

Theoretical and computational analysis of sizes of branch-and-bound trees

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Joint work with...



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Georgia Tech

1

Introduction

Integer program

$$\begin{array}{ll} \min & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x \in \mathbb{Z}^n \end{array} \quad (\text{IP})$$

Integer program

Integer program

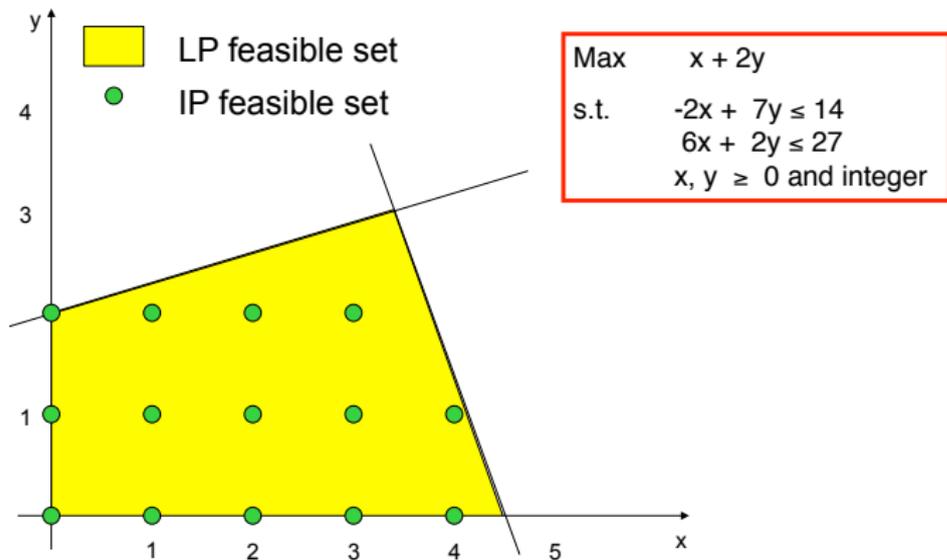
$$\begin{array}{ll} \min & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x \in \mathbb{Z}^n \end{array} \quad (\text{IP})$$

Many applications:

- ▶ Decision making with vast economic and societal impact
- ▶ Power systems, Sustainability, IMRT cancer treatment, Circuit design, Healthcare analytics, Network design, Supply chain Design, Urban mobility, Production planning, National security, etc.

Branch-and-Bound

Branch-and-bound is the basic algorithm underlying state-of-art IP solvers.

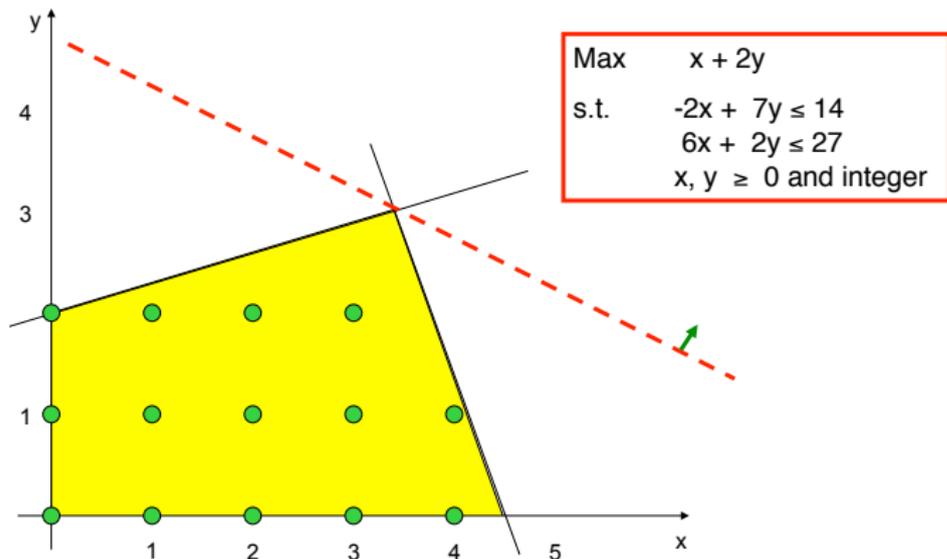


Example/Picture credit: Natasha Boland

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Solving Root Node



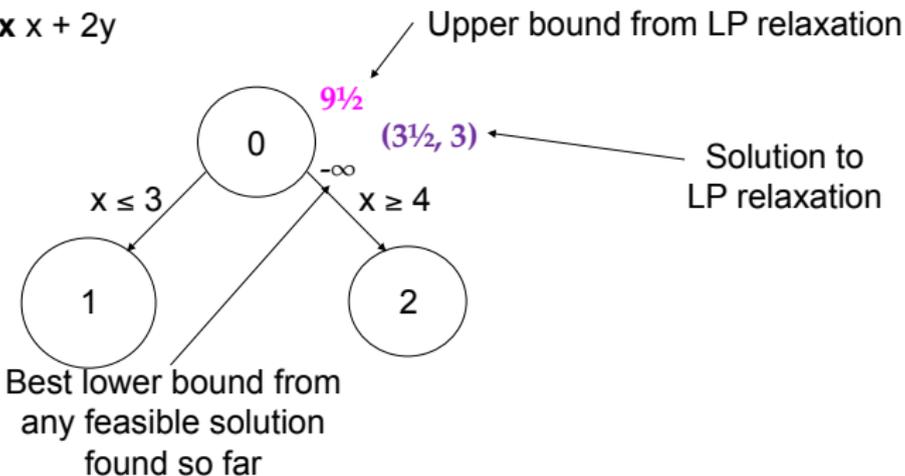
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Branch-and-Bound Tree

$$\max x + 2y$$

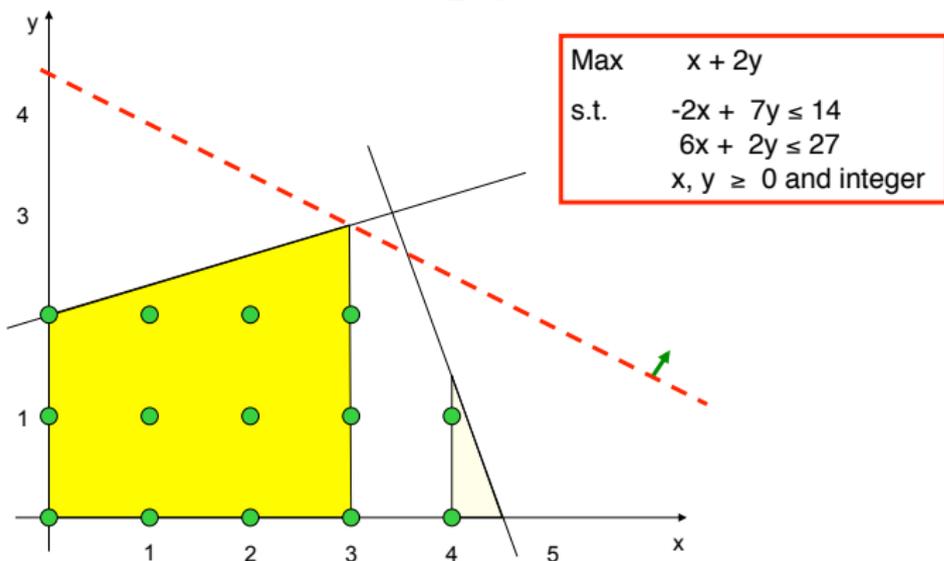


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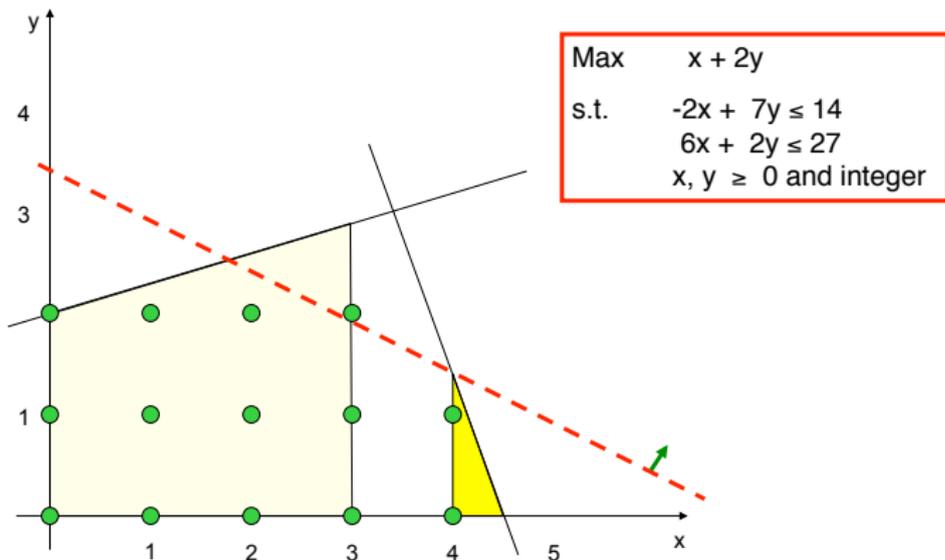
Branching process



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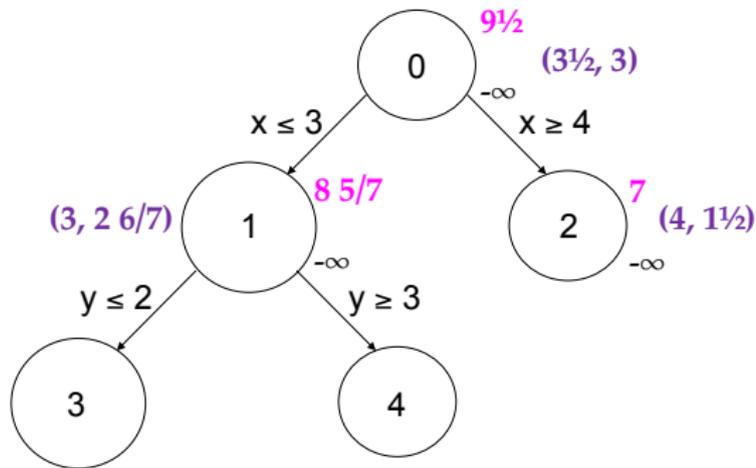


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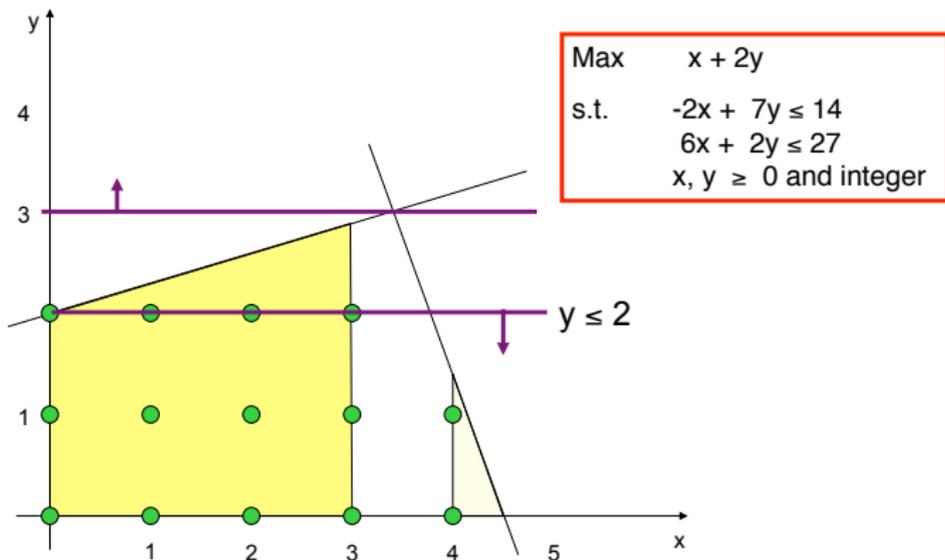
Branch-and-Bound Tree



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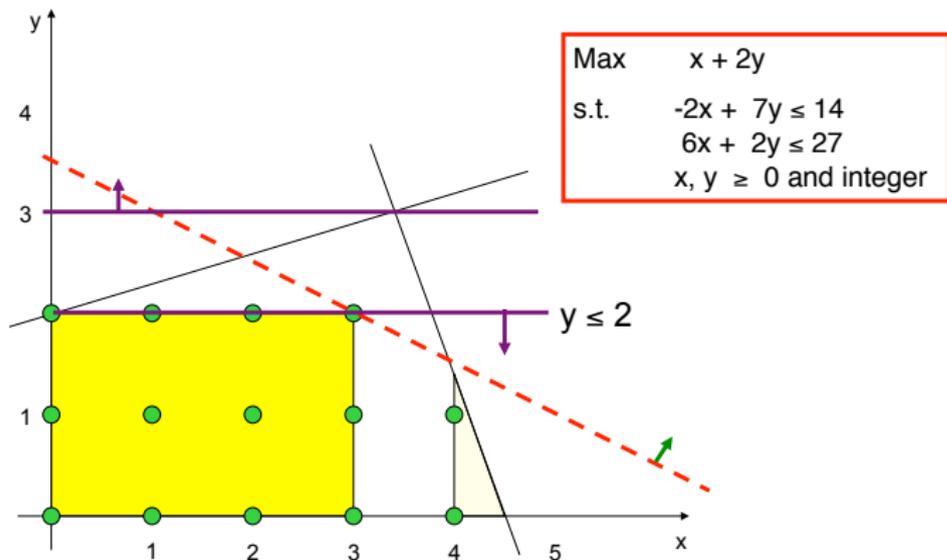
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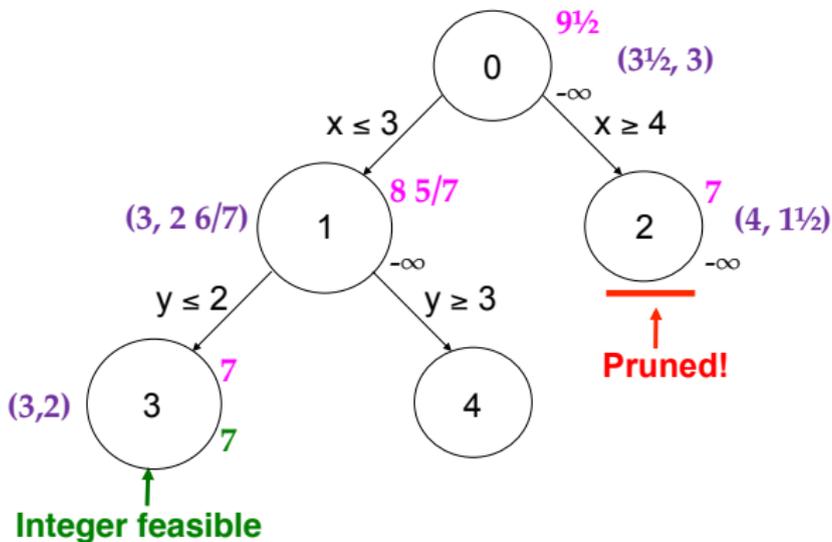


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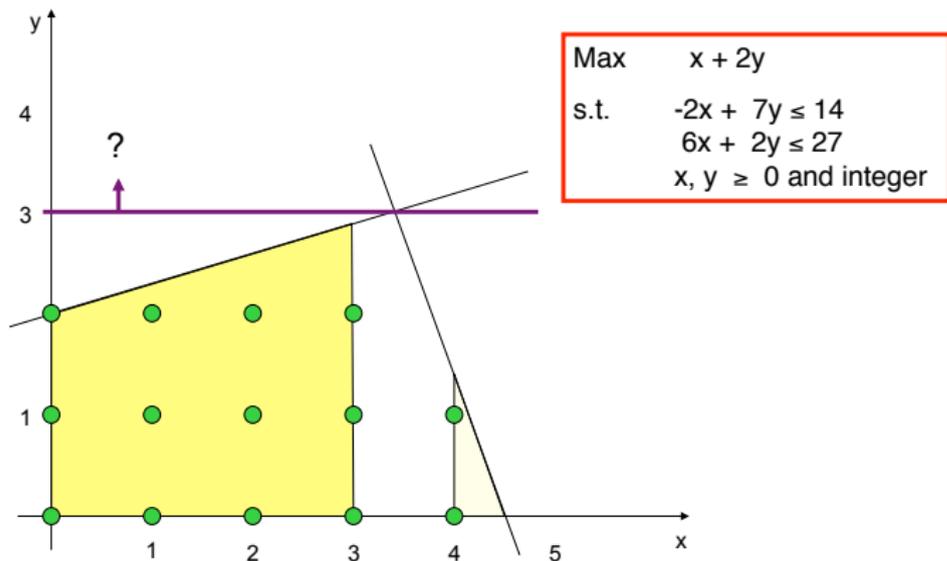
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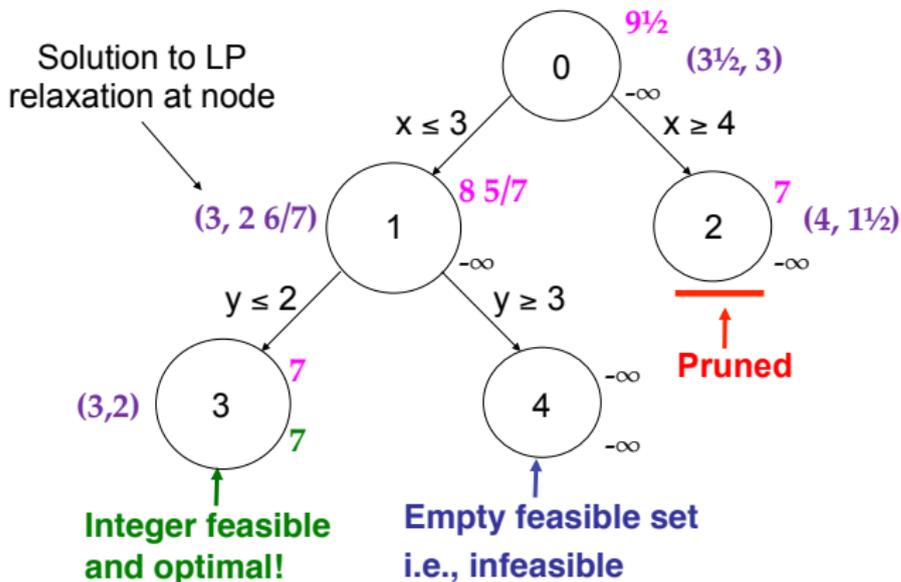


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Well-defined branch-and-bound algorithm

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- ▶ **Partitioning the feasible region of an LP at a node**
 - ▶ **Simple branch-and-bound:** Used in practise by solvers

$$x_j \leq \lfloor \hat{x}_j \rfloor \quad \text{---} \rightarrow \text{Added to left node}$$

$$x_j \geq \lceil \hat{x}_j \rceil \quad \text{---} \rightarrow \text{Added to right node}$$

Need rule to decide which variable to branch on: *Full strong branching*, *Reliability branching*, *Pseudocost branching*: will discuss some of these later.

- ▶ **General branch-and-bound:**

$$\pi^T x \leq \pi_0 \quad \text{---} \rightarrow \text{Added to left node}$$

$$\pi^T x \geq \pi_0 + 1 \quad \text{---} \rightarrow \text{Added to right node}$$

where $\pi \in \mathbb{Z}^n$ is an integer vector and $\pi_0 \in \mathbb{Z}$ is an integer.

Branch-and-bound procedure

- ▶ The branch and bound algorithm was invented by **Land and Doig** in 1960.



Ailsa Land

Picture credit: Wikipedia



Alison Doig

Branch-and-bound procedure

- ▶ The branch and bound algorithm was invented by **Land and Doig in 1960**.
- ▶ Almost 60 years now, but there is very little theoretical analysis of the branch-and-bound algorithm!

What kind of questions we want to answer

- ▶ What is known: There are simple examples (i.e. knapsack IPs) with n variables that require $\mathcal{O}(2^n)$ nodes when using simple branch-and-bound tree. [Jeroslow (1974)], [Chvátal (1980)]

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- ▶ Can we understand and analyse properties of some well-known rules for partitioning mentioned above? Hopefully this will lead to better rules.

2

Main results

2.1

Branch-and-bound solves (a class of) random IPs in polynomial time

Random model of IPs

We consider the following model of random IPs:

$$\begin{array}{ll} \max & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x \in \{0, 1\}^n \end{array} \quad \begin{array}{l} c \sim \text{Uniform}([0, 1]^n) \\ A \sim \text{Uniform}([0, 1]^{m \times n}) \\ , \end{array}$$

where $b = \beta \cdot n, \beta \in (0, \frac{1}{2})^m$.

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Incomplete literature review:

- ▶ Analysis of gap and enumerative algorithms: [Lueker (1982)], [Goldberg, Marchetti-Spaccamela (1984)], [Beier, Vocking (2003)], [Dyer, Frieze (1989)]

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- ▶ Analysis of gap and enumerative algorithms: [Lueker (1982)], [Goldberg, Marchetti-Spaccamela (1984)], [Beier, Vocking (2003)], [Dyer, Frieze (1989)]
- ▶ General branching: [Pataki, Tural, Wong (2010)]

Result for random IPs

Theorem (D., Dubey, Molinaro)

Consider a branch-and-bound algorithm using the following rules:

- ▶ *Partitioning rule: Variable branching, where any fractional variable can be used to branch on.*
- ▶ *Node selection rule: **Worst bound rule** (Select a node with largest LP value as the next node to branch on.)*

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Consider $n \geq m + 1$ and a random instance of IP described previously. Then with probability at least $1 - \frac{1}{n} - 2^{-\alpha \bar{a}_2}$, the branch-and-bound algorithm applied to this random instance produces a tree with at most

$$n^{\bar{a}_1} \cdot (m + \alpha \log m)$$

nodes for all $\alpha \leq \min\{30m, \frac{\log n}{\bar{a}_2}\}$, where \bar{a}_1 and \bar{a}_2 are constant depending only on m and β .

Result for random IPs

Simplified...

Theorem (D., Dubey, Molinaro)

Any branch-and-bound tree using the worst bound rule for node selection, solving the above problem has no more than $(n^{\mathcal{O}(m)})$ nodes with good probability.

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Nice follow up work [Borst, Dadush, Huiberts, Tiwari (2021)]

2.2

Lower bounds on size of general branch-and-bound tree

Lower bounds

- ▶ Remember when using general branch-and-bound, we are allowed to use general disjunctions:

$$\pi^T x \leq \pi_0 \quad \text{---} \text{> Added to left node}$$

$$\pi^T x \geq \pi_0 + 1 \quad \text{---} \text{> Added to right node}$$

where π is an integer vector and π_0 is an integer.

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- As explained before, most lower bounds are for simple branch-and-bound trees. We want results independent of computation complexity assumptions.
- Very recently, [Dadush, Tiwari (2020)] showed the following:

Theorem (Dadush, Tiwari)

Any (general) branch-and-bound tree that certifies the following instance is integer feasible requires at least $\frac{2^n}{n}$ leaf nodes:

$$C := \left\{ x \in \{0, 1\}^n \mid \sum_{j \in S} x_j + \sum_{j \in [n] \setminus S} (1 - x_j) \geq \frac{1}{2} \quad \forall S \subseteq [n] \right\}$$

Lets consider the cross-polytope again..

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- ▶ Consider any node of a general branch-and-bound tree where **two distinct** $0 - 1$ vectors v and w are feasible for the **branching-constraints** added to that node (v and w of course cannot belong to C or its LP relaxation).

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- ▶ So $\frac{v+w}{2}$ satisfies all the constraints at the node. Equivalently, the node is non-empty.
- ▶ In order to prove integer-infeasibility of C , every leaf node should be infeasible. **So from above, there must be at least 2^n leaf nodes!**

More results –I: Hardness of some combinatorial problems

Theorem (D., Dubey, Molinaro)

Let n be an even positive integer. Any branch-and-bound tree, solving the following instance

$$\begin{aligned} \max \quad & \sum_{j \in [n]} x_j \\ \text{s.t.} \quad & \sum_{k \in S} x_k \leq \frac{n}{2} - 1, \quad \forall S \subseteq [n], |S| = \frac{n}{2} \\ & x \in \{0, 1\}^n \end{aligned}$$

requires *at least* $2^{\Omega(n)}$ nodes.

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Theorem (D., Dubey, Molinaro)

Let P be LP relaxation of the usual **travelling salesman problem formulation** (with sub tour elimination) with n cities. There exist an objective function c , such that any branch-and-bound tree, solving the following instance

$$\begin{aligned} \max \quad & c^\top x \\ \text{s.t.} \quad & x \in P \\ & x \in \{0, 1\}^{\frac{(n)(n-1)}{2}} \end{aligned}$$

requires **at least $2^{\Omega(n)}$ nodes.**

More results –III: Smoothed analysis not possible

Random family of instances:

$$Q := \sum_{i \in I} \left(1 + N\left(0, \frac{1}{20^2}\right)\right) x_i + \sum_{i \notin I} \left(1 - \left(1 + N\left(0, \frac{1}{20^2}\right)\right) x_i\right) \geq \frac{1.6n}{20}, \forall I \subseteq [n]$$
$$x \in [0, 1]^n,$$

where each occurrence of $N(0, \frac{1}{20^2})$ is independent.

Theorem (D., Dubey, Molinaro)

With probability at least $1 - \frac{2}{e^{n/2}}$ the polytope Q is integer-infeasible and every branch-and-bound tree proving its infeasibility has at least $2^{\Omega(n)}$ nodes.

2.3

Analysis of full strong branching rule for partitioning

Full strong branching

Introduction

Main results

Random IPs

Lower bounds on size of
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**Analysis of full strong
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Strong branching applied
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A computational evaluation
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Proof Outlines

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- ▶ Let **OPT** := the optimal value of the LP at this node.
- ▶ Let $\text{OPT}_{j,0} :=$ the optimal value of the LP of the child node where we have the inequality $x_j \leq 0$.
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- ▶ Let $\text{OPT}_{j,1} :=$ the optimal value of the LP of the child node where we have the inequality $x_j \geq 1$.
- ▶ Let

$$\text{score}_j = \max \{ |\text{OPT} - \text{OPT}_{j,1}|, \epsilon \} \cdot \max \{ |\text{OPT} - \text{OPT}_{j,0}|, \epsilon \},$$

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A computational evaluation
of strong branching

Proof Outlines

- ▶ Full strong branching is a partitioning rule for **simple branch-and-bound trees**.
- ▶ Suppose \hat{x} is a LP optimal solution. Let $\hat{x}_j \in (0, 1)$ for $j \in F \subseteq [n]$.
- ▶ Let **OPT** := the optimal value of the LP at this node.
- ▶ Let **OPT**_{*j,0*} := the optimal value of the LP of the child node where we have the inequality $x_j \leq 0$.
- ▶ Let **OPT**_{*j,1*} := the optimal value of the LP of the child node where we have the inequality $x_j \geq 1$.
- ▶ Let

$$\text{score}_j = \max \{ |\text{OPT} - \text{OPT}_{j,1}|, \epsilon \} \cdot \max \{ |\text{OPT} - \text{OPT}_{j,0}|, \epsilon \},$$

where $\epsilon > 0$ is a small number related to machine precision.

- ▶ Let $j^* := \operatorname{argmax}_{j \in F} (\text{score}_j)$.

Full strong branching

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- ▶ Let $j^* := \operatorname{argmax}_{j \in F} (\text{score}_j)$.
- ▶ Branch on j^* .

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- ▶ Experimentally, full strong branching, works better than any other rule for **simple branch-and-bound trees** [Achterberg, Koch, and Martin (2005)].

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- ▶ However, this rule is not used in practise, because we need to solve $2|F|$ LPs just to decide one branching decision.

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- ▶ However, this rule is not used in practise, because we need to solve $2|F|$ LPs just to decide one branching decision.
- ▶ Recently there has been many attempts made to mimic full strong branching using machine learning. [Alvarez, Louveaux, and Wehenkel (2017)], [Gasse, Chetelat, Ferroni, Charlin, Lodi (2019)], [Khalil, Le Bodic, Song, Nemhauser, Dilkina (2016)], [Nair et al. (2020)]

Some questions..

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- ▶ How large is the tree produced by strong-branching **in comparison to the smallest possible branch-and-bound tree for a given instance**? Answering this question may lead us to finding better rules.
- ▶ A more refined questions is the following: it would be useful to understand the performance of strong-branching vis-à-vis different classes of instances.

2.3.1

Strong branching applied to specific problems

Vertex cover

Definition (Vertex cover)

The vertex cover problem over a graph $G = (V, E)$ can be expressed as the following integer program (IP)

$$\begin{array}{ll} \min & \sum_{v \in V} x_v \\ \text{s.t.} & x_u + x_v \geq 1, \quad uv \in E \\ & x_v \in \{0, 1\}, \quad v \in V \end{array}$$

Given an instance I of this IP, we let $\text{OPT}(I)$ denote **optimal objective function value** and $\text{OPT}_L(I)$ be the **optimal objective function of the LP relaxation** (i.e. when the variable constraints are $x_v \in [0, 1]$). Then let

$$\Gamma(I) := \text{OPT}(I) - \text{OPT}_L(I).$$

Strong branching works well for vertex cover

Theorem (D., Dubey, Molinaro, Shah)

*Let I be any instance of vertex cover on n nodes. Assume we **break ties within the worst-bound rule for node selection rule by selecting a node with the largest depth.***

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$$|\mathcal{T}_S(I)| \leq 2^{2\Gamma(I)+1} + \mathcal{O}(n).$$

Strong branching does not work well for other IP models

$$\left\{ (x, y) \in \{0, 1\}^n \times \{0, 1\}^n \mid y_i \leq 2x_i, y_i \leq 2 - 2x_i, \forall i \in [n], \sum_{i=1}^n y_i = 1 \right\}$$

Theorem

The smallest branch-and-bound tree that shows that the above set is integer infeasible requires no more than $4n + 1$ nodes. On the other hand, strong branching requires at least 2^n nodes.

2.3.2

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- ▶ It is not possible to analyse different problems analytically.

Optimal branch-and-bound tree

- ▶ It is not possible to analyse different problems analytically.
- ▶ So we came up with a Dynamic programming algorithm to compute the optimal branch-and-bound tree.

Theorem (D., Dubey, Molinaro, Shah)

There is a DP algorithm with running time $\text{poly}(\text{data}) \cdot 3^{O(n)}$ time to compute an optimal branch-and-bound tree for any binary MILP instance defined on n binary variables.

Ratio of geometric mean of branch-and-bound tree size to that of optimal tree size

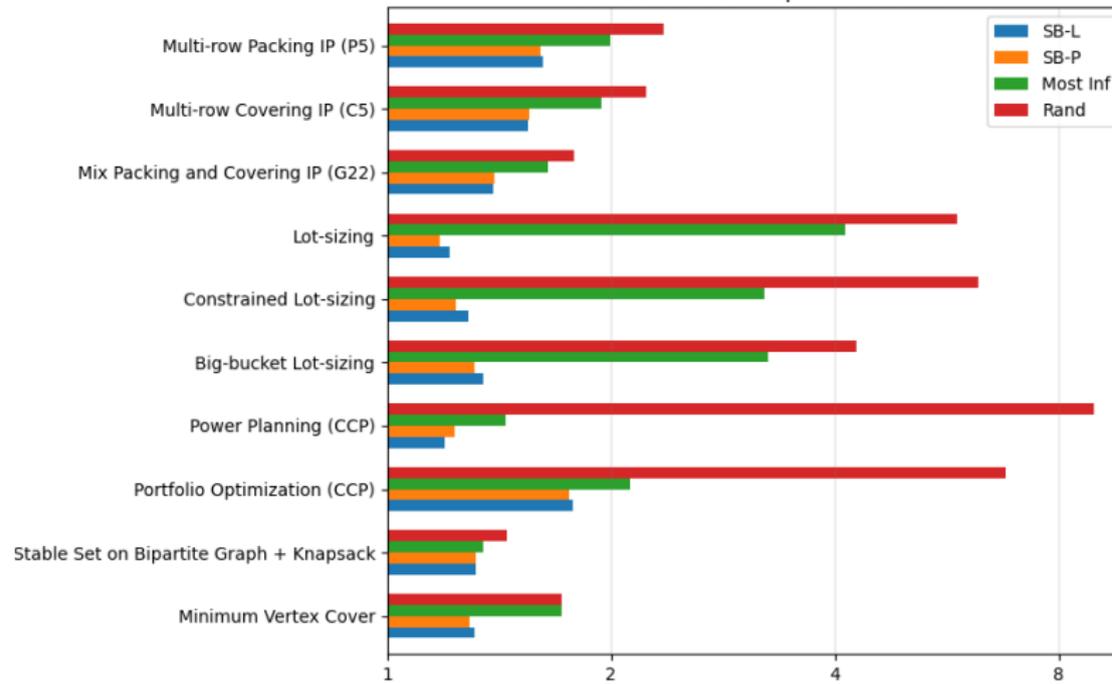


Figure: Ratio of geometric mean of branch-and-bound tree sizes to geometric mean of optimal tree sizes over all instances of a problem for various branching strategies. "Rand" stands for random, "Most Inf" stands for most infeasible, "SB-P" stands for strong-branching with product score function, and "SB-L" stands for strong-branching with linear score function.

3

Proof Outlines

3.1

Random IPs Theorem

Reminder...

$$\begin{array}{ll} \max & c^\top x \\ \text{s.t.} & Ax \leq b \\ & x \in \{0, 1\}^n \end{array} \quad \begin{array}{l} c \sim \text{Uniform}([0, 1]^n) \\ A \sim \text{Uniform}([0, 1]^{m \times n}) \\ , \end{array}$$

where $b = \beta \cdot n$, $\beta \in (0, \frac{1}{2})^m$.

Theorem (D., Dubey, Molinaro)

Any branch-and-bound tree *using the worst bound rule for node selection*, solving the above problem has no more than $(n^{\mathcal{O}(m)})$ nodes (with good probability).

Proof Sketch

$$\Delta(x) = \sum_{j \in [n]} \underbrace{(c_j - \langle \lambda^*, A^j \rangle)}_{\text{reduced cost}} \cdot \underbrace{(x_j^* - x_j)}_{\text{LP Opt.}},$$

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1. The number of internal nodes in a branch-and-bound tree is at most n times the number of good integer solutions G .

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1. The number of internal nodes in a branch-and-bound tree is at most n times the number of good integer solutions G .
2. The number of good integer solutions is at most $n^{O(m)}$ (with good probability).

We construct a mapping...

r : internal nodes $\rightarrow G$ as follows:

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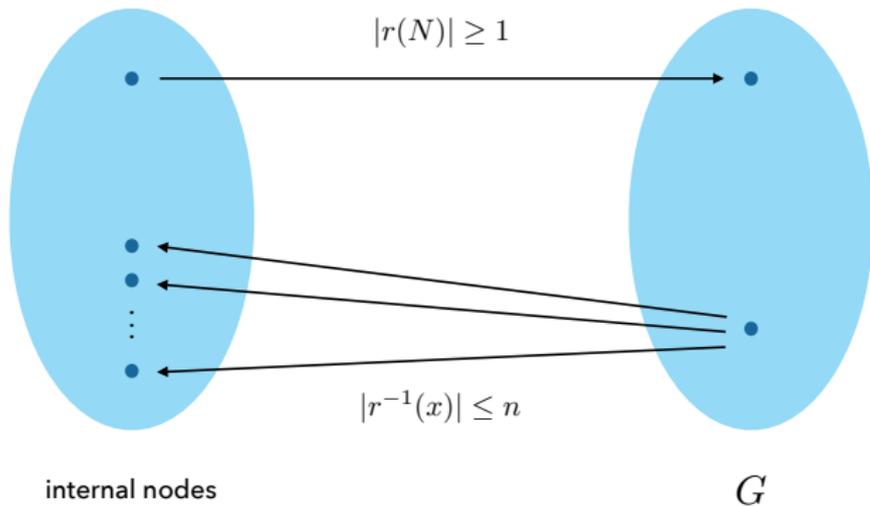
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Picture credit: Yatharth Dubey

3.2

Optimal branch-and-bound tree

Dynamic programming algorithm

$$\max_{x \in P \cap \{0,1\}^n} c^T x$$

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Algorithm 1 Computing Optimal Branch-and-bound Tree

Phase-1: Pruning by Infeasibility or Bound

- 1: Solve $\max_{x \in P \cap \{0,1\}^n} \langle c, x \rangle$; let x^* be the solution
- 2: Initialise: $\mathcal{S} \leftarrow \mathcal{F}$
- 3: **for** F in \mathcal{S} **do**
- 4: Solve $\max_{x \in F \cap P} \langle c, x \rangle$; let x_F^* be the optimal solution ($x_F^* = \emptyset$ if LP is infeasible)
- 5: **if** $x_F^* = \emptyset$ **or** $\langle c, x_F^* \rangle \leq \langle c, x^* \rangle$ **then**
- 6: $\overline{\text{OPT}}(F) \leftarrow 0$
- 7: $\mathcal{S} \leftarrow \mathcal{S} \setminus \{F\}$
- 8: **end if**
- 9: **end for**

Phase-2: Recursive bottom-up computation

- 10: Sort \mathcal{S} in order of increasing dimension
 - 11: **for** F in \mathcal{S} **do**
 - 12: $\overline{\text{OPT}}(F) \leftarrow 1 + \min_j (\overline{\text{OPT}}(F_{j,0}) + \overline{\text{OPT}}(F_{j,1}))$
 - 13: **end for**
 - 14: **return** $\overline{\text{OPT}}([0, 1]^n)$
-

Thank You.

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- ▶ Dey, Santanu S., Yatharth Dubey, and Marco Molinaro. "Lower Bounds on the Size of General Branch-and-Bound Trees." arXiv preprint arXiv:2103.09807 (2021).
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