

Learning to Cut in Integer Programming

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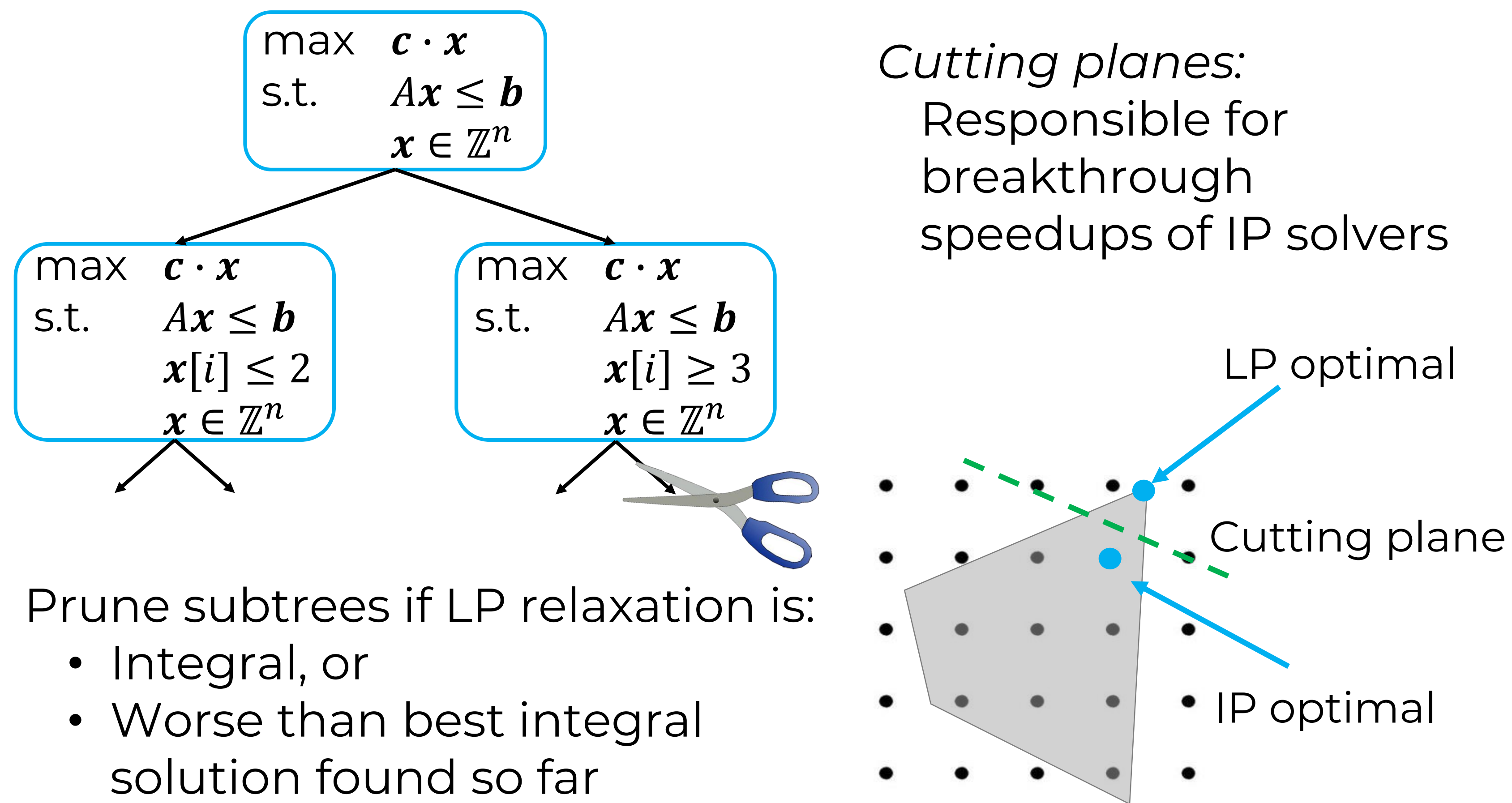
Joint with Nina Balcan (CMU), Tuomas Sandholm (CMU), and Ellen Vitercik (Stanford)

Branch-and-cut for integer programming

LP guidance to do informed search through feasible set

Choose variable i to branch on:

add constraints $x[i] \leq \lfloor x_{LP}^*[i] \rfloor$, $x[i] \geq \lceil x_{LP}^*[i] \rceil$



Our contribution:

First formal theory for using ML to select cutting planes

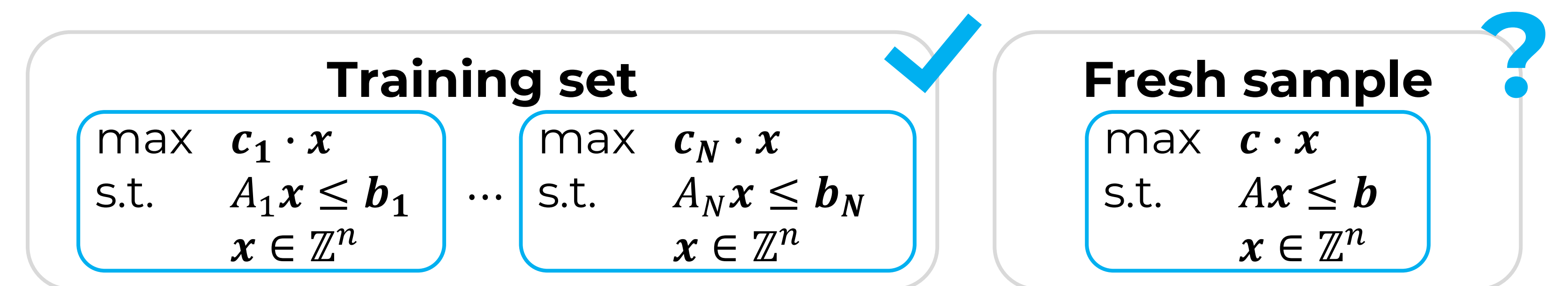
Learning to cut

Best cutting planes for **routing** problems likely not suited for **scheduling**

Application domain modeled by distribution over IPs

Key question: Sample complexity

If cut yields small B&C tree size on average over a training set...



...will it yield a small B&C tree on a fresh IP?

Sample complexity

- size of training set s.t. $|\text{empirical treesize} - \text{expected treesize}| \leq \epsilon$ for all cuts uniformly
- grows linearly in **pseudo-dimension**
- generalization of VC dimension

Cutting planes: Structure and sensitivity

Want to understand B&C tree as a *function* of cutting plane

Chvátal-Gomory Cuts:

$\alpha_1 x \leq \beta_1$ of the form $\lfloor uA \rfloor x \leq \lfloor ub \rfloor$, $u \in [0, 1]^m$

Theorem: For any IP, $O(\|A\|_{1,1} + \|b\|_1 + n)$ hyperplanes partition $[0, 1]^m$ into regions s.t. in each region the cutting plane given by u is the same

i.e. set of CG cuts “effectively finite”

More generally, when does B&C behave identically on:

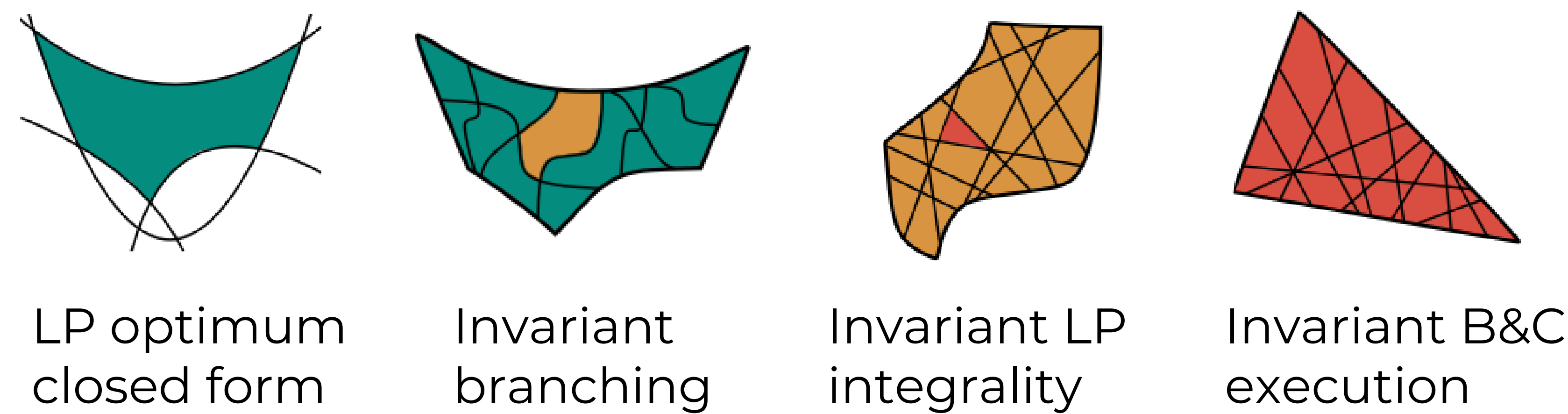
$$\begin{aligned} \max \quad & c \cdot x \\ \text{s.t.} \quad & Ax \leq b \\ & \alpha_1 x \leq \beta_1 \\ & x \in \mathbb{Z}^n \end{aligned}$$

vs

$$\begin{aligned} \max \quad & c \cdot x \\ \text{s.t.} \quad & Ax \leq b \\ & \alpha_2 x \leq \beta_2 \\ & x \in \mathbb{Z}^n \end{aligned}$$

Theorem: For any IP, $O(14^n(m + 2n)^{3n^2} \tau^{5n^2})$ degree ≤ 5 polynomial hypersurfaces partition \mathbb{R}^{n+1} into regions s.t. in each region the execution of B&C is the same
 τ = diameter of feasible polytope (roughly)

Proof. Derive piecewise closed form for LP optimum in terms of α, β . B&C actions defined by polynomial boundaries



Gomory Mixed Integer Cuts:

Parameterized by $u \in [-U, U]^m$, more nuanced rounding than CG cuts, an “infinite” class

Theorem: For any IP, $O(nU^2\|A\|_1\|b\|_1)$ hyperplanes, $2^{O(n^2)}(m + n)^{O(n^3)}\tau^{O(n^3)}$ degree ≤ 10 polynomial hypersurfaces partition $[-U, U]^m$ into regions s.t. in each region the execution of B&C is the same

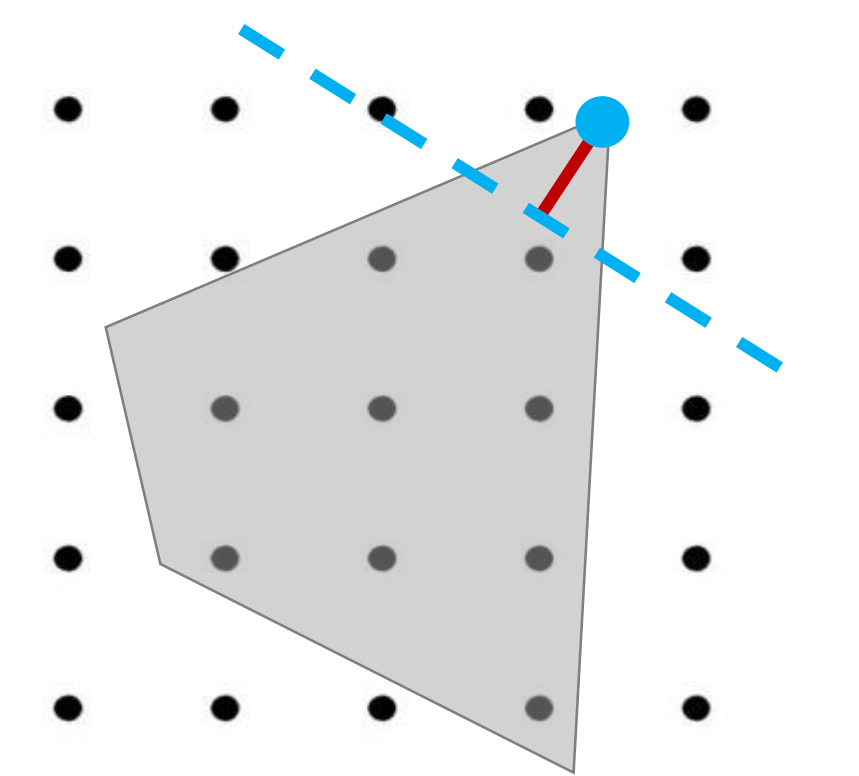
Learning to cut

Pseudo-dimensions of class of tree-size functions

- Chvátal-Gomory: $O(m \log(\|A\|_{1,1} + \|b\|_1 + n))$
- Gomory mixed integer: $O(mn^3 \log(mn\tau\|A\|_1\|b\|_1))$

Cut selection policies

Solvers often use *scoring rules* to choose from a pool of cuts

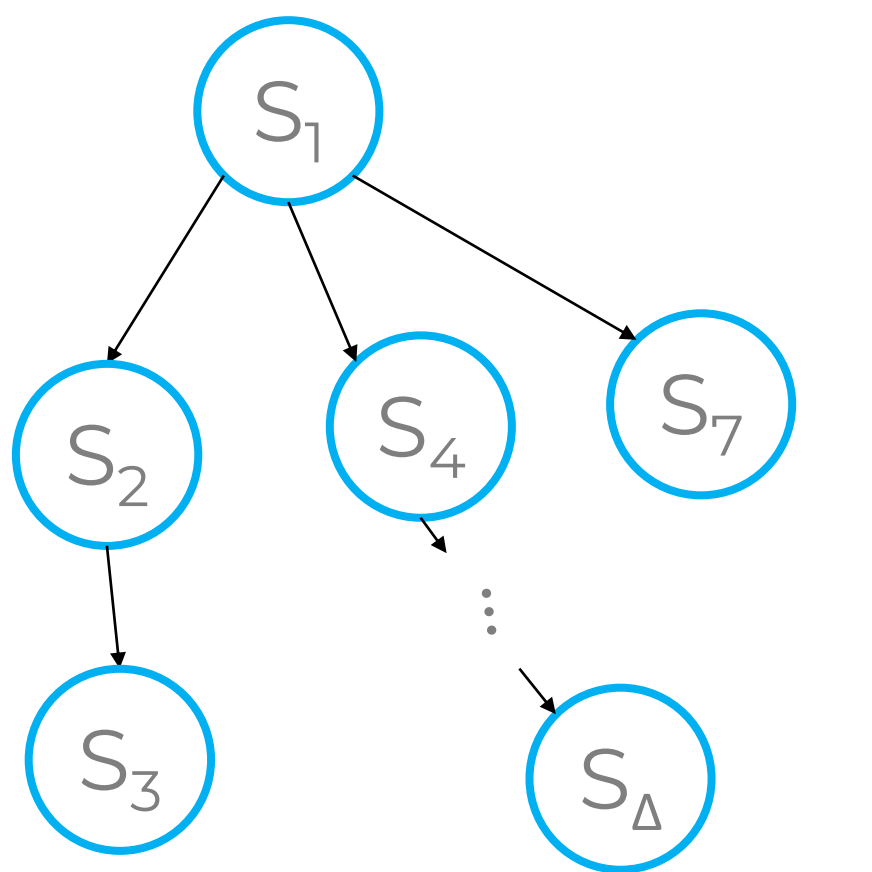


E.g., $\text{score}(\alpha^T x \leq \beta) = \text{distance between cut and } x_{LP}^*$

Given d scoring rules, learn mixture $\mu_1 \text{score}_1 + \dots + \mu_d \text{score}_d$

Theorem: Class of tree-size functions parameterized by μ has pseudo-dim (for CG cuts) $O(dm \log(\|A\|_{1,1} + \|b\|_1 + n))$

General tree search Model captures branching, cutting planes, node selection *simultaneously*



Theorem: b actions available at each node, take action that maximizes mixture of 2 scoring rules. Pseudo-dim = $O(\Delta^2 + \Delta \log b)$.

Distribution-dependent cut selection can help!

Tuning mixture of scoring rules to select **knapsack cover cuts** for various multiple-knapsack-problem distributions

