Parallelized Interactive Machine Learning on Autonomous Vehicles

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Abstract—Deep reinforcement learning (deep RL) has achieved superior performance in complex sequential tasks by learning directly from image input. A deep neural network is used as a function approximator and requires no specific state information. However, one drawback of using only images as input is that this approach requires a prohibitively large amount of training time and data for the model to learn the state feature representation and approach reasonable performance. This is not feasible in real-world applications, especially when the data are expansive and training phase could introduce disasters that affect human safety. In this work, we use a human demonstration approach to speed up training for learning features and use the resulting pre-trained model to replace the neural network in the deep RL Deep Q-Network (DQN), followed by human interaction to further refine the model. We empirically evaluate our approach by using only a human demonstration model and modified DQN with human demonstration model included in the Microsoft AirSim car simulator. Our results show that (1) pre-training with human demonstration in a supervised learning approach is better and much faster at discovering features than DQN alone; (2) initializing the DQN with a pre-trained model provides a significant improvement in training time and performance even with limited human demonstration; and (3) providing the ability for humans to supply suggestions during DQN training can speed up the network’s convergence on an optimal policy, as well as allow it to learn more complex policies that are harder to discover by random exploration.

Index Terms—deep reinforcement learning, interactive machine learning, autonomous vehicles, simulation

I. INTRODUCTION

As self-driving vehicles gain popularity and become a more viable transportation solution for their low accident rates, it would not be surprising to see tens to hundreds of thousands of these vehicles on the road in the next 5 years. This huge potential market has attracted many companies to invest in the technologies involved in self-driving, such as deep learning, computer vision, data processing, and so on. However, these new technologies face many challenges, in the form of road hazards, changing conditions, etc. Therefore, it will be crucial to develop methods that allow technically unskilled users to teach the algorithm in a way that allows them to customize the driving experience to their needs.

Human demonstration has long been the standard training approach for the self-driving industry. One fairly new method is the use of Convolution Neural Networks (CNNs) as a function approximator in deep RL. CNNs have revolutionized pattern recognition and are especially powerful in image recognition tasks. Because this approach uses convolution kernels to scan road images at different driving time points, fewer parameters will need to be trained compared to the total number of operations.

Deep RL algorithms, such as Deep Q-Network (DQN), suffer from poor initial performance compared with the classic RL algorithm, since they start as a tabula rasa. This also contributes to increased training time, because these algorithms need to learn the unspecified features in addition to the policy, in contrast to using handengineered features. In addition, complex domains, like autonomous driving, demand a low error margin in order to avoid safety issues. These problem is non-trivial and consequential in real-world applications.

In order to use deep RL to solve real-world problems with low error rates, there is a need to increase its speed and accuracy. One method is by using humans to provide demonstrations. Human demonstrations have been used in RL for a long time; however, this area has only recently garnered interest as a method that may speed training in deep RL.

One contribution of this work is its illustration of the results of applying human driving demonstration to a DQN algorithm by providing a pre-trained CNN model with later fine-tuning through human interaction. Using an interactive machine learning method will help individual self-driving vehicles to gain expertise by fine-tuning the pre-trained deep neural network that allows a self-driving agent to gain experience in an unfamiliar region without learning from scratch. Interactive learning could also help avoid risks arising from unfamiliar road conditions and new layouts, since interaction will be able easily guide the self-driving agent at an early stage by steering and take back the driver seat.

By including a human driver for demonstration we target three problems: (1) feature learning via human demonstration; (2) policy learning through DQN; and (3) interactive learning for novel environments. In this work, we address the first two problems, i.e. feature and policy learning, by speeding up the pre-trained CNN model with human demonstration to learn the underlying features in the hidden layers of the network.

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We address the third problem by augmenting the DQN learning process to allow a human teacher to provide suggestions during the episodes used by the DQN to gather training data.

The learning environment was structured as a simulation that can easily mimic any combination of real road conditions and city layout using the Unreal Engine software. In addition, we tested augmenting the training process through interactive learning using the same environment; simulated agents do not traditionally represent the same environmental accuracy as real vehicles, but the new simulation we used included manual tuning in the simulation, e.g., rigid body, forces and torques.

We tested our approach in both the Deep Q-Network (DQN) with and without human demonstration and evaluated its performance using the AirSim car simulator in a neighborhood environment domain. Our results show an increase in the speed of learning with a large improvement in self-driving performance. The generality of this approach suggests that it is feasible and necessary for deep RL algorithms to incorporate human demonstration and interaction.

II. RELATED WORK

Although our work does not fall directly under the umbrella of transfer learning, it is similar to the transfer learning methods in deep learning. At the domain of deep neural networks for image classification, Yosinski et al. have shown the benefits speed up of learning features from existing models when the datasets are similar [7]. In this work, we structured a human demonstration convolution network [1], then used the pre-trained model as source, and the CNN model was then used to initialize the RL agent’s network.

Existing research on pre-training in RL [9], [10] has shown improvements when using a pre-trained model on similar datasets. The capability of these studies were limited by the small number of parameters learned and by the state input. In our work, we used the raw images of simulation driving domain as input from the human driving demonstration. It is worth noting that the pre-training model needs to learn the features of states as well as policy.

Our approach of using supervised learning for pretraining is similar to that of [1]. In their model, pre-training involves learning to predict an action based on input image and minimizing the loss between predicted and actual actions provided by human volunteers. We used a similar approach, with image frames from human demonstrators as input data and labels provided by the action taken corresponding to each image frame. Another approach to pre-training is to learn the latent feature by using unsupervised learning through deep belief networks [9]. Although the approach is different, the fundamental goal is the same: to improve learning by using pretrained networks instead of random initialization.

Other recent work leveraging human input in deep RL included the use of human feedback to learn a reward function [11] and, similar to our system, pre-training of a network with human demonstration in DQN [12]. However, these examples of pre-training (combining large-margin supervised loss and temporal difference loss) are focused on close imitation of the demonstrator. In our work, we use only the cross-entropy loss and focus on learning features.

Another study, [13], also used supervised learning for human demonstration and learned networks to initialize the policy network for RL. However, the approach focused on a single domain and used a huge amount of data provided by human experts to train the supervised network. In contrast, our approach used a much smaller training dataset and illustrates the usability and feasibility of such an approach to affect the deep RL algorithm. Our study shows that a small amount of data gained from a non-expert is enough for a supervised neural network to learn important feature representation for driving from demo image frames; deep RL algorithm such as DQN can benefit from having the pre-trained model as a starting point.

III. DEEP REINFORCEMENT LEARNING

Reinforcement learning (RL) problems are normally modeled as a Markov Decision Process, represented by a tuple of states $S$, actions $A$, rewards $R$, transition probabilities $P$, and discount factor $\gamma$. The essence of RL is to let the agent explore an unknown environment by taking actions $a \in A$. After taking each action, the agent lands at a new state $s'$. A reward, $r \in R(s,a)$, is given based on the action taken and the next state, $s'$, of the agent. The aim of the RL algorithm is to let the agent learn to maximize the expected reward, $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$, for each state at time $t$. The importance of future and immediate rewards is determined by the discount factor, $\gamma \in [0,1]$: a value close to 0 suggests the agent should treat a future reward as important, and vice versa for values close to 0.

A. Deep Q-Network

The Deep Q-Network (DQN) algorithm is the rising star of the deep RL domain thanks to its ability to generalize and its flexibility in solving problems in different domains. The first implementation of DQN [14] was capable of learning to solve 49 Atari games directly from the screen pixels by combining Q-learning [15] with a deep convolutional neural network.

A classic Q-learning algorithm learns the value of state-action pairs instead of the value of states:

$$Q(s, a) = E_{\pi'}[r + \gamma \max_{a'} Q(s', a') | s, a]$$  (1)

and uses the expected discounted reward from performing actions $a$ in state $s$. The optimal policy $\pi^*$ was later calculated by maximizing the Q value $Q^*(s, a) = \max_{a} Q^*(s, a)$.

When in a domain with a state space that is fairly large or continuous (e.g., Atari games or driving), it is not feasible to directly compute the Q value. To allow the use of Q-learning algorithm in a more general state space, regardless of size and continuity, the DQN algorithm uses a constitutional neural network as a function approximation to estimate the Q function by $Q(s, a; \theta) \approx Q(s, a)$ where $\theta$ is the network’s weight parameters. At each iteration, i, the DQN is trained to minimize the mean-square error (MSE) between the Q-network

$$Q(s, a) = E_{\pi'}[r + \gamma \max_{a'} Q(s', a') | s, a]$$  (1)
and $y = r + \gamma \max_{\theta^i} Q(s', a'; \theta^i)$ where $\theta^i$ is the network’s weight from the previous iteration. The loss function in this approach can be expressed as

$$L_i(\theta) = E_{s,a,r,s'}[(y - Q(s, a; \theta))^2]$$

(2)

where $s, a, r, s'$ are state-action samples drawn from experience replay memory with a mini-batch of size 32. The reward $r$ is calculated using reward clipping that scales the scores by clipping all reward when positive at 1, negative at -1 and 0 when rewards are unchanged. The use of experience replay memory, a target network, and reward clipping helps to stabilize the learning. To ensure the agent obtains sufficient exploration of the state space, DQN also uses an action $\epsilon$-greedy policy.

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**B. Pre-Training Networks for Deep Reinforcement Learning**

Deep RL generally needs to balance two tasks at the same time: (1) feature learning and (2) policy learning. Even though Deep RL has already been quite successful at performing both tasks in parallel, to ensure model convergence and performance requires a long training time and a large amount of data. To address the feature learning task, we believe a supervised CNN model with human demonstration data input would dramatically speed up the learning process and quality, which from the leverage more resource on policy learning. In our work, deep RL learns feature representations by pre-training its network using human demonstrations from non-experts; we refer to this approach as a pretrained model. [16]

The pre-trained model method is similar to Bojarski’s End-to-End approach [1], using a deep CNN to learn the feature space. We also applied data augmentation to increase the sample size by adding artificial shifts and rotations. Unlike Bojarski’s work, our approach relies only on the center camera, and we also changed the dimension of input, convolution filter size, and network work output dimensions to fit our approach. We construct the network as a multi-classification model; we also assumed that humans could provide correction action (labels) while driving.

The model was parametrized by using an MSE loss function and an Adam optimizer [17] with a learning rate of 0.0001. The training library is Keras with Tensorflow backend. We used a batch size of 128. The CNN architecture followed the same structure, with different parameters for its input dimension, filter size, and output dimension. It included a normalization layer and five convolution layers, each with a dropout layer. It followed five flattened layers, each with a dropout layer. The activation function was ELU and the regulation function is L2. The original network’s output had a single output for each valid action, which was not appropriate for our work. Instead, we increased the output dimension to three: throttle, steering, and brake. The weights and biases learned from the pre-trained CNN were used to initialize the DQN network.

We were handling raw image data, so the first layer of normalization was extremely important, since normalization helps to generalize a model faster (due to the difference in lighting captured from the camera). We also applied normalization for the parameters that passed down the network in all fully connected layers. This normalization prevented learned parameters from either vanishing or exploding. The network had roughly 27 million connections and 250 parameters.

**C. Interactive Deep Q-Network**

As part of our work, we introduce the concept of human suggestion to the original DQN paradigm, which we call Interactive Deep Q-Network (IDQN). Recall that DQNs learn the optimal policy by first exploring the state space to learn rewards associated with visual input into the CNN used by the DQN. The visual input most often takes the form of a camera view, either of the state space or some small portion thereof. The Replay Memory stores tuples of these events, which take the form $[\text{image}, \text{action}, \text{reward}, \text{done}]$.

In order for an agent to discover the desired policy, the reward function must be properly set up such that the DQN can converge with discovered rewards. This means the reward policy can be tedious to build and must be reconfigured if some additional actions are desired. To solve this, we propose giving a human the ability to add suggestions to the agent in the form of adding extra tuples to the Replay Memory with elevated reward values for future training.

To accomplish this, a visual input system was designed to allow a trainer to suggest, either through a keyboard or GUI buttons, more appropriate actions the agent should take at a given point in time. When the trainer signals to add a suggestion, the last trained frame is re-added to the Replay Memory (but not the History, which is used for inference only) that will be later sampled from to continuously train the agent.

Over time, the trainer’s input is sampled against and due to its elevated reward shapes the policy the agent uses to incorporate the preferences the trainer is attempting to convey. The benefit is that the agent both learns the policy that maximizes the reward function at a faster rate as well as more complex policies that may only be known to the trainer providing the suggestions.

**IV. EXPERIMENT DESIGN**

We use AirSim [https://github.com/Microsoft/AirSim], an open source simulator based on Unreal Engine as an autonomous vehicle agent [8] Figure[1]. The deep reinforcement learning DQN and supervised learning CNN are both implemented using Tensorflow; the rest of the platform consisted of:

- Windows 10 Pro x64
- AirSim Neighborhood Binary
- Python 3.6.3
  - msgpack-rpc-python
  - numpy
  - opencv-python
  - pillow
A. Supervised Convolution Neural Network

Due to limited computational resources and time constraints, we used only four datasets from human driving demonstrations. Regardless, we still achieved values < 0.1 and 0.3 for the training and validation data, respectively. The images used are from the center scene image camera.

| Layer       | Dimension       |
|-------------|-----------------|
| Input       | 64 × 64 × 3     |
| Convolution2D | 24 × 5 × 5     |
| Dropout     | 0.5             |
| Convolution2D | 36 × 5 × 5     |
| Dropout     | 0.5             |
| Convolution2D | 48 × 5 × 5     |
| Dropout     | 0.5             |
| Convolution2D | 64 × 3 × 3     |
| Dropout     | 0.5             |
| Convolution2D | 64 × 3 × 3     |
| Dropout     | 0.5             |
| Fully Connected | 1164         |
| Dropout     | 0.5             |
| Fully Connected | 100          |
| Dropout     | 0.4             |
| Fully Connected | 50          |
| Dropout     | 0.25            |
| Fully Connected | 10           |
| Dropout     | 0.25            |
| Fully Connected | 3           |

TABLE I
CNN ARCHITECTURE

After collecting more than 1500 image frames from human demonstrations, we first constructed augmentation of the images Figure 2. Since we assumed the CNN model would only focus on the lower part of the image, the road, the images were cropped accordingly. To mimic real road conditions, we also included artificial shifts and rotations to help the network to learn from poor position or orientation data. The magnitude of these perturbations was randomly applied from a normal distribution with a mean of zero and standard deviation twice the standard deviation reported in Bojarski’s End-to-End approach paper.

As mentioned earlier, the CNN model has five convolution layers and four fully connected layers. We applied dropout layer after each layer to randomly remove a certain percentage of the learned parameters. For conventional layers, the dropout rates were all 0.5, and for fully connected layer the rates were 0.5, 0.4, 0.25, and 0. In this work, we also used an exponential linear unit as an activation function to include non-linearity. The batch sizes tested were 128 and 64; the batch size did not appear to have a large effect on model performance. Another difference from the original paper is that instead of using three cameras—left, right, and center—we used only a center camera because it’s the only option AirSim offers.

B. Deep Q-Network

For the Deep Q-Network (DQN) portion of our experiment, the original network used in Minh’s 2015 paper was used, sourced from an existing Python implementation included as an example in the AirSim GitHub repository. This code implemented the following DQN components:

- **Action Model** - CNN model used in action inference which is trained frequently (after 200 steps, then every 4 steps)
- **Target Model** - CNN model used in loss calculations which is cloned from the Action Model occasionally (every 1000 steps)
- **Replay Memory** - Holds up to 500,000 event tuples previously described which can provide mini-batches for training the Action Model
- **History** - Holds N recent visual inputs for historical sequence inputs
- **Linear Epsilon Annealing Explorer** - Scales the exploration rate of the agent based on a maximum random chance (100%) that is phased down to a minimum random chance (5%) over a given number of steps (5,000)
- **DQN Agent** - Wrapper class that combines the other components with functions to pick an action based on the CNN policy approximator and exploration policy.
observations based on actions taken, and retrain the model based on sampled mini-batches from the Replay Memory. The model is trained with a learning rate of 0.001, momentum of 0.95, and mini-batch size of 32 events.

For this experiment, the input consisted of 84 x 84 images from the simulated front camera, converted to grayscale. The action space consisted of: forward (no turning), left (-0.25 steering), and right (0.25 steering) all at a constant acceleration of 0.35. The reward function, which can be seen in Equation 3 measures the distance from the center of the street, angle from the centerline following the street, speed traveling, whether the car has left the boundaries of the street, and whether a collision has occurred.

\[ r(x) = \Delta d(x) + \angle c(x) + v(x) - e_{oob} - e_{collided} \]  

The last two measurements are considered catastrophic and result in an end to the episode and a large negative reward.

C. Human Suggestion for Deep Q-Network

In order to provide a mechanism for trainers to add suggestions during training, a GUI was developed which allowed the trainer to add suggestions to the agent during training. A representation of the pipeline which combines this GUI with the existing DQN agent and simulation system is shown in Figure 3. The training workflow follows the sequence:

1. Run AirSim simulator (choose Car mode)
2. Run the app.py Python script
3. Start the DQN Agent by pressing the space bar
4. The agent continues to explore the simulation space, making actions and learning the policy
5. (Suggestion Only) The trainer can use either the UP/LEFT/RIGHT arrow keys or the GUI buttons to suggest FORWARD, LEFT, or RIGHT actions respectively

D. Evaluation Criteria

MSE loss was used as one criterion for model learning from human demonstration. As with most supervised learning approaches, the measurements of performance are a function of the difference between the predicted action and the human-demonstrated action. Another measurement we included is the accident rate: fewer accidents indicated better-learning.

For IDQN, we looked at how the reward improves over the progression through episodes. Specifically, we measured the mean and standard deviation of the reward per episode, total reward gathered per episode, and the total number of steps taken per episode. We deem success as an improvement in the mean and standard deviation, which can indicate discovery of a better policy, as well as an increase in total reward per episode, which, if seen in concert with an increase in steps taken per episode, can indicate the episode lasted longer, meaning the car successfully traveled further down the street.

V. RESULTS

In the human demonstration part of the work, we achieved an average training loss of 0.1 and validation loss of 0.3, quite an improvement considering only 4 demonstration datasets were collected. For the CNN, we used an exponential linear unit (ELU) as the activation function. This not only helped avoid a vanishing gradient via the identity for positive values, it also improved the learning characteristic by including negative values, which allowed it to push the mean unit activation closer to zero. In essence, the ELU improved the network and sped up training.

One reason we did not achieve a loss of less than 0.001— as reported in the original Nvidia End-to-End learning paper [1]—is because of the extra predictions we included. Instead of a single output, our CNN model returned three results: throttle, brake, and steering angle. We believe a better metric might be loss divided by three, since the three outputs all contributed to the loss (presumably not equally).

Fig. 4. Results obtained from DQN vs. DQN with Human Suggestion (IDQN), showing Mean Episode Reward, Total Episode Reward, and Total Episode Steps Taken

Results from the IDQN experiment, shown in Figure 4, show some improvement in the form of a tightening of the standard deviation in mean reward per episode. We take this to mean that the policy has converged on a more optimal
approximation of the reward policy. In addition, we see that the total reward and total steps have both seen a measured increase, which, as noted previously, we take to mean the agent can travel further in the episode and thus gather more reward.

More generally, we saw the ability for the agent to learn more complex policy approximations. This was shown by the agent learning, though suggestions given to the agent during training, learning to make a left-hand turn at an intersection. In comparison, the original DQN agent failed to learn what to do at the intersection and simply ran into the fence at the opposite side of the street. This resulted in much larger total rewards/steps seen in three of the last four episodes in the IDQN agent in the results in Figure 4.

VI. CONCLUSION

We were not able to include the pre-trained mode in the Deep Q-Network, due to the complexity of the simulator environment and time strain. However, from the results for individual performance of the two models, we believe our approach is feasible.

Human demonstrations are partially responsible for the success of our approach. It will be important to investigate how the demonstrator’s performance and the amount of demonstration data affect the benefits of pre-training that network in future work. Human demonstration End-to-End learning could also be used as a comparison candidate for our approach. Although the suggestion for demonstration hours is more than 100 driving hours, from our work, we believe a much smaller sample could achieve similar results. In the pre-trained CNN model, we ignore the information collected from the depth and segmentation cameras. Several studies have shown that this information could further improve self-driving agents.

We also show that our IDQN approach is successful in increasing the speed and accuracy of training over the original DQN implementation. Additionally, the IDQN approach allows for the learning of more complex policy approximation to be learned without rebuilding a more complicated reward function to instruct the agent. In the future, we hope to take some direction from the work by Hausknecht [18] involving Deep Recurrent Q-Learning, which involves adding an LSTM layer to extract knowledge from sequential images used for input. This has the added benefit of learning policy in partially observable MDPs like the forward-facing camera used for input in the experiments conducted as part of our work. We also plan to investigate methods to limit the ability for the trainer to “over-train” by providing too many suggestions without seeing the appropriate feedback in the form of better results. This could be from either better instructions or better order of training from user suggestions for better transparency.

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