Comparing Transfer Learning in Humans and RL agents

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Abstract

Progressive Neural Networks (PNNs) are immune to catastrophic forgetting and can leverage prior knowledge via lateral connections to previously learned features (Rusu et al., 2016). We show that they also exhibit compositionality for previously learned concepts. We use PNNs to solve a series of Reinforcement Learning tasks and compare them with patterns of transfer learning in human cognition. Interestingly, we find that our networks exhibit characteristics of transfer that have also been demonstrated in human transfer learning tasks. Furthermore, when combined with a language component, our network[1] can transfer previously learned concepts from the source task and compose them to solve the target task.

1. Introduction

Transfer learning: the use of previously acquired knowledge and skills in new learning or problem-solving situations has existed as a psychological and educational framework for a long time (Steiner, 2001). As early as 1921, exist a series of behavioral experiments on the transfer of training (Norcross, 1921). The idea was adopted by the formal (or mental) discipline, believing that specific mental faculties could be strengthened by particular courses of training, then transferred to other situations.

The existence and properties of such transfers have been explored extensively in humans in different domains (Chobert et al., 2011; Cole et al., 2011; Steiner, 2001; Norcross, 1921; Olson, 2015; Yashar & Denison, 2017; Rusu et al., 2016) and has become a benchmark for the difference between human intelligence and artificial intelligence (AI). The current stage of AI is that it almost always needs to start from scratch, while humans are phenomenal at leveraging prior experiences to acquire new knowledge. Learning to solve complex sequences of tasks while both leveraging transfer and avoiding catastrophic forgetting is an essential element in covering this gap between human and machine intelligence.

Rusu et al. (Rusu et al., 2016) propose a novel network structure called Progressive neural networks to support transfer learning by explicitly incorporating lateral connections into its architecture. Catastrophic forgetting is prevented by instantiating a new neural network (a column) for each task being solved. At the same time, the transfer is enabled via lateral connections to features of previously learned columns (Figure 3). We aim to stimulate the learning behavior of an agent in a simple environment of multiple sizes, solving a variety of tasks with and without transfer of columns from prior training, and compare patterns of learning to those obtained from human experiments. As such, we expect to observe patterns similar to positive transfer and complex to simple transfer as well as evidence for compositionality.

[1] https://github.com/srikarym/CCM_project

2. Related work

Here we introduce some essential concepts previously found in human transfer learning literature. In the experiment section, we discuss the connection between our findings with each of the concepts introduced here.

2.1. Positive Transfer

Positive transfer occurs when prior learning assists new learning. There are numerous examples of positive transfer in different domains, which can be conceptual, procedural, or metacognitive (Steiner, 2001). It has been specially investigated in detail language, musical training, sequence learning, and motor skills (Steiner, 2001; Norcross, 1921; Chobert et al., 2011; Cole et al., 2011; Müssgens & Ullén, 2015; Yashar & Denison, 2017; Woltz et al., 2000; Postman & Stark, 1969).

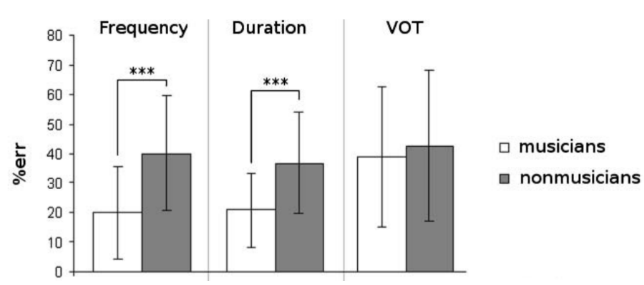

Figure 1. Positive transfer Processing of Syllables in Children trained in music (Chobert et al., 2011).

2.2. Negative transfer

Negative transfer happens when prior learning hinders or interferes with new learning. A common test for negative transfer is the AB-AC list learning paradigm from the verbal learning research of the 1950s and 1960s. In this paradigm, two lists of paired associates are learned in succession. If the second set of associations constitutes a modification of the first set of associations, negative transfer results in a learning rate that is slower than the first list (Postman & Stark, 1969; Woltz et al., 2000).

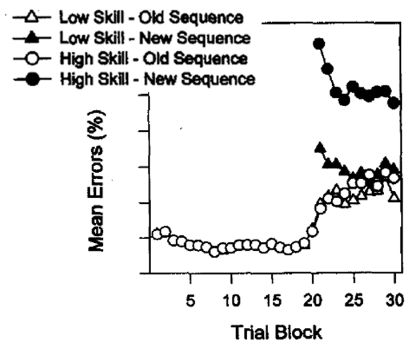

Figure 2. An Example of negative transfer during a sequential cognitive task (Woltz et al., 2000).

2.3. Compositionality

The notion of compositionality was first introduced as a constraint on the relation between the syntax and the semantics of languages. It was later postulated as an adequacy condition also for other representational systems such as structures of mental concepts, computer programs, and even neural architectures (Werning et al., 2012). Compositionality, which is the algebraic capacity to understand and create novel combinations from known components (Loula et al., 2018), has been known as a core human capability.

2.4. Instructed learning

One of the defining characteristics of human-level intelligence is the ability to rapidly restructure one's behavior into novel configurations from instruction (Cole et al., 2011) By following explicit instructions, humans instantaneously get the hang of tasks they have never performed before(Ruge et al., 2019). In most cases, explicitly instructed rules are implemented more efficiently than the inferred rule in the learning phase of a task (Pereg & Meiran, 2020) and is influenced by working memory load (Pereg & Meiran, 2019).

3. Background

In this section, we provide a brief overview of Progressive neural networks (Rusu et al., 2016).

3.1. Progressive Neural Networks

The idea of Progressive neural networks (PNNs) is to transfer knowledge across a series of tasks effectively. They can incorporate prior knowledge at each layer of the feature hierarchy. They are also immune to catastrophic forgetting. Contrast with transfer learning models that incorporate prior knowledge only at initialization, PNNs retain a pool of pre-trained models throughout training and learn lateral connections from these to extract useful features for new tasks. We show a PNN with three columns in Figure 3.

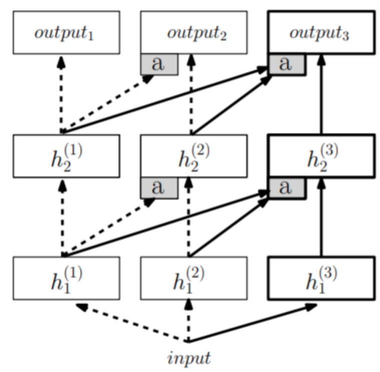

Figure 3. Architecture of a three column PNN. The first two columns on the left were trained on task 1 and task 2 respectively. The third column is trained on the target task, having access to the features from previous columns. The grey box labelled a represent the adapter layers. Figure source (Rusu et al., 2016).

Adapters were introduced to improve initial conditioning and perform dimensionality reduction. Let $h_i^{(k)}$ denote the hidden activation of column k at layer i. Defining the vector of anterior features $h_{i-1}^{(<k)} = [h_{i-1}^{(1)}, h_{i-1}^{(2)}, ...h_{i-1}^{(k-1)}]$, the feature at layer i is

$$h_i^{(k)} = \sigma\big(W_i^{(k)} h_{i-1}^{(k)} + U_i^{(k:j)} \sigma(V_i^{(k:j)} \alpha_{i-1}^{(<k)} h_{i-1}^{(<k)})\big)$$

where $W_i^{(k)} \in R^{n_i \times n_{i-1}}$ is the weight matrix of layer i of column k, $U_i^{(k:j)} \in R^{n_i \times n_j}$ are the lateral connections from layer $i-1$ of column j to layer i of column k, $V_i^{(k:j)} \in R^{n_{i-1} \times n_{i-1}^{<k}}$ is the projection matrix, and h_0 is the input to the network.

4. Experiments

4.1. Positive Transfer

For our initial experiments, we use the Empty environment from MiniGrid (Chevalier-Boisvert et al., 2018). The agent starts at the top-left tile, and the goal is to reach the bottom-right of the grid. The agent gets a reward of 1 upon successfully reaching the goal state. A small penalty is subtracted for the number of steps taken by the agent to reach the goal.

The observation is a partially observable view of the environment, which is of size 7x7x3. We show an example state of the environment in figure 4.

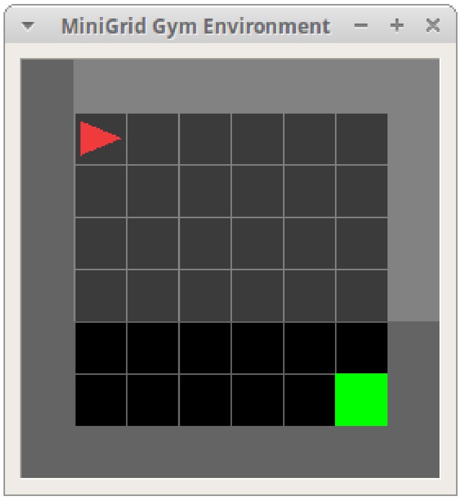

Figure 4. Example state of a 6x6 minigrid empty environment. The agent (shown in red) starts at the top left. Goal state (shown in green) is at the bottom right.

We train agents on four grid sizes: 5,6,8, and 16, with ten seeds for each grid size. Using these models, we train two-column PNNs on a grid size larger than the size of the training grid of column-1. We evaluate the transfer performance by measuring the number of steps required to reach a reward of 0.95. To avoid anomalies during training, we make sure that the agent obtains a reward greater than 0.95 for at least 1000 steps. We show the results in Table 1.

Model	Source grid	Target grid	# frames
Vanilla PPO	-	8	2,197,504
PNN	5	8	528,384
PNN	6	8	462,848
Vanilla PPO	-	16	2,310,144
PNN	5	16	1,247,232
PNN	6	16	821,248
PNN	8	16	603,136

Table 1. Number of frames taken by the models to obtain a reward of 0.95. PPO is the single column vanilla network. PNN is a 2 column progressive neural network trained on target grid size, using the model trained on source grid as column 1. We compute the median result over 10 seeds.

We can see that the number of steps required to reach optimal policy decreases drastically with the use of PNNs. Training a PNN on 8x8 converges faster when we use a model trained on 6x6 (M_{6x6}), when compared to using M_{5x5}. Solving a larger grid requires a significant amount of exploration before a reward is received. However, in smaller grids, the agent observes a much easier setup of the world. For example, in 5x5, the agent observes the right-side wall from the initial position, and can also observe the goal if it looks down from the initial position. In general, we observe that transfer from a larger grid is more beneficial than transfer from a smaller grid. We also observe a similar kind of positive transfer when we randomize the agent's initial position instead of always starting it at the top-left tile.

We perform the same experiments we did on the Empty environment on the Unlock environment described in the subsequent section. We observe a significant reduction in the number of steps required to reach optimal policy as we found in the Empty environment, with the improvement increasing as the grid size increases.

4.2. Experiments with Negative Transfer

We use the trained Empty environment with a single column PPO for grid sizes 5, 6, and 8 with ten different seeds. We transfer this to the Unlock task using two-column PNNs on all the three grid sizes. For the PNN experiment, while transferring from Empty to Unlock, we keep the grid size the same. We evaluate the transfer performance by measuring the number of steps required to reach a reward of 0.90. Again as previous experiments, to avoid anomalies during training, we make sure that the agent obtains a reward greater than 0.90 for at least 1000 steps. We use the trained single-column Unlock PPO results as a benchmark for comparison. We show the results in Figure 5.

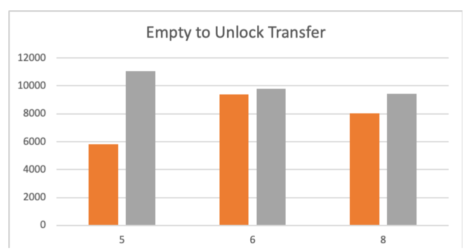

Figure 5. Transfer from Empty to Unlock for different grid sizes and median value was taken across 10 seeds. Y-axis represent number of frames taken to obtain a reward of 0.90. Gray and orange bars correspond to agents trained with and without transfer learning respectively.

We find patterns of negative transfer that were studied in (Woltz et al., 2000). We see that the negative transfer reduces as the grid size increases. We believe this is because agents trained on larger source grid size facilitate exploration, which helps an agent being trained in a complex environment such as Unlock. We observe similar results for the same experimental setup for the transfer from the Empty Random (Chevalier-Boisvert et al., 2018) environment to the Unlock Environment.

4.3. Transfer from complex to simpler task

After proving the presence of transfer in an easier empty-grid environment, to further strengthen our belief in the effectiveness of transfer learning, we decided to move towards testing transfer from a complex environment to a relatively more straightforward environment. The motivation behind this idea is that while learning complex tasks, the agent tends to explore more than it would typically do for more straightforward tasks. The model and behavior learned through this process encodes richer representation addressing the particular task. It would be interesting to check whether the same model can be used to transfer the knowledge effectively to solve a sub-task.

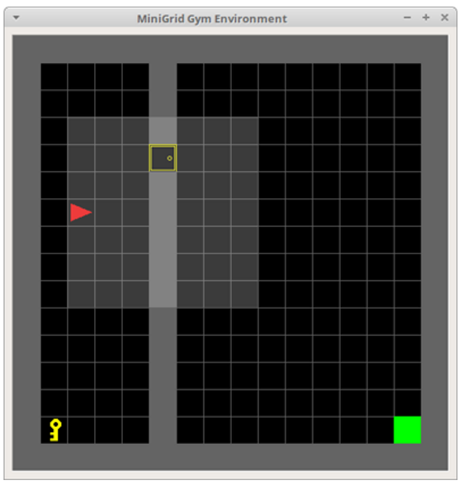

Figure 6. An example state of the door-key environment. The agent (shown in red) has to fetch a key (shown in yellow), go to the door (shown in yellow) and unlock it. After that it has to reach to the goal state (shown in green).

To seek an answer to this question, we start with a tough task called ”door-key” (Chevalier-Boisvert et al., 2018) as our source task. In door-key, the agent has to first pick up a key, open a door, and then get to the green square(Figure 6). The reward assignment policy is the same as an empty grid environment, where a reward of 1 is awarded if the agent successfully reaches the goal and reaching to goal in less number of steps lands higher reward values.

As our target task, we choose a simpler version of door-key called ”unlock” (Chevalier-Boisvert et al., 2018). In unlock, the agent has to pick a key, go to a door and unlock it (Figure 7). We first train door-key with a single column PPO for grid sizes 5, 6, and 8 and 10 different seeds. Then we train to unlock with a single column PPO for the same configurations. We then train multiple two-column PNNs on all the three grid sizes. While transferring from door-key to unlock, we keep the grid size the same. We evaluate the transfer performance by measuring the number of steps required to reach a reward of 0.95. Again as previous experiments, to avoid anomalies during training, we make sure that the agent obtains a reward greater than 0.95 for at least 1000 steps. We show the results in Figure 8.

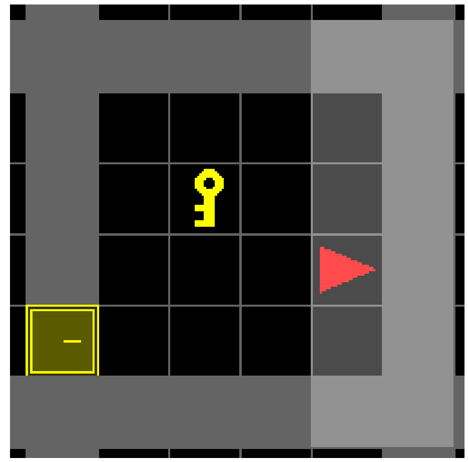

Figure 7. An example state of the unlock environment. The agent (shown in red) has to fetch a key (shown in yellow), go to the door (shown in yellow) and unlock it.

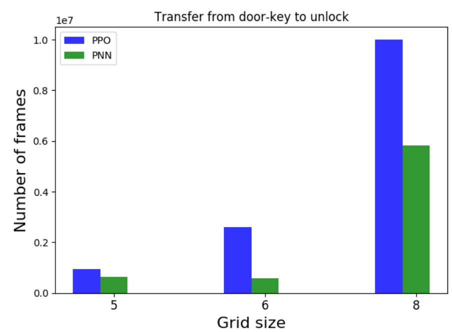

Figure 8. Transfer from door-key to unlock for different grid sizes and median value was taken across 10 seeds. The bars represent number of frames taken to obtain a reward of 0.95.

As the results demonstrate, there is a substantial positive transfer from door-key to unlock as the number of frames used to reach the reward of 0.95 reduces drastically, when we incorporate PNNs. This gives us a very interesting inference, which says that even though for a complex task (door-key), the agent is supposed to explore more than its sub-task (unlock), the patterns it ends up learning exhibit an optimal substructure property. We can relate this phenomenon to a dynamic programming paradigm, where an optimal solution to a problem is retrieved from an optimal solution to its sub-problems. Here we realize that phenomenon, where the optimal solution to ”door-key” is built from an optimal solution to its sub-problem ”unlock” and hence if we leverage the model learned for unlock and apply transfer learning to its sub-task, we can get much higher reward compared to learning the sub-task from scratch.

4.4. Compositionality and Transfer Learning

A critical challenge for artificial intelligence, in general, is the problem of compositionality. Neural networks have long been criticized for lacking compositionality (Lake, 2019). In contrast, humans can not only transfer what they learn from a task to another but also compose many aspects of their past learning experience into a meaningful structure in order to solve a complex task. For example, students can use concepts they learned in geometry and algebra to solve a new physics homework that requires previous knowledge of both geometry and algebra.

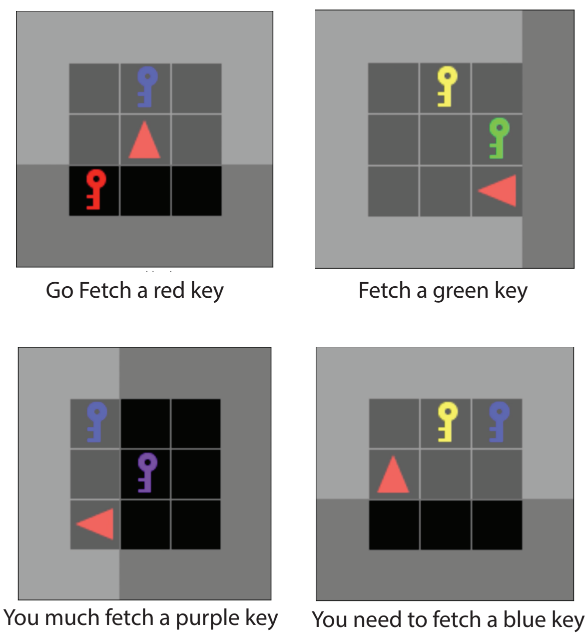

Figure 9. Example state of the first source task. The agent (shown in red triangle) receives textual instructions to fetch a key of correct color. Through this task, agent learns the concept of color, which is needed to solve the target task.

Here we investigate whether a PNN can transfer concepts learned from two old tasks to a target (new) task and compose these two concepts in order to solve the target task. To test this critical parallel between human's cognitive ability for compositionality and PNN, we carefully design a task. Designing a task to test such a challenging concept is difficult because it is nontrivial and hard to design a good experiment to reveal weather an agent can compose previously learned concepts.

We reason that the ability to use different composing elements and compose those elements into a meaningful structure requires operating on discrete rather than elements. Thus, we add a language component to our network. The agent receives textual instructions to complete two different source tasks (one involves learning the concept about color, and the other involves learning the concept about object type) and then transfer the two concepts gained to solve the target task (which requires the agent knowing both color and object type. The basic structure of the tasks are:

In the first source task, the agent is instructed to fetch a key of a specific color (out of five possible colors) through a natural language string (Figure 9). For example, in the example task shown in Figure 9a, the agent is asked to fetch a red key, and in Figure 9b, the agent is instructed to fetch a green key. If the agent successfully performs the action' pick-up' in front of the target key of the right color according to the textual instruction, the agent will receive a reward. If the agent fetches the wrong key, the task ends, which resets the environment.

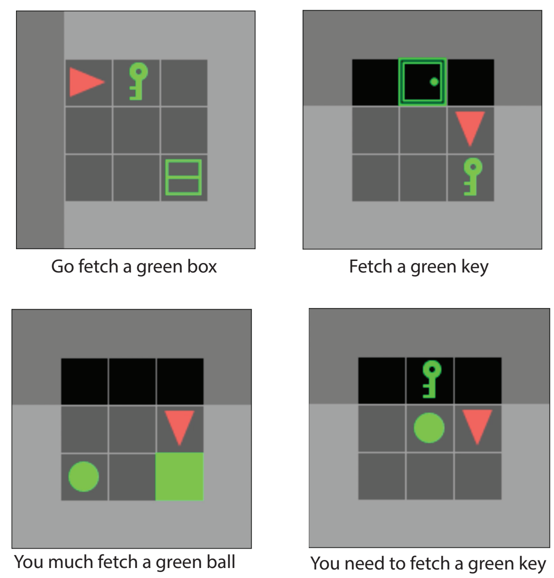

Figure 10. Example state of the second source task. The agent (shown in a red triangle) receives textual instructions to fetch a certain type of object of the same color. Through this task, the agent learns the concept of object color, which need to be transferred to solve the target task.

In the second source task, the agent is instructed to fetch one of three objects (a ball, a box, or a key) via textual input, as shown in Figure 10. These objects all have the same color. The agent gets a reward if it picks up the target key according to the textual instruction. If the agent fetches the wrong object, the task will end, and a new game will be started.

In the third task, which is the target task for the series of transfer learning tasks, the agent is instructed to fetch a specific object of a particular color (Figure 11). The agent will only be rewarded if it can pick up the right object of both correct color and type, and thus the task requires concepts of both color and object type.

To test if a PNN can perform a task involving compositionality by not only transferring knowledge from previous tasks but also composing the learned concepts to solve a new task, we designed a three-column network where the first two columns of the network correspond to two source tasks described above. When learning the target task, the third column receives inputs from both of the two previously learned columns (Figure 12).

We also design a control test where we train the agent from scratch (no transfer learning). We hypothesize that having learned to distinguish between different color and object types in the source tasks, the PNN would learn the target task faster than a network that directly learns the target task without any knowledge transfer. The learning result of both the two networks, one with transfer, one without transfer, is presented in figure 13. As we hypothesize, the agent with transfer learning obtained a reward of 0.9 after seeing 220k frames, which is 180k frames faster than without transfer learning, suggesting that the PNN architecture with language component allows the agent to efficiently compose the concept of color and object type (Figure 11).

It is important to note that even though our result shows that the PNN can effectively compose different concepts in the instruction, the agent learns very inefficiently when compared to a human. Previous works have shown that humans can learn and use novel functional concepts from very few examples (few-shot learning) and successfully applying familiar functions to novel inputs (Lake et al., 2019; Cole et al., 2013).

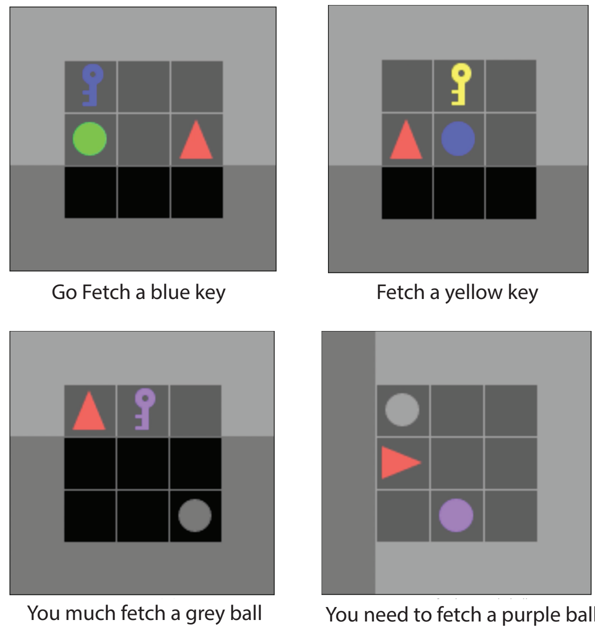

Figure 11. Example state of the target task. The agent (shown in a red triangle) receives textual instructions to fetch a certain type of object of a certain color. In order to solve this task, the agent needs to compose previously learned knowledge about both object type and color from the two source tasks.

5. Discussion

5.1. Positive Transfer

Positive transfer occurs when prior learning assists new learning. (Chobert et al., 2011) examine the transfer of the ability to process speech sounds from parent to child in 9-year-old musician and nonmusician children. They find that both the passive and active processing of duration and VOT deviants were enhanced in musicians when compared to nonmusician children.

We find patterns of positive transfer in Experiment 4.1. Solving the empty grid should be trivial for a human, due to the large amount of prior knowledge we are equipped with. In a 5x5 grid, if we see the goal position, we would immediately infer that the agent needs to reach the goal. Even for a larger grid, we would first explore to reach a state from which the goal position is observable, and then take the shortest path to the goal. However, transfer between grid sizes is highly beneficial for an RL agent, since it does not know that reaching the goal is the solution to the grid problem.

5.2. Transfer from complex to simpler task

In (Garcia et al., 2013), authors talk about training on highly similar stimuli that are difficult to discriminate (i.e., hard training), resulting in behavioral improvement. This work also discusses that the transfer of learning from highly to less discriminable stimuli may require longer periods of consolidation. Through our experiment of transfer from door-key to unlock, we observe this phenomenon, where training on harder tasks (Unlock) facilitates much faster and efficient learning of a somewhat easier task.

5.3. Compositionality, Instructed Learning and Transfer Learning

At the behavioral level, we demonstrate in this study that a PNN with a language component can efficiently transfer and compose previously learned concepts in an efficient manner. We show that the agent can efficiently combine two previously learned concepts to solve a new task. In the future, we can test if the network can be generalized to longer instructions incorporating more than two concepts. For example, we can first train the agent to learn to fetch an object of a certain color. We can then train the agent to use the key fetched to open the right door. In the final target task, the agent will have to first fetch a key of the correct

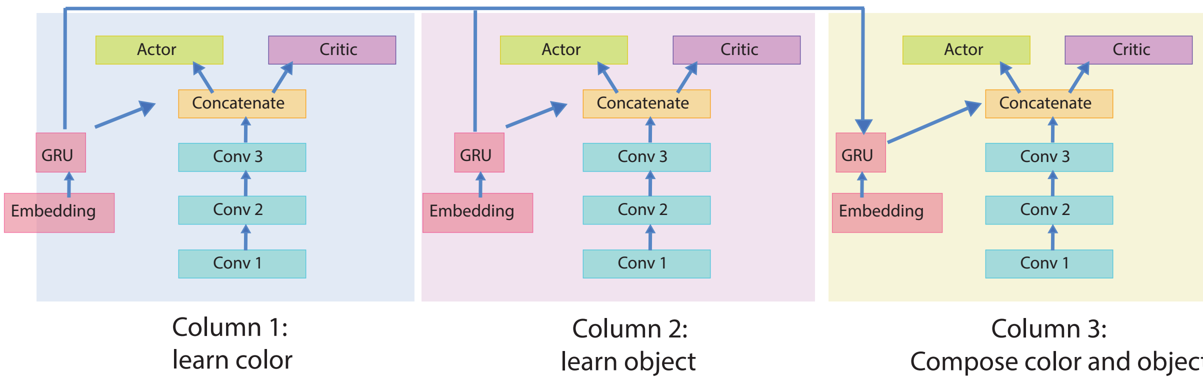

Figure 12. Architecture of a three-column neural network to solve the transfer learning task for language compositionality. We train the first column to distinguish different colors, and the second column to distinguish different object types. We train the third column on the target task where the agent needs to successfully compose both object color and type to solve the task.

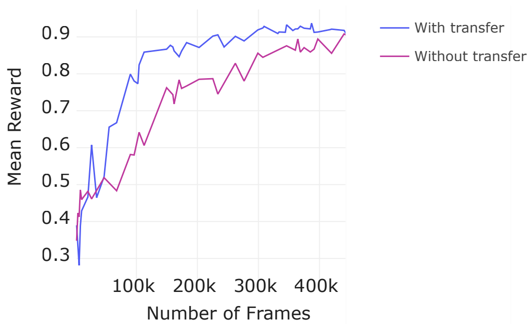

Figure 13. Result of the target task. Here we compare learning with three column transfer learning trained with PNN versus no transfer learning. Agent trained with transfer learning solves the task 100k frames faster than without transfer learning.

color, carry it to open the correct door, and finally pick up the right object behind the door. The agent will receive a long textual input (Figure 14). For example, 'you must fetch a blue key, use it to open the blue door, and then pick up the grey box.'

After the agent successfully learns this task, we can even instruct the agent to learn even more difficult tasks (Figure 15). For example, in the future, we can use the PNN to train the agent to go to a particular room to get the key and then use it to open the correct door, in order to fetch the ball and get rewarded. For instance, for the task in Figure (15), the agent will receive a mission like this: 'First, go to the red door, fetch the grey key, use it to open the grey door, finally pick up the grey ball.' Due to the sparseness of reward in this kind of environment as well as the existence of sub-goals in the task structure, the task is extremely hard to solve with the vanilla reinforcement learning algorithm. However, we can combine the PNN with concepts in curricular learning to train the agent to solve this challenging task in the future.

However, in order to train the agent on such complex tasks in a progressive manner, the number of columns will increase in proportion to the number of components of the target task, which will increase the number of trainable parameters. In addition, intuitively, it is unlikely that humans learn new concepts in this way. Thus, in the future, we can combine the PNN framework with new components that can automatically combine related columns into one single column and extract meaningful and transferable subgoals from multiple related tasks (Chen et al.).

Furthermore, the current RL methods are sample inefficient and generalize poorly when it comes to learning tasks with a compositional structure. Millions of demonstrations are needed to learn tasks that seem trivial by human standards. For the unlock and pick-up task shown in Figure 15, even with progressive training after 5 million frames, the agent still cannot solve the task. Tackling this challenge will likely require better networks and learning methods. Approaches that involve an explicit notion of modularity and subroutines, such as Neural Module Networks (Andreas et al., 2016) or Neural Programmer-Interpreters (Reed & De Freitas, 2015) is a promising direction.

6. Conclusion

Training an RL agent on tasks with compositional structure is a challenging problem. In this paper, we show that transfer learning with PNN helps improve the sample complexity

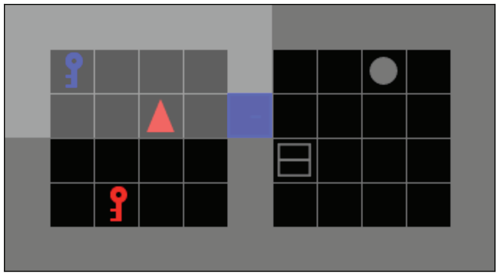

Figure 14. Potential future task to investigate compositionality of multiple concepts. The agent is the red triangle in the figure. The agent receives a long textual instruction: 'you must fetch a blue key, use it to open the blue door, and then pick up the grey box.'

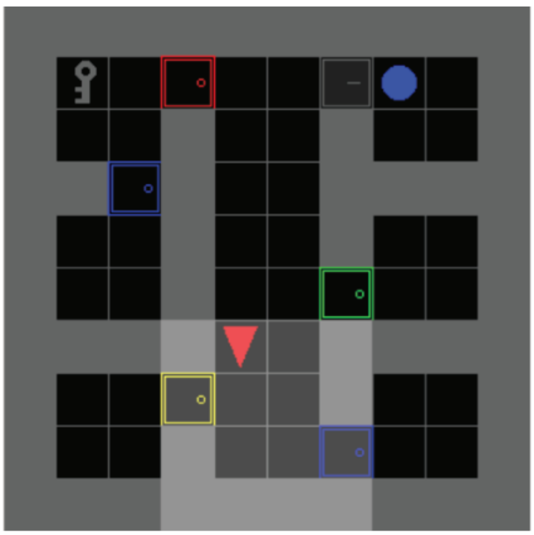

Figure 15. Potential future task to investigate the compositionality of multiple concepts in an even more complex environment. The agent is shown as a red triangle in the figure. The agent will receive a mission like this: 'First, go to the red door, fetch the grey key, use it to open the grey door, finally pick up the grey ball.'.

of the agent. We empirically demonstrate the presence of positive transfer from a simple to complex setting (smaller to larger grid size), complex to simpler setting (backward transfer), and compositionality of tasks. We also show the parallels between transfer in RL agents and the transfer of knowledge in humans.

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