Dissecting Deep-Q-Networks: Understanding their Ability to Play Vision Games

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Abstract

Deep Q Networks (DQNs) have emerged as a powerful tool in reinforcement learning, enabling machines to achieve human-level performance in challenging Atari games. However, the inherent opacity of DQNs limits our ability to understand how they make decisions, which is critical for improving their performance and designing better RL solutions. In this paper, we present a novel approach to interpret DQNs by analyzing their decision-making processes while playing Ping-pong-v4. We uncover the key neurons responsible for tracking the ping pong ball and the opponent's score, and we observe that the network performs a cost-risk analysis based on the visual scores in the game frames. Moreover, we demonstrate the importance of input pixels in the decision-making process, with the ping pong ball being the most significant feature followed by the racquets and scores. Our findings provide valuable insights into the internal workings of DQNs, which can aid in improving their interpretability, and also inform better decision-making in RL. Our code, models, and results are publicly available at https://github.com/rohitgandikota/interpret-dqn, making our approach readily accessible for future research in this field.

1 Introduction

Reinforcement learning has proven to be an effective technique utilized in a wide range of applications. For instance, it has enabled the achievement of superhuman performance in playing Atari 2600 video games and winning the Go competition against a professional player Mnih et al. (2015) Silver et al. (2016). Furthermore, reinforcement learning has been applied in the field of traditional computer vision tasks, such as image classification Ba et al. (2014); Mnih et al. (2014), captioning Ba et al. (2015), activity recognition Yeung et al. (2016), and object detection Caicedo and Lazebnik (2015); Bueno et al. (2017). In this work, we focus on RL agents playing Atari's PingPong-v4 using deep neural networks as function approximators (DQN).

Understanding deep neural networks has been active research in the recent decade. There are works that proposed visualizing the filters through deconvolution Zeiler and Fergus (2014). The initial findings of interpretability have shown progressive learning of filters indicating a hierarchy of filterting Forsyth et al. (1999). However, these methods represent a holistic view of neural networks as feature extractors. This work mainly

focuses on the specific roles of each neuron in the decision-making of the DQN. Some works have explored the behavior of a Convolutional Neural Network (CNN), by masking out image patches and visualizing the patches that have a maximum change in the activations Zeiler and Fergus (2014), Zhou et al. (2014). Alternatively, backpropagation variants can be employed to identify or generate significant image features Mahendran and Vedaldi (2015), Simonyan et al. (2014). Understanding the discriminative power of the CNN's hidden layers can also be accomplished by isolating, transferring, or limiting portions of the network and testing their capabilities on specialized problems Yosinski et al. (2014), Agrawal et al. (2014), Sharif Razavian et al. (2014). However, visualizations reduce the mechanisms of the network to images that require interpretation, leading us to aim to match representations of CNNs with labeled interpretations directly and automatically.

The examination of individual units within neural networks is particularly relevant to our current work. For example, in a study by Zhou et al. (2014), human evaluation determined that individual units functioned as object detectors in a network trained to classify scenes. Nguyen et al. (2016) generated prototypical images for individual units using a feature inversion mapping, in contrast to our approach of automatically assigning concept labels. Alain and Bengio (2016) proposed a method for testing intermediate layers by training simple linear probes that analyze the information dynamics among layers and their effect on the final prediction.

2 Deep Q Learning

The Markov Decision Process (MDP) is formally defined in this section, along with a discussion of the Q learning setup and the model architecture. The training procedure designed for this work is also covered.

2.1 MDP Formulation

To understand the crux of the work, we first define the MDP formally including the states, rewards, actions and transitions:

State The state of an MDP is to be formulated such that it is self-sufficient for the agent to take an action. In vision games like ping-pong, a still frame is not MDP satisfied as the direction of the ball is unclear based on a single frame as shown in Figure 1(a). Therefore, to make the state MDP-satisfied, we stack the frames of the previous state such that the agent has all the information at the current state as shown in Figure 1(b). The state consists of the racquets of both the agent and the opponent, the ball, and the scores of the agents.

Actions There are 6 pre-defined actions in the game space. The first 2 actions are $IDLE$ actions making the state unchanged. Actions 3 and 5 correspond to $LEFT$ where the racquet moves to the left and actions 4 and 6 correspond to $RIGHT$ where the agent moves right.

Rewards The reward function of the game state is very sparse. The agent incurs a -1 reward if the agent misses the ping pong ball at its side and gets a +1 reward if the ball is missed by the opponent.

Transition The game state is deterministic as it is a competitive beginner's game. The agent moves right with 100% probability if $RIGHT$ action is taken and left if

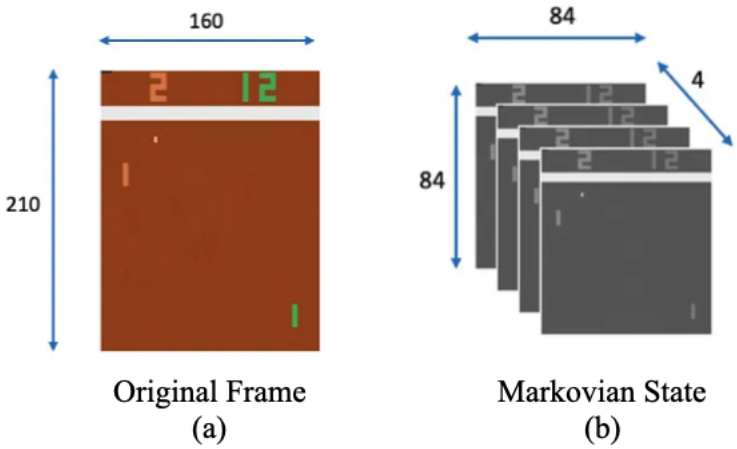


Figure 1: The original frame (a) from the game is an RGB image with no information on the direction of the ball making it non-Markovian. We, therefore, stack the frames (b) from previous time steps to impart the information to make the new state Markovian. We also preprocess the frames to make them gray-scaled and reduce the size to make them efficient.

$LEFT$ action is taken.

2.2 DQN

Although it may seem like the agent selects actions based on their immediate rewards, in reality, we teach the agent to calculate state-action values $Q(s, a)$ that consider both immediate and future rewards. These values can be computed using either a tabular approach, which requires tracking all state-action pairs, or function approximation. Given the size of our state-action space (84*84*4*255*6) where 84 is the patch size; 4 is the frame history; 255 is the DN range and 6 is the action space. We opted for function approximation through deep neural networks. Equation 1 presents the update rule for the sample-based, 1-step, tabular Q values, where γ indicates the discount factor that determines the priority between immediate and future rewards.

$$Q(s, a) = Q(s, a) + \alpha(r + \gamma max_{a'} Q(s', a') - Q(s, a)) \tag{1}$$

Given our use of a function approximator in the form of a deep convolutional network to predict Q values, we update the parameter λ using the equation presented in Equation 2.

$$\lambda \leftarrow \lambda + \alpha(r + \gamma max_{a'} Q_\lambda(s', a') - Q_\lambda(s, a)) \nabla_\lambda Q_\lambda(s, a) \tag{2}$$

Deep Q networks and Q learning algorithms are susceptible to overestimating Q values, which occurs as our Q value estimates approach their true values. This is because we use the same network to generate both values, and in our agent's training, this issue manifested as a consistent request for higher-resolution images. To address this problem, we introduce a target network, which involves maintaining a copy of the original network (with network parameters λ') and updating it less frequently than the primary network. By doing this, we can avoid any bias from the primary network

because the target network can pull the bias back. This mechanism is illustrated in Equation 3.

$$\begin{aligned} a' &= argmax_{a'} Q_\lambda(s', a') \\ \lambda \leftarrow \lambda + \alpha(r + \gamma Q_{\lambda'}(s', a') - Q_\lambda(s, a)) \nabla_\lambda Q_\lambda(s, a) \\ \lambda' &\leftarrow \lambda \text{ (every 4000 steps)} \end{aligned} \tag{3}$$

2.3 Training Details

We discuss the main training details of the DQN we train for playing Ping Pong V4. We also give some information on the deep network architecture.

Architecture: The network takes in an input image with dimensions 4 and outputs a vector of Q-values corresponding to each possible action. The network has three convolutional layers with 32, 64, and 64 filters respectively, followed by two fully connected layers with 512 and 6 units respectively. ReLU activations are used.

Hyperparameters: We compared the effects of appending the history frames in state representation and chose to append the last 4 frames as this yielded satisfactory initial results. We use a discount factor of 0.99 . We updated the target vector every 10000 iterations and trained the agent for 100000 iterations, with a batch size of 32. We used the RMS optimizer with a 1e-3 learning rate and random uniform initialization.

Replay Buffer: Since we used a function approximator, training the network with consecutive samples would lead to training inefficiency due to the high correlation between samples. Thus, we used a replay buffer to store the (s, a, r, s') tuples. We simulated the agent by starting from an image state s, taking action a based on Q values $(argmax_a Q(s, a) + noise)$, observing the reward r and next state s', and storing the tuple in the buffer. We used a buffer size of 50000, and once the buffer was full, we trained the network by randomly sampling pairs from the buffer. We replaced the tuple with the least error with new samples, essentially making it a pseudo-prioritized buffer.

Exploration: At the start of training, the network had no information about the task or the environment. Therefore, it was important to explore the actions initially. To achieve this, we added an exploration constant ϵ, which decreased over time as the agent learned more about the task. ϵ represents the probability at which the agent chooses a random action compared to the optimal action. We start with 100% exploration and then reduce it at 1e-5 decay till 10%.

We show the training curves in Figure 2 where the average reward is plotted against the number of training interactions and decaying exploration constant. We also show the average results of the DQN agent compared to random agent in Table 1. A random agent is an agent that takes random actions out of the 6 actions at each state. We observe a huge learning jump as the random agent always incurs a score of -22 (loses all the games) while the DQN gets a score of 16. We calculate the score as difference between the agent's score and the opponent's score.

3 Method

In this section, we discuss the methods used to interpret the DQN agent decision-making process. We use two different methods to interpret the process: first, a dissection method to understand the learned parameters of the neural network. Second, a

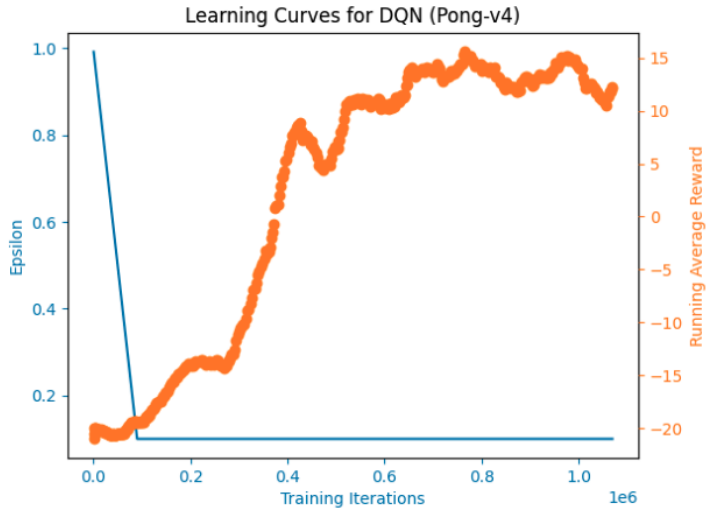


Figure 2: The learning curves of the DQN agent show a healthy learning curve and increasing rewards with reduced exploration. This shows that the agent learns to take better greedy action over time as the exploration is clearly reduced. We achieve an average reward of +15 for a game.

Agent	**Average Score**
Random	-22
DQN	+16

Table 1: The average scores over 1000 games show that the DQN actually wins the games compared to a random agent which always looses. We stop the game if either of the agents reach a score of 22 as this is an in-built feature of the atari game.

visual method to understand the important pixels in the input image responsible for a decision made by the agent.

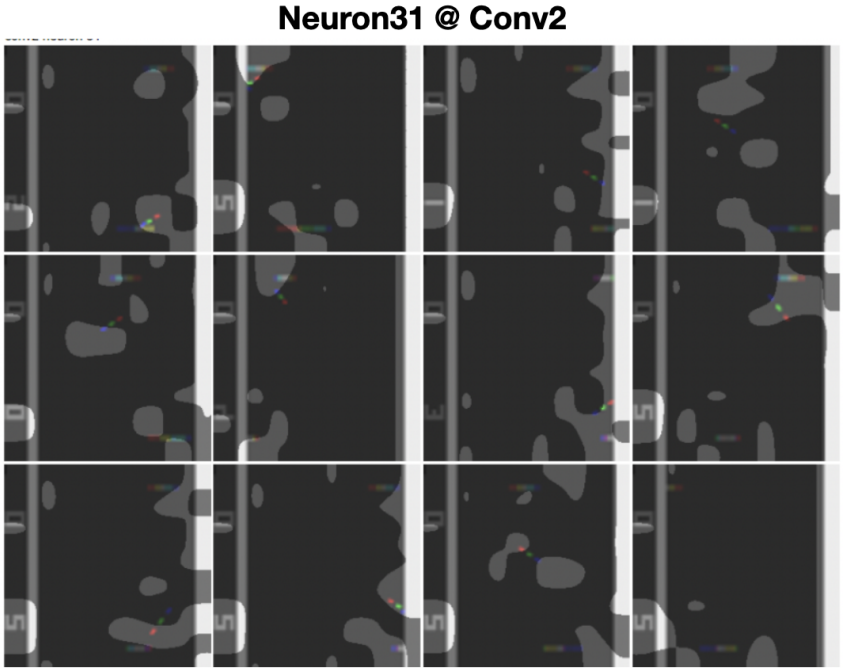


Figure 3: The top activating regions of the neuron31 in the Conv2 layer has always been the agent's score. This shows that each neuron has a fixed role in looking at certain regions of the input frame.

3.1 Neuron Dissection

We present an approach for elucidating the significance of learned parameters in Deep Q Networks (DQNs) by visualizing the salient features extracted by individual neurons. Specifically, we investigate the DQN at a convolution layer L and record the activation maps $\mathcal{A}_L^i$. Subsequently, we employ a Viterbi backtracking-based method to identify the activation maps with the highest influence on the final layer N prediction p. To accomplish this, we gather the maximum activations responsible for the prediction from the previous layer $max(\mathcal{A}_{N-1}^1, \mathcal{A}_{N-1}^2 ..., \mathcal{A}_{N-1}^i)$, where i represents the total number of neurons/filters in layer $N-1$. We repeat this procedure until the layer L is reached, and then visualize the top activation maps. In the case where activation $\mathcal{A}_{L+1}^j$ is the highest in layer $L+1$, the neuron activation in layer L with the highest activation among n neurons is:

$$\mathcal{A}_L^i = max(\mathcal{A}_L^{1,j}, \mathcal{A}_L^{2,j}, \mathcal{A}_L^{3,j}, ..\mathcal{A}_L^{n,j}) \tag{4}$$

Where $\mathcal{A}_L^{i,j}$ represents all the activation map that goes from neuron i in layer L to neuron j on layer $L+1$

In Figure 4, we visualize the top activations from the first convolution layer for the current frame in Figure 4(a). The network decides to move $RIGHT$ and we backtrack

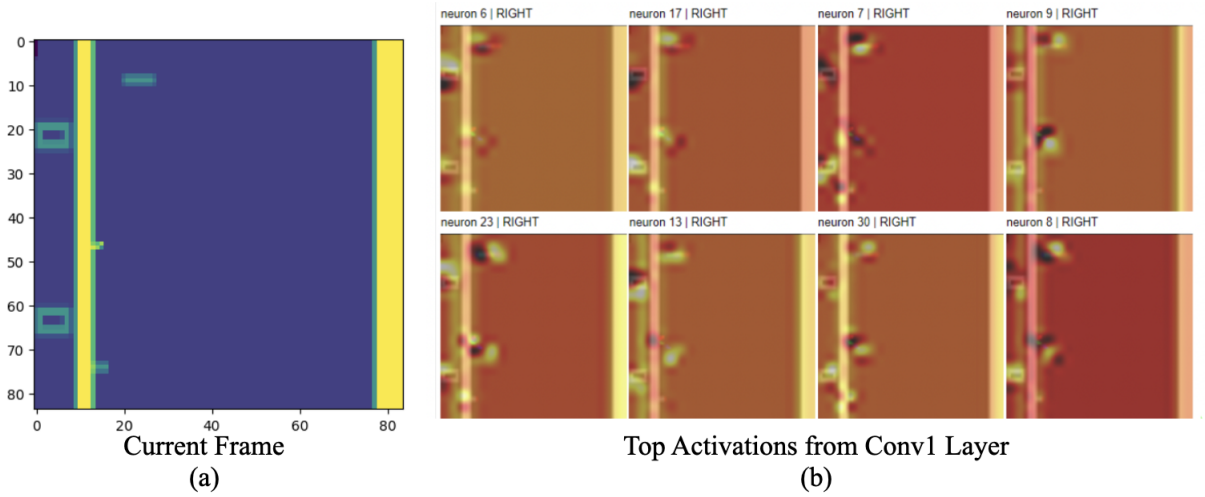


Figure 4: We look at the top activating activation maps at convolution layer 1 for the current frame in (a). We find that neuron8 looks particularly at the ball and racquets, while neuron30 also looks at the boundary to the left to understand the bounce of the ball.

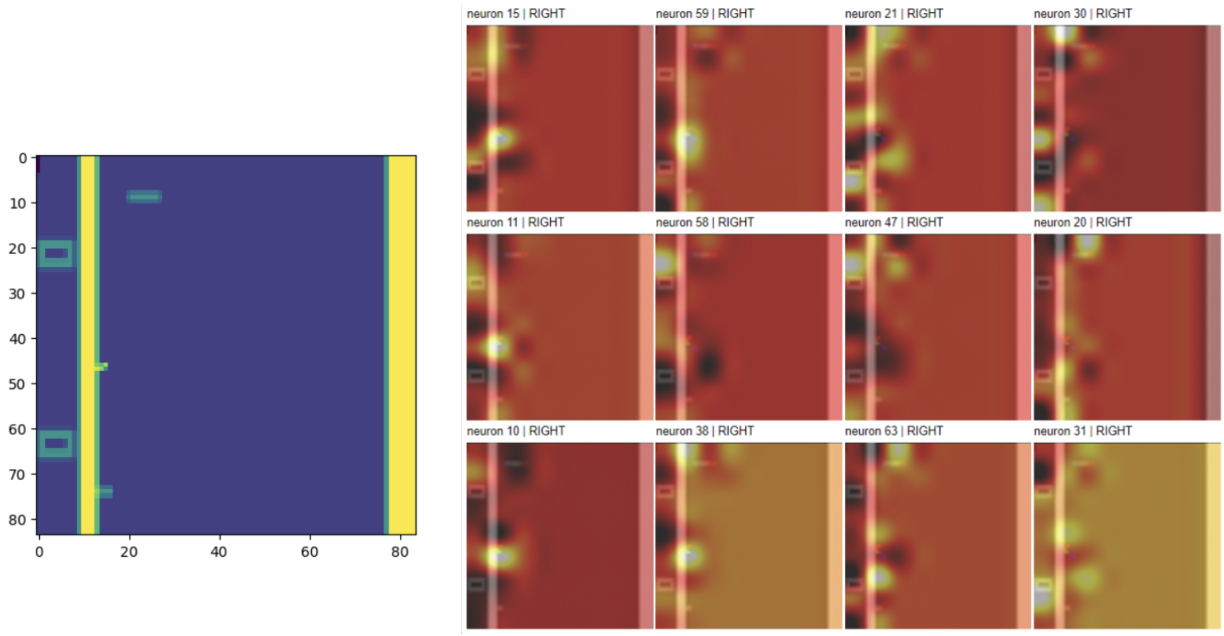
the neurons responsible for that action. We find that the top neurons at the first layer are very specific and look at the ping pong ball and the racquets. We find that all the top 6 neurons look precisely at the ball and racquets while a few also keep a track of the boundaries to keep a track of the bounce (like neuron30 in Figure 4(b))

In Figure 5, we visualize the top activations from the second convolution layer for the current frame in Figure 5(a). We observed that the top 2 neurons (15 and 59) mainly focus on the ball. Interestingly the DQN agent assigns neuron 47 to keep a check on the opponent's score in Figure 5 and neuron 31 to keep track of its own score. We observed that based on these scores, the agent does a cost-risk analysis to take an action. If the opponent's score is high, and the agent is at risk of losing, it plays defensively. When the score is low and the agent is winning, it takes an aggressive role.

3.2 Network Dissection

In addition to the sample-based analysis, we also performed a network-based analysis to examine the network parameters rather than individual sample activations. To accomplish this, we executed the network over a large sample of 50,000 frames, and we identified the 12 regions where each neuron exhibited the strongest activation in this dataset. Figure 3 depicts Neuron31 from the convolution 2 layer, which we scrutinized to determine if it primarily focused on the agent's score. We observed that these neurons have a fixed designation for what to observe in a frame most of the time. We present additional findings in Figures 7,8, and9.

Our analysis revealed that Neuron 17 in Conv 1 is assigned to look at the boundary for the occurrence of bounce in the game, as shown in Figure 7. On the other hand, Neuron 17 in Conv 2 is responsible for guarding the regions near the boundaries. We believe that it alerts the decision before the ball hits the boundary, which would significantly alter the trajectory, as demonstrated in Figure 8. Finally, certain neurons



Current Frame
(a)

Top Activations from Conv2 Layer
(b)

Figure 5: We look at the top activating activation maps at convolution layer 2 for the current frame in (a). We find that the top 2 neurons (15 and 59) look at the ball and racquets. Interestingly, we observed that neuron 47 looks at the opponent's score, and neuron 31 looks at its own score. We observed that the agent takes more risks if the agent score is much lower compared to its own to finish the game earlier and plays defense when the scores are not too drastic. Interesting cost-risk analysis that the agent does before making a move.

solely track the ball and racquets, such as Neuron 13 in the Conv 2 layer, as illustrated in Figure 9.

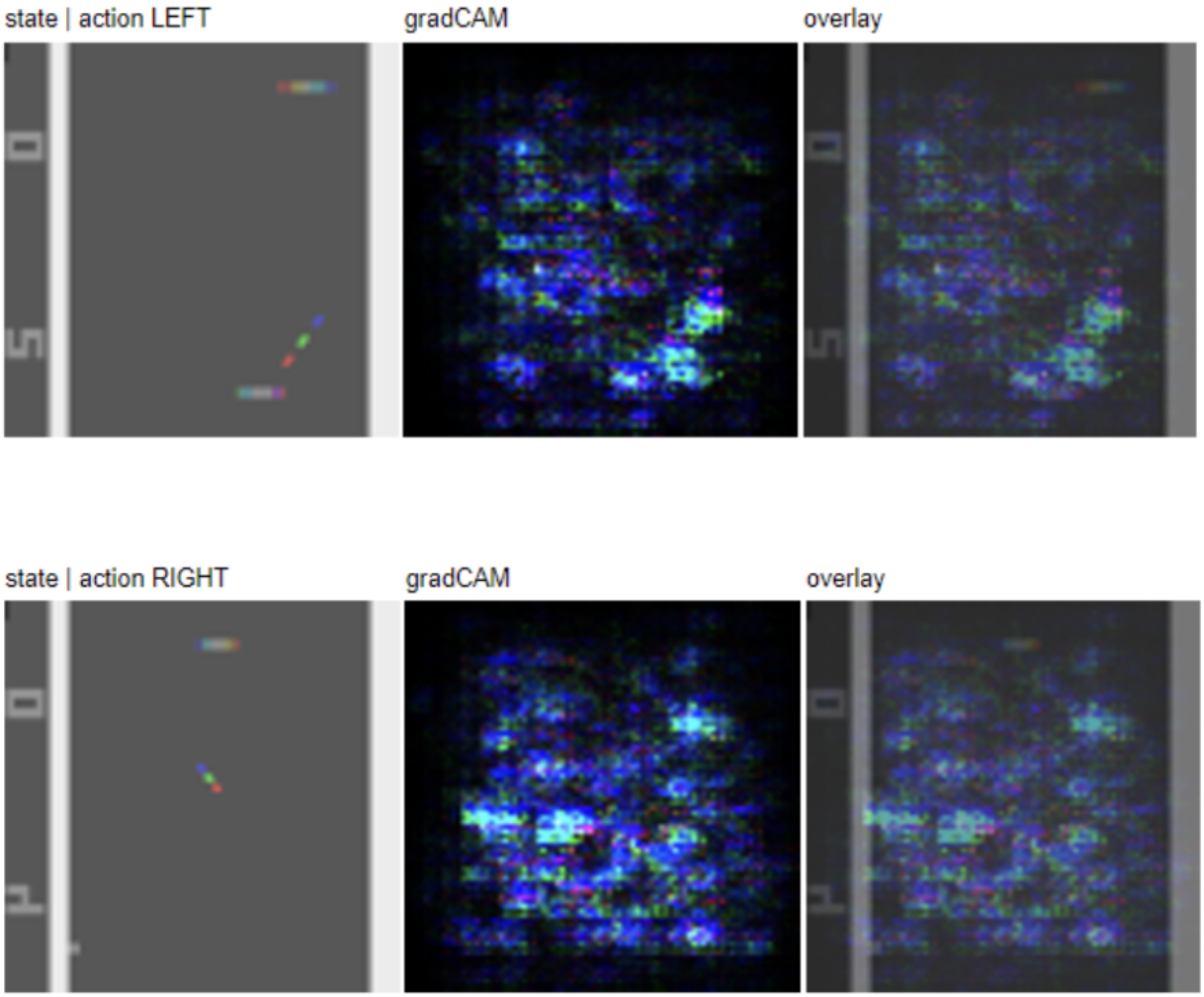


Figure 6: We look at the gradients at the perturbed inputs. We find that the gradients are high near the regions where the ball is present and also at the regions of the racquet. This is a very good interpretation of the DQN that suggests that the regions of the images with balls and racquets are the most important in decision-making.

3.3 Smooth-Grad CAM

he importance of input pixels in classification can be understood by looking at the gradients of perturbed inputs, as proposed by Smilkov et al. (2017). In our study, we applied a similar strategy to understand the important pixels in the input region for making Q-value decisions. We added noise to the input frames, passed them through the network, and ran a backprop on the network using the desired action as a label. We then visualized the resulting gradients at the input level in Figure 6. The ball and racquets were found to be the most important pixels in the image for decision-making by the network.

However, we also observed a significant amount of noise in the gradients, which is expected due to the perturbations introduced by ReLU activations and the higher frequencies in the image domain. This observation is consistent with Adebayo et al. (2018), who noted that although gradients are a useful idea, it can be challenging to use them for visualization due to the noise they introduce.

4 Conclusion

This work aimed to gain a deeper understanding of how Deep Q-Network (DQN) networks can achieve human-level performance in playing Atari games. By analyzing the neurons in the network and visualizing their top activations, we discovered that certain neurons in the network had specific roles, such as tracking scores or the ball. We also found that these neurons consistently performed the same tasks for all the inference/test samples. Additionally, by examining the model's treatment of input pixels, we identified that the model gives high importance to regions with balls and racquets. Our research suggests that interpretability can be a useful tool in developing more efficient and safer reinforcement learning agents. The source code, models and more results are available at https://github.com/rohitgandikota/interpret-dqn

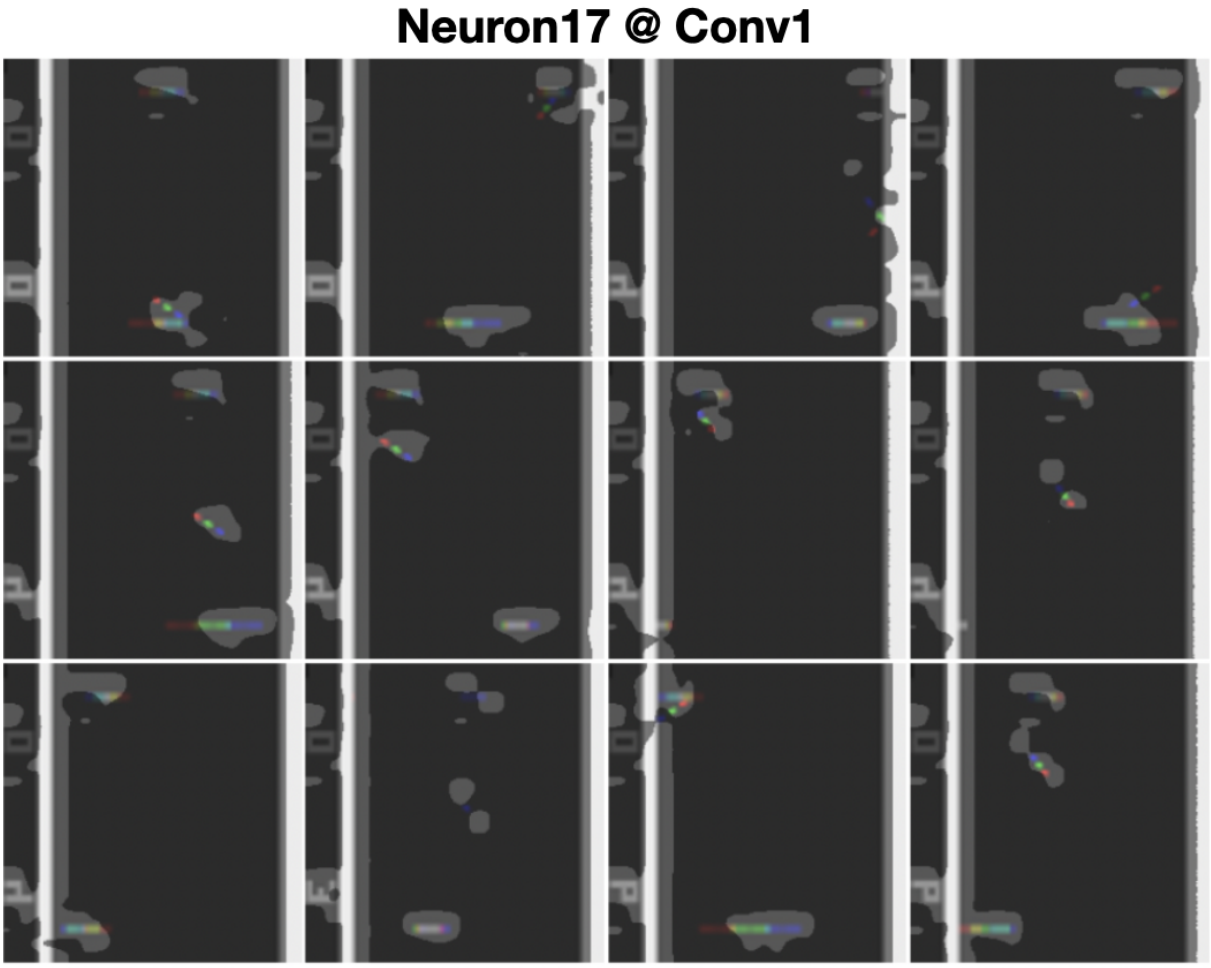


Figure 7: The top activating regions of the neuron17 in the Conv1 layer has always been the ball and the racquets. It is interesting to find that this neuron also looks at the boundaries of the game keeping track of the bounce. This shows that each neuron has a fixed role in looking at certain regions of the input frame.

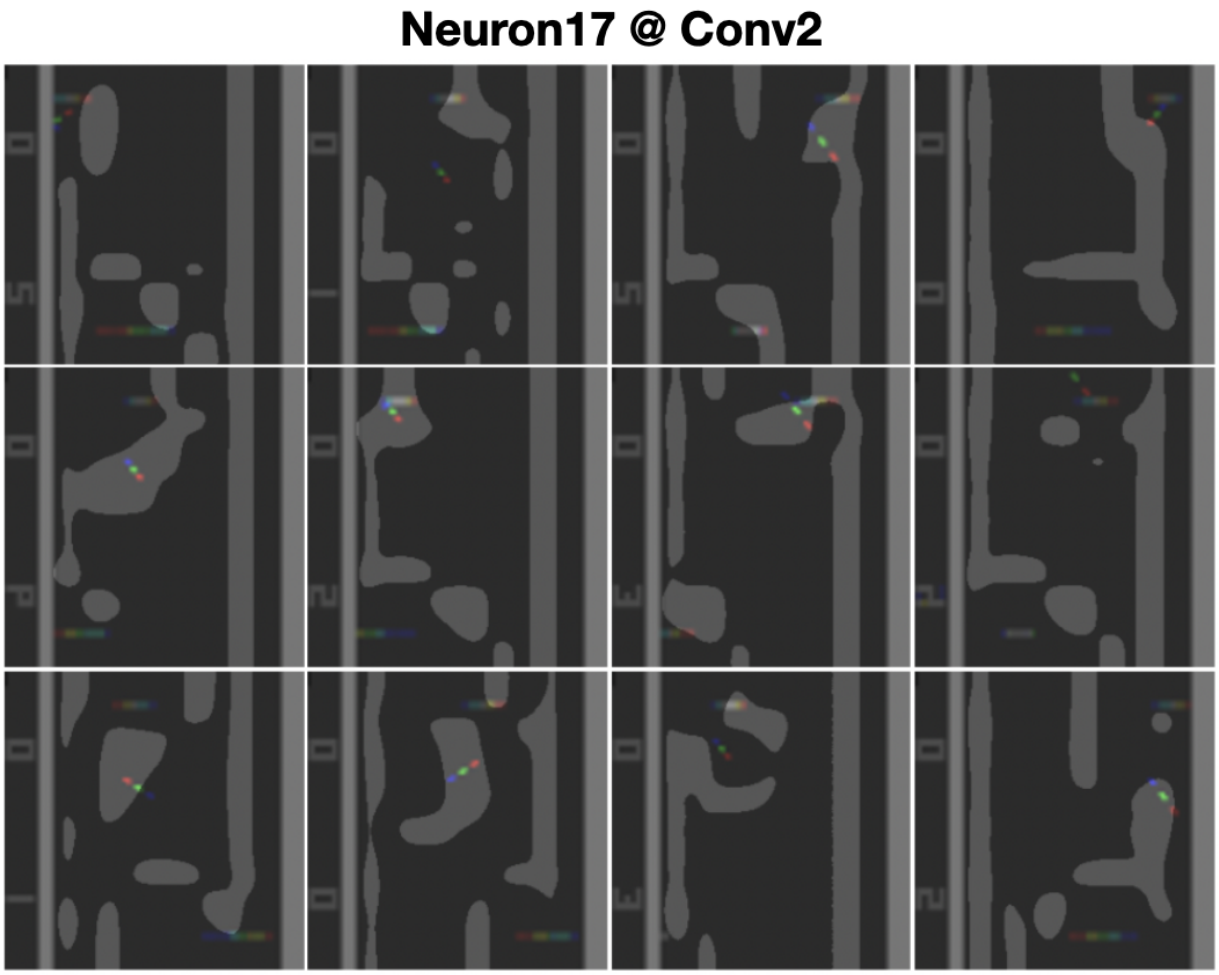


Figure 8: The top activating regions of the neuron17 in the Conv2 layer has always been the regions near This neuron and seems to be the one that is responsible to alert the model before the ball is about to hit the boundary. This shows that each neuron has a fixed role in looking at certain regions of the input frame.

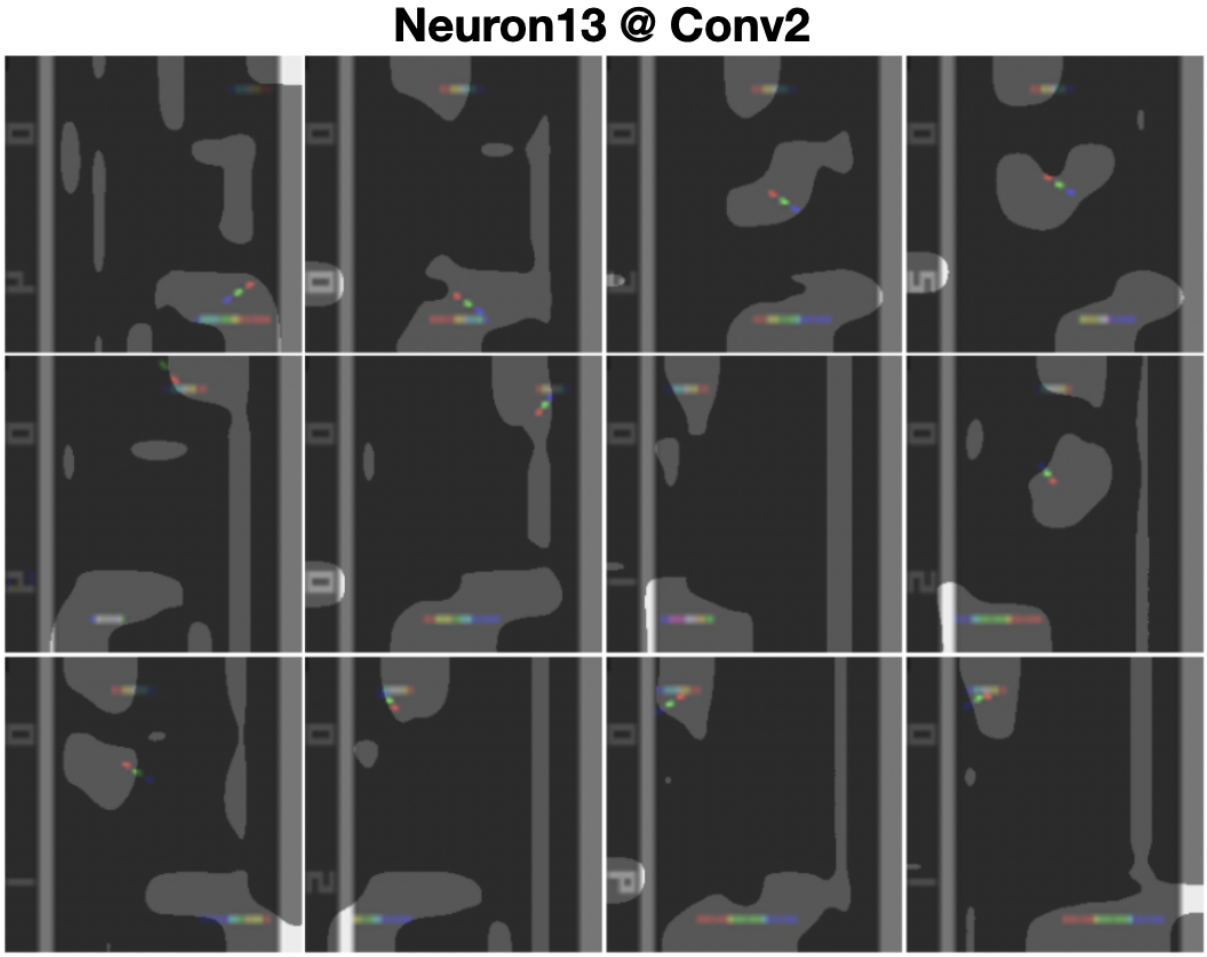


Figure 9: The top activating regions of the neuron13 in the Conv2 layer has always been only the ball and the racquets. This shows that each neuron has a fixed role in looking at certain regions of the input frame.

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