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

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

<u>**BatchUpdateExperienceReplay**(D, $\hat{Q}$)</u>

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

- 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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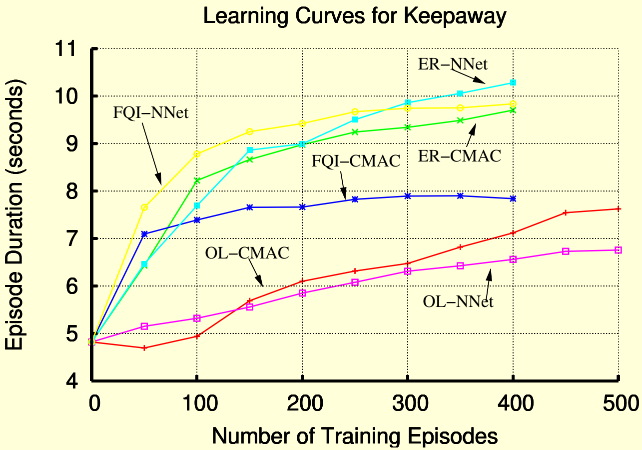
- $\hat{Q}$ approximated by (1) tile coding, (2) neural network with 1 hidden layer.

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.

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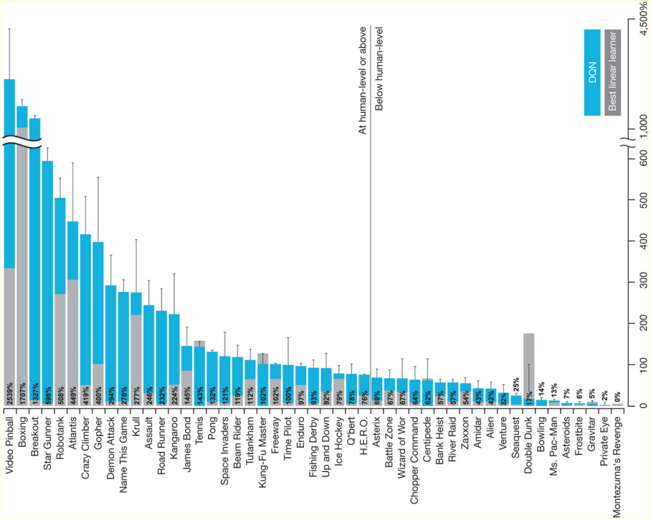
  Observe early, middle, and late stages of training.

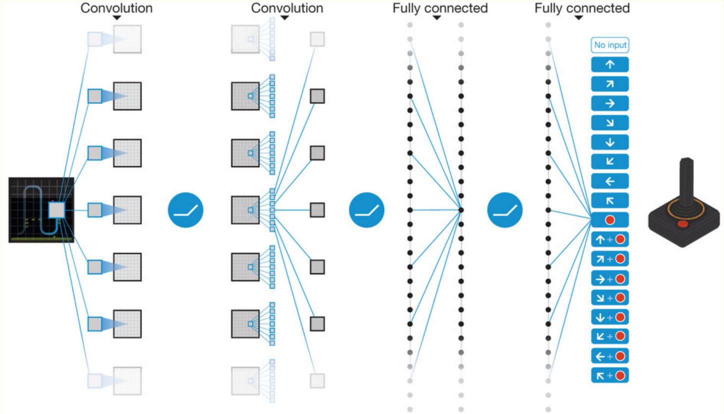
Atari 2600 Games: Aggregate Results



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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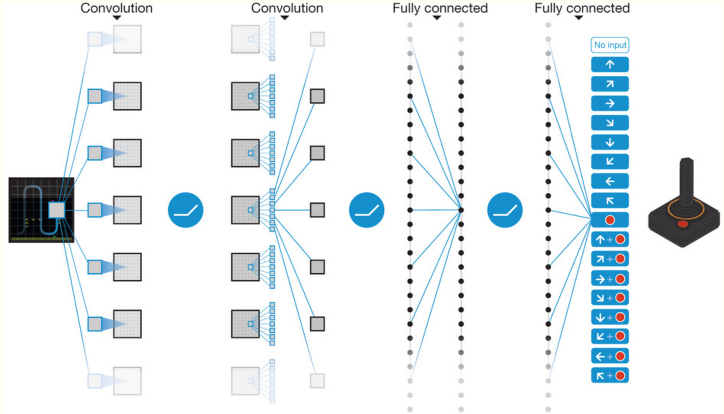

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- Tens of thousands of weights! How to train?

DQN Algorithm

- Batch RL, using experience replay.
  - A “mini-batch” of (s, a, r, s') tuples replayed for a few iterations.
  - Q network for providing targets not updated after every atomic update, but still at regular intervals.

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- Applied and evaluated on ≈ 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).