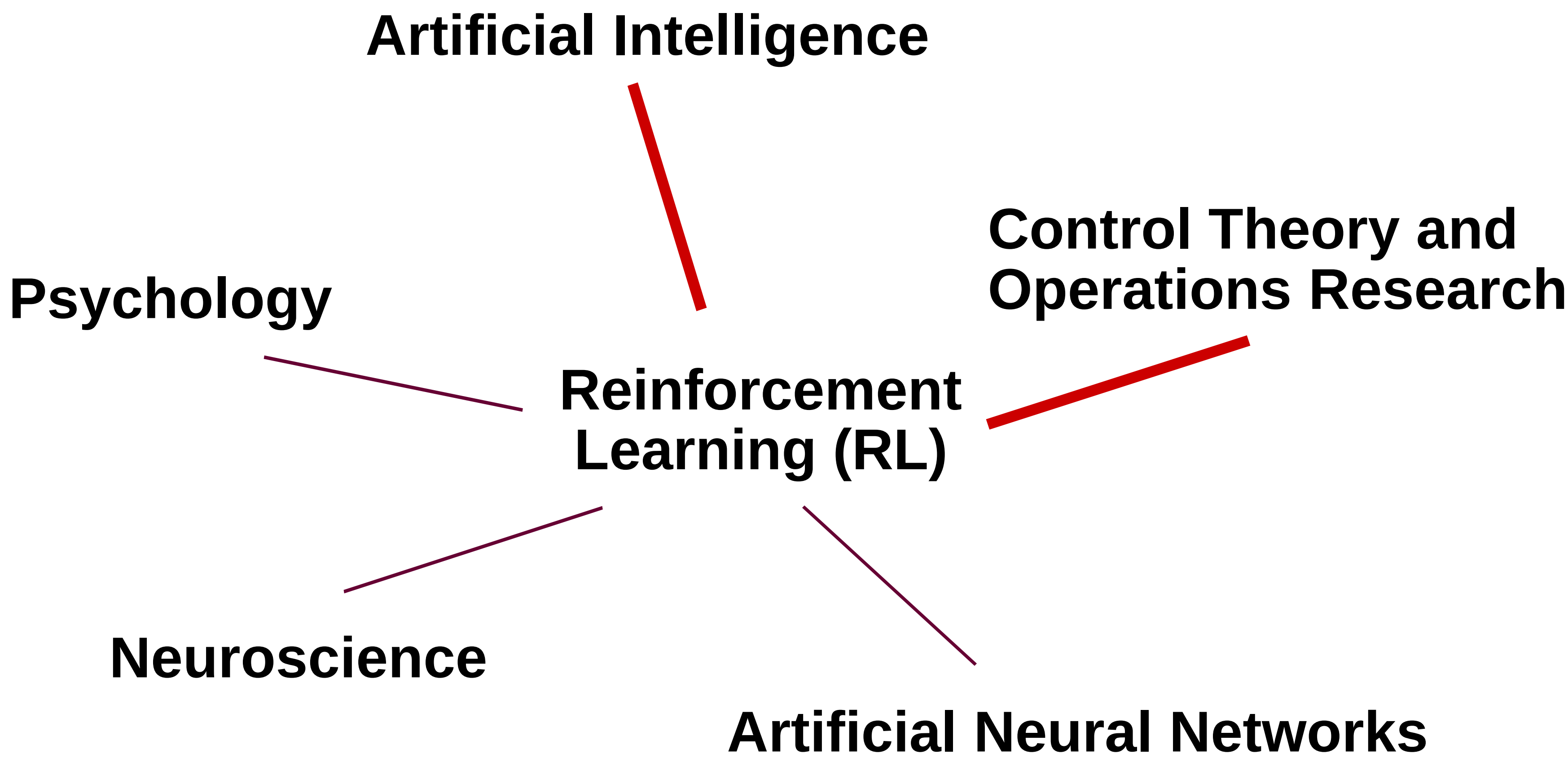
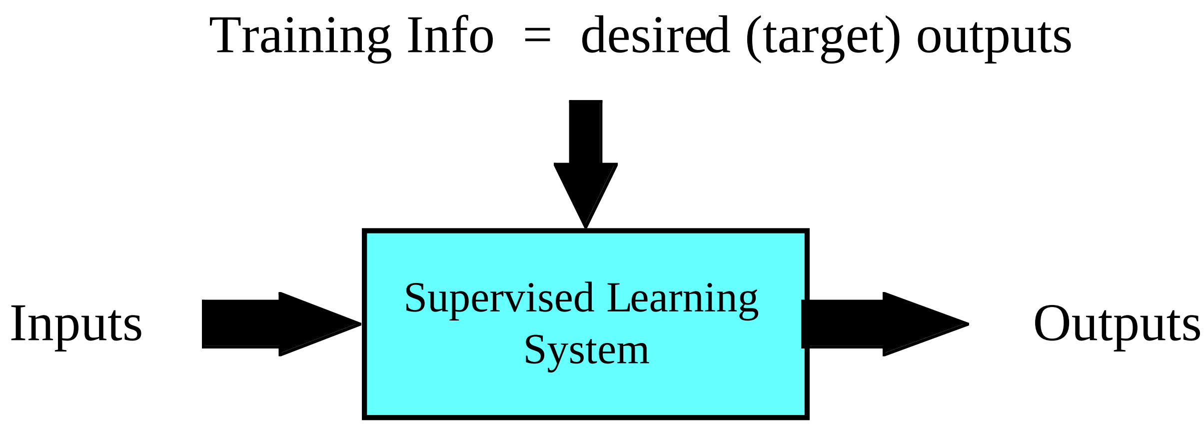
# Chapter 1: Introduction



# What is Reinforcement Learning?

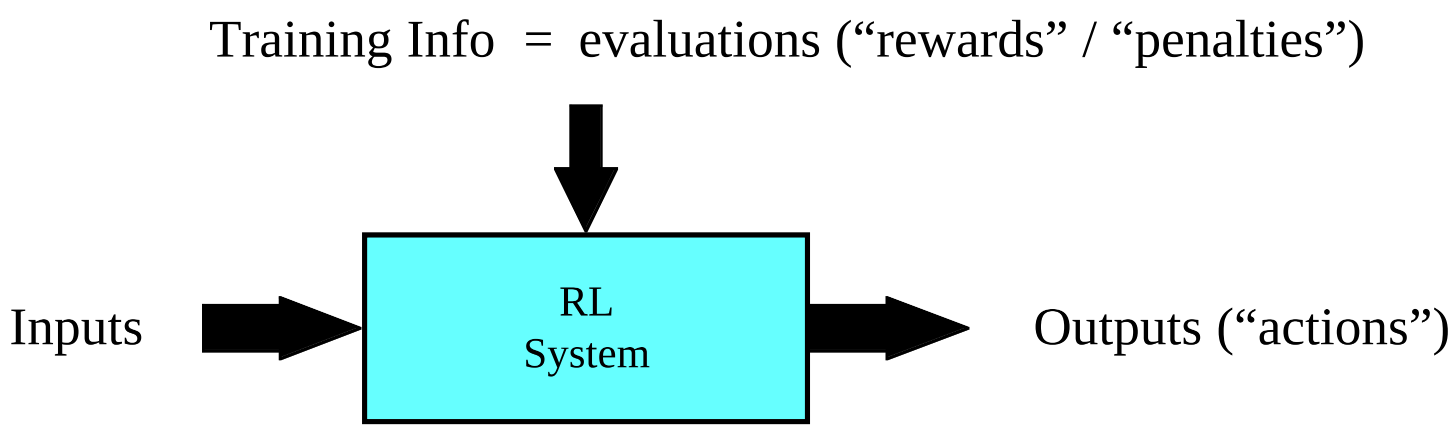
- Learning from interaction
- Goal-oriented learning
- Learning about, from, and while interacting with an external environment
- Learning what to do—how to map situations to actions—so as to maximize a numerical reward signal

# Supervised Learning




Error = (target output – actual output)

# Reinforcement Learning



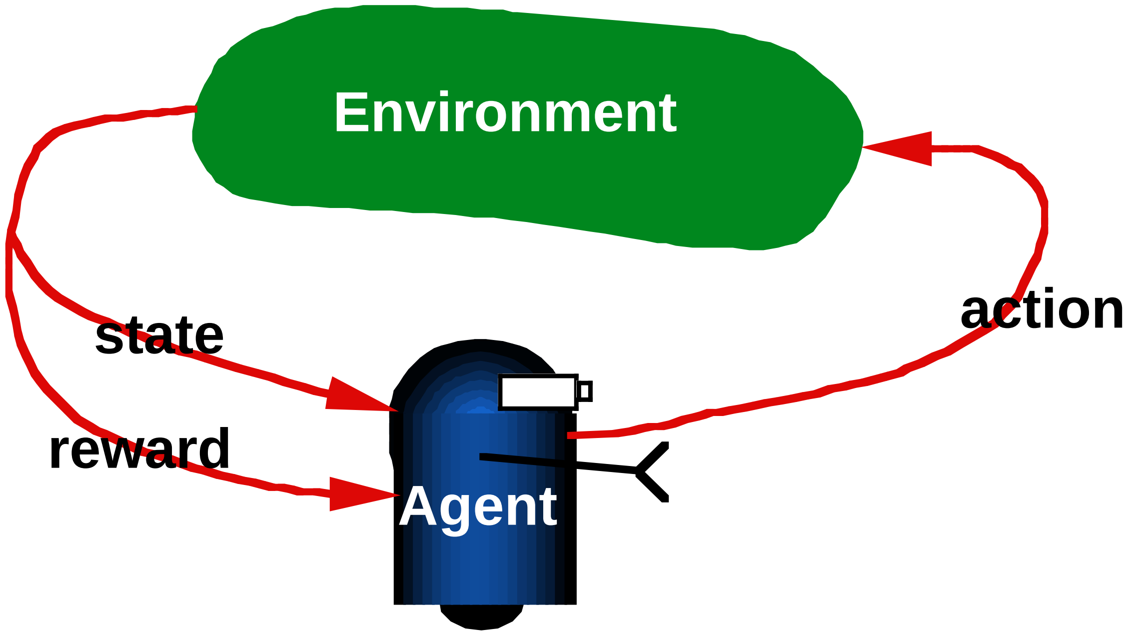

Objective: get as much reward as possible

# Key Features of RL

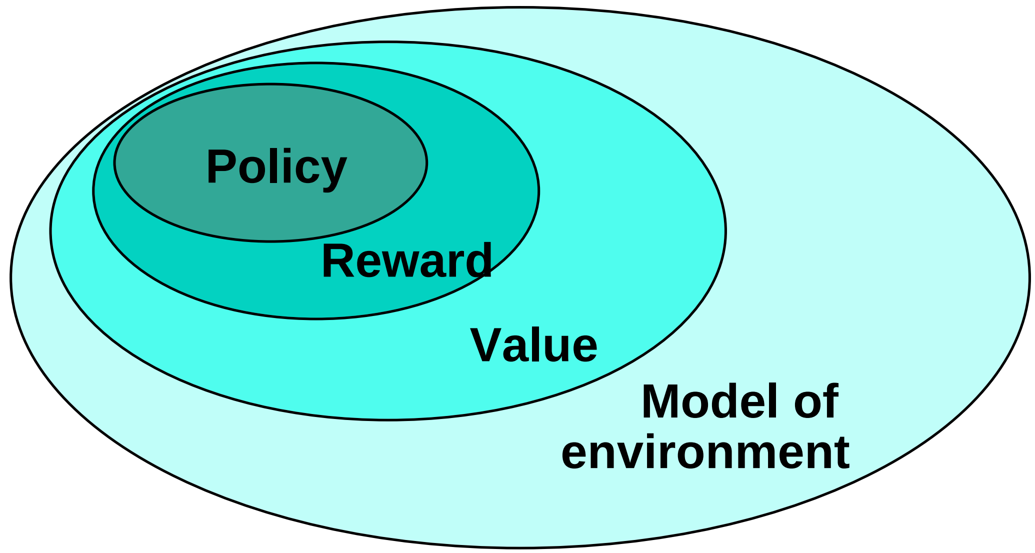
- Learner is not told which actions to take
- Trial-and-Error search
- Possibility of delayed reward
    - Sacrifice short-term gains for greater long-term gains
- The need to ***explore*** and ***exploit***
- Considers the whole problem of a goal-directed agent interacting with an uncertain environment

# Complete Agent

- Temporally situated
- Continual learning and planning
- Object is to ***affect*** the environment
- Environment is stochastic and uncertain

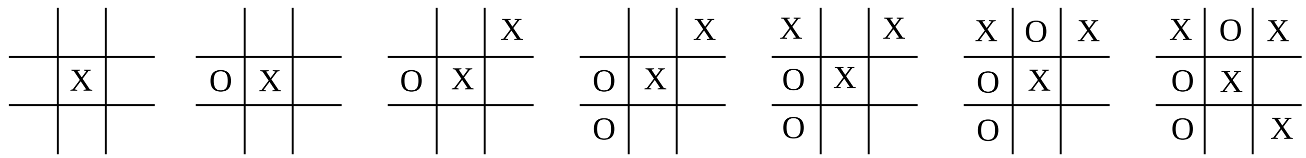


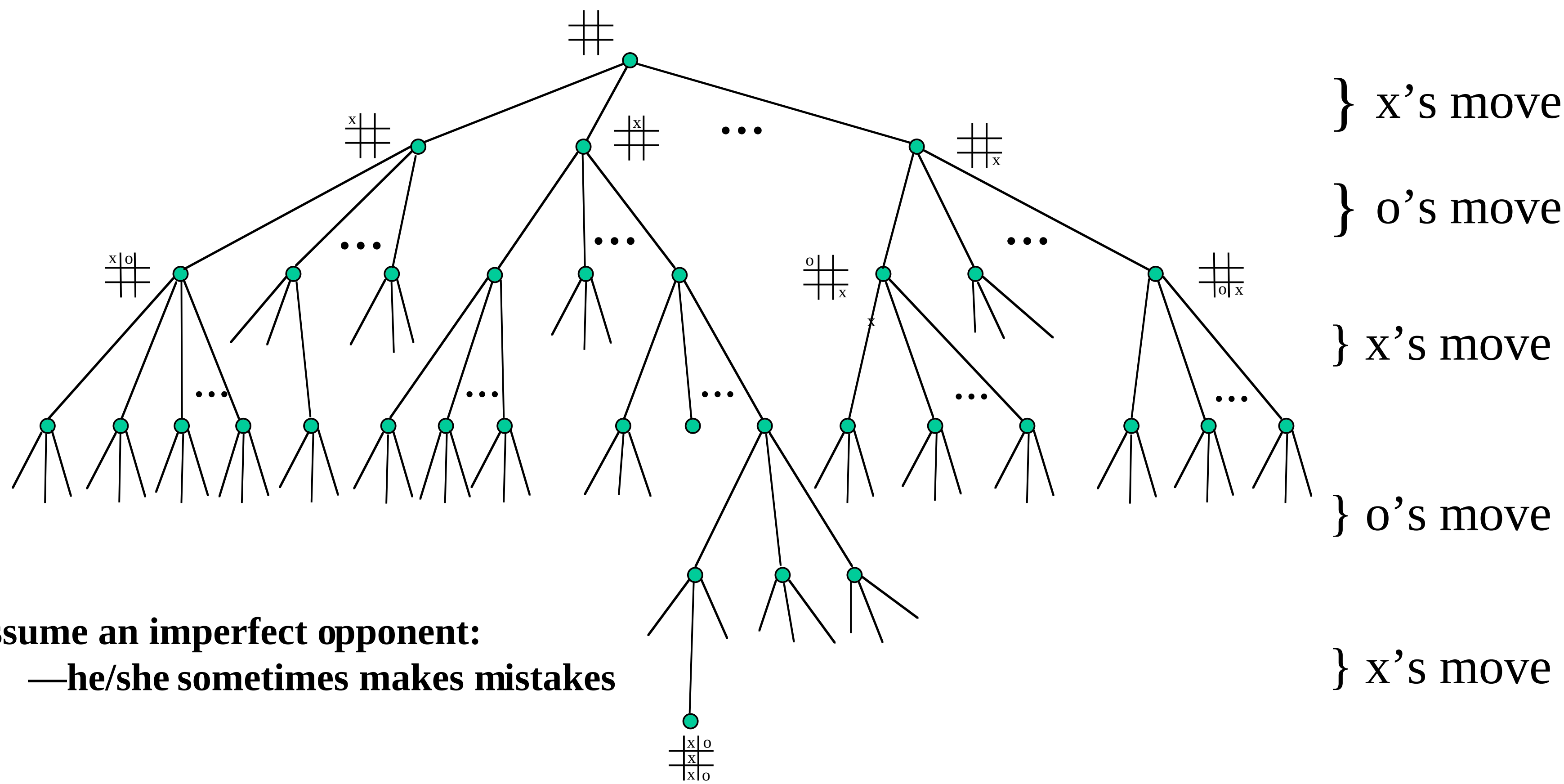
# Elements of RL




- **Policy**: what to do
- **Reward**: what is good
- **Value**: what is good because it *predicts* reward
- **Model**: what follows what

# An Extended Example: Tic-Tac-Toe

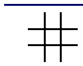
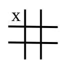
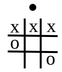
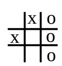
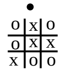




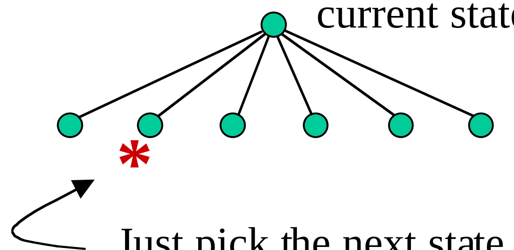

**Assume an imperfect opponent:**
**—he/she sometimes makes mistakes**

# An RL Approach to Tic-Tac-Toe

1. Make a table with one entry per state:

| State | $V(s)$ – estimated probability of winning | |
|---|---|---|
|  | .5 | ? |
|  | .5 | ? |
| ⋮ | ⋮ | |
|  | 1 | win |
| ⋮ | ⋮ | |
|  | 0 | loss |
| ⋮ | ⋮ | |
|  | 0 | draw |

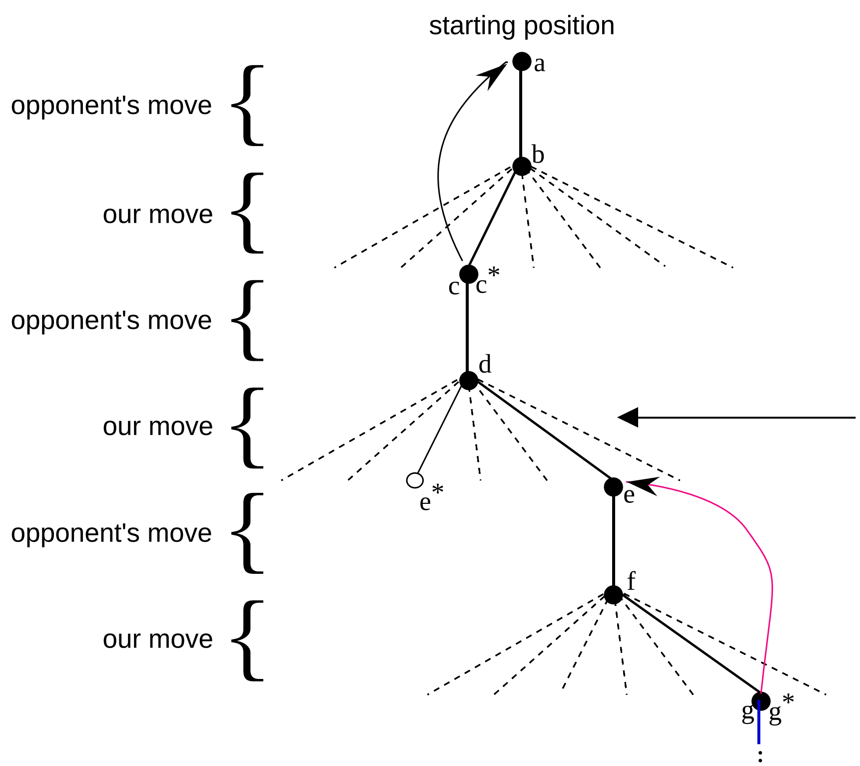
2. Now play lots of games.
To pick our moves,
look ahead one step:




Just pick the next state with the highest estimated prob. of winning — the largest $V(s)$; a ***greedy*** move.

But 10% of the time pick a move at random; an ***exploratory move***.

# RL Learning Rule for Tic-Tac-Toe




**“Exploratory” move**

$s$ – the state before our greedy move

$s'$ – the state after our greedy move

We increment each $V(s)$ toward $V(s')$ – a ***backup***:

$$V(s) \leftarrow V(s) + \alpha\big[V(s') - V(s)\big]$$

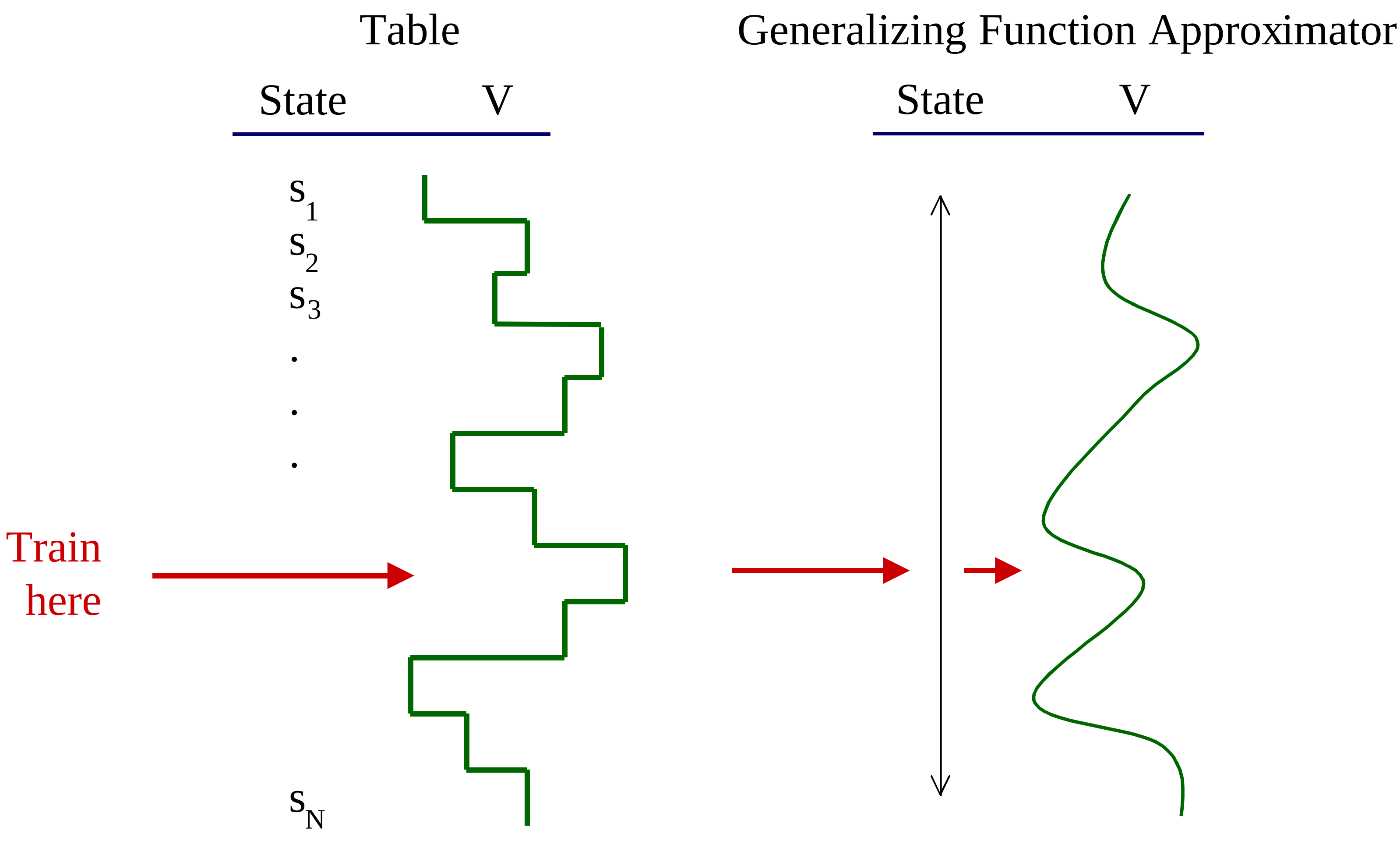
a small positive fraction, e.g., $\alpha = .1$

the ***step - size parameter***

# How can we improve this T.T.T. player?

- Take advantage of symmetries
  - representation/generalization
  - How might this backfire?
- Do we need “random” moves? Why?
  - Do we always need a full 10%?
- Can we learn from “random” moves?
- Can we learn offline?
  - Pre-training from self play?
  - Using learned models of opponent?
- . . .

# e.g. Generalization



# How is Tic-Tac-Toe Too Easy?

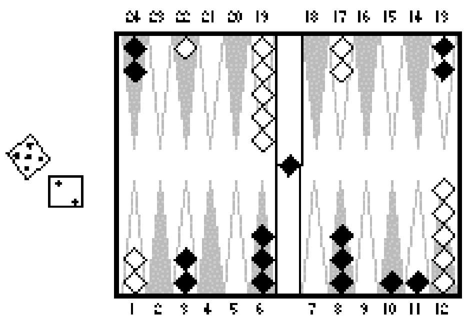
- Finite, small number of states
- One-step look-ahead is always possible
- State completely observable
- . . .

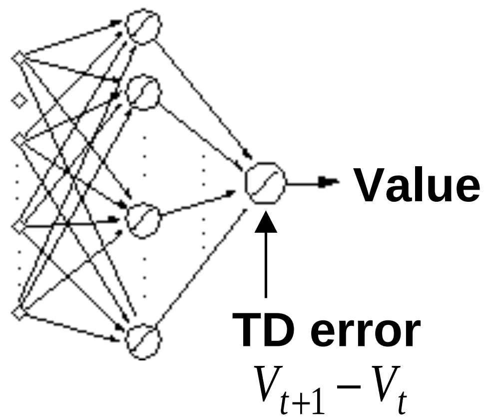
# Some Notable RL Applications

- **TD-Gammon**: Tesauro
  - world's best backgammon program
- **Elevator Control**: Crites & Barto
  - high performance down-peak elevator controller
- **Inventory Management**: Van Roy, Bertsekas, Lee&Tsitsiklis
  - 10–15% improvement over industry standard methods
- **Dynamic Channel Assignment**: Singh & Bertsekas, Nie & Haykin
  - high performance assignment of radio channels to mobile telephone calls

# TD-Gammon

**Tesauro, 1992–1995**






**Action selection by 2–3 ply search**

Start with a random network

Play very many games against self

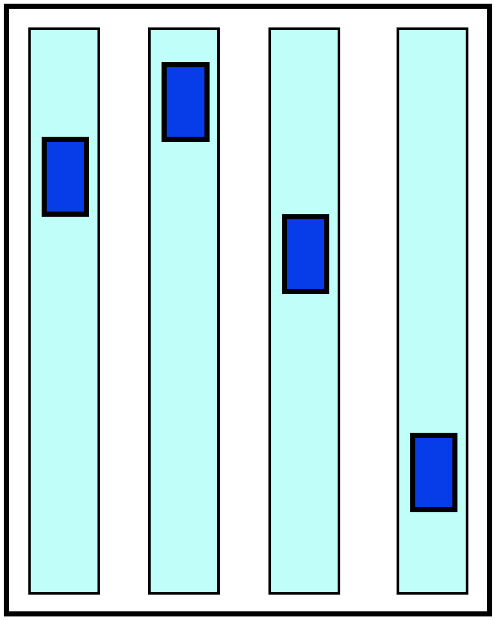
Learn a value function from this simulated experience

**This produces arguably the best player in the world**

# Elevator Dispatching

Crites and Barto, 1996

**10 floors, 4 elevator cars**



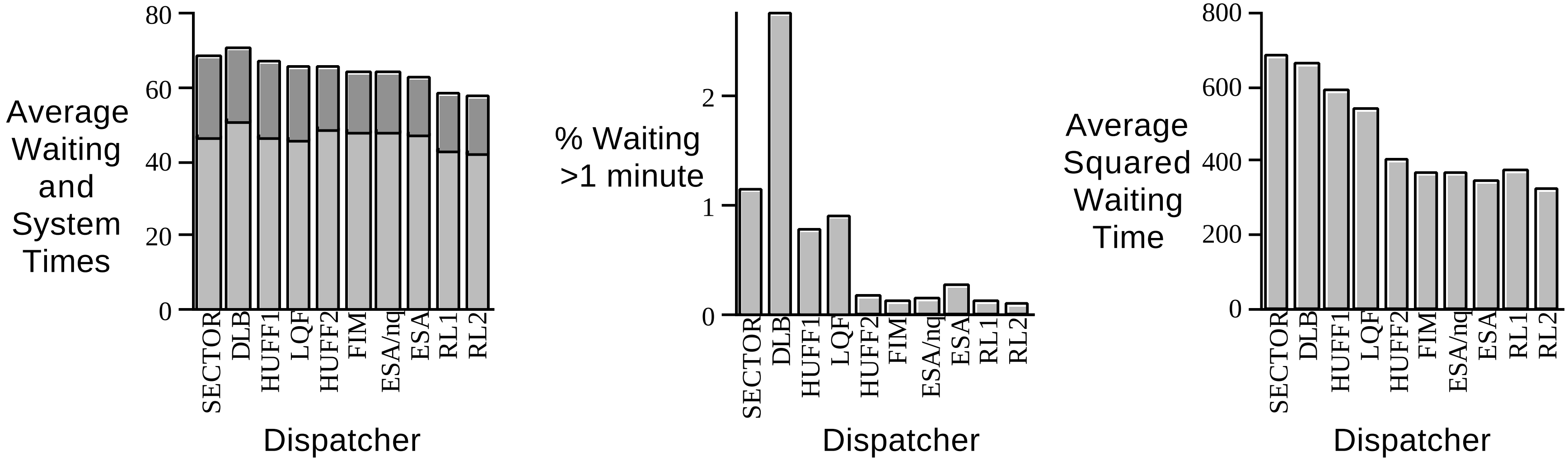
STATES: button states; positions, directions, and motion states of cars; passengers in cars & in halls

ACTIONS: stop at, or go by, next floor

REWARDS: roughly, –1 per time step for each person waiting

**Conservatively about $10^{22}$ states**

# Performance Comparison

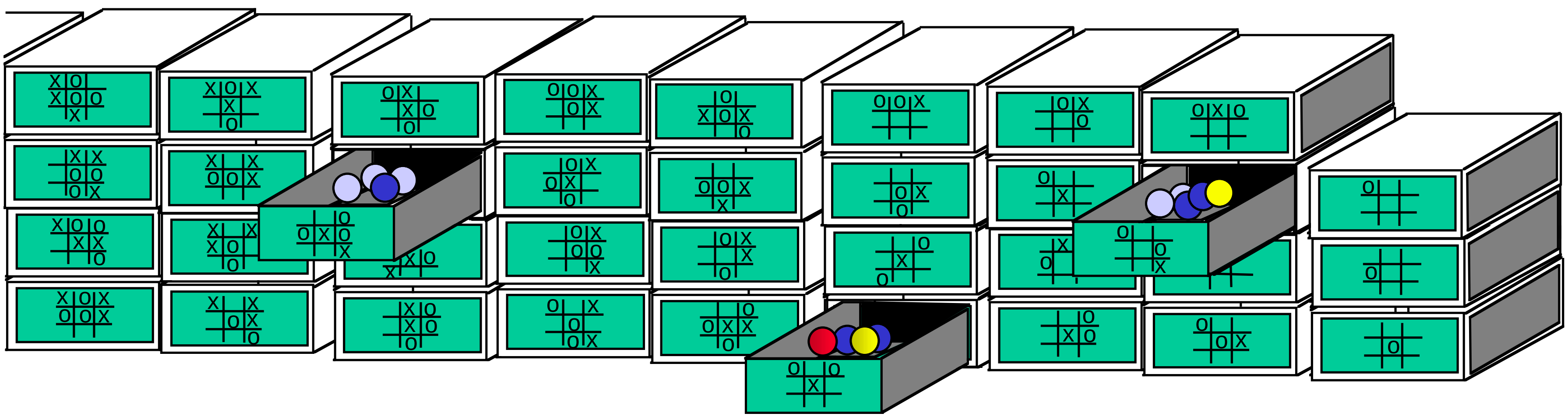


# Some RL History

| Trial-and-Error learning | Temporal-difference learning | Optimal control, value functions |
|---|---|---|
| Thorndike ($\Psi$)<br>1911 | Secondary reinforcement ($\Psi$) | Hamilton (Physics)<br>1800s |
| | | Shannon |
| Minsky | Samuel | Bellman/Howard (OR) |
| Klopf | Holland | |
| | Witten | Werbos |
| Barto et al. | | |
| | Sutton | |
| | | Watkins |

# MENACE (Michie 1961)

"Matchbox Educable Noughts and Crosses Engine"



# The Book

- Part I: The Problem
  - Introduction
  - Evaluative Feedback
  - The Reinforcement Learning Problem
- Part II: Elementary Solution Methods
  - Dynamic Programming
  - Monte Carlo Methods
  - Temporal Difference Learning
- Part III: A Unified View
  - Eligibility Traces
  - Generalization and Function Approximation
  - Planning and Learning
  - Dimensions of Reinforcement Learning
  - Case Studies

# The Course

- One chapter per week (with some exceptions)
- Read the chapter for the first class devoted to that chapter
- Written homeworks: basically all the non-programming assignments in each chapter. Due second class on that chapter.
- Programming exercises (not projects!): each student will do approximately 3 of these, including one of own devising (in consultation with instructor and/or TA).
- Closed-book, in-class midterm; closed-book 2-hr final
- Grading: 40% written homeworks; 30% programming homeworks; 15% final; 10% midterm; 5% class participation
- See the web for more details

# Next Class

- Introduction continued and some case studies
- Read Chapter 1
- Hand in exercises 1.1 — 1.5