A comprehensive review of the video-to-text problem

Jesus Perez-Martín1 · Benjamin Bustos1 · Silvio Jamil F. Guimarães2 · Ivan Sipiran3 · Jorge Pérez1 · Grethel Coello Said3

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Abstract
Research in the Vision and Language area encompasses challenging topics that seek to connect visual and textual information. When the visual information is related to videos, this takes us into Video-Text Research, which includes several challenging tasks such as video question answering, video summarization with natural language, and video-to-text and text-to-video conversion. This paper reviews the video-to-text problem, in which the goal is to associate an input video with its textual description. This association can be mainly made by retrieving the most relevant descriptions from a corpus or generating a new one given a context video. These two ways represent essential tasks for Computer Vision and Natural Language Processing communities, called text retrieval from video task and video captioning/description task. These two tasks are substantially more complex than predicting or retrieving a single sentence from an image. The spatiotemporal information present in videos introduces diversity and complexity regarding the visual content and the structure of associated language descriptions. This review categorizes and describes the state-of-the-art techniques for the video-to-text problem. It covers the main video-to-text methods and the ways to evaluate their performance. We analyze twenty-six benchmark datasets, showing their drawbacks and strengths for the problem requirements. We also show the progress that researchers have made on each dataset, we cover the challenges in the field, and we discuss future research directions.

Keywords Vision-and-language · Video-to-text · Video captioning · Video description retrieval · Matching-and-ranking · Deep learning · Joint multi-modal embedding · Visual-semantic embedding · Visual-syntactic embedding
1 The video-to-text problem

The form of communication that we humans use the most is natural language. It is essential that systems such as interactive Artificial Intelligence (AI) and helper robots be capable of generating text, and many applications are developed to automatically generate text from non-linguistic data. Natural Language Generation (NLG) is characterized by Reiter and Dale (2000) as the production of understandable texts from some underlying non-linguistic representation of information. This definition of NLG is usually associated with the data-to-text generation (Eisenstein 2019; Gatt and Krahmer 2018), assuming the exact input can vary substantially. Today, text generation from unstructured perceptual input, such as a raw image or video, has become an important challenge. In this review, we specifically tackle the NLG from videos as a fundamental problem to bridge vision and language.

The Web is the largest multimedia repository. The search and analysis of documents (e.g., audio, video, image, and 3D objects) have increased, leading to the current interest in research in this field. Notably, researchers devoted considerable effort to analyze and retrieve video content, being video understanding, one of the multimedia areas that constitute an open field of research. Advances in computer technology make the user experience a priority.

Specifically, the automatic generation of natural language descriptions of videos poses a challenge for computer vision and multimedia information retrieval communities. Solving it can be useful for video indexing and retrieval, surveillance systems (Sah et al. 2019) (real-time generation of video captions for several simultaneous cameras), robotics (answering questions about the environment), sign language translation, and assistance for the visually impaired. For instance, the automatic video description/caption generation would significantly reduce the problem of video retrieval from text to a two-step process: (1) the generation of textual stories from each video in the dataset, and (2) the text-similarity search between the query and video-related descriptions. This kind of model might help users filter what is attractive to them among the videos on YouTube, searching the videos by their textual stories. However, to deal with the retrieval problem, researchers have proposed other better techniques analyzed in this review.

In Multimedia Information Retrieval, several tasks are based on relating the multimedia data and natural language. When these tasks are focused on any kind of visual content, e.g., images and videos, we lead with a recent research field, the automatic vision-language intersection. In this field, to bridge vision and language, we can, for example, generate text from visual contents or vice versa, and determine (from a dataset or corpus) the most relevant multimedia data to a text query or vice versa. When these tasks receive videos as input, we are dealing with the video-to-text (VTT) problem. Figure 1 shows a detailed categorization of VTT from three aspects: tasks, techniques, and domains.

The VTT research has currently grown in interest thanks to the massive success of deep learning in Computer Vision and Natural Language Processing (NLP). Deep learning is state-of-the-art for several vision tasks, such as activity recognition on videos (Kong and Fu 2018) and object detection (Ren et al. 2017). However, these models require extensive training data to obtain high performance and are usually pre-trained on some large-scale action recognition and video classification datasets. The recent creation of more than twenty-five video-text datasets and benchmarks has partially removed the impediment of the lack of large-scale annotated video datasets for addressing the VTT problem. Likewise, some institutions have proposed competitions to evaluate the VTT methods, in which the teams are asked to submit results for a set of videos.
One of the first video-text datasets was proposed by Chen D and Dolan W (2011) in 2011, which consists of 1970 videos extracted from YouTube. After that, many techniques for the automatic acquisition of videos and the collection of most representative descriptions have been developed, increasing data and contributing to more diversity and realism. In 2018, Mahdisoltani et al. (2018b) presented the Something-Something dataset, one of the largest, with 20,847 videos. Almost all existing large-scale video captioning/description datasets are monolingual (English), and the proposed VTT methods are restricted to English. However, some datasets like VaTeX (Wang et al. 2019c) have driven the study of multilingual video-to-text (English and Chinese), which is very important to achieve a real application of these methods worldwide.

As we will discuss in this review, the VTT problem can be mainly addressed by two types of methods: matching-and-ranking-based techniques or NLG-based techniques. Although the way to evaluate the results in both categories is not the same, the metrics used in both cases come from other tasks related to the VTT problem. In the literature, authors have reported some automatic assessments, and the majority of them have come from the metrics used for information retrieval, image captioning, and machine translation tasks. Researchers quantitatively evaluate the models based on natural language correctness and the semantics’ relevance to the respective input videos, which is not an easy task (Celikyilmaz et al. 2020). There is no standard evaluation method, and some metrics have not shown sufficient robustness for the Video Description/Captioning task compared to the expensive human evaluation.

In the rest of this section we present the VTT tasks and techniques relevant to this review. First, we present the automatic generation of natural language descriptions from videos, also known as video captioning or video description. Next, we present two other tasks: the text retrieval from video task (Sect. 1.2) and the dense video captioning/description task (Sect. 1.3). Finally, in Sect. 1.4, we mention other vision-text tasks, which are not part of the scope of this review but can be important as complementary tasks to speed up and improve the quality of VTT solutions significantly.

Outline of the document: The next three sections offer an overview of the fundamentals of neural models for two essential tasks of VTT, analyzing the principal strategies and models covered in the literature for description generation and matching-and-ranking techniques. In particular, in Sect. 2, we describe how to learn visual features from videos and re-utilize the existing image visual feature extractors. In Sect. 3, an important aspect that we delve into is how sequential decoders learn to generate texts from encoded input videos’ representations. While Sect. 4 analyzes how state-of-the-art methods produce meaning representations in a joint space from videos and texts by two encoders. These two sections also cover the most successful strategies for optimizing the models and present the most reported evaluation metrics for both techniques. We cover the related competitions in Sect. 5, and we describe the standard datasets for benchmarking VTT methods in Sect. 6. To show the state-of-the-art results in each dataset, in Sect. 7, we analyze and compare the reported results of the covered methods, presenting a new overall score to measure the relevance and establish a comparison between the description generation methods. Finally, Sect. 8 concludes the review, discussing the main research challenges in the VTT problem identified throughout the document.

1.1 Video captioning/description

Predicting a single sentence from an image (image captioning) has been a fundamental problem for several years (Chen and Zitnick 2015; Donahue et al. 2015; Gan et al. 2017a; Karpathy and Fei-Fei 2015; Kiros et al. 2014; Kuznetsova et al. 2014; Mao et al. 2014;
Rohrbach et al. 2013; Vinyals et al. 2015). More recently, that problem was extended to generate descriptions from a video with only one event (Chen et al. 2020b; Gan et al. 2017b; Gao et al. 2019; Guadarrama et al. 2013; Hemalatha and Chandra Sekhar 2020; Hou et al. 2019; Kojima et al. 2002; Krishnamoorthy et al. 2013; Liu et al. 2018; Pan et al. 2016b; Pasunuru and Bansal 2017; Rohrbach et al. 2013; Thomason et al. 2014; Venugopalan et al. 2015b; Zhang et al. 2017), or with multiple events (Shen et al. 2017; Wang et al. 2018b; Zhou et al. 2018c). As a text generation task, video captioning is substantially more difficult than image captioning since spatial-temporal information in videos introduces diversity and complexity regarding the visual content and the structure of associated textual descriptions. Although several proposals in the literature for video captioning can generate relevant sentence descriptions, they still have several limitations. Two of them are the existence of gaps in semantic representations and the often generation of syntactically incorrect sentences, which harms their performance on standard datasets.

Depending on the video duration, the problem is normally divided into short-video captioning or long-video captioning. Basically, for short-video captions, we treat videos from five to 20 seconds with a single event. Our goal is to generate a sentence to describe that event. For longer videos, we usually deal with untrimmed videos. These videos are typically five to ten minutes long with multiple events. We need to automatically detect

**Fig. 1** The Video-to-Text problem, tasks, techniques, and domains. In this review we cover the video-to-text problem from the two fundamental techniques by which it has been addressed: retrieval-based (matching-and-ranking-based) and language generation-based (NLG-based)
significant events in the video and generate multiple sentences to describe the different events.

In general, we can divide the different video-to-text solutions into two categories (sub-tasks of VTT): one based on retrieval, which selects the sentence from an available corpus through a video-to-text match (see Fig. 3); and another based on generation techniques, which basically generates a sentence using a captioning model (see Fig. 2). For several years, these two VTT subtasks have been evaluation tasks in the Annual TREC Video Retrieval Evaluation (TRECVID) Challenge, generating a great interest in the vision+language research community. However, we must clarify that despite the common points between both tasks, they are entirely different. Although text retrieval may seem like a viable approach for video captioning in scenarios where we have a number of manual annotations for a video and the task is to choose the best, the main goal of the video captioning task is merely to generate a new sentence from the input video.

1.2 Text retrieval from video

The VTT subtask based on retrieval is also called the VTT matching and ranking sub-task and aims to rank a list of sentences for a given video based on their semantic relevance (see Fig. 3). Training models for retrieving texts from videos could be considered a task without relevant real-world applications due to the current limitations for producing benchmarks with a number of textual descriptions, but this is not entirely true. These models are usually trained in a cross-modal strategy through learning a shared embedding space, that can indifferently embed both modalities.

This ability makes this task suitable as a pre-training technique for transferring knowledge about video descriptions to other downstream tasks (Goodfellow et al. 2016), such as the cross-modal fine-grained action retrieval (Wray et al. 2019). The actions could be treated as phrases and be represented with valuable contextual and grounded information learned from video descriptions. Due to this application and the rapid emergence of videos on the Web, the cross-modal retrieval between videos and texts has attracted growing attention.

Specifically, a current dominant approach for matching models (Dong et al. 2019; Ging et al. 2020) is based on (but not limited to) training three components: a video encoder, a text encoder, and a joint embedding. However, simple joint embeddings are insufficient to represent complicated visual and textual details, such as scenes compositions, objects relations, and particular actions (Chen et al. 2020c). This review categorizes the state-of-the-art proposals according to the different directions adopted to combine these components and the levels of abstraction proposed for encoding videos and texts.

For example, given a manner of representing frames (see Sect. 2), to encode the visual information, three abstraction levels have been explored: (1) global, frequently based on a pooling operation over frame representations; (2) temporal, based on recurrent architectures over the frame representations; (3) local, which applies convolution operations over the sequence of temporal states for enhancing local patterns. These three levels have also been explored for encoding texts, replacing the frame representations with word representations produced by pre-trained word-embeddings.

Although these three different representation levels have been considered in both encodings, the fine-grained semantics and syntax have not been explicitly considered. In our recent work (Perez-Martin et al. 2021), we have applied cross-modal retrieval for learning representations with implicit syntactic information and generate more syntactically correct
descriptions from videos. Additionally, as we will detail in Sect. 4.3, the cross-modal distances in the embedding information can be used to improve the standard loss function employed for training the retrieval-based models: the **ranking loss function**.

### 1.3 Dense video captioning/description

Dense video captioning is the task of predicting a semantic and syntactically correct sequence of words for each interesting event occurring in an input video. We cannot introduce how to deal with this task without analyzing how the event detection methods work. A typical event detection method usually follows a two-stage approach, including a candidate proposal generation stage and a proposal selection stage. Many event candidates are proposed in the proposal stage by sliding window or neural networks such as single-stream temporal action proposals (SST) (Buch et al. 2017). Then, the event classifier is designated to predict event confidence for each candidate. Proposals with confidence higher than a threshold will be selected as the final proposal of the event.

One main limitation of this approach is that the methods need to generate enough candidates, usually thousands of them, to ensure covering all correct events. Moreover, the temporal relationships between the events are usually neglected, which results in the selection of events with high redundancy. However, the most successful methods for dense video captioning usually work on a similar two-stage process: they first perform an events-proposal stage deciding a set of candidate intervals in the video that needs to be described, and then select the correct events and create the captions.

So, the videos where the challenging task dense video captioning/description is framed are much longer and complicated video sequences. For evaluating these models, ActivityNet Competition includes the “Dense-Captioning Events in Videos” task\(^1\) since 2017. In this task, given a video as input, the participants must submit a temporally localized description for each relevant event in the video. Then, for training models, we need videos with temporally localized descriptions. In this sense, the ActivityNet Captions dataset, the YouCook2 dataset, and the HowTo100M dataset are the most reported dataset, covered in Sect. 6).

Deep dive into state-of-the-art for dense video captions is not in the scope of this review. However, we cover several works for this task that also report experimental results on video captioning or text retrieval tasks in the following sections.

### 1.4 Other vision-text tasks

Bridging vision and natural language is a longstanding goal in computer vision and multimedia research, becoming a focus of research in linguistic and natural language processing (NLP) communities. **Vision-language intersection** represents a fundamental challenge for research areas like video analysis and understanding, human-computer interaction, and deep learning applications for vision and language. Although video description generation and retrieval are the main topics of this review, it is sometimes more effective to train a simpler model to solve a complementary task and then move on to confront the final task (Goodfellow et al. 2016). This strategy that involves

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\(^1\) Dense-Captioning Events in Videos task of ActivityNet 2019 challenge website: http://activity-net.org/challenges/2019/tasks/anet_captioning.html.
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training simple models on different tasks before facing the difficulty of training the desired model to perform the desired task is collectively known as pre-training. Some complementary VTT tasks that can be considered for pre-training — but are not part of the scope of this work — are:

- **Visual question-answering**, where the input is a question posed about some visual content (image or video), and the output is the answer (Yu et al. 2015b; Srivastava et al. 2019; Manmadhan and Kovoor 2020).
- **Caption-based image/video retrieval**, given a caption and a pool of images, aims to retrieve the target image that is best described by the caption (Lu et al. 2020).
- **Grounding referring expressions**, where the inputs are a natural language expression and an image, and the output is the target region referred to by expression (Lu et al. 2020).
- **Video generation from text**, in which the goal is to generate a plausible and diverse video from an input text. Here the broad picture and object motion must be determined by the text input (Li et al. 2017).
- **Multi-modal verification**, given one or more images and a natural language statement, aims to determine the correctness or predict their semantic relationship (Lu et al. 2020).
2 Visual representation

Formally, while image captioning aims at converting from a fixed-length sequence (image) to a variable-length sequence of words, video captioning attempts to convert from a variable-length sequence (video frames) to a variable-length sequence of words. Then, we can formulate the video captioning problem as follows. Let \( x = (x_1, x_2, \ldots, x_n) \) be the sequence of video frames. We want to construct a model, say \( M(\cdot) \), such that, with input \( x \), the model outputs a sequence \( y = (w_1, w_2, \ldots, w_m) \) of words such that \( y \) correctly represents the information contained in \( x \). In a machine learning context, we usually want to learn \( M(\cdot) \) from a set of examples \((x, y)\).

Given this formulation, a critical step in the definition of \( M(\cdot) \) is the representation of the sequence of frames \( x \). The strategy to use in this step is so decisive that simply modifying it can be a major bottleneck to the entire system’s performance. These representations must be able to gather valuable information about videos in our dataset.

Visual media are unstructured perceptual data that inherently carry a very high-dimensional representation. This high dimensionality represents a challenge for machine learning systems trying to extract high-level semantic information directly from such visual contents. To address this challenge, researchers have traditionally represented images and videos with smaller feature vectors that attempt to encode the most relevant information present in them. This feature extraction step is crucial in any visual understanding pipeline. It serves as input for subsequent modules and can cause a drastic change in the model’s performance. This section reviews some feature extraction techniques for images and videos and identifies the best-performing ones, which will be used in designing our video understanding methods later on.

2.1 How do we work with images?

Traditionally, tasks such as object recognition have relied on using hand-crafted features to represent images. However, recently, deep Convolutional Neural Networks (CNN), which learn to extract features necessary for the task entirely from the data (with grid-like topology), have become a popular choice for image feature extraction, producing state-of-the-art performance in these traditional tasks. The first example of that was the spectacular improvement in image classification accuracy seen on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012, with the first use of CNNs in this competition. In this challenge, involving classifying the input images to one of thousand classes, the submission by (Krizhevsky et al. 2012) using a deep CNN outperformed all the others by a large margin. This set of further exploration into CNN architectures has driven up the ImageNet classification task’s performance even to surpass the human classification accuracy (He et al. 2015).

More interestingly, the deep CNNs pre-trained on the large ImageNet dataset for the classification task generalize very well to other datasets and tasks (Yosinski et al. 2014). That is, if we use the weights from CNNs pre-trained on ImageNet to initialize the networks before training them on other datasets and tasks, we can learn much better models than just using random initialization. Alternatively, using activations from some higher layer of an ImageNet pre-trained CNN as off-the-shelf image features has also been shown to produce state-of-the-art results (Donahue et al. 2014; Shetty and Laaksonen 2016) on several datasets and tasks, such as object detection, instance
segmentation, scene recognition, and image and video captioning. We will follow this idea, i.e., use activations from CNNs pre-trained on ImageNet as feature input to our captioning model, without any fine-tuning of the CNNs for this task. GoogLeNet (Szegedy et al. 2015), VGG (Simonyan and Zisserman 2015), and ResNet (He et al. 2016) architectures, which won the different categories of later ILSVRC competitions, have been popular models for such feature extraction in the community with the immediate availability of code and pre-trained models.

2.2 Video features

However, in the case of videos, how do we proceed? To answer this question, we first need to understand what a video is. Formally, a video is a 3D signal with 2D spatial coordinates and another temporal coordinate $t$. In the case of images, we have only the spatial dimension. In videos, we have temporal dimension and if we slice this cube at a specific value of $t$ at a temporal point, what we recover from that is an image that’s a frame. Understanding what a video is, we can explain what we can do to represent video and leverage the CNN architectures to process these sequences.

Before deep learning, the standard approach for representing videos involved two major stages. In the first stage, local visual features that describe a region of the video are extracted either densely (Wang et al. 2011; Wang and Schmid 2013; Rohrbach et al. 2013) or at a sparse set of interest points (Dollar et al. 2005; Laptev 2005). Next, these raw features get combined into a fixed-sized representation. One popular approach to doing this combination was to quantize all features using a learned k-means dictionary (codebook) and accumulate the visual words throughout the video into histograms (Laptev et al. 2008; Barbu et al. 2012; Rohrbach et al. 2013). One of the first improvements to this standard approach was proposed by Rohrbach et al. (2013). They included both actions and objects on top of the dense trajectory features, replacing the raw features with the higher-level representations of attribute classifier outputs. While the raw video features tend to be too noisy to compute reliable distances, it has been shown that using the vector of attribute classifier outputs instead of the raw video features improves similarity estimates between videos (Regneri et al. 2013). This difference led researchers soon after to start using the CNNs to obtain generic high-level features from videos instead of the noisy raw features. So, we now describe how to use deep learning for extracting visual features from videos, re-utilize the existing image visual feature extractors, and incorporate these visual content representations into video captioning models.

2.2.1 Single frame models

For this approach, we fit every frame to a CNN individually. A small neural network transforms all outputs on the top of a pooling operation, e.g., max, sum, or average, to obtain one feature vector for the whole video. This is a straightforward model where we can reuse a CNN pre-trained for images and process all frames in parallel. However, this approach’s limitation is that these pooling operations are not aware of the temporal order. This strategy is generally applied for short video clips with a single main event, performed from beginning to end.
2.2.2 CNN + recurrent neural networks (RNN)

Here, we try to leverage both worlds’ best by including an RNN layer for combining the individual CNN representations instead of the pooling operation. At the end of the input sequence, the model learns a representation, encoding the whole sequence’s information. We are aware of the signal’s temporal evolution with this approach, but we have to do as many sequential steps as frames in the video. This approach is part of the so-called **dynamic encoding** strategy, and we analyze methods based on it in Section 3.2.3.

One aspect to consider when we try to process the sequences of frames of a video is the occurrence of cuts between the scenes. The visual and semantic information in one video segment can be very different from that of the adjacent segments. With RNN, we try to learn to combine this information. However, we can go further and incorporate explicit information about when these changes occur in the video. This step is known as **boundary detection** and has been incorporated into determining visual representations as a particular case of **Hierarchical Recurrent Network Encoders** (HRNE). Section 3 covers works that include boundary detection as a crucial component of the description generation.

In this sense, determining the pixel-level correspondence —mapping where each pixel goes in the next frame—, known as the **optical flow** problem (Wang et al. 2019b), contributes to obtain more discriminative visual representations. Although it is not part of the scope of this work to detail the state-of-the-art techniques on optical flow estimation, much progress has been made in this field (Ilg et al. 2017; Meister et al. 2018; Varol et al. 2018), which can help the reader in its comprehension. Specifically, Varol et al. (2018) studied the impact of optical flow vector fields as a low-level representation. They demonstrated the importance of high-quality optical flow estimation for learning accurate action models. Those authors found that using optical flows as inputs to 3D-CNNs results in higher performance than can be obtained from RGB inputs, but that the best performance could be achieved by combining RGB and optical flows.

2.2.3 3D convolutions (C3D)

Following the deep CNN models’ success on static images, why not extend these convolutions to the temporal coordinate as well? We can add an extra dimension to standard CNN and assume that hierarchical representations of spatiotemporal data will be created. The video needs to be split into chunks, with a fixed number of frames that fit the receptive field of C3D. Usually, chunks of 16 frames are sufficient for representing the short temporal dynamics present in the video. The models need extensive training data and are usually pre-trained on some large-scale action recognition and video classification datasets, such as the Sports-1M (Karpathy et al. 2014), 20BN-something-something (Mahdisoltani et al. 2018b), ActivityNet (Heilbron et al. 2015), and Charades (Sigurdsson et al. 2016). The recent creation of all these datasets has partially removed the lack of enough labeled videos to address the video classification task and pre-train robust video features extractors.

2.2.4 From 2D-CNN to 3D-CNN

It is not straightforward to see how to pre-train the C3D models. We have good models on images, but if we need to train these huge 3D nets on thousands or millions of videos, it can take a considerable time. So we want to reuse some models that we have already pre-trained. A way to do this is taking the pre-trained 2D-CNN and simply “inflate” the filters,
replicating the same filter on the temporal dimension. Then we initialize the C3D with that instead of random weights and fine-tune for the specific task. Following this idea, (Carreira and Zisserman 2017) proposed the Inception 3D (I3D) architecture, which “inflate” all the 2D convolution filters used by the Inception V1 architecture (Szegedy et al. 2015) into 3D convolutions and carefully choose the temporal kernel size in the earlier layers. They, similarly to more recent work such as R(2+1)D (Tran et al. 2018), ECO (Zolfaghari et al. 2018), and (Xie et al. 2018), consider the large-scale Kinetics (Carreira and Zisserman 2017) for training the model. For a detailed examination of the architectures of various 2D-CNN with spatiotemporal 3D convolutional kernels on current video datasets, we refer the reader to Hara et al. (2018). As a result of their analysis, they conclude that 3D-CNNs and Kinetics can contribute to significant progress in various video-related tasks such as action detection, video summarization, and optical flow estimation.

2.2.5 Spatial features

Basically, no single video feature extraction method has achieved the best performance across tasks and datasets. The recent progress achieved on challenging image-related tasks such as object detection and instance segmentation (Abbas et al. 2019) has propitiated that recent video captioning methods also include spatial features based on identifying object regions on sampled frames (Pan et al. 2020; Zhou et al. 2019; Zhang et al. 2020). Unlike frame-level 2D-CNN, the region features provide more fine-grained details of the video. Usually, for each frame, methods use an object detector such as the ResNeXt-101 backbone-based Faster R-CNN (Ren et al. 2017) pre-trained on Visual Genome (Krishna et al. 2017b) or MSCOCO (Chen et al. 2017) datasets.

The VTT tasks require us to identify objects and their attributes while also capturing the actions and movements that occur in the video. Then, it is widespread to combine these features for representing the video content, encoding both the appearance and motion information. Given the input video $x$, several state-of-the-art methods compress it into a global representation that we denote by $\rho(x)$, which combines two standard visual features extractors. Specifically, to avoid the intrinsic redundancy present in video frames, $p$ frames are sampled from $x$, and 2D-CNN feature vectors $(a_1, a_2, \ldots, a_p)$ and 3D-CNN feature vectors $(m_1, m_2, \ldots, m_p)$ are extracted, representing the appearance and motion information, respectively. Then, these features are concatenated and averaged to produce $\rho(x)$, that is, $\rho(x) = \frac{1}{p} \sum_{i=1}^{p} [a_i, m_i]$.

3 Methods for generating video descriptions

In the previous section, we talked about video captioning’s difficulty compared with image captioning, but a video contains more information than an image. This comparison gives rise to the natural question of whether having a video implies greater or lesser difficulty in generating descriptions. A video is a sequence of a lot of consecutive frames, sometimes with audio information. From this sequence, we can get much information like the motion and object transformations in time. We want to capture all this information for generating more relevant descriptions, but how to capture that motion information and introduce it in the generation process? This section covers the essential methods proposed in the literature to answer these questions and solve the automatic VTT translation task. These methods can be grouped according to whether they are based on deep learning or not, the type of
decoder they use (in the case of those based on the encoder-decoder framework), among other criteria. The goal is to analyze distinctive aspects of each method, such as the proposed architecture, the datasets used to train the models, and the extracted visual features.

### 3.1 Template-based models

One of the early approaches to successfully generate a video description is the template-based approach. Here, the goal is to generate sentences within a reduced set of templates that assure grammatical correctness. These templates organize the results of a first stage of recognition of the relevant visual content. This approach is also called Subject-Verb-Object (SVO) triplets, and there are some works based on it (Kojima et al. 2002; Krishnamoorthy et al. 2013; Rohrbach et al. 2013; Guadarrama et al. 2013; Thomason et al. 2014; Xu et al. 2015b; Yu et al. 2015a). For the sake of space, in this review, we cannot examine in detail these works, and we refer the reader to Aafaq et al. (2019b) for more details.

This early work for the video captioning task, based on the two-stage SVO approach, provided several lessons that aided in the later work. We now analyze two of them.

An essential aspect of the first stage of visual recognition, is the explicit visual content identification. It mainly includes the recognition and classification of actor, action, object, and scene in the video. The success of deep learning in tasks such as object detection and action recognition allowed us to put the explicit visual recognition aside and reuse a CNN. This CNN, pre-trained on a large number of images, can produce accurate global representations and generic high-level features from video frames, reducing noise (see Sect. 2.2). However, more recent work reaffirms the importance of the explicit visual content identification and local features for video captioning. Pan et al. (2020) achieve state-of-the-art performance by aiming to ground the words in the frames. While Zhou et al. (2019) and Zhang et al. (2020) additionally aim to model the interactions between objects. We study these methods as Spatial Attention (SA)-based approaches in Sect. 3.2.4.

Another essential aspect of SVO approach is rigidly producing sentences with syntactic correctness by using a reduced set of templates. As we explain in the next section, the most successful video captioning methods have a strong dependency on the effectiveness of semantic representations learned from visual models, but often produce syntactically incorrect sentences that harm their performance on standard datasets. Because of this, recent deep-learning-based methods address this limitation by considering the learning of representations with syntactic information as an essential component of video captioning approaches (Hou et al. 2019; Wang et al. 2019a; Perez-Martin et al. 2021, 2020b). These methods, along with the SVO-based methods, have shown that videos, in addition to the appearance, motion, audio and semantic information, have implicit syntactic information that can be directly extracted from visual information. We examine these works as Syntactic Guiding (SyG)-based approaches in Sect. 3.2.4.

### 3.2 Deep learning-based models

Although the template-based approach shows a pragmatic way to generate the description of videos, the sentences are very rigid and have limited vocabulary. This limitation is a consequence of deciding a set of “relevant” objects, actions, and scenes to be recognized and the loss of human language’s richness in the templates. For any sufficiently rich domain, the required complexity of rules and templates makes the time-consuming manual
The high performance that deep learning models show for many areas of computer vision (e.g., action recognition task (Ji et al. 2013; Donahue et al. 2015; Feichtenhofer et al. 2017; Kong and Fu 2018)) and multimedia information retrieval (Sermanet et al. 2013; Girshick et al. 2014; Girshick 2015; Redmon et al. 2016; Liu et al. 2016; Dai et al. 2016; Ren et al. 2017) proves the effectiveness of neural networks for learning representations without requiring directly extracted features from the input data. These networks operate as complex functions that propagate linear transformations of input values through nonlinear activation functions (e.g., the sigmoid or the hyperbolic tangent functions) to get outputs that can be further propagated to the upper layers of the network. Consistent with this high-performance, deep learning-based video description methods have seen remarkable growth across all metrics in recent years. This section analyzes the pros and cons of a vast number of ways to combine neural networks for video captioning, which are part of state-of-the-art methods.

3.2.1 Encoder-decoder framework

As in neural machine translation (Eisenstein 2019), one way of solving a video-caption problem is using neural network models based on the encoder-decoder architecture (Cho et al. 2014). The aim is to train a model that first constructs an encoded representation from \( x \), say \( \text{ENC}(x) \), and then, using \( \text{ENC}(x) \) as input, decodes it to produce the sequence \( y \) one word at a time. Commonly, the encoder and decoder use classical building blocks such as CNNs and RNNs but with some crucial additions to mix visual, semantic, and syntactic features from the training data to boost its performance. Some of these combinations are end-to-end trainable deep network models where the two stages are learned simultaneously. These models use backpropagation for going from pixels to text sequences instead of using bounding boxes, pose estimation, or any form of frame-by-frame analysis as an intermediate representation. Fig. 4 shows the main components of state-of-the-art encoder-decoder-based methods.

**Encoder:** The encoder network \( \text{ENC}(\cdot) \) converts the source frame sequence \( x \) into a real-valued representation. This representation holds the information, the features that represent the input. It might be a variable-size or a fixed-size set of feature vectors, a vector, or a matrix representation.

\[
z = \text{ENC}(x)
\]  

(1) The selection of \( \text{ENC}(\cdot) \) depends on the type of input. For example, in machine translation, it is natural to use an RNN since the input is a variable-length sequence of symbols. In contrast, in the case of selecting a fixed number of frames from all videos or using a simple pooling operation, the \( \text{ENC}(\cdot) \) will have a fixed-size.

**Decoder:** The decoder network \( \text{DEC}(\cdot) \) generates the corresponding output \( y \) from the encoded representation \( z \) (encoding). As in the encoder, \( \text{DEC}(\cdot) \) must be chosen according to the type of output. In the case of video description generation, the output is a language description, and an RNN is a suitable architecture to use:

\[
y = \text{DEC}(z)
\]  

(2) The decoder is typically an RNN that generates one word at a time according to an internal state, the previously generated word, and the entire input \( z \) or part of it. So far, the proposed
models use a wide range of variations of RNN in the decoder stage of the video description generation problem. In Sect. 3.3, we review some strategies that could be used for training the entire architecture.

Significant improvements in video captioning encoder-decoder models have been achieved by incorporating advanced techniques such as neural attention, deep RNNs, bidirectional RNN, ensemble translation models, beam search, scheduled sampling, professional learning, reinforcement learning, and the efficient self-attention with the transformer architecture. The next sections review several state-of-the-art video captioning models that use these techniques and enhance the quality of generated captions by guiding the decoding process with learned representations such as semantic and syntactic representations.

3.2.2 Fixed encoder

Unsurprisingly, the early deep learning-based models replaced and retained some strategies that were useful in template-based models. Models proposed by Donahue et al. (2015) and Venugopalan et al. (2015b) incorporated two-layered Long Short-Term Memory (LSTM)-based decoders for text generation but maintained a fixed-size representation for encoding the video. On the one hand, Donahue et al. (2015) used the Conditional Random Field (CRF)-based approach (Rohrbach et al. 2013) to predict SVO triplets. On the other hand, Venugopalan et al. (2015b) followed the single frame-based approach analyzed in Sect. 2.2.1, using a previously trained CNN (Krizhevsky et al. 2012).

As we mentioned in Sect. 2, recognizing the actions and movements that occur in the video is essential for video representation. Yao et al. (2015) were the first to incorporate 3D-CNN features to encode the videos, but in contrast to other 3D-CNN formulations, the input to their 3D-CNN consists of features derived from three hand-designed image descriptors, i.e., HoG (Dalal and Triggs 2005), HoF, and MbH (Wang et al. 2009). They also incorporated an attention model in the temporal dimension that we will analyze later. The advantage of these 3D features is that they allow the encoders to accurately represent short-duration actions in a subset of consecutive frames.

A vast number of models of the state-of-the-art have incorporated temporal representations into their encoder process. For example, Gan et al. (2017b) proposed the Semantic Compositional Network (SCN) to understand individual semantic concepts from images effectively. They also offered an extension for videos extracting 2D-CNN and 3D-CNN features to adequately represent the video’s visual content. The model generates two feature vectors from executing average pooling operations on all 2D-CNN features and all 3D-CNN features. Until that moment, the video’s spatiotemporal representation combined appearance and motion, basically concatenating both vectors.

3.2.3 Dynamic encoder

Like the template-based approach, the mentioned strategy of single-frame-based encoding suffers the loss of valuable temporal information due to the aggregation operations. To avoid this loss of information and obtain more meaningful representations, more sophisticated ways of encoding video features were proposed in later work, using, for example, an RNN-based encoder (Venugopalan et al. 2015a, 2016; Xu et al. 2015a; Srivastava et al. 2015; Yu et al. 2016; Baraldi et al. 2017). For instance, Srivastava et al. (2015) have proposed an unsupervised learning model using a Long Short Term Memory (LSTM) layer in
Recurrent encoders are intuitive to some extent, but better input encodings can be learned not only by processing the video stream from left to right by a single recurrent layer but by looking to the future or incorporating more layers. The Hierarchical Neural Encoder (HRNE) (Pan et al. 2016a) proposed by Baraldi et al. (2017) can learn to adapt its temporal connections according to the current input data. They built a time boundary-aware recurrent cell on top of an LSTM unit that learns patterns with full temporal dependencies. When a boundary is detected, the LSTM’s internal state is reinitialized, and a representation of the ended segment is given to the output. The boundary-aware layer’s output is encoded through an additional recurrent layer and passed (as a vector) to the decoder.

To reduce the ambiguity of generated descriptions, Zhang et al. (2017) learn to construct the video’s spatiotemporal representation by incorporating an adaptive fusion component, which dynamically selects one of the three following combination strategies: (1) concatenation, for appearance-centric entities; (2) sum or max, motion-centric entities; and (3) dynamic, for correlation-centric entities. Although this work did not improve much over previous work, they were the first to replace the static patterns for fusing the features from different channels in the encoder (Chen et al. 2017b; Wang et al. 2019a). More sophisticated adaptive fusions have also been included in the decoder to select the most accurate information for generating each word (Hu et al. 2019; Perez-Martin et al. 2020a, 2021). We analyze them in the next section.

Methods based on recurrent encoders improved the state-of-the-art on video description generation. However, comparing their results with the results of techniques based on fixed encoders, the improvement is not very great. In this sense, authors like Yu et al. (2016) observed that the encoder has poor performance for tasks like the detection of
small objects, implying incorrect object names in the sentences. Consequently, the recurrent encoders are not the best option for videos of fine-grained activities, interaction with small objects, and datasets with very detailed descriptions, like the Charades Captions dataset (Sigurdsson et al. 2016; Wang et al. 2018d). The sentences in these datasets usually describe fine-grained actions that happen within a short duration and imply ambiguous information between them.

3.2.4 RNN-based decoder

Feed-forward and CNNs fail to adequately represent sequential structures because they cannot remember previous information. For example, they forget a frame in a video sequence just as they analyze the next one. In contrast, the formulation of RNNs (Rumelhart et al. 1986) allows them to remember information for a long time as their natural behavior.

The RNN-based decoder takes the encoder output as input and starts generating text, one token at a time, conditioned on the input representation and the previously generated tokens. In each step \( t \), from the recurrent cell output, it produces a probability distribution \( \hat{y}_t \) over a target vocabulary \( V \) of possible output tokens, and choose one. The model maps this word to a vector representation using a pre-trained word embedding, which is used as input of the recurrent cell at the next step:

\[
\hat{y}_t = \text{softmax}(W_p \cdot h_t + b_p),
\]

where \( h_t \) is the output of the recurrent cell at time step \( t \), and \( W_p \) and \( b_p \) are parameters to be learned.

The decoder essentially works as a classifier, but it is aware of the whole input and the previously predicted sequence at each step. Then, we can define the probability of generating the output sequence \( Y = y_1, \ldots, y_m \) from the input sequence \( X = x_1, \ldots, x_n \) as:

\[
p(Y|X; \Theta) = \prod_{i=1}^{m} p(y_i|y_1, \ldots, y_{i-1}, X; \Theta),
\]

where \( \Theta \) are the model parameters.

This perspective on text generation problems is very different from the template-based or pre-neural approaches. Here, text generation is consistent with the input and fluent in the target distribution, but it brought some exciting problems that did not exist before. The vanilla RNN can model temporal dependency for a small-time gap, but it usually fails to capture long-term temporal information. As for modeling natural languages, Long Short-Term Memory (LSTMs) (Hochreiter and Schmidhuber 1997) and Gated Recurrent Units (GRUs) (Cho et al. 2014) have been very successful in video captioning decoders. Two variants of these networks explored in video captioning are the Semantic-LSTM (Pan et al. 2017; Gan et al. 2017b; Yuan et al. 2018; Chen et al. 2020b) and the two-layered LSTM (Venugopalan et al. 2015a; Zhou et al. 2019). Venugopalan et al. (2015b) proposed to use a two-layered LSTM (Graves et al. 2013), where the hidden state of the first LSTM layer is the input to the second for caption generation. With this modification, the model simultaneously learns one stage of latent “meaning” and a more deep stage of fluid grammatical structures. Yu et al. (2016) proposed a hierarchical-RNN (h-RNN) model to exploit spatiotemporal attention mechanisms. Their model can decode through a sentence and paragraph generator. Specifically, a GRU layer, which simplifies the LSTM architecture, first takes the video features as input and generates a short sentence. Then, another
| Method                    | Encoder            | Decoder   |
|--------------------------|--------------------|-----------|
| Donahue et al. (2015)    | ✓ 2D-CNN ✓ 3D-CNN ✓ R-CNN ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Venugopalan et al. (2015b) | ✓ 2D-CNN ✓ 3D-CNN ✓ R-CNN ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Rohrbach et al. (2015a)  | ✓ 2D-CNN ✓ 3D-CNN ✓ R-CNN ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Xu et al. (2015b)        | ✓ 2D-CNN ✓ 3D-CNN ✓ R-CNN ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Yao et al. (2015)        | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Yu et al. (2016)         | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | GRU ✓ |
| Venugopalan et al. (2016) | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Pan et al. (2017)        | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Baraldi et al. (2017)    | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | GRU ✓ |
| Zhang et al. (2017)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Gan et al. (2017b)       | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Nina et al. (2018)       | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Yuan et al. (2018)       | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Wang et al. (2018d)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Chen et al. (2018c)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | GRU ✓ |
| Gao et al. (2019)        | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Hou et al. (2019)        | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Wang et al. (2019a)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Zhou et al. (2019)       | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Chen et al. (2020b)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Chen et al. (2020a)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | GRU ✓ |
| Zhang et al. (2020)      | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
| Pan et al. (2020)        | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | Transf. ✓ |
| Perez-Martin et al. (2020a) | ✓ ✓ ✓ ✓ Fixed ✓ Dynamic ✓ Graph ✓ | LSTM ✓ |
For each method we check the main characteristics of its encoder and decoder. In the case of the encoder, we check the type of visual features used to represent the videos (2D-, 3D-, and/or R-CNN) and the strategy used to encapsulate the features (fixed-, dynamic-, or graph-based). In the case of the decoder, we show the architecture (Arch.) used, and we check if the model uses Temporal Attention (TA), Spatial Attention (SA), Semantic Guiding (SeG) or Syntactic Guiding (SyG). Finally, we check if the models are trained through Reinforcement Learning (RL) strategy and if the model are an ensemble of several models.

| Method          | Encoder  | Decoder | Arch. | TA | SA | SeG | SyG | RL |
|-----------------|----------|---------|-------|----|----|-----|-----|----|
| Perez-Martin et al. (2021) | ✓       | ✓       | ✓     | ✓  | ✓  | ✓   | ✓   | ✓  |
A comprehensive review of the video-to-text problem

recurrent layer is responsible for paragraph generation, combining the sentence generator’s sentence vectors. The paragraph generator captures the dependencies between the sentences and generates a sequence of relevant and consecutive sentences. Table 1 shows the architecture used for elaborating the state-of-the-art methods’ decoders.

We now look into more advanced techniques for neural text production from videos, and show how later work focused on integrating key ideas from template-based approaches into the deep learning paradigm. First, we show how sequential decoders can be improved using attention, external knowledge, joint embeddings, semantic guiding, and syntactic guiding. Then we analyze some reinforcement learning-based methods and how to ensemble some models video captioning models for improving the results.

Temporal Attention (TA)-based approaches: When we defined the encoder in Equation 1, we mentioned that the encoding \(z\) could be a variable-size or a fixed-size set of feature vectors, but we did not exemplify the variable-size. The decoders based on visual attention, instead of taking as input a fixed global representation of the video, takes into account an input representation (usually called “context vector”) built from the current decoder hidden state and all the input visual features (or the corresponding encoder hidden states). With this vector, the decoder can decide “where to look” during word prediction in each step. Analyzing the types of encoders, we mentioned that Yao et al. (2015) used an attention mechanism as part of their model. They incorporated a temporal attention mechanism adapted from soft attention (Bahdanau et al. 2015) that allows the decoder to weight each temporal feature vector. Basically, the context vector is created by the sum of the encoder state weighted by their probability. To understand how these probabilities are obtained, we refer the reader to Bahdanau et al. (2015). Intuitively, this model simulates the human attention that sequentially focuses on the most significant parts of the information over the video sequence to make predictions.

After that, the temporal-attention mechanisms have been widely used for video captioning (Gao et al. 2019; Nina et al. 2018; Perez-Martin et al. 2021; Wang et al. 2018d; Yu et al. 2016; Zhang et al. 2017, 2020). Gao et al. (2019) and Perez-Martin et al. (2020a) proposed an attention model able to decide whether to depend on the visual information or language context model. They proposed a hierarchical LSTM with two layers and an adaptive attention model that extends temporal visual attention. Perez-Martin et al. (2020a) get better results by including compositional LSTM and conditioning the adaptive gate and semantic layer by a temporal-attention mechanism. Although these attention mechanisms are one of the main drivers of recent progress in video description generation models, we have a limited ability to understand how well temporal attention works in models because most datasets contain short videos.

Spatial Attention (SA)-based approaches: As we mentioned at the beginning of this section, captioning methods based on object detectors perform two stages, i.e., determine object proposals and fill them into predefined sentence templates. In contrast, the deep learning-based works we have analyzed in this section neglect the explicit identification of objects in the video and only work on the frame-level and chunk-level. An interesting point of using the object-level information is that we can also model the interaction between them by building meaningful connections and incorporate this information in the generation process for better visual grounding capability. Recent video captioning methods (Pan et al. 2020; Zhang et al. 2020; Zhou et al. 2019) have explored the graph-based representations of spatial and temporal relationships between objects. Specifically, Zhou et al. (2019) processed the ActivityNet Captions benchmark for linking the captions to the evidence in the video by annotating each noun phrase with the corresponding bounding box in one of the frames. This dataset allows producing grounding-based video captioning models that
learn to jointly generate words and refine the grounding of the objects generated in the description. These region-based annotations allow adopting a spatial-attention mechanism similar to the temporal attention mechanisms or a more sophisticated model like self-attention (Ging et al. 2020; Lei et al. 2020; Sun et al. 2019a; Vaswani et al. 2017; Zhou et al. 2018c, 2019).

Although Zhou et al. (2019) learn to attend to object regions in the frames, they only learn to ground the nouns. They cannot explicitly model their relations, e.g., the relation “mixing” between the nouns “person” and “food”. To model these interactions Pan et al. (2020) and Zhang et al. (2020) proposed Object Relational Graphs (ORGs), which can learn the interaction among different objects dynamically. These topological graphs can be automatically constructed according to criteria such as objects’ location in the frames (spatial) and the detection of objects in consecutive frames (temporal). After that, the node features can be updated during relational reasoning by graph convolutional networks (GCN) (Kipf and Welling 2017). These three methods (Pan et al. 2020; Zhang et al. 2020; Zhou et al. 2019) utilize an object detector such as the ResNeXt-101 backbone-based Faster R-CNN pre-trained on MS-COCO (Chen et al. 2015) or Visual Genome (VG) (Krishna et al. 2017b) to extract object features in each frame.

Joint Embedding: For tasks like video-text retrieval, i.e., video retrieval from descriptions and video description retrieval from videos (Dong et al. 2018, 2019; Fang et al. 2015; Ging et al. 2020; Miech et al. 2018; Mithun et al. 2019), the joint visual-semantic embeddings have a successful application. These embeddings are constructed by combining two models: a language model that maps the captions to a language representation vector, and a visual model that obtains a visual representation vector from visual features. Both models are trained for projecting those representations into a joint space, minimizing a distance function. Dong et al. (2019) obtain high-performance in retrieval tasks by using the same multi-level architecture for both models (based on RNNs) and training with the triplet-ranking-loss function (Faghri et al. 2018). Ging et al. (2020) also use the same architecture (based on Transformers (Vaswani et al. 2017)) for both models but produce the final embedding based on interactions between local context (clip/sentence features) and global context (video/paragraph features). With this, they can learn the embedding from videos and paragraphs and explore different granularity levels in the process. In other words, they learn two embedding representations: the local context, which is learned by projecting the sentences (paragraph parts) and clips (video parts); and the global context, which is learned considering the full video and the complete paragraph and transforming the local embedding. This hierarchical learning enforces the interactions within and between these hierarchical contextual embeddings. For training the model, they adopt a cross-modal strategy that we analyze in Sect. 4.3.

These embeddings have also been explored for video captioning to perform a particular form of transfer learning and domain adaptation (Gao et al. 2017; Ging et al. 2020; Liu et al. 2018; Pan et al. 2016b). These methods explore the representations captured by the joint embedding’s visual models for improving the generalization in the captioning setting. In LSTM-E (Pan et al. 2016b), a joint embedding component is utilized to bridge the gap between visual content and sentence semantics. This embedding is trained by minimizing the relevance loss and coherence loss simultaneously. This minimization guarantees, coherently and smoothly, the perplexity of the generated sentence: the contextual relation between the sentences’ words. SibNet (Liu et al. 2018) exploits autoencoder for visual information and a visual-semantic embedding for semantic information. A disadvantage of these joint embeddings is that they only consider the implicit contextual relations between the words in the sentence using pre-trained word embeddings. To improve the
syntax correctness of generated sentences, Perez-Martín et al. (2021) learn a new representation of videos with suitable syntactic information. They propose a joint visual-syntactic embedding, trained for retrieving POS tagging\(^2\) sequences from videos. Section 3.2.4, explains how they incorporated the visual model in the decoder to alleviate the video content’s syntactic inconsistency.

Semantic Guiding (SeG)-based approaches: Another way of exploiting informative semantics is by learning to ensemble the result of visual perception models (Chen et al. 2020b; Gan et al. 2017b; Long et al. 2018; Pan et al. 2017; Perez-Martín et al. 2020a, 2021; Yuan et al. 2018; Xu et al. 2019b). Pan et al. (2017) incorporated the transferred semantic attributes learned from two sources (images and videos) inside a CNN-RNN framework. For this, they integrated a transfer unit to dynamically control the impact of each source’s semantic attributes as an additional input to LSTM. Gan et al. (2017b) included the semantic meaning via a semantic-concept-detector model, which predicts each concept’s probability that appears in the video by a multi-label classification approach. They incorporated concept-dependent weight tensors in LSTM for composing the semantic representations.

In contrast, Yuan et al. (2018) proposed the Semantic Guiding Long Short-Term Memory (SG-LSTM), a framework that jointly explores visual and semantic features using two semantic guiding layers. These layers process three kinds of semantic features: global-, object-, and verb-semantic. They predict these features by selecting the 300 most-frequent subjects, verbs, and objects from the MSVD corpus and training three MLP (one for each kind of semantic feature) as standard multi-label classifiers. Explicitly, they compute the representations \(g_a = \text{MLP}(f, m)\), \(o_a = \text{MLP}(f)\) and \(v_a = \text{MLP}(m)\), where \(f\) is the average 2048-dimensional pool\(^5\) layer from ResNet-152 pre-trained on ImageNet dataset, \(m\) is the 512-dimensional pool\(^5\) layer from C3D pre-trained on Sport-1M dataset and \([f, m]\) is their concatenation.

More recently, Chen et al. (2020b) modified the model SCN-LSTM (Gan et al. 2017b). They used \(\text{tanh}(\cdot)\) to activate the raw cell input instead of \(\sigma(\cdot)\). Their model includes a semantic-related video feature term at each recurrent step. Also, these authors assumed that captions should be both accurate and concise. They proposed a sentence-length-related loss function that keeps a balance between those criteria, incorporating a penalty weight (related to the generated sentence length) to the sum of the logarithm probability of the CELoss (Goodfellow et al. 2016) function. A deficiency of this work is that the model fails when tested using a beam search strategy. Maybe this is a result of the absence of the penalty weight in the testing phase.

The same authors, Chen et al. (2020a), improved this method, proposing the VNS-GRU approach. They maintained the semantic information but improved the form of computing the penalty weight in the optimization process. For that, they proposed professional learning that aims, in the training algorithm, to assign higher weights to the samples with lower loss. An advantage of this is that the model can learn unique words and complicated grammar structures.

All these methods show the benefits of describing the videos according to dynamic visual and semantic information. However, these models’ performance strongly depends on the quality of semantic concept detection models, which makes it difficult to generate words that are not included in the set of concepts to be classified. This strong dependence can be alleviated by including an adaptive mechanism (Hu et al. 2019; Perez-Martín et al.

\(^2\) https://www.nltk.org/book/ch05.html.
that selectively determines the visual and semantic information required to generate each word.

**Syntactic Guiding (SyG)-based approaches:** Although some recent works in image captioning (Deshpande et al. 2019; He et al. 2019) and video captioning (Hou et al. 2019; Wang et al. 2019a) have explored the use of syntactic information in the generation process, its impact has not been widely explored. For the video captioning task, Hou et al. (2019) created a model that first generates a sequence of POS tags and a sequence of words, and then learns the joint probability of both sequences using a probabilistic directed acyclic graph. Wang et al. (2019a) integrated a syntactic representation in the decoder, also learned by a POS sequence generator. These models’ weakness is that they neither directly exploit the relationship between syntactic and visual representations nor between syntactic and semantic representations.

In contrast, as we mentioned in Sect. 3.2.4, Perez-Martin et al. (2021) proposed a method to learn a visual-syntactic embedding and obtain syntactic representations of videos instead of learning to generate a sequence of POS tags. They also include two compositional layers to obtain visual-syntactic-related and semantic-syntactic-related representations. In detail, their decoder is based on three recurrent layers based on the compositional-LSTM network (Chen et al. 2020b; Gan et al. 2017b), and an additional layer to combine the outputs of the three recurrent layers defined by two levels of what they called **fusion gates**. Unlike other architectures (Baraldi et al. 2017; Gao et al. 2019; Pan et al. 2016a), how their recurrent layers are combined follows a similar scheme to the transformer’s multi-head; they are not deeply connected. So, the computation of the three layers can be done in parallel.

### 3.2.5 Ensembles

Some video captioning works have achieved outstanding performance by assembling several models (Chen et al. 2018b; Nina et al. 2018; Song et al. 2019b). This strategy is usually adopted in benchmarks competitions where participant teams can submit several runs of their model, e.g., TRECVID (see Sect. 5.3). Usually, one of these runs is the ensemble of models used in the other runs. In this sense, Chen et al. (2018b) proposed a model for dense video captioning task, which is composed of four components: (1) segment feature extraction (ResNet, i3D, VGGish, and LSTM); (2) proposal generation, for selection of fragments of the video; (3) caption generation; and (4) re-ranking. Specifically, for the third component, they ensemble three different caption generation models: (1) a vanilla caption model, based on an LSTM decoder; (2) a temporal attention caption model; and (3) a topic guided caption model, based on a semantic concept detector. The combination of outputs of different decoders has also been adopted for other methods (Hou et al. 2019; Nina et al. 2018). The model proposed by Nina et al. (2018) relies on distinct decoders that train a visual encoder following a multitask learning paradigm (Caruana 1998). While Hou et al. (2019) (analyzed in Sect. 3.2.4) incorporated a decoder for POS tags generation and computed the joint probability with the natural language decoder.

Song et al. (2019b) achieved the best results on the TRECVID VTT 2019 challenge (see Sect. 5.3). In this case, they proposed a model that consisted of four main parts: (1) video semantic encoding; (2) description generation with temporal and semantic attention; (3) reinforcement learning optimization; and (4) ensemble from multi-aspects. The ensemble proposed for the fourth part is based on choosing the video’s best-generated description by re-ranking the captions using the weighted sum of **fluency** and **relevancy** scores. The
third part, based on reinforcement learning, has also been adopted by several state-of-the-art methods. We now briefly analyze some of these methods, and general aspects of this strategy are exposed in Sect. 3.3.

### 3.2.6 Reinforcement learning (RL)-based methods

Throughout this section, we have exposed the different strategies that avant-garde works have adopted for the video captioning task. Some of these works also incorporate reinforcement learning as part of their models’ training process (Chen et al. 2018c; Li and Gong 2019; Pasunuru and Bansal 2017; Phan et al. 2017a; Wang et al. 2018d, 2019a; Wei et al. 2020). In Sect. 3.3, we study how, unlike cross-entropy-based methods, these models are trained to optimize one evaluation metric (reward) directly. An advantage of these models is that they are not limited to a specific evaluation metric. We can extend them using other reasonable rewards.

An essential issue for video description generation is the selection of the most informative frames. In this sense, Chen et al. (2018c) have introduced the efficient PickNet method. PickNet is an RL-based model that chooses the most informative frames to represent the whole video. It picks for encoding around 33.3% of sampled frames only (6 frames for MSVD and 8 for MSR-VTT, on average), largely reducing the computation cost. The goal of this method is to reduce noise and increase efficiency without losing efficacy. The model calculates each frame selection’s regard in function to minimize the visual diversity and textual discrepancy. The authors decided only to use the appearance features because extracting motion features was very time-consuming for the model, deviating from cutting down the computation cost for video captioning. An advantage of this model is that it can be easily incorporated into any other model to increase efficiency.

### 3.3 Loss functions for optimization

In previous sections, we studied the state-of-the-art techniques for creating effective methods that produce a sequence of words from an input video. However, we have not detailed how these models are trained. This section analyzes the different objective functions for video captioning methods. In particular, we include an analysis of sequence-level- and reinforcement-learning-based strategies.

After estimating each word’s probability distribution in the vocabulary by Equation 3, most video-captioning models are trained by the cross-entropy loss minimization (CELoss). With CELoss, the model is trained to be good at greedily predicting the next correct word of the reference caption. Given a target caption, $\hat{y} = (\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_L)$ describing an input video, one minimizes:

$$
\mathcal{L}_\Theta = -\sum_{i=1}^{L} \log p_{\Theta}(\hat{w}_i | \hat{w}_{<i}),
$$

where $\Theta$ are all the learnable parameters of the captioning model, $\hat{w}_i$ is the $i$-th word in the ground-truth caption, and $\hat{w}_{<i}$ are the first $i - 1$ words in the ground-truth caption. $p_{\Theta}(\hat{w}_i | \hat{w}_{<i})$ is modeled by a logistic function as the decoder network’s output layer, understood as the probability distribution of words in the vocabulary.

However, at test time, the model has only access to its predictions, which may not be correct. Additionally, video captioning’s popular evaluation metrics are based on $n$-gram
overlapping between the generation and reference captions, e.g., BLEU (Papineni et al. 2002). This discrepancy leads to a problem called exposure bias (Ranzato et al. 2016) in sequential decoders. Due to this discrepancy, the word-level CELoss function is not directly related to the most used evaluation metrics for video captioning (Ranzato et al. 2016; Pasunuru and Bansal 2017). Some state-of-the-art works show that conventional CELoss cannot extract the effectiveness of their models.

To overcome this limitation while operating with explicit supervision at the sequence level, Chen et al. (2020b) proposed a loss function that weights the CELoss according to the length of the reference captions.

\[ L'_{\theta} = -\frac{1}{L} \sum_{t=1}^{L} \log p_{\theta}(\hat{w}_t | \hat{w}_{<t}), \]  

where \( L \) is the length of the ground-truth caption, and \( \beta \in [0, 1] \) is a hyperparameter of the model. The hyperparameter \( \beta \) regulates the length of the generated sentences. The higher the value of \( \beta \), the lower the loss produced by the function, and vice versa. Thus, a value of \( \beta \) near 0 implies that the model rapidly adapts to generate concise sentences that could affect their syntactic correctness.

Another strategy to overcome this limitation is to expose the model to its own predictions rather than just the training data, and directly optimize the task-specific evaluation metric. The models trained following this strategy commonly use policy gradients and mixed-loss methods for reinforcement learning (Pasunuru and Bansal 2017). Instead of maximizing the likelihood of prediction at each step, the model first generates the whole sequence. A reward (often one of the evaluation metrics at test time, e.g., CIDEr) is estimated by comparing the output text to the ground-truth description. The reward is then used to update the model parameters, learning to maximize the evaluation metric during training.

In particular, state-of-the-art methods based on reinforcement learning use a standard algorithm called policy learning, which allows us to maximize a non-differentiable reward efficiently. These methods view the description generation model as an agent that interacts with an environment with access to reference texts. Each input video represents a state, and each action is an output text generated by the agent. The agent predicts an output caption \( \hat{y} \) using policy \( p(\hat{y} | x, \Theta) \), where \( x \) is the input video and \( \Theta \) are model parameters. After each action, the agent receives an immediate reward corresponding with how well the final caption resembles the reference text. The transition between states is trivial because the inputs are interdependent. The models learn to optimize the policy such that the agent can take an optimal action optimizing its reward given a state.

The reward function plays a crucial role here, which is defined such as that it captures the critical aspects of the target output concerning the benchmark dataset. Several methods (Chen et al. 2018c; Li and Gong 2019; Pasunuru and Bansal 2017; Phan et al. 2017a; Wang et al. 2018d, 2019a) use the CIDEr score as the reward over the MSVD and MSR-VTT datasets. In particular, Pasunuru and Bansal (2017) proposed CIDEnt-RL, which penalizes the phrase-matching metric (CIDEr) based reward when the entailment score is low. While Phan et al. (2017a) compared the performance using different metrics as a reward, i.e., BLEU-4, METEOR, ROUGE_L, and CIDEr. Although the improvement on different metrics is unbalanced because the improvements on other metrics are not as large as the specific metric directly optimized, they obtain the best performance for all metrics optimizing the CIDEr score.
3.4 Description generation-specific evaluation metrics

In the literature for NLG-based techniques to address the VTT problem, authors have reported some automatic assessments. The majority of them have come from the metrics used for machine translation and image captioning tasks. For the VTT translation task, the state-of-the-art works report several n-gram-overlap-based metrics to automatically evaluate the quality of the output text (candidate) with the dataset’s paired descriptions (references), being the most-reported metrics:

- **BLEU** (Bilingual Evaluation Understudy (Papineni et al. 2002), 2002), based on n-gram precision;
- **ROUGE** (Recall Oriented Understudy of Gisting Evaluation (Lin 2004), 2004), based on n-gram recall;
- **METEOR** (Metric for Evaluation of Translation with Explicit Ordering (Banerjee and Lavie 2005), 2005), based on n-gram with synonym matching; and
- **CIDEr** (Consensus-based Image Description Evaluation (Vedantam et al. 2015), 2015), based on precision and recall by TF-IDF weighting of n-gram similarity.

A range of other automated metrics has been proposed for machine translation. The explicit semantic match metrics define the similarity between human-written references and model generated candidate by extracting semantic information units from text beyond n-grams. These metrics operate on semantic and conceptual levels and correlate well with human judgments (Celikyilmaz et al. 2020). The **SPICE** (Semantic Proportional Image Captioning Evaluation (Anderson et al. 2016), 2015) metric has also been reported for video captioning. This metric uses scene graphs to parse the candidate sentence to semantic tokens, such as object classes, relationship types, or attribute types. In this section, we present the definition of these metrics and briefly discuss their advantages and limitations. For more details on the evaluation of text generation models, we refer the reader to Celikyilmaz et al. (2020), a recent review on NLG evaluation methods.

Early video description generation works (Guadarrama et al. 2013; Krishnamoorthy et al. 2013; Rohrbach et al. 2013) used the **SVO Accuracy** to measure whether the generated SVO triplets coheres with ground truth. This metric does not evaluate the quality of the generated sentence. It aims to focus on the matching of general semantics and ignores visual and language details.

**Bilingual Evaluation Understudy computation (BLEU)** (Papineni et al. 2002) is based on the match between n-grams (a sequence of n words) of the candidate sequence and one or some reference sequences. **BLEU** is a weighted geometric mean of n-gram precision scores, defined as:

\[
p_n = \frac{\sum_s \min(c(s, \hat{y}), c(s, y))}{\sum_s c(s, \hat{y})},
\]

where \( \hat{y} \) is the candidate sequence, \( y \) is the reference sequence, \( s \) is a n-gram sequence of \( \hat{y} \), and \( c(s, \hat{y}) \) is the number of times that \( s \) appears in \( \hat{y} \). The BLEU-N metric is then:

\[
\log \text{BLEU-N} = \min(1 - \frac{p_n}{c}, 0) + \sum_{n=1}^{N} w_n \log p_n,
\]

where \( w_n \) are weights for n-gram scores.
where \( c \) and \( r \) are the lengths of the candidate and reference sequences, respectively. \( N \) is the total number of \( n \)-gram precision scores to use, and \( w_n \) is the weight for each precision score, which is often set to be \( 1/N \).

Equation 7 counts the position-independent matches among the candidate’s \( n \)-grams and the reference’s \( n \)-grams and computes the percent of matches (precision). For video captioning, the most reported version is BLEU-4 with uniform weights \( w_n = 1/N \). BLEU was originally designed to evaluate long texts, and its use as an evaluation measure for individual sentences may not be fair.

Recall Oriented Understudy of Gisting Evaluation (ROUGE) (Lin 2004) is a set of metrics designed for determining the quality of automatic summarization of long texts. Although mainly designed for evaluating summarization, it has also been widely used for evaluating short text production approaches, such as image captioning and video captioning. It computes the \( n \)-gram recall score of the candidate sentences with respect to those of reference (Lin 2004). Similar to BLEU, it also is computed varying the number of \( n \)-grams. Let \( c_{\text{match}}(s) \) be the number of times that the \( n \)-gram \( s \) co-occur in the candidate sequence. The ROUGE-N score is then:

\[
\text{ROUGE-N} = \frac{\sum_{y \in R} \sum_{s \in y} c_{\text{match}}(s)}{\sum_{y \in R} \sum_{s \in y} C(s)}
\]

where \( s \in y \) is a \( n \)-gram sequence of the reference \( y \in R \). The denominator \( \sum_{y \in R} \sum_{s \in y} C(s) \) of the equation is the total sum of the number of \( n \)-grams occurring at the reference summary side. Note that the number of \( n \)-grams in the denominator increases as more descriptions become available for reference.

In the same paper, the authors proposed several ROUGE-N variants, such as ROUGE-L, which is the most used variant for image and video captioning evaluation. For ROUGE-L, the longest common subsequence (LCS)-based \textbf{F-measure} is computed to estimate the similarity between the candidate sentence and the reference. In other words, it measures the longest matching sequence of words using LCS. One advantage of using LCS is that it does not require consecutive matches, but it requires in-sequence matches that indicate sentence-level word order (Lin 2004). The other advantage is that the \( n \)-gram length does not need to be predefined since ROUGE-L automatically includes the longest common \( n \)-grams shared by the reference and candidate text.

Formally, given two sequences \( \hat{y} \) and \( y \), the LCS(\( \hat{y}, y \)) the length of the LCS of \( \hat{y} \) and \( y \). Let \( m \) the length of \( \hat{y} \) and let \( n \) the length of \( y \). The LCS-based \textbf{F-measure} is then:

\[
\begin{align*}
R_{\text{lcs}} &= \frac{\text{LCS}(\hat{y}, y)}{m}, \\
P_{\text{lcs}} &= \frac{\text{LCS}(\hat{y}, y)}{n}, \\
F_{\text{lcs}} &= \frac{(1 + \beta^2) R_{\text{lcs}} P_{\text{lcs}}}{R_{\text{lcs}} + \beta^2 P_{\text{lcs}}},
\end{align*}
\]

where \( \beta = \frac{R_{\text{lcs}}}{P_{\text{lcs}}} \) when \( \frac{\partial F_{\text{lcs}}}{\partial P_{\text{lcs}}} = \frac{\partial F_{\text{lcs}}}{\partial R_{\text{lcs}}} \). Notice that ROUGE-L is one when \( \hat{y} = y \) since \( \text{LCS}(\hat{y}, y) = m \) or \( n \); while ROUGE-L is zero when \( \text{LCS}(\hat{y}, y) = 0 \), \textit{i.e.}, there is nothing in common between \( \hat{y} \) and \( y \).

Another metric that has been widely used for evaluating image and video captioning models is the \textbf{Metric for Evaluation of Translation with Explicit Ordering (METEOR)} (Banerjee and Lavie 2005). Compared to BLEU (based on precision only),
METEOR is based on the harmonic mean of the uni-gram precision and recall, in which recall is weighted higher than precision (Celikyilmaz et al. 2020). This metric couples BLEU scores \( \forall n \in \{1, 2, 3, 4\} \) into a single performance value, and it was designed to improve correlation with human judgments. Some variants of this metric also introduce the semantic match for addressing the reference-translation variability problem. These variants allow morphological variation, synonyms, stems, and paraphrases to be recognized as valid translations.

The classic version of the METEOR score between a candidate translation and a reference translation is defined as follows. First, the uni-gram precision \( P \) and recall \( R \) are respectively calculated by:

\[
P = \frac{u}{u_c}, \quad \text{and} \quad R = \frac{u}{u_r},
\]

where \( u \) is the number of uni-grams in the candidate translation that also appear in the reference translation, \( u_c \) is the number of uni-grams in the candidate translation, and \( u_r \) is the number of uni-grams in the reference translation.

Next, the \( F_{\text{mean}} \) is computed by combining the precision and recall (defined in Equation 10) via a parameterized harmonic mean (Rijsbergen 1979):

\[
F_{\text{mean}} = \frac{P \times R}{\alpha \times P + (1 - \alpha) \times R},
\]

To account for gaps and differences in word order, METEOR calculates a fragmentation penalty. This calculation uses the total number of matched uni-grams \( u \) (averaged over candidate and reference) and the number of chunks \( ch \), where a chunk is defined as a set of adjacent uni-grams in the candidate and reference. The penalty \( p \) is then computed by:

\[
p = \gamma \left( \frac{ch}{u} \right)^{\beta},
\]

where \( \gamma \) determines the maximum penalty \( (0 \leq \gamma \leq 1) \), and \( \beta \) determines the functional relation between the fragmentation and the penalty. The penalty has the effect of reducing the \( F_{\text{mean}} \) (defined in Equation 11) if there are no bi-grams or longer matches.

The final METEOR score is then calculated by:

\[
\text{METEOR} = F_{\text{mean}} \times (1 - p)
\]

Another metrics that also considers both precision and recall is Consensus-based Image Description Evaluation (CIDEr) considers. CIDEr was originally proposed for image captioning by Vedantam et al. (2015) and is based on the consensus protocol and the average cosine similarity between \( n \)-grams in the candidate caption and the reference captions.

Intuitively, CIDEr measures how often \( n \)-grams in the candidate caption are present in the reference captions. For this, CIDEr assumes that \( n \)-grams that do not appear in the reference captions should not be in the candidate sentence. While \( n \)-grams that commonly occur across the corpus should be given lower weights, they are likely to be less informative. Given these assumptions, a Term Frequency Inverse Document Frequency (TF-IDF) weight is calculated for each \( n \)-gram.

Given the \( i \)-th input video \( x_i \), the set of reference captions \( Y_i = \{ y_{i1}, \ldots, y_{im} \} \) and a candidate caption \( \hat{y} \), all words in both candidate and references are first mapped to their stem
or root forms. For example, “generates”, “generation”, “generated” and “generating” are all reduced to “generate”. Then, the TF-IDF weighting $g_k(y_{i})$ for $k$-th $n$-gram $\omega_k$ and the $y_{ij}$ reference caption is obtained by:

$$g_k(y_{i}) = \frac{h_k(y_{ij})}{\sum_{\omega_i \in \Omega} h_i(y_{ij})} \log \left( \frac{|V|}{\sum_{x_j \in V} \min(1, \sum_{q} h_q(y_{ij}))} \right).$$  (14)

where $h_k(y_{ij})$ represents the number of times that the $n$-gram $\omega_k$ occurs in the reference caption $y_{ij}$, $\Omega$ is the vocabulary of all $n$-grams, and $V$ is the set of all videos in the dataset.

The average cosine similarity between them calculates the CIDEr$_n$ score for a particular $n$-gram between the candidate caption $\hat{y}_i$ and the reference captions $Y_i$:

$$\text{CIDEr}_n(\hat{y}_i, Y_i) = \frac{1}{m} \sum_{j} \frac{g^p(\hat{y}_i) \times g^p(y_{ij})}{\|g^p(\hat{y}_i)\| \|g^p(y_{ij})\|},$$  (15)

where $g^p(\hat{y}_i)$ is a vector formed by the $g_k(\hat{y}_i)$ weights and $g^p(y_{ij})$ is a vector formed by $g_k(y_{ij})$ weights, corresponding to all $n$-grams of length $n$ of the candidate $\hat{y}_i$ and the references $y_{ij}$, respectively. $\|g^p(\hat{y}_i)\|$ and $\|g^p(y_{ij})\|$ are the magnitudes of these vectors.

To capture richer semantics and grammatical properties, the authors proposed to compute a higher-order (longer) $n$-grams. They combined the scores from $n$-grams varying lengths as follows:

$$\text{CIDEr}(\hat{y}_i, Y_i) = \sum_{n=1}^{N} w_n \text{CIDEr}_n(\hat{y}_i, Y_i)$$  (16)

Here, the authors found that uniform weights $w_n = 1/N$ and $N = 4$ work the best, empirically. Likewise, for benchmark evaluation on image and video captioning, the most popular version of this metric, CIDEr-D (Vedantam et al. 2015; Chen et al. 2015), is used. CIDEr-D, among other modifications, prevents higher scores for descriptions that erroneously fail for human judgments. CIDEr-D does this, by clipping, for a specific $n$-gram, the number of candidate occurrences to the number of reference occurrences. These modifications result in the following version of Equation 15:

$$\text{CIDEr-D}_n(\hat{y}_i, Y_i) = \frac{10}{m} \sum_{j} \left( \exp \left( \frac{-l(\hat{y}_i) - l(y_{ij})^2}{2\sigma^2} \right) \times \frac{\min(g^p(\hat{y}_i), g^p(y_{ij})) \cdot g^p(y_{ij})}{\|g^p(\hat{y}_i)\| \|g^p(y_{ij})\|} \right),$$  (17)

where $l(\hat{y}_i)$ and $l(y_{ij})$ denote the lengths of candidate and reference sentences respectively, and $\sigma = 6$ is usually used. This penalty and the factor ten produce that, unlike other metrics, the scores can be higher than one but lower than ten.

### 3.4.1 Explicit semantic match-based metrics

Beyond $n$-grams, the semantic content matching metrics measure the similarity between the generated caption and the reference captions in the dataset by extracting explicit semantic information units. These metrics have shown well-correlation with human judgments.

The **Semantic Proportional Image Captioning Evaluation (SPICE)** metric (Anderson et al. 2016) is based on tuples of scene graphs of the generated candidate description
and all reference descriptions. These scene graphs encode the related video in a skeleton form, parsing the descriptions using two stages: (1) syntactic dependencies extraction and (2) a rule-based graph mapping. This skeleton represents the texts as semantic tokens, such as object classes, relationship types, or attribute types. After a proper parsing, SPICE then computes the F-SCORE using the candidate and reference scene graphs over the conjunction of logical tuples representing semantic propositions in the scene graph.

Better than improved versions of METEOR and CIDEr, SPICE also uses synonyms match by the encoding into semantic scene graphs. However, one limitation (not widely reported) of this metric is its dependency on the parsing quality. Another major limitation is that even though SPICE correlates well with human evaluations, it ignores the generated captions’ fluency (Celikyilmaz et al. 2020; Sharif et al. 2018).

**Semantic Text Similarity (STS)** was introduced in the TRECVID 2016 as an experimental semantic similarity metric (Han et al. 2013), and it has been used in this competition (Awad et al. 2016, 2017, 2018, 2019, 2020), in addition to BLEU, METEOR, and CIDEr metrics. This metric measures how semantically similar is the submitted description to the ground-truth description. It is based on distributional similarity, and Latent Semantic Analysis (LSA) complemented with semantic relations extracted from WordNet.

### 3.4.2 Limitations

Most video captioning metrics have been adopted from machine translation or image captioning and do not well-measure the quality of the generated descriptions from videos. Automated metrics should agree well with human judgment to be useful in practice. In this sense, BLEU and ROUGE are not optimal (Reiter 2018; Schluter 2017) and have been shown to correlate with humans weakly (Vedantam et al. 2015; Hodosh et al. 2015). In contrast, the METEOR and CIDEr metrics have shown a better correlation with humans when judging the overall quality of language descriptions for image and video captioning tasks. Specifically, CIDEr shows a high agreement with consensus as assessed by humans (Vedantam et al. 2015). Simultaneously, METEOR addresses the problem of reference description variability, allowing the recognition of morphological variants and synonyms as adequate descriptions.

Due to this discrepancy between metrics, the automatic evaluation is often accompanied by human evaluators accessing the candidate texts for their intrinsic qualities (e.g., correctness, fluency, factuality, and discourse coherency and consistency) (Celikyilmaz et al. 2020) and human preferences. Human evaluations have several challenges. They are expensive, time-consuming and the people who are going to evaluate will require extensive domain expertise. To ease this process, some crowd-sourcing platforms like Amazon Mechanical Turk (AMT) exist. We can post the method’s outputs with a detailed description of how people must evaluate, and we get our results based on convinced voting. However, that also has downsides, such as checking evaluations and evaluators’ consistency and quality without knowing them.

In the VTT task of the TRECVID Challenge (see Sect. 5.3), the organizers address this limitation by evaluating the automatic video descriptions with the Direct Assessment (DA) method (Awad et al. 2020) in addition to standard metrics. DA is an accurate method proposed by Graham et al. (2018) to control crowd-sourcing quality, which is efficient and cost-effective for tuning automatic evaluation metrics. They addressed the limitations of crowd-sourced judgments by automatically modifying candidate captions and degrading their quality, and examining how human judges rated the degraded captions.
They demonstrated that this process is ten times more effective at finding significant differences between competing systems than previous methodologies. Furthermore, the use of DA for evaluating the variable number of annual participants in the TRECVID-VTT task has shown its scalability, robustness, and replicability.

4 Methods for matching and ranking video descriptions

In the previous section, we saw how the state-of-the-art methods for video captioning produce texts from videos. Particularly, we detailed how encoder-decoder networks could be used to model text production, where the input video is first encoded into a continuous representation that is the input to the decoder. The decoder then predicts the output words sequence, one word at a time, conditioned both on the input representation and the previously generated word.

In contrast, the retrieval methods aim to return an ordered list (ranking), in which the text descriptions most likely to match (annotated) with the video appear first. For achieving this aim, the models are generally trained in a multimodal learning way (Goodfellow et al. 2016). The model must capture a representation in video modality, a representation in text modality, and in a joint distribution that relates both modalities.

This joint distribution is also called common embedding space and is usually trained for ensuring that visual and textual samples are close if and only if they are semantically similar. As we introduced in Sect. 1.2, this common embedding space enables multiple applications in vision-language tasks. Some of these tasks are text-to-image/video retrieval and image/video-to-text retrieval, visual question answering (Yu et al. 2017c; Tapaswi et al. 2016), video summarization with natural language (Plummer et al. 2017), and temporal grounding (i.e., temporal localization) in videos (Bojanowski et al. 2015; Hendricks et al. 2017). Almost all of these works show that the vision-language embedding need not be trained on domain-specific data but can be learned from standard still image-language datasets and transferred to video. Therefore, understanding how video-text retrieval methods work can help you develop new models for any of these tasks. Any technique that improves the text-video embeddings has the potential improve any method relying on such representations.

The authors have proposed two models, principally: (1) based on single encoding; and (2) based on siamese encoding. These two categories of models implicate that the similarity rank can be computed into three different “spaces”: the visual features space, the textual features space, and the joint embedding space. Into each one of these categories, there are some techniques widely used in state-of-the-art research, such as concepts-guiding retrieval, dual encoding, and hierarchical learning. This section analyzes the most important works for each technique, summarized in in Table 2, according to their distinctive characteristics.

4.1 Single encoding-based methods

Early deep learning-based retrieval methods aim to learn to encode only one of the modalities (text or video). The other modality was encoded by pre-trained models, which were not updated in the training process. In other words, these models learned to convert from only one modality to a representation of the other modality computed with a pre-trained model. When the fixed model is the video encoder, we say that the similarity is computed in the
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video feature space (see Fig. 5a) Snoek et al. 2016, 2017b. In contrast, when the fixed model is the text encoder, we say that the similarity is computed in the textual feature space (see Fig. 5b) (Le et al. 2016; Marsden et al. 2016; Markatopoulou et al. 2016; Yang et al. 2016).

The video encoder learned by Marsden et al. (2016) was based on the combination of three semantic representations of ten sampled key-frames of the video. These three semantic representations are: a 365-dimensional place representation, associated with the prediction of different scene categories (e.g., airport terminal, cafeteria, and hospital room); a 1,000-dimensional object representation; and a 94-dimensional action representation, each one referring to a crowd behavior concept (e.g., fight, run, mob, parade, and protest). The authors fine-tuned the VGG-16 architecture (Simonyan and Zisserman 2015) pre-trained on the ImageNet dataset and Places2 dataset (Zhou et al. 2018a) for the object and place representations, respectively. While for the action representation, the authors fine-tuned the AlexNet architecture (Krizhevsky et al. 2012) pre-trained on the WWW dataset (Shao et al. 2015). Finally, to retrieve the captions, they computed the similarity scores combining the word2vec (Li et al. 2015) representations of video representations and the objects, places, and actions that appear in each description of the corpus.

The incorporation of semantic representation based on an explicit concept detector model has also been explored by other works (Chen et al. 2017a; Zhang et al. 2016; Yang et al. 2016), assuming that one important clue is whether a concept appears in the video. However, as we analyzed for SeG-based video captioning approaches in Sect. 3.2.4, training the detectors could be a drawback. The training data (frames-annotated) could be not enough and can produce a harmful dependency. These models require answering several questions to be adopted, e.g., how to specify the concepts, how to train good classifiers for these concepts, and how to select relevant concepts for the video. For that, recent state-of-the-art works attempt to deal with the retrieval task in a concept-free manner (Dong et al. 2019; Ging et al. 2020).

In contrast to models that learn video encoders only, Snoek et al. (2016) and Snoek et al. (2017b) described an approach based on capturing video representations from texts (see Fig. 5a.). They used these representations of the corpus’ captions to calculate an input video’s relevance scores right there, in the video representation space. That approach is Word2VisualVec (Dong et al. 2016), which uses a 500-dimensional sentence representation as input. The model proposed by Snoek et al. (2016) first computes this sentence representation by mean-pooling the embeddings of each word in the sentence, In contrast, the model proposed by Snoek et al. (2017b) incorporated a GRU network for processing the texts. The word embeddings were computed with the word2vec model (Li et al. 2015) pre-trained on a Flickr tags’ corpus. Then, an MLP maps the sentence representation in a 2048-dimensional video feature space. The video representations are the concatenation of the average of sampled frames’ visual features (extracted with a pre-trained GoogleNet model (Szegedy et al. 2015)) and a 1024-dimensional bag of quantized Mel-frequency Cepstral Coefficients (MFCC) vectors (Davis and Mermelstein 1980; Wang et al. 2003). Finally, they trained the models minimizing the Mean Squared Error (MSE) between the vectors’ sentence descriptions and vectors extracted from the video.

4.2 Siamese encoding-based methods

The single encoding-based methods take advantage of data but to some extent. The representations learned by those models do not benefit from all the training data available to
perform this **zero-shot learning** task (Goodfellow et al. 2016). Another way to attack the retrieval of textual descriptions is to learn two mapping functions (one from video representation and another from caption representation) and a relation function between the two mapped representations (see Fig. 5c.). For simplification, we can incorporate the relation function as part of the last operations performed by each mapping function, and the aim is then to learn the functions $f(\cdot)$ and $g(\cdot)$ (encoders) that project videos and texts into a joint embedding space\(^3\) respectively. These encoders anchor the concepts in one representation in the other and vice versa (Goodfellow et al. 2016). Section 4.3 explains how to train these models to enable **zero-data learning**, and we now analyze the architecture of some state-of-the-art works based on this approach.

One of the first solutions that train the parameters of both encoders was proposed by Le et al. (2016) and Phan et al. (2017b). These methods are based on Embedding Convolutional Neural Network (ECNN) (Yang et al. 2016), which defines $f(\cdot)$ as the single-frame approach (see Sect. 2.2.1) and $g(\cdot)$ as the ParagraphVector (Le and Mikolov 2014) with the Bag-of-Words (BoW) approach. They were among the first to employ 3D-CNN to generate the frame-level representations instead of the 2D-CNN used in ECNN (Yang et al. 2016). While Le et al. (2016) trained the model minimizing the $L_2$ distances between two representations, Phan et al. (2017b) obtained better results by defining the similarity measure $s(\cdot, \cdot)$ in the common space as the dot product:

$$s(x, y) = f(x) \cdot g(y),$$

where $x$ represents a video and $y$ represents a text.

More recently, Mithun et al. (2017) observed that the existing image-caption datasets are larger and more varied than the existing video-caption datasets. They assumed that, when retrieving a video description, a few **key-frames** are enough to summarize the entire video. Hence, the authors proposed to extract the **key-frames** of the video and treat the problem as image-text retrieval. For this, once the model extracts the 2D-CNN from the input video frames employing AlexNet (Krizhevsky et al. 2012), a sparse coding-based approach (Elhamifar et al. 2016) is used to obtain a representative subset of frames. Given this subset, they tuned a joint embedding pre-trained on the MS-COCO dataset (Chen et al. 2015). For encoding images/frames, the authors used the ResNet-152 model (He et al. 2016), and for encoding texts, they employed a GRU-based text encoder (Cho et al. 2014). For training, the authors used cosine similarity between the embedded visual features and text descriptors.

Chen et al. (2017a) proposed a model that combines, in a distinctive way, a concept detector model with a joint embedding model, adding the scores from both models and training them simultaneously. Specifically, for the text encoder and joint embedding, the authors proposed three methods. In the first method, they first calculate the dot product between the embedding of each word and the video and then obtain the final score for each caption averaging them. In the second method, trying to avoid a limitation of the first one (deals with each word separately), the authors used convolution operations with kernels in the count of words: one, two, and three, learning the sentence’s local structure. The final score is then the sum of scores obtained from the representations produced for each kernel.

---

\(^3\) Joint embeddings are usually done by mapping semantically associated inputs from two or more domains (e.g., images and text) into a common vector space.
In the last method, they improved the second one keeping in mind that not all the words have the same weight in the sentence.

In contrast, Yu et al. (2017a) proposed to learn the mapping matrices \( U \) and \( V \) following the objective function:

\[
\min_{U,V,f}(U, V, X, Y) = C(U, X, Y) + L(U, V, X) + N(U, V),
\]

where \( C(\cdot, \cdot, \cdot) \) is a linear regression for keeping the frames with the same semantics close, \( L(\cdot, \cdot, \cdot) \) is a correlation analysis term, and \( N(\cdot, \cdot) \) is the regularization term.

Specifically, the authors defined \( C(U, X, Y) \) as:

\[
C(U, X, Y) = \beta ||X^T U - Y||_F^2,
\]

where \( 0 \leq \beta \leq 1 \), \( X \) and \( Y \) denote the feature matrices of frames and semantics respectively, and \( U \) is a mapping matrix of weights to be learned. To obtain \( Y \), the authors pre-trained a semantic detector on Wikipedia and Pascal Sentence image-vector pairs datasets (Rashtchian et al. 2010) with ten and twenty categories, respectively. They extracted 2048-dimensional CNN features for frames, and for captions, they extracted 100-dimensional features with the Sentence2Vector model (Saha et al. 2017).

### 4.2.1 Dual encoding-based methods

More recently, Dong et al. (2019) and Ging et al. (2020) proposed to use the same architecture for both encoders. The architecture proposed by Dong et al. (2019) is based on multi-level encoding. In contrast, the architecture proposed by Ging et al. (2020) is based on multi-contextual embeddings. In the first one (Dong et al. 2019), three encoding levels are combined inside each branch, and then, the relationship between these combinations is captured in the joint embedding. In the second one (Ging et al. 2020), two distinct levels of granularity of texts and videos are combined using two contextual embeddings, and then, the final embedding is a combination of them.

Specifically, the encoding levels explored by Dong et al. (2019) are: a global encoding obtained by mean pooling, a temporal-aware encoding computed by bi-directional GRU (biGRU), and a local-enhanced encoding resulted from a multi-kernel convolution of the biGRU outputs. While the granularity levels by contextual embeddings explored by Ging et al.
are: local context learned by projecting the sentences (parts of the paragraph) and clips (segments of the video), and global context learned considering the full video and the complete paragraph and transforming the local embedding. As we mentioned in Sect. 3.2.4, the contextual embeddings are obtained by transformer-based models (Vaswani et al. 2017), and their optimization process is analyzed in the next Sect. 4.3.

Based on the multi-level encoding (Dong et al. 2019), Song et al. (2019b) also proposed a model of three encoding levels. However, in the text-side encoder, they use in the first level a mean pooling of word embeddings initialized by GloVe instead of word2vec (Mikolov et al. 2013; Li et al. 2015). Besides, they based the architecture on BERT instead of biGRU and fine-tuned its last layer. Finally, they employed the TRECVID VTT 2016 (Awad et al. 2016), TRECVID VTT 2017 (Awad et al. 2017), TGIF (Li et al. 2016), MSR-VTT (Xu et al. 2016), and VaTeX (Wang et al. 2019c) video captioning datasets as the train set, and TRECVID VTT 2018 (Awad et al. 2018) as the validation set. For video representation, they extracted features from ResNeXt-101 (Xie et al. 2017), I3D, and audio (VGGish).

4.3 Loss functions for optimization

As we have explained throughout this section, recent methods for matching & ranking video descriptions use two encoders \( f(\cdot) \in \mathbb{R}^d \) and \( g(\cdot) \in \mathbb{R}^d \) for mapping the videos and captions into a joint space, respectively. After defining these mapping functions’ structure, we need to determine how to train them to obtain accurate representations that capture both modalities’ relationship. The triplet-ranking-loss function is a standard margin-based loss for training retrieval models. Motivated on the nearest-neighbor classification technique (Weinberger et al. 2005), Schroff et al. (2015) proposed this loss function for the Face Recognition problem (Parkhi et al. 2015).

Let \((x, y) \in D\) a video-description pair of the dataset and assume that \(y^*\) is an arbitrary description in the dataset not associated with \(x\) (a negative example). Their projections in the joint space are \(f(x) = z_x, g(y) = z_y, \) and \(g(y^*) = z_{y^*}\). Assume \(\text{dist}(\cdot, \cdot)\) is a distance function in \(\mathbb{R}^d\). This loss function tries to ensure that the distance between the anchor \(z_x\) and positive encoding \(z_y\) is less than the distance between the anchor and any negative encoding. We would like the following to hold:

\[
\text{dist}(z_x, z_y) + \alpha < \text{dist}(z_x, z_{y^*}),
\]

where \(\alpha\) is a margin that is enforced between positive and negative pairs. This gives rise to a natural optimization problem in which one wants to minimize:

\[
L_\Theta = \max \left\{ 0, \ \text{dist}(z_x, z_y) + \alpha - \text{dist}(z_x, z_{y^*}) \right\}
\]

This formulation is the classic version of triple-ranking loss and is used in many different applications with the same formulation or minor variations. However, in the literature, it can be found under other names such as ranking loss, margin loss, contrastive loss, triplet loss, and hinge loss, which can be confusing. For VTT, researchers have adapted several distance functions and triplets selection approaches. For example, Dong et al. (2019) proposed to use the improved marginal ranking loss (Faghri et al. 2018), which penalizes the model taking into account the hardest negative examples. In this improved version, one considers a tuple \((x, y, x^*, y^*)\) where \((x, y) \in D, y^*\) is the closest negative example for \(x, \) and \(x^*\) is the closest negative example for \(y)\). Their projections in the joint space are
$f(x) = z_x$, $g(y) = z_y$, $f(x^*) = z_{x^*}$, and $g(y^*) = z_{y^*}$. They trained the model attending to the loss function:

$$L'_\theta = \max \left\{ 0, \ \text{dist}(z_x, z_y) + \alpha - \text{dist}(z_{x^*}, z_{y^*}) \right\}$$

$$+ \max \left\{ 0, \ \text{dist}(z_x, z_y) + \alpha - \text{dist}(z_{x^*}, z_{y^*}) \right\}$$

(23)

where the distance function $\text{dist}(\cdot, \cdot)$ they used was the cosine distance function.

Recently, Ging et al. (2020) have proposed another form of training their cooperative hierarchical models. In the context of video-paragraph datasets, they introduced a **cross-modal cycle-consistency loss** to enforce the semantic alignment between clips and sentences. The cycle-consistency uses transitivity as an objective for training (Chen et al. 2019d; Dwibedi et al. 2019; Wang et al. 2019b; Zhu et al. 2017), and it has been used for tasks like temporal video alignment (Dwibedi et al. 2019) and visual question answering (Chen et al. 2019d). In contrast to previous models (Dwibedi et al. 2019) that only work on the video domain, Ging et al. (2020) aligned video and text in a cross-modal way. They defined the cyclical structure as follows.

Given a sequence of video clip embeddings $Z_x = \{z_{x1}, \ldots, z_{xn}\}$ of an input video $x$ and sentence embeddings $Z_y = \{z_{y1}, \ldots, z_{ym}\}$ of the reference paragraph $y$. We first find the soft nearest neighbor (Dwibedi et al. 2019) of each sentence embedding $z_{yi}$ in the clip sequence by:

$$\hat{z}_x = \sum_{j=1}^{n} \alpha_j z_{xj},$$

(24)

where $\alpha_j$ represents the similarity score of clip embedding $z_{xj}$ to sentence embedding $z_{yi}$, computed by:

$$\alpha_j = \frac{\exp(-\|z_{yi} - z_{xj}\|^2)}{\sum_{k=1}^{n} \exp(-\|z_{yi} - z_{xk}\|^2)}$$

We then cycle back from $\hat{z}_x$ to the sentences embeddings sequence $Z_y$ and calculate the soft location by:

$$\hat{i} = \sum_{j=1}^{m} \beta_j,$$

(25)

where $\beta_j$ represents the similarity score of sentence embedding $z_{yj}$ to the soft clip embedding $\hat{z}_x$, computed by:

$$\beta_j = \frac{\exp\left(-\|\hat{z}_x - z_{yj}\|^2\right)}{\sum_{k=1}^{n} \exp\left(-\|\hat{z}_x - z_{yk}\|^2\right)}$$

Given these to locations $i$ and $\hat{i}$ in the sequence of sentence embeddings $Z_y$, we assume that the embedding $z_{yi}$ is semantically cycle-consistent if and only if it cycles back to the original location, i.e., $i = \hat{i}$. This loss aims to penalize deviations from cycle-consistency for
sampled sets of clips and sentences, which encourages semantic alignment between vision and text representations in the joint embedding space. The objective is then, the distance between the source index $i$ and the soft destination index $\hat{i}$:

$$L_{CMC} = \| i - \hat{i} \|^2$$  \hspace{1cm} (26)

For the final loss of the model, the authors combined $L_{CMC}$ with four other losses. Three of these losses are based on ranking losses (Equation 23) obtained from clip-sentence level, video-paragraph level, and global context level. The other one, proposed by Zhang et al. (2018), models the clustering of low-level and high-level semantics in the joint embedding space:

$$L_{cluster} = L_{low} + L_{high}$$  \hspace{1cm} (27)

Here, the $L_{low}$ part models the low-level semantics clustering by the sum of $L^i_\Theta$ (defined in Equation 23) for all tuples $(z_{xi}, z_{yi}, z_{x'j}, z_{y'j})$ such that $(x', y') \in D$ and $x' \neq x$. So, $z_{x'j}$ and $z_{y'j}$ are clip-sentence-level intra-modality negative examples such that $z_{x'j}$ is a negative example for $z_{xi}$ computed by the video encoder $f(\cdot)$, and $z_{y'j}$ is a negative example for $z_{yi}$ computed by the text encoder $g(\cdot)$.

$$L_{low} = \sum_{i} \sum_{j(x', y') \in D, x' \neq x} \left( \max \left\{ 0, \text{dist}(z_{xi}, z_{yi}) + \gamma - \text{dist}(z_{xi}, z_{x'j}) \right\} ight.$$  

$$+ \max \left\{ 0, \text{dist}(z_{xi}, z_{yi}) + \gamma - \text{dist}(z_{y'j}, z_{yi}) \right\}$$

where $\gamma$ is a constant margin.

The $L_{high}$ part captures the high-level semantics clustering by the sum of $L^i_\Theta$ (defined in Equation 23) for all tuples $(z_x, z_y, z_x', z_y')$ such that $(x', y') \in D$ and $x' \neq x$. So, $z_{x'}$ and $z_{y'}$ are video-paragraph-level intra-modality negative examples such that $z_x$ is a negative example for $z_{x'}$ computed by the video encoder $f(\cdot)$, and $z_{y'}$ is a negative example for $z_y$ computed by the text encoder $g(\cdot)$.

$$L_{high} = \sum_{i} \sum_{(x', y') \in D, x' \neq x} \left( \max \left\{ 0, \text{dist}(z_x, z_y) + \rho - \text{dist}(z_{x'}, z_{x'}) \right\} ight.$$  

$$+ \max \left\{ 0, \text{dist}(z_x, z_y) + \rho - \text{dist}(z_{y'}, z_y) \right\}$$

where $\rho$ is a constant margin.

### 4.4 Retrieval-specific evaluation metrics

As we explained for description generation-specific evaluation metrics in Sect. 3.4, almost all metrics used to evaluate the VTT methods come from other related tasks. Specifically, for evaluating the output of retrieval-based methods, authors have reported some automatic assessments from the information retrieval field. Below we review the most-reported measures for these methods: Mean Reciprocal Rank (MIR) and Recall at K (R@K).
A standard evaluation metric for information retrieval methods is the **Mean Inverted Rank** (Craswell 2009). It is a statistical measure that calculates the average over a set of \( n \) queries. Different scores are attributed inversely proportional to the rank of the first correct answer in the answer list.

\[
\text{MIR} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{\text{rank}_i},
\]

where \( \text{rank}_i \) is the rank position of the first correct answer of the \( i \)-th query.

MIR has been used in the Matching & Ranking subtask of the TRECVID challenge from 2017 but has not been frequently reported in the literature of video-text retrieval methods. It is appropriate to evaluate models where there is only one relevant result or only cares about the highest-ranked one.

In the context of recommendation systems, we are most likely interested in recommending top-\( k \) items to the user. So it makes more sense to compute **precision** and **recall** metrics in the first \( k \) items instead of all the items. Thus, in the context of VTT, the notion of precision and recall at \( k \), where \( k \) is a user-definable integer to match the top-\( k \) recommended descriptions. **Recall at \( k \)** is then the proportion of relevant descriptions found in the top-\( k \) recommendations:

\[
\text{R@}k = \frac{r@k}{r},
\]

where \( r@k \) is the number of recommended descriptions at \( k \) that are relevant, and \( r \) is the total number of relevant descriptions.

Several state-of-the-art works report R@\( k \) results for some values of \( k \), e.g., R@1, R@5, R@10, R@50. These works also report the **mean average precision (mAP)** and **median rank (MR)** scores. The mAP score considers whether all of the relevant items tend to get ranked highly. Then, when there is only one relevant answer in the corpus, MIR and mAP are exactly equivalent under the standard definition of mAP. For comparing methods performance, higher R@\( k \) and mAP, and smaller MR indicates better performance. Usually, for evaluating the quality of learned joint embeddings, the authors also report these scores for the opposite problem: video retrieval from an input text.

### 4.5 Summary

Table 2 shows a summary of the papers we described for the retrieval-based methods. We can point out that there are authors such as Snoek et al. (2016) that, in 2016, based their proposal on the CNN scheme only, but in 2017, incorporated a recurrent-based encoder for the textual branch (CNN+RNN combination). Also, we can notice that, over the years, there has been a tendency to develop methods based on learning a generic representation into a joint space. For this, the researchers have proposed different ways of encoding each modality. Recent works (Dong et al. 2019; Ging et al. 2020; Song et al. 2019b) proposed to use models with the same structure to compute both encodings with transformer-based architectures (Ging et al. 2020; Song et al. 2019b).
| Space          | Method                  | Visual branch               | Textual branch               |
|---------------|-------------------------|-----------------------------|-----------------------------|
| Textual features | Marsden et al. (2016)   | VGG, AlexNet, SVO           | weighted sum, word2vec      |
|               | Yang et al. (2016)      | CaffeNet                    | ECNN, average, word2vec     |
| Visual features | Snoek et al. (2016)     | GoogLeNet, MFCC             | average, word2vec, Word2Vec |
|               | Snoek et al. (2017b)    | ResNeXt-101                 | average, BoW, word2vec, GRU |
|               | Chen et al. (2017a)     | ResNet, i3D                 | average, word2vec, TCNN, attention |
|               | Zhang et al. (2016)     | VGG, C3D                    | SAN, word2vec, TCNN         |
|               | Le et al. (2016)        | C3D                         | ECNN, BoW, ParagraphVector  |
|               | Yu et al. (2017a)       | CNN                         | FC, BoW, word2vec, sentence2vec, FC |
|               | Mithun et al. (2017)    | ResNet                      | average, MLP, word2vec, GRU |
|               | Nguyen et al. (2017a)   | ResNet, C3D                 | average, FC, word2vec, LSTM |
|               | Li et al. (2018b)       | ResNext, ResNet             | average, FC, BoW, word2vec, GRU, FC |
|               | Dong et al. (2019)      | ResNeXt-101                 | biGRU-CNN, one-hot, biGRU-CNN |
|               | Song et al. (2019b)     | ResNeXt-101, I3D, VGGish    | BERT, GloVe, BERT           |
|               | Ging et al. (2020)      | ResNet-152, C3D             | Transformer, GloVe, Transformer |

For each method we mention the main characteristics of its visual and textual branches. We mention the type of visual/textual features used to represent the videos/descriptions in the Features columns. Besides, we summarize the strategy used to encapsulate and project these features in Encoder columns. And in the case of visual branch, we also check if the method uses concept detectors (CD) as a high-level representation.
5 Evaluation benchmarks

Stimulating research on the vision-language intersection, researchers have proposed conferences and workshops where VTT is a central topic. Some of these meetings and some companies have organized exciting VTT competitions (challenges) in recent years. These contests can be centered on describing videos from any domain or videos from a specific domain, such as LSMDC for movie description or ActivityNet for human activities description. This section covers these competitions, introducing their evaluation tasks and datasets and explaining how the participant teams are evaluated. Table 3 shows the number of annual participant teams reported for each competition task. In the following Sect. 6, the reader can find the details on the construction and composition of related datasets.

5.1 The large scale movie description challenge (LSMDC)

The LSMDC competition and workshop have been organized in conjunction with ECCV’16 and ICCV’15, ’17, and ’19. The competition is based on a unified version of the MPII-MD (Rohrbach et al. 2015b) (see Sect. 6.2.2) and M-VAD (Torabi et al. 2015) (see Sect. 6.2.1) movie datasets. This combined dataset is considered one of the most challenging datasets due to the low performance achieved for all metrics. These datasets use Audio Descriptions (AD) / Descriptive Video Service (DVS) resources for the visually impaired, transcribed and aligned with the video. The original task implies the generation of single-sentence descriptions for each movie fragment. The challenge consisted of two phases (test sets): public evaluation and blind (without ground-truth descriptions) evaluation.

In the first edition, hosted on ICCV’15, the winners were decided based on the human evaluation only. Additionally, the challenge included an automatic evaluation server based on MS COCO Caption Evaluation API. For human evaluation, each evaluator was asked to rank four generated sentences and a reference sentence from 1 (lower) to 5 (better) concerning four criteria: grammar, correctness, relevance, and helpful for blind.

Two other tasks were assessed in the posterior challenge’s editions (2016 and 2017): (1) movie annotation and retrieval, and (2) movie fill-in-the-blank. In the last edition, hosted on ICCV’19, organizers presented a new competition version focused on Multi-sentence Movie Description Generation. For this new challenge, it is essential to determine “who is who” and identify characters to provide a coherent and informative narrative. The tasks assessed in this edition were:

- **Multi-Sentence Description**, focusing on the description of videos, and putting generic “SOMEONE”-s in place of all the occurring character names.
- **Fill-in the Characters**, focusing on filling-in the character IDs locally (within a set of five clips).

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4 label:note:lsmdcLSMDC 2017 challenge website: https://sites.google.com/site/describingmovies/lsmdc-2017
5 LSMDC 2019 challenge website: https://sites.google.com/site/describingmovies/lsmdc-2019
6 ICCV Workshop for LSMDC 2015 challenge website: https://sites.google.com/site/describingmovies/workshop-at-iccv-15
7 MS COCO Caption Evaluation: https://github.com/tylin/coco-caption
• **Multi-Sentence Description with Characters**, which combines both description generation and *filling-in* the local character IDs.

### 5.2 Video to language challenge

The Video to Language Challenge is one of the scenarios of the Microsoft Multimedia Challenge\(^8\). Only two editions have been held until this moment, in 2016 and 2017. This challenge is based on the MSR-VTT dataset, but the participants can use other public or private datasets (images or videos) to train their models. For the evaluation, a complete and natural sentence describing the content of each test set’s video had to be submitted. The performance was evaluated against sentences previously generated by a human during the evaluation stage.

The 2017 edition (hosted on ACMMM’17) was based on both automatic evaluation and human evaluation. Specifically, two ranking lists of teams were produced by combining their scores on each evaluation metric. For the automatic evaluation rank, the organizers proposed to combine its ranking positions in four ranking lists following this equation:

\[
R = R_{\text{BLEU}-4} + R_{\text{METEOR}} + R_{\text{ROUGE}_L} + R_{\text{CIDEr}},
\]

where \(R_{\text{BLEU}-4}, R_{\text{METEOR}}, R_{\text{ROUGE}_L}, R_{\text{CIDEr}}\) are the rank positions of the team for each metric. The smaller the final rank, the better performance.

Simultaneously, the human evaluation rank is based on three scores (on the scale of 1-5): *coherence* \(S_c\), *relevance* \(S_r\), and *helpful for blind* \(S_{hb}\). The final human evaluation is given by:

\[
S = S_c + S_r + S_{hb},
\]

where the higher the final score, the better performance.

Then the final rank is divided into two lists, one in terms of \(R\) and one in terms of \(S\).

### 5.3 TREC video retrieval evaluation (TRECVID)

The National Institute of Standards and Technology (NIST) and other US-gov-ernment agencies sponsor the TREC conference series. Over almost twenty years, the TRECVID conference of TREC has pushed the progress in content-based digital video exploitation by using open evaluation metrics. This effort has allowed a better understanding of how the methods can effectively process videos and evaluate their performance. Specifically, some of the tasks that have been part of TRECVID are:

- **Ad-hoc Video Search (AVS)**, for the video retrieval from a text query
- **Instance Search (INS)**, for retrieving specific instances of individual objects, persons, and locations
- **Video to Text Description (VTT)**

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\(^8\) Microsoft Multimedia Challenge website: [http://ms-multimedia-challenge.com/2017/challenge](http://ms-multimedia-challenge.com/2017/challenge)
The VTT task was incorporated, as a pilot-task, in the TRECVID’16 conference (Awad et al. 2016). That year, given a development set of 2,000 Twitter Vine videos of Twitter and two sets of descriptions, the goal was to train models for resolving the following subtasks:

- **Matching and Ranking**: Requires, for each video, submitting a ranked list of the most likely text descriptions for each set of descriptions.
- **Description Generation**: Requires submitting a generated text description for each video.

After that, the number of videos increased (7,485 videos in 2020), and new sources were used. In Sect. 6.1.6, we analyze how these datasets have been constructed. Likewise, in the 2020 edition, five automatic evaluation metrics, *i.e.*, BLEU, METEOR, CIDEr, SPICE, and STS, in addition to human evaluation, were used for the Description Generation subtask.

For the VTT task of TRECVID’21, a new multi-modality subtask, called **Fill-in the Blanks**, has been announced. For this subtask, the most appropriate word or words to fill in the blank and complete each video’s sentence must be submitted. The blank will represent a single concept but not necessarily a single word. The scoring will be done using manual evaluation only. Assessors will view the video and its associated sentence with the system-generated word to determine how well it fills in the blank.
5.4 ActivityNet

A challenge with more annual participants than TRECVID is the International Challenge on Activity Recognition, also called ActivityNet Large-Scale Activity Recognition Challenge (before 2018), a CVPR Workshop from 2016. It centers on recognizing daily life and detecting and captioning multiple events in a video. The challenge has hosted six diverse tasks in these editions, aiming to drive semantic video understanding limits and link the visual content with human captions. The organizers based three of the six tasks on the challenging ActivityNet Captions dataset (Krishna et al. 2017a), described in Sect. 6.4.2. These tasks focus on trace evidence of activities in time in the form of proposals, class labels, and captions. Specifically, its task, Dense-Captioning Events in Videos, involves both detecting and describing events in a video. The leader-boards of 2018, 2019, and 2020 have been obtained by server evaluation using the Avg. METEOR metric (see Sect. 3.4).

5.5 VATEX video captioning challenge

The recent VATEX Video Captioning Challenge aims to benchmark progress towards models that can describe the videos in various languages such as English and Chinese. This challenge is based on the dataset with the same name, described in Sect. 6.1.5. The first edition of the challenge was hosted at an ICCV’19 Workshop and the second edition at a CVPR’20 Workshop. In 2020, the challenge had two tracks: Video Captioning and Video-guided Machine Translation. For the Video Captioning track, the teams should submit generated captions for English or Chinese languages. While, for the Video-guided Machine Translation track, the participants should submit English-to-Chinese translations using video information as the additional spatiotemporal context.

A drawback of this challenge competition is that for evaluating submissions, human evaluation is not performed. The scoring is obtained by automatic evaluation only, computing for both tracks the BLEU-1, BLEU-2, BLEU-3, BLEU-4, METEOR, ROUGE-L, and CIDEr-D metrics.

6 Datasets for video-to-text

As mentioned in the previous sections, VTT methods require datasets to train and validate the models. In this sense, several datasets have been recently created to supports the training of neural VTT models. They vary in terms of the number of reference descriptions for each video, the length of these references (number of words and sentences), domain specificity, and other aspects discussed in this section.

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9 labelnote:actnettaskDense-Captioning Events in Videos task of ActivityNet 2019 challenge website: http://activity-net.org/challenges/2019/tasks/anet_captioning.html.
10 labelnote:actnet18Captioning tab in ActivityNet 2018 evaluation website: http://activity-net.org/challenges/2018/evaluation.html.
11 labelnote:actnet19Captioning tab in ActivityNet 2019 evaluation website: http://activity-net.org/challenges/2019/evaluation.html.
12 VATEX Captioning Challenge website: https://eric-xw.github.io/vatex-website/index.html.
For training the VTT models, we have found more than twenty-five annotated datasets that we can group according to the video domain and different ways the descriptions are obtained (see Fig. 6).

On the one hand, according to the video domain, we basically have four types of video datasets:

- **Open domain**, with videos randomly extracted from online video platforms like YouTube
- **Cooking videos**, with videos related to cooking activities only
- **Human Activities videos**, with videos that show people performing specific actions, like *instructional* videos
- **Movie videos**, for videos extracted from films

On the other hand, according to the source of the textual annotations, a big group of datasets utilizes a manual annotation process usually performed on the Amazon Mechanical Turk service. This service is based on crowd workers who watch the video and generate a textual description of them. However, the biggest dataset (HowTo100M Miech et al. (2019)) has been constructed using automatic subtitles or narrations due to the low cost of this technique.

As shown in and 7, extensive results have been reported on datasets with videos in the open domain and human annotations. Specifically, the most-reported dataset in the literature is MSVD, followed by MSR-VTT, MPII-MD, M-VAD, and ActivityNet Captions. The popularity of MSVD and MSR-VTT is because they are the first to use open-domain videos and many associated captions with each video (more than 40 and 20, respectively). While MPII-MD, M-VAD, ActivityNet Captions, and TRECVID VTT datasets are popular for their domain specificity and their uses in respective competitions and Workshops (see and 5).

Aafaq et al. (2019b) included a comparative table between almost used video-caption/description pairs datasets. In contrast, in this section, we include other general characteristics in Table 4. We detail the corpus’s vocabulary composition\(^\text{13}\), the average length of captions, and the percent of tokens that appear in the GloVe-6B\(^\text{14}\) dictionary in Table 5. We show the most reported splits sets and the total size of the datasets in Table 6. Additionally, all datasets’ references and the tables presented in this section are publicly available in our GitHub repository\(^\text{15}\).

We organize the analysis of datasets for VTT in the rest of this section focusing on five VTT facets: open video description, movie description, cooking description, activity description, and dense video description. However, if the reader is interested in datasets with text sequences of a specific length, we suggest following the order shown in Table 5. In this Table, we sorted the datasets according to the average length of captions.

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\(^\text{13}\) Categorizing and tagging words: [http://www.nltk.org/book/ch05.html](http://www.nltk.org/book/ch05.html).

\(^\text{14}\) Global Vectors for Word Representation (GloVe) website: [https://nlp.stanford.edu/projects/glove/](https://nlp.stanford.edu/projects/glove/)

\(^\text{15}\) Datasets summary available at: [https://github.com/jssprz/video_captioning_datasets](https://github.com/jssprz/video_captioning_datasets)
6.1 Datasets for open video description

6.1.1 Microsoft video description corpus (MSVD)

This dataset, also called YoutubeVideos2Text, was proposed by Chen D and Dolan W (2011), considering YouTube video clips of short duration (from four to ten seconds) with a single event. Several crowd workers of the Amazon Mechanical Turk\textsuperscript{16} (AMT) service (Rashtchian et al. 2010) annotated each video clip. Each annotator wrote a sentence describing the event or the video’s main action in a language of their choice. Initially, 2,089 clips and 85,550 descriptions were compiled in English, with 41 descriptions for each video on average. However, due to the dynamism of YouTube, the current public data consists of 1,970 clips from 1,464 different videos. There are at least 27 annotations for more than 95% of the videos, with an average number of words of around 7.1, which indicates those descriptions are relatively short and simple sentences.

6.1.2 Microsoft research-video to text (MSR-VTT) or MSR-VTT-10K

Proposed by Xu et al. (2016), it collects videos from a commercial video search engine. Different AMT workers produced 20 human-written reference captions for each video. The videos are about general topics in our life. They are grouped into 20 categories (e.g., music, people, TV show, and movie). In total MSR-VTT contains 10,000 clips from 7,180 different videos and 200,000 sentences (20 per clip). The duration of each video clip is from 10 to 30 seconds and contains audio information as well. The average number of words per description is around 9.3, indicating more complicated sentences than other datasets like

\textsuperscript{16} MTurk is an online framework that allows researchers to post annotation tasks, called HITs (Human Intelligence Task)
| Dataset | Type | Caps. Source | Localization | Audio | Long-Caps. |
|---------|------|--------------|--------------|-------|------------|
| MSVD (Chen D and Dolan W 2011) | Open (YouTube) | Annotators (MTurk) | ✓ | ✓ | ✓ |
| MPII Cooking Act. (Rohrbach et al. 2012a) | Cooking | in-house actors | ✓ | ✓ | ✓ |
| MPII Cooking C. Act. (Rohrbach et al. 2012b) | Cooking | in-house actors | ✓ | ✓ | ✓ |
| YouCook (Das et al. 2013) | Cooking | Annotators (MTurk) | ✓ | ✓ | ✓ |
| TACoS (Regneri et al. 2013) | Cooking | Annotators (MTurk) | ✓ | ✓ | ✓ |
| TACoS-Multilevel (Rohrbach et al. 2014) | Cooking | Annotators (MTurk) | ✓ | ✓ | ✓ |
| M-VAD (Torabi et al. 2015) | Movie | DVS | ✓ | ✓ | ✓ |
| MPII-MD (Rohrbach et al. 2015b) | Movie | Script + DVS | ✓ | ✓ | ✓ |
| LSDMC (see footnote 4) | Movie | Script + DVS | ✓ | ✓ | ✓ |
| MSR-VTT (Xu et al. 2016) | Open | Annotators (MTurk) | ✓ | ✓ | ✓ |
| MPII Cooking 2 (Rohrbach et al. 2016) | Cooking | in-house actors | ✓ | ✓ | ✓ |
| Charades (Sigurdsson et al. 2016) | Daily indoor act. | Annotators (MTurk) | ✓ | ✓ | ✓ |
| VTW-full (Zeng et al. 2016) | Open (YouTube) | Owner/Editor | ✓ | ✓ | ✓ |
| TGIF (Li et al. 2016) | Open | crowdworkers | ✓ | ✓ | ✓ |
| TRECVID-VTT’16 (Awad et al. 2016) | Open | Annotators | ✓ | ✓ | ✓ |
| Co-ref+Gender (Rohrbach et al. 2017) | Movie | DVS | ✓ | ✓ | ✓ |
| ActivityNet Caps. (Krishna et al. 2017a) | Human act. | Annotators (MTurk) | ✓ | ✓ | ✓ |
| TRECVID-VTT’17 (Awad et al. 2017) | Open (Twitter) | Annotators | ✓ | ✓ | ✓ |
| YouCook2 (Zhou et al. 2018b) | Cooking | viewer/annotator | ✓ | ✓ | ✓ |
| Charades-Ego (Sigurdsson et al. 2018) | Daily indoor act. | Annotators (MTurk) | ✓ | ✓ | ✓ |
| 20BN-s-s V2 (Mahdisoltani et al. 2018a) | Human-obj. interact. | Annotators (MTurk) | ✓ | ✓ | ✓ |
| TRECVID-VTT’18 (Awad et al. 2018) | Open (Twitter) | Annotators | ✓ | ✓ | ✓ |
| TRECVID-VTT’19 (Awad et al. 2019) | Open (Twitter+Flick) | Annotators | ✓ | ✓ | ✓ |
| VaTeX (see footnote 20) (Wang et al. 2019c) | Open | Annotators (MTurk) | ✓ | ✓ | ✓ |
| HowTo100M (Miech et al. 2019) | Instructional (YouTube) | Subtitles | ✓ | ✓ | ✓ |
| TRECVID-VTT’20 (Awad et al. 2020) | Open (Twitter+Flick) | Annotators | ✓ | ✓ | ✓ |

The cells of the last three columns are marked: (1) if the dataset contains temporal-localization information related to each description, (2) if the videos of the dataset contain audio, and (3) if corpus’ descriptions are more than eleven words long on average.
Table 5  Corpus details. Average length of captions, vocabulary (unique words) composition of each dataset’s corpus, and percent of tokens that appear in the GloVe-6B dictionary.

| Corpus                                      | Avg. cap. len. | Vocabulary Tokens | Nouns | Verbs | Adjectives | Adverbs | % of tokens in GloVe-6B |
|----------------------------------------------|----------------|-------------------|-------|-------|------------|---------|-------------------------|
| HowTo100M (Miech et al. 2019)                | 4.16           | 593,238           | 491,488 | 198,859 | 219,719    | 76,535  | 36.64                   |
| VTW-full (Zeng et al. 2016)                  | 6.40           | 23,059            | 13,606 | 6,223  | 3,967      | 846     | -                       |
| 2OBN-s-s V2 (Mahdisoltani et al. 2018a)      | 6.76           | 7,433             | 6,087  | 1,874  | 1,889      | 361     | 74.51                   |
| MSVD (Chen D and Dolan W 2011)               | 7.14           | 9,629             | 6,057  | 3,211  | 1,751      | 378     | 83.44                   |
| TACoS-Multilevel (Rohrbach et al. 2014)      | 8.27           | 2,863             | 1,475  | 1,178  | 609        | 207     | 91.86                   |
| MSR-VTT, 2016 (see footnote 17)(Xu et al. 2016) | 9.27          | 23,527            | 19,703 | 8,862  | 7,329      | 1,195   | 80.74                   |
| LSDMC (see footnote 4)                       | 10.66          | 24,267            | 15,095 | 7,726  | 7,078      | 1,545   | 88.57                   |
| MPII-MD (Rohrbach et al. 2015b)              | 11.05          | 20,650            | 11,397 | 6,100  | 3,952      | 1,162   | 88.96                   |
| TGIF (Li et al. 2016)                        | 11.28          | 10,646            | 6,658  | 3,993  | 2,496      | 626     | 97.85                   |
| M-VAD (Torabi et al. 2015)                   | 12.44          | 17,609            | 9,512  | 2,571  | 3,560      | 857     | 94.99                   |
| ActivityNet Caps. (Krishna et al. 2017a)      | 14.72          | 10,162            | 4,671  | 3,748  | 2,131      | 493     | 94.00                   |
| VTeX-en (see footnote 20) (Wang et al. 2019c) | 15.25          | 28,634            | 23,288 | 12,796 | 10,639     | 1,924   | 76.84                   |
| TRECVID-VTT’20 (Awad et al. 2020)            | 18.90          | 11,634            | 7,316  | 4,038  | 2,878      | 542     | 93.36                   |
| Charades (Sigurdsson et al. 2016)            | 23.91          | 4,010             | 2,199  | 1,780  | 651        | 265     | 90.00                   |
| Charades-Ego (Sigurdsson et al. 2018)        | **26.30**      | 2,681             | 1,460  | 1,179  | 358        | 190     | 91.12                   |

The words categorization have been calculated by POS-tagging with *universal tagset* mapping. We sorted the corpus according to the average length of captions. Highest values are highlighted in bold and second highest are underlined.
Table 6  Number of video clips and captions in the standard splits of each video-caption/description pairs dataset

| Dataset                                      | Train set | Validation set | Testing set | Total |
|----------------------------------------------|-----------|----------------|-------------|-------|
|                                              | Clips     | Captions       | Clips       | Captions | Clips | Captions | Clips | Captions |
| MSVD (Chen D and Dolan W 2011)               | 1,200     | 48,779         | 100         | 4,291    | 670   | 27,768    | 1,970 | 80,838   |
| TACoS (Regneri et al. 2013)                  | –         | –              | –           | –        | –     | –         | 7,206 | 18,227   |
| Charades-Ego (Sigurdsson et al. 2018)        | 6,167     | 12,346         | 1,693       | 1,693    | –     | –         | 7,860 | 14,039   |
| TRECVID-VTT’20 (Awad et al. 2020)            | 7,485     | 28,183         | –           | –        | 1,700 | –         | 9,185 | 28,183   |
| Charades (Sigurdsson et al. 2016)            | 7,985     | 18,167         | 1,863       | 6,865    | –     | –         | 9,848 | 25,032   |
| MSR-VTT, 2017 (see footnote 18)              | 10,000    | 200,000        | –           | –        | 3,000 | 60,000    | 13,000 | 260,000  |
| TACoS-Multilevel (Rohrbach et al. 2014)      | –         | –              | –           | –        | –     | –         | 14,105 | 52,593   |
| ActivityNet Caps. (Krishna et al. 2017a)     | 10,024    | 36,587         | 4,926       | 17,979   | 5,044 | 18,410    | 19,994 | 72,976   |
| V\xTeX (see footnote 20) (Wang et al. 2019c) | 25,991    | 259,910        | 3,000       | 30,000   | 6,000 | 60,000    | 34,991 | 349,910  |
| M-VAD (Torabi et al. 2015)                   | 36,921    | 36,921         | 4,717       | 4,717    | 4,951 | 4,951     | 46,589 | 46,589   |
| MPII-MD (Rohrbach et al. 2015b, 2017)        | 56,822    | 56,861         | 4,927       | 4,930    | 6,578 | 6,584     | 68,327 | 68,375   |
| LSDMC (see footnote 4)                       | 91,908    | 91,941         | 6,542       | 6,542    | 10,053| 10,053    | 108,503| 108,536  |
| TGIF (Li et al. 2016)                        | 80,850    | 80850          | 10,831      | 10,831   | 34,101| 34,101    | 125,782| 125,781  |
| 20BN-s-s V2 (Mahdisoltani et al. 2018a)      | 168,913   | 1,689,913      | 24,777      | 24,777   | 27,157| –         | 220,847| 1,714,690|
| MSR-VTT, 2016 (see footnote 17)              | 6,512     | 130,260        | 498         | 9,940    | 2,990 | 59,800    | 507,502| 200,000  |
| HowTo100M (Miech et al. 2019)                | –         | –              | –           | –        | –     | –         | 139,668,840| 139,668,840|

We sorted the datasets according to the total number of clips.
MSVD. Moreover, this was the dataset for the first Video to Language Challenge\(^\text{17}\), as we mentioned in Sect. 5.2.

In the second MSR Video to Language Challenge in 2017\(^\text{18}\), the organizers used a combination of the train, validation, and test sets as the new training data. Moreover, they released an additional test set of 3,000 video clips. Specifically, this dataset version contains about 50 hours and 260,000 clip-sentence pairs in total, covering the most comprehensive categories and diverse visual content.

6.1.3 Video titles in the wild (VTW)

Zeng et al. (2016) proposed this dataset for video title generation. The descriptions of this dataset make up a very diverse vocabulary. The data includes 18,100 video clips with one sentence per clip. On average, each word appears only in two sentences, and each clip has a duration of 1.5 minutes. Besides, the authors provided a sentence-only example per video. Attending to the diverse vocabulary (see Table 5), its sophisticated sentences were produced by editors instead of simple sentences produced by Turkers. This vocabulary characteristic allows the dataset to be used for language-level understanding tasks, including video question answering (Aafaq et al. 2019b).

6.1.4 Tumblr GIF (TGIF)

This dataset, proposed by Li et al. (2016), comprises Tumblr’s\(^\text{19}\) one-year GIF publications. The interest in creating a dataset with GIF was because very few academic works dealt with them. GIFs have a short duration and tell a visual story without audio. To obtain fluent descriptions, 931 workers participated in the GIFs annotation, preferably speaking English as their native language. Each worker described at least 800 GIFs, guaranteeing the descriptions’ diversity. TRECVID challenge participants have widely explored this dataset’s use as an additional data source for training models, improving their methods’ performance.

6.1.5 VaTeX

More recently, Wang et al. (2019c) proposed the \textit{VaTeX}\(^\text{20}\) dataset, a multilingual video captioning dataset. This dataset covers 600 human activities and a variety of video domains, reusing a subset of the videos from the Kinetics-600\(^\text{21}\) dataset (Carreira and Zisserman 2017). Twenty individual human annotators (AMT workers) paired each video with ten English and ten Chinese captions. Each caption is from an individual worker and should describe all the important characters and actions shown in the video clips with ten or more words. The dataset comprises over 41,250 unique videos and 825,000 unique captions (every caption is unique in the whole corpus). Finally, in Table 5, we show the linguistic complexity (vocabulary distribution) of this dataset.

\(^\text{17}\) labelnote:msrvtt16MSR-VTT-10K dataset website: \url{http://ms-multimedia-challenge.com/2016/dataset}

\(^\text{18}\) labelnote:msrvtt17MSR-VTT 2017 dataset website: \url{http://ms-multimedia-challenge.com/2017/dataset}

\(^\text{19}\) Tumblr website: \url{https://www.tumblr.com}

\(^\text{20}\) labelnote:vatex\textit{VaTeX} dataset website: \url{https://eric-xw.github.io/vatex-website/index.html.}

\(^\text{21}\) Kinetics dataset website: \url{https://deepmind.com/research/open-source/kinetics}
into the English (\textsc{VTeX-en}) and the Chinese (\textsc{VTeX-zh}) corpus, which evidences that \textsc{VTeX} has greater difficulty than other datasets like MSR-VTT.

### 6.1.6 TRECVID-VTT

Since 2016, the TRECVID organizers have proposed a new version of the development and test sets of the VTT task. For all these versions, a rigorous and monitored annotation process has been performed. The annotators are asked to combine in one sentence four facets if applicable (Awad et al. 2016, 2017, 2018, 2019, 2020):

- Who is the video describing (such as objects, persons, animals)?
- What are the objects and beings doing (such as actions, states, events)?
- Where (such as locale, site, place, geographic)?
- When (such as time of day, season)?

To answer these questions and produce the video descriptions, the annotators receive training for the task. Their work is monitored, and feedback is provided. The NIST personnel is available for any questions or confusion during the process. This annotation process differentiates the TRECVID datasets from other datasets, which produce arguably better/more detailed descriptions than crowd-sourced datasets.

Furthermore, for each of the videos, the annotators rated how difficult it was to describe them. The composition of each one of these datasets is as follows:

- **TRECVID-VTT’16** (Awad et al. 2016) consists of 2,000 Twitter Vine videos randomly selected. Each one with a duration of approximately six seconds. Eight annotators made the textual descriptions. For each video, two annotations were made by two different annotators, for a total of 4,000 textual descriptions, divided into two sets.
- **TRECVID-VTT’17** (Awad et al. 2017) is composed of 1,880 Twitter Vine videos. The videos were divided amongst ten annotators, with each video being annotated by at least two and at most five.
- **TRECVID-VTT’18** (Awad et al. 2018) is composed of 1,903 Vine videos manually annotated by exactly five assessors. Each assessor rated how likely is it that other assessors will write similar descriptions into not likely, somewhat likely, and very likely. Additionally, the task organizers manually removed videos with unrelated segments that are hard to describe, animated videos, and unappropriated and offensive videos.
- **TRECVID-VTT’19** (Awad et al. 2019), in contrast to the previous versions, was enriched by using two video sources. Specifically, **TRECVID-VTT’19** contains 1,044 Vine videos used in the challenge since 2016 and 1,010 video clips extracted from 91 Flickr videos. The 2,054 videos were annotated following the same criteria as in 2018.
- **TRECVID-VTT’20** (Awad et al. 2020) contains short videos (ranging from 3 seconds to 10 seconds) from the 2016 to 2019 versions. There are 9,185 videos with captions. Each video has between 2 and 5 captions written by dedicated annotators. The video sources have the following distribution: 6,475 from Twitter Vine, 1,010 from Flickr, and 1,700 from the V3C dataset.
6.2 Datasets for movie description

6.2.1 Montreal video annotation dataset (M-VAD)

Torabi et al. (2015), researchers of the Mila group of the University of Montreal, proposed this dataset to address the movie description task. M-VAD is a large-scale dataset based on Descriptive Video Service\textsuperscript{22} (DVS). The authors eliminated the sentences obtained from the first narrated three minutes and the four final minutes of the film because the DVS’s narrator at that moment could read, for example, the credits of the film. With 46,523 video clips in total, M-VAD consists of 84.6 hours of videos from 92 Hollywood films. Each video clip was annotated automatically with a single narrative, using the vocabulary detailed in Table 5. The usual split consists of 36,921 train clips, 4,717 validation clips, and 4,951 test clips.

6.2.2 Max Planck institute for informatics-movie description (MPII-MD)

Rohrbach et al. (2015b) proposed this dataset by including transcribed ADs (audio descriptions for the blind) with temporal alignment to full-length 55 HD movies. For this, the authors proposed a semiautomatic approach of two phases to obtain ADs’ transcriptions and make them correspond to the video. They selected 39 movie scripts for the first phase and filtered the sentences with a reliable alignment score (the ratio of matched words in the near-by monologues) of at least 0.5. The obtained sentences were then manually aligned to video, filtering all those sentences that did not correspond to the film’s dialogues, such as the cast’s sentences. This approach’s importance is that, until that moment, there were not many available transcriptions from ADs. In total, the dataset\textsuperscript{23} contains a smaller number of video clips (from 94 unique movies) than the sentences, 68,337 and 68,375, respectively, because, in some cases, a video clip is annotated with more than one sentence. The vocabulary distribution of this corpus is shown in Table 5.

6.2.3 LSMDC

This dataset is considered one of the most challenging datasets due, to some extent, to the low performance and reported metrics scores of several models. The dataset is a unified version of the M-VAD (Torabi et al. 2015) and MPII-MD (Rohrbach et al. 2015b) datasets. These datasets use Audio Descriptions (AD) / Descriptive Video Service (DVS) resources for the visually impaired, transcribed and aligned with the video. Moreover, this is the competition dataset with the same name, as described in and 5.1.

\textsuperscript{22} Descriptive Video Service (DVS) is a major specialized in audio description, which aims to describe the visual content in form of narration. These narrations are commonly placed during natural pauses in the original audio of the video, and sometimes during dialogues.

\textsuperscript{23} MPII-MD dataset website: www.mpi-inf.mpg.de
6.2.4 MPII-MD co-ref+gender

Rohrbach et al. (2017) introduced the dataset for Grounded and Co-Referenced Characters (MPII-MD Co-ref+Gender) dataset, including annotations on language and visual side for the goal to learn the visual co-reference resolution on the MPII-MD dataset (Rohrbach et al. 2015b). On the language side, the authors included information to know when different mentions refer to the same person. On the visual side, they relate the names (“aliases”) with the visual appearances. In total they labeled 45,325 name mentions and 17,839 pronouns (“he” and “she”). The character mentioned in the original MPII-MD descriptions were replaced with “MaleCoref” (“FemaleCoref”), otherwise with “MaleName” (“Female-Name”). MPII-MD Co-ref+Gender dataset also includes bounding box annotations for character heads. It keeps the same split sets of the MPII-MD dataset.

6.3 Datasets for cooking description

6.3.1 MP-II cooking activities

Rohrbach et al. (2012a) proposed this fine-grained cooking activities dataset. These authors video recorded participants cooking different dishes, such as “fruit salad”, “pizza”, or “cake”, and annotated the videos with activity categories on time intervals. Moreover, the authors annotated a subset of frames with the human pose. They recorded 12 participants performing 65 different cooking activities, such as “cut slices”, “pour”, or “spice”. Consequently, the dataset contains a total of 5,609 annotations. Overall, they recorded 44 videos with a total length of more than 8 hours or 88,175 frames.

6.3.2 MPII cooking composite activities

In this case, Rohrbach et al. (2012b) focused on composite activities and thus incorporated significantly more dishes/composites, which are slightly shorter and more straightforward than in the previous dataset. Although, this dataset contains more videos and activities than MP-II Cooking dataset. In total, they recorded 22 participants in 212 videos and 41 activities.

6.3.3 YouCook

Das et al. (2013) collected the data from 88 videos downloaded from YouTube, roughly uniformly split into six different cooking styles, such as baking and grilling. The training consists of 49 videos with frame-by-frame object and action annotations (as well as several pre-computed low-level features). The test set consists of 39 videos. Each video has several human-provided natural language descriptions. On average, there are 8 paragraph descriptions per video, each one has 67 words on average, and the average number of words per sentence is 10.

24 MPII-MD Co-ref+Gender dataset website: www.mpi-inf.mpg.de
25 MP-II Cooking Activities dataset website: www.mpi-inf.mpg.de
26 MPII Cooking Composite Activities dataset website: www.mpi-inf.mpg.de
27 YouCook dataset website: http://web.eecs.umich.edu/~jjcorso/r/youcook/
6.3.4 Saarbrucken corpus of textually annotated cooking scenes (TACoS)

This dataset, proposed by Regneri et al. (2013), was constructed on top of the MP-II Cooking Composite Activities dataset (Rohrbach et al. 2012b). They extend it with multiple textual descriptions collected by crowd-sourcing via MTurk. To provide coherent descriptions and to facilitate the alignment of sentences describing activities with their proper video segments, they also provide approximate time-stamps as a textual annotation. Specifically, the dataset contains 26 fine-grained cooking activities in 127 videos. It contains 20 different descriptions per video, 17,334 action descriptions with 11,796 sentences, and 146,771 words.

6.3.5 Textually annotated cooking scenes multi-level (TACoS-Multilevel)

This dataset (Rohrbach et al. 2014) addressed the challenging task of the coherent multi-sentence video description on the cooking domain. Based on the TACoS dataset (Regneri et al. 2013), they also collected the annotations via MTurk. For each one of the 127 videos, 28 AMT workers wrote the textual descriptions for three levels of details for each video. For the first level, they wrote a detailed description with a maximum of 15 sentences. For the second level, they wrote a brief description of three to five sentences. For the third level, they wrote a single sentence. In general, each video has 20 triplets of descriptions, of which approximately 2,600 were collected from TACoS dataset videos.

6.3.6 YouCook2

Zhou et al. (2018b) proposed the largest instructional dataset27 until now, where all descriptions are imperative English sentences. Unlike YouCook dataset (Das et al. 2013), this dataset contains 2,000 YouTube videos from 89 cooking recipes, with 5.26 minutes on average, for a total of 176 hours. Like the ActivityNet Captions dataset (see and 6.4.2), the videos were manually annotated with temporal localization and captions. They are the two most extensive datasets used to evaluate the models for dense video description task. On average, YouCook2 has 22 videos per recipe, each video has 7.7 temporal-localized segments, and each description has 8.8 words.

6.4 Datasets for activity description

6.4.1 Charades

Sigurdsson et al. (2016) selected 9,848 videos of daily indoor activities collected through 267 MTurk workers. Each worker received scripts with the objects and the actions from a fixed vocabulary, and they recorded videos acting out the script. The dataset contains 66,500 temporal annotations for 157 action classes, 41,104 labels for 46 object classes, and 27,847 textual descriptions of the videos.

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28 TACoS-Multilevel dataset website: www.mpi-inf.mpg.de
29 Charades dataset website: https://allenai.org/plato/charades/

6.4.2 ActivityNet captions

Krishna et al. (2017a) proposed this dataset, which includes temporally annotated sentence descriptions. Videos cover a wide range of complex human activities that interest people in their daily lives. In the current version of the dataset, each sentence covers a unique segment of the video and describes multiple events that can co-occur (overlap). On average, each of the 20,000 videos (849 hours in total) contains 3.65 temporally localized sentences, with 15.25 words describing 36 seconds and 31% of its respective video. The ActivityNet Challenge uses this dataset for addressing the scenario where multiple events co-occur. Section 5.4 describes this competition.

6.4.3 Charades-ego

More recently, Sigurdsson et al. (2018), based on scripts from the Charades dataset (Sigurdsson et al. 2016), proposed a new dataset for addressing one of the biggest bottlenecks facing egocentric vision research, providing a link from first-person to abundant third-person data on the web (Sigurdsson et al. 2018). This dataset has 112 actors performing 157 different actions, with semantically paired first and third-person videos. Although these two datasets were not proposed for the VTT problem, the human-written scripts and descriptions included for each video allow their use as additional data to train and validate VTT models (Hu et al. 2019).

6.4.4 20BN-something-something dataset V2

Mahdisoltani et al. (2018a) proposed this dataset as the second release of the 20BN-something-something dataset, which, unlike the first release, considers captioning in addition to classification. Many crowd workers created the dataset. This version has 220,847 videos (vs. 108,499 in V1). In total, there are 318,572 annotations involving 30,408 unique objects. The descriptions compose 174 template labels replacing each object mention (nouns) for the “SOMETHING” word.

6.4.5 HowTo100M

Recently, Miech et al. (2019) proposed the large-scale HowTo100M dataset, which contains 1.2 million instructional YouTube videos from 12 categories such as home-and-garden, computers-and-electronics, and food-and-entertaining. The dataset was constructed by querying YouTube for everyday activities from WikiHow and filtering to videos that contained English subtitles, appeared in the top 200 search results, had more than 100 views, and was less than 2,000 seconds long. Each video in the dataset is split into clips according to the video’s YouTube subtitles’ time intervals. This process results in 136 million video clips. For corpus construction, narrated captions have been processed. Therefore, the authors removed many stop words that are...
not relevant for learning the text-video joint embedding (Miech et al. 2019). On average, each video produces 110 clip-caption pairs, with an average duration of 4 seconds per clip and 4.16 words (after excluding stop-words) per caption. Additionally, the highest and second-highest level task category from WikiHow was included.

The major drawback of this corpus, and generally of all corpus constructed from automatic subtitles, is the large number of unknown tokens that occur. In the How-To100M’s corpus, only 36.64% of words in the vocabulary (217,361 of the 593,238 unique words) appear in the widely used GloVe-6B dictionary, which has 400,000 tokens.

### 7 State-of-the-art results, an analysis

In this section, we present a comparison and analysis of the experimental results and the performance of various state-of-the-art techniques as reported. Although, there is no standard evaluation methodology for evaluating the VTT methods. A set of automatic evaluation metrics, introduced in Sects. 3.4 and 4.4, have been widely reported by researchers at “convenience.” Generally, experimental results of the works in the literature use the codes released on the Microsoft COCO evaluation server (Chen et al. 2015) to enable systematic evaluation and benchmarking, reporting the BLEU-N, METEOR, ROUGE-L, and CIDEr-D automated metrics.

The most-reported metric in the literature is METEOR (defined in Equation 13), followed by BLEU-4 (defined in Equation 7). Simultaneously, the two most reported datasets are MSVD and MSR-VTT. Additionally, unlike other datasets, almost all MSR-VTT experiments report all four metrics: BLEU-4, METEOR, ROUGE-L, and CIDEr-D. This discrepancy in the number of times each metric is reported does hard to compare the methods’ performance and select the best and most generalizable solution. To deal with this lack, in this section, we rank state-of-the-art methods according to an overall score defined as follows.

Some recent works (Chen et al. 2020b, a) have proposed overall scores to evaluate the performance of the video captioning models. Following this idea, we computed the $S_{\text{overall}}$ score for all state-of-the-art methods as an overall judgment of their automatic evaluation-based performance. Let $\mathcal{M} = \{\text{BLEU-4, ROUGE-L, METEOR, CIDEr-D}\}$ the set of metrics we consider for the overall score, and $\mathcal{M}_t \subseteq \mathcal{M}$ the set of metrics that method $t$ reported. We define $S_{\text{overall}}(t)$ as:

$$S_{\text{overall}}(t) = \sum_{\mu \in \mathcal{M}_t} \alpha_{\mu} \frac{\mu(t)}{\max_q (\mu(q))}, \quad (32)$$

where $\mu(t)$ is the score that method $t$ obtained for metric $\mu$, and $\max_q (\mu(q))$ represents the maximum score obtained by any of the state-of-the-art methods for metric $\mu$. We use uniform weights $\alpha_{\mu} = \frac{1}{|\mathcal{M}_t|}$ for almost all datasets, but they can be changed to pay more attention to some metrics than others. For example, we can represent the human judgment correlation of each metric in each dataset. Some competitions, such as TRECVID-VTT, annually report the metrics correlation with human evaluation (Awad et al. 2019).
7.1 State of the art on description generation methods

Table 7 summarizes the benchmark results of state-of-the-art techniques on the MSVD dataset. The recent SemSynAN (Perez-Martin et al. 2021) and VNS-GRU (Chen et al. 2020a) methods dominate for all metrics. These two methods, along with SCN-LSTM + sampling (Chen et al. 2020b) and AVSSSN (Perez-Martin et al. 2020a), surpass the 1.00 score for the CIDEr metric. These four methods are based on compositional RNN-based decoders that compose intermediate learned representations into the generation process. Likewise, SemSynAN (Perez-Martin et al. 2021) and VNS-GRU (Chen et al. 2020a) incorporate variational dropout strategies in the decoder model for regularization. One of the differences between these two methods is that SemSynAN (Perez-Martin et al. 2021) pre-train a joint embedding for extracting syntactic representations (Hou et al. 2019; Wang et al. 2019) from videos, while VNS-GRU (Chen et al. 2020a) train the model by adopting a professional learning strategy for enlarging the generated vocabulary.

Table 8 shows that these two methods also achieve the highest $S_{overall}$ scores for the MSR-VTT dataset, but they are not the best for CIDEr. The POS tagging-based GFN-POS_RL(IR+M) (Wang et al. 2019a) approach and the reviewing network-based REVnet$_{v3}$-RL (Li et al. 2019) method show the impact of Reinforcement Learning. They achieve the best CIDEr score by using RL to directly optimize it, explaining the increase in performance and the margin with the other metrics.

In Table 9, we summarize the results on the Charades dataset. One of the first reported results on this dataset is for the HRL-16$^{33}$ (Wang et al. 2018d) method. Although this model achieves the best $S_{overall}$ score, the more recent CAM-RNN(GoogleNet) (Zhao et al. 2019) method surpassed HRL-16 for METEOR by an absolute margin of 0.002. The method proposed by Wei et al. (2020) reports the poor performance. This method is based on a recurrent encoder, which has not shown robustness for recognizing fine-grained activities and generating detailed descriptions.

Regarding the benchmarking for movie description, results reported on the complex M-VAD dataset are inferior in general. For the three datasets showed in Table 10, all papers report METEOR. On M-VAD, SF-SSAG-LSTM (Xu et al. 2019b), followed by BAE (Baraldi et al. 2017), achieves the best METEOR score. While, only SA (Yao et al. 2015), HRNE (Pan et al. 2016a), and MHB (Sah et al. 2020) report results for BLEU-4, being MHB (Sah et al. 2020) the best one. In contrast, on the MPII-MD dataset, only BAE (Baraldi et al. 2017) reports the four metrics, LSTM-TSA$_{IV}$ (Pan et al. 2017) obtains the best-reported result for METEOR, and no experiments results have been reported since 2017.

Table 11 shows the state-of-the-art results on two cooking-videos datasets, i.e., TACoS-Multilevel and YouCook2. For the TACoS-Multilevel dataset, h-RNN (Yu et al. 2016) obtained the best result for BLEU, METEOR, and CIDEr. For the challenging YouCook2 dataset, the researchers report results using the validation set’s ground-truth proposals (localization), MART (Lei et al. 2020) is shown as the best method, achieving the best score for all metrics they reported.

As we mentioned in Sect. 6.4.2, the ActivityNet Captions dataset also includes temporal events localization and reference descriptions for these events. To exploit this information to its full extent, the researchers have evaluated their captioning methods

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$^{33}$ labelnote:hr16They achieved the results on the Charades Caption dataset, which was obtained by pre-processing the raw Charades dataset.
using the ground-truth localization (like in YouCook2 dataset) or trying to predict them. The results of these experiments are reported on the validation set. For this dataset, the testing videos’ ground-truth is not revealed and is evaluated by the official test server (see footnote 9) as part of the ActivityNet Challenge (see and 5.4).

| Method                                | BLEU-4 | ROUGE-L | METEOR | CIDEr-D | $S_{\text{overall}}$ |
|---------------------------------------|--------|---------|--------|---------|---------------------|
| ReBiLSTM(shortcut) (Bin et al. 2019)  | 0.373  | –       | 0.303  | –       | 0.649               |
| BAE (Baraldi et al. 2017)             | 0.425  | –       | 0.324  | 0.635   | 0.660               |
| LSTM-GAN+attn. (Yang et al. 2018)     | 0.429  | –       | 0.304  | –       | 0.693               |
| CAM-RNN (Zhao et al. 2019)            | 0.424  | 0.694   | 0.334  | 0.543   | 0.699               |
| MHB (Nguyen et al. 2017b)             | 0.430  | 0.687   | 0.332  | 0.711   | 0.734               |
| aLSTMs (Gao et al. 2017)              | 0.508  | –       | 0.333  | 0.748   | 0.743               |
| STAT_V (Yan et al. 2020)              | 0.520  | –       | 0.333  | 0.738   | 0.746               |
| LSTM-TSA$_{1V}$ (Pan et al. 2017)     | 0.528  | –       | 0.335  | 0.740   | 0.752               |
| TDDF(VGG+C3D) (Zhang et al. 2017)     | 0.458  | 0.697   | 0.333  | 0.730   | 0.753               |
| TSA-ED (Wu et al. 2018)               | 0.517  | –       | 0.340  | 0.749   | 0.753               |
| hLSTMmat (Gao et al. 2019)            | 0.530  | –       | 0.336  | 0.738   | 0.753               |
| SCN-LSTM (Gan et al. 2017b)           | 0.511  | –       | 0.335  | 0.777   | 0.754               |
| MS-RNN(R) (Song et al. 2019a)         | 0.533  | –       | 0.338  | 0.748   | 0.759               |
| Wei et al. (2020)                     | 0.468  | –       | 0.344  | 0.857   | 0.762               |
| TDConvED (R) (Chen et al. 2019a)      | 0.533  | –       | 0.338  | 0.764   | 0.764               |
| PickNet(V+L) (Chen et al. 2018c)      | 0.523  | 0.692   | 0.333  | 0.765   | 0.784               |
| MTLE+ResNet (Nina et al. 2018)        | 0.530  | –       | 0.318  | –       | 0.788               |
| GRU-EVE (Aafaq et al. 2019a)          | 0.479  | 0.715   | 0.350  | 0.781   | 0.788               |
| topic-guided (Chen et al. 2019b)      | 0.492  | 0.710   | 0.339  | 0.830   | 0.795               |
| Res-F2F (Tang et al. 2019)            | 0.524  | –       | 0.357  | 0.843   | 0.797               |
| RecNet(RL)$_{1V}$ (Zhang et al. 2019a)| 0.529  | –       | 0.348  | 0.859   | 0.798               |
| RecNet$_{1V}$(SA-LSTM) (Wang et al. 2018a) | 0.523  | 0.698   | 0.341  | 0.803   | 0.799               |
| MSAN$_{3+3}$ (Sun et al. 2019b)       | 0.564  | –       | 0.353  | 0.796   | 0.801               |
| Non-local enc. (Lee et al. 2019)      | 0.497  | 0.717   | 0.337  | 0.845   | 0.802               |
| ECO (Zolfaghari et al. 2018)          | 0.535  | –       | 0.350  | 0.858   | 0.802               |
| M$^3$-IC (Wang et al. 2018c)          | 0.528  | –       | 0.333  | –       | 0.804               |
| E2E(beam-search) (Li and Gong 2019)   | 0.503  | 0.708   | 0.341  | 0.875   | 0.810               |
| Attr-Attn(I+C+A+L+M) (Xiao and Shi 2019) | 0.565  | –       | 0.354  | 0.861   | 0.821               |
| Joint-VisualPOS (Hou et al. 2019)     | 0.528  | 0.715   | 0.361  | 0.878   | 0.834               |
| GFN-POS_RL(IR+M) (Wang et al. 2019a)  | 0.539  | 0.721   | 0.349  | 0.910   | 0.840               |
| ORG-TRL (Zhang et al. 2020)           | 0.543  | 0.739   | 0.364  | 0.952   | 0.866               |
| SCN-LSTM+sampling (Chen et al. 2020b) | 0.618  | 0.768   | 0.378  | 1.030   | 0.929               |
| AVSSN (Perez-Martin et al. 2020a)     | 0.623  | 0.783   | 0.392  | 1.077   | 0.954               |
| SemSynAN (Perez-Martin et al. 2021)   | 0.644  | 0.795   | 0.419  | 1.115   | 0.990               |
| VNS-GRU (Chen et al. 2020a)           | 0.649  | 0.785   | 0.411  | 1.15    | 0.992               |

We consider the experiments results reported by works from 2017. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{\text{overall}}$ score, defined in Equation 32.
Table 8 State-of-the-art for description generation on MSR-VTT dataset

| Method                          | BLEU-4 | ROUGE-L | METEOR  | CIDEr-D | $S_{overall}$ |
|---------------------------------|--------|---------|---------|---------|--------------|
| ReBiLSTM (shortcut) (Bin et al. 2019) | 0.339  | –       | 0.266   | –       | 0.786        |
| LSTM-GAN+attn. (Yang et al. 2018)     | 0.360  | –       | 0.261   | –       | 0.800        |
| aLSTMs (Gao et al. 2017)             | 0.380  | –       | 0.261   | –       | 0.822        |
| M$^2$-VC (Wang et al. 2018c)        | 0.381  | –       | 0.266   | –       | 0.831        |
| Two-stream (Gao et al. 2019)        | 0.397  | –       | 0.270   | 0.421   | 0.833        |
| Wei et al. (2020)                  | 0.385  | –       | 0.269   | 0.437   | 0.834        |
| TDConvED (R) (Chen et al. 2019a)   | 0.395  | –       | 0.275   | 0.428   | 0.841        |
| MS-RNN(R) (Song et al. 2019a)      | 0.398  | 0.593   | 0.261   | 0.409   | 0.842        |
| STAT_L (Yan et al. 2020)           | 0.393  | –       | 0.271   | 0.439   | 0.843        |
| MTLE+ResNet (Nina et al. 2018)     | 0.392  | 0.593   | 0.266   | 0.421   | 0.844        |
| RecNet$_{local}$ (Wang et al. 2018a) | 0.391  | 0.593   | 0.266   | 0.427   | 0.850        |
| PickNet(V+L) (Chen et al. 2018c)    | 0.389  | 0.595   | 0.272   | 0.421   | 0.852        |
| TDDF(VGG+C3D) (Zhang et al. 2017)  | 0.373  | 0.592   | 0.278   | 0.438   | 0.855        |
| Attr-Attn(I+C+A+L+M) (Xiao and Shi 2019) | 0.401  | –       | 0.272   | 0.455   | 0.859        |
| RecNet(RL)$_{hy}$ (Zhang et al. 2019a) | 0.393  | –       | 0.277   | 0.495   | 0.884        |
| GRU-EVE (Aafaq et al. 2019a)       | 0.383  | 0.607   | 0.284   | 0.481   | 0.891        |
| E2E (Li and Gong 2019)             | 0.404  | 0.610   | 0.270   | 0.483   | 0.893        |
| DenseVidCap (Shen et al. 2017)     | 0.414  | 0.611   | 0.283   | 0.489   | 0.912        |
| HR1 (Wang et al. 2018d)            | 0.413  | 0.617   | 0.287   | 0.480   | 0.913        |
| Res-F2F (Tang et al. 2019)         | 0.414  | 0.613   | 0.290   | 0.489   | 0.919        |
| Joint-VisualPOS (Hou et al. 2019)  | 0.423  | 0.628   | 0.297   | 0.491   | 0.935        |
| HACA (Wang et al. 2018e)            | 0.434  | 0.618   | 0.295   | 0.497   | 0.939        |
| GFN-POS_RL(IR+M) (Wang et al. 2019a) | 0.413  | 0.621   | 0.287   | 0.534   | 0.939        |
| REVnet$_{hy}$-RL (Li et al. 2019)  | 0.424  | 0.623   | 0.281   | 0.532   | 0.941        |
| ORG-TRL (Zhang et al. 2020)        | 0.436  | 0.621   | 0.288   | 0.509   | 0.941        |
| CST_GT_None (Phan et al. 2017a)    | 0.441  | 0.624   | 0.291   | 0.497   | 0.942        |
| SCN-LSTM+sampling (Chen et al. 2020b) | 0.438  | 0.624   | 0.289   | 0.514   | 0.947        |
| topic-guided (Chen et al. 2019b)   | 0.449  | 0.628   | 0.296   | 0.518   | 0.962        |
| VNS-GRU (Chen et al. 2020a)        | 0.460  | 0.633   | 0.295   | 0.520   | 0.970        |
| MSAN$_{hy}$, (Sun et al. 2019b)    | 0.468  | –       | 0.295   | 0.524   | 0.975        |
| AVSSN (Perez-Martin et al. 2020a)  | 0.455  | 0.643   | 0.314   | 0.506   | 0.979        |
| SemSynAN (Perez-Martin et al. 2021) | 0.464  | 0.647   | 0.304   | 0.519   | 0.984        |

We consider the experiments results reported by works from 2017. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{overall}$ score, defined in Equation 32.

Table 9 State-of-the-art for description generation on Charades dataset

| Method                          | BLEU-4 | ROUGE | METEOR  | CIDEr-D | $S_{overall}$ |
|---------------------------------|--------|-------|---------|---------|--------------|
| Wei et al. (2020)               | 0.127  | –     | 0.172   | 0.216   | 0.827        |
| CAM-RNN(GoogleNet) (Zhao et al. 2019) | 0.129  | –     | 0.197   | 0.188   | 0.832        |
| TSA-ED (Wu et al. 2018)         | 0.135  | –     | 0.178   | 0.208   | 0.839        |
| HRL-16 (see footnote 33) (Wang et al. 2018d) | 0.188  | 0.414 | 0.195   | 0.232   | 0.997        |

The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{overall}$ score, defined in Equation 32.
Table 10  State-of-the-art for description generation on Movie Description datasets

| Method | BLEU-4 | ROUGE | METEOR | CIDEr-D | $S_{\text{overall}}$ |
|--------|--------|-------|--------|---------|--------------------|
| M-VAD dataset | | | | | |
| HRNE (Pan et al. 2016a) | 0.007 | – | 0.068 | – | 0.760 |
| Visual-Labels (Rohrbach et al. 2015a) | – | – | 0.064 | – | 0.771 |
| SA (Yao et al. 2015) | 0.007 | – | 0.057 | 0.061 | 0.796 |
| S2VT (Venugopalan et al. 2015a) | – | – | 0.067 | – | 0.807 |
| LSTM-E (Pan et al. 2016b) | – | – | 0.067 | – | 0.807 |
| Glove+DeepFusion (Venugopalan et al. 2016) | – | – | 0.068 | – | 0.819 |
| LSTM-TSA IV (Pan et al. 2017) | – | – | 0.072 | – | 0.867 |
| BAE (Baraldi et al. 2017) | – | – | 0.073 | – | 0.880 |
| MHB (Sah et al. 2020) | 0.010 | – | 0.069 | – | 0.916 |
| SF-SSAG-LSTM (Xu et al. 2019b) | – | – | 0.083 | – | 1.000 |
| MPII-MD dataset | | | | | |
| SMT (Rohrbach et al. 2015b) | – | – | 0.056 | – | 0.700 |
| Glove+DeepFusion (Venugopalan et al. 2016) | – | – | 0.068 | – | 0.850 |
| Visual-Labels (Rohrbach et al. 2015a) | – | – | 0.070 | – | 0.875 |
| S2VT (Venugopalan et al. 2015a) | – | – | 0.071 | – | 0.888 |
| LSTM-E (Pan et al. 2016b) | – | – | 0.073 | – | 0.913 |
| BAE (Baraldi et al. 2017) | 0.008 | 0.167 | 0.070 | 0.108 | 0.969 |
| LSTM-TSA IV (Pan et al. 2017) | – | – | 0.080 | – | 1.000 |
| LSMDC dataset | | | | | |
| MTLE+ResNet (Nina et al. 2018) | 0.005 | – | 0.055 | 0.087 | 0.753 |
| GEAN+GNet+C3D+Scene (Yu et al. 2017b) | –* | 0.156 | 0.072 | 0.093 | 0.970 |
| CT-SAN (Yu et al. 2017c) | 0.008 | 0.159 | 0.071 | 0.100 | 0.997 |

In this table we considered the results reported in each paper on the M-VAD, MPII-MD and LSMDC datasets. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{\text{overall}}$ score, defined in Equation 32.

*did not report BLEU-4, but reported BLEU-3 = 0.021

Table 11  State-of-the-art for description generation on Cooking datasets

| Method | BLEU-4 | ROUGE | METEOR | CIDEr-D | $S_{\text{overall}}$ |
|--------|--------|-------|--------|---------|--------------------|
| TACoS-Multilevel | | | | | |
| JEDDi-Net (Xu et al. 2019a) | 0.181 | 0.509 | 0.239 | 1.040 | 0.769 |
| h-RNN (Yu et al. 2016) | 0.305 | – | 0.287 | 1.602 | 1.000 |
| YouCook2 (validation set, using ground-truth proposals*) | | | | | |
| M. Transformer (Zhou et al. 2018c) | 0.142 | – | 0.112 | – | 0.441 |
| VideoBERT+S3D (Sun et al. 2019a) | 0.433 | 0.288 | 0.119 | 0.006 | 0.577 |
| MART (Lei et al. 2020) | 0.800 | – | 0.159 | 0.357 | 1.000 |

In this table we considered the results reported in each paper on the TACoS-Multilevel and YouCook2 datasets. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{\text{overall}}$ score, defined in Equation 32.

*YouCook2 Captions dataset includes temporal localization of video segments, and captions related to segments. For this, to evaluate the video captioning task only, it is needed to use the ground-truth video segments information.
Table 12  State-of-the-art for description generation on ActivityNet Captions dataset

| Method | Validation set predicting event proposals | Test using GT proposals* | Server (see footnote 9) |
|--------|------------------------------------------|--------------------------|------------------------|
|        | BLEU-4 | ROUGE | METEOR | CIDEr-D | BLEU-4 | ROUGE | METEOR | CIDEr-D | METEOR |
| DEM (Krishna et al. 2017a)  | – | – | – | – | – | – | – | – | – |
| LSTM-A3 (Yao et al. 2017)  | 0.031 | 0.143 | 0.087 | 0.148 | – | – | – | – | – |
| RUC+CMU (see footnote 10) (Chen et al. 2018b)  | **0.040** | – | **0.124** | – | **0.040** | – | 0.138 | **0.565** | 0.085 |
| M. Transformer (Zhou et al. 2018c)  | 0.022 | – | 0.096 | – | 0.027 | – | 0.111 | – | **0.101** |
| Bi-SST (Wang et al. 2018b)  | 0.023 | 0.191 | 0.096 | 0.127 | – | – | – | – | 0.097 |
| SDVC (Mun et al. 2019)  | 0.009 | – | 0.088 | **0.306** | 0.013 | – | 0.131 | **0.435** | 0.082 |
| JEDDi-Net (Xu et al. 2019a)  | 0.016 | **0.196** | 0.086 | **0.199** | – | – | – | – | 0.088 |
| DaS (Zhang et al. 2019b)  | 0.021 | **0.212** | **0.103** | 0.129 | 0.016 | 0.229 | 0.107 | 0.314 | – |
| RecNet(RL)_local (Zhang et al. 2019a)  | – | – | – | – | 0.017 | **0.235** | 0.105 | 0.384 | – |
| RUC+CMU (see footnote 11) (Chen et al. 2019c)  | – | – | – | – | – | – | **0.143** | – | 0.099 |
| COOT (video+clip) (Ging et al. 2020)  | – | – | – | – | **0.109** | **0.315** | **0.160** | 0.282 | – |

In this table we considered the results reported in each paper on the ActivityNet Captions dataset and the evaluation servers of 2018 (see footnote 10) and 2019 (see footnote 11) editions of the ActivityNet Challenge. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by year and those of the same year by the METEOR score reported by Test server.

*ActivityNet Captions dataset includes temporal action proposal, temporal action localization, and captions related to each action (video segment). For this, to evaluate the video captioning task only, it is needed to use the ground-truth video segments information.
The dense video captioning problem using the ground-truth localization of events is similar to the video description generation problem. We do not need to predict event proposals before captioning the video. As we can see in Table 12, for these experiments, COOT (video+clip) (Ging et al. 2020) achieved the best performance for BLEU-4, ROUGE, and METEOR. In comparison, RUC+CMU (see footnote 11) (Chen et al. 2019c) achieved the best performance for CIDEr and the second-best one for BLEU-4.

Likewise, the authors of almost these methods have participated in the annual ActivityNet Challenge, evaluated on the official test server’s test set. This server reports the Avg-METEOR score, being M. Transformer (Zhou et al. 2018c) and RUC+CMU (see footnote 11) (Chen et al. 2019c) achieved the best performance for CIDEr and the second-best one for BLEU-4.

Table 13 shows the state-of-the-art results on the TRECVID-VTT datasets for the description generation subtask. In the TRECVID Challenges, the STS metric is also reported (see and 5.3). In 2019, scores increased for all metrics compared with 2018. Likewise, in 2020, although videos from a new video source were incorporated, scores also increased compared to the 2019 results, except BLEU-4.

Finally, Table 14 lists the results on the recent VaTeX dataset. The Baseline results for this dataset were reported by Wang et al. (2019c) when the dataset was proposed. The methods ORG-TRL (Zhang et al. 2020), Top-down + X-LAN (Lin et al. 2020), and X-Linear+Transformer (Guo et al. 2020) participated in the VaTeX video captioning challenge 2020 (see and 5.5) and report their results. The use of multiple

| Method                  | Dataset          | BLEU-4 | METEOR | CIDEr | CIDEr-D | SPICE | STS  |
|-------------------------|------------------|--------|--------|-------|--------|-------|------|
| MTLE+ResNet (Nina et al. 2018) | TRECVID-VTT’2016 | 0.122  | 0.374  | 0.423 | –      | –     | 0.462|
| RUC_CMU (Chen et al. 2017a)   | TRECVID-VTT’2017 | 0.023  | 0.198  | 0.408 | –      | –     | –    |
| INF (Chen et al. 2018a)      | TRECVID-VTT’2018 | 0.024  | 0.231  | 0.416 | 0.585  | –     | 0.433|
| RUC_AIM3 (Song et al. 2019b) | TRECVID-VTT’2019 | 0.064  | 0.306  | 0.154 | 0.332  | –     | 0.484|
| RUC_AIM3 (Zhao et al. 2020)  | TRECVID-VTT’2020 | 0.056  | 0.310  | 0.303 | –      | 0.110 | –    |

| Method                  | BLEU-4 | ROUGE | METEOR | CIDEr-D | $S_{\text{overall}}$ |
|-------------------------|--------|-------|--------|---------|----------------------|
| NITS-VC (Singh et al. 2020) | 0.220  | 0.430 | 0.180  | 0.270   | 0.593                |
| Baseline (Wang et al. 2019c) | 0.285  | 0.470 | 0.216  | 0.451   | 0.742                |
| ORG-TRL (Zhang et al. 2020) | 0.321  | 0.489 | 0.222  | 0.497   | 0.793                |
| Top-down + X-LAN (Lin et al. 2020) | 0.392  | 0.527 | 0.250  | 0.760   | 0.962                |
| X-Linear+Transformer (Guo et al. 2020) | **0.407** | **0.537** | **0.258** | **0.814** | **1.000** |

In this table we considered the results reported in each paper on the VaTeX dataset. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the methods by the $S_{\text{overall}}$ score, defined in Equation 32.
## Table 15

State-of-the-art for Matching-and-Ranking on MSVD dataset. In this table we considered the results reported in each paper on the MSVD dataset for both facets of the task: description retrieval from videos (Description retrieval) and video retrieval from text descriptions (Video retrieval).

| Method                  | Description retrieval | Video retrieval | Avg. Sums of Recalls |
|-------------------------|-----------------------|-----------------|----------------------|
|                         | R@1  | R@5  | R@10 | MR  | mAP | R@1  | R@5  | R@10 | MR  | mAP | Recalls |
| W2VV (Dong et al. 2018) | 18.5  | 36.7  | 45.1  | -   | -   | -    | -    | -    | -   | -   | 0.230  | 100.3* |
| i3D (Mithun et al. 2018)| 21.3  | 43.7  | 53.3  | 9   | 0.722 | 15.4 | 39.2 | 51.4 | 10  | 0.432 | 112.2  |
| ResNet (Mithun et al. 2018) | 23.4  | 45.4  | 53.0  | 8   | 0.752 | 16.1 | 41.1 | 53.5 | 9   | 0.427 | 116.3  |
| Fusion (Mithun et al. 2018) | 31.5  | 51.0  | 61.5  | 5   | 0.417 | 20.3 | 47.8 | 61.1 | 6   | 0.283 | 136.6  |
| Dual Encoding (Dong et al. 2019) | -    | -    | -    | -   | -   | -    | -    | -    | -   | -   | 0.232  |

Higher recall at K (R@1, R@5, R@10) and mAP, and smaller Median Rank (MR) indicates better performance. Methods are sorted by year. For overall comparison, we compute the average between the sums of recalls of each facet. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the results by the Avg. Sum. of Recalls column.
| Method                        | Description retrieval | Video retrieval | Avg. Sums of Recalls |
|------------------------------|-----------------------|----------------|---------------------|
|                              | R@1  | R@5 | R@10 | MR | mAP | R@1  | R@5 | R@10 | MR | mAP | Recalls |
| ResNet (Mithun et al. 2018) | 10.5  | 26.7 | 35.9  | 25 | 0.267 | 5.8  | 17.6 | 25.2  | 61 | 0.297 | 60.9 |
| i3D+Audio (Mithun et al. 2018) | 9.3  | 27.8 | 38.0  | 22 | 0.162 | 5.7  | 18.4 | 26.8  | 48 | 0.243 | 63.0 |
| W2VV (Dong et al. 2018)     | 11.8  | 28.9 | 39.1  | 21 | 0.058 | 6.1  | 18.7 | 27.5  | 45 | 0.131 | 66.1 |
| Fusion (Mithun et al. 2018) | 12.5  | 32.1 | 42.4  | 16 | 0.134 | 7.0  | 20.9 | 29.7  | 38 | 0.214 | 72.3 |
| Dual Encoding (Dong et al. 2019) | 13.0 | 30.8 | 43.3  | 15 | 0.065 | 7.7  | 22.0 | 31.8  | 32 | 0.155 | 74.3 |
| HGR (Chen et al. 2020c)     | 9.2  | 26.2 | 36.5  | 24 | –    | 15.0 | 36.7 | 48.8  | 11 | –    | 86.2 |
| S3D (Miech et al. 2020)     | –    | –   | –     | –  | –    | 9.9  | 24.0 | 32.4  | 29.5 | –    | 95.8* |
| HowTo100M (Miech et al. 2019) | –    | –   | –     | –  | –    | 14.9 | 40.2 | 52.8  | 9  | –    | 116.9* |

Higher recall at K (R@1, R@5, R@10) and mAP, and smaller Median Rank (MR) indicates better performance. For overall comparison, we compute the average between the sums of recalls of each facet. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the results by the Avg. Sum. of Recalls column.
Table 17  State-of-the-art for Matching-and-Ranking on ActivityNet Captions dataset (val-1 split). In this table we considered the results reported in each paper on the ActivityNet Captions dataset for both facets of the task: description retrieval from videos (Description retrieval) and video retrieval from text descriptions (Video retrieval).

| Method                  | Description retrieval | Video retrieval                  | Avg. Sums of Recalls |
|-------------------------|-----------------------|----------------------------------|----------------------|
|                         | R@1 | R@5 | R@10 | R@50 | MR  | R@1 | R@5 | R@10 | R@50 | MR  | Recalls |
| LSTM-YT (Venugopalan et al. 2015a) | 0.0  | 7.0  | –    | 38.0 | 98  | 0.0  | 4.0  | –    | 24.0 | 102 | 36.5    |
| DENSE (Krishna et al. 2017a)          | 18.0 | 36.0 | –    | 74.0 | 32  | 14.0 | 32.0 | –    | 65.0 | 34  | 119.5   |
| HSE (Zhang et al. 2018)               | 44.2 | 76.7 | –    | 97.0 | 2   | 44.4 | 76.7 | –    | 97.1 | 2   | 218.1   |
| COOT (Ging et al. 2020)               | 60.9 | 87.4 | –    | 98.6 | 1   | 60.8 | 86.6 | –    | 98.6 | 1   | 246.3   |

Higher recall at K (R@1, R@5, R@10, R@50), and smaller Median Rank (MR) indicates better performance. For overall comparison, we compute the average between the sums of recalls of each facet. The highest results for each metric are highlighted in bold and the second highest are underlined. We sorted the results by the Avg. Sum. of Recalls column.
features such as I3D, ECO, and audio, and the hybrid reward strategy proposed by X-Linear+Transformer (Guo et al. 2020) reports the highest result on the VaTeX dataset. They were the winners of the English video captioning competition.

7.2 State of the art on retrieval methods

In this study, we also compare the state-of-the-art VTT methods based on retrieval strategy. As we study in and 4, these works are generally based on learning a joint video-text embedding, which can perform the retrieval in both directions. For that, some papers report performances for both video retrieval and description retrieval facets.

Table 15 shows the results on the MSVD dataset. Mithun et al. (2018) reported three versions of their model, and their Fusion version reports the best Sum of Recalls result. Table 16 lists the retrieval-based results on the MSR-VTT dataset. For this dataset, Mithun et al. (2018) also achieved good performance, but Dual Encoding (Dong et al. 2019) model achieves the best Sum of Recalls performance of the methods that reported description retrieval experiments. Table 17 shows the experimental results for retrieval-based methods on the ActivityNet Captions dataset. The recent COOT (Ging et al. 2020) approach achieves the best results for all metrics, obtaining a median rank for retrieval in both directions of one. Compared to the other methods, this is the first approach based on Transformers that reports retrieval experiments on this dataset. Finally, for TRECVID-VTT datasets, the description retrieval methods are evaluated by MIR score. In 2018, Li et al. (2018b) obtained the highest result with 0.516. While in 2019, Song et al. (2019b) improved that result, obtaining 0.727.

8 Discussion and conclusions

In this review, we have analyzed the state-of-the-art techniques for developing VTT solutions. The techniques based on Deep Learning have achieved promising results for both description generation and retrieval-based methods. Despite the significant progress in descriptive text generation and retrieval tasks for several benchmark datasets, we can say that the state-of-the-art methods fail to extract/capture all the complex spatiotemporal information present in videos. There is still much work to do for understanding the diversity regarding the visual content in videos and the structure of associated textual descriptions.

As a text generation task, video captioning requires predicting a semantic and syntactically correct sequence of words given some context video. Early works followed the strategy of detecting Subject, Verb, and Object, forming an SVO triplet, and then a sentence. This approach requires the models to recognize the subjects and objects that participate in the action we want to describe, achieving their best results in specific environments, such as sports or cooking. It occurs because, in this kind of video clip, the number of objects and actions is limited, and the duration is generally short.

Recent works clearly show that videos contain implicit dimensions with valuable information about the possible descriptions in addition to the appearance and motion. Directly from visual information, we can extract semantic and syntactic information to guide the text generation process (see Sects. 3.2.4 and 3.2.4). However, having a strong dependence on only one of them can harms the models’ performance on standard datasets, producing
semantic gaps or syntactically incorrect sentences. It is essential to determine how to combine these information channels adaptively. Here, learning to ensemble both retrieval and generation techniques has been shown as a promising strategy.

The VTT field is strongly related to other tasks like action recognition. Many of the challenges that emerge in solving these tasks will also appear addressing video-text translation. For instance, the video-text translation approaches also need to generalize over variations within one target class, distinguish between different classes in the input, and accurately depict the critical activities in a video clip. Here, the representation of informative semantics by learning to ensemble visual perception models plays a crucial role in video captioning. Some state-of-the-art methods report that learning high-level discriminative features (Pan et al. 2017; Gan et al. 2017b; Snoek et al. 2017a) and incorporating visual classifiers in the encoding process (Rohrbach et al. 2015a; Xu et al. 2015b; Otani et al. 2016; Pan et al. 2016b) are useful approaches to deal with these variations. These methods show the benefits of describing the videos according to dynamic visual and semantic information. However, these models’ performance has a strong dependence on the quality of semantic concept detection models.

To accurately distinguish between different classes from visual information, the models must be trained on high-quality, diverse captions that describe a wide variety of videos at scale. Creating large-scale datasets for VTT requires a significant and expensive human effort for their annotation because collecting a large number of references can be time-consuming and difficult for less common languages. To deal with this limitation, some researchers aimed to preserve the models’ generalization properties by collecting their training data from interesting combinations of several existing datasets (Chen et al. 2018b; Snoek et al. 2017a; Li et al. 2018a). In contrast, other works aimed to develop more robust models (Gan et al. 2017b; Baraldi et al. 2017; Pan et al. 2017), but these models do not preserve the generalization properties well.

Recent works have shown the benefits of pre-training the models for multi-modal vision and language tasks and fine-tuning on the specific downstream tasks. For example, we can pre-train a joint embedding for multi-modal tasks such as visual question answering or cross-modal retrieval and then fine-tuning its visual encoding on the video captioning task. This technique could require more data for learning an accurate generic representation in the embedding space. Generally, this data is automatically obtained from the subtitles and narrations provided by the online video platforms. However, a major drawback of this kind of corpus, is the large number of unknown tokens that occur. The HowTo100M’s corpus is an excellent example of this issue, in which only 36.64% of words in the vocabulary appear in the widely used GloVe-6B dictionary. This high “noise” in the captions is an interesting aspect of the training process we must learn to take advantage of.

Several researchers employ one of the evaluation metrics to select the best checkpoint model for testing, such as BLEU, CIDEr, or METEOR. However, some works (Vedantam et al. 2015; Hodosh et al. 2015; Chen et al. 2020a) have shown that a single measure cannot reflect the video description/caption generation methods’ overall performance and generalization properties. There is no standard evaluation method for video-text translation models, and current metrics have not shown sufficient robustness (Aafaq et al. 2019b). Most VTT metrics have been adopted from machine translation or image captioning and do not measure the quality of the generated descriptions from videos well. These metrics give very different performance measures for the same method and are not perfectly aligned with human judgments (Aafaq et al. 2019b; Awad et al. 2018; Vedantam et al. 2015). Some of the annual competitions provide a good contribution to deal with these evaluation issues.
In addition to automatic evaluation, these competitions carry out a human evaluation process of the participants’ solutions.

Another contribution in this sense can be the use of explicit semantic match-based metrics, such as SPICE. However, even though SPICE correlates well with human evaluations, it depends on its internal parser quality and ignores the generated captions’ fluency. Section 3.4.2 summarizes some other limitations that carry the current evaluation metrics for video captioning.

Further research is still needed on dense captioning in long videos with multiple events that co-occur. ActivityNet Competition started in 2017 to include this challenging subtask on the large-scale ActivityNet Captions dataset, a very representative dataset for training the models. Future research could also be processing the audio information of videos, which has not been widely explored in the state-of-art approaches. In the video caption/description generation task, the audio can be used for multi-modal research as extra knowledge to refine generated descriptions. Some datasets like MSR-VTT include audio information, and several techniques for audio processing can be fine-tuned in the experiments.

In this comprehensive review, we have categorized and analyzed the most important approaches for the Video-to-Text problem. We have also reviewed and compared the automatic evaluation metrics and the loss functions used in the optimization process. Moreover, we have reviewed the popular benchmark datasets and the most related competitions commonly used for training and testing the models. Lastly, we have summarized and analyzed the state-of-the-art results on each one of the principal datasets.

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Authors and Affiliations

Jesus Perez-Martín1 · Benjamin Bustos1 · Silvio Jamil F. Guimarães2 · Ivan Sipiran3 · Jorge Pérez1 · Grethel Coello Said3

Benjamin Bustos
bebustos@dcc.uchile.cl

Silvio Jamil F. Guimarães
sjamil@pucminas.br

Ivan Sipiran
isipiran@dcc.uchile.cl

Jorge Pérez
jperez@dcc.uchile.cl

Grethel Coello Said
grethelyusel@gmail.com

1 IMFD, Department of Computer Science, University of Chile, Beauchef 851, Santiago, Chile
2 Computer Science Department, Pontifical Catholic University of Minas Gerais, Belo Horizonte, Minas Gerais, Brazil
3 Department of Computer Science, University of Chile, Beauchef 851, Santiago, Chile