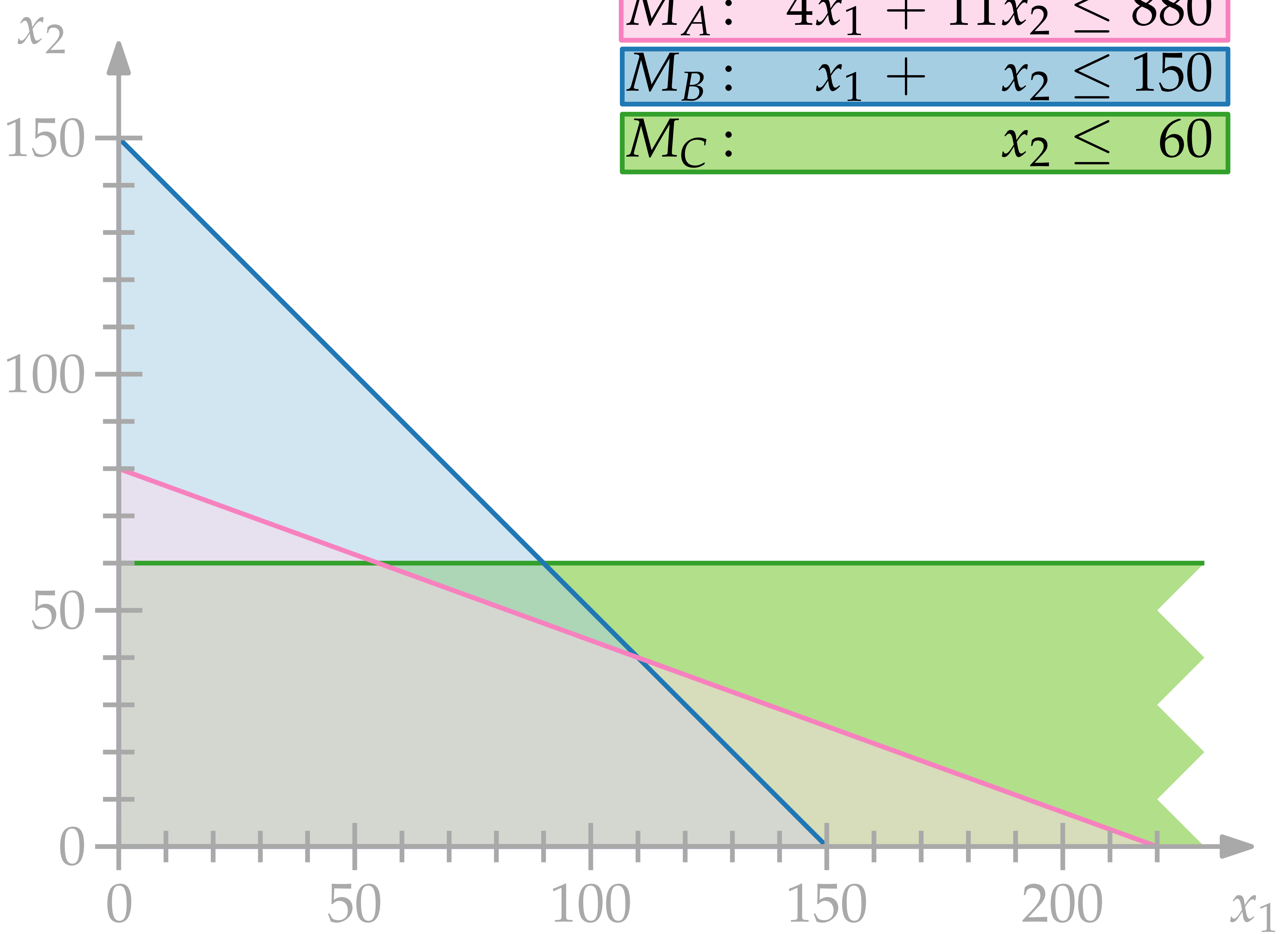

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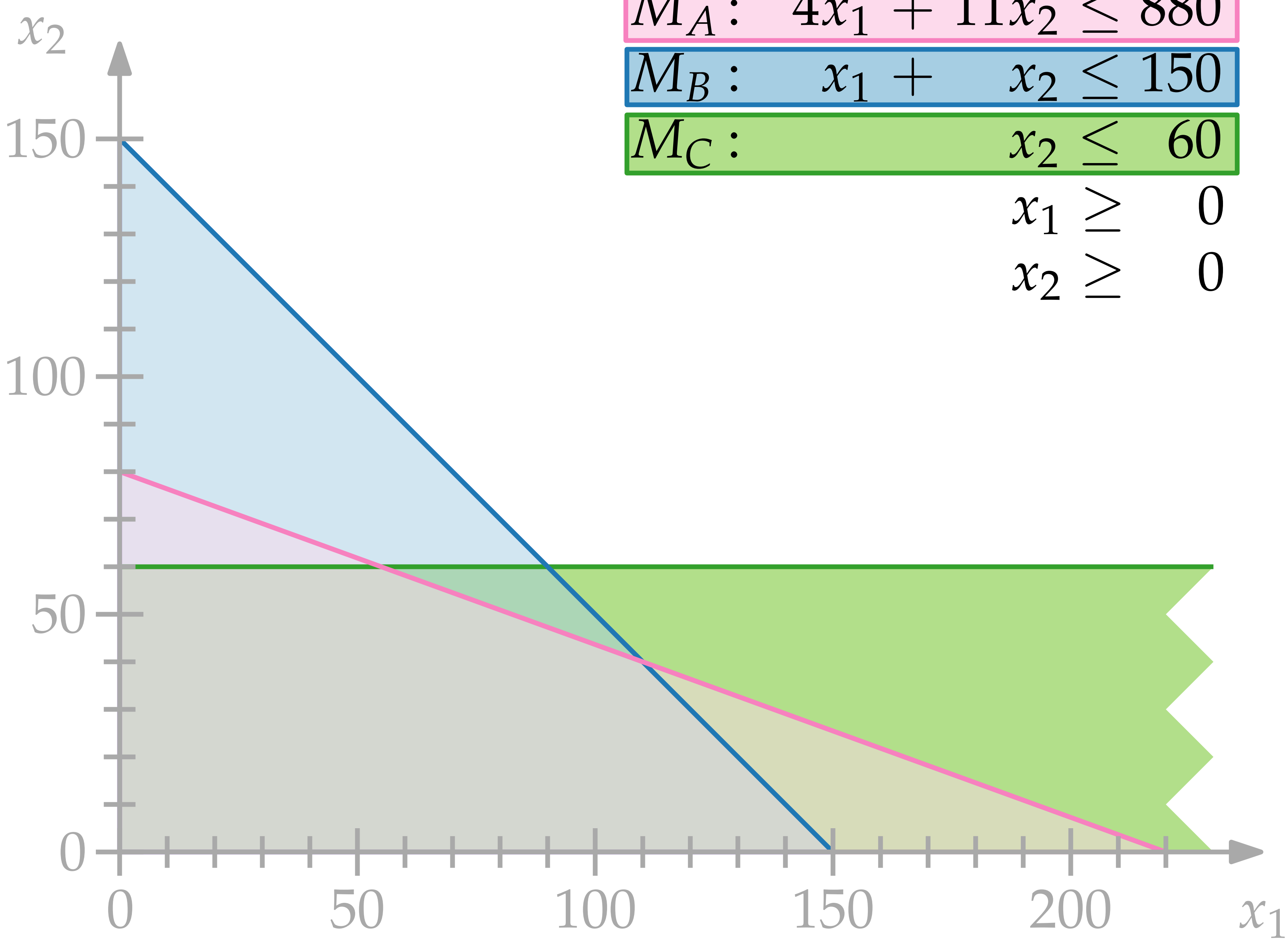

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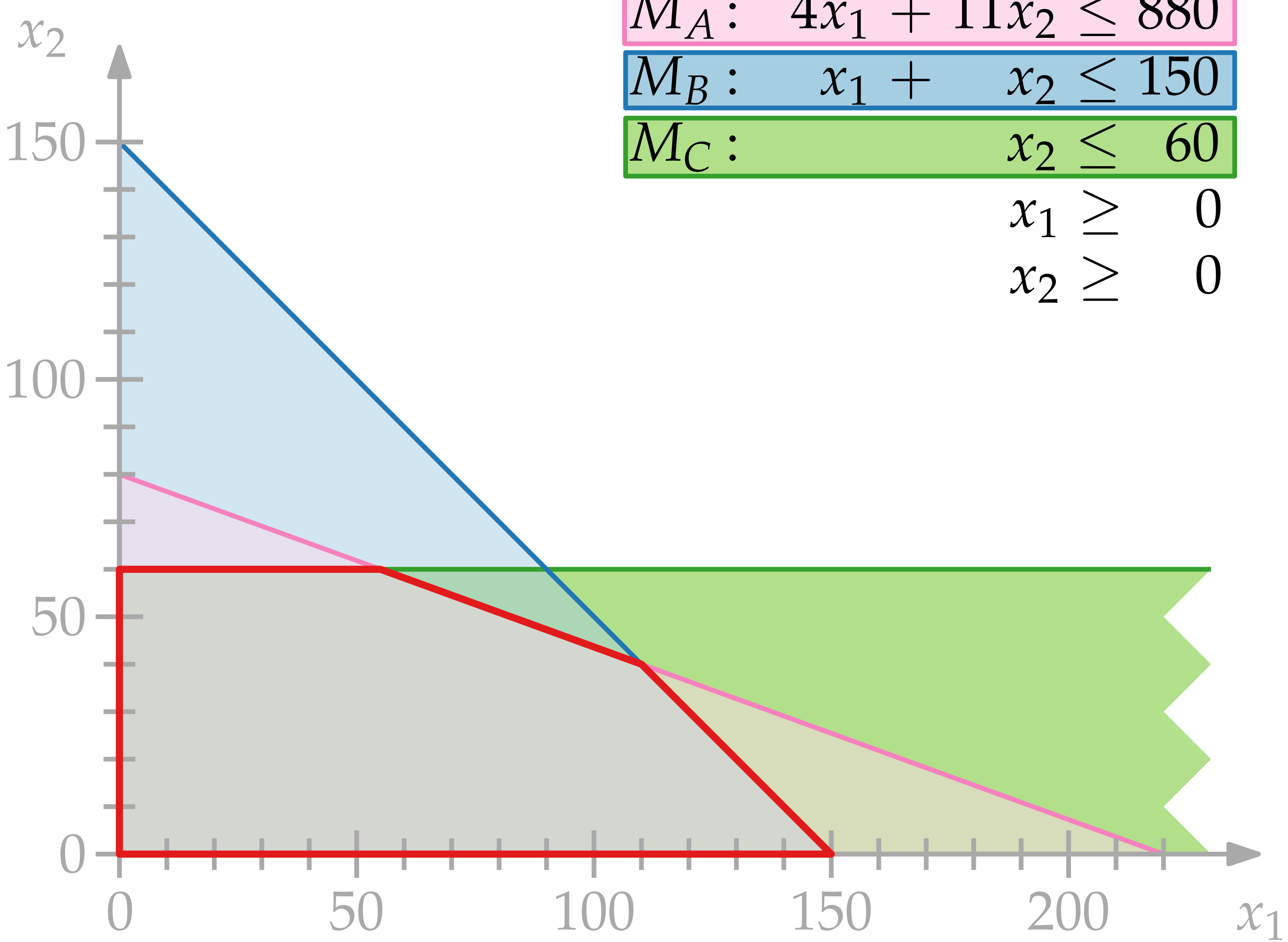

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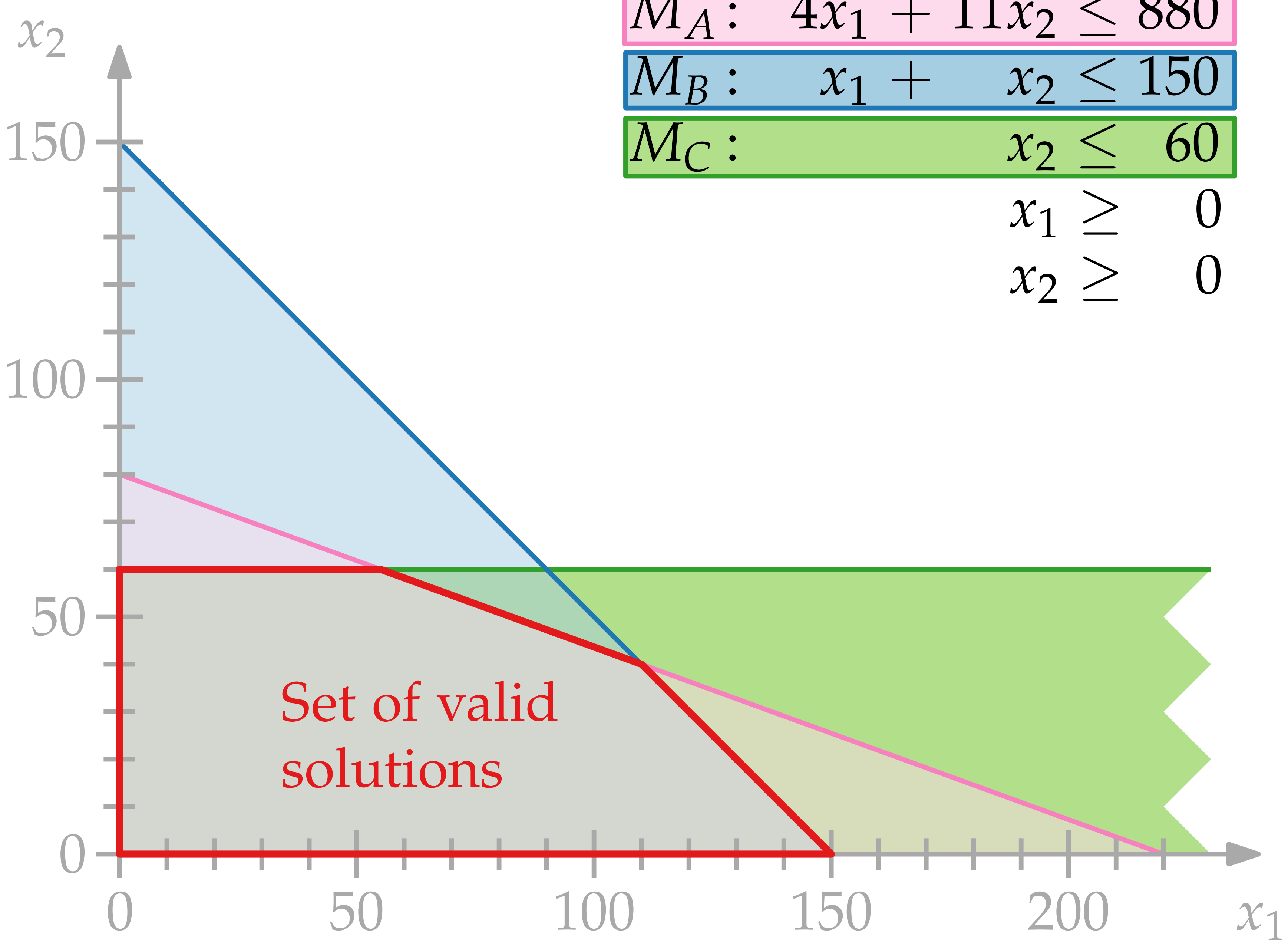

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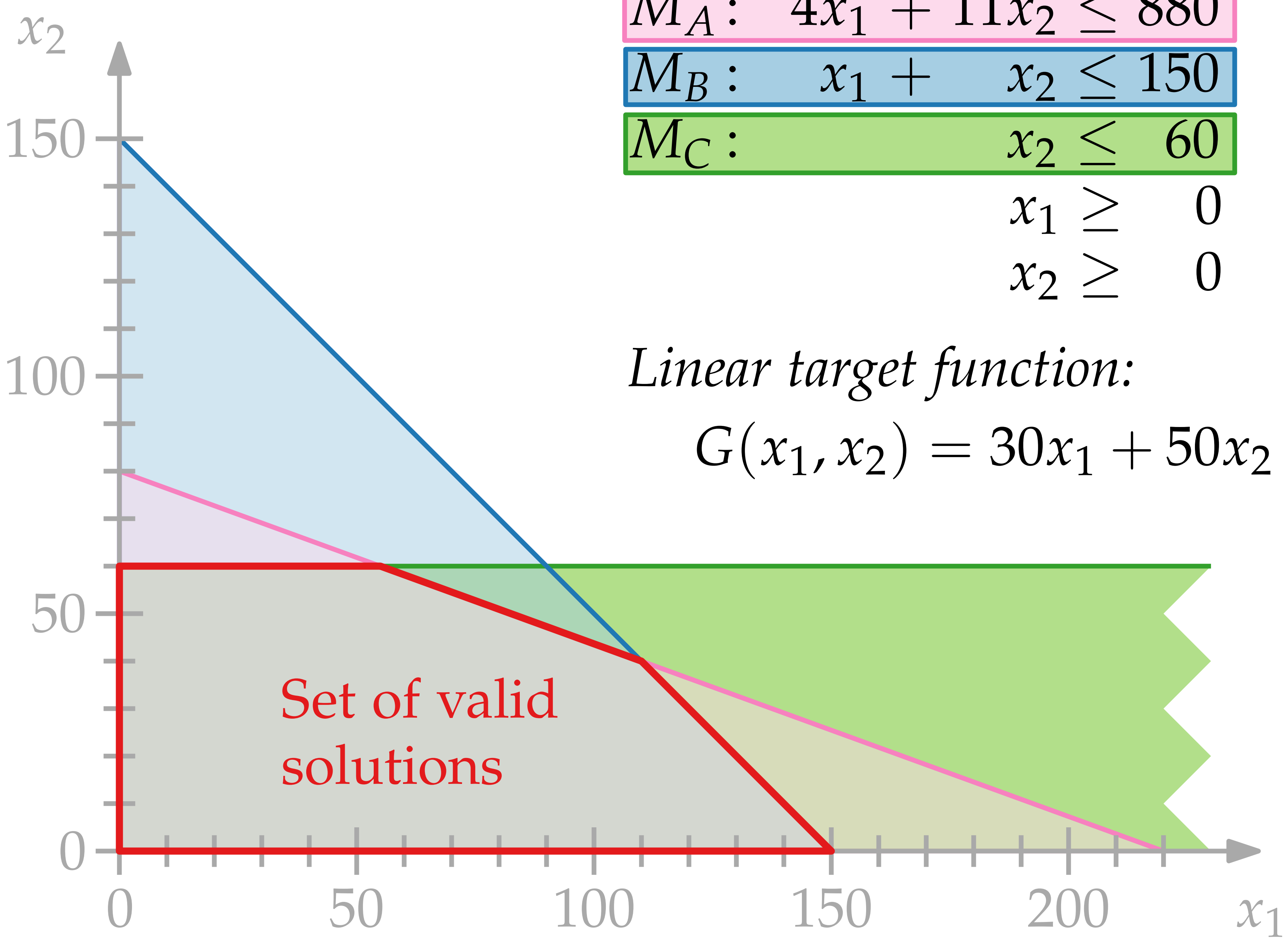

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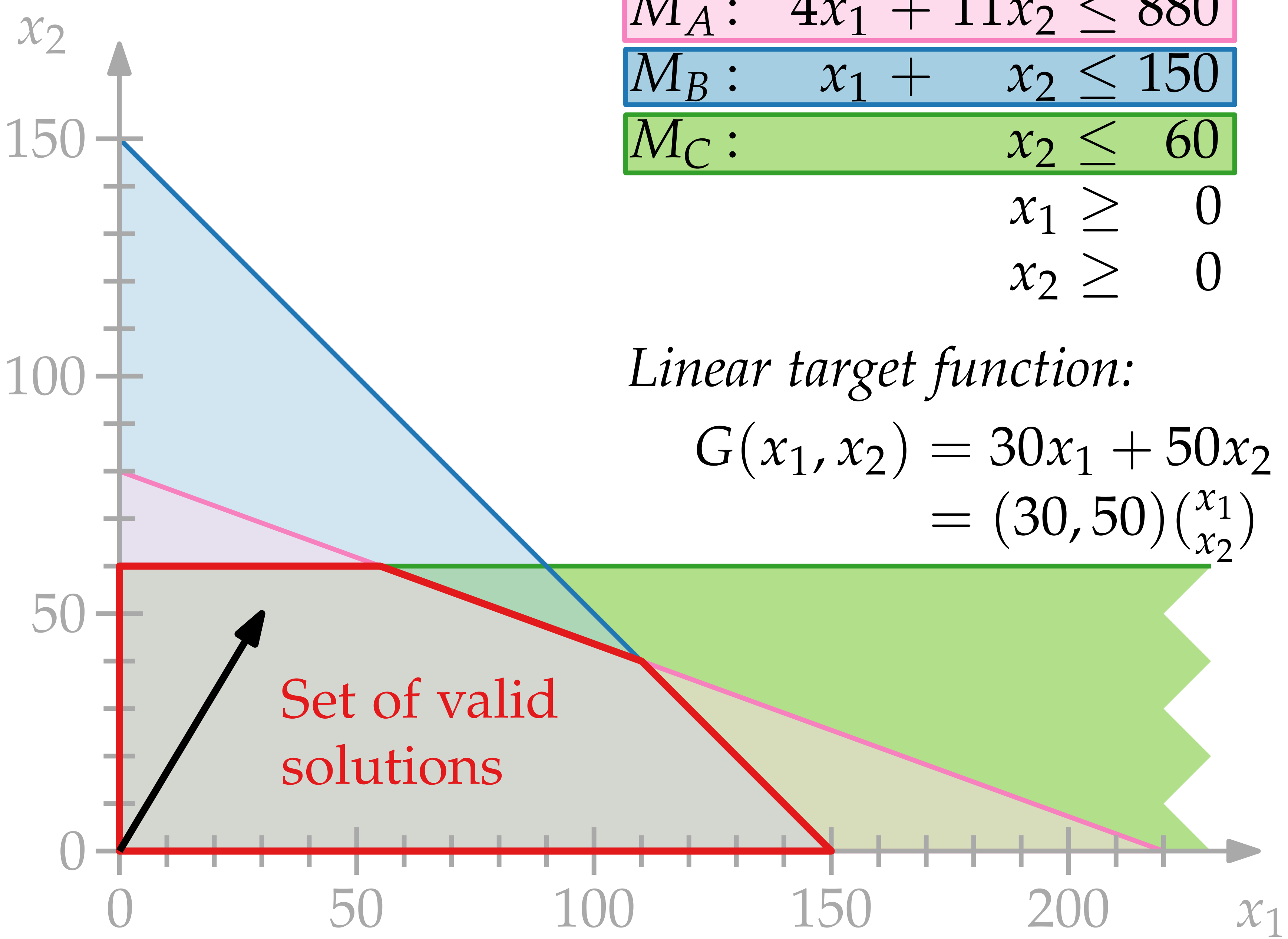

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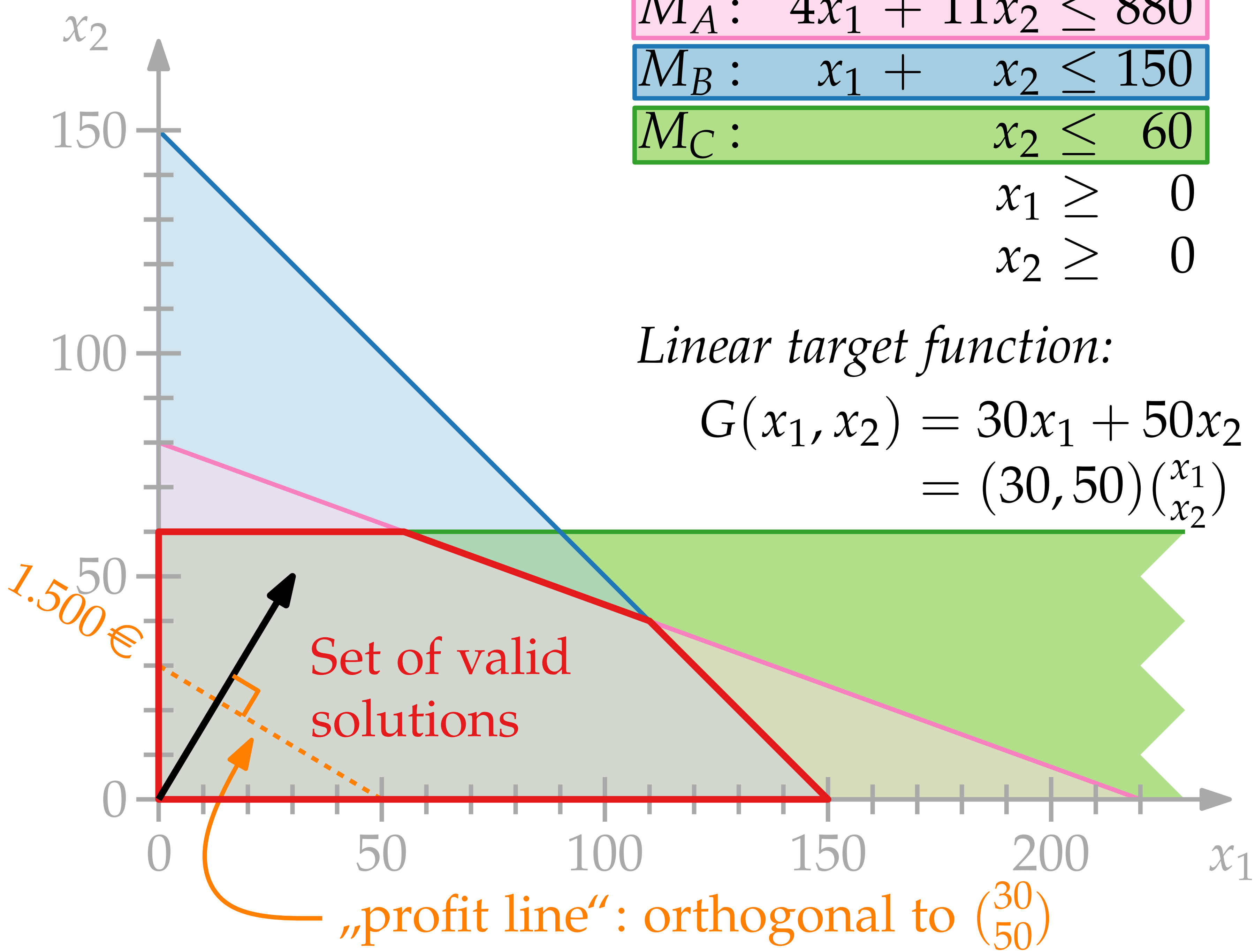

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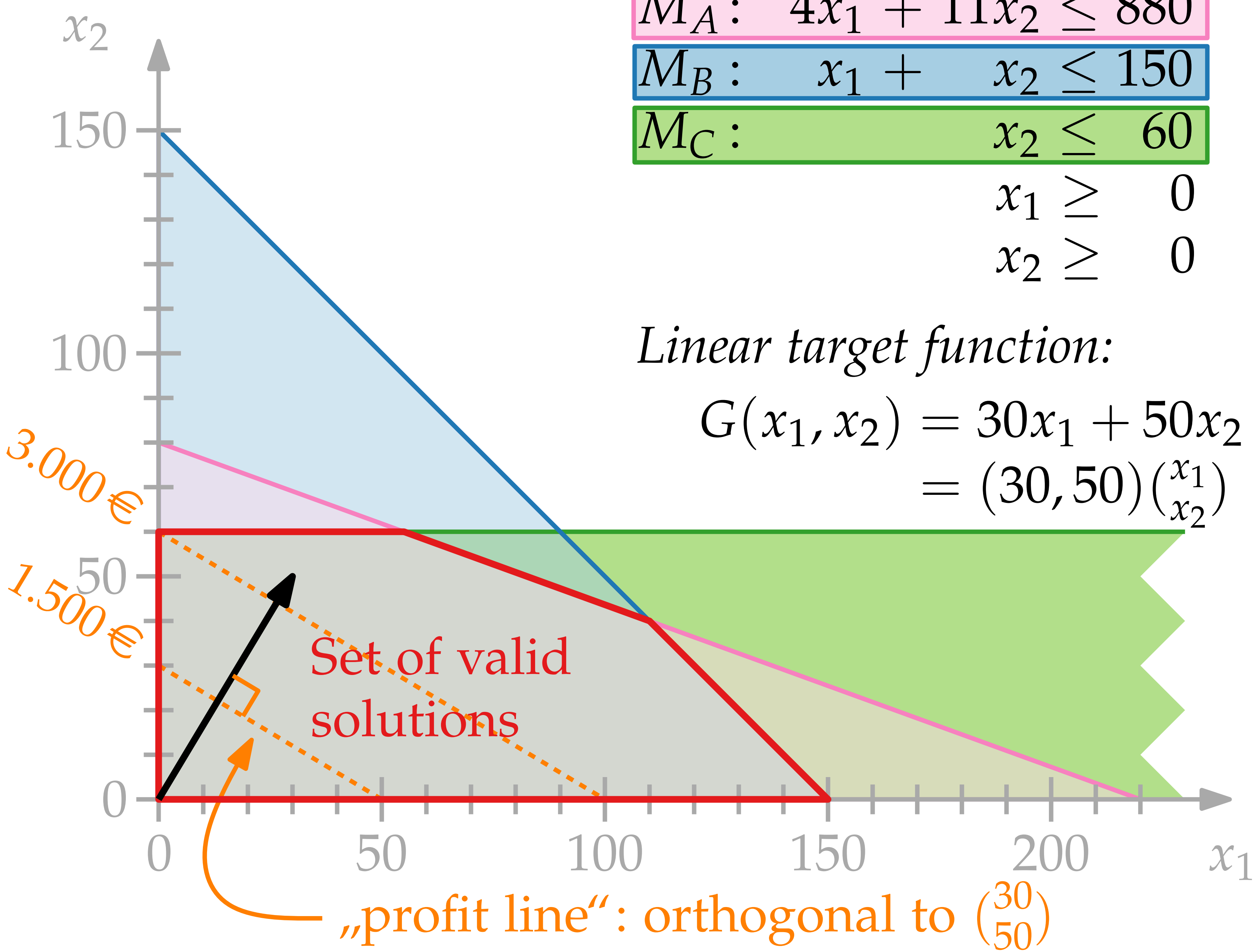

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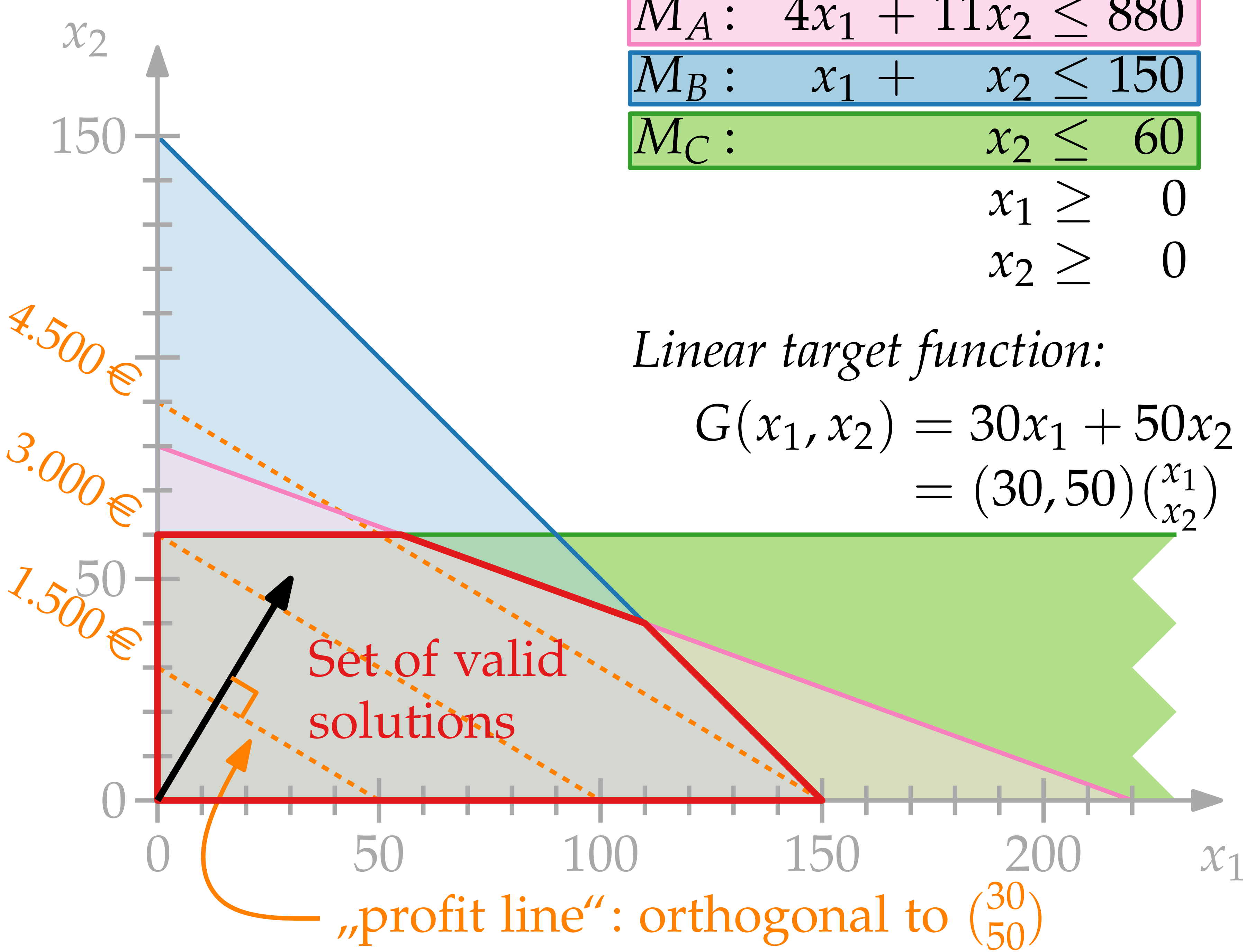

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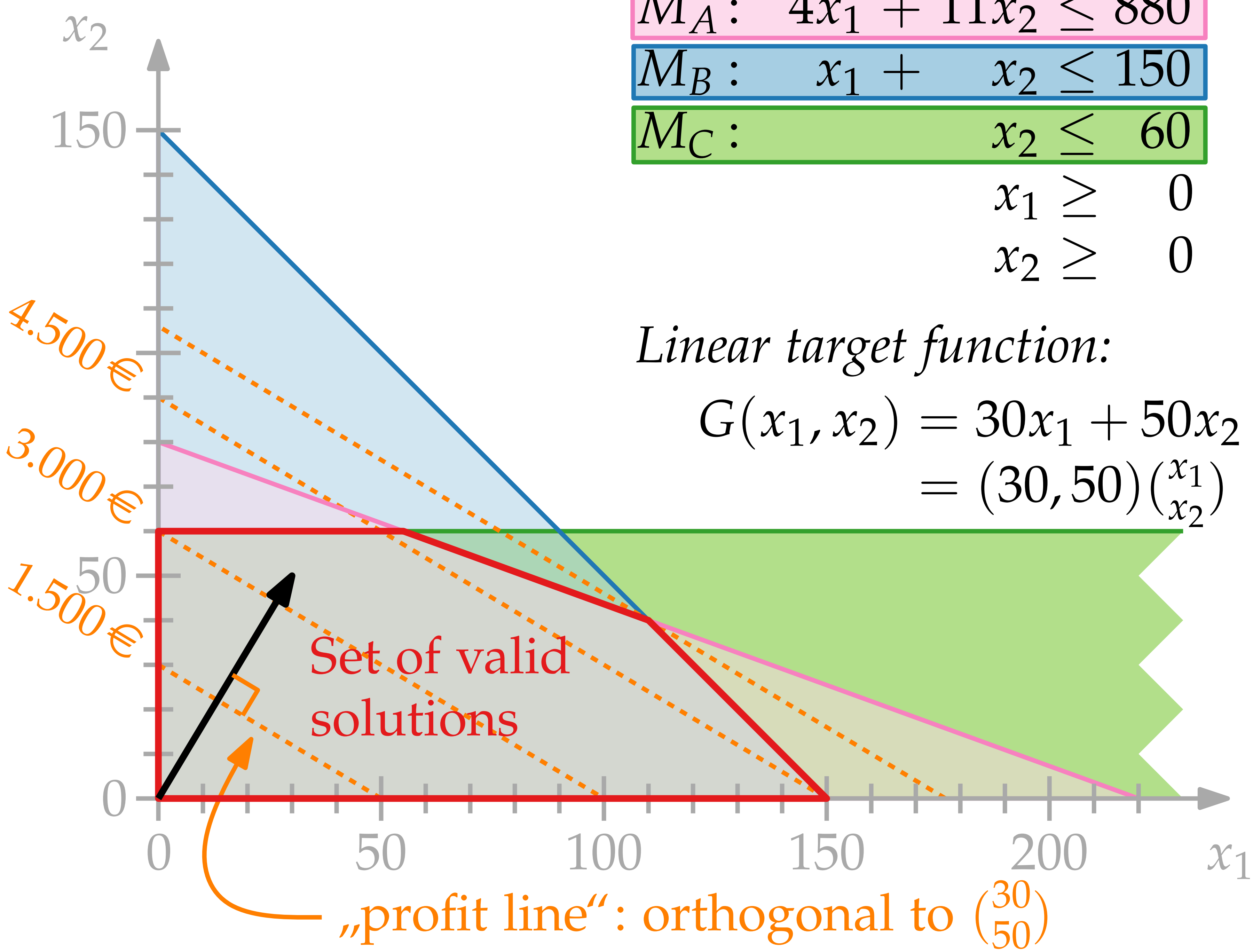

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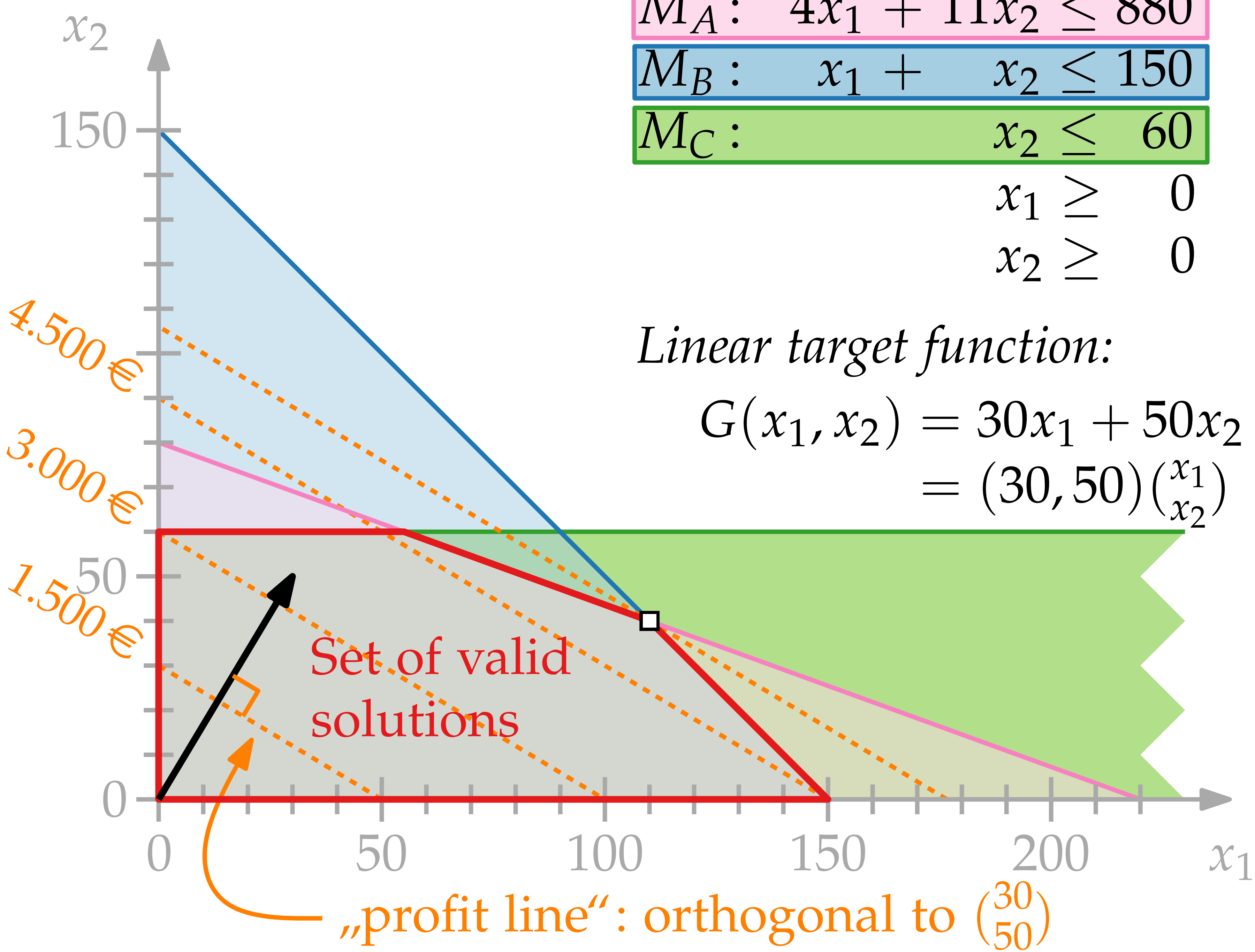

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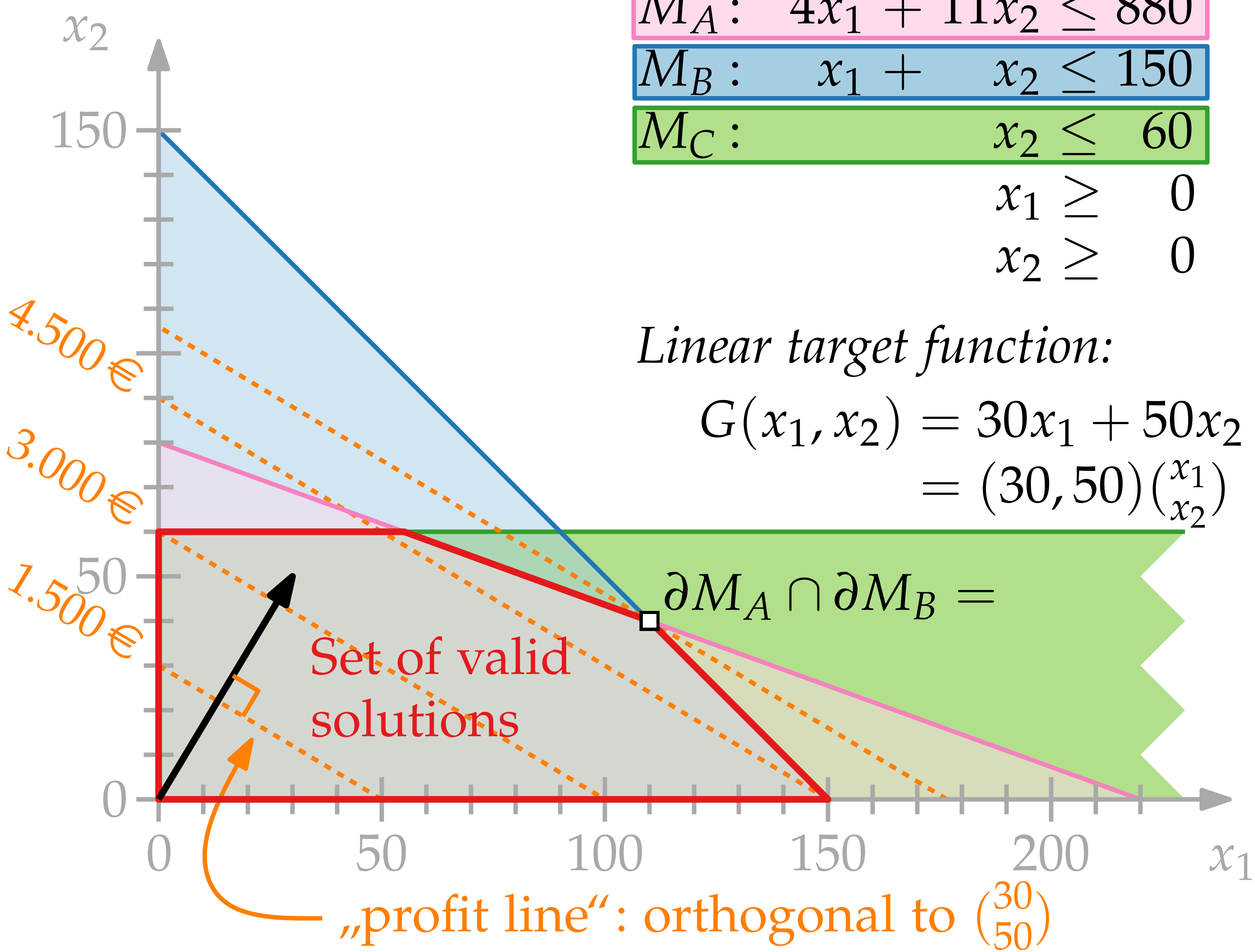

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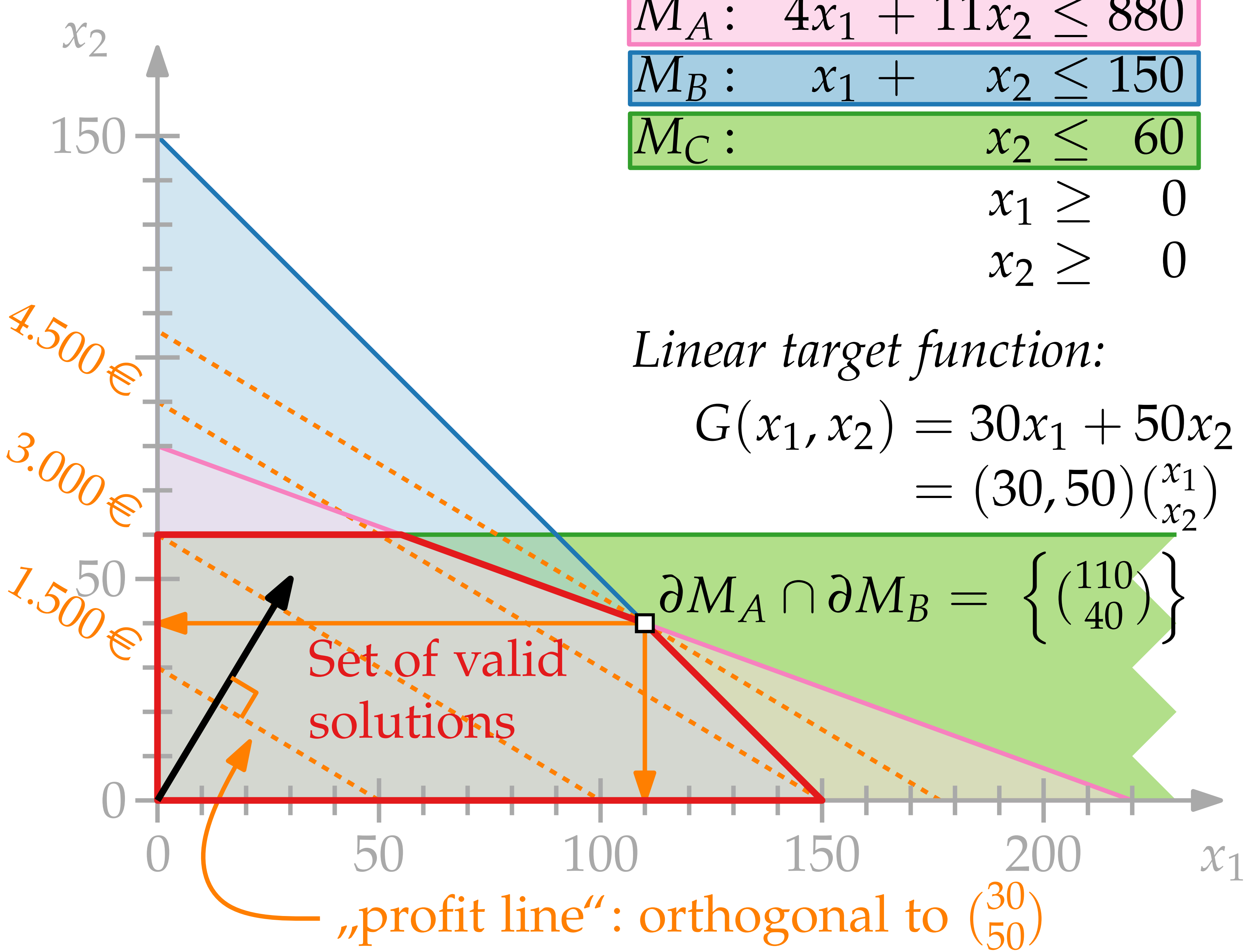

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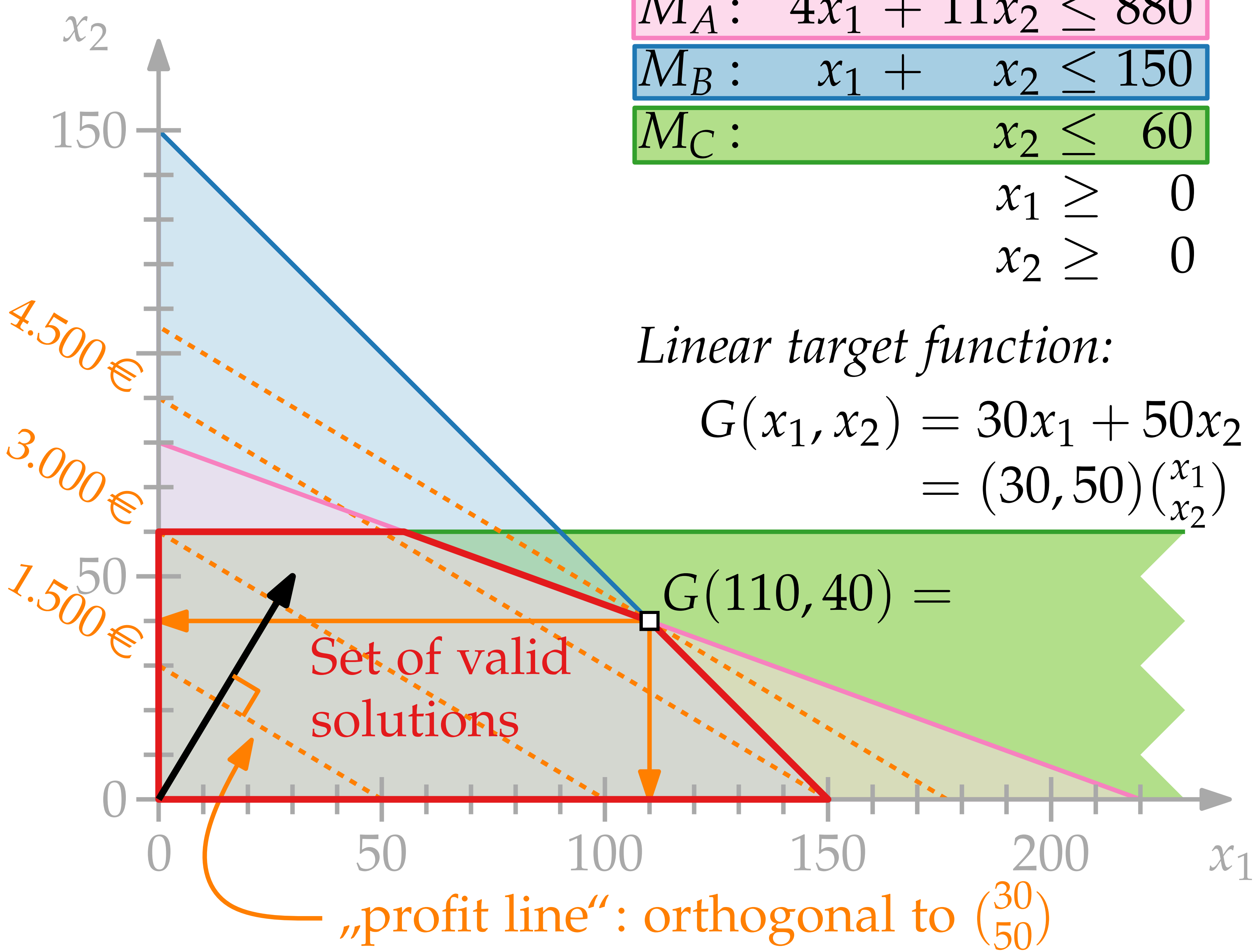

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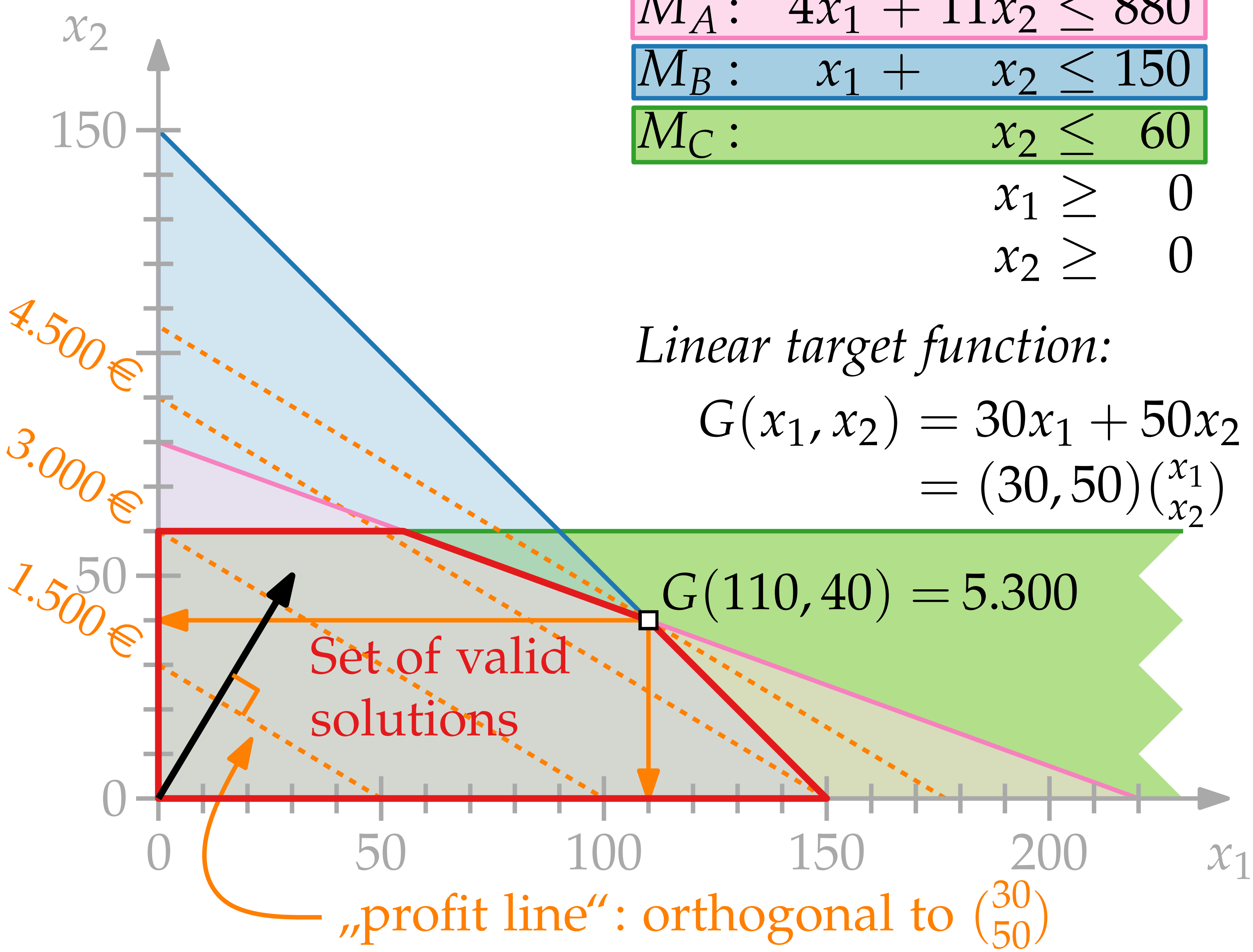

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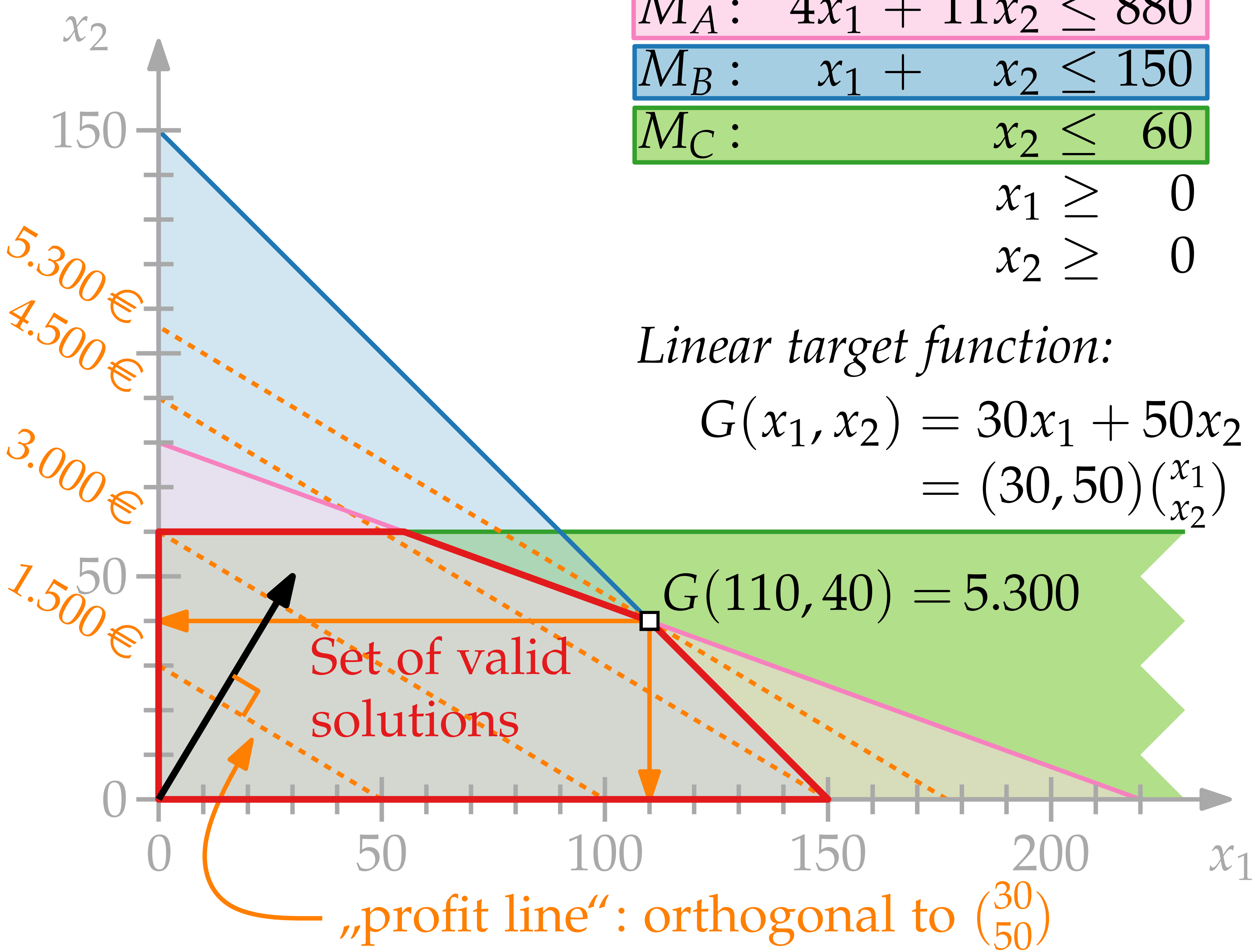

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Part II:
Upper Bounds for LPs

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Motivation: Upper and Lower Bounds

Consider hard NP-Minimization Problem.

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Decision Problem:
For given S, is $\mathrm{obj}(S)$ an **upper bound** for OPT?

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Examples:

- Vertex Cover: lower bound by matchings
- TSP: lower bound by MST or Cycle Cover

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Example. $c = \begin{pmatrix} 7 \\ 1 \\ 5 \end{pmatrix}$ $A = \begin{pmatrix} 1 & -1 & 3 \\ 5 & 2 & -1 \end{pmatrix}$ $b = \begin{pmatrix} 10 \\ 6 \end{pmatrix}$

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$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
& 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
& & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 2 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$\boxed{\begin{array}{lrcrcrcr} \textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\ \textbf{subject to} & x_1 2 & - & x_2 1 & + & 3x_3 & \geq & 10 \\ & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\ & & & & & x_1, x_2, x_3 & \geq & 0 \end{array}}$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$\begin{array}{lrcrcrcr} \textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\ \textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10 \\ & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\ & & & & & x_1, x_2, x_3 & \geq & 0 \end{array}$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10\,10 \\
& 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
& & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10\,10 \\
 & 5x_1\,10 & + & 2x_2\,2 & - & x_3\,3 & \geq & 6\,9 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 14 + & & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 2 & - & x_2 1 & + & 3x_3\, 9 & \geq & 10 10 \\
 & 5x_1 10 + & & 2x_2 2 & - & x_3\, 3 & \geq & 6 9 \\
 & & & x_1, x_2, x_3 & & & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1\,14 & + & x_2\,1 & + & 5x_3 & & \\
\textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10\,10 \\
 & 5x_1\,10 & + & 2x_2\,2 & - & x_3\,3 & \geq & 6\,9 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1\,14 & + & x_2\,1 & + & 5x_3\,15 & & \\
\textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10\,10 \\
 & 5x_1\,10 & + & 2x_2\,2 & - & x_3\,3 & \geq & 6\,9 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrrrrrrrl}
\textbf{minimize} & 7x_1 & 14 + & x_2 & 1 + & 5x_3 & 15 & = & 30 \\
\textbf{subject to} & x_1 & 2 - & x_2 & 1 + & 3x_3 & 9 & \geq & 10\,10 \\
 & 5x_1 & 10 + & 2x_2 & 2 - & x_3 & 3 & \geq & 6\,9 \\
 & & & & & x_1, x_2, x_3 & & \geq & 0
\end{array}
$$

Valid solution?

$x = (2, 1, 3)$

Linear Programming – Upper Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1\,14 & + & x_2\,1 & + & 5x_3\,15 & = & 30 \\
\textbf{subject to} & x_1\,2 & - & x_2\,1 & + & 3x_3\,9 & \geq & 10\,10 \\
 & 5x_1\,10 & + & 2x_2\,2 & - & x_3\,3 & \geq & 6\,9 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

Valid solution?

$x = (2, 1, 3)$

$\Rightarrow \mathrm{obj}(x) = 30$ is upper bound for OPT

Approximation Algorithms

Lecture 4:
Linear Programming and LP-Duality

Part III:
Lower Bounds for LPs

Philipp Kindermann

Summer Semester 2020

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\boxed{
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \rotatebox{-90}{$\geq$} & & \rotatebox{-90}{$\geq$} & & \rotatebox{-90}{$\geq$} & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\boxed{
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
}
$$

$$7x_1 + x_2 + 5x_3 \;\geq\; x_1 - x_2 + 3x_3$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
& \rotatebox{90}{$\leq$} & & \rotatebox{90}{$\leq$} & & \rotatebox{90}{$\leq$} & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
& 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
& & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \mathrm{OPT} \geq 10$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \;\geq\; x_1 - x_2 + 3x_3 \;\Rightarrow\; \mathrm{OPT} \geq 10$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \geq & & \geq & & \geq & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & + & & + & & & & \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \;\geq\; x_1 - x_2 + 3x_3 \;\Rightarrow\; \mathrm{OPT} \geq 10$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \geq & & \geq & & \geq & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & + & & + & & + & & \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \mathrm{OPT} \geq 10$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \mathrm{OPT} \geq 10$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 10 + 6
\end{aligned}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \rotatebox{90}{$\le$} & & \rotatebox{90}{$\le$} & & \rotatebox{90}{$\le$} & & \\
\textbf{subject to} & x_1 & - & x_2 & + & 3x_3 & \geq & 10 \\
 & + & & + & & + & & \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \mathrm{OPT} \geq 10$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 10 + 6 \qquad \Rightarrow \mathrm{OPT} \geq 16
\end{aligned}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & \\
\textbf{subject to} & 2\cdot x_1 & - & 2\cdot x_2 & + & 2\cdot 3x_3 & \geq & 2\cdot 10 \\
 & + & & + & & + & & \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \text{OPT} \geq 10$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 10 + 6 \qquad \Rightarrow \text{OPT} \geq 16
\end{aligned}
$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \geq & & \geq & & \geq & & \\
\textbf{subject to} & 2\cdot x_1 & - & 2\cdot x_2 & + & 2\cdot 3x_3 & \geq & 2\cdot 10 \\
 & + & & + & & + & & \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \mathrm{OPT} \geq 10$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 10 + 6 \qquad \Rightarrow \mathrm{OPT} \geq 16
\end{aligned}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq 2 \cdot (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 2 \cdot 10 + 6
\end{aligned}$$

Linear Programming – Lower Bounds

Optimize (i.e., minimize or maximize) a linear (*objective*) function subject to linear inequalities (*constraints*).

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & 2\cdot x_1 & - & 2\cdot x_2 & + & 2\cdot 3x_3 & \geq & 2\cdot 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \geq x_1 - x_2 + 3x_3 \Rightarrow \text{OPT} \geq 10$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 10 + 6 \qquad \Rightarrow \text{OPT} \geq 16
\end{aligned}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq 2 \cdot (x_1 - x_2 + 3x_3) + (5x_1 + 2x_2 - x_3) \\
&\geq 2\cdot 10 + 6 \qquad \Rightarrow \text{OPT} \geq 26
\end{aligned}
$$

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & {\scriptstyle 2\cdot}\, x_1 & - & {\scriptstyle 2\cdot}\, x_2 & + & {\scriptstyle 2\cdot}\, 3x_3 & \geq & {\scriptstyle 2\cdot}\, 10 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq 2 \cdot (x_1 - x_2 + 3x_3) + 1 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq 2 \cdot 10 + 1 \cdot 6 \qquad \Rightarrow \mathrm{OPT} \geq 2 \cdot 10 + 1 \cdot 6
\end{aligned}
$$

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & y_1(\,x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & 5x_1 & + & 2x_2 & - & x_3 & \geq & 6 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq 2 \cdot (x_1 - x_2 + 3x_3) + 1 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq 2 \cdot 10 + 1 \cdot 6 \quad \Rightarrow \mathrm{OPT} \geq 2 \cdot 10 + 1 \cdot 6
\end{aligned}
$$

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcrl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & y_1(\,x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
& y_2(\,5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
& & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq 2 \cdot (x_1 - x_2 + 3x_3) + 1 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq 2 \cdot 10 + 1 \cdot 6 \quad \Rightarrow \mathrm{OPT} \geq 2 \cdot 10 + 1 \cdot 6
\end{aligned}
$$

Linear Programming – Lower Bounds

$$\begin{array}{rrcrcrcrl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & & \\
\textbf{subject to} \; y_1(& x_1 & - & x_2 & + & 3x_3 \,) & \geq & 10\, y_1 \\
y_2(& 5x_1 & + & 2x_2 & - & x_3 \,) & \geq & 6\, y_2 \\
& & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

Linear Programming – Lower Bounds

$$\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to}\ y_1(& x_1 & - & x_2 & + & 3x_3\ ) & \geq & 10\,y_1 \\
y_2(& 5x_1 & + & 2x_2 & - & x_3\ ) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

$10y_1 + 6y_2$ is lower bound for OPT

Linear Programming – Lower Bounds

$$\begin{array}{lrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & y_1(\,x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & y_2(\,5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

Bounds for y_1, y_2:

Linear Programming – Lower Bounds

$$\begin{array}{rrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \text{\tiny$\ge$} & & \text{\tiny$\ge$} & & \text{\tiny$\ge$} & & \\
\textbf{subject to} \; y_1(& x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & + & & + & & + & & \\
y_2(& 5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

Bounds for y_1, y_2:

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} \; y_1(& x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
y_2(& 5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}
$$

$$y_1 \quad + \quad 5y_2 \quad \leq \quad 7$$

Bounds for y_1, y_2:

Linear Programming – Lower Bounds

$$
\begin{array}{rrcrcrcr}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} \quad y_1\big(& x_1 & - & x_2 & + & 3x_3\big) & \geq & 10\, y_1 \\
y_2\big(& 5x_1 & + & 2x_2 & - & x_3\big) & \geq & 6\, y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}
$$

Bounds for y_1, y_2:

$$
\begin{array}{rcrcr}
y_1 & + & 5y_2 & \leq & 7 \\
-y_1 & + & 2y_2 & \leq & 1
\end{array}
$$

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcrcl}
\textbf{minimize} & & 7x_1 & + & x_2 & + & 5x_3 & & & \\
& & \rotatebox{90}{$\geq$} & & \rotatebox{90}{$\geq$} & & \rotatebox{90}{$\geq$} & & & \\
\textbf{subject to} & y_1(& x_1 & - & x_2 & + & 3x_3 &) & \geq & 10\,y_1 \\
& & + & & + & & + & & & \\
& y_2(& 5x_1 & + & 2x_2 & - & x_3 &) & \geq & 6\,y_2 \\
& & & & & & x_1, x_2, x_3 & & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}
$$

Bounds for y_1, y_2:

$$
\begin{array}{rcrcl}
y_1 & + & 5y_2 & \leq & 7 \\
-y_1 & + & 2y_2 & \leq & 1 \\
3y_1 & - & y_2 & \leq & 5
\end{array}
$$

Linear Programming – Lower Bounds

$$
\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \text{\rotatebox{90}{$\le$}} & & \text{\rotatebox{90}{$\le$}} & & \text{\rotatebox{90}{$\le$}} & & \\
\textbf{subject to} \; y_1(& x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & + & & + & & + & & \\
y_2(& 5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}
$$

Bounds for y_1, y_2:

$$
\begin{array}{rcrcl}
y_1 & + & 5y_2 & \leq & 7 \\
-y_1 & + & 2y_2 & \leq & 1 \\
3y_1 & - & y_2 & \leq & 5 \\
 & & y_1, y_2 & \geq & 0
\end{array}
$$

Linear Programming – Lower Bounds

$$\begin{array}{llllllll}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
\textbf{subject to} & y_1(\,x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & y_2(\,5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

$$7x_1 + x_2 + 5x_3 \geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3)$$

$$\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2$$

$$\begin{array}{llllll}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}$$

Linear Programming – Lower Bounds

Primal

$$\begin{array}{llcrcrcrcl}
\textbf{minimize} & & 7x_1 & + & x_2 & + & 5x_3 & & & \\
 & & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & & \\
\textbf{subject to} & y_1(& x_1 & - & x_2 & + & 3x_3 &) & \geq & 10\,y_1 \\
 & & + & & + & & + & & & \\
 & y_2(& 5x_1 & + & 2x_2 & - & x_3 &) & \geq & 6\,y_2 \\
 & & & & & & x_1, x_2, x_3 & & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

$$\begin{array}{lrcrcl}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}$$

Linear Programming – Lower Bounds

$$\begin{array}{lrcrcrcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & \\
 & \rotatebox{90}{$\le$} & & \rotatebox{90}{$\le$} & & \rotatebox{90}{$\le$} & & \\
\textbf{subject to}\; y_1(& x_1 & - & x_2 & + & 3x_3) & \geq & 10\,y_1 \\
 & + & & + & & + & & \\
y_2(& 5x_1 & + & 2x_2 & - & x_3) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}$$

Primal

$$7x_1 + x_2 + 5x_3 \geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3)$$

$$\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2$$

$$\begin{array}{lrcrcl}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}$$

Dual

Linear Programming – Lower Bounds

$$
\begin{array}{llcccccccl}
\textbf{minimize} & & 7x_1 & + & x_2 & + & 5x_3 & & & \text{Primal} \\
 & & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & \text{\rotatebox{90}{$\geq$}} & & & \\
\textbf{subject to} & y_1(& x_1 & - & x_2 & + & 3x_3 &) & \geq & 10\, y_1 \\
 & & + & & + & & + & & & \\
 & y_2(& 5x_1 & + & 2x_2 & - & x_3 &) & \geq & 6\, y_2 \\
 & & & & & & x_1, x_2, x_3 & & \geq & 0
\end{array}
$$

$$
\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \text{OPT} \geq 10y_1 + 6y_2
\end{aligned}
$$

$$
\begin{array}{lccccl}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \text{Dual} \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}
$$

Any feasible solution to the **dual** program provides a lower bound for the optimum of the **primal** program.

Linear Programming – Lower Bounds

Primal

$$
\begin{array}{lrcrcrlcl}
\textbf{minimize} & 7x_1 & + & x_2 & + & 5x_3 & & & \\
\textbf{subject to} & y_1(\,x_1 & - & x_2 & + & 3x_3\,) & \geq & 10\,y_1 \\
 & y_2(\,5x_1 & + & 2x_2 & - & x_3\,) & \geq & 6\,y_2 \\
 & & & & & x_1, x_2, x_3 & \geq & 0
\end{array}
$$

$$7x_1 + x_2 + 5x_3 \;\geq\; y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3)$$

$$\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2$$

Dual

$$
\begin{array}{lrcrcl}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}
$$

Any feasible solution to the **dual** program provides a lower bound for the optimum of the **primal** program.

$x = (7/4, 0, 11/4)$ both $y = (2, 1)$ provide objective value 26.

Linear Programming – Lower Bounds

Primal

$$\begin{array}{llcccccccc}
\textbf{minimize} & & 7x_1 & + & x_2 & + & 5x_3 & & & \\
\textbf{subject to} & y_1(& x_1 & - & x_2 & + & 3x_3 &) & \geq & 10\,y_1 \\
 & y_2(& 5x_1 & + & 2x_2 & - & x_3 &) & \geq & 6\,y_2 \\
 & & & & & & x_1, x_2, x_3 & & \geq & 0
\end{array}$$

$$\begin{aligned}
7x_1 + x_2 + 5x_3 &\geq y_1 \cdot (x_1 - x_2 + 3x_3) + y_2 \cdot (5x_1 + 2x_2 - x_3) \\
&\geq y_1 \cdot 10 + y_2 \cdot 6 \Rightarrow \mathrm{OPT} \geq 10y_1 + 6y_2
\end{aligned}$$

Dual

$$\begin{array}{lccccc}
\textbf{maximize} & 10y_1 & + & 6y_2 & & \\
\textbf{subject to} & y_1 & + & 5y_2 & \leq & 7 \\
 & -y_1 & + & 2y_2 & \leq & 1 \\
 & 3y_1 & - & y_2 & \leq & 5 \\
 & & & y_1, y_2 & \geq & 0
\end{array}$$

Any feasible solution to the **dual** program provides a lower bound for the optimum of the **primal** program.

$x = (7/4, 0, 11/4)$ both $y = (2, 1)$ provide objective value 26. OPT

Primal – Dual

Primal Program

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Primal – Dual

Primal Program

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Dual Program

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Primal – Dual

Primal Program

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Dual Program

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Dual Program of the Dual Program

Primal – Dual

Primal Program

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Dual Program

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Dual Program of the Dual Program

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Approximation Algorithms

Lecture 4:
Linear Programming and LP-Duality

Part IV:
LP-Duality and Complementary Slackness

Philipp Kindermann

Summer Semester 2020

LP-Duality

Primal

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Dual

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

LP-Duality

$$\begin{array}{rrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Primal

$$\begin{array}{rrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Dual

Theorem. The primal program has a finite optimum
$\Leftrightarrow$ the dual program has a finite optimum.

LP-Duality

Primal

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Dual

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Theorem. The primal program has a finite optimum $\Leftrightarrow$ the dual program has a finite optimum. Moreover, if $x^* = (x_1^*, \ldots, x_n^*)$ and $y^* = (y_1^*, \ldots, y_m^*)$ are *optimal* solutions for the primal and dual program (resp.), then

LP-Duality

$$\begin{array}{rrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

Primal

$$\begin{array}{rrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Dual

Theorem. The primal program has a finite optimum $\Leftrightarrow$ the dual program has a finite optimum. Moreover, if $x^* = (x_1^*, \ldots, x_n^*)$ and $y^* = (y_1^*, \ldots, y_m^*)$ are *optimal* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j^* = \sum_{i=1}^{m} b_i y_i^* .$$

Weak LP-Duality

$$\begin{array}{llll} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

$$\begin{array}{llll} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & A^\intercal y & \leq & c \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

Weak LP-Duality

$$
\begin{array}{llcl}
\textbf{minimize} & c^\intercal x & & \\
\textbf{subject to} & Ax & \geq & b \\
& x & \geq & 0
\end{array}
\qquad
\begin{array}{llcl}
\textbf{maximize} & b^\intercal y & & \\
\textbf{subject to} & A^\intercal y & \leq & c \\
& y & \geq & 0
\end{array}
$$

Theorem. If $x = (x_1, \dots, x_n)$ and $y = (y_1, \dots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i .$$

Weak LP-Duality

$$\begin{array}{llcl} \textbf{minimize} & c^\top x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

$$\begin{array}{llcl} \textbf{maximize} & b^\top y & & \\ \textbf{subject to} & A^\top y & \leq & c \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

Weak LP-Duality

$$\begin{array}{lrcl} \textbf{minimize} & c^{\mathsf{T}} x & & \\ \textbf{subject to} & Ax & \geq & b \\ & x & \geq & 0 \end{array}$$

$$\begin{array}{lrcl} \textbf{maximize} & b^{\mathsf{T}} y & & \\ \textbf{subject to} & A^{\mathsf{T}} y & \leq & c \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \, .$$

Proof.

$$\sum_{j=1}^{n} c_j x_j \geq \qquad\qquad \geq \sum_{i=1}^{m} b_i y_i \, .$$

Weak LP-Duality

minimize	$c^\intercal x$		
subject to	Ax	$\geq$	b
	x	$\geq$	0

maximize	$b^\intercal y$		
subject to	$A^\intercal y$	$\leq$	c
	y	$\geq$	0

Theorem. If $x = (x_1, \dots, x_n)$ and $y = (y_1, \dots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \qquad \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

minimize	$c^\intercal x$		
subject to	Ax	$\geq$	b
	x	$\geq$	0

maximize	$b^\intercal y$		
subject to	$A^\intercal y$	$\leq$	c
	y	$\geq$	0

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \qquad\qquad \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

minimize	$c^\intercal x$		
subject to	Ax	$\geq$	b
	$\boxed{x}$	$\boxed{\geq}$	$\boxed{0}$

maximize	$b^\intercal y$		
subject to	$\boxed{A^\intercal y}$	$\boxed{\leq}$	$\boxed{c}$
	y	$\geq$	0

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \qquad\qquad \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & \boxed{x \geq 0} & & \end{array}$$

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & \boxed{A^\intercal y \leq c} & & \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \dots, x_n)$ and $y = (y_1, \dots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \sum_{j=1}^{n} \boxed{\left(\sum_{i=1}^{m} a_{ij} y_i \right)} x_j = \qquad \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

minimize	$c^\intercal x$		
subject to	Ax	$\geq$	b
	$\boxed{x}$	$\boxed{\geq}$	$\boxed{0}$

maximize	$b^\intercal y$		
subject to	$\boxed{A^\intercal y}$	$\boxed{\leq}$	$\boxed{c}$
	y	$\geq$	0

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then
$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i\,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \sum_{j=1}^{n} \boxed{\left(\sum_{i=1}^{m} a_{ij} y_i\right)} x_j = \sum_{j=1}^{n} \left(\sum_{i=1}^{m} a_{ij} y_i x_j\right) \geq \sum_{i=1}^{m} b_i y_i\,.$$

$\geq$

Weak LP-Duality

$$\begin{array}{llll} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & \boxed{x \quad \geq \quad 0} & & \end{array}$$

$$\begin{array}{llll} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & \boxed{A^\intercal y \quad \leq \quad c} & & \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \dots, x_n)$ and $y = (y_1, \dots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then

$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \sum_{j=1}^{n} \boxed{\left(\sum_{i=1}^{m} a_{ij} y_i \right)} x_j = \sum_{i=1}^{m} \left(\sum_{j=n}^{m} a_{ij} y_i x_j \right) \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

$$\begin{array}{lrcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & \boxed{x \geq 0} & & \end{array}$$

$$\begin{array}{lrcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & \boxed{A^\intercal y \leq c} & & \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then
$$\sum_{j=1}^{n} c_j x_j \geq \sum_{i=1}^{m} b_i y_i \,.$$

Proof.

$$\sum_{j=1}^{n} \boxed{c_j} x_j \geq \sum_{j=1}^{n} \boxed{\left(\sum_{i=1}^{m} a_{ij} y_i \right)} x_j = \sum_{i=1}^{m} \left(\sum_{j=1}^{n} a_{ij} x_j \right) y_i \geq \sum_{i=1}^{m} b_i y_i \,.$$

Weak LP-Duality

$$\begin{array}{llcl} \textbf{minimize} & c^\intercal x & & \\ \textbf{subject to} & Ax & \geq & b \\ & \boxed{x \quad \geq \quad 0} & & \end{array} \qquad\qquad \begin{array}{llcl} \textbf{maximize} & b^\intercal y & & \\ \textbf{subject to} & \boxed{A^\intercal y \quad \leq \quad c} & & \\ & y & \geq & 0 \end{array}$$

Theorem. If $x = (x_1, \ldots, x_n)$ and $y = (y_1, \ldots, y_m)$ are *valid* solutions for the primal and dual program (resp.), then
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minimize	$c^\intercal x$
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The feasible solutions of an LP with n variables from a **convex polytope** in $\mathbb{R}^n$ (intersection of halfspaces).

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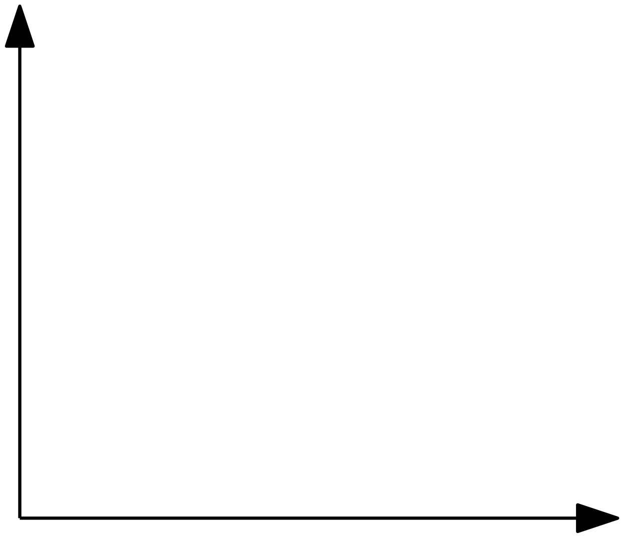

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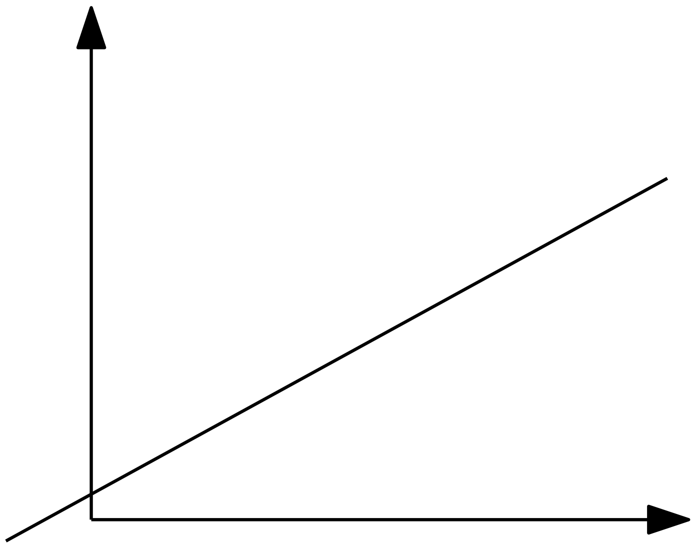

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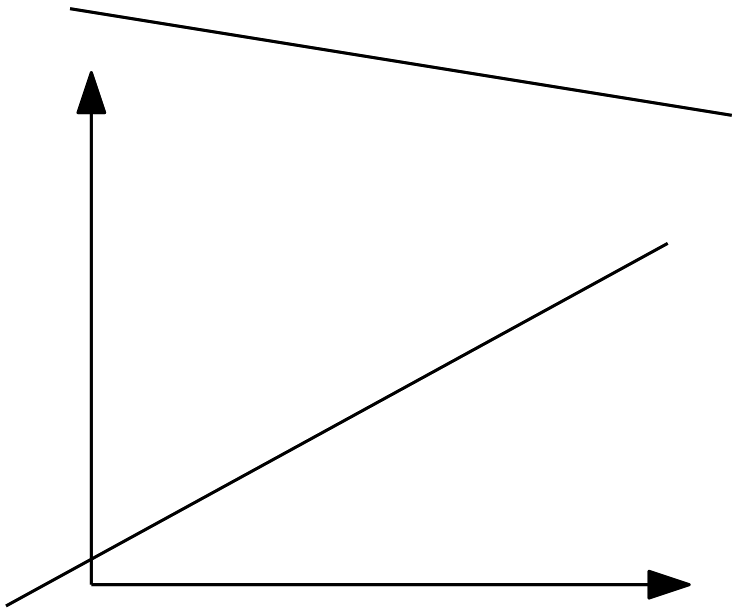

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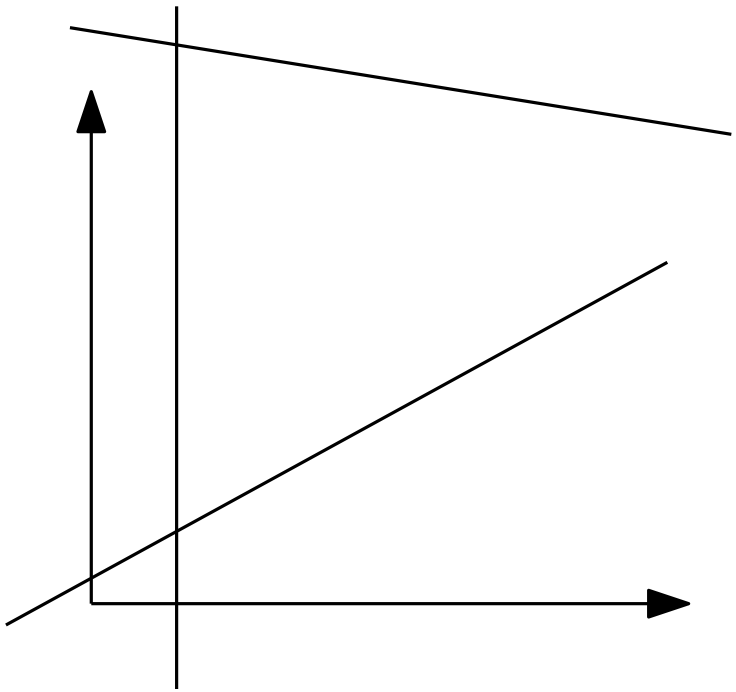

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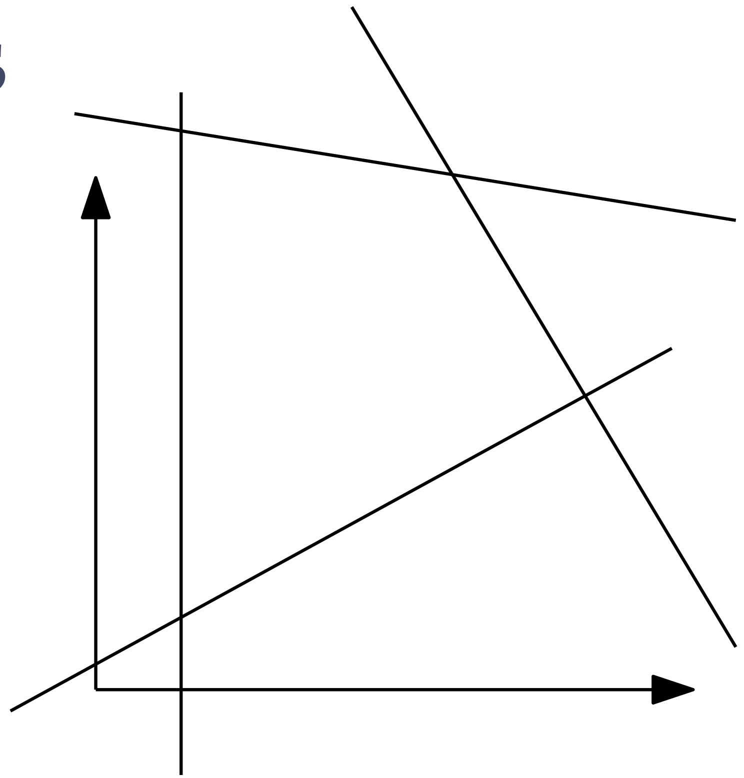

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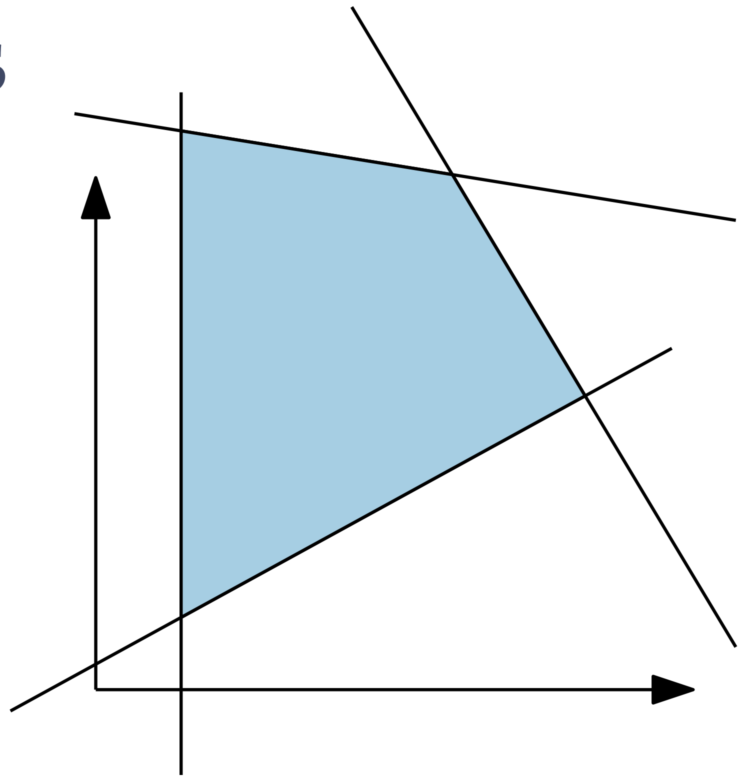

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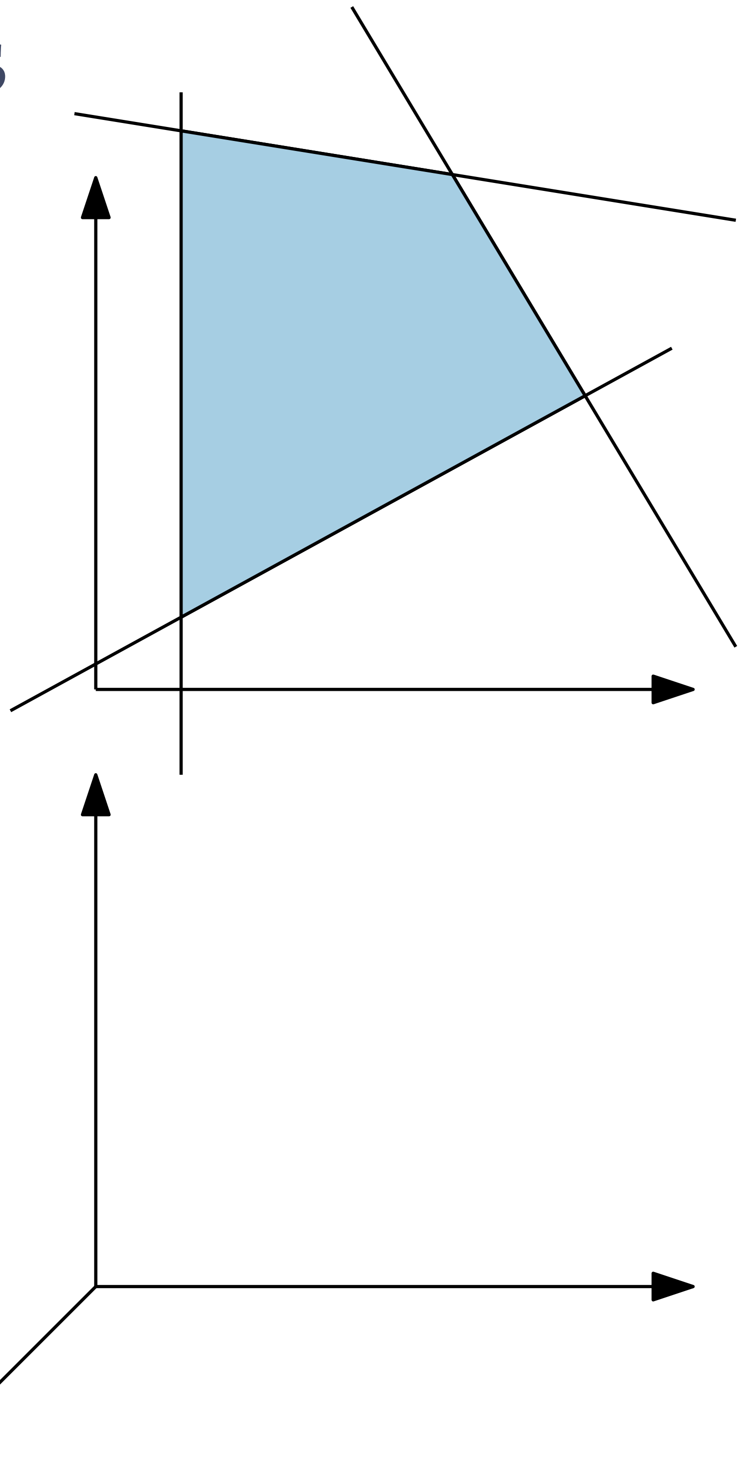

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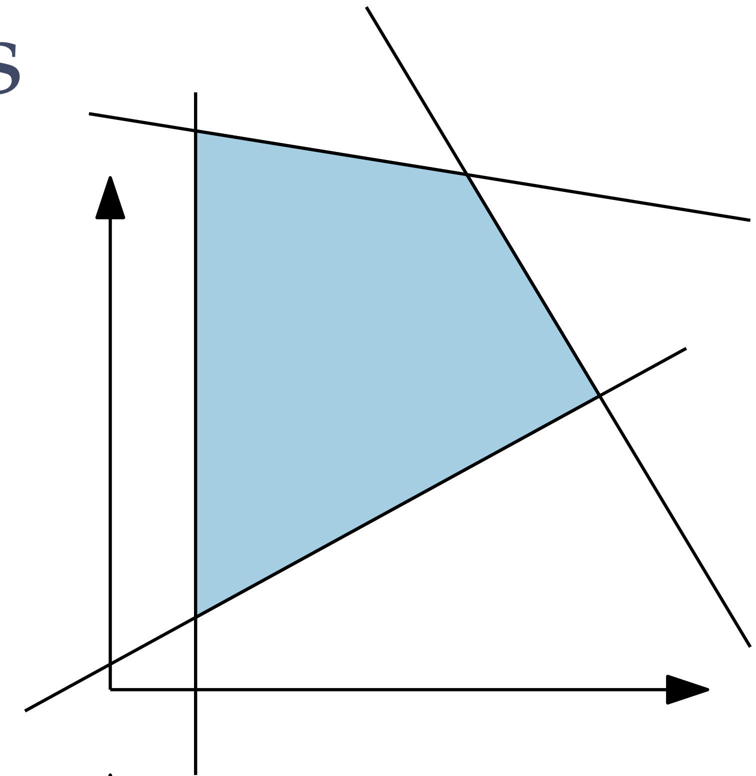

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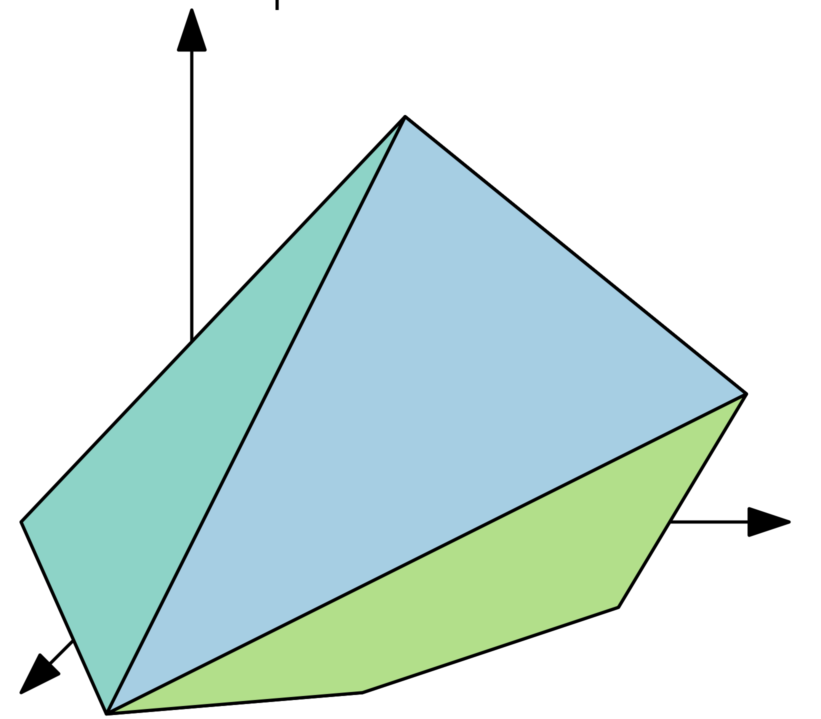

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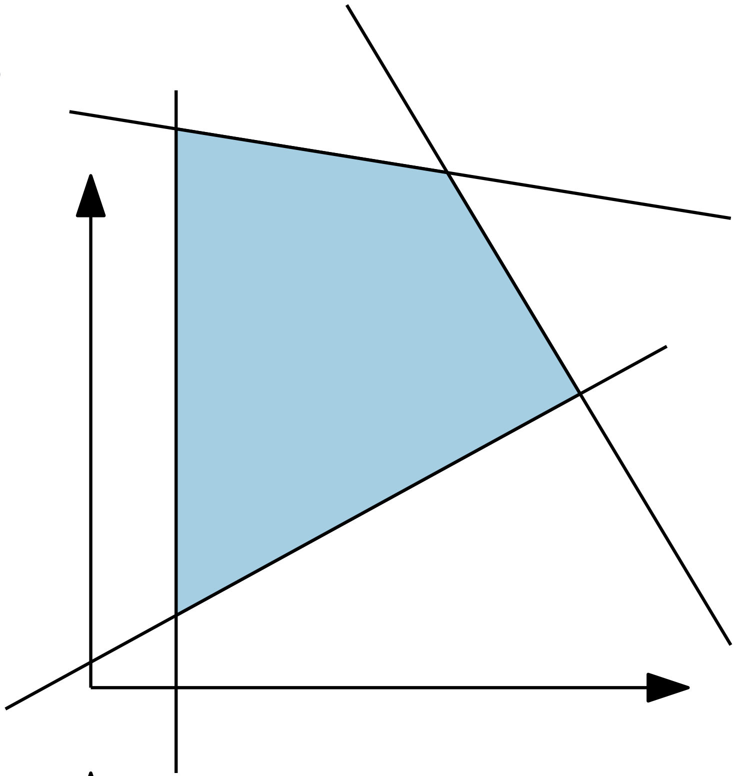
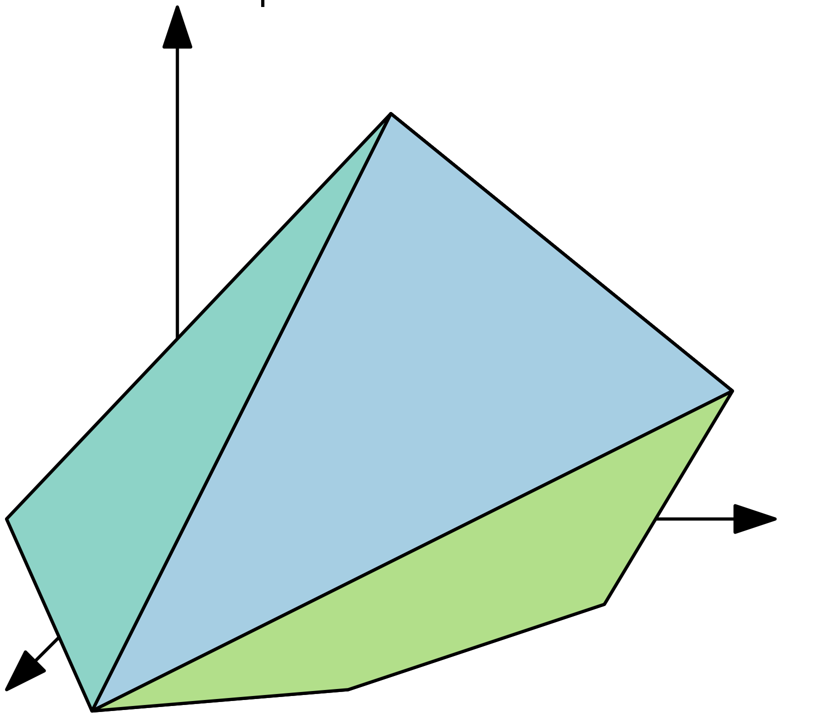
The feasible solutions of an LP with n variables from a **convex polytope** in $\mathbb{R}^n$ (intersection of halfspaces).

Corners of the polytope are called **extreme point solutions** $\Leftrightarrow$ n linearly independent inequalities (constraints) are satisfied with equality.





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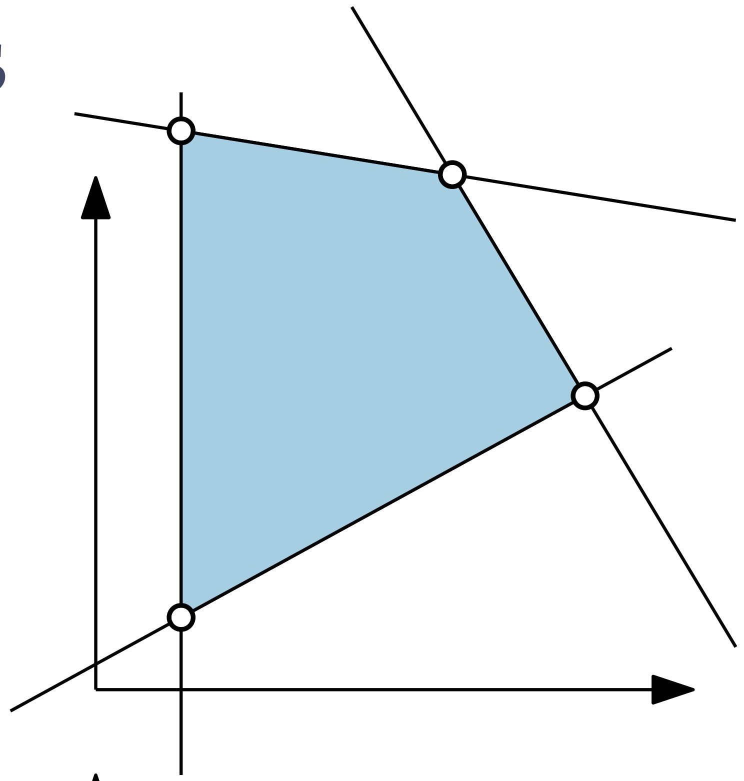

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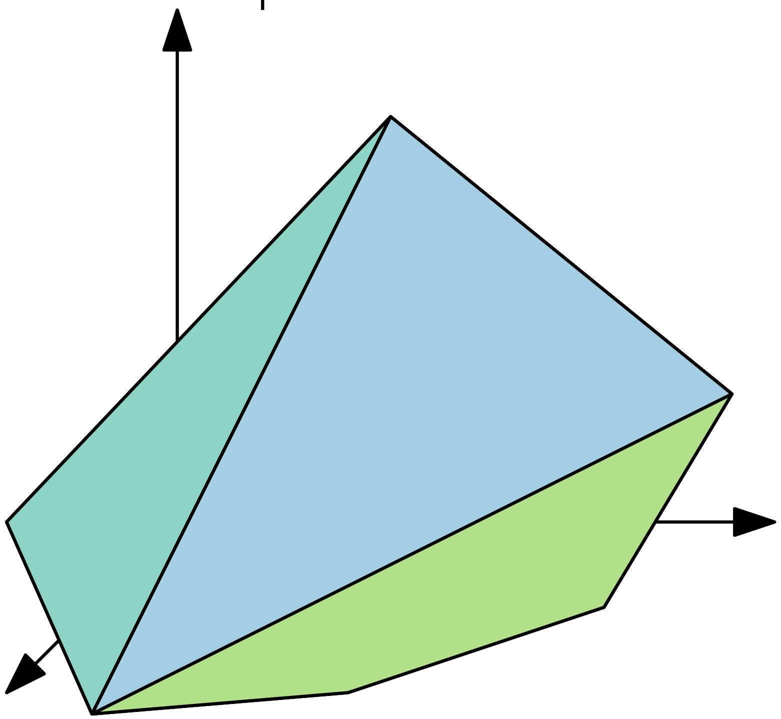

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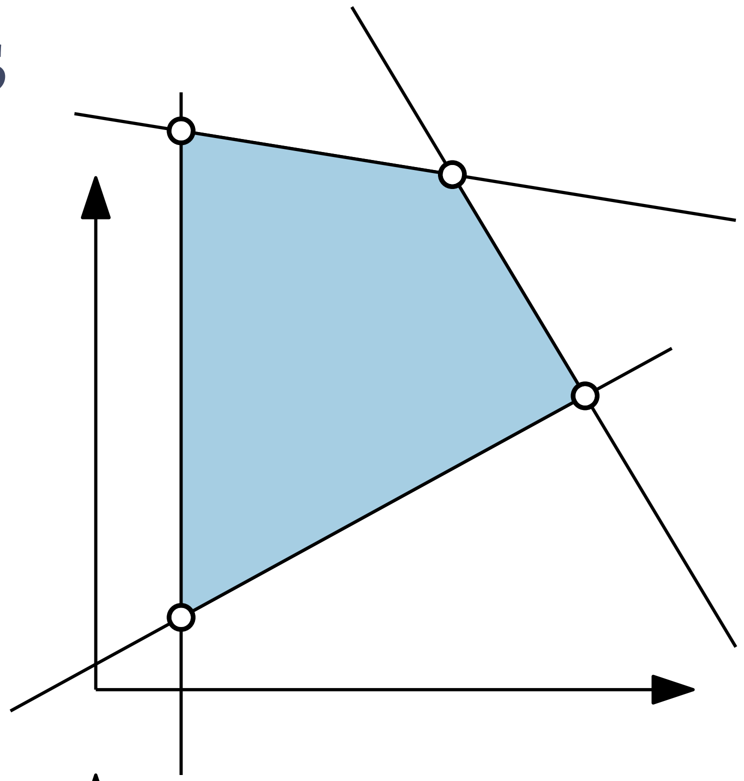

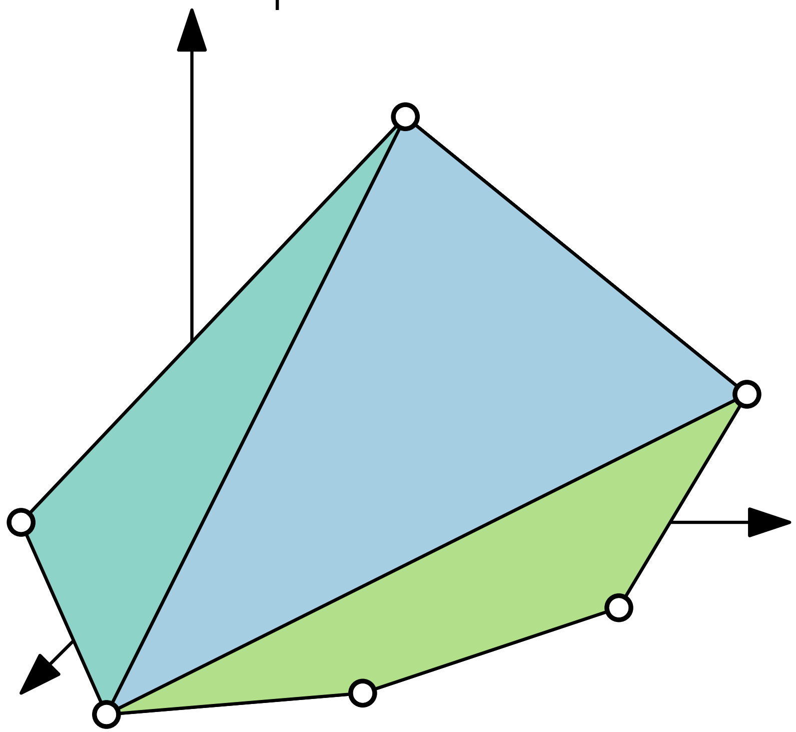

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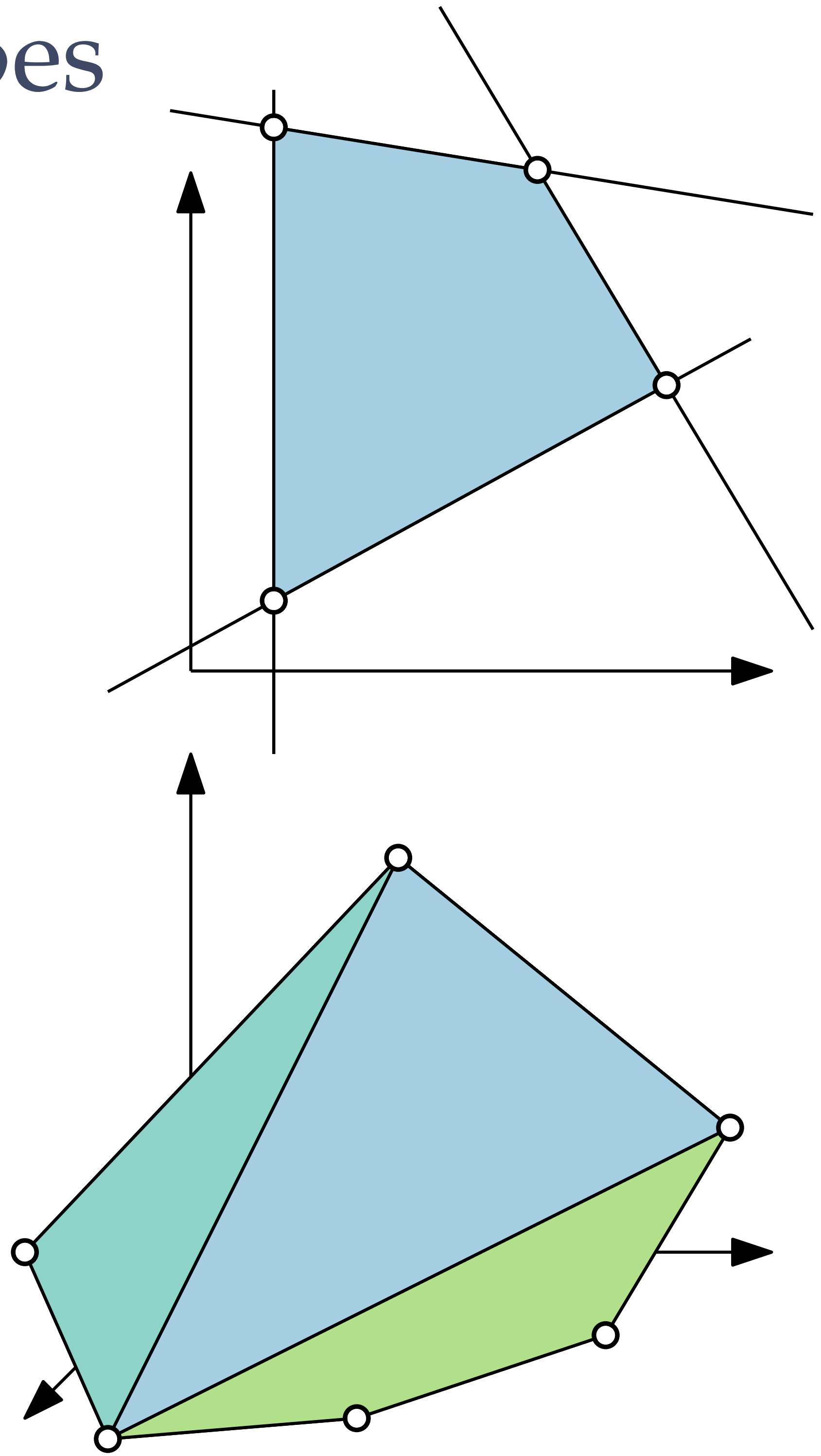
When an optimal solution exists, some extreme point will also be optimal.



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LP-Relaxation provides lower bound: $\mathrm{OPT}_{\mathrm{LP}} \leq \mathrm{OPT}_{\mathrm{ILP}}$

Approximation Algorithms

Lecture 4:
Linear Programming and LP-Duality

Part V:
Min-Max-Relationships

Philipp Kindermann

Summer Semester 2020

Max-Flow-Problem

Given: A directed graph $G = (V, E)$ with edge capacities $c \colon E \to \mathbb{Q}_+$ and two special vertices: the source s and sink t.

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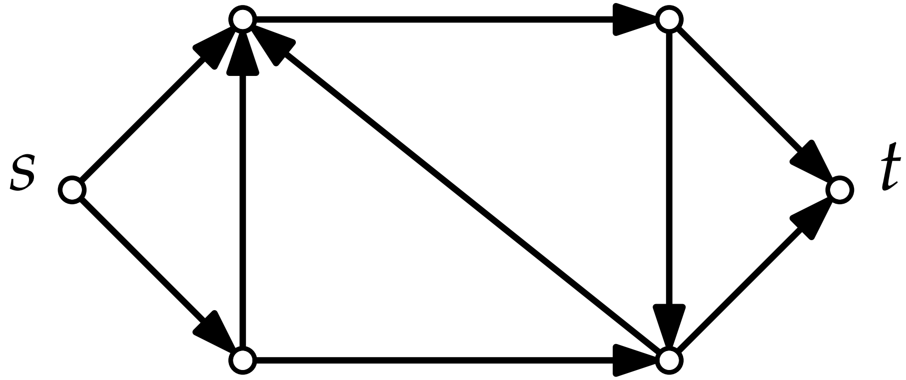

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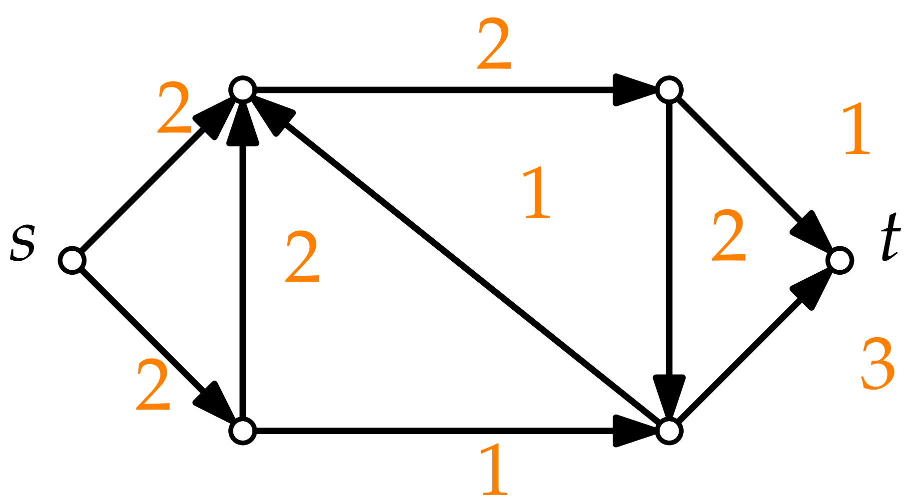

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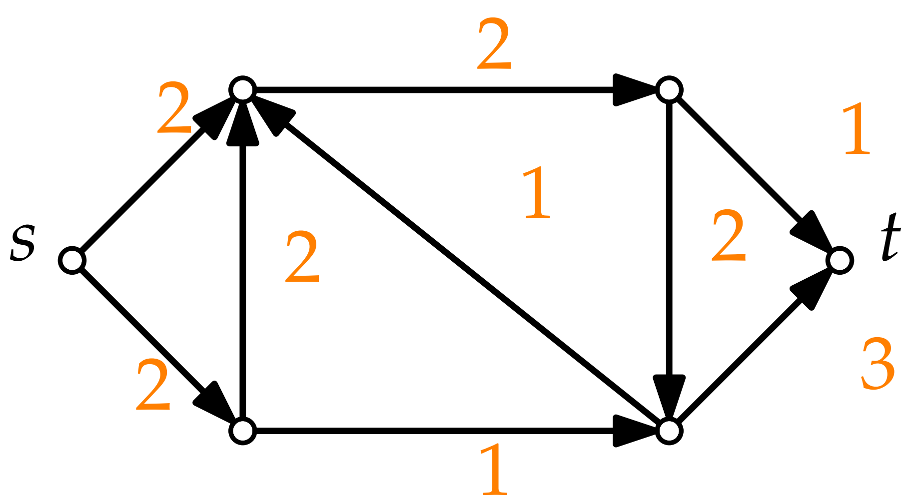

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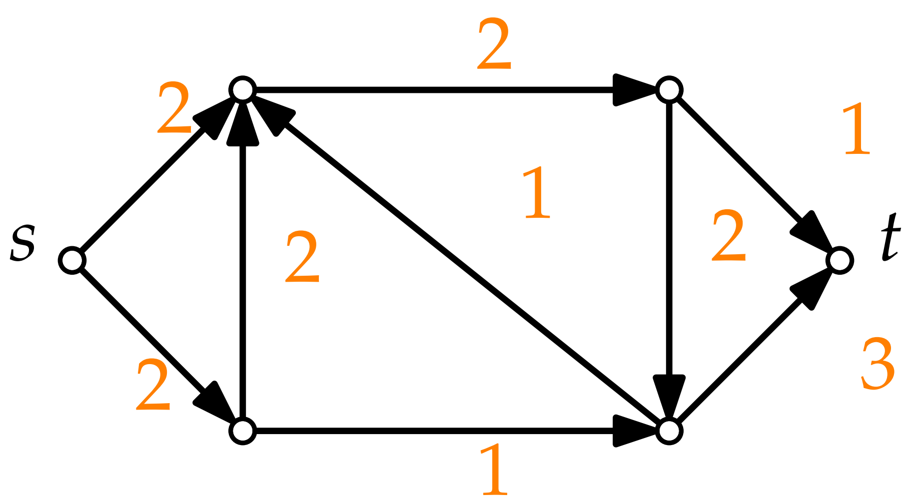

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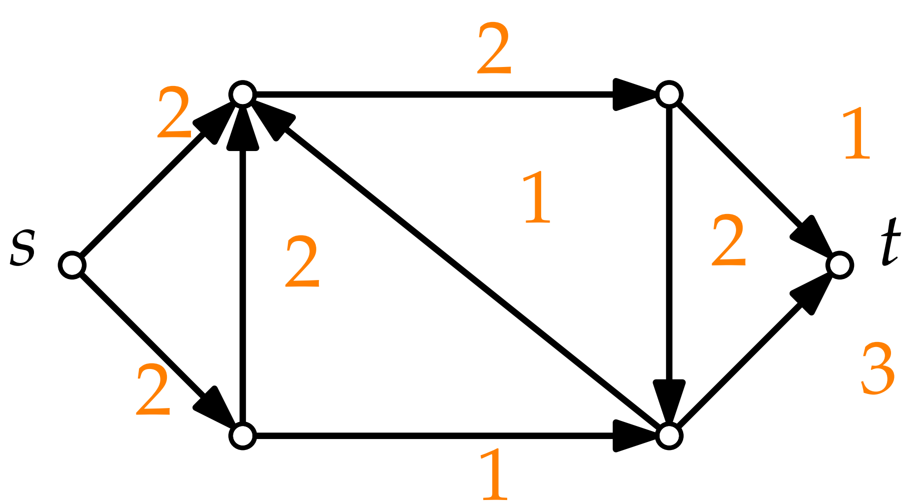
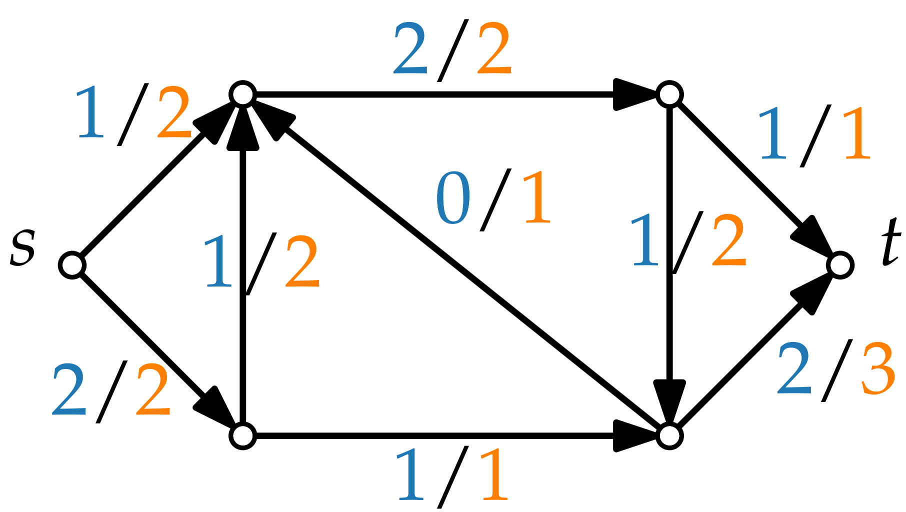


Max-Flow-Problem

Given: A directed graph $G = (V, E)$ with edge capacities $c \colon E \to \mathbb{Q}_+$ and two special vertices: the source s and sink t.

Find: A maximum s–t-flow (i.e., non-negative edge weights f), such that

- $f(u,v) \leq c(u,v)$ for each edge $(u,v) \in E$
- $\sum_{(u,v)\in E} f(u,v) = \sum_{(v,z)\in E} f(v,z)$ for each vertex $v \in V - \{s,t\}$



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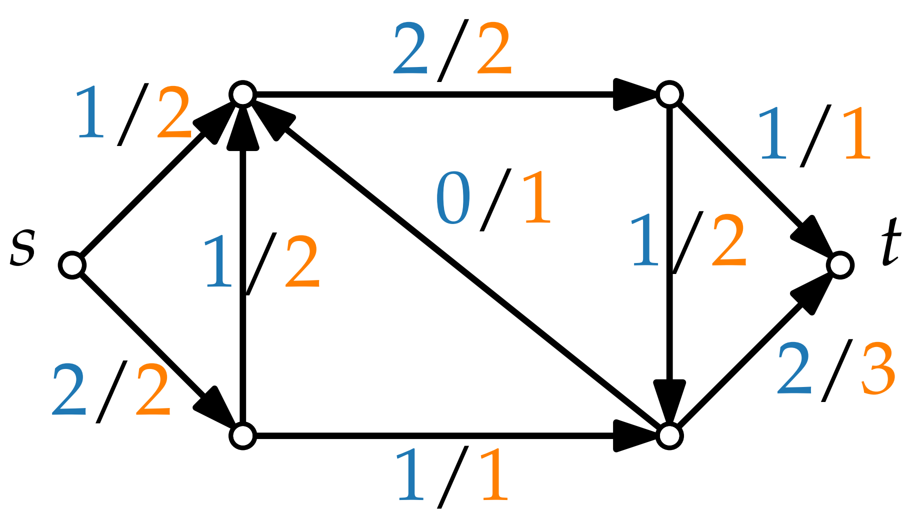
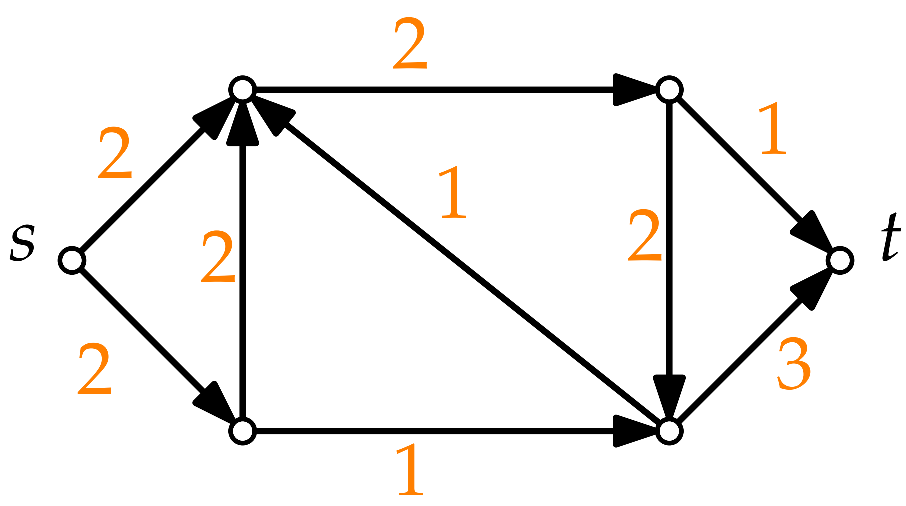
The **flow value** is the inflow to t minus the outflow from t.



Min-Cut-Problem

Given: A directed graph $G = (V, E)$ with edge capacities $c \colon E \to \mathbb{Q}_+$ and two special vertices: the source s and sink t.

Find: An s–t-cut, i.e., a vertex set X with $s \in X$ and $t \in \overline{X}$, such that the total weight $c(X, \overline{X})$ of the edges from X to $\overline{X}$ is minimum.



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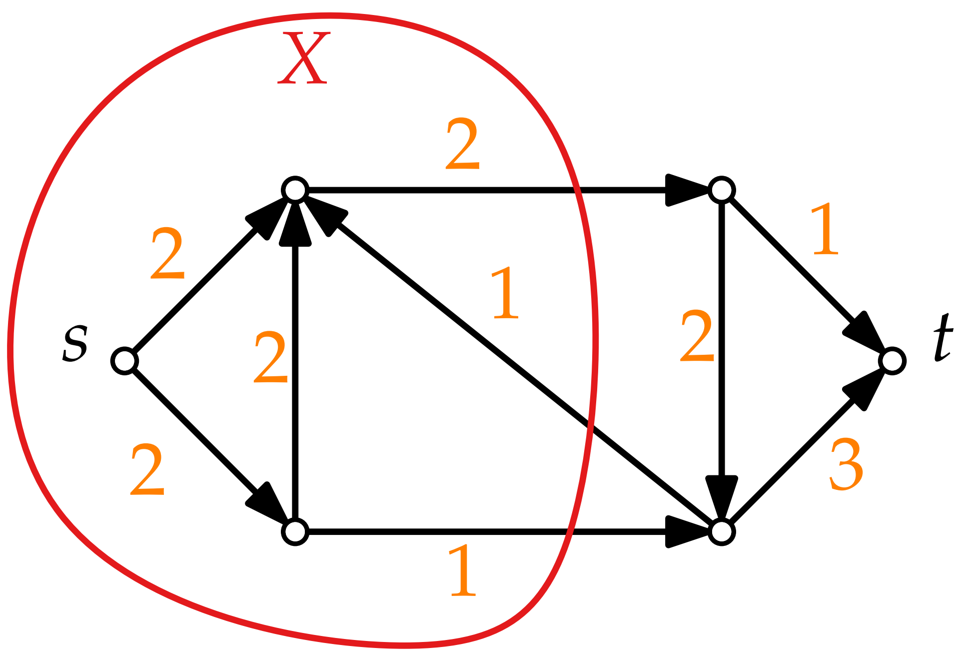

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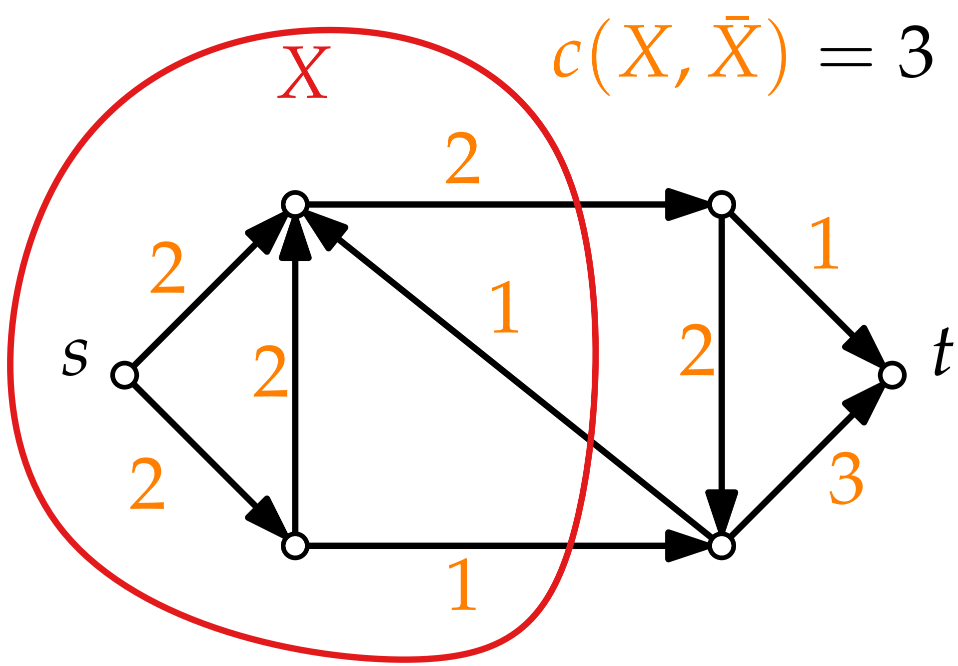

Max-Flow-Min-Cut-Theorem

Theorem. The value of a maximum s–t-flow and the weight of a minimum s–t-cut are the same.

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Proof. Special case of LP-Duality …

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maximize
subject to

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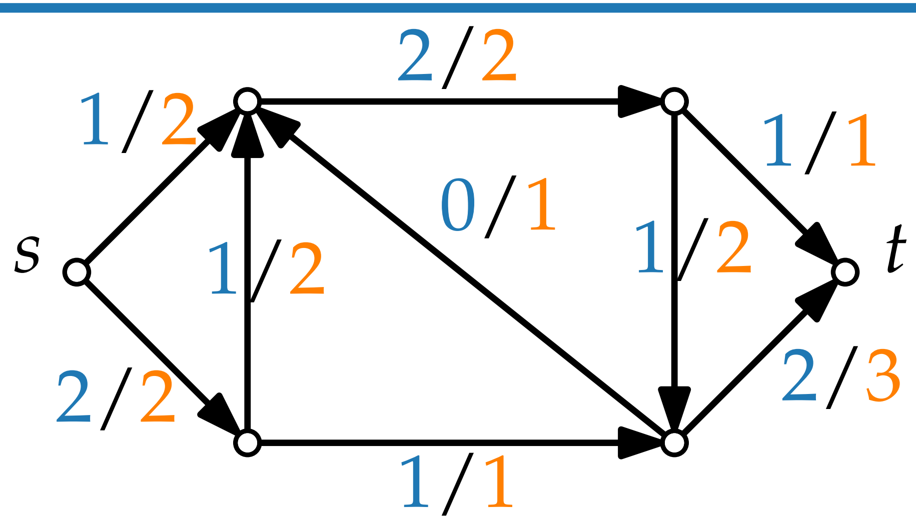

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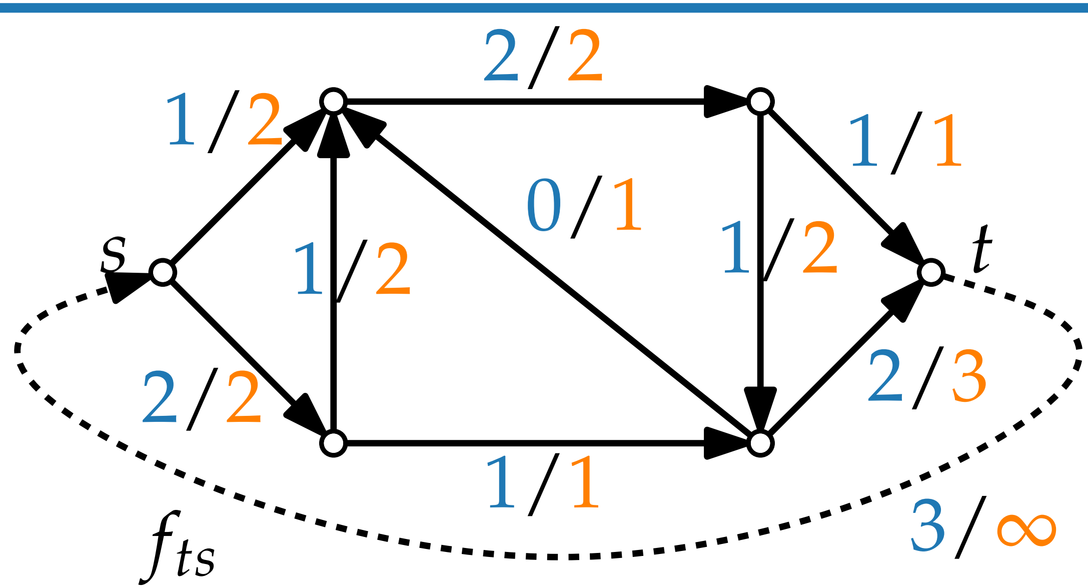

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maximize	f_{ts}	
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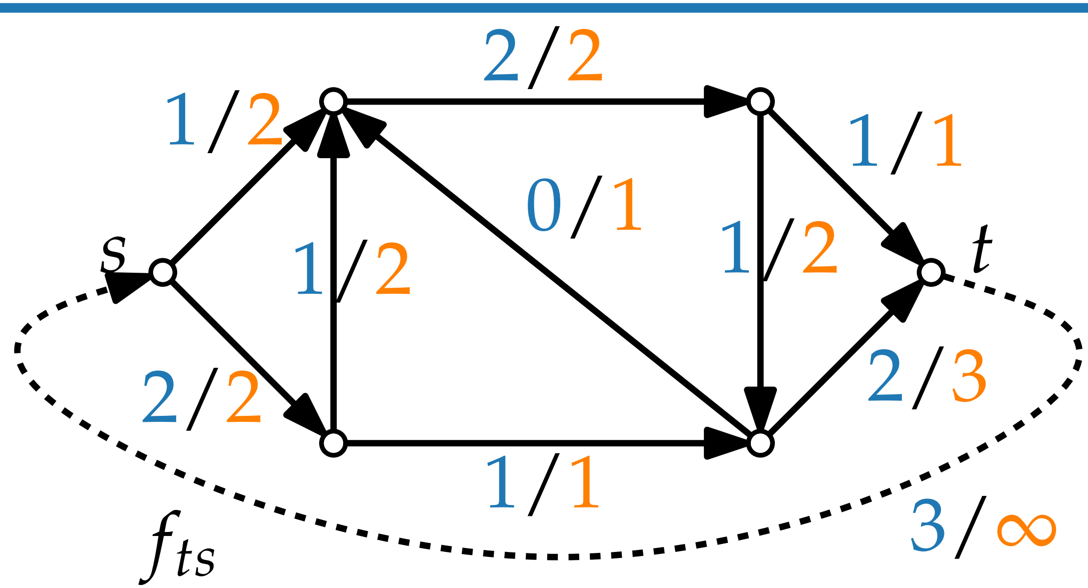

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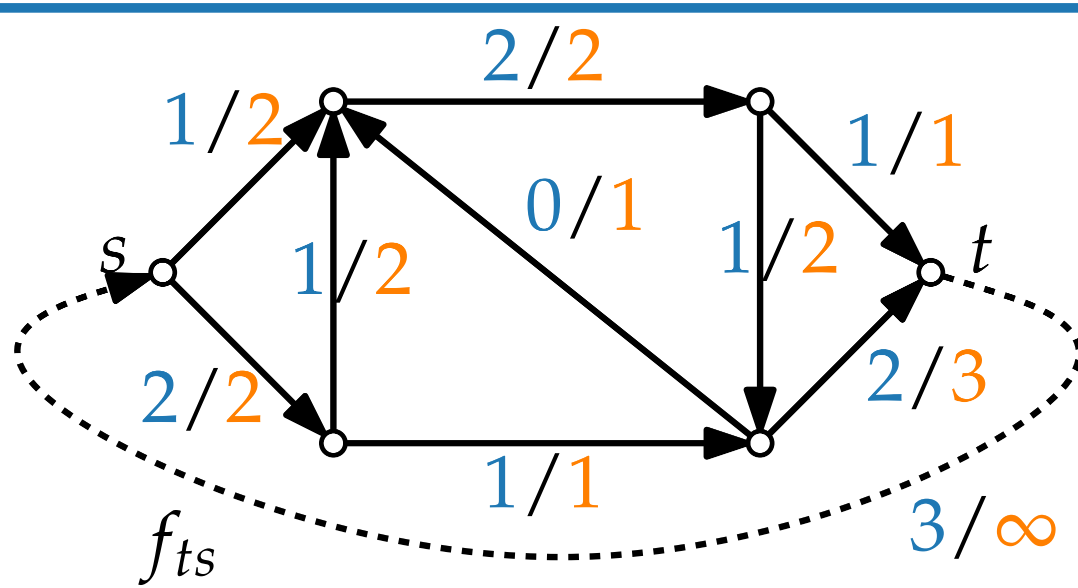
$$\sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \leq 0 \qquad \forall v \in V$$



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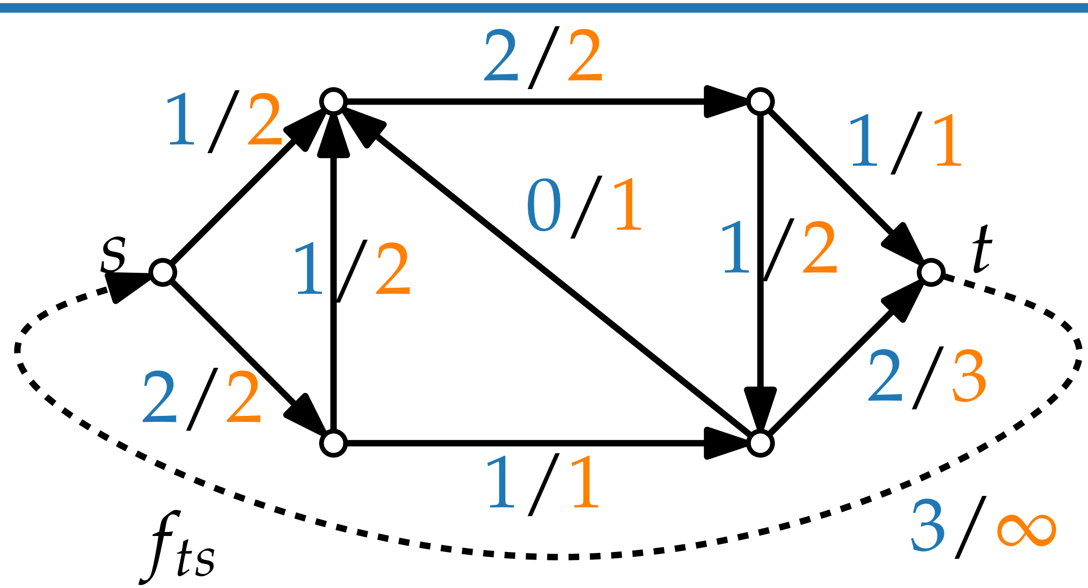

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maximize $c^\intercal x$

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maximize $c^\top x \;\; = \sum_{(u,v)\in E} (0 \cdot f_{uv}) \;\; +1 \cdot f_{ts} \;\; \Rightarrow c = (0, \ldots, 0, 1)$

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Which constraints contain $f_{uv} \neq f_{ts}$?

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& f_{uv} \ge 0 & \forall (u,v) \in E &
\end{array}$$

maximize $c^\mathsf{T} x \; = \sum_{(u,v)\in E} (0 \cdot f_{uv}) \; + 1 \cdot f_{ts} \;\; \Rightarrow c = (0, \dots, 0, 1)$

Which constraints contain $f_{uv} \neq f_{ts}$? d_{uv}, p_u

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Which constraints contain $f_{uv} \neq f_{ts}$? $\qquad d_{uv}, p_u, p_v$

$$\Rightarrow d_{uv} - p_u + p_v \ge 0$$

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Which constraints contain $f_{uv} \neq f_{ts}$? $\qquad d_{uv},\ p_u,\ p_v$

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Which constraints contain f_{ts}?

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Which constraints contain $f_{uv} \neq f_{ts}$? d_{uv}, p_u, p_v

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Which constraints contain $f_{uv} \neq f_{ts}$? $\quad d_{uv},\, p_u,\, p_v$

$$\Rightarrow d_{uv} - p_u + p_v \geq 0$$

Which constraints contain f_{ts}? $\quad p_s,\, p_t$

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\end{array}
$$

$$
\begin{array}{ll}
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 \qquad \forall (u,v) \in E \setminus \{(t,s)\} \\
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\end{array}
$$

$$
\begin{array}{llr}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \ge 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
& p_s - p_t \ge 1 & \\
& d_{uv} \ge 0 & \forall (u,v) \in E \\
& p_u \ge 0 & \forall u \in V
\end{array}
$$

Approximation Algorithms

Lecture 4:
Linear Programming and LP-Duality

Part VI:
Dual LP of Max Flow

Philipp Kindermann

Summer Semester 2020

Dual LP – Interpretation as ILP

$$\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
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 & d_{uv} \cancel{\geq 0} \in \{0,1\} & \forall (u,v)\in E \\
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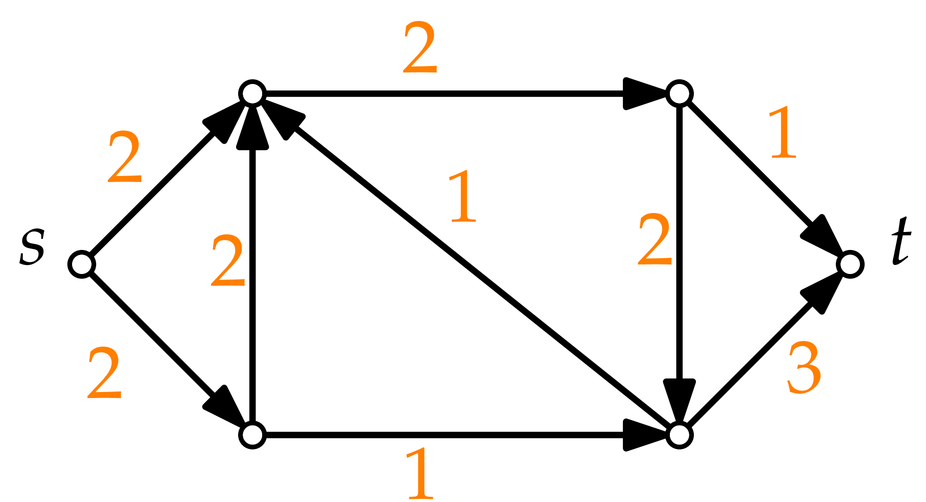

Dual LP – Interpretation as ILP

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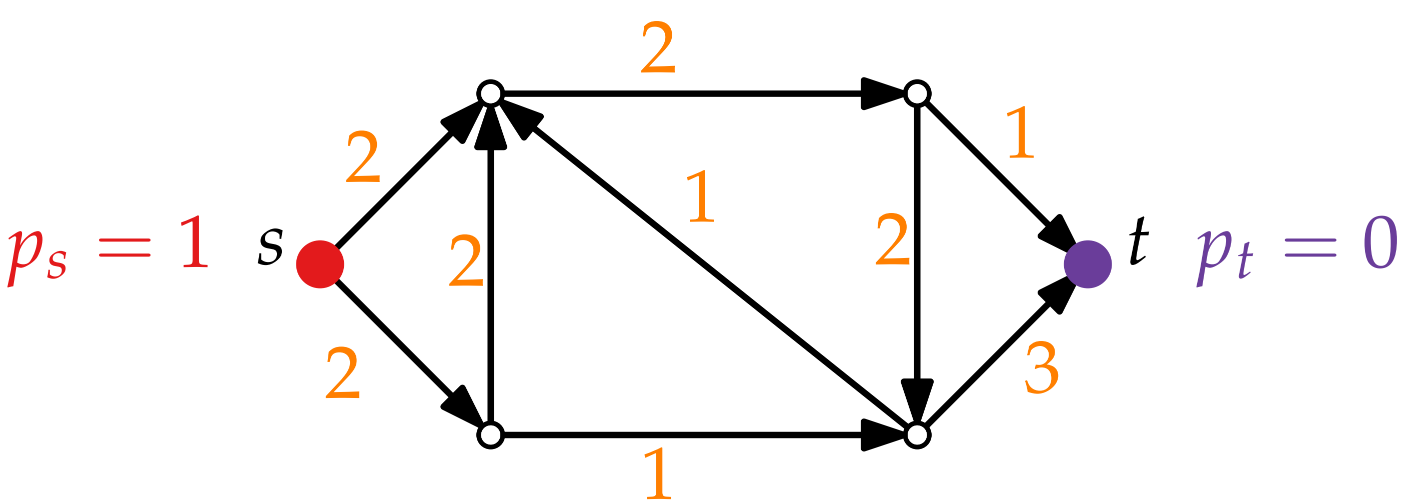
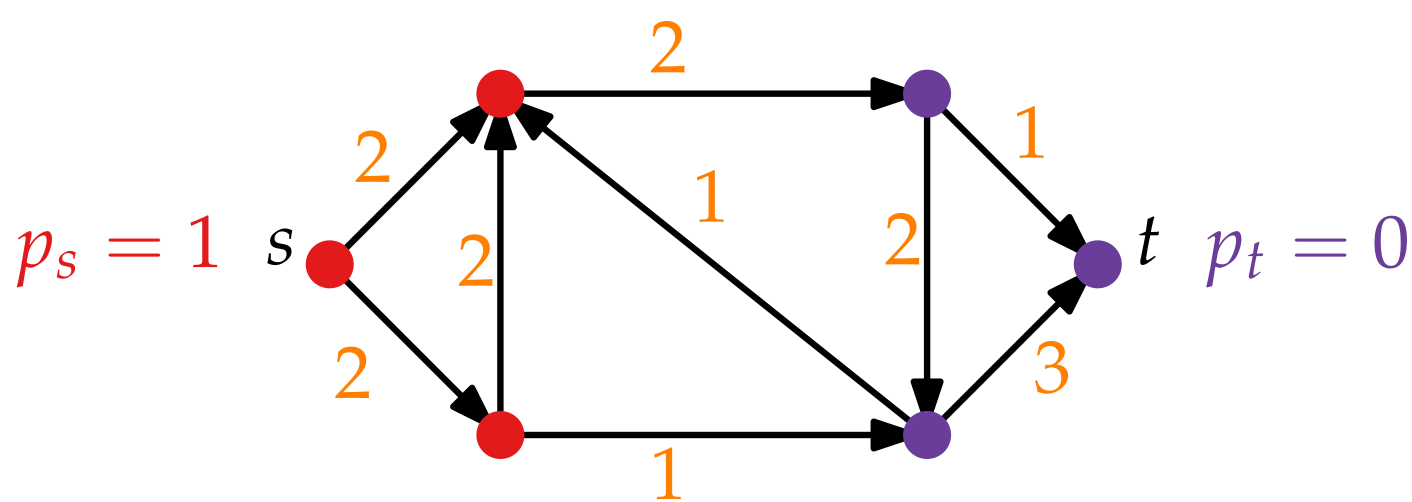
\end{array}
$$



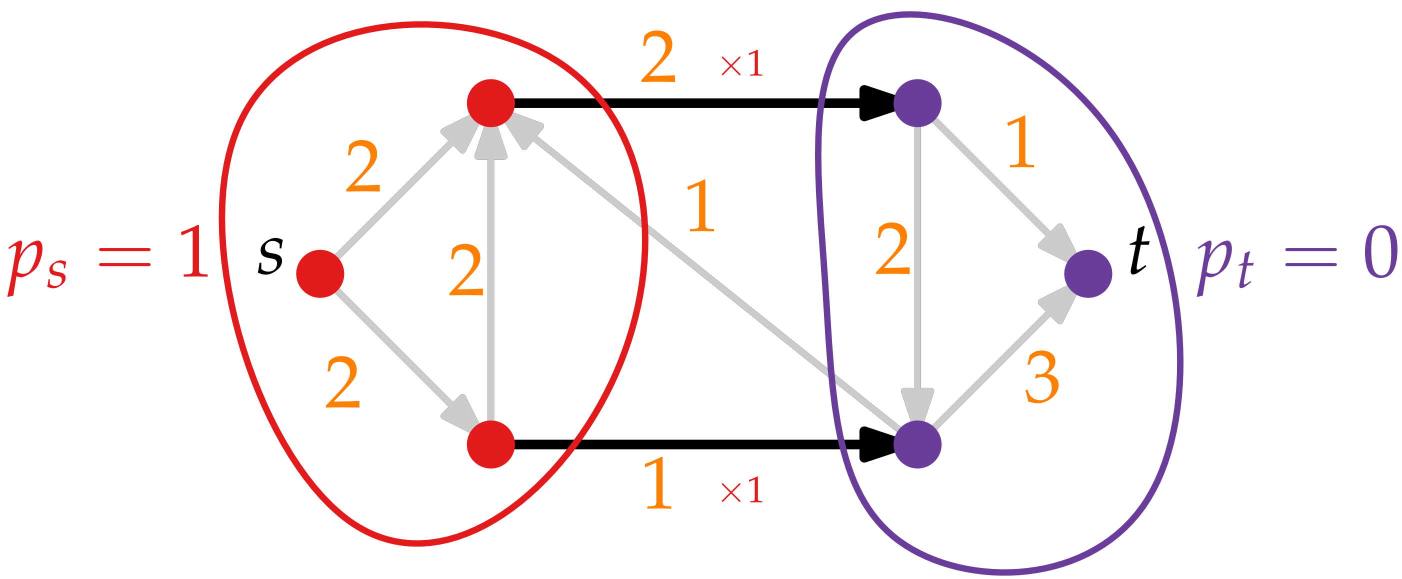
Dual LP – Interpretation as ILP

$$
\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \cancel{\geq 0} \in \{0,1\} & \forall (u,v)\in E \\
 & p_u \cancel{\geq 0} \in \{0,1\} & \forall u \in V
\end{array}
$$



Dual LP – Interpretation as ILP

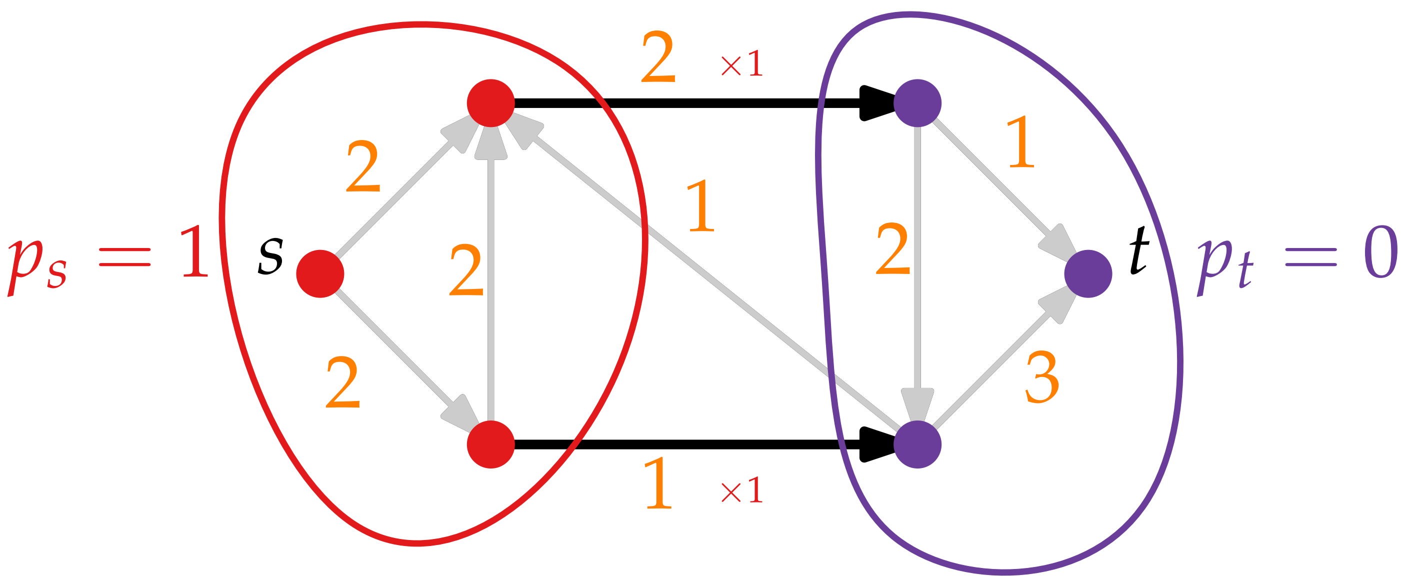
$$\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\
& p_s - p_t \geq 1 & \\
& d_{uv} \cancel{\geq 0} \in \{0,1\} & \forall (u,v)\in E \\
& p_u \cancel{\geq 0} \in \{0,1\} & \forall u\in V
\end{array}$$



Dual LP – Interpretation as ILP

$$
\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \cancel{\geq 0} \in \{0,1\} & \forall (u,v)\in E \\
 & p_u \cancel{\geq 0} \in \{0,1\} & \forall u\in V
\end{array}
$$

equivalent to Min-Cut!



Dual LP – Factional Cuts

$$\begin{array}{lll} \textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} & \\ \textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\ & p_s - p_t \geq 1 & \\ & d_{uv} \geq 0 & \forall (u,v)\in E \\ & p_u \geq 0 & \forall u \in V \end{array}$$

Dual LP – Factional Cuts

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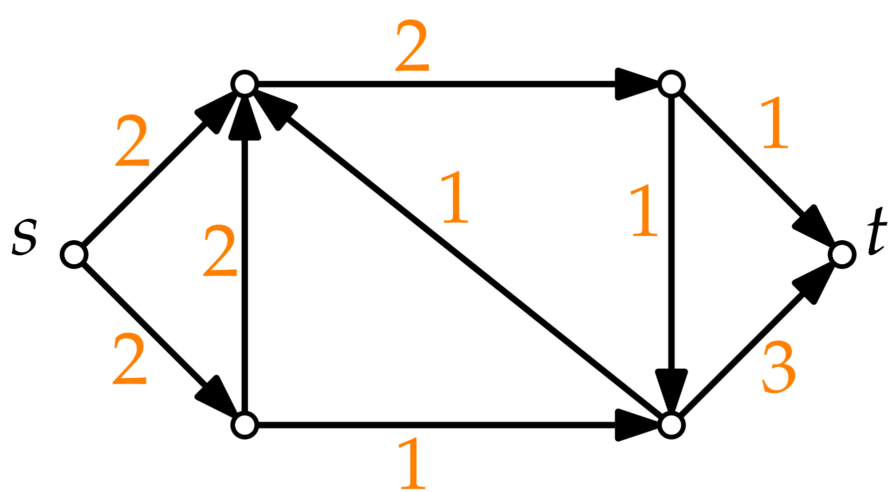
\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \geq 0 & \forall (u,v) \in E \\
 & p_u \geq 0 & \forall u \in V
\end{array}
$$



Dual LP – Factional Cuts

$$\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} & \\
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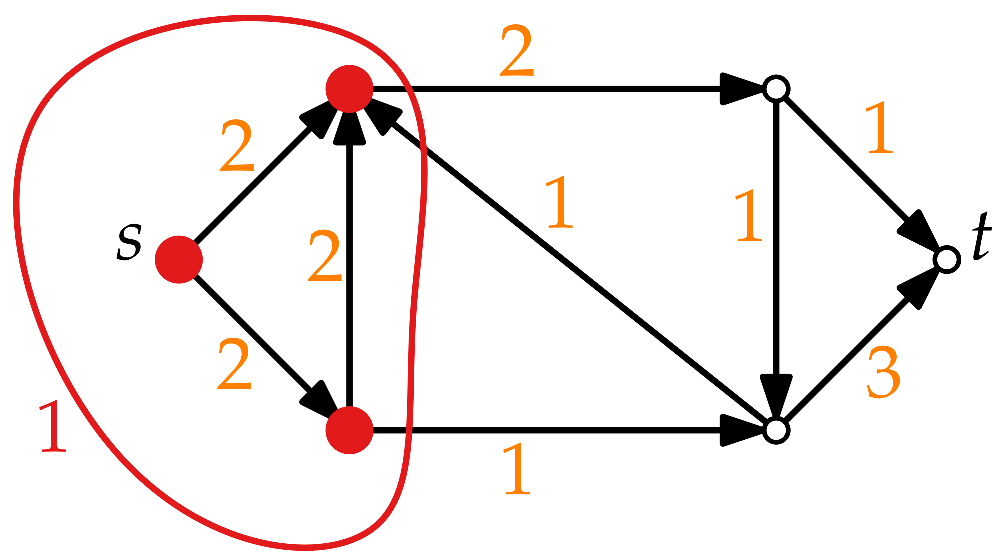
& p_s - p_t \geq 1 & \\
& d_{uv} \geq 0 & \forall (u,v)\in E \\
& p_u \geq 0 & \forall u\in V
\end{array}$$



Dual LP – Factional Cuts

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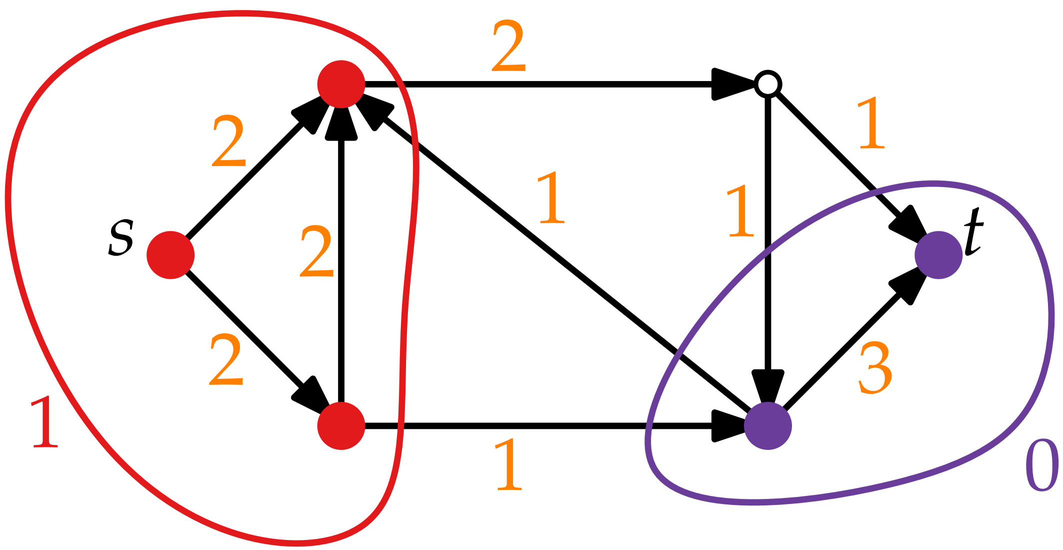
 & p_u \geq 0 & \forall u \in V
\end{array}
$$



Dual LP – Factional Cuts

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\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} & \\
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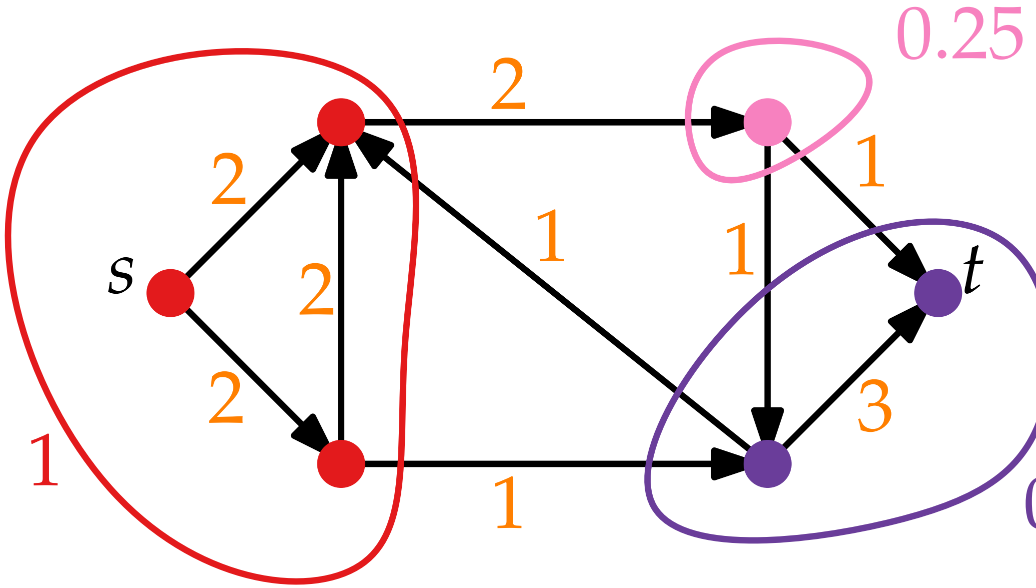
& d_{uv} \geq 0 & \forall (u,v)\in E \\
& p_u \geq 0 & \forall u \in V
\end{array}
$$



Dual LP – Factional Cuts

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\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\
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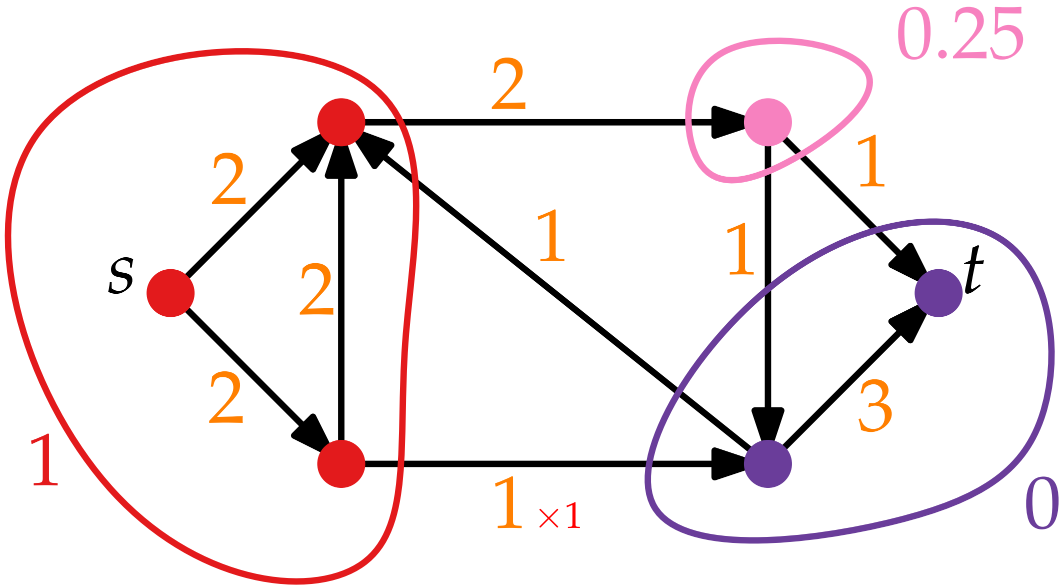
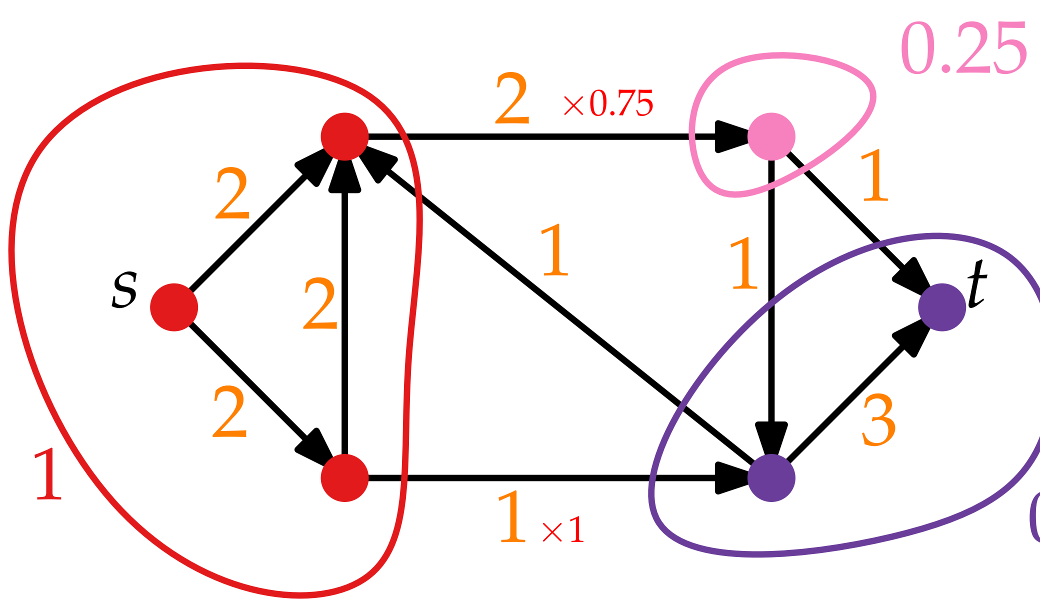
& p_u \geq 0 & \forall u\in V
\end{array}
$$



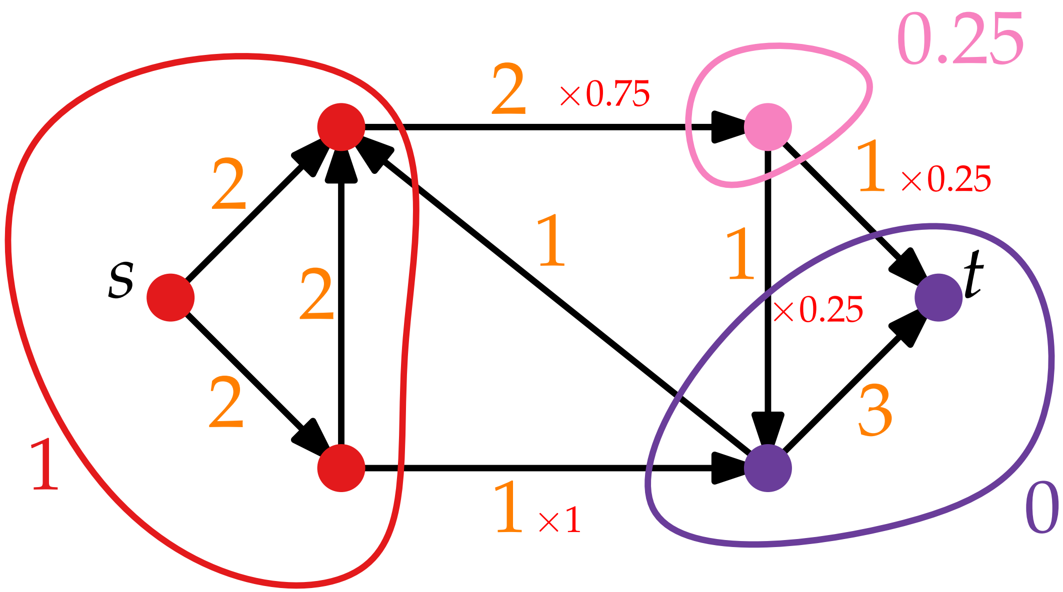
Dual LP – Factional Cuts

$$\begin{aligned}
\textbf{minimize} \quad & \sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} \equiv \text{LP-Relaxation of the ILP} \\
\textbf{subject to} \quad & d_{uv} - p_u + p_v \geq 0 && \forall (u,v) \in E \setminus \{(t,s)\} \\
& p_s - p_t \geq 1 \\
& d_{uv} \geq 0 && \forall (u,v) \in E \\
& p_u \geq 0 && \forall u \in V
\end{aligned}$$



Dual LP – Factional Cuts

$$
\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \equiv \text{LP-Relaxation of the ILP} \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \geq 0 & \forall (u,v) \in E \\
 & p_u \geq 0 & \forall u \in V
\end{array}
$$

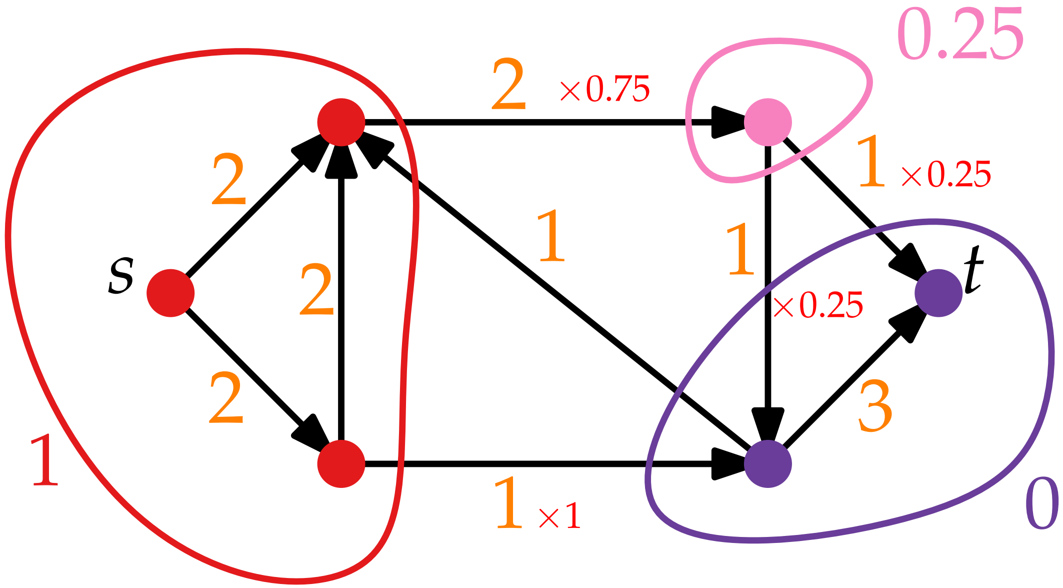


Dual LP – Factional Cuts

$$\begin{array}{lll} \textbf{minimize} & \sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} & \\ \textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\ & p_s - p_t \geq 1 & \\ & d_{uv} \geq 0 & \forall (u,v) \in E \\ & p_u \geq 0 & \forall u \in V \end{array}$$

≡ LP-Relaxation of the ILP

Each s–t-path $s = v_0, \ldots, v_k = t$ has length ≥ 1 w.r.t. d:



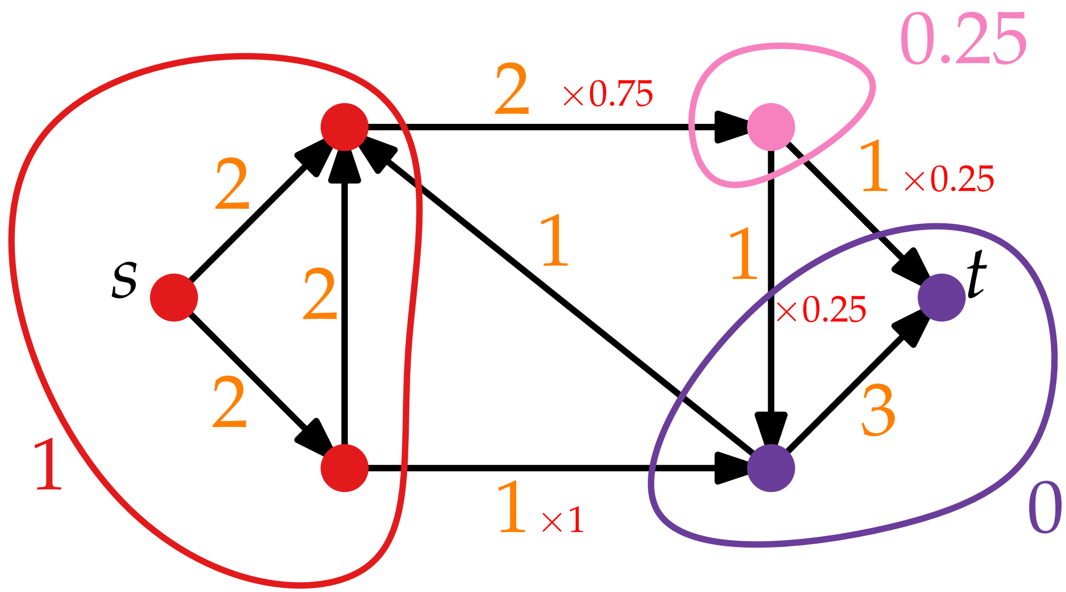
Dual LP – Factional Cuts

$$\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \equiv \text{LP-Relaxation of the ILP} \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \geq 0 & \forall (u,v) \in E \\
 & p_u \geq 0 & \forall u \in V
\end{array}$$

Each s–t-path $s = v_0, \ldots, v_k = t$ has length ≥ 1 w.r.t. d:

$$\sum_{i=0}^{k-1} d_{i,i+1} \geq \sum_{i=0}^{k-1} (p_i - p_{i+1})$$

$$= p_s - p_t$$



Dual LP – Factional Cuts

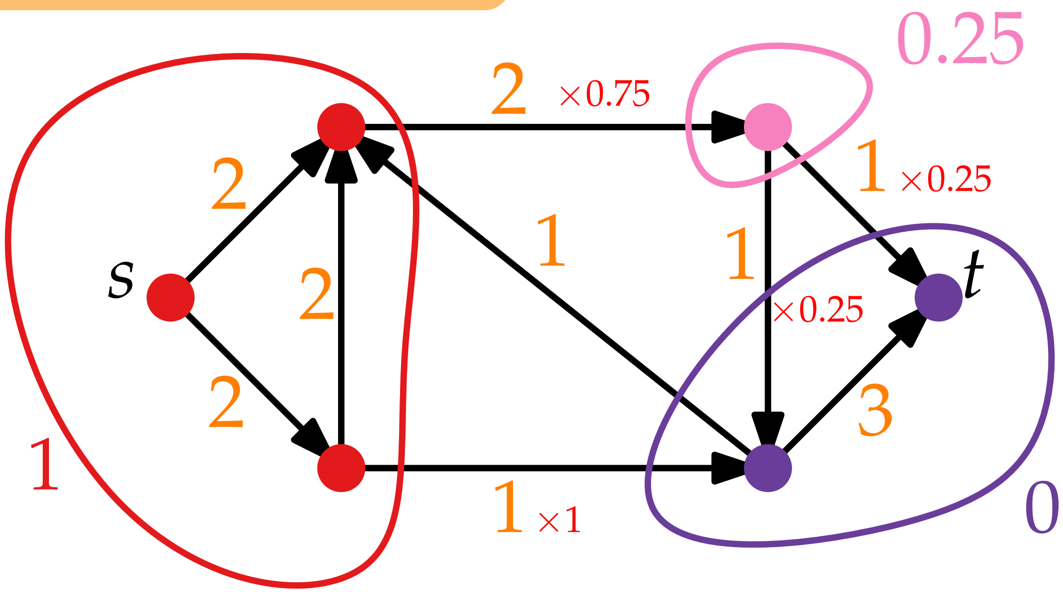
$$\begin{array}{llr}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv}\cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v)\in E\setminus\{(t,s)\} \\
& p_s - p_t \geq 1 & \\
& d_{uv} \geq 0 & \forall (u,v)\in E \\
& p_u \geq 0 & \forall u \in V
\end{array}$$

$\equiv$ LP-Relaxation of the ILP

Each extreme-point solution is **integral!** (HA)

Each s–t-path $s = v_0, \ldots, v_k = t$ has length ≥ 1 w.r.t. d:

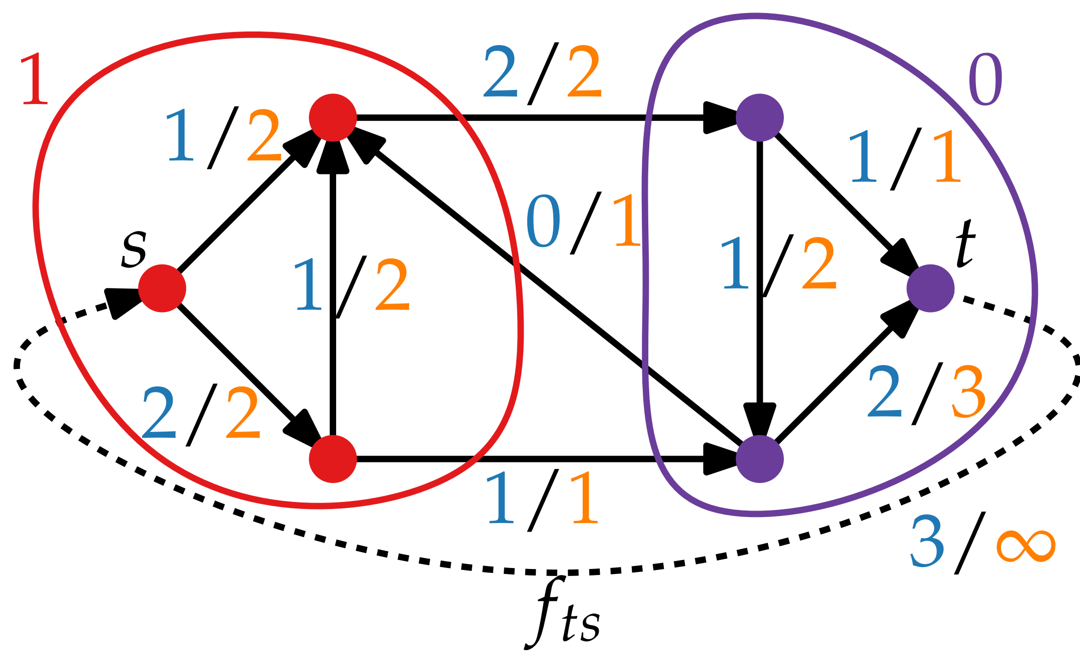
$$\sum_{i=0}^{k-1} d_{i,i+1} \geq \sum_{i=0}^{k-1} (p_i - p_{i+1})$$
$$= p_s - p_t$$



Dual LP – Complementary Slackness

$$\begin{array}{lll}
\textbf{maximize} & f_{ts} & \\
\textbf{subject to} & f_{uv} \leq c_{uv} & \forall (u,v) \in E \setminus \{(t,s)\} \\
& \sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \leq 0 & \forall v \in V \\
& f_{uv} \geq 0 & \forall (u,v) \in E
\end{array}$$

$$\begin{array}{lll}
\textbf{minimize} & \sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
& p_s - p_t \geq 1 & \\
& d_{uv} \geq 0 & \forall (u,v) \in E \\
& p_u \geq 0 & \forall u \in V
\end{array}$$

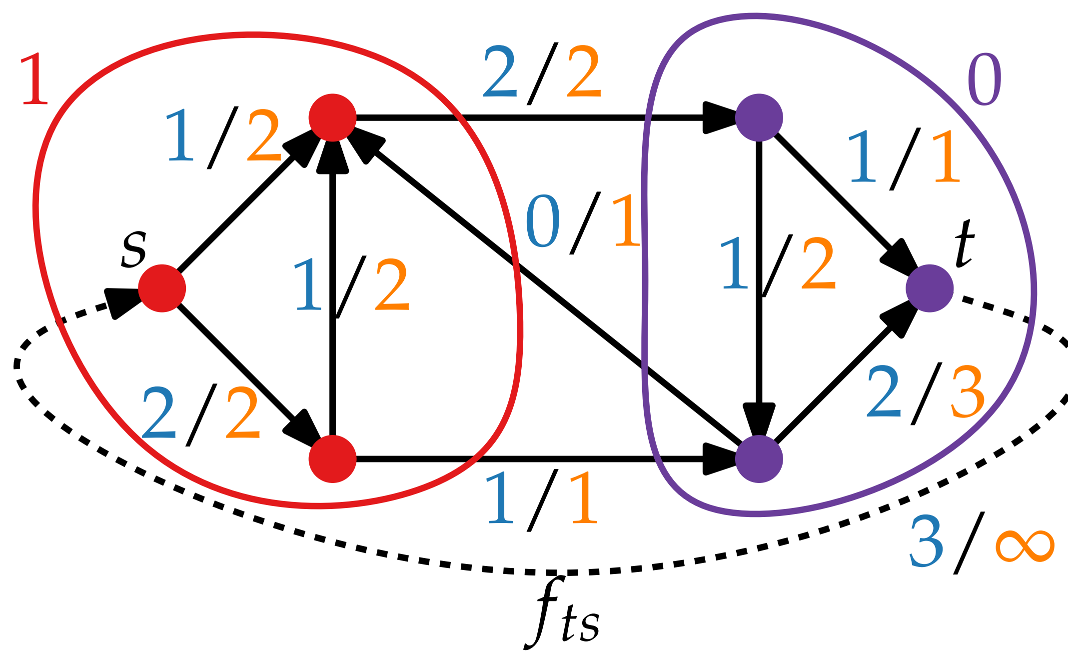


Dual LP – Complementary Slackness

$$
\begin{array}{lll}
\textbf{maximize} & f_{ts} & \\
\textbf{subject to} & f_{uv} \leq c_{uv} & \forall (u,v) \in E \setminus \{(t,s)\} \\
 & \displaystyle\sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \leq 0 & \forall v \in V \\
 & f_{uv} \geq 0 & \forall (u,v) \in E
\end{array}
$$

$$
\begin{array}{lll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} & \\
\textbf{subject to} & d_{uv} - p_u + p_v \geq 0 & \forall (u,v) \in E \setminus \{(t,s)\} \\
 & p_s - p_t \geq 1 & \\
 & d_{uv} \geq 0 & \forall (u,v) \in E \\
 & p_u \geq 0 & \forall u \in V
\end{array}
$$

For a max flow and min cut:



Dual LP – Complementary Slackness

maximize f_{ts}

subject to $f_{uv} \le c_{uv}$ $\quad \forall (u,v) \in E \setminus \{(t,s)\}$

$$\sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \le 0 \qquad \forall v \in V$$

$f_{uv} \ge 0$ $\quad \forall (u,v) \in E$

minimize $$\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv}$$

subject to $d_{uv} - p_u + p_v \ge 0$ $\quad \forall (u,v) \in E \setminus \{(t,s)\}$

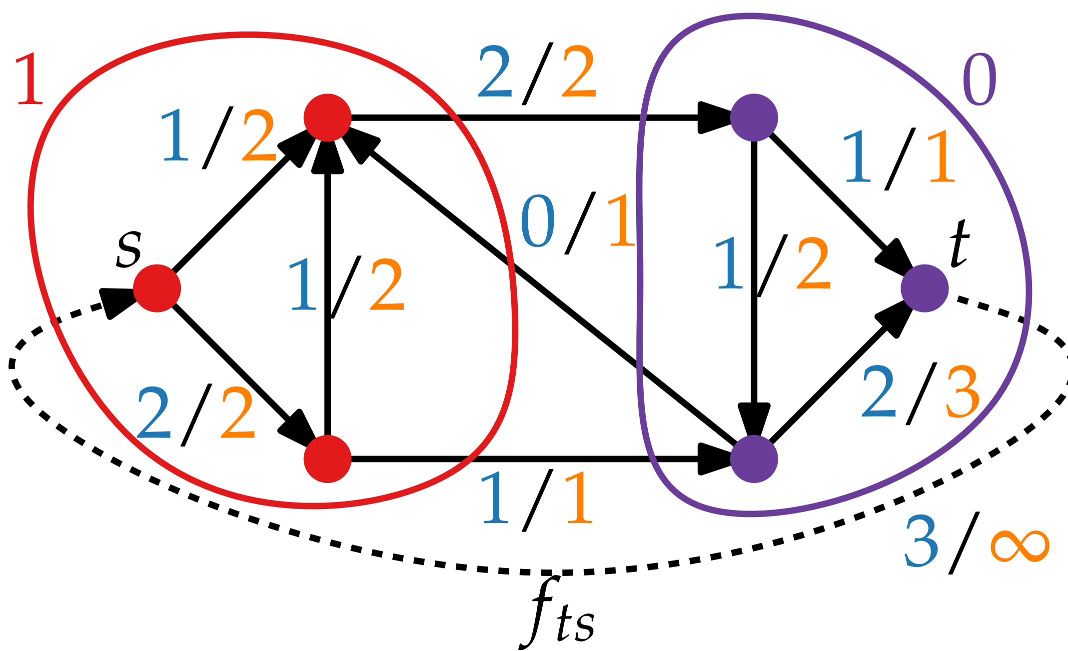
$p_s - p_t \ge 1$

$d_{uv} \ge 0$ $\quad \forall (u,v) \in E$

$p_u \ge 0$ $\quad \forall u \in V$

For a max flow and min cut:

- For each forward edge (u,v) of the cut: $f_{uv} = c_{uv}$.



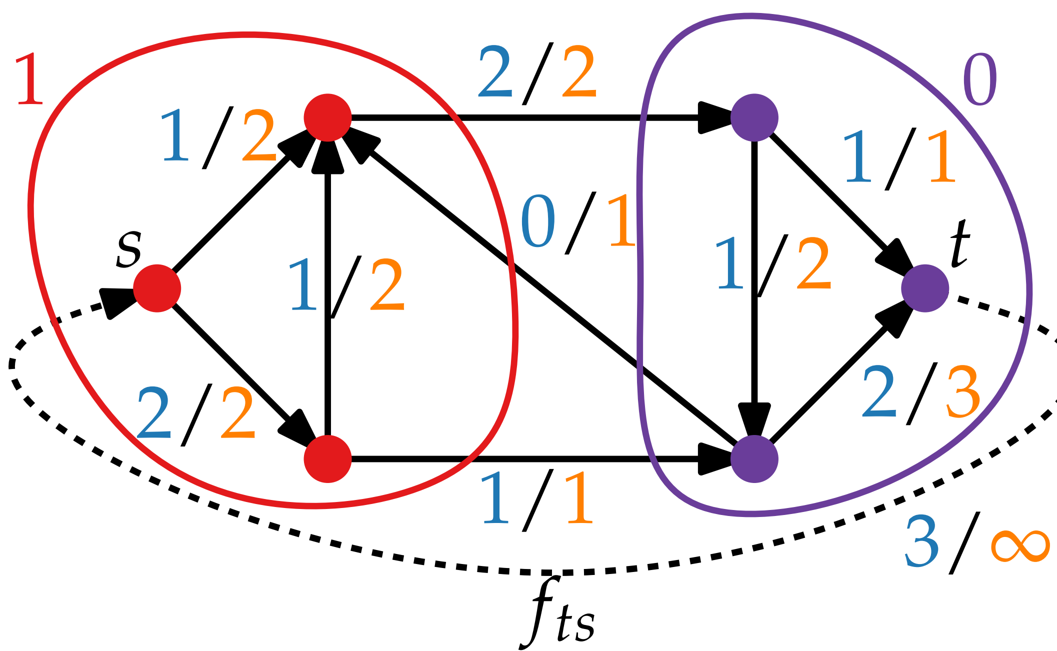
Dual LP – Complementary Slackness

maximize	f_{ts}	
subject to	$f_{uv} \leq c_{uv}$	$\forall (u,v) \in E \setminus \{(t,s)\}$
	$\displaystyle\sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \leq 0$	$\forall v \in V$
	$f_{uv} \geq 0$	$\forall (u,v) \in E$

minimize	$\displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv}$	
subject to	$d_{uv} - p_u + p_v \geq 0$	$\forall (u,v) \in E \setminus \{(t,s)\}$
	$p_s - p_t \geq 1$	
	$d_{uv} \geq 0$	$\forall (u,v) \in E$
	$p_u \geq 0$	$\forall u \in V$

For a max flow and min cut:

- For each forward edge (u,v) of the cut: $f_{uv} = c_{uv}$.
  ($d_{uv} = 1$, so by dual CS: $f_{uv} = c_{uv}$.)



Dual LP – Complementary Slackness

maximize f_{ts}

subject to

$f_{uv} \leq c_{uv}$ $\quad \forall (u,v) \in E \setminus \{(t,s)\}$

$\sum_{u\colon (u,v) \in E} f_{uv} - \sum_{z\colon (v,z) \in E} f_{vz} \leq 0$ $\quad \forall v \in V$

$f_{uv} \geq 0$ $\quad \forall (u,v) \in E$

minimize $\sum_{(u,v) \in E \setminus \{(t,s)\}} c_{uv} \cdot d_{uv}$

subject to

$d_{uv} - p_u + p_v \geq 0$

$p_s - p_t \geq 1$

$d_{uv} \geq 0$

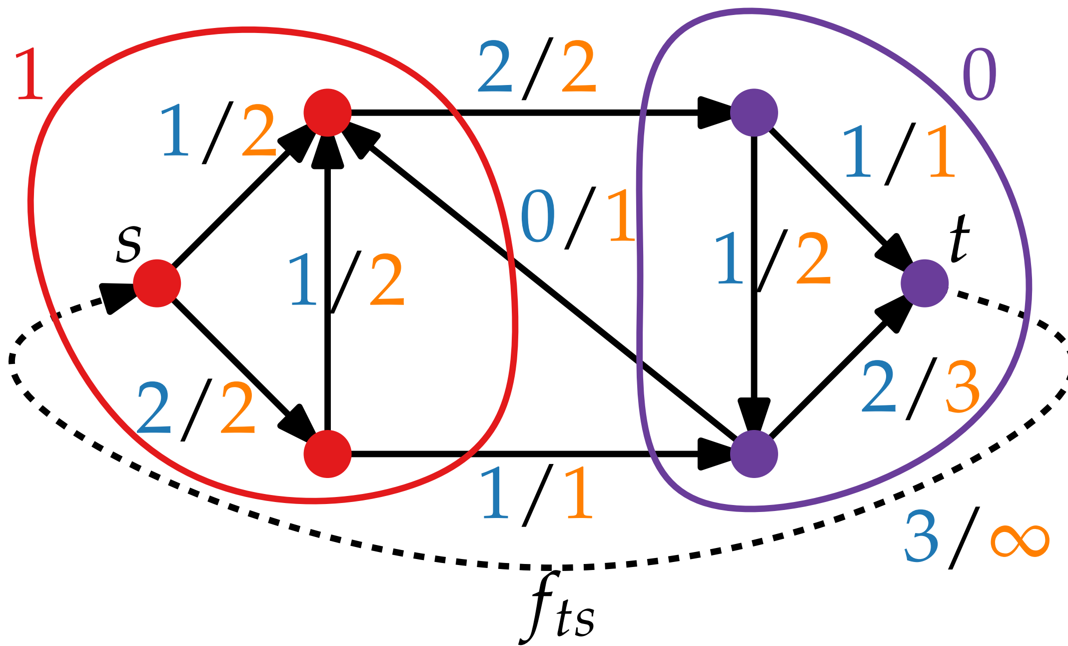
$p_u \geq 0$

Primal CS:
$\forall j$: Either $x_j = 0$ or $\sum_{i=1}^{m} a_{ij} y_i = c_j$

Dual CS:
$\forall i$: Either $y_i = 0$ or $\sum_{j=1}^{n} a_{ij} x_j = b_i$

For a max flow and min cut:

- For each forward edge (u,v) of the cut: $f_{uv} = c_{uv}$.
  ($d_{uv} = 1$, so by dual CS: $f_{uv} = c_{uv}$.)



Dual LP – Complementary Slackness

$$\begin{array}{lll} \textbf{maximize} & f_{ts} & \\ \textbf{subject to} & f_{uv} \le c_{uv} & \forall (u,v) \in E \setminus \{(t,s)\} \\ & \sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \le 0 & \forall v \in V \\ & f_{uv} \ge 0 & \forall (u,v) \in E \end{array}$$

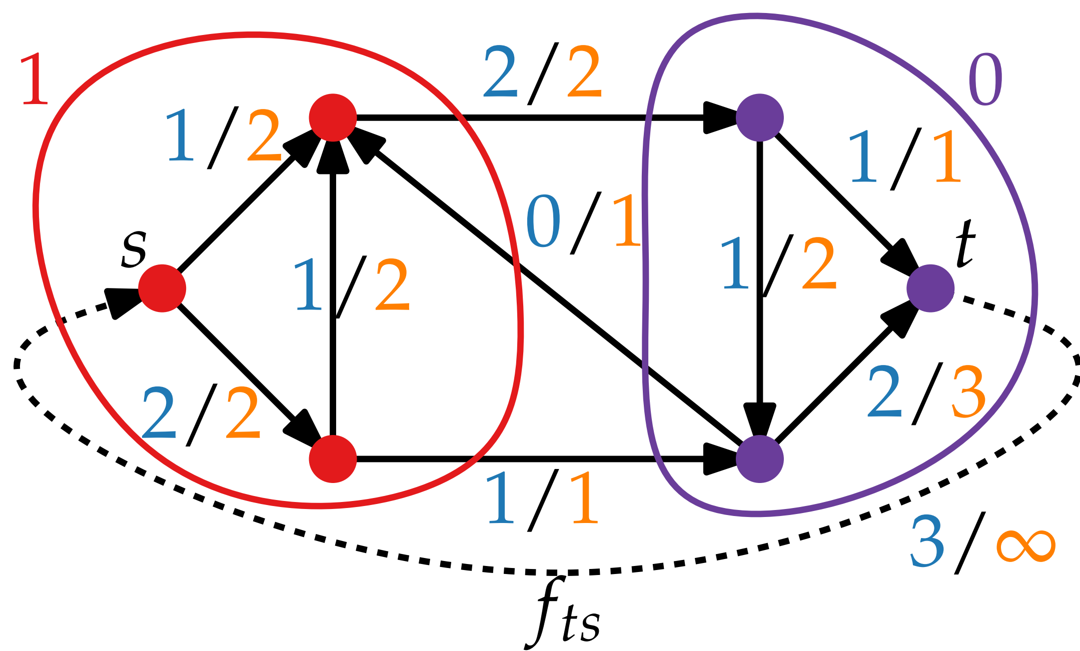
$$\begin{array}{ll} \textbf{minimize} & \sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} \\ \textbf{subject to} & d_{uv} - p_u + p_v \ge 0 \\ & p_s - p_t \ge 1 \\ & d_{uv} \ge 0 \\ & p_u \ge 0 \end{array}$$

Primal CS:
$\forall j$: Either $x_j = 0$ or $\sum_{i=1}^{m} a_{ij} y_i = c_j$

Dual CS:
$\forall i$: Either $y_i = 0$ or $\sum_{j=1}^{n} a_{ij} x_j = b_i$

For a max flow and min cut:

- For each forward edge (u,v) of the cut: $f_{uv} = c_{uv}$.
  ($d_{uv} = 1$, so by dual CS: $f_{uv} = c_{uv}$.)
- For each backward edge (u,v) of the cut: $f_{uv} = 0$.



Dual LP – Complementary Slackness

$$
\begin{array}{lll}
\textbf{maximize} & f_{ts} & \\
\textbf{subject to} & f_{uv} \le c_{uv} & \forall (u,v) \in E \setminus \{(t,s)\} \\
& \displaystyle\sum_{u\colon (u,v)\in E} f_{uv} - \sum_{z\colon (v,z)\in E} f_{vz} \le 0 & \forall v \in V \\
& f_{uv} \ge 0 & \forall (u,v) \in E
\end{array}
$$

$$
\begin{array}{ll}
\textbf{minimize} & \displaystyle\sum_{(u,v)\in E\setminus\{(t,s)\}} c_{uv} \cdot d_{uv} \\
\textbf{subject to} & d_{uv} - p_u + p_v \ge 0 \\
& p_s - p_t \ge 1 \\
& d_{uv} \ge 0 \\
& p_u \ge 0
\end{array}
$$

Primal CS:
$\forall j$: Either $x_j = 0$ or $\sum_{i=1}^{m} a_{ij} y_i = c_j$

Dual CS:
$\forall i$: Either $y_i = 0$ or $\sum_{j=1}^{n} a_{ij} x_j = b_i$

For a max flow and min cut:

- For each forward edge (u,v) of the cut: $f_{uv} = c_{uv}$.
  ($d_{uv} = 1$, so by dual CS: $f_{uv} = c_{uv}$.)
- For each backward edge (u,v) of the cut: $f_{uv} = 0$.
  (Otherwise, by primal CS: $d_{uv} - 0 + 1 = 0$.)