# C2KD: Cross-Lingual Cross-Modal Knowledge Distillation for Multilingual Text-Video Retrieval

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#### **Abstract**

Multilingual text-video retrieval methods have improved significantly in recent years, but the performance for other languages lags behind English. We propose a Cross-Lingual Cross-Modal Knowledge Distillation method to improve multilingual text-video retrieval. spired by the fact that English text-video retrieval outperforms other languages, we train a student model using input text in different languages to match the cross-modal predictions from teacher models using input text in English. We propose a cross entropy based objective which forces the distribution over the student's text-video similarity scores to be similar to those of the teacher models. We introduce a new multilingual video dataset, Multi-YouCook2, by translating the English captions in the YouCook2 video dataset to 8 other languages. Our method improves multilingual text-video retrieval performance on Multi-YouCook2 and several other datasets such as Multi-MSRVTT and VATEX. We also conducted an analysis on the effectiveness of different multilingual text models as teachers. The code, models, and dataset are available at https://github.com/roudimit/c2kd.

#### 1 Introduction

Text-video retrieval, or the task of searching for videos with text queries, is becoming increasingly important as more videos are uploaded to the internet. Currently, most methods developed for this task are trained and evaluated with English text. The focus of this work is to improve the performance of text-video retrieval on more languages.

Learning a multilingual multimodal embedding space (Huang et al., 2021; Akula et al., 2021) has been useful for multilingual text-video retrieval. Text in different languages and video are processed by separate encoders and projected into the shared embedding space, where text and video that are semantically related should be close together regardless of the language. During inference, text

queries and candidate videos are projected into the embedding space, and videos are ranked according to the similarity scores between the text and video embeddings. These methods are trained with a cross-modal contrastive objective on video datasets with parallel text translations in multiple languages, which are often derived from the original captions in English using machine translation. They leverage recently available multilingual models pre-trained on many languages (Devlin et al., 2019; Conneau et al., 2020) to process text in different languages with only a single encoder.

While these methods have improved multilingual text-video retrieval, the performance for English is usually higher than for other languages. Two possible reasons are: (1) multilingual text translated from English often has errors; (2) the multilingual text models are pre-trained on large-scale text data, but there is more data for English than other languages.

To address the gap in performance between English and multilingual text-video retrieval, we propose C2KD: Cross-Lingual Cross-Modal Knowledge Distillation. Our method trains a student model to learn better multilingual text-video similarity scores by learning from the English textvideo scores of multiple trained and frozen teachers. The student learns to pull together video and multilingual text embeddings by optimizing their text-video scores through the contrastive loss. We introduce a framework where several trained and frozen teachers simultaneously process the English translations of the student's inputs and predict English text-video scores. Further, we propose a cross entropy based objective between the student's multilingual text-video scores and the teachers' English text-video scores. This teaches the student to learn multilingual text-video scores which are more aligned with the English scores, thus improving the multilingual text-video retrieval performance.

We applied our method to three existing multilin-

gual text-video datasets: Multi-MSRVTT (Huang et al., 2021), VATEX (Wang et al., 2019), and RUD-DER (Akula et al., 2021). Since these datasets are mainly focused on open-domain videos, we collected the Multi-YouCook2 dataset as an extension of the YouCook2 (Zhou et al., 2018) cooking video dataset to test the model in a domain which requires more fine-grained reasoning, such as understanding specific ingredients in recipes. Our results show that C2KD can improve the multilingual text-video retrieval performance on all datasets, despite the variety in languages, domains, and dataset sizes.

In summary, our contributions are: (1) We propose the C2KD method which guides a student model to learn better multilingual text-video similarity scores by learning from the text-video scores of teachers using English text translations as input. (2) We propose a cross entropy based objective between the student and teacher text-video similarity scores to distill the cross-modal knowledge from the teachers. (3) We collected the Multi-YouCook2 dataset with parallel text translations in 9 languages for over 10k video clips. (4) Our method improves the multilingual text-video performance on four datasets. We conduct an analysis on the impact of different teachers to gain further insights. The code, models, and dataset are available at https://github.com/roudimit/c2kd.

#### 2 Related Work

Multilingual Text-Video Retrieval. Recent work introduced methods and datasets to improve multilingual text-video retrieval. Multilingual multimodal pretraining (Huang et al., 2021) demonstrated text-video retrieval in 9 languages with a single model. They released the Multi-MSRVTT dataset by machine-translating the English text captions from the MSR-VTT video dataset (Xu et al., 2016) into 8 other languages. Their model is trained with a cross-modal contrastive objective to pull together the embeddings of parallel text translations and video inputs together. In separate work, the RUDDER (Akula et al., 2021) dataset was introduced with captions in languages spoken in India. They propose to augment the text-video triplet loss with hard negatives which improved performance in a low-resource setting. We observed that performance for English text-video retrieval typically outperformed other languages, which motivated our approach.

Multilingual Learning. Multilingual text-video

retrieval methods rely on pre-trained multilingual text encoders to handle many languages with a single model. MBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) learn multilingual representations through masked language modeling. LaBSE (Feng et al., 2022) is instead trained to maximize the similarity of translation pairs in a shared embedding space. In our experiments, we evaluated these different models and found LaBSE to be the best encoder for multilingual text-video retrieval.

Cross-Lingual & Cross-Modal Knowledge Distillation. Another approach for training a multilingual text model with good sentence embeddings is to distill the knowledge (Hinton et al., 2015) from a monolingual model. Distill Sentence BERT (Reimers and Gurevych, 2020) is initialized from XLM-R and trained to output similar multilingual embeddings to Sentence BERT (Reimers and Gurevych, 2019) using English translations as input. Our C2KD approach has a similar idea, but it incorporates visual context. We use English text as input to several cross-modal teachers, and train a student to output similar text-video similarity scores using text in other languages.

Of most relevance to our work, Teach-Text (Croitoru et al., 2021) introduced cross-modal Knowledge Distillation for English text-video retrieval. They use teacher retrieval models with various English text embeddings and train a student to output similar text-video similarity scores with a regression loss. Our approach has several major differences. First, our text and models are multilingual. Second, we enforce the teachers to use English input instead of using the same multilingual input as the students. Third, we use a cross entropy objective between the student and teacher text-video scores instead of using a regression loss, which is more effective since it considers the context of all of the text-video pairs in the batch. We compare our objective to theirs in Section 4.4.

Finally, some multilingual knowledge distillation methods were proposed for visual question answering based on images (Raj Khan et al., 2021; Gupta et al., 2022a).

Other Multilingual Video Datasets. Several multilingual video datasets are designed for other tasks, such as captioning (Wang et al., 2019; Su et al., 2021), sentiment analysis (Bagher Zadeh et al., 2020; Gupta et al., 2022b), moment detection (Lei et al., 2021), audio-visual speech recog-

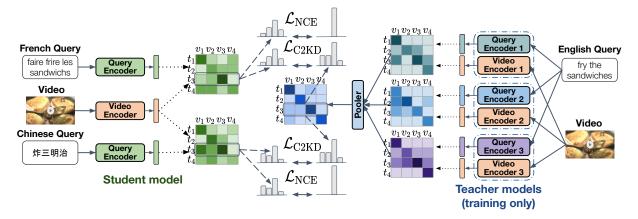


Figure 1: **Overview of C2KD.** A multilingual student model computes text-video similarity scores for a batch of video and text inputs, while teacher models process the same video and English translations. The student is trained with two objectives.  $\mathcal{L}_{NCE}$  (described in Section 3.1) trains the model to have high text-video scores for text and video pairs using the cross entropy loss.  $\mathcal{L}_{C2KD}$  (described in Section 3.3) distills the knowledge from the teacher English text-video scores using a cross entropy loss.

nition (Ephrat et al., 2018), and audio-video retrieval (Rouditchenko et al., 2021b). Instructional videos with captions from automatic speech recognition have been used for learning word embeddings (Sigurdsson et al., 2020) and visually-guided machine translation (Sanabria et al., 2018). However, the transcriptions often have errors and can be unrelated to the visuals. Our Multi-YouCook2 dataset contains captions which were originally written by human annotators in English (Zhou et al., 2018), which makes them visually relevant.

Concurrent Work. Madasu et al. (2023) propose a similar framework to improve multilingual text-video retrieval. However, their method uses knowledge transfer from multilingual text, while our method uses knowledge transfer from English text. They use a separate encoder for English and multilingual text, while our final model uses a single encoder for all languages.

## 3 Method

# 3.1 Text-Video Contrastive Loss

We handle the problem of learning multilingual text-video representations. For simplicity, we first describe the approach for learning with English text and then explain how to extend it to more languages. We consider a dataset  $D_{en} = \{(t_i, v_i)\}_{i=1}^N$  of paired videos and English captions. The goal of text-video retrieval is to learn text and vision models,  $f(\cdot)$  and  $g(\cdot)$  respectively, which output embeddings that are similar to each other when the input text caption  $t_i$  and video  $v_i$  are semantically related (ie. describing similar concepts), and

have low similarity when they are unrelated. In this work, we use cosine similarity by L2-normalizing the outputs of  $f(\cdot)$  and  $g(\cdot)$  and taking the dot-product.

The Noise-Contrastive Estimation loss (NCE) (Gutmann and Hyvärinen, 2010; Jozefowicz et al., 2016; Oord et al., 2018) has been commonly used to learn text-video representations (Sun et al., 2019; Rouditchenko et al., 2021a). Given a batch of B text-video pairs, let  $\mathbf{S}$  be the text-video similarity matrix, with  $\mathbf{S}_{ij} = f(t_i)^{\top} g(v_j)$ . With temperature  $\tau$ , the NCE loss is given as:

$$\mathcal{L}_{NCE} = -\sum_{i=1}^{B} \log \frac{\exp(\mathbf{S}_{ii}/\tau)}{\sum_{k=1}^{B} \exp(\mathbf{S}_{ik}/\tau)}.$$
 (1)

This can be interpreted as the cross entropy loss between the distribution over normalized text-video similarity scores in S and the one-hot distribution. Specifically, let  $Q_{t_i}(v_j)$  be the probability that video  $v_j$  matches with text  $t_i$ :

$$Q_{t_i}(v_j) = \frac{\exp(\mathbf{S}_{ij}/\tau)}{\sum_{k=1}^{B} \exp(\mathbf{S}_{ik}/\tau)}.$$
 (2)

The target distribution,  $P_{t_i}(v_j)$ , is one-hot (since the correct match for text  $t_i$  is video  $v_i$ ):

$$P_{t_i}(v_j) = \begin{cases} 1, & \text{if } i = j \\ 0, & \text{otherwise.} \end{cases}$$
 (3)

Given the equation for cross entropy,

$$\mathcal{L}_{CE} = -\sum_{i=1}^{B} \sum_{j} P_{t_i}(v_j) \log Q_{t_i}(v_j), \quad (4)$$

we can see immediately that Eq. 1 is equivalent to Eq. 4. In Section 3.3, we introduce an additional cross entropy based objective between a new target distribution  $P'_{t_i}(v_j)$  and  $Q_{t_i}(v_j)$ .

To extend this to a dataset of videos paired with captions in L languages, ie.  $D_{multi} = \{(t_i^1, t_i^2, \dots, t_i^L, v_i)\}_{i=1}^N$ , we compute a text-video similarity matrix for each language, ie.  $\mathbf{S}^l$ , where  $\mathbf{S}^l_{ij} = f(t_i^l)^\top g(v_j)$ . Then we apply  $\mathcal{L}_{NCE}$  to each matrix and take the sum of the losses. This pulls together the embeddings of videos and their paired captions in different languages.

During inference, f and g are used to encode text and video inputs. For a given text query, videos are ranked by their cosine similarity to the text.

#### 3.2 C2KD Method

Although  $\mathcal{L}_{NCE}$  can be used to learn multilingual text-video representations, the performance for English text-video retrieval is usually higher than for other languages, as mentioned in the introduction. This implies that of all the languages, the English text-video similarity scores are most accurate. Our key idea is to use the English text-video similarity scores to improve the scores for other languages.

The method is illustrated in Figure 1. We first train M teacher models using  $D_{multi}$  and  $\mathcal{L}_{NCE}$ , and then freeze their parameters. The teacher models have the same architecture, except the text encoders are different so that complementary information from different models can be used. Next, we begin training a student model with  $D_{multi}$ and  $\mathcal{L}_{NCE}$ . For each batch of video and multilingual text, the teachers are simultaneously provided with the video and English translations as input. Each teacher produces an English text-video similarity matrix. We apply a pooler function  $\Psi: \mathbb{R}^{M \times B \times B} \to \mathbb{R}^{B \times B}$  to the M teacher similarity matrices to get a single similarity matrix S', where  $S'_{ij}$  is the similarity score at row i and column j. In our experiments, we experimented with different pooler functions such as mean, max, and min. We train the student with  $\mathcal{L}_{NCE}$  and a 2nd objective,  $\mathcal{L}_{C2KD}$  (introduced in Section 3.3), which encourages the student's text-video similarity scores from captions in different languages to be similar to the teacher English text-video scores in S'. Note that only the student model is used during inference.

## 3.3 Knowledge Distillation Objective

We introduce a distillation objective that encourages the student's multilingual text-video similarity scores to be similar to the teacher English text-video scores in  $\mathbf{S}'$ . The main idea is that instead of using the one-hot distribution  $P_{t_i}(v_j)$  in  $\mathcal{L}_{NCE}$ , we use a new distribution  $P'_{t_i}(v_j)$  obtained from the teacher English text-video scores in  $\mathbf{S}'$ . Specifically, let  $P'_{t_i}(v_j)$  be the probability that video  $v_j$  matches with text  $t_i$ :

$$P'_{t_i}(v_j) = \frac{\exp(\mathbf{S'}_{ij}/\tau)}{\sum_{k=1}^{B} \exp(\mathbf{S'}_{ik}/\tau)}$$
 (5)

We apply the cross entropy loss between  $P'_{t_i}(v_j)$  (generated by the teacher English text-video similarity scores) and  $Q_{t_i}(v_j)$  (generated by the student multilingual text-video similarity scores):

$$\mathcal{L}_{C2KD} = -\sum_{i=1}^{B} \sum_{j} P'_{t_i}(v_j) \log Q_{t_i}(v_j), \quad (6)$$

Note that the temperature  $\tau$  in  $\mathcal{L}_{C2KD}$  is controlled separately to the one in  $\mathcal{L}_{NCE}$ . We apply  $\mathcal{L}_{C2KD}$  to each of the student text-video similarity matrices using text in different languages and take the sum of the losses. The final objective is given by:

$$\mathcal{L} = \alpha \mathcal{L}_{NCE} + (1 - \alpha) \mathcal{L}_{C2KD} \tag{7}$$

where  $\alpha$  is a balance hyperparameter.

The difference between  $\mathcal{L}_{NCE}$  and  $\mathcal{L}_{C2KD}$  is the target distribution; the former uses a one-hot distribution while the latter uses soft-labels produced by the teachers.  $\mathcal{L}_{NCE}$  makes rigid assumptions about which captions are similar to which video clips (only paired examples should match), whereas  $\mathcal{L}_{C2KD}$  enables the model to have leeway in assigning higher scores to pairs which are not ground-truth pairs, but still have some semantic similarity. Also,  $\mathcal{L}_{C2KD}$  shares the same cross entropy objective as the original KD (Hinton et al., 2015), but it is more technically advanced since it distills teacher cross-modal matrices instead of just the logits from uni-modal encoders. Further, our cross-modal distillation is consistent with the retrieval task.

Others have also observed that the contrastive loss may be too strict in a cross-modal setting and have proposed complementary objectives such as captioning (Patrick et al., 2021) and clustering (Chen et al., 2021; Liu et al., 2022). However,

to the best of our knowledge, it is novel to use the contrastive loss in a cross-modal setting with target distributions generated from the text-video similarity scores of several teachers.

# 4 Experiments

#### 4.1 Datasets

Multi-MSRVTT (Huang et al., 2021) is a multilingual version of the MSRVTT (Xu et al., 2016) video dataset. The video categories are general, such as "sports" and "vehicles." The original dataset contains 10k videos from YouTube, each annotated with 20 captions in English. The captions were translated to 8 other languages with machine translation. We followed the setup in prior work (Huang et al., 2021) and used a training set of 6.5k videos, validation set of 497 videos, and test set of 1k videos.

Multi-YouCook2 is our multilingual extension of the YouCook2 (Zhou et al., 2018) video dataset. The original dataset contains 2k cooking videos from YouTube. The video categories are about recipes, such as "spaghetti and meatballs." Each video was segmented into smaller clips containing recipe steps and annotated with text captions of the recipe steps in English. Inspired by the procedure to collect Multi-MSRVTT (Huang et al., 2021), we translated the captions to 8 other languages using machine translation. Sample clips and captions are shown in Figure 2. Following the setup in prior English text-video work (Miech et al., 2019), we used 9,586 training clips and 3,350 evaluation clips. VATEX (Wang et al., 2019) contains videos each with 10 English and 10 Chinese captions. The videos were selected from an action classification dataset (Kay et al., 2017). Following prior work (Huang et al., 2021), we use the official training set of 26k videos and split the validation set equally into 1.5k validation and 1.5k test videos. Note that we made our own split since theirs was not released, and we will release our split.

**RUDDER** (Akula et al., 2021) contains instructional videos with captions in languages spoken in India. This dataset is by far the smallest and could be considered a low-resource multilingual video dataset. The dataset contains English captions but the original work did not use them. Therefore, we created a split of 2.2k training clips and 1k evaluation clips, where each clip in the evaluation set has a caption in English and 3 other languages.



Figure 2: Multi-YouCook2 sample video clips and multilingual captions.

# 4.2 Implementation Details

For the student text model f, we use LaBSE (Feng et al., 2022). We discuss the teacher text models in Section 4.4. For the video model g, we first extract features from CLIP ViT-B/32 (Radford et al., 2021) at 1 FPS and process them with a 2-layer Transformer (Vaswani et al., 2017). Due to GPU memory limitations, we do not update the weights of the CLIP model. We set  $\tau$  in  $\mathcal{L}_{NCE}$  to 0.05 and  $\tau$  in  $\mathcal{L}_{C2KD}$  to 0.1. We found the best pooler function  $\Psi$  and balance  $\alpha$  to be different for each dataset. We specify the values and discuss other hyperparameters in the Appendix.

## 4.3 Experimental Setup

We use the standard R@K metrics (recall at rank K, higher is better). All of our reported results are the average of three runs. Note that random chance performance is different on each dataset due to varying evaluation set size. In the zero-shot setting, models are trained on English text-video pairs only and evaluated using captions in all languages. In the translate-train setting, the models are trained on text-video pairs in all languages. Note that C2KD is only applicable to the translate-train setting since it requires multilingual text during training.

| Method                               | Set. | en   | de   | fr   | cs   | zh   | ru   | vi   | sw   | es   | Avg↑ |
|--------------------------------------|------|------|------|------|------|------|------|------|------|------|------|
| Random Chance                        | N/A  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  | 0.1  |
| PO <sup>†</sup> (Akula et al., 2021) | ZS   | 17.7 | 15.1 | 14.8 | 13.0 | 11.6 | 12.6 | 7.1  | 4.9  | 15.6 | 12.5 |
| MMP (Huang et al., 2021)             | ZS   | 23.8 | 19.4 | 20.7 | 19.3 | 18.2 | 19.1 | 8.2  | 8.4  | 20.4 | 17.5 |
| NCE                                  | ZS   | 21.9 | 18.9 | 18.7 | 18.2 | 16.3 | 17.5 | 9.1  | 12.8 | 20.5 | 17.1 |
| PO <sup>†</sup> (Akula et al., 2021) | TT   | 17.0 | 17.0 | 17.2 | 16.1 | 14.6 | 16.0 | 8.6  | 11.5 | 16.8 | 15.0 |
| MMP (Huang et al., 2021)             | TT   | 23.1 | 21.1 | 21.8 | 20.7 | 20.0 | 20.5 | 10.9 | 14.4 | 21.9 | 19.4 |
| NCE                                  | TT   | 23.3 | 21.1 | 22.3 | 20.9 | 20.3 | 19.6 | 12.1 | 17.2 | 21.5 | 19.8 |
| C2KD (ours)                          | TT   | 26.4 | 24.7 | 25.4 | 24.0 | 23.4 | 23.1 | 13.6 | 20.3 | 25.5 | 23.0 |

Table 1: **Multilingual text-video retrieval on Multi-MSRVTT** (**R@1**). †: our implementation, Set.=Setting, ZS=Zero-Shot (trained on English text-video only), TT=Translate-Train (trained on text-video in all languages).

| Method                                | Set. | en   | de   | fr   | cs   | zh   | ru   | vi   | ja   | es   | Avg↑ |
|---------------------------------------|------|------|------|------|------|------|------|------|------|------|------|
| Random Chance                         | N/A  | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| PO <sup>†</sup> (Akula et al., 2021)  | ZS   | 10.1 | 2.5  | 2.7  | 2.1  | 1.4  | 1.6  | 2.2  | 1.2  | 2.3  | 2.9  |
| MMP <sup>†</sup> (Huang et al., 2021) | ZS   | 12.7 | 3.7  | 3.3  | 2.7  | 2.0  | 2.5  | 2.3  | 1.8  | 2.4  | 3.7  |
| NCE                                   | ZS   | 14.4 | 7.0  | 6.4  | 5.1  | 3.5  | 4.7  | 5.0  | 2.7  | 6.3  | 6.1  |
| PO <sup>†</sup> (Akula et al., 2021)  | TT   | 10.0 | 9.1  | 9.1  | 8.6  | 6.7  | 9.0  | 6.3  | 7.5  | 9.1  | 8.4  |
| MMP <sup>†</sup> (Huang et al., 2021) | TT   | 11.3 | 10.4 | 10.6 | 10.1 | 8.3  | 9.3  | 8.4  | 9.1  | 10.4 | 9.8  |
| NCE                                   | TT   | 14.9 | 13.1 | 13.0 | 12.1 | 9.6  | 12.1 | 10.9 | 10.0 | 13.2 | 12.1 |
| C2KD (ours)                           | TT   | 15.5 | 14.0 | 13.9 | 12.8 | 10.4 | 13.1 | 11.4 | 11.3 | 14.1 | 12.9 |

Table 2: Multilingual text-video retrieval on Multi-YouCook2 (R@1). †: our implementation, Set.=Setting, ZS=Zero-Shot (trained on English text-video only), TT=Translate-Train (trained on text-video in all languages).

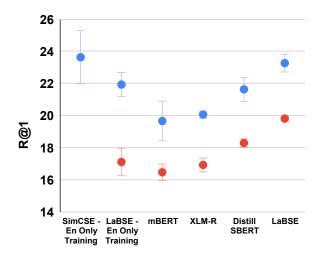


Figure 3: **Text encoder study.** The blue dots show text-video retrieval performance using English. The red dots show the average text-video retrieval performance using 9 languages.

# 4.4 Ablation Studies and Analysis

In this section, we conduct an analysis in order to justify our choices for the student and teacher models, as well as the design of our distillation setup. All of the studies were done on Multi-MSRVTT. The bars in the figures report the standard deviation of three runs.

**Text encoders.** We compare different text encoders in Figure 3 when trained for text-video retrieval ( $\mathcal{L}_{NCE}$  only,  $\alpha$ =1). LaBSE and Distill SBERT outperformed mBERT and XLM-R,

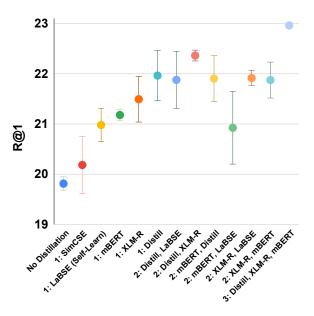


Figure 4: **Ablation on the number of teachers.** Using LaBSE as the student, we applied different combinations of models as teachers.

which are not trained with sentence level objectives. When trained with multilingual captions, LaBSE's performance on English is comparable to SimCSE's, a recent English-only sentence embedding model (Gao et al., 2021). Finally, LaBSE's performance across all languages, including English, improved when trained on multilingual captions. Given that LaBSE is the strongest multilingual model, we use it as our student text encoder.

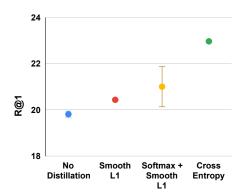


Figure 5: Ablation on the Knowledge Distillation objective.

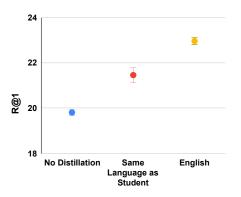


Figure 6: Ablation on the language used with the teachers.

|                                       |      | English (en) |      | Chinese ( |      | $\overline{(zh)}$ |      |
|---------------------------------------|------|--------------|------|-----------|------|-------------------|------|
| Model                                 | Set. | R@1          | R@5  | R10       | R@1  | R@5               | R@10 |
| Random Chance                         | N/A  | 0.07         | 0.33 | 0.67      | 0.07 | 0.33              | 0.67 |
| MMP (Huang et al., 2021)              | ZS   | 44.4         | 80.5 | 88.7      | 29.7 | 63.2              | 75.5 |
| MMP (Huang et al., 2021)              | TT   | 44.3         | 80.7 | 88.9      | 40.5 | 76.4              | 85.9 |
| PO <sup>†</sup> (Akula et al., 2021)  | ZS   | 37.7         | 77.0 | 87.7      | 25.7 | 57.3              | 72.5 |
| MMP <sup>†</sup> (Huang et al., 2021) | ZS   | 39.9         | 79.1 | 89.3      | 26.9 | 60.4              | 75.3 |
| NCE                                   | ZS   | 42.0         | 81.0 | 90.6      | 28.0 | 63.4              | 75.6 |
| PO <sup>†</sup> (Akula et al., 2021)  | TT   | 37.5         | 77.1 | 88.2      | 33.2 | 70.9              | 83.9 |
| MMP <sup>†</sup> (Huang et al., 2021) | TT   | 41.3         | 78.9 | 88.8      | 34.1 | 74.3              | 85.2 |
| NCE                                   | TT   | 42.6         | 81.0 | 90.6      | 38.0 | 75.4              | 88.0 |
| C2KD (ours)                           | TT   | 43.1         | 82.1 | 91.5      | 39.6 | 77.0              | 88.6 |

Table 3: **Multilingual text-video retrieval on VA-TEX.** Upper and lower halves separated due to different test splits. †: our implementation, Set.=Setting, ZS=Zero-Shot (trained on English text-video only), TT=Translate-Train (trained on text-video in all languages).

**Teacher models.** In Figure 4, we show the performance of our C2KD method with one, two, and three teachers. With one teacher, we found that SimCSE was the worst teacher, which was surprising considering its strong English-only performance. However, recent work has shown that the best teacher might not be the strongest model (Gong et al., 2022). Using LaBSE as its own teacher is feasible, but it is better to use a different model as the teacher. Distill SBERT was the best



Figure 7: Qualitative text-video retrieval results on Multi-YouCook2. Left: results for NCE baseline method without C2KD. Right: results with C2KD. Videos shown as 2 frames. Top 3 results for each query are shown with the correct match highlighted in green.

teacher, which is reasonable considering it is the most similar to LaBSE in using a sentence-level objective. With two teachers, we found that any combination of Distill SBERT, mBERT, and XLM-R could improve the performance over any individual teacher. However, including LaBSE either didn't help the performance or made it worse. Given these results, we used Distill SBERT, mBERT, and XLM-R as the final set of teachers, which obtained the best results.

**Knowledge Distillation objective.** We compare distillation objectives between the student and teacher text-video similarity scores in Figure 5. For

|                                       | Set. | Eng | glish (e | en)  | H   | Hindi (/ | (ii) | Ka         | nnada ( | (kn) | Ma  | arathi ( | $\overline{mr}$ |
|---------------------------------------|------|-----|----------|------|-----|----------|------|------------|---------|------|-----|----------|-----------------|
| Model                                 |      | R@1 | R@5      | R10  | R@1 | R@5      | R@10 | R@1        | R@5     | R@10 | R@1 | R@5      | R@10            |
| Random Chance                         | N/A  | 0.1 | 0.5      | 1.0  | 0.1 | 0.5      | 1.0  | 0.1        | 0.5     | 1.0  | 0.1 | 0.5      | 1.0             |
| PO <sup>†</sup> (Akula et al., 2021)  | ZS   | 4.2 | 12.7     | 17.7 | 1.8 | 6.6      | 10.2 | 1.8        | 5.7     | 9.1  | 2.8 | 7.7      | 12.8            |
| MMP <sup>†</sup> (Huang et al., 2021) | ZS   | 4.8 | 13.5     | 20.9 | 1.9 | 6.4      | 10.8 | 1.5        | 4.4     | 7.6  | 2.3 | 7.4      | 11.5            |
| NCE                                   | ZS   | 5.1 | 14.4     | 21.6 | 2.3 | 8.0      | 12.5 | 2.1        | 6.6     | 11.5 | 2.8 | 8.5      | 13.5            |
| PO <sup>†</sup> (Akula et al., 2021)  | TT   | 4.3 | 13.4     | 18.7 | 2.9 | 10.2     | 15.4 | 2.3        | 7.9     | 13.2 | 3.7 | 11.5     | 17.0            |
| MMP <sup>†</sup> (Huang et al., 2021) | TT   | 5.1 | 13.4     | 19.3 | 3.1 | 10.5     | 15.2 | 3.0        | 7.8     | 12.1 | 2.9 | 11.5     | 17.6            |
| NCE                                   | TT   | 5.6 | 16.6     | 23.4 | 4.2 | 11.8     | 16.8 | <b>3.7</b> | 10.7    | 15.8 | 5.1 | 14.1     | 19.9            |
| C2KD (ours)                           | TT   | 6.3 | 16.8     | 25.9 | 4.3 | 13.2     | 19.4 | 4.4        | 12.4    | 17.8 | 5.1 | 14.8     | 22.3            |

Table 4: **Multilingual text-video retrieval on RUDDER.** †: our implementation, Set.=Setting, ZS=Zero-Shot (trained on English text-video only), TT=Translate-Train (trained on text-video in all languages).

English text-video retrieval, TeachText (Croitoru et al., 2021) proposed to regress the teacher textvideo scores using a Smooth L1 Loss. We found that this objective could only give a minor improvement over the baseline without distillation. While the TeachText approach considers each text-video score independently, our proposed  $\mathcal{L}_{C2KD}$  loss instead considers the context of all the text-video scores by normalizing them with softmax and applying the cross entropy loss. As shown in Figure 5, this significantly outperforms the regression based method. To gain further insight, we tried an intermediate approach of combining softmax normalization and Smooth L1 Loss, which performed only slightly better than Smooth L1 loss. This shows that it is essential to use a loss such as cross entropy which considers the distribution over the text-video scores instead of treating them independently.

Teacher language. In Figure 6, we compare the results when different languages are used by the teachers. Using the same multilingual text as input to the student and teachers improves the results over no distillation, likely due to the complementary information provided by different text encoders. However, our proposed method of using English with the teachers performs better. This result matches our intuition that English should be the best language to use with the teachers since English text-video retrieval is typically higher than other languages.

#### 4.5 Main Results

With the best student (LaBSE) and teacher models (Distill SBERT, mBERT, and XLM-R) at hand, we tested C2KD on four datasets. For comparison, we also implemented the baselines (Huang et al., 2021; Akula et al., 2021) since their code was not released. The "NCE" method corresponds to our baseline without distillation ( $\mathcal{L}_{NCE}$  only,  $\alpha$ =1). We applied C2KD to this method.

Table 1 shows the multilingual text-video retrieval results on Multi-MSRVTT. C2KD improves performance across languages, with average R@1 improving from 19.8 to 23.0 (+16.2% relative). The largest improvement is on Spanish (es), from 21.5 to 25.5 (+18.6% relative). Our method also improves the performance on English. Finally, we note that while performance for Vietnamese (vi) improved, it is still much lower than for other languages. We manually expected the captions and found the translations to be poor with unrelated symbols such as musical notes inserted.

Table 2 shows the results on Multi-YouCook2. The performance across languages is similar, which suggests that the quality translation is consistent. Applying our C2KD method to the baseline, we see improvements for all languages. The average R@1 improves from 12.1 to 12.9 (+6.6% relative). The largest improvement is on Japanese, from 10.1 to 11.3 (+11.9% relative).

Table 3 shows the results on VATEX. The retrieval performance is generally higher than on the other datasets, which could be attributed to the large training set. Nonetheless, C2KD can improve the performance for both English and Chinese in all metrics. Chinese R@1 is improved from 38 to 39.6 (+4.2% relative).

Table 4 shows the results on RUDDER. The dataset is much smaller than the others, so the retrieval performance is generally lower. However, C2KD still improves the results across languages and metrics. The largest improvement is on R@10 for Hindi, from 16.8 to 19.4 (+15.9% relative).

Overall, C2KD consistently improved performance across languages and domains, with significant improvements on some languages. Also, our results accurately represent the performance since we ran each experiment three times and report the average.

#### 4.6 Qualitative Results

Figure 7 shows qualitative retrieval results on Multi-YouCook2. Without C2KD, the baseline method often retrieves clips that are only partially related to the query, ie., for "add the beef and tofu to the pot," the clips will only show either beef or tofu. Using C2KD, the model can handle more complex queries and retrieve clips that are relevant to all of the ingredients mentioned in the text.

Retrieval using unseen languages. Qualitative results show that our C2KD model can retrieve videos using text in *unseen languages* (languages for which no text-video pairs were available), thanks to LaBSE's text pre-training in over 100 languages. For example, in our multilingual text-video retrieval demo<sup>1</sup>, our model can match videos with text in Ukrainian and Igbo, even though the model was not trained with text-video pairs in those languages (although LaBSE was pre-trained with text in those languages).

## 5 Conclusion

In this work, we introduce Cross-Lingual Cross-Modal Knowledge Distillation (C2KD) to improve multilingual text-video retrieval performance. Motivated by the observation that English retrieval outperforms other languages, our method trains a student using input multilingual text to output similar text-video similarity scores compared with teachers using input English text. We propose an objective based on cross entropy to distill the cross-modal knowledge from the teachers which considers the context of all of the text-video pairs in the batch. We applied C2KD to four datasets and obtained an improvement in multilingual text-video retrieval across languages and domains. Finally, we introduce the Multi-YouCook2 dataset with captions in 9 languages and will make the data public to spur more research in this direction. Ideas for future work include applying multilingual text augmentation and paraphrasing strategies to generate more data.

## Limitations

In this work, we sought to improve multilingual text-video retrieval and reduce the gap with English performance. C2KD improved multilingual text-video retrieval across datasets and languages. On Multi-MSR-VTT, the average gap in perfor-

mance between non-English languages and English was 16.5% before applying C2KD and 14.4% after applying C2KD. On Multi-YouCook2, the gap was 20.8% before and 18.4% after. Although our method reduced the gap, the performance for English is still higher than the other languages. We attribute this to several factors. First, C2KD improved the performance for English as well as for other languages, making it harder to close the gap. Second, multilingual text translated from English often has errors. For example, as we noted on Multi-MSRVTT, the performance for Vietnamese (vi) is much lower than the other languages, and we found the translations to be of poor quality. Third, the multilingual text models such as LaBSE are pre-trained on more English data than any other language. We expect that the gap between English performance and other languages will decrease as machine translation models and multilingual text encoders improve. Also, our datasets have at most 9 languages, and it will take further research to develop massively multilingual text-video retrieval.

### **Ethics Statement**

Text-video retrieval is an important task that can improve the experience of searching for videos on the internet. Our approach aims to make text-video retrieval more equitable by improving the performance for more languages besides English. We believe that our work can help both researchers and practitioners develop better multilingual text-video models. We also collected multilingual captions for the YouCook2 dataset and plan to release them, which is permitted by YouCook2's license (MIT license).

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#### References

Jayaprakash Akula, Rishabh Dabral, Preethi Jyothi, and Ganesh Ramakrishnan. 2021. Cross lingual video and text retrieval: A new benchmark dataset and algorithm. In *Proceedings of the 2021 International Conference on Multimodal Interaction*, pages 595–603.

AmirAli Bagher Zadeh, Yansheng Cao, Simon Hessner, Paul Pu Liang, Soujanya Poria, and Louis-Philippe

<sup>&</sup>lt;sup>1</sup>https://github.com/roudimit/c2kd

- Morency. 2020. CMU-MOSEAS: A multimodal language dataset for Spanish, Portuguese, German and French. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1801–1812, Online. Association for Computational Linguistics.
- Brian Chen, Andrew Rouditchenko, Kevin Duarte, Hilde Kuehne, Samuel Thomas, Angie Boggust, Rameswar Panda, Brian Kingsbury, Rogerio Feris, David Harwath, et al. 2021. Multimodal clustering networks for self-supervised learning from unlabeled videos. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8012–8021.
- Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, Online. Association for Computational Linguistics.
- Ioana Croitoru, Simion-Vlad Bogolin, Marius Leordeanu, Hailin Jin, Andrew Zisserman, Samuel Albanie, and Yang Liu. 2021. Teachtext: Crossmodal generalized distillation for text-video retrieval. In *Proceedings of the IEEE/CVF Inter*national Conference on Computer Vision, pages 11583–11593.
- Yann N Dauphin, Angela Fan, Michael Auli, and David Grangier. 2017. Language modeling with gated convolutional networks. In *International conference on machine learning*, pages 933–941. PMLR.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Ariel Ephrat, Inbar Mosseri, Oran Lang, Tali Dekel, Kevin Wilson, Avinatan Hassidim, William T. Freeman, and Michael Rubinstein. 2018. Looking to listen at the cocktail party: A speaker-independent audio-visual model for speech separation. *ACM Trans. Graph.*, 37(4).
- Fangxiaoyu Feng, Yinfei Yang, Daniel Cer, Naveen Arivazhagan, and Wei Wang. 2022. Language-agnostic BERT sentence embedding. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 878–891, Dublin, Ireland. Association for Computational Linguistics.
- Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. SimCSE: Simple contrastive learning of sentence

- embeddings. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6894–6910, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Yuan Gong, Sameer Khurana, Andrew Rouditchenko, and James Glass. 2022. Cmkd: Cnn/transformer-based cross-model knowledge distillation for audio classification. *arXiv* preprint arXiv:2203.06760.
- Kshitij Gupta, Devansh Gautam, and Radhika Mamidi. 2022a. cvil: Cross-lingual training of vision-language models using knowledge distillation. In 2022 26th International Conference on Pattern Recognition (ICPR), pages 1734–1741. IEEE.
- Vikram Gupta, Trisha Mittal, Puneet Mathur, Vaibhav Mishra, Mayank Maheshwari, Aniket Bera, Debdoot Mukherjee, and Dinesh Manocha. 2022b. 3massiv: multilingual, multimodal and multi-aspect dataset of social media short videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21064–21075.
- Michael Gutmann and Aapo Hyvärinen. 2010. Noisecontrastive estimation: A new estimation principle for unnormalized statistical models. In *AISTATS*.
- Geoffrey Hinton, Oriol Vinyals, Jeff Dean, et al. 2015. Distilling the knowledge in a neural network. *NIPS Deep Learning Workshop*, 2(7).
- Po-Yao Huang, Mandela Patrick, Junjie Hu, Graham Neubig, Florian Metze, and Alexander G Hauptmann. 2021. Multilingual multimodal pretraining for zero-shot cross-lingual transfer of vision-language models. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 2443–2459.
- Rafal Jozefowicz, Oriol Vinyals, Mike Schuster, Noam Shazeer, and Yonghui Wu. 2016. Exploring the limits of language modeling. *arXiv preprint arXiv:1602.02410*.
- Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, et al. 2017. The kinetics human action video dataset. *arXiv preprint arXiv:1705.06950*.
- Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *ICLR*.
- Jie Lei, Tamara Berg, and Mohit Bansal. 2021. mTVR: Multilingual moment retrieval in videos. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 726–734, Online. Association for Computational Linguistics.

- Alexander Liu, SouYoung Jin, Cheng-I Lai, Andrew Rouditchenko, Aude Oliva, and James Glass. 2022. Cross-modal discrete representation learning. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3013–3035, Dublin, Ireland. Association for Computational Linguistics.
- Avinash Madasu, Estelle Aflalo, Gabriela Ben Melech Stan, Shao-Yen Tseng, Gedas Bertasius, and Vasudev Lal. 2023. Improving video retrieval using multilingual knowledge transfer. In Advances in Information Retrieval: 45th European Conference on Information Retrieval, ECIR 2023, Dublin, Ireland, April 2–6, 2023, Proceedings, Part I, pages 669–684. Springer.
- Antoine Miech, Ivan Laptev, and Josef Sivic. 2017. Learnable pooling with context gating for video classification. *arXiv* preprint arXiv:1706.06905.
- Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. 2019. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2630–2640
- Aaron van den Oord, Yazhe Li, and Oriol Vinyals. 2018. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc.
- Mandela Patrick, Po-Yao Huang, Yuki Asano, Florian Metze, Alexander Hauptmann, Joao Henriques, and Andrea Vedaldi. 2021. Support-set bottlenecks for video-text representation learning. *ICLR*.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning*, pages 8748–8763. PMLR.
- Humair Raj Khan, Deepak Gupta, and Asif Ekbal. 2021. Towards developing a multilingual and codemixed visual question answering system by knowledge distillation. In *Findings of the Association for Computational Linguistics: EMNLP 2021*, pages

- 1753–1767, Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 3982–3992, Hong Kong, China. Association for Computational Linguistics.
- Nils Reimers and Iryna Gurevych. 2020. Making monolingual sentence embeddings multilingual using knowledge distillation. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 4512–4525, Online. Association for Computational Linguistics.
- Albert Reuther, Jeremy Kepner, Chansup Byun, Siddharth Samsi, William Arcand, David Bestor, Bill Bergeron, Vijay Gadepally, Michael Houle, Matthew Hubbell, Michael Jones, Anna Klein, Lauren Milechin, Julia Mullen, Andrew Prout, Antonio Rosa, Charles Yee, and Peter Michaleas. 2018. Interactive supercomputing on 40,000 cores for machine learning and data analysis. In 2018 IEEE High Performance extreme Computing Conference (HPEC), pages 1–6. IEEE.
- Andrew Rouditchenko, Angie Boggust, David Harwath, Brian Chen, Dhiraj Joshi, Samuel Thomas, Kartik Audhkhasi, Hilde Kuehne, Rameswar Panda, Rogerio Feris, Brian Kingsbury, Michael Picheny, Antonio Torralba, and James Glass. 2021a. AVLnet: Learning Audio-Visual Language Representations from Instructional Videos. In *Interspeech*, pages 1584–1588.
- Andrew Rouditchenko, Angie Boggust, David Harwath, Samuel Thomas, Hilde Kuehne, Brian Chen, Rameswar Panda, Rogerio Feris, Brian Kingsbury, Michael Picheny, and James Glass. 2021b. Cascaded Multilingual Audio-Visual Learning from Videos. In *Proc. Interspeech* 2021, pages 3006–3010.
- Ramon Sanabria, Ozan Caglayan, Shruti Palaskar, Desmond Elliott, Loïc Barrault, Lucia Specia, and Florian Metze. 2018. How2: a large-scale dataset for multimodal language understanding. In Workshop on Visually Grounded Interaction and Language (ViGIL). NeurIPS.
- Nina Shvetsova, Brian Chen, Andrew Rouditchenko, Samuel Thomas, Brian Kingsbury, Rogerio S Feris, David Harwath, James Glass, and Hilde Kuehne. 2022. Everything at once-multi-modal fusion transformer for video retrieval. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20020–20029.
- Gunnar A Sigurdsson, Jean-Baptiste Alayrac, Aida Nematzadeh, Lucas Smaira, Mateusz Malinowski,

Joao Carreira, Phil Blunsom, and Andrew Zisserman. 2020. Visual grounding in video for unsupervised word translation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10850–10859.

Lin Su, Nan Duan, Edward Cui, Lei Ji, Chenfei Wu, Huaishao Luo, Yongfei Liu, Ming Zhong, Taroon Bharti, and Arun Sacheti. 2021. GEM: A general evaluation benchmark for multimodal tasks. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 2594–2603, Online. Association for Computational Linguistics.

Chen Sun, Fabien Baradel, Kevin Murphy, and Cordelia Schmid. 2019. Learning video representations using contrastive bidirectional transformer. arXiv preprint arXiv:1906.05743.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.

Xin Wang, Jiawei Wu, Junkun Chen, Lei Li, Yuan-Fang Wang, and William Yang Wang. 2019. Vatex: A large-scale, high-quality multilingual dataset for video-and-language research. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4581–4591.

Jun Xu, Tao Mei, Ting Yao, and Yong Rui. 2016. Msrvtt: A large video description dataset for bridging video and language. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5288–5296.

Luowei Zhou, Chenliang Xu, and Jason J Corso. 2018. Towards automatic learning of procedures from web instructional videos. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

## A Appendix

Table 5 shows the final values of the  $\alpha$  (balance) and  $\Psi$  (pooler) hyperparameters determined via grid-search. As shown by the table, a larger weight on  $\mathcal{L}_{C2KD}$  is optimal for most of the datasets. We have also tried a multitask setup where no pooler is used and  $\mathcal{L}_{C2KD}$  is applied to each teacher text-video similarity matrix, but this approach did not work as well.

| Parameter          | MSRVTT | YouCook2 | VATEX | RUDDER |
|--------------------|--------|----------|-------|--------|
| $\alpha$ (Balance) | 0.5    | 0.1      | 0.1   | 0.1    |
| Ψ (Pooler)         | Min    | Min      | Max   | Mean   |

Table 5: Final values of the balance and pooler hyperparameters determined via grid-search.

For the video model, we use a maximum video length of 30s. Following the 2-layer, 4-head trans-

former, we mean-pool the outputs and apply a projection into the shared embedding space with a dimension of 512. Following prior work in text-video learning, we use non-linear feature gating in the projection layer (Dauphin et al., 2017; Miech et al., 2017) and we do not use positional embeddings in the video transformer (Shvetsova et al., 2022).

We used the HuggingFace models and tokenizers for LaBSE<sup>2</sup>, XLM-R<sup>3</sup>, mBERT<sup>4</sup>, Distill SBERT<sup>5</sup>, and SimCSE<sup>6</sup>. We use a maximum of 40 tokens. Following the text encoders, we mean-pool the outputs and apply a projection into the shared embedding space.

We used a single V100 GPU with 32 GB memory for all of our experiments, and each experiment took one hour on average. We trained the models for 20 epochs for MSR-VTT, 10 epochs for Multi-YouCook2, 30 epochs for VATEX, and 20 epochs for RUDDER. The batch size was 64 videos. The initial learning rate was 1e-4 with an exponential decay of 0.9 except on RUDDER where we reduced it to 5e-5 due to the smaller dataset size. Models were trained with the Adam optimizer (Kingma and Ba, 2015). We implemented the models in PyTorch (Paszke et al., 2019) and used mixed-precision.

<sup>&</sup>lt;sup>2</sup>https://huggingface.co/sentence-transformers/LaBSE

<sup>&</sup>lt;sup>3</sup>https://huggingface.co/xlm-roberta-base

<sup>&</sup>lt;sup>4</sup>https://huggingface.co/bert-base-multilingual-uncased

<sup>&</sup>lt;sup>5</sup>https://huggingface.co/sentence-transformers/distiluse-base-multilingual-cased-v2

<sup>&</sup>lt;sup>6</sup>https://huggingface.co/princeton-nlp/sup-simcse-roberta-base