Condensed Movies: Story Based Retrieval with Contextual Embeddings

Max Bain[0000–0002–2345–5441], Arsha Nagrani[0000–0003–2190–9013], Andrew Brown[Ⅰ], and Andrew Zisserman[0000–0002–8945–8573]

Visual Geometry Group, University of Oxford
http://www.robots.ox.ac.uk/~vgg/research/condensed-movies
{maxbain,arsha,abrown,az}@robots.ox.ac.uk

Abstract. Our objective in this work is the long range understanding of the narrative structure of movies. Instead of considering the entire movie, we propose to learn from the ‘key scenes’ of the movie, providing a condensed look at the full storyline. To this end, we make the following four contributions: (i) We create the Condensed Movie Dataset (CMD) consisting of the key scenes from over 3K movies: each key scene is accompanied by a high level semantic description of the scene, character face tracks, and metadata about the movie. Our dataset is scalable, obtained automatically from YouTube, and is freely available for anybody to download and use. It is also an order of magnitude larger than existing movie datasets in the number of movies; (ii) We introduce a new story-based text-to-video retrieval task on this dataset that requires a high level understanding of the plotline; (iii) We provide a deep network baseline for this task on our dataset, combining character, speech and visual cues into a single video embedding; and finally (iv) We demonstrate how the addition of context (both past and future) improves retrieval performance.

Keywords: story understanding, video retrieval, context, movie dataset

1 Introduction

Imagine you are watching the movie ‘Trading Places’, and you want to instantly fast forward to the scene where ‘Billy reveals the truth to Louis about the Dukes bet, a bet which changed both their lives’. In order to solve this task automatically, an intelligent system would need to watch the movie up to this point, have knowledge of Billy, Louis and the Duke’s identities, understand that the Duke made a bet, and know the outcome of this bet (Fig. 1). This high level understanding of the movie narrative requires understanding characters’ identities, their motivations and conversations, their behaviour and the overall impact of these on situations. Since movies and TV shows can provide an ideal source of data to test this level of story understanding, there have been a number of movie related datasets and tasks released recently by the computer vision community [4, 40, 48, 55].

However, despite this recent proliferation of movie-related datasets, high level semantic understanding of human narratives still remains a largely unsolved task. This is because of a number of reasons: (i) semantic annotation is expensive and
Billy reveals the truth to Louis about the Duke’s bet which changed both their lives.

Fig. 1: Story-based Retrieval: Retrieval of a key scene in a movie from a text based query. Note how the retrieval of the correct scene (highlighted in green) for the given query is based on the knowledge of past scenes in the movie – one where Duke makes a bet and another scene showing their lives before the bet (as homeless).

challenging to obtain, inherently restricting the size of current movie datasets to only hundreds of movies [4, 40, 48, 55]; (ii) movies are very long (roughly 2 hours) and video architectures struggle to learn over such large timescales; (iii) there are legal and copyright issues surrounding a majority of these datasets [4, 48, 55], which hinder their widespread adoption in the community; and finally (iv) the subjective nature of the task makes it difficult to define objectives and metrics – for example recent results [4] have called into question the effectiveness of some multimodal video understanding models in the movieQA benchmark [51], that are outperformed by text-only models.

A number of different works have recently creatively identified that certain domains of videos, such as narrated instructional videos [33, 46, 59] and lifestyle vlogs [15, 20] are available in huge numbers on YouTube and are a good source of supervision for video-text models as the speech describes the video content. In a similar spirit, videos from the MovieClips channel on YouTube1, which contains the key scenes or clips from numerous movies, also contains a semantic text description that describes the content of each clip. We download these videos to create a dataset of ‘condensed’ movies, called the Condensed Movie Dataset (CMD) which provides a condensed snapshot into the entire storyline of a movie. In addition to just the video, we also download and clean the high level semantic descriptions accompanying each key scene (Figures 2 and 3) that describes characters, their motivations, actions, scenes, objects, interactions and relationships. Our dataset consists of over 3000 movies, and for each movie we obtain associated metadata (such as cast lists, year, genre).

Armed with this new source of supervision, we then devise a text-to-video retrieval task that requires our model to have a higher level of story or narrative understanding than those trained on existing video retrieval datasets [2, 39, 56]. For example LSMDC [39], which is created from DVS2, contains mostly low-level descriptions of what is visually occurring in the scene, e.g. ‘Abby gets in the basket’, unlike the descriptions in our dataset (Fig. 3), which often require information from past or future scenes for correct retrieval. In order to tackle this, we devise a Mixture of Embedding Experts model [32] that can learn from the subtitles, faces, objects, actions and scenes from past

1 https://www.youtube.com/user/movieclips
2 Descriptive Video Services
and future clips. We also introduce a novel character embedding module which allows the model to reason about the identities of characters present in each clip and description. This is unlike other movie related tasks – e.g. text-video retrieval on the LSMDC dataset [39] or graph retrieval on the MovieQA [51] dataset that ignore identities.

Applications of this kind of story-based retrieval include semantic search and indexing of movies as well as intelligent fast forwards. The CMD dataset can also be used for semantic video summarization and automatic description of videos for the visually impaired (DVS services are currently available at a huge manual cost).

Concisely, in this work we make the four following contributions; (i) we curate the Condensed Movie Dataset (CMD) containing the key scenes from over 3K different movies. The metadata and semantic descriptions accompanying the videos in our dataset help to tell a concise story for each movie. We also implement a pipeline to robustly obtain character IDs for all the facetracks in the videos of our dataset. Compared to other datasets, our dataset has an order of magnitude more movies and hence more unique identities; (ii) we propose a new story-based text-to-video retrieval task on our dataset for both cross-movie and within-movie retrieval (iii) we provide a baseline for this task on our dataset, using a popular Mixture of Embedding Experts (MoEE) model [32] to incorporate information about scene, faces, motion, objects and speech, and show the benefits of adding in each expert; and finally (iv) we adapt this model to allow the incorporation of past and future context in the video embeddings. This combined with a novel character module allows further improvements to retrieval performance on our dataset.

We will release all data, code, models and features to the research community.

2 Related Work

**Video Understanding from Movies:** There is an increasing effort to develop video understanding techniques that go beyond action classification from cropped, short temporal snippets [16, 23, 34], to learning from longer, more complicated videos that promise a higher level of abstraction [1, 33, 42, 45]. Movies and TV shows provide an ideal test bed for learning long-term stories, leading to a number of recent datasets focusing exclusively on this domain [40, 48, 51, 55]. Early works, however, focused on using film and TV to learn human identity [10, 14, 37, 43, 47] or human actions [5, 12, 26, 31] from the scripts accompanying movies. Story-based tasks include the visualization and grouping of scenes which belong to the same story threads [13], the visualization of TV episodes as a chart of character interactions [48], and more recently, the creation of more complicated movie graphs [53] (MovieGraphs [53] is the most exhaustively annotated movie dataset to date). This requires understanding multiple factors such as human interactions, emotions, motivation, scenes and other factors that affect behavior. There has also been a recent interest in evaluating stories through visual question answering [51]. In contrast, we propose to evaluate story understanding through the task of video-text retrieval, from a set of key scenes in a movie that condense most of the salient parts of the storyline. Unlike retrieval through a complex graph [53], retrieval via text queries can be a more intuitive way for a human to interact with an intelli-
gent system, and might help avoid some of the biases present inherently in VQA datasets [4].

Table 1: Comparison to other movie and TV show datasets. For completeness, we also compare to video datasets that have character ID or action annotation only. These datasets do not possess the story-level annotation that our dataset has. Freely available is defined here as accessible online at no cost. *Refers to number of TV shows. † 15 min segments from 430 movies.

| Dataset            | #Movies | #Hours | Freely available | Annotation Type                        |
|--------------------|---------|--------|------------------|----------------------------------------|
| Sherlock [36]      | 1*      | 4      |                  | Character IDs                           |
| BBT [41]           | 1*      | 44     |                  | Character IDs                           |
| TVQA [27]          | 6*      | 460    |                  | VQA                                    |
| AVA [16]           | 430     | 107.5† | ✓                | Actions only                           |
| MovieGraphs [54]   | 51      | 93.9   |                  | Descriptions, graphs                   |
| MovieQA (video) [52] | 140   | 381    |                  | VQA                                    |
| LSMDC [39]         | 202     | 158    |                  | Captions                               |
| MSA [55]           | 327     | 516    |                  | Plots                                  |
| Condensed Movies (Ours) | 3605  | 1270   | ✓                | Descriptions, metadata, character IDs  |

Video-Text Retrieval: A common approach for learning visual embeddings from natural language supervision is to learn a joint embedding space where visual and textual cues are adjacent if they are semantically similar [29, 32]. Most of these works rely on well annotated datasets in which descriptive captions are collected for short, isolated video clips, with descriptions usually focusing on low-level visual content provided by annotators (eg. LSMDC [39], MSR-VTT [56], DiDeMo [2]). Unlike these works, we propose to perform retrieval across condensed movie clips that define a coherent story. Works that attempt story based retrieval across full movies include [49], which aligns plot sentences to shots. This, however, is challenging because often there is no shot that matches a plot sentence perfectly, and shots cover very small timescales. Unlike this work our semantic descriptions are more true to the clips themselves, and the clips are roughly 2 minutes in length. Our method draws inspiration from the powerful joint embedding models proposed by [29, 32] (which in turn are inspired by the classical Mixture-of-Experts [22] model), with the key extension that we add in context both from past and future clips, as well as a novel character module. The idea of exploiting surrounding context has also been explored by [25], albeit for the task of video captioning. They introduce a new captioning module that uses contextual information from past and future events to jointly describe all events, however unlike our context that can span the timescale of an entire movie, this work focuses on short term context (few seconds before and after a particular clip).

Comparison to other Movie Datasets: Existing movie datasets often consist of short clips spanning entire, full length movies (which are subject to copyright and difficult for public release to the community). All such datasets also depend on
exhaustive annotation, which limit their scale to hundreds of movies. Our dataset, in contrast, consists of only the key scenes from movies matched with high quality, high level semantic descriptions, allowing for a condensed look at the entire storyline. A comparison of our dataset to other datasets can be seen in Table 1.

3 Condensed Movie Dataset

Fig. 2: The Condensed Movie Dataset (CMD). Top: Samples of clips and their corresponding descriptions from *The Karate Kid* (1984) and *The Thomas Crown Affair* (1999), in the first and second row respectively. In movies, as in real life, situations follow from other situations and the combination of video and text tell a concise story. Note: Everytime a character is mentioned in the description, the name of the actor is present in brackets. We remove these from the figure in the interest of space. Bottom, from left to right: Histogram of movie genres, movie release years, description length and duration of video clips. Best viewed online and zoomed in.

We construct a dataset to facilitate machine understanding of narratives in long movies. The dataset consists of the *key scenes* from over 3K movies, accompanied with rich story-level metadata. The total number of hours of video in the dataset is 1,270 hours, and the detailed statistics can be seen in Table 2 and Figure 2 (bottom row). Our dataset has the following key properties:

1) **Condensed Storylines:** The distribution of video lengths in our dataset can be seen in Fig. 2 – with just the key scenes, each movie has been condensed into roughly 20 minutes each. The combination of video and text for all the key scenes tells a concise story, with the accompanying descriptions focusing on intent, emotion, relationships between characters and high level semantics (Figures 2 and 3).
(2) **Online Longevity:** All the videos are obtained from the licensed, freely available YouTube channel: MovieClips\(^3\). We note that a common problem plaguing YouTube datasets today [6, 16, 23, 35] is the fast shrinkage of datasets as user uploaded videos are taken down by users (over 15% of Kinetics-400 [23] is no longer available on YouTube at the time of writing, including videos from the eval sets). We believe our dataset has longevity due to the fact that the movie clips on the licensed channel are rarely taken down from YouTube.

(3) **Scalable:** We note that this is an active YouTube channel and is constantly growing as new movies are released and added. Hence there is a potential to increase the size of the dataset in the future.

### 3.1 Dataset Collection

In this section we describe our dataset collection pipeline.

**Video Clips:** The video data consists of over 34,000 clips from over 3,600 movies (see Table 2). For each movie there is a set of ordered clips (typically 10 or so) covering the salient parts of the film (examples can be seen in Fig. 2, top two rows). Each around two minutes in length, the clips contain the same rich and complex story as full-length films but with durations an order of magnitude less. For each video, the subtitles are also automatically downloaded from YouTube. These are a mix of high quality, human generated subtitles and automatic captions. Subtitles are missing for 36.7% of the videos. Preprocessing details, including the filtering of noisy videos and the cropping of outros are described in the implementation details (Sec. 5.2).

**Video Title and Description:** The videos are accompanied by descriptions of the events occurring in the clip in context to the entire film. These descriptions are professionally-written and contain rich semantics such as intent, relationship, emotion and context (Fig. 3). Further, the descriptions contain the actor names, providing ground truth actor identification for key characters in the scene.

**Metadata:** For each movie, we acquire the genres, release year, cast lists and plot synopses from Wikipedia and IMDBs.

**Facetracks and Character IDs:** For each of the clips, we detect and track faces, and extract a single average pooled face embedding for each track (see Sec. 5.2). We then devise a web-based pipeline to obtain character names for each of the facetracks in every video in the dataset. Our technique involves the creation of a character embedding bank (CEB) which contains a list of the characters that will appear in the movie (obtained from the cast list), and a corresponding embedding vector extracted from a deep CNN model pretrained on human faces [8]. Character IDs are then assigned by computing the similarity between the embeddings from the face tracks and the embeddings in the CEB (using cosine similarity) and assigning an ID to a track when the similarity score is above a certain threshold. This pipeline is described in detail in Sec. 4. We note that this is an automatic method and so does not yield perfect results, but a quick manual inspection shows that it is accurate 96% of the

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\(^3\) https://www.youtube.com/user/movieclips/. Screenshots of the channel are provided in supplementary material
Table 2: **Dataset Statistics.** We provide the mean duration of video clips in seconds, and the mean length of accompanying descriptions in words. uniq. chars. refers to the number of unique movie characters present across all the movies.

| #movies | #videos | vid. dur. (s) | descrip. len. (w) | #facetracks | #uniq. chars |
|---------|---------|---------------|-------------------|--------------|--------------|
| 3,605   | 33,976  | 134           | 19                | 439,969      | 8,375        |

4 Story Based Retrieval

Our goal is to be able to retrieve the correct ‘key scene’ over all movies in the dataset, given just the high level description. Henceforth, we use the notation ‘video clip’ to refer to one key scene (the video clips in our dataset are roughly 2 minutes long) and ‘description’ to refer to the high level semantic text accompanying each video. In order to achieve this, we learn a common embedding space for each video and the description accompanying it. More formally, if $V$ is the video and $T$ is the description, we learn embedding functions $f$ and $g$ such that the similarity $s = \langle f(V), g(T) \rangle$ is high only if $T$ is the correct semantic description for the video $V$. Inspired by previous works that achieve state-of-the-art results on video retrieval tasks [30, 32], we encode each video as a combination of different streams of descriptors. Each descriptor is a semantic representation of the video learnt by individual experts (that encode concepts such as scenes, faces, actions, objects and the content of conversational speech from subtitles). By using pretrained networks that are trained on large-scale datasets for each semantic task separately, we exploit expert-specific knowledge from domain specific datasets, and obtain a robust, low-dimensional basis to encode each video.
Inspired by [32], we base our network architecture on a mixture of ‘expert’ embeddings model, wherein a separate model is learnt for each expert, which are then combined in an end-to-end trainable fashion using weights that depend on the input caption. This allows the model to learn to increase the relative weight of motion descriptors for input captions concerning human actions, or increase the relative weight of face descriptors for input captions that require detailed face understanding. We take this one step further, however, and note often the text query not only provides clues as to which expert is more valuable, but also whether it is useful to pay attention to a previous clip in the movie. In regular movie datasets, the space of possible previous clips can be prohibitively large [49], however this becomes feasible with our condensed movie dataset.

In this manner, the model can learn to increase the relative weight of a past video feature if a caption is referring to something that happened previously, eg. ‘Zip is still angry about their previous altercation’. We also experiment with adding in information from future clips, and show results in Sec. 5.3.

Besides doing just cross-movie retrieval, we also adapt our model to perform within-movie retrieval. We note that characters are integral to a storyline, and hence for the case of within-movie retrieval, we introduce a character module, which computes a weighted one-hot vector for the characters present in the description query and another for each video clip in the dataset. The presence of characters in each video clip is determined by our character identity pipeline detailed below. We note that for cross-movie retrieval, the retrieval task becomes trivial given the knowledge of the characters in each movie, and hence to make the task more challenging (and force the network to focus on other aspects of the story), we remove the character module for this case.

![Model architecture](image)

**Fig. 4: Model architecture:** An overview of our Contextual Mixture of Embedding Experts (CMoEE) model that computes a similarity score between a query sentence \( T \) and a video \( V \) as a weighted combination of expert embeddings, from the current and past video clips. For visual clarity, the character module is omitted.

Since our model can be used to code multiple clips to provide context, we call it a Contextual Mixture of Embedding Experts (CMoEE) model. A visual overview of the model can be seen in Fig. 4. In the next section we outline the character identity
pipeline that we use to obtain character identities, and then for more clarity, we describe each component of the model in detail in the following sections.

**Character Identity Pipeline:** We note that often character identities are the focal point of any storyline, and many of the descriptions reference keys characters. Hence we obtain estimates of which characters are present in each video clip (this is done offline, and not on-the-fly during training). We describe in detail the process of building the character embedding bank as mentioned in Sec. 3.1, and state some figures on the number of annotations obtained. We follow a three step scalable pipeline to assign character IDs to each of the face-tracks where possible, crucially without any human annotation. First, we use the cast lists obtained for each of the featured movies from IMDb to get a total list of 28,379 actor names. Note we use the names of the actors and not characters (the cast lists provide us with the mapping between the two). 200 images are then downloaded from image search engines for each of these names. Faces are detected and face-embeddings extracted for each of the faces in the downloaded images (see Sec. 5.2 for details). Second, we automatically remove embeddings corresponding to false positives from each set of downloaded images. We achieve this by clustering each of the face-embeddings in the downloaded images into identity clusters (we use agglomerative clustering [21] with a cosine distance threshold of 0.76 - embeddings that have a lower similarity than this threshold are not merged into the same cluster). We make the assumption that the largest cluster of face-embeddings corresponds to the actor ID that was searched for. If the largest cluster is smaller than a certain threshold (the value 30 is used) then we remove the actor ID with the conclusion that too few images were found online (commonly the case for relatively unknown cast/crew members). Finally for the remaining actor IDs, the embeddings in the largest cluster are average pooled and L2 normalised into a single embedding. This process leaves us with 13,671 cast members in the character embedding bank. Facetracks are then annotated using the character embedding bank by assigning a character ID when the cosine similarity score between a facetrack embedding and character embedding is above a certain threshold (we use 0.8 as a conservative threshold to prioritize high precision). Ultimately, we are able to recognize 8,375 different characters in 25,760 of the video clips.

### 4.1 Model Architecture

**Expert Features** Stories in movies are communicated through many modalities including (but not limited to) speech, body language, facial expressions and actions. Hence we represent each input video \( V \) with \( K \) different expert streams (in our case, \( K = 5 \) – face, subtitles, objects, motion and scene, but our framework can be extended to more experts as required).

Each input stream is denoted as \( I_i \), where \( i = 1...K \). Adopting the approach proposed by [32], we first aggregate the descriptors of each input stream over time, using a temporal aggregation module (see Sec. 5 for details), and the resulting time-aggregated descriptor is embedded using a gated embedding module (for the precise details of the gated embedding module, please see [32]). We then finally project each embedding to a common dimension \( D \) using a fully connected layer, giving us one

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4 value found empirically using cross-validation on a subset of manually annotated samples
expert embedding $E_{Vi}$ for each input stream $i$. All $K$ embeddings of dimension $D$ are shown in Fig. 4 as a single block of size $K \times D$.

**Text Query Encoder** The query description input is a sequence of BERT word embeddings [11] for each input sentence. These individual word embedding vectors are then aggregated into a single vector $h(T)$ representing the entire sentence using a NetVLAD [3] aggregation module. This vector $h(T)$, is then used to predict the mixture weights (described in the next section). We then project $h(T)$ to the same dimensions as the video expert features using the same gated embedding module followed by a fully connected layer as for the video experts (described above), once for each input source $i$, giving us expert embeddings $E_{Ti}$. Hence the final output is of dimensions $K \times D$.

**Learning from the surrounding context** In [32], the resulting expert embeddings $E_{Vi}$ are then weighted using normalized weights $w_i(T)$ estimated from the text description $T$, to obtain the final similarity score $s$. This is done by combining the similarity scores $s_i(T,I_i)$ between the query sentence $T$ and different expert streams of the input descriptors $I_i$ from the video. More formally, this is calculated as:

$$s(T,V) = \sum_{i=1}^{K} w_i(T) s_i(T,I_i), \quad \text{where} \quad w_i(T) = \frac{e^{h(T)\tau a_i}}{\sum_{j=1}^{K} e^{h(T)\tau a_j}} \quad (1)$$

where $h(T)$ is the aggregated text query representation described above and $a_i, i=1...K$ are learnt parameters used to obtained the mixture weights.

In this work, however, we extend this formulation in order to incorporate past and future context into the retrieval model. We would like the model to be able to predict weights for combining experts from past and future clips - note we treat each expert separately in this formulation. For example, the model might want to heavily weight the subtitles from a past clip, but downweight the scene representation which is not informative for a particular query. More formally, given the total number of clips we are encoding to be $N$, we modify the equation above as:

$$s(T,V) = \sum_{n=1}^{N} \sum_{i=1}^{K} w_{i,n}(T) s_{i,n}(T,I_{i,n}), \text{where} \quad w_{i,n}(T) = \frac{e^{h(T)\tau a_{i,n}}}{\sum_{m=1}^{N} \sum_{j=1}^{K} e^{h(T)\tau a_{j,m}}} \quad (2)$$

Hence instead of learning $K$ scalar weights $a_i, i=1...K$ as done in [32], we learn $K \times N$ scalar weights $a_{i,n}, i=1...K,n=1...N$ to allow combination of experts from additional clips. If only using clips from the past, this becomes a causal model and can be used for online learning.

**Dealing with missing streams** We note that these experts might be missing for certain videos, eg. subtitles are not available for all videos and some videos do not
have any detected faces. When expert features are missing, we zero-pad the missing experts and compute the similarity score. This is the standard procedure followed by existing retrieval methods using Mixture of Embedding Experts models [29, 32]. The similarity score is calculated only from the available experts by renormalizing the mixture weights to sum to one, allowing backpropagation of gradients only to the expert branches that had an input feature. We apply this same principle when dealing with missing video clips in the past, for example if we are training our model with $N=1$ past clips, for a video clip which is right at the start of the movie (has no past), we treat all the experts from the previous clip as missing so that the weights are normalized to focus only on the current clip.

**Character Module** The character module computes the similarity between a vector representation of the character IDs mentioned in the query $y$ and a vector representation of the face identities recognised in the video $x$. The vector representations are computed as follows: For the query, we search for actor names in the text from the cast list (supplied by the dataset) and create a one-hot vector $y$ the same length as the cast list, where $y_i = 1$ if actor $i$ is identified in any face track in the video and $y_i = 0$ otherwise. For the face identities acquired in the face recognition pipeline (described earlier), we compare the following three methods: first, we encode a one-hot vector $x$ in a manner similar to the query character encoding. While this can match the presence and absence of characters, we note that often only the key characters are mentioned in the description, while the clips contain lots of background characters. Hence inspired by [50], we also propose a second method ("track-frequency normalised"), where $x_i$ is the number of face tracks for identity $i$. Lastly, in "track length normalised", our vector encodes the total amount of time a character appears in a clip i.e. $x_i$ is the sum of all track lengths for actor $i$, divided by the total sum of all track lengths in the clip.

The character similarity score $s_C = \langle y, x \rangle$ is then modulated by it’s own scalar mixture weight $w_C(T)$ predicted from $h(T)$ (as is done for the other experts in the model). This similarity score is then added to the similarity score obtained from the other experts to obtain the final similarity score, i.e. $s(T,V) = \sum_{i=1}^{K} w_i(T)s_i(T,I_i) + w_C(T)s_C(T,V)$.

**Training Loss** As is commonly used for video-text retrieval tasks, we minimise the Bidirectional Max-margin Ranking Loss [44]:

$$\mathcal{L}_r = \frac{1}{N_B} \sum_{i=1,j \neq i}^{N_B} \max(0, m + s^j_i - s^i_j) + \max(0, m + s^i_j - s^j_i)$$

(4)

where $s^j_i$ is the similarity of the $i^{th}$ video $V_i$ and the $j^{th}$ description $T_j$, computed as the cosine of the angle between their final embeddings, $s^j_i = \langle f(V_i), g(T_j) \rangle$, $N_B$ is the batch size, and $m$ is a fixed constant which is set as a hyperparameter.
Table 3: Training splits for cross-movie retrieval (left) and within-movie retrieval (right). For within-movie retrieval, we restrict the dataset to movies which have at least 5 video clips in total.

|                  | Cross-Movie |        |        |       | Within-Movie |        |        |       |
|------------------|-------------|--------|--------|-------|--------------|--------|--------|-------|
|                  | TRAIN       | VAL    | TEST   | TOTAL | TRAIN        | VAL    | TEST   | TOTAL |
| #Movies          | 2,551       | 358    | 696    | 3,605 | 2,469        | 341    | 671    | 3,481 |
| #Video clips     | 24,047      | 3,348  | 6,581  | 33,976| 23,963       | 3,315  | 6,581  | 33,859|

5 Experiments

5.1 Experimental Set-up

We train our model for the task of cross-movie and within-movie retrieval. The dataset is split into disjoint training, validation and test sets by movie, so that there is no overlapping movies between the sets. The dataset splits can be seen in Table 3. We report our results on the test set for both text-video and video-text retrieval using standard retrieval metrics including median rank (lower is better), mean rank (lower is better) and R@K (recall at rank K higher is better).

Cross-movie Retrieval: For the case of cross-movie retrieval, the metrics are reported over the entire test set of videos, i.e. given a text query, there is a ‘gallery’ set of 33,976 possible matching videos in the case of text-video retrieval (Table 3). We report R@1, R@5, R@10, mean and median rank. For the cross-movie retrieval setting, we compare to a baseline of random weights, the MoEE model without any additional context [32], and our CMoEE model with varying levels of context (number of past or future clips added into the video embedding during training and test time).

Within-movie Retrieval: In order to evaluate the task of within-movie retrieval, we remove all movies that contain less than 5 video clips from the dataset. For each query text, the possible gallery set consists only of the videos in the same movie as the query. In this setting the retrieval metrics are calculated separately for each movie and then averaged over all movies. We report R@1, mean and median rank. Our main motivation for showing results in this setting is to demonstrate the powerful boost provided by our character module.

We finally show the results of an ablation study demonstrating the importance of different experts for this task on the task of cross-movie retrieval. In the next sections, we first describe the implementation details of our models and then discuss quantitative results. Qualitative results are provided in the supplementary material.

5.2 Implementation Details

Data Preprocessing: Each video is accompanied by an outro at the end of the clip which contains some advertising and links to other movies. This is automatically removed by manually noticing that each outro has a consistent length of either 10s (if the clip is uploaded before May 2017) or 30s if uploaded after. To get the cast list and other meta-data the movie name was obtained for each video from scraping the video titles. Noisy clips such as mashups of various different movies into one are manually removed.
**Expert Features:** In order to capture the rich content of a video, we draw on existing powerful representations for a number of different semantic tasks. These are first extracted at a frame-level, then aggregated by taking the mean to produce a single feature vector per modality per video.

**RGB object** frame-level embeddings of the visual data are generated with an SENet-154 model [18] pretrained on ImageNet for the task of image classification. Frames are extracted at 25 fps, where each frame is resized to $224 \times 224$ pixels. Features collected have a dimensionality of 2048.

**Motion** embeddings are generated using the I3D inception model [9] trained on Kinetics [23], following the procedure described by [9].

**Face** embeddings for each face track are extracted in three stages: (1) Each frame is passed through a dual shot face detector [28] (trained on the Wider Face dataset [57]) to extract bounding boxes. (2) Each box is then passed through an SENet50 [17] trained on the VGGFace2 dataset [7] for the task of face verification, to extract a facial feature embedding, which is L2 normalised. (3) A simple tracker is used to connect the bounding boxes temporally within shots into face tracks. Finally the embeddings for each bounding box within a track are average pooled into a single embedding per face track, which is again L2 normalised. The tracker uses a weighted combination of intersection over union and feature similarity (cosine similarity) to link bounding boxes in consecutive frames.

**Subtitles** are encoded using BERT embeddings [11] averaged across all words.

**Scene** features of 2208 dimensions are encoded using a DenseNet161 model [19] pretrained on the Places365 dataset [58], applied to $224 \times 224$ pixel centre crops of frames extracted at 1fps.

**Descriptions** are encoded using BERT embeddings, providing contextual word-level features of dimensions $W \times 1024$ where $W$ is the number of tokens. These are concatenated and fed to a NetVLAD layer to produce a feature vector of length of 1024 times the number of NetVLAD clusters for variable length word tokens.

**Training details and hyperparameters:** The CMoEE model is implemented with PyTorch [38]. Optimization is performed with Adam [24], using a learning rate of 0.001, and a batch size of 32. The margin hyperparameter $m$ in Eq. 4 is set to a value of 0.121, the common projection dimension $D$ to 512, and the description NetVLAD clusters to 10. Training is stopped when the validation loss stops decreasing.

## 5.3 Results

Results for cross-movie retrieval can be seen in Table 4. We first provide a baseline on our new dataset for both text-video and video-text retrieval using a MoEE model. We show that the results are far greater than random, demonstrating that story-based retrieval is possible on this dataset. We then demonstrate that adding in context further boosts performance, showing that it is useful to add information from other parts of the movie to each video clip to enable effective retrieval. We experiment with adding in different amounts of context, eg. 1, 2 or 3 past clips, 1, 2 or 3 future clips, and 1 past clip and 1 future clip. We find in general that the model is robust to the amount of context added. Results for within-movie retrieval can be seen in Table 5. We show that adding in the character module provides a significant boost (almost
Table 4: Cross-movie retrieval results on the CMD test set of 3,605 video clips, with varying levels of context for both text-video and video-text retrieval. Random weights refers to the MEE model architecture with random initialization. R@k denotes recall@k (higher is better), MdR and MnR denote median rank and mean rank resp. (lower is better). Context PX FY denotes training and testing with X past and Y future clips.

| Method              | Context | Text $\Rightarrow$ Video |          | Video $\Rightarrow$ Text |          |
|---------------------|---------|----------------------------|----------|--------------------------|----------|
|                     |         | R@1 | R@5 | R@10 | MdR | MnR | R@1 | R@5 | R@10 | MdR | MnR |
| Random weights      | –       | 0.0 | 0.1 | 0.2  | 3209 | 3243.5 | 0.0 | 0.1 | 0.2  | 3171 | 3214 |
| MoEE [32]           | –       | 4.7 | 14.9 | 22.1 | 65  | 285.3  | 6.4 | 18.6 | 25.7 | 55  | 266.0 |
| CMoEE (ours)        | P3      | 5.6 | 17.1 | 25.7 | 50  | 253.8  | 8.1 | 21.8 | 30.1 | 41  | 233.3 |
| CMoEE (ours)        | P1      | 5.4 | 17.6 | 25.7 | 51  | 260.7  | 8.2 | 20.9 | 29.0 | 45  | 243.6 |
| CMoEE (ours)        | P2      | 5.0 | 16.1 | 24.5 | 53  | 250.3  | 7.4 | 20.8 | 28.9 | 45  | 231.9 |
| CMoEE (ours)        | F1      | 5.6 | 17.4 | 25.9 | 51  | 252.3  | 7.8 | 21.4 | 29.1 | 43  | 235.3 |
| CMoEE (ours)        | F2      | 5.1 | 17.0 | 25.5 | 49  | 248.1  | 7.9 | 22.1 | 30.9 | 40  | 229.9 |
| CMoEE (ours)        | F3      | 5.4 | 17.1 | 25.9 | 50  | 247.0  | 7.6 | 20.9 | 30.6 | 43  | 227.0 |
| CMoEE (ours)        | P1F1    | 5.0 | 16.4 | 25.3 | 51  | 249.4  | 7.3 | 20.1 | 28.0 | 47  | 228.6 |

Table 5: Within-Movie Retrieval results on the CMD test set. All movies with less than 5 video clips are removed. Metrics are computed individually for each movie and then averaged (m-MdR refers to the mean of the median rank obtained for each movie). We show the results of 3 different variations of embeddings obtained from the character module.

| Method                             | Text $\Rightarrow$ Video | Video $\Rightarrow$ Text |
|------------------------------------|--------------------------|--------------------------|
|                                    | m-R@1 | m-MdR | m-MnR | m-R@1 | m-MdR | m-MnR |
| Random weights                     | 11.1  | 5.32  | 5.32  | 10.7  | 5.32  | 5.30  |
| MoEE                               | 38.9  | 2.20  | 2.82  | 37.9  | 2.23  | 2.84  |
| MoEE + Character Module [one-hot]  | 45.5  | 1.91  | 2.60  | 44.2  | 1.98  | 2.60  |
| MoEE + Character Module [track-freq norm] | **47.2** | **1.85** | **2.49** | **45.6** | **1.92** | **2.56** |
| MoEE + Character Module [track-len norm] | 46.2  | 1.88  | 2.53  | 44.3  | 1.96  | 2.58  |

Table 6: Expert ablations on the CMD dataset. The value of different experts in combination with a baseline set for text-video retrieval (left) and (right) their cumulative effect (here Prev. denotes the experts used in the previous row).

| Experts               | Text $\Rightarrow$ Video |          | Text $\Rightarrow$ Video |          |
|-----------------------|--------------------------|----------|--------------------------|----------|
|                       | R@1 | R@5 | R@10 | MdR | MnR | R@1 | R@5 | R@10 | MdR | MnR |
| Scene                 | 0.8 | 3.2 | 5.9  | 329 | 776.3 | Scene | 0.8 | 3.2 | 5.9  | 329 | 776 |
| Scene+Face            | 3.7 | 12.7 | 19.7 | 100 | 443.1 | 3.7 | 12.7 | 19.7 | 100 | 443.1 |
| Scene+Obj             | 1.0 | 4.6 | 8.0  | 237 | 607.8 | 3.9 | 13.1 | 20.5 | 79 | 245.5 |
| Scene+Action          | 1.9 | 6.4 | 10.5 | 193 | 575.0 | 4.0 | 14.0 | 20.4 | 78 | 233.3 |
| Scene+Speech          | 2.3 | 8.3 | 12.4 | 165 | 534.7 | 5.4 | 17.6 | 25.7 | 51 | 260.7 |

a 10% increase in R@1 compared to the MoEE without the character module), with the best results obtained from normalizing the character embeddings by the track frequency. The value of different experts is assessed in Table 6. Since experts such as subtitles and face are missing for many video clips, we combine individual experts with the features produced by the ‘scene’, the expert with the lowest performance that is consistently available for all clips (as done by [29]). In Table 6, right, we show the cumulative effect of adding in the different experts. The highest boosts are obtained from the face features and the speech features, as expected, since we hypothesize that these are crucial for following human-centric storylines.
6 Conclusion

In this work we learn to encode videos for the task of story-based text retrieval, from a dataset of clips following succinct and clear storylines in movies. We demonstrate that adding in a character module with knowledge of identities and encoding past and future clips as context improves retrieval performance. Future work will involve incorporating additional information such as plot summaries mined from Wikipedia and IMDb, that can fill in the gaps between key scenes and might improve the ability of our model to link clips together.
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A Qualitative Retrieval Results

We provide qualitative results for our best cross-movie retrieval CMoEE model (corresponding to row 3, Table 4 of the main paper) in Fig. 5.

B Character Module

The character module, described in Section 4 of the main paper, uses automatically annotated facetracks in the video and actor names in the text to produce a single
Out on a date with Michael, Lelaina gets uncomfortable when he gives her a compliment and asks about her friends.

Bill puts Bobby on the stand, and uses a hockey metaphor to draw out the truth.

Chucky chases Tyler into a haunted house ride at a nearby carnival. Right as he captures Tyler, he gets half his face cut off by an automated scythe.

Fig. 5: **Qualitative results of the CMoEE model (P3) for cross-movie retrieval.** On the left, we provide the input query, and on the right, we show the top 4 video clips retrieved by our model on the CMD test set. A single frame for each video clip is shown. The matching clip is highlighted with a green border, while the rest are highlighted in red (best viewed in colour). Note how our model is able to retrieve semantic matches for situations (row 1: male/female on a date), high level abstract concepts (row 2: the words ‘stand’ and ‘truth’ are mentioned in the caption and the retrieved samples show a courtroom, men delivering speeches and a policeman’s office) and also notions of violence and objects (row 3: scythe). 

similarity score. Examples of the annotated facetracks can be found in Fig. 6 and an overview of the character module can be found in Fig. 7.
When Detective Austin (Mark Harmon) and Colonel Caldwell (Sean Connery) have their coffee break interrupted by an obnoxious man looking for a fight (Rick Zumwalt), Colonel Caldwell helpfully ...

**Fig. 6:** Facetracks in the dataset automatically annotated by the character identification pipeline described in Section 4 of the main paper.

**Fig. 7:** Visual Representation of our Character Module. We show how our character module matches actor names in the caption (left) to actors identified from the video clip (right) using our character embeddings banks. In this example, the video identities are represented by a vector $x$, where each element $x_i$ is the number of facetracks for identity $i$, and the caption identities are represented by a binary vector $y$, where $y_i$ is 1 if identity $i$ is present in the caption and 0 otherwise.