Preference-Based Policy Iteration

Leveraging Preference Learning for Reinforcement Learning

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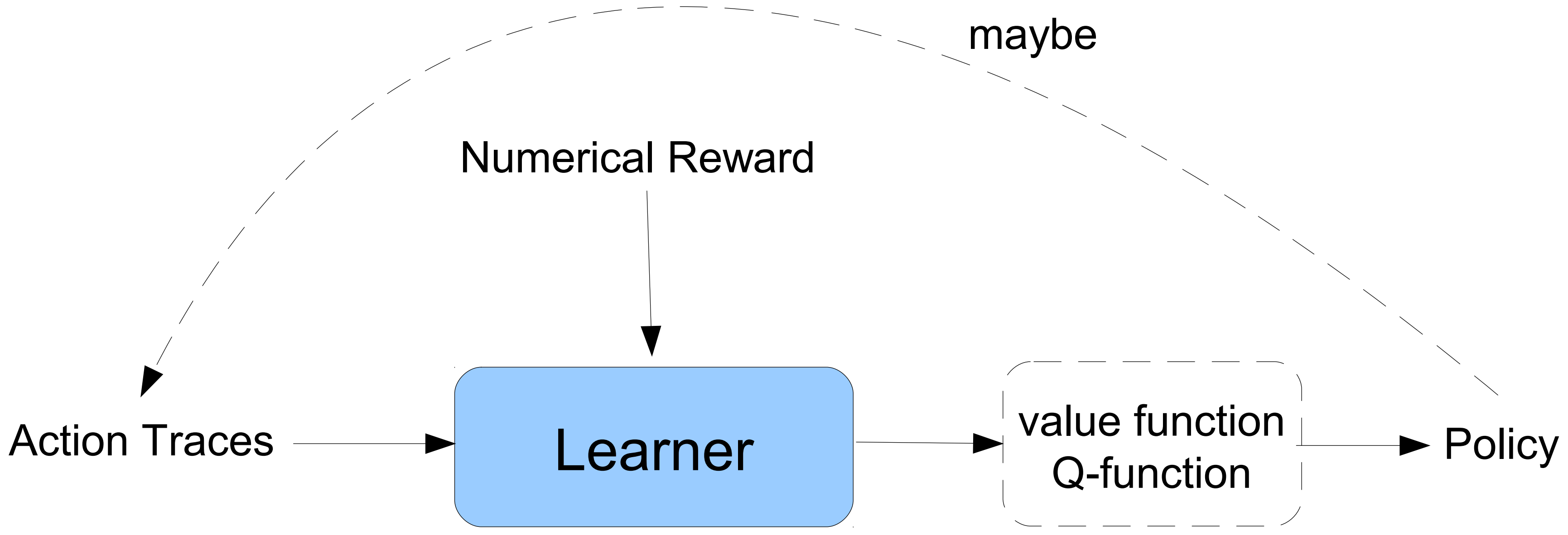
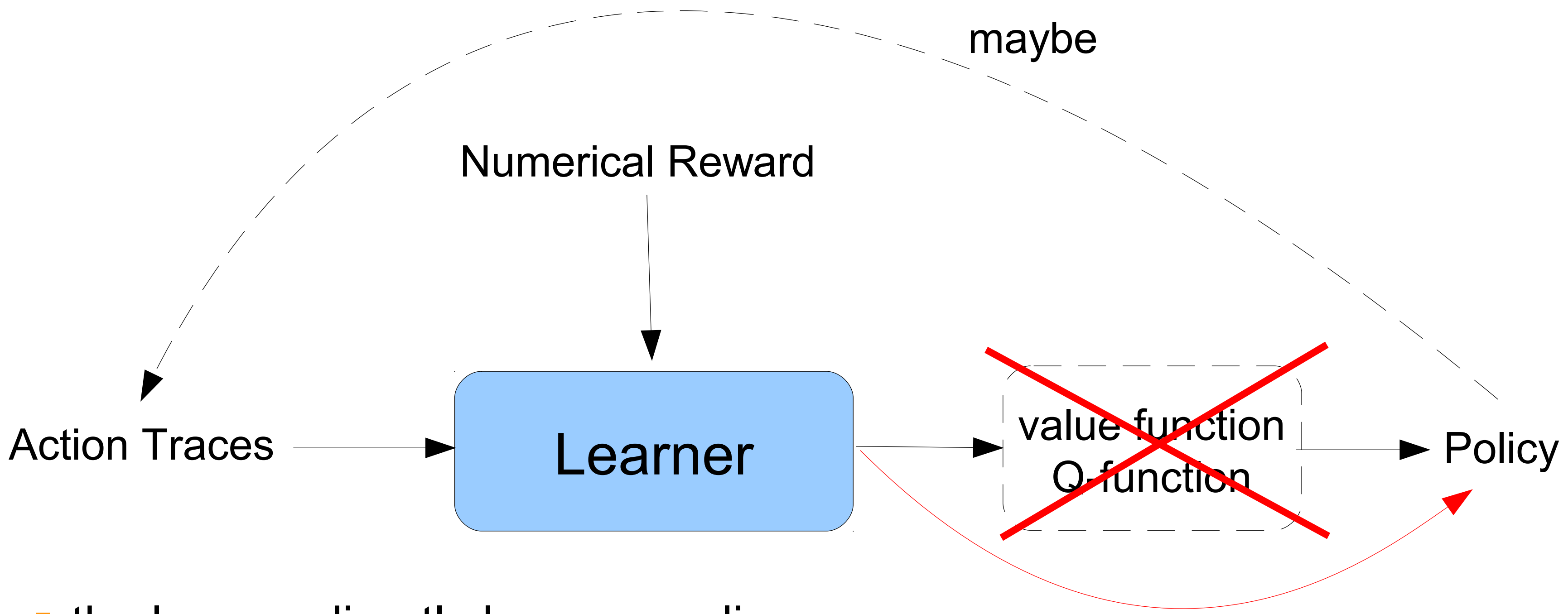
Classical Reinforcement Learning



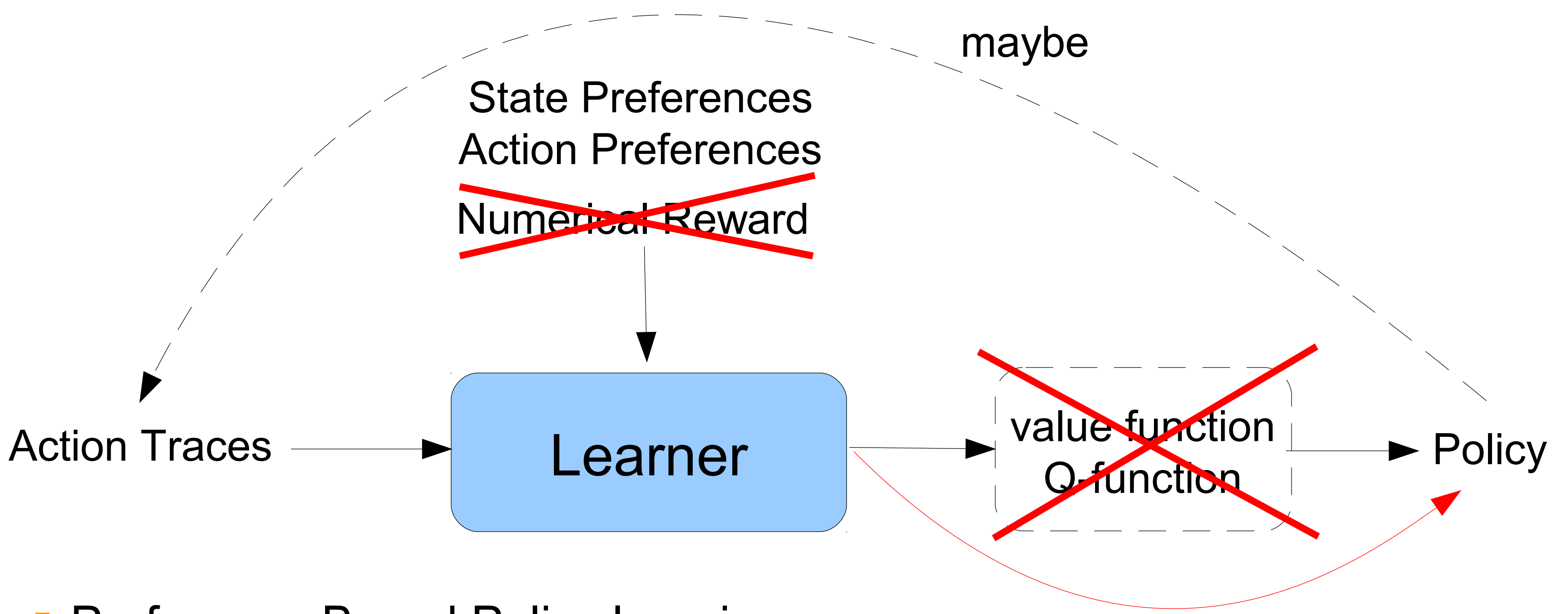
- the learner produces a function which estimates the value of states or state/action pairs
  - e.g., Q-learning, TD(λ), ...
- the policy uses this function for making actions
  - e.g. greedy or ε-greedy policies

Policy learning



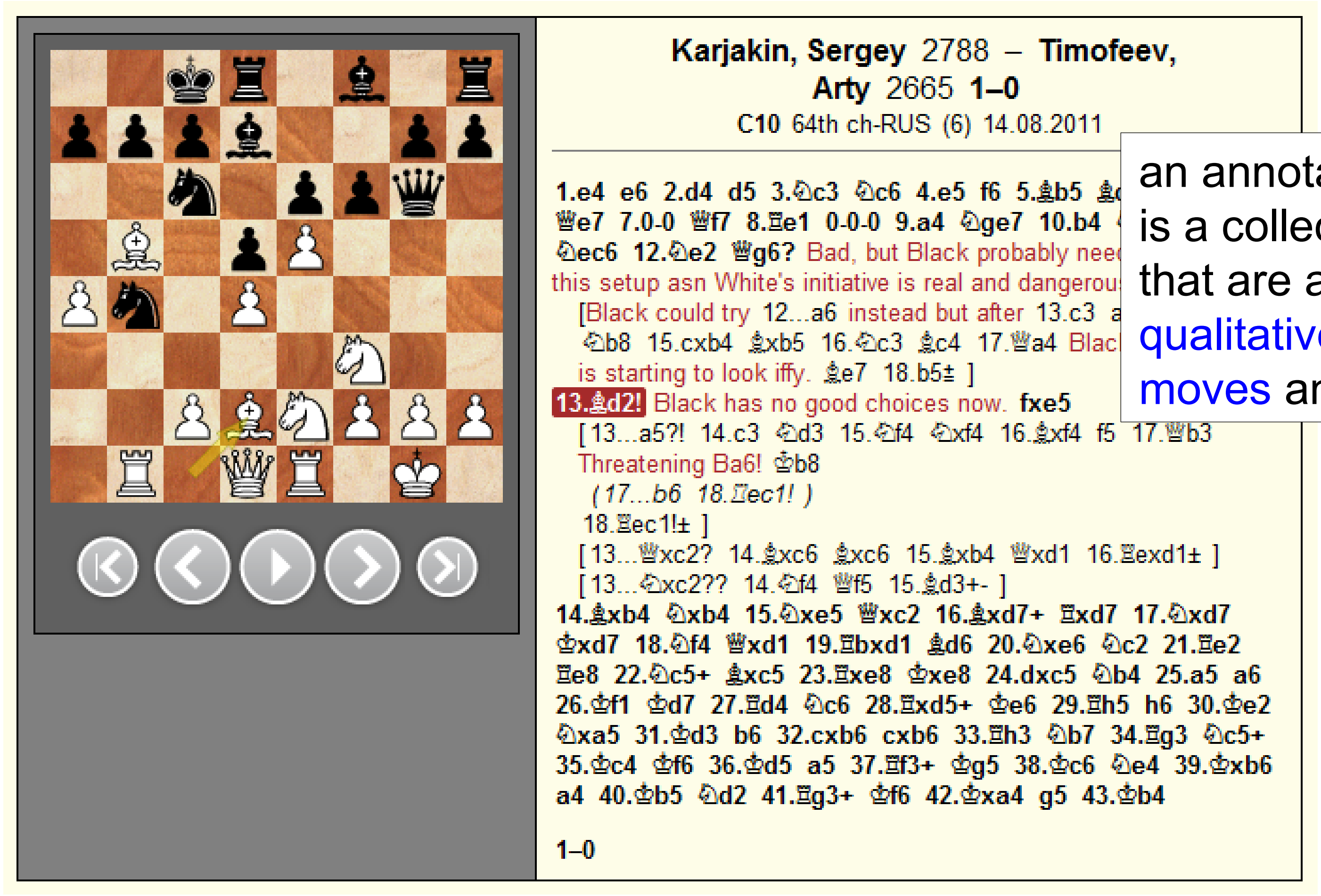
- the learner directly learns a policy
  - *actor-critic methods* learn both a value function (critic) and a policy (actor)
  - *policy gradient methods* search in the space of parametrized policies
    - e.g., a policy is a linear function that maps a state description to continuous actions
- estimation of expected reward may not be necessary

Vision:
Preference-Based Reinforcement Learning



- Preference-Based Policy learning:
  - the policy function is a label ranker that ranks all actions in a given state
  - we know their order (best to last) but not their value
- Training information:
  - Action preferences and State preferences

Example: Annotated Chess Games



Karjakin, Sergey 2788 – **Timofeev, Arty** 2665 **1–0**
C10 64th ch-RUS (6) 14.08.2011

1.e4 e6 2.d4 d5 3.♘c3 ♘c6 4.e5 f6 5.♗b5 ♗
♕e7 7.0-0 ♕f7 8.♖e1 0-0-0 9.a4 ♘ge7 10.b4
♘ec6 12.♘e2 ♕g6? Bad, but Black probably nee
this setup asn White's initiative is real and dangerou
[Black could try 12...a6 instead but after 13.c3 a
♘b8 15.cxb4 ♗xb5 16.♘c3 ♗c4 17.♕a4 Blac
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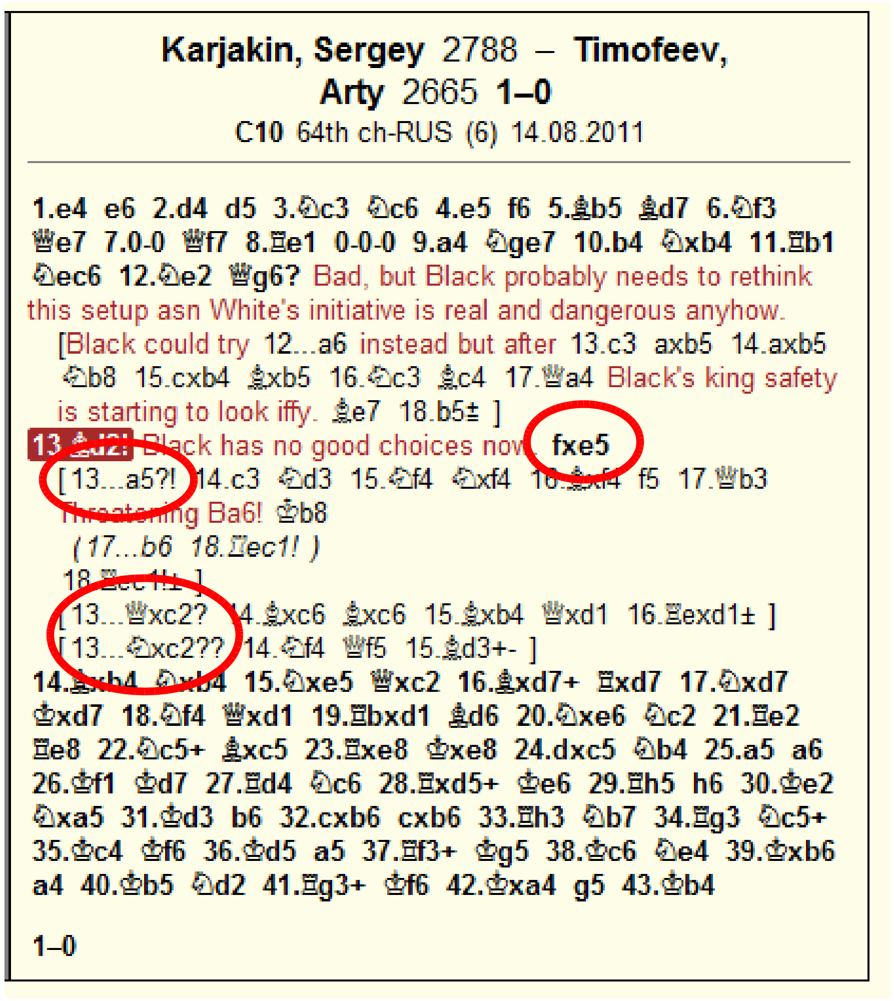
[13...a5?! 14.c3 ♘d3 15.♘f4 ♘xf4 16.♗xf4 f5 17.♕b3
Threatening Ba6! ♔b8
(17...b6 18.♖ec1!)
18.♖ec1!±]
[13...♕xc2? 14.♗xc6 ♗xc6 15.♗xb4 ♕xd1 16.♖exd1±]
[13...♘xc2?? 14.♘f4 ♕f5 15.♗d3+-]
14.♗xb4 ♘xb4 15.♘xe5 ♕xc2 16.♗xd7+ ♖xd7 17.♘xd7 ♔xd7 18.♘f4 ♕xd1 19.♖bxd1 ♗d6 20.♘xe6 ♘c2 21.♖e2 ♖e8 22.♘c5+ ♗xc5 23.♖xe8 ♔xe8 24.dxc5 ♘b4 25.a5 a6 26.♔f1 ♔d7 27.♖d4 ♘c6 28.♖xd5+ ♔e6 29.♖h5 h6 30.♔e2 ♘xa5 31.♔d3 b6 32.cxb6 cxb6 33.♖h3 ♘b7 34.♖g3 ♘c5+ 35.♔c4 ♔f6 36.♔d5 a5 37.♖f3+ ♔g5 38.♔c6 ♘e4 39.♔xb6 a4 40.♔b5 ♘d2 41.♖g3+ ♔f6 42.♔xa4 g5 43.♔b4

1–0

an annotated chess game is a collection of trajectories that are annotated with qualitative rewards for moves and states

Example: Annotated Chess Games



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(17...b6 18.♖ec1!)

18.♖ec1!±]

[13...♕xc2? 14.♗xc6 ♗xc6 15.♗xb4 ♕xd1 16.♖exd1±]

[13...♘xc2?? 14.♘f4 ♕f5 15.♗d3+-]

14.♗xb4 ♘xb4 15.♘xe5 ♕xc2 16.♗xd7+ ♖xd7 17.♘xd7 ♔xd7 18.♘f4 ♕xd1 19.♖bxd1 ♗d6 20.♘xe6 ♘c2 21.♖e2 ♖e8 22.♘c5+ ♗xc5 23.♖xe8 ♔xe8 24.dxc5 ♘b4 25.a5 a6 26.♔f1 ♔d7 27.♖d4 ♘c6 28.♖xd5+ ♔e6 29.♖h5 h6 30.♔e2 ♘xa5 31.♔d3 b6 32.cxb6 cxb6 33.♖h3 ♘b7 34.♖g3 ♘c5+ 35.♔c4 ♔f6 36.♔d5 a5 37.♖f3+ ♔g5 38.♔c6 ♘e4 39.♔xb6 a4 40.♔b5 ♘d2 41.♖g3+ ♔f6 42.♔xa4 g5 43.♔b4

1–0

- it is hard to give an exact reward signal for a move
- it is easier to specify which of two moves is better

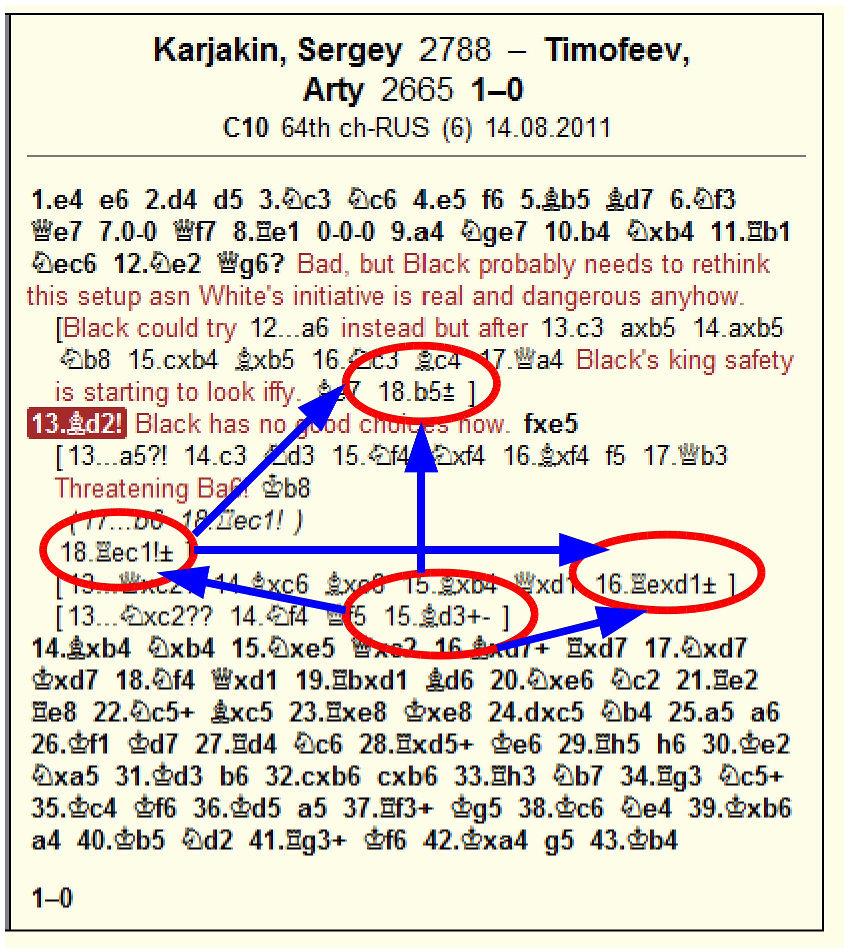
→ ***Action Preferences***

(!! □ ! □ !? □ ?! □ ? □ ??)

13th move for black:

fxe5 □ a5 □ £xc2 □ ¤xc2

Example: Annotated Chess Games



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14.♗xb4 ♘xb4 15.♘xe5 ♕xc2 16.♗xd7+ ♖xd7 17.♘xd7 ♔xd7 18.♘f4 ♕xd1 19.♖bxd1 ♗d6 20.♘xe6 ♘c2 21.♖e2 ♖e8 22.♘c5+ ♗xc5 23.♖xe8 ♔xe8 24.dxc5 ♘b4 25.a5 a6 26.♔f1 ♔d7 27.♖d4 ♘c6 28.♖xd5+ ♔e6 29.♖h5 h6 30.♔e2 ♘xa5 31.♔d3 b6 32.cxb6 cxb6 33.♖h3 ♘b7 34.♖g3 ♘c5+ 35.♔c4 ♔f6 36.♔d5 a5 37.♖f3+ ♔g5 38.♔c6 ♘e4 39.♔xb6 a4 40.♔b5 ♘d2 41.♖g3+ ♔f6 42.♔xa4 g5 43.♔b4

1–0

- it is hard to give an exact reward signal for a move
- it is easier to specify which of two moves is better

→ ***Action Preferences***

(!! ! !? ?! ? ??)

- it is hard to give an exact numerical score for a position
- it is easier to give a qualitative evaluation for a position

→ ***State Preferences***

(+- ± ^{2} ^{3} µ -+)

Approximate Policy Iteration with Roll-Outs
(Lagoudakis & Parr, ICML-03)

- Assumption:
  - we have a generative model of the underlying Markov process
  - we can use this model for sampling action traces and reward signals

  → we can perform *roll-outs* (generate action traces / trajectories)

Roll-Out

- Estimate the value $Q^{\pi}(s,a)$ for performing action a in state s and following policy π thereafter
- by performing the action and then repeatedly following the policy for at most T steps
- and returning the average of the observed rewards

- and use these roll-outs for training a policy...

Approximate Policy Iteration with Roll-Outs
(Lagoudakis & Parr, ICML-03)

- Key idea:
  - determine the best action in each state
  - train a conventional classifier (e.g., decision tree) as a policy

API

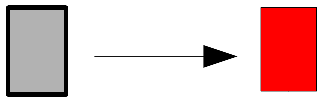
1. start with policy π_0
2. for each state s
   - evaluate all actions with **Roll-Out**
   - determine the best action a^* (the one with highest estimated Q-value)
   - generate a training example (s,a^*) if a^* is significantly better than all other actions in state s
3. use all training examples to train a policy $\pi\colon S \rightarrow A$
4. goto 2. (until stop)

Classifier

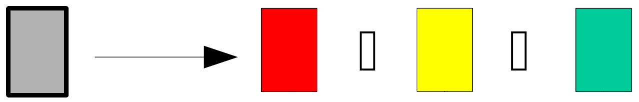
Label Ranking
(e.g., Hüllermeier, Fürnkranz, Cheng, Brinker, AIJ 2008)

The task in label ranking is to order a set of labels

- **Classification:**
  - pick one of a set of items



- **(Label) Preference Learning:**
  - predict a (partial or total) order $\Pi(A)$ relation on a set of items A



Label rankers can be trained with label preferences

- In our case we want to rank all actions based on the state description
- trained on action preferences of the type $(s, a_i \succ a_j)$

Preference-Based Policy Iteration

- Key idea:
  - compute preferences between pairs of actions
  - train a label ranker as a policy

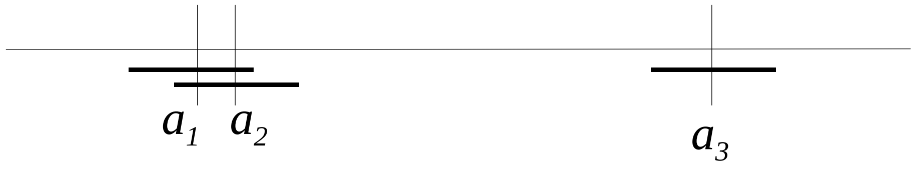
PBPI

1. start with policy π_0
2. for each state s
   - evaluate all actions with **Roll-Out**
   - for all action pairs (a_i, a_j) determine if a_i is significantly better than a_j
   - generate a training example $(s, a_i \succ a_j)$ if it is
- use all training examples to train a policy $\pi: S \rightarrow \Pi(A)$
1. goto 2. (until stop)

Label Ranker

Advantages of a preference-based framework

- Often there is no natural numerical value
  - a preference-based formulation allows to deal with qualitative feedback
- It is difficult to optimize multiple objectives
  - a preference-based framework allows to flexibly define preferences over states according to multiple criteria (e.g., Pareto dominance)
- It may impossible or infeasible to determine the best action
  - but it is often easier to compare two actions
  - in the case of roll-outs:



a_1 is not significantly better than a_2
$\rightarrow$ no training example for API

but we know a_1 □ a_3 and a_2 □ a_3
$\rightarrow$ 2 training examples for PBPI

Case Study 1
Learning from Action Preferences

Algorithms: each using a Neural Network as a base classifier

- **API**: Approximate Policy Iteration (Lagoudakis & Parr, ICML-03)
  - uses roll-outs to determine the best action
- **PAPI**: Pairwise Approximate Policy Iteration
  - uses all preferences that involve the best action (pairwise classification)
- **PBPI**: Preference-Based Policy Iteration
  - uses all preferences (also those involving suboptimal actions)

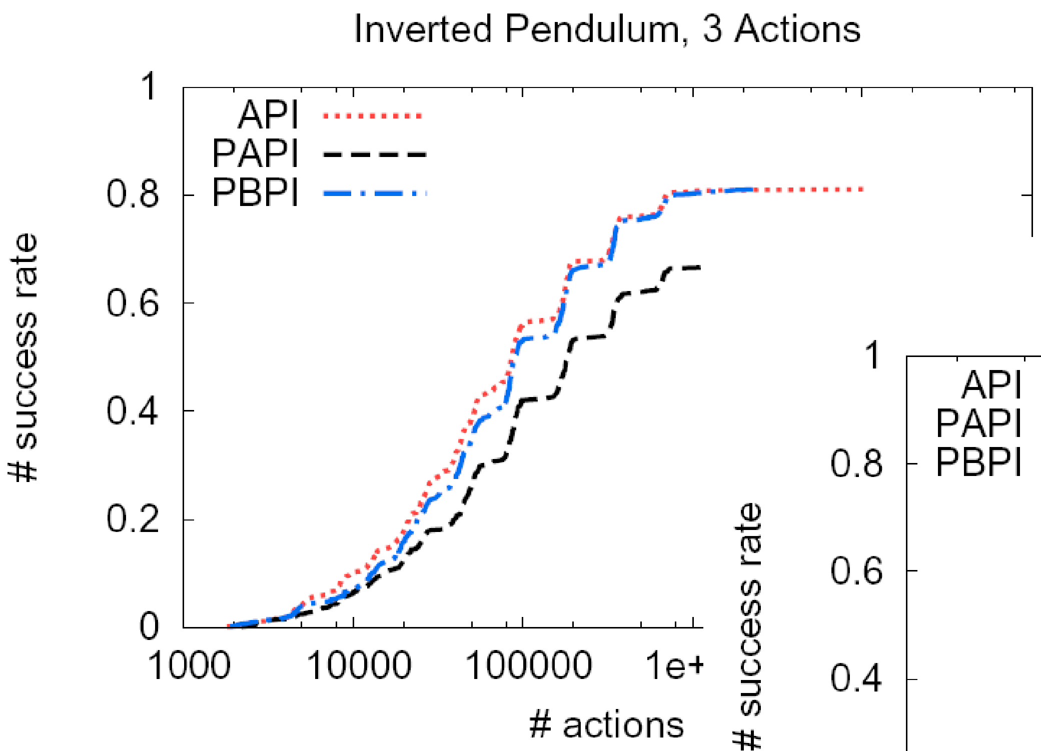
Domains: Standard RL benchmarks, each with 3, 5, 9, 17 actions

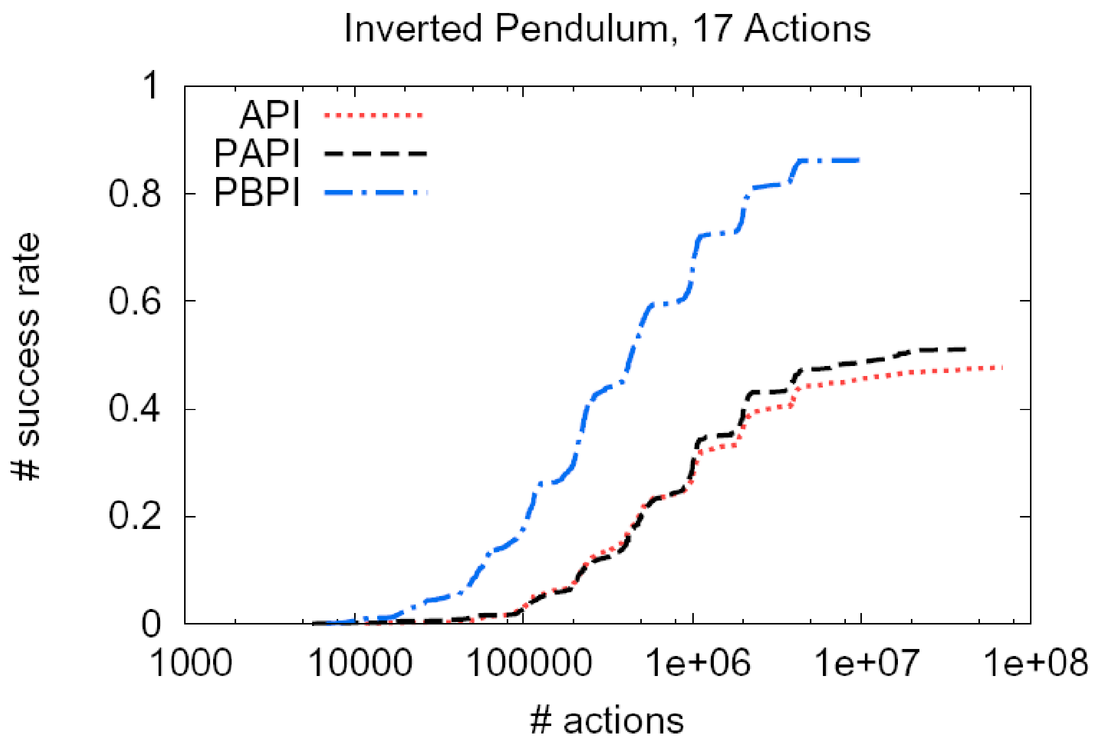
- Inverted Pendulum
- Mountain Car

Evaluation: following (Lagoudakis & Parr, ICML-03)

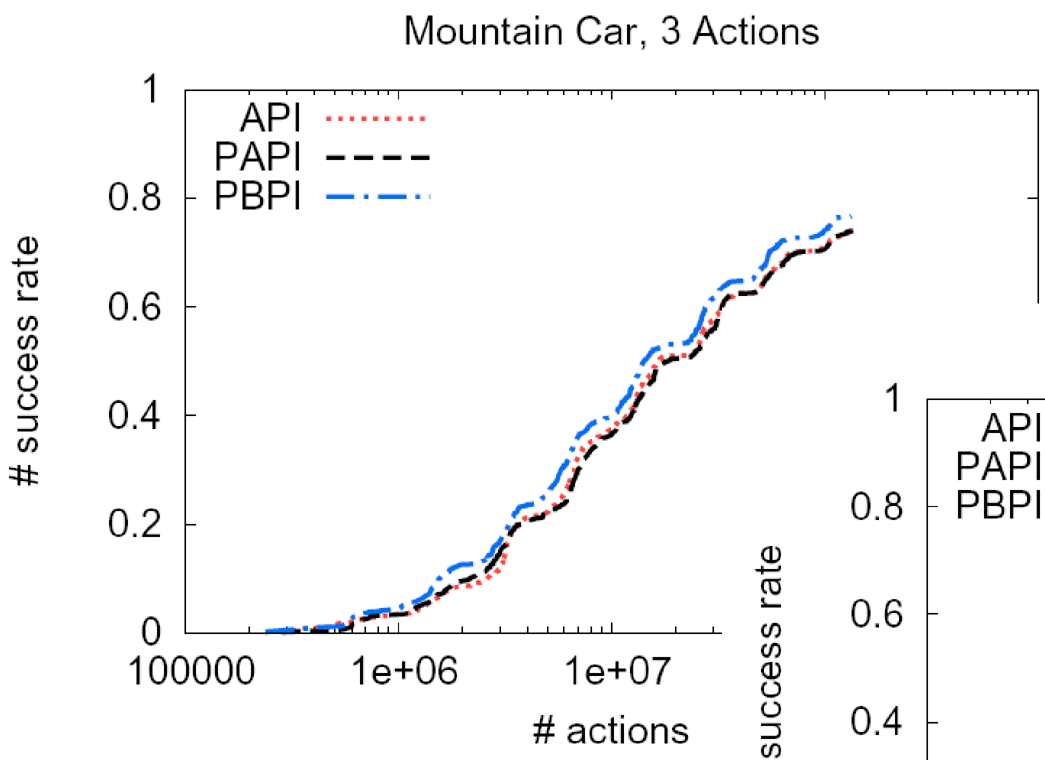
- try a variety of different parametrizations (starting states etc.)
- run each until successful or at most 10 policy iterations
- plot cumulative distribution of success rate over total number of actions taken to reach this success rate

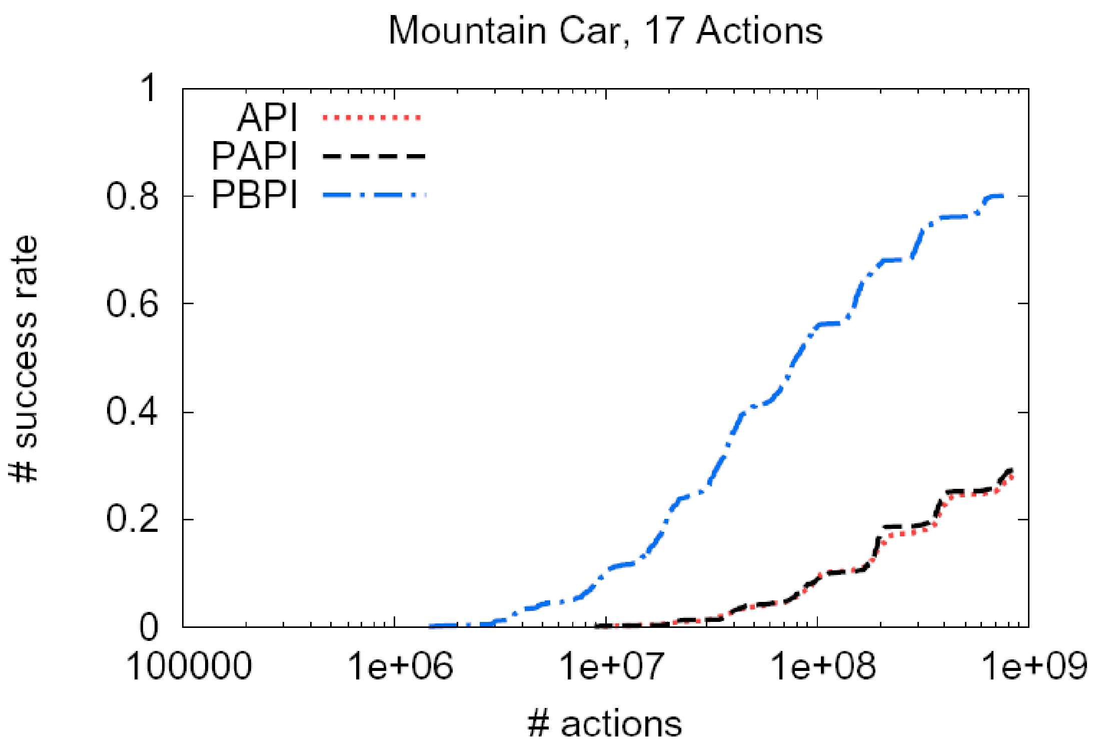
Results: Inverted Pendulum





Results: Mountain Car





Complete vs. Partial State Evaluation

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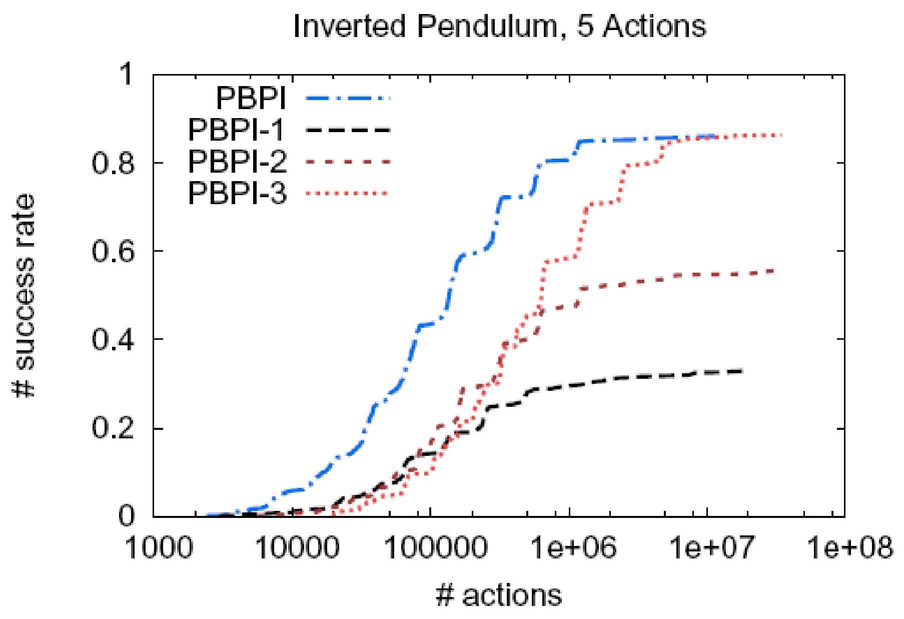
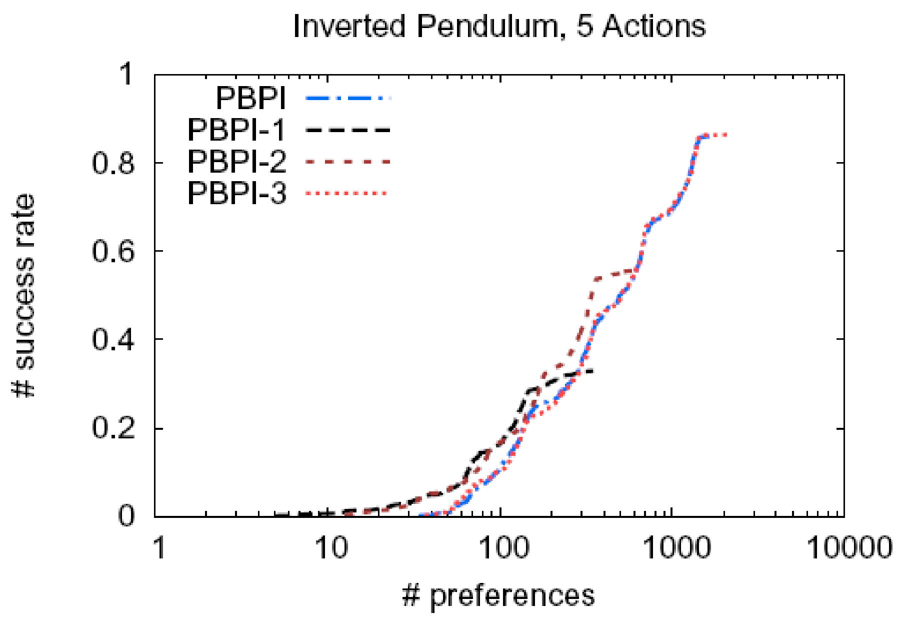




In each case PBI-i does only generate one preference per state

- PBI-1: visits the same number of states as PBI
- PBI-2: visits k/2 as many states (2 roll-outs vs. k roll-outs)
- PBI-3: visits k(k-1)/2 as many states (generates the same #preferences)

Case Study 2
Learning from Qualitative Feedback

Domain: Clinical trials of cancer treatment (Zhao et al. 2009)

- the goal is to devise a treatment policy for cancer patients
- action is the amount of medication that the patient is given

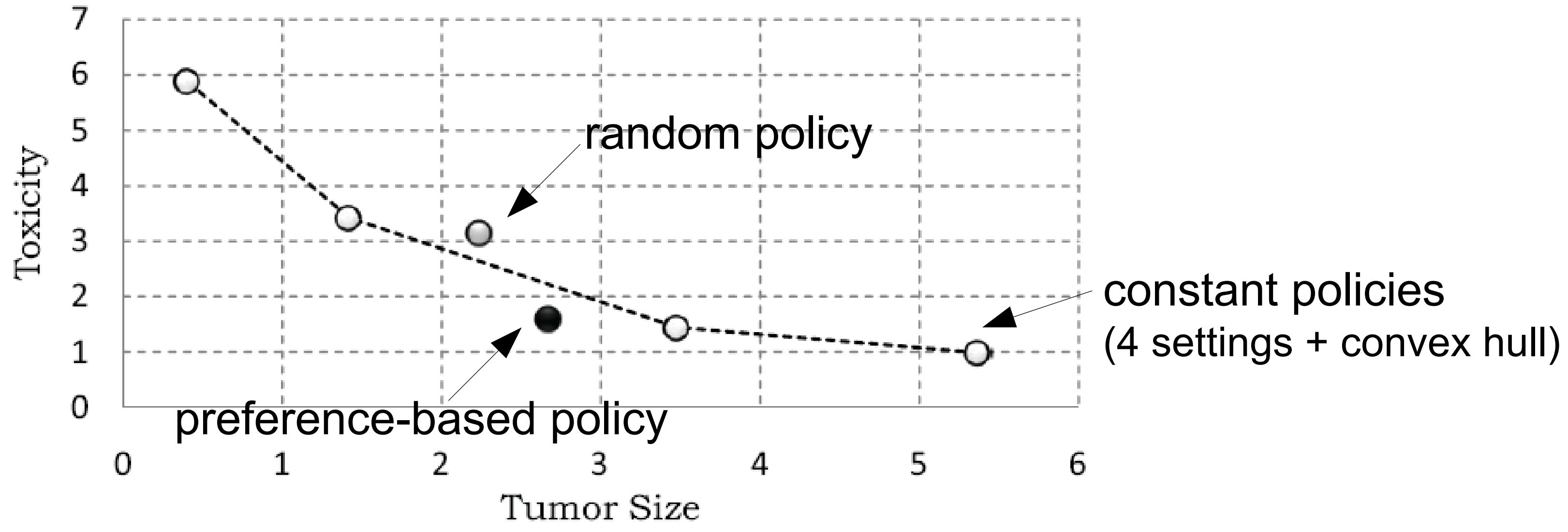
Characteristics:

- Numerical reward functions are artificial
  - The death of a patient is worse than all other results but cannot be given a reasonable number
- Multi-Objective definition of state preferences (Pareto-dominance)

Treatment A is better than Treatment B if

- *at every time point, the patient treated with A feels better than the patient treated with B and*
- *the patient treated with A is more healthy than patient B at the end*

Case Study 2
Learning from Qualitative Feedback



Conclusions

- First step towards a framework that lifts conventional reinforcement learning into a qualitative setting
  - where reward is not absolute but relative in comparison to alternatives
- We proposed a preference-based extension of approximate policy iteration
  - which we evaluated on 2 case studies
- Case Study 1 demonstrated the utility of using additional preferences
  - a label ranker can use more information and produce better results than a classifier
- Case Study 2 demonstrated an application where
  - numerical reward signals are somewhat artificial and
  - multiple objectives can be formulated in the form of preferences

Open Questions

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- How can we unify state and action preferences?
  - Key idea: Preferences over trajectories
- How can we integrate (qualitative) preference information and (quantitative) reward signals?
- How can we integrate off-line experience (annotated games) with on-line experience?
- Is there an on-line version of preference-based RL?
- Can we back up rankings of actions between states? What if we don't have a generative model?
- Can we really do this for chess?

While you ask questions...

Special issue of *Machine Learning* on **Preference Learning**

Editors: Eyke Hüllermeier and Johannes Fürnkranz

Submission Deadline: **December 31, 2011**