Learning from the memory of Atari 2600

Jakub Sygnowski[*] and Henryk Michalewski[†]

University of Warsaw
Department of Mathematics, Informatics, and Mechanics

May 5, 2016

Abstract

We train a number of neural networks to play games Bowling, Breakout and Seaquest using information stored in the memory of a video game console Atari 2600. We consider four models of neural networks which differ in size and architecture: two networks which use only information contained in the RAM and two mixed networks which use both information in the RAM and information from the screen.

As the benchmark we used the convolutional model proposed in [12] and received comparable results in all considered games. Quite surprisingly, in the case of Seaquest we were able to train RAM-only agents which behave better than the benchmark screen-only agent. Mixing screen and RAM did not lead to an improved performance comparing to screen-only and RAM-only agents.

1 Introduction

An Atari 2600 controller can perform one of 18 actions[1] and in this work we are intended to learn which of these 18 actions is the most profitable given a state of the screen or memory. Our work is based on deep Q-learning [12] – a reinforcement learning algorithm that can learn to play Atari games using

---

[*]J.Sygnowski@students.mimuw.edu.pl

[†]H.Michalewski@mimuw.edu.pl

[1]For some games only some of these 18 actions are used in the gameplay. The number of available actions is 4 for Breakout, 18 for Seaquest and 6 for Bowling.

only input from the screen. The deep Q-learning algorithm builds on the Q-learning [24] algorithm, which in its simplest form (see [14, Figure 21.8]) iteratively learns values $Q(state, action)$ for *all* state-action pairs and lets the agent choose the action with the highest value. In the instance of Atari 2600 games this implies evaluating all pairs $(screen, action)$ where $action$ is one of the 18 positions of the controller. This task is infeasible and similarly, learning *all* values $Q(state, action)$ is not a realistic task in other real-world games such as chess or Go.

This feasibility issues led to generalizations of the Q-learning algorithm which are intended to limit the number of parameters on which the function Q depends. One can arbitrarily restrict the number of features which can be learned[2], but instead of using manually devised features, the deep Q-learning algorithm[3] presented in [12] builds them in the process of training of the neural network. Since every neural network is a composition of a priori unknown linear maps and fixed non-linear maps, the aim of the deep Q-learning algorithm is to learn coefficients of the unknown linear maps.

In the deep Q-learning algorithm the game states, actions and immediate rewards are passed to a *deep convolutional network*. This type of network abstracts features of the screen, so that various patterns on the screen can be identified as similar. The network has a number of output nodes – one for each possible action – and it predicts the cumulative game rewards after making moves corresponding to actions.

A number of decisions was made in the process of designing of the deep Q-learning algorithm (see [12, Algorithm 1] for more details): (1) in each step there is some probability ε of making a random move and it decreases from $\varepsilon = 1$ to $\varepsilon = 0.1$ in the course of training, (2) the previous game states are stored in the *replay memory*; the updates in the Q-learning are limited to a random batch of events polled from that memory, (3) the updates of unknown linear maps in the neural network are performed according to the gradient of the squared loss function which measures discrepancy between the estimation given by the network and the actual reward. In this work we use the same computational infrastructure as in [12], including the above decisions (1)-(3).

---

[2]E.g. we may declare that $Q(state, action) = \theta_1 f_1(state, action) + \theta_2 f_2(state, action)$, where f_1, f_2 are some fixed pre-defined functions, for example f_1 may declare value 1 to the state-action pair $(screen, fire)$ if a certain shape appears in the bottom-left corner of the screen and 0 otherwise and f_2 may declare value 1 to $(screen, left)$ if an enemy appeared on the right and 0 otherwise. Then the Q-learning algorithm learns the best values of θ_1, θ_2.

[3]This algorithm is also called a deep q-network or DQN.

Related work

The original algorithm in [12] was improved in a number of ways in [21, 11, 9]. This includes changing network architecture, choosing better hyperparameters and improving the speed of algorithm which optimizes neural network's loss function. These attempts proved to be successful and made the deep Q-learning algorithm the state-of-the-art method for playing Atari games.

Instead of the screen one can treat the RAM state of the Atari machine as the game state. The work [10] implemented a classical planning algorithm on the RAM state. Since the Atari 2600 RAM consists of only 128 bytes, one can efficiently search in this low-dimensional state space. Nevertheless, the learning in [10] happens during the gameplay, so it depends on the time limit for a single move. In contrast, in [12] the learning process happens before the gameplay - in particular the agent can play in the real-time. To the best of our knowledge the only RAM-based agent not depending on search was presented in [2]. We cite these results as `ale_ram`.

In our work we use the deep Q-learning algorithm, but instead of using screens as inputs to the network, we pass the RAM state or the RAM state and the screen together. In the following sections we describe the games we used for evaluation, as well as the network architectures we tried and hyperparameters we tweaked.

The work [12] as the main benchmark

The changes to the deep Q-learning algorithm proposed in [11] came at a cost of making computations more involved comparing to [12]. In this work we decided to use as the reference result only the basic work [12], which is not the state of the art, but a single training of a neural network can be contained in roughly 48 hours using the experimental setup we describe below. This decision was also motivated by a preliminary character of our study – we wanted to make sure that indeed the console memory contains useful data which can be extracted during the training process using the deep Q-learning algorithm. From this perspective the basic results in [12] seem to be a perfect benchmark to verify feasibility of learning from RAM. We refer to this benchmark architecture as `nips` through this paper.
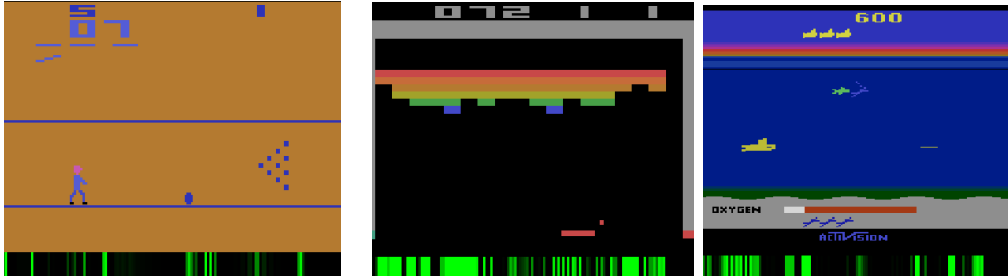
Figure 1: From left to right Bowling, Breakout and Seaquest. The 128 vertical bars and the bottom of every screenshot represent the state of the memory, with black representing 0 and lighter color corresponding to higher values of a given memory cell.

2 The setting of the experiment

2.1 Games

Bowling – simulation of the game of bowling; the player aims the ball toward the pins and then steers the ball; the aim is to hit the pins [4, 17].

Breakout – the player bounces the ball with the paddle towards the layer of bricks; the task is to destroy all bricks; a brick is destroyed when the ball hits it [6, 18].

Seaquest – the player commands a submarine, which can shoot enemies and rescue divers by bringing them above the water-level; the player dies if he fails to get a diver up before the air level of submarine vanishes [15, 20].

We've chosen these games, because each of them offers a distinct challenge. Breakout is a relatively easy game with player's actions limited to moves along the horizontal axis. We picked Breakout because disastrous results of learning would indicate a fundamental problem with the RAM learning. The deep Q-network for Seaquest constructed in [12] plays at an amateur human level and for this reason we consider this game as a tempting target for improvements. Also the game state has some elements that possibly can be detected by the RAM-only network (e.g. oxygen-level meter or the number of picked divers). Bowling seems to be a hard game for all deep Q-network models. It is an interesting target for the RAM-based networks, because visualizations suggest that the state of the RAM is changing only very slightly.

2.2 Technical architecture

By one experiment we mean a complete training of a single deep Q-network. In this paper we quote numerical outcomes of 30 experiments which we performed[4]. For our experiments we made use of Nathan Sprague's implementation of the deep Q-learning algorithm [13] in Theano [3] and Lasagne [8]. The code uses the Arcade Learning Environment [2] – the standard framework for evaluating agents playing Atari games. Our code with instructions how to run it can be found on github [19]. All experiments were performed on a Linux machine equipped with Nvidia GTX 480 graphics card. Each of the experiments lasted for $1 - 3$ days. A single epoch of a RAM-only training lasted approximately half of the time of the screen-only training for an architecture with the same number of layers.

2.3 Network architectures

We performed experiments with four neural network architectures which accept the RAM state as (a part of) the input. The RAM input is scaled by 256, so all the inputs are between 0 and 1.

All the hyperparameters of the network we consider are the same as in [12], if not mentioned otherwise (see Appendix A). We only changed the size of the replay memory to $\approx 10^5$ items, so that it fits into 1.5GB of Nvidia GTX 480 memory[5].

3 Plain approach

Here we present the results of training the RAM-only networks `just_ram` and `big_ram` as well as the benchmark model `nips`.

Neural network 1: `just_ram`(outputDim)

Input: RAM
Output: A vector of length outputDim
1 $hiddenLayer1 \leftarrow DenseLayer(RAM, 128, rectify)$
2 $hiddenLayer2 \leftarrow DenseLayer(hiddenLayer1, 128, rectify)$
3 $output \leftarrow DenseLayer(hiddenLayer2, outputDim, no\ activation)$
4 **return** $output$

---

[4]The total number of experiments exceeded 100, but this includes experiments involving other models and repetitions of experiments described in this paper.

[5]We have not observed a statistically significant change in results when switching between replay memory size of 10^5 and $5 \cdot 10^5$.

The next considered architecture consists of the above network with two additional dense layers:

Neural network 2: `big_ram`(outputDim)

Input: RAM
Output: A vector of length outputDim

1 $hiddenLayer1 \leftarrow DenseLayer(RAM, 128, rectify)$
2 $hiddenLayer2 \leftarrow DenseLayer(hiddenLayer1, 128, rectify)$
3 $hiddenLayer3 \leftarrow DenseLayer(hiddenLayer2, 128, rectify)$
4 $hiddenLayer4 \leftarrow DenseLayer(hiddenLayer3, 128, rectify)$
5 $output \leftarrow DenseLayer(hiddenLayer4, outputDim, no\ activation)$
6 **return** $output$

The training process consists of *epochs*, which are interleaved by test periods. During a test period we run the model with the current parameters, the probability of doing a random action $\varepsilon = 0.05$ and the number of test steps (frames) being 10 000. Figures 2, 3 and 4 show the average result per *episode* (full game, until player's death) for each epoch.
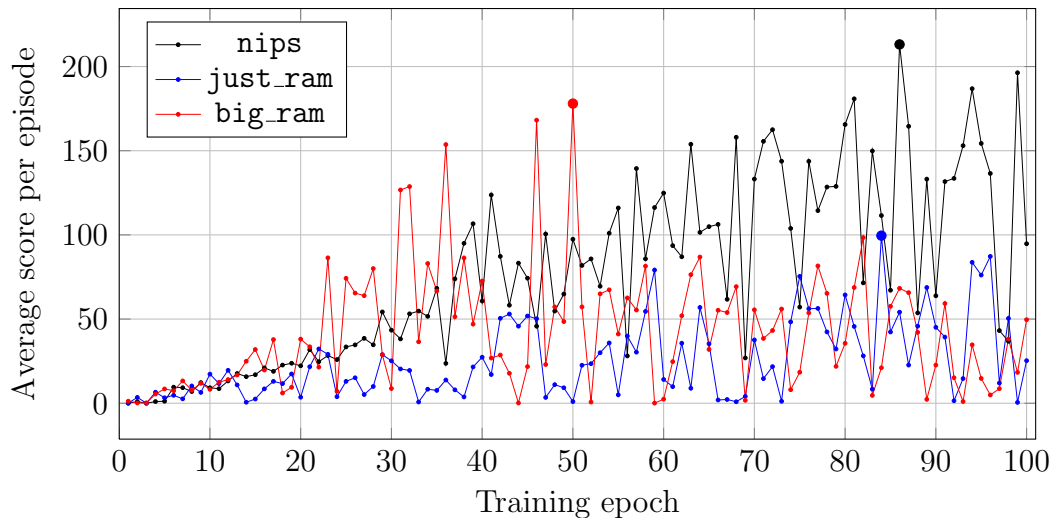

Figure 2: Training results for Breakout for three plain models: `nips`, `just_ram`, `big_ram`.

Figures 2,3,4 show that there is a big variance of the results between epochs, especially in the RAM models. Because of that, to compare the models, we chose the results of the best epoch[6]. We summarized these results

---

[6]For Breakout we tested networks with best training-time results. The test consisted of choosing other random seeds and performing 100 000 steps. For all networks, including `nips`, we received results consistently lower by about 30%.
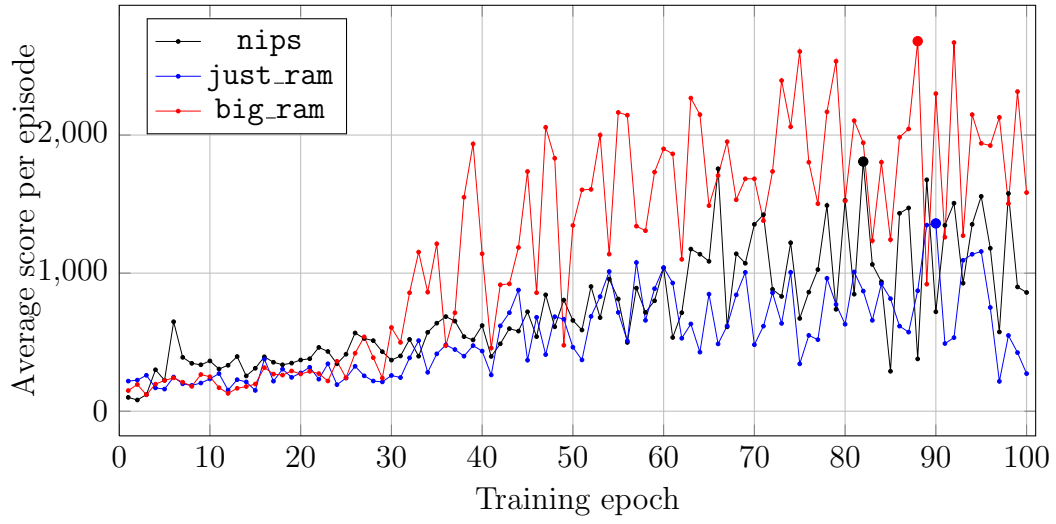
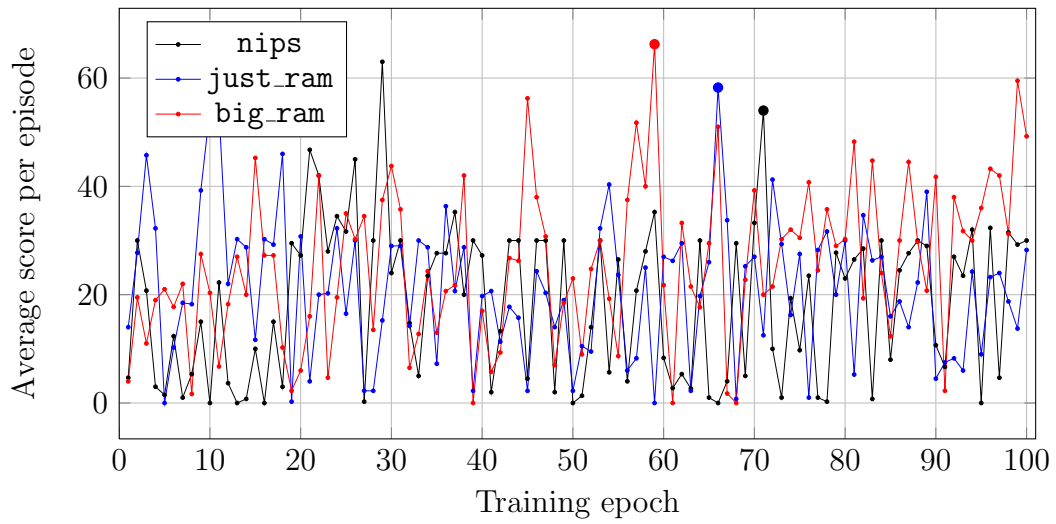*Figure 3: Training results for Seaquest for three plain models: `nips, just_ram, big_ram`.*

Figure 4: Training results for Bowling for three plain models: `nips, just_ram, big_ram`.

in Table 1, which also include the results of `ale_ram`[7].

	Breakout	Seaquest	Bowling
`nips` best	**213.14**	1808	54.0
`just_ram` best	99.56	1360	58.25
`big_ram` best	178.0	**2680**	**66.25**
`ale_ram`	4.0	593.7	29.3

Table 1: Table summarizing test results for basic methods.

In Breakout the best result for the `big_ram` model is weaker than those obtained by the network `nips`. In Seaquest the best result obtained by the `big_ram` network is better than the best result obtained by the network `nips`. In Bowling our methods give a slight improvement over the network `nips`, yet in all considered approaches the learning as illustrated by Figure 4 seem to be poor and the outcome in terms of gameplay is not very satisfactory. We decided to not include in this paper further experiments with Bowling and leave it as a topic of a further research.

4   Regularization

Training a basic RAM-only network leads to high variance of the results (see the figures in the previous section) over epochs. This can be a sign of overfitting. To tackle this problem we've applied *dropout* [16], a standard regularization technique for neural networks.

Dropout is a simple, yet effective regularization method. It consists of "turning off" with probability p each neuron in training, i.e. setting the output of the neuron to 0, regardless of its input. In backpropagation, the parameters of switched off nodes are not updated. Then, during testing, all neurons are set to "on" – they work as in the course of normal training, with the exception that each neuron's output is multiplied by p to make up for the skewed training. The intuition behind the dropout method is that it forces each node to learn in absence of other nodes. The work [23] shows an experimental evidence that the dropout method indeed reduces the variance of the learning process.

---

[7]The `ale_ram`'s evaluation method differ – the scores presented are the average over 30 trials consisting of a long period of learning and then a long period of testing, nevertheless the results are much worse than of any DQN-based method presented here.

We've enabled dropout with probability of turning off a neuron $p = \frac{1}{2}$. This applies to all nodes, except output ones. We implemented dropout for two RAM-only networks: `just_ram` and `big_ram`. This method offers an improvement for the `big_ram` network leading to the best result for Seaquest in this paper. The best epoch results are presented in the Table 2 and the intermediate training results for Seaquest are shown in Figure 5.
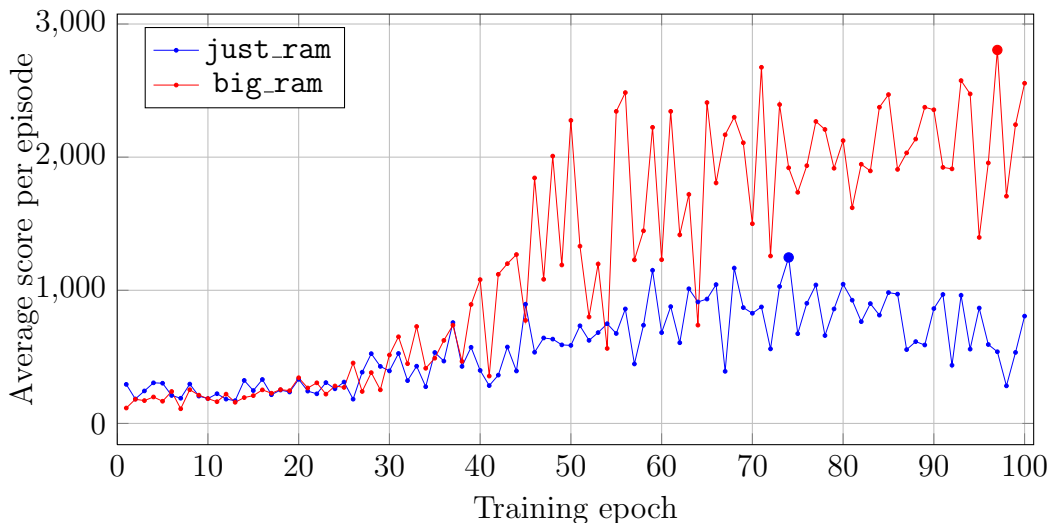

Figure 5: Training results for Seaquest with dropout $p = 0.5$ for models just_ram, big_ram. This figure suggests that indeed dropout reduces the variance of the learning process.

	Breakout	Seaquest
`just_ram` with dropout best	130.5	1246.67
`big_ram` with dropout best	122.25	**2805**

Table 2: Summary of test results for training which involves regularization with the dropout method with the parameter $p = 0.5$.

5 Decreasing learning rate

We also tried to reduce the variance of the learner through reduction of the learning rate from 0.0002 to 0.0001.

The learning rate is a parameter of the algorithm *rmsprop* that decides how parameters are changed in each step. Bigger learning rates correspond to moving faster in the parameter space, making learning faster, but more noisy.

We expected that the drastic changes in performance between consecutive epochs, as illustrated by Figures 2 and 3, may come from stepping over optimal values when taking too big steps. If it is the case, decreasing the step size should lead to slower learning combined with higher precision of finding minima of the loss function.

The results of these experiments can be found in Table 3. Comparing to the training without regularization, scores improved only in the case of Breakout and the `just_ram` network, but not by a big margin.

	Breakout	Seaquest
`just_ram` best	137.67	1233.33
`big_ram` best	112.14	2675

Table 3: Summary of test results for modified learning rate.

6 Frame skip

Atari 2600 was designed to use an analog TV as the output device with 60 new frames appearing on the screen every second. To simplify the search space we impose a rule that one action is repeated over a fixed number of frames. This fixed number is called the *frame skip*. The standard frame skip used in [12] is 4. For this frame skip the agent makes a decision about the next move every $4 \cdot \frac{1}{60} = \frac{1}{15}$ of a second. Once the decision is made, then it remains unchanged during the next 4 frames.

Low frame skip allows the network to learn strategies based on a super-human reflex. High frame skip will limit the number of strategies, hence learning may be faster and more successful.

In the benchmark agent `nips`, trained with the frame skip 4, *all* 4 frames are used for training along with the sum of the rewards coming after them. This is dictated by the fact that due to hardware limitations, Atari games sometimes "blink", i.e. show some objects only every few frames. For example, in the game Space Invaders, if an enemy spaceship shoots in the direction of the player, then shots can be seen on the screen only every second frame and an agent who sees only the frames of the wrong parity would have no access to a critical part of the game information.

In the case of learning from memory we are not aware of any critical loses of information when intermediate RAM states are ignored. Hence in our models we only passed to the network the RAM state corresponding to the

last frame corresponding to a given action[8].

The work [5] suggests that choosing the right frame skip can have a big influence on the performance of learning algorithms (see also [7]). Figure 6 and Table 4 show a significant improvement of the performance of the `just_ram` model in the case of Seaquest. Quite surprisingly, the variance of results appeared to be much lower for higher `FRAME SKIP`.

As noticed in [5], in the case of Breakout high frame skips, such as `FRAME SKIP = 30`, lead to a disastrous performance. Hence we tested only lower `FRAME SKIP` and for `FRAME SKIP = 8` we received results slightly weaker than those with `FRAME SKIP = 4`.

	Breakout	Seaquest
`just_ram` with `FRAME SKIP` 8 best	82.87	2064.44
`just_ram` with `FRAME SKIP` 30 best	-	2093.24
`big_ram` with `FRAME SKIP` 8 best	102.64	2284.44
`big_ram` with `FRAME SKIP` 30 best	-	2043.68

Table 4: Table summarizing test results for training which involves higher `FRAME SKIP` value. For Breakout `FRAME SKIP`= 30 does not seem to be a suitable choice.
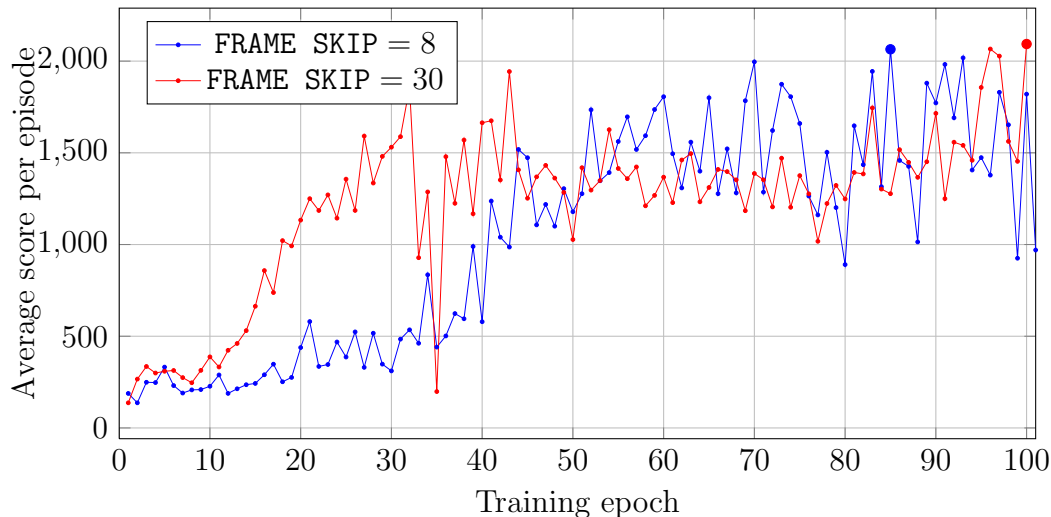

Figure 6: Training results for Seaquest with `FRAME SKIP` = 8 and `FRAME SKIP` = 30 for the model `just_ram`.

---

[8]We also tried to pass all the RAM states as a $(128 * \texttt{FRAME SKIP})$-dimensional vector, but this didn't lead to an improved performance.

11

7 Mixing screen and memory

One of the hopes of future work is to integrate the information from the RAM and information from the screen in order to train an ultimate Atari 2600 agent. In this work we made some first steps towards this goal. We consider two mixed network architectures. The first one is `mixed_ram`, where we just concatenate the output of the last hidden layer of the convolutional network with the RAM input and then in the last layer apply a linear transformation without any following non-linearity.

Neural network 3: `mixed_ram`(outputDim)

Input: RAM,screen
Output: A vector of length outputDim

1   $conv1 \leftarrow Conv2DLayer(screen, rectify)$
2   $conv2 \leftarrow Conv2DLayer(conv1, rectify)$
3   $hidden \leftarrow DenseLayer(conv2, 256, rectify)$
4   $concat \leftarrow ConcatLayer(hidden, RAM)$
5   $output \leftarrow DenseLayer(concat, outputDim, no\ activation)$
6   **return** $output$

The other architecture is a deeper version of `mixed_ram`. We allow more dense layers which are applied in a more sophisticated way as described below.

Neural network 4: `big_mixed_ram`(outputDim)

Input: RAM,screen
Output: A vector of length outputDim

1   $conv1 \leftarrow Conv2DLayer(screen, rectify)$
2   $conv2 \leftarrow Conv2DLayer(conv1, rectify)$
3   $hidden1 \leftarrow DenseLayer(conv2, 256, rectify)$
4   $hidden2 \leftarrow DenseLayer(RAM, 128, rectify)$
5   $hidden3 \leftarrow DenseLayer(hidden2, 128, rectify)$
6   $concat \leftarrow ConcatLayer(hidden1, hidden3)$
7   $hidden4 \leftarrow DenseLayer(concat, 256, rectify)$
8   $output \leftarrow DenseLayer(hidden4, outputDim, no\ activation)$
9   **return** $output$

The obtained results presented in Table 5 are reasonable, but not particularly impressive. In particular we did not notice any improvement over the benchmark `nips` network, which is embedded into both mixed architectures. This suggests that in the `mixed_ram` and `big_mixed_ram` models the additional information from the memory is not used in a productive way.

	Breakout	Seaquest
`mixed_ram` best	143.67	488.57
`big_mixed_ram` best	67.56	1700

Table 5: Table summarizing test results for methods involving information from the screen and from the memory.

8   RAM visualization

We visualized the first layers of the neural networks in an attempt to understand how they work. Each column in Figure 7 corresponds to one of 128 nodes in the first layer of the trained `big_ram` network and each row corresponds to one of 128 memory cells. The color of a cell in a given column describes whether the high value in this RAM cell negatively (blue) or positively (red) influence the activation level for that neuron. Figure 7 suggests that the RAM cells with numbers $95 - 105$ in Breakout and $90 - 105$ in Seaquest are important for the gameplay – the behavior of `big_ram` networks depend to the the high extent on the state of these cells.
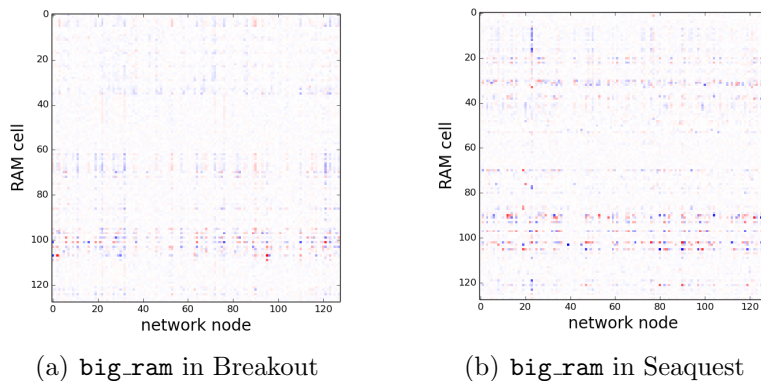

(a) `big_ram` in Breakout   (b) `big_ram` in Seaquest

Figure 7: Visualization of the parameters of the first layer of the trained Q-networks.

9   Conclusions

We trained a number of neural networks capable of playing Atari 2600 games: Bowling, Breakout and Seaquest. The novel aspect of this work is that the networks use information stored in the memory of the console. In all games the RAM agents are on a par with the screen-only agent `nips`. The RAM

agents trained using methods described in this work were unaware of more abstract features of the games, such as counters controlling amount of oxygen or the number of divers in Seaquest.

In the case of Seaquest, even a simple `just_ram` architecture with an appropriately chosen `FRAME SKIP` parameter as well as the `big_ram` agent with standard parameters, performs better than the benchmark `nips` agent. In the case of Breakout, the performance is below the screen-only agent `nips`, but still reasonable. In the case of of Bowling methods presented in [12] as well as those in this paper are not very helpful – the agents play at a rudimentary level.

10   Future work

10.1   Games with more *refined* logic

Since in the case of Seaquest the performance of RAM-only networks is quite good, a natural next target would be games such as Pacman or Space Invaders, which similarly to Seaquest offer interesting tactical challenges.

10.2   More sophisticated architecture and better hyperparameters

The recent papers [11, 21, 9, 25] introduce more sophisticated ideas to improve deep Q-networks. We would like to see whether these improvements also apply to the RAM models.

It would be also interesting to tune hyperparameters in a way which would specifically address the needs of RAM-based neural networks. In particular we are interested in:

- better understanding what the deep Q-network learns about specific memory cells; can one identify critical cells in the memory?

- improving stability of learning and reducing variance and overfitting,

- more effective joining of information from the screen and from the memory,

- trying more complex, deeper architectures for RAM.

10.3 Recurrent neural networks and patterns of memory usage

Reading the RAM state while running the deep Q-learning algorithm gives us an access to a practically unlimited stream of Atari 2600 memory states. We can use this stream to build a recurrent neural network which takes into account previous RAM states.

In our view it would also be interesting to train an *autoencoder*. It may help to identify RAM patterns used by Atari 2600 programmers and to find better initial parameters of the neural network [22].

10.4 Patterns as finite state machines

The work of D. Angluin [1] introduced the concept of learning the structure of a finite state machine through queries and counter-examples. A game for Atari 2600 can be identified with a finite state machine which takes as input the memory state and action and outputs another memory state. We are interested in devising a neural network which would learn the structure of this finite state machine. The successive layers of the network would learn about sub-automata responsible for specific memory cells and later layers would join the automata into an automaton which would act on the whole memory state.

11 Acknowledgements

References

[1] Dana Angluin. "Learning Regular Sets from Queries and Counterexamples". In: *Inf. Comput.* 75.2 (1987), pp. 87–106. DOI: 10.1016/0890-5401(87)90052-6. URL: http://dx.doi.org/10.1016/0890-5401(87)90052-6.

[2] M. G. Bellemare et al. "The Arcade Learning Environment: An Evaluation Platform for General Agents". In: *Journal of Artificial Intelligence Research* 47 (June 2013), pp. 253–279.

[3]   James Bergstra et al. "Theano: a CPU and GPU Math Expression Compiler". In: *Proceedings of the Python for Scientific Computing Conference (SciPy)*. Oral Presentation. Austin, TX, June 2010.

[4]   *Bowling (video game)*. URL: https://en.wikipedia.org/wiki/Bowling_(video_game) (visited on 04/15/2016).

[5]   Alex Braylan et al. "Frame Skip Is a Powerful Parameter for Learning to Play Atari". In: *AAAI-15 Workshop on Learning for General Competency in Video Games*. 2015. URL: http://nn.cs.utexas.edu/pub-view.php?PubID=127530.

[6]   *Breakout (video game)*. URL: https://en.wikipedia.org/wiki/Breakout_(video_game) (visited on 04/15/2016).

[7]   Aaron Defazio and Thore Graepel. "A Comparison of learning algorithms on the Arcade Learning Environment". In: *CoRR* abs/1410.8620 (2014). URL: http://arxiv.org/abs/1410.8620.

[8]   *Lasagne - lightweight library to build and train neural networks in Theano*. URL: https://github.com/lasagne/lasagne.

[9]   Yitao Liang et al. "State of the Art Control of Atari Games Using Shallow Reinforcement Learning". In: *arXiv preprint arXiv:1512.01563* (2015).

[10]   Nir Lipovetzky, Miquel Ramirez, and Hector Geffner. "Classical Planning with Simulators: Results on the Atari Video Games". In: *International Joint Conference on Artificial Intelligence (IJCAI)*. 2015.

[11]   Volodymyr Mnih et al. "Human-level control through deep reinforcement learning". In: *Nature* 518.7540 (Feb. 2015), pp. 529–533. URL: http://dx.doi.org/10.1038/nature14236.

[12]   Volodymyr Mnih et al. "Playing Atari With Deep Reinforcement Learning". In: *NIPS Deep Learning Workshop*. 2013.

[13]   *Nathan Sprague's implementation of DQN*. URL: https://github.com/spragunr/deep_q_rl (visited on 04/15/2016).

[14]   Stuart J. Russell and Peter Norvig. *Artificial Intelligence - A Modern Approach (3. internat. ed.)* Pearson Education, 2010. ISBN: 978-0-13-207148-2. URL: http://vig.pearsoned.com/store/product/1,1207,store-12521_isbn-0136042597,00.html.

[15]   *Seaquest (video game)*. URL: https://en.wikipedia.org/wiki/Seaquest_(video_game) (visited on 04/15/2016).

[16] Nitish Srivastava et al. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting". In: *Journal of Machine Learning Research* 15 (2014), pp. 1929–1958. URL: http://jmlr.org/papers/v15/srivastava14a.html.

[17] *The Bowling manual*. URL: https://atariage.com/manual_html_page.php?SoftwareID=879 (visited on 04/25/2016).

[18] *The Breakout manual*. URL: https://atariage.com/manual_html_page.php?SoftwareID=889 (visited on 04/25/2016).

[19] *The repository of our code*. URL: https://github.com/sygi/deep_q_rl.

[20] *The Seaquest manual*. URL: https://atariage.com/manual_html_page.html?SoftwareLabelID=424 (visited on 04/25/2016).

[21] Hado Van Hasselt, Arthur Guez, and David Silver. "Deep reinforcement learning with double Q-learning". In: *arXiv preprint arXiv:1509.06461* (2015).

[22] Pascal Vincent et al. "Extracting and Composing Robust Features with Denoising Autoencoders". In: *Proceedings of the 25th International Conference on Machine Learning*. ICML '08. Helsinki, Finland: ACM, 2008, pp. 1096–1103. ISBN: 978-1-60558-205-4. DOI: 10.1145/1390156.1390294. URL: http://doi.acm.org/10.1145/1390156.1390294.

[23] David Warde-Farley et al. "An empirical analysis of dropout in piecewise linear networks". In: 2014. URL: http://arxiv.org/abs/1312.6197.

[24] Christopher J. C. H. Watkins and Peter Dayan. "Technical Note Q-Learning". In: *Machine Learning* 8 (1992), pp. 279–292. DOI: 10.1007/BF00992698. URL: http://dx.doi.org/10.1007/BF00992698.

[25] Matteo Hessel Hado van Hasselt Marc Lanctot Nando de Freitas Ziyu Wang Tom Schaul. "Dueling Network Architectures Learning". In: *arXiv preprint arXiv:1511.06581* (2015).

A Parameters

The list of hyperparameters and their descriptions. Most of the descriptions come from [11].

hyperparameter	value	description
minibatch size	32	Number of training cases over which each stochastic gradient descent (SGD) update is computed.
replay memory size	100 000	SGD updates are randomply sampled from this number of most recent frames.
phi length	4	The number of most recent frames experienced by the agent that are given as input to the Q network in case of the networks that accept screen as input.
update rule	`rmsprop`	Name of the algorithm optimizing the neural network's objective function
learning rate	0.0002	The learning rate for rmsprop
discount	0.95	Discount factor γ used in the Q-learning update. Measures how much less do we value our expectation of the value of the state in comparison to observed reward.
epsilon start	1.0	The probability (ε) of choosing a random action at the beginning of the training.
epsilon decay	1000000	Number of frames over which the ε is faded out to its final value.
epsilon min	0.1	The final value of ε, the probability of choosing a random action.
replay start size	100	The number of frames the learner does just the random actions to populate the replay memory.

Table 6: Parameters