

# Computational Approaches to Mixed Integer Second Order Cone Optimization (MISOCO)

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# Outline

- 1 Conic Optimization with Linear Approximations
- 2 COLA solver
- 3 DisCO solver
- 4 Valid Inequalities and Conic Cut Generation Library
- 5 Computational Experiments
- 6 Conclusion

# MISOCO definition

- We are interested in solving Mixed Integer Second Order Conic Optimization (MISOCO) problems.
- MISOCO is a generalization of Mixed Integer Linear Optimization (MILP).
- MISOCO can be formulated as follows,

$$\begin{aligned} \min \quad & c^\top x \\ s.t. \quad & Ax = b \\ & x \in \mathbb{L}^1 \times \cdots \times \mathbb{L}^k \\ & x_i \in \mathbb{R}_+ \quad i \in I \\ & x_j \in \mathbb{Z}_+ \quad j \in J. \end{aligned} \tag{MISOCO}$$

# Outer Approximation Algorithm for SOCO

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Solve linear relaxation (LP) of the problem.

**if** LP is infeasible **then**

    SOCO is infeasible, STOP.

**end if**

**if** LP is unbounded **then**

**while** LP is unbounded **do**

        Determine direction of unboundedness

**if** Direction is feasible for all conic constraints **then**

            SOCO is unbounded, STOP.

**else**

            Add cuts using direction of unboundedness.

**end if**

        Solve LP.

**end while**

**end if**

Get LP solution

**while** Solution is not feasible for conic constraints **do**

    Add cuts using solution.

    Solve LP.

**if** LP is infeasible **then**

        SOCO is infeasible, STOP.

**end if**

    get LP solution.

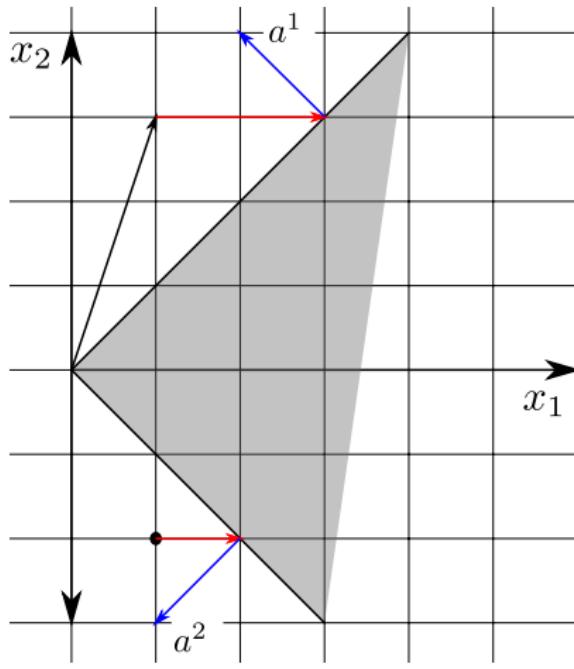
**end while**

LP solution is optimal for SOCO, STOP.

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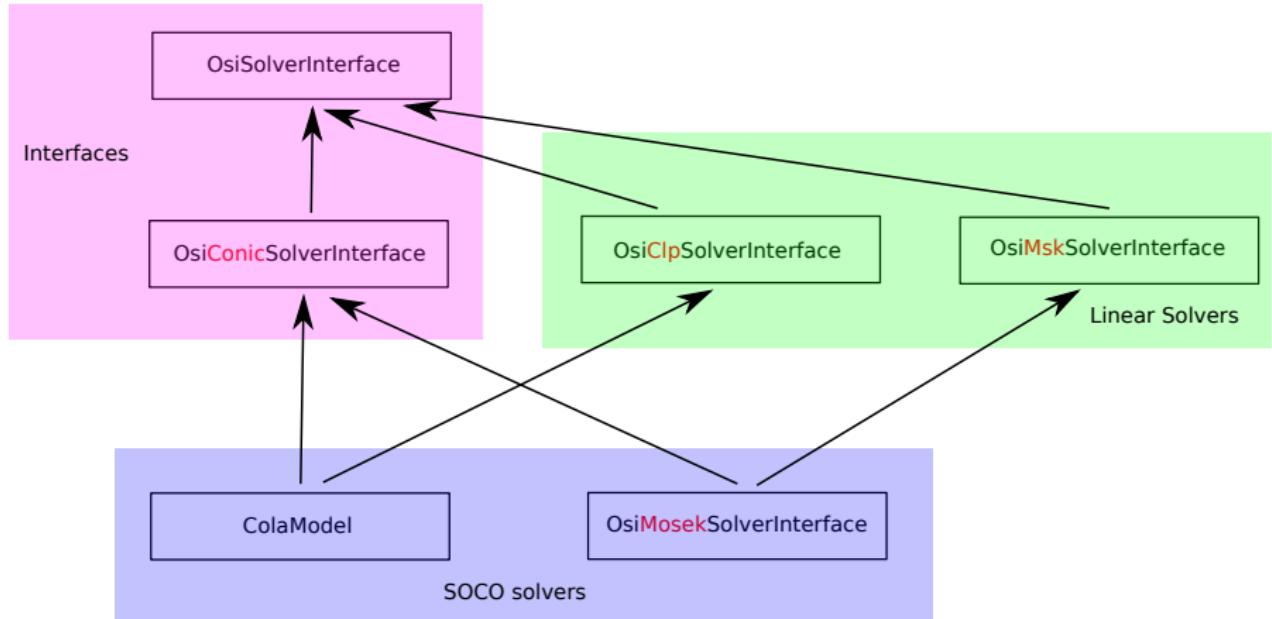
# Separating Infeasible Directions/Solutions

Figure: Separation Example



- Implements outer approximation algorithm.
- All-written in C++ language.
- Implements *conic* OSI, which is an extension of OSI.
- Cola uses CLP to solve LP relaxations.
- Reads problems in Mosek's extended MPS format, uses COIN Utils for this.
- *Conic* OSI can be used to build models.
- Takes advantage of simplex method's warm-start capabilities.

Figure: COLA's relationship to COIN-OR projects



# COLA Performance Statistics

- NC: Number of Conic constraints the instance has.
- LC: Size of Largest Conic constraint.
- SS: Separation Supports generated.
- MSS: Maximum number of Separation Supports generated for a cone.
- NLP: Number of linear optimization problems solved.
- CPU: CPU seconds spent during execution of COLA.

# COLA performance on CBLIB problems 1

**Table:** COLA statistics on CBLIB 2014 Part 1

instance	NC	LC	SS	MSS	NLP	CPU
chainsng-1000-1	2994	3	14479	10	11	13.01
classical_200_1	1	201	1055	1055	1056	114.11
classical_50_1	1	51	328	328	329	1.89
estein4_A	9	3	36	6	7	0.01
estein4_B	9	3	44	6	9	0.02
estein4_C	9	3	60	10	11	0.02
estein4_nr22	9	3	41	6	7	0.0
estein5_A	18	3	109	11	14	0.02
estein5_nr21	18	3	99	9	11	0.03
pp-n1000-d10000	1000	3	16107	18	19	7.19
pp-n100-d10000	100	3	1613	18	19	0.12
pp-n10-d10000	10	3	161	17	18	0.02
robust_50_1	2	52	260	134	135	0.78
robust_100_1	2	102	577	297	298	7.64
robust_200_1	2	202	960	499	500	64.86
shortfall_100_1	2	101	533	502	503	11.44
shortfall_100_2	2	101	674	630	631	19.28
shortfall_100_3	2	101	573	527	528	12.55
shortfall_200_1	2	201	719	690	691	53.67
shortfall_200_2	2	201	876	841	842	77.74
shortfall_50_1	2	51	307	284	285	1.73
shortfall_50_2	2	51	344	320	321	2.13
shortfall_50_3	2	51	451	408	409	3.58

# COLA performance on CBLIB problems 2

Table: COLA statistics on CBLIB 2014 Part 2

instance	NC	LC	SS	MSS	NLP	CPU
sssd-strong-25-8	24	3	243	13	15	0.07
sssd-strong-30-8	24	3	260	13	14	0.07
sssd-weak-20-8	24	3	171	8	9	0.03
sssd-weak-25-8	24	3	171	8	9	0.04
sssd-weak-30-8	24	3	165	8	9	0.03
turbine07_aniso	25	3	53	9	11	0.01
turbine07GF	25	3	10	4	5	0.0
turbine07_lowb_aniso	25	3	64	10	12	0.03
turbine07_lowb	27	9	81	8	9	0.02
turbine07	26	9	67	12	14	0.02
turbine54GF	119	3	25	10	11	0.05
turbine54	120	9	220	11	13	0.05
uflquad-nopsc-10-150	1500	3	14281	16	20	14.68
uflquad-nopsc-20-150	3000	3	29063	17	30	74.84
uflquad-nopsc-30-100	3000	3	29108	23	39	66.91
uflquad-nopsc-30-150	4500	3	42809	19	39	156.26
uflquad-nopsc-30-200	6000	3	55650	19	40	332.71
uflquad-nopsc-30-300	9000	3	83624	16	41	819.0
uflquad-psc-10-150	1500	3	10837	13	23	14.08
uflquad-psc-20-150	3000	3	18164	15	37	70.09
uflquad-psc-30-100	3000	3	16595	22	49	69.07
uflquad-psc-30-150	4500	3	23675	19	50	128.58
uflquad-psc-30-200	6000	3	33972	19	50	291.65
uflquad-psc-30-300	9000	3	54083	19	50	978.33

# DisCO solver

- A branch and bound framework to solve MISOCO.
- Uses *conic* OSI to manipulate relaxation problems.
- By default it uses COLA to solve relaxations.
- Cplex and Mosek can also be used through conic OSI interface.
- Extends COIN-OR's High-Performance Parallel Search (CHiPPS) framework for conic problems.
- Similar design to Gómez's ICLOPS (developed in his PhD work), major difference is it uses conic OSI and COLA.
- Simplex is used when COLA is chosen as solver.
- DisCO can use COIN-OR's CGL when COLA is chosen as solver.

# Valid Inequalities for MISOCO

We have the following cuts for MISOCO problems,

- Conic mixed-integer rounding (MIR) cuts given by [Atamturk and Narayanan(2010)] for general mixed integer case,
- Conic Gomory cuts given by [Çezik and Iyengar(2005)] for mixed 0–1 problems,
- Convex cuts defined by [Stubbs and Mehrotra(1999)] for mixed 0–1 convex problems,
- **Disjunctive conic cuts (DCC)** and **disjunctive cylindrical cuts (DCyC)** defined by [Belotti et al.(2013) Belotti, Góez, Pólik, Ralphs, and Terlaky] for general mixed integer case,
- Two term disjunctions defined by [Kılınç-Karzan and Yıldız(2014)] for general mixed integer case.

# Disjunctive Cuts by Belotti et al.

SOCO feasible region is given by

$$Ax = b$$

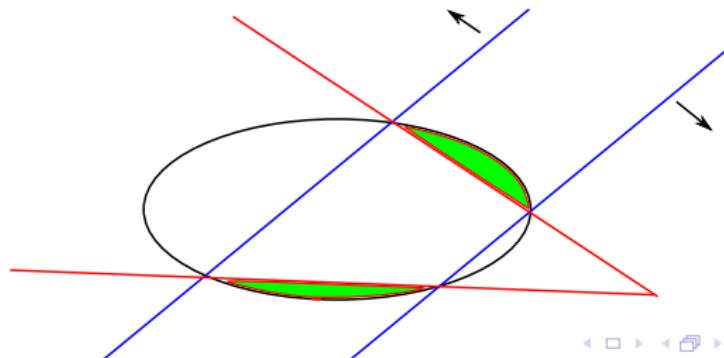
$$x \in \mathbb{L}^1 \times \cdots \times \mathbb{L}^k.$$

We convert the problem into the following form using  $x = x^0 + Hw$ ,

$$w^\top Q^i w + 2q^{i\top} w + \rho^i \leq 0 \quad i \in \{1, \dots, k\}$$

$$a^{i\top} x \geq \alpha^i \quad i \in \{1, \dots, k\},$$

where  $H$  is the null space basis of  $A$  and  $x^0$  is any point such that  $Ax^0 = b$ .



# Conic MIR

Assume conic constraints in the following form,

$$\|Ax + Gy - b\| \leq d^\top x + e^\top y - h.$$

Introduce variables  $(t_1, t_{2:m+1}) \in \mathbb{R} \times \mathbb{R}^m$ ,

$$\begin{aligned} t_1 &\leq d^\top x + e^\top y - h, \\ t_{i+1} &\geq |a_i x + g_i y - b_i| \quad i = 1, \dots, m, \\ t_1 &\geq \|t_{2:m+1}\|. \end{aligned}$$

For a fixed row we define following set,

$$\mathcal{S} := \{(x, y, t) \in \mathbb{Z}_+^n \times \mathbb{R}_+^p \times \mathbb{R} : t \geq |ax + gy - b|\}.$$

Following is an MIR inequality for  $\mathcal{S}$  for  $\alpha > 0$ ,

$$\sum_{j=1}^n \varphi_{f_\alpha} \left( \frac{a_j}{\alpha} \right) x_j - \varphi_{f_\alpha} \left( \frac{b}{\alpha} \right) \leq \frac{(t + y^+ - y^-)}{|\alpha|}.$$

# Conic MIR implementation

Cones in CBLIB are in the following form,

$$x_1 \geq \|x_{2:n}\|$$

We can lift this formulation as follows,

$$\begin{aligned} t &\geq |x_j| \\ x_1 &\geq \|(x_2, \dots, t, \dots, x_n)\|. \end{aligned}$$

Assume one of the rows in constraint matrix implies  $x_j = a^\top x + b^\top y + \beta$ . Then generate MIR cut using following,

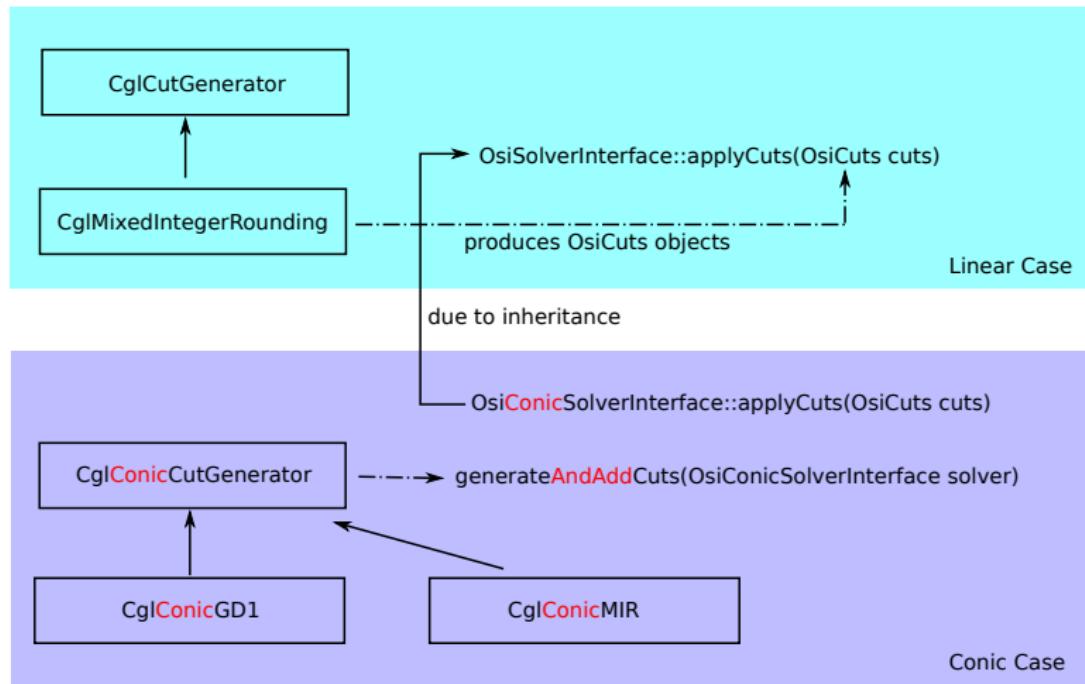
$$t \geq |a^\top x + b^\top y + \beta|.$$

Modify cone constraint as,

$$x_1 \geq \|(x_2, \dots, t, \dots, x_n)\|.$$

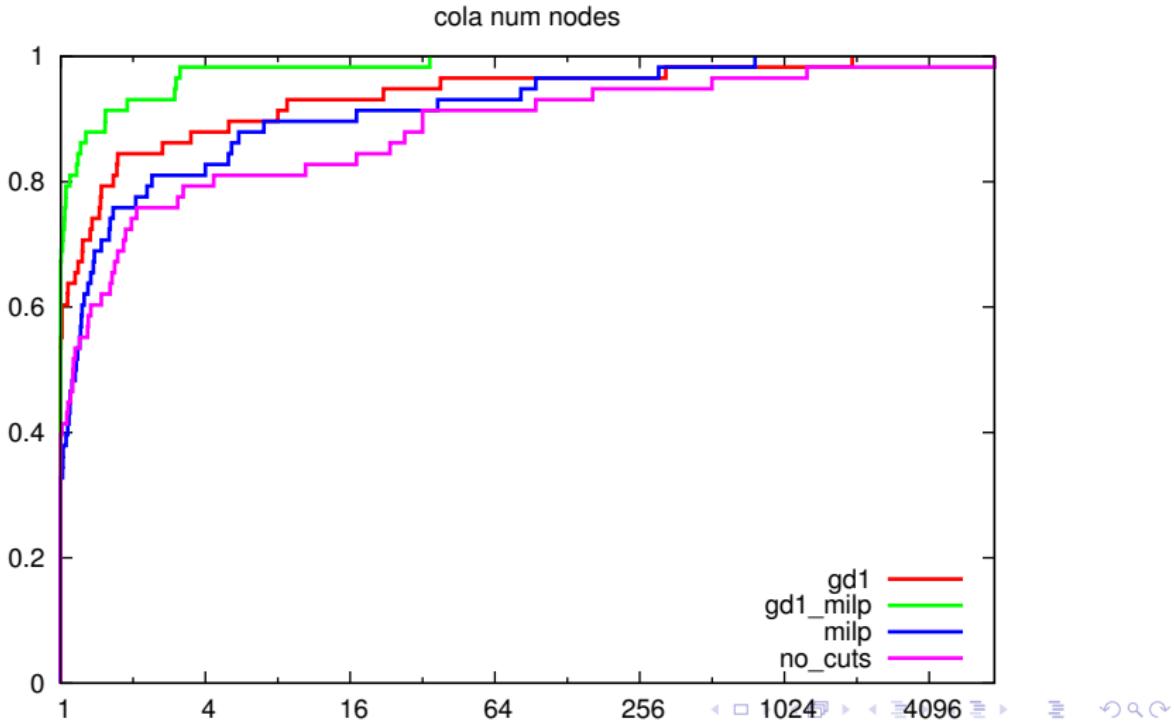
# Implementing Conic Cuts

Figure: Conic CGL's relationship to COIN-OR projects



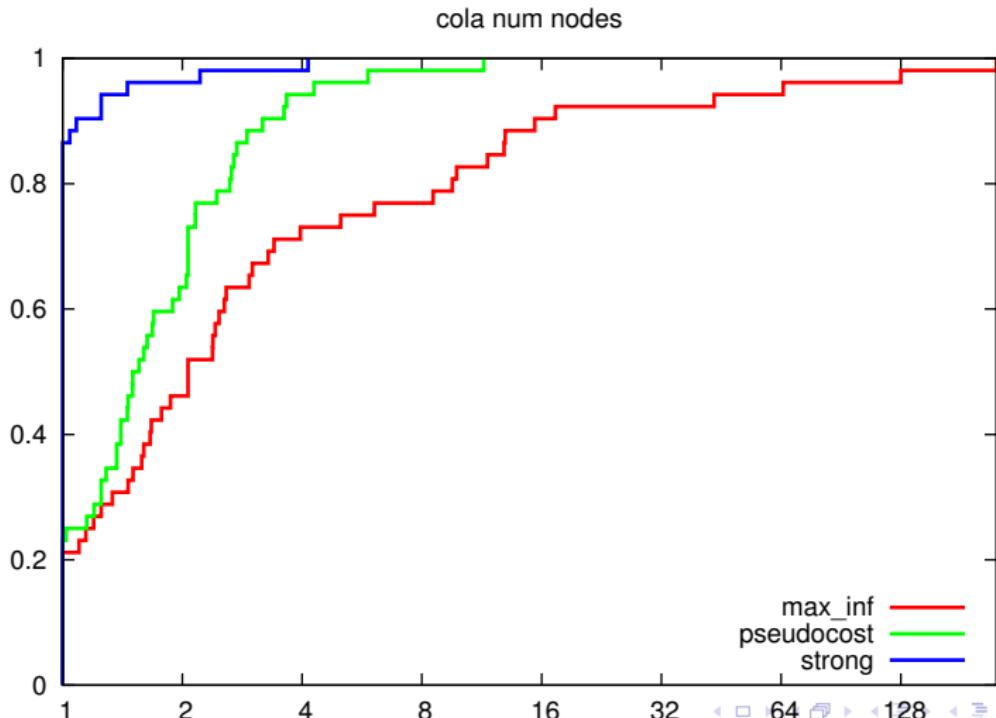
# COLA with various cut strategies

Figure: COLA cut strategies, number of nodes



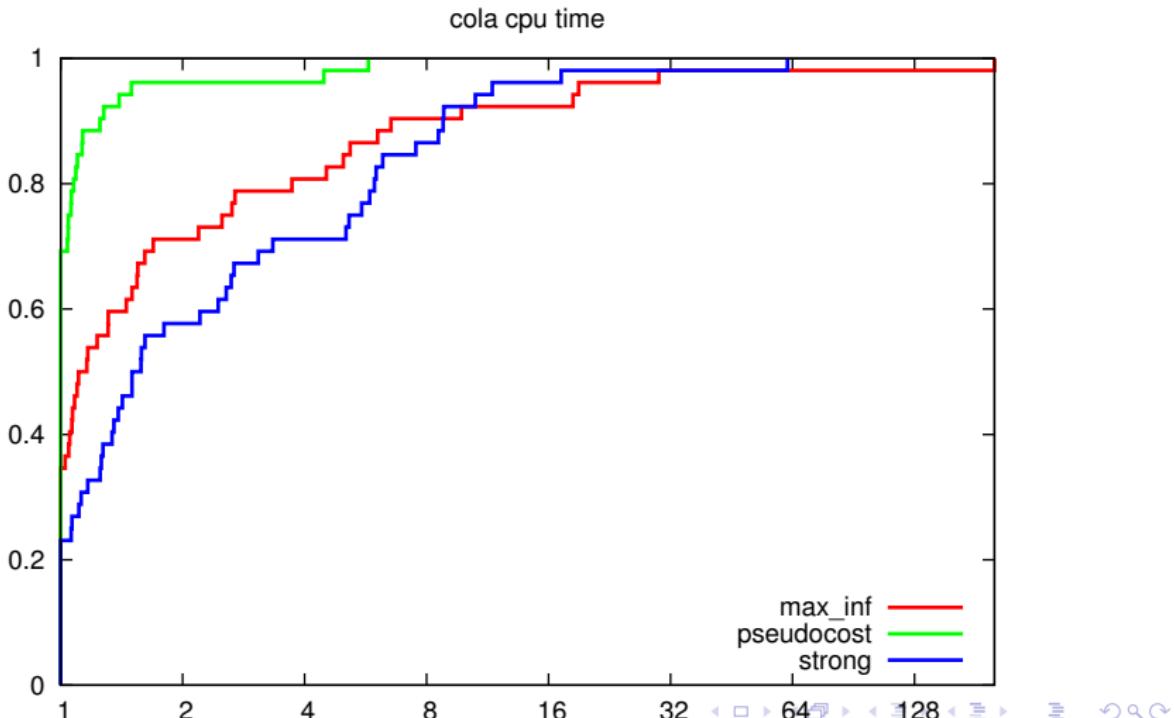
# DisCO Branching Experiments with COLA–Nodes

Figure: COLA branching strategy number of nodes



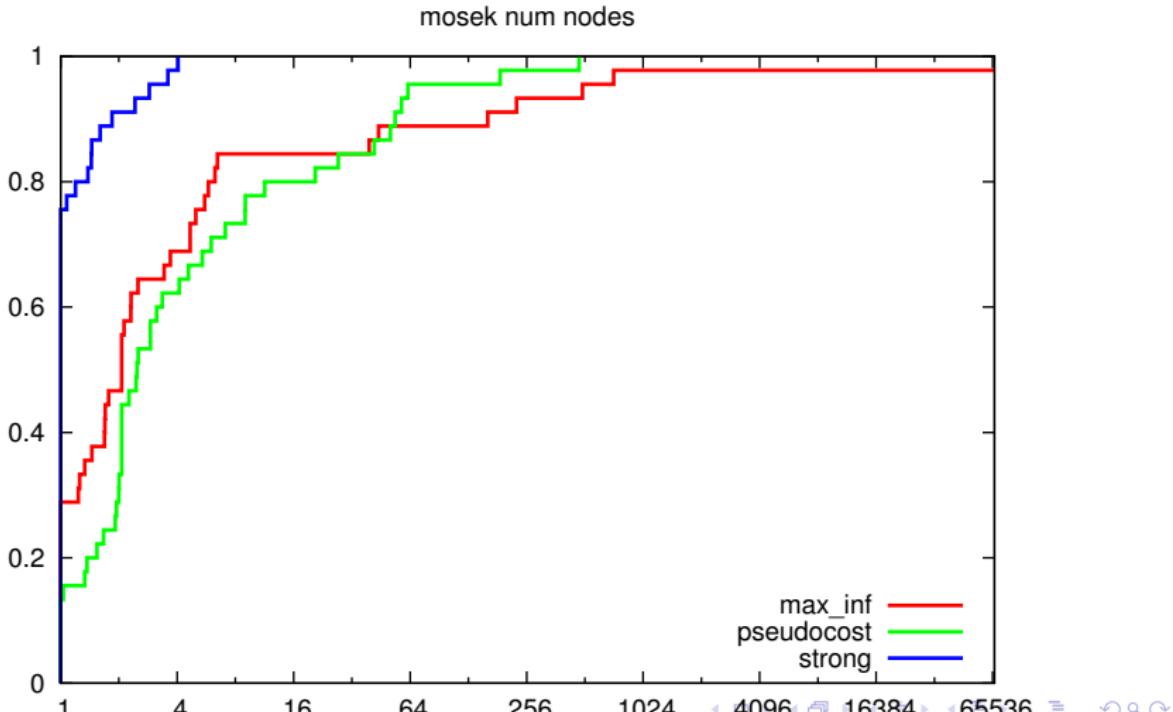
# DisCO Branching Experiments with COLA–CPU time

Figure: COLA branching strategy CPU time



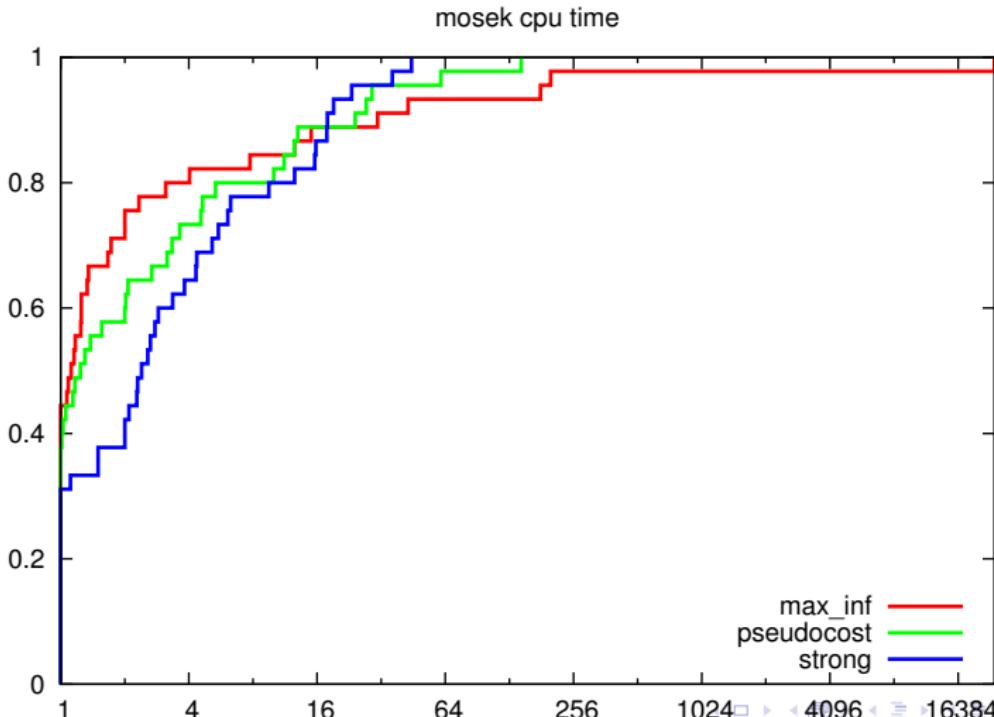
# DisCO Branching Experiments with Mosek–Nodes

Figure: Mosek branching strategy, number of nodes



# DisCO Branching Experiments with Mosek–CPU time

Figure: Mosek branching strategy, CPU time



# Contributions

- Outer approximation algorithm performance results on continuous problems.
- Testing outer approximation algorithm on discrete problems in a branch and bound framework.
- Implementation details for conic MIR.
- Software tools conic OSI, interface for Mosek, COLA, DisCO.
- Comparing performance of outer approximation method to IPM in branch and bound framework.
- Comparison of different branching strategies for MISOCO.
- Performance of disjunctive cuts given by Belotti et. al.

# Clone, Try, Contribute

<https://github.com/aykutbulut>

<https://github.com/coin-or>

# References



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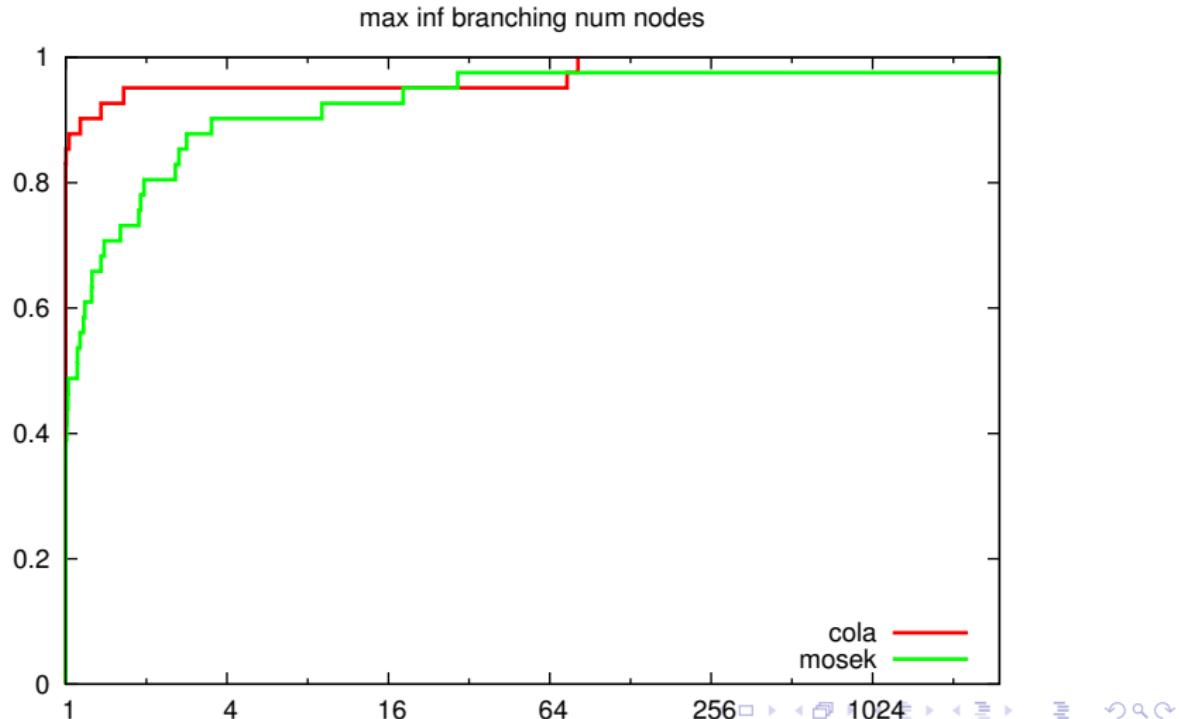
# End of presentation

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Thank you for listening!

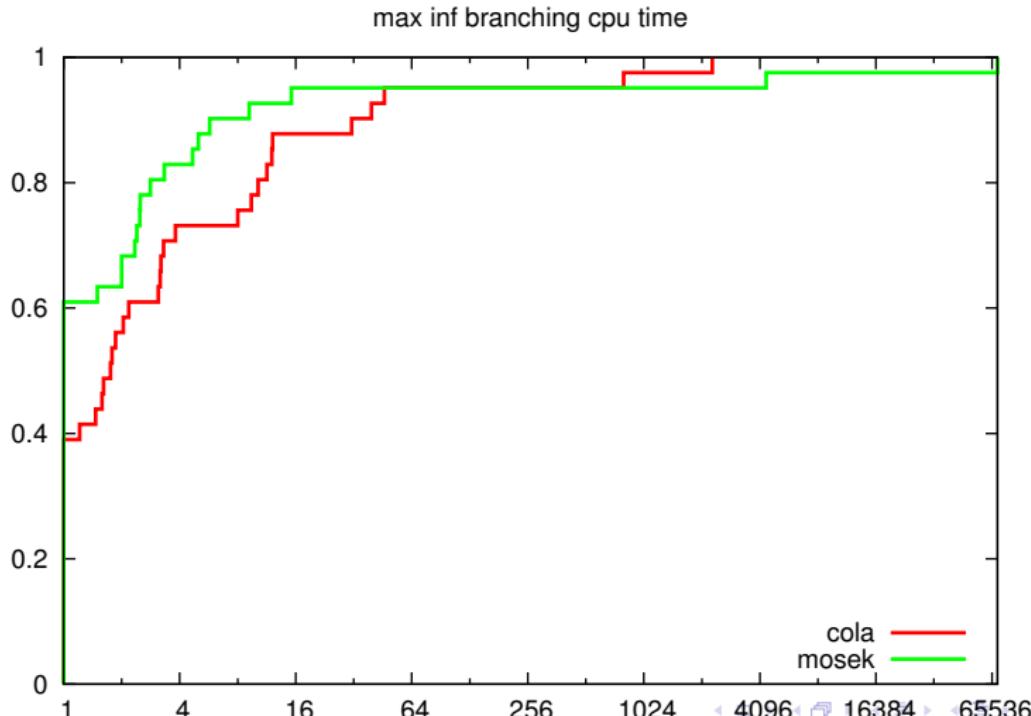
# Maximum Infeasibility Branching–Nodes

Figure: COLA vs Mosek with maximum infeasibility, number of nodes



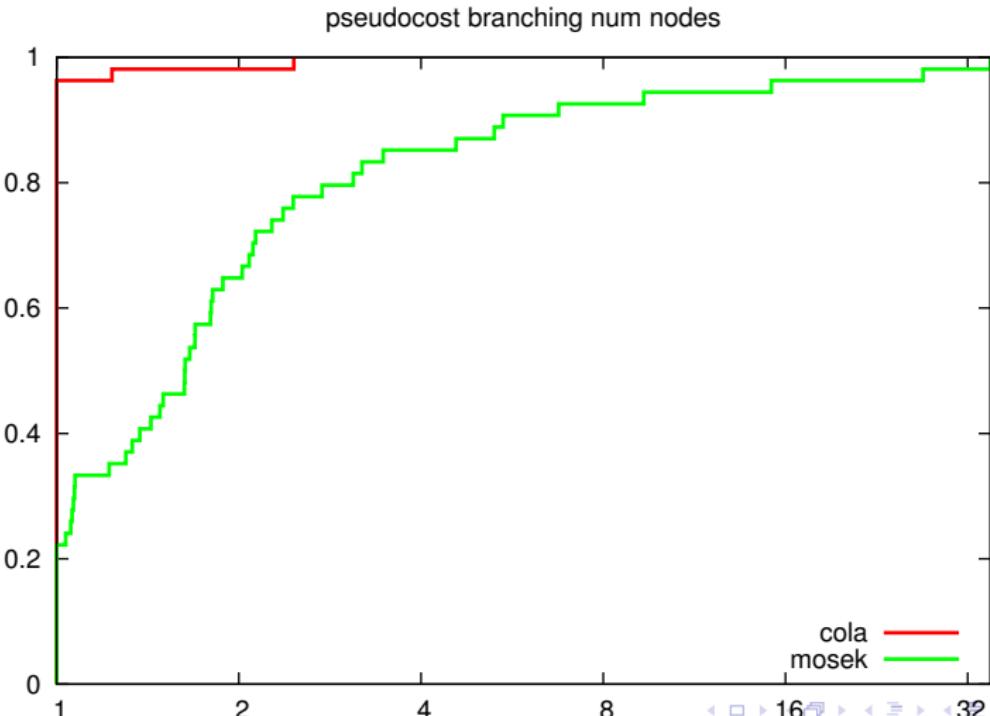
# Maximum Infeasibility Branching–CPU time

Figure: COLA vs Mosek with maximum infeasibility, CPU time



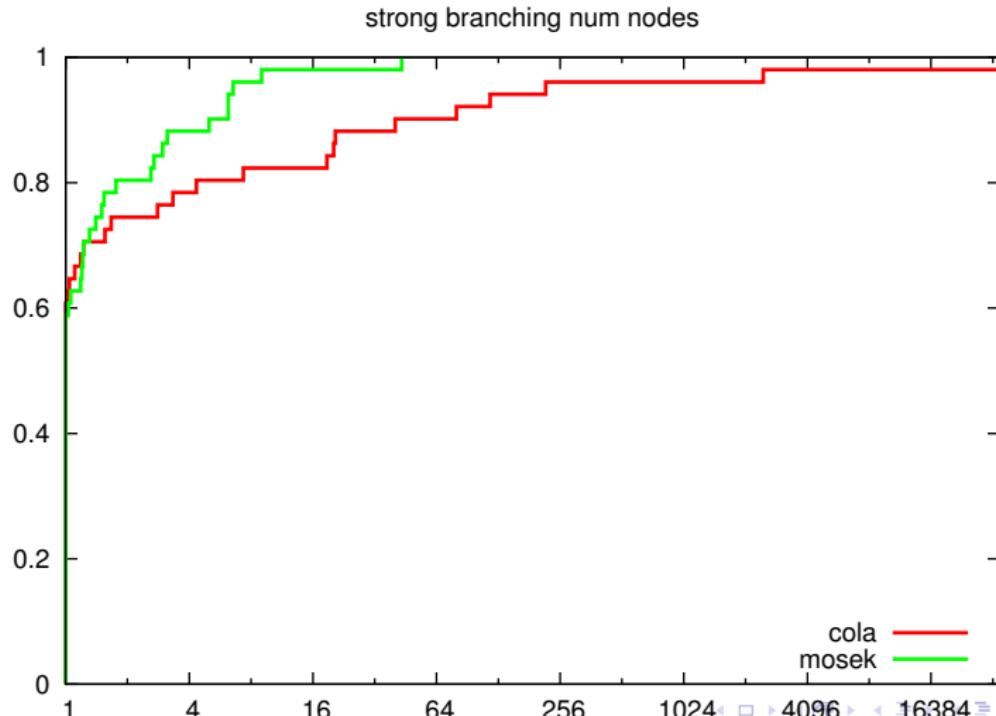
# Pseudocost Branching

Figure: COLA vs Mosek with pseudocost, number of nodes



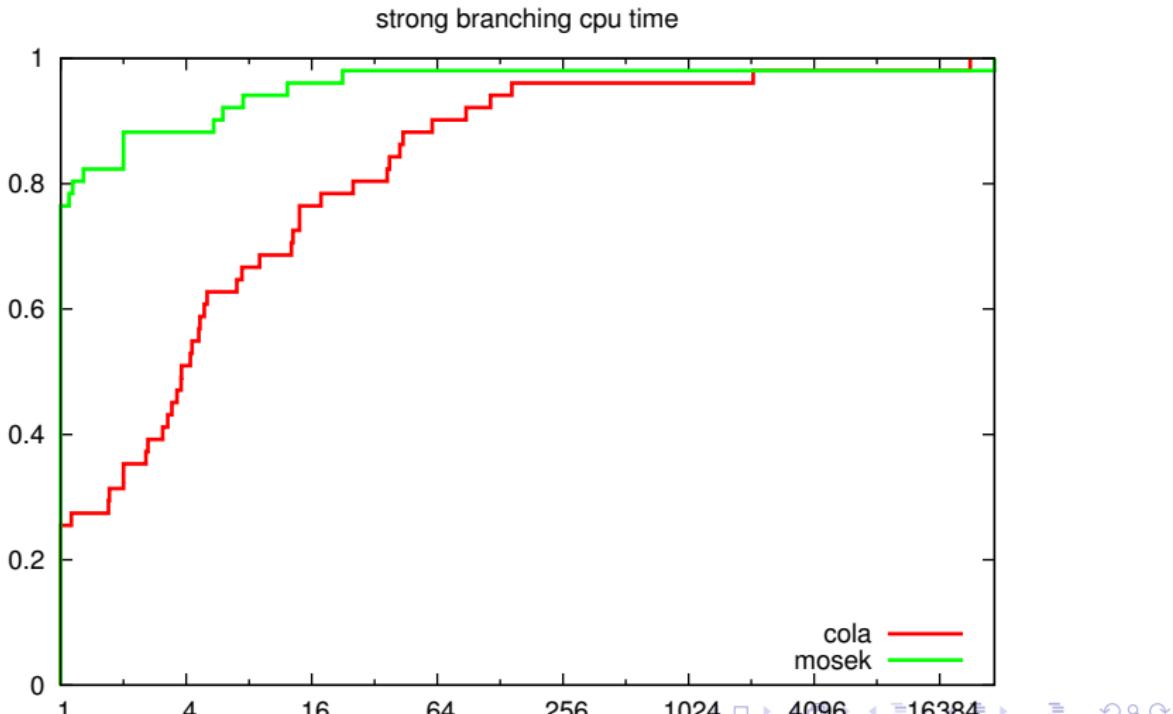
# Strong Branching–Nodes

Figure: COLA vs Mosek with strong branching, number of nodes



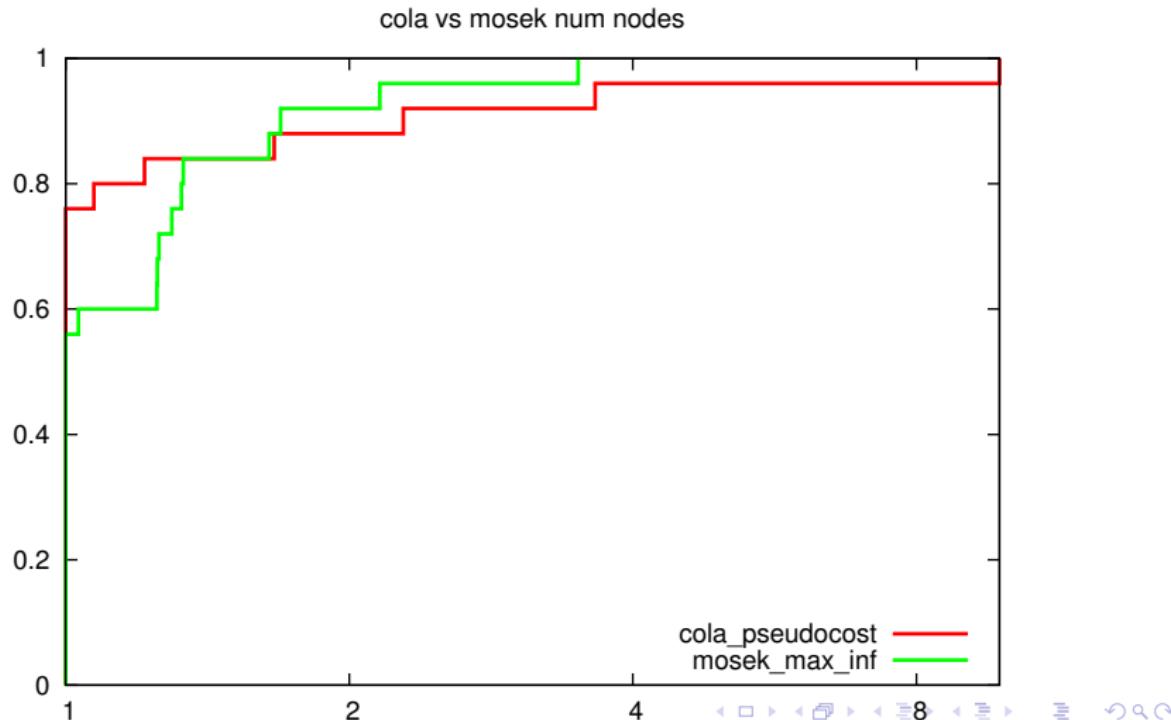
# Strong Branching–CPU time

Figure: COLA vs Mosek with strong branching, CPU time



# COLA–Pseudocost vs Mosek–Max Inf, Nodes

Figure: COLA pseudocost vs Mosek maximum infeasibility, number of nodes



# COLA–Pseudocost vs Mosek–Max Inf, CPU time

Figure: COLA pseudocost vs Mosek maximum infeasibility, CPU time

