Factored MDPs

• Vector state/action

$$S = S_1 \times \cdots \times S_N$$
 $A = A_1 \times \cdots \times A_N$

- Each component has $scope \ Z_n \subseteq \{1, ..., N\}$
- Transitions for *n*th component of state

$$(x_{Z_n,t}, a_{Z_n,t}) \Rightarrow x_{n,t+1}$$

• *n*th reward term

$$(x_{Z_n,t}, a_{Z_n,t}) \Rightarrow r_{n,t}$$

- *HN* tables, each with $\prod_{m \in \mathbb{Z}_n} |\mathcal{S}_m \times \mathcal{A}_m|$ entries
 - Versus H tables, each with $|\mathcal{S} \times \mathcal{A}| = \prod_{m=1} |\mathcal{S}_m \times \mathcal{A}_m|$
 - Also...dimensionality of table entries

Thompson Sampling

- Priors for each table entry
 - Dirichlet over probability vectors
 - Normal-gamma over reward distributions

Algorithm

- Sample factored MDP from distribution
- Apply optimal policy for one episode
- Update distribution
- Repeat

Regret bounds

- Depend on number of parameters rather than numbers of states and actions
- Intractable MDP

A Recommendation System Model

Consider recommending movies

- N movies
- Sequence of H recommendations for each customer
- Customer accepts/rejects each
- Goal: high acceptance rate

MDP formulation

• state: $r_t \in \{0, 1\}$

• action: $s_t \in \{-1, 0, 1\}^N$

• reward: $a_t \in \{1, \dots, N\}$

• Parameterization

$$\mathbb{E}[r_t = 1 | s_t, a_t] = \begin{cases} \frac{\exp(\theta_{a_t}^\top s_t)}{1 + \exp(\theta_{a_t}^\top s_t)} & \text{if } s_{a_t, t} = 0\\ 0 & \text{otherwise} \end{cases}$$

Thompson Sampling

- Independent priors over parameters
 - Possibly finite support
- Algorithm
 - Sample parameters from posterior via Gibbs sampling
 - Apply optimal policy for one episode
 - Repeat
- Gibbs sampling
 - Sample parameters from priors
 - Iterate over components
 - Fix all other components θ_a
 - Sample component from one-dimensional distribution

$$\prod_{n=1}^{N} p_n(\theta_{an}) \prod_{k:a^k=a} \frac{\exp(\theta_a^{\top} s^k)}{1 + \exp(\theta_a^{\top} s^k)}$$

- Regret bound?
- Intractable MDP