# Chapter 3. Reinforcement Learning

## in RL for Adaptive Dialogue Systems, V. Rieser & O. Lemon

## Course: Autonomous Machine Learning

Patrick Emaase

Biointelligence Laboratory
School of Computer Science and Engineering
Seoul National University

http://bi.snu.ac.kr

# How can we develop an Autonomous Learning Dialogue Systems?

What concepts, behavior representation do we need to consider?

# Summary

- Learning – Interaction between agent and world
  - Percepts received by an agent acts and improves agent's ability to behave optimally in the future to achieve the goal

- Reinforcement Learning – Achieve goal successfully
  - Learn how to behave successfully to achieve a goal while interacting with external environment, Learn via experience
    - Game playing – know when its win or loss

  - Well suited for dialogue strategy development – as dialogue is learned by evaluative feedback with delayed rewards and exploration

# Summary

- Scope:
  - RL in dialogue development – Skills {↑,↓}
  - Empirical Justification – Why, Hence..
  - Dialogue Simulation – How to generalize

- Peter Rabbit – Rewards known
  - Mischievous and disobedient - Exploratory
  - Chased, escapes, rests, regrets
  - Obedience: Sumptuous meal, mother's love
  - Disobedience: Losses clothes, stomach ache

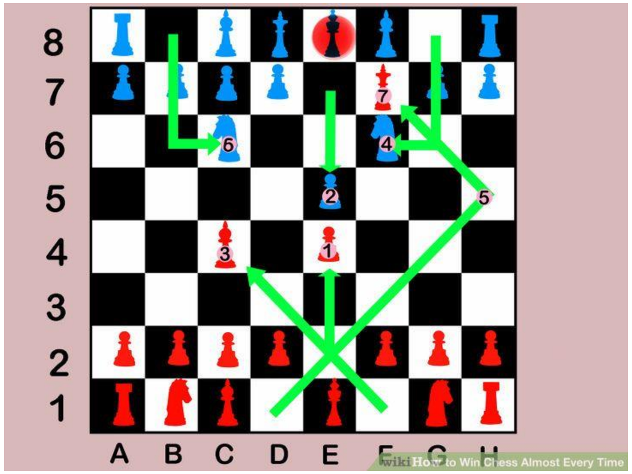
Peter Rabbit: An agent receiving rewards

- RL: Objectives
  - Model dialogue as a sequence of action (in global point-wise estimates)
  - Mimic behaviour observed in non-stationary corpus and explore new strategies

# Contents

# Nature of Dialogue Interaction

- Dialogue is Temporal
  - Goodness of action – depends on dialogue progress; planning nec.
    - Actions affects the state, options and opportunities
  - ∴ SL not suitable for dialogue strategy; potential for “multi-expert” learning

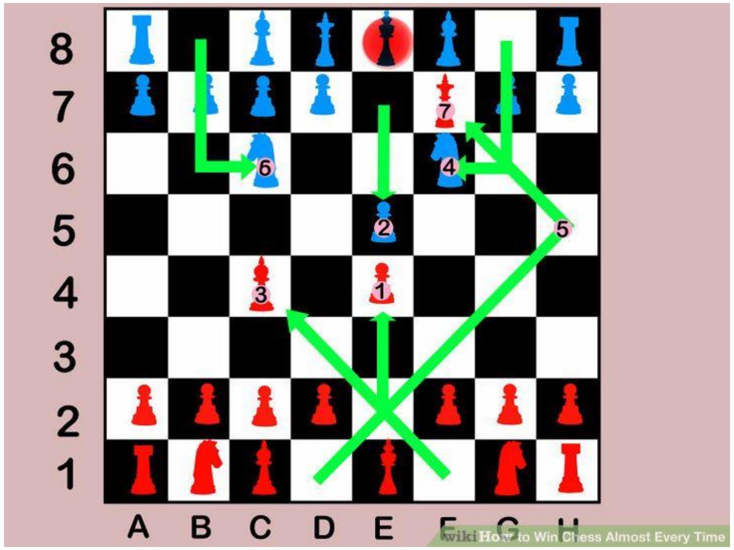



- RL – Sequential decisions process
  - Based on delayed rewards (benefits apparent at the end of the dialogue; avoids local minima

- RL – Chess player may sacrifice prawn for promising strategy at the long-run

# Nature of Dialogue Interaction

- Dialogue is Dynamic
  - Interaction in stochastic environment – Dynamic {conditions change, differential reaction by agents - unpredictable}. Need robust strategy
  - ∴ chess players strategize – think ahead {sequence of action choices}
    - Good player dynamically explores; winning – rewarded; loosing – punished
    - Language Learners – improve communicative skills over time {encouragement, correction}

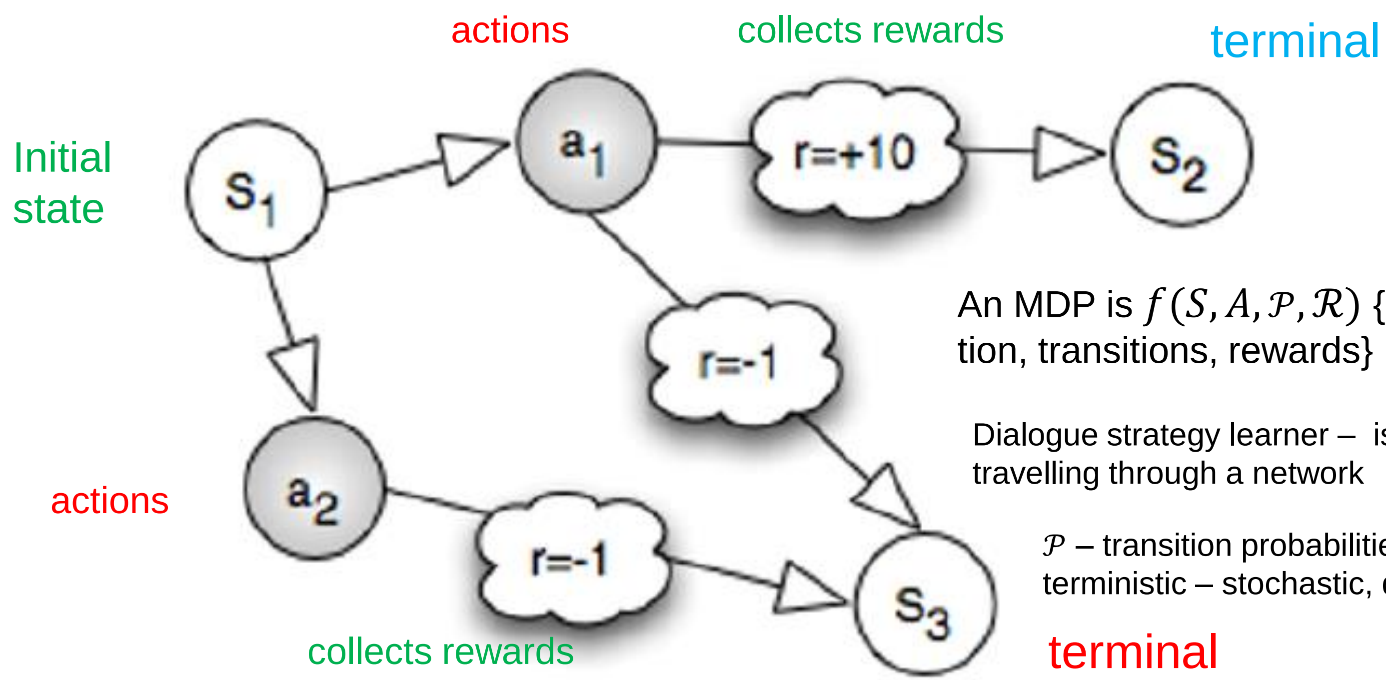


# In conclusion

- Reinforcement Learning:
  - Learns by exploration – learning robust strategies, appropriate for unseen states
  - Learns by experience
  - Simulation Based RL – Ensures enough exploration
  - Explores most strategies at low cost

# RL – based Dialogue Strategy Learning

- Dialogue as a Markov Decision Process




An MDP is $f(S, A, \mathcal{P}, \mathcal{R})$ {state, ac tion, transitions, rewards}

Dialogue strategy learner – is an agent travelling through a network

$\mathcal{P}$ – transition probabilities {none de terministic – stochastic, dynamic

**Fig. 3.2** RL with Markov Decision Process (MDP): The learning agent travels through a network of interconnected states. At time $t$, the agent is in state $s_t$, takes an action $a_t$, transitions into state $s_{t+1}$ according to the transition probability $p(s_{t+1}|s_t. a_t)$, and receives rewards $r_{t+1}$

# RL – based Dialogue Strategy Learning

- Specialized MDP – accounts temporal nature of dialogue
  - Markov Property requires that the state and reward at time $t+1$ only depends on the state and action at time $t$.
    - State at step $t$ information available to agent about its environment; Summarize past sensations, retains all "essential" info
  - Markov Property:

$$P(s_{t+1}, r_{t+1} | s_t, a_t, s_{t-1}, a_{t-1}, r_{t-1}, \ldots, s_0, a_0) \approx P(s_{t+1}, r_{t+1} | s_t, a_t) \tag{3.1}$$

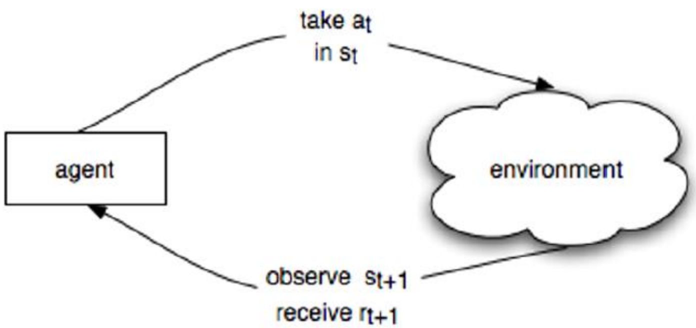



**Fig. 3.2** The agent interacting with a stochastic environment and actively influencing its behavior by taking action $a_t$ in state $s_t$, The changes in the environment are observed $(o_{t+1})$ and a reward is received $r_{t+1}$

# Dialogue as a MDP

- State space ($S$) – reachable states for agent
- Action set ($A$) – All actions available to agent
- State transition function ($\mathcal{P}$) – dynamics of environment
  - Next state $s' \in S$ is likely to follow when taking action $a \in A$ in states $s \in S$. $\mathcal{P}$ is defined over $\mathcal{P}: S \times A \times S \longrightarrow [0,1]$ where:

$$\mathscr{T}_{ss'}^{a} = P(s_{t+1} = s' | a_t = a, s_t = s); \tag{3.2}$$

- Reward function – Value for a decision
  - For state $s_t$ and action $a_t$ expected reward value:

$$\mathscr{R}_{ss'}^{a} = E(r_{t+1} | s_t = s, a_t = a, s_{t+1} = s); \tag{3.3}$$

  - Reward critical for learning

# Dialogue as a MDP

- State space ($S$) – reachable states for agent
  - Dialogue features – knowledge about dialogue history ($\check{s}_d$), user input action ($\check{a}_u$) [e.g. confidence values], and task level features ($\check{s}_u$)
- Action set ($A$) – All actions available to agent
  - Dialogue actions to be learned represented as abstract semantic Speech Acts on the intentional level
- State transition function ($\mathcal{P}$) – dynamics of environment
  - Next state $s' \in S$ is likely to follow when taking action $a \in A$ in states $s \in S$. $\mathcal{P}$ is defined over $\mathcal{P}: S \times A \times S \longrightarrow [0,1]$ where:

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$$\mathscr{R}_{ss'}^{a} = E(r_{t+1} | s_t = s, a_t = a, s_{t+1} = s); \tag{3.3}$$

# Partially Observable MDP (POMDP)

- History and State
  - History – Sequence of observations, actions, rewards
    - $H_t = O_1, R_1, A_1, \ldots, O_{t-1}, R_t, A_t$ {all observable variables up to time *t*}
  - State – information used to determine what happens next

$$S_t = f(H_t)$$

- Information state – (Markov state) contains useful info
  - Environment State $S_t^e$ – Environment's private representation
    - Data for picking next observation/reward
  - Agent State $S_t^a$ - agent's internal representation
    - Info agent uses to pick next action, used by RL algorithm
  - Can be any function of history

$$S_t^a = f(H_t)$$

# Partially Observable MDP (POMDP)

- Definition
  - A state $S_t$ is Markov if and only if

$$\mathbb{P}[S_{t+1}|S_t] = \mathbb{P}[S_{t+1}|S_1, \dots, S_t]$$

"The future is independent of the past given the present"

- Once the state is known, the history may be thrown away – The state is a sufficient statistic of the future

- The environment state $S_t^e$ is Markov, the history $H_t$ is Markov

# Rat Example

# Partially Observable MDP (POMDP)

- MDP – entire space is fully observable
  - Uncertainty represented as state feature encoding [low, high;  or confirmed or unconfirmed
- Fully observability: Agent directly observes the environment state; $O_t = S_t^a = S_t^e$; Agent state = environment state = information state

- Partial Observability: agent indirectly observes environment
  - Observes current state, agent state ≠ environment state

- In POMDP - Agent constructs its own state representation $S_t^a$ providing
  - Complete History: $S_t^a = H_t$
  - Beliefs of environment state: $S_t^a = (\mathbb{P}[S_t^e = s^1], \ldots, \mathbb{P}[S_t^t = s^n])$
  - Recurrent neural network: $S_t^a = \sigma(S_{t+1}^a W_s + O_t W_0)$

# POMDP – Belief Monitory

- Belief Monitoring –
  - POMDP encodes uncertainty by representing current dialogue state *s* as a belief state *b(s)* – distribution of the possible states
  - Belief Monitoring - Update belief state based current observation *o*
- Belief state update:

$$b'(s') = P(s'|o', a, b(s)) = k \times P(o'|s', a_s) \sum_{s \in S} P(s'|a, s) b(s); \qquad (3.4)$$

  - $b'(s')$ = estimated belief state, $P(s'|o', a, b)$ = probability of being in a state $s'$ given observation $o'$, the user action a and the current belief state *b(s).*
  - Re-written as probability of observing $o'$ in state $s'$ and given a system action $a_s$, given transition probability for current belief state to the new state $s$, $k$ is normalization constant

- **POMDP:** Can track multiple hypotheses simultaneously; fast backtrack and correct errors; User's goal info accumulates over dialogue turns; scaling up problem – computationally very expensive and intractable for dialogue system
- MDP – Looses alternative hypothesis info; complex in error discovery and correction
  - Approximation possible

# Reinforcement Learning problem

- MDP – allows dialogue management strategy (policy) {agent's behavior} to map state to action $\pi: S \longrightarrow A$

- Elements of RL – {Policy, action, Reward, discount factor}
  - Policy $\pi$ – Selections action of highest rewards during a dialogue
    - Deterministic policy - $a = \pi(s)$
    - Stochastic policy - $\pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$
  - The final Reward $\mathcal{R}$ - total discounted return received from time $t$. Discount factor $\gamma$ – weights rewards {immediate rewards 0; further future -1}; $\gamma$=0 RL maximizes the immediate utility; $\gamma$=1 takes into consideration future rewards.

$$\mathscr{R}_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots = \sum_{k=0}^{T} \gamma^k r_{t+k+1} \qquad (3.5)$$

  - Reward $\mathcal{R}_t$ - intrinsic desirability of a state or action; policy discovered via trial-and-error search through interaction btw. learning agent and its dynamic environment

# Reinforcement Learning problem

- Value Function $V^{\pi}(s)$
  - Long term desirability of a state considering all likely subsequent states
  - $V$ – value of a state; is future expected reward for visiting states s following policy $\pi$ subsequently

$$V^{\pi}(s) = E_{\pi}(\mathscr{R} | s_t = s) \qquad (3.6)$$

  - Value function $V$ is a prediction of future reward; evaluates goodness/badness of a state; selects actions

- Q-function $Q^{\pi}(s, a)$ - Expected return
  - The value function can be re-written as the Q-function $Q^{\pi}(s, a)$ - is expected return for taking action $a$ in a given state $a$ and following policy $\pi$ thereafter

$$Q^{\pi}(s, a) = E_{\pi}(\mathscr{R} | s_t = s, a_t = a) \qquad (3.7)$$

  - $V^{\pi}(s)$ and $Q^{\pi}(s, a)$ can be formulated recursively using Bellman equations

# Bellman Equations

- Using equation 3.2 and 3.3 the resulting equations are Bellman's equations

$$V^{\pi}(s) = \sum_a \pi(s,a) \sum_{s'} \mathscr{T}^a_{ss'}[\mathscr{R}^a_{ss'} + \gamma V^{\pi}(s')] \tag{3.8}$$

$$Q^{\pi}(s,a) = \sum_{s'} \mathscr{T}^a_{ss'}[\mathscr{R}^a_{ss'} + \gamma V^{\pi}(s')] \tag{3.9}$$

- Bellman equations describe the expected reward for taking action prescribed by policy $\pi$. The equations for the optimal policy $\pi^*$ are referred to as Bellman optimality equations:

$$V^*(s) = \max_a \sum_{s'} \mathscr{T}^a_{ss'}[\mathscr{R}^a_{ss'} + \gamma V^*(s')] \tag{3.10}$$

$$Q^*(s,a) = \sum_{s'} \mathscr{T}^a_{ss'}[\mathscr{R}^a_{ss'} + \gamma \max_a Q^*(s',a')] \tag{3.11}$$

  - Finding an optimal policy by solving the Bellman Optimality Equations requires accurate knowledge of the environment dynamics, time and space

# Summary

- The **value of a state** is the expected return starting from that state; depends on the agent's policy:

$$\textbf{State-value function for policy } \pi:$$

$$V^{\pi}(s) = E_{\pi}\{R_t \mid s_t = s\} = E_{\pi}\left\{\sum_{k=0}^{\infty}\gamma^k r_{t+k+1} \mid s_t = s\right\}$$

- The **value of taking an action in a state under policy $\pi$** is the expected return starting from that state, taking that action, and thereafter following $\pi$:

$$\textbf{Action-value function for policy } \pi:$$

$$Q^{\pi}(s,a) = E_{\pi}\{R_t \mid s_t = s, a_t = a\} = E_{\pi}\left\{\sum_{k=0}^{\infty}\gamma^k r_{t+k+1} \mid s_t = s, a_t = a\right\}$$

# Bellman Equation for a Policy $\pi$

The basic idea:

$$\begin{aligned} R_t &= r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \gamma^3 r_{t+4} \cdots \\ &= r_{t+1} + \gamma \left( r_{t+2} + \gamma r_{t+3} + \gamma^2 r_{t+4} \cdots \right) \\ &= r_{t+1} + \gamma R_{t+1} \end{aligned}$$

So:

$$\begin{aligned} V^\pi(s) &= E_\pi \left\{ R_t \mid s_t = s \right\} \\ &= E_\pi \left\{ r_{t+1} + \gamma V\left(s_{t+1}\right) \mid s_t = s \right\} \end{aligned}$$

Or, without the expectation operator:

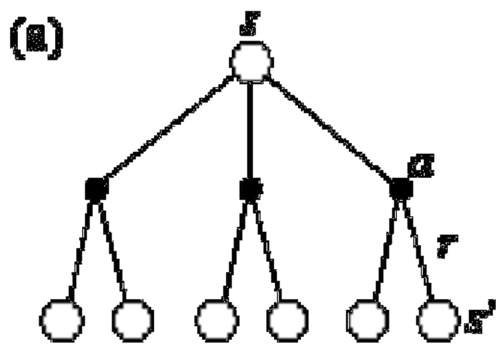
$$V^\pi(s) = \sum_a \pi(s,a) \sum_{s'} P_{ss'}^a \left[ R_{ss'}^a + \gamma V^\pi(s') \right]$$

# More on the Bellman Equation

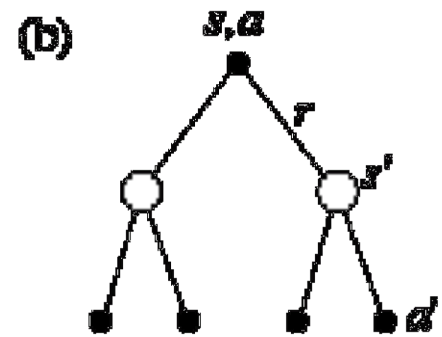
$$V^{\pi}(s) = \sum_{a} \pi(s,a) \sum_{s'} P_{ss'}^{a} \left[ R_{ss'}^{a} + \gamma V^{\pi}(s') \right]$$

This is a set of equations (in fact, linear), one for each state.
The value function for $\pi$ is its unique solution.

**Backup diagrams**:



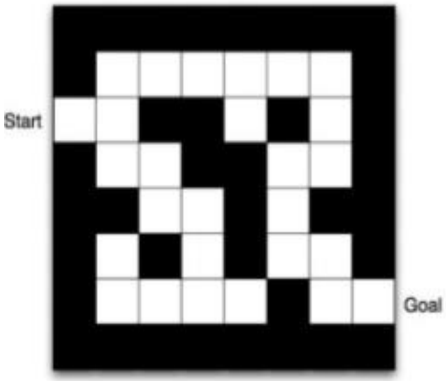

for $V^{\pi}$

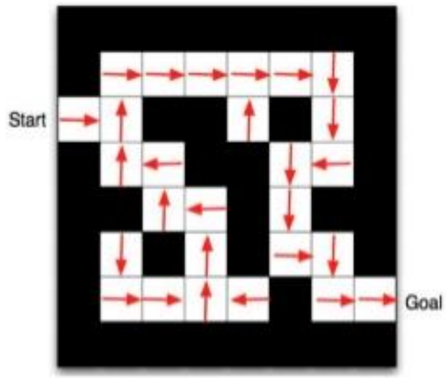



for $Q^{\pi}$

# RL Algorithms

Maze example: r = -1 per time-step and policy



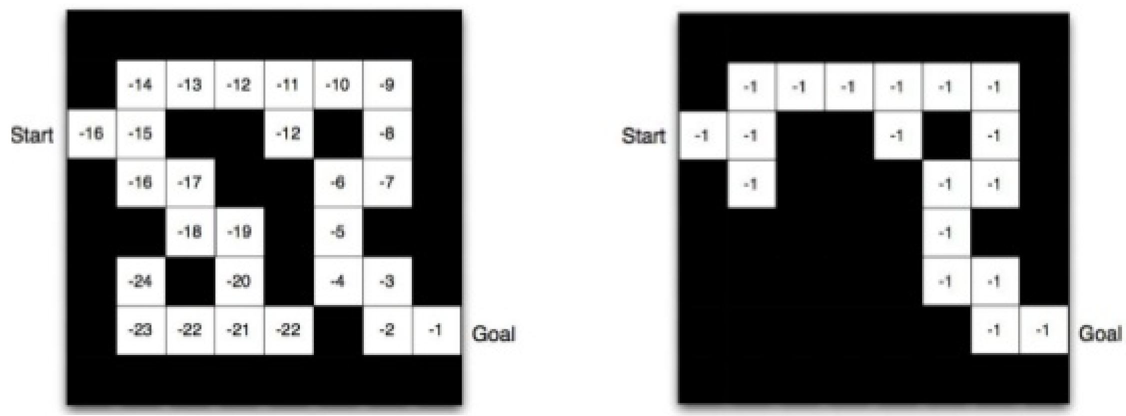

Actions: N, E, S, W; States: Agents location;
Arrows: policy $\pi(s)$ for each state $s$.

- A Model – predicts what the environment will do next
- $\mathcal{P}$ predicts the next states
- $\mathcal{R}$ predicts the next (intermediate) rewards
  - Agent may have an internal model of the environment
  - Dynamics: how actions change the state
  - Rewards: How much reward from each state

- Categorizing RL agents
  - Value Based
    - No policy (implicit)
    - Value function
  - Policy Based
    - Policy
    - No Value Function
  - Actor Critic model
    - Policy
    - Value Function

# RL Algorithms

Maze example: Value function and Model




- Grid layout represents the transition model $\mathcal{P}_{ss'}^{a}$
- Numbers represents immediate reward $\mathcal{R}_{s}^{a}$

- Categorizing RL agents
  - Model Free
    - Policy and/or Value Function; No model; Example: Dynamic Programming (DP)
  - Model Based
    - Policy and or Value Function; Model; ex. Temporal Difference and Monte Carlo

# Algorithms for RL

- Dynamic Programming
  - Model based approach;
- Temporal Difference and Monte Carlos
  - Model-free (simulation) – explicitly models the dynamics of the environment

- Mechanisms of RL algorithms
  - Learn by incrementally updating the expected Q-values for each action pairs, estimating the Bellman optimality equation
    - Initialize Q-values to arbitrary value
    - Visualize process as a matrix of states vs actions
    - Update state-action pair $Q_k$ for each iteration $k$

  - Equation form

$$NewEstimate \leftarrow OldEstimate + StepSize[Target - OldEstimate] \qquad (3.12)$$

Where Step-size – Learning rate $(\alpha)$; $[Target\ - OldEstimate]$ – error to achieve $Q^*$

# Algorithms for RL

| | $s_1$ | $s_2$ | $s_3$ | $s_4$ |
|---|---|---|---|---|
| $a_1$ | 0.0 | 0.0 | 0.0 | 0.0 |
| $a_2$ | 0.0 | 0.0 | 0.0 | 0.0 |
| $a_3$ | 0.0 | 0.0 | 0.0 | 0.0 |

Initialized state

$\pi^*$

Optimal policy selects $a$ with highest expecte d value in each state $s$

| | $s_1$ | $s_2$ | $s_3$ | $s_4$ |
|---|---|---|---|---|
| $a_1$ | 2.40 | 1.80 | **4.05** | 0.46 |
| $a_2$ | **3.67** | 1.38 | 2.01 | **2.78** |
| $a_3$ | 0.9 | **2.90** | 2.52 | 1.24 |

Terminal state

- Stopping criterion: Q-value convergence [difference ≤ some threshold

# DP vs TD – Differences

- DP - Difference based on update of Q-values
  - Updates Q-value *off-line for every* possible state action pair in a single iteration
  - Requires explicitly model of the dynamics of the environment
    - Transition function fully defines the probability of moving from state $s \rightarrow s'$
    - Given transition probability and reward functions: $P(s'|s,a); R(s,a)$ we can:

$$Q_t(s,a) \leftarrow R(s,a) + \sum_{s'} P(s'|s,a) \max_{a} Q_t(s',a') \qquad (3.13)$$

- TP – Model-free
  - No need for full model of the transition function
  - Requires some sample episodes of state transitions; not all
    - Requires online exploration of large state-action pairs
    - Only sampled transitions contribute to improved $Q^*$; requires online exploration

$$Q_t(s,a) \leftarrow Q_t(s,a) + \alpha \left[ \underbrace{R(s,a) + Q_t(s',a')}_{Target} - \underbrace{Q_t(s,a)}_{OldEstimate} \right] \qquad (3.14)$$

# Advantages of TD Learning

- TD methods do not require a model of the environment, only experience
- TD, but not MC, methods can be fully incremental
  - You can learn before knowing the final outcome
    - Less memory
    - Less peak computation
  - You can learn without the final outcome
    - From incomplete sequences
- Both MC and TD converge (under certain assumptions), but which is faster?

# SARSA Algorithm

- Commonly used is SARSA ($\lambda$). $\lambda$ - eligibility trace factors to ensure rapid converge
- Reflects updating Q-values based on ($a_t$,$s_t$, $r_{t+1} a_{t+1}$ , $s_{t+1}$).
- Is a greedy method updating the policy be greedy w.r.t current estimate

**Algorithm 1** *SARSA*

```
Q(s,a) ⇐ arbitrarily

repeat {for each episode:}
    Initialise s
    Choose a from s using policy derived from Q (e.g. ε-greedy)
    for all steps in the episode do
        Take action a, observe r, s'
        Choose a' from s' using policy derived from Q (e.g. ε-greedy)
        Q(s,a) ← Q(s,a) + α[r + γQ(s',a') − Q(s,a)]
        s ← s'; a ← a';
    end for
until s is terminal
```

# Basic facts – So far

- What are do these exploration and exploitation strategies mean?
  - Offline – Data is fixed, agent learns from previous interaction
  - Online – agents interacts with environment including previously explored states
  - On-policy – Learns about policy currently executing

- Exploration – Find more information about the environment
- Exploitation – maximize/exploit know information to maximize reward

- Prediction: Evaluates the future for a given policy
- Control: Optimize the future, finding the best policy
- Learning: Using the history, predict (determine future) state while exploring the best policy [What, how, why, where]

# Curse of Dimensionality

- Is exponential growth of policies with state and action spaces
  - Four binary features and 3 action states = $3^{2^4} \rightarrow 43{,}046{,}721$ policies
- To reduce state space for learning proposed [many approaches]
  - Feature reduction; Reduction of possible state-action combinations; Summarizing similar states

# Dialogue - application

- Dialogue is represented as vector of real valued features $f(s)$ – learns function approximation; $f(s)$ is mapped to vector of estimate $Q(s,a)$
- Given the weight weights trained on data, Q-function is re-written as the inner product of state vector $f(s)$ and weighted vector $w_a$:

$$Q^{\pi}(s,a) = f(s)^T w_a = \sum_i f(s) w_{ai} \tag{3.15}$$

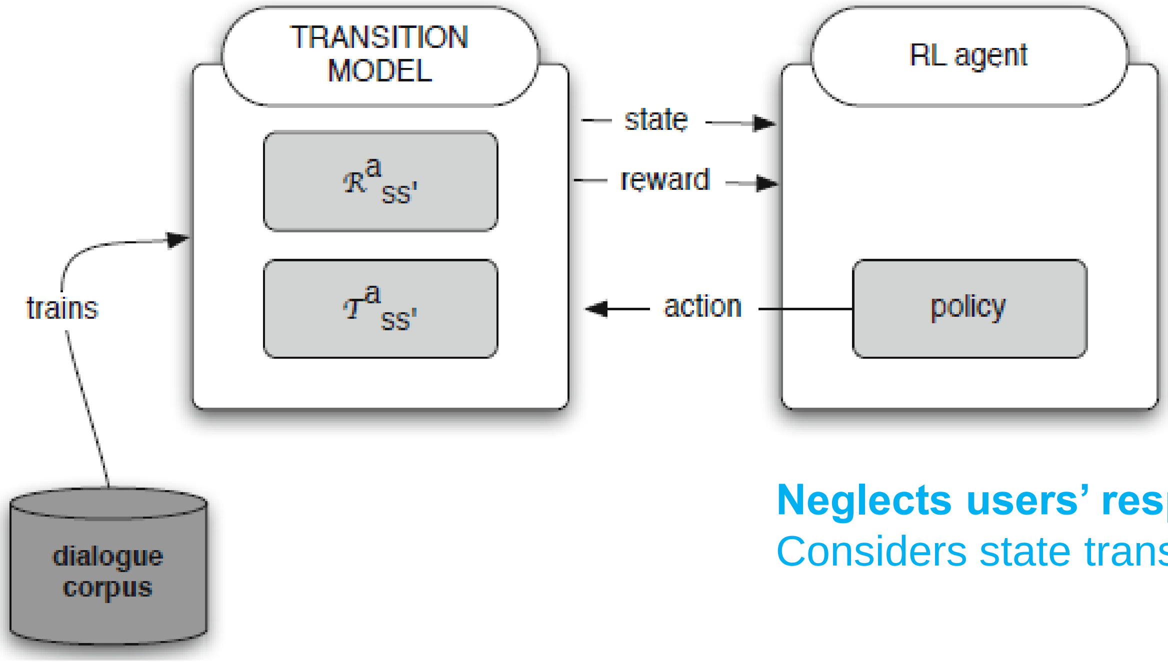
- Two are treated as similar if they share features – affected in training
- Similarity measure is called Linear Kernel

- Simulation-based RL offers cheap learning by training the policy

# So far ….

- Agent-environment interaction
  - States
  - Actions
  - Rewards
- Policy: stochastic rule for selecting actions
- Return: the function of future rewards the agent tries to maximize
- Episodic and continuing tasks
- Markov Property
- Markov Decision Process
  - Transition probabilities
  - Expected rewards
- Value functions
  - State-value function for a policy
  - Action-value function for a policy
  - Optimal state-value function
  - Optimal action-value function
- Optimal value functions
- Optimal policies
- Bellman Equations
- The need for approximation

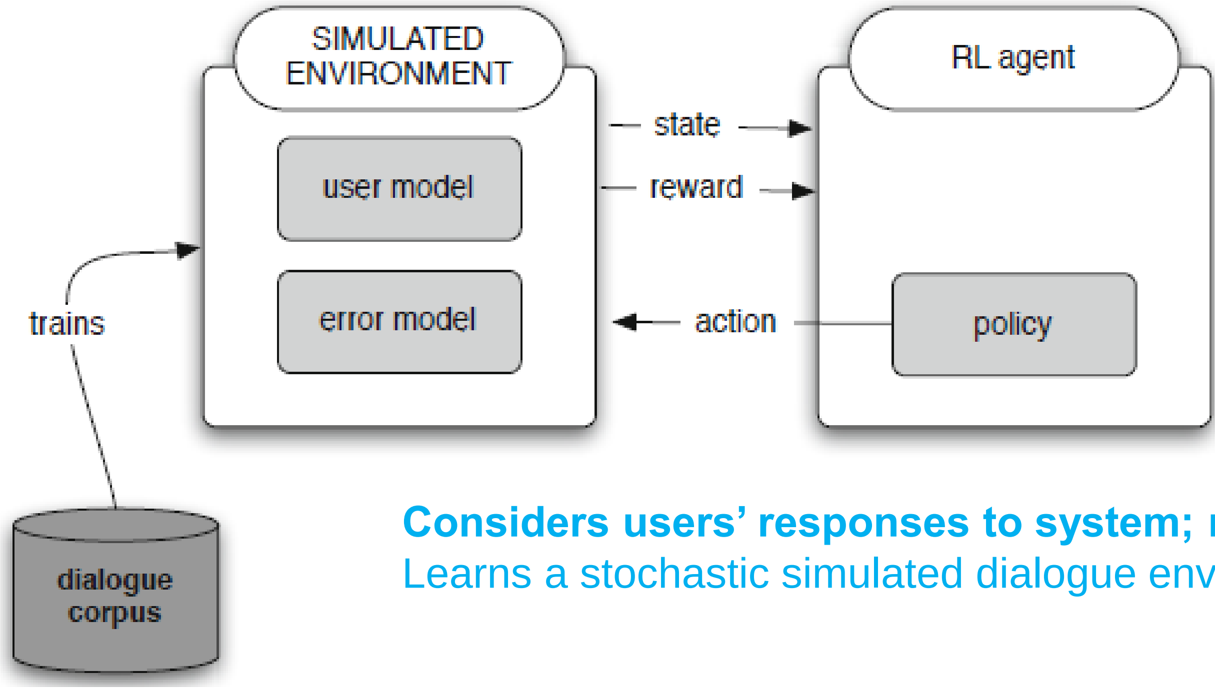
# Model-based RL




**Neglects users' responses to system**
Considers state transitions and rewards only

- Approaches explicitly models dynamics of environment; learning via off-line [limited agent-environment interaction]
- Limitation: Corpora not large enough all transition probabilities; learning limited to explored a-s combinations [inflexibility]; learning from fixed data – working systems already exist – What system do we need?

# Model-based RL




**Considers users' responses to system; model the future**
Learns a stochastic simulated dialogue environment from data

- Involves two phases: Simulated environment and RL agent (DS)
  - SE including components – trained via SL; includes user and error model [Dual architecture, CLS -> differential training];
  - Dialogue strategy training – trained by simulated MC or TD for systematic exploration, near optimal solution exploration; generalize unseen dialogue states

# Simulation-Based RL

- Model-free approach that directly approximates value function via online interaction;

- Advantages
  - Large training episodes generated – exhaustive strategies exploration
  - Exploration of strategies not in the training data [Unseen strategies exploration]
  - No prior fixing of state space and actions – dynamic scaling & modeling of dialogue

- Challenges
  - Quality of learned strategy depends on quality of simulated environment
  - Reward signal not readable from data; yet reward function must explicitly constructed
  - Simulation results inability to replicate real user-dialogue performance
  - Simulated components need in-domain data training – expensive to collect & train

- Hence generalizability and automatic dialogue learning feasible

# Dialogue Simulation – WOZ

- Goal of Wizard-of- Oz: Characterize human behavior and user preferences; develop a language model and/or acoustic model for prototype system

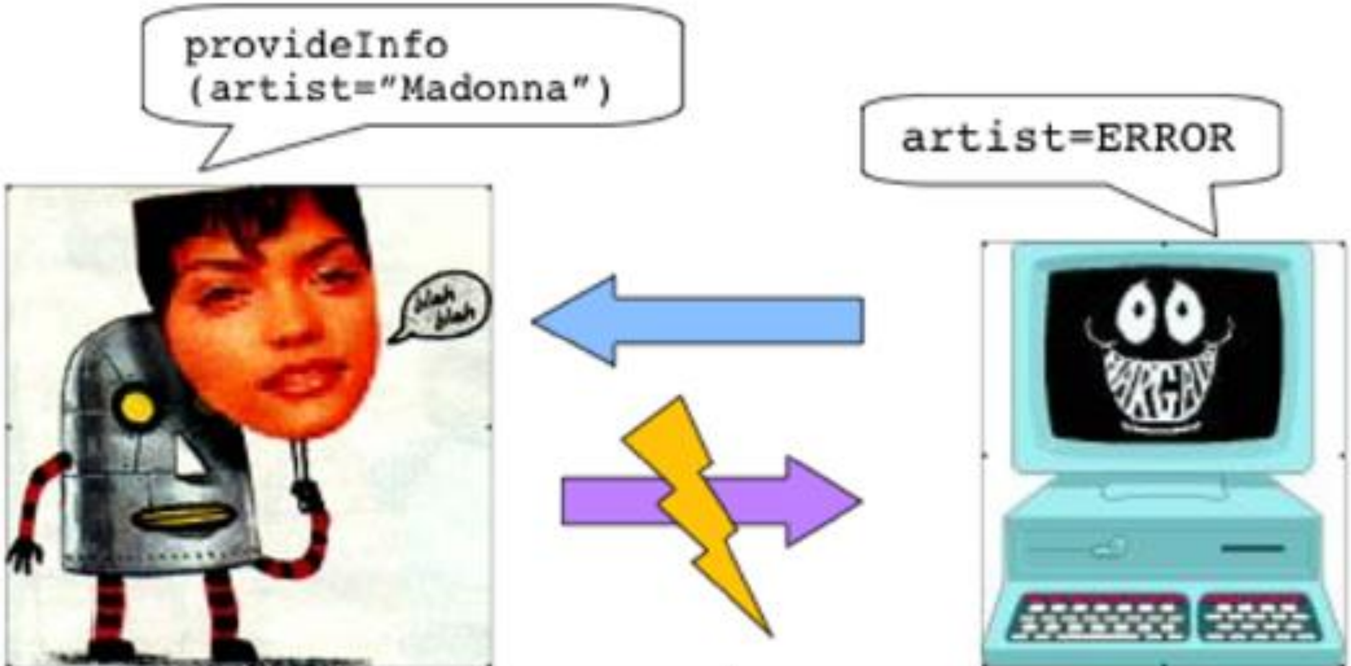
- Procedure: Simulate, evaluate, generalize – development system
  - Hidden operator (wizard) simulates some aspects of human behavior in dialogue [ensure real HCI illusion considering human dynamics in communication]
  - Subjects evaluate by filling out questionnaires
  - Generalize human behavior, develop models

- Dialogue simulation need to be able to approximate real HCI in order to facilitate dialogue system development and testing

# Wizard of Oz simulation


Wizard simulates dialogue behavior; user interacts in they are talking to the belief that they are talking to a machine, rates a machine and rates the dialogue behavior

# DS: Computer Based Simulation




$$a_u \rightarrow \tilde{s}_u \rightarrow \tilde{a}_s \rightarrow a_s$$

Dialogue manager interacts with a simulated user over a noisy channel

# DS: Computer-based Simulation

- Goals: Testing and debugging prototype systems; automatic strategy development [RL, SL]
- Error model: Simulates error prone ASR;
- Variation from real HCI due to:
  - Quality of simulated components
  - Simulated users cannot rate the system according to their preferences

- Discussion: Learnt Framework
  - Simulated Environment for RL from data collected in WOZ experiment
    - Enables automatic strategy learning

# Application Domains

- Information-Seeking Dialogue Systems
- Multimodal Output Planning and Information Presentation
- Multimodal Dialogue Systems for In-car digital Music Player

# Conclusion

- Learning – Interaction between agent and world
  - Percepts received by an agent acts and improves agent’s ability to behave optimally in the future to achieve the goal

- Reinforcement Learning – Achieve goal successfully
  - Learn how to behave successfully to achieve a goal while interacting with external environment, Learn via experience
    - Game playing – know when  its win  or loss

  - Well suited for dialogue strategy development – as dialogue is learned by evaluative feedback with delayed rewards and exploration