Continual Learning: 4th CLVISION CVPR Workshop

Anonymous CVPR submission

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1. Introduction

The main motivation behind the CLVISION workshop is to mitigate the problem of catastrophic forgetting. Catastrophic forgetting typically happens when an artificial neural network is trained to do a new task. In which case the neural network will forget how to do the old task in favor of the new task [1]. If catastrophic forgetting can be prevented that opens the door for more advanced learning models that can continually learn as well as learn new tasks without needing to use separate models or explicitly tell the AI what task it is doing. The main challenges are trying to train the model for a new task without giving it data on old tasks during the new training session and the model still retaining it's ability to complete the old tasks [1]. As well as trying to decipher between the tasks in front of it. The domain that this workshop would fall under is just neutral networks. It is a very broad topic that can be applied to almost any application area.

1.1. Links to workshop and paper deadline

2020 1st edition:
https://sites.google.com/view/clvision2020/
2021 2nd edition:
https://sites.google.com/view/clvision2021/
2022 3rd edition:
https://sites.google.com/view/clvision2022/
2023 4th edition:
https://sites.google.com/view/clvision2023

The paper submission deadline for the 4th edition is 7 March 2023.

2. Dataset description

The 2023 competition has not been posted yet so I will go over the dataset from 2022 and hopefully the 2023 version will be posted soon. It was hosted on CodaLab. There are 3 different competitions instance classification, instance detection and category detection. Instance classification is for images. Instance detection and category detection use videos. During the training phase you are allowed more than 70M parameters for the model, but the solution can not have more than 70M parameters + a replay buffer. The number of classes for instance classification is known ahead of time. You are allowed to have pretrained weights but are not allowed to use the pretraining data. You are not allowed to tune after training. In other words, you must be able to predict the output for a training instance immediately after the training phase. The execution time cannot exceed more than 12 hours.

2.1. CLVISION 2nd edition competitions

There were two different challenges this year. One has a supervised learning track, and the other was reinforced learning. The supervised track the score was based on the weighted scores of the final performance on all past tasks, online cumulative performance, and a runtime score. There were 17 submissions on this track and the weighted scores ranged from 0.26 to 0.94. In the top 10 it was from 0.62 to 0.94.

The reinforced learning there were two participants, and the performance metric was the same as the other track and the two scores were 0.42 and 0.45.

2.2. CLVISION 3rd edition competitions

There were three different tracks this time as mentioned before they were the instance classification track, instance detection track and the category detection track.

The instance classification track had 37 different participants the score was based on the average correct classification from stream of 15 experiences. The scores of from 20 to 2 were spread out across the range of 0.5004 to 0.5232 while the number 1 score was 0.5635.

The instance detection track had 16 participants and the score was based on the average mean class accuracy for the 15 different classes. The ranges for the top 20 was

0.0005 to 0.5594 and the ranges for the top 10 are 0.3582 to 0.5594.

The category detection track had 11 different participants and the score was based on the average mean accuracy precision. The scores ranged from 0.0698 to 0.5465. Top 5 ranged from 0.3706 to 0.5465.

3. Research Papers

These research papers should be able to provide a brief overview of basic concepts in continual learning as well as where is the research is currently headed.

3.1. Three types of incremental learning

Three types of incremental learning is a paper done by one of the organizers. This paper is meant to clarify and formalize distinction between different kinds of problems in continual learning making evaluating and comparing algorithms very difficult [1]. The first of the three types is task incremental learning which is defined by having a distinct set of tasks where the task is explicitly provided [1]. Which means catastrophic forgetting is not a problem as you can have a separate outer layer to separate tasks. The second kind of incremental learning is called domain incremental learning which is done with tasks that have like each other. It is like task incremental learning, but the tasks are not provided. An example of this would be driving in different conditions [1]. That last type is class incremental learning where the deep learning model must be able to distinguish between all classes. Which is done by solving for each individual task it was trained for and solving between two individual tasks. For example, being trained for cats vs dogs then later on trained for horses vs cows. Then algorithm should be able to distinguish between cats vs cows [1].

3.2. Progress and Compress

This paper starts out by defining what the theoretical best continual learning model should do even though some of these are often at odds with each other [2]. Which are (1) should not catastrophically forget. (2) Should be able to take knowledge from previous tasks and be able to learn new tasks quicker and better. This is called positive forward transfer. (3) Should be scalable such that it should be trainable on a large number of tasks. (4) Should be able to get immediate improved performance on past tasks as it is learning new tasks. This is called positive backwards transfer. (5) Should be able to learn without task labels or ideally task boundaries [2]. The progress and compress framework is a process where it separates the learning process into two phases. The progress phase where it actively learns how to do new tasks and the compress phase where it puts the new task into its knowledge base [2].

3.3. Continual Learning for Robotics

This paper provides a summery of some popular continual learning strategies. One of them is dynamic architectures approach where the model dynamically changes to accommodate the new task in such a way that it will not interfere with the old model and older tasks [3]. Another one is regularization approaches in this approach the model regulates the amount of change that the weights can undergo to prevent overfitting to the new problem and forgetting old tasks [3]. Another approach covered is a rehearsal approach where raw samples of past tasks are saved into memory and whenever there is training for a new task the samples of old tasks are pulled from memory and are trained along side the new task so the old tasks will not degrade overtime [3]. The fourth one covered in the paper is generative replay which is like the rehearsal approach but modelled on data distributions and are therefore able to sample data from past experience when learning on new data [3]. The final approach is a hybrid approach. Most continual learning approaches are usually dual architecture strategies as they will have a fast learning and slow learning mechanisms to learn continually [3].

References

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