PixL2R: Guiding Reinforcement Learning using Natural Language by Mapping Pixels to Rewards

Prasoon Goyal [1] **Scott Niekum** [1] **Raymond J. Mooney** [1]

Abstract

Reinforcement learning (RL), particularly in sparse reward settings, often requires prohibitively large numbers of interactions with the environment, thereby limiting its applicability to complex problems. To address this, several prior approaches have used natural language to guide the agent's exploration. However, these approaches typically operate on structured representations of the environment, and/or assume some structure in the natural language commands. In this work, we propose a model that directly maps pixels to rewards, given a free-form natural language description of the task, which can then be used for policy training. Our experiments on the Meta-World robot manipulation domain show that language-based rewards significantly improve learning. Further, we analyze the resulting framework using multiple ablation experiments to better understand the nature of these improvements.

1. Introduction

While reinforcement learning (RL) has been successfully used to solve many problems, designing good reward functions continues to remain a challenge, limiting its applicability to more complex problems. To address this problem, several methods have been proposed that involve guiding an agent using natural language commands.

However, these techniques are still quite restrictive, often requiring object properties to be predefined (MacGlashan et al., 2014; Arumugam et al., 2017; Williams et al., 2017), assuming some structure in the natural language commands (Bahdanau et al., 2018), and/or requiring hand-designed features (Kuhlmann et al., 2004; Branavan et al., 2012b), which is challenging to scale. In this work, we propose a framework that makes no such assumptions, and directly learns to map pixels to rewards given a free-form natural language description of the task. Our model is based on the framework proposed by Goyal et al. (2019), which we describe next.

[1]Department of Computer Science, The University of Texas at Austin. Correspondence to: Prasoon Goyal <pgoyal@cs.utexas.edu>.

2. Prior Work: LEARN

Consider an extension of the standard Markov Decision Process (MDP), defined as $M' = \langle S, A, T, R, \gamma, L \rangle$, where L is an instruction describing the task using natural language, and the other quantities are as defined in a standard MDP. Goyal et al. (2019) proposed a framework for learning in this modified MDP (which they denote as MDP+L) consisting of the following two phases.

Phase 1: A neural network – the LanguagE Action Reward Network (LEARN) – is trained to predict whether a given trajectory and language are related or not. This requires paired ⟨trajectory, language⟩ data in the environment. As a preprocessing step, each trajectory is first encoded into an *action frequency vector*, which is a vector of size $|A|$, with the i^{th} component proportional to the number of times action i appears in the trajectory. The neural network takes this action frequency vector and language as inputs to predict the relatedness between the trajectory and language, which is modelled as a binary classification problem.

Phase 2: Next, a policy is trained for a new task in the MDP+L setting – the extrinsic reward from the environment is assumed to be sparse (i.e. 1 if the agent successfully completes the task, and 0 otherwise), and the agent additionally gets a language command describing the task. At every step, an action frequency vector is created from the sequence of past actions and passed to the pretrained LEARN model along with the given command. The LEARN model generates probabilities over classes `RELATED` and `UNRELATED`, which are used to generate intermediate rewards for reward shaping (Ng et al., 1999).

A significant limitation of this work is that the relatedness model only uses the frequency with which each action is executed in the trajectory. As such, information in the language instructions that requires knowledge of the state (e.g. how to interact with objects) is not helpful.

For instance, consider the domain shown in Figure 1, which

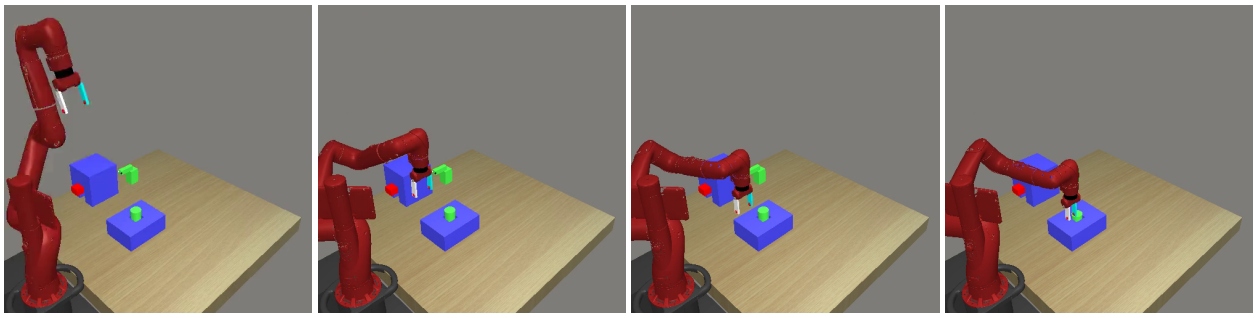

Figure 1. A simulated robot completing a task in the Meta-World domain

is adapted from the recently released Meta-World benchmark (Yu et al., 2019). The scene consists of a robot interacting with an object in the presence of zero or more other objects. Different scenarios can be created in the domain by randomizing the set of objects in the scene and their positions. Since linguistic descriptions of such tasks would typically be in terms of the object to be interacted with, whose position could change across different scenarios, learning a relatedness model between actions and language without taking into account the state (i.e. the image) will not generalize across scenarios. Thus, we extend prior work to learn a relatedness model between sequences of states and language descriptions, and show that generating language-based scores from the resulting model improves the efficiency of policy training on unseen scenarios.

3. Approach

To apply the framework described in Section 2 to domains where using the state information is crucial to understanding language (e.g. the domain in Figure 1), we propose PixL2R, which takes in the pixel representations of the states and a natural language description of the task, and maps them to rewards. The framework consists of a supervised learning phase (Section 3.1) and a policy training phase (Section 3.2) as in prior work, but with modifications as described below.

3.1. PixL2R: Pixels and Language to Reward

First, a relatedness model between a trajectory and a language is learned given paired data. Our model is based on that proposed by Goyal et al. (2019); however, instead of representing a trajectory using an action frequency vector before feeding into the neural network, we feed the sequence of frames in the trajectory directly into the neural network.

3.1.1. Network Architecture

Using sequence of frames instead of an action frequency vector requires addressing perceptual aliasing and occlusion. Thus, our network architecture is designed to take multiple views as inputs. Specifically, we use three different viewpoints.

An independent CNN is used for encoding the sequence of frames from each viewpoint to generate a fixed-size representation for each frame. These sequence of vectors are concatenated across the views to generate a single sequence of fixed-size vectors, which is then passed through a two-layer LSTM to get an encoding of the entire trajectory.

The language description is converted to a one-hot representation, and passed through an embedding layer, followed by a two-layer LSTM. The outputs of the LSTMs encoding the trajectory and the language are then concatenated, and passed through a sequence of fully-connected layers to generate a relatedness score.

See supplementary material (Section A) for the viewpoints used, and a diagram of the neural network.

3.1.2. Data Augmentation

Frame dropping. Given an input trajectory, each frame is independently selected with a probability 0.1, and dropped with a probability 0.9. The resulting sequence of frames is passed through the network. This makes the training faster by reducing the input size, as well as making the network robust to minor variations in trajectories. During policy training, the trajectories are uniformly subsampled to keep 1 frame in every 10.

Incomplete trajectories. Since during policy training, the model will have to make predictions for incomplete trajectories, we use incomplete trajectories during supervised training as well. To do this, given a trajectory of length L, we sample $l \sim Uniform\{1, \ldots, L\}$, and use the first l frames of the trajectory.

3.1.3. Training Objectives

Classification. First, we trained the neural network using binary classification, as in the original work. The final output of the network is a two-dimensional vector, corre-

sponding to the logits for the two classes – `RELATED` and `UNRELATED`.

Since partial trajectories might be difficult to classify as related or unrelated, we experiment with an alternate regression-based setting, described below.

Regression. In this setting, the model predicts a single relatedness score between the given trajectory and language, which is mapped to $[-1, 1]$ using the $\tanh()$ function. The ground truth score is defined as $s \cdot \frac{l}{L}$, where $s = 1$ for positive and $s = -1$ for negative examples, l is the length of the incomplete trajectory and L is the length of the complete trajectory as described above. Thus, given a description, a complete related trajectory has a ground truth score of 1, while a complete unrelated trajectory has a score of -1. Shorter trajectories smoothly interpolate between these values, with very small trajectories having a score close to 0. The network is trained to minimize the mean squared error.

3.2. Policy Training Phase

Having learned a PixL2R model as described above, the relatedness scores from the model can be used to generate language-based intermediate rewards during policy training on new scenarios. During policy training, the agent receives a natural language description of the goal, in addition to the reward from the environment. The PixL2R model is used to score trajectories executed by the agent against the given natural language description, to generate intermediate rewards. We used potential-based shaping rewards (Ng et al., 1999), which are of the form $F(s_t) = \gamma \cdot \phi(s_t) - \phi(s_{t-1})$, where s_t is the state at timestep t and $\phi : S \rightarrow \mathbb{R}$ is a potential function. In our case, s_t is the sequence of states encountered by the agent up to timestep t in the current episode. Ng et al. (1999) and Grzes (2017) show that potential-based shaping rewards do not change the optimal policy, that is, the optimal policies under the original reward function R and the new reward function $R + F$ are identical.

For the classification setting, we used the potential function $\phi(s_t) = p_R(s_t) - p_U(s_t)$, as defined by Goyal et al. (2019). Here, p_R and p_U are the probabilities assigned to the classes `RELATED` and `UNRELATED` respectively. For the regression setting, the relatedness score predicted by the model is directly used as the potential for the state. Note that for both the settings, the potential of any state lies in $[-1, 1]$.

4. Experiments

4.1. Dataset

We use Meta-World (Yu et al., 2019), a recently proposed benchmark for meta-reinforcement learning, which consists of a simulated Sawyer robot and everyday objects such as a faucet, windows, coffee machine, etc. Tasks in this domain involve the robot interacting with these objects, such as turning the faucet clockwise, opening the window, pressing the button on the coffee machine, etc. Completing these tasks requires learning a policy for continuous control in a 4-dimensional space (3 dimensions for the end-effector position, and the fourth dimension for the force on the gripper). While the original task suite consists of only one object in every task, we create new environments which contain one or more objects in the scene, and the robot needs to interact with a pre-selected object amongst those.

In a sparse reward setting, the agent is given a non-zero reward only on successfully interacting with the pre-selected object. In the absence of any other learning signal, the agent might have to learn to approach and interact with multiple objects in the scene in order to figure out the correct object. Using natural language to describe the task in addition to the sparse reward helps alleviate this issue.

Different scenarios were created by randomizing the object to be interacted with, the distractor objects, and their positions. Amazon Mechanical Turk was then used to obtain free-form natural language descriptions for these tasks. The details of the process, as well as some example descriptions can be found in the supplementary material (Section C).

4.2. Policy Training with Language-based Rewards

To empirically evaluate the effectiveness of PixL2R, the following setup was used. We had a total of 16 test scenarios, with 3 descriptions for each. More details of the training/validation/test splits can be found in the supplementary material (Section B). Each policy training was run for 500,000 timesteps using the PPO algorithm, and the number of successful completions of the task were recorded. The maximum episode length was restricted to 500 timesteps. The robot's end-effector was set to a random position within a predefined region at the beginning of each episode.

First, 15 policies were trained using sparse rewards (`Sparse`) on each test scenario with different seeds. Next, policies were trained with language-based rewards using the regression setting, in addition to the sparse rewards (`Sparse+RGR`). For each scenario, 5 policies were trained with different seeds for each of the 3 test descriptions, resulting in a total of 15 policy training runs per scenario.

A comparison of policy training curves for `Sparse` and `Sparse+RGR` rewards is shown in Figure 2 (left). Each curve is obtained by averaging over all runs (16 scenarios $\times$ 15 runs per scenario) for that reward type. The results verify that language-based rewards result in higher performance on average than sparse ones.

Next, language-based rewards were used in addition to hand-designed rewards using a similar methodology, and the corresponding learning curves for `Dense` and `Dense+RGR`

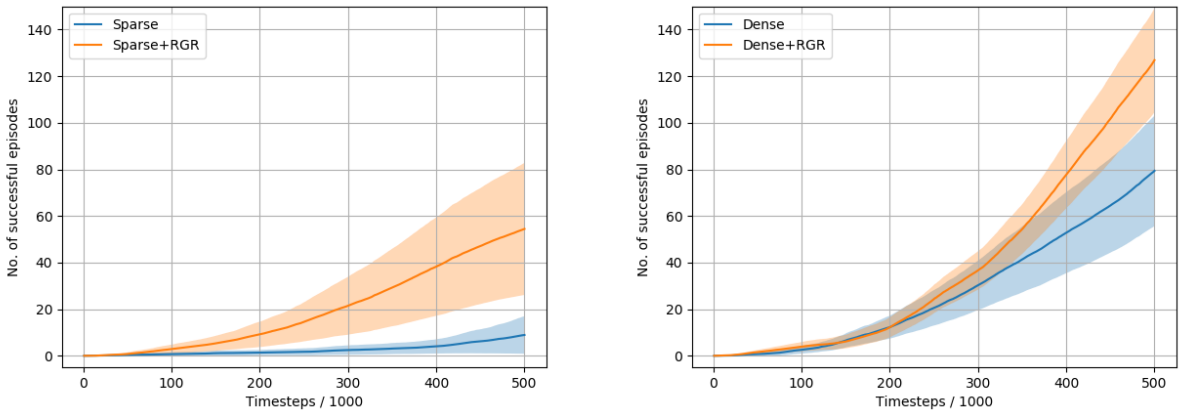

Figure 2. A comparison of policy training curves for different reward models. The shaded regions denote 95% confidence intervals.

are shown in Figure 2 (right). Interestingly, we find that using language-based rewards in conjunction with hand-designed rewards result in an improvement even over hand-designed rewards.

Further, the improvements were found to be statistically significant, both in sparse and dense reward settings, suggesting that the proposed approach can be used to make policy training more efficient in both sparse and dense reward settings.

For the dense reward setting, policy training with language-based rewards using the classification setting (`Dense+CLS`) was also performed. Although it results in an improvement in the mean successful episodes over `Dense` rewards, the improvement was not statistically significant, suggesting that the proposed regression setting helps learning more effectively from partial trajectories. More details for the results on the classification setting, as well as other additional experiments used to analyze the supervised learning phase can be found in the supplementary material (Section C).

5. Related Work

A number of prior approaches have been proposed to use language to guide a learning agent.

Some approaches involve mapping natural language instructions directly to an action sequence to be executed (Tellex et al., 2011; Sung et al., 2018). Our approach is different from these approaches in that we use language to generate auxiliary rewards, that can then be used to learn a policy using standard RL, allowing the agent to learn in more complex settings where offline learning is insufficient.

Other prior approaches map natural language to a reward function (MacGlashan et al., 2014; Arumugam et al., 2017; Williams et al., 2017). All these approaches assume a specific structure of the reward functions, while our approach does not make any such assumptions.

A number of approaches require designing state- and/or linguistic features to guide the learning agent (Kuhlmann et al., 2004; Branavan et al., 2012b; Kaplan et al., 2017; Waytowich et al., 2019), whereas we propose to learn the association between language and trajectories from a small set of human-provided descriptions.

Some approaches learn to ground language while interacting with the environment (Branavan et al., 2012a; Misra et al., 2018; Bahdanau et al., 2018). Our approach involves a separate supervised learning phase to ground language, which does not require interacting with the environment.

Fu et al. (2019) learn a language-conditioned reward function, but require knowledge of environment dynamics to compute the optimal policy during training. Narasimhan et al. (2015) use natural language to transfer dynamics across environments. Blukis et al. (2019) generate a state visitation distribution given a natural language instruction, which is then used to generate rewards for policy training.

6. Conclusion

We proposed an approach for mapping pixels to rewards, conditioned on a free-form natural language description of the task. Given paired ⟨trajectory, language⟩ data, first, a relatedness model – PixL2R – is learned between a sequence of states and a natural language description using supervised learning. This model is then used to generate intermediate rewards for policy training, for a task with natural language description. Our experiments on a simulated robot manipulation domain show that the proposed approach can significantly speed up policy learning, both in sparse and dense reward settings.

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A. Neural Network architecture

Figure 3 shows the viewpoints used in our model. Figure 4 shows a diagram of the neural network architecture described in Section 3.1.1.

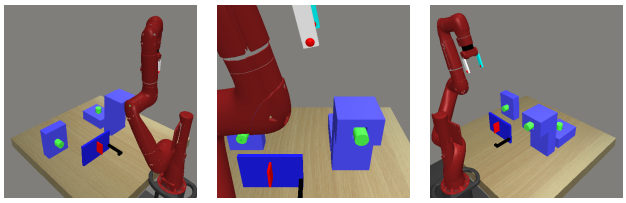

Figure 3. Viewpoints used for data collection and experiments.

B. Dataset Details

First, 13 tasks were selected from the Meta-World task suite. This gave us a total of 9 objects to interact with (for 4 objects, multiple tasks can be defined, e.g. turning a faucet clockwise or counter-clockwise). We then created 100 scenarios for each task as follows: In each scenario, the task-relevant object is placed at a random location on the table. Then, a new random location is sampled, and one of the remaining objects is placed at this position. This process is repeated until the new random location is close to an already placed object. This results in 1300 scenarios in total, with a variable number of objects in each scenario.

A policy was trained for each of these scenarios independently using PPO (Schulman et al., 2017), which was then used to generate one video of the robot completing the task in the scenario. For this purpose, we used the dense rewards defined in the original Meta-World benchmark for various tasks. The median length of trajectories across all generated videos is 131 frames. Note that our algorithm does not need the policies used to generate the videos, so they could also be collected using human demonstrations.

To collect English descriptions from videos of the robot performing the tasks, Amazon Mechanical Turk (AMT) was used. Since the models of the objects in the environment are coarse, it is usually non-trivial to recognize the real-world objects they represent from the models alone. To guide the AMT workers to use the names of real-world objects the models represent, we showed a table of the models with prototypical images of real-world objects that closely match the models (shown in Figure 5). This enabled us to get descriptions that use the real-world object names, without priming the workers with specific words.

Table 1. Examples of descriptions collected using AMT.

Object Id	Description
0	Press the button.
0	Pressing the button
1	Push peg in to hole.
1	Push the green button.
2	Turn on the coffee maker
2	push in the green button
3	Push toaster handle down
3	Push down the red block.
4	pressing down the object
4	pull down the red switch
5	move the plate down
5	push down the slider
6	Close the door
6	Open the door.
7	twisting the cube
7	rotate the object
8	Rotate the lever anticlockwise
8	Turn the faucet to the right.
9	rotating the object
9	turn on the faucet
10	Open the window.
10	Open the yellow window.
11	Slide the window to the left.
11	Close the Window.
12	pull out the green block
12	Pull out the green piece

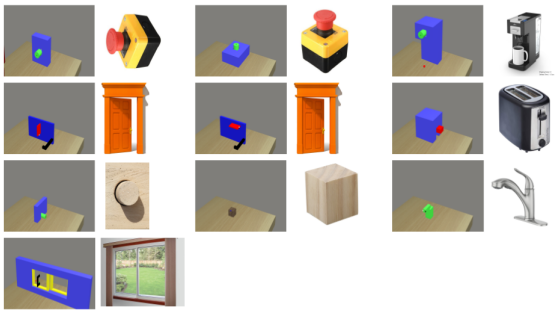

Figure 5. List of objects used

We obtained 520 descriptions in total, for an average of 40 descriptions per task. Some example descriptions collected are shown in Table 1.

C. Details of the Experiments

C.1. Experimental Setup

For each of the 13 tasks (see Section B), the 100 scenarios were randomly split into 80 training, 17 validation and 3 test scenarios.

For each of the test scenarios, first, policy training was run with 15 random seeds, both in the sparse reward setting (`Sparse`; 1 if the agent reaches the goal, and 0 other-

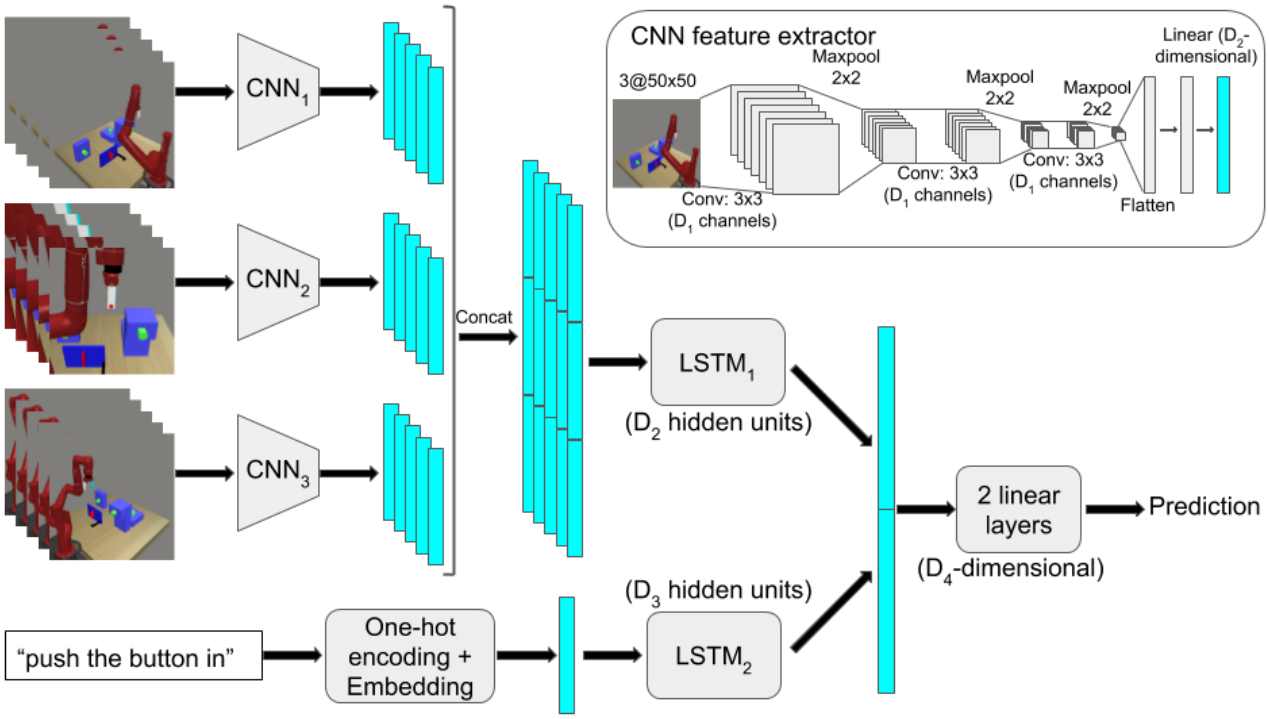

Figure 4. Neural network architecture: The sequence of frames from the three viewpoints are passed through three separate CNN feature extractors. The resulting feature vectors are concatenated across views. The sequence is then passed through an LSTM to obtain an encoding of the trajectory. The given linguistic description is converted to one-hot representation, and passed through an embedding layer, followed by an LSTM. The outputs of the two LSTMs is concatenated and passed through a sequence of 2 linear layers (with a ReLU activation between them) to generate the final prediction.

wise) and the hand-designed dense reward setting (`Dense`; defined in the original Meta-World benchmark). Then, a Kruskal-Wallis test was used for each scenario to identify scenarios where there was a statistical significant difference between the number of successful episodes with sparse rewards and with dense rewards, and the mean successful episodes with dense rewards was higher than the mean successful episodes with sparse rewards. All subsequent comparisons were done on the 16 (out of 39) scenarios for which this was true. Intuitively, these 16 tasks are too difficult to learn from sparse rewards, while they can be learned using dense rewards. Therefore, language-based dense rewards should be useful on these tasks. The remaining tasks are presumably either too simple that they can be learned with sparse rewards alone, or are too difficult to learn within 500,000 timesteps even with hand-designed dense rewards.

C.2. Word-level Analysis

In order to understand how the supervised learning phase is using different words in the description, the supervised model was used to make predictions on the test set, and the gradient of the loss was computed with respect to the continuous representation of the words in the descriptions (i.e. after the embedding layer). The mean of the absolute values of these gradients is then a measure of how much the prediction is affected by the corresponding word. The values are reported in Table 2, which were scaled so that the maximum value for any description is 1.

Table 2. Average magnitude of gradients for different words in a description for the relatedness score prediction.

	Descriptions **Average magnitude of gradient for each word**						
1.	push 0.53	the 0.30	green 1.00	button 0.94			
2.	push 0.42	down 0.57	the 0.34	red 1.00	block 0.91		
3.	pull 0.16	down 0.31	the 0.15	lever 0.75	on 0.58	the 0.36	toaster 1.00
4.	turn 0.94	on 1.00	the 0.44	faucet 0.87			
5.	slide 0.52	the 0.23	green 0.94	lever 1.00	to 0.77	the 0.30	left 0.78
6.	open 0.83	the 0.32	window 1.00				

First, we observe that for all the descriptions, the words describing the main object have a very high average gradient

magnitude – *green* and *button* in description 1, *red* and *block* in description 2, *lever* and *toaster* in description 3, *faucet* in description 4, *green* and *lever* in description 5, and *window* in description 6. Several verbs also have a high average gradient magnitude – *turn on* in description 4 and *open* in window. Verbs in other descriptions do not have a high gradient magnitude because for those descriptions, the object affords only one possible interaction, thus making the verb less discriminatory. For the objects *faucet* and *window*, there are two possible actions each (*turning the faucet on or off* and *opening or closing the window*); thus the verb also carries useful information for these objects.

This analysis suggests that the model learns to identify the most salient words in the description that are useful to predict the relatedness between a trajectory and language.

C.3. Ablations

Having established that policy training works better with the language-based rewards, we ran some ablation experiments as described below. All the ablation experiments were performed with language-based rewards added to dense rewards, since most applications of RL currently use dense hand-designed rewards (which could be suboptimal for complex tasks), and it would be informative to learn which design decisions are most important to get an improvement by using language-based rewards in such settings.

- `LastFrame`: Instead of using the sequence of frames in the trajectory, only the last frame of the trajectory was used, both for training the PixL2R model, as well as for policy training.
- `MeanpoolLang`: The LSTM used to encode the language was replaced with the mean-pooling operation.
- `MeanpoolTraj`: The LSTM used to encode the sequence of encoded frames was replaced with the mean-pooling operation.
- `SingleView`: Instead of using 3 viewpoints for the trajectory, only one viewpoint was used.
- `Dense+CLS`: Instead of the regression loss, classification loss was used, as proposed in (Goyal et al., 2019).

For each ablation, the same setup was used as for `Dense+RGR` – training the PixL2R model with 8 random sets of values of hyperparameters, and choosing the model with the best validation accuracy. This model is used to generate rewards for policy training, for each of the 16 scenarios with 5 random seeds for all the 3 descriptions.[1]

The mean successful episodes across all runs are reported in Table 3. Further, the p-values for Wilcoxon tests between each ablation and the `Dense` rewards is reported, from which we can make the following observations:

Table 3. Comparison of various ablations to the Dense+RGR model. We report the mean number of successful episodes for each model, and the p-values for Wilcoxon test between the ablated and Dense models.

Setting	Mean Successful Episodes	p-value w.r.t. Dense
Dense	79.4	-
Dense+RGR	126.9	0.0340
LastFrame	133.5	0.0114
MeanpoolLang	138.3	0.0004
MeanpoolTraj	78.4	0.9601
SingleView	100.4	0.3789
Dense+CLS	102.0	0.6384

- Using only the last frame (`LastFrame`), or using mean-pooling instead of an LSTM to encode the language (`MeanpoolLang`) does not substantially affect the performance of the model. In both these cases, the resulting model is still statistically significantly better than `Dense` rewards. Both of these results agree with intuition, since the last frame can be used to predict the progress in the task, and since the linguistic descriptions are not particularly complex in the given domain, simply looking at which words are present or absent is often sufficient to identify the task without using the ordering information between the words.
- Using mean-pooling instead of an LSTM to encode the sequence of frames (`MeanpoolTraj`) drastically reduces the number of successful episodes, and the resulting model is no longer statistically significantly better than `Dense`. Again, this agrees with intuition, since it is not possible to infer the direction of movement of the robot from an unordered set of frames.
- Using a single view instead of multiple views (`SingleView`) results in a decrease in the number of successful episodes, and the resulting model is no longer statisticially significantly better than `Dense`. As mentioned earlier, using frames to represent trajectories (instead of actions as in prior work) requires addressing challenges such as perceptual aliasing and occlusion, and these ablation results suggest that using multiple viewpoints alleviates these issues.
- Using classification loss instead of regression (`Dense+CLS`) also leads to a drop in performance, again making the resulting model no longer statistically significantly better than `Dense`. This is consistent with our initial observation, as described in Section 3.1.3, wherein, the learning problem becomes more difficult due to partial trajectories when the classification loss is used.

[1] For `SingleView`, we used 8 random sets of hyperparameter values for *each* of the three viewpoints, and chose the model with the best validation accuracy.