

Algorithms in Gurobi



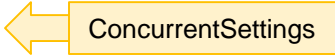
GUROBI
OPTIMIZATION

What's Inside Gurobi Optimizer

- ▶ Algorithms for continuous optimization
- ▶ Algorithms for discrete optimization
- ▶ Automatic presolve for both LP and MIP
- ▶ Algorithms to analyze infeasible models
- ▶ Automatic parameter tuning tool
- ▶ Parallel and distributed parallel support
- ▶ Gurobi Compute Server
- ▶ Gurobi Instant Cloud
- ▶ Programming interfaces
- ▶ Gurobi modeling language based on Python
- ▶ Full-featured interactive shell

Gurobi LP Algorithms

Continuous: LP / QP / QCP

- ▶ Presolve
- ▶ Primal & dual simplex method
 - Numerically stable (most challenging part)
- ▶ Parallel barrier method with crossover
 - Can effectively exploit multiple cores
- ▶ Concurrent optimization 
 - Run both simplex and barrier simultaneously
 - Solution is reported by first one to finish
 - Great use of multiple CPU cores
 - Best mix of speed and robustness
 - Deterministic and non-deterministic versions available

Presolve

▶ Goal

- Reduce the problem size

▶ Example

$$x + y + z \leq 5 \quad (1)$$

$$u - x - z = 0 \quad (2)$$

.....

$$0 \leq x, y, z \leq 1 \quad (3)$$

$$u \text{ is free} \quad (4)$$

▶ Reductions

- Redundant constraint
 - (3) $\Rightarrow x + y + z \leq 3$, so (1) is redundant
- Substitution
 - (2) and (4) $\Rightarrow u$ can be substituted with $x + z$

Primal and Dual LP

- ▶ Primal Linear Program:

$$\min \quad c^T x$$

$$s.t. \quad Ax = b$$

$$x \geq 0$$

- ▶ Weighted combination of constraints (y) and bounds (z) yields

$$y^T Ax + z^T x \geq y^T b \quad (\text{with } z \geq 0)$$

- ▶ Dual Linear Program:

$$\max \quad y^T b$$

$$s.t. \quad y^T A + z^T = c^T$$

$$z \geq 0$$

Strong Duality Theorem:

$$c^T x^* = y^{*T} b$$

(if primal and dual are both feasible)

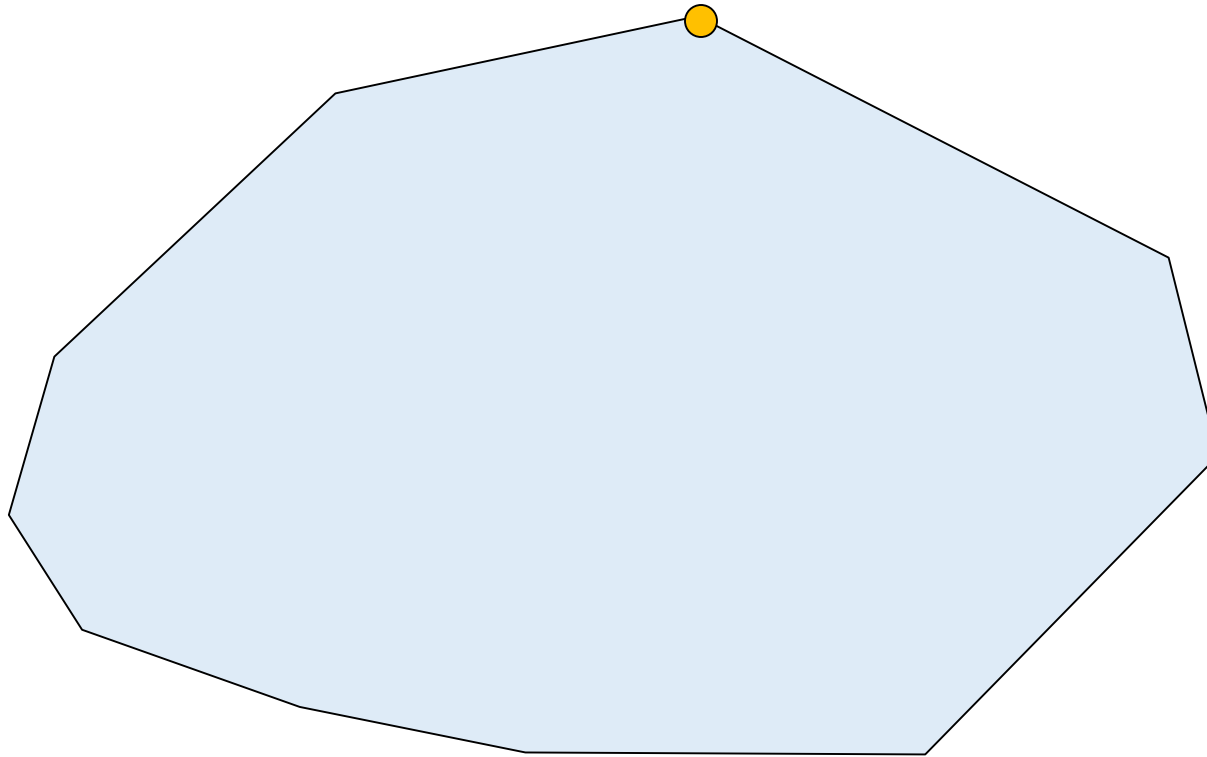
Karush-Kuhn-Tucker Conditions

► Conditions for LP optimality:

- Primal feasibility: $Ax = b$ ($x \geq 0$)
- Dual feasibility: $A^T y + z = c$ ($z \geq 0$)
- Complementarity: $x^T z = 0$

	<u>Primal feas</u>	<u>Dual feas</u>	<u>Complementarity</u>
Primal simplex	Maintain	Goal	Maintain
Dual simplex	Goal	Maintain	Maintain
Barrier	Goal	Goal	Goal

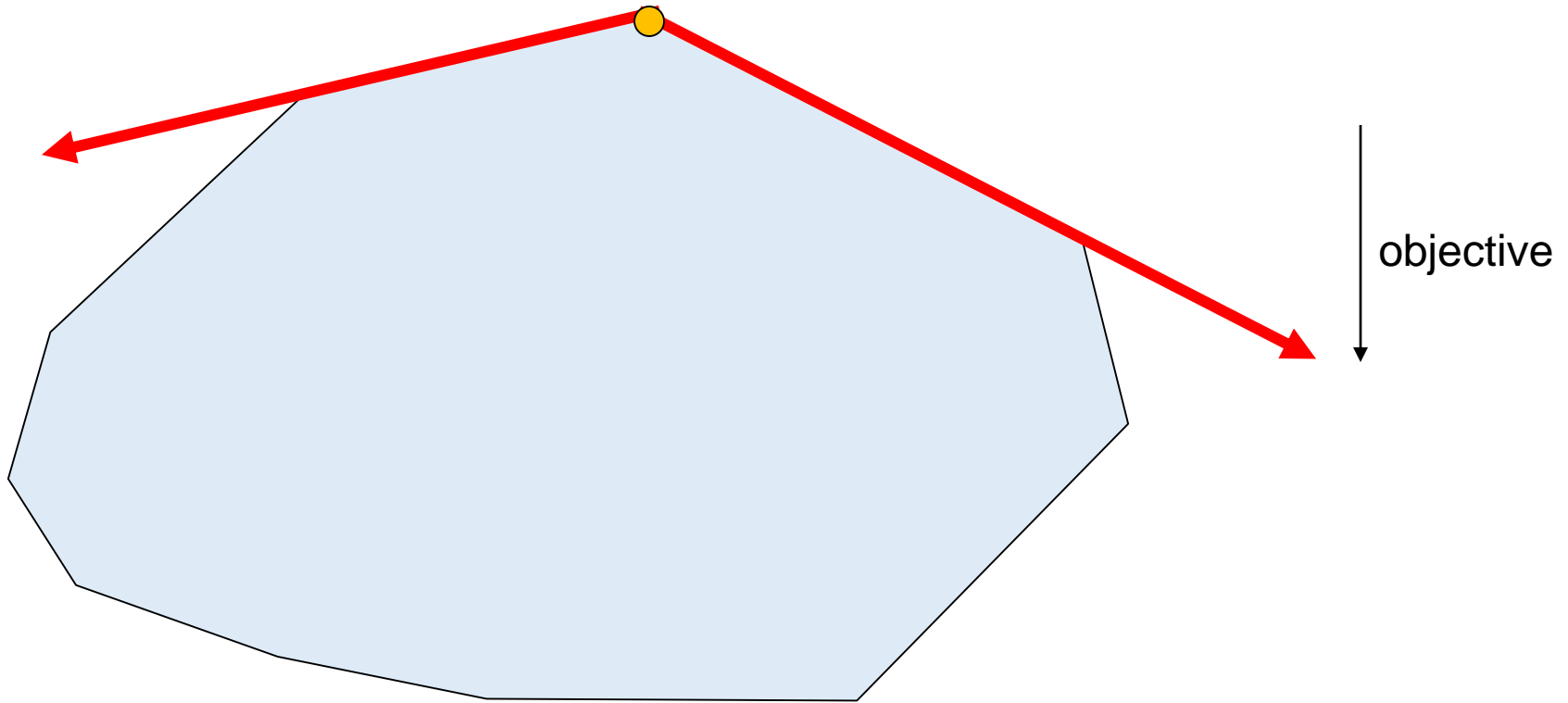
Simplex Algorithm



↓
objective

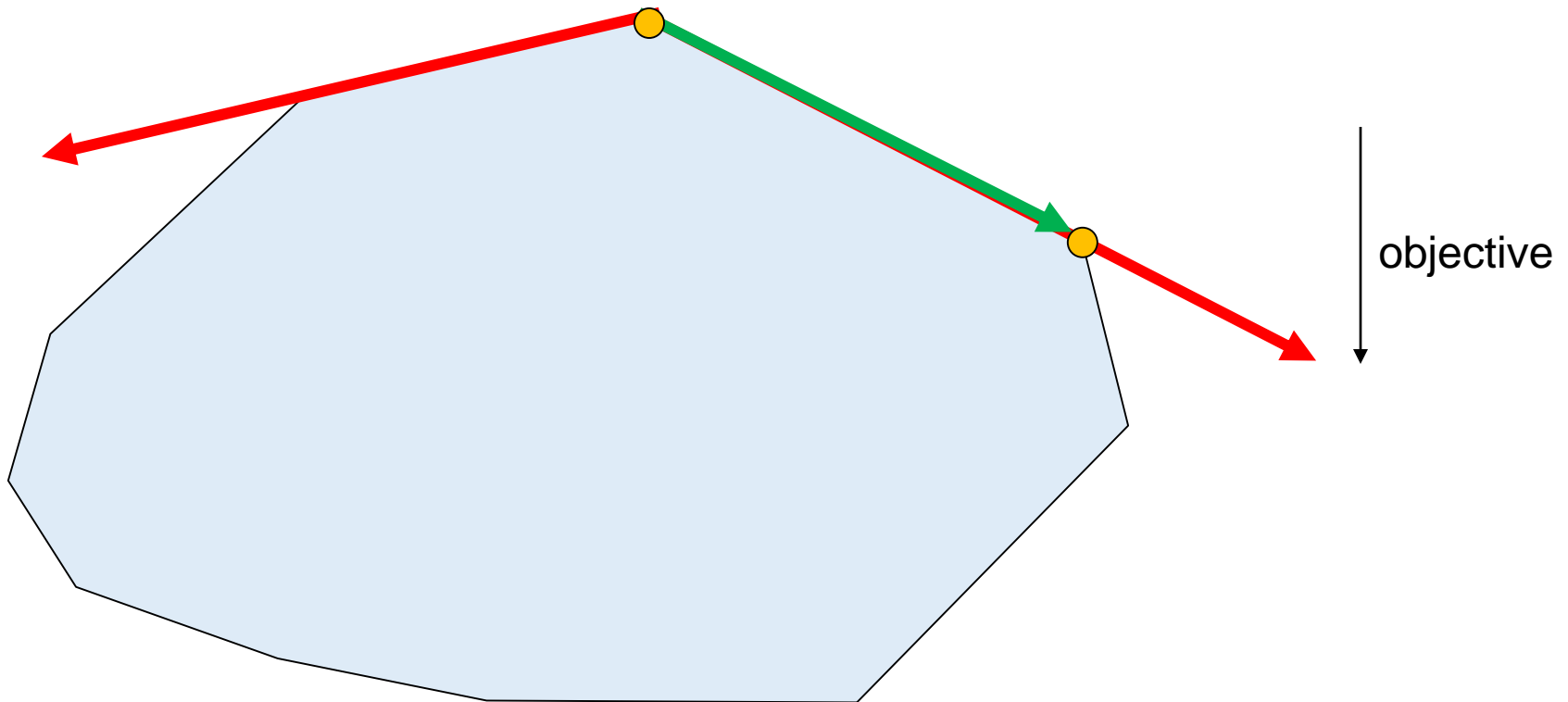
- ▶ **Phase 1:** find some feasible vertex solution

Simplex Algorithm



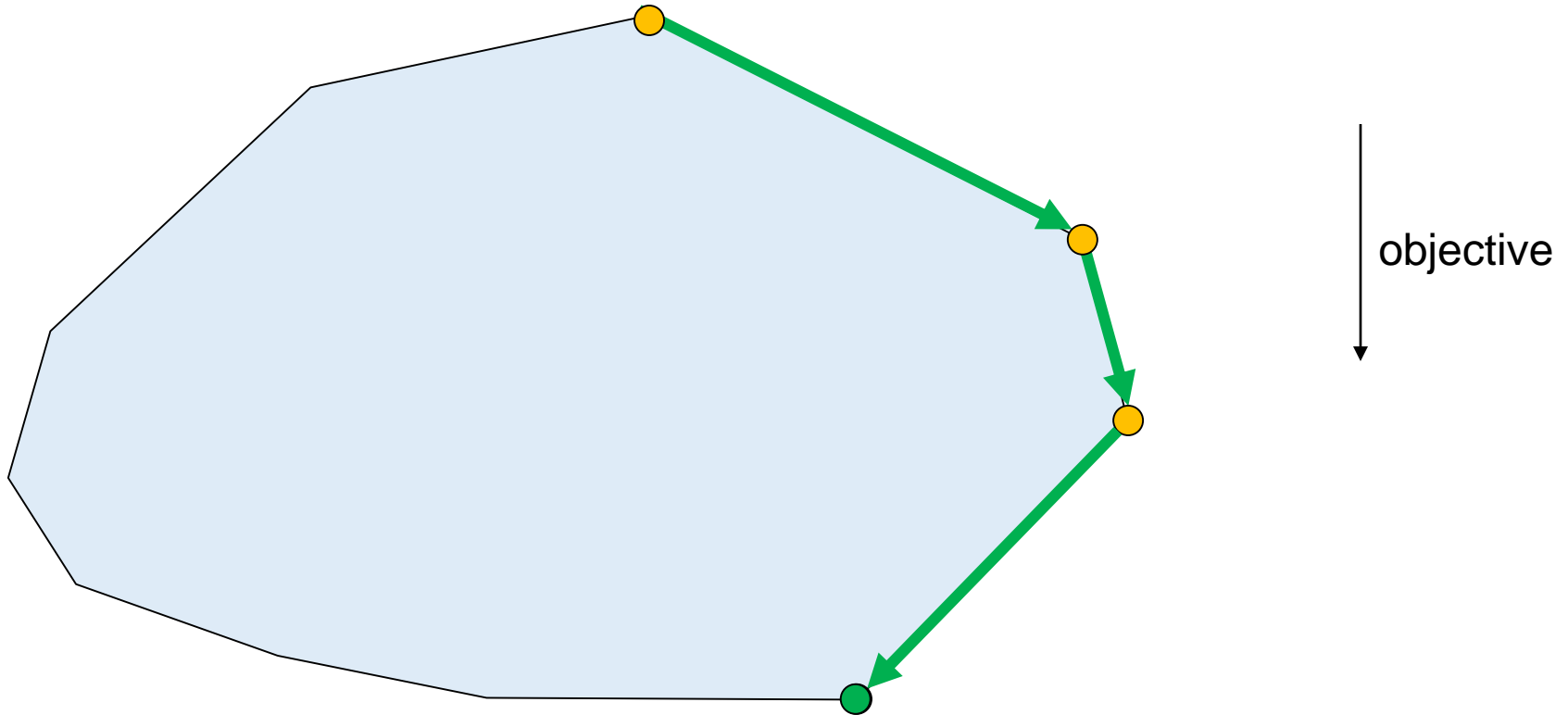
- ▶ **Pricing:** find directions in which objective improves and select one of them

Simplex Algorithm



- ▶ **Ratio test:** follow outgoing ray until next vertex is reached

Simplex Algorithm



- ▶ Iterate until no more improving direction is found

Simplex Algorithm – Linear Algebra

- ▶ Primal feasibility constraints

$$Ax = b$$

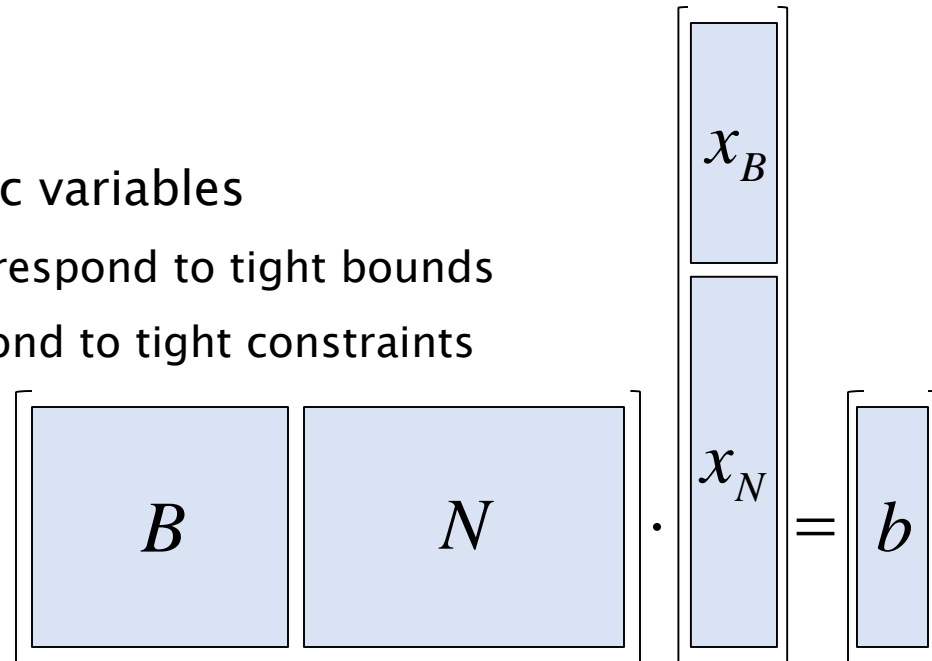
- ▶ Partition into basic and non-basic variables

- Non-basic structural variables correspond to tight bounds
- Non-basic slack variables correspond to tight constraints

$$Bx_B + Nx_N = b$$

- ▶ Solve for basic variables

$$x_B = B^{-1}(b - Nx_N)$$



- ▶ Solved by maintaining

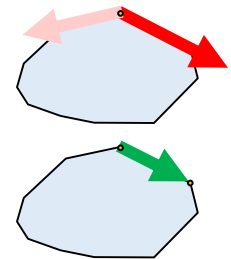
$$B = LU$$

Primal Simplex Algorithm – Pivoting

$$Bx_B = b - Nx_N$$
$$B = LU$$
$$LUx_B = b - Nx_N$$
$$Lw = b - Nx_N$$
$$Ux_B = w$$

▶ Simplex pivot:

- Choose a non-basis variable to enter the basis (Pricing)
 - Pick one with a negative reduced cost
 - Push one variable out of the basis (Ratio test)
 - Update primal and dual variables, reduced costs, basis, basis factors, etc.
 - Main work in each iteration: 2 (+1 for pricing norms) linear system solves
- ▶ Apply simplex pivots until no more negative reduced cost variables exist (optimality)



Simplex Algorithm – Pricing

- ▶ Dual variables

$$y = (B^{-1})^T c_B$$

- ▶ Reduced costs

$$z = c - A^T y$$

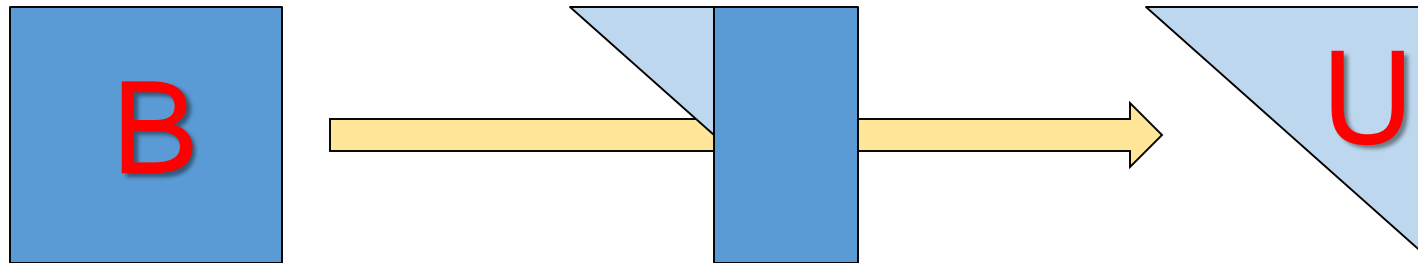
- ▶ Reduced costs give pricing information

- Change in objective per unit change in variable value
- All reduced costs non-negative: proof of optimality
- Multiple variables with negative reduced costs: pick one of them
 - steepest edge pricing: geometrically sound interpretation of what a "unit change" in the variable value means

SimplexPricing, NormAdjust
↓

Simplex Numerics – B = LU

- ▶ LU factorization of basis matrix
 - Gauss elimination algorithm



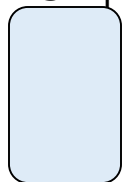
pivot element

$$\textcircled{3x_1}$$

$$6x_1$$

$$1x_1$$

$$3x_1$$



elimination

$$- 3x_2 \quad + 1x_3 \quad = 0$$

$$+ 2x_2 \quad + 2x_3 \quad = 8$$

$$+ 0.3333x_3 \quad = 0$$

$$- 3x_2 \quad + 1x_3 \quad = 0$$

$$8x_2 \quad \text{[light blue box]} \quad = 8$$

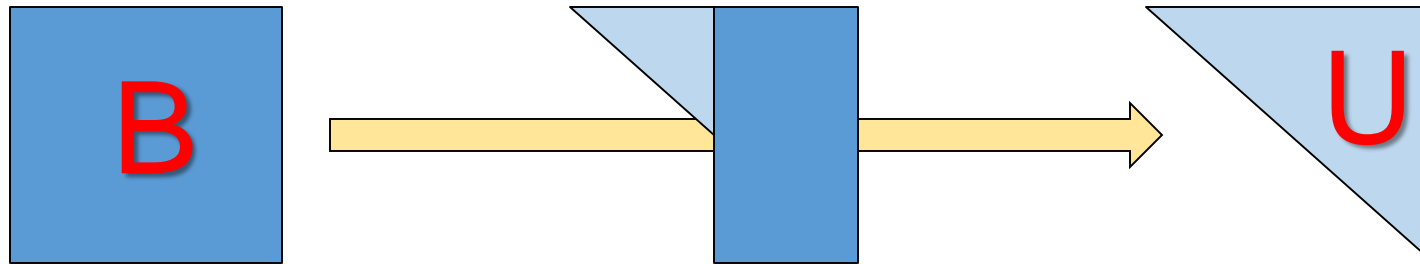
$$\text{fill } 1x_2 \quad \text{[pink box]} - 0.0000333x_3 \quad = 0$$

cancellation

almost cancellation

Simplex Numerics – B = LU

- ▶ LU factorization of basis matrix
 - Gauss elimination algorithm



pivot element $3x_1$

$$\begin{array}{rcl} 3x_1 & - 3x_2 & + 1x_3 & = 0 \\ 6x_1 & + 2x_2 & + 2x_3 & = 8 \\ 1x_1 & & + 0.3333x_3 & = 0 \end{array}$$

elimination

$$\begin{array}{rcl} 3x_1 & - 3x_2 & + 1x_3 & = 0 \\ 8x_2 & & & = 8 \\ \text{fill } 1x_2 & - 0.0000333x_3 & & = 0 \end{array}$$

→

$$\begin{array}{rcl} x_2 & = & 1 \\ x_3 & = & 30000 \\ x_1 & = & -9999 \end{array}$$

Presolve Aggregator Numerics

pivot element $3x_1$

$$\begin{array}{rcl}
 3x_1 & - 3x_2 & + 1x_3 = 0 \\
 6x_1 & + 2x_2 & + 2x_3 \leq 8 \\
 1x_1 & & + 0.3333x_3 = 0
 \end{array}
 \Rightarrow x_1 := x_2 - 1/3x_3$$

$$\begin{array}{rcl}
 & 8x_2 & \leq 8 \\
 & 1x_2 - 0.0000333x_3 & = 0
 \end{array}
 \Rightarrow x_3 := 30000 x_2$$

Interior-Point Method


- ▶ Basic algorithm (Karmarkar, Fiacco & McCormick, Dikin):
 - Modify KKT conditions:

$$\begin{array}{l}
 Ax = b \\
 A^T y + z = c \\
 x^T z = 0
 \end{array}
 \quad \longrightarrow \quad
 \begin{array}{l}
 Ax = b \\
 A^T y + z = c \\
 X z = \mu e
 \end{array}
 \quad (X = \text{diag}(x))$$

- ▶ Linearize complementarity condition

$$\begin{pmatrix} -\theta & A^T \\ A & 0 \end{pmatrix}
 \begin{pmatrix} dx \\ dy \end{pmatrix}
 =
 \begin{pmatrix} r2 \\ r1 \end{pmatrix}
 \quad (\text{augmented system})$$

$$\begin{array}{l}
 \theta_j = z_j / x_j \\
 x_j \cdot z_j = 0 \text{ at optimality, so } \theta_j \rightarrow 0 \text{ or } \infty
 \end{array}$$

- ▶ Further simplification: $A \theta^{-1} A^T dy = b$ (normal equations)
- ▶ Iterate, reducing μ in each iteration
- ▶ Provable convergence  BarConvTol, BarQCPCConvTol

Computational Steps

▶ Setup steps:

- Presolve (same for simplex)
- Compute fill-reducing ordering

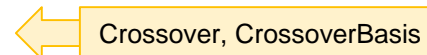


▶ In each iteration:

- Form $A \theta^{-1} A^T$
- Factor $A \theta^{-1} A^T = L D L^T$ (Cholesky factorization)
- Solve $L D L^T x = b$
- A few Ax and $A^T x$ computations
- A bunch of vector operations

▶ Post-processing steps:

- Perform crossover to a basic solution
 - Optional step, but usually required for LP relaxations in a MIP solve



Essential Differences

- ▶ **Simplex:**
 - Thousand/millions of iterations on extremely sparse matrices
 - Each iteration extremely cheap
 - Few opportunities to exploit parallelism
 - Can be warm-started
- ▶ **Barrier:**
 - Dozens of expensive iterations
 - Much denser matrices
 - Lots of opportunities to exploit parallelism
 - How to warm-start barrier is still an unsolved research topic

LP Performance

- ▶ Performance results:
 - Gurobi 6.0, quad-core Xeon E3-1240
 - Dual simplex on 1 core, barrier on 4 cores
 - Models that take > 1 s

	<u>GeoMean</u>
Dual simplex	2.50
Primal simplex	5.27
Barrier	1.28
Concurrent	1.00
Det. concurrent	1.10

Gurobi MIP Algorithms

MIP Building Blocks

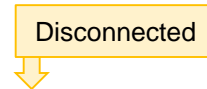
- ▶ **Presolve** ← Presolve, PrePasses, AggFill, Aggregate, DualReductions, PreSparsify, ImproveStartTime, ...
 - Tighten formulation and reduce problem size
- ▶ **Solve continuous relaxations** ← Method, NodeMethod
 - Ignoring integrality
 - Gives a bound on the optimal integral objective
- ▶ **Cutting planes** ← Cuts, CutPasses, CutAggPasses, GomoryPasses, CliqueCuts, CoverCuts, FlowCoverCuts, ...
 - Cut off relaxation solutions
- ▶ **Branching variable selection** ← VarBranch
 - Crucial for limiting search tree size
- ▶ **Primal heuristics** ← Heuristics, MinRelNodes, PumpPasses, RINS, SubMIPNodes, ZeroObjNodes
 - Find integer feasible solutions

MIP Presolve

▶ Goals:

- Reduce problem size
- Strengthen LP relaxation
- Identify problem sub-structures
 - Cliques, implied bounds, networks, disconnected components, ...

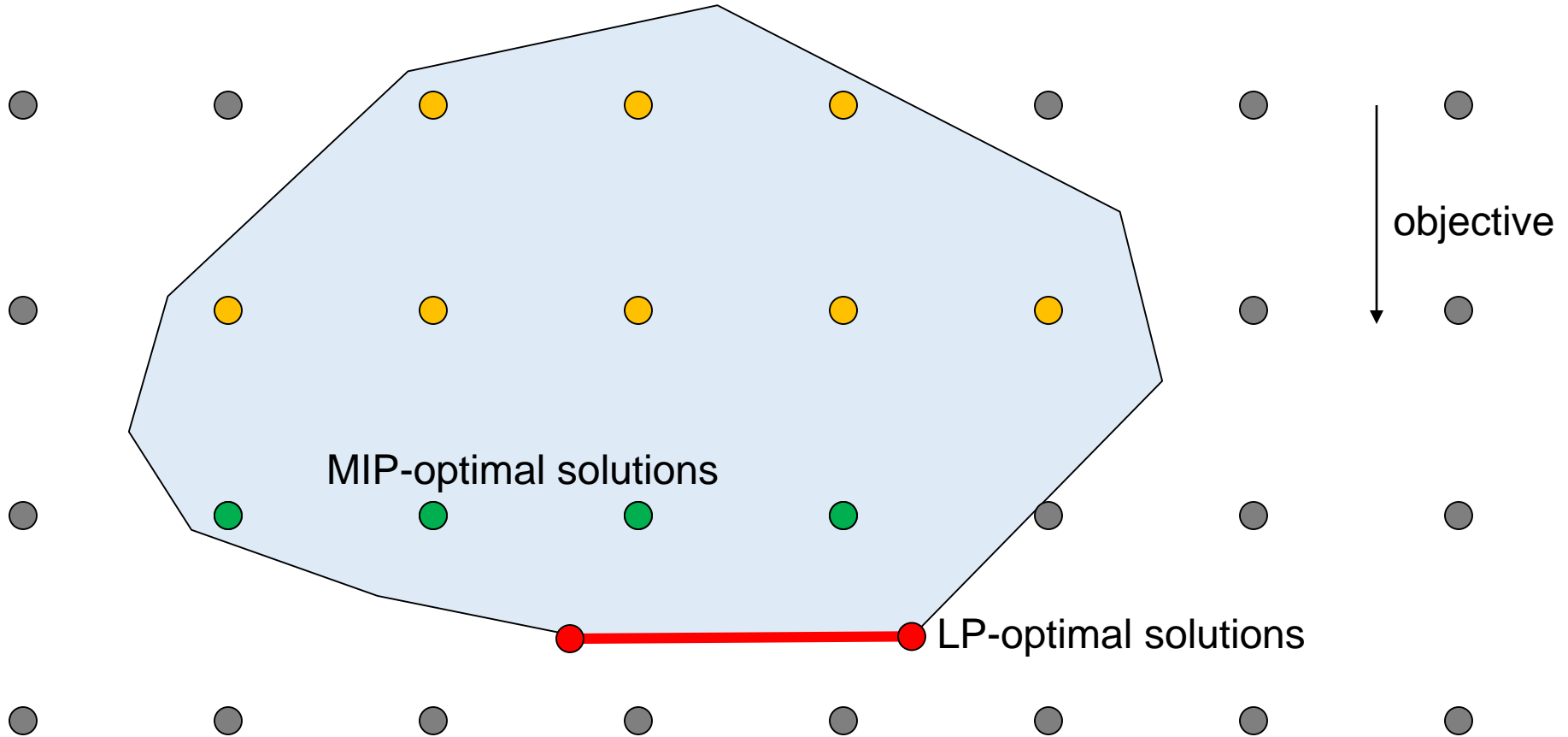
Disconnected



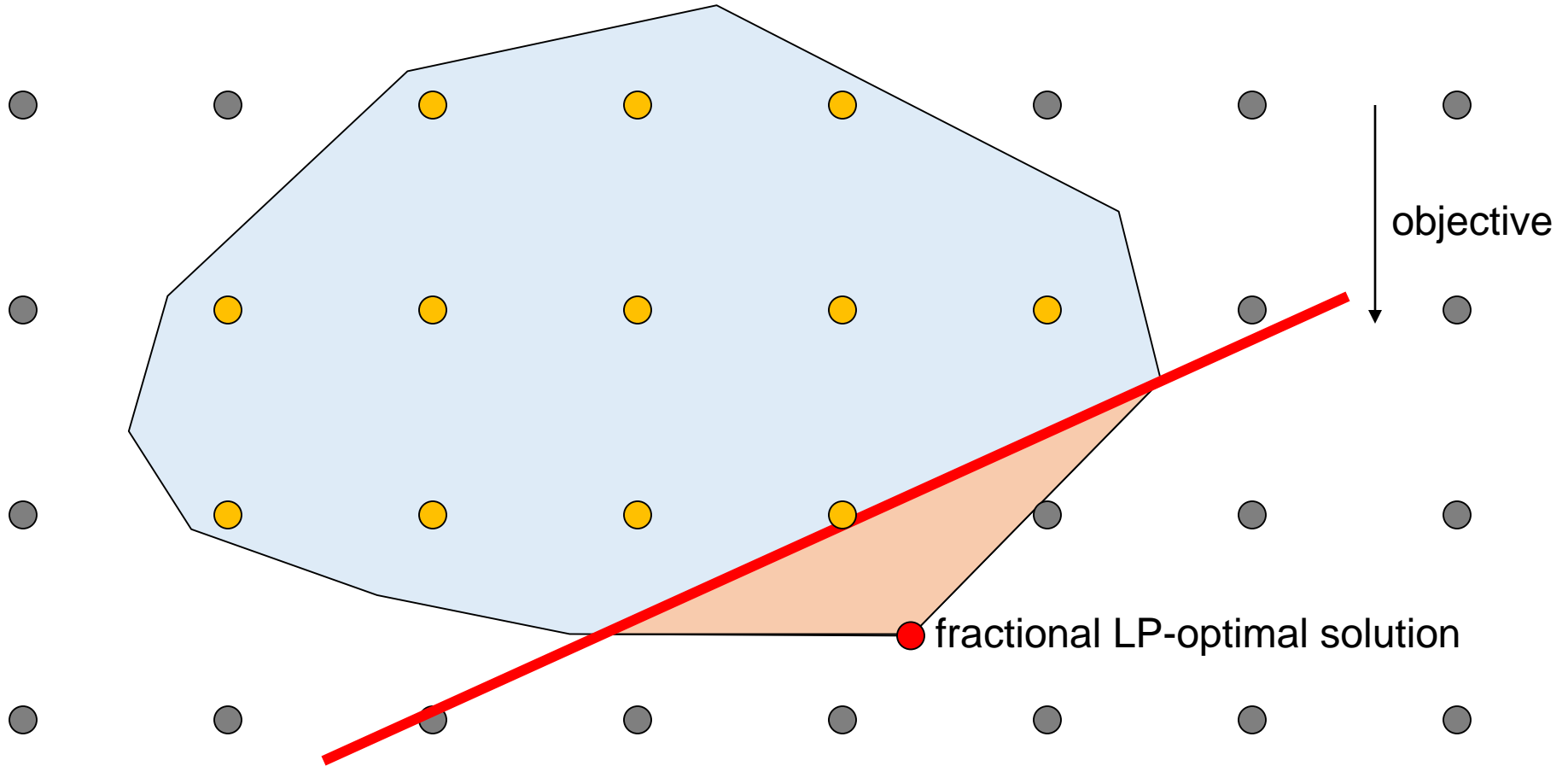
▶ Similar to LP presolve, but more powerful:

- Exploit integrality
 - Round fractional bounds and right hand sides
 - Lifting/coefficient strengthening
 - Probing
- Does not need to preserve duality
 - We only need to be able to uncrush a primal solution
 - Neither a dual solution nor a basis needs to be uncrushed

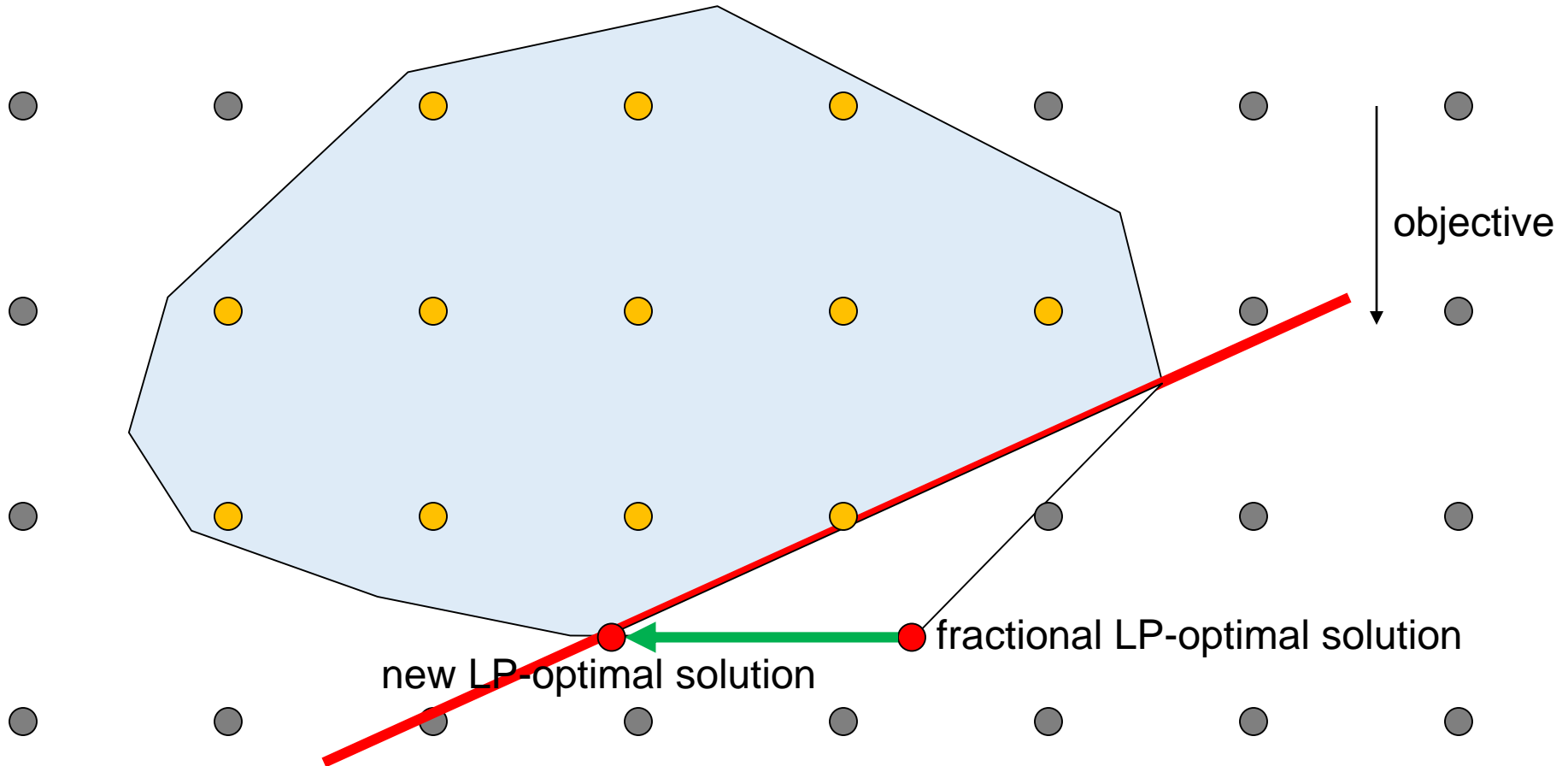
MIP – LP Relaxation



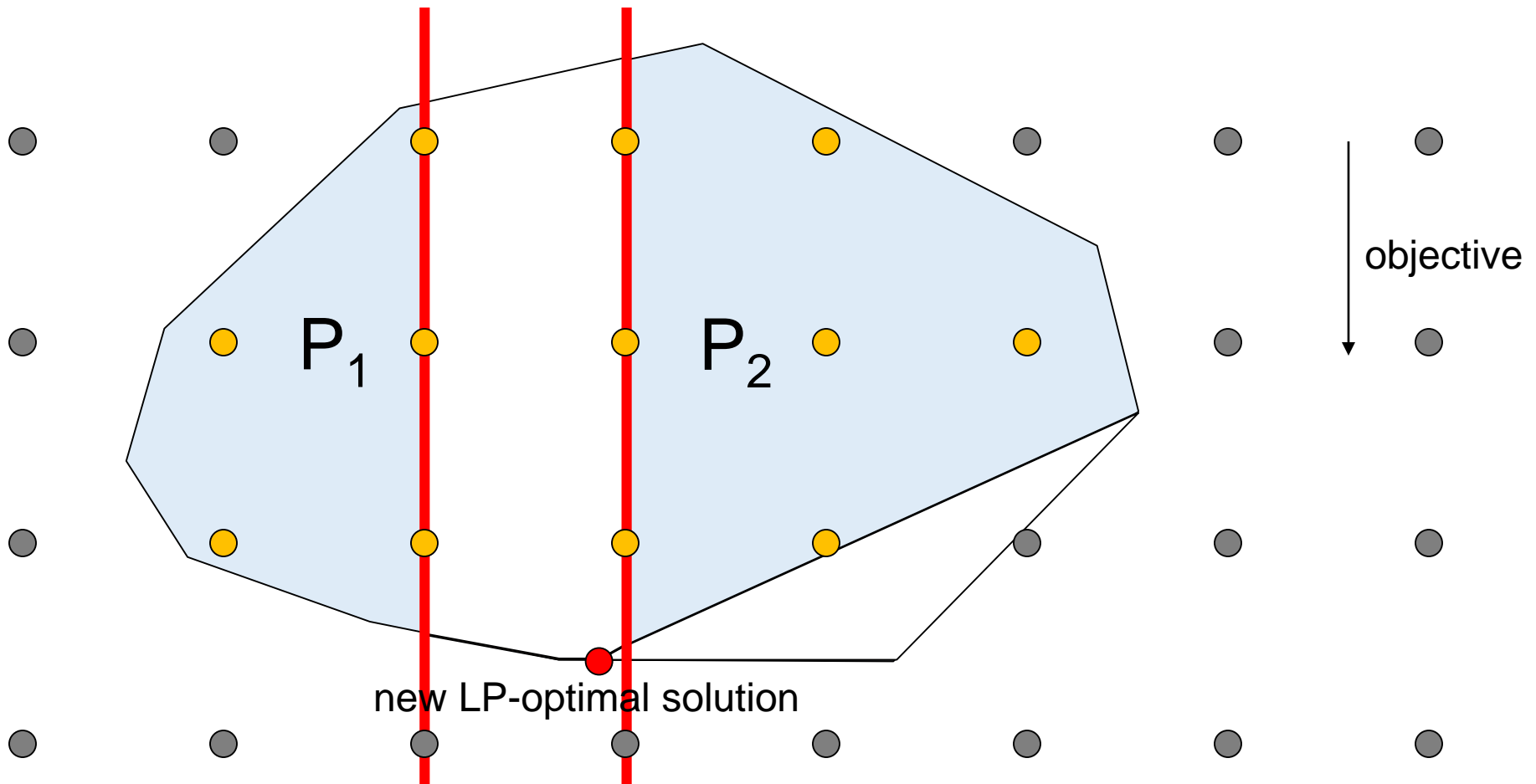
MIP – Cutting Planes



MIP – Cutting Planes



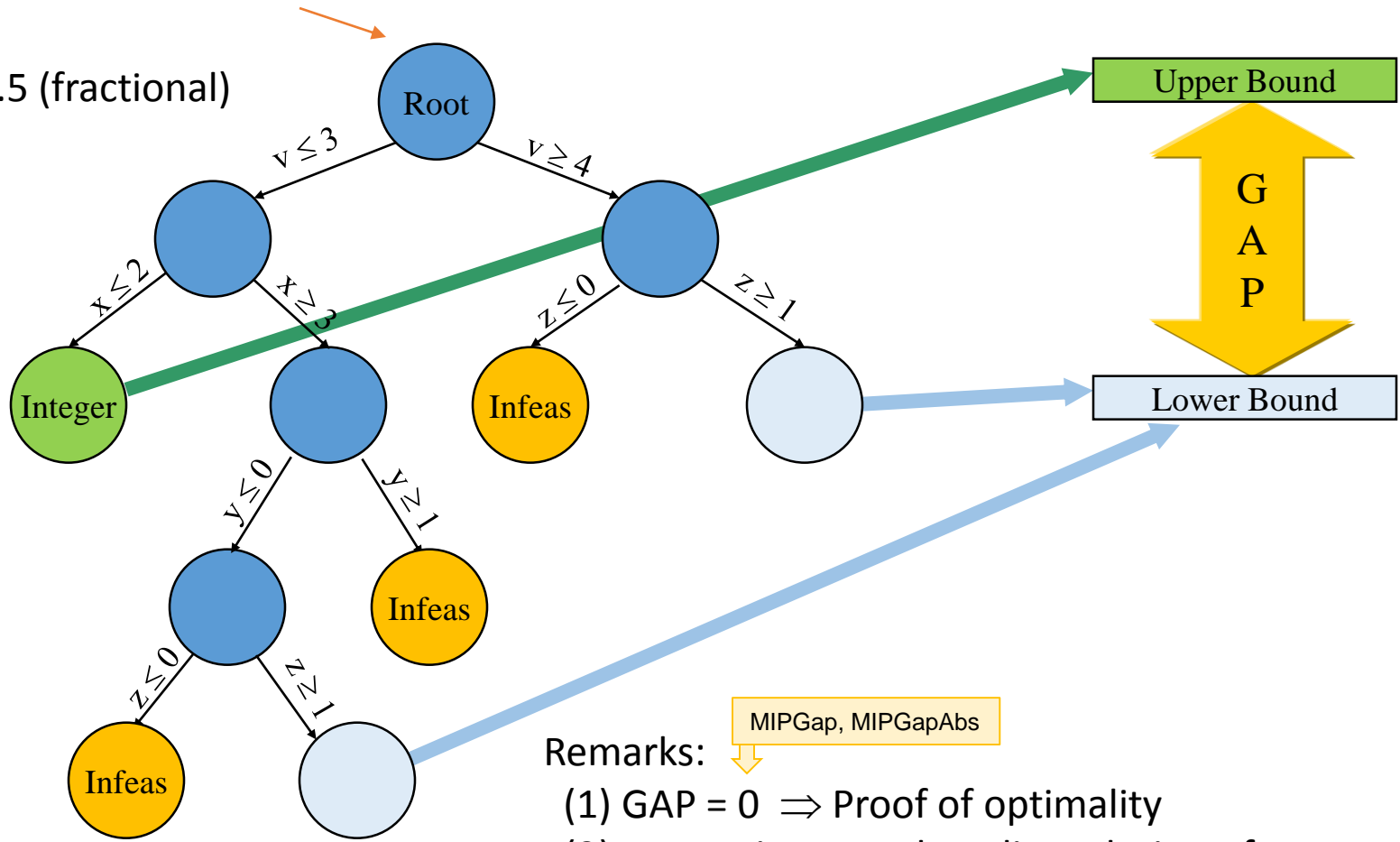
MIP – Branching



LP based Branch-and-Bound

Solve LP relaxation:

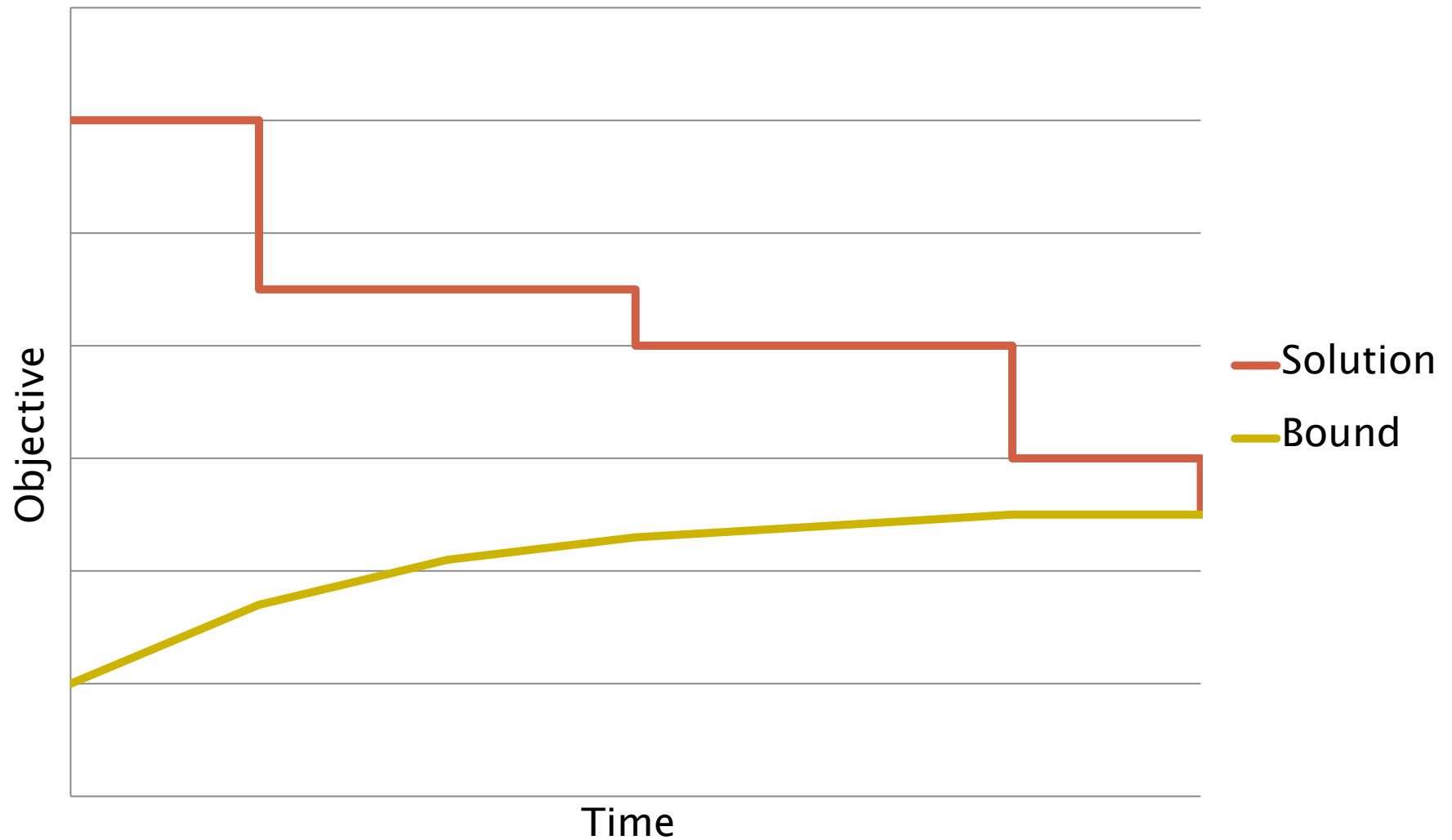
$v=3.5$ (fractional)



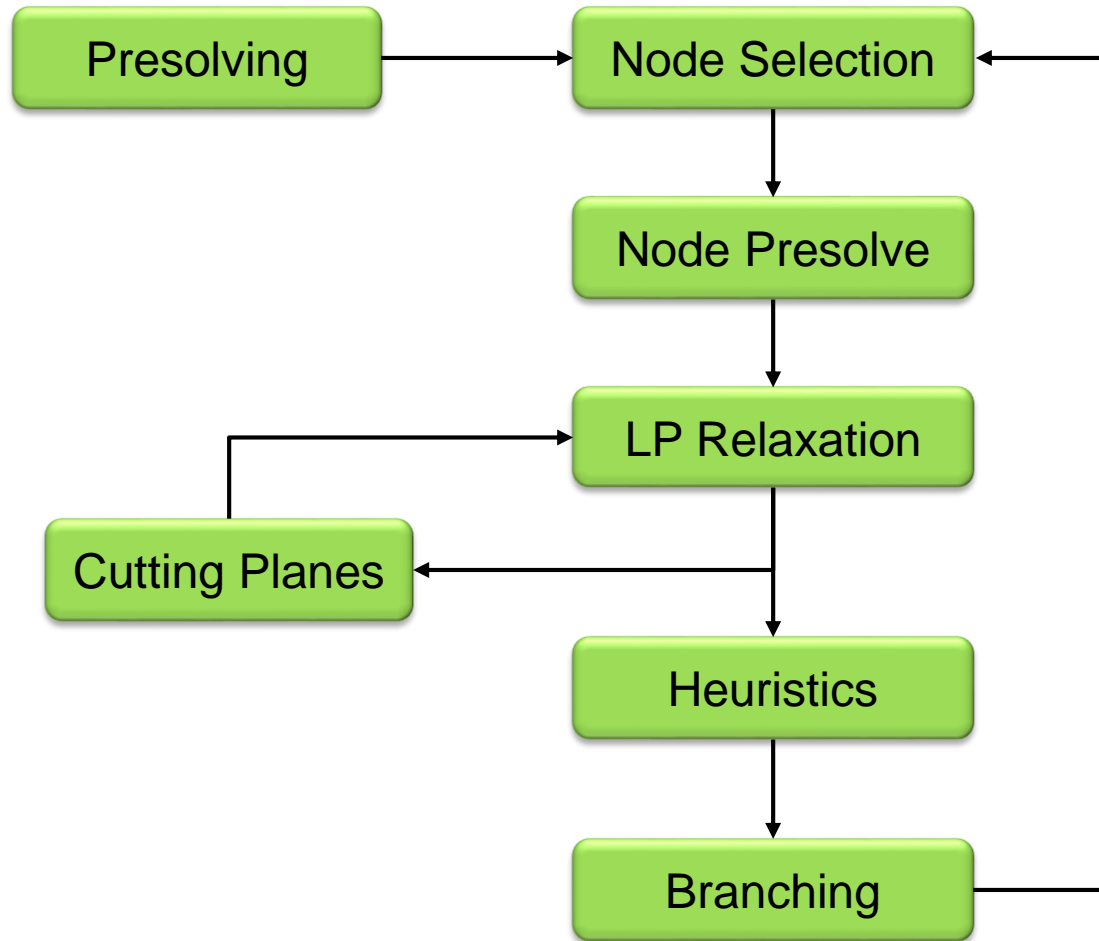
Remarks:

- (1) $GAP = 0 \Rightarrow$ Proof of optimality
- (2) In practice: good quality solution often enough

Solving a MIP Model



Branch-and-Cut



Branch-and-Cut

Presolving

```
Gurobi Optimizer version 6.0.0 (linux64)
Copyright (c) 2014, Gurobi Optimization, Inc.

Read MPS format model from file /models/mip/roll3000.mps.bz2
Reading time = 0.03 seconds
roll3000: 2295 rows, 1166 columns, 29386 nonzeros
Optimize a model with 2295 rows, 1166 columns and 29386 nonzeros
Coefficient statistics:
  Matrix range      [2e-01, 3e+02]
  Objective range   [1e+00, 1e+00]
  Bounds range      [1e+00, 1e+09]
  RHS range         [6e-01, 1e+03]
Presolve removed 1308 rows and 311 columns
Presolve time: 0.08s
Presolved: 987 rows, 855 columns, 19346 nonzeros
Variable types: 211 continuous, 644 integer (545 binary)
```

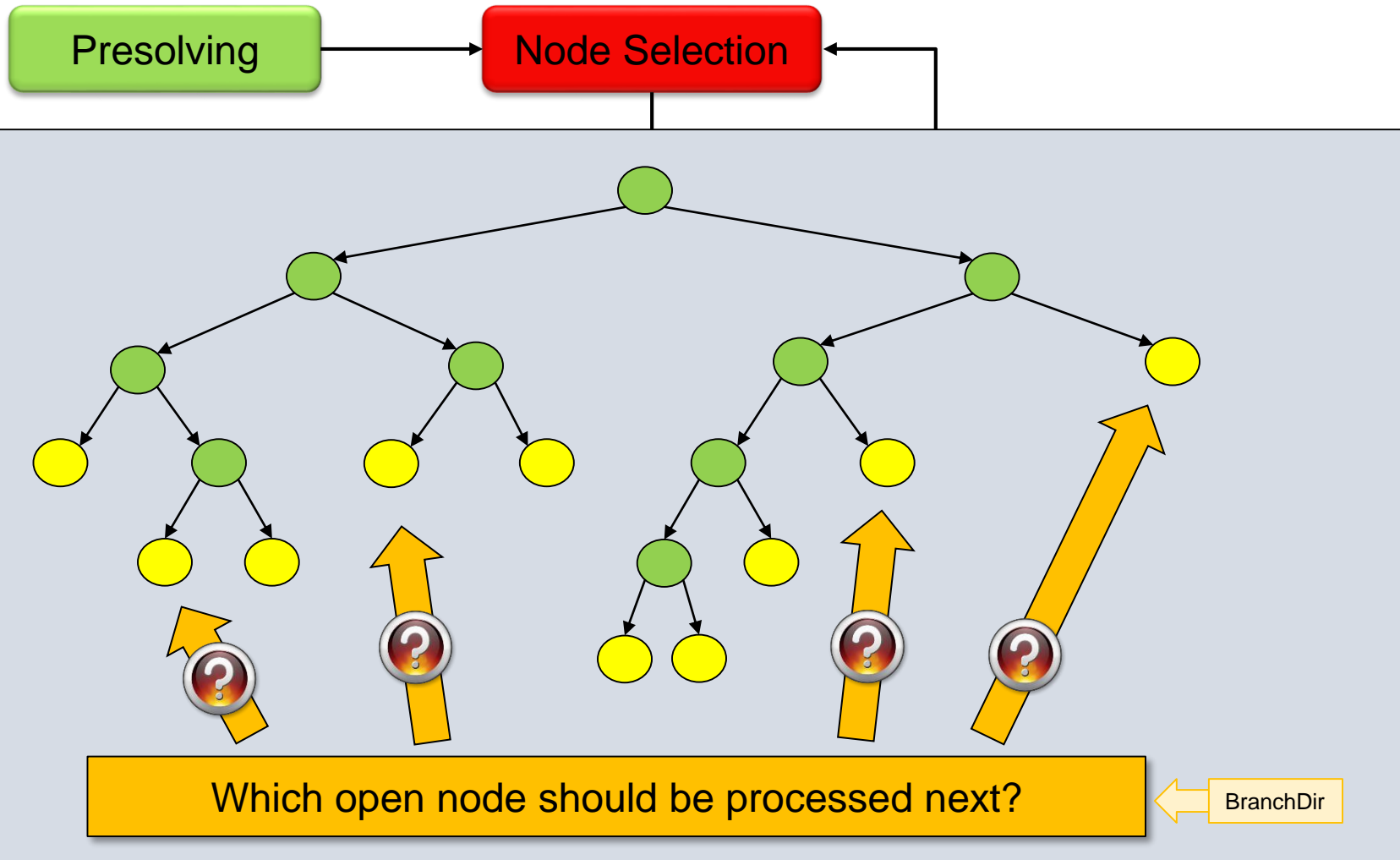
Cutting Planes

```
Root relaxation: objective 1.112003e+04, 1063 iterations, 0.03 seconds
```

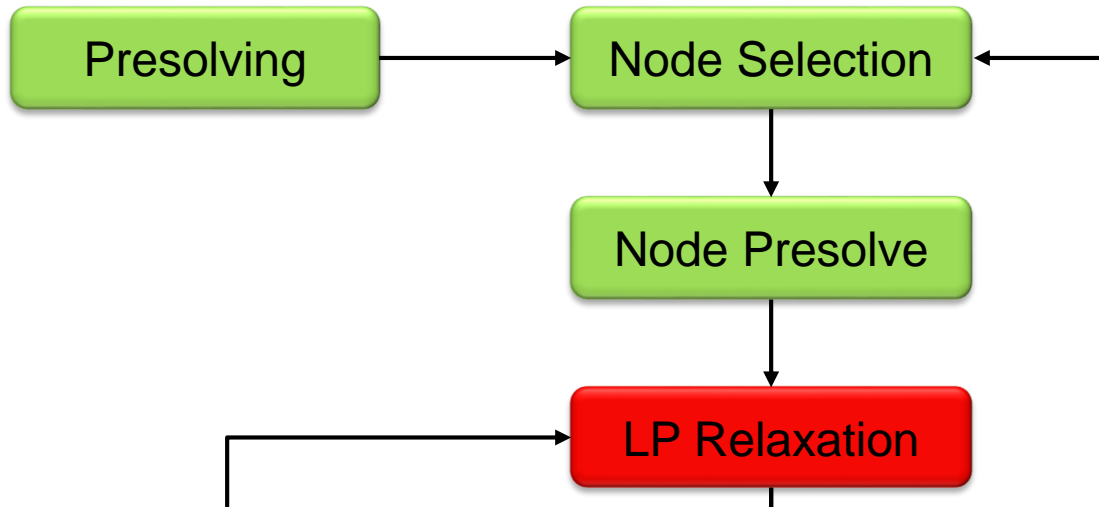
Nodes		Current Node			Objective Bounds			W
Expl	Unexpl	Obj	Depth	IntInf	Incumbent	BestBd	Gap	It/No
0	0	11120.0279	0	154	-	11120.0279	-	-
0	0	11526.8918	0	207	-	11526.8918	-	-
0	0	11896.9710	0	190	-	11896.9710	-	-

Branching

Branch-and-Cut



Branch-and-Cut



Presolved: 987 rows, 855 columns, 19346 nonzeros
 Variable types: 211 continuous, 644 integer (545 binary)
 Root relaxation: objective 1.112003e+04, 1063 iterations, 0.03 seconds

Nodes		Current Node			Objective Bounds			Work			
Expl	Unexpl	Obj	Depth	IntInf	Incumbent	BestBd	Gap	It/Node	Time		
0	0	11120.0279	0	154	- 11120.0279	-	-	-	0s		
0	0	11526.8918	0	207	- 11526.8918	-	-	-	0s		
0	0	11896.9710	0	190	- 11896.9710	-	-	-	0s		
...											
H	327	218			13135.000000	12455.2162	5.18%	42.6	1s		
H	380	264			13093.000000	12455.2162	4.87%	41.6	1s		
H	413	286			13087.000000	12455.2162	4.83%	41.4	1s		
	1066	702	12956	2676	31	192	13087.0000	12629.5426	3.50%	47.7	5s

Branch-and-Cut

Presolving

Presolved: 987 rows, 855 columns, 19346 nonzeros
Variable types: 211 continuous, 644 integer (545 binary)

Root relaxation: objective 1.112003e+04, 1063 iterations, 0.03 seconds

Nodes		Current Node			Objective Bounds				
Expl	Unexpl	Obj	Depth	IntInf	Incumbent	BestBd	Gap	It/M	
0	0	11120.0279	0	154	-	11120.0279	-	-	
0	0	11526.8918	0	207	-	11526.8918	-	-	
0	0	11896.9710	0	190	-	11896.9710	-	-	
0	0	12151.4022	0	190	-	12151.4022	-	-	
0	0	12278.3391	0	208	-	12278.3391	-	-	
...									
5485	634	12885.3652	52	143	12890.0000	12829.0134	0.47%	54.5	

Cutting Planes

Cutting planes:
Learned: 4
Gomory: 46
Cover: 39
Implied bound: 8
Clique: 2
MIR: 112
Flow cover: 27
GUB cover: 11
Zero half: 91

Explored 6808 nodes (357915 simplex iterations) in 27.17 seconds
Thread count was 4 (of 8 available processors)

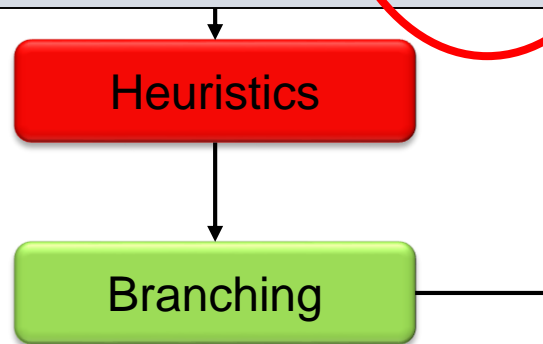
Branch-and-bound

Presolved: 987 rows, 855 columns, 19346 nonzeros
 Variable types: 211 continuous, 644 integer (545 binary)
 Root relaxation: objective 1.112003e+04, 1063 iterations, 0.03 seconds

Nodes		Current Node				Objective Bounds			Work	
Expl	Unexpl	Obj	Depth	Int	Inf	Incumbent	BestBd	Gap	It/Node	Tim
0	0	11120.0279	0	154		- 11120.0279		-	-	0s
0	0	11526.8918	0	207		- 11526.8918		-	-	0s
0	0	11896.9710	0	190		- 11896.9710		-	-	0s
...										
0	0	12448.7684	0	181		- 12448.7684		-	-	0s
H	0					16129.000000	12448.7684	22.8%	-	0s
H	0					15890.000000	12448.7684	21.7%	-	0s
	0	2	12448.7684	0	181	15890.0000	12448.7684	21.7%	-	0s
H	142	129				15738.000000	12450.7195	20.9%	43.8	1s
H	112	189				14596.000000	12453.8870	14.7%	42.3	1s
H	117	181				13354.000000	12453.8870	6.74%	42.6	1s
*	134	181		40		13319.000000	12453.8870	6.50%	42.1	1s
H	254	190				13307.000000	12453.8870	6.41%	41.3	1s
H	284	194				13183.000000	12453.8870	5.53%	42.6	1s
H	286	194				13169.000000	12453.8870	5.43%	42.7	1s

Presolving

Cutting Plane



Branch-and-Cut

Presolving

```
Presolved: 987 rows, 855 columns, 19346 nonzeros
Variable types: 211 continuous, 644 integer (545 binary)

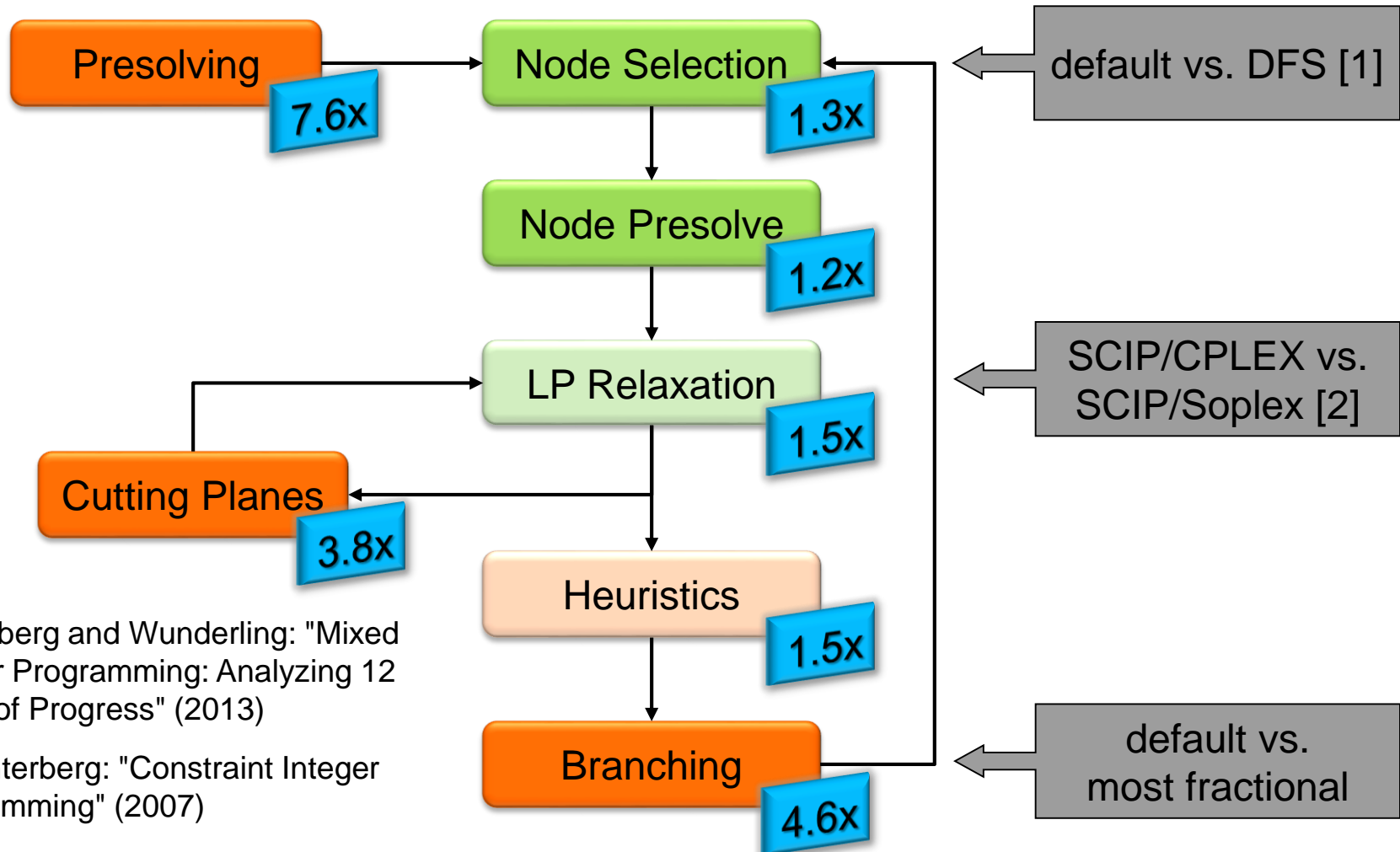
Root relaxation: objective 1.112003e+04, 1063 iterations, 0.03 seconds
```

Nodes		Current Node			Objective Bounds			Work	
Expl	Unexpl	Obj	Depth	IntInf	Incumbent	BestBd	Gap	It/Node	Time
0	0	11120.0279	0	154	-	11120.0279	-	-	0s
0	0	11526.8918	0	207	-	11526.8918	-	-	0s
0	0	11896.9710	0	190	-	11896.9710	-	-	0s
...									
H	0	0	0	181	15890.000000	12448.7684	21.7%	-	0s
	0	2	12448.7684	0	181	15890.0000	12448.7684	21.7%	-
...									
1066	702	12956.2676	31	192	13087.0000	12629.5426	3.50%	37.2	5s
1097	724	12671.8285	8	147	13087.0000	12671.8285	3.17%	41.6	10s
1135	710	12732.5601	32	126	12890.0000	12727.1362	1.26%	44.6	15s
3416	887	12839.9880	46	136	12890.0000	12780.7059	0.85%	49.7	20s
5485	634	12885.3652	52	143	12890.0000	12829.0134	0.47%	54.5	25s

Cutting Plane

Branching

Performance Impact of MIP Solver Components (CPLEX 12.5 or SCIP)



Achterberg and Wunderling: "Mixed Integer Programming: Analyzing 12 Years of Progress" (2013)

[1] Achterberg: "Constraint Integer Programming" (2007)

[2] <http://plato.asu.edu/ftp/milpc.html>

Thank You