CS 747, Autumn 2022: Lecture 21

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Autumn 2022

Reinforcement Learning

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

2. Applications
   - Keepaway soccer
   - Atari 2600 games

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Batch RL outer loop

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

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

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

$\quad$ Follow π for N episodes; gather data $D' = (s_i, a_i, r_i, s_{i+1})_{i=1}^{L}$.

$\quad D \leftarrow D \cup D'$.

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

Experience Replay

- Reference: Lin (1992).
- Assume $\hat{Q}$ is function-approximated, say by a neural network.

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 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

- Reference: Ernst, Geurts, Wehenkel (2005).
- Idea: obtain $\hat{Q}$ using supervised learning. Wait—labels?

BatchUpdateFittedQIteration(D)

$\hat{Q}_0 \leftarrow \mathbf{0}$.
For $i = 0, 1, \ldots, H - 1$:
  For $j \in \{1, 2, \ldots, L\}$: //Create a labeled data set.
    $x_j \leftarrow \text{FeatureVector}(s_j, a_j)$.
    $y_j \leftarrow r_j + \gamma \max_{a \in A} \hat{Q}_i(s_{j+1}, a)$.
  $\hat{Q}_{i+1} \leftarrow \text{SupervisedLearning}((x_j, y_j)_{j=1}^{L})$.
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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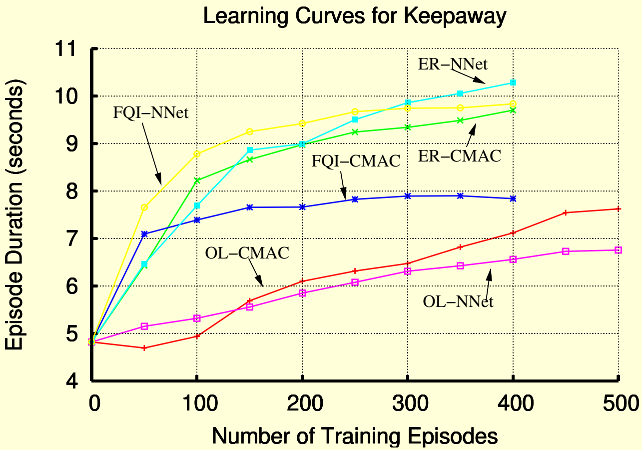
- $\hat{Q}$ approximated by (1) tile coding, (2) neural network with 1 hidden layer.

Comparison: On-line vs. Batch RL



Batch Reinforcement Learning in a Complex Domain. Shivaram Kalyanakrishnan and Peter Stone, In Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2007), pp.650–657, IFAAMAS, 2007.

Breakout

- Human-level control through deep reinforcement learning.
  Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg, and Demis Hassabis, Nature, 518:529–533, 2015.

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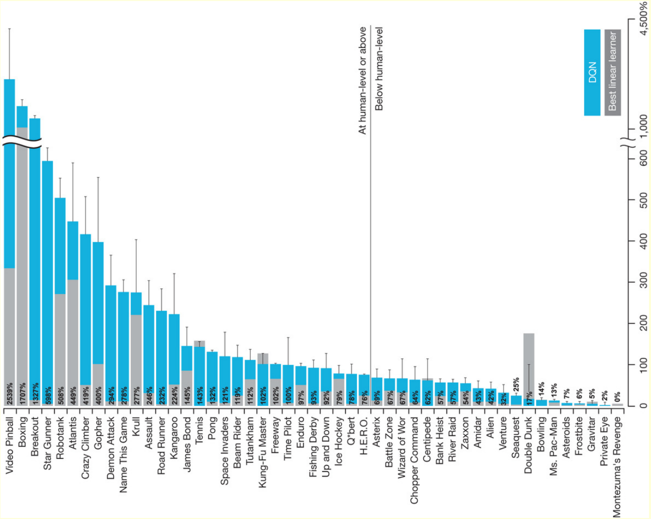
  Observe early, middle, and late stages of training.

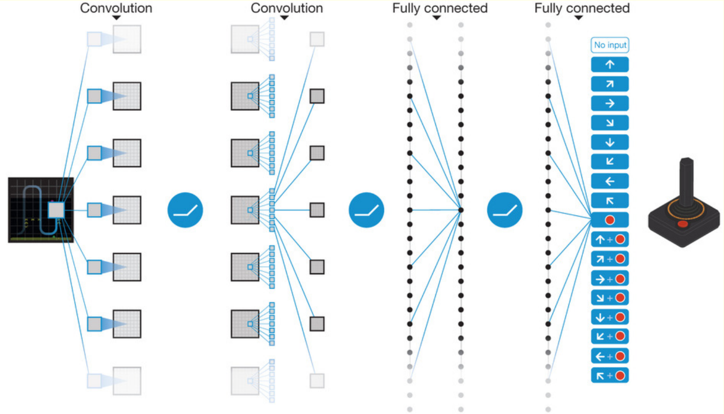
Atari 2600 Games: Aggregate Results



From Mnih *et al. (2015)*; for full reference see Slide 9.

Neural Network-based Representation of Q

- **Input:** 4 most-recent 84×84 frames. **Output:** 18 action values.



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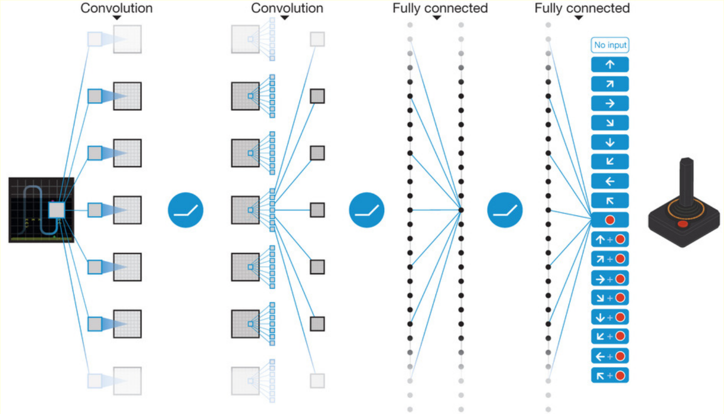

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- Tens of thousands of weights! How to train?

DQN Algorithm

- Batch RL, using experience replay.
  - A “mini-batch” of (s, a, r, s') tuples replayed for a few iterations.
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- Applied and evaluated on ≈ 50 games.
- Code published: many implementations now available.
- Results have been improved, new algorithms (such as A3C) have emerged.

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- **Next class:** Model-based methods (again).