

Exact Augmented Lagrangian Duality in Mixed-Integer Nonlinear Optimization

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We consider general MI(N)LPs

$$\begin{aligned} z^* &= \min_x c^\top x \\ \text{s.t. } Ax &= b \\ Bx &\geq f \\ x &\in \mathbb{R}^{n_1} \times \mathbb{Z}^{n_2} \end{aligned}$$

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Problem Setting

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Let $X = \{x \in \mathbb{R}^{n_1} \times \mathbb{Z}^{n_2} : Bx \geq f\}$

Lagrangian Duality

Primal Problem

$$\begin{aligned} z^* &= \min_x c^\top x \\ \text{s.t. } & Ax = b \\ & x \in X \end{aligned}$$

Lagrangian Dual Problem

$$z^{\text{LD}} = \sup_{\lambda \in \mathbb{R}^m} z^{\text{LR}}(\lambda)$$

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Strong duality does not hold in general, i.e., $z^* > z^{\text{LD}}$

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with $\psi(u) > u$ if and only if $u \neq 0$, $\psi(0) = 0$

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Literature Review

Asymptotic Result

Exact Penalty Parameters

Guarantees From a Given Penalty Parameter

Conclusion

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Growing interest in the discrete community

	Asymptotic	Exactness	Poly. size	Poly. time	Opt. set
ILP (Boland and Eberhard 2014)	✓	✓	↑		↑
MILP (Feizollahi et al. 2016)	✓	✓	↑		✓
MIQP (Gu et al. 2020)	✓	✓	✓		
MICP (Bhardwaj et al. 2024)	✓	✓			

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MINLP (our work)	✓	✓			✓

Assumption (Compactness)

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Assumption (Penalty Function)

The penalty function $\psi : \mathbb{R}^m \rightarrow \mathbb{R}_{\geq 0}$ is

1. continuous, i.e., $\lim_{u \rightarrow u^*} \psi(u) = \psi(u^*)$;
2. positive definite, i.e., $\psi(u) > 0$ for all $u \neq 0$ and $\psi(0) = 0$.

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Bounding the Augmenting Term

Let $\lambda \in \mathbb{R}^m$. Let x_ρ denote any solution of

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$$\rho\psi(Ax_\rho - b) \leq \kappa$$

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$$z_\rho^{\text{LR}^+}(\lambda) \leq z^*$$

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$$\begin{aligned} c^\top x_\rho + \lambda^\top (Ax_\rho - b) + \rho\psi(Ax_\rho - b) &\leq c^\top x^* \\ \iff \rho\psi(Ax_\rho - b) &\leq c^\top x^* - c^\top x_\rho + \lambda^\top (b - Ax_\rho) \end{aligned}$$

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$$\begin{aligned} & c^\top x_\rho + \lambda^\top (Ax_\rho - b) + \rho\psi(Ax_\rho - b) \leq c^\top x^* \\ \iff & \rho\psi(Ax_\rho - b) \leq c^\top x^* - c^\top x_\rho + \lambda^\top (b - Ax_\rho) \\ \implies & \rho\psi(Ax_\rho - b) \leq \max_{y, z \in X} \{c^\top y - c^\top z + \lambda^\top (b - Az)\} \end{aligned}$$

Asymptotic Result (Part 1)

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Let $\varepsilon > 0$. Any $\rho \geq \frac{1}{\varepsilon}\kappa$ guarantees that $\psi(Ax_\rho - b) \leq \varepsilon$.

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Let $\varepsilon \rightarrow 0$ ($\rho \rightarrow \infty$)

There is a limit point of (a sub-sequence of) $(x_\rho)_{\rho>0}$, say $x_\infty \in X$

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This shows that x_∞ is feasible for the primal problem!

$$z^* = \lim_{\rho \rightarrow \infty} z_\rho^{\text{LR}+}(\lambda)$$

Asymptotic Result (Part 3)

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$$z^* = \sup_{\rho > 0} z_\rho^{\text{LR}+}(\lambda)$$

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It holds

$$\psi(Ax_\rho - b) \leq \delta/2$$

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So it must be that $\psi(Ax_\rho - b) \leq 0 \implies Ax_\rho = b$

Problem Assumption already fails for some MILPs (Feizollahi et al., 2016)

Norm Penalty Functions

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By equivalence of norms, there exists $\gamma > 0$ such that $\|\cdot\| \leq \gamma\|\cdot\|'$

$$\begin{aligned}z^* &= \min_{x \in X} c^\top x + \lambda^\top (Ax - b) + \rho \|Ax - b\| \\ &\leq \min_{x \in X} c^\top x + \lambda^\top (Ax - b) + \rho \gamma \|Ax - b\|' \\ &\leq z^*\end{aligned}$$

Thus $\rho\gamma$ is exact for $\|\cdot\|'$

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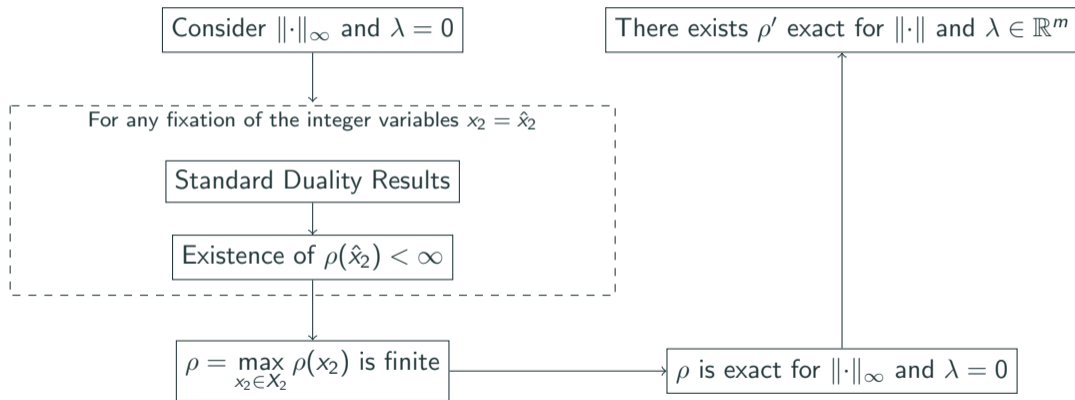
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Lemma 2 The choice of λ does not matter

Say $\rho < \infty$ is exact for $\|\cdot\|_2$ and $\lambda = 0$

$$\begin{aligned}z^* &= \min_{x \in X} c^\top x + \rho \|Ax - b\|_2 \\ &= \min_{x \in X} c^\top x + \lambda^\top (Ax - b) - \lambda^\top (Ax - b) + \rho \|Ax - b\|_2 \\ &\leq \min_{x \in X} c^\top x + \lambda^\top (Ax - b) + \|\lambda\|_2 \|Ax - b\|_2 + \rho \|Ax - b\|_2 \\ &= \min_{x \in X} c^\top x + \lambda^\top (Ax - b) + (\|\lambda\|_2 + \rho) \|Ax - b\|_2\end{aligned}$$

Exact Penalty Parameter: How to Prove It



Exact Penalty Parameter: The Proof

Fix the integer part in the primal, say, $x_2 = \hat{x}_2$ with $x = (x_1, x_2)$

$$\begin{aligned} z^*(\hat{x}_2) &= \min_{x_1} c_1^\top x_1 + c_2^\top \hat{x}_2 \\ \text{s.t. } Ax_1 &= b - A\hat{x}_2 \\ g(x_1, \hat{x}_2) &\leq 0 \\ x_1 &\in \mathbb{R}^{n_1} \end{aligned}$$

We distinguish two cases

1. Feasible case: $z^*(x_2) < \infty$
2. Infeasible case: $z^*(x_2) = \infty$

Feasible Case

As per the previous lemma, let's use $\psi(\cdot) = \|\cdot\|_\infty$ and $\lambda = 0$

$$\begin{aligned} z^*(\hat{x}_2) - c_2^\top \hat{x}_2 = & \min_{x_1} c_1^\top x_1 \\ & \text{s.t. } A_1 x_1 = b - A_2 \hat{x}_2 \\ & B_1 x_1 \geq f - B_2 \hat{x}_2 \end{aligned}$$

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$$\begin{aligned} z^*(\hat{x}_2) - c_2^\top \hat{x}_2 &= \min_{x_1} c_1^\top x_1 &= \max_{\mu, \lambda} (b - A_2 \hat{x}_2)^\top \mu + (f - B_2 \hat{x}_2)^\top \lambda \\ &\text{s.t. } A_1 x_1 = b - A_2 \hat{x}_2 &\text{s.t. } A_1^\top \mu + B_1^\top \lambda = c_1 \\ &B_1 x_1 \geq f - B_2 \hat{x}_2 &\lambda \geq 0 \end{aligned}$$

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$$B_1 x_1 \geq f - B_2 \hat{x}_2 \quad \lambda \geq 0$$

$$z_\rho^{\text{LR}+}(\hat{x}_2) - c_2^\top \hat{x}_2 = \min_{x_1} c_1^\top x_1 + \rho \|A_1 x_1 + A_2 \hat{x}_2 - b\|_\infty$$
$$\text{s.t. } B_1 x_1 \geq f - B_2 \hat{x}_2$$

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$$z_\rho^{\text{LR}+}(\hat{x}_2) - c_2^\top \hat{x}_2 = \min_{x_1} c_1^\top x_1 + \rho \|A_1 x_1 + A_2 \hat{x}_2 - b\|_\infty = \max_{\mu, \lambda} (b - A_2 \hat{x}_2)^\top \mu + (f - B_2 \hat{x}_2)^\top \lambda$$
$$\text{s.t. } B_1 x_1 \geq f - B_2 \hat{x}_2 \quad \text{s.t. } A_1^\top \mu + B_1^\top \lambda = c_1$$
$$\lambda \geq 0$$
$$\|\mu\|_1 \leq \rho$$

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$$\text{s.t. } B_1 x_1 \geq f - B_2 \hat{x}_2 \quad \text{s.t. } A_1^\top \mu + B_1^\top \lambda = c_1$$
$$\lambda \geq 0$$
$$\|\mu\|_1 \leq \rho$$

Any $\rho > \|\mu^*\|_1$ is large enough!

Infeasible Case

It is sufficient to choose ρ such that

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Any ρ such that $z_{\rho}^{\text{LR}+}(\hat{x}_2) > \text{UB}$ is large enough!

Infeasible Case

We need to solve the “bilevel” problem

$$\begin{array}{ll} \min_{\rho} & \rho \\ \text{s.t.} & z_{\rho}^{\text{LR}+}(\hat{x}_2) \geq \text{UB} \end{array}$$

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$$\text{s.t.} \quad \left\{ \begin{array}{l} \min_{x_1} \quad c_1^{\top} x_1 + \rho \|A_1 x_1 + A_2 \hat{x}_2 - b\|_{\infty} \\ \text{s.t.} \quad B_1 x_1 \geq f - B_2 \hat{x}_2 \end{array} \right\} \geq \text{UB}$$
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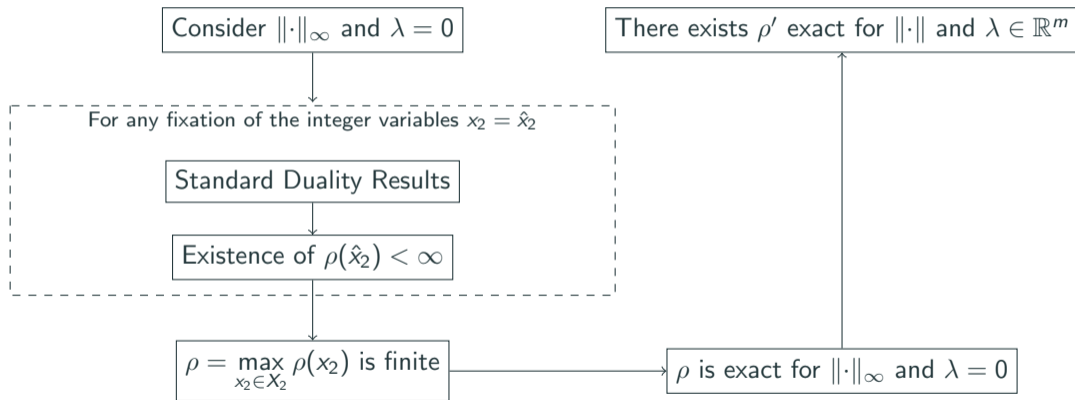
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$$= \min_{\rho} \rho$$
$$\text{s.t.} \quad \left\{ \begin{array}{l} \max_{\lambda, \mu} \quad (b - A_2 \hat{x}_2)^{\top} \mu + (f - B_2 \hat{x}_2)^{\top} \lambda \\ \text{s.t.} \quad A_1^{\top} \mu + B_1^{\top} \lambda = c_1 \\ \lambda \geq 0 \\ \|\mu\|_1 \leq \rho \end{array} \right\} \geq \text{UB}$$
$$\rho \geq 0$$

Single-level reformulation

$$\begin{aligned} \min_{\rho, \mu, \lambda} \quad & \rho \\ \text{s.t.} \quad & (b - A_2 \hat{x}_2)^\top \mu + (f - B_2 x_2)^\top \lambda \geq \text{UB} \\ & A_1^\top \mu + B_1^\top \lambda = c_1 \\ & \lambda \geq 0 \\ & \|\mu\|_1 \leq \rho \end{aligned}$$

This problem is feasible (Farkas Lemma) and lower bounded by zero.

Exact Penalty Parameter: How to Prove It



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Primal Problem

$$\begin{aligned} z^* &= \min_x c^\top x \\ \text{s.t. } Ax &= b \\ x &\in X \end{aligned}$$

Perturbed Primal Problem

$$\begin{aligned} \tilde{z}_\varepsilon^* &= \min_x c^\top x \\ \text{s.t. } \|Ax - b\|_\varphi &\leq \varepsilon \\ x &\in X \end{aligned}$$

Relation to a Perturbed Problem

Assume that ψ has “some relation” to a norm:

$$\psi(u) \leq \varepsilon \implies \|u\|_{\varphi} \leq \varphi^{-1}(\varepsilon)$$

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x_ρ is feasible for the perturbed primal problem!

For any $\rho \geq \kappa/\varphi(\varepsilon)$,

$$\tilde{z}_\varepsilon^* \leq z_\rho^{\text{LR}+}(\lambda) \leq z^*$$

From Exact Penalty Parameter to Sensitivity

Let x^ε denote an optimal point of the perturbed problem

Let $\psi = \|\cdot\|_2$ and let $\rho^* < \infty$ be such that

$$z^* = z_{\rho^*}^{\text{LR}^+}(\lambda)$$

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$$z^* - (\|\lambda\|_2 + \rho^*)\varepsilon \leq \tilde{z}_\varepsilon^*$$

Combining

- $\tilde{z}_\varepsilon^* \leq z_\rho^{\text{LR}+}(\lambda) \leq z^*$, for any $\rho \geq \kappa/\varphi(\varepsilon)$
- $z^* - (\|\lambda\|_2 + \rho^*)\varepsilon \leq \tilde{z}_\varepsilon^*$

Approximation Guarantees

Combining

- $\tilde{z}_\varepsilon^* \leq z_\rho^{\text{LR}+}(\lambda) \leq z^*$, for any $\rho \geq \kappa/\varphi(\varepsilon)$
- $z^* - (\|\lambda\|_2 + \rho^*)\varepsilon \leq \tilde{z}_\varepsilon^*$

- If $\psi = \|\cdot\|$, then

$$z^* - o\left(\frac{1}{\rho}\right) \leq z_\rho^{\text{LR}+}(\lambda) \leq z^*$$

- If $\psi = \frac{1}{2}\|\cdot\|_2^2$, then

$$z^* - o\left(\frac{1}{\sqrt{\rho}}\right) \leq z_\rho^{\text{LR}+}(\lambda) \leq z^*$$

This generalizes Theorem 2 of Feizollahi et al. (2016)

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In the Future

- Use these results to derive algorithms for multi-level optimization problems