Playing Atari with Deep Reinforcement Learning (13.12)

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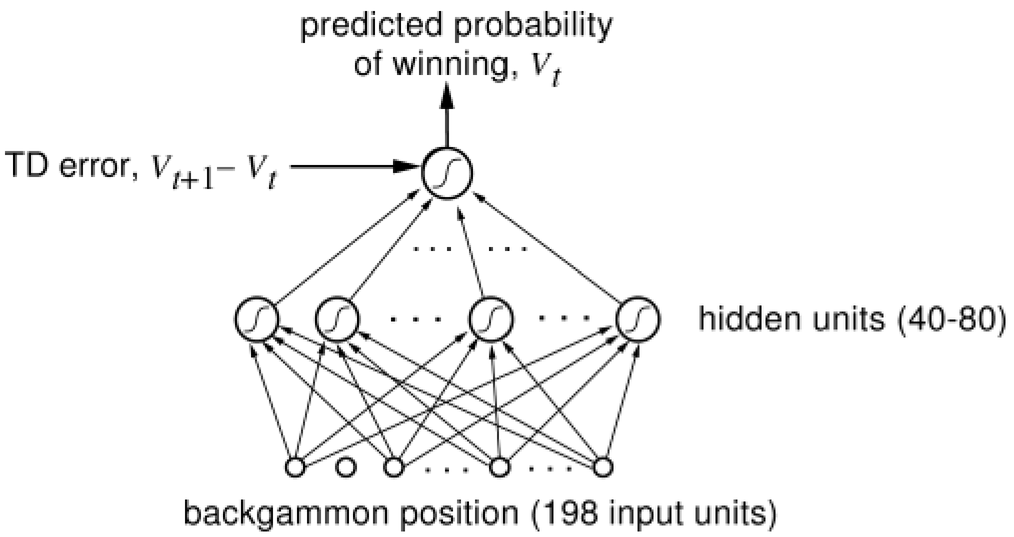
Previous Applications of RL

- Linear value functions or policy representations
  - Rely on hand-crafted features
  - Feature representation determines performance
- Can diverge with model-free RL, nonlinear approximation, off-policy

TD-gammon

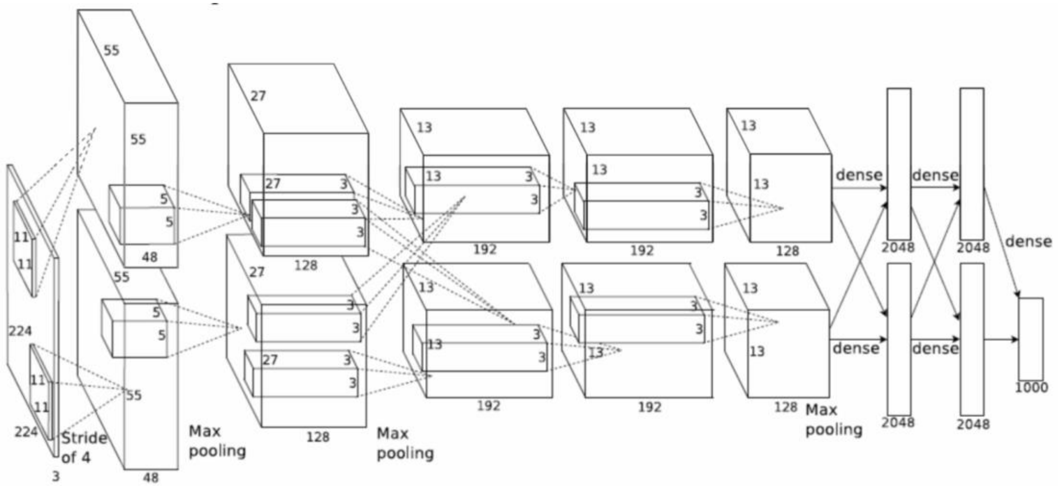
- Superhuman-level Backgammon playing RL agent
- Model-free algorithm with one-hidden-layer MLP
- Considered a “special case”



https://users.auth.gr/kehagiat/Research/GameTheory/12CombBiblio/BackGammon.html

Meanwhile, in Deep Learning…

- CNN, MLP, RNN
  - Extract high-level features from raw data
  - Works in both supervised and unsupervised learning



- Will it work on Reinforcement Learning?

http://fromdata.org/2015/10/01/imagenet-cnn-architecture-image/

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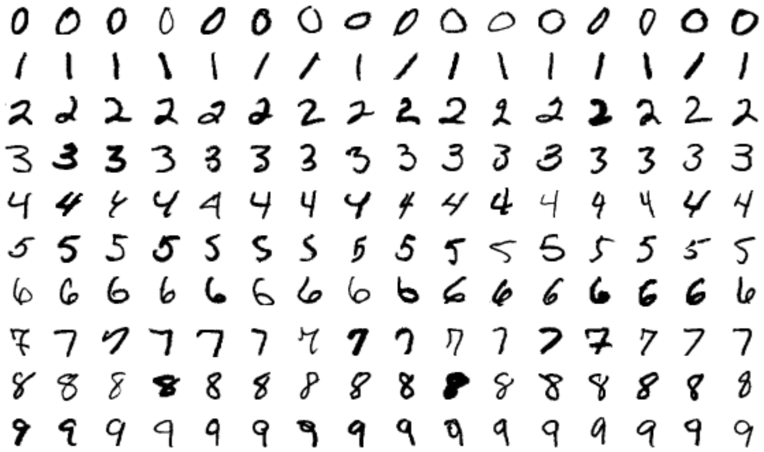
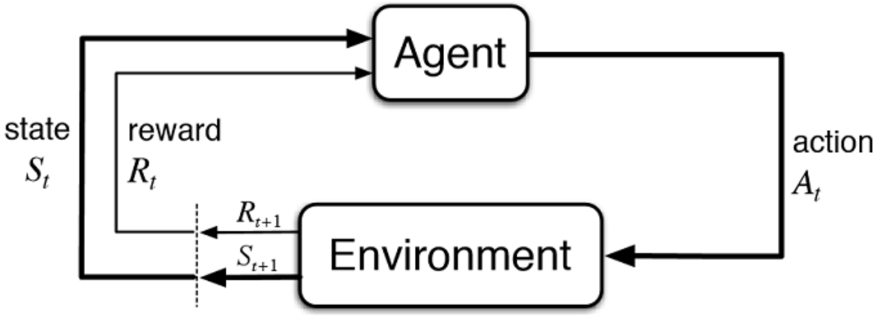
Problems of combining DL and RL

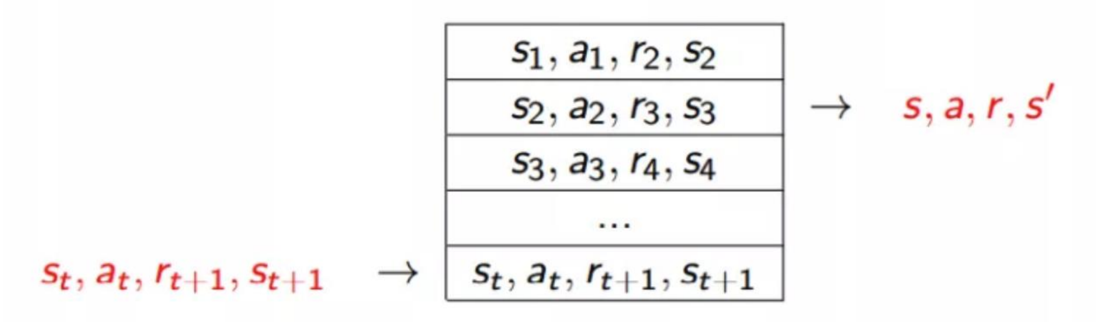
- No labelled data: only sparse, noisy, delayed rewards
- Breaks most underlying assumptions of deep learning algorithms
  - Highly correlated data
  - Moving distribution of data





Proposal: Experience Replay

- Idea originally by Long-Ji Lin
- Save transitions in a *replay memory D*
- Randomly sample previous transitions to update parameters



https://pdfs.semanticscholar.org/54c4/cf3a8168c1b70f91cf78a3dc98b671935492.pdf

Advantages of Experience Replay

1. Achieve greater data efficiency
    - Each experience is used multiple times
2. Break correlation between samples
    - Randomly sampled experience is nonconsecutive
3. Average the behavior distribution
    - Current parameters does not affect incoming data distribution

Preprocessing

- Originally 210×160 image with 128 color palette
- Gray-scale and downsampled to 110×84
- Cropped to 84×84
  - Only to fit particular GPU implementation
- *Frame stacking*
  - Stack 4 preprocessed frames as input
  - Need multiple frames for velocity, etc.

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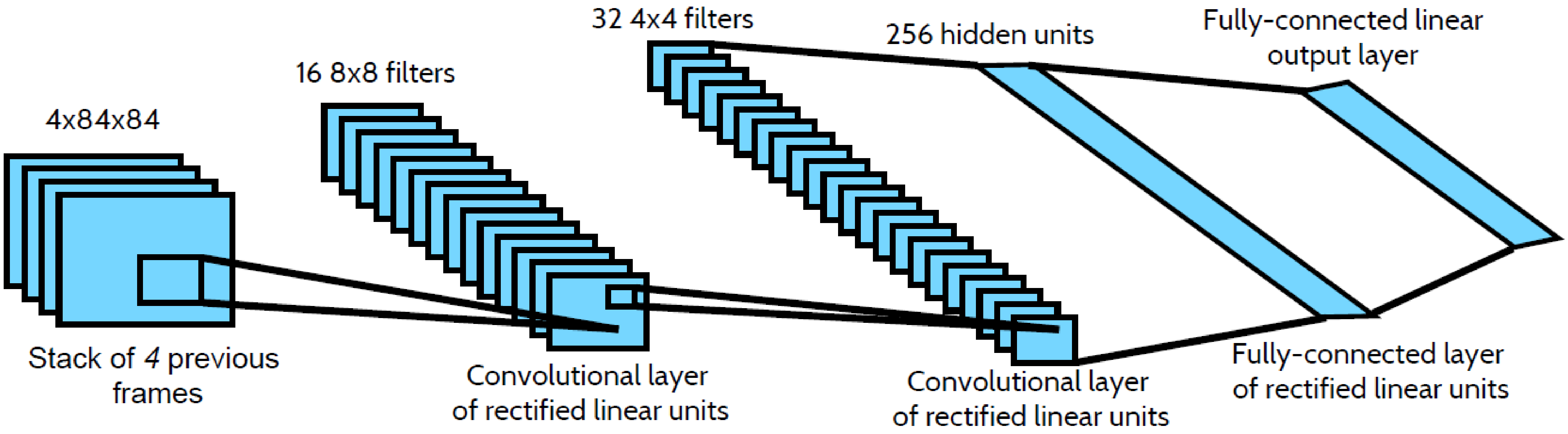
Model Architecture: Deep Q-Networks (DQN)

- Return Q values for all 10 actions



https://nthu-datalab.github.io/ml/labs/17_DQN_Policy_Network/17-DQN_&_Policy_Network.html

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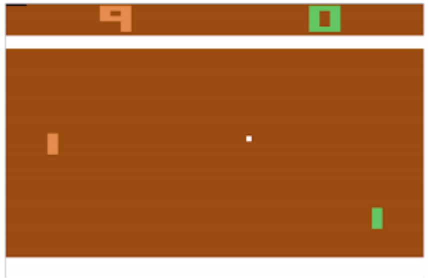
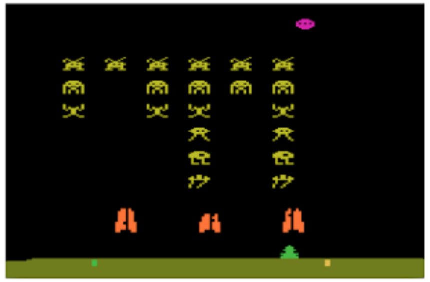
Environment: Atari 2600

- 7 games selected
- Create **a single agent** that can play as many games possible
  - No game-specific information
  - No hand-designed features
  - Same network architecture and hyperparameters






https://github.com/mgbellemare/Arcade-Learning-Environment

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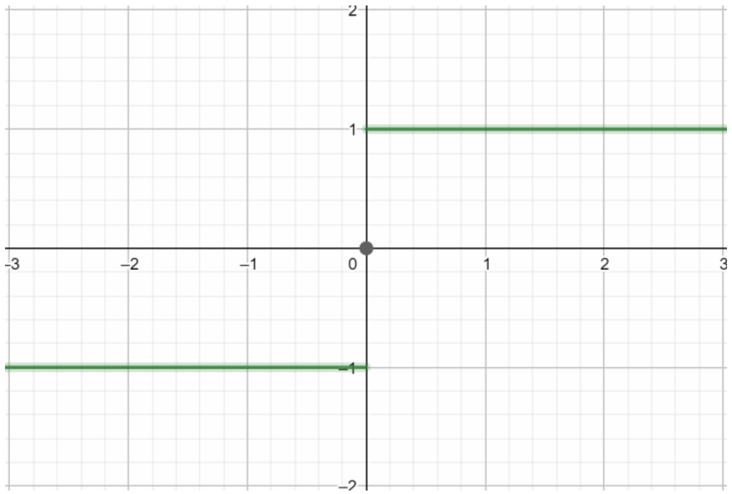
Reward Clipping



- Clip all rewards to $\{-1, 0, 1\}$
  - Fix all positive reward as $+1$
  - Fix all negative rewards as -1
  - Leave zero rewards unchanged

- Limits scale of error derivatives for different games
- Cannot differentiate between rewards of different magnitude

Frame Skipping

- Agent sees and selects actions on every k^{th} frame
- Action is repeated on skipped frames
- Agent can play roughly k times more games

https://danieltakeshi.github.io/2016/11/25/frame-skipping-and-preprocessing-for-deep-q-networks-on-atari-2600-games/

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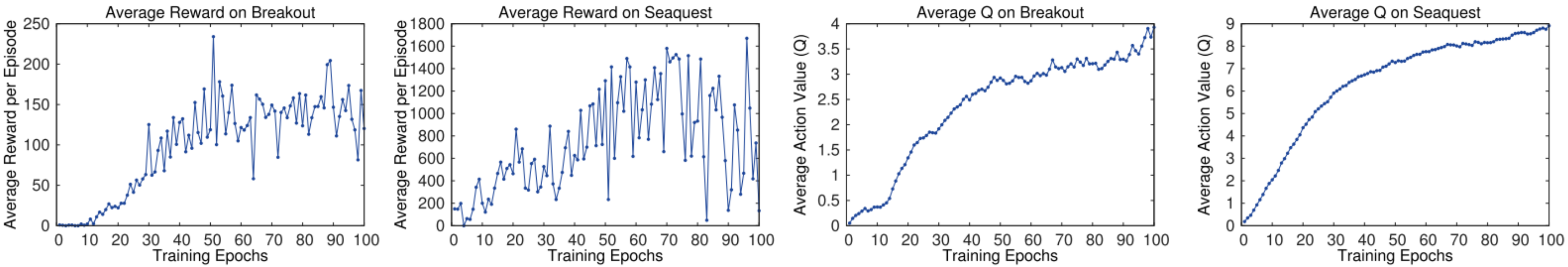
Training and Stability

- How to evaluate agent during training?
  - Total episodic reward: very noisy
  - Policy's estimated Q function: smooth



- Did not encounter any divergence issue in practice

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Result on Atari 2600

- Outperform all previous RL algorithms in 6 games
- Surpass expert human player in 3 games

	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

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Thank you!

Original Paper: https://arxiv.org/abs/1312.5602

Paper Recommendations:

- [1502] Human-level control through Deep Reinforcement Learning
- [1511.05952] Prioritized Experience Replay
- [1712.01275] A Deeper Look at Experience Replay

You can find more content in www.endtoend.ai/slides

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