Chapter 1

Conclusion

Many aspects of the OceanQA dataset and the H-PERL approach have been discussed in previous chapters. This chapter therefore aims to summarise these details, and particularly focus on the strengths and weaknesses of our VideoQA architecture. We also attempt to compare our approach qualitatively to existing work in VideoQA. Finally, we conclude by outlining a number of possible extensions to our architecture, some of which may help to address the drawbacks of the approach, or apply the approach to different tasks.

1.1   Summary of H-PERL

In Chapter **??** we described the H-PERL architecture as a hybrid architecture - composed of both neural networks and symbolic reasoning modules - made of a pipeline of components. Each component in the architecture extracts a particular concept from the video or question. These concepts include: objects, including type and position; object properties, such as colour and rotation; binary relations between objects, such as close; and events between two consecutive video frames.

Chapters **??** and **??** each outlined specific H-PERL models. The hardcoded model, outlined in Chapter **??**, used mostly manually engineered components. These components allowed the hardcoded model to find and correct errors in the object detection, but also made it less adaptable to new environments. The trained model, described in Chapter **??**, continued to use some engineered components, but trained its *core* components using QA pairs. The trained model also proved the usefulness of hybrid models, by allowing background knowledge of the environment to be used to find the set of effects which occur in a video.

In Chapter **??**, which outlined the performance differences between the models, we saw that the trained model was significantly faster than the hardcoded model, and that the error correcting abilities of the hardcoded model made it slightly more accurate. We also noticed that both models we heavily reliant on highly accurate object detection, but that the trained model was less susceptible to a reduction in accuracy due to noisy data.

Chapter **??** noted that one of H-PERL's key strengths was its adaptability to other tasks; as long as there exists QA pairs with which a component can learn a particular concept, many different QA tasks can be solved. Chapter **??** also mentioned a number of requirements that each H-PERL model has, as well as a number of assumptions that needed to be made about the data. These requirements and assumptions could be deemed quite strict, however, future extensions to our architecture may be able to overcome them.

We now summarise the weaknesses of the current state of the H-PERL approach that have been encountered throughout this report:

1. Both H-PERL models require a highly accurate object detector, which, for many environments, is a very difficult requirement to meet.

2. The H-PERL architecture relies on a hardcoded question parser, which limits each model's ability to adapt to new environments, since, in the general case, parsing questions by-hand is almost impossible.

3. Currently, H-PERL relies on datasets containing specific questions which can be used to train components individually. In a general question-answering setting this will not be the case; questions will require knowledge of many different concepts to answer.

4. H-PERL can currently only solve environments which require knowledge of only: objects, object properties, relations between objects and events. This assumption is too simplistic for many environments.

5. Unlike other machine learning methods, an environment specification must be provided to each H-PERL model. For complex environments, this may be very difficult to generate.

Of course, as well as disadvantages, H-PERL also comes with many advantages. We now list the following strengths of the H-PERL approach:

1. Firstly, H-PERL is highly accurate on the OceanQA dataset; with one of the models answering 99.1% of questions correctly.

2. Since H-PERL stores information extracted from a video symbolically, it is very simple to analyse, understand and explain the model's behaviour.

3. The hardcoded H-PERL model was able to correct errors in an earlier component by reasoning about uncertainty. And, indeed, there are many more possibilities for further symbolic error correction functionality to be added, since H-PERL represents information about each video explicitly.

4. Both H-PERL models proved the utility of background knowledge injection. The hardcoded model was able to use an entire $\mathcal{AL}$ model to detect events, and the trained model was able to use ASP rules to detect effects.

5. After symbolic information has been extracted from the video, all of the questions for that video can be answered in one go, meaning the architecture can be quite fast. This is in contrast to some VideoQA implementations which make use of attention; each question is applied to the attention module individually in order to extract the relevant parts of the video.

There may be many more strengths and weaknesses of the H-PERL approach, such as training and evaluation speed or efficiency. However, given that time and resources for the project were limited, it was not always possible to conduct such performance evaluations or quantitative comparisons to other models. We also note that Section 1.3 mentions a number of possible improvements to H-PERL which may help to mitigate some of its weaknesses.

1.2 Comparison with Existing Models

We spend the second part of this section comparing H-PERL to the Neuro-Symbolic Dynamic Reasoning [10] model, since, to the best of our knowledge, it is currently the only other hybrid VideoQA implementation. Firstly, though, we compare H-PERL to some of the existing neural end-to-end VideoQA approaches.

1.2.1 End-to-End Architectures

Both H-PERL and all of the end-to-end neural network approaches presented in Chapter **??** attempt to extract features from the video. One of the key differences between the two approaches is that H-PERL makes these features explicit, while end-to-end networks do not, instead the information in the video is stored implicitly, in a vector. Clearly, storing information explicitly makes the model more transparent, but, in many cases, it is very difficult, especially for the real-world datasets used by many of the implementations in Chapter **??**.

A further difference between H-PERL and end-to-end networks is that H-PERL uses a hardcoded question parser, whereas many existing VideoQA implementations use a neural component, and again store the information extracted from the question implicitly. H-PERL's use of a hardcoded question parser makes it less adaptable to other datasets. It also makes applying H-PERL to free-form, natural language questions without templates impossible.

Finally, attention mechanisms have been used by a number of recent VideoQA implementations [4, 8, 9, 6, 2, 11, 1, 5]. These allow the model to focus on the most relevant part of the video, based on the current question. While object detection may be considered an attention mechanism in H-PERL, the attention is not dynamically updated for each question. Adding an attention mechanism to H-PERL could allow the model to focus on only the relevant objects of a video, however, a lack of attention allows H-PERL to answer every question for a given video at the same time. Adding an attention mechanism may therefore slow each model down. We consider this idea further in Section 1.3.

1.2.2   NS-DR Model

The Neuro-Symbolic Dynamic Reasoning (NS-DR) model was outlined in Chapter **??**. We now compare this model to the H-PERL models described in previous chapters.

At a high level, the Neuro-Symbolic Dynamic Reasoning (NS-DR) model, which was outlined in Chapter **??**, is very similar to H-PERL. Both approaches make use of some form of object recognition (NS-DR uses Mask R-CNN [3], while H-PERL uses Faster R-CNN [7]), both models extract attributes or properties of objects using neural networks, both approaches attempt to extract event information from the video, and finally, in order to find answers to questions, both models execute programs with the data extracted from the video.

However, when the approaches are analysed in depth a number of key differences emerge, which we list as follows:

- NS-DR uses a single 'object-centric' component, the video frame parser. This component roughly corresponds to two different H-PERL components: the object detector, properties component. The NS-DR video frame parser is also pre-trained on non-QA data - data other than QA pairs. Whereas, in H-PERL, only the object detector is pre-trained; the properties component can be trained using QA pairs. In this sense H-PERL is more adaptable to new environments, since each environment requires only a trained object detector and a dataset containing properties questions.

- While H-PERL makes use of symbolic event components, NS-DR uses a neural event prediction engine which models objects and relations between objects as a graph. This likely makes NS-DR's event detection less transparent, since it is harder to tell how the model came to a particular conclusion, but may improve accuracy.

- NS-DR uses a neural question parser which constructs a functional program, with which the output of the event prediction component is executed. Training this question parser requires additional supervised data, in the form of pairs of natural language questions and their corresponding functional program. H-PERL's question parser is manually engineered specifically for the OceanQA environment. In this case, both question parsing components would be difficult to adapt to new environments, since one would need to either engineer a new component or have a dataset of questions and functional programs available.

- Finally, we note that the methods for answer generation are similar in the two models, except that NS-DR uses a trained question parsing component to generate a program to be executed, whereas H-PERL uses a manually engineered question-anwering component, and that H-PERL uses logic programming to both represent the video information and to find the answer to the question.

1.3 Future Work

Bibliography

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