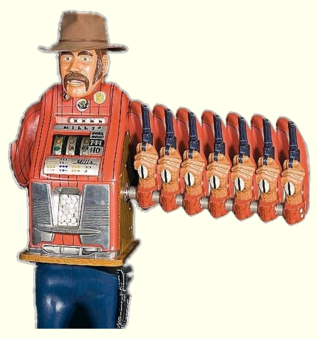
VOI-AWARE MCTS

ECAI 2012

David Tolpin, Solomon Eyal Shimony
Ben Gurion University of the Negev,
Beer Sheva, Israel

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.

Regret minimization:

- Simple regret (**SR**): the reward of the last pull only is collected.
- Cumulative regret (**CR**): 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 at every node of a rollout.

Metareasoning

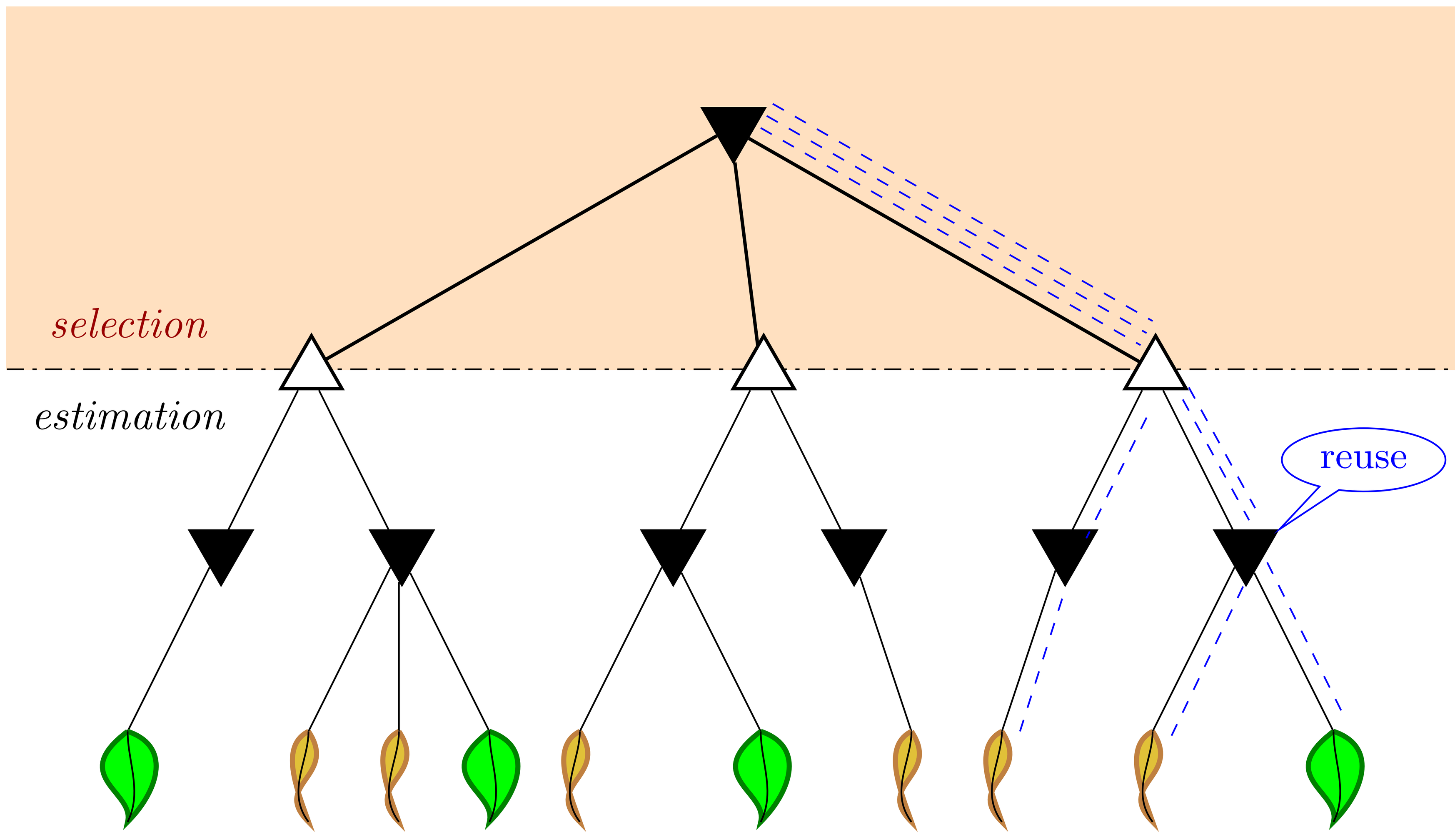
- A problem-solving agent can perform *base-level* actions from a known set $\{A_i\}$.
- Before committing to an action, the agent may perform a sequence of *meta-level* deliberation actions from a set $\{S_j\}$.
- At any given time there is a base-level action A_α that maximizes the agent's *expected 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.

Acknowledgments

- 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 better 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

Hybrid sampling scheme

1. At the root node: sample based on the VOI estimate.
2. At non-root nodes: sample using UCT.

Upper Bounds on VOI

Upper bounds on intrinsic VOI Λ_i^b of testing the ith arm N times:

$$\Lambda_\alpha^b < \frac{N\overline{X}_\beta^{n_\beta}}{n_\alpha+1}\cdot 2\exp\left(-1.37(\overline{X}_\alpha^{n_\alpha} - \overline{X}_\beta^{n_\beta})^2 n_\alpha\right)$$

$$\Lambda_{i|i\ne\alpha}^b < \frac{N(1-\overline{X}_\alpha^{n_\alpha})}{n_i+1}\cdot 2\exp\left(-1.37(\overline{X}_\alpha^{n_\alpha} - \overline{X}_i^{n_i})^2 n_i\right)$$

Sample Redistribution

MCTS re-uses rollouts generated at earlier search states.

1. Estimate VOI as though the information is discarded.
2. Stop early if the VOI is below a certain threshold.
3. Save the unused sample budget for search in future states.

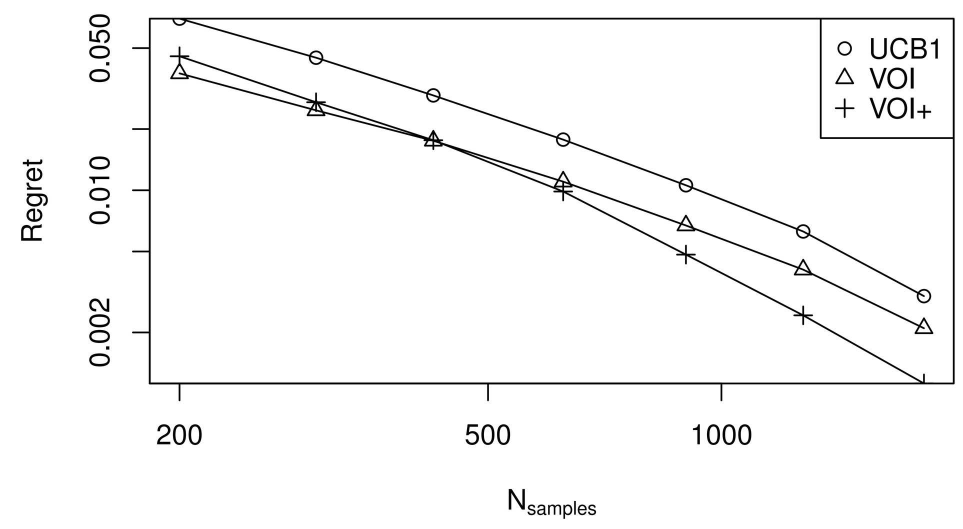
The cost of a sample is the VOI of increasing a future budget by one sample.

Experiments

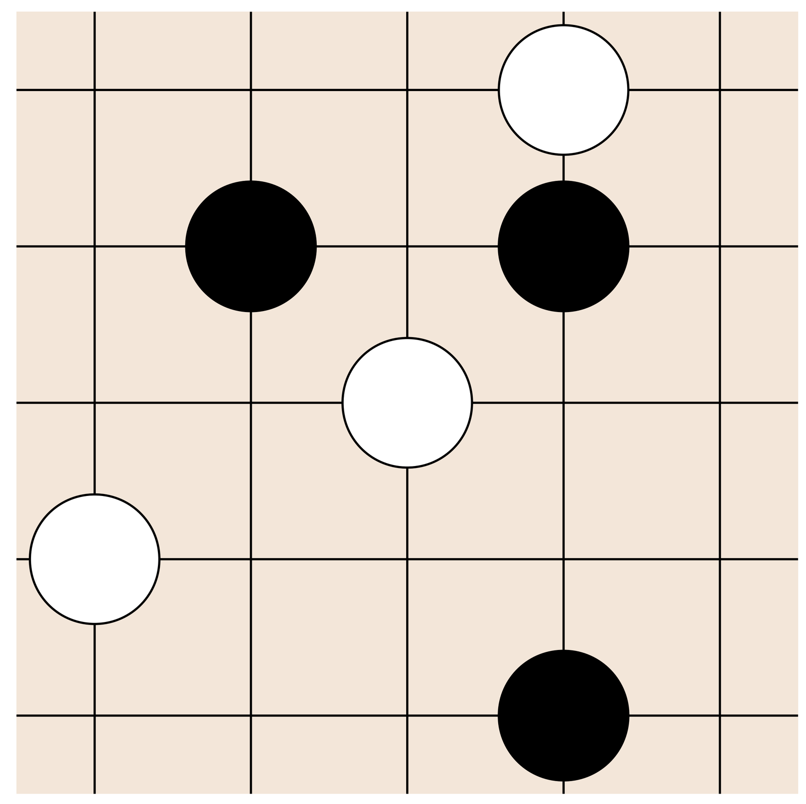
- VOI-based sampling is better than UCB1 for simple regret in Bandits.
- The hybrid scheme outperforms UCT.

Multi-armed Bandits

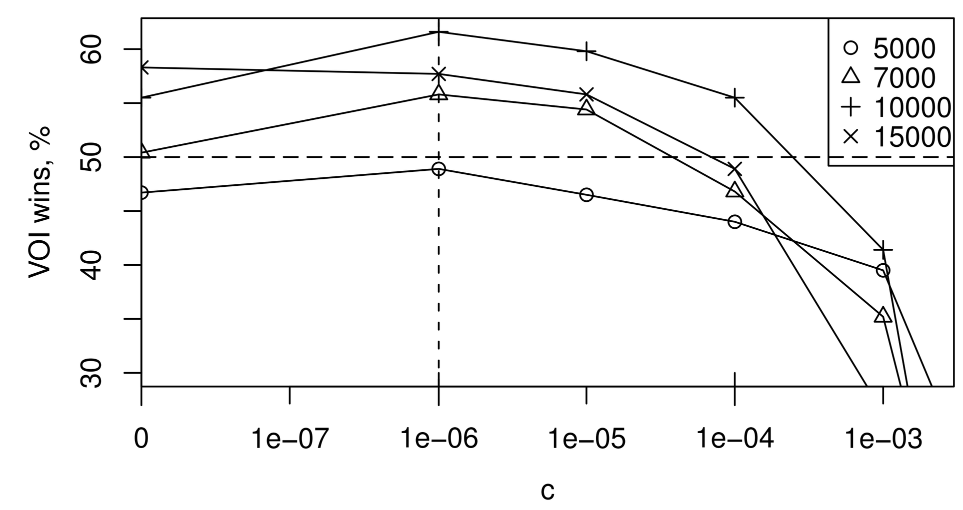
25 arms, 10000 trials



Computer Go



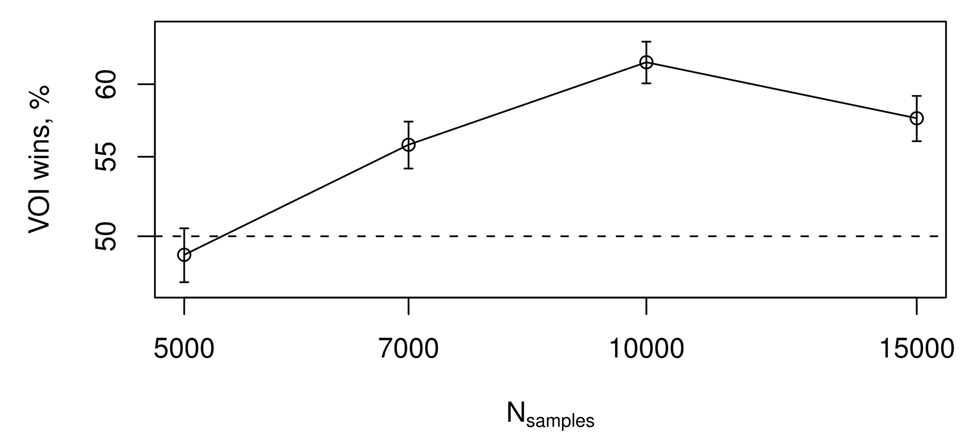
Tuning the Sample Cost



Best results for sample cost $\approx 10^{-6}$: winning rate of 64% for 10000 samples per ply.

Winning rate vs. number of samples

Sample cost fixed at 10^{-6}:



Best results for intermediate $N_{samples}$:

- When $N_{samples}$ is too low, poor moves are selected.
- When $N_{samples}$ is too high, the VOI of further sampling is low.

Contributions

- Hybrid MCTS sampling scheme.
- Upper bounds on VOI for *simple regret* in Multi-armed Bandits.
- VOI-based stopping and sample redistribution.

Future Work

- Better VOI estimates.
- VOI-based sampling for non-root nodes.
- Application to other domains.