Deep Reinforcement Learning with Swin Transformer

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Abstract—Transformers are neural network models that utilize multiple layers of self-attention heads. Attention is implemented in transformers as the contextual embeddings of the ‘key’ and ‘query’. Transformers allow the re-combination of attention information from different layers and the processing of all inputs at once, which are more convenient than recurrent neural networks when dealt with a large number of data. Transformers have exhibited great performances on natural language processing tasks in recent years. Meanwhile, there have been tremendous efforts to adapt transformers into other fields of machine learning, such as Swin Transformer and Decision Transformer. Swin Transformer is a promising neural network architecture that splits image pixels into small patches and applies local self-attention operations inside the (shifted) windows of fixed sizes. Swin Transformer has shown top-ranking performances in many image classification and object detection benchmarks. Similar attempts have been made in the field of reinforcement learning. Decision Transformer has successfully applied transformers to off-line reinforcement learning and showed that random-walk samples from Atari games are sufficient to let an agent learn optimized behaviors. The key technique that combines reinforcement learning with transformers in Decision Transformer is to embed reward signals as returns-to-go tokens and adjust dynamically the values of returns-to-go as the game proceeds. However, it is considerably more challenging to combine online reinforcement learning with transformers. In this article, we further explore the possibility of not modifying the reinforcement learning policy, but only replacing the convolutional neural network architecture with the self-attention architecture from Swin Transformer. Namely, we target at changing how an agent views the world, but not how an agent plans about the world. We conduct our experiment on 49 games in Arcade Learning Environment. The results show that using Swin Transformer in reinforcement learning achieves significantly higher evaluation scores across the majority of games in Arcade Learning Environment. Thus, we conclude that online reinforcement learning can benefit from exploiting self-attentions with spatial token embeddings.

Index Terms—Machine Learning, Reinforcement Learning, Deep Learning, Convolutional Neural Networks, Computer Vision, Transformers, Self-attention, Atari

I. INTRODUCTION

Both reinforcement learning (RL) and natural language processing (NLP) are considered sub-fields of Artificial Intelligence (AI). They both deal with temporal sequences but RL relies on the Markov decision process (MDP) instead of neural networks (NNs) to build the temporal decision-making model, which describes the discrete-time stochastic control process that can be solved mathematically through dynamic programming.

Prior to the birth of transformers, the most common deep learning (DL) solution to NLP tasks is to utilize recurrent neural networks (RNNs). RNNs take a variable length of inputs and use internal states to process the tokens sequentially. Long short-term memory (LSTM) [6] was invented to solve the vanishing or exploding gradient problems in RNNs by gating mechanisms. LSTM allows error to propagate into the earliest tokens in the sequence at the cost of encoding the entire context into vectors with a fixed length. Afterwards, attention mechanisms were introduced into RNNs to handle the long-term dependency dilemma. Soft attention [1] methods attend to only the relevant inputs for predicting the next word. Thus, the error can propagate into those relevant parts of the network that produces the hidden states. However, only the last hidden state is able to be represented together with its own attention-based context vector.

The Transformer makes use of the self-attention network and demonstrates stronger capabilities than previous attention-based RNNs [17]. One of the main improvements from the Transformer is to encode each hidden state with its own attention-based context vector, which yields significantly richer contextual representations when stacked over multiple NN layers. The contextual information is also exempted from sequential strictness. Another main improvement is to use positional embeddings to encode relative positions of the input tokens.

Recent researches have focused on the viability of replacing convolutional neural networks (CNNs) with transformers. Vision Transformer (ViT) successfully adapted transformers from the NLP into computer vision (CV) field [4]. There were also some researches using ViT in RL [7], [14], but training ViT in RL is tremendously costly due to its quadratic complexity relative to the input image size. Swin Transformer further improved ViT in terms of both less computational overhead and better accuracy [9]. Applying transformers to CV tasks can be challenging due to the variable attributes, e.g. scale, in the visual entities. On the other hand, Swin Transformer is exempted from solving the long-term dependency problem of NLP as it works with fixed numbers of pixels but not variable lengths of sequences. Moreover, it demonstrates the strength of establishing long-range dependencies between
remote pixels or between pixels and entities in the image, of which convolutional layers cannot simply achieve.

RL studies intelligent behaviors in environments, which typically requires an agent to maximize the obtained rewards. One of the main challenges in RL is to balance the rate of exploration over exploitation. The outcomes of past exploration need to be stored and the agent can then use those to predict expected rewards in future runs. Q-values are values that record such outcomes of an action at a certain state. Q-learning keeps tracks of those Q-values and uses the Bellman Optimality Equation by (Eq. [1]) \[18\] to update the policy. Here, $Q^*(s, a)$ is the Q-value at state $s$ of action $a$, $r_{t+1}$ is the result value obtained by advancing to state $s_{t+1}$ at time instant $t + 1$.

\[
Q^*(s, a) = E\{r_{t+1} + \gamma \max_{a'} Q^*(s_{t+1}, a'|s_t = t, a_t = a)\} \tag{1}
\]

RL algorithms can be categorized as on-policy and off-policy algorithms. On-policy algorithms act and update on the same policy, and off-policy algorithms act and update by different policies. Q-learning is off-policy because the actual action it takes at $s_{t+1}$ is allowed to be different from the greedy action $\max_a Q(s, a)$.

Combining RL policies with NNs has also become a common practice in the field of RL. Especially, CNNs have been applied to games that have image displays in Deep reinforcement learning (DRL). Deep Q-learning Network (DQN) is one of the DRL methods that store Q-values in NNs instead and produce the predictions by the network output. DQN has achieved human or superhuman level performances on many of the Atari games \[10\].

Decision Transformer is a recent invention that adapted transformers into the RL field \[2\]. Unlike Swin Transformer, Decision Transformer views RL problems as the same sequence modeling problems as NLP does, which abandons the traditional value function and policy gradient methods in RL and replaces them by a causally masked transformer. One of the major limitations of Decision Transformer is that it only works on off-line RL. States, actions and returns must be known prior to the training of the model. In other words, the agent lacks the opportunity to sample optimized trajectories based on the improved model. Although the original paper of Decision Transformer demonstrated its capabilities to generate better unseen trajectories from sub-optimal ones, convergence is not guaranteed if the environment is not fully explored and stored into the off-line samples.

Meanwhile, Decision Transformer needs to encode the so-called returns-to-go values, which are the remaining amount of rewards the agent is supposed to obtain in the future. Returns-to-go values do not need to be set precisely to what the expected outcomes are. Instead, they can be values that are reasonably large and the agent is still capable of associating them with good actions. Nonetheless, the inclusion of returns-to-go requires us to have a grasp of what the values should be for each different game, which contradicts the goal to train a model that can perform well on all Atari games without specific parameter tunings.

\section{Method}

We seek for another way of combing transformers with DRL. The long-term dependency problem of temporal sequence modeling is especially dominant in RL, as do we not know in advance the sparsity of the reward. Different with the variable length of input tokens, the image pixels are always fixed throughout the training of RL. Thus, we argue that it is more economic to introduce spatial self-attentions instead of temporal self-attentions in DRL.

Meanwhile, Decision Transformer only works with offline RL because it needs the future reward information in advance in order to encoded tokens in a way that can associate actions with rewards. Online RL policies have mathematically well-formulated convergence proofs and have shown promising applications and results across various fields. An obvious approach of applying self-attentions to online RL is to leave the RL policy untouched and simply construct the self-attention NN network because integrating Swin Transformer into DRL does not need to modify the RL policy. As a result, those well-known traditional value function or policy gradient approaches can be improved by utilizing spatial self-attentions.

Double Q-learning \[5\] is a widely adopted algorithm that improves upon Q-learning. Q-learning tends to overestimate the Q-values because the policy updates on the target values selected by the $\max$ operator, which perpetuates the approximation errors in the direction of overestimation. Overestimation in Q-learning can have undesired effects and lead to suboptimal performances of the agent \[15\]. Unrealistic Q-values can potentially destabilize the weights in NNs when the actions in the replay buffer are always drawn from the same trajectory. Double Q-learning avoids overestimation by having two separate Q-function values. Only one of them is updated at once according to either (Eq. 2) or (Eq. 3).

\[\alpha(s, a) \text{ is the learning rate, } a^* = \arg\max_a Q^A(s', a), \text{ and } \beta^* = \arg\max_a Q^B(s', a) \text{ at the next state } s'. \text{ This update rule also indicates that Double Q-learning might suffer from underestimation instead of overestimation because the target approximation is a weighted estimate of unbiased expected values, which are lower or equal to the maximum expected values } \tag{2}\]

\[Q^A(s, a) = Q^A(s, a) + \alpha(s, a)(r + \gamma Q^B(s', a^* - Q^A(s, a)) \tag{2}\]

\[Q^B(s, a) = Q^B(s, a) + \alpha(s, a)(r + \gamma Q^A(s', b^* - Q^B(s, a)) \tag{3}\]

The convention of realizing Double Q-learning in DQN is to keep a copy of the policy Q-network, which is called a target network. This reduces the amount of computational overhead \[16\] comparing to maintaining two different networks. As a result, we need to synchronize the policy network and target network after a certain amount of steps, which itself is a hyper-parameter to be tuned.

The pseudo-code of our DQN is shown in Algorithm \[11\]. Here, $r$ is the reward, $\gamma$ is the discounting factor, $\epsilon$ is the exploration ratio, $\text{maxFrames}$ is the maximal number of total frames, and $L(\cdot)$ is the loss function, i.e., Smooth L1 loss in this case.

$Q^A_\theta$ is the policy network and $Q^B_\theta$ is the target network, which is a copy of $Q^A_\theta$. $\text{syncFrames}$ is the number of frames
Algorithm 1 Double Q-learning

```
Input: c, γ, maxFrames, syncFrames, L()
Parameter: D, Q^A, Q^B
Output: Q^B
1: frames ← 0
2: while frames < maxFrames do
3: Initialize the environment
4: while Game not finished do
5: frames ← 4
6: if random() < c then
7: Choose an action randomly
8: else
9: Choose an action through Q^A
10: end if
11: Store s, a, s', r, terminal into replay buffer D
12: Draw minibatch of s, a, s', r, terminal from D
13: Update Q^A according to Algorithm 2
14: end while
15: if frames%syncFrames == 0 then
16: Q^B ← Q^A
17: end if
18: end while
19: return Q^A
```

Algorithm 2 Network Update

```
Input: s, a, s', r, terminal, L()
Parameter: Q^A, Q^B
Output: Q^B
1: target = r + γQ^A(s', a') ∗ (1 − terminal)
2: Compute loss by L(Q^B(s, a), target)
3: Update Q^B by loss with gradient descent
4: return
```

between the synchronizations of two networks. In Algorithm 2, \( a^* \) is \( \text{argmax}_a Q^A(s', a) \), \( s \) is the current state, \( s' \) is the next state, \( a \) is the action, \( \text{terminal} \) is a flag indicating if the game terminates or not.

We improve DQN by replacing the CNNs with Swin Transformer, which convolves upon the inputs to produce the spatial embeddings. Image pixels are grouped into small patches and transposed so that the output channels become hidden embeddings. Each basic layer contains a number of Swin blocks, illustrated on the bottom left in Fig. 2. Patches are grouped into local windows before the self-attention operation, which is performed through a grouped 1D convolutional layer. This exploitation of locality reduces the computational complexity from quadratic to linear when the window size is fixed. Afterwards, there are two linear layers with the number of hidden units proportional to the embedding dimensions, followed by reshaping operations that reverse the window partition.

One shortcoming of utilizing locality is that there lacks self-attentions among different local windows. To effectively overcome this, the window partition is shifted in successive blocks to introduce cross-window connections. Namely, the first and third blocks displace the windows by a number of patches, so that the windows are overlapped over different neighboring blocks. Neighboring patches are merged after all but the last basic layers in order to build hierarchical feature maps. Patch merging also reduces the dimensions of embeddings by adding a linear layer afterwards.

III. EXPERIMENTAL DETAILS

Our experiments are conducted across 49 Atari games of Arcade Learning Environment (ALE). We later include evaluation curves of 10 games for a more detailed examination. The NN architecture of our DQN is shown in Fig. 1. The list of chosen parameters for DQN is shown in Table I.

We use Adam as our optimizer and the learning rate remains the same for both DQN and Swin DQN. Adam is an optimization algorithm that uses the adaptive estimates of lower order moments of the gradient [8].

A full illustration of our Swin DQN is in Fig. 3. The list of parameters specified for Swin DQN is shown in Table II. The rest of the parameters are kept the same as in DQN. We use three layers of Swin blocks in our NN. Those layers contain 2, 3, 2 Swin blocks and 3, 3, 6 attention heads, respectively. The patch size is set to \( 3 \times 3 \), which yields \( 28 \times 28 \) patches since the input is \( 84 \times 84 \) for each channel. The embedding dimension for each patch is 96. This suggests that the token size after patch embedding is \( 784 \times 96 \). The matrix operation of self-attentions is conducted through a grouped 1D convolutional layer, with patches allocated into local windows. In our case, it suggests \( 7 \) patches per local window and the windows are shifted by \( 3 \) patches for the first and third blocks. The number of groups of 1D convolutional layer is equal to the number of attention heads. The MLP ratio 4 means that the linear layers inside Swin blocks have \( 4 \times \) embedding dimension hidden units, which are 384. The drop path rate 0.1 states that there is a 10% chance that the input is kept as is in skip connections.

There are random no-operation (no-op) steps of \([0,30]\) at the start of each game to help introduce stochasticity into the environment. We set the seed of the Atari environment fixed on the purpose of training, but randomly select seeds for a more concrete evaluation phase. Randomly seeded games are initialized for every single episode of the evaluation.

| TABLE I | PARAMETERS USED IN DQN |
|---------|------------------------|
| Input   | 84 × 84 × 4            |
| Optimizer | Adam                |
| Adam learning rate | 0.0000625 |
| Initial \( \epsilon \) | 0.99          |
| Final \( \epsilon \) | 0.01           |
| \( \epsilon \) decay frames | 1M            |
| SyncFrames | 40000     |
| Frames per step | 4             |
| Steps per evaluation | 250000 |
| MaxFrames | 200M          |
| Replay size | 1M          |
| Batch size | 32            |

IV. RESULTS

Currently, we show results in 10 Atari games. We will strive to obtain results of 49 games in camera-ready version.
Fig. 2. The architecture of our Swin DQN. The top shows the step-by-step procedure. The bottom left box contains structures inside a Swin block. The details of patch merging, window partition and window merging are also illustrated on the bottom right.

### TABLE II

PARAMETERS SPECIFIED IN SWIN DQN

| Parameters          | Value |
|---------------------|-------|
| Layers              | 3     |
| Blocks each layer   | 3, 2  |
| Heads each layer    | 3, 3, 6 |
| Patch size          | 3 x 3 |
| Window size         | 7 x 7 |
| Embedding dimension | 96    |
| MLP ratio           | 4     |
| Drop path rate      | 0.1   |

The mean evaluation scores and confidence intervals for 10 games are shown in Fig. 3. Each evaluation score is a mean of 5 runs in a single training round, from randomly seeded environments. Double DQN is our implementation with the exactly same policies and parameters to Swin DQN. It is obvious to see that Swin DQN outperforms Double DQN by a large margin in almost all games. Swin DQN shows drastically higher scores throughout the whole training process except for the beginning part. The gaps between those two score curves remain at a significant level for the majority of the games.

In few of the games (i.e., Video Pinball, Tutankham), Swin DQN shows tiny improvements comparing to Double DQN during the training process, but it still reaches slightly higher scores than Double DQN at the end nonetheless.

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In Tennis, both Swin DQN and Double DQN reach the highest possible scores (24) at the end. However, Swin DQN converges at around 2M steps and Double DQN around 4M steps. We can see that there is a significant difference of scores from 1.5M to 3M steps, and there is a significant drop of performance for Double DQN. Because Tennis is an adversarial game, successfully striking back might not always be as good as not to serve in this game and double DQN being stuck in this period longer indicates stronger modeling power of this kind of adversity using Swin Transformer.

In most games, Swin DQN does not show faster convergence than Double DQN in the first few training frames. This observation can be explained by the complexity of the Swin model. Swin transformer designed in our experiment has a larger network structure and in turn requires more input data than CNNs. Thus, the strength of the Swin DQN has to be demonstrated after a proper amount of training updates.

Table III shows the maximal evaluation scores for each game. We compare Swin DQN to Double DQN, Bootstrapped DQN (Boot-DQN) [12] and the Nature DQN [11]. Algorithms with the best performance for each game are highlighted. It is clear that Swin DQN performs the best out of the four algorithms, in terms of maximal evaluation scores. Those high normalized human scores suggest that our algorithm is capable of human or superhuman level performances, especially in Breakout, Time Pilot, and video Pinball.

### V. DISCUSSION

It is clear that Swin DQN has superior performances than Double DQN in our experiment. On the other hand, the amounts of improvements vary across different games. In many games, the improvements are as significant as multiple times of original scores. In few games, the improvement is less prominent. This may stem from the diversity of Atari games. Different games have various settings and require multiple sets of skills. Some games are more challenging than others because the rewards are extremely sparse, which require efficient exploration. Some games have great complexity of features and require subtle world modeling. Some games are adversarial and the behaviors of opponents need to be taken into account.

One of the main advantage of using Swin transformer in image recognition tasks is that it can establish entity/pixel attention connections. In some games, those connections are crucial in order to solve the puzzles, but might contribute trivially in other games. Thus, the amount of improvement
caused by using the self-attention structure varies among games to games. There are games that can be hard to humans, but not to agents, and vice versa. For examples, those models in Table III obtain far higher scores than humans in the game of Video Pinball due to the lack of complexity between entities/pixels in this game, which is also the reason why Swin DQN does not outperforms Double DQN significantly. However, it is clear the Swin DQN does perform the best out of all the compared models in terms of the scores.

Although it would be interesting to check if Swin Transformer can also improve policy gradient based RL approaches, we observe that Swin Transformer does not help with Proximal Policy Optimization (PPO) [13]. PPO algorithms are policy gradient methods that use surrogate loss functions to perform the stochastic gradient descent. In particular, the scores are considerably lower with the same amount of training steps if using Swin Transformer. One explanation to this observation is that self-attentions help build understandings of the environment only after an appropriate amount of training steps, but PPO methods require the agent to sample actions directly from the model policy. This acting strategy might suffer from the stability issues of the Swin model and thus result in insufficient exploration. On the other hand, \( \epsilon \) based exploration does not fully act on sampled actions from the model, but performs mostly random actions at the beginning. This can explain the opposite effects we observe by applying Swin Transformer to DQN and PPO.

VI. CONCLUSION

Our results show that Swin Transformer improves the DQN algorithm significantly in the majority of Atari games. Spatial self-attentions not only benefits CV tasks, but also image-based RL tasks. Swin DQN is a totally different approach comparing to Decision Transformer. We argue that there is no need to replace the current RL policies with temporal decision-making sequence model, but introducing spatial self-attentions alone is sufficient to increase the performances of current DRL models drastically. The linear complexity of Swin Transformer also makes self-attentions affordable in DRL and we expect transformers to have deeper influences on DRL in the future.

Further influences of combing Swin Transformer with policy gradient based algorithms can also be examined. We argue that \( \epsilon \) based exploration suits the Swin Transformer better because it helps with the stability of the transformer model, which in turn indicates that many RL algorithms can potentially benefit from Swin Transformer if they are used together with behavior policies similar to the \( \epsilon \) based exploration.

Our hyper-parameters of the Swin Transformer backbone are chosen by the grid search, yet this structure might not be with the least necessary parameters. Swin DQN is still computationally more costly than DQN. It is desirable to keep...
NNs small enough without jeopardizing the performances. Thus, experimenting Swin DQN with less layers or less attention heads can be crucial future work.

The positive effects of self-attentions in Atari games lead us to the expectations that real world control tasks can also benefit from self-attentions. We often need to direct our attentions to a small area in our visual filed in solving physical control tasks and this leaves the room to the transformers. DRL can potentially be more applicable in solving physical problems with the help of Swin Transformer in the future.

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