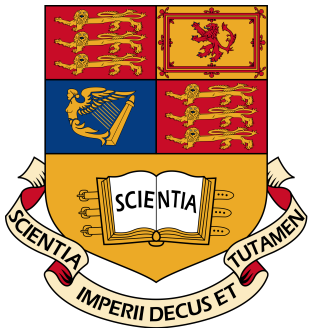


DEPARTMENT OF COMPUTING

IMPERIAL COLLEGE OF SCIENCE, TECHNOLOGY AND MEDICINE

Learning and Reasoning with Spacio-Temporal Properties for Understanding Scene Sequences

INTERIM REPORT

Author:
Ross Irwin

Supervisors:
Prof. Alessandra Russo
Dr. Krysia Broda

February 8, 2020

Contents

Chapter 1

Introduction

Writing algorithms which can answer questions on pictures or videos with a high level of accuracy and generality has been a goal of researchers in the AI community for many years. Recently, a lot of progress has been made in this area; with advances in neural network models and the production of larger datasets allowing reseachers to significantly improve accuracy on question answering models.

Formally, Visual Question Answering (VQA) [4] is a task where, given an image and a question posed in natural language about the image, a model is required to produce an open-ended answer to the question. Video Question Answering (VideoQA) is a related task where a model is given a video (mulitple images in sequence) and a question. These questions can be related to a single frame of the video, effectively making VideoQA a superset of the VQA task.

This project will attempt to produce a hybrid model for VideoQA - one which makes use of both neural networks and knowledge representation and reasoning methods based on first-order logic. In particular, we will investigate learning spatial relations within frames using neural networks and learning a symbolic model of an environment using inductive logic programming.

1.1 Motivation

VQA and VideoQA tasks attract attention because of their difficulty; both problems are considered "AI-complete" - they require knowledge from multiple modalities beyond a single sub-domain [3]. Building systems which have a deep understanding of the world would be a significant achievement for AI research; allowing many tasks which require significant human time and effort to be automated. Solving the VideoQA problem, which requires image understanding, natural language understanding and commensense reasoning, could be a major step towards this.

Furthermore, subproblems of VideoQA have already been shown to have applications in real-world tasks, for example event recognition has been used for identifying attacks on computer networks [12], detecting credit card fraud [49] and recognising cardiac arrhythmias [43].

Finally, the use of a hybrid model for VideoQA brings with it a number of advantages. Firstly, representing knowledge in logical form allows the injection of commensense or background knowledge which can improve accuracy in question answering tasks [40]. Secondly, there has recently been a significant increase in research related to explainable AI methods - machine learning techniques that enable human users to understand, trust and manage emerging artificially intelligent partners [5]. Extracting the knowledge from a neural network into logical form could be an important step toward explaining and understanding their behaviour.

1.2 Problem Description

As mentioned above, the VideoQA problem can be defined as building a model which, when presented with a short video and an open-ended, natural language question about the video, can produce a natural language answer to the given question. In our case we are looking to design a hybrid model for VideoQA. More specifically, convolutional neural networks (CNNs) will be used to extract knowledge from each frame of the video. This knowledge, along with the question to be answered, will be represented in a fashion that is amenable to searching for the answer to the question. This framing of the problem leads us to outline the following sub-problems, which will need to solved in order to produce a satisfactory VideoQA model:

1. **Object Detection**. Given a frame, we need a model which can produce a rough estimate (a bounding box, for example) of the location of an object in the frame. We will also need a model which can classify each detected object into a set of predefined classes.

2. **Property Extraction**. Given an object, which is the output of the *object detection* model above, we need an algorithm which can produce a set of values for that object for some set of predefined properties. For example, we might need to give a value for the colour, size or shape of an object.

3. **Event Detection**. Given two sequential frames, we need a model which can classify the event(s) which occurred between the two frames into a set of predefined classes (possibly including a catch-all 'no event' class). This model will also be required to list all objects involved in the event and what their role in the event was. This will require some level of object tracking so that it is clear how objects are related between frames.

4. **Question and Knowledge Representation**. Given the outputs of the models above and the natural language question, we need a way of representing the background knowledge, the question and the knowledge contained in the frames of the video. These must be represented in a manner that allows an answer to the question to be found.

1.3 Objectives

A lot of research has been conducted on building end-to-end neural network models to solve VideoQA tasks (see Chapter 3 for examples), but very little prior work has been done on hybrid models. The main aim of this project, therefore, is to explore the possibility of adding logical representation of knowledge to existing deep learning techniques. The following are the primary objectives of the project:

1. Construct a hybrid VideoQA model which allows injection of background knowledge and helps to increase the explainability of the model.
2. Find a challenging dataset for training the model (or construct a dataset if none are suitable)
3. Compare qualitatively (and quantitatively, if possible) existing approaches to our own hybrid model.
4. Investigate the possibility of learning domain-dependent logical rules, rather than having them hard coded for each environment.

Chapter 2

Background

This chapter introduces some technical background which will likely be required as part of the project. It includes an introduction to neural networks and CNNs, a comparison of some existing object tracking and object detection algorithms and a discussion on knowledge representation and reasoning and symbolic rule learning.

2.1 Deep Learning

Deep neural networks (DNNs) have emerged as a very successful algorithm for machine learning; deep learning has been used to beat records in tasks such as image recognition, speech recognition and language translation [33]. Many different architectures have been proposed to solve various tasks, these architectures include convolutional neural networks (CNNs), which are designed to process data that come in the form of multiple arrays [33], and recurrent neural networks (RNNs), which are designed to process sequences of arbitrary length [36]. The following section gives a brief introduction to CNNs and describes some of their use cases.

2.1.1 Convolutional Neural Networks

CNNs contain three types of layers: convolution, pooling and fully connected. Units (artificial neurons) in a convolution layer are organised into feature maps. The inputs to each unit in a feature map come from the outputs of the units in a small region of the previous layer, the output of the unit is then calculated by passing the weighted sum of its inputs through an activation function such as ReLU. The set of weights, also known as a filter or kernel, is the part of the layer which is learned through backpropagation. The value of each unit in a feature map is calculated using the same kernel. Each feature map in a layer has its own kernel. Pooling layers reduce the size of the input by merging multiple units into one. A typical pooling operation is max-pooling, which computes the maximum of a local patch of units. Finally, in fully-connected layers (which are typically placed

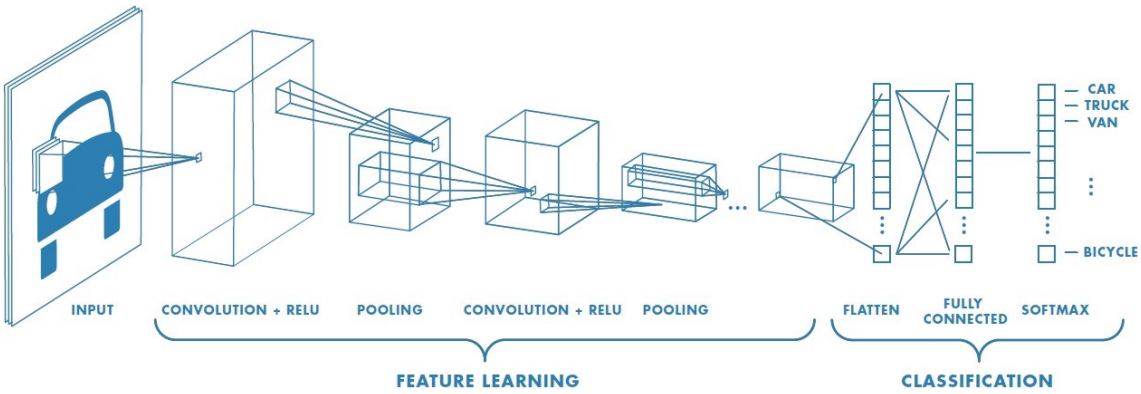


Figure 2.1: An example of a CNN architecture. The input image is passed through a series of convolution and pooling layers before being flattened into a one-dimensional layer and passed through one final fully connected layer. The softmax classification function is then applied at the output.

at the output of the CNN) every unit in a layer is connected to every unit in the previous layer. An example CNN architecture is shown in Figure 2.1.

CNNs have proven to be adept at a number of tasks involving images, including image classification [26] and object detection [44, 46]. We explore these further in Section 2.2.

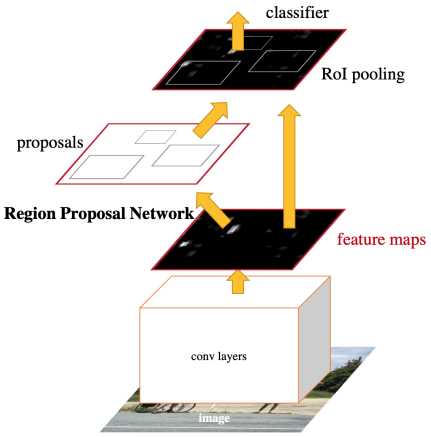
2.2 Image Processing

2.2.1 Object Detection

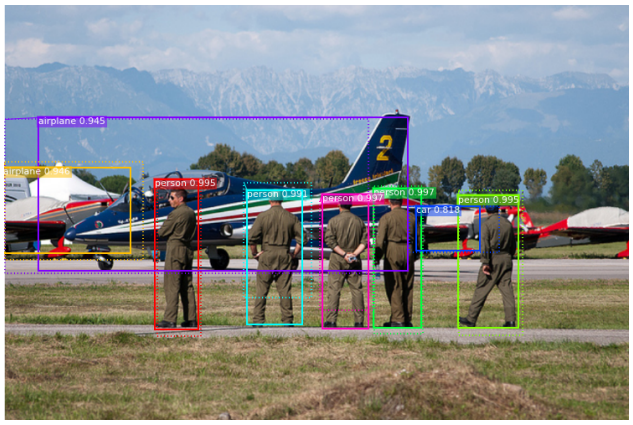
The object detection task could formally be defined as designing a model which, when given an image, can produce a rough localisation of objects of interest in the image (in the form of a bounding box) and classify each of these objects into a set of predefined classes. In this section we introduce two well known object detection algorithms, *Faster R-CNN* [46] and *You Only Look Once* (YOLO) [44].

Faster R-CNN is an evolution of previous object detection algorithms, R-CNN [19] and Fast R-CNN [18]. Faster R-CNN builds on its predecessors by adding a region proposal network (RPN) - a neural network which takes an image and produces a set of region of interest (RoI) proposals. This method of region proposal is much faster than previous algorithms (such as those used in [19] and [18]) since it is able to make use of the GPU, as opposed to requiring the CPU. Faster R-CNN then uses a similar classifier and bounding box regressor as Fast R-CNN at the output; this section of the network also receives the feature maps from the final layer of the RPN, in this sense the initial layers of the network are shared between the region proposal section and the classifier/regressor section. A diagram of the Faster R-CNN architecture is shown in Figure 2.2a.

The three object detection algorithms mentioned above all work by first producing region proposals, then producing a more accurate localisation and a class score



(a) Diagram of the Faster R-CNN architecture. Figure from [46].



(b) An example of the bounding boxes and confidence scores produced by an object detection algorithm. Image from [1].

Figure 2.2

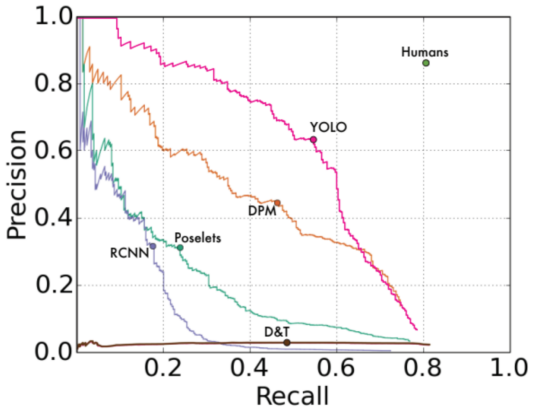
for each region and finally removing any low-scoring or redundant regions. This requires the algorithm to 'look' at the image multiple times (around 2000 times for R-CNN). You Only Look Once (YOLO) is a significantly more efficient algorithm which, as the name suggests, takes a single look at the image. A convolutional neural network is used to simultaneously predict multiple bounding boxes and the class probabilities for each box. As well as being very fast, YOLO makes fewer than half the number of background errors (where the algorithm mistakes background patches for objects) as Fast R-CNN [45]. YOLO is, however, slightly less accurate than some of the slower methods for object detection [44].

2.2.2 Commonly Used Metrics

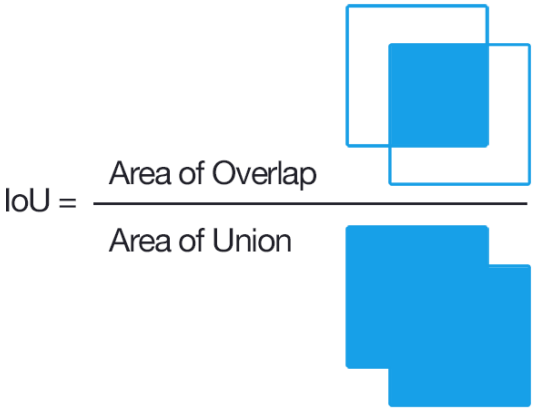
In this section we present some commonly used metrics for classification and object detection tasks. We use TP, TN, FP and FN to mean True Positive, True Negative, False Positive and False Negative, respectively.

Firstly, for classification tasks the following terminology is commonly used:

- $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$. The accuracy is the ratio of correct predictions to the total number of predictions.
- $Precision = \frac{TP}{TP+FP}$. The precision is the ability of a classifier to not label the negative data as positive.
- $Recall = \frac{TP}{TP+FN}$. The recall is the ability of the classifier to find the positively-labelled data.
- $F_1 = 2 * \frac{precision*recall}{precision+recall}$. The F_1 score is a way of combining the precision and recall scores.



(a) Example precision-recall curves for various object detection models. Image from [45].



(b) Visual explanation of the intersection over union metric. Image from [47].

Figure 2.3: Precision-recall curves and definition of intersection over union

Each object detector model will output a confidence score for each object classification it makes. We can then set a threshold value which determines what is counted as a classification of an object. Altering this threshold value will give different precision and recall values for the model, which can then be plotted on a precision-recall graph. Example precision-recall curves are shown in Figure 2.3a.

For object detection tasks, where a bounding box is produced to estimate an object's position, metrics which measure the accuracy of the detection are required. One very common metric is the Average Precision (AP), which is roughly defined as the area under the precision-recall curve (although estimates of this value are usually used). In order to assess how well a model localises an object in an image, the Interesection over Union (IoU) is calculated between the ground-truth bounding box and the box produced by the model. Figure 2.3b gives a visualisation of IoU. Each IoU threshold will produce its own precision-recall curve.

2.2.3 Multiple Object Tracking

Multiple Object Tracking (MOT) is a computer vision task that aims to identify and track objects from a sequence of images without any prior knowledge about the appearance or number of targets [10]. Most object tracking methods share a very similar pipeline [10], as follows:

- **Detection**. Each input frame is analysed to identify objects.
- **Feature Extraction**. Algorithms extract appearance, motion and/or interaction features from objects.
- **Affinity Computation**. Features are used to compute a similarity score between objects.

- **Association**. Similarity scores are used to associate detections and compute the object trajectories.

The Simple Online and Realtime Tracking (SORT) [8] algorithm is one of the best performers [10]. It makes use of Faster R-CNN for object detection, the Kalman filter [23] framework for predicting object motion, IoU as a similarity function and the Hungarian algorithm [27] for association. Whereas SORT attempts to track objects using motion prediction, other algorithms focus on extracting features from objects and using these to match objects in successor frames. Commonly used features include Histogram of Orientated Gradients (HOG) [11], Scale Invariant Feature Transform (SIFT) [37] and Speeded-Up Robust Features (SURF) [7]. More recent methods tend to use features extracted directly from a CNN.

2.3 Knowledge Representation and Reasoning

Knowledge representation and reasoning is concerned with how intelligent agents store and manipulate their knowledge. In this section we discuss Answer Set Programming, a logic programming framework, action languages, which can be used to define the behaviour of a system, and methods for learning logical rules.

2.3.1 Answer Set Programming

Answer Set Programming (ASP) is a form of declarative logic programming that can be used to solve difficult search problems. Whereas imperative programs define an algorithm for finding a solution to a problem, logic programs simply define a problem, it is then the job of logic program solvers to find the solution. ASP also differs from Prolog, also used for logic programming, in that ASP programs are purely declarative. This means that reordering rules, or atoms within rules, has no effect on the output of the solver [13]. ASP solvers work by finding the answer sets of the program, where each rule in the program imposes restrictions on possible answer sets. An answer set can be thought of as a set of ground atoms which satisfies every rule of the program (although the full definition of an answer set is too in-depth for this discussion).

The following templates are some of the possible forms of rules in an ASP program:

$$a \text{ :- } b_1, ..., b_k, not\ b_{k+1}, ..., not\ b_m. \tag{2.1}$$

$$l\{c_1; ...; c_n\}u \text{ :- } b_1, ..., b_k, not\ b_{k+1}, ..., not\ b_m. \tag{2.2}$$

$$\text{:- } b_1, ..., b_k, not\ b_{k+1}, ..., not\ b_m. \tag{2.3}$$

Where a and each b_i and c_i are atoms in first-order logic, l and u are integers.

The left hand side of the rule is known as the head, and the right hand side is known as the body. The not in the rule body stands for negation-as-failure, which

means that $not\ b_i$ will be satisfied when b_i cannot be proved. Each rule requires that when the body is satisfied - that is, when every member of the body is satisfied - the head must be satisfied. Rule 2.2 is known as a *choice rule*. The head of a choice rule can be satisfied by any subset, S, of the atoms inside the brackets, provided $l \leq |S| \leq u$; in effect, a choice rule creates possible answer sets. The bounds can be left off, in which case they take default values of 0 and the size of the choice set, respectively. Finally, rule 2.3 is known as a *constraint*. The body of a constraint must not be satisfied; intuitively, a constraint rules out answer sets.

As well as negation as failure, ASP also has a notion of 'strong negation'. The strong negation of an atom p is written $\neg p$. Strong negation can be thought of as classical negation, although it does not always have the same properties. In practice, ASP solvers implement strong negation by treating $\neg p$ as an additional atom, and enforce that no answer set can contain both p and $\neg p$.

$$P = \left\{ \begin{array}{l} p \text{ :- } a. \\ \{a; b\} \text{ :- } f. \\ \text{:- } d. \\ f. \end{array} \right\} \tag{2.4}$$

As an example, the two answer sets of the above program, P, are $\{f, a, p\}$ and $\{f\}$. The final rule of the program is known as a *fact*. Facts must be in all answer sets.

2.3.2 The Action Language $\mathcal{AL}$

Action languages are formal models for describing the behaviour of dynamic systems. In this section we present the version of $\mathcal{AL}$ given in [17]. $\mathcal{AL}$'s signature contains three special sorts: *statics*, *fluents* and *actions*. Fluents are partitioned into two sorts: *inertial* and *defined*. Statics and fluents are both referred to as 'domain properties'. A 'domain literal' is a domain property or its negation. Statements in $\mathcal{AL}$ can be of the following form:

$$a \textbf{ causes } l_{in} \textbf{ if } p_0, ..., p_m \tag{2.5}$$

$$l \textbf{ if } p_0, ..., p_m \tag{2.6}$$

$$\textbf{impossible } a_0, ..., a_k \textbf{ if } p_0, ..., p_m \tag{2.7}$$

Where:
- a is an action
- l and $p_0, ..., p_m$ are domain literals
- l_{in} is a literal formed by an inertial fluent

Statement 2.5 is known as a *causal law*, 2.6 as a *state constraint* and 2.7 as an *executability condition*. A collection of $\mathcal{AL}$ statements is known as a 'system decription'. An $\mathcal{AL}$ system description can be used to model the behaviour of dynamic systems with discrete states; each state can be seen as the set of fluents which are true and transitions between states are caused by actions. It is possible to encode a given $\mathcal{AL}$ system description, along with a number of 'domain-independent' axioms, in ASP. The method for creating this encoding is given in Appendix A.

2.3.3 Symbolic Rule Learning

Inductive Logic Programming [42] (ILP) is a field of symbolic AI research concerned with learning symbolic rules which, when combined with background knowledge, entail a set of positive examples and do not entail any negative examples. ILASP [32] (Inductive Learning of Answer Set Programs) is an ILP framework for learning ASP programs.

The authors of [28] define the *Learning from Answer Sets* (ILP_{LAS}) task (which is the task solved by the original version of ILASP), by first defining a *partial interpretation*. A partial interpretation E is a pair of sets of atoms E^{inc} and E^{exc}, known as the *inclusions* and *exclusions* of E. An answer set A *extends* E if it contains all of the inclusions ($E^{inc} \subseteq A$) and none of the exlusions ($E^{exc} \cap A = \emptyset$). An ILP_{LAS} task is then defined as the tuple $T = \langle B, S_M, E^+, E^- \rangle$, where B is the background knowledge, S_M is the search space, E^+ and E^- are the partial interpretations for the positive and negative examples, respectively. An hypothesis H is known as an inductive solution of T if and only if all of the following are true:

1. $H \subseteq S_M$
2. $\forall e^+ \in E^+ \; \exists A \in AS(B \cup H)$ *such that* A *extends* e^+
3. $\forall e^- \in E^- \; \nexists A \in AS(B \cup H)$ *such that* A *extends* e^-

Where $AS(P)$ refers to the answer sets of a program P.

Later versions of ILASP are capable of solving more complex tasks, including learning weak constraints [31] (a method for specifying preferences in ASP), learning from context dependent examples [30] and learning from noisy examples [29].

Chapter 3

Related Work

3.1 Datasets for VideoQA

A number of datasets are available for the VideoQA problem, in this section we discuss each of the available datasets. A comparison of all the datasets discussed in this section is shown in Table 3.1.

The MovieQA dataset [54] is a VideoQA dataset consisting of 14,944 multiple-choice questions about parts of movies. The clips come from a collection of 408 movies and the Question-Answer (QA) pairs were generated by humans. The questions and each of the possible answers are written in natural language, and there are five possible answers for each question.

Zeng et al. [62] create a much larger VideoQA dataset by automatically generating QA pairs from videos and their associated descriptions collected online. Their dataset consists of 18,100 videos as well 151,263 and 21,352 automatically generated QA pairs in the training and validation sets, respectively. The dataset also contains 2,461 human-generated QA pairs to be used for testing. Their questions and answers are free-form natural language, however, a large number of their answers are yes and no (32.5% and 32.5%, respectively).

The TGIF-QA dataset [22] is commonly used for assessing the performance of VideoQA models. The dataset contains 165,165 human-generated QA pairs collected from 71,741 GIFs, sourced from the TGIF dataset [35], which contains a number of GIFs and associated descriptions. There are four possible types of questions in the TGIF-QA dataset, three of which are specific to VideoQA; requiring temporal knowledge to answer. The question types are as follows:

- **Repetition Count**. Counting the number of repetitions of an action. There are 11 possible answers (0, ..., 9, 10+).
- **Repeating Action**. A multiple-choice question about identifying an action that has been repeated in the video.

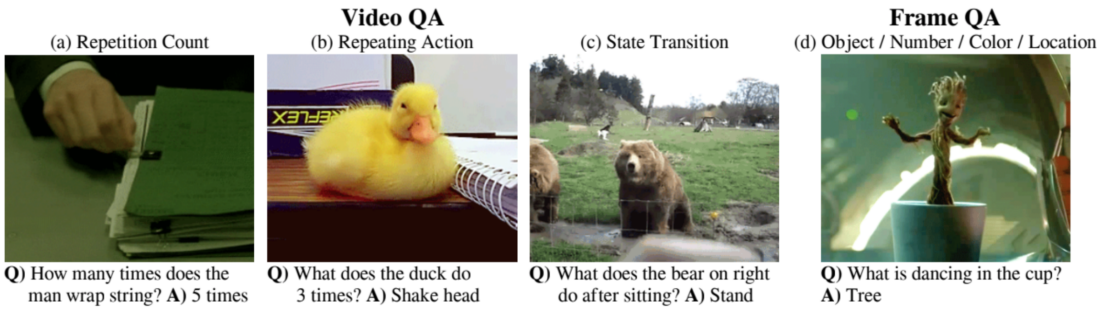


Figure 3.1: Example videos and QA pairs included in the TGIF-QA dataset, split by question type. Figure from [22].

- **State Transition**. A multiple-choice question about identifying the state before or after another state.
- **FrameQA**. Open-ended questions related to a single frame.

For the VideoQA questions the authors created templates for questions and used a large number of human annotators to speed up the generation process. The FrameQA questions are generated using the descriptions from the TGIF dataset. A number of quality control checks were also included.

Zhu et al. [63] have proposed a VideoQA dataset containing fill-in-the-blank (FIB) style questions, with multiple-choice answers. The dataset contains over 100,000 real-world video clips and 400,000 questions. The dataset is generated from three different annotated video sources. On top of questions which ask the model to describe the present (describe the current video), for two of three video sources the authors also introduce two additional question types: infer the past and predict the future. For these two types of questions the model is asked a question on a part of the video which it is not explicitly given; these questions require the model to use some form of commonsense reasoning to generate a correct answer. One of the advantages of using a multiple-choice dataset, such as this, is that it is more amenable to quantitative evaluation than datasets with long free-form answers, since answers are either right or wrong.

The EgoVQA dataset [14] attempts to address the lack of first-person VideoQA datasets. The dataset contains 581 QA pairs with both multiple-choice questions (with 5 possible answers per question) and open-ended questions. The dataset was created by manually generating QA pairs from a pre-existing set of 16 first-person videos. The authors also show that existing VideoQA models only marginally outperformed random choice on some types of questions in their dataset. They conjecture that existing models struggle to separate attentions on camera wearers from attentions on third persons.

Xu et al. [58] generate two VideoQA datasets by converting video captions into QA pairs. The first dataset, known as MSVD-QA, is generated from the Microsoft Research Video Description Corpus [9] which is used in many video captioning

experiments. MSVD-QA contains 1,970 video clips and 50,505 QA pairs. Similarly, the second dataset, known as MSRVTT-QA, is generated from the MSR-VTT dataset [59]. The MSRVTT-QA dataset contains 10,000 video clips and 243,680 QA pairs.

The YouTube2Text-QA dataset [60] is another large dataset for VideoQA generated from a pre-existing video description dataset, in this case the YouTube2Text [20] dataset is used. The YouTube2Text-QA dataset consists of 1,970 videos and 99,421 QA pairs.

The TVQA dataset [34] contains 21,793 video clips and 152,545 QA pairs based on 6 popular TV shows. The QA pairs were annotated manually using *Amazon Mechanical Turk*. Workers were asked to generate questions in the format: [What/How/Where/Why/Who/Other] _____ [when/before/after] _____. The second part of the question localises the relevant video moment within the clip, while the first part contains the question about that moment. The answers to the questions are given in multiple-choice format, with five candidate answers for each question.

The PororoQA dataset [24] is created from video clips and subtitles of the children's cartoon series, *Pororo*. The dataset contains 8,913 multiple-choice QA pairs and 16,066 video clips.

Finally, the MovieFIB dataset [38] is a large-scale fill-in-the-blank style dataset generated from movie descriptions. The dataset contains 128,085 video clips and 348,998 QA pairs. The questions concern entities, actions and objects; answering these questions therefore implies that a model has some level of visual understanding of the scene, rather than being able to answer based purely on the given partial sentence. Answers are open-ended (not multiple choice) but each answer is only a single word.

Table 3.1: Comparison of discussed VideoQA datasets. Each row contains data on: the number of videos/clips, the number of QA pairs, whether the uses multiple-choice questions, whether the dataset uses fill-in-the-blank questions and the video source.

Dataset	#Videos	#QA pairs	MC	FIB	Source
MovieQA	408[1]	14,944	Y	N	Movies
Zeng et al.	18,100	175,076	N	N	Online videos
TGIF-QA	71,741	165,165	Y[2]	N	Online videos
Zhu et al.	>100,000	400,000	Y	Y	Various
EgoVQA	16	581	Y	N	First-person videos
MSVD-QA	1,970	50,505	N	N	Video desc. corpus
MSRVTT-QA	10,000	243,680	N	N	Video desc. corpus
Youtube2Text-QA	1,970	99,421	Y	N	YouTube videos
TVQA	21,793	152,545	Y	N	TV shows
PororoQA	16,066	8,913	Y	N	Cartoon series
MovieFIB	128,085	348,998	N	Y	Movie description

[1] Full length movies. Some of the QAs come with timestamps, allowing more video clips.

[2] FrameQA questions (53,083 QA pairs) are not MC.

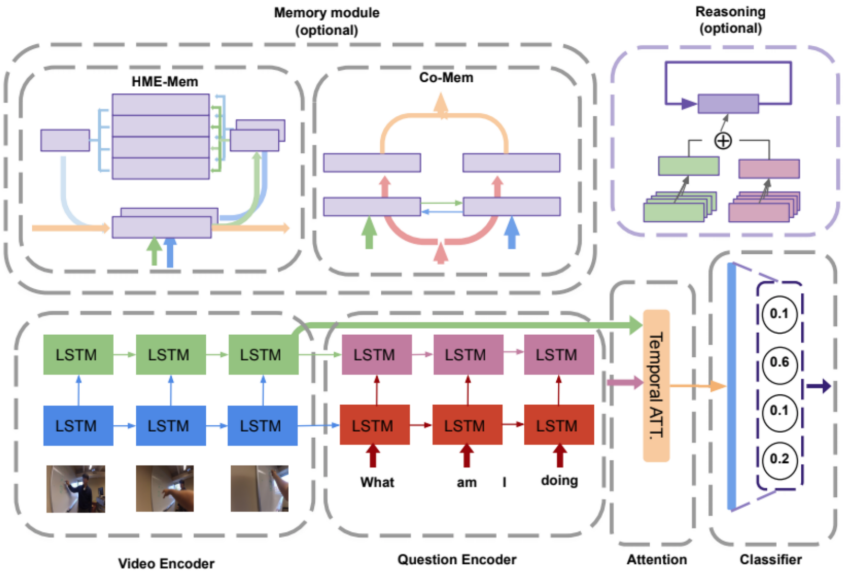


Figure 3.2: Typical VideoQA architecture. Figure from [14].

3.2 VideoQA Implementations

All of the datasets described in the section above (except [14]) were presented along with original neural network models for solving the VideoQA task. This section attempts to summarise some of these approaches, along with a few others [16, 61, 15, 51]. However, since the focus of our approach will not be an end-to-end neural architecture, we do not give detailed descriptions. An example of a typical VideoQA neural architecture is given in Figure 3.2.

All models from work previously presented here contain a video encoder for extracting features from frames of the video. These usually include both appearance and motion features, which are extracted from pre-trained networks (ResNet [21], VGG [50] or GoogLeNet [53], for appearance, and C3D [55], for motion). The features extracted from each frame are then usually passed into LSTM or GRU networks to obtain encodings for the whole video.

Questions are often encoded by generating word embeddings for each word of the sentences and then passing the list of words to a sentence encoder, such as the LSTM or GRU architectures.

Visual attention [41] is used to help neural networks focus on the most relevent areas of an image or video. Applying attention mechanisms to associate a question with its most relevant frames (or areas within frames) has become a key part of more recent VideoQA models [22, 58, 60, 34, 16, 61, 15, 24]. Temporal attention is commonly applied to help the model focus on the most salient frames of the video, however, [22] applies both temporal and spatial attention, which also allows the model to attend to the most relevant regions of a frame.

3.3 External Knowledge for VQA

While VideoQA research has focused on end-to-end neural network architectures, some recent research in VQA (single frame setting) has experimented with using explicit reasoning layers and integrating external knowledge. A number of VQA datasets which require some form of external 'commonsense' reasoning have been proposed recently [39, 57, 56]. It has been shown that end-to-end neural networks which do not attempt to make use of knowledge which is external to the training data perform poorly on some of these datasets [39]. This section discusses some of the attempts that have been made to integrate external knowledge into VQA systems.

The authors of the three datasets outlined above propose models which make use of external knowledge, ususally stored in some structured knowledge base (KB). Examples of KBs include DBpedia [6], which stores structured information extracted from Wikipedia, and ConceptNet [52], which contains automatically generated 'commonsense' relations between objects.

As opposed to using a structured KB, the authors of [39] provide a neural network model which is trained to find the answer to an image-question pair from Wikipedia articles. They also propose a number of methods for combining this network with state-of-the-art VQA models and show that this provides an improvement in performance on their dataset.

The authors of [2] propose a model which first extracts properties from an image using a pre-trained neural network and represents these properties explicitly using logic. They also extract relations between nouns, adjectives and the question word from the question and represent these in logic. Finally, they reason over the extracted relations using a probabilistic reasoning engine to find the most likely answer. This method of reasoning not only allows the model to make use of external knowledge, but also helps improve the transparency and explainability of the model.

Chapter 4

Project Plan

In order to provide a plan of the work to be completed, this chapter firstly describes what has been achieved so far, provides possible solutions to some of the key problems which need to be solved and outlines possible methods for evaluating the performance of a completed system.

4.1 Completed Work

Many VideoQA datasets were outlined in the related work discussion in Chapter 3. However, these pre-existing datasets do not contain the semantic information required to extract symbolic properties from objects in each frame. Most of these datasets provide nothing more than a sequence of images, a question and an answer. While this is sufficient to train an end-to-end neural network, since it learns implicit features, it does not allow us to train a network which can extract explicit object properties, which are required for logical reasoning. Although it would be possible to extract some information using a network pre-trained on ImageNet [48], for example, we would only be able to extract bounding boxes and classes for each object, whereas we would prefer to extract richer details such as colour, rotation or size. Furthermore, we cannot guarantee that every object in a scene is part of the ImageNet dataset, therefore it would be possible for a network to miss some objects entirely.

For this reason we have decided to generate a dataset which provides the information needed for logical reasoning, as a starting point for building our model. The dataset emulates a simple retro game environment. Since the focus of this project is to investigate logical reasoning and the learning of symbolic rules, we do not attempt to make the job of the neural network difficult by creating very complex scenes; each frame is very simple with a flat background and no variation in object shape. Each image is also quite small at only 128x128 pixels, which will allow for faster network training.

An example sequence of frames from the current version of the dataset is shown in Figure 4.1.

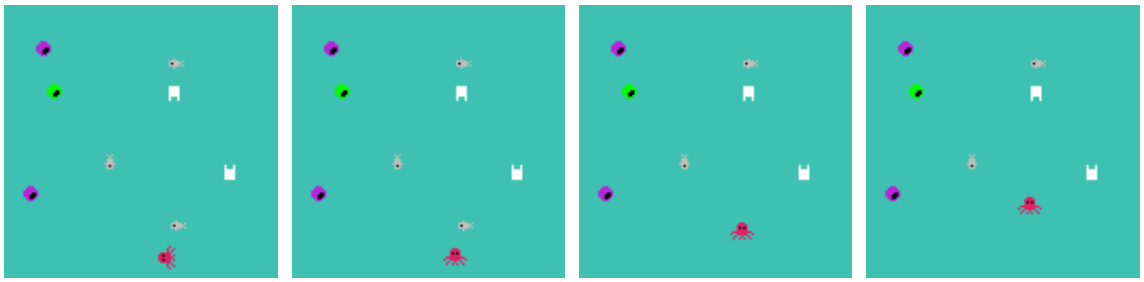


Figure 4.1: An example sequence of frames from the initial version of the dataset. The octopus first rotates, then moves towards the fish and eats it.

The key elements of the dataset are the following:

- **Octopus**. The 'main' character in the frames - the octopus is the only character which moves and its properties change as it comes into contact with other objects.
- **Fish**. The fish are always silver, but can have any rotation. When the octopus comes close to the fish, the fish disappears (gets eaten).
- **Plastic Bag**. Similarly to the fish, the plastic bags are always white but can have any rotation. Each bag is harmful to the octopus, so both objects disappear when in close contact.
- **Rock**. Rocks can have four colours: brown, blue, purple and green, but always face upright. While an octopus is near a rock the octopus' colour will match that of the rock (it will be camouflaged).

The idea behind the dataset is to show object property changes which have well-defined semantics that are non-trivial to learn. For example, given the location and colour of objects from two successive frames, we would like to investigate whether ILASP could learn that the octopus only changes colour when it is close to a rock (and what exactly it means to be close). At the moment we only have a very early version of the dataset and we may well be required to add more objects with more complex semantics in later stages of the project. In later versions of the dataset we also intend to provide information on the events which occur between frames, but this has not yet been included.

Each object in each frame is labelled with the following information:

- **Class**. The object type, as described above.
- **Bounding Box**. We provide the upper left and lower right coordinates of the box around the object.
- **Colour**. The current colour of the object.
- **Rotation**. The compass direction the object is currently facing in. This is given as an integer between 0 and 3.

4.2 Implementation Plan

In Chapter 1 we outlined four key challenges that we think will need to solved in order to build a functioning hybrid VideoQA model. We now describe our initial ideas for how these can be overcome:

1. **Object Detection**. A number of models exist for this task, as shown in Chapter 2. We propose to adapt one of these models to fit our own dataset and train it to be capable of producing bounding boxes and class labels for each object in a frame.

2. **Property Extraction**. Now that we have access to a dataset with the required object information, we can simply build a neural network which takes the output of the *object detection* step and produces the required properties of the object. It may also be interesting to investigate whether this network can be directly combined with the object detection network, classifying each property in the same way as the object class.

3. **Event Detection**. Earlier we outlined a number of object tracking methods that can be used to track multiple objects through frames simultaneously. We could compare the performance differences between using motion and appearance features for this task. Once we have a working object tracker we will need to use it to classify an event between two frames. To start with, we could assume we are given an $\mathcal{AL}$ system description of the environment and write an ASP program which, when given the properties extracted from two successive frames, classifies an event between those frames. Building on this, we could investigate ways to use the event information provided in the dataset to train neural networks to do some of this classification for us. This may also require the use of ILASP, since we may not be able to ask a network to predict which objects were involved in an event when there are an arbitrary number of objects.

4. **Question and Knowledge Representation**. We will need to investigate ways of representing the question in ASP in a form that, when given the information from the video, allows us to find an answer. This will probably require creating templates for questions and answers. In the later stages of the project it may also be interesting to investigate how we could learn $\mathcal{AL}$ descriptions using ILASP, rather than assume them.

From the challenges described above, we outline the following set of milestones in the development of a working hybrid VideoQA model:

1. Construct an initial dataset of videos (QA pairs not required at this stage).

2. Build neural network(s) for object detection and property extraction, and train them on the constructed dataset.

3. Investigate different object tracking methods and build an algorithm that, when given the object properties for each frame, can assign the properties to specific objects using an appropriate tracking method.
4. Write an ASP program which, when given an $\mathcal{AL}$ system description encoding and object properties for each frame, classifies an event between two frames.
5. Construct a dataset enriched with templated questions and answers, and find a way to encode the questions in ASP.
6. Build a complete VideoQA model which makes use of the above algorithms to find the required answer to a question when given a sequence of frames.

It is possible that some of these milestones may prove to be too challenging within the timeframe. However, since most of the above milestones are stand-alone, progress can still be made in other areas. It is also the case that some subcomponents can be created artificially. For example, if the neural networks did not work, we could simply provide the correct output in order to test the rest of the system.

After building a working hybrid VideoQA model, a key extension for the project would be to remove as much prior information about the environment as possible. This could mean trying to learn $\mathcal{AL}$ system descriptions, removing the additional semantic information from the dataset (and only working with bounding boxes and class labels), or ditching question templates in favour of free-form questions and answers.

With this in mind, we outline the following possible extensions to the VideoQA model which would, in theory, allow it operate on other VideoQA datasets:

- Remove prior $\mathcal{AL}$ encodings of the environment and investigate the possibility of using ILASP to learn the system description instead. It will also be necessary to find another method for classifying events, since we cannot use $\mathcal{AL}$ system descriptions. Neural networks may be helpful, but it would be preferable to avoid adding event labels to the dataset.
- Remove additional object property labels from the dataset and work with bounding boxes and classes alone, as this would better emulate the information provided by an object detection dataset. Some form of unsupervised learning may be heplful for this, and making use of the information provided by the answers to questions will almost certainly be required.
- Investigate ways of encoding the information provided by free-form questions and asnwers in ASP. This could make the model much more applicable to pre-existing VideoQA datasets but is probably a research project in its own right.
- Investigate adding additional layers of difficulty to the dataset. For example, we could allow non-deterministic actions, or other external events with more complex semantics.

4.3 Evaluation Plan

Finally, this section outlines some evaluation strategies which could help to provide an insight into the performance of our model.

Firstly, throughout model construction we will want to ensure that each subcomponent is performing well. For this reason, it will be useful to compare quantitatively possible subcomponent implementations. For example, we will want to compare different object tracking methods, as well different neural network implementations. The metrics described in Chapter 2 will he helpful for this. It will also be important to evaluate the runtime of the ASP programs which use $\mathcal{AL}$ encodings. Since these programs ground the rules first, which can be very slow, it may be worth comparing the performance of $\mathcal{AL}$ with other frameworks used for reasoning about the dynamics of a system, such as the Event Calculus [25].

When we have a complete model we can use traditional VideoQA metrics, such as accuracy, to evaluate its performance. To do this we will firstly need to split the dataset into training and testing subsets, and ensure that none of the testing data is used for training or tuning the model. We can then apply the testing data to the model and record the number of correct and incorrect answers. It may also be helpful to train some of the end-to-end VideoQA models on our dataset and compare their performance to ours. It is worth noting, however, that, because it makes use of the templates for questions, our model has a significant advantage over any model which does not use this pre-defined information. We could still use these evaluations as baselines.

Finally, after building and evaluating our VideoQA model, it may be interesting to investiage how its performance degrades as we artificially alter the performance of individual components. It may be the case that by having a pipelined model, such as ours, with multiple learning components, the overall model performance is not severely affected by a single underperforming component.

Bibliography

[1] W. Abdulla. *Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow*. URL: https://github.com/matterport/Mask_RCNN (visited on 01/15/2020).

[2] Somak Aditya, Yezhou Yang, and Chitta Baral. "Explicit reasoning over end-to-end neural architectures for visual question answering". In: *Thirty-Second AAAI Conference on Artificial Intelligence*. 2018.

[3] Somak Aditya, Yezhou Yang, and Chitta Baral. "Explicit Reasoning over End-to-End Neural Architectures for Visual Question Answering". In: *CoRR* abs/1803.08896 (2018).

[4] Aishwarya Agrawal et al. "Vqa: Visual question answering". In: *International Journal of Computer Vision* 123.1 (2017), pp. 4–31.

[5] Alejandro Barredo Arrieta et al. *Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI*. 2019. arXiv: 1910.10045 [cs.AI].

[6] Sören Auer et al. "Dbpedia: A nucleus for a web of open data". In: *The semantic web*. Springer, 2007, pp. 722–735.

[7] Herbert Bay et al. "Speeded-up robust features (SURF)". In: *Computer vision and image understanding* 110.3 (2008), pp. 346–359.

[8] Alex Bewley et al. "Simple online and realtime tracking". In: *2016 IEEE International Conference on Image Processing (ICIP)*. IEEE. 2016, pp. 3464–3468.

[9] David L Chen and William B Dolan. "Collecting highly parallel data for paraphrase evaluation". In: *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*. Association for Computational Linguistics. 2011, pp. 190–200.

[10] Gioele Ciaparrone et al. "Deep learning in video multi-object tracking: A survey". In: *Neurocomputing* (2019).

[11] Navneet Dalal and Bill Triggs. "Histograms of Oriented Gradients for Human Detection". In: *International Conference on Computer Vision & Pattern Recognition (CVPR '05)*. Vol. 1. IEEE Computer Society, 2005, pp. 886–893.

[12] Christophe Dousson, Pierre Le Maigat, and France Telecom R&d. "Chronicle Recognition Improvement Using Temporal Focusing and Hierarchization". In: *IJCAI*. 2007, pp. 324–329.

[13] Thomas Eiter, Giovambattista Ianni, and Thomas Krennwallner. “Answer Set Programming: A Primer”. In: *Reasoning Web. Semantic Technologies for Information Systems: 5th International Summer School 2009*. Ed. by Sergio Tessaris et al. Springer Berlin Heidelberg, 2009, pp. 40–110.

[14] Chenyou Fan. “EgoVQA - An Egocentric Video Question Answering Benchmark Dataset”. In: *The IEEE International Conference on Computer Vision (ICCV) Workshops*. 2019.

[15] Chenyou Fan et al. “Heterogeneous Memory Enhanced Multimodal Attention Model for Video Question Answering”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019, pp. 1999–2007.

[16] Jiyang Gao et al. “Motion-appearance co-memory networks for video question answering”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018, pp. 6576–6585.

[17] Michael Gelfond and Yulia Kahl. *Knowledge representation, reasoning, and the design of intelligent agents: The answer-set programming approach*. Cambridge University Press, 2014.

[18] Ross Girshick. “Fast r-cnn”. In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 1440–1448.

[19] Ross Girshick et al. “Rich feature hierarchies for accurate object detection and semantic segmentation”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014, pp. 580–587.

[20] Sergio Guadarrama et al. “Youtube2text: Recognizing and describing arbitrary activities using semantic hierarchies and zero-shot recognition”. In: *Proceedings of the IEEE international conference on computer vision*. 2013, pp. 2712–2719.

[21] Kaiming He et al. “Deep residual learning for image recognition”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 770–778.

[22] Yunseok Jang et al. “Tgif-qa: Toward spatio-temporal reasoning in visual question answering”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2017, pp. 2758–2766.

[23] Rudolph Emil Kalman et al. “A new approach to linear filtering and prediction problems [J]”. In: *Journal of basic Engineering* 82.1 (1960), pp. 35–45.

[24] Kyung-Min Kim et al. “DeepStory: Video Story QA by Deep Embedded Memory Networks”. In: IJCAI17. AAAI Press, 2017, 20162022.

[25] Robert A. Kowalski and Marek J. Sergot. “A logic-based calculus of events”. In: *New Generation Computing* 4 (1985), pp. 67–95.

[26] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. “ImageNet Classification with Deep Convolutional Neural Networks”. In: *Advances in Neural Information Processing Systems 25*. Ed. by F. Pereira et al. Curran Associates, Inc., 2012, pp. 1097–1105.

[27] Harold W Kuhn. “The Hungarian method for the assignment problem”. In: *Naval research logistics quarterly* 2.1-2 (1955), pp. 83–97.

[28] Mark Law, Alessandra Russo, and Krysia Broda. “Inductive Learning of Answer Set Programs”. In: *Logics in Artificial Intelligence*. Springer International Publishing, 2014, pp. 311–325.

[29] Mark Law, Alessandra Russo, and Krysia Broda. “Inductive learning of answer set programs from noisy examples”. In: *arXiv preprint arXiv:1808.08441* (2018).

[30] Mark Law, Alessandra Russo, and Krysia Broda. “Iterative learning of answer set programs from context dependent examples”. In: *Theory and Practice of Logic Programming* 16.5-6 (2016), pp. 834–848.

[31] Mark Law, Alessandra Russo, and Krysia Broda. “Learning weak constraints in answer set programming”. In: *Theory and Practice of Logic Programming* 15.4-5 (2015), pp. 511–525.

[32] Mark Law, Alessandra Russo, and Krysia Broda. *The ILASP system for learning Answer Set Programs*. `www.ilasp.com`. 2015.

[33] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. “Deep learning”. In: *Nature* 521 (2015), pp. 436–444.

[34] Jie Lei et al. “Tvqa: Localized, compositional video question answering”. In: *arXiv preprint arXiv:1809.01696* (2018).

[35] Yuncheng Li et al. “TGIF: A new dataset and benchmark on animated GIF description”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016, pp. 4641–4650.

[36] Pengfei Liu, Xipeng Qiu, and Xuanjing Huang. “Recurrent neural network for text classification with multi-task learning”. In: *arXiv preprint arXiv:1605.05101* (2016).

[37] David G Lowe. “Distinctive image features from scale-invariant keypoints”. In: *International journal of computer vision* 60.2 (2004), pp. 91–110.

[38] Tegan Maharaj et al. “A Dataset and Exploration of Models for Understanding Video Data through Fill-in-the-Blank Question-Answering”. In: *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2016), pp. 7359–7368.

[39] Kenneth Marino et al. “Ok-vqa: A visual question answering benchmark requiring external knowledge”. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019, pp. 3195–3204.

[40] Kenneth Marino et al. “OK-VQA: A Visual Question Answering Benchmark Requiring External Knowledge”. In: *CoRR* abs/1906.00067 (2019).

[41] Volodymyr Mnih, Nicolas Heess, Alex Graves, et al. “Recurrent models of visual attention”. In: *Advances in neural information processing systems*. 2014, pp. 2204–2212.

[42] Stephen Muggleton. “Inductive logic programming”. In: *New generation computing* 8.4 (1991), pp. 295–318.

[43] Ren Quiniou et al. “Intelligent Adaptive Monitoring for Cardiac Surveillance”. In: *Computational Intelligence in Healthcare 4: Advanced Methodologies*. Ed. by Isabelle Bichindaritz et al. Springer Berlin Heidelberg, 2010, pp. 329–346.

[44] Joseph Redmon and Ali Farhadi. “Yolov3: An incremental improvement”. In: *arXiv preprint arXiv:1804.02767* (2018).

[45] Joseph Redmon et al. “You only look once: Unified, real-time object detection”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016, pp. 779–788.

[46] Shaoqing Ren et al. “Faster r-cnn: Towards real-time object detection with region proposal networks”. In: *Advances in neural information processing systems*. 2015, pp. 91–99.

[47] Adrian Rosebrock. *Intersection over Union (IoU) for object detection*. Nov. 7, 2016. URL: `https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection` (visited on 01/15/2020).

[48] Olga Russakovsky et al. “ImageNet Large Scale Visual Recognition Challenge”. In: *IJCV* 115.3 (2015), pp. 211–252.

[49] Nicholas Poul Schultz-Møller, Matteo Migliavacca, and Peter Pietzuch. “Distributed Complex Event Processing with Query Rewriting”. In: *Proceedings of the Third ACM International Conference on Distributed Event-Based Systems*. Association for Computing Machinery, 2009.

[50] Karen Simonyan and Andrew Zisserman. “Very deep convolutional networks for large-scale image recognition”. In: *arXiv preprint arXiv:1409.1556* (2014).

[51] Gursimran Singh. “Spatio-temporal relational reasoning for video question answering”. PhD thesis. University of British Columbia, 2019.

[52] Robyn Speer, Joshua Chin, and Catherine Havasi. “Conceptnet 5.5: An open multilingual graph of general knowledge”. In: *Thirty-First AAAI Conference on Artificial Intelligence*. 2017.

[53] Christian Szegedy et al. “Going deeper with convolutions”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2015, pp. 1–9.

[54] Makarand Tapaswi et al. “MovieQA: Understanding Stories in Movies through Question-Answering”. In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2015), pp. 4631–4640.

[55] Du Tran et al. “Learning spatiotemporal features with 3d convolutional networks”. In: *Proceedings of the IEEE international conference on computer vision*. 2015, pp. 4489–4497.

[56] Peng Wang et al. “Explicit Knowledge-based Reasoning for Visual Question Answering”. In: *IJCAI-17*. 2017, pp. 1290–1296.

[57] Peng Wang et al. “Fvqa: Fact-based visual question answering”. In: *IEEE transactions on pattern analysis and machine intelligence* 40.10 (2018), pp. 2413–2427.

[58] Dejing Xu et al. “Video Question Answering via Gradually Refined Attention over Appearance and Motion”. In: *MM ’17*. 2017.

[59] Jun Xu et al. “MSR-VTT: A Large Video Description Dataset for Bridging Video and Language”. In: IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[60] Yunan Ye et al. “Video question answering via attribute-augmented attention network learning”. In: *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*. ACM. 2017, pp. 829–832.

[61] Youngjae Yu et al. “End-to-End Concept Word Detection for Video Captioning, Retrieval, and Question Answering”. In: *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2016), pp. 3261–3269.

[62] Kuo-Hao Zeng et al. “Leveraging Video Descriptions to Learn Video Question Answering”. In: *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*. AAAI Press, 2017, 4334–4340.

[63] Linchao Zhu et al. “Uncovering the temporal context for video question answering”. In: *International Journal of Computer Vision* 124.3 (2017), pp. 409–421.

Appendix A

ASP encoding of $\mathcal{AL}$

In this appendix we present a method for encoding an $\mathcal{AL}$ system description in ASP, as described in [17]. We need to encode three different parts of the system description: the signature, the $\mathcal{AL}$ statements and some domain-independent axioms.

We encode the signature of the system description, $sig(SD)$, as follows:

- For each constant symbol c of sort $sort\_name$ other than $fluent$, $static$ or $action$, $sig(SD)$ contains

$$sort\_name(c). \tag{A.1}$$

- For every static g of SD, $sig(SD)$ contains

$$static(g). \tag{A.2}$$

- For every intertial fluent f of SD, $sig(SD)$ contains

$$fluent(inertial, f). \tag{A.3}$$

- For every defined fluent f of SD, $sig(SD)$ contains

$$fluent(defined, f). \tag{A.4}$$

- For every action a of SD, $sig(SD)$ contains

$$action(a). \tag{A.5}$$

In the following we refer to the ASP encoding of the $\mathcal{AL}$ system description as $\Pi(SD)$, where $\Pi(SD)$ includes $sig(SD)$. We introduce a relation $holds(f, i)$ which says that fluent f is true at timepoint i. We also introduce the notation $h(l, i)$ where l is a domain literal and i is a step, which will not be used in the ASP program, but will instead be replaced by either $holds(f, i)$ if $l = f$, or by $\neg holds(f, i)$ if $l = \neg f$.

We encode the $\mathcal{AL}$ statements as follows:

- If the maximum number of steps is $< max >$, then $\Pi(SD)$ includes

$$\#const\ n = \ < max > . \tag{A.6}$$
$$step(0..n). \tag{A.7}$$

- For every causal law, a **causes** l **if** $p_0, ..., p_m$ $\Pi(SD)$ contains

$$h(l, I+1) \text{ :- } h(p_0, I), ..., h(p_m, I), occurs(a, I), I < n. \tag{A.8}$$

- For every state constraint, l **if** $p_0, ..., p_m$ $\Pi(SD)$ contains

$$h(l, I) \text{ :- } h(p_0, I), ..., h(p_m, I). \tag{A.9}$$

- For every executability condition, **impossible** $a_0, ..., a_k$ **if** $p_0, ..., p_m$ $\Pi(SD)$ contains

$$\neg occurs(a_0, I); ...; \neg occurs(a_k, I) \text{ :- } h(p_0, I), ..., h(p_m, I). \tag{A.10}$$

The ; in the head of rule A.10 stands for logical disjunction and can be read as meaning at least one of $a_0, ..., a_k$ must not occur at timepoint I.

In order to complete our encoding of an $\mathcal{AL}$ system description we need to add a number of domain-independent axioms. These axioms are not specific to any system or task, but rather convey commonsense knowledge that should apply to many systems. It is worth noting, however, that in certain situations some or all of these axioms may not make sense and should not be used.

We encode the domain-independent knowledge as follows:

- The inertia axiom states that inertial fluents will keep their state unless explicitly changed:

$$\begin{aligned} holds(F, I+1) \text{ :- } & fluent(inertial, F), \\ & holds(F, I), \\ & not\ \neg holds(F, I+1), \\ & I < n. \end{aligned} \tag{A.11}$$

$$\begin{aligned} \neg holds(F, I+1) \text{ :- } & fluent(inertial, F), \\ & \neg holds(F, I), \\ & not\ holds(F, I+1), \\ & I < n. \end{aligned} \tag{A.12}$$

- The closed-world assumption (CWA) for defined fluents states that defined fluents which are not known to be true are assumed to be false.

$$\neg holds(F, I) \text{ :- } fluent(defined, F), step(I), not\ holds(F, I). \tag{A.13}$$

- The CWA for actions states that actions that are not known to occur are assumed to not occur.

$$\neg occurs(A, I) \text{ :- } action(A), step(I), not\ occurs(A, I). \tag{A.14}$$

Finally, in order to make use of system description encoding we would include information on which events occured, using the $occurs(A, I)$ predicate, and information on the different states of the system using $holds(F, I)$ and $\neg holds(F, I)$.

Briefcase Example

We now consider a simple, example domain: a briefcase with two clasps (from [17]). There is a single action, toggle, which moves a given clasp into the up position if it is down, and vice-versa. If both clasp are up the briefcase is open, otherwise, it is closed.

The signature of the domain consists of sort clasp, which can take value 1 or 2, inertial fluent $up(C)$, defined fluent $open$ and action $toggle(C)$, where C is one of the clasps.

A schema for the system description is as follows:

$$toggle(C) \textbf{ causes } up(C) \textbf{ if } \neg up(C) \tag{A.15}$$
$$toggle(C) \textbf{ causes } \neg up(C) \textbf{ if } up(C) \tag{A.16}$$
$$open \textbf{ if } up(1), up(2) \tag{A.17}$$

This is known as a schema for a system description since it contains variables. Individual rules can be obtained by grounding the variables. So each of the first two schema rules would produce two ground rules, one where $C = 1$ and another where $C = 2$.

Following the procedure outlined above, we would encode this system description into the following ASP program:

```
% Possible timesteps
#const n = 1.
step(0..n).

% Signature
clasp(1).
clasp(2).

fluent(inertial, up(C)) :- clasp(C).
fluent(defined, open).
action(toggle(C)) :- clasp(C).
```

```
% Domain dependent rules
holds(up(C), I+1) :- occurs(toggle(C), I),
                     -holds(up(C), I),
                     I<n.

-holds(up(C), I+1) :- occurs(toggle(C), I),
                      holds(up(C), I),
                      I<n.

holds(open, I) :- holds(up(C), I), holds(up(2), I).

% Domain independent rules
holds(F, I+1) :- fluent(inertial, F),
                 holds(F, I),
                 not -holds(F, I+1),
                 I<n.

-holds(F, I+1) :- fluent(inertial, F),
                  -holds(F, I),
                  not holds(F, I+1),
                  I<n.

-holds(F, I) :- fluent(defined, F), step(I),
                not holds(F, I).

-occurs(A, I) :- action(A), step(I),
                 not occurs(A, I).
```

In a similar fashion to system description schemas, ASP programs allow variables. ASP solvers will first ground the program by computing the the *relevant grounding* - the set of ground rules which could be used by the program. The relevant grounding can be infinite so care needs to taken to ensure that it can be computed.