MovieQA: Understanding Stories in Movies through Question-Answering

Makarand Tapaswi¹, Yukun Zhu³, Rainer Stiefelhagen¹
Antonio Torralba², Raquel Urtasun³, Sanja Fidler²

¹Karlsruhe Institute of Technology, ²Massachusetts Institute of Technology, ³University of Toronto

{tapaswi,rainer.stiefelhagen}@kit.edu, torralba@csail.mit.edu, {yukun,urtasun,fidler}@cs.toronto.edu

http://movieqa.cs.toronto.edu

Figure 1: Our MovieQA dataset contains 7702 questions about 294 movies. The questions can be answered by using multiple sources of information: full-length movies, subtitles, scripts, and plots. Here, we show example QAs from The Matrix. A subset of our QAs are timestamped to parts in the movie and thus can be answered using videos.

Abstract

We introduce the MovieQA dataset which aims to evaluate automatic story comprehension from both video and text. The dataset consists of 7702 questions about 294 movies with high semantic diversity. The questions range from simpler “Who” did “What” to “Whom”, to “Why” and “How” certain events occurred. Each question comes with a set of five possible answers; a correct one and four deceiving answers provided by human annotators. Our dataset is unique in that it contains multiple sources of information – full-length movies, plots, subtitles, scripts and for a subset DVS from [28]. We analyze our data through various statistics and intelligent baselines. We further extend existing QA techniques to show that question-answering with such open-ended semantics is hard. We plan to create a benchmark with an active leader board, to encourage inspiring work in this challenging domain.

1. Introduction

Fast progress in Deep Learning as well as a large amount of available labeled data has significantly pushed forward the performance in many visual tasks such as image tagging, object detection and segmentation, action recognition, and image/video captioning. We are steps closer to applications such as assistive solutions for the visually impaired, or cognitive robotics, which require a holistic understanding of the visual world by reasoning about all these tasks in a common framework. However, a truly intelligent machine would ideally also infer high-level semantics underlying human actions such as motivation, intent and emotion, in order to react and, possibly, communicate appropriately. These topics have only begun to be explored in the literature [23, 43].

A great way of showing one’s understanding about the scene is to be able to answer any question about it [20]. This idea gave rise to several question-answering datasets which provide a set of questions for each image along with multiple-choice answers. These datasets are either based on RGB-D images [20] or a large collection of static photos such as Microsoft COCO [1, 41]. The types of questions typically asked are what is there and where is it, what attributes an object has, what is its relation to other objects in the scene, and how many objects of certain type are present. While these
questions verify the holistic nature of our vision algorithms, there is an inherent limitation in what can be asked about a static image. High-level semantics about actions and their intent is mostly lost and can typically only be inferred from temporal, possibly life-long visual observations.

Movies provide us with snapshots from people’s lives that link into stories, allowing an experienced human viewer to get a high-level understanding of the characters, their actions, and the motivations behind them. Our goal is to create a question-answering dataset to evaluate machine comprehension of both, complex videos such as movies and their accompanying text. We believe that this data will help push automatic semantic understanding to the next level, required to truly understand stories of such complexity.

This paper introduces MovieQA, a large-scale question-answering dataset about movies. Our dataset consists of 7702 questions about 294 movies with high semantic diversity. For 34 of these movies, we have timestamp annotations indicating the location of the question in the video. The questions range from simpler Who did What to Whom that can be solved by vision alone, to Why and How something happened, questions that can only be solved by exploiting both the visual information and dialogs. Each question has a set of five possible answers; one correct and four deceiving answers provided by the human annotators. Our dataset is unique in that it contains multiple sources of information: full-length movies, subtitles, scripts, and plots, as illustrated in Fig. 1. For a subset of our movies, DVS (described video for the blind) is also available from [28]. We analyze our data through various statistics and intelligent baselines that mimic how different “students” would approach the quiz. We further extend existing QA techniques to work with our data and show that question-answering with such open-ended semantics is hard.

We plan to create an online benchmark, encouraging inspiring work in this challenging domain. We expect this benchmark to be online in early 2016\(^1\). It will have 15,000 questions and 75,000 answers, with the test set ground-truth for 5,000 questions held-out. Various sub challenges will evaluate performance with different sources of information (visual and various forms of text).

2. Related work

Integration of language and vision is a natural step towards improved understanding and is receiving increasing attention from the research community. This is in large part due to efforts in large-scale data collection such as Microsoft’s COCO [19], Flickr30K [40] and Abstract Scenes [44] providing tens to hundreds of thousand images with natural language captions. Another way of conveying semantic understanding of both vision and text is by retrieving semantically meaningful images given a natural language query [11]. An interesting direction, particularly for the goals of our paper, is also the task of learning common-sense knowledge from captioned images [36]. This has so far been demonstrated only on synthetic clip-art scenes which enable perfect visual parsing.

Video understanding via language. In the video domain, there are fewer works on integrating vision and language, likely due to less available labeled data. In [9, 37], the authors caption video clips using LSTMs, [29] formulates description as a machine translation model, while older work uses templates [3, 7, 16]. In [18], the authors retrieve relevant video clips for natural language queries, while [25] exploits captioned clips to learn action and role models. For TV series in particular, the majority of work aims at recognizing and tracking characters in the videos [2, 4, 24, 31]. In [6, 30], the authors aligned videos with movie scripts in order to improve scene prediction. [35] aligns movies with their plot synopses with the aim to allow semantic browsing of large video content via textual queries. Just recently, [34, 43] aligned movies to books with the aim to ground temporal visual data with verbose and detailed descriptions available in books.

Question-answering. QA is a popular task in NLP with significant advances made recently with neural models such as memory networks [32], deep LSTMs [10], and structured prediction [38]. In computer vision, [20] proposed a Bayesian approach on top of a logic-based QA system [17], while [21, 26] encoded both an image and the question us-

\(^1\)http://movieqa.cs.toronto.edu
choice answers, only one of which is correct. The system quiz comprises of a set of questions, each with 5 multiple-
automatic systems will have to answer. For each movie, a main. Our data consists of quizzes about movies that the of information that can be exploited in this challenging do-
poral data. We collect a dataset with very diverse sources
marks that evaluates semantic understanding over long tem-
...plied over a long temporal domain. QA Datasets. Most available datasets focus on image [15, 19, 40, 44] or video description [5, 28, 8]. Particularly relevant to our work is the MovieDescription dataset [28] which transcribed text from the Described Video Service (DVS), a narration service for the visually impaired, for a collection of 100 movies. For QA, [20] provides questions and answers (mainly lists of objects, colors, etc.) for the NYUv2 RGB-D dataset, while [1, 41] do so for MS-COCO with a dataset of a million QAs. While these datasets are unique in testing the vision algorithms in performing various tasks such as recognition, attribute induction and counting, they are inherently limited to static images. In our work, we collect a large QA dataset of about 300 movies with challenging questions that require semantic reasoning over a long temporal domain.

Our dataset is also related to purely text-datasets such as MCTest [27] which contains 660 short stories with multi-choice QAs, and [10] which converted 300K news summaries into Cloze-style questions. We go beyond these datasets by having significantly longer text, as well as multiple sources of available information (video clips, plots, subtitles, scripts and DVS). This makes our data one of a kind.

3. MovieQA dataset

The goal of our paper is to create a challenging benchmark that evaluates semantic understanding over long temporal data. We collect a dataset with very diverse sources of information that can be exploited in this challenging domain. Our data consists of quizzes about movies that the automatic systems will have to answer. For each movie, a quiz comprises of a set of questions, each with 5 multiple-choice answers, only one of which is correct. The system has access to various sources of textual and visual information, which we describe in detail below.

We collected 294 movies with subtitles, and obtained their extended summaries in the form of plot synopses from Wikipedia. Additionally, we crawled imsdb for scripts, which were available for 40% (117) of our movies. A fraction of our movies (45) come from the MovieDescription dataset [28] which contains movies with DVS transcripts.

Plot synopses. Plot synopses are extended movie summaries that fans write after watching the movie. This makes them faithful to the story that takes place in the movie. Synopses widely vary in detail, and range from one to 20 paragraphs, but focus on describing content that is directly relevant to the story. They rarely contain detailed visual information such as how a character looks or dresses, and mainly focus on describing the movie events, character interactions and at times emotions. Plots are thus in many ways what a perfect automatic algorithm should get from “watching” the movie. We exploit such plots to gather our quizzes.

Videos and subtitles. An average movie is about 2 hours in length and has over 198K frames and almost 2000 shots. Note that on its own, video contains information about e.g., who did what to whom, but does not contain sufficient information to explain why something happened. Dialogs play an important role, and only both modalities together allow us to fully understand the story. Note that subtitles do not contain speaker information.

DVS is a service that narrates movie scenes to the visually impaired by inserting relevant descriptions in between dialogs. These descriptions contain sufficient “visual” information about the scene that allows the visually impaired audience to follow the movie. DVS is thus a proxy for a perfect vision system, and potentially allows quizzes to be answered without needing to process the videos.

Scripts. The scripts that we collected are written by screenwriters and serve as a guideline for movie making. They typically contain detailed descriptions of scenes, and, unlike subtitles, contain both dialogs and speaker information. Scripts are thus similar, if not richer in content to DVS+subtitles, however are not always entirely faithful to the movie as the director may aspire to artistic freedom.

3.1. QA Collection method

Since videos are difficult and expensive to provide to annotators, we used plot synopses as a proxy for the movie. Thus, while creating quizzes, our annotators were only looking at text and were “forced” to ask questions that are at a higher semantic level and more story-like. In particular, we split our annotation efforts into two parts to ensure high quality of the collected data.

Q and correct A. Our annotators were first asked to select a movie from a provided list, and were then shown its plot synopsis one paragraph at a time. For each paragraph, the annotator had the freedom of forming any number and
In our instructions, we asked the annotators to provide context to each question, such that the person taking their quiz would be able to answer it by watching the movie alone (without having access to the synopsis). The purpose of this was to ensure questions that are localizable in the video and story as opposed to generic questions such as “What are they talking about?”

In our instructions, we asked the annotators to provide context to each question, such that the person taking their quiz would be able to answer it by watching the movie alone (without having access to the synopsis). The purpose of this was to ensure questions that are localizable in the video and story as opposed to generic questions such as “What are they talking about?”

We trained our annotators for about one to two hours and gave them the option to re-visit and correct their data. We paid them by the hour, a strategy that allowed us to collect more thoughtful and complex QAs, rather than short questions and single-word answers.

**Multi-choice.** In the second step of data collection, we collected multiple-choice answers for each question. Our annotators were shown a paragraph and a question at a time, but not the correct answer. They were then asked to answer the question correctly as well as to provide 4 wrong answers. These answers were either deceiving facts from the same paragraph or common-sense answers. The annotator was also allowed to re-formulate or correct the question. We used this to sanity check all the questions received in the first step, and was one of the main reasons as to why we split our data collection into two phases.

We will provide these clips as part of our benchmark.

**Time-stamp to video.** Parallel to our movie QA collection, we asked in-house annotators to align each sentence in the plot synopsis to video, by marking the beginning and end (in seconds) in the video that the sentence describes. Long and complicated sentences were often aligned to multiple, non-consecutive video clips. Annotation took roughly 2 hours per movie. Since we have each QA aligned to a sentence (or multiple ones) in the plot synopsis, this alignment provides QA time-stamped with corresponding video clips. We will provide these clips as part of our benchmark.

### 3.2. Dataset Statistics

In the following, we present some statistics about the questions and answers in our MovieQA dataset. Table 2 presents an overview of popular and recent Question-Answering datasets in the field. Most datasets (except MCTest) use very short answers and are thus limited to covering simpler visual / textual forms of understanding. To the best of our knowledge, our dataset is also the first to use videos in the form of movies.

**Multi-choice QA.** So far, we have collected a total of 7702 QAs about 294 movies. Each question comes with one correct and four deceiving answers. Table 1 presents an overview of the dataset along with the information about the train/test splits, which will be used to train and evaluate the automatic QA models. Unlike most previous datasets, our questions and answers are fairly long and have on average about 9 and 5 words, respectively. We create a video-based approach to handle these longer inputs.

We are currently working on increasing the number of QAs to 15k. We will update the tables and make the data publicly available soon.

---

**Table 2: A comparison of various QA datasets.** First three columns depict the modality in which the story is presented. AType: answer type; AW: average # of words in answer(s); MC (N): multiple choice with N answers; FITB: fill in the blanks; *estimated information.

| Dataset                  | Modality | Data source          | AType                  | #Q | AW |
|--------------------------|----------|----------------------|------------------------|----|----|
| Visual Madlibs [41]      | Temporal | temporal text+vis comprehension | MC (5) | 7,702 | 4.64 |
| VQA (v1) [1]             | Temporal | visual: counts, colors, objects | MC (4) | 75,208* | 2.59 |
| MovieQA                  | Temporal | visual: scene, objects, person, ... | MC (5) | 7,702 | 4.64 |
| MCTest [27]              | Text     | Children stories     | MC (4) | 660 | 3.40 |
| TC4L [39]                | Visual   | Synthetic            | Word                  | 20×2,000 | 1.0 |
| CNN+DailyMail [10]       | Temporal | News articles        | Word                  | 1,000,000* | 1* |
| bAbI [39]                | Text     | Reasoning for toy tasks | MC (4) | 75,208* | 2.59 |
| Multi-choice QA          | Temporal | Movie stories        | MC (5) | 7,702 | 4.64 |

**Figure 3:** Length stats of MovieQA quizzes based on the first word in the question. Area of a bubble indicates # of quest. of this type.

**Figure 4:** Stats of our dataset questions based on answer types.

**Table 1:** Overview of the MovieQA dataset. AType: answer type; AW: average # of words in answer(s); MC (N): multiple choice with N answers; FITB: fill in the blanks; *estimated information.

| Data source | AType | #Q | AW |
|-------------|-------|----|----|
| Children stories | MC (4) | 660 | 3.40 |
| Synthetic | Word | 20×2,000 | 1.0 |
| News articles | Word | 1,000,000* | 1* |
| Movie stories | MC (5) | 7,702 | 4.64 |
answers (only one of which is correct) corresponding to subtitles, or video shots. Each story...

| Text type | covers # movies | #sent. / movie | avg. length |
|-----------|----------------|----------------|-------------|
| Plot      | 294            | 35.7           | 20.3        |
| Subtitle  | 294            | 1530.7         | 6.3         |
| Script    | 117            | 2887.3         | 8.3         |
| DVS       | 45             | 698.5          | 10.2        |

Table 3: Statistics of the various text sources used for answering.

4. Multi-choice Question-Answering

We investigate a number of intelligent baselines for question-answering ranging from very simple ones to more complex architectures, building on the recent work on automatic QA. We also study inherent biases in the data and try to answer the quiz based simply on characteristics such as word length or within answer diversity.

Formally, let $S$ denote the story, which can take the form of any of the available sources of information – e.g. plots, subtitles, or video shots. Each story $S$ has a set of questions, and we assume that the (automatic) student reads one question $q_j^S$ at a time. Let $\{a_j^S\}_{j=1}^M$ be the set of multiple choice answers (only one of which is correct) corresponding to $q_j^S$, with $M = 5$ in our dataset.

The general problem of multi-choice question answering can be formulated by a three-way scoring function $f(S, q_j^S, a_j^S)$. This function evaluates the “quality” of the answer given the story and the question. Our goal is thus to pick the correct answer $a_j^S$ for $q_j^S$ that maximizes $f$:

$$j^* = \arg \max_{j=1...M} f(S, q_j^S, a_j^S) \quad (1)$$

We next discuss different possibilities for $f$. We drop the superscript $(\cdot)^S$ for simplicity of notation.

4.1. The Hasty Student

We first consider $f$ which ignores the story and attempts to answer the question directly based on latent biases and similarities. We call such a baseline as the “hasty student” since he/she does not care to read/watch the actual story.

The extreme case of a hasty student is to try and answer the question by only looking at the answers. Here, $f(S, q, a) = g_{H1}(a|a)$, where $g_{H1}()$ captures some properties of the answers.

**Answer length.** We use the number of words in the multiple choices to select the correct answer. This idea explores the bias in the data where the number of words in the correct answer is slightly larger than the number of words in wrong answers. We choose the correct answer by: (i) selecting the longest answer; (ii) selecting the shortest answer; or (iii) selecting the answer with the most different length.

**Within answer similarity/difference.** While still looking only at the answers, we compute a distance between all answers based on their representations (discussed in Sec. 4.4). We then select the correct answer as either the most similar or most distinct among all answers.

**Q and A similarity.** We now consider a hasty student that looks at both the question and answer, $f(S, q, a_j) = g_{H2}(q, a_j)$. We compute similarity between the question and each answer and pick the most similar answer.

4.2. The Searching Student

While the hasty student ignores the story, we consider a student that tries to answer the question by trying to locate a subset of the story $S$ which is most similar to both the question and the answer. The similarity of the question and the answer is ignored in this case.

The scoring function $f$ is thus factorized into two parts:

$$f(S, q, a_j) = g_1(S, q) + g_1(S, a_j) \quad (2)$$

We use two possible similarity functions: a simple cosine similarity defined over a window, and one using a neural architecture. We describe these next.

**Cosine similarity with a sliding window.** We aim to find the best window of $H$ sentences (or shots) in $S$ that
maximize similarity between the story and the question, and the story and the answer. We define our similarity function:
\[
f(S, q, a_j) = \max_l \sum_{t=1}^{t=H} g_{ss}(s_k, q) + g_{ss}(s_k, a_j),
\]
where \(s_k\) denotes a sentence (or shot) from the story \(S\). We use \(g_{ss}(s, q) = x(s)^T x(q)\) as a dot product between the (normalized) representations of the two sentences (shots). We discuss these representations in detail in Sec. 4.4.

**Searching student with a convolutional brain (SSCB).** Instead of factoring \(f(S, q, a_j)\) as a fixed (unweighted) sum of two similarity functions \(g_l(S, q)\) and \(g_t(S, a_j)\), we build a neural network that learns such a function. Assuming the story \(S\) is of length \(n\), e.g., \(n\) sentences in the plot, or \(n\) shots in the video clip, \(g_l(S, q)\) and \(g_t(S, a_j)\) can be seen as two vectors of length \(n\). The \(k\)-th entry in e.g., the former vector is \(g_{ss}(s_k, q)\). We further combine all \([g_l(S, a_j)]_j\) for the 5 answers into a \(n \times 5\) matrix. We then replicate the vector \(g_l(S, q)\) \(5\)-times, and stack the question and answer matrix together to obtain a tensor of size \(n \times 5 \times 2\).

Our neural similarity model is a convolutional neural net (CNN), shown in Fig. 5, that takes this tensor, and several layers of \(1 \times 1\) convolutions to approximate a family of functions \(\phi(g_l(S, q), g_t(S, a_j))\). We also add a max pooling layer with kernel size 3 to allow for scoring the similarity within a window in the story. The last convolutional output is a matrix of size \(n/3 \times 5\), and we apply both mean and max pooling across the storyline, add them, and make predictions using the softmax. We train our network on a randomized train/val split of our training set using cross-entropy loss and Adam optimizer [12].

### 4.3. Memory Network for Complex QA

Memory Networks were originally proposed specifically for QA tasks and model complex three-way relationships between the story, question, and an answer. We briefly describe MemN2N proposed by [32] and suggest simple extensions to make it suitable for our data and task.

The original MemN2N takes a story and a question related to it. The answering is restricted to single words and is done by picking the most likely word from the vocabulary \(V\) of 20-40 words. This is not directly applicable to our domain, as our data set does not have a fixed set of answers.

A question \(q\) is encoded as a vector \(u \in \mathbb{R}^d\) using a word embedding \(B \in \mathbb{R}^{d \times |V|}\). Here, \(d\) is the embedding dimension, and \(u\) is obtained by mean-pooling the representations of words in the question. Simultaneously, the sentences of the story \(s_t\) are encoded using word embeddings \(A\) and \(C\) to provide two different sentence representations \(m_l\) and \(c_l\), respectively. Here, \(m_l\), the representation of sentence \(l\) in the story, is used in conjunction with \(u\) to produce an attention-like mechanism which selects sentences in the story most similar to the question via a softmax function:
\[
p_l = \text{softmax}(u^T m_l).
\]

The probability \(p_l\) is used to weight the second sentence embedding \(c_l\), and the story representation \(o = \sum_i p_i c_i\) is obtained by pooling the weighted sentence representations across the story. Finally, a linear projection \(W \in \mathbb{R}^{|V| \times d}\) decodes the question \(u\) and the story representation \(o\) to provide a soft score for each vocabulary word
\[
a = \text{softmax}(W(o + u)),
\]
and finds the answer \(\hat{a}\) as the top scoring word. The free parameters to train are the \(B, A, C,\) and \(W\) embeddings for different words which can be shared across different layers.

Due to its fixed set of output answers, the MemN2N in the current form is not designed for multi-choice answering with open, natural language answers. We propose two key modifications to make the network suitable for our task.

**Memory Network for natural language answers.** To allow the Memory Network to rank multiple answers written in natural language, we can add an additional embedding layer \(F\) which maps each multi-choice answer \(a_j\) to a vector \(g_j\). Note that \(F\) is similar to previous word embeddings \(B, A\) and \(C\), but operates on answers instead of question and story respectively. To predict the correct answer, we compute the similarity between the answers \(g\), the embedding \(u\) of the question and the story representation \(o\):
\[
a = \text{softmax}((o + u)^T g)
\]
and simply pick the most probably answer as correct. In our general QA formulation, this is equivalent to
\[
f(S, q, a_j) = g_{M1}(S, q, a_j) + g_{M2}(q, a_j),
\]
that is, a function \(g_{M1}\) that considers the story, question and answer, and a second function \(g_{M2}\) that directly considers similarities between the question and the answer.

**Weight sharing and fixed word embeddings.** The original MemN2N learns embeddings for each word based directly on the task of question-answering. However, to scale this to large vocabulary data sets like ours, this requires unreasonable amounts of training data. For example, training a model with vocabulary size 12000 (obtained from plot synopses) and \(d = 100\) would entail learning 1.2M parameters.
for each embedding. To prevent overfitting, we can share all word embeddings $B, A, C, F$ of the memory network. Nevertheless, this is still a large amount of parameters.

We make the following crucial modification that allows us to use the Memory Network for our dataset. We drop $B, A, C, F$ and replace them by a fixed (pre-trained) word embedding $Z \in \mathbb{R}^{d_1 \times |V|}$ obtained from the Word2Vec model and learn a shared linear projection layer $T \in \mathbb{R}^{d_2 \times d_1}$ to map all sentences (stories, questions and answers) into a common space. Here, $d_1$ is the dimension of the Word2Vec embedding, and $d_2$ is the projection dimension. Thus, the new encodings are

$$u = T \cdot Z q, m_i = T \cdot Z s_i, \text{ and } g_j = T \cdot Z a_j.$$  \hspace{1cm} (8)

Answer prediction is performed as before in Eq. 6.

We initialize the projections either using an identity matrix $d_1 \times d_1$ or using PCA to lower the dimension from $d_1 = 300$ to $d_2 = 100$. Training is performed using stochastic gradient descent with a batch size of 32 for plots and DVS. For subtitles and scripts we needed to use a batch size of 16 to ensure that the story data fits in our 6GB Titan Black GPU memory.

4.4. Representations for Text and Video

TF-IDF is a popular and successful feature in information retrieval. In our case, we treat plots (or the other forms of text) of different movies as documents and compute a weighting for each word. We set all words to lower case, use stemming and compute the vocabulary $V$ which consists of all words $w$ in the documents. We represent each sentence (or question or answer) as a bag-of-words weighted with an TF-IDF score for each word.

Word2Vec. A disadvantage of TF-IDF is that it is unable to capture the similarities between words. We use the skip-gram model proposed by [22] and train it on roughly 1200 movie plots to obtain domain-specific, 300 dimensional word embeddings. A sentence is then represented by mean-pooling its word embeddings. We normalize the resulting vector to have unit norm.

SkipThoughts. While the sentence representation using mean pooled Word2Vec discards word order, SkipThoughts [14] use a Recurrent Neural Network to capture the underlying sentence semantics. We use the pre-trained model by [14] to compute a 4800 dimensional sentence representation.

Video. To answer questions from the video, we learn an embedding between a shot and a sentence, which maps the two modalities in a common space. In this joint space, one can score the similarity between the two modalities via a simple dot product. This allows us to apply all of our proposed question-answering techniques in their original form.

To learn the joint embedding we follow [43] which extends [13] to video. Specifically, we use the GoogLeNet architecture [33] as well as hybrid-CNN [42] for extracting frame features, and mean-pool the representations over all frames of a shot. The embedding is then a linear mapping of the shot representation and an LSTM on word embeddings on the sentence side. The model evaluates the dot product of mapped vectors on both sides using the ranking loss. We train the embedding on the MovieDescription Dataset [28] as in [43].

5. QA Evaluation

We present results for question-answering with the proposed intelligent baselines on our MovieQA dataset. We study how various sources of information influence the performance, and how different level of complexity encoded in $f$ affects the quality of automatic QA.

Protocol. Note that we have two primary tasks for evaluation. (i) Text-based: where the story is represented with plots, subtitles, scripts and/or DVS; and (ii) Video-based: which uses video and dialogs (subtitles). For each task, the train and test split statistics are presented in Table 1. We will provide more details on the project page with the release of our dataset.

Metrics. Multiple choice QA leads to simple and objective evaluation. We measure accuracy as the number of questions where an automatic model chooses the correct answer over the total number of questions.

In addition to accuracy, we propose to use another metric “Quiz Score” (QS) inspired by real-world multiple-choice examinations. This metric penalizes students for choosing wrong answers and also (albeit by a smaller amount) for unanswered questions. Similar to the concept of “refuse to predict” schemes, we want to stress that it might be better to leave answers blank (say “I don’t know”) than pick the wrong answer. We plan to use this scoring scheme in the leader board rankings for the benchmark.

The score is computed as

$$\text{Quiz Score} = 100 \cdot \frac{\#CA - 0.25 \cdot \#WA - 0.05 \cdot \#UA}{\text{Total no. of questions}}.$$  

CA, WA and UA stand for correct, wrong and unanswered questions respectively.

Answering to maximize Quiz Score. An easy way to decide which questions are not worth attempting (leave unanswered) is to learn a threshold on a subset of the training set. We learn a threshold on the difference between the top 2 highest scoring options via grid search, by optimizing for the Quiz Score as the metric. The difference in score between the top 2 options can be considered as our model confidence in answering questions correctly. We then use the learned threshold on the test set to decide whether a question should be answered.
Table 4: The question-answering Accuracy and Quiz Score (in paranthesis) for the “Hasty Student” who tries to answer questions without looking at the story.

| Answer length | longest | shortest | different |
|---------------|---------|----------|-----------|
| Within answer similarity | TF-IDF | SkipT | w2v |
| similar        | 17.8 (-3.4) | 27.0 (8.5) | 25.8 (7.3) |
| distinct       | 23.8 (4.5)  | 16.7 (-4.2) | 13.9 (-5.0) |
| Question answer | TF-IDF | SkipT | w2v |
| similar        | 10.0 (-5.0) | 20.3 (0.3) | 20.7 (0.3) |

5.1. Hasty Student

The first part of Table 4 shows performance of the three models when trying to answer questions based on the length of the answers. Selecting the longest answer performs better (28.2%) than random (20%) while the answer with the most different length is only slightly better at 22.6%. The second part of Table 4 presents results when using feature-based similarity within answers. We see that the most similar answer is likely to be correct when the representations are generic and try to capture the semantics of the sentence (Word2Vec, SkipThoughts). On the other hand, when using TF-IDF, discriminating between different names is very easy and thus the most distinct answer is likely to be more correct. Finally, in the last part of Table 4 we see that questions and answers are very different from each other. Especially, TF-IDF performs worse than random since words in the question rarely appear in the answer.

Performance of the methods using our second metric “Quiz Score” is indicated by numbers in paranthesis in the Table 4. We see the bias towards longer answers results in the highest QS. More interestingly, while the difference between accuracy for within-answer similarity and answer length is not high (27.0% vs. 28.2%), the large difference in QS (8.5 vs. 18.7) reveals that answer length is a more confident way to predict answers. Most other methods result in a quiz score close to 0.

5.2. Hasty Turker

To analyze the quality of our collected multi-choice answers and their deceiving nature, we tested humans (via AMT) on a subset of 200 QAs. The turkers were not shown the story in any form and were asked to pick the best possible answer given the question and a set of options. The purpose of this experiment is to analyze whether our multi-choice answers are difficult enough, so as to even deceive humans when provided with no context. We asked each question to 10 turkers, and rewarded each with a bonus if their answer agreed with the majority.

The results are presented in Fig. 6. The overall accuracy is computed as the number of all correct answers over all annotators. We also compute accuracy of majority vote, which is the number of times a correct answer was chosen by the majority of the turkers divided by the total number of questions. Finally, Q with corr. ans. never picked is the percentage of questions for which none of the turkers selected the correct answer.

In Fig. 6 (a) we see that 27.6% of all answers were correct, and 37% questions got a correct answer via the majority vote. Since some of the questions and answers reveal the identity of the movie (e.g. a reference to “Darth Vader”, “Indiana Jones”, “Borat”), we decided to also select a subset of these questions for which the names did not necessarily indicate a movie. This removed the possibility of an annotator actually remembering the movie while answering the question. We present the results of this experiment (evaluated on 135 QAs) in Fig. 6 (b). While the overall accuracy is closer to random, it is still slightly higher (24.7% overall accuracy and 30.4% by majority vote). This may indicate that some of the wrong answers are somewhat correlated, making the test slightly easier for a human. It also indicates that a machine which takes into account all answers should likely do better than looking at each answer in isolation.
The small bias of answer length in our dataset was not noticed by the turkers. 31.3% of the annotators chose the longest answer as the correct one, and in fact 37.3% of them picked the shortest answer.

5.3. Searching Student

Cosine similarity in window. The first three rows of Table 5 present results of the proposed method using different representations and input story types. Using the plot to answer questions outperforms other information sources such as subtitles, scripts or DVS. This is most likely due to the fact that the data was collected using plot synopses and while framing the QAs annotators often reproduce parts of the plot verbatim.

We show the results of using Word2Vec or SkipThought representations in the following rows of Table 5. Both perform significantly worse than the TF-IDF representation and Word2Vec is consistently better than SkipThoughts. We suspect that while Word2Vec and SkipThoughts are good at capturing the overall semantic structure of the words and sentences respectively, but proper nouns – names, places – are often hard to distinguish. This is more evident as we move from individual word representations (Word2Vec) towards the sentence representation (SkipThoughts) which is then likely to ignore the subtleties between different names.

Fig. 7 presents a breakup of the overall accuracy based on the first word of the questions. The story here is the plot synopsis and answering method employed is the searching student with cosine similarity. While TF-IDF works better on all question types, the difference between TF-IDF with respect to the semantic representations is extremely high when answering questions of type “Who” and “Where”. On “Why” and “How”, we see a more gradual decay in performance.

Influence of window. We notice that the window size $H$ significantly influences the results of using TF-IDF based representations on stories of subtitles and scripts. We believe that this results from two factors: (i) the questions are about the story and answering them by just looking at one dialog is a very hard task; and (ii) the TF-IDF representation in particular sees more words which directly makes matching less sparse and easier.

We analyze the case of using subtitles as stories and show the variation in accuracy in Fig. 8. Each subtitle, on average, corresponds to 4.74 seconds of video. The figure shows that the performance improves strongly up to a window of size 100 – which corresponds to about 8 minutes of video – and then shows small improvement thereafter.

SSCB. The middle rows of Table 5 show the result of our neural similarity model. Here we also tried to combine all text features (SSCB fusion) via our CNN. We randomly split the training set into 80% train / 20% val, keeping all questions / answers of the same movie in the same split, and train our model on train and monitor performance on val. During training, we also create several model replicas and pick the ones with the best validation performance.

Table 5 shows that the neural model outperforms the simple cosine similarity on most tasks, while the fusion method achieves the highest performance on two out of four story types. Overall, the accuracy is capped at 35% for most modalities showing the difficulty of our dataset.

5.4. Memory network

The original MemN2N which allows to train the word embeddings overfits strongly on our dataset leading to a test error near random performance ($\sim 20\%$). However, our modifications help in restraining the learning. Table 5 presents results for MemN2N with Word2Vec initialization and a linear projection layer. Using plot synopses, we see a performance similar to SSCB on Word2Vec features. However, with longer stories, the attention mechanism in the network is able to sift through thousands of story sentences and perform well on DVS, subtitles and scripts. This shows that complex three-way scoring functions are needed to tackle such complex QA sources. In terms of modalities, the network performs best for scripts which contain the most information (descriptions, dialogs and speaker information).
Table 5: The question-answering Accuracy and Quiz Score (in paranthesis). First section presents results for the Searching student with cosine similarity. The second section presents results for the Convolutional network SSCB and in the last row we present results for the modified Memory Network.

| Method     | Plot | DVS  | Subtitle | Script |
|------------|------|------|----------|--------|
| TFIDF      | 56.32 (45.5) | 28.42 (12.4) | 31.09 (14.2) | 29.51 (13.5) |
| SkipThought| 31.05 (14.0)  | 23.72 (2.8)   | 21.39 (1.4)   | 22.96 (0.8)   |
| Word2Vec   | 38.08 (23.0)  | 25.85 (8.1)   | 25.49 (7.0)   | 25.28 (5.8)   |
| TFIDF SSCB | 57.48 (50.0)  | 30.98 (12.4)  | 34.11 (16.0)  | 29.81 (6.7)   |
| SkipThought SSCB | 31.74 (15.1)  | 24.15 (2.2)   | 23.59 (5.0)   | 21.85 (0.3)   |
| Word2Vec SSCB | 37.04 (21.6)  | 25.43 (5.7)   | 26.18 (7.8)   | 28.01 (7.4)   |
| SSCB fusion | 58.95 (48.8)  | 27.78 (11.5)  | 35.32 (19.0)  | 32.73 (12.8)  |
| MemN2N (w2v, linproj) | 38.19 (22.5)  | 35.13 (18.4)  | 35.20 (18.9)  | 40.02 (23.6)  |

Table 6: The question-answering Accuracy and Quiz Score (in paranthesis) on Video-based QA. First section presents results for the Searching student with convolutional brain. The second section presents results for the modified Memory Network.

| Method         | Shot        | Subt        | Shot+Subt   |
|----------------|-------------|-------------|-------------|
| SSCB Full movie | 21.27 (-3.4) | 25.09 (3.8) | 26.00 (3.9) |
| SSCB Video clips | 22.18 (-0.7) | 22.36 (0.5) | 22.55 (0.1) |
| MemN2N Full movie | **24.45 (3.5)** | **34.56 (17.3)** | **26.47 (6.3)** |

5.5. Video baselines

We now evaluate two of our best performing QA models, SSCB and MemN2N, on the split of our data that has video. We evaluate two settings: answering questions by “watching” the full movie, or via the ground-truth video clips (time-stamped sentences from the plot to which the question/answer refers to). The results are shown in Table 6.

Since visual information alone is insufficient to answer high level semantic questions we also combine video and dialog (subtitles). We encode each subtitle as before using Word2Vec. For SSCB we perform late fusion of the CNNs for the two modalities. For the memory network we create two branches, one for each modality, and sum up the scores before the final softmax. We train the full model jointly.

6. Conclusion

We introduced the MovieQA data set which aims to evaluate automatic story comprehension from both video and text. The dataset currently stands at 7702 multiple choice questions from 294 movies with high semantic diversity. Our dataset is unique in that it contains several sources of information – full-length movies, subtitles, scripts, plots and DVS. We provided several intelligent baselines and extend existing QA techniques to analyze the difficulty of our task.

Acknowledgment

We thank the annotators on upwork, Lea Jensterle and Marko Boben for helping us with data collection. We thank Soča Fidler for sharing her rich experience as an English teacher, her advice and help with data collection. We thank Relu Patrascu for his untiring help with numerous infrastructure related problems. MT and RS were supported by the Deutsche Forschungsgemeinschaft (DFG) under contract no. STI-598/2-1. MT was supported by a Research Travel Grant by the Karlsruhe House of Young Scientists (KHYS) for his visit to U. of Toronto.

Appendix

We present a variety of examples from the MovieQA data set. The questions are picked at random and show a glimpse of the diversity in our data set.

Tables 8, 9, 10 show examples of questions and multiple-choice answers from our data set along with corresponding story parts in the video. Note that while we depict a single video frame for simplicity, we need to consider a much longer duration around the frame to answer the video. Tables 11 and 12, show examples of questions and multiple-choice answers with corresponding story parts from the subtitles and plot synopses respectively.

Discussion of examples. The first interesting observation we make is that even for yes/no questions, the annotators typically came up with 4 deceiving answers (e.g. Table 9, bottom row, middle column). While some of the questions can be answered by vision alone (e.g., Table 9, top row, first column), most of them require both vision and dialogs. For example, in Table 10, bottom row and first column, the question asks “What happens between Alex and Isabel on the night of their daughter’s birth?”. The question clearly points to a visual scene, but within the scene we need the dialog to answer the question (“They get divorced”). For some questions, e.g. Table 11, bottom row, middle column, the answer to the question “What are Mark and Ricky doing in the woods?” can be obtained both from vision (two people smoking) as well as dialog (the two people are talking about smoking).

Corresponding to Fig. 4, Table 7 shows examples of the questions grouped by answer type. Note how a question with the same answer type need not start with the same first word (e.g. Location, Person name).
| Person name (who)          | Who is Epps attracted to?  
                              | What is the nickname of Jeff Lebowski? |
|----------------------------|----------------------------|
| Reasoning (why)            | Why does Arwen wish to stay in Middle Earth?  
                              | Why is Bruce afraid of bats? |
| Abstract (what)            | What power does the green essence contain?  
                              | As explained at the hearing, what was the primary cause of the accident? |
| Reason:action (how)        | How does Kale pass the time when he first begins his house arrest sentence?  
                              | How does Hal defeat Parallax? |
| Location (where)           | What is the name of the gym, where the CD is left behind?  
                              | Where does Aragorn lead the Fellowship? |
| Action (what)              | What does WALL-E do once he thinks that EVE has shut down?  
                              | What do Jane and Kevin do one year after meeting? |
| Object/Thing (what)        | What does the group find in the trolls’ cave?  
                              | What do the men who assault the Dude destroy in his home? |
| Person type (what)         | Who is Daniel Cleaver?  
                              | What is Rachel Dawes’s profession? |
| Yes/No (is, does)          | Does Madeleine accept money for her work for Arthur Case?  
                              | Is Faramir Denethor’s oldest son? |
| Causality (what happens)   | What does Mark do after Bridget visits him and asks him forgiveness?  
                              | What happens during Miley’s date with Travis? |
| Objective (what)           | What is a Sarang, lunar facility designed for?  
                              | What does Mr. Bradley plan to do in the town? |
| Event/Time (when)          | On what day is the location of the secret door to Lonely Mountain visible on the map?  
                              | When do Ben and Andie start truly bonding? |
| Count (how many)           | How many people form the Fellowship of the Ring?  
                              | How much money does Lester get after blackmailing his boss? |
| Others                     | How does Epps feel about the Canadian laborer later on?  
                              | What kind of job does Elaine offer Skeeter as a result of the success of her book? |
                              | What is the life-span of a Nexus-6 model replicant?  
                              | How far is the ISS from Explorer? |
                              | What does Charlie Anderson represent?  
                              | Does the film begin before or after Mozart’s death? |

Table 7: Example questions from the MovieQA data set based on answer type.

References

[1] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh. VQA: Visual Question Answering. In *ICCV*, 2015. 1, 3, 4
[2] M. Baeuml, M. Tapaswi, and R. Stiefelhagen. Semi-supervised Learning with Constraints for Person Identification in Multimedia Data. In *CVPR*, 2013. 2
[3] A. Barbu, A. Bridge, Z. Burchill, D. Coroian, S. Dickinson, S. Fidler, A. Michaux, S. Massman, S. Narayanaswamy, D. Salvi, L. Schmidt, J. Shangguan, J. Siskind, J. Waggoner, S. Wang, J. Wei, Y. Yin, and Z. Zhang. Video-In-sentences Out. In *UAI*, 2012. 2
[4] P. Bojanowski, F. Bach, I. Laptev, J. Ponce, C. Schmid, and J. Sivic. Finding Actors and Actions in Movies. *ICCV*, pages 2280–2287, 2013. 2
[5] D. L. Chen and W. B. Dolan. Collecting highly parallel data for paraphrase evaluation. In *ACL*, 2011. 3
[6] T. Cour, C. Jordan, E. Miltsakaki, and B. Taskar. Movie/Script: Alignment and Parsing of Video and Text Transcription. In *ECCV*, 2008. 2
[7] P. Das, C. Xu, R. F. Doell, and J. J. Corso. A Thousand Frames in Just a Few Words: Lingual Description of Videos through Latent Topics and Sparse Object Stitching. *CVPR*, 2013. 2
[8] P. Das, C. Xu, R. F. Doell, and J. J. Corso. A thousand frames in just a few words: Lingual description of videos through latent topics and sparse object stitching. In *CVPR*, 2013. 3
| Movie | The Lord of the Rings: The Fellowship of the Ring | Harry Potter and the Chamber of Secrets | The Lord of the Rings: The Return of the King |
|-------|-------------------------------------------------|----------------------------------------|---------------------------------------------|
| Question | Who destroys Sauron in the battlefield? | What does Harry trick Lucius into doing? | Why does Arwen wish to stay in Middle Earth? |
| Video Shot | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| Answer | Isildur | Freeing Dobby | Arwen sees her son with Aragorn in her visions |
| Option 1 | Smeagol | Releasing Dobby to Harry’s care | Because she is too weak to travel |
| Option 2 | Gollum | Releasing Dobby to Dumbledore’s care | Because she wants to die on Middle Earth |
| Option 3 | The Ring | Releasing Dobby to Hagrid’s care | Because she likes Middle Earth |
| Option 4 | Bilbo | Admitting he put Tom Riddle’s diary in Ginny’s cauldron | Because her son asked to stay |

| Movie | The Help | The Adjustment Bureau | 10 Things I Hate About You |
|-------|----------|-----------------------|--------------------------|
| Question | What happened to Constantine shortly after she moved to Chicago? | Why does David abandon Elise at the hospital after she sprains her ankle? | How does Patrick convince Kat to go with him to the prom? |
| Video Shot | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| Answer | She died | To protect both Elise and himself from Thompson’s threats | By serenading her, accompanied by a marching band |
| Option 1 | She got a new job | Because he wants to be with someone that can walk | He offers to pay her |
| Option 2 | She fell sick | He wants to run the Bureau and he cannot do it with a limping wife | He tells her he loves her |
| Option 3 | She won the lottery | He does not abandon her, he stays with her | He doesn’t; Joey does |
| Option 4 | 2 and 4 above | He wants to save her from World War I and the Great Depression | He blackmails her |

Table 8: Example questions and multiple-choice answers from the MovieQA data set shown along with representative frames of the movie.
| Movie                          | The Green Lantern | Amadeus | Indiana Jones and the Last Crusade |
|-------------------------------|-------------------|---------|-----------------------------------|
| **Question**                  | What happens in the scene shown during the end credits? | How does Mozart humiliate Salieri in front of the Emperor? | What does Indy do to the grave robbers in the beginning of the movie? |
| **Video Shot**                | ![Image](image1)  | ![Image](image2) | ![Image](image3) |
| **Answer**                    | Sinestro steals a yellow ring causing his green uniform to turn yellow | When Salieri plays his music, Mozart plays it from memory, critiques it and improves it | He steals their golden crucifix |
| **Option 1**                  | Sinestro steals a green ring, places it on his finger, causing his yellow uniform to turn green | He accuses Salieri of stealing the music from his 1786 opera The Marriage of Figaro | He kills them while they’re sleeping |
| **Option 2**                  | Sinestro changes color from green to yellow to green again | He says that Salieri has a gift from God | He calls a museum and tells them that he found people that stole the golden crucifix |
| **Option 3**                  | Sinestro dresses in yellow to match the stolen green ring | He plays music on the piano and makes Salieri play it from memory in front of the Emperor | He steals their horses |
| **Option 4**                  | Sinestro steals a yellow suit causing his ring to turn yellow | He plays music on the piano and asks Salieri to improve on his version in front of the Emperor | He tells the Boy Scouts to beat up the grave robbers |

| Movie                          | Chasing Amy | E.T. the Extra-Terrestrial | Anna Karenina |
|-------------------------------|-------------|---------------------------|--------------|
| **Question**                  | How does Alyssa feel after Holden leaves her booth in the end of the movie? | Do aliens leave one of their own on Earth on purpose? | When does Anna openly show her feelings for Vronsky at the horse races? |
| **Video Shot**                | ![Image](image4)  | ![Image](image5) | ![Image](image6) |
| **Answer**                    | She is shaken and sad | No, they leave it accidentally | When his horse falls and injures him |
| **Option 1**                  | She is happy that he finally left | Yes, they leave it on purpose | When the horse kills Vronsky |
| **Option 2**                  | She does not feel anything special | No, it falls off the spaceship | When he wins the race |
| **Option 3**                  | She is angry with Holden | Yes, they leave it as a spy | She waits for him after the race and confesses |
| **Option 4**                  | She is feeling aggressive | They don’t leave any of their kind on Earth | When he notices that she is pregnant |

Table 9: Example questions and multiple-choice answers from the MovieQA data set shown along with representative frames of the movie. Notice that even for a yes/no question (bottom row, middle column) the annotators came up with 4 wrong answers.
|
|---|---|---|---|
| **Movie** | Notting Hill | Silver Linings Playbook | Titanic |
| **Question** | Why does Will put inappropriate questions to the actors at the Ritz Hotel? | Why does Pat get involved in the fight? | How does Jack meet his end? |
| **Answer** | Because he hasn’t seen the film | Because he is trying to help his brother | He freezes to death |
| **Option 1** | Because he is a pervert | Because he likes to fight | He drowns as he can’t swim |
| **Option 2** | Because Spike prepared the questions | Because someone calls him a good-luck charm | He is rescued but dies from frostbite |
| **Option 3** | Because he didn’t like the film | Because they attack him and he is protecting himself | He dies as an old man in his bed |
| **Option 4** | Because he thinks that the film has wrong political views | Because they slapped his father and he is protecting him | He dies after braving several obstacles in his later life |

| **Movie** | Fools Rush In | Meet the Parents | The Truman Show |
|---|---|---|---|
| **Question** | What happens between Alex and Isabel on the night of their daughter’s birth? | Who does Greg meet at the Byrnes’? | What happens to the show at the end of the movie? |
| **Answer** | Their divorce become final | Pam’s parents and their cat Mr. Jinx | The show is cancelled |
| **Option 1** | They remarry | Pam’s father Mr. Jinx | The show goes on without Truman |
| **Option 2** | They fight and separate | Jack and Dina Jinx | The show goes on with Truman |
| **Option 3** | Alex screams at Isabel and leaves her | Pam’s brother Jack and sister Dina | The movie doesn’t say what happened with the show |
| **Option 4** | Alex asks Isabel for divorce | Greg’s parents | Truman decides he wants to continue with the show |

*Table 10: Example questions and multiple-choice answers from the MovieQA data set shown along with representative frames of the movie. Notice that some of the questions can be answered by vision alone, while others may require vision to localize a scene, but answer the question using the dialogs in the scene.*
| Movie                              | The Perks of Being a Wallflower | Amadeus                                                                 | Snatch.                                                                 |
|-----------------------------------|---------------------------------|-------------------------------------------------------------------------|-------------------------------------------------------------------------|
| **Question**                      | Where does Charlie meet Sam and Patrick? | Does Salieri admire Mozart’s genius before he meets him in person? | Why does a robber tell Franky to buy a gun from Boris?                  |
| Subtitles                         | - So, uh... do you like football? - Love it. - Maybe you know my brother, then. - Hey, Sam. | - He was my idol. - Mozart. - I can’t think of a time when I didn’t know his name. | - When you get to London... - if you want a gun... - call this number. - Boris? |
| Answer                            | At a football game | Yes, he thinks his talent is a God’s gift                              | Because the robber and Boris want to steal the diamond from Franky       |
| Option 1                          | At a party                     | He doesn’t think that Mozart is really a genius                       | He wants to hook him up                                                |
| Option 2                          | At school                      | He thinks Mozart is totally overrated                                | He plans on robbing and killing him                                    |
| Option 3                          | On the street                  | No, he thinks Mozart is good but not a gift from God                  | Because otherwise Boris would kill him                                 |
| Option 4                          | At a baseball game             | He does not know anything about Mozart so he does not know whether he is good or not | The robber plans to steal a painting from Franky                        |

| Movie                              | The Lord of the Rings: The Return of the King | The Client                                                                 | The Hobbit: An Unexpected Journey                                      |
|-----------------------------------|-----------------------------------------------|---------------------------------------------------------------------------|-------------------------------------------------------------------------|
| **Question**                      | Who sees Denethor trying to kill himself and Faramir on a bonfire? | What are Mark and Ricky doing in the woods?                               | How does Gandalf want Bilbo to help the Dwarves?                        |
| Subtitles                         | - Gandalf! - Gandalf! - Denethor has lost his mind! - He’s burning Faramir alive! | - I wish. Sit here. - Don’t try to swallow the smoke yet. - You’re not ready for that. - You’ll just choke and puke all over the place. - Suck a little and blow. | - The task I have in mind will require a great deal of stealth... - ...and no small amount of courage. - But if we are careful and clever, I believe that it can be done. - That’s why we need a burglar. |
| Answer                            | Pippin                                      | They are smoking cigarettes                                              | He wants Bilbo to serve as their burglar                               |
| Option 1                          | Aragorn                                     | They are cutting woods                                                   | By Killing the Orcs                                                    |
| Option 2                          | Gandalf                                     | They are having sex                                                      | Give them the Elven Blades                                            |
| Option 3                          | Eowyn                                       | They are shooting deer                                                   | To give them the Hobbit Fighters                                    |
| Option 4                          | Sam                                         | They are trying to kill each other                                       | To become their leader                                                |

Table 11: Example questions and multiple-choice answers from the MovieQA data set shown along with corresponding subtitles from the movie. Note that more text from the subtitle is relevant to the question, but we only show the key piece.
| Movie                      | Moon                                                                 | American Gangster                                                                 | Revolutionary Road                                                                 |
|----------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| **Question**               | What do the two Sams learn from Gerty about themselves?               | How many years does Lucas serve in prison?                                        | Why does April die?                                                                 |
| **Plot Sentence(s)**       | After a heated argument and physical altercation, they together coerce Gerty into revealing that they are both clones of the original Sam Bell. | ... provides evidence that leads to more than one-hundred further drug-related convictions, while he himself is sentenced to 70 years in prison, of which he serves 15 years and is released in 1991. | April dies in the hospital due to complications following the abortion. |
| **Answer**                 | That they are both clones of Sam Bell                                  | 15 years                                                                         | She performs an abortion on her own                                               |
| **Option 1**               | That one of them is a clone of the other                               | 70 years                                                                          | Due to injuries from an accident                                                  |
| **Option 2**               | That both of them were activated after the rover crash                | 50 years                                                                          | She kills herself                                                                 |
| **Option 3**               | That they are both going back to Earth                                 | 17 years                                                                          | Due to a drug overdose                                                           |
| **Option 4**               | That they are both clones of Gerty                                    | 35 years                                                                          | She is shot                                                                       |

| Movie                      | The Firm                                                              | Reality Bites                                                                      | Star Wars: Episode III - Revenge of the Sith                                      |
|----------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| **Question**               | Who tells Mitch about corrupt business of the Firm?                  | What is “In Your Face”?                                                           | What does Palpatine reveal to Anakin?                                              |
| **Plot Sentence(s)**       | Mitch realizes he is now trapped, but after two associates of the firm die under mysterious circumstances, he is approached by FBI agents who inform him that while some of BL&L’s business is legitimate, their biggest client is the Morolto Mafia family from Chicago. | He works at an MTV-like cable channel called “In Your Face” as an executive, and after learning about a documentary she’s been working on, wants to get it aired on his network. | Palpatine entices Anakin with knowledge of the dark side of the Force, including the power to “cheat death”. When Palpatine reveals himself as the Sith Lord Darth Sidious, Anakin reports his treachery to Mace Windu, ... |
| **Answer**                 | The FBI                                                               | It is an MTV-like cable channel                                                   | His knowledge of the dark side of the Force, including the power to cheat death    |
| **Option 1**               | The Firm’s senior partners                                            | A TV show                                                                         | That he is Darth Vader                                                            |
| **Option 2**               | Mitch’s coworkers                                                     | A radio talk show                                                                  | How to kill the Jedi Master                                                       |
| **Option 3**               | The Moroltos                                                          | A newspaper column                                                                | Where Padme is                                                                    |
| **Option 4**               | One of the Firm’s clients                                             | A book                                                                            | That the Jedi Council favors Anakin                                               |

Table 12: Example questions and multiple-choice answers from the MovieQA data set shown along with corresponding sentence of the plot.