Narration Generation for Cartoon Videos

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Abstract

Research on text generation from multimodal inputs has largely focused on static images, and less on video data. In this paper, we propose a new task, narration generation, that is complementing videos with narration texts that are to be interjected in several places. The narrations are part of the video and contribute to the storyline unfolding in it. Moreover, they are context-informed, since they include information appropriate for the timeframe of video they cover, and also, do not need to include every detail shown in input scenes, as a caption would. We collect a new dataset from the animated television series Peppa Pig. Furthermore, we formalize the task of narration generation as including two separate tasks, timing and content generation, and present a set of models on the new task.

1 Introduction

Text generation from visual or multimodal inputs has been an overarching goal and a point of convergence of the Computer Vision and Natural Language Processing communities (Gatt and Krahmer, 2018). Research in this direction has been propelled by the proposal and study of several tasks, with examples including image caption generation (see Bernardi et al. 2016 for a survey), visual question generation (Mostafazadeh et al., 2016), caption explanation (Hendricks et al., 2016), visual question answering explanation (Li et al., 2018) and multimodal machine translation (Calixto et al., 2017; Lala and Specia, 2018). Progress in corresponding video tasks, such as video description, video question answering (Zeng et al., 2017; Xu et al., 2017; Tapaswi et al., 2016) and video overview generation (Gorinski and Lapata, 2018) has been slower, probably due to the extra challenge posed by the temporal nature of videos. In this paper, we present narration generation, a new text generation task from movie videos. We believe that the introduction of this task will challenge existing techniques for text generation from videos.

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1Please contact the authors if you need access to code or data.
as it requires temporal contextual reasoning and inference on storylines.

A narration is a commentary commonly used in movies, series or books. It can be delivered by a story character, a non-personal voice or the author of a book and may communicate a story that is parallel to the plot, fill in details that are not directly perceivable, or help in guiding the viewers/readers through the plot. **Narration generation** refers to the task of automatically generating the text of such narrations. Our focus is on video data, especially videos that are part of episodic broadcasts, such as television series.

To facilitate research in the direction of automatic narration generation, we create a new narration dataset. Following the spirit of previous work on image captioning from abstract scenes (Zitnick and Parikh, 2013) and cartoon video question answering (Kim et al., 2016), we collect videos from the animated series **Peppa Pig**. We posit that abstracting away from related, but nonetheless hard problems, such as processing real-life videos and understanding complex, real-life dialogue between adults, will make for clean and isolated evaluation of the text generation techniques themselves.

Narration generation in the way we set it up, is a new task, distinct from video descriptions in certain aspects. Importantly, narrations are not metadata; they are meant to be uttered and become part of videos. Compared to descriptions, narrations provide high-level, less grounded information on events taking place in videos. In general, they do not articulate objects or actions that can be directly seen in the images and even in cases where they do, the description is tied to the context of the overall story. For example, the scene of Figure 1(1b), could be accurately described by “a pig in a bed, with a toy tucked up with it”. The narration, however, is context-aware: it refers to the pig as “George” and the toy as “Mr Dinosaur”.

Moreover, a narration may refer to events or objects that cannot be seen in the image. Image captioning algorithms face striking challenges when it comes to objects absent from query images, which can be easily inferred by humans (Bernardi et al., 2016), such as the “bus” in the caption of an image showing people waiting for a bus on a bench. Narrations may include contextual mentions to absent objects, such as the reference to “Mr Dinosaur” in Figure 1(2b); something that a viewer not familiar with the storyline could not have guessed. Finally, narrations may convey information less related to their accompanying video and more to the overall plot: Figure 1(3b), for example, makes a remark on Peppa looking after her brother, while the image just shows Peppa near a puddle.

Video narration generation bears resemblance to the task of automatic generation of sports broadcasts, known as sportscasts (Chen and Mooney, 2008). While sportscasts can have narrative structure (Herman et al., 2010), they are generated on the fly, and contain information related to what has been shown in the video up to the point of their utterance. Conversely, the narrations of our dataset are third-person omniscient narrations: the narrator knows everything related to the storyline and may use information that is being shown to the viewers while the narration is uttered or use forward references to events that are to unfold later in the video. In terms of content, sports commentary that does not simply describe the game, known as “color commentary” (Lee et al., 2014) is more relevant to movie narrations.

Our work is a step towards the direction of narrative content generation and serves as a proxy problem for several applications. Examples include not only sports, but also other types of commentary (such as director’s commentary in movies) or content for news summary videos (see Figure 2).

The contributions of this paper are as follows:
- We introduce and formalize the task of narration generation from videos.
- We develop a new cartoon video dataset for the task of narration generation.
- We present several models for narration gen-

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Footnote:
https://edition.cnn.com/us/live-news/george-floyd-protests-06-01-20/index.html, accessed 1 June 2020, 11:00.
Table 1: Statistics of the Peppa Pig dataset.

|                         | Value   |
|-------------------------|---------|
| **episodes**            | 209     |
| **total time**          | 1045 min|
| **time excl. intro & outro** | 927 min |
| **narrations**          | 1803    |
| **dialogue length (avg)** | 56.9 tokens |
| **narration length (avg)** | 10.7 tokens |
| **narration vocabulary** | 1771 words |
| **narration unique vocabulary** | 257 words |

A preprocessing step was carried out to make sure that all the videos are stripped out of unnecessary parts (each episode starts with the main character introducing herself and her family and usually ends with a song), subtitles are synchronized with the video, subtitle text is normalized, and each token of the text is aligned with a corresponding timeframe (a process called forced alignment). The resulting dataset is aligned at the token level, for image, audio and text modalities. Furthermore, sentences uttered by the narrator were semi-manually annotated. The annotation is relatively light, and does not require expert or crowdsourced annotators. Detailed account of the preprocessing and annotation steps can be found in Appendix B.

### Features

For each episode, we calculate feature vectors for the image and audio modalities, as follows. For image frames taken at the middle of each token, we use ResNet-50 (Residual Networks; He et al. 2016) and VGG-19 (from the the work of Visual Geometry Group; Simonyan and Zisserman 2014). For audio excerpts, after stripping the dialogues from the audio track, we calculate Mel-Frequency Cepstral Coefficients (MFCC; Mermelstein 1976) and VGGish features (Hershey et al., 2017; Gemmeke et al., 2017), which are reported to produce state-of-the-art results in audio classification and have also been used for video description (Hori et al., 2018).

### Comparison with Other Datasets

Our dataset adds to the set of existing datasets for multimodal video understanding. Table 2 lists features of several datasets pertaining to text generation from videos, such as video description and video question answering. The Peppa Pig dataset is the first dataset on narration generation.

### Narration as Video Summary

Narrations convey or hint at main events taking place during episodes. As such, they can be thought of as a form of video summary. In order to explore whether this is true for our dataset, we compare plot summaries and narrations using ROUGE, in order to assess the capability of an oracle narrator model as a summarizer. The generally low scores (16.42 ROUGE-1, 3.23 ROUGE-2 F1) lead to the conclusion that narration generation is quite a distinct task from summarization, and points to the value of a

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3 Information on the content of the dialogues is already present in the text modality.

4 This is the name of the pretrained model we used, available from [https://github.com/tensorflow/models/tree/master/research/audioset](https://github.com/tensorflow/models/tree/master/research/audioset).
Table 2: Multimodal datasets for tasks related to text generation from videos.

| dataset          | domain | task             | videos | avg len (sec) | vocab len (min) |
|------------------|--------|------------------|--------|--------------|-----------------|
| MSVD (Chen and Dolan, 2011) | open   | description      | 1,970  | 10           | 13,010          |
| MPII Cooking (Rohrbach et al., 2012) | cooking | description      | 44     | 600          | -               |
| YouCook (Das et al., 2013)       | cooking | description      | 88     | -            | 2,711           |
| TACoS (Regneri et al., 2013)     | cooking | description      | 127    | 360          | 28,292          |
| TACoS-ML (Rohrbach et al., 2014) | cooking | description      | 185    | 360          | -               |
| MPII-MD (Rohrbach et al., 2015)  | movie  | description      | 94     | 3.9          | 24,549          |
| M-VAD (Torabi et al., 2015)      | movie  | description      | 92     | 6.2          | 17,609          |
| MovieQA (Tapaswi et al., 2016)   | movie  | QA               | 408    | 7,200        | -               |
| PororoQA (Kim et al., 2016)      | cartoon | QA               | 171    | 432          | 3,729           |
| Peppa Pig         | cartoon | narration        | 209    | 300          | 1,771           |

3 Narration Generation

We formalize the task of narration generation as follows. Assuming a set of $M$ videos, for which $N$ modalities are available, we regard each video as a sequence of $T$ elements $x^k_{ji}$, $j \in \{1, 2, ..., M\}$, $i \in \{1, 2, ..., T\}$, $k \in \{1, 2, ..., N\}$, where $k$ indexes the modalities and $T$ varies between videos. The task is to identify which elements should belong to narration and generate appropriate text for them.

The segmentation in $T$ elements can be done in three different levels: dialogue-narration (D/N), token, and time. The first type splits the video in points where the dialogue ends and the narration begins and vice versa. The second type splits the video in every token of the dialogue, and the third is a time scale, meaning that the video can be split in any timestamp. Our proposed models use only the first two types of segmentation.

We divide the task of narration generation in two separate tasks, timing and content generation, each solving a particular challenge related to it.

Narration Timing refers to the task of figuring when to place narrations in a video. We model timing as a tagging task, where each time step is tagged with a label indicating whether narration follows in the sequence.

Depending on the type of input data, a narration may interrupt the flow of speech in the video (as is the case with Peppa Pig: while the narrator speaks, characters do not engage in dialogue) or it may be superimposed to the rest of the speech (in sportscasts, narrations overlap with other video sounds). In the former case, finding the timing can be regarded as an easier task, since a pause in dialogue can pinpoint the beginning of a narration. We model and experiment with the more general of the two, this is why we use incremental models that make predictions at each time step using information only from the previous and current time steps. This is a common setup not only in language modeling, but also in real-time (Cho and Esipova, 2016) or multimodal reasoning applications (Fermann et al., 2018). The constraint of incrementality, which can be satisfied using a unidirectional Long-Short Term Memory model (LSTM; Hochreiter and Schmidhuber 1997), is important, since look-ahead models allow information flow from future nodes, hinting the existence of narration.

Specifically, for this task, we use the token-level segmentation of the dataset and feed an incremental sequential model with multimodal representations (tokens along with corresponding image and audio features). Each token is annotated with a binary label, indicating whether there is at least one narration token in a window of $n$ tokens right after it. The obvious choice is $n = 1$, where each tag indicates whether the immediate next token belongs to narration. Additionally, inspired by work on speech dialogue turn-taking (Skantze, 2017), where $n > 1$ is used, we create annotations with $n = 5$. We refer to the two annotation schemes as Timing@1 and Timing@5. Figure 3 contains an annotation example from the Peppa Pig dataset.
Predicting the presence of narration in upcoming time steps is in fact a proxy of the timing problem, hence offering an upper bound on it. Using the actual narration text (and consequently the correct tokenization, which provides correct offsets when extracting images and audio excerpts to feed to the model), makes the task easier than it really is.

**Content Generation** refers to the task of figuring *what* to include in the narrations. In order to deal with content generation, we assume that timing is already solved and videos are correctly segmented into chunks of dialogue and narration.

We hypothesize that a human assigned with the task of coming up with a good narration for a specific part of a video would need to have access to information from several sources. The content of the dialogue preceding the narration is of utmost importance. Equally important are the actions or events taking place in the part of the video that is to be narrated. A narration generator model should have access to the same information, hence we propose a model with the following features:

- it takes into account the output of a multimodal dialogue encoder, which encodes dialogue data. We instantiate a token-level LSTM encoder, which combines information from text, image and audio.
- it takes into account the output of a video encoder, which encodes the part of the video to be narrated. Since the corresponding text is the desired output of our decoder, this is a video and audio decoder. Note that this encoder in principle does not have access to the narration tokenization, so it should not use the token segmentation, but a time segmentation (e.g. segment every 5ms).

A schematic overview of our proposed narrator model can be seen in Figure 4. We call this model *Dialogue Video Narrator (DiViNa)*.

**Multimodal representation** Efficient fusion of representations from different modalities in one, multimodal representation is an open research problem and the choice of fusion method reportedly has significant impact on downstream applications (Baltrusaitis et al., 2019). Broadly, fusion techniques are categorized in *early* (concatenation of representations at the feature level), *late* (concatenation of the output of modality-specific modules) and *hybrid fusion* methods (Attrey et al., 2010). Since we introduce the dataset and task, for simplicity, we employ early fusion in all our models.

4 Experiments

This section describes our experiments for both narration timing and content generation. This being a new task, we also present a set of baselines and report their effectiveness.

**Experimental Setup** For all models described, we use a similar experimental setup. LSTMs with one layer of hidden size 500 are used in places where sequence models are needed. We use GloVe embeddings (Pennington et al., 2014) of size 300 for text, ResNet-50 features for image and the concatenation of VGGish and MFCC features for audio. The input of multimodal modules is the concatenation of the representations of the different modalities, passed through a linear layer and a ReLU activation. The output size of this layer is 300. We train using the Adam optimizer (Kingma and Ba, 2014), with an initial learning rate of 0.001. During narration content generation training, we use teacher forcing (Williams and Zipser, 1989) with probability 0.5. Generation is performed using a beam search decoder, with beam size of 3.

4.1 Experiments on Timing

We conduct experiments on timing, by training an incremental sequence tagging model, using the Timing@1 and Timing@5 annotations. We experiment with unimodal (text-only) and multimodal (text, audio and video) models. The evaluation of the output of timing models is done using precision, recall and F1, as is appropriate for a tagging task. We train until the performance on the validation set stops increasing and report results on the test set. The corresponding results can be seen in Table 3. It appears that our models do not have a particularly hard time identifying whether narration follows in the next time steps. Interestingly, the multimodal variants outperform the unimodal ones.

4.2 Experiments on Generation

We experiment with several variations of our model and some simpler, text-only retrieval baselines. Note that the models described in this section are trained and evaluated in dialogue/narration pairs; a different split than that used for narration timing.

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6We decided on this particular combination after preliminary examination of all combinations of the features of the dataset.
puddles, you must wear your boots. Peppa ... brother, George

Figure 3: An excerpt of an episode of the Peppa Pig dataset, where all the levels of segmentation and tagging schemes for narration timing are shown. Timing@n refers to the annotation scheme, where binary labels indicate whether narration is present in a n-token window right after each token.

Figure 4: Dialogue Video Narrator (DiViNa) model. Green nodes operate on dialogue (trimodal input; text, audio, image), while yellow ones on the part of the video to be narrated (bimodal input; image and audio only). The outputs of the two encoders are used to initialize the decoder, which generates the narration text.

Table 3: Results for narration timing, using the Timing@1 (T@1) and Timing@5 (T@5) annotations. Multimodal variants use image, audio and text information.

| model               | pr  | rec | f1  |
|---------------------|-----|-----|-----|
| T@1, text-only      | 52.8| 71.9| 60.9|
| T@1, multimodal     | 58.8| 69.4| 63.6|
| T@5, text-only      | 48.7| 63.9| 55.3|
| T@5, multimodal     | 55.3| 61.0| 58.0|

The retrieval baselines work as follows: for each dialogue of the test split, instead of generating a narration from scratch, they select one from the training set, by identifying the dialogue from the training set that is closer to it. All presented retrieval methods use cosine similarity as a similarity metric. Four retrieval baselines are tested:

- **Retrieval-tfidf** uses Term Frequency - Inverse Document Frequency (TF-IDF) representation for dialogues and narrations.
- **Retrieval-BERT** makes use of pre-trained Bidirectional Encoder Representations from Transformers (BERT; Devlin et al. 2019) to represent both narrations and dialogues.\(^7\)
- **Retrieval-CCA** uses Canonical Correlation Analysis (CCA; Hotelling 1935) to project the dialogue and narration spaces to a shared space. At test time, dialogue representations are projected to the shared space and the narrations whose projections are closest to them are selected. For this baseline, TF-IDF vectors are used for both dialogues and narrations. The CCA dimensionality is 300.\(^8\)

We compare the output of the baselines with that of several variants of the DiViNa model:

- **DiViNa** is the model depicted on Figure 4. The dialogue encoder takes as input the concatenation of text, audio and image information at each timestep $t$:
  \[ x_t = \text{ReLU}(W[x_T^T; x_A^T; x_I^T]). \]

The video encoder operates on the part of the video to be narrated; its input is image and audio at each timestep $t'$:
  \[ y_t = \text{ReLU}(W[y_I^T; y_A^T]). \]

The hidden states of the last elements of those encoders, $h_T^{(d)}, h_T^{(v)}$, respectively, are used to initialise the decoder, after being passed through a linear layer to reduce its size:
  \[ h_0 = \text{ReLU}(W[h_T^{(d)}; h_T^{(v)}]). \]

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\(^7\)We used bert-as-a-service (https://github.com/hanxiao/bert-as-service) with the BERT-Base, Uncased pre-trained model.

\(^8\)We also experimented with 100, 500 and 1000; all yielded lower performance.
| model                  | BLEU-1 | BLEU-2 | BLEU-3 | ROUGE-L | METEOR | CIDEr |
|------------------------|--------|--------|--------|---------|--------|-------|
| Retrieval-tfidf        | 17.73  | 10.37  | 6.18   | 16.43   | 9.16   | 30.84 |
| Retrieval-CCA          | 13.45  | 7.45   | 4.74   | 12.77   | 6.39   | 21.20 |
| Retrieval-BERT         | 14.83  | 7.81   | 4.70   | 13.98   | 7.16   | 19.41 |
| DiNa+att               | 8.19   | 3.88   | 2.34   | 12.00   | 4.84   | 4.36  |
| DiViNa                 | 17.35  | 9.65   | 6.22   | 15.25   | 7.99   | 24.02 |
| DiViNa+att             | 15.70  | 8.59   | 5.82   | 13.71   | 6.88   | 25.42 |
| Di²ViNa                | 17.67  | 10.26  | 6.76   | 15.23   | 8.17   | 23.61 |
| Di²ViNa+att            | 18.45  | 9.88   | 5.94   | 15.54   | 7.82   | 22.04 |
| DiViNa+mmd             | 23.20  | 13.71  | 8.95   | 20.51   | 11.15  | 49.29 |
| DiViNa+att+mmd         | 20.43  | 12.03  | 7.86   | 17.71   | 9.22   | 40.82 |
| Di²ViNa+mmd            | 24.57  | 15.90  | 11.72  | 21.70   | 12.06  | 67.24 |
| Di²ViNa+att+mmd        | 22.93  | 14.79  | 10.36  | 19.96   | 10.74  | 52.93 |

Table 4: Results for narration content generation. The first section of the table refers to text-only baselines, while the rest of the table refers to multimodal models. The third section includes results for models using the multimodal decoder (mmd), thus having information about the desired length of the narration. The highest values are in boldface, while the highest scores for models that do not use the mmd are in italics.

- **DiViNa+att** is the DiViNa model equipped with an attention mechanism over the states of the dialogue encoder. For this and other attentive variants, we make use of dot product attention (Luong et al., 2015), where the attention scores between encoder ($h_i$) and decoder ($h^{(dec)}_t$) hidden states are calculated as follows:

$$\text{score}(h^{(dec)}_t, h_i) = h^{(dec)}_t ^\top h_i.$$  

- **DiNa+att** is a variant of the DiViNa+att model, with no video encoder. The narration is generated based on the preceding dialogue only; hence, the decoder is initialised with $h_0 = \text{ReLU}(Wh^{(d)}_T)$.

- **Di²ViNa, Di²ViNa+att**: Motivated by the omniscience of the narrator in the dataset, these models use the dialogue that follows the video to be narrated. This is achieved by encoding the dialogue following the narration using a separate dialogue encoder and feeding its output $h^{(fd)}_{T'}$ to the decoder:

$$h_0 = \text{ReLU}(W[h^{(d)}_T; h^{(v)}_T; h^{(fd)}_{T'}]).$$

The Di²ViNa variants are the only models that look ahead in time while generating narrations, thus being able to incorporate forward reference information. DiViNa variants use only past and present information; a setup consistent with sports commentary.

- **DiViNa+mmd**: In order to be able to use the audio and image representations which are available for the narration part, we use a multimodal decoder (mmd). The basic function of such a decoder is shown in Figure 5. During training, the fusion of image, audio and text representations is given to the decoder at each time step. Even when not using teacher forcing (i.e., when feeding the predictions of the previous step to the next step), the input of the decoder is the concatenation of the “correct” audiovisual representations and the word embedding of the token generated by the previous step. At test time, decoding proceeds for as many steps as the number of audiovisual representations available.

An obvious limitation of mmd is that it cannot generate narrations of arbitrary length. This is not necessarily a constraint though, since some narration setups call for narrations of predefined length, as is the case for the Peppa Pig dataset. Since multimodal information is necessary at each timestep, quantization of the video chunk to be narrated should be done before the start of the decoding process. The known quantization assumption is quite fair, since an estimation of the length of the narration will most likely be available in all situations (for example, it can be calculated by dividing the time between two dialogues with the mean time it takes a narrator to utter a word). In our experiments, we exploit the known tokenization of narrations to extract multimodal representations to
Figure 5: Multimodal Decoder used in mmd variants of DiViNa and comparison with Text-only decoder. At each timestep, audio (A) and image (I) representations are fed to the decoder, along with the word embedding of the corresponding token (T). In this case, the previously generated token is used (no teacher forcing).

feed to the decoder. As such, this model variant has access to more information than its counterparts.

In all models containing a video encoder for the narration part, we made the simplifying choice to use the correct tokenization of the narration from the dataset, despite the fact that, normally, a narrator model will not have access to that information.

Narration generation is a natural language generation (NLG) task, and as such, its evaluation is not straightforward. Automatic evaluation of NLG systems is an open problem and widely used metrics are under heavy criticism by the community (Callison-Burch et al., 2006). Following previous work on NLG, ranging from image captioning (Xu et al., 2015) to summarization (See et al., 2017), we report a set of word overlap metrics, complementary to each other. In the case of narration generation, these metrics compare narrations from the dataset with those generated by our systems, without considering the videos. The scores for all models can be seen in Table 4.

The generally low scores of the retrieval models suggest that the task of narration generation is not trivial and highlights the need for more sophisticated generative models. Quite interestingly though, the simple TF-IDF retrieval baseline not only outperforms other text-only retrieval baselines, but also performs on par with some of the simplest generation multimodal models.

The significantly lower performance of DiNa+att suggests that encoding the video of the part to be narrated is of high importance. Equally important is encoding the upcoming dialogue, as suggested by the generally higher scores of the Di²ViNa variants. The attentive variants of all models seem to perform lower than their non-attentive counterparts. A reason for that may be that they base their predictions more on the preceding dialogue (since they attend to it), while the contributions of the other encoders are downgraded. These results highlight a distinctive quality of the task of narration generation: the significance of effective combination of information from the past (preceding dialogue), the present (video to be narrated) and the future (upcoming dialogue).

The fact that variants using the multimodal decoder (mmd) outperform all other variants does not come as a surprise, since they have access to more information during decoding and also generate narrations of the right length, by design. Examples of the generated narrations are shown in Figure 6.

| M: Peppa and jumping up and down in muddy puddles. Everyone loves jumping up. |
| GT: Everyone in the whole world loves jumping up and down in muddy puddles. |
| M: Suzy sheep has come to play on the. |
| GT: Peppa has come to play with Suzy sheep. |
| M: It is bedtime for Peppa and George are very sleepy. |
| GT: It is nighttime. Peppa and George are going to bed. |

Figure 6: Examples of output of Di²ViNa+mmd, paired with respective ground truth narrations (M stands for model, GT for ground truth).

5 Conclusions

In this paper, we introduce and formalize the task of narration generation from videos. Narration generation refers to the task of accompanying videos with text snippets in several places: text that is meant to be uttered by a narrator and become part of the video. The task of narration generation adds to the set of research tasks related to text generation from multimodal input. The problem includes a timing (figuring out when to narrate) and a content generation (figuring out what to include in the narration) part. Due to this dual nature of the problem, along with the fact that the content of narrations is, in general, context-aware and not particularly descriptive of the images shown in the video, we believe that this is a new and challenging task.

To facilitate research in the direction of automatic narration generation, we create a dataset from the animated television series Peppa Pig, whose episodes include narration. We propose neural models to tackle both problems of narration timing.
and content generation and report the first results on the newly introduced task and dataset.

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A Dataset Characteristics

Figure 7: Histograms of characteristics of Peppa Pig narrations. The length of narrations in sentences and tokens, the start time position within the episode and the number of narrations per episode are listed.

B Dataset Preprocessing

Each episode was preprocessed as follows:

- Double episodes were split to two separate episodes and corresponding subtitles were manually synchronized with the video.

- Each episode was trimmed to the correct length. Commonly, episodes start with an “introduction” part, in which Peppa, the main character, introduces herself and her family. This part, which usually lasts less than two minutes, was manually removed from the episodes of the dataset.

- The audio channel was extracted from each episode.

- We performed normalization of the text, by manually inspecting it. Since Peppa Pig is a cartoon targeting young children, animal sounds and sound effects are abundant in its dialogues. We manually identified and normalized such instances. As an example, all the occurrences of “oink”, “ooink”, “oinking”, “big oink”, “loud snort” etc. were normalized to “pig sound” for text application and to a special noise token (“{ns}”) for forced alignment purposes (see next step).

- The subtitles were aligned with the audio channel in the token level. We used the Penn Forced Aligner (p2fa; Yuan and Liberman 2008) for that.

- After forced alignment, using ffmpeg, we extracted frames (snapshots from the video) for every token, at timestamps corresponding to the beginning, the end and the middle of the token timeframe.

- Annotation of the narrator: the sentences uttered by the narrator were semi-manually annotated. Some subtitles, especially those that contained the first utterance of the narrator after a dialogue between the characters, begin with a tag (“[NARRATOR]” – subtitles are mostly meant for the hearing impaired, since Peppa Pig is aimed at preschoolers). However, the use of this cue is not consistent, and also, it is not used more than once in consecutive narrator subtitles. First, we annotated the subtitles beginning with the “NARRATOR” tag as belonging to the narrator, and a second manual pass was done to ensure that all narrations are properly tagged as such.

- MFCC features were calculated using the tool aubio.

- The preprocessing and the annotation was done by the authors, as it is relatively light and does not require expert or crowdsourced annotators.

C Narration as Video Summary

Besides their apparent purpose in books and videos, narrations can also serve as a form of summary. Consider for example, narrations from two episodes of Peppa Pig along with their corresponding plot summaries (from IMDb) and plot sentences (from Wikipedia), shown in Figure 8. Clearly, the narrations are more elaborate, but do not fail to convey the main events taking place during the episode. Narrations and plot summaries

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10 most video files contained two episodes. 
11 https://www.ffmpeg.org/
12 https://aubio.org/
13 www.imdb.com
14 en.wikipedia.org/wiki/List_of_Peppa_Pig_episodes, not available for all episodes.
can both be regarded summaries of the video, in
different layers of abstraction.

| narration |
|-----------|
| It is raining today, so Peppa and George cannot play outside. Peppa loves jumping in muddy puddles. George likes to jump in muddy puddles, too. Peppa likes to look after her little brother, George. Peppa and George are having a lot of fun. Peppa has found a little puddle. George has found a big puddle. George wants to jump into the big puddle first. Peppa and George love jumping in muddy puddles. Peppa and George are wearing their boots. Mummy and Daddy are wearing their boots. Peppa loved jumping up and down in muddy puddles. Everyone loves jumping up and down in muddy puddles. |

| plot summary |
|--------------|
| It is raining and Peppa is sad because she cannot go outside. When the rain stops, Peppa and George get to play one of their favourite games - jumping in muddy puddles. Things get very muddy indeed when Mummy and Daddy Pig join in. |

| plot |
|------|
| Peppa and George get very muddy after playing their favourite game - Muddy Puddles. |

| narration |
|-----------|
| Mommy Pig is working on her computer. Daddy Pig is making soup for lunch. Mommy Pig has a lot of important work to do. Peppa and George love to watch Mommy work on the computer. Oh, dear, the computer is not meant to do that. Daddy Pig is going to mend the computer. Daddy Pig has mended the computer. |

| plot summary |
|--------------|
| Peppa and George accidentally break Mummy Pig’s computer, so Daddy Pig tries to fix it. |

| plot |
|------|
| Peppa breaks Mummy Pig’s computer while she is working. |

To further explore this idea, we compare the plot summaries and the narrations of the dataset, in order to assess the capabilities of an oracle narrator model as a summarizer. We work on the full dataset and construct “summaries” by concatenating all the correct narration sentences for each episode. Table 5 reports ROUGE scores (Lin, 2004) for full length summaries and limited length summaries (75 bytes). 

| 75 bytes | metric | prec | rec | f1 |
|----------|--------|------|-----|----|
| ROUGE-1  | 19.98  | 19.40| 19.65|
| ROUGE-2  | 5.61   | 5.48 | 5.53 |
| ROUGE-L  | 15.32  | 17.87| 16.47|

| full length | metric | prec | rec | f1 |
|-------------|--------|------|-----|----|
| ROUGE-1     | 31.74  | 11.88| 16.42|
| ROUGE-2     | 6.27   | 2.37 | 3.23 |
| ROUGE-L     | 28.22  | 10.55| 14.58|

Table 5: ROUGE scores (precision, recall and F1) comparing the plot summaries to the corresponding narration sentences of each episode.

Figure 8: Narrations and plot summaries from two episodes, Episode 1: Muddy Puddles and Episode 7: Mummy Pig at Work.