RL for Large State Spaces: Value Function Approximation

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* Based in part on slides by Daniel Weld

Large State Spaces

- When a problem has a large state space we can not longer represent the V or Q functions as explicit tables
- Even if we had enough memory
  - Never enough training data!
  - Learning takes too long
- What to do??

Function Approximation

- Never enough training data!
  - Must generalize what is learned from one situation to other “similar” new situations
- Idea:
  - Instead of using large table to represent V or Q, use a parameterized function
    - The number of parameters should be small compared to number of states (generally exponentially fewer parameters)
  - Learn parameters from experience
  - When we update the parameters based on observations in one state, then our V or Q estimate will also change for other similar states
    - I.e. the parameterization facilitates generalization of experience

Linear Function Approximation

- Define a set of state features f1(s), …, fn(s)
  - The features are used as our representation of states
  - States with similar feature values will be considered to be similar

- A common approximation is to represent V*(s)* as a weighted sum of the features (i.e. a linear approximation)

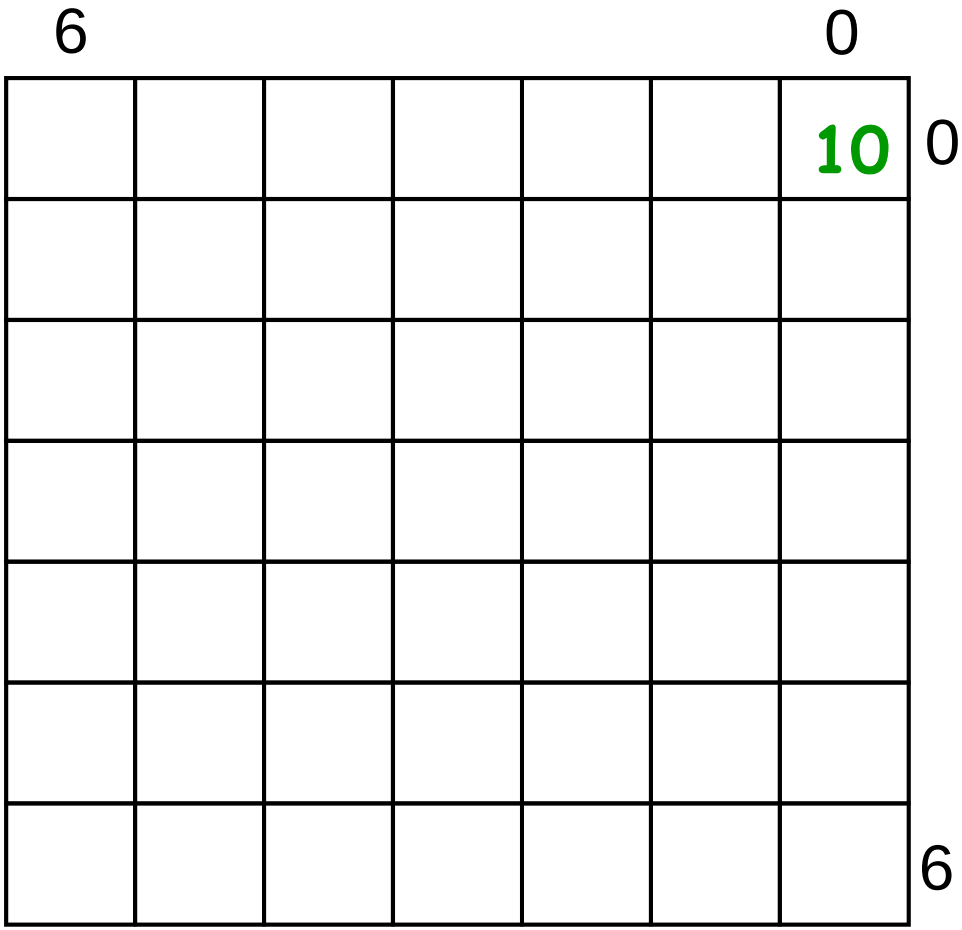
$$\hat{V}_\theta(s) = \theta_0 + \theta_1 f_1(s) + \theta_2 f_2(s) + \ldots + \theta_n f_n(s)$$

- The approximation accuracy is fundamentally limited by the information provided by the features

- Can we always define features that allow for a perfect linear approximation?
  - Yes. Assign each state an indicator feature. (I.e. i'th feature is 1 iff i'th state is present and θ_i represents value of i'th state)
  - Of course this requires far too many features and gives no generalization.

Example

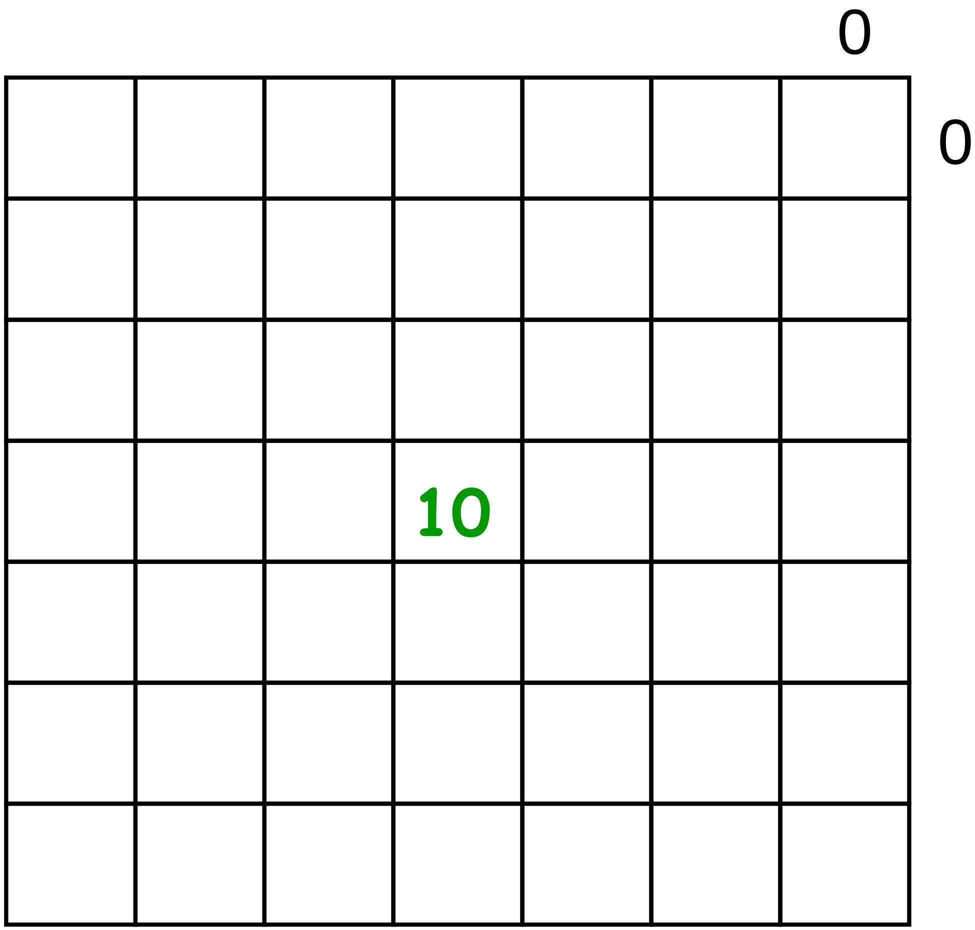
- Grid with no obstacles, deterministic actions U/D/L/R, no discounting, -1 reward everywhere except +10 at goal
- Features for state s=(x,y): f1(s)=x, f2(s)=y (just 2 features)
- $V(s) = \theta_0 + \theta_1 x + \theta_2 y$
- Is there a good linear approximation?
  - Yes.
  - $\theta_0 = 10$, $\theta_1 = -1$, $\theta_2 = -1$
  - (note upper right is origin)



- V(s) = 10 - x - y subtracts Manhattan dist. from goal reward

But What If We Change Reward …

- $V(s) = \theta_0 + \theta_1 x + \theta_2 y$
- Is there a good linear approximation?
  - No.

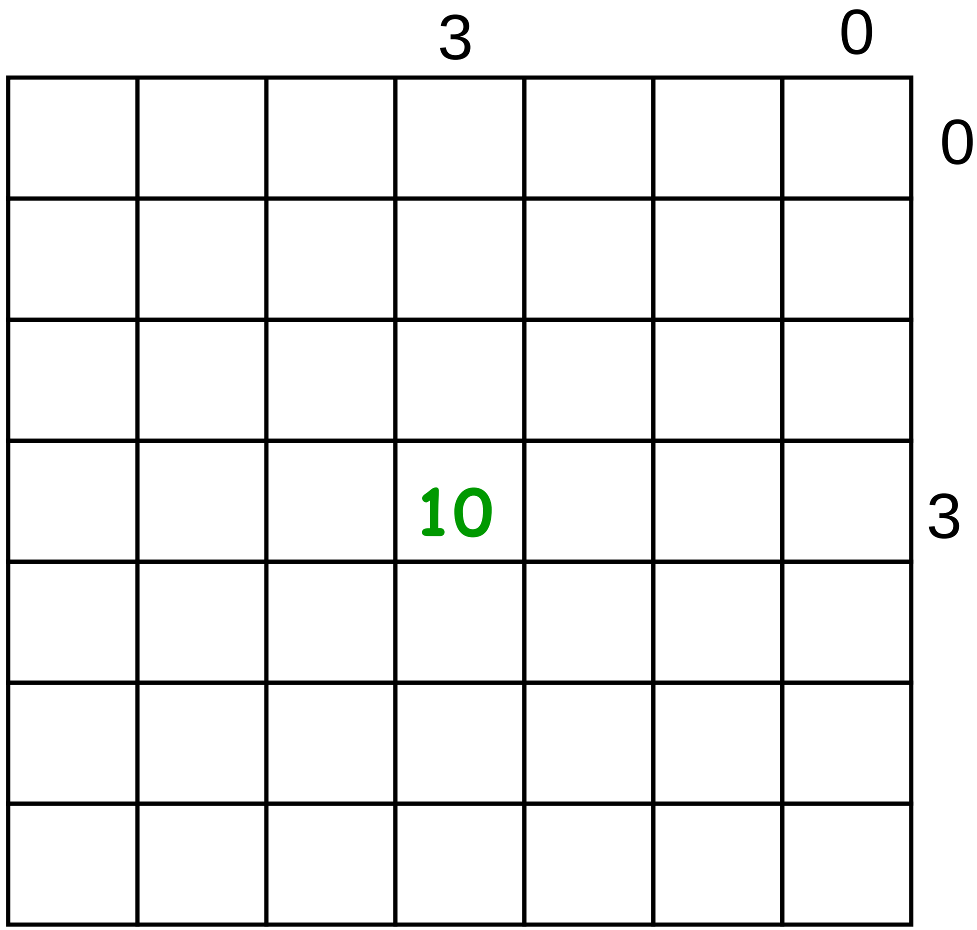


But What If…

- $V(s) = \theta_0 + \theta_1 x + \theta_2 y + \theta_3 z$

- Include new feature z
  - z= |3-x| + |3-y|
  - z is dist. to goal location

- Does this allow a good linear approx?
  - $\theta_0 = 10$, $\theta_1 = \theta_2 = 0$, $\theta_3 = -1$



Linear Function Approximation

- Define a set of features $f_1(s)$, …, $f_n(s)$
  - The features are used as our representation of states
  - States with similar feature values will be treated similarly
  - More complex functions require more complex features

$$\hat{V}_\theta(s) = \theta_0 + \theta_1 f_1(s) + \theta_2 f_2(s) + \ldots + \theta_n f_n(s)$$

- Our goal is to learn good parameter values (i.e. feature weights) that approximate the value function well
  - How can we do this?
  - Use TD-based RL and somehow update parameters based on each experience.

TD-based RL for Linear Approximators

1. Start with initial parameter values
2. Take action according to an explore/exploit policy (should converge to greedy policy, i.e. GLIE)
3. Update estimated model (if model is not available)
4. Perform TD update for each parameter

$$\theta_i \leftarrow ?$$

5. Goto 2

What is a "TD update" for a parameter?

Aside: Gradient Descent

- Given a function $E(\theta_1, \ldots, \theta_n)$ of n real values $\theta = (\theta_1, \ldots, \theta_n)$ suppose we want to minimize E with respect to θ
- A common approach to doing this is gradient descent
- The gradient of E at point θ, denoted by $\nabla_\theta E(\theta)$, is an n-dimensional vector that points in the direction where *f* increases most steeply at point θ
- Vector calculus tells us that $\nabla_\theta E(\theta)$ is just a vector of partial derivatives

$$\nabla_\theta E(\theta) = \left[\frac{\partial E(\theta)}{\partial \theta_1}, \ldots, \frac{\partial E(\theta)}{\partial \theta_n} \right]$$

where $$\frac{\partial E(\theta)}{\partial \theta_i} = \lim_{\varepsilon \to 0} \frac{E(\theta_1, \ldots \theta_{i-1}, \theta_i + \varepsilon, \theta_{i+1}, \ldots, \theta_n) - E(\theta)}{\varepsilon}$$

- Decrease E by moving θ in negative gradient direction

Aside: Gradient Descent for Squared Error

- Suppose that we have a sequence of states and target values for each state $\langle s_1, v(s_1) \rangle, \langle s_2, v(s_2) \rangle, \ldots$
  - E.g. produced by the TD-based RL loop
- Our goal is to minimize the sum of squared errors between our estimated function and each target value:

$$E_j(\theta) = \frac{1}{2}\left(\hat{V}_\theta(s_j) - v(s_j)\right)^2$$

squared error of example j

our estimated value for j'th state

target value for j'th state

- After seeing j'th state the **gradient descent rule** tells us that we can decrease error wrt $E_j(\theta)$ by updating parameters by:

$$\theta_i \leftarrow \theta_i - \alpha \frac{\partial E_j}{\partial \theta_i}$$

learning rate

Aside: continued

$$\theta_i \leftarrow \theta_i - \alpha \frac{\partial E_j}{\partial \theta_i} = \theta_i - \alpha \frac{\partial E_j}{\partial \hat{V}_\theta(s_j)} \frac{\partial \hat{V}_\theta(s_j)}{\partial \theta_i}$$

$$E_j(\theta) = \frac{1}{2}\left(\hat{V}_\theta(s_j) - v(s_j)\right)^2$$

$$\hat{V}_\theta(s_j) - v(s_j)$$

depends on form of approximator

- For a linear approximation function:

$$\hat{V}_\theta(s) = \theta_1 + \theta_1 f_1(s) + \theta_2 f_2(s) + \ldots + \theta_n f_n(s)$$

$$\frac{\partial \hat{V}_\theta(s_j)}{\partial \theta_i} = f_i(s_j)$$

- Thus the update becomes: $\theta_i \leftarrow \theta_i + \alpha\left(v(s_j) - \hat{V}_\theta(s_j)\right) f_i(s_j)$
- For linear functions this update is guaranteed to converge to best approximation for suitable learning rate schedule

TD-based RL for Linear Approximators

1. Start with initial parameter values
2. Take action according to an explore/exploit policy (should converge to greedy policy, i.e. GLIE) Transition from s to s'
3. Update estimated model
4. Perform TD update for each parameter

$$\theta_i \leftarrow \theta_i + \alpha\left(v(s) - \hat{V}_\theta(s)\right) f_i(s)$$

5. Goto 2

What should we use for "target value" v(s)?

- Use the TD prediction based on the next state s'

$$v(s) = R(s) + \beta \hat{V}_\theta(s')$$

this is the same as previous TD method only with approximation

TD-based RL for Linear Approximators

1. Start with initial parameter values
2. Take action according to an explore/exploit policy (should converge to greedy policy, i.e. GLIE)
3. Update estimated model
4. Perform TD update for each parameter

$$\theta_i \leftarrow \theta_i + \alpha\Big(R(s) + \beta\hat{V}_\theta(s') - \hat{V}_\theta(s)\Big) f_i(s)$$

5. Goto 2

- Step 2 requires a model to select greedy action
- For some applications (e.g. Backgammon) it is easy to get a compact model representation (but not easy to get policy), so TD is appropriate.
- For others it is difficult to small/compact model representation

Q-function Approximation

- Define a set of features over state-action pairs: $f_1(s,a), \ldots, f_n(s,a)$
  - State-action pairs with similar feature values will be treated similarly
  - More complex functions require more complex features

$$\hat{Q}_\theta(s,a) = \theta_0 + \theta_1 f_1(s,a) + \theta_2 f_2(s,a) + \ldots + \theta_n f_n(s,a)$$

Features are a function of states and actions.

- Just as for TD, we can generalize Q-learning to update the parameters of the Q-function approximation

Q-learning with Linear Approximators

1. Start with initial parameter values
2. Take action a according to an explore/exploit policy (should converge to greedy policy, i.e. GLIE) transitioning from s to s'
3. Perform TD update for each parameter

$$\theta_i \leftarrow \theta_i + \alpha\Big(\underbrace{R(s) + \beta \max_{a'} \hat{Q}_\theta(s',a')}_{\text{estimate of Q(s,a) based on observed transition}} - \hat{Q}_\theta(s,a)\Big) f_i(s,a)$$

4. Goto 2

estimate of Q(s,a) based
on observed transition

- TD converges close to minimum error solution
- Q-learning can diverge. Converges under some conditions.

Defining State-Action Features

- Often it is straightforward to define features of state-action pairs (example to come)
- In other cases it is easier and more natural to define features on states $f_1(s)$, …, $f_n(s)$
  - Fortunately there is a generic way of deriving state-features from a set of state features
- We construct a set of *n* x |*A*| state-action features

$$f_{ik}(s,a) = \begin{cases} f_i(s), \; if \;\; a = a_k \\ 0, \; otherwise \end{cases} \qquad i \in \{1,..,n\}, k \in \{1,..,|A|\}$$

Defining State-Action Features

- This effectively replicates the state features across actions, and activates only one set of features based on which action is selected

- $\hat{Q}_\theta(s, a) = \sum_k \sum_i \theta_{ik} f_{ik}(s, a)$

$$= \sum_i \theta_{ik} f_{ik}(s, a_k), \quad \text{where } a = a_k$$

- Each action a_k has its own set of parameters $\{\theta_{ik}\}$.

Example: Tactical Battles in Wargus

- Wargus is real-time strategy (RTS) game
  - Tactical battles are a key aspect of the game

5 vs. 5

10 vs. 10

- **RL Task**: learn a policy to control *n* friendly agents in a battle against *m* enemy agents
  - Policy should be applicable to tasks with different sets and numbers of agents

Example: Tactical Battles in Wargus

- **States**: contain information about the locations, health, and current activity of all friendly and enemy agents
- **Actions**: Attack(F,E)
  - causes friendly agent F to attack enemy E
- **Policy**: represented via Q-function Q(s,Attack(F,E))
  - Each decision cycle loop through each friendly agent F and select enemy E to attack that maximizes Q(s,Attack(F,E))
- Q(s,Attack(F,E)) generalizes over any friendly and enemy agents F and E
  - We used a linear function approximator with Q-learning

Example: Tactical Battles in Wargus

$$\hat{Q}_\theta(s,a) = \theta_1 + \theta_1 f_1(s,a) + \theta_2 f_2(s,a) + \ldots + \theta_n f_n(s,a)$$

- Engineered a set of relational features
  $\{f_1$(s,Attack(F,E)), …., f_n(s,Attack(F,E))$\}$

- **Example Features**:
  - # of other friendly agents that are currently attacking E
  - Health of friendly agent F
  - Health of enemy agent E
  - Difference in health values
  - Walking distance between F and E
  - Is E the enemy agent that F is currently attacking?
  - Is F the closest friendly agent to E?
  - Is E the closest enemy agent to E?
  - …

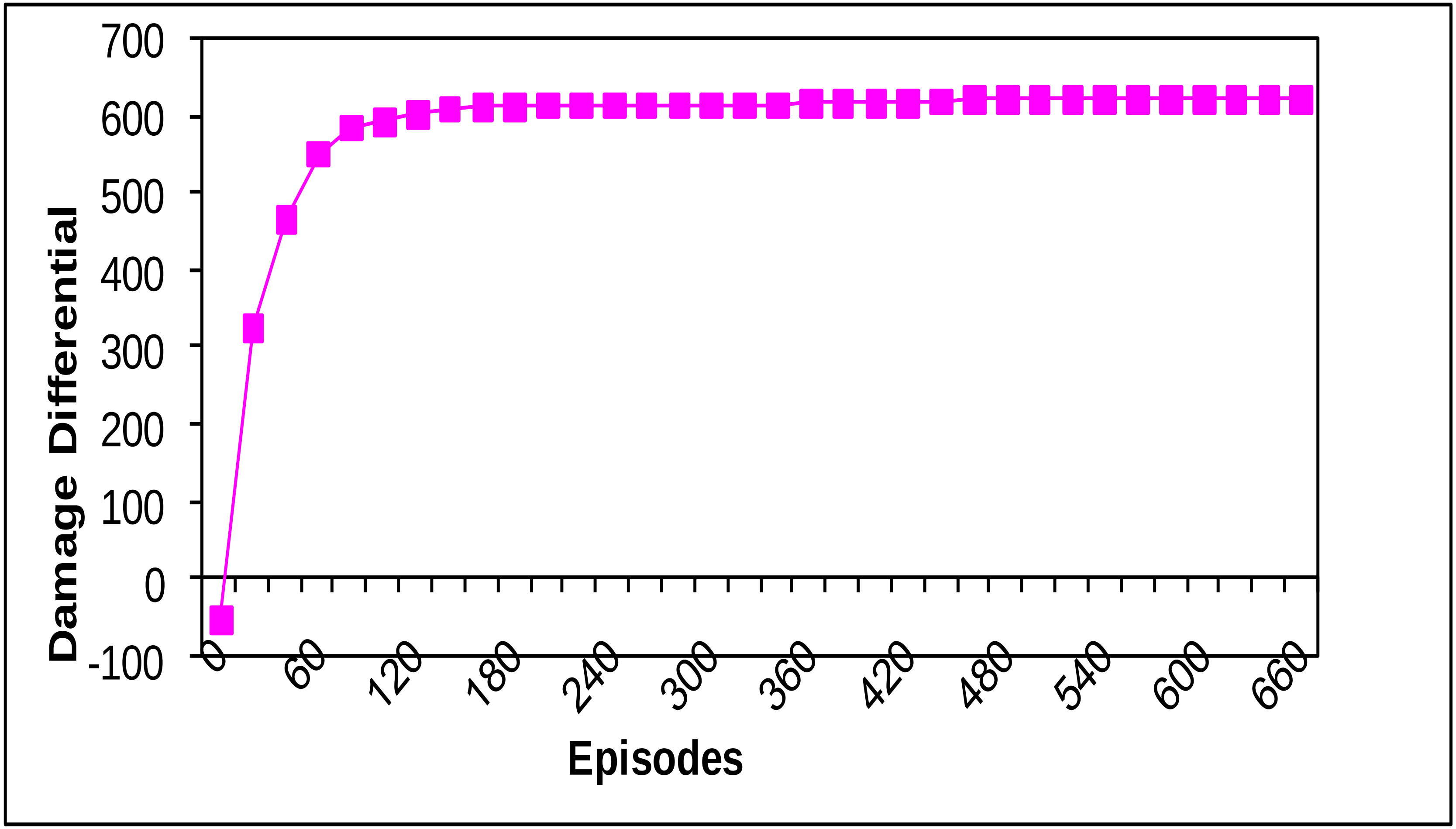
- Features are well defined for any number of agents

Example: Tactical Battles in Wargus

Initial random policy

Example: Tactical Battles in Wargus

- Linear Q-learning in 5 vs. 5 battle



Example: Tactical Battles in Wargus

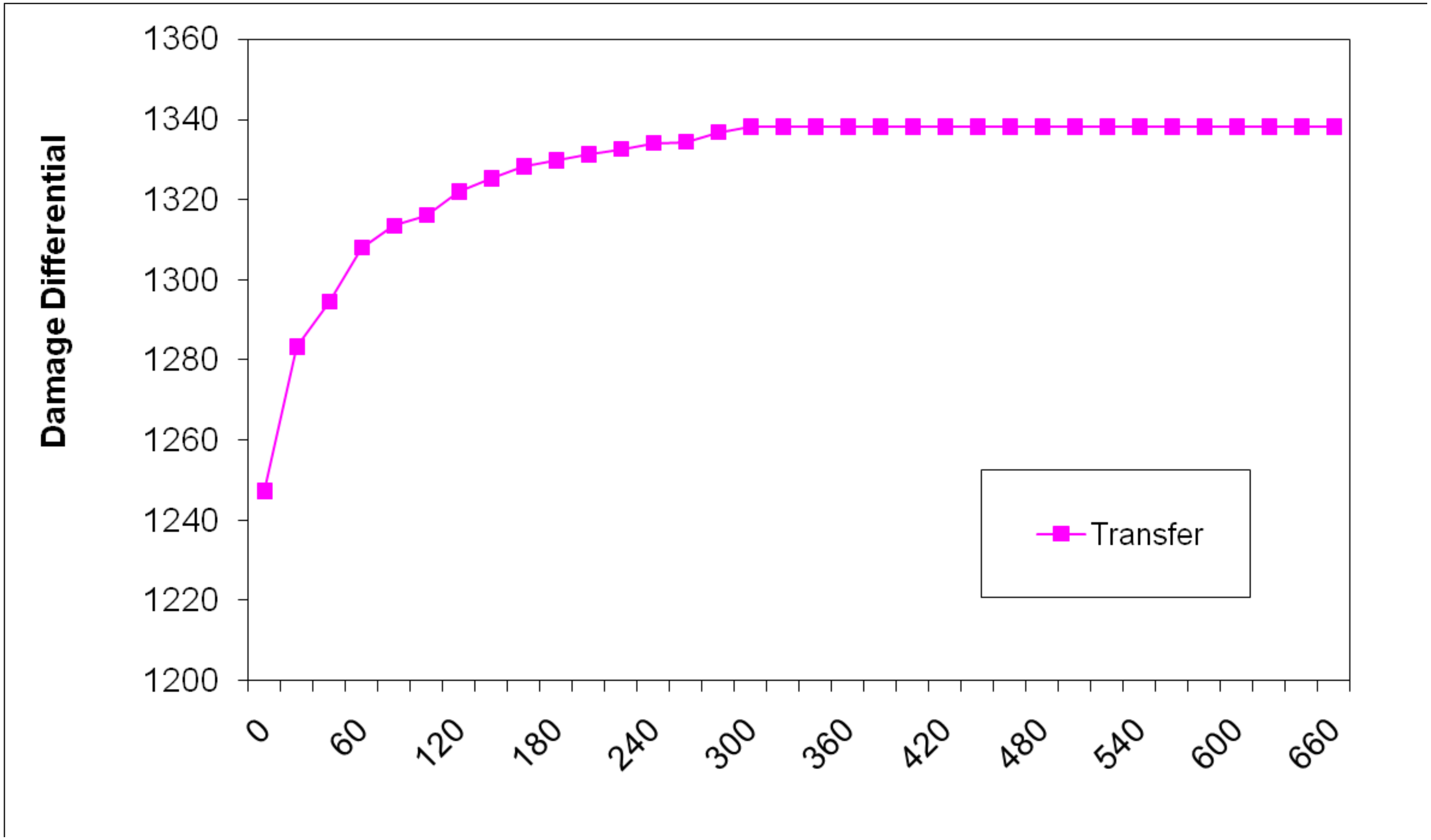
Learned Policy after 120 battles

Example: Tactical Battles in Wargus

10 vs. 10 using policy learned on 5 vs. 5

Example: Tactical Battles in Wargus

- Initialize Q-function for 10 vs. 10 to one learned for 5 vs. 5
  - Initial performance is very good which demonstrates generalization from 5 vs. 5 to 10 vs. 10



Q-learning w/ Non-linear Approximators

$\hat{Q}_\theta(s,a)$ is sometimes represented by a non-linear approximator such as a neural network

1. Start with initial parameter values
2. Take action according to an explore/exploit policy (should converge to greedy policy, i.e. GLIE)
3. Perform TD update for each parameter

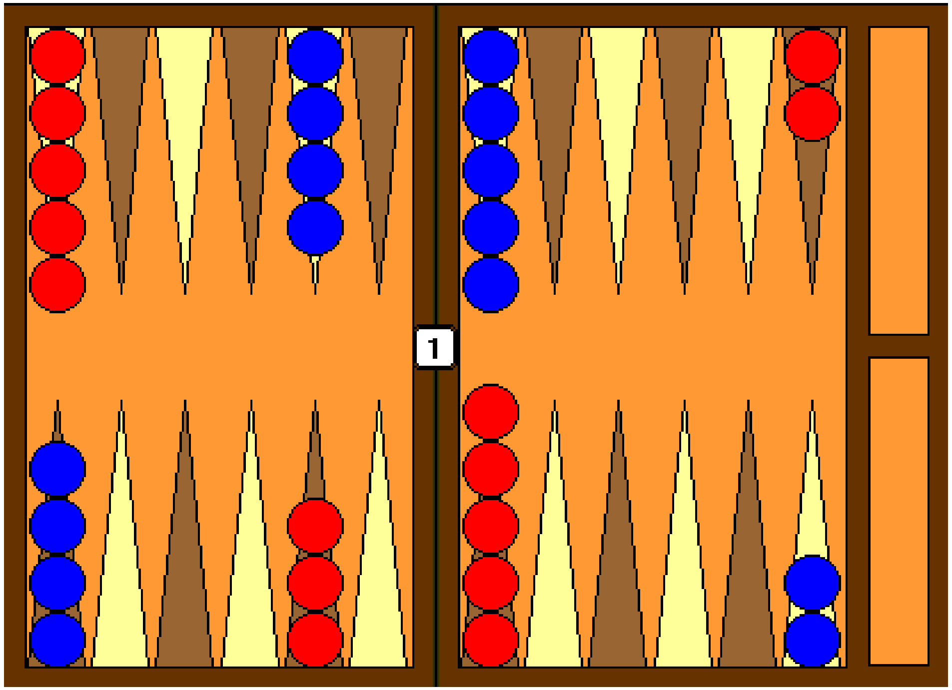
$$\theta_i \leftarrow \theta_i + \alpha\left(R(s) + \beta \max_{a'} \hat{Q}_\theta(s',a') - \hat{Q}_\theta(s,a)\right)\frac{\partial \hat{Q}_\theta(s,a)}{\partial \theta_i}$$

calculate closed-form

4. Goto 2

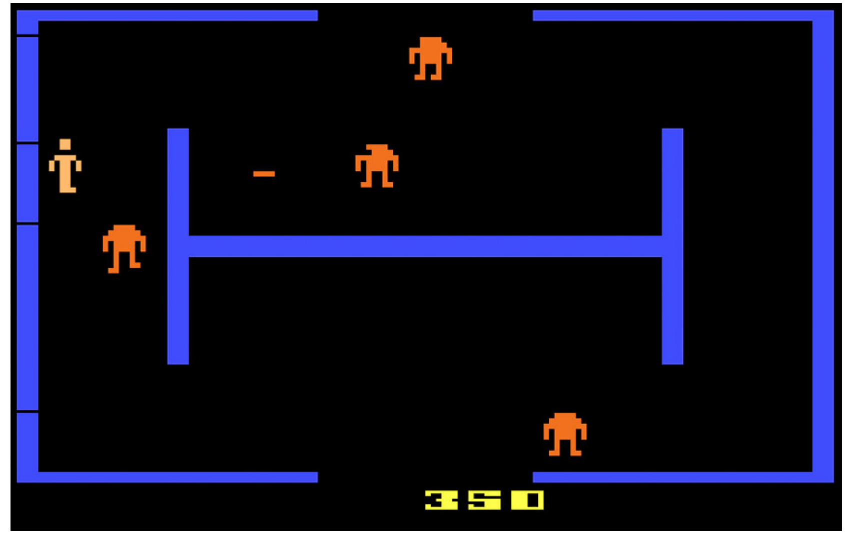
- Typically the space has many local minima and we no longer guarantee convergence
- Often works well in practice

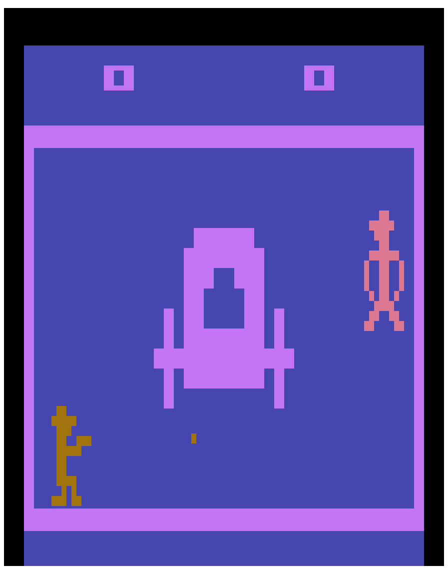
~Worlds Best Backgammon Player

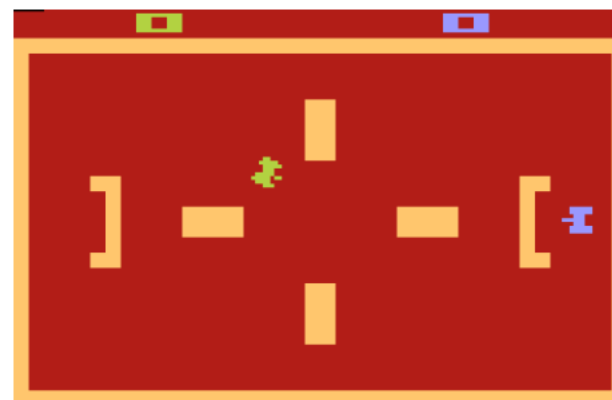


- Neural network with 80 hidden units
- Used Reinforcement Learning for 300,000 games of self-play
- One of the top (2 or 3) players in the world!

AI for General Atari 2600 Games





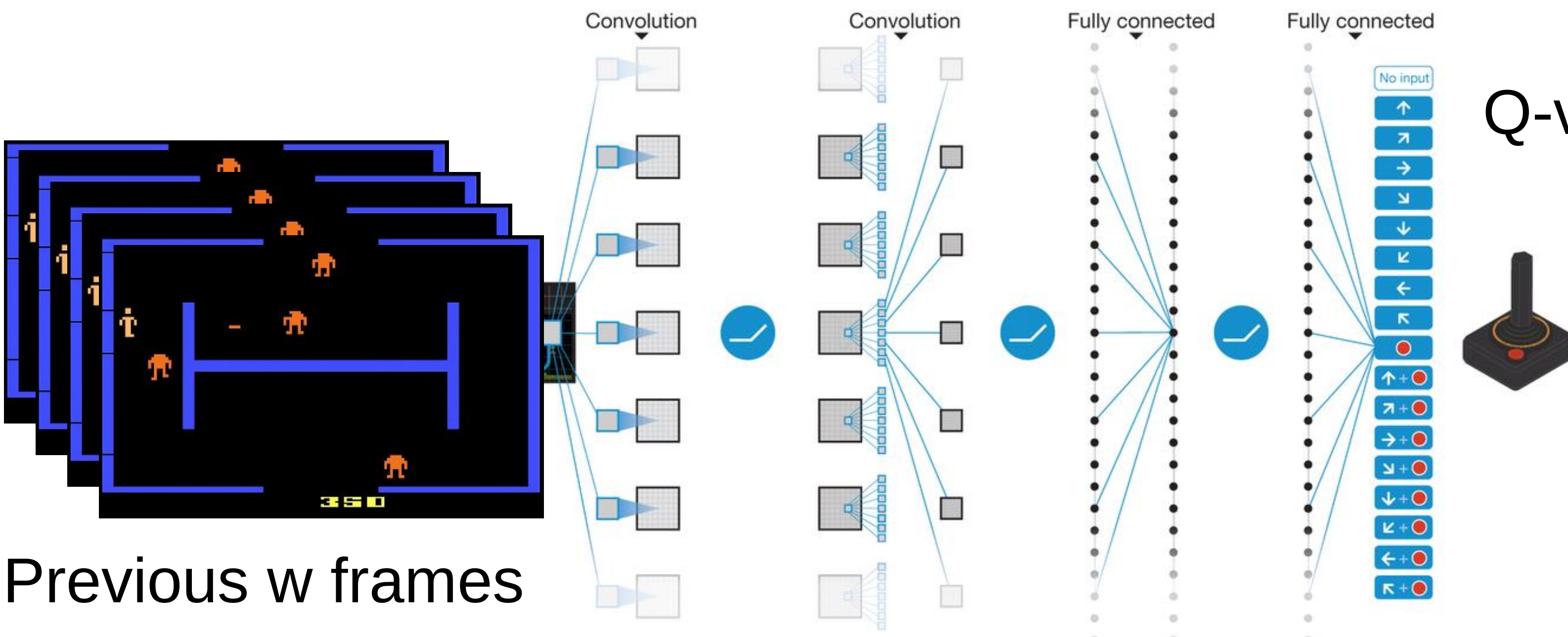


Playing Atari With Deep Reinforcement Learning

NIPS Deep Learning Workshop, 2013.

Deep Q-Networks for Policies: Atari

- Network input = Observation history
  - Window of previous screen shots in Atari
- Network output = One output node per action (returns Q-value)



Q-values

Previous w frames

DQN : Q-Learning w/ Randomized Experience Replay

1. Initial "experience replay" data set D
2. Initialize parameter values to θ
3. Take action according to an explore/exploit policy based on θ
4. Add observed transition (s, a, r, s') to D (limit size of D to N)
5. Randomly sample a transition (s_k, a_k, r_k, s'_k) from D
6. Perform a TD update for each parameter based on mini-batch
   $\theta \leftarrow \theta + \alpha\left(r_k + \mathrm{B}\max_{a'} \hat{Q}_\theta(s'_k, a') - \hat{Q}_\theta(s_k, a_k)\right)\nabla_\theta Q(s_k, a_k)$
7. Goto 3

DQN : Mini-Batches

1. Initial "experience replay" data set D
2. Initialize parameter values to θ
3. Take action according to an explore/exploit policy based on θ
4. Add observed transition (s, a, r, s') to D (limit size of D to N)
5. Randomly sample a mini-batch of B transition $\{(s_k, a_k, r_k, s'_k)\}$ from D
6. Perform a TD update for each parameter based on mini-batch
$$\theta \leftarrow \theta + \alpha \sum_k \left(r_k + \mathrm{B} \max_{a'} \hat{Q}_\theta(s'_k, a') - \hat{Q}_\theta(s_k, a_k) \right) \nabla_\theta \, Q(s_k, a_k)$$
7. Goto 3

DQN versus Traditional Q-learning

- Experience replay allows for reuse of data
  - More efficient use of experience
- Randomly sampling batches for updates versus updating on latest sample
  - Claim that this breaks correlation among updates which reduces variance
- Quantize the rewards to be 1, 0, or -1 (depending on sign of true reward)
  - Helps limit impact of any one update
  - Helps selecting learning parameters that work across games
  - Could fundamentally change the optimal policy

DQN Results

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa [3]	996	5.2	129	−19	614	665	271
Contingency [4]	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690
HNeat Best [8]	3616	52	106	19	1800	920	**1720**
HNeat Pixel [8]	1332	4	91	−16	1325	800	1145
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075