MCTS BASED ON SIMPLE REGRET

AAAI 2012

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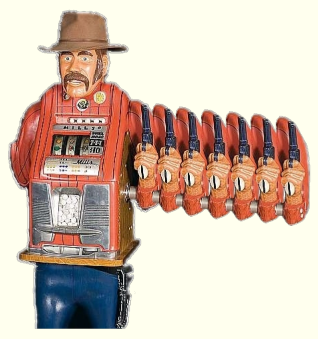
Multi-armed Bandits



- A set of K arms.
- Each arm can be pulled multiple times.
- When the ith 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: $b_i = \overline{X}_i + \sqrt{\frac{c\log(n)}{n_i}}$
- UCB is nearly optimal in minimizing the *cumulative regret.*
- **UCT** extends UCB to MCTS by invoking UCB in every node of a rollout.

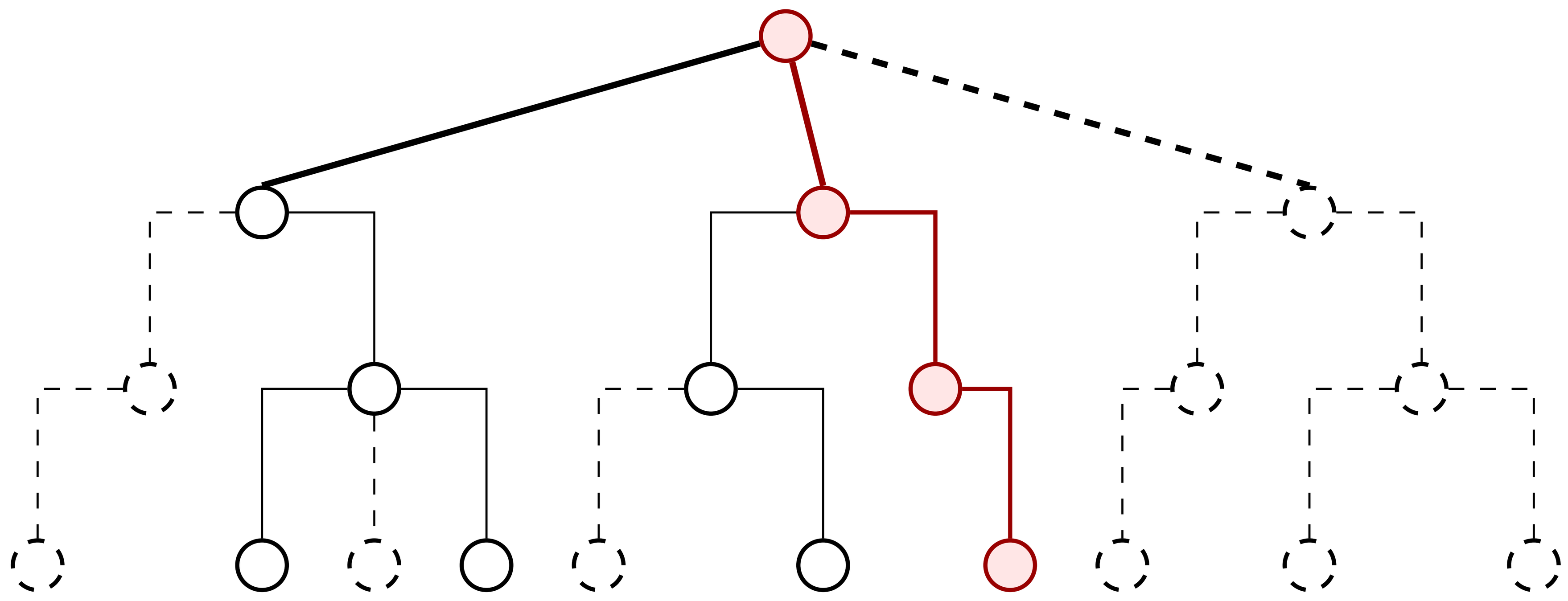
Metareasoning

- 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.

Acknowledgements

- IMG4 Consortium under the MAGNET program of the Israeli Ministry of Trade and Industry
- Israel Science Foundation grant 305/09
- Lynne and William Frankel Center for Computer Sciences
- Paul Ivanier Center for Robotics Research and Production Management

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.

```
Rollout(node, depth=1)
  if IsLeaf(node, depth)
    return 0
  else
    if depth=1 then action ← FirstAction(node)
    else action ← NextAction(node)
    next ← NextState(node, action)
    reward ← Reward(node, action, next)
           + Rollout(next, depth+1)
    UpdateStats(node, action, reward)
    return reward
```

Sampling for Simple Regret

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

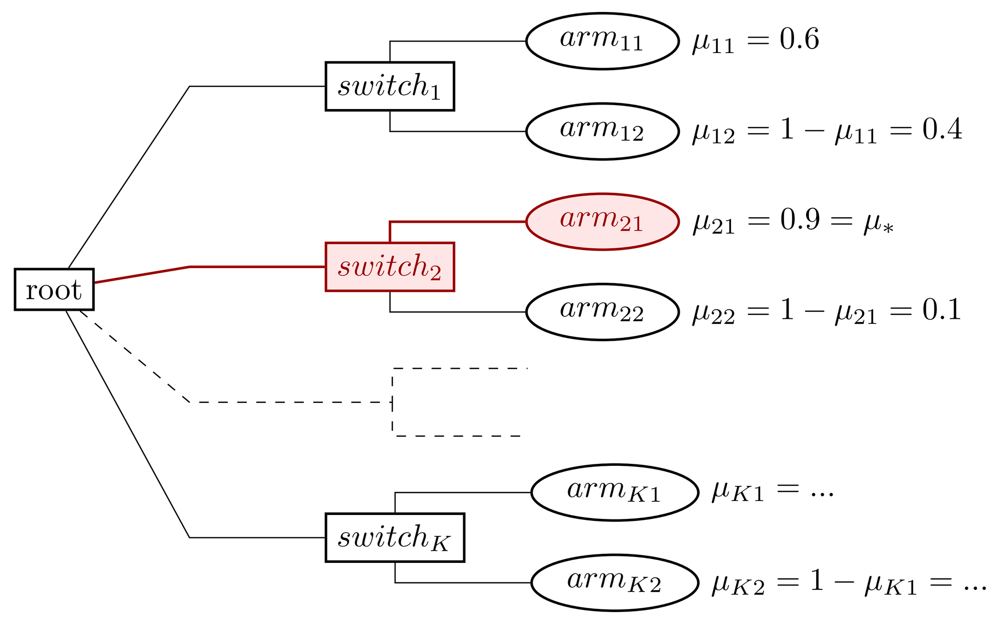
$$VOI_\alpha \approx \frac{\overline{X}_\beta}{n_\alpha + 1}\exp\left(-2(\overline{X}_\alpha - \overline{X}_\beta)^2 n_\alpha\right)$$

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

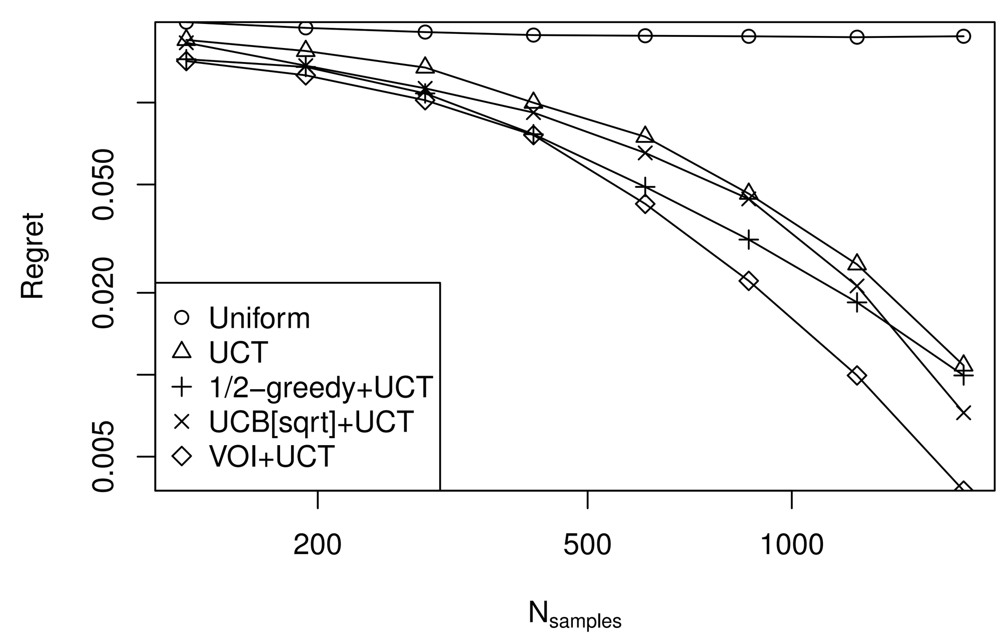
Experiments

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

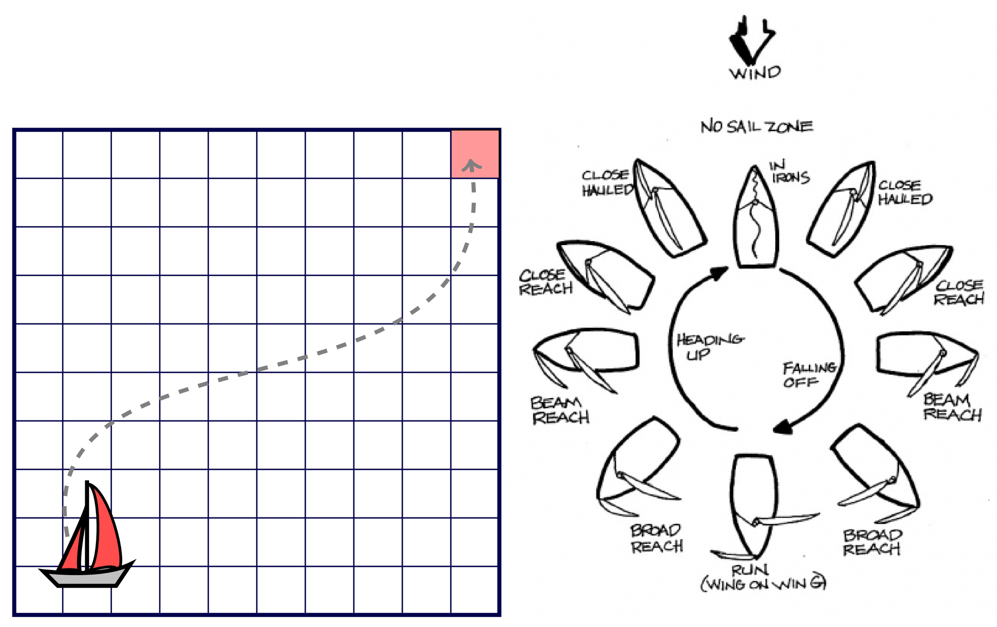
Random Trees



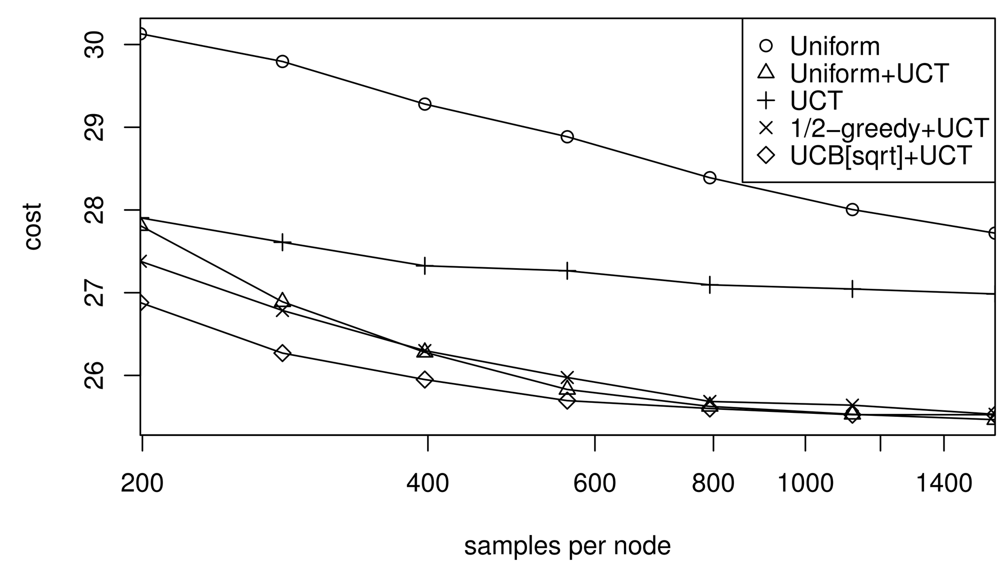
Regret vs. number of samples:



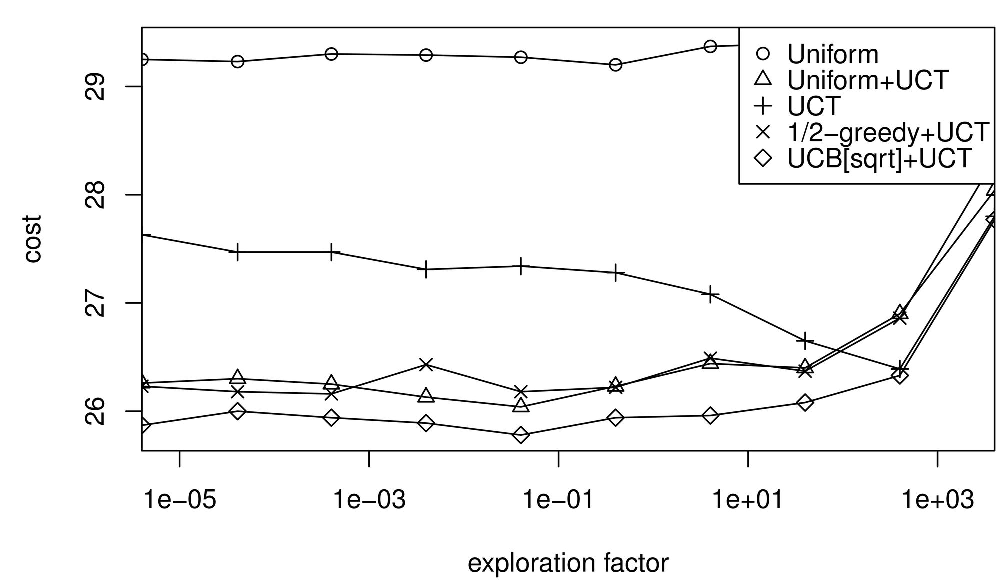
Sailing Domain



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.