CS 747, Autumn 2023: Lecture 22

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Autumn 2023
Reinforcement Learning

1. Batch reinforcement learning
   ▶ Experience replay
   ▶ Fitted Q iteration

2. Applications
   ▶ Keepaway soccer
   ▶ Atari 2600 games
Reinforcement Learning

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2. Applications
   - Keepaway soccer
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Batch Updates to $\hat{Q}$

- We are back to value function-based learning (with function approximation).

On-line methods such as Q-learning “extract” very little information from each transition; are computationally lightweight. In many applications, samples are more expensive than computation; need to get more out of samples.

Batch RL keeps transitions in memory, performs more computationally-intensive updates.

Batch RL outer loop

$\hat{Q} \leftarrow 0$, $D \rightarrow \emptyset$.

Repeat for ever: //Each iteration is a batch.

$\pi \leftarrow \epsilon$-greedy($\hat{Q}$).

Follow $\pi$ for $N$ episodes; gather data $D' = (s_i, a_i, r_i, s_{i+1})$. $L_i = 1$.

$D \leftarrow D \cup D'$.

$\hat{Q} \leftarrow \text{BatchUpdate}(D, \hat{Q})$. // $\hat{Q}$ optional in RHS.
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Follow $\pi$ for $N$ episodes; gather data $D' = (s_i, a_i, r_i, s_{i+1})_{i=1}^L$.

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$\hat{Q} \leftarrow \text{BatchUpdate}(D, \hat{Q})$. //$\hat{Q}$ optional in RHS.
Experience Replay

- Assume $\hat{Q}$ is function-approximated, say by a neural network.

\[
\text{BatchUpdateExperienceReplay}(D, \hat{Q})
\]

Repeat $M$ times:
- Pick $(s, a, r, s')$ uniformly at random from $D$.
- Tweak $\hat{Q}$ so that for input $(s, a)$, the output “better-matches” target $r + \gamma \max_{a' \in A} \hat{Q}(s', a')$ (for example, by one step of gradient descent).

Return $\hat{Q}$.

- Sometimes $\hat{Q}$ reset/forgotten before the batch update.
- $M$ usually large; hence multiple updates using each sample.
Fitted Q Iteration

- Idea: obtain $\hat{Q}$ using supervised learning. Wait—labels?

```batchupdatefittedqiteration

$\hat{Q}_0 \leftarrow 0.
\text{For } i = 0, 1, \ldots, H - 1:\n\quad \text{For } j \in \{1, 2, \ldots, L\}: //\text{Create a labeled data set.}
\quad \quad x_j \leftarrow \text{FeatureVector}(s_j, a_j).
\quad \quad y_j \leftarrow r_j + \gamma \max_{a \in A} \hat{Q}_i(s_{j+1}, a).
\quad \hat{Q}_{i+1} \leftarrow \text{SupervisedLearning}((x_j, y_j)_{j=1}^L).
\text{Return } \hat{Q}_H.$
```

- Will not diverge if the supervised learning model is an **averager** (nearest neighbour methods, decision trees, etc.).
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Keepaway Task, Learning Architecture

- **See video:** [https://www.cs.utexas.edu/~AustinVilla/sim/keepaway/mp4/InitialResults/learn360.mp4](https://www.cs.utexas.edu/~AustinVilla/sim/keepaway/mp4/InitialResults/learn360.mp4).

  - Only learn policy of keeper with ball.
  - **States:** specified distances, angles between players, play area.
  - **Actions:** hold ball; pass to closer teammate; pass to farther teammate.
  - **Reward:** time between state and next state.
  - No discounting.

  $\hat{Q}$ approximated by (1) tile coding, (2) neural network with 1 hidden layer.
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Comparison: On-line vs. Batch RL

Learning Curves for Keepaway

Breakout

- Human-level control through deep reinforcement learning.

Breakout

- **Human-level control through deep reinforcement learning.**

  See video: [https://www.youtube.com/watch?v=TmPfTpjtdgg](https://www.youtube.com/watch?v=TmPfTpjtdgg).
Human-level control through deep reinforcement learning.


See video: https://www.youtube.com/watch?v=TmPfTpjtdgg.
Observe early, middle, and late stages of training.
Atari 2600 Games: Aggregate Results

From Mnih et al. (2015); for full reference see Slide 9.
Neural Network-based Representation of $Q$

- **Input:** 4 most-recent $84 \times 84$ frames. **Output:** 18 action values.

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- **Tens of thousands of weights!** How to train?
DQN Algorithm

- Batch RL, using experience replay.
  - A “mini-batch” of \((s, a, r, s')\) tuples replayed for a few iterations.
  - Q network for providing targets not updated after every atomic update, but still at regular intervals.
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- Applied and evaluated on \(\approx 50\) Atari games.
- Code published: many implementations now available.
- Results on Atari have subsequently been improved, new algorithms (such as A3C) have emerged.
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- **Next class:** Model-based methods (again).