Distilling Knowledge from Language Models for Video-based Action Anticipation

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Abstract

Anticipating future actions in a video is useful for many autonomous and assistive technologies. Prior action anticipation work mostly treats this as a vision modality problem, where the models learn the task information primarily from the video features in the target action anticipation datasets. In this work, we propose a method to make use of the text-modality that is available during the training, to bring in complementary information that is not present in the target action anticipation datasets. In particular, we leverage pre-trained language models to build a text-modality teacher that is able to predict future actions based on text labels of the past actions extracted from the input video. To further adapt the teacher to the target domain (cooking), we also pretrain the teacher on textual instructions from a recipes dataset (Recipe1M). Then, we distill the knowledge gained by the text-modality teacher into a vision-modality student to further improve its performance. We empirically evaluate this simple cross-modal distillation strategy on two video datasets (EGTEA-GAZE+ and EPIC-KITCHEN 55). Distilling this text-modality knowledge into a strong vision model (Anticipative Vision Transformer) yields consistent gains across both datasets, (3.5% relative improvement on top1 class mean recall for EGTEA-GAZE+, 7.2% on top5 many-shot class mean recall for EPIC-KITCHEN 55) and achieves new state-of-the-results.

1 Introduction

Anticipating future actions in a scenario based on a set of input video frames is an important capability for many applications in augmented reality (Salamin et al., 2006; Azuma, 2004), robotics (Duarte et al., 2018; Schydlo et al., 2018), and autonomous driving (Chaabane et al., 2020; Suzuki et al., 2018). Most supervised models for this task use a pre-trained video encoder backbone to extract representations of the input frames and use them in a decoder or a classifier to predict a future action (Carion et al., 2020; Dessalene et al., 2021; Liu et al., 2020; Sener et al., 2020). Given training video datasets with action annotations (annotations not available in the test/target dataset), the models learns to fine-tune the encoder representation of the video frames in order to map it to the future action. However, the generalization of such models is limited by how well these video datasets cover the possible action sequence distributions. In other words, the knowledge that is learnt for predicting future actions is essentially limited to the information in the video modality alone.

Although the task itself is defined only over videos, the knowledge about action sequences can also be obtained from text resources. As the task is essentially predicting the future action based on the past action sequence, it can be thought of as very similar to the standard language modelling task. Recent language models, (e.g. BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019c)), are often pre-trained on large collections of unlabeled texts with billions of tokens, where they acquire a wide-variety of knowledge including large scale knowledge about common action sequences. In this work, we show that we can augment video-based anticipation models with this knowledge from the text modality that is external to the target dataset.

To this end, we propose a simple cross-modal distillation approach, where we distill the knowledge gained by a language model from the text modality of the data into a vision modality model. We build a teacher using a pre-trained language model which already carries general knowledge about action sequences. We adapt this teacher to the action sequences in the video domain by fine-tuning them for the action prediction task. Then, we train a vision-modality student, which is now tasked with both predicting the target action label as well as matching the output probability distribution of the
Clean the board → takeout pan → wash the onion → clean the fish → cut the onion → heat the pan → pour oil in pan → [MASK] the fish.

Clean the board → takeout pan → wash the onion → clean the fish → cut the onion → heat the pan → pour oil in pan → fry [MASK].

| Masked action sequence | BERT @top5 |
|------------------------|-----------|
| Clean the board → takeout pan → wash the onion → clean the fish → cut the onion → heat the pan → pour oil in pan → [MASK] the fish. | fry, cook, boil, wash, clean |
| Clean the board → takeout pan → wash the onion → clean the fish → cut the onion → heat the pan → pour oil in pan → fry [MASK]. | pan, fish, chicken, it, onion |

Table 1: Given a sequence of actions extracted from a video, BERT@top5 shows the top5 prediction made by a standard pretrained BERT for the masked verb and object of the next action.

Our empirical evaluation shows that this cross-modal training yields consistent improvements over a state-of-the-art Anticipative Vision Transformer model (Girdhar and Grauman, 2021) on two egocentric action anticipation datasets. Adapting the teacher to the task domain by pretraining on domain relevant texts yields further gains and the gains are stable for different language models. Interestingly, our analysis shows that the language model based teacher can provide gains even when it is not necessarily better than the vision student, suggesting that distillation benefits can also come from the complementary of knowledge, as in the case of the text modality.

In summary we make the following contributions: (i) We point out the issue of supervised models being limited by the action sequence knowledge that is contained in the training videos. (ii) We show that a simple distillation scheme can effectively incorporate text-derived knowledge from a teacher into a vision-based student. (iii) We show that text-derived knowledge about actions sequences contain complementary information that is useful for the anticipation task, especially for the case where the action label space is large. (iv) Using a strong action anticipation model as a student, we achieve new state-of-the-art results on two action anticipation datasets.

2 Related Work

**Action Anticipation:** There has been a wide range of solutions for action anticipation ranging from hierarchical representations (Lan et al., 2014), unsupervised representation learning (Vondrick et al., 2016), to encoder-decoder frameworks that decode future actions at different time scales (Furnari and Farinella, 2019), and transformers trained on multiple auxiliary tasks (Girdhar and Grauman, 2021). However, all these models only use the vision modality features of the observed video to train the model for the anticipation task.

Other works have also shown the utility of modeling text-modality. One recent work has developed a two-phase approach for the task of future instruction generation in free-form given a partial input video (Sener and Yao, 2019). This involves first learning a text2text encoder-decoder to predict the future instruction from past sequence instructions and then replacing the text encoder with a video encoder to do the task based on the video. However, learning to project image and text features in a shared space requires lots of properly aligned text and its corresponding image. Another solution models label semantics with a hand engineered deterministic label prior based on the global co-occurrence statistics of the action labels from the overall training data (Camporese et al., 2021), which can be ineffective in case the underlying joint label distribution is complex. In contrast, our work proposes a different approach to leverage the text in the training data by using language models to learn the complex underlying distribution of action sequences in the video and then distill this knowledge into a vision model to improve their performance.

**Knowledge Distillation:** Knowledge distillation has been shown to be effective in many different applications areas in vision (Chen et al., 2017), NLP (Sanh et al., 2019), and speech (Mun’im et al., 2019), typically for model compression, where the teacher and student operate over the same modality. In this work, we are interested in cross-modal knowledge distillation. Some recent works considers different views of the video or image data as different modality. (Liu et al., 2019b) distills knowledge from flow-based model to RGB-frame-based model, (Gupta et al., 2016) proposes distillation from labeled RGB images to depth and optical flow based models, (Dai et al., 2021) proposes distilling the knowledge of Global Contextual Relations and the Action Boundary to RGB student model. Other work deals with modalities come from other domains, (Thoker and Gall, 2019) proposes learning
from RGB videos to recognize actions for another modality, (Hu et al., 2020; Chen et al., 2020) work involves knowledge distillation for retrieval task between vision and language, whereas (Wang et al., 2020)’s work involves cross modal knowledge distillation from text to speech.

The most relevant work to ours a recent system that improves language understanding of text models by transferring the knowledge of a multi-modal teacher trained on a video-text dataset, into a student language model with a text dataset (Tang et al., 2021). In contrast, our proposed method for action anticipation transfers knowledge gained by a text-based teacher model into a vision-based student model.

**Multimodal transformers:** Due to the recent prevalence of multimodal data and applications (Lin et al., 2014; Sharma et al., 2018; Antol et al., 2015; Krishna et al., 2017; Ordonez et al., 2011; Abu Farha et al., 2018; Talmor et al., 2021; Afouras et al., 2018), there has been plethora of recent work on multimodal transformers. One commonly used approach used to train these models is to learn a cross-modal representation for both the modalities in a shared space. (Radford et al., 2021; Wehrmann et al., 2020) learns to align image-text pairs in a shared space, for cross-modal retrieval, (Liu et al., 2019a), for grounded image representation, (Tan and Bansal, 2020; Li et al., 2019), for grounded text representation, among others. (Hu and Singh, 2021) adds an additional dimension of multitask training by training the model on multiple language-vision based tasks. (Tsimpoukelli et al., 2021) adapts a vision model to a frozen large LM to transfer it’s few-shot capability to a multimodal setting (vision and language). However all these proposed method rely of large-scale image-text aligned datasets for the training the model, which may not be always available, for e.g. EGTEA-GAZE+ video dataset has only 10.3K labelled action sequences. Our proposed method has no such requirement, as it does not require direct image-text alignment for the anticipation task.

3 **Language-to-vision knowledge distillation for action anticipation**

Our goal is to develop a model to predict the class label of a future action based on information from an observed video sequence. In this task setting, the model has access to both, video and annotated action segments (action text) during the train time, but needs to make the inference only using the video sequence. The input to the prediction model is a sequence of video frames up until time step $t$: $X = (X_1, X_2, \ldots, X_t)$, and the desired output of the model is the class label $Y$ of the action at time $t + \tau$, where $\tau$ is the anticipation time.

To learn an anticipation model, we assume there is training data of the following form: $D = \{(X^i, L^i, Y^i)\}_{i=1}^n$, where $X^i = (X_{t_1}^i, \ldots, X_{t_k}^i)$ is the $i^{th}$ training video sequence, $Y^i$ is the class label of the future action at time $t^i + \tau$, and $L^i = (L_{1}^i, \ldots, L_{k_{i}}^i)$ is the sequence of action label of the action segments in the video sequence $X^i$. Each human action can span multiple time steps, so the number of actions $k_i$ might be different from the number of video frames $t^i$.

Our task is to learn a model $g$ that can predict the future action label based on the video sequence $X^i$ only. A common approach is to optimize cross entropy loss between the model’s predicted label $g(X^i)$ and the ground truth label $Y^i$ of each training instances, i.e., to minimize: $\sum I(L(g(X^i)), Y^i)$, where $L$ denotes the cross-entropy loss. Although the sequence of action labels $L^i$ is available in the training data, the semantics associated with these labels is not properly used by the existing methods for training the anticipation model.

Here we propose to learn a text-based anticipation model $g_{text}$ and use it to supervise the training of the video-based anticipation model $g$. This training approach utilizes the knowledge from the text domain, which is easier to learn than the vision-based knowledge, given the abundance of event sequences described in text corpora. Hereafter, we will refer to the language-based model as the teacher, and the vision-based model as the student.

3.1 **Overview**

The overview of our proposed method is shown in Figure 1. We augment video-based action anticipation models (students) with information distilled from text-based models (teachers) that have access to knowledge from large scale action sequences. To this end we fine-tune a pre-trained language model on the action sequences in the training data. However, unlike the student, the teacher gets to see the action labels of the input video segment to make its predictions (Figure 1a). Then, we train a video-based model as the student that learns from this text-based teacher (Figure 1b).

The text-based teacher in our setting is built us-
The input to the teacher is a sequence of action phrases $L = (L_1, \ldots, L_k)$ that denote the sequence of actions observed in the input video segment. The teacher first uses a standard language model $\phi_{LM}$ to produce a single vector $f_{txt}$ that represents the input sequence $L$. In transformer-based language models, a special token (e.g., [CLS] in BERT) is prepended to the input sequence. The output contextual representation of this special token is used as the final representation of the entire input sequence.

The teacher then uses this $f_{txt}$ vector to predict the output labels using the standard linear transformation $(W, b)$ followed by a softmax layer. In addition, we also train the teacher to predict the main verb $Y_{vb}$ and the noun $Y_{nn}$ of the action $Y$. These are predicted using separate linear transformations $(W_{vb}, b_{vb})$ and $(W_{nn}, b_{nn})$, which are then followed by softmax.

The full set of predictions for input $L = (L_1, \ldots, L_k)$ is obtained as:

$$f_{txt} = \phi_{LM}(L_1, \ldots, L_k)$$

$$\hat{Y}_{vb} = \text{softmax}(W_{vb}f_{txt} + b_{vb})$$

$$\hat{Y}_{nn} = \text{softmax}(W_{nn}f_{txt} + b_{nn})$$

To fine-tune the teacher model, we minimize the weighted sum of the cross-entropy loss between the predicted action, verb and noun and their corresponding ground truth.

$$L_{txt}(Y, \hat{Y}_{vb}, \hat{Y}_{nn}) = \lambda L(Y, \hat{Y}_{vb}) + \lambda_n L(Y_{nn}, \hat{Y}_{nn}) + \lambda_{vb} L(Y_{vb}, \hat{Y}_{vb})$$

To better adapt the LMs to the action sequences in the target domain (cooking), we can also pretrain the teacher LM base on domain relevant texts.

Figure 1: METHOD OVERVIEW: Training. The observation video has two sets of features, a sequence of $T$ image frames $X$, and a sequence of action labels (e.g., cut-onion, peel-onion etc.) $L$ corresponding to the $K$ action segments in $X$. (a) We train a teacher model to predict $Y$ using the text features $L$. Then we distill the knowledge gained by the teacher on text features into the student model that operates on vision modality $X$. For this, (b), we train a student model on the vision modality feature $X$ while using the corresponding prediction from the teacher model as a label prior. Inference. During the inference or test time, the trained student model is used to predict the future action using only the vision modality of the observed video.
(e.g. cooking recipes) using Masked Language Modelling task, before fine-tuning them on the task specific video datasets.

3.3 Student

The student is trained to take the frames in the video segment $X = (X_1, ..., X_t)$ as input and predict the future action $Y$ as output. Though the applicability of the proposed distillation method is not restricted to any particular class of student model, we use the recent state-of-the-art Anticipative Vision Transformer (AVT) (Girdhar and Grauman, 2021) as our student model. In AVT, the video to action prediction is done in two stages, first a backbone network $B$ generates the feature representation of the individual frames in $X$ in a non-contextual manner.

$$z_1, ..., z_t = B(X_1), ..., B(X_t)$$

This is then followed by a transformer based decoder head network $D$, that generates the contextual representation of the frames by transforming the frame features $z_i$’s in an autoregressive manner.

$$f_{v1}, ..., f_{vt} = D(z_1, ..., z_t)$$

$$Y_{vj} = \text{softmax}(W_s f_{vj} + b_s) \quad \forall j \in \{1, ..., t\}$$

$$\hat{Y} = Y_{vt}$$

The feature representations from the head network $f_{vj}$’s are then used to make predictions for the anticipated action $\hat{Y}_{vj}$ at time unit $j$. The anticipated action $\hat{Y}$ for the input video $X$ is simply the predicted label at time unit $t$ i.e. $\hat{Y}_{vt}$. During training the model is also supervised for two other auxiliary tasks namely future feature prediction and intermediate action prediction (see (Girdhar and Grauman, 2021) for details). We denote this combined training loss function as $L_{AVT}$.

For the teacher to student distillation, we want the AVT’s output distribution over action classes $\hat{Y}$ to match the teacher’s distribution $\hat{Y}_{t_{txt}}$. To this end, we minimize the KL divergence between the teacher prediction $\hat{Y}_{t_{txt}}$ and student predictions $\hat{Y}^\gamma$, after smoothing the distributions using a temperature parameter $\gamma$, following the standard distillation technique (Hinton et al., 2015).

$$L_S = L_{AVT} + \lambda_s \cdot D_{KL}(\hat{Y}_{t_{txt}}^\gamma \parallel \hat{Y}^\gamma) \quad (2)$$

4 Experimental Setup

4.1 Datasets

1. Anticipation Datasets  We evaluate the proposed method on two different datasets that are

| Dataset         | Segments | Classes | $\tau$ |
|-----------------|----------|---------|--------|
| Epic 55         | 28.6K + 9K | 2,513   | 1.0 sec|
| EGTEA-Gaze+     | 7.3K + 3K  | 106     | 0.5 sec|

Table 2: Datasets on which the proposed method is benchmarked. Segments indicate the number of action segments in the train + test set. Classes are the number of action classes in the dataset, $\tau$ is the fixed anticipation time.

summarised in Table. 2. Both the datasets, Epic-Kitchen 55 (Damen et al., 2018) and EGTEA-Gaze+ (Li et al., 2018), are egocentric (first-person) videos of people cooking some recipe. Note the proposed method is broadly applicable to other types of dataset as long as the input video segments in the training set contain action sequence annotations. For the Epic-Kitchen 55 dataset, we use the standard train-test split followed in (Furnari and Farinella, 2019). For the EGTEA-Gaze+ dataset, we report performance on the first of the three train-test splits following previous work by (Girdhar and Grauman, 2021).

2. Domain-Relevant Dataset  The teacher can be improved further by adapting its language model (LM) to domain relevant texts. To test the effectiveness of this, we use the Recipe1M dataset (Marin et al., 2019) to pre-train the LM. The Recipe1M dataset contains one million recipes along with associated images (which are not used in this work). The instructions in a recipe can be seen as a sequence of cooking actions to be performed.

4.2 Performance Metrics

For the EGTEA-Gaze+, we report the performance on top-1 accuracy (Acc@1) and class mean recall (Rec@1) as reported by (Girdhar and Grauman, 2021). For the Epic-Kitchen 55 dataset, there are a set of action classes that occur only in the train set but not in the test set and vice versa, and existing action anticipation methods, including our proposed work does not support zero-shot learning. Therefore top-5 many-shot class-mean recall ($MS$-$Rec@5$) as mentioned in (Furnari et al., 2018) is our primary metric of interest for model evaluation.

4.3 Implementation Details

1. Teacher Training:  The teacher model is a classification layer on top a pre-trained language model. For the main set of experiments we used ALBERT (Lan et al., 2019) as the base language
model. Our choice here is motivated by two main factors: (i) the pre-training task for ALBERT focuses on modeling the inter-sentence coherence which is important when modeling the sequence of disparate action phrases (ii) it enables faster training of deeper models which was important for the initial hyperparameter searching. For the EGTEA-GAZE+ dataset, we trained the model for 4 epochs by minimizing the weighted cross-entropy loss due to the high degree of class imbalance in the dataset (≈ 1 : 24). For the EPIC-Kitchen-55 dataset, the model was trained for 8 epochs using regular cross-entropy loss instead of weighted cross-entropy as a lot of classes in the test label space are not present in the train-set, and vice versa.

The classification head is a single linear layer ($W \cdot x + b$) that projects the feature representation of the input action sequence into the label space of the target dataset. For optimizing on both the datasets, we used the AdamW ([Loshchilov and Hutter, 2017]) optimizer, with a learning rate of $10^{-5}$ and weight decay of $10^{-7}$. The context window for the Epic-Kitchen was set to 5 action segments whereas for the EGTEA-GAZE+ it was set to 15 action segments. The teacher training was performed on two Nvidia RTX Titan-X GPUs. The teacher training for the EGTEA-GAZE+ takes about 2–4 hours depending on the LM base whereas the EPIC-Kitchen-55 takes about 3-5 hours to train.

2. Teacher Pre-training: We first parse each instruction in the Recipe1M dataset into a sequence event tuples of the form (subject, verb, object) using open information extraction system (Stanovsky et al., 2018) made available by AllenNLP (Gardner et al., 2018). To match the action label structure we see in the video datasets, we represent each instruction using the sequence of action, i.e. <verb, object> part of the event. The actions in the action sequence are sorted by the discourse order of their corresponding verb in the instruction. The language model is pretrained on these (verb, object) sequences using the standard masked language modeling objective (Devlin et al., 2019), where some token in the sequence is masked at random and the model is tasked with predicting the masked token.

For pre-training, the language models were trained on the Recipe1M dataset for 200K steps with a batch size of 16. The optimizer used was AdamW ([Loshchilov and Hutter, 2017]), with a learning rate of $10^{-5}$ and weight decay of $10^{-7}$. LM pre-training was performed on a single Nvidia A100 GPU with the training time varying from 12 hrs for the smallest model (DistilBERT) to 24 hrs for BERT, RoBERTa, and ALBERT.

3. Student Training: For the student training, all the hyperparameters and initial conditions (parameter initialization) are exactly identical to the ones used to train the AVT (Girdhar and Grauman, 2021) baseline model. So any change in the performance from the baseline is the result of adding the knowledge distillation. The distillation loss coefficient $\lambda_s$, for the EGTEA-GAZE+ dataset was set to 150, whereas for the EPIC-Kitchen 55 it was set to 20.

4. Top-K logit distillation: The label space of EPIC-Kitchen 55 has 2, 513 classes, out of which only 31% of the classes in the training data are present in the test data. This leads to the teacher model assign relatively low probability values to many classes, which may not be reliable signals for distillation. Therefore, instead of matching the probability distribution over all the action classes, we only match the relative probability distribution of the top-50 classes with the highest teacher probabilities. For this, we consider the classes corresponding to the top-50 logits from the teacher prediction, normalize them, and only minimized the KL-Divergence between them and their corresponding logits of the student prediction. The student training was performed on either Nvidia Tesla V100 GPU and the training time was ∼ 24 hrs for EGTEA-GAZE+ and ∼ 6 hrs for the EPIC-55 dataset.

5 Results and Analysis

We present the results of text to video knowledge distillation on the AVT (Girdhar and Grauman, 2021) model as the student. AVT is the state-of-the-art model for action anticipation on the EGTEA-GAZE+ and EPIC-Kitchen 55 datasets on all performance metrics.

For each of these datasets, we consider the AVT variants with the best performance as our baseline and student model. For the EGTEA-GAZE+ dataset, we consider AVT-h + AVT-b in (Girdhar and Grauman, 2021) as our baseline model. Similarly for the EPIC-Kitchen 55 dataset, we consider, AVT-h + irCSN152 in (Girdhar and Grauman, 2021) as our baseline model. Throughout this section, we refer to AVT-h + AVT-b and AVT-h + irCSN152 as
AVT-1 and AVT-2 respectively. The baseline models distilled with LM based teacher is denoted as AVT-1 (or 2) + LM Distillation and in case teacher LM is pre-trained on the recipe domain text, the resulting model is referred to as AVT-1 (or 2) + RcpLM Distillation. We tried to reproduce the AVT model to use as our student and obtain stronger results than the published version (see Table 3), on all but one metric. We use this stronger implementation as our baseline and our student model.

5.1 Does Knowledge distillation from Language Models help?

Table 3 shows the result of training the state-of-the-art baseline model, with and without the text to vision knowledge distillation, for the EGTEA-GAZE+ and EPIC-Kitchen 55 dataset. We can observe that applying text to vision knowledge distillation to the AVT-1 leads to performance gains on both the datasets. For EGTEA-GAZE+ dataset, adding knowledge distillation leads to 2.1% and 2% relative percentage improvement over AVT-1 on the Acc@1 and Rec@1 metrics respectively. For the EPIC-Kitchen 55 dataset, adding knowledge distillation leads to a relative performance gain of 3.5% over AVT-2 on MS-Rec@5 metric.

5.2 Does domain-adaptive pre-training of teacher improves the task performance?

To analyze the effect domain adaptive pre-training on the task, we pre-train the teacher LM on the Recipe1M dataset through the MLM task. The pre-trained model was then finetuned on the task-specific video dataset for the anticipation task. As seen in Table 3, the performance gain of the teacher directly translates to the performance gain of the student. For EGTEA-GAZE+ dataset, pretraining teacher leads to 3.9% and 3.4% relative improvement over the AVT-1 on Acc@1 and Rec@1 metric compared to 2.1% and 2% relative improvement when not pretraining the teacher. For the EPIC-Kitchen 55 dataset, teacher pre-training leads to a relative improvement of 7.2% on MS-Rec@5 metric compared to only 3.5% when not pre-training the teacher.

5.3 How sensitive is the distillation to the choice of Language Model?

In order to analyze the sensitivity of the distillation scheme towards the choice of the language model, we also trained multiple teachers with different pre-trained LMs. The result of using different teachers for the anticipation task is specified in Table 4. From the table, we can observe that all the teacher distilled models perform better than the baseline on all the metrics for both the datasets. This indicates that the text modality has some information that complementary to the vision modality that if properly exploited can lead to improved performance for the anticipation task.
5.4 Should the teacher be always better than the student?

To understand the impact of the quality of the teachers, we measured the performance of the teacher models by themselves on the anticipation task as shown in Table 5. For the EPIC-Kitchen 55 dataset, the teacher performance is much better than the video-only baseline, whereas, for the EGTEA-GAZE+ dataset, the baseline vision model’s performance is much better than any of the teachers. Despite this, the performance gain due to distillation is greater for the EGTEA-GAZE+ dataset compared to the EPIC-Kitchen 55 dataset, as seen in Table 3. This suggests that what matters more for distillation in this case is the complementary information gained from the text modality that is not already present in the vision modality.

| Model                     | EGTEA-GAZE+ | EPIC-55  |
|---------------------------|-------------|----------|
|                           | Acc@1       | Rec@1    | MS-Rec@5 |
| AVT (Girdhar and Grauman, 2021) | 43.52       | 34.87    | 15.25    |
| Rcp-ALBERT Teacher        | 21.66       | 22.63    | 21.78    |
| Rcp-BERT Teacher          | 22.05       | 23.39    | 21.43    |
| Rcp-RoBERTa Teacher       | 19.98       | 21.58    | 22.41    |
| Rcp-ELECTRA Teacher       | 21.46       | 23.71    | 15.19    |
| Rcp-DistillBERT Teacher   | 21.86       | 22.58    | 21.56    |

Table 5: Analyzing the teacher performance on the anticipation task. For the EGTEA-GAZE+ dataset, the teacher performance is much lower than the video only AVT model, whereas, for the EPIC-Kitchen 55 dataset, the teacher performance is much better than the video-only baseline model. AVT variants used for the EGTEA-GAZE+ and EPIC-Kitchen 55 baselines are AVT-1 and AVT-2, respectively.

6 Conclusions

Action anticipation is a challenging problem that requires training large capacity video models. In this work, we showed how the textual modality of the input videos, which is often ignored in training, can be leveraged to improve the performance of the video models. In particular, we can exploit the large scale knowledge acquired by pre-trained language models to build a text-modality teacher that can provide useful complementary information about the action sequences to a vision modality student. This cross-modal distillation strategy yields consistent gains achieving new state-of-the-art results on multiple datasets. Last, the gap between the performance of the teacher and the student models for domains with large label space suggests that there is still room for improvement with better distillation techniques.
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