mAnI: Movie Amalgamation using Neural Imitation
Visualizing the Movie while Reading a Book

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ABSTRACT
Cross-modal data retrieval has been the basis of various creative tasks performed by Artificial Intelligence (AI). One such highly challenging task for AI is to convert a book into its corresponding movie, which most of the creative film makers do as of today. In this research, we take the first step towards it by visualizing the content of a book using its corresponding movie visuals. Given a set of sentences from a book or even a fan-fiction written in the same universe, we employ deep learning models to visualize the input by stitching together relevant frames from the movie. We studied and compared three different types of setting to match the book with the movie content: (i) Dialog model: using only the dialog from the movie, (ii) Visual model: using only the visual content from the movie, and (iii) Hybrid model: using the dialog and the visual content from the movie. Experiments on the publicly available MovieBook dataset shows the effectiveness of the proposed models.

CCS CONCEPTS
•Computing methodologies → Cognitive science; Learning latent representations;

KEYWORDS
creative AI, multi-modal learning, deep learning

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1 INTRODUCTION
Being able to fluently understand, retrieve, and generate cross-modal data, like humans do, has been the holy grail search in Artificial Intelligence (AI). Language and vision has been considered as the most common and challenging domains to measure the growth of artificial intelligence. Describing an image in words (image captioning) and imagining a text through images (visual abstraction/description) is highly natural and seamless for human beings. While reading a gripping novel or a book, we often tend imagine the storyline and the plots through visuals. If a corresponding movie or video exists for a book, most of the imaginative visuals are borrowed from the movie and mapped with the book stories. Another common example is of the movie director (or a movie creation crew), who produces a movie from a book or storyline through creative visualizations.

Consider the example book snippet from *Harry Potter and the Philosopher’s Stone* -

> Professor McGonagall peered sternly over her glasses at Harry. “I want to hear you’re training hard, Potter, or I may change my mind about punishing you.” Then she suddenly smiled. “Your father would have been proud,” she said. “He was an excellent Quidditch player himself.”

Prof. McGonagall

It is natural for readers to imagine and visualize this book snippet through snippets from the corresponding movie. Figure 1 shows two possible visualizations of the book snippet as imagined by two different readers. These visualizations provide information rich interpretations to the books. The examples are not only restricted to the actual book snippets but also towards any fandom, as the following one -

> “As such I do not expect anyone to understand the subtleties of using machine learning in creativity”, scowled Snape, as he charged into the dark classroom and glared into Harry’s pale blue eyes. “However, our celebrity Harry Potter,” he paused, “could probably enlighten us with what would happen if I added a LSTM over a CNN”

Fan Fiction

Figure 2 shows two possible visualizations of the fan fiction of the same book, *Harry Potter and the Philosopher’s Stone*. Motivated by such human behaviors, in this research, we attempt to describe constituent parts of a book or a story through its corresponding movie visuals.

The publicly available MovieBook [18] dataset contains manually defined alignment of 11 movies with their corresponding books. Given a book snippet, we retrieve a sequence of movie snippets describing that book snippet, using three independent models:

(1) **Dialog model**: Relevant movie snippets are retrieved by matching the text dialog of the movie with the input book snippet using a skip-thought model [4]

(2) **Visual model**: Relevant movie snippets are retrieved by matching only the visual cues of the movie scene with the input book snippet using a neural-storyteller model ¹

(3) **Hybrid model**: Relevant movie snippets are retrieved using both the text dialog and the visual cues from the movie scene

The rest of the paper is organized as follows; Section 2 talks about existing literature, Section 3 details the dataset used in this

¹https://github.com/ryankiros/neural-storyteller
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were able to perform both video to text generation and text based video. The representation for each frame was obtained using a deep Book2Movie the book content as the input which is, in general, more prose and of information such as movie plot, movie video, subtitle, scripts, and proposed by Tapaswi et al. [11]. A memory network based question results in 8 different tasks without the need for task adaptation. came up with an unsupervised method of learning sentence repre-

sentation called skip-thought vectors which provided comparable results in 8 different tasks without the need for task adaptation.

Ng et al. [17] considered each frame of a video as a word in a sentence and learnt an LSTM network to temporally embed the video. The representation for each frame was obtained using a deep CNN making the overall network as a CNN-LSTM deep network. Donahue et al. [3] proposed a Long-Term Recurrent Convolutional Network (LRCN) model for conditionally embedding the video based on the task to be performed. Venugopalan et al. [14] learnt a sequence to sequence model to encode a video frame sequence using an LSTM network and decode its corresponding caption using a conditional LSTM. For understanding large pieces of text, using an LSTM network and decode its corresponding caption us-

ing a sequence to sequence model to encode a video frame sequence based on the task to be performed. Venugopalan et al. [14] learnt a sequence to sequence model to encode a video frame sequence using an LSTM network and decode its corresponding caption using a conditional LSTM. For understanding large pieces of text, Le and Mikolov [5] extended a word representation word2vec to learn paragraph and document level representation. Arora et al. [1] proposed a simple method of averaging the word embeddings over a sentence and modifying it using PCA. Recently, Kiros et al. [4] came up with an unsupervised method of learning sentence representation called skip-thought vectors which provided comparable results in 8 different tasks without the need for task adaptation.

The closest work to our research is the MovieQA system proposed by Tapaswi et al. [11]. A memory network based question answering system is built on a movie corpus using multiple sources of information such as movie plot, movie video, subtitle, scripts, and Described Video Service (DVS) transcriptions. Our work considers the book content as the input which is, in general, more prose and descriptive than a movie plot or script. Tapaswi et al. [10] further proposed Book2Movie which aims to align book chapters to its corresponding movie scenes. We are working at a much granular level of sentences rather than an entire chapter, which is a more challenging task. Our work is built upon Zhu et al. [18] aligning books and movies at sentence level. While they have performed experiments on describing movies in terms of the book, we attempt to describe the book in terms of the movie which is considered a much more creative problem.

2 LITERATURE STUDY

The defined problem statement requires the understanding of both the domains: video analysis and natural language processing. Textual content and concept based video retrieval has been well explored in the literature [2, 6, 8]. Yang and Meinel [16] used Optical Character Recognition (OCR) and Automatic Speech Recognition (ASR) to transcribe content from video lectures and perform querying over the extracted content. Tian et al. [12] further extended this by tracking textual content across the frames in a video for a better content generation. Xu et al. [15] learnt a joint text-video embedding model built over independently learnt deep models of language semantic understanding and video embedding. Thus, they were able to perform both video to text generation and text based video retrieval using the joint model.

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3 DATASET

Built upon the work by Zhu et al. [18], the MovieBook dataset is the highly relevant for our problem statement. The dataset contains visual clips (roughly spanning for few seconds) from movies, corresponding dialogue text (SRT) for the visual clips, and small chunks of book text (roughly 3-10 lines) for 11 different books. A manual alignment is available for a part of each book and each alignment is done using one of the three cues: (i) Visual cue based on the movie clip, (ii) Dialog cue based on the dialog spoken during that clip, and (iii) Audio cue based on the audio during that clip. The properties of this dataset are shown in Table 1. From the collection of 11 book-movie pairs, there are a total of 29,436 book paragraphs, 19,985 movie shots, and 16,909 sentences in dialogue subtitles. Using this corpus, a total of 1,449 (book paragraph, movie shot) pairs were manually aligned using the dialog subtitles while 621 pairs were aligned using the visual content of the movie shot.

Additional to the MovieBook dataset, a huge corpus of books is used to train a model for sentence representation. The Book-Corpus dataset has more than 11,000 from 16 different genres containing more than 11 million sentences and a skip-thought model [4] is trained to learn a sentence representation. The pre-trained model is already publicly available at: https://github.com/ryanKiros/skip-thoughts.

4 PROPOSED APPROACH

The overall proposed approach has three different models and is illustrated in Figure 3. The individual steps and their training procedure is explained in detail in this section.

4.1 Book Sentence and Movie Dialog Representation

For every chunk of the book or a dialog snippet, a sentence representation model is learnt using skip-thought vectors [4], one of the state-of-art models for unsupervised learning of text sequences. The skip-thought vector model is a natural encoder-decoder style

| TABLE 1: Statistics for MovieBook dataset [18] with ground-truth for alignment between books and their movie releases. |
| Title                  | # sent. | # words | # unique words avg. | # words per sent. | max # words per sent. | # para. graphs | # shots | # sent. in subtitles | # dialog align. | # visual align. |
|------------------------|---------|---------|---------------------|------------------|----------------------|----------------|---------|-----------------------|-----------------|----------------|
| Some Girl              | 12,003  | 1,05,349| 3,949               | 15               | 135                  | 3,537          | 2,604   | 2,255                 | 16              | 104            |
| Fight Club             | 4,229   | 48,946  | 1,833               | 14               | 90                   | 2,082          | 2,365   | 1,864                 | 104             | 42             |
| No Country for Old Men | 8,050   | 69,824  | 1,704               | 10               | 68                   | 3,189          | 1,348   | 889                   | 223             | 47             |
| Harry Potter and the Sorcerers Stone | 6,458 | 78,956 | 2,863               | 15               | 227                  | 925            | 2,647   | 1,227                 | 164             | 73             |
| Shawshank Redemption   | 2,562   | 40,140  | 1,360               | 18               | 115                  | 637            | 1,252   | 1,879                 | 44              | 12             |
| The Green Mile         | 9,467   | 13,324  | 3,043               | 17               | 119                  | 2,760          | 2,350   | 1,846                 | 208             | 102            |
| American Psycho        | 11,992  | 1,45,611| 4,632               | 16               | 422                  | 3,945          | 1,012   | 1,311                 | 278             | 85             |
| One Flew Over the Cuckoo Nest | 7,103 | 11,979 | 2,949               | 19               | 192                  | 2,236          | 1,671   | 1,553                 | 64              | 25             |
| The Firm               | 15,498  | 1,35,529| 3,685               | 11               | 85                   | 5,223          | 2,423   | 1,775                 | 82              | 60             |
| Brokeback Mountain     | 638     | 10,640  | 470                 | 20               | 175                  | 167            | 1,205   | 1,228                 | 80              | 20             |
| The Road               | 6,688   | 58,793  | 1,580               | 10               | 74                   | 2,345          | 1,108   | 782                   | 126             | 49             |
| All                    | 38,238  | 9,80,699| 9,032               | 15               | 156                  | 29,436         | 19,985  | 16,909                | 1,449           | 541            |

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extension of skip-gram model for word embedding learning. Given a tuple of three sentences, \( \{ s_{i-1}, s_i, s_{i+1} \} \), the RNN model encodes the sentence \( s_i \) and two decoders attempt to predict the sentence \( s_{i-1} \) and \( s_{i+1} \), conditional on the encoding, as shown in Figure 4. Thus, such a model requires tuples of three sentences and can be trained in an unsupervised fashion. Kiros et al. [4] further show that a generic sentence representation model trained on a huge corpus of books can be directly used in eight different applications without the need for fine-tuning or task adaptation. Owing to the generalizable nature of the skip-thought model, we use the available pre-trained model for directly extracting the representation of both book sentences and movie dialogue.

### 4.2 Movie Video Representation

Representing videos as an embedded vector representation is well studied. In this research, we want to textually describe a movie clip so that semantic similarity could be computed with the book snippet. Image captioning and video captioning techniques could generate a single sentence caption for an image or a video. Recently, neural-storyteller\(^2\) conditioned the image caption on an RNN to generate a longer story to explain a single image. In this research, we explain the neural-storyteller style of model to generate a longer story for a video than for a single image. Given a video frame, an image caption is generated for every frame using an encoder-decoder model as proposed in [10]. Conditioned on the combined frame captions, an RNN decoder generates a story explaining the entire video clip. The details of the model is explained here: https://github.com/ryankiros/neural-storyteller and the process is illustrated in Figure 5. From an input video sequence, frame are sampled at regular intervals at 2fps. For every frame, a caption is generated using a standard image captioning model. All the generated captions are pooled and provided as input to a conditional LSTM decoder, which generates a story that represents the entire video sequence and not each frame in the video. It can be observed from the generated story shown in Figure 5, that the swimming pool is semantically being mapped to water, the person is being mapped as “her” due to the presence of long hair, and specific semantic attributes are extracted such as shirtless man, being top of surfboard. These semantically extracted text could be used to map with the book paragraph which are typically descriptive, in nature.

\(^2\)https://github.com/ryankiros/neural-storyteller
4.3 Extraction through Dialog Model

In this model, a similarity metric learnt between the book sentences and only the dialog (SRT) in the video, without leveraging any visual content of the movie. Given a pair of book sentence and dialog, their respective representations, $\bar{b}$ and $\bar{d}$ are computed using the skip-thought model. As proposed in [9], $\bar{b} \cdot \bar{d}$ and $\text{abs}(|\bar{b} - \bar{d}|)$ are computed and concatenated. Over these representations, a regression based semantic similarity model is trained [9].

During test phase, for a given book sentence or a random fan fiction sentence, its skip-thought representation is calculated and the semantic relevance is computed against all the dialog sentences available. A list of those dialog sentences above a threshold, $t$, is shortlisted as the relevant movie parts that explains the input book sentence. The video clips corresponding to the retrieved dialog sentences are stitched together and provided to the user.

4.4 Extraction through Visual Model

For this model, only the book sentences and the video clips are used while the dialog sentences are not used. For a given video clip, a story explaining that video clip is automatically generated using the approach proposed in the Section 4.2. For the automatically extracted story, a skip-thought representation is extracted, so that, both the book sentence and video clips is in the same feature space.

In this space, the similarity classifier can be trained and tested in the similar way, as explained in Section 4.3.

4.5 Extraction through Hybrid Model

To match a book with the corresponding video clip, in this hybrid model, we leverage both the video information as well as the dialog information. For a given book sentence, the similarity score for all the dialog sentences is obtained using the dialog model explained in Section 4.3 and the similarity score is obtained with all the video clips using the Visual model explained in Section 4.4. A sum score fusion is performed between the two lists of obtained similarity score, and a the threshold is applied on the fused score. The movie clips corresponding to the retrievals are stitched to provide the book visualization.

5 EXPERIMENTAL STUDY

The experiments are conducted on the publicly available MovieBook Corpus. The only trainable model is the semantic similarity model explained in Section 4.3. The entire data is split between 60% for training, 20% for validation, and 20% testing. Thus, for the Dialog model, there are 1842 for training samples and 616 test samples while for the Visual model 776 samples are used for training and 258 samples for testing. To compare with the proposed similarity model, a cosine distance based similarity metric as well the similarity model proposed by Tai et al. [9] and trained on SICK dataset, are used.
The performance of the proposed pipeline is evaluated using top-k Movie Retrieval Accuracy (MRA). This measure calculates the percentage of book sentences input for which all the retrieved movie clips are from the same movie as the input. The performance of the Dialog model and the Visual model are shown in Figure 6 and Figure 7, respectively. The major observations obtained from the results are as follows:

1. A rank-10 MRA of 80% is obtained for the Dialog model and 71% MRA is obtained for the Visual model, using the proposed approach. The proposed semantic similarity fared better or comparable to the other two approaches, showing the effectiveness of the similarity method.

2. Although the dataset provides the ground truth alignment, the exact aligned video snippet retrieval accuracy for a given book sentence is irrelevant for our experiments. For a given book sentence, there can be multiple parts in the movie that is semantically related and retrieving those movie snippets is the creative task at hand and not just the manually aligned movie snippet. Thus, the movie retrieval accuracy is a strong measure to evaluate our creative system rather than the exact alignment retrieval accuracy.

To show the effectiveness of the combined Dialog and Visual Model, a Hybrid model was trained on the entire test set and the results are shown in Figure 8. The results shows that the hybrid model performs better than the individual models at all ranks, suggesting to use both the modalities for matching during movie retrieval. From Figure 8, it can observed that the Dialog model performs much better than the Visual model, suggesting that the dialog has richer information than the visual content. The same observation is extended to the Hybrid model, as the Hybrid does not show a rapid improvement compared to the Dialog model. However, there are certain caveats in this comparison as the Visual model is trained on a much smaller dataset compared with the Dialog model. A working example of the Dialog Model and the Visual Model is shown in Figure 9 and Figure 10, respectively.

### 6 CONCLUSION AND FUTURE WORK

In this research, we proposed a creative system which could visualize a snippet of book content using its corresponding movie visuals. We devised three models to retrieve semantically similar movie content of a book snippet: (i) a dialog model which use only the dialog content from the movie, (ii) a visual model which uses only the visual content from the movie, and (iii) a hybrid model which combines both the visual and dialog content from the movie.
**Book Line:** "Harry - your a wizard." There was silence inside the hut. Only the sea and the whistling wind could be heard. "I'm a what?" gasped Harry. "A wizard, of course," said Hagrid, sitting back down on the sofa, which groaned and sank even lower, "and a thumping goodun, I'd say, once you've been trained up a bit., With a mum and dad like yours, what else would you be?

**SICK Similarity:** Subtitle [00.15.04.701 to 00.15.06.620] Learned what You're a wizard Harry

**Cosine Similarity:** Subtitle [00.15.06.620 to 00.15.10.373] You're a wizard Harry. I'm a what A wizard!

**Book-Movie Similarity:** Subtitle [00.15.06.620 to 00.15.10.373] You're a wizard Harry. I'm a what A wizard!

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**Book Passage:** The thing is"-he frowned-"she acts like she … of it till about Wednesday of the next week, …and move to the swimming pool. The pool always scared me; I was always afraid … be sucked off down the drain and clean out to sea …. real brave around water … Columbia; I'd walk the scaffolding around the falls with all the other men, scrambling around with water roaring green and white all around me and the mist making rainbows, without even any hobnails like the men wore.

**SICK Similarity:** Shots retrieved: 01.08.39.722 to 01.08.44.135

**Cosine Similarity:** Shots retrieved: 00.48.07.056 to 00.48.11.311

**Book-Movie** Shots retrieved : 01.09.39.722 to 01.09.44.135

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**Figure 9:** A working example of the results obtained by the Dialog Model. The input book line and the video retrievals from the "Harry Potter: The Philosopher's Stone" movie using the three similarity measures.

**Figure 10:** A working example of the results obtained by the Visual Model. The input book line and the video retrievals from the "One Flew Over the Cuckoo's Nest" movie using the three similarity measures.
A frame-wise conditional LSTM based decoder is used to generate a single story explaining a movie snippet. Experimental results on the publicly available MovieBook dataset, shows the effectiveness of the proposed hybrid model providing around 80% rank-10 retrieval accuracy.

In future, we plan to extend this approach by creatively generating animated images and video snippets that explains a book snippets [7] [13]. Thus, the proposed pipeline could be used for unseen book or for books which do not have a corresponding movie and their corresponding visual abstractions could be generated. Such a creative system would eventually be of great use for creative directors and advertisement film makers as they can visualize stories and scripts before the movie is being produced.

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