

Scenario-Based Robust Optimization of Tree Structures

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joint work with Spyros Angelopoulos, Alex Elenter and Georgii Melidi

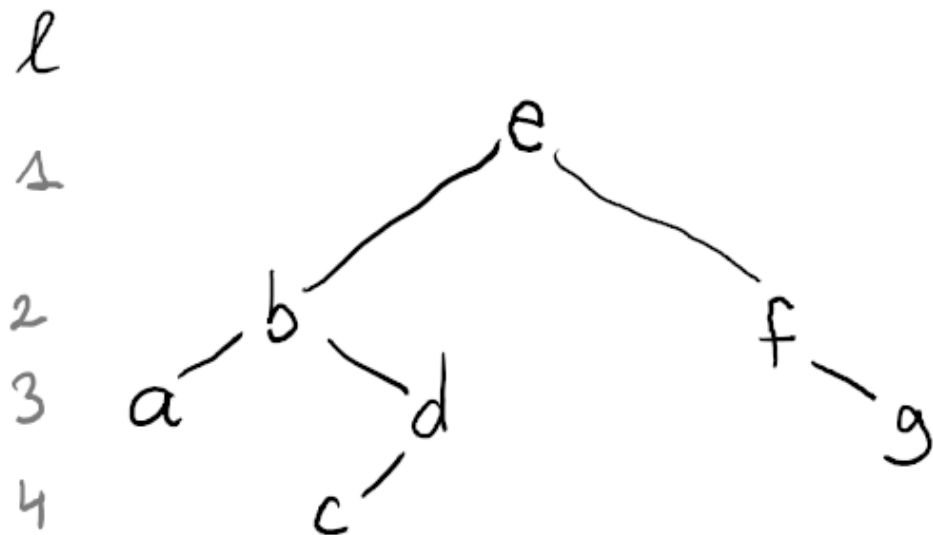
Binary search trees

Input distribution p over an alphabet

Output binary search tree with levels ℓ

Cost $p \cdot \ell := \sum_i p_i \ell_i$

Optimal tree by dynamic programming
in time $O(n^2)$ [Knuth 1971]



Our model

Algorithm chooses a tree (ℓ)

Adversary chooses a distribution p^j out of k given scenarios.

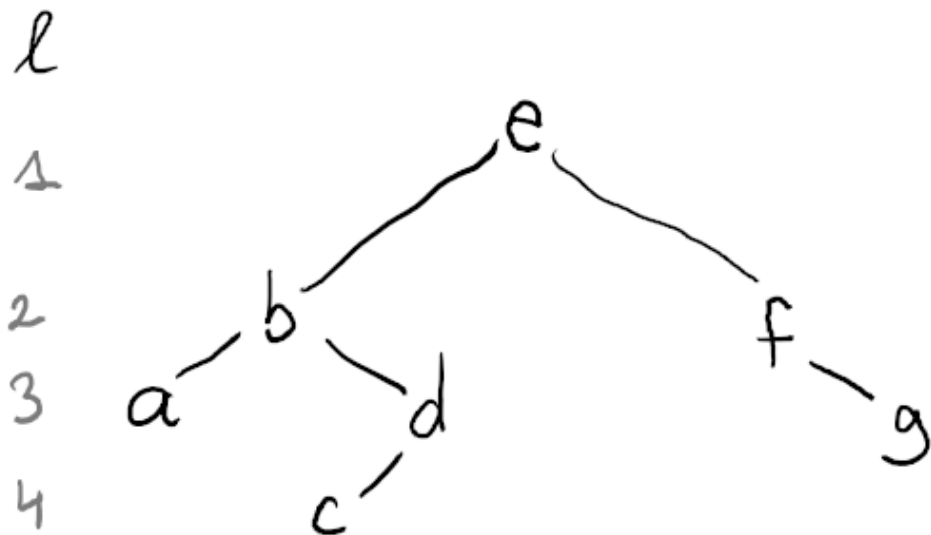
Possible measures
cost, ratio, regret

Input distribution p over an alphabet

Output binary search tree with levels ℓ

Cost $p \cdot \ell := \sum_i p_i \ell_i$

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Our model

$\min_{\ell} \max_j$

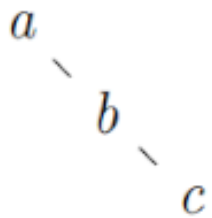
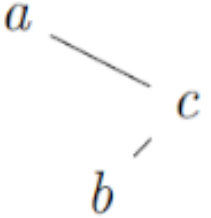
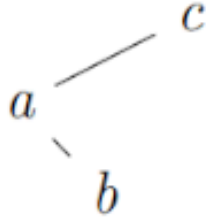
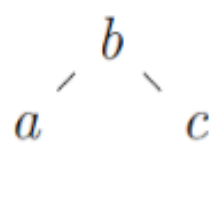
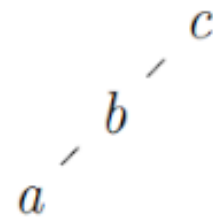
Cost $p^j \cdot \ell$

Ratio $\frac{p^j \cdot \ell}{\min_{\ell^*} p^j \cdot \ell^*}$

Regret

$$p^j \cdot \ell - \min_{\ell^*} p^j \cdot \ell^*$$

$$p^1 = (0, \frac{1}{4}, \frac{3}{4}), \quad p^2 = (\frac{4}{9}, \frac{2}{9}, \frac{1}{3})$$

					
cost for p^1	11/4	9/4	7/4	3/2	5/4
cost for p^2	17/9	16/9	16/9	17/9	19/9
worst cost	11/4	9/4	16/9	17/9	19/9
competitive ratio	11/5	9/5	7/5	6/5	19/16
regret	3/2	1	1/2	1/4	1/3

- **Binary Search with Distributional Predictions**

Dinitz, Im, Lavastida, Moseley, Niaparast, Vassilvitskii, 2024

- Predicted distribution \hat{p}
- Real distribution p with distance η from \hat{p}
- Create binary search tree with cost $O(H(p) + \eta)$ and this is optimal.
- Tree alternates between two strategies

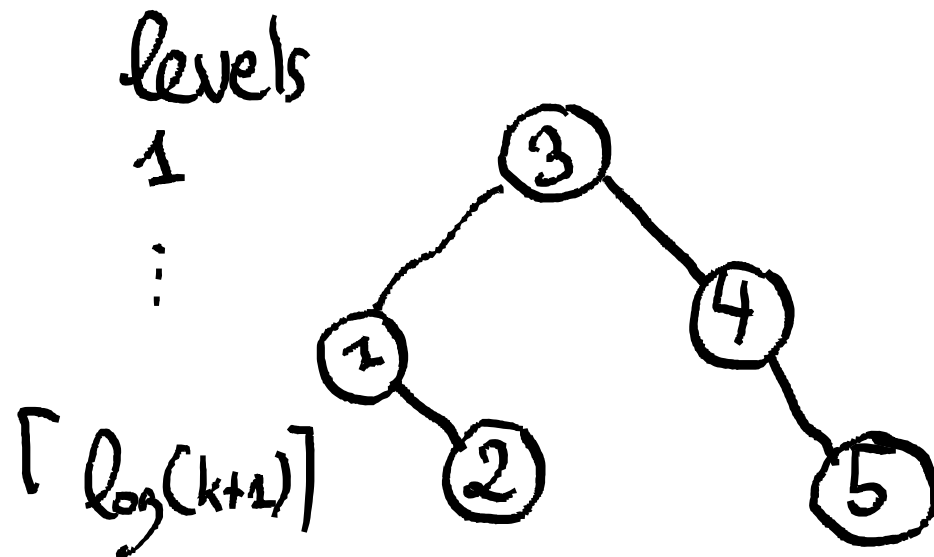


- It is **NP-hard** to optimize the cost, already for $k = 2$ scenarios
- **Competitive ratio** is $\lceil \log_2(k + 1) \rceil$
- **Pareto frontier** of costs can be computed in polynomial time, for constant k

distributions

	k keys				
	1	2	3	4	5
k scenarios	1	0	0	0	0
	0	1	0	0	0
	0	0	1	0	0
	0	0	0	1	0
	0	0	0	0	1

any BST




```
# optimal trees for each scenario
opt_ell = [opt_bst(p_i) for p_i in p]

# recursive construction on key interval
def bst(interval, next_level=1):
    # keys with minimum level for each scenario
    for all scenario i:
        S[i] = argmin opt_ell[i][x] for x in interval
        mid = median of S
        ell[mid] = next_level
        left, right = interval
        bst(left, mid-1, next_level+1)
        bst(mid+1, right, next_level+1)
```

key

opt_ell

Scenario 1	m	m	2	3	5	4	5	.	.	.
2	m	n	3	4	2	4	3	.	.	.
k	m	n	4	3	4	2	3	.	.	.

Computed ell

recursion

Hard open question

- Suppose we have a keys *belonging* to scenario 1, and b to scenario 2

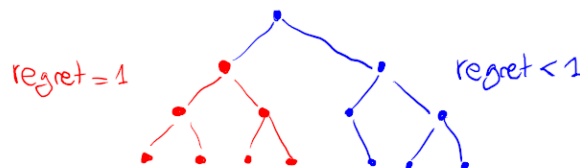
- $p^1 = (0, 0, \frac{1}{a}, 0, \frac{1}{a})$

- $p^2 = (\frac{1}{b}, \frac{1}{b}, 0, \frac{1}{b}, 0)$

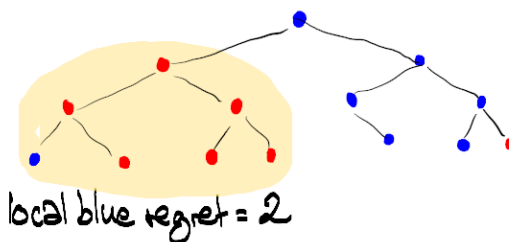
- Conjecture** There is a binary search tree with regret 1.

In other words, a tree with levels ℓ such that for each scenario j we have $p^j \cdot \ell \leq 1 + \min_{\ell^*} p^j \cdot \ell^*$.

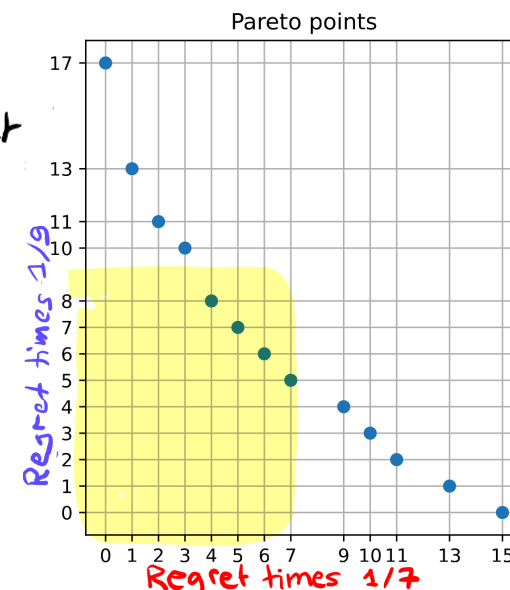
SIMPLE EXAMPLE



Example where locally we need to exceed the regret



Full understanding of the Pareto-curve could be necessary for the proof.



Thank you