

Mixed-Integer MPC for Real-Time Decision Making

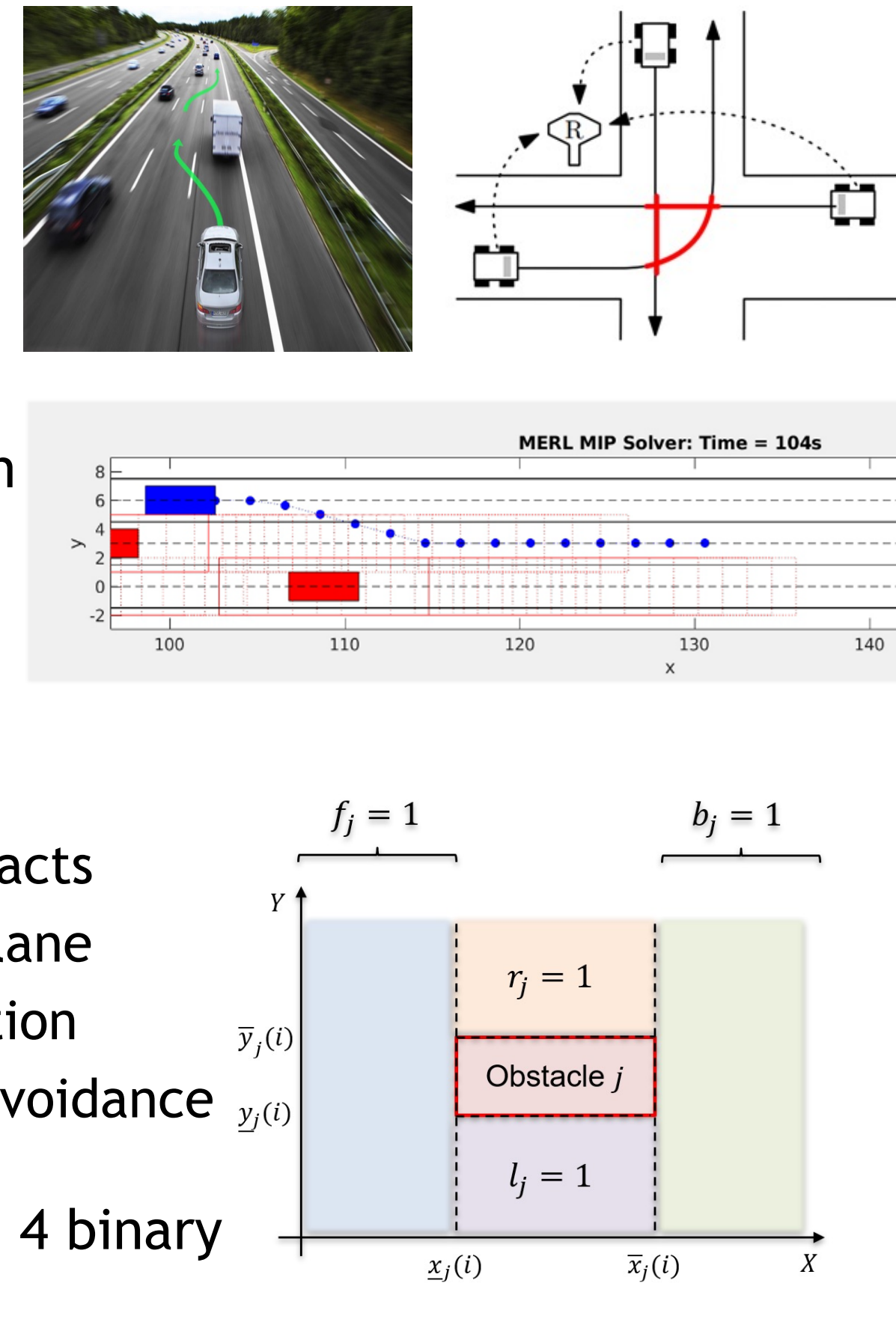
MI-MPC provides a general-purpose modeling framework for real-time decision making.

We are particularly interested in an MI-MPC formulation of a high-level motion planning task for an autonomous vehicle, including discrete decisions resulting from lane changes, static and dynamic obstacles

The MI-MPC framework solves an MIQP problem at every sampling time instant.

- Switches in system dynamics, e.g., contacts
- Discrete decisions, e.g., pass or stay in lane
- Quantized decisions, e.g., on/off actuation
- Disjoint constraint sets, e.g., obstacle avoidance

For example, using big-M formulation and 4 binary variables



Infeasible IPM: Projection to Dual Feasibility

Equality-constrained optimization for minimum-norm projection on constraint

$$\min_{\Delta\lambda, \Delta\mu} \frac{1}{2} \|\Delta\lambda\|^2 + \frac{1}{2} \|\Delta\mu\|^2, \text{ s.t. } F_y^T \Delta\lambda + G_y^T \Delta\mu = -r_y^k$$

But projection does not guarantee nonnegativity of Lagrange multipliers, i.e., $\mu \geq 0$

Proposed approach: modified optimization problem for projection on constraint

Solve equality-constrained optimization problem to compute projection step

$$\min_{\Delta x, \Delta\lambda, \Delta\mu} \frac{1}{2} \|\Delta x\|_Q^2 + \frac{1}{2} \|\Delta\lambda\|_{\epsilon_{\text{dual}}}^2 + \frac{1}{2} \|\Delta\mu\|_{W^k}^2$$

$$\text{s.t. } \begin{bmatrix} Q & & \\ & F^T & G^T \\ & 0 & -W^k \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta\lambda \\ \Delta\mu \end{bmatrix} = - \begin{bmatrix} 0 \\ r_y^k \\ 0 \end{bmatrix}$$

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is equivalent to solving KKT system to compute Newton-type search direction

$$\begin{bmatrix} H & F^T & G^T \\ F & -\epsilon_{\text{dual}} I & 0 \\ G & 0 & -W^k \end{bmatrix} \begin{bmatrix} \Delta z \\ \Delta\lambda \\ \Delta\mu \end{bmatrix} = - \begin{bmatrix} 0 \\ r_y^k \\ 0 \end{bmatrix}$$

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is equivalent to solving reduced KKT system to compute search direction Δz

$$\left(H + \frac{1}{\epsilon_{\text{dual}}} F^T F + G^T W^{k-1} G \right) \Delta z = - \begin{bmatrix} 0 \\ r_y^k \\ 0 \end{bmatrix}$$

which is used to compute projection step for Lagrange multipliers $(\Delta\mu^k, \Delta\lambda^k)$:

$$\Delta\lambda = \frac{1}{\epsilon_{\text{dual}}} F \Delta z, \quad \Delta\mu = W^{k-1} G \Delta z$$

$W^k = \text{diag}(w^k)$ and $w_i^k = \frac{s_i^k}{\mu_i^k} > 0$
 $\|\Delta\mu\|_{W^k}^2 = \sum_i \left(\frac{s_i^k}{\mu_i^k} \Delta\mu_i^k \right)^2$

Indirectly enforces positivity constraints $\mu \geq 0$
Active inequality constraints:
 $s_i \rightarrow 0$ and $\mu_i > 0 \Rightarrow w_i = \frac{s_i}{\mu_i} \rightarrow 0$ (small penalty)
Inactive inequality constraints:
 $\mu_i \rightarrow 0$ and $s_i > 0 \Rightarrow w_i = \frac{s_i}{\mu_i} \rightarrow \infty$ (large penalty)

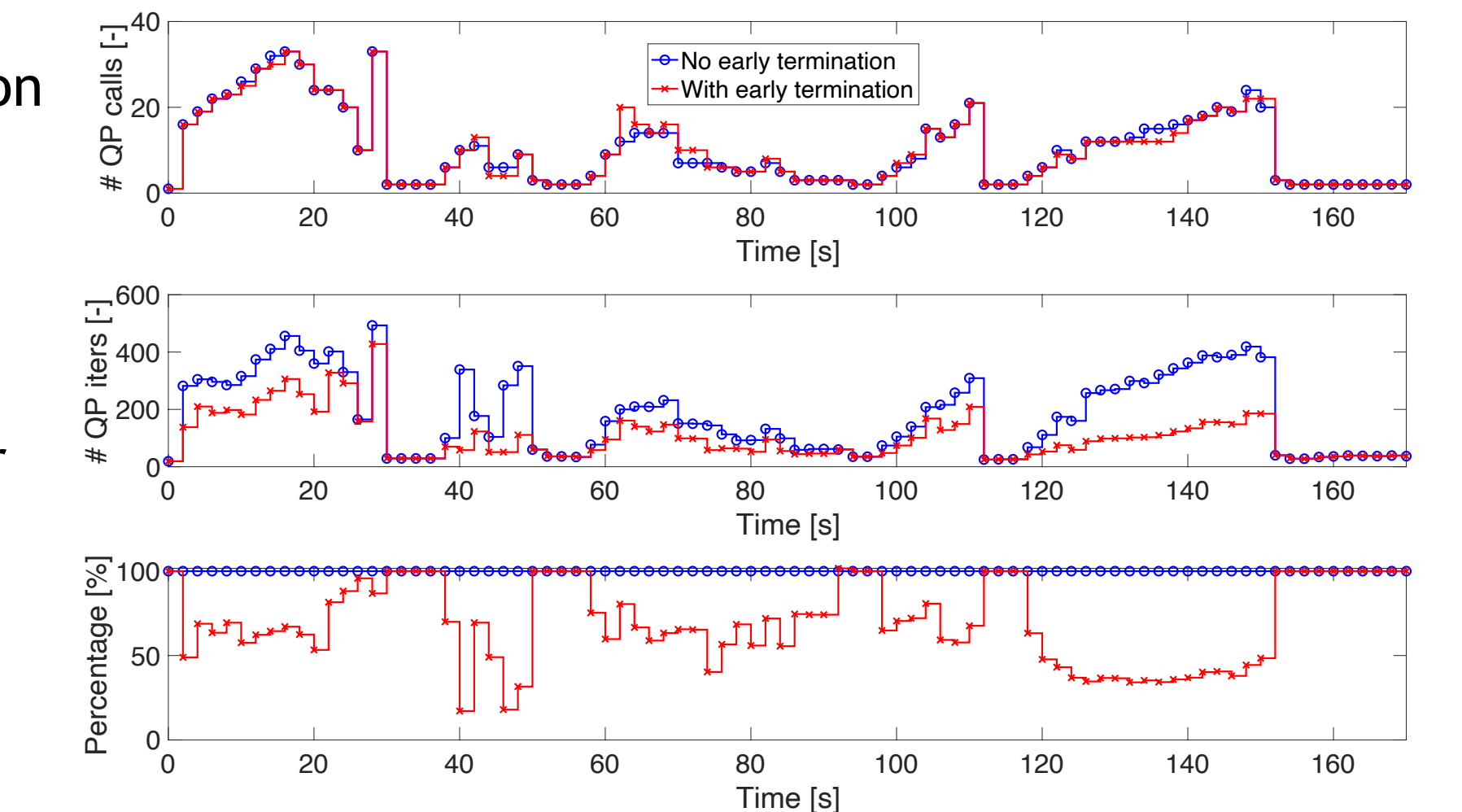
Projection corresponds to IPM iteration with different right-hand side: obtain dual feasibility while maintaining optimality conditions

We can reuse the KKT matrix factorization between IPM iterations and projection steps for computational efficiency

Simulation Results: Real-Time Vehicle Decision Making

QP Calls and Total Iterations

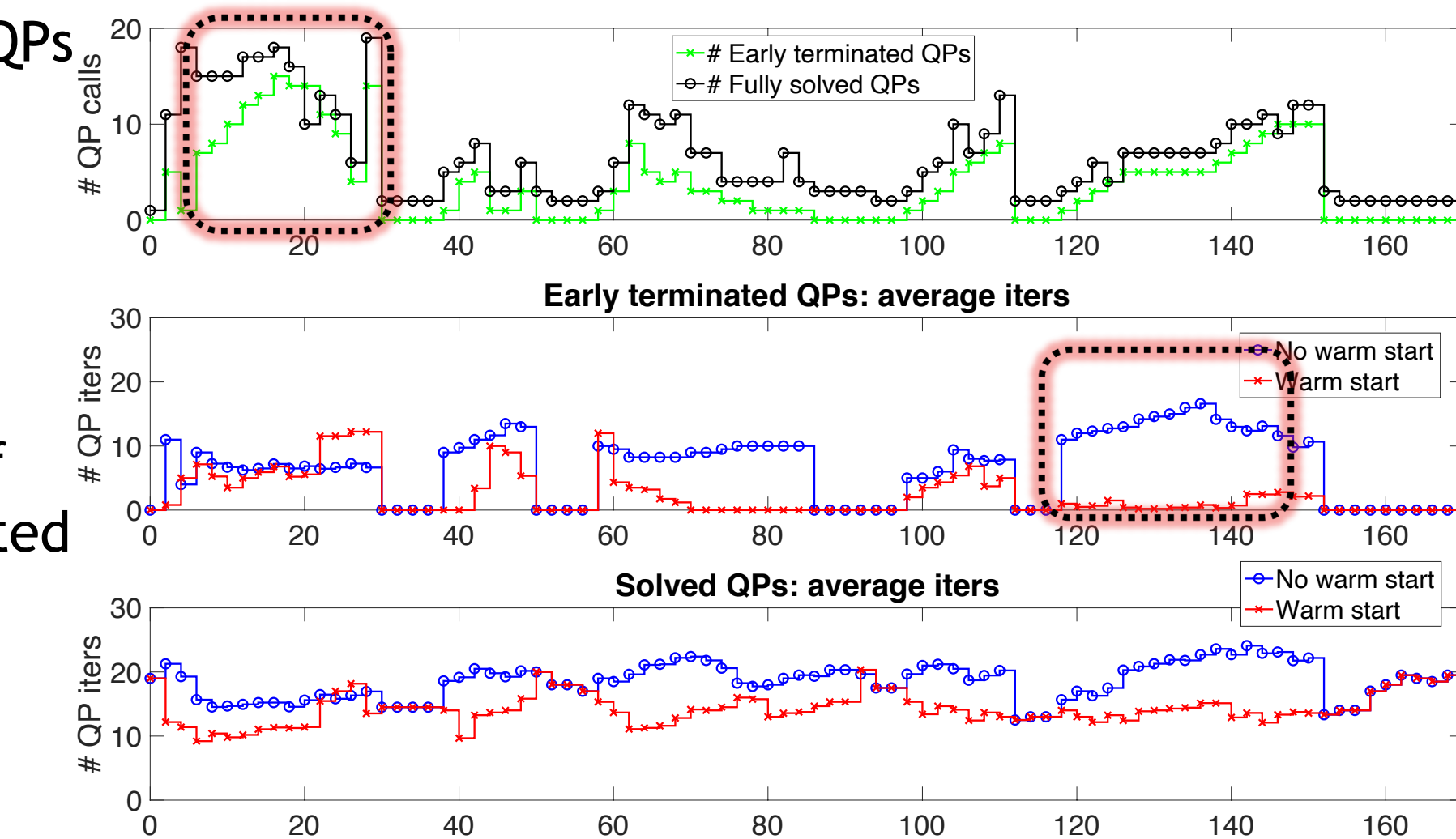
blue: No early termination
red: Early termination



➤ Early termination reduces total number of QP iterations by 42%.

Early Terminated versus Fully Solved QPs

green: Early terminated QPs
black: Fully solved QPs
blue: No warm start
red: Warm start



➤ Early termination happens often, 36% of QPs are early terminated

➤ Early termination benefits from warm starting IPM and takes less QP iterations.

Infeasibility Detection

Number of IPM Iterations for Certificate Versus Early Termination With and Without Warm Starting

	QP # 1	QP # 2	QP # 3
Certificate of primal infeasibility	40	45	38
Early termination: cold started	10	12	10
Early termination: warm started	0	0	11

- Early termination requires considerably less IPM iterations than the computation of a certificate of infeasibility.
- Warm starting can reduce the number of IPM iterations further and it can lead to immediate termination, i.e., termination at 0 iterations.

Conclusions

An efficient early termination strategy based on a projection step tailored to IPMs, in order to reduce the computational cost within B&B method in solving MI-MPC.

Early termination of QP solvers in MI-MPC works well in

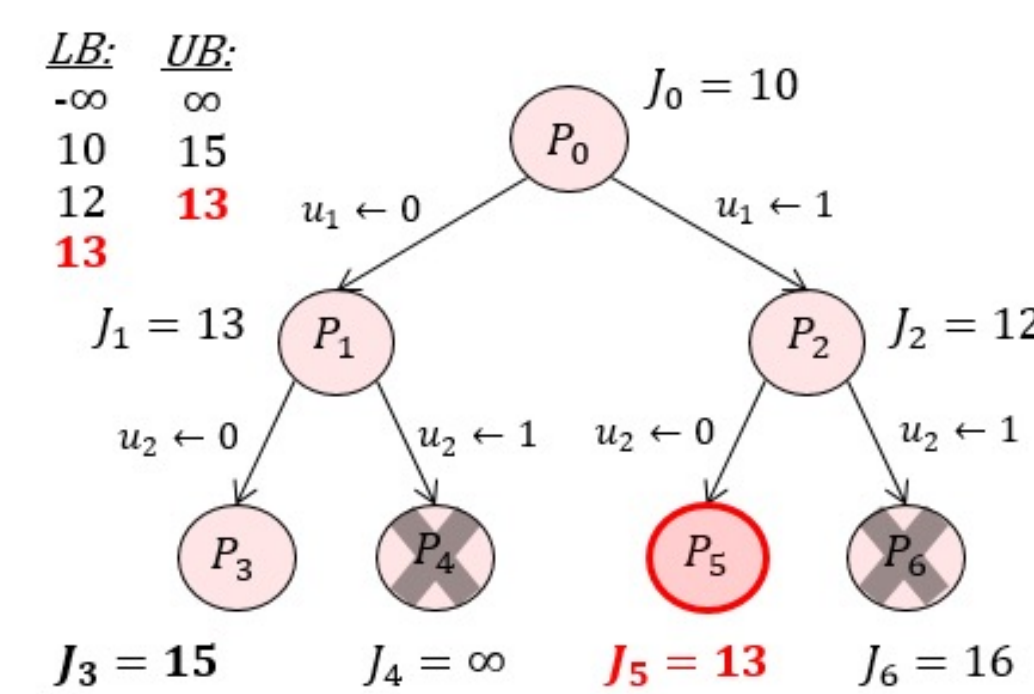
- terminating QPs whose objective value $> UB$;
- detecting infeasible QPs.

Early termination is performed by using Newton-type IPM iterations

- reuses KKT matrix factorizations for computational efficiency;
- intuitively guarantees the inequality constraint, i.e., positivity in μ ;
- projection also makes progress towards convergence.

Branch-and-Bound Algorithm for MIQP

- Convex QP relaxations solved to obtain lower bounds (LB)
- Each integer-feasible solution forms an upper bound (UB) for the MIQP solution
- A node can be pruned due to LB $>$ UB (P_6) or infeasibility (P_4)



Early termination of QP solvers in B&B: aim to prune node without need to solve convex QP

If dual feasible objective $\psi(\cdot) > UB$, then primal optimal objective $\phi^* > UB$:
 $\psi(\mu, \lambda) \leq \psi^* \leq \phi^* \leq \phi(x, y)$

- Terminate the QP solver before convergence.
- Also effective in detecting primal infeasibility.

QP Formulations and Infeasible IPM Solver

Primal QP Formulation

$$\min_{x, y} \phi(x, y) := \frac{1}{2} x^T Q x + h_x^T x + h_y^T y$$

$$\text{s.t. } G_x x + G_y y \leq g,$$

$$F_x x + F_y y = f,$$

Dual QP Formulation

$$\hat{h}(\mu, \lambda) := h_x + G_x^T \mu + F_x^T \lambda,$$

$$\max_{\mu, \lambda} \psi(\mu, \lambda) := -\frac{1}{2} \|\hat{h}(\mu, \lambda)\|_{Q^{-1}}^2 - \begin{bmatrix} g \\ f \end{bmatrix}^T \begin{bmatrix} \mu \\ \lambda \end{bmatrix}$$

$$\text{s.t. } G_y^T \mu + F_y^T \lambda = -h_y,$$

$$\mu \geq 0,$$

• Infeasible IPM: Newton-type iteration

$$\begin{bmatrix} H & F^T & G^T \\ F & 0 & 0 \\ G & 0 & -W^k \end{bmatrix} \begin{bmatrix} \Delta z^k \\ \Delta\lambda^k \\ \Delta\mu^k \end{bmatrix} = - \begin{bmatrix} r_y^k \\ r_y^k \\ r_y^k \end{bmatrix}$$

• Problem: infeasible IPM iterations generally do not satisfy dual feasibility until convergence

• Proposed solution: computationally efficient projection to obtain dual feasible solution guess for early termination of infeasible IPM

Early Termination of IPM: Infeasibility detection

- Certificate of primal infeasibility (i.e., unboundedness of dual) the following set of equations is strictly infeasible

$$Gz < g, \quad Fz = f,$$

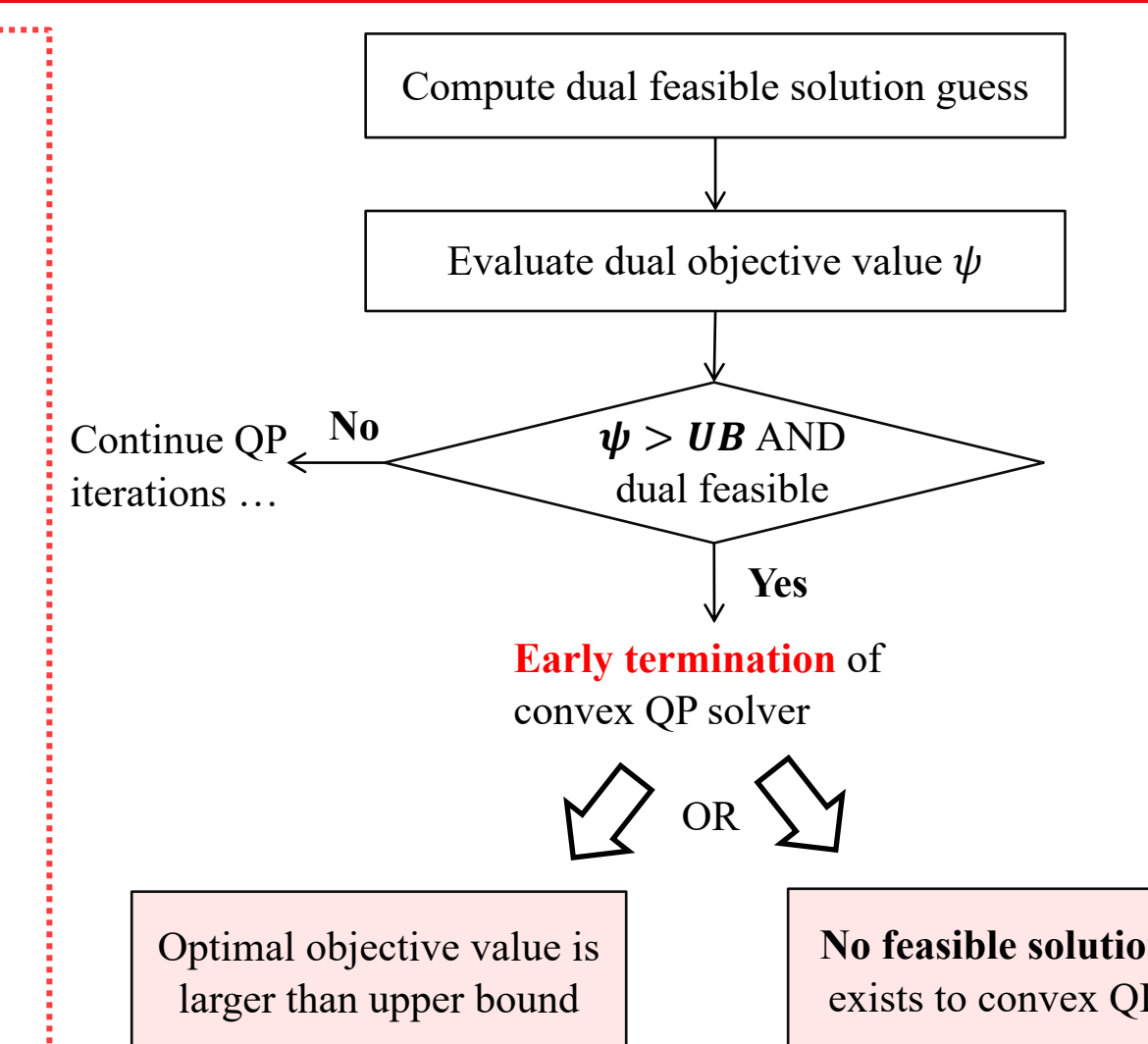
if and only if there exists a pair $(\tilde{\mu}, \tilde{\lambda})$ such that (Farkas' lemma)

$$G^T \tilde{\mu} + F^T \tilde{\lambda} = 0, \quad g^T \tilde{\mu} + f^T \tilde{\lambda} < 0, \quad \tilde{\mu} > 0$$

- Instead, our proposed early termination technique can be used for infeasibility detection and requires limited computational cost (projection based on reuse of KKT matrix factorization).

- Intuition behind using early termination for infeasibility detection:

Proposition 4.3: If the sequence of IPM iterates $\{(z^k, \mu^k, \lambda^k, s^k)\}$ satisfy $\mu^{k^T} s^k \leq \mu^{0^T} s^0$ and $\|\mu^k\| \rightarrow \infty$, then the dual objective $\psi(\mu^k, \lambda^k) \rightarrow \infty$.



Algorithm 1 Early termination for IPM in B&B method.

1: Input: Warm start $\{(z^0, \mu^0, \lambda^0, s^0)\}$, tol , and UB .
2: while $\max\{r^k, \|r^k\|\} > tol$ do
3: if $\psi(\mu^k, \lambda^k) > UB$ & dual feasible then
4: break while loop. \triangleright Early termination
5: else if $\psi(\mu^k, \lambda^k) > UB$ then
6: Compute projection step $(\Delta\mu, \Delta\lambda)$ in (13).
7: $\mu \leftarrow \mu^k + \Delta\mu$, $\lambda \leftarrow \lambda^k + \Delta\lambda$, and
8: $r_y \leftarrow F_y^T \lambda + G_y^T \mu + h_y$.
9: if $\mu > 0$ & $\|r_y\| < tol$ then
10: $\mu^k \leftarrow \mu$, $\lambda^k \leftarrow \lambda$, $r_y^k \leftarrow r_y$, and
11: dual feasible $\leftarrow 1$.
12: if $\psi(\mu^k, \lambda^k) > UB$ then
13: break while loop. \triangleright Early termination
14: end if
15: end if
16: end if
17: Perform an IPM iteration (8), e.g., see [18].
18: end while