

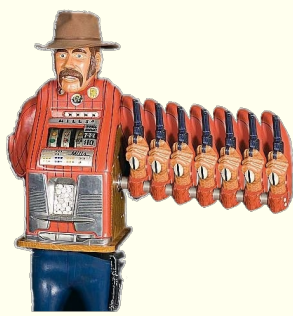
MCTS BASED ON SIMPLE REGRET

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MULTI-ARMED BANDITS

- A set of K arms.
- Each arm can be pulled multiple times.
- When the i th arm is pulled, a random reward X_i is encountered.
- Simple regret: the reward of the last pull only is collected.
- Cumulative regret: all rewards are accumulated.



UCB AND UCT

- UCB(c) pulls arm i that maximizes upper confidence bound b_i on the reward:
$$b_i = \bar{X}_i + \sqrt{\frac{c \log(n)}{n_i}}$$
- UCB is nearly optimal in minimizing the cumulative regret.
- UCT extends UCB to MCTS by invoking UCB in every node of a rollout.

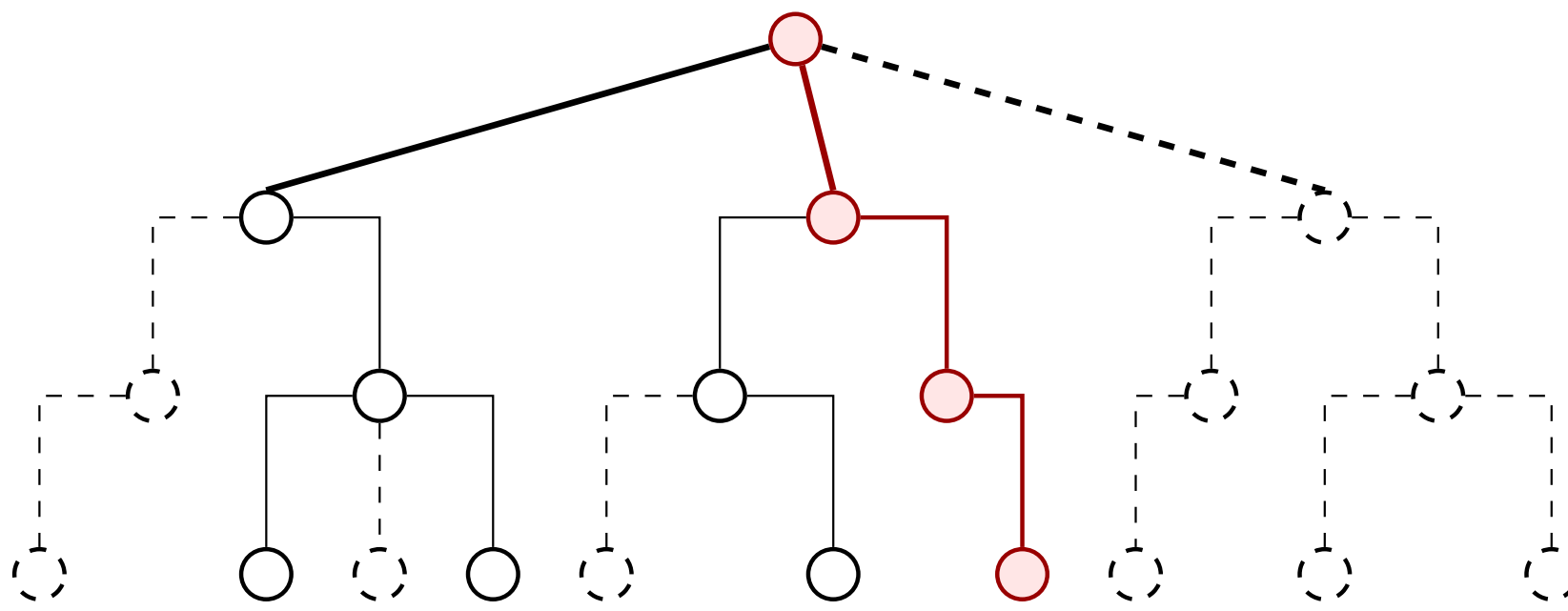
METAREASONING

- A problem-solving agent can perform *base-level* actions from a known set $\{A_i\}$.
- Before committing to an action, the agent may perform a sequence of *meta-level* deliberation actions from a set $\{S_j\}$.
- At any given time there is a base-level action A_α that maximizes the agent's expected utility.
- The value of information VOI_j is the expected difference between the expected utilities of the new and the old selected base-level action after meta-level action S_j is taken.
- The agent selects a meta-level action that maximizes the VOI, or A_α if no meta-level action has positive VOI.

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MONTE-CARLO SAMPLING IN TREES



- MCTS performs multiple *rollouts* to partially explore the search space.
- At the current root node, the sampling is aimed at finding the first move to perform: minimizing the simple regret is more appropriate at the root node.
- Deeper in the tree, minimizing cumulative regret results in a more precise estimate of the value of the state.
- An improvement over UCT can be achieved by combining different sampling schemes on the first step and during the rest of a rollout.

MAIN RESULTS

The SR+CR MCTS Scheme

- Selects an action at the current root suitable for minimizing the simple regret.
- Then selects actions according to UCB, that approximately minimizes the cumulative regret.

```

1 ROLLOUT(node, depth=1)
2   if IsLEAF(node, depth)
3     return 0
4   else
5     if depth=1 then action ← FIRSTACTION(node)
6     else action ← NEXTACTION(node)
7     next ← NEXTSTATE(node, action)
8     reward ← REWARD(node, action, next)
9             + ROLLOUT(next, depth+1)
10    UPDATESTATS(node, action, reward)
11    return reward

```

Sampling for Simple Regret

- ϵ -greedy sampling ($\epsilon = \frac{1}{2}$).
- Modified version of UCB (optimized for simple regret).
- VOI-aware sampling:

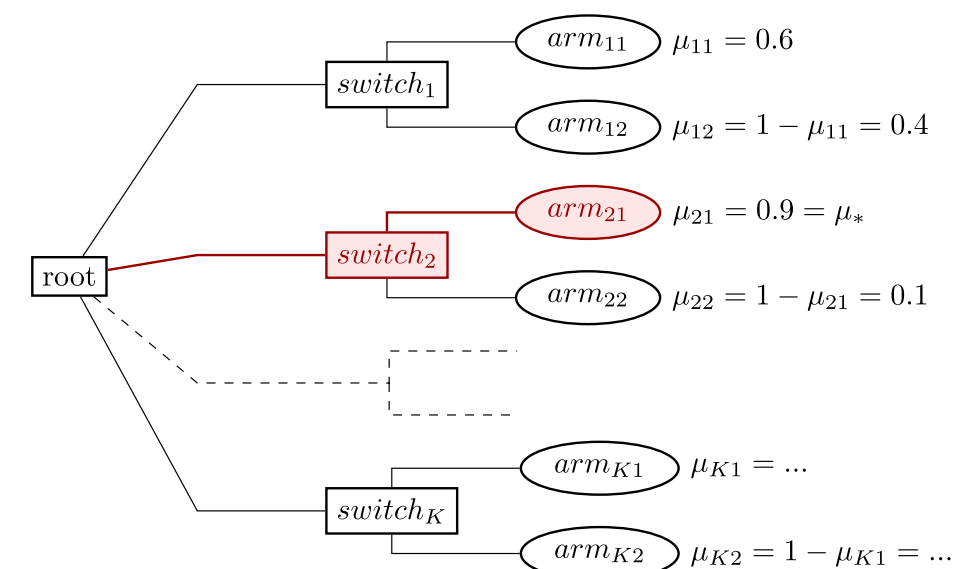
$$VOI_\alpha \approx \frac{\bar{X}_\beta}{n_\alpha + 1} \exp\left(-2(\bar{X}_\alpha - \bar{X}_\beta)^2 n_\alpha\right)$$

$$VOI_i \approx \frac{1 - \bar{X}_\alpha}{n_i + 1} \exp\left(-2(\bar{X}_\alpha - \bar{X}_i)^2 n_i\right), i \neq \alpha$$

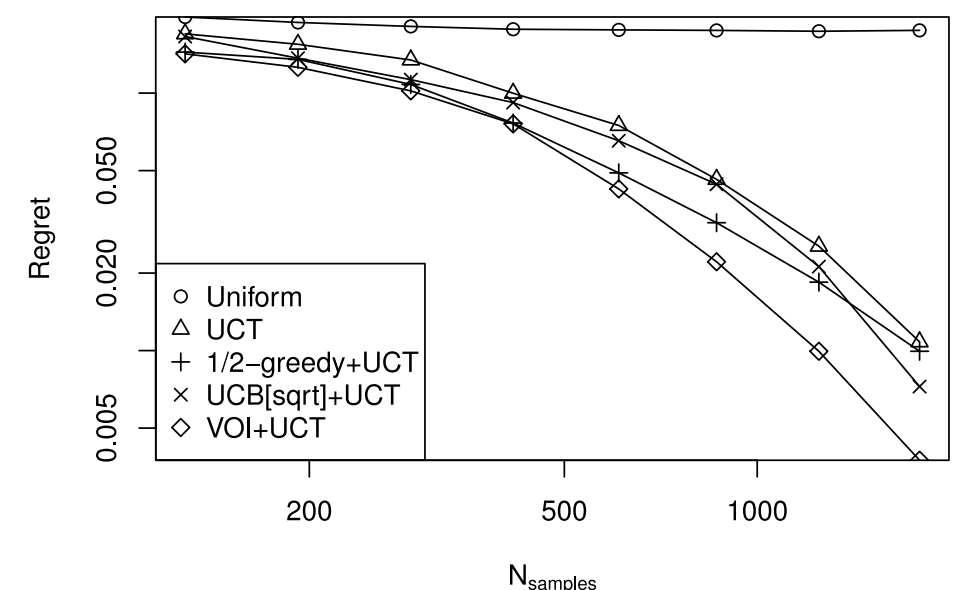
EXPERIMENTS

- SR+CR outperforms UCT.
- SR+UCT(c) is less dependent on tuning of the exploration factor c .

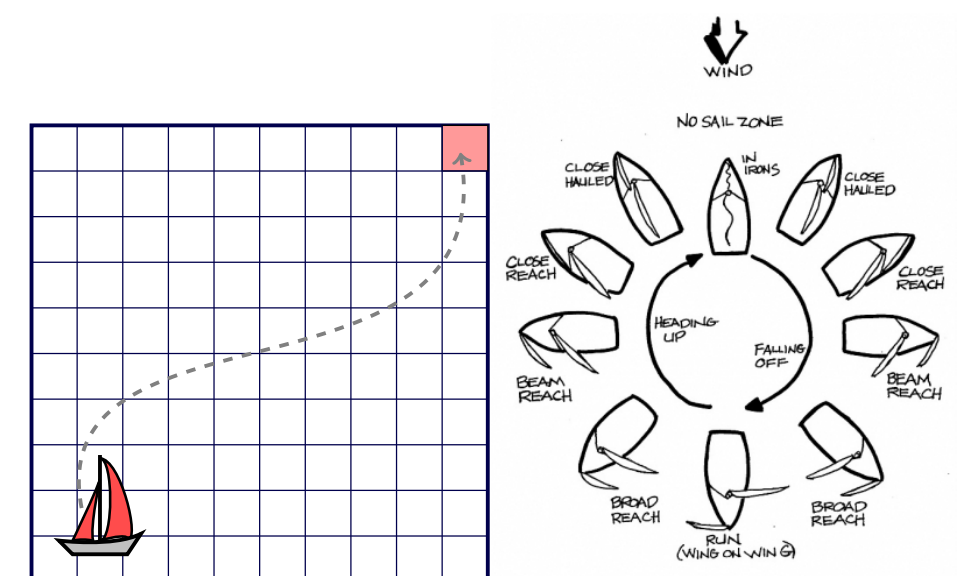
Random Trees



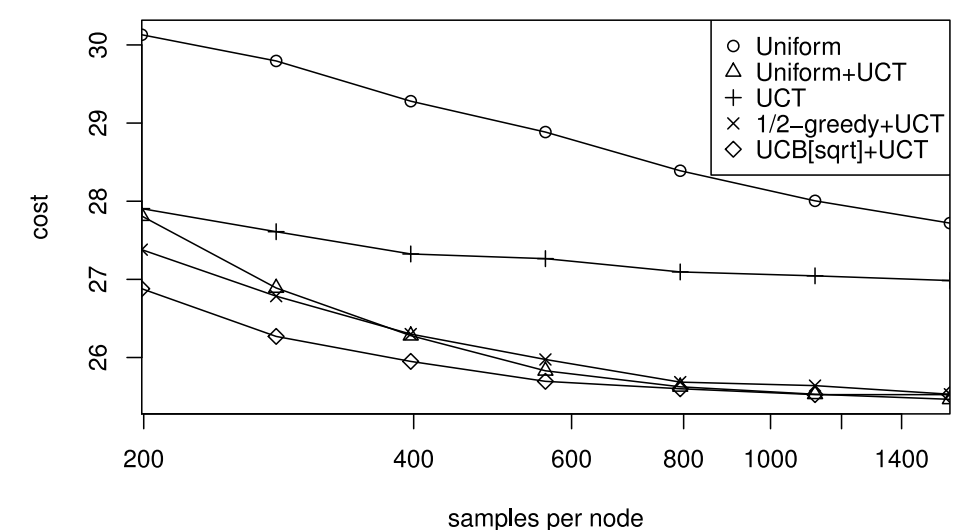
Regret vs. number of samples:



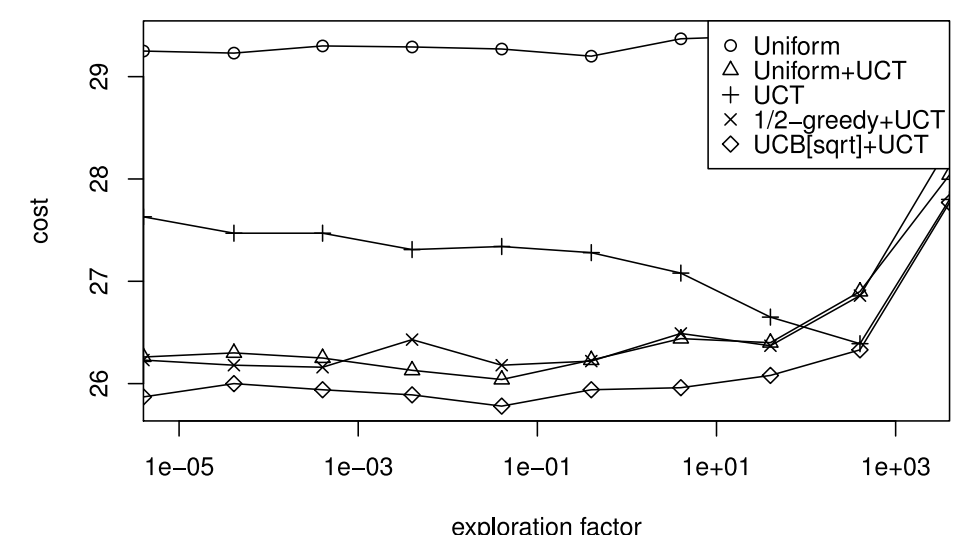
Sailing Domain



Path cost vs. number of samples:



Path cost vs. exploration factor:



CONTRIBUTIONS

- Improved MCTS scheme — SR+CR.
- SR+CR performs better than unmodified UCT.
- VOI-aware sampling for minimizing simple regret.

FUTURE WORK

- Rational metareasoning in MCTS: theory and VOI estimates.
- Better sampling for non-root nodes.
- Application to Computer Go and other complex domains.

