Online Feature Discovery in Relational Reinforcement Learning

Scott Sanner

University of Toronto

Overview

1. **Use well-known techniques:**
   - **Monte Carlo RL** (i.e., $TD(\lambda = 1)$)
   - **Naïve Bayes classifier**
   - **Locally-weighted regression**
   - **Apriori data mining algorithm**

2. **Combine them in a novel way that...**
   - **Is space/time efficient for large relational state spaces**
   - **Achieves encouraging empirical results in game domains**

     (TicTacToe, Othello, Backgammon)

RRL: Advantages and Challenges

- **RRL is a natural representation/learning paradigm:**
  - **Describe state using relational features:** $\{At(O,1,1), At(X,2,3)\}$
  - **Admits compact descriptions:**
    - **Closed-world assumption (CWA):** If not inferred true, assume false
    - **Quantifiers/Connectives:** $\exists p, r.\ At(p,r,1) \wedge At(p,r,2) \wedge At(p,r,3)$
- **But, benefits are not without drawbacks:**
  - **Very large ground relational state space:**

    40 ground atoms $= 2^{40}$ states
  - **Need robust learning for sparse data:**

    few samples per state $\implies$ high variance
  - **Must focus on time/space efficient approximations**

RRL: Addressing these Challenges

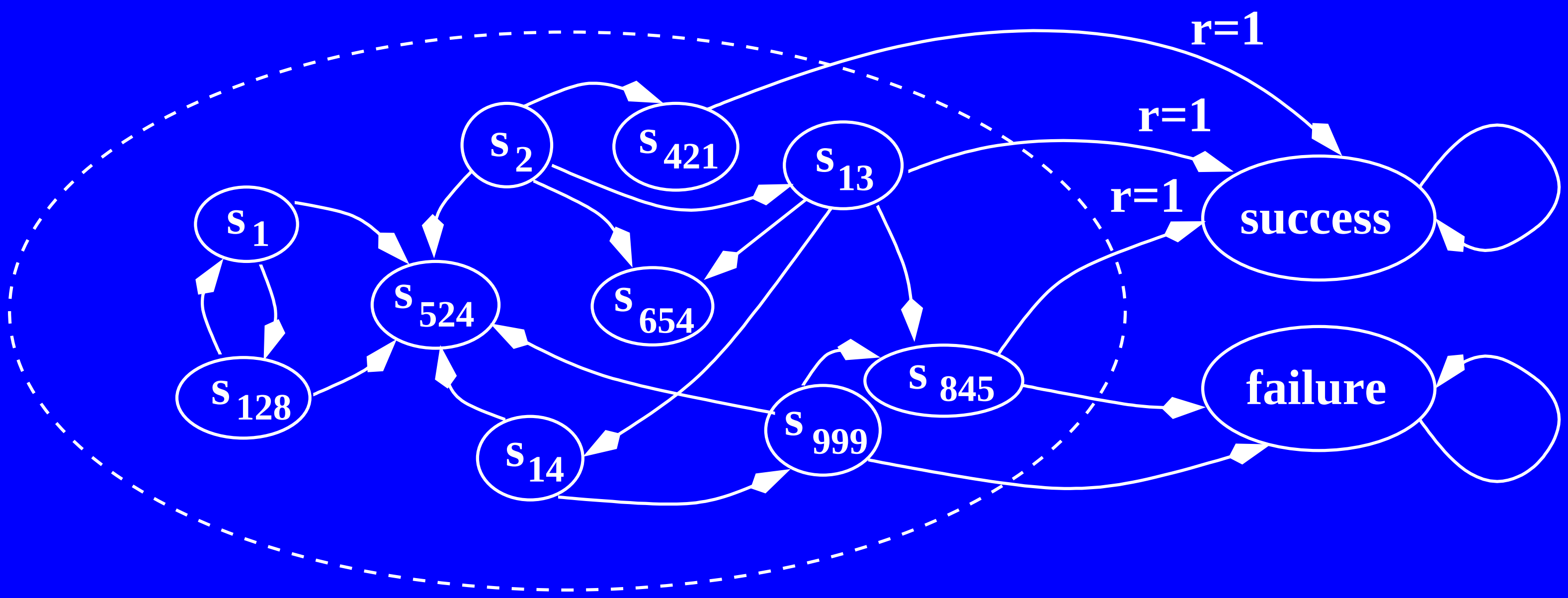
- **General solution difficult, focus on restricted setting:**
  - **Goal-oriented tasks** (e.g., planning, games w/ stationary opp.)
  - **Indefinite horizon, undiscounted MDP domains**
  - **Single terminal reward of success/failure**

- $\Rightarrow$ **Value function** $=$ **probability of success**

- **Allows us to address previous RRL challenges:**
  - **Very large state spaces:** Naïve Bayes repr. of value function
  - **Robust learning:** Augment with high-freq. joint features (Apriori alg.)
  - **Efficient approximation:** Use ML estimate of value fun. (closed-form)

Theoretic Preliminaries

- Under a fixed policy π, MDP reduces to a Markov chain:



- Undiscounted, only non-zero reward is on success trans.

- Value function is prob. of reaching success in ∞ limit:

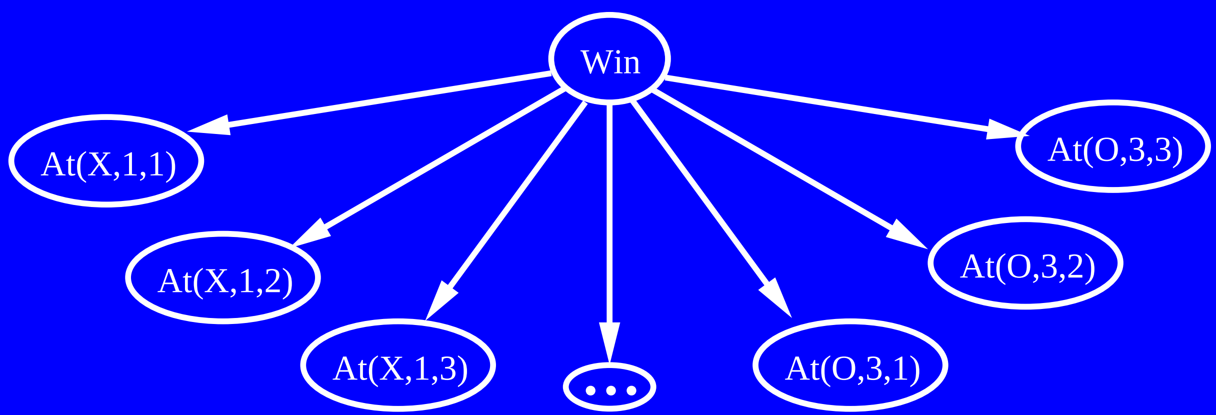
$$V_\pi(s) = E_\pi[\sum_{t=0}^{\infty} r^t | S^{t=0} = s] \ = \ P(S^{t=\infty} = success | S^{t=0} = s, \pi)$$

Relational State Representation

- $\{R_1, \ldots, R_i\}$: **Set of relations used to describe a state**
- $\{A_1, \ldots, A_j\}$: **Set of relation attribute types**
  - **TicTacToe:** $At(Mark, Pos, Pos)$; $Mark = \{X, O\}$, $Pos = \{1, 2, 3\}$
  - 18 **ground atoms:** $\{At(X, 1, 1), At(X, 1, 2), \ldots, At(O, 3, 2), At(O, 3, 3)\}$
  - 2^{18} possible truth assignments = $262, 144$ states
- $F = \{F_1, \ldots, F_n\}$: **Ground rel. atoms (boolean features)**
- $f = \{f_1, \ldots, f_p, \bar{f}_{p+1}, \ldots, \bar{f}_n\}$: **Feature truth assignment**
  - Order true/positive features first, false/negative features last
  - Represent **state** f as $\{f_1, \ldots, f_p\}$, make CWA
  - *Space efficient* because typically $p \ll n$

Value Function Representation

- **Computational and representational issues aside:**
  - Let W be a boolean variable denoting eventual win/success
  - Optimal value function under a fixed policy is $P(W|F_1,\ldots,F_n)$
  - Learning = direct estimate of $P(W|F_1,\ldots,F_n)$ from trial data
- **Unfortunately, $P(W|F_1,\ldots,F_n)$ is intractably large. . . so approximate it with a naïve Bayes net, e.g.,**



- **ML parameters are just observed frequencies**

Efficient Policy Evaluation

- **Still many features, need to eval policy efficiently:**
  - Focus on policy evaluation via *after-state* analysis
  - Policy eval. is just choice of highest valued after-state
  - This is state that maximizes log winning odds $\log(\frac{P(w|f)}{P(\bar{w}|f)})$

$$\log \frac{P(w|f)}{P(\bar{w}|f)} = \log \frac{P(w)}{P(\bar{w})} + \sum_{i=1}^{p} \log \frac{P(f_i|w)}{P(f_i|\bar{w})} + \sum_{i=p+1}^{n} \log \frac{P(\bar{f}_i|w)}{P(\bar{f}_i|\bar{w})}$$

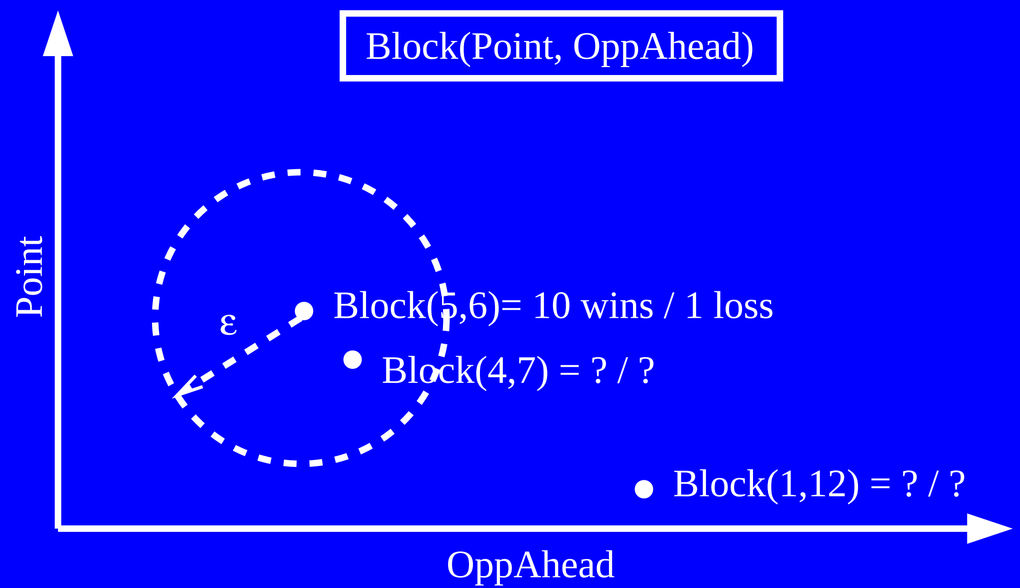
Let $C = \log \frac{P(w)}{P(\bar{w})} + \sum_{i=1}^{n} \log \frac{P(\bar{f}_i|w)}{P(\bar{f}_i|\bar{w})}$ (common to all states)

$$\log \frac{P(w|f)}{P(\bar{w}|f)} = C + \sum_{i=1}^{p} \left(\log \frac{P(f_i|w)}{P(f_i|\bar{w})} - \log \frac{P(\bar{f}_i|w)}{P(\bar{f}_i|\bar{w})} \right)$$

- **Find best after-state by looking at only positive features!**

Exploiting Relational Structure

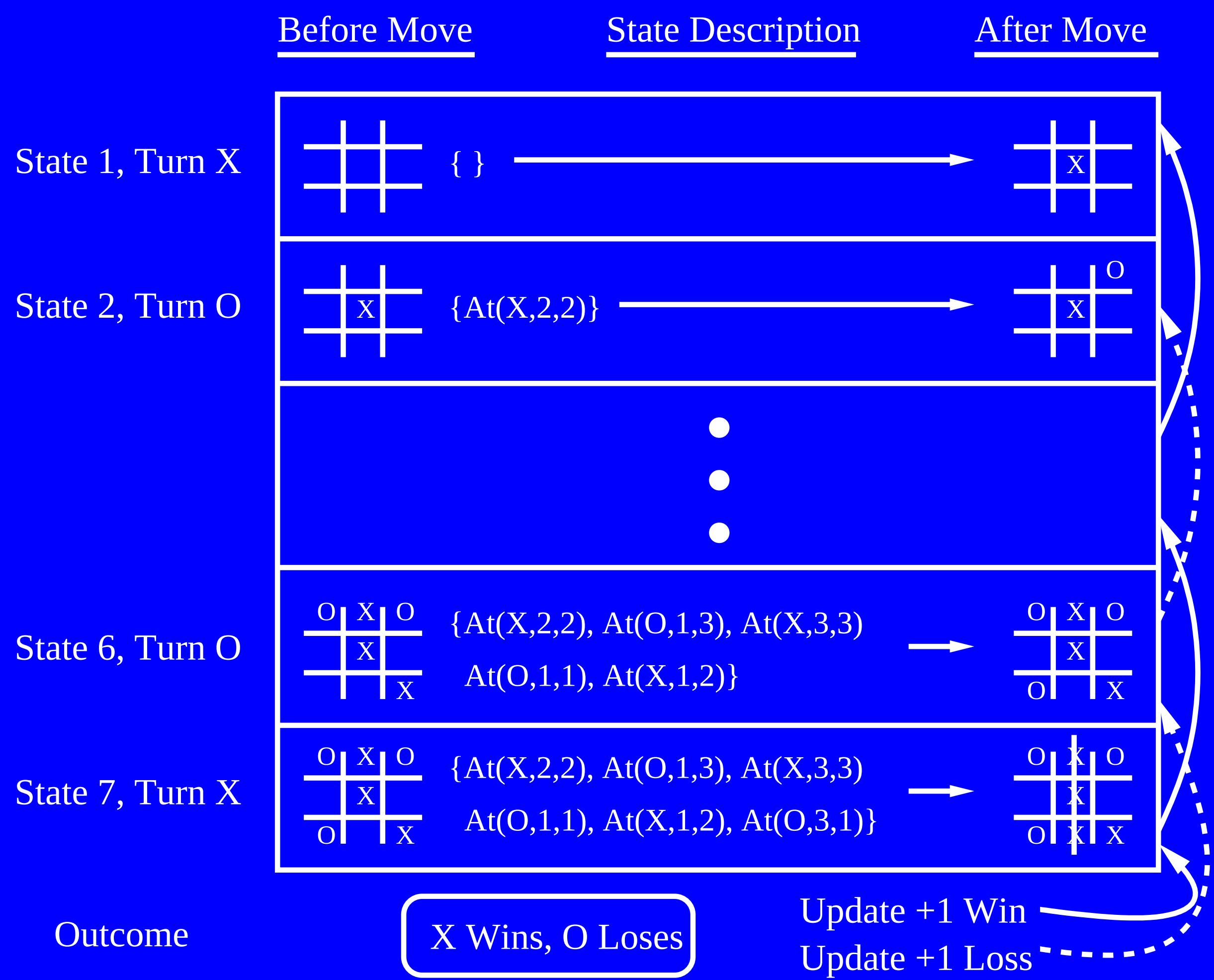
- **Example:** Predicting feature odds given nearby features. . .



- **Idea:** Locally weighted regression in n-D feature attr. space
  - Take Euclidean metric of user-defined attribute distances
  - Compute odds of target feat. as weighted combination of “nearby” feats.
- **Advantages:** Generalization, reduced storage, fast lookup

Training Example

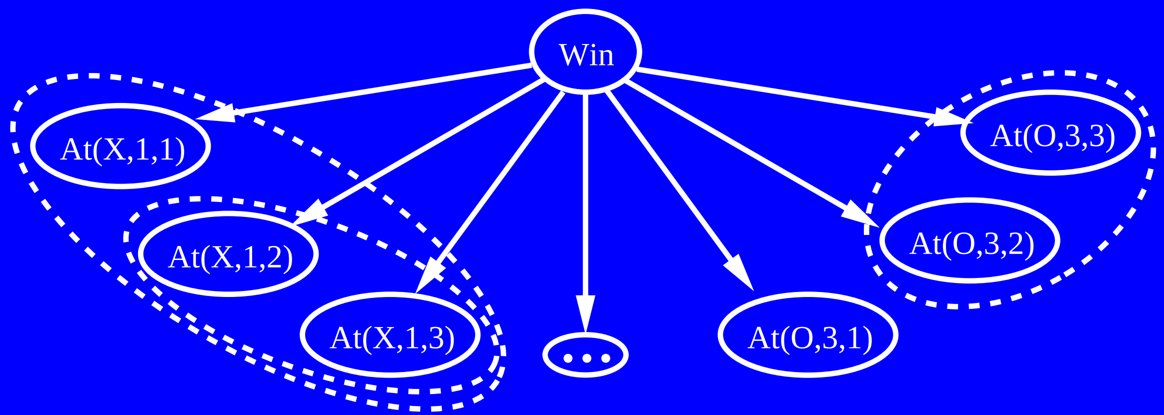
- **On each trial, apply policy π for current value function:**



- **End of trial: Update win/loss counts for $P(W)$, $P(F_i|W)$ CPTs**

Learning Structure

- **Linear expressiveness of naïve Bayes often inadequate**
- **Join nodes to learn nonlinear structure, e.g.,**



- **Max-likelihood join maximizes mutual cond. entropy:**
  - $\Delta l^*(\theta|D) = C + M \cdot I(F_a, F_b|W)$ (M is number of samples)
  - But for n features, must keep track of $O(n^2)$ calculations
- **Instead, use Apriori to mine features w/ freq. $>$ threshold**
  - Efficient; maximizes ~VOI; frequent joint features $\Longrightarrow$ low variance

Empirical Results

- **Evaluation of Described RRL Approach:**
  - **Domains:** TicTacToe (18 gf), Othello (13,200), Backgammon (786,816)
  - **Opponent:** TicTacToe (opt.), Othello (interm.), Backgammon (pubeval)
  - **Structure Learning:** None; Apriori w/ 2 freq. thresh. $\longrightarrow$ cap at 2000
  - **Training:** 5000 games vs. opp. in $<$ 20 min, $<$ 3Mb on 1 GhZ PIII

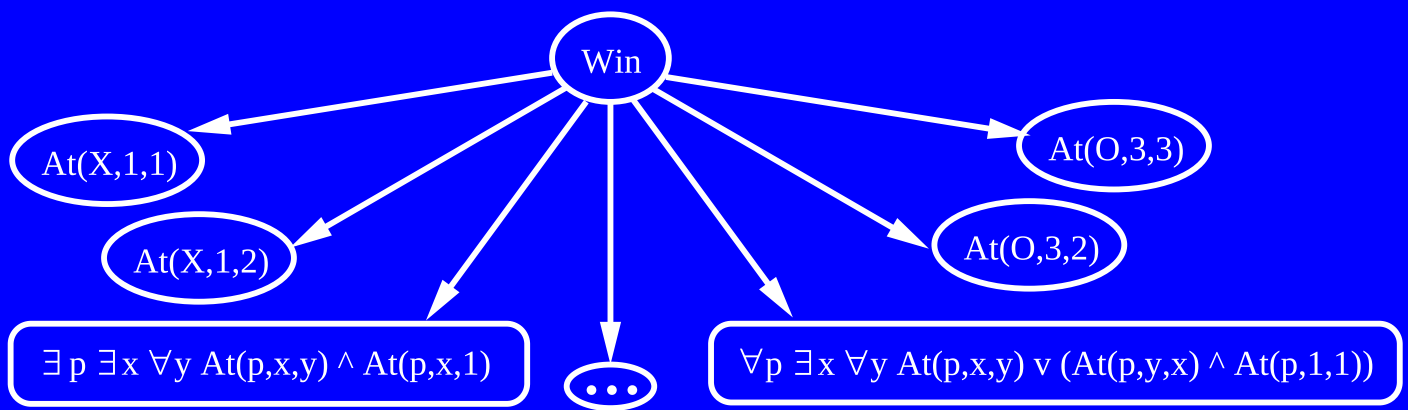
Structure Learning	Win/Draw %	Domain
None Apriori (Freq=1) Apriori (Freq=50)	28.3 % 100.0 % 45.8 %	Tic-Tac-Toe
None Apriori (Freq=1) Apriori (Freq=50)	61.3 % 49.4 % 99.1 %	Othello
None Apriori (Freq=1) Apriori (Freq=50)	46.5 % 45.4 % 51.5 %	Backgammon

Future Work I

- **Better feature discovery:**
  - Directly mine frequent and informative features (e.g., LargeBayes)
- **Avoiding local minima:**
  - Only exploration due to “optimistic” priors, better explore/exploit?
  - Policy constantly changing $\Longrightarrow$ value shift; use param decay?
  - Switch to a more direct policy gradient method?
- **POMDPs/PSRs:**
  - Relational representation often an abstraction $\Longrightarrow$ state aliasing
  - Features may just be observations on actual state!
  - Optimal evaluation may require representation of history or future

Future Work II

- **Relational Bayes net structure learning:**
  - Probabilistic Relational Models: Retain efficient policy evaluation?
- **First-order feature discovery:**
  - Nodes can be general first-order formulae:



  - How to generate structure: (n)FOIL? What about feature overlap?
  - MRF or Factor Graph? How to est. parameters efficiently? Δ-rule?