

HLVU : A New Challenge to Test Deep Understanding of Movies the Way Humans do

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ABSTRACT

In this paper we propose a new evaluation challenge and direction in the area of High-level Video Understanding. The challenge we are proposing is designed to test automatic video analysis and understanding, and how accurately systems can comprehend a movie in terms of actors, entities, events and their relationship to each other. A pilot High-Level Video Understanding (HLVU) dataset of open source movies were collected for human assessors to build a knowledge graph representing each of them. A set of queries will be derived from the knowledge graph to test systems on retrieving relationships among actors, as well as reasoning and retrieving non-visual concepts. The objective is to benchmark if a computer system can "understand" non-explicit but obvious relationships the same way humans do when they watch the same movies. This is long-standing problem that is being addressed in the text domain and this project moves similar research to the video domain. Work of this nature is foundational to future video analytics and video understanding technologies. This work can be of interest to streaming services and broadcasters hoping to provide more intuitive ways for their customers to interact with and consume video content.

CCS CONCEPTS

• **Information systems** → **Retrieval tasks and goals.**

KEYWORDS

video understanding, multimedia, information retrieval, video ontology

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1 INTRODUCTION

Video understanding is a very difficult problem to solve. All current video analysis technology relies on detection, recognition and analysis of certain specific visual concepts such as people, objects, actions, activities or events. All these visual concepts recognition are usually done in isolation from the context of the video and only focusing on visual clues. This is one of the reasons why the current state of the art is lacking high level video understanding capabilities that connect the entities of a video with different events or relations. For example, given a two hour movie the current computer vision systems are not able to understand the relationship between different characters and develop a deep understanding of the video context. There has been efforts to encourage research in high level video understanding such as the "MovieQA" and "The Large Scale Movie Description Challenge" [9]. However these tasks revolve around isolated visual concepts retrieval and not about testing systems for their overall understanding of entities, relations and events within the video/movie. Early visions of this kind of work [7] proposed to use visual and audio descriptors, in addition to employing semantic analysis and linking with external knowledge sources in order to populate a knowledge graph.

The goal of our proposed research is to design and build datasets and evaluation benchmarks to foster the interest of the research community to develop systems which can extract available information from a video (e.g. a movie characters, their story lines, and relationships), and to use this information to reason about other, more hidden background information, and eventually to populate a knowledge graph with all extracted and reasoned information. In the next section we present an overview to related work in this area followed by more technical details discussing a pilot dataset collection of open source movies, the human annotation framework, query design and preprocessing, and our proposed evaluation roadmap and future directions. This is an ambitious new area of research which is to be run initially as a Grand Challenge at ACM Multimedia 2020 and as a workshop at ACM ICMI 2020 respectively. TRECVID workshop participants will be invited to participate in this new task.

2 RELATED WORK

Integrating vision and language research has recently gained a lot of attention to promote image and video understanding. Most

approaches adopt the question answering paradigm as their evaluation framework. For example in [2] the authors propose the task of visual question answering for images. They provide a dataset containing 0.25M images, 0.76M question and 10M answers. However, most question types target very specific visual facets in the image such as what, where, number of objects, and what is the attributes or relation of an object to others.

MovieQA [11] is a dataset which aims to evaluate automatic story comprehension from video and text. It consists of 14,944 multiple choice questions, each with 5 multiple-choice answers, only one of which is correct, from about 408 movies with high semantic diversity. The movies have been segmented into video clips of maximum 200s durations where participants have to answer a question related to this video clip. The dataset itself comes with multiple answering sources for the questions such as plot synopses, scripts, subtitles, and audio descriptions. Annotators essentially used the plot synopses to come up with the set of questions and answers instead of watching the whole movie.

Following from this, [8] explored the biases in the MovieQA dataset and found that by using an appropriately trained word embedding, about half of the Question-Answers can be answered by looking at the questions and answers alone, completely ignoring the narrative context from video clips, subtitles, and movie scripts.

A large-scale dataset of corresponding movie trailers, plots, posters, and metadata was developed by [5] who study the effectiveness of visual, audio, text, and metadata-based features for predicting high-level information about movies such as their genre or estimated budget.

The large-scale movie description challenge [9] was first held as a workshop at the International Conference on Computer Vision (ICCV) 2015. This was held as a unified challenge on Text generation using single video clip, and Text generation using single video clip as well as its surrounding context. This challenge was later also held at ICCV 2017. It was held as two challenges: The large scale movie description and understanding challenge [LSMDC] and [MovieQA]. The LSMDC task included Movie description, Movie annotation and retrieval, and Movie fill-in-the-blank task. The MovieQA task included Question-answering in movies and video retrieval based on plot synopses sentences. A follow-up challenge was also held at ICCV 2019.

Early visions of the proposed work [7] explored the usage of visual and audio descriptors, in addition to employing semantic analysis and linking with external knowledge sources in order to populate a knowledge graph. Under this approach, time-stamped multi-modal signals of the video would be uplifted into a format that could be utilised by the applications semantic model and the resulting knowledge graph could be searchable in a newly meaningful way.

ActivityNet [4] is a large scale video benchmark for human activity understanding. ActivityNet provides samples from 203 activity classes with an average of 137 untrimmed videos per class and 1.41 activity instances per video, for a total of 849 video hours. All ActivityNet videos are obtained from online video sharing websites. Amazon Mechanical Turk (AMT) workers are used to determine if videos contain the intended activity class. AMT workers also label the beginning and end points of each activity.

The How2 dataset [10] was introduced by Sanabria et al. This is a large scale multimodal language understanding dataset to aid in the development human like language understanding capabilities, where machines should be able to jointly process multimodal data, and not just text, images, or speech in isolation.

The TRECVID Instance Search (INS) [3] task is a benchmarking task run at NIST (U.S. National Institute of Standards and Technology) to measure systems performance on the retrieval of specific instances of either persons, locations, or objects. In the last three years the task targeted pairs of instances such as the retrieval of video shots of specific people in given locations within the British Broadcasting Corporation (BBC) Eastenders TV series. While recently the task targeted video shots of specific people doing specific actions in the Eastenders world.

TRECVID Video to Text (VTT) [3] is a benchmarking task also run at NIST to evaluate the performance of systems that automatically generate a single sentence description for short videos. Videos are typically shorter than 10 seconds in length and are taken from social media to represent real world situations. Although ActivityNet, INS and VTT benchmarks are all important efforts to encourage research in recognition and video semantics, they are still considered component tasks and not targeting the real holistic problem of high-level video understanding the way humans do.

3 TECHNICAL DETAILS

3.1 Dataset

The procurement of suitable datasets is vital for the undertaking of this new research area. The authors have spent time identifying Movies with a Creative Commons (CC) license [6] which can be disseminated to participating researchers for the purpose of this research. The most important criteria in selecting the movies were reasonable video quality, duration of more than 15 min at least, and self contained story lines with clear actors, relations, events and entities. In total, a pilot dataset of about 11 hrs has been collected from public websites such as Vimeo¹ and the Internet Archive².

Table 1 shows the current set of collected movies, their genre and durations. All movies have been deemed by the authors to be suitable for this research, and will be disseminated to participants as appropriate. The main challenge in this new task is related to the methods and techniques teams use and not the size of data set, We consider this data set to be large enough for the Grand Challenge and workshop in the first year of this task. The authors have also been in deliberations with the BBC regarding the licensing of the TV show *Land Girls* for use in this data set, and the licensing of this series has been approved and will be available for subsequent years of this task. This is a 3-season / 15-episode series set in World War 2 about the lives of a group of women doing their part for Britain in the *Women's Land Army* during the war.

Due to the limited number of movies available for this task, the above list will be split 50-50 between a development set and test set. Final ground truths for movies selected as the development set will be made available to participants. Participating researchers will

¹<https://vimeo.com/>

²<https://archive.org/>

Movie	Genre	Duration
Honey	Romance	86 min
Let's Bring Back Sophie	Drama	50 min
Nuclear Family	Drama	28 min
Shooters	Drama	41 min
Spiritual Contact The Movie	Fantasy	66 min
Super Hero	Fantasy	18 min
The Adventures of Huckleberry Finn	Adventure	106 min
The Big Something	Comedy	101 min
Time Expired	Comedy / Drama	92 min
Valkaama	Adventure	93 min

Table 1: The HLVU Dataset of open source movies

also be encouraged to procure their own suitable development sets and to share among other participating researchers.

3.2 Human Annotation Framework

A group of human assessors will be recruited to provide manual annotations to the above HLVU dataset. These annotations will be the basis from which queries and ground-truth are generated. Each of the movies listed above will be watched at least twice by annotators. The first time is to familiarize themselves with the movie story line and the main actors. In the second time watching the movie they will be asked to use the yEd [1] graphing tool to develop a knowledge graph encompassing all of the actors, entities, relationships, and events. An example knowledge graph developed using this software, modelled on *The Simpsons*, is shown in Figure 1. In this example Knowledge Graph we map out the relations between the main characters of the show, in the way that generated Knowledge Graph's should map out the relations between main characters of the movie used in the dataset for this task.

Annotators will be provided with a primary list of possible relations between characters from which they must choose the most accurate relationship. Table 2 provides some examples of the possible relations between characters and their inverse. If needed, they will be allowed to introduce new relationships as well.

In addition to the yEd graphing tool, a specially developed in-house annotation tool will also be used by annotators to save image captions of each of the actors and entities. This should also be used to list all the different actions which take place in the relationship between two people. Additionally this should be used to list key actions and events an individual has been involved in. These actions and events referred to here are not meant to be an exhaustive list and will be those actions and events that human annotators consider to be the key actions or events which may define the relationship between two individuals. In addition, the tool can be used to enable the annotators to document all the different events that happened during the movie and eventually enabling the development of a global ontology of events and actions relevant to the whole HLVU dataset. An example screen shot from using this annotation tool is shown in figure 2.

Relationship	Inverse Relationship
Child of	Parent of
Spouse of	Spouse of
Sibling of	Sibling of
Descendant of	Ancestor of
Friend of	Friend of
In Relationship With	In Relationship With
Ambivalent Of	Is Not Liked By
Employee of	Employer of
Attends	Attended By
Colleague of	Colleague of
Apprentice of	Mentor of
Student of	Teacher of
Supervisor of	Subordinate of
Superintendent at	Responsibility of

Table 2: Example Relationships Between Characters

3.3 Query Development

The yEd graphing tool described in the previous section has the capability of exporting all entities and relationships to xgml or tgf format which can be used in the query development process to read all entities and relationships and develop different types of queries for evaluation purposes. The actions and events which may define the relationship between people may be derived from the in-house annotation tool described in the previous section as well. The following are a set of proposed query types which may be used to evaluate participating systems. Each query type tries to capture and test the systems for their comprehension of the tested movies from different points of view and levels of difficulty:

3.3.1 A- Fill in the graph space: Fill in spaces in the Knowledge Graph (KG). Given the listed relationships, events or actions for certain nodes, where some nodes are replaced by variables X, Y, etc., solve for X, Y etc. Example: **X** Married To Marge. **X** Friend Of Lenny. **Y** Volunteers at Church. **Y** Neighbor Of **X**. Solution for **X** and **Y** in that case would be: **X** = Homer, **Y** = Ned Flanders. A more formal query example may look like the following xml block (asking who is the spouse of "Marge"):

```
<Q.A>
  <Q.Id.1>
    <Subject>Person:Unknown_1</Subject>
    <Pred>Relation:Spouse_of</Pred>
    <Object>Person:Marge</Object>
  </Q.Id.1>
</Q.A>
```

3.3.2 B- Question Answering: This query type represents questions on the resulting KG, including actions and events, of the movies in the described dataset. For example, based on the Simpsons KG below, how many children does Marge have? By counting the 'Parent Of' edges from Marge to other nodes, we can see that Marge has two children, Bart and Lisa. Other possible questions may be for example: What does Ms. Krabappel do for a living? and the answer

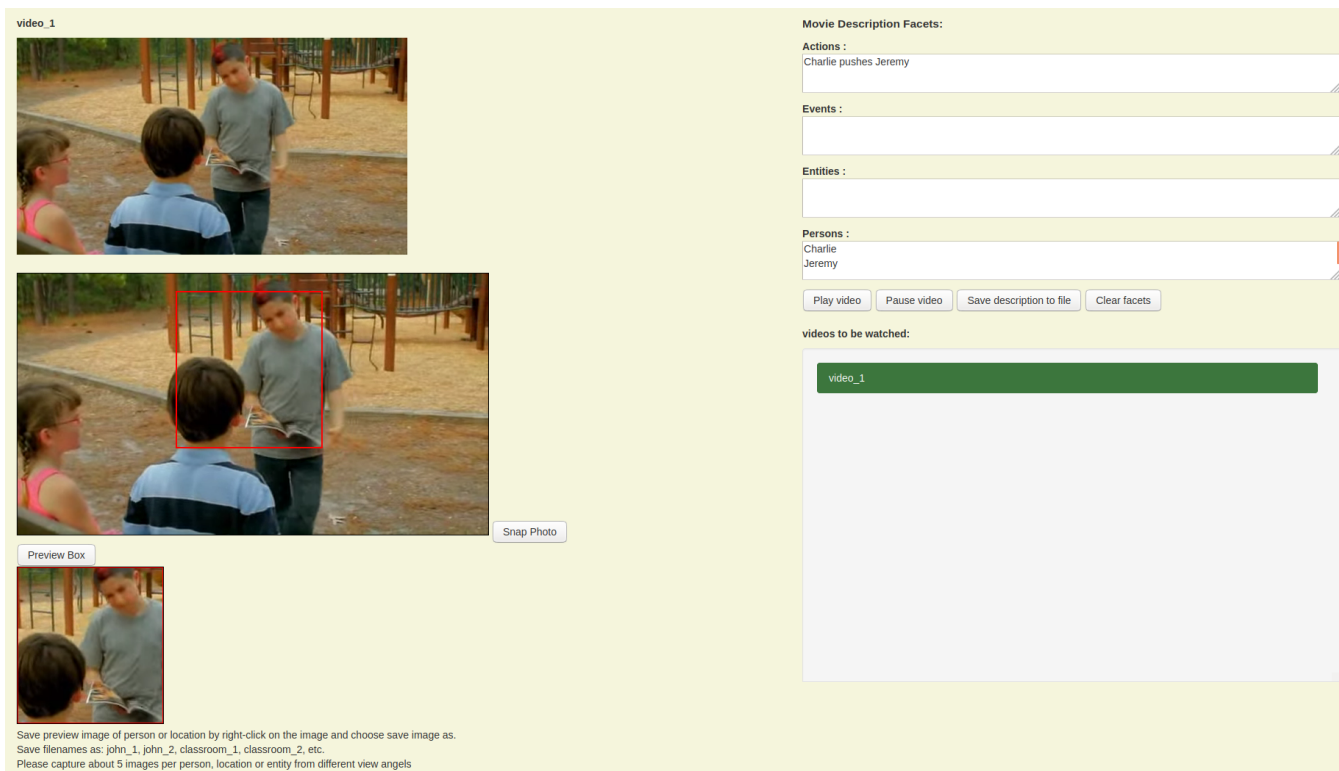


Figure 2: A screen shot of the annotation tool used for listing the defining actions and events for entities or relationships

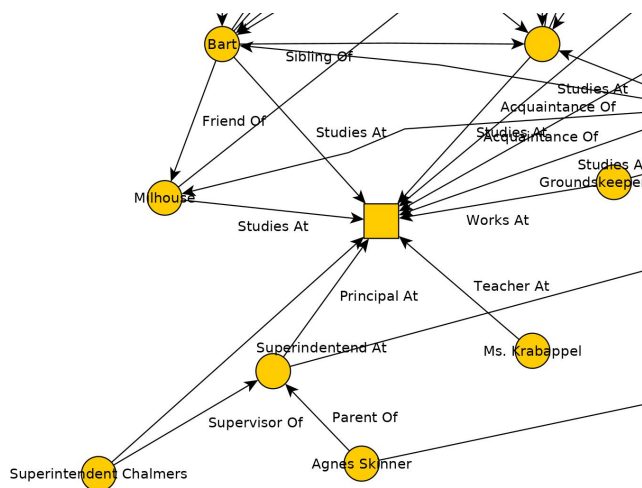


Figure 3: Visible region of graph with three blank nodes to be filled in.

```
<Target>Person:Lenny</Target>
</Q.Id.1>
</Q.C>
```

3.4 Evaluation Framework

Using the annotation and graphing tools described above, we can develop evaluation software to read as inputs the ground truth provided by these annotation and graphing tools, in addition to reading as input the submissions of participating teams, automatically evaluating each team's submissions, scoring and ranking results based on the selected evaluation metric. We should note here that systems will be given a set of image and/or video examples for the different actors and entities including important locations, each with a name Id. In addition, the final ontology of relationships, events, and actions will also be given so that systems can align the different query mentions of people, relations, entities, etc and return results from the given ontology classes as well. For illustration purposes, the following is a system response for each of the three query types and a proposed metric to score submissions:

3.4.1 A- Fill in the graph space: Given the partial graph query illustrated in figure 3, systems are asked to fill in the three blank spaces in the KG. The query itself will be given in xml format as illustrated in the query development section above. The ground truth for this example is: Lisa is sibling of Bart. Springfield Elementary is where Milhouse and Bart study at, and Principal Skinner is the principal. An example response by a system is shown below giving a set of answers for each unknown graph node being asked about in addition to a confidence score. Results will be treated as ranked list of result items per each unknown variable and the Reciprocal Rank

score will be calculated per unknown variable and Mean Reciprocal Rank (MRR) per query [13].

```
<Q.A>
  <Q.Id.1>
    <Person:Unknown_1><Ans_1><Confidence>
    <Person:Unknown_1><Ans_2><Confidence>
    ...
    ...
    <Person:Unknown_2><Ans_n><Confidence>
  </Q.Id.1>
</Q.A>
```

The MRR measurement (Eq. 1) evaluates systems which return a ranked list of answers to questions. For this reason we consider it the most appropriate evaluation measurement for use in this query type. It is the average of the reciprocal ranks of results for a group of queries. For example, in three ranked lists submitted to answer three unknown variables in a query, if the answer to the first query is ranked second in the list, the answer to the second query is ranked first in the list and the answer to the third is ranked fourth, this gives $\frac{1}{2}$, 1, and $\frac{1}{4}$. This averages to give an MRR score of $\frac{7}{12}$.

$$MRR = \frac{1}{Q} \sum_{i=1}^Q \frac{1}{RANK_i} \quad (1)$$

3.4.2 B- Question Answering: Multiple choice questions will be provided for participants to answer which will be based on the KG. For an example on the format and types of questions asked to participants please see the Query Development section above. The below is an example of a system response and the evaluation metric (Eq. 2) proposed for this query type.

```
<Q.B>
  <Q.Id.1>
    <Answer>Relation: Z</Answer>
  </Q.Id.1>
</Q.B>
```

$$Score = \frac{CorrectAnswers}{TotalQuestions} \quad (2)$$

3.4.3 C- Relations between characters: In this query type, systems are asked to submit all valid paths from a source node to another target node with the goal of maximizing recall and precision. NIST will first evaluate whether each path is a valid path (i.e the submitted order of nodes and edges leads to a path from the source person to the target person of the query) and report the recall, precision and F1 measures [12]:

$$Recall = \frac{NumberOfSubmittedValidPaths}{NumberOfValidGTPaths} \quad (3)$$

$$Precision = \frac{NumberOfSubmittedValidPaths}{NumberOfSubmittedPaths} \quad (4)$$

$$F1_Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (5)$$

Below is an example of a system response to a query asking for all paths from the Simpsons characters Superintendent Chalmers to Lenny:

```
<Q.C>
  <Q.Id.1>
    <path=1>
      <Source>Person:Superintendent Chalmers</Source>
      <edge>Relation:Superintendent_At</edge>
      <node>Entity:Springfield Elementary</node>
      <edge>Relation:Studied_At_By</edge>
      <node>Person:Bart</node>
    .
    .
    <Target>Person:Lenny</Target>
  </path>
  <path=2>
    <Source>Person:Superintendent Chalmers</Source>
    .
    .
    </path>
  <path=3>
    .
    .
    </path>
  </Q.Id.1>
</Q.C>
```

The evaluation framework described above will provide a way to accurately and automatically evaluate the Knowledge Graphs produced by participating researchers. This allows for consistent scoring methods to be applied to this task which increases confidence in results and allows for easy expansion of the task and number of participants.

4 CONCLUSIONS AND FUTURE DIRECTIONS

In this paper we discussed a proposed new evaluation benchmark and associated pilot dataset (HLVU) to promote research in holistic and deep video understanding. The evaluation paradigm aims for long duration self contained story lines in movies and targets automatic systems to eventually build complete knowledge graphs representing the movie characters, relationships, and key actions and events associated with them. The different query types presented aim to test the current automatic computer vision systems' capabilities and measure if they can "understand" video story lines the way humans do. The future plans for this evaluation benchmark is to organize an ACM Multimedia Grand Challenge and a workshop at ACM ICMI to host the evaluation campaign encouraging researchers to explore the dataset, discuss challenges and lessons learned trying to solve the associated problems with deep video understanding of the small world of movies. Also, securing more long term stable and large-scale dataset of licensed or open source

movies including soap opera series of closed world story lines is a major future plan to continue measuring progress and the state of the art in this new domain.

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