Learning to Branch
Maria-Florina Balcan et. al. : learning the optimal weight of different scoring rules

Branch & Bound

Example: In Figure 1, the algorithm rst explores the root. At this point, it has the option of exploring either the left or the right child. Since the optimal objective value of the right child (136) is greater than the optimal objective value of the left child (135), B&B will next explore the pink node (marked 1). Next, B&B can either explore either of the pink node's children or the orange node (marked 2). Since the optimal objective value of the orange node (135) is greater than the optimal objective values of the pink node's children (120), B&B will next explore the orange node. After that B&B can explore either of the orange node's children or either of the pink node's children. The optimal objective value of the green node (marked 3) is higher than the optimal objective values of the orange node's right child (116) and the pink node's children (120), so B&B will next explore the green node. At this point, it nds an integral solution, which satis es all of the constraints of the original MILP (1). This integral solution has an objective value of 133. Since all of the other leafs have smaller objective values, the algorithm cannot nd a better solution by exploring those leafs. Therefore, the algorithm fathoms all of the leafs and terminates.

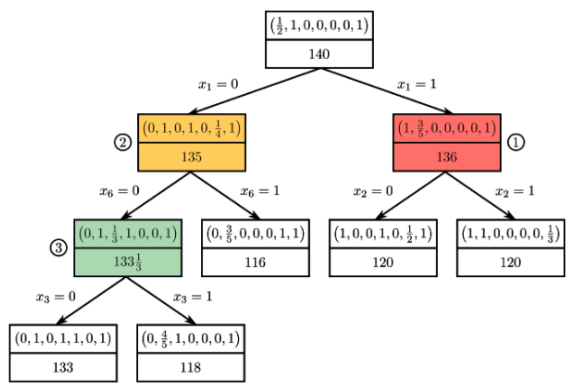

Figure 1: Illustration of Example 2.2

MILP [Kolesar, 1967]:

$$\begin{array}{ll} \text{maximize} & 40x_1 + 60x_2 + 10x_3 + 10x_4 + 3x_5 + 20x_6 + 60x_7 \\ \text{subject to} & 40x_1 + 50x_2 + 30x_3 + 10x_4 + 10x_5 + 40x_6 + 30x_7 \le 100 \\ & x_1, \ldots, x_7 \in \{0, 1\}. \end{array} \quad (1)$$

Variable Selection Policy: Variable selection policies typically depend on a real-valued score per variable

- "Most fractional"
- Linear scoring rule [Linderoth and Savelsbergh, 1999].
- Product scoring rule [Achterberg, 2009].
- Entropic lookahead scoring rule [Gilpin and Sandholm, 2011].
- Alternative de nitions of the linear and product scoring rules
  - **Pseudo-cost branching** [Benichou et al., 1971, Gauthier and Ribi ere, 1977, Linderoth and Savelsbergh, 1999]
  - **Reliability branching** [Achterberg et al., 2005].

Node Selection Policy

- Best bound policy: it selects the unfathomed leaf containing the MILP Q with the maximum LP relaxation objective value.
- Depth-first policy: selects the next unfathomed leaf in the tree in depth-first order.

Proposed algorithm: Numerous partitioning techniques (e.g., variable selection) have been proposed, but there is no theory describing which technique is optimal. We show how to use machine learning to **determine an optimal weighting of any set of partitioning procedures for the instance** distribution at hand using samples from the distribution.

Via experiments, we show that learning an optimal weighting of partitioning procedures can dramatically reduce tree size.