

Parallelizing the dual revised simplex method

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- Background
- Two parallel schemes
 - Single iteration parallelism
 - Multiple iteration parallelism
- An open source parallel simplex solver

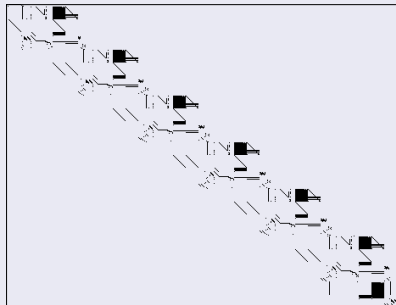
Linear programming (LP)

$$\begin{array}{ll}\text{minimize} & \mathbf{c}^T \mathbf{x} \\ \text{subject to} & \mathbf{Ax} = \mathbf{b} \quad \mathbf{x} \geq \mathbf{0}\end{array}$$

Background

- Fundamental model in optimal decision-making
- Solution techniques
 - Simplex method (1947)
 - Interior point methods (1984)
- Large problems have
 - 10^3 – 10^8 variables
 - 10^3 – 10^8 constraints
- Matrix A is (usually) sparse

Example



STAIR: 356 rows, 467 columns and 3856 nonzeros

Solving LP problems

$$\begin{array}{ll}\text{minimize} & f_P = \mathbf{c}^T \mathbf{x} \\ \text{subject to} & A\mathbf{x} = \mathbf{b} \quad \mathbf{x} \geq \mathbf{0} \quad (P)\end{array}$$

$$\begin{array}{ll}\text{maximize} & f_D = \mathbf{b}^T \mathbf{y} \\ \text{subject to} & A^T \mathbf{y} + \mathbf{s} = \mathbf{c} \quad \mathbf{s} \geq \mathbf{0} \quad (D)\end{array}$$

Optimality conditions

- For a partition $\mathcal{B} \cup \mathcal{N}$ of the variable set with nonsingular **basis matrix** B in

$$B\mathbf{x}_B + N\mathbf{x}_N = \mathbf{b} \text{ for (P)} \quad \text{and} \quad \begin{bmatrix} B^T \\ N^T \end{bmatrix} \mathbf{y} + \begin{bmatrix} \mathbf{s}_B \\ \mathbf{s}_N \end{bmatrix} = \begin{bmatrix} \mathbf{c}_B \\ \mathbf{c}_N \end{bmatrix} \text{ for (D)}$$

with $\mathbf{x}_N = \mathbf{0}$ and $\mathbf{s}_B = \mathbf{0}$

- Primal** basic variables $\mathbf{x}_B$ given by $\hat{\mathbf{b}} = B^{-1}\mathbf{b}$
- Dual** non-basic variables $\mathbf{s}_N$ given by $\hat{\mathbf{c}}_N^T = \mathbf{c}_N^T - \mathbf{c}_B^T B^{-1}N$
- Partition is optimal if there is
 - Primal feasibility** $\hat{\mathbf{b}} \geq \mathbf{0}$
 - Dual feasibility** $\hat{\mathbf{c}}_N \geq \mathbf{0}$

Simplex algorithm: Each iteration

	$\mathcal{N}$	RHS
$\mathcal{B}$	$\hat{\mathbf{a}}_q$	$\hat{\mathbf{b}}$
	$\hat{\mathbf{a}}_{pq}$ $\hat{\mathbf{a}}_p^T$	$\hat{b}_p$
	$\hat{\mathbf{c}}_q$ $\hat{\mathbf{c}}_N^T$	

Dual algorithm: Assume $\hat{\mathbf{c}}_N \geq \mathbf{0}$ Seek $\hat{\mathbf{b}} \geq \mathbf{0}$

Scan $\hat{b}_i, i \in \mathcal{B}$, for a good candidate p to leave $\mathcal{B}$ CHUZR

Scan $\hat{c}_j/\hat{a}_{pj}, j \in \mathcal{N}$, for a good candidate q to leave $\mathcal{N}$ CHUZC

Update: Exchange p and q between $\mathcal{B}$ and $\mathcal{N}$

Update $\hat{\mathbf{b}} := \hat{\mathbf{b}} - \theta_p \hat{\mathbf{a}}_q$ $\theta_p = \hat{b}_p/\hat{a}_{pq}$ UPDATE-PRIMAL

Update $\hat{\mathbf{c}}_N^T := \hat{\mathbf{c}}_N^T - \theta_d \hat{\mathbf{a}}_p^T$ $\theta_d = \hat{c}_q/\hat{a}_{pq}$ UPDATE-DUAL

Simplex method: Computation

Standard simplex method: Major computational component

Update of tableau:

$$\hat{N} := \hat{N} - \frac{1}{\hat{a}_{pq}} \hat{\mathbf{a}}_q \hat{\mathbf{a}}_p^T$$

where $\hat{N} = B^{-1}N$

- Hopelessly inefficient for sparse LP problems
- Prohibitively expensive for large LP problems

Revised simplex method: Major computational components

$$\pi_p^T = \mathbf{e}_p^T B^{-1} \quad \text{BTRAN}$$

$$\hat{\mathbf{a}}_p^T = \pi_p^T N \quad \text{PRICE}$$

$$\hat{\mathbf{a}}_q = B^{-1} \mathbf{a}_q \quad \text{FTRAN}$$

$$\text{Invert } B \quad \text{INVERT}$$

Simplex method: Algorithmic enhancements

Row selection: Dual steepest edge (DSE)

- Weight $\hat{b}_i$ by w_i : measure of $\|B^{-T} \mathbf{e}_i\|_2$
- Requires additional FTRAN but can reduce iteration count significantly

Column selection: Bound-flipping ratio test (BFRT)

- Minimizes the dual objective whilst remaining dual feasible
 - Dual variables may change sign if corresponding primal variables can flip bounds
- Requires additional FTRAN but can reduce iteration count significantly

Exploiting parallelism: Background

Data parallel standard simplex method

- Good parallel efficiency of $\hat{N} := \hat{N} - \frac{1}{\hat{a}_{pq}} \hat{\mathbf{a}}_q \hat{\mathbf{a}}_p^T$ **was** achieved
- Only relevant for dense LP problems

Data parallel revised simplex method

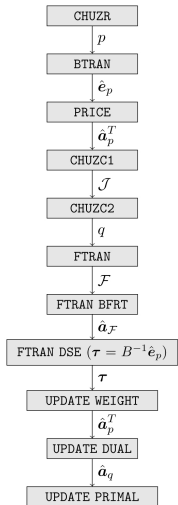
- Only immediate parallelism is in forming $\pi_p^T N$
- When $n \gg m$ significant speed-up **was** achieved Bixby and Martin (2000)

Task parallel revised simplex method

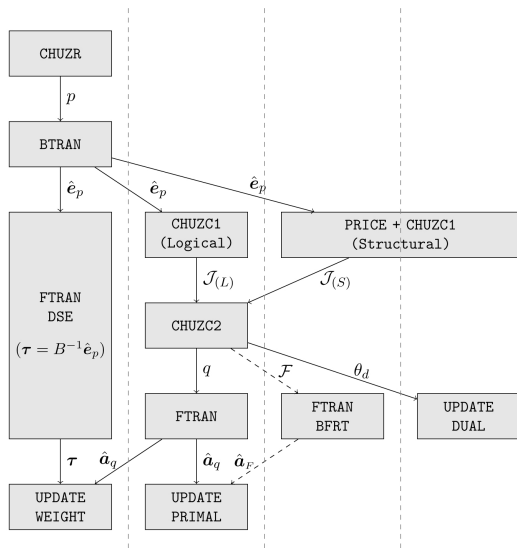
- Overlap computational components for different iterations
Wunderling (1996), H and McKinnon (1995-2005)
- Modest speed-up **was** achieved on general sparse LP problems

Single iteration parallelism: Dual revised simplex method

- Computational components appear sequential
- Each has highly-tuned sparsity-exploiting serial implementation
- Exploit “slack” in data dependencies



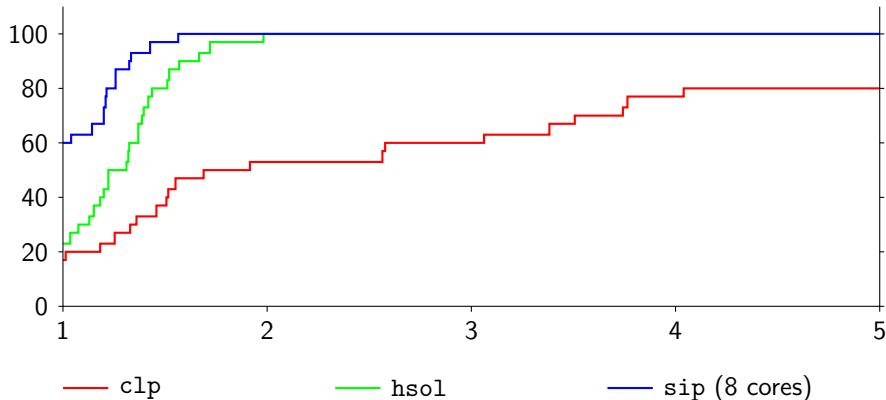
Single iteration parallelism: Computational scheme



- Parallel PRICE to form $\hat{\mathbf{a}}_p^T = \boldsymbol{\pi}_p^T N$
- Other computational components serial
- Overlap any independent calculations
- Only four worthwhile threads unless $n \gg m$ so PRICE dominates
- More than Bixby and Martin (2000)
- Better than Forrest (2012)

Huangfu and H (2014)

Single iteration parallelism: clp vs hsol vs sip



Performance on spectrum of 30 significant LP test problems

- sip on 8 cores is 1.15 times faster than hsol
- hsol (sip on 8 cores) is 2.29 (2.64) times faster than clp

Multiple iteration parallelism

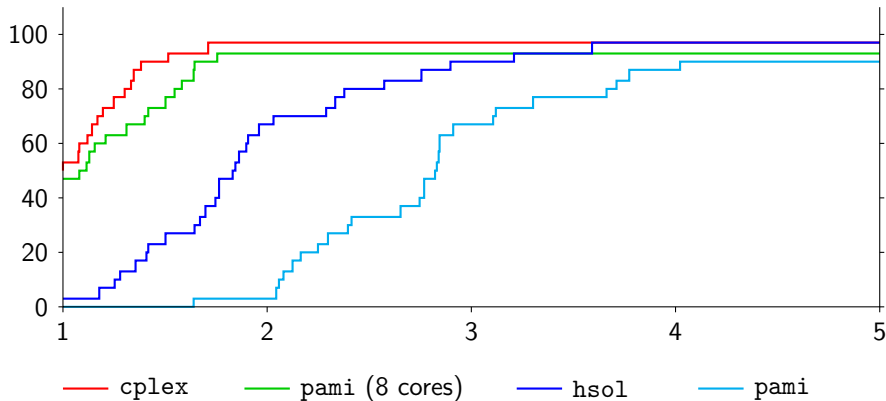
- sip has too little work to be performed in parallel to get good speedup
- Perform standard dual simplex minor iterations for rows in set $\mathcal{P}$ ($|\mathcal{P}| \ll m$)
- Suggested by Rosander (1975) but never implemented efficiently *in serial*

	$\mathcal{N}$	RHS
$\mathcal{B}$	$\hat{\mathbf{a}}_{\mathcal{P}}^T$	$\hat{\mathbf{b}}$
		$\hat{b}_{\mathcal{P}}$
	$\hat{\mathbf{c}}_N^T$	

- Task-parallel multiple BTRAN to form $\boldsymbol{\pi}_{\mathcal{P}} = B^{-1} \mathbf{e}_{\mathcal{P}}$
- Data-parallel PRICE to form $\hat{\mathbf{a}}_p^T$ (as required)
- Task-parallel multiple FTRAN for primal, dual and weight updates

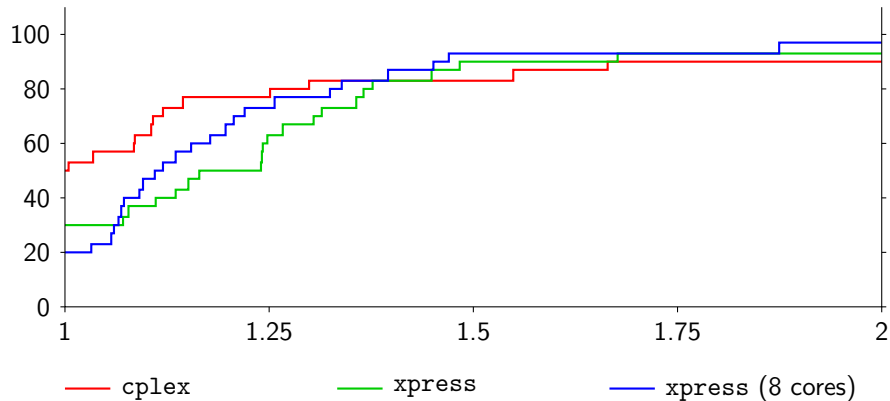
Huangfu and H (2011–2014)

Multiple iteration parallelism: cplex vs pami vs hsol



- pami is less efficient than hsol in serial
- pami speedup more than compensates
- pami performance approaching cplex

Multiple iteration parallelism: cplex vs xpress



- pami ideas incorporated in [FICO Xpress](#) (Huangfu 2014)

hsol: An open source parallel simplex solver

- hsol and its variants (sip and pami) are high performance codes
- Useful open-source resource?
 - Reliable?
 - Well-written?
 - Better than clp?
- Limitations
 - No presolve
 - No crash
 - No advanced basis start

hsol: Performance and reliability

Extended testing using 159 test problems

- 98 Netlib
- 16 Kennington
- 4 Industrial
- 41 [Mittelman](#)

Exclude 7 which are “hard”

Reliability on 152 test problems

- `hsol`, `sip` and `pami` fail on `cycle`
- `pami` with 8 threads fails on `stat96v1`

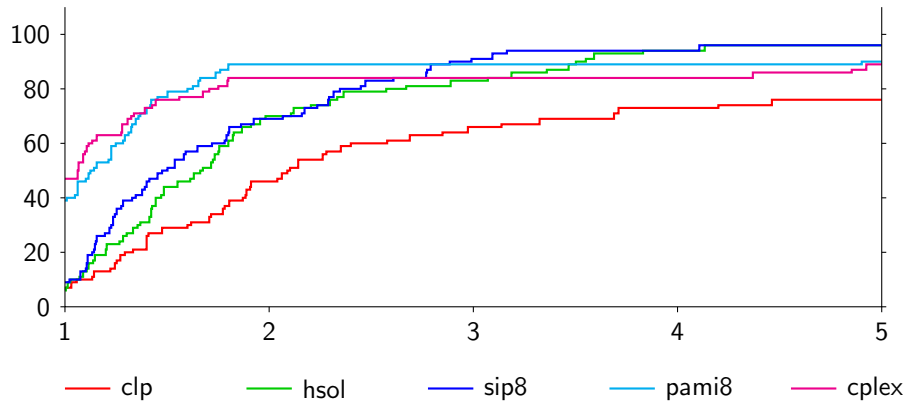
Performance

Benchmark against c1p (v1.16) and cplex (v12.5)

- Dual simplex
- No presolve
- No crash

Ignore results for 82 LPs with minimum solution time below 0.1s

hsol: Performance and reliability



hso1: Addressing limitations

Presolve

Prototype implementation of a full range of presolve techniques

Galabova (2016)

Crash

- Standard crash procedures are simple to implement
- Questionable value for dual simplex:
dual steepest edge is expensive to initialise when $B \neq I$

Advanced basis start

- Essential for hso1 to be used in MIP and SLP solvers
- Only complication is dual steepest edge

- Two parallel schemes for general LP problems
 - Meaningful performance improvement
 - Have led to publicised advances in a leading commercial solver
- High performance open-source parallel simplex solver in preparation

Slides: http://www.maths.ed.ac.uk/hall/NLAO_16/

Paper: Q. Huangfu and J. A. J. Hall

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Technical Report ERGO-14-011, School of Mathematics, University of Edinburgh, 2014

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