TVR: A Large-Scale Dataset for Video-Subtitle Moment Retrieval

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Abstract

We introduce a new multimodal retrieval task - TV show Retrieval (TVR), in which a short video moment has to be localized from a large video (with subtitle) corpus, given a natural language query. Different from previous moment retrieval tasks dealing with videos only, TVR requires the system to understand both the video and the associated subtitle text, making it a more realistic task. To support the study of this new task, we have collected a large-scale, high-quality dataset consisting of 108,965 queries on 21,793 videos from 6 TV shows of diverse genres, where each query is associated with a tight temporal alignment. Strict qualification and post-annotation verification tests are applied to ensure the quality of the collected data. We present several baselines and a novel Cross-modal Moment Localization (XML) modular network for this new dataset and task. The proposed XML model surpasses all presented baselines by a large margin and with better efficiency, providing a strong starting point for future work. Extensive analysis experiments also show that incorporating both video and subtitle modules yields better performance than either alone. Lastly, we have also collected additional descriptions for each annotated moment in TVR to form a new multimodal captioning dataset with 262K captions, named the TV show Caption dataset (TVC). Here models need to jointly use the video and subtitle to generate a caption description. Both datasets are publicly available at https://tvr.cs.unc.edu.

1. Introduction

Enormous numbers of multimodal videos (with audio and/or text) are being uploaded to the web every day. To enable users to search through these videos and find what they want, an efficient and accurate method for retrieval of video data is crucial. Recent works [1, 9] introduced the task of Single Video Moment Retrieval (SVMR), whose goal is to retrieve a moment from a single video via a natural language query. [8] extended SVMR to Video Corpus Moment Retrieval (VCMR), where the system is required to retrieve the most relevant moments from a large video corpus instead of from a single video. However, all of these works rely on a single modality (video) as the context source for retrieval. In practice, videos are often associated with other modalities such as audio or text, e.g., subtitles for movie/TV-shows or audience discourse accompanying live stream videos. These associated modalities could be equally important sources for retrieving user-relevant moments. Figure 1 shows a query example.

Figure 1. TVR example (videos from the TV show Grey’s Anatomy). Dotted green box shows the temporal annotation for the given query. Text inside dashed boxes under the frames is the associated subtitles. To better retrieve a relevant moment from the video corpus, a system needs to comprehend both videos and subtitles and recognize fine-grained actions and people/objects.

Query: Alex is on the phone with Izzie and he is updating her on the heart situation.

Video: Bailey: I don’t care if he’s sleeping, just wake him up.
Izzie: There were two donors, Izzie. Our heart flatlined.
Meredith: This is what I’m saying…

Query Type: video-subtitle
shows for building multimodal datasets, we select TV shows as our data collection resource as they typically involve rich social interactions between actors, involving both activities and dialogues. During data collection, we present annotators with videos and associated subtitles to encourage them to write multimodal queries. Additionally, a tight temporal timestamp is labeled for each pair of video and query. We do not use predefined fixed segments (as in [1]) but choose to freely annotate the timestamps for more accurate localization. Furthermore, query types are collected for each query to indicate whether it is more related to the video, the subtitle, or both. To ensure high quality of the collected data, we set up a strict qualification test and post-annotation quality verification. In total, we have collected 108,965 high-quality queries on 21,793 videos from 6 TV shows, producing the largest dataset of this kind. Our analysis shows that 67% of the queries have more than one action and 66% of the queries involve more than one person, significantly larger than previous datasets [1, 25, 9, 17]. Such characteristics make TVR an interesting testbed for studying social interactions between people.

With the TVR dataset, we next extend the VCMR task to a more realistic multimodal setup where both video and subtitle text context need to be considered (i.e., ‘Video-Subtitle Corpus Moment Retrieval’ but for simplicity, we will call it the TVR task). Next, to present some initial models that can address this task, we propose Cross-modal Modal Moment Localization (XML), a hierarchical model that is able to do efficient moment retrieval using information from both videos and subtitles. For each video, we first encode its video and subtitle representation separately via two self-encoders, then given a language description for retrieval, we use a query module to decompose it into visual query vectors and subtitle query vectors and fuse them with the above context features for each video, generating video-level confidence scores. On top of the selected videos, we apply an efficient 1D convolutional start-end detector to compute the temporal matching scores and pick the best moment. Compared with previous baselines [10, 38, 9] which are designed for retrieving a moment from a single video and require an early fusion of the query and video features, our approach not only achieves better retrieval performance but also substantially better efficiency. As a side benefit, our learned 1D convolutional filters exhibit a certain degree of interpretability as shown in Section 5.3.

To summarize, our contributions are 3-fold: (i) We introduce TVR, a large-scale, high-quality multi-modal dataset for moment retrieval tasks from large video corpuses. TVR consists of 108,965 queries on 21,793 videos. (ii) We propose XML, an efficient approach for the TVR task. Comprehensive experiments and analyses show XML surpasses all previous baselines by a large margin and runs with better efficiency. (iii) Lastly, we have also collected additional descriptions for each annotated moment in TVR to form a new multimodal captioning dataset with 262K captions, named the TV show Caption dataset (TVC), where a joint understanding of the video and subtitle is needed to generate a caption description. Details of TVC are presented in the supplementary file.

2. Related Work

The goal of natural language based moment retrieval is to retrieve a relevant moment from a single video [1, 9, 10] or from a large video corpus [8]. In the following, we present a brief overview of the community efforts on these tasks and make distinctions between existing works and ours.

Datasets for Language based Moment Retrieval Several datasets have been proposed for language-driven moment retrieval, e.g., DiDeMo [1], ActivityNet Captions [17], CharadesSTA [9], and TACoS [25], where queries can be localized solely from visual signals. Among them, there are two types of data collection: (i) uniformly chunking the video into clips and letting an annotator pick one (or more) and write an unambiguous description [1]. For example, moments in DiDeMo [1] are created from fixed 5-seconds segments. This is efficient for data collection but provides coarse temporal annotations which may be less favorable for training retrieval systems [10]. In TVR, the timestamps are freely annotated to more accurately capture important moments. (ii) converting a video paragraph into separate query sentences [25, 9, 17]. While it is natural for people to use temporal connectives (e.g., ‘first’, ‘then’, etc) and anaphora (e.g., pronouns) [25] in a paragraph, these words make each separate sentence less suitable as a query for retrieval tasks. In comparison, the TVR annotation process encourages annotators to write multimodal queries individually without requiring the context of a paragraph.

Models for Language-based Moment Retrieval Existing approaches for SVMR typically involve an expensive early fusion of queries and videos [9, 10, 38, 4, 34]. For example, [10] uses an LSTM to encode the concatenation of encoded video feature and query feature, then applies two Multi-Layer Perceptron (MLP) layers to generate the START and END scores. While they showed promising performance on moment retrieval from a single video tasks, the time-costly early fusion between the query feature and each video becomes infeasible [8] when dealing with VCMR.

Another line of work [1, 8] uses Squared Euclidean Distance between the query feature and each moment proposal feature to rank the proposals with respect to a given query. However, the number of proposals is usually much larger than the number of clips as each proposal covers different clips, making the ranking time-consuming. In contrast,
XML calculates retrieval scores using the inner product between the encoded query feature and each clip feature only, which greatly reduces the computation cost.

3. Dataset

Our TVR dataset is built on 21,793 videos from 6 long-running TV shows across 3 genres (sitcom, medical, crime), provided by TVQA [18]. Videos are paired with subtitles and are on average 76.2 seconds in length. In the following, we describe how we collected TVR and provide a detailed analysis of the data.

3.1. Data Collection

We used Amazon Mechanical Turk (AMT) for TVR data collection. Each AMT worker was asked to write a query using information from the video and/or subtitle, then mark the START and END timestamps to define a moment that matches the written query. This query-moment pair is required to be a unique match within the given video, i.e., the query should be a referring expression that uniquely localizes the moment. We additionally ask workers to select a query type from three types: video-only - queries relevant to the visual content only, text-only - queries relevant to the subtitles only, and video-text - queries that involve both. In our pilot study, we found workers preferred to write text-only queries. A similar phenomenon was observed in TVQA [18], where people can achieve 72.88% accuracy by reading the subtitles only. Therefore, to ensure that we collect a balance of queries requiring one or both modalities, we split the data annotation into two rounds - visual round and textual round. For the visual round, we encourage workers to write descriptions related to the visual content, including both video-only and video-text queries. For the textual round, we encourage text-only and video-text descriptions.

Quality Control We ensure high quality of the collected data with the following strategies:

Qualification Test: We designed a set of 12 multiple-choice questions as our qualification test and only let workers who correctly answer at least 9 questions participate in our annotation task, ensuring that workers understand our task requirements well. In total, 1,055 workers participated in the test, with a pass rate of 67%. Adding this qualification test greatly improved data quality.

Automatic Check: During collection, we used an automatic tool checking that all required annotations (query, timestamps, etc) have been performed and each query contains at least 8 words and is not copied from the subtitle.

Manual Check: Additional manual check of the collected data was done in house. Those disqualified queries were re-annotated and workers with disqualified queries were banned from our worker list.

Post-Annotation Verification: To verify the quality of the collected data, we performed a post-annotation verification experiment. We set up another AMT task where workers were required to rate the quality of the collected query-moment pairs based on relevance, is the query-moment pair a unique-match, etc. The rating was done in a likert-scale manner with 5 options: strongly agree, agree, neutral, disagree and strongly disagree. Results show that 92% of the pairs have a rating of at least neutral. We further analyzed the group of queries that were rated as strongly disagree, and found that 80% of them were still of acceptable quality: e.g., slightly mismatched timestamps (≤ 1 sec.). This verification was conducted on 3,600 query-moment pairs.

After the TVR data collection, we decided to further extend the dataset’s usefulness to the community by collecting extra descriptions for each annotated moment, making it a large-scale multimodal video captioning dataset. This dataset, TV show Caption (TVC), contains 262K captions from 108K moments. Similar to the retrieval task, our multimodal video captioning task requires systems to gather information from both videos and subtitles for generating relevant descriptions. Each training moment is paired with 2 descriptions, and each testing moment is paired with 4 descriptions for more accurate evaluation. More details of TVC are presented in the supplementary file.

3.2. Data Analysis and Comparison

Table 1 shows an overview of TVR and its comparison with other video moment retrieval datasets. TVR contains 109K human annotated query-moment pairs on 22K videos. Moments are annotated with tight START and END timestamps enabling training and evaluating on more precise localization. Additionally, each query in TVR is labeled with a query type indicating whether this retrieval is based on video, subtitle or both, which can be used for deeper analysis of the system. Figure 2 shows the distribution of the query types with an example for each.

The vocabulary size of TVR is 57,103, which is significantly larger than the other datasets. This makes the textual understanding of TVR more challenging.
As TVR is collected on TV shows, queries often involve rich interactions between characters. Table 2 shows a comparison of the percentages of queries that involve more than one action or person across different datasets. 66% of the TVR queries involve at least two people and 67% of them involve at least two actions, both of which are significantly higher than those of other datasets. This makes TVR an interesting testbed for studying multimodal interactions between people.

4. Cross-modal Moment Localization (XML)

In TVR, the goal is to retrieve a moment from a large video corpus \( V = \{v_i\}_{i=1}^n \) given a natural language query \( q_j \). Each video \( v_i \) is represented as a list of consecutive short clips, i.e., \( v_i = [c_{i,1}, c_{i,2}, ..., c_{i,t}] \), each associated with temporally aligned subtitle sentences. The retrieved moment is denoted as \( v_i[t_{st}, t_{ed}] = [c_{i,t_{st}}, c_{i,t_{st}+1}, ..., c_{i,t_{ed}}] \). To address TVR, we propose a hierarchical Cross-modal Moment Localization (XML) network. XML performs efficient video-level retrieval from its shallower layers and more fine-grained moment retrieval in its deeper layers by predicting the START and END indices. Thus, XML can flexibly perform either video-retrieval or moment-retrieval.

4.1. Input Representations

To represent videos, we consider both appearance and motion features. For appearance features, we extract 2048D ResNet-152 [11] features at 3FPS and max-pool the features every 1.5 seconds to get a clip-level feature. For motion features, we extract 1024D I3D [3] features every 1.5 seconds. The ResNet-152 model is pre-trained on ImageNet [5] for image recognition, and the I3D model is pre-trained on Kinetics-600 [14] for action recognition. The final input video feature is the L2-normalized concatenation of the two features, denoted as \( E^v \in \mathbb{R}^{1\times3072} \).

We extract contextualized text features using the 12-layer RoBERTa [21], a variant of BERT [7] pre-trained on large amounts of text. Specifically, we first fine-tune the pre-trained RoBERTa model using the queries and subtitle sentences in TVR train-split with masked language model objective [7]. Then, we fix the parameters and extract contextualized token embeddings from the second-to-last layer [19]. For queries, we directly use the extracted token embeddings as inputs, denoted as \( E^v \in \mathbb{R}^{l_q \times 768} \). For subtitles, we first extract token-level embeddings, then max-pool the token-level embeddings every 1.5 seconds to get a 768D clip-level feature vector. For clips where there are no subtitles, we simply use a 768D zero vector to represent the textual information. We denoted the final subtitle embedding as \( E^s \in \mathbb{R}^{l_s \times 768} \).

The extracted features are then separately projected into a low-dimensional space using a linear layer with ReLU activation. We then add learned positional encoding [7] to the projected features. Note we use different positional encoding for query and context (video, subtitle), as the positional encoding for context may also indicate the temporal location of the features. Without ambiguity, we reuse the symbols by denoting the projected features as \( E^v \in \mathbb{R}^{l_q \times d}, E^s \in \mathbb{R}^{l_s \times d}, E^v \in \mathbb{R}^{l_s \times d}, \) where \( d \) is hidden size.

4.2. Query and Context Encoding

To better illustrate our encoding layers, we first describe the background for scaled dot-product attention [31]. Given query matrix \( Q \in \mathbb{R}^{l_q \times d_q} \), key matrix \( K \in \mathbb{R}^{l_k \times d_k} \) and value matrix \( V \in \mathbb{R}^{l_v \times d_v} \), the attentional output (shape \( \mathbb{R}^{l_q \times d_w} \)) is computed as:

\[
A(Q,K,V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V.
\]

The formulation of scaled dot-product attention is quite general. It can be used as both self-attention [31] where the three matrices are all the same, and cross-attention [31] where \( Q \) is from a different modality.

**Query**  As our input queries can be related to either visual or textual information, we adopt a modular design to dynamically decompose the query into two modality vectors. Specifically, the query feature is encoded using a **Self-**
**Encoder** (See Figure 3 bottom-left). It consists of a self-attention [31] layer and a linear layer, with a residual [11] connection followed by layer normalization [2]. We denote the encoded query as $H^q \in \mathbb{R}^{l \times d}$. Then, we apply two trainable modular weight vectors $w_m \in \mathbb{R}^{d \times m} \in \{v, s\}$ to compute the attention scores of each query word w.r.t. the video $(v)$ and subtitle $(s)$ modalities. The scores are used to aggregate the information of $H^q$ to generate a modularized query vector $q^m \in \mathbb{R}^d$ [37]:

$$q^m = \text{softmax}(w_q^T H^q) H^q,$$

where $m \in \{v, s\}$.

**Context** Given the video features $E^v$ and subtitle features $E^s$, we use two Self-Encoders to compute their single-modal contextualized features $H^v_0 \in \mathbb{R}^{l \times d}$ and $H^s_0 \in \mathbb{R}^{l \times d}$. Then, we encode their cross-modal representations via two Cross-Encoders (see Figure 3 bottom-left). The Cross-Encoder takes as input the self-modality and cross-modality features, and encodes the two via cross-attention [31] followed by a linear layer, a residual connection, a layer normalization, and another Self-Encoder. Note the Cross-Encoder works bi-directionally, i.e., in the video stream, the $Q$ matrix is $H^v_0$ and both $K$ and $V$ are $H^s_0$, and vice versa in the subtitle stream. We denote the final video and subtitle representations as $H^v_1$ and $H^s_1$, respectively.

**4.3. Convolutional Start-End Detector**

Given the above $H^v_1, H^s_1$ and query vectors $q^v, q^s$, we compute the query-clip matching scores $S_{\text{query-clip}} \in \mathbb{R}^l$:

$$S_{\text{query-clip}} = \frac{1}{2} (H^v_1 q^v + H^s_1 q^s).$$

Next, we apply two trainable 1D convolution filters (no bias) on top of the scores to generate the START (st) and END (ed) scores:

$$S_{\text{st}} = \text{Conv1D}_{\text{st}}(S_{\text{query-clip}}),$$

$$S_{\text{ed}} = \text{Conv1D}_{\text{ed}}(S_{\text{query-clip}}).$$

The scores are normalized with softmax to output the probabilities $P_{\text{st}}, P_{\text{ed}} \in \mathbb{R}^l$. The convolution filters learn to detect the left edges (START) and right edges (END) for the 1D matching scores. We show its interpretability in Section 5.3.

**4.4. Training and Inference**

**Video Retrieval** Given the modularized queries $q^v, q^s$ and the encoded contexts $H^v_0, H^s_0$, we compute the video retrieval score as:

$$s_{\text{vr}} = \frac{1}{2} \sum_{m \in \{v, s\}} \text{max}(H^m_0 q^m, H^m_0 q^m),$$

which essentially computes the cosine similarity between each encoded clip and query and picks the maximum. The final video-level score is the average of the scores from the two modalities. During training, we sample two negative pairs of $(q_i, v_j)$ and $(q_j, v_i)$ for each positive pair of $(q_i, v_i)$ to calculate a combined hinge loss as [37]:

$$L_{\text{vr}} = \frac{1}{n} \sum_{i} \text{max}(0, \Delta + s_{\text{vr}}(v_i|q_i) - s_{\text{vr}}(v_i|q_i))$$

$$+ \max(0, \Delta + s_{\text{vr}}(v_i|q_j) - s_{\text{vr}}(v_i|q_i)).$$
Single Video Moment Retrieval. Given the START and END probabilities \( P_{st}, P_{ed} \), we define the single video moment retrieval loss as:

\[
L^{svmr} = -\frac{1}{N} \sum_{i} \left[ \log(P_{st}(t_{st}^i)) + \log(P_{ed}(t_{ed}^i)) \right],
\]

where \( t_{st}^i \) and \( t_{ed}^i \) are the ground-truth indices. At inference, the confidence score of a predicted START-END span \([t_{st}^i, t_{ed}^i]\) is computed as:

\[
s^{svmr}(t_{st}^i, t_{ed}^i) = P_{st}(t_{st}^i)P_{ed}(t_{ed}^i), \quad t_{st}^i \leq t_{ed}^i.
\]

Video-Subtitle Corpus Moment Retrieval. Our final training loss combines both: \( L = L^{vr} + \lambda L^{svmr} \), where the hyperparameter \( \lambda \) is set as 0.01 in our experiments. At inference, we compute the overall video-subtitle corpus moment retrieval score by combining both video retrieval and single video moment retrieval scores:

\[
s^{vscmr}(v_j, t_{st}, t_{ed}; q_i) = s^{svmr}(t_{st}, t_{ed}|v_j, q_i) \exp(\alpha s^{vr}(v_j|q_i)),
\]

where \( s^{vscmr}(v_j, t_{st}, t_{ed}|q_i) \) is the retrieval score of moment \( v_j[t_{st}, t_{ed}] \) w.r.t. the query \( q_i \). The exponential term and the hyper-parameter \( \alpha \) are used to balance the importance of the two scores. A higher \( \alpha \) encourages the model to output more moment predictions from the top retrieved videos. Empirically, we find \( \alpha=20 \) works well. At inference, for each query, we first retrieve top 100 videos based on \( s^{vr} \), then rank all the moments in the 100 videos by \( s^{vscmr} \) to give the final predictions.

5. Experiments

We split TVR into 80% train, 10% val, 5% test-public, and 5% test-private. test-public will be used for a public leaderboard, test-private is reserved for future challenges. In the following, we compare XML with multiple baseline methods on test-public set and present a detailed ablation study on val set.

5.1. Baselines

Moment Frequency. We first discretize the video-length normalized start-end timestamps [1], then use the most frequent one as the moment prediction. For video, we randomly sample one from the corpus.

Moment Context Network (MCN). MCN is proposed in [1] for single video moment retrieval task. It localizes moments by comparing the squared Euclidean Distance between the temporally aggregated global and local context features with the query feature.

Clip Alignment with Language (CAL). Instead of representing a moment as a single aggregated vector as in MCN, CAL [8] represents each moment as a set of clips. The final moment-query distance is calculated as the average of the squared euclidean distances between its clips to the query.

Extractive Clip Localization (ExCL). ExCL [10] uses a start-end predictor, predicting the start and end indices by applying an LSTM and two MLPs on top of the concatenated and encoded video and query features. Experimental results show ExCL achieves strong performance on ActivityNet Captions [17] and TACoS [25].

Retrieval and Re-ranking. While MCN and CAL can directly rank moments over the whole video corpus, one could also first retrieve a set of candidate videos using a given method and then re-rank the moments in the candidate videos using another method. This is similar to the method used in [8]. We consider using Mixture of Embedding Experts (MEE) [22] for video retrieval. MEE is designed for text to video retrieval and has demonstrated strong performance on LSMDC [26] and MSR-VTT [35].

5.2. Metrics and Implementation Details

Metrics. Following [8, 9], we use average recall at K (R@K) over all queries as our metric. A prediction is correct if: (i) its predicted video matches the ground truth; (ii) its predicted span has high overlap with the ground truth. Temporal intersection over union (IoU) is used to measure the overlap between the predicted span and the ground truth span. We report R@K for \( K \in \{1, 5, 10, 100\} \) with IoU \( \in \{0.5, 0.7\} \) to account for missing annotations.

Implementation Details. XML ¹ is implemented using PyTorch [24]. The hidden size is set to 256. We use Adam [16] with an initial learning rate of 1e-4, \( \beta_1 = 0.9, \beta_2 = 0.999 \), L2 weight decay of 0.01, learning rate warm-up over the first 5 epochs. We train XML for at most 100 epochs with early stop, the batch size is set to 128. All baselines are configured to use the same hidden size as XML, with total number of parameters 3M. We train the baselines following the original papers and spent similar amounts of time to tune their performance as we did for XML. We use the same features for all the models. To support retrieval using subtitle for the baselines, we simply add a separate subtitle stream and average the final predictions from both video and subtitle streams. Non-maximum suppression with temporal IoU threshold of 0.5 is applied whenever we observe better val set performance.

5.3. TVR Results

Comparison with Baselines. Table 3 shows the results on TVR test-public set, containing 5,445 queries and 1,089

¹https://github.com/jayleicn/TVRetrieval
videos. In the following, we discuss R@1 IoU=0.7, unless otherwise stated. We additionally report the run time of the methods, which is averaged from 3 runs on an RTX 2080Ti GPU. Across all metrics, we observe significant performance improvement over the strong baseline methods. The best baseline performance is obtained by the retrieval + re-ranking method MEE [22] + CAL [8] (TEF). Our best method, XML (TEF) is able to get 5x higher performance (3.32 vs 0.66) with 6.3x speedup (25.5s vs 161.5s). Compared with MEE + ExCL [10], XML (TEF) achieves 8.3x performance improvement (3.32 vs 0.40) and 51.3x speedup (25.5s vs 1307.2s). The huge difference in run time is because ExCL uses very expensive early fusion.

### Ablation of Input Modalities
To show the importance of using both video and subtitle, we compare with XML variants that use only video or subtitle. Table 4 shows the results of this comparison. Firstly, the model with both modalities as inputs has better overall performance than the single modality models, which proves that both modalities are useful for the task. Secondly, we observe that models trained on one modality do not perform well on the queries tagged by another modality. For example, the XML (video) model that uses only video performs much worse on subtitle queries compared to XML (sub) model (0.73 vs 1.87).

### Ablation of Model Architecture
Table 5 presents a model architecture ablation. We first compare with different self-encoder architectures, replacing our transformer style encoder with a bidirectional LSTM encoder [18] or a CNN encoder [36, 19]. We observe worse performance after the change, and attribute this performance drop to the ineffectiveness of LSTMs and CNNs to capture long-term dependencies [12, 31]. Next, we compare XML with a variant that uses a max-pooled query instead of the modularized queries. Across all metrics, XML performs better than the variant without modular queries. Finally, we study the

### Table 3. Comparison with baselines on TVR test-public set. We show top-2 scores in each column in bold. Model references: MCN [1], CAL [8], MEE [22], ExCL [10]. TEF indicates models with Temporal Endpoint Feature [1].

| Model          | Video | Subtitle | IoU=0.5 |           | IoU=0.7 |           | Run Time ↓ |
|----------------|-------|----------|---------|-----------|---------|-----------|------------|
|                |       |          | R@1     | R@5       | R@10    | R@100     | (seconds)  |
| Chance         | -     | -        | 0       | 0.02      | 0.04    | 0.33      |            |
| Moment Frequency| -    | -        | 0.06    | 0.07      | 0.11    | 0.28      |            |
| Proposal based methods |     |          |         |           |         |           |            |
| TEF-only       | -     | -        | 0       | 0.09      | 0.15    | 0.79      |            |
| MCN            | ✓     | ✓        | 0.02    | 0.15      | 0.24    | 2.20      |            |
| MCN (TEF)      | ✓     | ✓        | 0.04    | 0.11      | 0.17    | 1.84      |            |
| CAL            | ✓     | ✓        | 0.09    | 0.31      | 0.57    | 3.42      |            |
| CAL (TEF)      | ✓     | ✓        | 0.04    | 0.17      | 0.31    | 2.48      |            |
| Retrieval + Re-ranking |     |          |         |           |         |           |            |
| MEE + MCN      | ✓     | ✓        | 0.92    | 3.69      | 5.58    | 17.91     | 0.42 1.89 2.98 10.84 |
| MEE + MCN (TEF)| ✓     | ✓        | 1.36    | 3.89      | 5.79    | 19.34     | 0.62 2.04 3.21 11.66 |
| MEE + CAL      | ✓     | ✓        | 0.97    | 3.75      | 5.80    | 18.66     | 0.39 1.69 2.98 11.52 |
| MEE + CAL (TEF)| ✓     | ✓        | 1.23    | 4.00      | 6.52    | 20.07     | 0.66 1.93 3.09 12.03 |
| MEE + ExCL     | ✓     | ✓        | 0.92    | 2.53      | 3.60    | 6.01      | 0.33 1.19 1.73 2.87 |
| MEE + ExCL (TEF)| ✓    | ✓        | 1.01    | 2.50      | 3.60    | 5.77      | 0.40 1.21 1.73 2.96 1307.2 |
| XML            | ✓     | ✓        | 7.25    | 17.41     | 23.69   | 37.89     | 3.25 8.21 11.7 19.6 |
| XML (TEF)      | ✓     | ✓        | 7.88    | 18.15     | 24.22   | 38.18     | 3.32 9.02 12.43 19.91 25.5 |

Table 4. XML performance on TVR val set by query types, with different input modalities.

| Model          | IoU=0.7 |           |           |           |           |
|----------------|---------|-----------|-----------|-----------|-----------|
|                | R@1     | R@5       | R@10      | R@100     |
| Query Type: Video 74.32% |         |           |           |           |
| XML (video)    | 2.05    | 5.24      | 7.26      | 13.00     |
| XML (sub)      | 0.82    | 1.94      | 2.94      | 5.31      |
| XML (video+sub) | 2.57    | 5.88      | 7.93      | 13.83     |
| Query Type: Subtitle 8.85% |         |           |           |           |
| XML (video)    | 0.73    | 3.53      | 5.29      | 9.85      |
| XML (sub)      | 1.87    | 5.19      | 8.30      | 16.7      |
| XML (video+sub) | 1.56    | 5.71      | 8.30      | 15.25     |
| Query Type: Video+Subtitle 16.83% |         |           |           |           |
| XML (video)    | 2.07    | 4.91      | 7.20      | 12.92     |
| XML (sub)      | 2.40    | 6.92      | 9.54      | 15.54     |
| XML (video+sub) | 3.22    | 7.58      | 10.85     | 18.43     |

Table 4. XML performance on TVR val set by query types, with different input modalities.

| Model | IoU=0.7 |           |           |           |
|-------|---------|-----------|-----------|-----------|
|       | R@1     | R@5       | R@10      | R@100     |
| Self-Encoder Type |         |           |           |           |
| XML (LSTM) | 2.12    | 4.48      | 6.48      | 10.90     |
| XML (CNN)  | 2.45    | 5.53      | 7.45      | 12.79     |
| Modular Query |         |           |           |           |
| XML (No modular query) | 2.46    | 5.71      | 7.89      | 14.72     |
| Conv. Start-End Detector |         |           |           |           |
| XML (Conv. k = 1) | 1.94    | 5.66      | 8.21      | 13.68     |
| XML (Conv. k = 3) | 2.49    | 6.38      | 8.92      | 17.02     |
| XML (Conv. k = 7) | 2.53    | 6.27      | 8.11      | 13.80     |
| XML       | 2.62    | 6.10      | 8.45      | 14.86     |

Table 5. Ablation of model architecture on TVR val set. Our full XML model in the last row is configured with transformer encoder, modular query and k = 5. All models use both videos and subtitles. We show top-2 scores in each column in bold.
Barney: But still, you think, this is different. The platinum rule doesn’t apply to me. And that’s step 2.

Rachel: Three-pound lobster?
Joey: You know what? Bring her both. And I’ll have the same.

Rachel: Three-pound lobster? Joey: You know what? Bring her both. And I’ll have the same.

Not that I don’t enjoy talking about high school. Because I do. Maybe we can talk about something else.

Barney: But still, you think, this is different. The platinum rule doesn’t apply to me. And that’s step 2.

Barney: He is our Neil Armstrong. Spacesuit up, Ted, ‘cause you’re going to the moon.

Barney: But still, you think, this is different. Barney: The platinum rule doesn’t apply to me. And that’s step 2.

Figure 4. Qualitative examples of XML. We show top-3 retrieved moments for each query. Top row shows the query word modular attention weights for video and subtitle respectively. Left column shows a correct prediction, right column shows a failure case. Text inside dashed boxes is the subtitles with the predicted moments. Ground truth is shown as the green bar under the video frames. Best viewed in color.

Figure 5. Example of the convolution filters applying on the input query-clip similarity scores. Ground-truth span is indicated by the two arrows labeled by ‘GT’. Note the two filters output stronger responses on the left edges (START) and right edges (END).

Learned Convolution Filters Figure 5 shows an example of the learned convolution filters with $k=5$. Given the query-clip similarity scores, the filters output stronger responses to the left edges (START) and right edges (END) and thus detect them. Interestingly, the learned weights $\text{Conv1D}_{\text{st}}$ and $\text{Conv1D}_{\text{ed}}$ in Figure 5 are similar to the edge detectors in image processing [29].

Qualitative Analysis Figure 4 shows two examples of the top-3 moment predictions on TVR $val$ set. In the top row, we also show the query word attention scores for video and subtitle, respectively. Figure 4 (left) shows a correct prediction. The top-2 moments are from the same video and are both correct. The third moment is retrieved from a different video. While incorrect, it is still relevant as it also happens in a ‘restaurant’. Figure 4 (right) presents a failure. It is worth noting that the false moments are very close to the correct prediction with minor differences (‘on the shoulder’ vs ‘around the shoulder’). Besides, it is also interesting to see which words are important for video or subtitle. For example, the words ‘waitress’, ‘restaurant’, ‘menu’ and ‘shoulder’ get the most weight for video; while the words ‘Rachel’, ‘menù’, ‘Barney’, ‘Ted’ have higher attention scores for subtitle.

Figure 5 shows an example of the convolution filters with $k=5$. Given the query-clip similarity scores, the filters output stronger responses to the left edges (START) and right edges (END) and thus detect them. Interestingly, the learned weights $\text{Conv1D}_{\text{st}}$ and $\text{Conv1D}_{\text{ed}}$ in Figure 5 are similar to the edge detectors in image processing [29].

Qualitative Analysis Figure 4 shows two examples of the top-3 moment predictions on TVR $val$ set. In the top row, we also show the query word attention scores for video and subtitle, respectively. Figure 4 (left) shows a correct prediction. The top-2 moments are from the same video and are both correct. The third moment is retrieved from a different video. While incorrect, it is still relevant as it also happens in a ‘restaurant’. Figure 4 (right) presents a failure. It is worth noting that the false moments are very close to the correct prediction with minor differences (‘on the shoulder’ vs ‘around the shoulder’). Besides, it is also interesting to see which words are important for video or subtitle. For example, the words ‘waitress’, ‘restaurant’, ‘menu’ and ‘shoulder’ get the most weight for video; while the words ‘Rachel’, ‘menù’, ‘Barney’, ‘Ted’ have higher attention scores for subtitle.
6. Conclusion

In this work, we present TVR, a large-scale dataset designed for multimodal video-subtitle moment retrieval tasks. Detailed analyses show TVR is of high quality and is more challenging than previous datasets. We further propose Cross-modal Moment Localization (XML), an efficient model suitable for the TVR task.

Acknowledgement

This research is supported by NSF Awards #1633295, 1562098, 1405822, DARPA MCS Grant #N66001-19-2-4031, DARPA KAIROS Grant #FA8750-19-2-1004, Google Focused Research Award, and ARO-YIP Award #W911NF-18-1-0336.

A. Additional TVR Data Details

A.1. Data Collection

Qualification Test  Figure 6 shows a question from our qualification test. This particular question is designed to make sure the annotators write relevant and correct descriptions (queries).

Post-Annotation  The post-annotation rating was done in a likert-scale manner with 5 options as shown in 7. Results show that 92% of the pairs have a rating of at least neutral. We further analyzed the group of queries that were rated as strongly disagree and found 80% of them were still of acceptable quality: e.g., slightly mismatched timestamps (≤ 1 second). For the group of queries that were rated as disagree, this number is 90%. The distribution of the collected ratings is shown in Figure 8.

A.2. Data Analysis

Analysis of Annotated Moments  Figure 9 shows the moment length distribution of TVR. The majority of the moments are relatively short, with an average length of 9.1 seconds, median length of 5 seconds. As a comparison, the average length of the videos is 76.2 seconds. Figure 10 shows the video-length normalized moment center distributions. More moments are located at the beginning of the videos.

Analysis of Annotated Queries  Figure 11 shows the query length distribution. The average length of the queries is 13.4 words, the median length is 12 words.
Figure 10. TVR video-length normalized moment center distribution.

Figure 11. TVR query length distribution.

Table 6. Video-Subtitle Corpus Moment Retrieval on 1M videos with 100 queries. TVR test-public set results are included as reference. We show top scores in each column in bold. Model references: MCN [1], CAL [8], MEE [22], ExCL [10]. TEF indicates models with Temporal Endpoint Feature [1].

| Model                  | IoU=0.5 | Search 100 queries in 1M videos | R@1          | R@5          | R@10         | R@100        |
|------------------------|---------|--------------------------------|--------------|--------------|--------------|--------------|
|                        | feat time (s) | feat size (GB) | retrieval time (ms) |
| Retrieval + Re-ranking |         |                  |              |              |              |              |
| MEE + MCN (TEF)        | 0.62    | 2.04              | 131          | 326          | 10.8         |              |
| MEE + CAL (TEF)        | 0.66    | 1.93              | 841          | 2,235        | 15.2         |              |
| MEE + ExCL (TEF)       | 0.40    | 1.21              | -            | > 1h         |              |              |
| XML (TEF)              | 3.32    | 9.02              | 29           | 76           | 4.5          |              |

Table 7. XML results on TVR val set, with different video features. All methods use both videos and subtitles. We show top scores in each column in bold.

| Model                  | IoU=0.5 | IoU=0.7       |
|------------------------|---------|---------------|
|                        | R@1    | R@5          | R@1          | R@5        |
| XML (ResNet)           | 2.28   | 5.1          | 5.1          | 0.94       | 4.41        |
| XML (I3D)              | 2.22   | 5.77         | 7.88         | 0.41       | 14.23       |
| XML (ResNet+I3D)       | 2.62   | 6.1          | 8.45         | 0.05       | 14.86       |

Table 8. Single Video-Subtitle Moment Retrieval (SVSMR) results on TVR val set. We show top-2 scores in each column in bold. Model references: MCN [1], CAL [8], MEE [22], ExCL [10].

| Model                  | Video Subtitle | IoU=0.5 | IoU=0.7       |
|------------------------|---------------|---------|---------------|
|                        | R@1    | R@5          | R@1          | R@5        |
| Chance                 | -      | -            | 3.24         | 12.79      | 14.2         |
| Moment Frequency       | -      | -            | 7.72         | 18.93      | 12.27        |
| TEF-only               | -      | -            | 9.63         | 24.86      | 14.92        |
| MEE                    | ✓      | ✓            | 13.08        | 39.61      | 20.37        |
| MCE                    | ✓      | ✓            | 16.86        | 40.55      | 24.15        |
| CAL                    | ✓      | ✓            | 12.07        | 39.52      | 20.17        |
| CAL (TEF)              | ✓      | ✓            | 17.61        | 42.08      | 21.4         |
| ExCL                   | ✓      | ✓            | 31.34        | 47.4       | 28.01        |
| ExCL (TEF)             | ✓      | ✓            | 31.31        | 48.54      | 28.89        |
| XML                    | ✓      | ✓            | 30.75        | 51.2       | 31.11        |
| XML (TEF)              | ✓      | ✓            | 31.43        | 51.66      | 31.11        |

B. Additional TVR Results

B.1. Comparison on TVR task

Retrieval Efficiency on 1M videos We consider Video-Subtitle Corpus Moment Retrieval on a video corpus containing 1M videos with 100 queries as [8]. Each video containing 20 clips with max moment length of 14 clips. Each query containing 15 words. We report the following metrics: (i) feature encoding time (feature time), which measures the time for encoding the video and subtitle features. (ii) encoded feature size (feature size) measures the disk space needed to store the encoded video and subtitle features. We do not report this number for ExCL [10] as it does not have the ability to pre-encode the features. (iii) retrieval time (retrieval time) measures the time needed to retrieval relevant moments for 100 new queries. It includes time for encoding the queries and performing approximate nearest neighbor search [13]. The time spent on data loading, pre-processing, feature extraction on backend models (i.e., ResNet-152, I3D, RoBERTa), etc is ignored since they should be similar if not the same for all the methods. This experiment was conducted on an RTX 2080Ti GPU and an Intel(R) Xeon(R) Silver 4114 CPU @ 2.20GHz x 40, with PyTorch [24] and FAISS [13].

The results are shown in Table 6. Our XML (TEF) model is more efficient than all the baselines. Compared to the best baseline methods MEE + MCN (TEF), XML (TEF) is 2.6x faster in retrieval, 4.5x faster in feature encoding and needs 67% less disk space to store the encoded features. Besides, it also has 5.4x higher performance (IoU=0.7, R@1, on TVR test-public set). Note that MEE + ExCL(TEF) has very poor retrieval time performance, as it requires early fusion of video (subtitle) and query features. In comparison, the other 3 methods are able to encode the video (subtitle) features offline and use highly optimized nearest neighbor search and inner product to perform the final search task.

Feature Ablation We tested XML model with different visual features. Results are shown in Table 7. The model that uses both static appearance features (ResNet) and action features (I3D) performs better than using only one of the features, demonstrating the importance of recognizing both the objects and the actions in the TVR task.

B.2. Comparison on TVR subtasks

Table 8 shows the results on the subtask Single Video-Subtitle Moment Retrieval (SVSMR) on TVR val set. The task is to retrieve moments from a single video (with subtitle). XML achieves comparable performance with the state-of-the-art method ExCL [10]. However, note that XML runs more efficiently, as stated in the main text Section 5.3 and supplementary Section B.1.
Table 9. Video-Subtitle Retrieval (VSR) results on TVR val set. We show top-2 scores in each column in bold. Model references: MCN [1], CAL [8], MEE [22].

| Model       | Dataset | Domain | #moment | #desc. | #desc. per | desc. src. | desc. type |
|-------------|---------|--------|---------|--------|------------|------------|------------|
| MCN (TEF)   | TVC     | TV show| 108K    | 262K   | 3          | ✓          | ✓          |
| CAL (TEF)   | TVC     | TV show| 108K    | 262K   | 3          | ✓          | ✓          |
| MEE         | TVC     | TV show| 108K    | 262K   | 3          | ✓          | ✓          |

Table 10. Comparison of TVC with existing video captioning datasets. caption src. = caption sources, it indicates where the captions are raised from.

C.1. Data Collection and Analysis

To promote better coverage of the video (subtitle) content, we encourage annotators to write descriptions that are of different types from existing ones, e.g., we encourage annotators to write video-only and video-text type descriptions if there already exists a text-only description. For each moment in the TVR training set, we collect one extra description, together with the original description forms the TVC training set with 2 descriptions for each moment. For each moment in TVR val/test sets, we collect 4 extra descriptions as the TVC val/test sets. The original val/test descriptions in TVR are not used to ensure data integrity. Details regarding data split are presented in Table 14.

Table 10 gives an overview of TVC and its comparison with recent video captioning datasets. In total, TVC contains 262K descriptions paired with 108K moments. TVC is unique as its captions may also describe dialogues/subtitles while the captions in the other datasets are only describing the visual content. Figure 14 compares the description type distribution between TVR and TVC. As we encouraged annotators to write different types of descriptions, the description type distribution is more balanced in TVC compared to that of TVR. Figure 15 shows the description length distribution of TVC, the average length is 14.4 words (13.4 for TVR), median length is 13 words (12 for TVR).

C.2. Multimodal Transformer

To provide a strong initial baseline for the TVC multimodal video captioning task, we designed a MultiModal Transformer (MMT) captioning model which follows the classical encoder-decoder transformer architecture [31]. It takes both video and subtitle as encoder inputs to generate

tions (TVC), is a large-scale multimodal video captioning dataset. Figure 12 shows two TVC examples. Similar to TVR, the TVC task requires systems to gather information from both video and subtitle to generate relevant descriptions. In the following, we present a brief analysis of the TVC dataset and some initial baselines for the TVC task.

C.3. Qualitative Examples

We show additional qualitative examples from the XML model in Figure 16 and Figure 17. We show top-3 predictions for the video-subtitle corpus moment retrieval task, as well as associated predictions (with convolution filter responses) for single video-subtitle moment retrieval task.

C. TV show Captions

As stated in the main text, after the TVR data collection, we extended TVR by collecting extra descriptions for each annotated moment. This dataset, named TV show Capt-

Figure 12. TVC caption description examples. Each caption description is followed by a description type tag. Text inside dashed boxes is the subtitles associated with the moments. For brevity, here we only show frames from the moments.
the captions from the decoder. Figure 13 gives an overview of the designed model.

**Input Representation** We use the concatenation of I3D [3] feature and ResNet-152 [11] feature to represent videos. The features are pre-processed in the same way as the XML model for the TVR task (see Section 4.1 in the main text). To represent subtitles, we use trainable 300D word embeddings. Next, we project raw video features and subtitle word features into a common embedding space using linear layers and layernorm [2] layers. The projected video embedding $E^v \in \mathbb{R}^{l_v \times d}$ and subtitle embedding $E^s \in \mathbb{R}^{l_s \times d}$ are then concatenated at length dimension as the input to the encoder: $E^{ctx} = [E^v; E^s]$, where $E^{ctx} \in \mathbb{R}^{(l_v + l_s) \times d}$ stands for the context embedding, $d$ is hidden size.

**Encoder and Decoder** Both the encoder and decoder follow the standard design [31] with 2 layers, i.e., $N=2$. The decoder access encoder outputs at each layer with a multi-head attention [31]. We refer readers to [31] for a more detailed explanation of the model architecture.

**Training and Inference** We train the model using Maximum Likelihood Estimation (MLE), i.e., we maximize the likelihood of generating the ground truth words. At inference, we use greedy decoding instead of beam search as it performs better in our experiments.

**C.3. Experiments**

We use the same data split for TVC as in TVR, see Section D for more details. We report numbers on standard metrics, including BLEU@4 [23], METEOR [6], Rouge-L [20], CIDEr-D [32].

We first compare MMT models with different input modalities. The results are shown in Table 11. Across all metrics, the model with both videos and subtitles performs better than the models with only one of them. Which shows both videos and subtitles are important for describing the moments. Next, we compare models with different visual features. The results are shown in Table 12. Models with both appearance features (ResNet) and motion feature (I3D) performs better than only using one of them.
| Model           | B@4 | METEOR | Rouge-L | CIDEr-D |
|-----------------|-----|--------|---------|---------|
| MMT (sub)       | 6.33| 13.92  | 7.73    | 33.76   |
| MMT (video)     | 9.98| 15.23  | 30.44   | 36.07   |
| MMT (video+sub) | 10.87| 16.91  | 32.81   | 45.38   |

Table 11. Captioning Results on TVC test-public set.

| Model               | B@4 | METEOR | Rouge-L | CIDEr-D |
|---------------------|-----|--------|---------|---------|
| MMT (ResNet)        | 9.92| 16.24  | 31.76   | 43.94   |
| MMT (I3D)           | 10.25| 16.48  | 31.98   | 43.7    |
| MMT (ResNet+I3D)    | 10.53| 16.61  | 32.35   | 44.39   |

Table 12. Feature ablation on TVC val set. All the models use both videos and subtitles.

C.4. Qualitative Examples

Qualitative examples of MMT are shown in Figure 18.

D. Data Release and Public Leaderboards

Data and leaderboards for both TVR and TVC are publicly available at [https://tvr.cs.unc.edu](https://tvr.cs.unc.edu). In the following, we describe data split and usage in details.

We split TVR into 80% train, 10% val, 5% test-public and 5% test-private such that videos and their associated queries appear in only one split. This setup is the same as TVQA [18]. Details of the splits are presented in Table 13. test-public will be used for a public leaderboard, test-private is reserved for future challenges. val set should only be used for parameter tuning, it should not be used in the training process in any means, including but not limited to pre-train the language features.

TVC follows the same data split as the TVR, but with different number of descriptions per moment, i.e., the training moments are paired with 2 descriptions while the moments in other splits are paired with 4 descriptions. Details are presented in Table 14. The rules on split usage are also the same as the TVR.

| Split               | Query Types |
|---------------------|-------------|
|                     | video | sub | video+sub | all       |
| train               | 64,745/17,435 | 7,956/5,372 | 14,474/9,708 | 87,175/17,435 |
| val                 | 8,097/2,179 | 964/681 | 1,834/1,241 | 10,895/2,179 |
| test-public         | -     | -   | -         | 5,450/1,090 |
| test-private        | -     | -   | -         | 5,450/1,090 |

Table 13. TVR split info by query types. Each data cell represents #queries/#videos. Test sets details are masked.

| Split          | #desc. | #moments | #videos | #desc./moment |
|----------------|--------|----------|---------|---------------|
| train          | 174,350| 86,603   | 17,435  | 2             |
| val            | 43,580 | 10,481   | 2,179   | 4             |
| test-public    | 21,780 | 5,420    | 1,089   | 4             |
| test-private   | 21,800 | 5,422    | 1,090   | 4             |

Table 14. TVC split info.
Figure 16. Qualitative examples of XML. We show top-3 retrieved moments for video-subtitle corpus moment retrieval (top) and single video moment retrieval results (bottom, with convolution filter responses) for each query. Text inside dashed boxes is the subtitles with the predicted moments. Ground truth is shown as the green bar under the video frames. Best viewed in color.
Figure 17. Qualitative examples of XML. We show top-3 retrieved moments for video-subtitle corpus moment retrieval (top) and single video moment retrieval results (bottom, with convolution filter responses) for each query. Text inside dashed boxes is the subtitles with the predicted moments. Ground truth is shown as the green bar under the video frames. Best viewed in color.
Beckett: No, Castle, I'm talking about my life. I don't know what to do about my life...

Ground-Truth Captions
• Beckett rolls over to lay on her back. (video-only)
• Beckett is visibly worried and speaks to Castle while they are in bed. (video-only)
• Castle and Beckett discuss her vacation when they're in bed. (video-text)
• Beckett is talking to Castle about losing her job. (text-only)

Generated Captions:
• Beckett tells Castle that she is going to be honest. (model: sub)
• Beckett and Castle are in bed and they are in bed. (model: video)
• Beckett and Castle are in bed together, and Beckett is sleeping in bed. (model: video + sub)

Sheldon: ...with Adamantium like Wolverine.

Penny: Are they working on that?

Ground-Truth Captions
• Sheldon holds out a large pile of cash with his right hand in front of Sheldon. (video-only)
• Sheldon is holding something in his hand out to Penny. (video-only)
• Astonished, Penny makes a question, to which Sheldon gives a serious answer while presenting her with money. (video-text)
• Penny questions Sheldon as to whether somebody is trying something. (text-only)

Generated Captions:
• Sheldon asks penny if she is feeling like a certain way. (model: sub)
• Sheldon tells penny that she is not sure. (model: video)
• Sheldon is standing in front of penny as he speaks to her. (model: video + sub)

Alexis: Once we realized Mandy hadn't really cheated on him.

Ground-Truth Captions
• Alexis runs her hand through her hair when Castle is looking at her. (video-only)
• Alexis fixes her hair as she speaks to Castle beside her. (video-only)
• Alexis runs her hair when Castle is looking at her. (video-only)
• The girl adjust her hair while Castle stares at her. (video-only)

Generated Captions:
• Alexis and castle walk into the room together. (model: sub)
• Beckett and castle are talking to each other. (model: video)
• Alexis and castle stand in front of each other as they stand in front of each other. (model: video + sub)

Cameron: or should we just start running a thousand different tox screens?...

Ground-Truth Captions
• House grabs a file and opens it up. (video-only)
• House picks a file, place it on a table then opens it. (video-only)
• House opens a file and says he won't read it. (video-text)
• House jokes about tox screens when Foreman suggests it's something different. (video-text)

Generated Captions:
• House and Cameron are having a conversation with each other. (model: sub)
• House puts a red box on the table and takes a red coffee cup. (model: video)
• House picks up a red mug and takes it off. (model: video + sub)

Rachel: You've been here for two months now. And your boss is required to hand in a performance evaluation.

Ground-Truth Captions
• Tag prepares to leave before being reeled back in by Rachel. (video-only)
• As Tag is leaving, Rachel tells him about his evaluation because of how long he has been there. (video-text)
• Tag is surprised to learn that Rachel will evaluate him. (video-text)
• Rachel tells Tag that he will put his performance into his evaluation. (text-only)

Generated Captions:
• Tag tells Rachel that he has been in his office. (model: sub)
• Rachel walks into the office and picks up a book. (model: video)
• Tag walks into Rachel's office and hands her a file. (model: video + sub)

Chandler: We could trade later.

Monica: Yeah, I'm good...

Ground-Truth Captions
• Monica and Chandler touch their babies together in the hospital. (video-only)
• Monica is trying to reposition the baby in her arms. (video-only)
• Chandler and Monica hold their babies close by then decide to keep them. (video-text)
• Monica and Chandler try to figure out how to swap holding babies. (video-only)

Generated Captions:
• Chandler and Monica walk into the apartment and chandler closes the door. (model: sub)
• Monica and Chandler are holding baby Emma as they are in the baby room. (model: video)
• Monica hands Chandler a towel and he takes it and then chandler picks it up. (model: video + sub)

Figure 18. Qualitative comparison of MMT. Text inside dashed boxes is the subtitles associated with the moments. Each ground-truth caption description is followed by a description type tag. We show comparison among models trained with only videos (video), subtitles (sub), or both (video + sub).
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