What's new in HiGHS

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HiGHS: Open-source software for large-scale sparse linear optimization

HiGHS: Hall, ivet Galabova, Huangfu, Schork

minimize $f = \frac{1}{2} \mathbf{x}^T Q \mathbf{x} + \mathbf{c}^T \mathbf{x}$ such that $A \mathbf{x} = \mathbf{b}$; $\mathbf{x} \ge \mathbf{0}$, $x_i \in \mathbb{Z}$, $\forall i \in \mathcal{I}$

Features

- Simplex and interior point solvers for LP
- Branch-and-cut solver for MIP
- Active set solver for QP
- Written in C++
- Interfaces to other languages and systems



Availability

- Open-source (MIT license)
- No third-party code
- https://HiGHS.dev/

The world's best open-source linear optimization software

Mittelmann (2023)

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HiGHS: History

HiGHS: Project

- Integration of Galabova's presolve and Huangfu's dual simplex solver (2016)
- Creation of name (2018)
- Integration of Schork's interior point solver (2019)
- Development of active set solver for QP by Feldmeier (2018-date)
- Development of new MIP solver and LP/MIP presolve by Gottwald (2020-2022)

HiGHS: JuMP

- JuMP first interested in HiGHS (2019)
- JuMP-HiGHS interface developed by Dowson and Galabova (2020)
- JuMP maintains HiGHS binaries (2021-date)
- HiGHS has become the default solver in JuMP documentation (2020-date)

Employees

- Julian Hall: Almost full-time!
- Ivet Galabova: Integration and Development Manager
- Filippo Zanetti: IPM researcher

Contributors

- Oscar Dowson: JuMP, Julia, documentation and ...
- Michael Feldmeier: QP
- Rohit Goswami: Meson build and ...
- Luke Marshall: Column generation, decomposition and modelling language
- Stefan Vigerske: Model file reading and ...
- Others



HiGHS: Callbacks

- New in HiGHS 1.6.0 for C++ and C
- Single user-defined generic method

- Logging callbacks
 - All HiGHS messages
 - Data logging from MIP solver
- Improving solution in MIP solver
- Interrupt from solvers for LP and MIP, but not (yet) QP
- No MIP cut callbacks (yet!)

HiGHS: A Python interface

- Not everyone uses Julia, so a Python presence for HiGHS is essential
- SciPy is a very valuable basic host for black-box solvers
- Python-based PuLP and Pyomo modelling languages want HiGHS!

highspy (WIP)

- Built using pybind11
- Allows HiGHS C++ classes, structures and enums to be used in Python
- Can be slow to extract results

pip install highspy

- Easy installation for Python users
- No need for C++ libraries
- Available for HiGHS 1.5.4

highspy modelling (WIP)

- Independent modelling with HiGHS
- Handy in Colab
- Not competing with JuMP!

```
import highspy
```

```
h = highspy.Highs()
h.readModel("ml.mps")
h.run()
```

```
solution = h.getSolution()
```

```
# By using __getitem_
value = [solution.col_value[i]
         for i in range(h.getNumCol())]
```

```
# By copying first to list
col_value = list(solution.col_value)
value = [col value[i]]
         for i in range(h.getNumCol())]
```

- MIP with 32504 variables
- Solve time: 1.6s
- Extraction time:
 - Using getitem: 11s
 - Copying to list: 0.0022s



Historically

- Priority has been performance
- Advanced users have worked from header files and CMake build system!

Documentation

https://ergo-code.github.io/HiGHS/

- Uses Documenter.jl
- Parses C API docstrings
- Python-based
- Colab notebooks (WIP)

- For whom are we writing documentation?
- What do we document?
- Full Python-based documentation is WIP
- Documentation for HiGHS is still not great!

Leona Gottwald wrote us an amazing MIP solver, but left us in autumn 2022

Solver	Gurobi	COPT	FSCIPX	FSCIP	HiGHS	SCIPC	SCIP	Cbc	Matlab
Speed	1	2.01	6.26	7.51	8.77	8.92	10.9	16.3	33.3
Solved	227	204	172	163	158	152	137	107	72

- Much scope for further improvement in HiGHS
 - HiGHS is single threaded
 - Multicore version would be great!
 - Catch up (non-deterministic) FSCIPX and FSCIP!
 - Other MIP techniques still to be added
- Debugging and development are coming slowly
- Possible PhD student starting in September 2024



HiGHS: IPM solver

Aim: Develop the world's best open-source IPM solver for

minimize
$$f = \frac{1}{2} \mathbf{x}^T Q \mathbf{x} + \mathbf{c}^T \mathbf{x}$$
 such that $A\mathbf{x} = \mathbf{b}$; $\mathbf{x} \ge \mathbf{0}$
Have to solve $\begin{bmatrix} -Q - \Theta^{-1} & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \mathbf{\Delta} \mathbf{x} \\ \mathbf{\Delta} \mathbf{y} \end{bmatrix} = \begin{bmatrix} \mathbf{f} \\ \mathbf{d} \end{bmatrix}$

- Have to write most of it from scratch due to MIT license
 - Quasi-definite decomposition code for non-diagonal Q (at least)
 - Positive definite decomposition code for Newton matrix $G = A(Q + \Theta^{-1})^{-1}A^T$ if
 - Q is diagonal
 - Q = 0 (LP) so $G = A \Theta A^T$
 - Not graph partitioning code since latest Metis can be used
- The team
 - Jacek Gondzio: IPM consultant
 - Filippo Zanetti: IPM researcher (2023-)
 - Yanyu Zhou: PhD student (2024-)

HiGHS: IPM solver

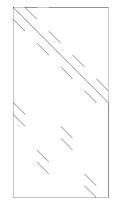
First steps

- Written a prototype solver ProtoIPM (Zanetti)
- Experimented with existing direct solvers (H and Zhou)
 - Cholmod for Newton system
 - SSIDS, MA86 and QDLDL for Newton and augmented system

What are their strengths/limitations?

Motivating example

- Industrial client reported HiGHS IPM failing 7,504,855 rows, 3,752,404 columns; 18,742,867 nonzeros
- LP identified as having a single column with m/2 nonzeros
- Can it be solved by IPM using direct decomposition but avoiding the dense column?
- Study "toy" instance of industrial model



2689 rows 1345 columns 672 of count 3 336 of count 4 336 of count 5 1 of count 1344 6384 nonzeros

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• Problem:

- If A has a single full column, then $G = A \Theta A^T$ is full
- Cost of forming and factorizing G is prohibitive
- Same issue with dense columns—containing O(m) nonzeros—in A
- Solution:
 - If A_d are the dense columns in A, consider $G = A_s \Theta_s A_s^T + A_d \Theta_d A_d^T$
 - Represent G using $G_s \equiv A_s \Theta_s A_s^T = LL^T$ and Sherman–Morrison–Woodbury formula
 - Needs G_s to be nonsingular
- OK in theory:
 - A contains I and this is obviously sparse
 - Entries of Θ_s are positive
 - G_s is positive definite

What can go wrong?

Consider the LP
minimize
$$f = \begin{bmatrix} -2 \\ -1 \end{bmatrix}^T \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$
 such that $\begin{bmatrix} 1 & -1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} 2 \\ 4 \end{bmatrix}; \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \ge \mathbf{0}$

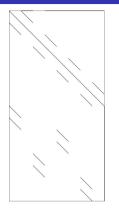
					Θ_3		
1	2.0	0.7	2	1	0.8	0.8	If first column is
2	0.8	2.2	0.3	1	0.3	4	[-1
3	1.0	2.2	10^{1}	4	10^{-1}	10^{1}	• $A_s = \begin{bmatrix} -1 & 1 \\ 1 \end{bmatrix}$
					10^{-2}		L
					10^{-2}		• $\Theta_s ightarrow \left[heta_2 ight.$ (
					10-4		$\begin{bmatrix} 1 \end{bmatrix}$
7	3.0	1.0	10 ⁵	10^{4}	10^{-5} 10^{-6}	10-4	• $G_s \rightarrow \theta_2 \begin{bmatrix} 1 \\ -1 \end{bmatrix}$
8	3.0	1.0	10 ⁶	10 ⁵	10 ⁻⁶	10^5	E.

treated as dense

•
$$A_s = \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix}$$
 is full rank
• $\Theta_s \rightarrow \begin{bmatrix} \theta_2 & 0 & 0 \end{bmatrix}^T$
• $G_s \rightarrow \theta_2 \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$

• In general:

- Entries of Θ_s can range over many orders of magnitude
- Some terms in $G_s = \sum_{i \in S} \Theta_i \boldsymbol{a}_i \boldsymbol{a}_i^T$ are computationally (near-)zero
- G_s may be (near-)singular
- Well-conditioned G_s needs m sufficiently large values in Θ_s
 - Large values of Θ_i correspond to $x_i \to x_i^* > 0$: **basic** variables
 - There are only *m* basic variables
 - Dense columns are usually basic!
- Choice of dense columns may be too restricted



2689 rows 1345 columns 672 of count 3 336 of count 4 336 of count 5 1 of count 1344 6384 nonzeros How about the industrial problem?

Solver	Time	Comment
Gurobi	0.02	Presolve very effective Using Schork's PCG
HiGHS	0.72	Using Schork's PCG
ProtoIPM	6.92	Vanilla Newton
	5.99	Newton (1 dense column)
	0.65	Augmented system

• Why is Newton little better with 1 dense column?

Dense column only used for first 3 of 22 iterations Solver fails if the use of dense column is forced

• Why isn't SSIDS doing better with the augmented system?

IPM solver: Augmented system

Observation

Decompose

 $\begin{bmatrix} -\Theta^{-1} & A^T \\ A & 0 \end{bmatrix}$

Choosing
$$-\Theta_1^{-1}$$
, ..., $-\Theta_n^{-1}$ as pivots yields partial decomposition
$$\begin{bmatrix} I \\ -A\Theta & I \end{bmatrix} \begin{bmatrix} -\Theta^{-1} & A^T \\ A\Theta A^T \end{bmatrix}$$

Equivalent to the elimination that yields the Newton system

- \bullet Initial pivots come from $-\Theta^{-1}$ and cause fill-in in the (2,2) block
- Hope to choose pivots from (2,2) block before pivoting on dense column(s)
- Large Θ_i for basic variables yields small Θ_i^{-1}
 - General indefinite decomposition views these as bad pivots
 - Some pivots good for sparsity are postponed
 - Fill-in is greater than suggested by structural analysis
- Perturb small pivots so that they can be used

Corresponds to solving LP with small quadratic term: regularization

Prototype augmented system solver for HiGHS

- Symmetric systems are special case of asymmetric systems!
- HiGHS has efficient code to decompose B = LU
- How does its performance compare with SSIDS?

Augmented system solvers applied to i-002-168							
Solver	LP time	Factorize time	Fill-in	Residual error			
SSIDS	0.62	0.53	4.71	1e-12			
HiGHS	0.35	0.27	1.36	1e-12			

- SSIDS is parallel
- SSIDS is constrained by diagonal pivots

- How general is this behaviour?
- Test single augmented system solve for Netlib and Mittelmann LPs

So	lver	Factorize time	Fill-in	Residual error	Solution error
SS	IDS	0.079	10.74	2.8 e-14	7.4e-14
Hi	GHS	0.030	2.82	1.4e-12	2.6e-14

HIGHS

- Transformed gradware into software
- World-beating open-source performance
- Using software to create Impact
- Developing a better IPM solver
 May even generate research output!
- Like running a small software company
- Hugely fulfilling!

https://HiGHS.dev/

Q. Huangfu and J. A. J. Hall.

Novel update techniques for the revised simplex method.

Computational Optimization and Applications, 60(4):587–608, 2015.

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Parallelizing the dual revised simplex method. Mathematical Programming Computation, 10(1):119–142, 2018.

L. Schork and J. Gondzio.

Implementation of an interior point method with basis preconditioning. Mathematical Programming Computation, pages 1-33, 2020.