# Pump-Priming Projects “Online Performance of Reinforcement Learning” and “Sequential Forecasting and Partial Feedback”

Peter Auer

University of Leoben, Austria

Bled, 29 January 2008

# Online performance of reinforcement learning with internal reward functions

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Goals:

- Online analysis of reinforcement learning
- Online analysis for continuous state spaces
- Design of internal reward functions

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# Sequential Forecasting and Partial Feedback: Applications to Machine Learning

Proposers:

- Peter Auer (Austria), Nicolò Cesa-Bianchi (Italy), Claudio Gentile (Italy), András György (Hungary), Gábor Lugosi (Spain), Yishay Mansour (Israel), Csaba Szepesvári (Canada)

Goals:

- Use machine learning techniques for parameter tuning
- Use inverse reinforcement learning for apprenticeship learning
- Sequential forecasting when the target (e.g. user interest) is changing

# Activities (partial list)

- Hired a post doctoral researcher (Christos Dimitrakakis) and a PhD student (Ivett Szabó).
- Organized the PASCAL workshop "Principled methods of trading exploration and exploitation Workshop" in London.
- Organized PASCAL "Exploration vs. Exploitation Challenge".
- Organized NIPS workshop "On-line trading of Exploration and Exploitation Workshop" in Canada.
- Organized a workshop on reinforcement learning in Tübingen. Remi Munos took the initiative to reestablish the **European Workshop on Reinforcement Learning**, Lille 2008.
- Expertise from these projects is used in a new **7th framework STREP: PinView** (Personal Information Navigator Adapting Through Viewing).

# Scientific outcome (partial list)

- P. Auer and R. Ortner: Logarithmic Online Regret Bounds for Undiscounted Reinforcement Learning, **NIPS 2006**.
- P. Auer, R. Ortner, and C. Szepesvari: Improved Rates for the Stochastic Continuum-Armed Bandit Problem, **COLT 2007**.
- G. Neu and Cs. Szepesvári: Apprenticeship learning using inverse reinforcement learning and gradient methods, **UAI 2007**.
- A. György, T. Linder, G. Lugosi, and Gy. Ottucsák: The on-line shortest path problem under partial monitoring, **JMLR 2007**.
- R. Ortner: Linear Dependence of Stationary Distributions in Ergodic Markov Decision Processes, **OR Letters 2007**.
- R. Ortner: Pseudometrics for State Aggregation in Average Reward Markov Decision Processes, **ALT 2007**.
- Ch. Dimitrakakis and Ch. Savu-Krohn: Cost-minimising strategies for data labelling - optimal stopping and active learning, **FoIKS 2008**.
- P. Auer, R. Ortner, T. Jaksch: Near-optimal Regret Bounds for Reinforcement Learning, submitted.

# ML algorithms for parameter optimization: UCT

- The UCT (upper confidence for trees) algorithm [KS 2006] is a method for exploring trees, based on the UCB algorithm for the bandit problem.
- Used also in MoGo (world champion in computer Go, Sylvain Gelly et al.).
- For parameter optimization, a tree is built by hierarchically splitting the parameter interval:
  - At an interior node, select a branch (i.e. subinterval) according to UCB, and descend.
  - At a leaf, split the leaf (i.e. split the interval) and sample from the 'unvisited' child node.

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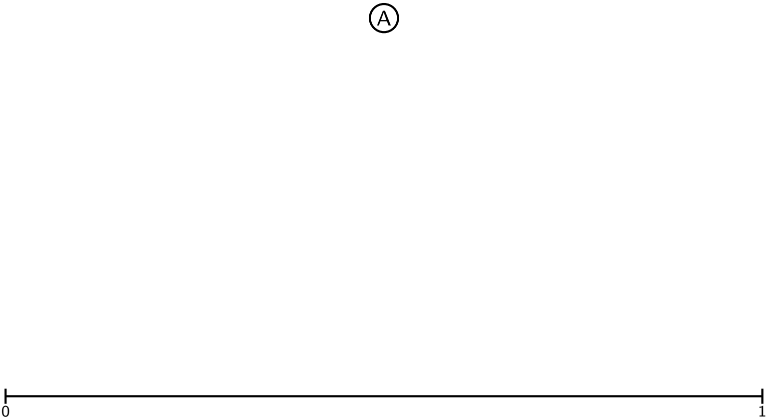
# Example for parameter optimization with UCT



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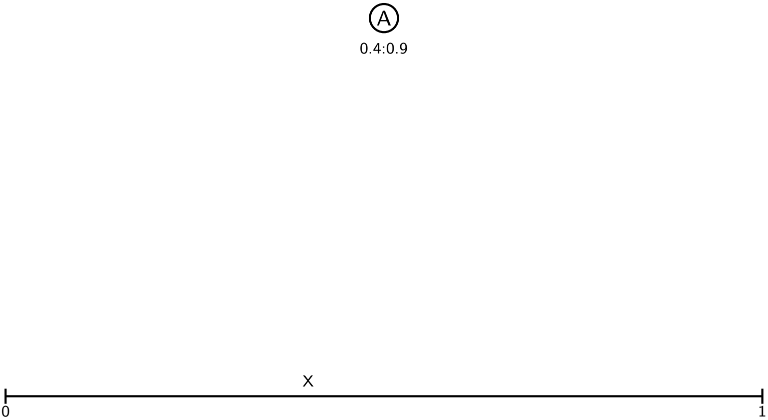

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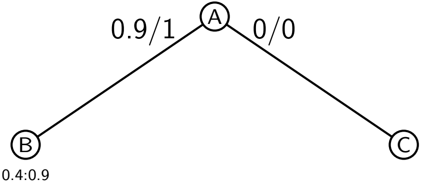


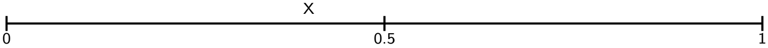

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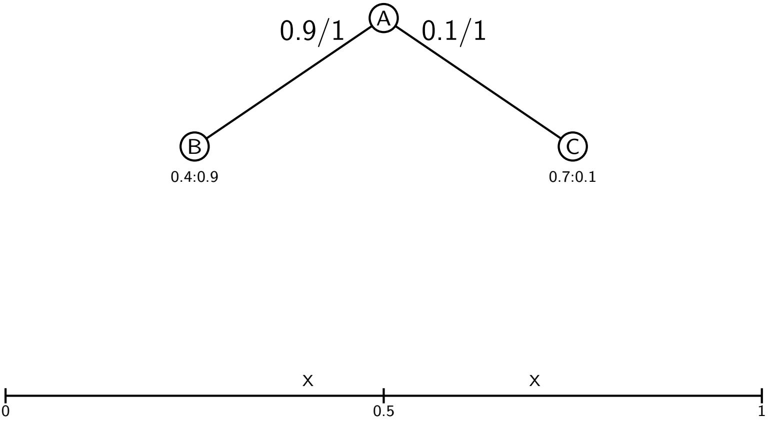

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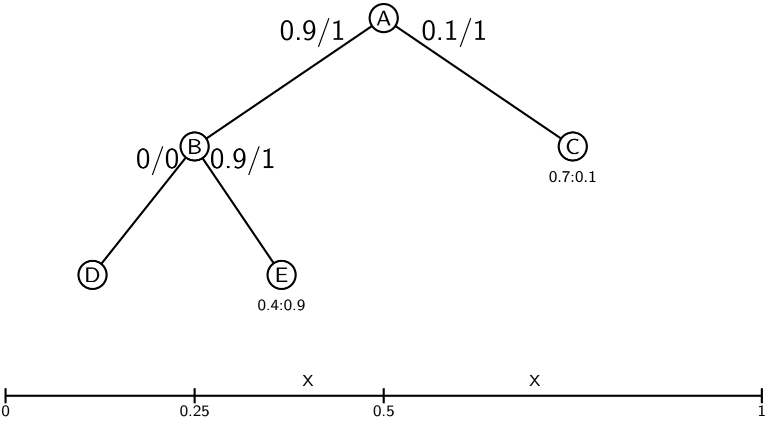

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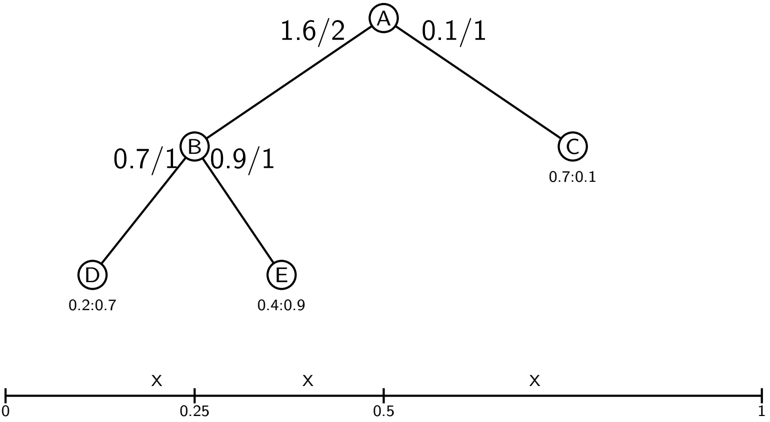

# Application of UCT parameter optimization

- Churn prediction of a telecommunication company using the RPROP algorithm with 7 parameters.
- UCT converged to a good solution five times faster than RSPSA (Resilient Simultaneous Perturbation Stochastic Approximation).

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- UCT converged to a good solution five times faster than RSPSA (Resilient Simultaneous Perturbation Stochastic Approximation).
- One RPROP run took approx. 12 hours. On 50 processors, the parameter tuning took approx 3 weeks.

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# Apprenticeship learning using inverse reinforcement learning and gradient methods

Inverse reinforcement learning (IRL):

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- Imitate behavior in observed states!

- Problem: does not generalize well.
- Extract a reward function that explains the observed behavior!

# Solving the IRL task

Consider (linearly) parameterized rewards, $r_\theta(s) = \sum_{i=1}^{n} \theta_i \phi_i(s)$.

- Find a parameter vector $\theta$ which generates a behavior that is close to the observed expert behavior.
- Define closeness:

$$J(\theta) = \sum_{s \in \mathcal{S}} \mu_E(s)(\pi_\theta(s) - \pi_E(s))^2$$

  ($\mu_E$ – estimate of the expert's stationary distribution, $\pi_\theta$ – optimal policy for $\theta$, $\pi_E$ – expert's policy).
- Natural gradient techniques can be applied to improve performance.

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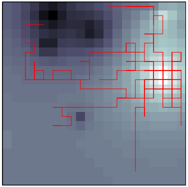
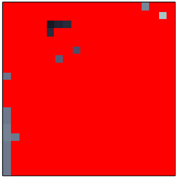
Expert trajectories



Low error region

Direct policy imitation

Low error region



IRL

Markov decision process (MDP) $M$:

$$\begin{aligned}
\mathcal{S} &\quad \ldots \quad \text{state space} \\
\mathcal{A} &\quad \ldots \quad \text{action space} \\
r(s,a) &\quad \ldots \quad \text{reward in } [0,1] \text{ for choosing} \\
&\qquad\qquad \text{action } a \text{ in state } s \\
p(s'|s,a) &\quad \ldots \quad \text{transition probability to state } s' \\
&\qquad\qquad \text{when choosing action } a \text{ in state } s' \\
\pi^* : \mathcal{S} \to \mathcal{A} &\quad \ldots \quad \text{optimal policy} \\
R_T(\pi) = \sum_{t=1}^{T} r(s_t, a_t) &\quad \ldots \quad \text{total reward of policy } \pi \text{ after } T \text{ steps,}
\end{aligned}$$

$s_t$ are the (random) states visited by $\pi$,

and $a_t$ are the chosen actions

# Undiscounted online regret

We are interested in the online regret of a strategy $\pi$:

$$\Delta_T(\pi) := R_T(\pi^*) - R_T(\pi)$$

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Discounted regrets are not very useful for online analysis:
For $\gamma \in [0, 1)$,

$$\sum_{t=0}^{\infty} \gamma^t r(s_t^*, a_t^*) - \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) = O(1).$$

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# Bounds on the regret

For $S = |\mathcal{S}|$ states and $A = |\mathcal{A}|$, our $\mathrm{UCRL}$ algorithm achieves

$$\Delta_T(\mathrm{UCRL}) = \tilde{O}\left(DS\sqrt{AT}\right),$$

where $D$ denotes the **diameter** of the MDP: This is the time, such that for any pairs of states $s_1, s_2 \in \mathcal{S}$ there is a policy which moves from $s_1$ to $s_2$ within $D$ steps on average:

$$D = \max_{s_1, s_2} \min_{\pi} \mathbb{E}\left[T(s_2|\pi, s_1)\right]$$

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Matching lower bound:
There are MDPs such that for any algorithm

$$\Delta_T = \Omega\left(\sqrt{DSAT}\right).$$

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# Relation to other work: PAC-like bounds

- $E^3$ by Kearns and Singh (1998):
  After $poly(1/\epsilon, S, A, T^{\epsilon}_{mix})$ steps the per-trial regret is at most $\epsilon$.
- Analysis of Rmax by Kakade (2003):
  Bound on the number of actions which are not $\epsilon$-optimal:

$$\#\{t : a_t \neq a^{\epsilon}_t\} = \tilde{O}\left(S^2 A (T^{\epsilon}_{mix}/\epsilon)^3\right)$$

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- For small $\epsilon$, $T^{\epsilon}_{mix} > D/\epsilon$.

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- Main difference (recall $D = \max_{s_1,s_2} \min_\pi \mathbb{E}\left[T(s_2|\pi, s_1)\right]$):
$$D_{\max} = \max_{s_1,s_2} \max_\pi \mathbb{E}\left[T(s_2|\pi, s_1)\right]$$

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# The UCRL algorithm: Upper Confidence Reinforcement Learning

- The algorithm runs in rounds $k = 1, 2, \ldots$, each starting at some time $t_k$.
- A new round starts when the occurrences of some state-action pair $(s, a)$ have doubled,
$$N(s, a; t_{k+1}) = 2 \cdot N(s, a; t_k).$$
- Within a round, a fixed policy $\tilde{\pi}_k : \mathcal{S} \to \mathcal{A}$ is used.
- The policy $\tilde{\pi}_k$ is chosen such that it maximizes the expected reward for the best (maximal reward) *plausible* MDP, in respect to the current empirical estimates $\hat{p}(\cdot|s, a; t_k)$.
- An MDP $\tilde{M}$ is plausible if

$$||\tilde{p}(\cdot|s, a; t_k) - \hat{p}(\cdot|s, a; t_k)||_1 \leq \sqrt{\frac{const \cdot S}{N(s, a; t_k)}} \log t_k.$$

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- In undiscounted reinforcement learning we can use *bias updates*

$$\lambda(s) \leftarrow \max_a \left[ r(s,a) + \sum_{s'} \lambda(s') p(s'|s,a) \right]$$

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- The bias update converges (for non-periodic MDPs) to $\lambda(\cdot)$ with $0 \leq \lambda(s) \leq D$.

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# Details of UCRL: Bias and regret

- The bias $\lambda(\cdot)$ solves the equation

$$\lambda(s) = \max_a \left[ r(s,a) - \rho^* + \sum_{s'} \lambda(s') p(s'|s,a) \right]$$

where $\rho^*$ is the optimal per-trial reward.

- The advantage of starting in state $s$ over starting in state $s'$ — followed by an infinite number of trials — is given by $\lambda(s) - \lambda(s')$.

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- The advantage of starting in state $s$ over starting in state $s'$ — followed by an infinite number of trials — is given by $\lambda(s) - \lambda(s')$.
- For each time a non-optimal action $a \neq a^* = a^*(s)$ is chosen, a regret $\delta$ is suffered,

$$\begin{aligned} \delta &= r(s,a^*) - r(s,a) + \sum_{s'} \lambda(s')[p(s'|s,a^*) - p(s'|s,a)] \\ &\leq r(s,a^*) - r(s,a) + D\,||p(\cdot|s,a^*) - p(\cdot|s,a)||_1 \end{aligned}$$

# Details of UCRL: Analysis

We compare per-trial rewards $\tilde{\rho}_k$ and $\rho_k$ for the chosen policies $\tilde{\pi}_k$ in the optimistic MDP $\tilde{M}_k$ and in the true MDP, resp.

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- **Tracking changes:**
  Allow changes in the MDP which need to be picked up by the learning algorithm.
- **Continuous state/action spaces:**
  - Difficult in a general setting
  - Progress for simplified (bandit) setting
  - Extend this to more interesting settings
- **Autonomous rewards:**
  Design autonomous reward functions which drive both the consolidation and the extension of learned knowledge, mimicking cognitive behavior.