Efficient entity-based reinforcement learning

Vince Jankovics, Michael Garcia Ortiz, Eduardo Alonso
City, University of London
{vince.jankovics, michael.garcia-ortiz, e.alonso}@city.ac.uk

Abstract
Recent deep reinforcement learning (DRL) successes rely on end-to-end learning from fixed-size observational inputs (e.g. image, state-variables). However, many challenging and interesting problems in decision making involve observations or intermediary representations which are best described as a set of entities: either the image-based approach would miss small but important details in the observations (e.g. objects on a radar, vehicles on satellite images, etc.), the number of sensed objects is not fixed (e.g. robotic manipulation), or the problem simply cannot be represented in a meaningful way as an image (e.g. power grid control, or logistics).

This type of structured representations is not directly compatible with current DRL architectures, however, there has been an increase in machine learning techniques directly targeting structured information, potentially addressing this issue.

We propose to combine recent advances in set representations with slot attention and graph neural networks to process structured data, broadening the range of applications of DRL algorithms. This approach allows to address entity-based problems in an efficient and scalable way. We show that it can improve training time and robustness significantly, and demonstrate their potential to handle structured as well as purely visual domains, on multiple environments from the Atari Learning Environment and Simple Playgrounds.

1 Introduction
Reinforcement learning is concerned with how agents can take decisions based on their observations and act optimally in their environment. Recently, deep reinforcement learning has incorporated deep neural networks to learn how to act directly from raw observations, by interacting with the environment. It was demonstrated on very challenging tasks that it was possible to learn very complex behaviors (walking, navigation), occasionally surpassing humans (Atari, Go, Starcraft) [Vinyals et al., 2019; Badia et al., 2020; Schrittwieser et al., 2019].

Most of DRL models learn a policy from raw sensory data, such as image (R,G,B), joints, or representation of a game as an image (Go). This fixed-size data format is ubiquitous in the field, because it is appropriate for a large variety of problems where observations provided to the agents are predetermined and always in the same format, and because the fixed memory size allows to leverage parallel processing to dramatically accelerate learning.

However, this approach is not suitable for all decision making problems. First of all, certain problems cannot be efficiently represented as fixed-size tensors. Solving problems that require reasoning on a dynamically changing observation space (i.e. where the closed-world assumption does not hold) has always been challenging for artificial intelligence [Milch et al., 2004]. For example, tasks such as the control of a power grid or the tracking of objects by nature represent the observation space as a set of entities. The solution often proposed is to convert the observation space into a fixed size encoding, which is suboptimal. That way the structure of the problem is lost and has to be rediscovered by the DNN architecture during training.

Even in the case of observation spaces that are naturally static size, certain problems can benefit from converting these observations into structured representations. For example, a robot operating in a human environment receives as inputs RGB camera images, but these images can be converted into objects that constitutes the scene (and their properties). Operating at the level of entities potentially has many advantages: representations are more compact, disentangled, and knowledge transfer is better. Compositional reasoning using objects, relations, and actions is crucial for human cognition [Spelke and Kinzler, 2007], which motivated several recent works in machine learning to represent scenes as a set of objects and their properties, and the relations between them [Battaglia et al., 2018; Chang et al., 2016].

In this paper, we propose to address this challenge by combining different neural architectures allowing to process sets and graphs, so that an agent can learn from structured representations in a seamless, end-to-end fashion.

In order to test our proposed entity-based policy architecture, in the case when entities are not provided by the environment, we use a simple color-based segmentation module, since we are dealing with games that have very simple graphics. However, this approach can be extended with a
pre-trained object detection model that would enable this approach to be used on real-world problems.

We use a standard actor-critic policy with a shared encoder [Andrychowicz et al., 2020]. We only focus on the choice of the encoder (while keeping the actor and critic branches the same), and compare how this encoder performs when considering the observation space as a set or as a graph.

Related work

Using abstract structures in RL problems has been studied for a long time. In [Džeroski et al., 2001] the authors explore the use of relational learning to induce general rules that an agent can utilise, while in [Guestrin et al., 2003; Diuk et al., 2008] the authors formulate an object-based Markov Decision Process (MDP) approach that directly models the environment in terms of objects and their interactions. These approaches allow to train agents on structured data, however they do not scale to complex problems that require the use of DRL. In more recent works, [Garnelo et al., 2016] explore neuro-symbolic policies, however it is not clear if their approach would scale beyond their test environment.

In [Baker et al., 2020], the authors propose to train agents using structured observations (set of entities in the scene and their properties). However, they do not address the problem of varying input size. Each agent has a fixed amount of slots to represent each entity (one per slot), and these slots are masked with mask-attention when the corresponding entities are not in the field of view of the agent. We argue that this approach has several limitations. First of all, the total possible number of entities needs to be known in advance by the designer, which is not flexible, and does not allow transfer to new environments. Then, the model accounts for all entities and masks the ones it is not supposed to see to focus on only the observed entities, which is wasteful and significantly less efficient. In real-world environments where a variable number of entities can be present this approach would not scale.

There has been an increase in algorithms that operate directly on sets, where we expect the model to be invariant to the order of the input. E.g. the self-attention module [Vaswani et al., 2017] is often used, but it is limited to deal with sets of constant cardinality (i.e. number of set elements). The slot-attention module [Locatello et al., 2020] can learn representations from sets of different cardinality. It is important to note that in principle the size of the input set does not need to be known in advance, but in practice only fixed-size problems have utilized this algorithm (for computational and implementation reasons). We utilise the theoretical flexibility of
the slot-attention module and provide an efficient implementation that enables learning on variable size input spaces.

Graph neural networks (GNN) solve a similar problem, but with the possibility to capture relationships between entities as edges of the input graph. GNN-based RL approach has been explored in domain specific problems (e.g., [Marot et al., 2021; Gammelli et al., 2021]). Even though it can yield good results if enough resources are available [Vinyals et al., 2019; Baker et al., 2020], we argue that in general an object based approach could outperform approaches that rely on a fixed length input vector with zero-padding.

There have been attempts to use GNNs to learn a structured policy on various domains [Wang et al., 2018; Kipf et al., 2019], but they only focused on fixed observation spaces, and focus on learning a structured latent representation, which limit their use to closed-world problems and make them impractical for real-world applications.

3 Methods

In this section we describe first the environments that we used for testing, the visual and entity-based approaches and the RL policy structure in more details.

3.1 Environments

In order to assess and evaluate the proposed methods for entity-based Reinforcement Learning, we use two simulation environments. The Atari Learning Environment (ALE) allows us to present results on established DRL benchmarks to validate the approach. However, Entity-based representations are not directly accessible in ALE. In order to conduct a thorough and fair comparison between vision-based and entity-based RL, we use Simple-Playgrounds [Garcia Ortiz et al., 2021], that allows both visual observations (top-down or from the point of view of the agent) and entity-based observations.

For our experiments on ALE, we use the standard action space without any modifications. We benchmark our method on Pong, but any game can be processed with our pipeline, as Figure 2 demonstrates. In the remaining of the section, we will focus more in detail on the environments developed with the SPG simulator.

Simple Playgrounds

In SPG, an agent moves in a room and interacts with different entities. To simplify, we limited the interactions to contact interactions, triggered when an agent touches or is in the close proximity of an entity.

The actions of the agent in SPG are 2 independent discrete values, the first for forward and backward motion and the second for rotation around the center of the agent, both taking values from \{−1, 0, 1\} where 0 is the no-action.

In our proposed scenarios, an agent can encounter different kinds of entities:

- **Walls** are fixed, non movable. They surround the limits of the playground making it a closed environment (room).
- **Candies** are absorbed on contact and provide a reward of +5.
- **Poisons** are absorbed on contact and provide a negative reward of -5.
- **Fireballs** are moving in the environment, following a pre-set trajectory, and provide a negative reward from \{−5, −2, −1\} (depending on the color) when in contact with the agent.
- **Dispensers** are fixed and generate Candies in another location of the playground when in contact with the agent.
- **Red Portal** teleports the agent to **Blue Portal** and vice versa.

These simple entities allow to create RL tasks which require non-trivial sequential decision making. Using Portals also invalidates the Euclidian space assumption that agents could usually rely on for navigation tasks.

CandyPoison scenario: **Poisons** and **Candies** are spread randomly in the playground (see Figure 1a). The agent must collect **Candies** while avoiding **Poisons**. This scenario is analogous to the minigame CollectMineralShards from SC2LE [Vinyals et al., 2017].

CandyFireballs scenario: **Candies** are spread randomly in the playground (see Figure 1b). 3 moving **Fireballs** that cause negative reward if the agent gets close to them. The agent must learn to collect **Candies** while avoiding
Figure 3: (a) a simplified DispenserFireballs scenario, (b) as a fully connected graph and (c) represented as a graph with connections between the 2 nearest neighbours and a connection between the portals.

Fireballs. As the trajectory of the fireball is a sequence of random waypoints, it prevents the agent from remembering sequences of actions and force it to learn a policy based on its observations.

DispenserFireballs scenario: This environment is designed to demonstrate multi-step planning by including a Dispenser object that needs to be activated to drop Candies in a random location of the environment (see Figure 1c). The location change at every episode. To access the location of the Candies, the agent must cross a central region occupied by a wall of moving Fireballs. Alternatively it can use Portals to avoid this region and teleport directly to the other side of the playground. The agent needs to learn that there is a shortcut that breaks the Euclidean symmetry of the space.

3.2 Visual baselines

In order to evaluate our entity-based RL approach, we compare it to purely visual baselines that process raw RGB values with a convolutional neural network (CNN) encoder as described in [Mnih et al., 2013].

In ALE, visual observations are provided as RGB images that correspond to a top-down visualisation of the game. In SPG, this RGB information corresponds to the agent’s view of the surrounding scene as a 1D strip together with the distance of the observed entities.

3.3 Entity-based observations

In SPG: the simulator allows direct access to the entities present in the scene, in the form of a sensor that detects non-occluded entities within a determined range and field of view. In our experiments, we set the range to 400 pixels and the field of view to 360 degrees, and we use the same settings to construct the entity-based observations, i.e. the amount of information is the same in both settings.

The observations are ego-centric to the agent, so each object is described by a feature vector \( x = [t, d, \sin(\alpha), \cos(\alpha)] \), where \( t \) is a one-hot encoding of the type of the object (as the number of types are known for each scenario), \( d \) is the distance from the agent and \( \alpha \) is the relative angle of the observed entity. To keep the periodic prior of the angles we use a \( \sin / \cos \) transformation. We normalize \( d \) with the maximum observation range.

In ALE: there are no built-in entity-based observations, so we utilize a pipeline that allows our entity-based policy to be applied to any purely visual problem. We obtain entities by applying a simple segmentation algorithm (since entities in the ALE environments we use have a single color). This algorithm separates the scenes by identifying blobs of regions that have the same pixel values, and calculates their centroid and bounding box.

Each extracted entity is described by \( x = [r, g, b, x, y, dx, dy, s] \), where \( r, g, b \) is the color of the entity, \( x, y \) are the absolute coordinates, \( dx, dy \) are bounding box dimensions and \( s \) is the stack location of the feature in the frame-stack. We normalize the coordinates to the height and width of the game, and \( s \) to the number of stacks. Since in general the type of the entity is not known (unlike in SPG) we rely on a more flexible approach that uses the color itself. The assumption is that similar entities have similar colors, which typically holds in Atari.

In more complex visual scenarios we could rely on already existing high-performance object detection models (e.g. [Ren et al., 2015]), which would allow our proposed policy architecture to be used on real-world problems.

The entity-based observations is presented to the policy network as either a set of entities, or as a graph, where we can capture relationships between the entities. In this paper we create a fully connected graph from the observed entities, but arbitrary relationships can be captured with different edge types, e.g. spacial distance, as illustrated in Figure 3.

3.4 Policies

Image-based RL: For the purely visual case we use a simple CNN to process the observations of the agent. The difference between SPG and Atari is that in SPG the visual observations are provided as a 1D strip as the agent perceives its environment, while in Atari it is a 2D top-down representation. In the SPG case there is also occlusion, since objects
Figure 4: Training curves for all the SPG test scenarios. The solid lines show the base scenarios while the dashed are their large versions. (a) shows CandyPoison, (b) CandyFireballs and (c) DispenserFireballs.

Entity-based RL: For the entity-based approach we use slot-attention to process entities in the form of a set, or GNN encoders to process entities in the form of a graph.

Pre-processing of the observations: For SPG environments, we do not apply any pre-processing to the observations. For Atari we follow the same pre-processing as described in [Mnih et al., 2013], namely frame-skip and frame-stack. While for the CNN architecture the stacking can be done along the color dimension, in the entity-based representation we include the stack-depth as part of the input features, forming a set of entities that captures their temporal evolution. Note that we do not associate the entities explicitly across frames, i.e. it is up to the policy network to learn the corresponding temporal relationships. This could be improved with an approach that matches entities between frames, e.g. see [Creswell et al., 2021].

3.5 RL algorithm

We use PPO [Schulman et al., 2017] as the learning algorithm that optimises the agent’s behaviour in an on-policy setting.

In an actor-critic approach the learnt policy \( \pi(a_t|s_t) \) represents the probability of choosing an action \( a_t \) given the state \( s_t \), and \( v_f(s_t) \) provides an estimate of the value function for a given state. We use a shared latent-space with separate policy and value-function heads [Andrychowicz et al., 2020].
| Environment         | CNN  | SA  | GNN |
|---------------------|------|-----|-----|
| CandyPoison         | 258  | 233 | 342 |
| CandyFireballs      | 528  | 283 | 580 |
| DispenserFireballs  | 66   | 190 | 225 |
| CandyPoison-large   | 177  | 66  | 225 |
| CandyFireballs-large| 231  | 146 | 235 |
| DispenserFireballs-large| -6   | -4  | -8  |
| Pong (@5.5M)       | -10.07 | -10.19 | 6.57 |

Table 1: Mean reward acquired by the agent across the episodes. The SPG episodes terminate after a fixed 1000 timesteps, while the Atari episodes terminate once the agent dies in the game. For Pong we report the result after 5.5M environment steps, while for SPG it's 4M, except for the DispenserFireballs scenarios where it is 8M.

5 Conclusion

We provided an end-to-end approach to RL problems that involves dynamic observations spaces with unknown number of entities. Our method can be applied to any sequential decision-making problems that can be captured as a set of entities that the agent interacts with. We demonstrate the validity of the approach on the ALE benchmark and on Simple Playgrounds.

We also provide a direct comparison with purely visual RL architectures, and show that even with a very simple entity-extraction algorithm the training speed can be increased dramatically, and in complex scenarios that requires multi-step planning our approach still performs well while the visual method fails to learn the optimal behaviour.

Furthermore, since our approach only focuses on the relevant bits of information, instead of processing the whole visual input, it can achieve better performance with significantly lower number or parameters. In future works a rigorous comparison will be done to find the lower bound of our approach that can still find the optimal behaviour in an environment.

Finally, the use of neural networks to learn entity-based representations from raw sensory inputs is out of the scope of this paper. However it represents a very promising area for further explorations and experiments. We plan to replace the simple segmentation module by a learnt segmentation (or object detection) architecture (either pre-trained or end-to-end), and explore more complex real-world problems.

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