A SOUND APPROACH: USING LARGE LANGUAGE MODELS TO GENERATE AUDIO DESCRIPTIONS FOR EGOCENTRIC TEXT-AUDIO RETRIEVAL

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ABSTRACT

Video databases from the internet are a valuable source of text-audio retrieval datasets. However, given that sound and vision streams represent different "views" of the data, treating visual descriptions as audio descriptions is far from optimal. Even if audio class labels are present, they commonly are not very detailed, making them unsuited for text-audio retrieval. To exploit relevant audio information from video-text datasets, we introduce a methodology for generating audiocentric descriptions using Large Language Models (LLMs). In this work, we consider the egocentric video setting and propose three new text-audio retrieval benchmarks based on the EpicMIR and EgoMCQ tasks, and on the EpicSounds dataset. Our approach for obtaining audio-centric descriptions gives significantly higher zero-shot performance than using the original visual-centric descriptions. Furthermore, we show that using the same prompts, we can successfully employ LLMs to improve the retrieval on EpicSounds, compared to using the original audio class labels of the dataset. Finally, we confirm that LLMs can be used to determine the difficulty of identifying the action associated with a sound.

Index Terms— text-audio retrieval, large language models, generated audio descriptions, egocentric data

1. INTRODUCTION

Searching the ever-expanding supply of audio and video media hosted online has become a key technical challenge. Concurrently, LLMs have become more powerful, exhibiting early signs of commonsense reasoning and primitive world modelling [2]. Given their extensive text-based knowledge about the sensory world, in this work we ask whether LLMs can improve search capabilities for other modalities such as audio and video. In particular, we consider the task of egocentric audio retrieval from text queries.

Our strategy is to employ text as an intermediate medium for aligning vision and audio signals by leveraging the textbased knowledge that an LLM possesses about sight and sound. Concretely, we use LLMs to generate plausible *audio* descriptions for videos when given their *visual* descriptions. To do so, we leverage the LLM's in-context learning capability, and provide it with exemplars of the desired mapping – pairs of visual-centric and corresponding audiocentric descriptions. This few-shot shot approach is made possible by the existence of a small collection of content that has been annotated with both visual-centric and audiocentric descriptions. In this work, we source these pairs from overlapping samples between the Kinetics700-2020 [3] and AudioCaps [4] datasets (we refer to these examples as Kinetics \cap AudioCaps). Fig. 1 shows examples of few-shot generated audio descriptions produced with our approach.

With this "converter" in hand, we scale its application to the conversion of full text-video datasets to text-audio datasets. Specifically, we construct two text-audio datasets derived from egocentric video retrieval tasks sourced from EpicKitchens [5] and Ego4D [6], and demonstrate the value of this data empirically. We additionally apply a similar methodology to the *audio class labels* of EpicSounds to improve retrieval results. We also demonstrate that LLMs can usefully predict when the action within a video can be reliably determined solely from its audio track, with applications for curating new text-audio datasets.

2. RELATED WORK

Text-audio retrieval and LLMs. Text-audio retrieval entails searching for the most appropriate audio file for a given textual query. This task was popularised by [7, 8] (though related themes were studied previously [9]), and has seen recent improvements through the use of transformer-based models [10]. In adjacent fields, there has been a surge of efforts that harness LLMs, e.g. GPT-4 [11], Vicuna [12], and Llama [13, 2], for multimodal tasks that require visionlanguage [14, 15, 16, 17] and audio-language understanding [18]. [17] and [16] demonstrate the benefits of using LLM-generated textual class descriptions for zero-shot image classification and open-vocabulary object detection respectively. More closely related to our approach, [18] employ ChatGPT [1] for standardizing audio descriptions across various audio-centric datasets. These refined text-audio pairs are

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Acknowledgements. This work is supported by the EPSRC (VisualAI EP/T028572/1 and DTA Studentship), the Royal Academy of Engineering (RF\201819\18\163), an Isaac Newton Trust Grant and the DFG - EXC 2064/1 - project 390727645. We are grateful to Jaesung Huh, Triantafyllos Afouras and Bernie Huang for their helpful comments and suggestions.

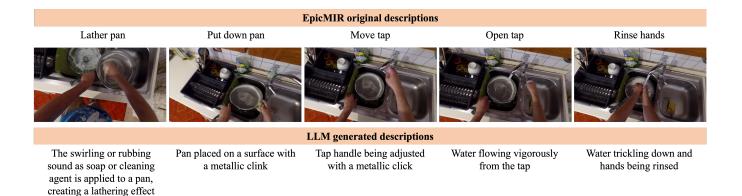


Fig. 1. Frames from the EpicKitchens dataset together with the corresponding original visual descriptions from EpicMIR shown above and those generated with our approach (using the ChatGPT LLM [1]) below.

then used to pretrain text-audio models. In contrast to prior work which focuses predominantly on audio-centric datasets (as characterized by the availability of audio descriptions or labels), we focus on leveraging datasets that generally possess only visual-centric descriptions.

Egocentric audio-visual understanding. While most video datasets are captured from a third-person perspective, recent research has shifted towards egocentric data, filmed from a first-person viewpoint. The egocentric datasets, EpicK-itchens [5] and Ego4D [6], have been used for various tasks, such as action recognition [19, 20], moment localization and video retrieval [21, 22, 23, 24] with a focus on the video stream. We, however, focus specifically on their audio tracks.

In a similar vein to [25], we analyse how to best exploit the audio information in the egocentric video setting. Also related, recent work introduced EpicSounds [26], an audio classification benchmark on the EpicKitchens [5] dataset. In contrast to these approaches, we consider the retrieval task rather than classification and employ LLMs to automatically generate additional audio descriptions for text-audio retrieval.

3. DATASETS AND APPROACH

We first summarise existing relevant datasets in Sec. 3.1. Next, we detail our proposed method for employing Large Language Models (LLMs) in two key areas: firstly, to bridge the gap between visual and audio descriptions; and secondly, to create audio descriptions from audio labels. This approach is aimed at improving text-audio retrieval in egocentric datasets, as discussed in Sec. 3.2. We introduce our AudioEpicMIR, AudioEgoMCQ and EpicSoundsRet benchmarks in Sec. 3.3. Lastly, we present our method for evaluating the level of informativeness of audio samples in Sec. 3.4.

3.1. Datasets and tasks

EpicKitchens [5] & EpicMIR [27]. EpicKitchens contains 100 hours of recordings filmed from first-person perspective. The Multi-Instance Action Retrieval (EpicMIR) [27] task based on EpicKitchens consists of finding the most relevant

video given a text query, and vice-versa. The test set contains 9,668 videos and corresponding visual descriptions in the form verb/s + noun/s. The average number of words per sentence is 2.93 with standard deviation 1.17.

Ego4D [6] & EgoMCQ [21]. Ego4D is the largest egocentric dataset with over 3,670 video hours and accompanying narrations. The EgoMCQ [21] task based on Ego4D consists of 39,751 pairs containing one description and 5 video clips each. It aims at finding the correct clip for a given description. EpicSounds [26] is sourced from the EpicKitchens dataset. It contains only those audio tracks that are useful for the audio classification task as verified through manual annotations. 44 different classes are labelled for 10,276 test audio chunks.

Kinetics700-2020 [3] contains 10s clips from YouTube and corresponding activity labels which are in the form verb/s + noun/s. The average word count is 2.09 with a standard deviation of 0.79.

AudioCaps [4] is curated from YouTube and contains 10s audio files and text descriptions. It serves as a common benchmark dataset for audio captioning and text-audio retrieval.

3.2. Audio description generation methodology

As noted in Sec. 1, we find that there are a number of clips in common between Kinetics700-2020 [3] and AudioCaps [4] (283 in total). We use example correspondences to condition the LLM to generate audio descriptions in the style of AudioCaps given access to visual verb-noun descriptions. This approach is shown in Fig. 2, where we first give a general task description, together with heuristic constraints that were obtained by manual experimentation on a handful of samples (a form of "prompt engineering").

We combine these instructions with few-shot paired examples of visual descriptions and audio descriptions sampled from Kinetics \cap AudioCaps. In particular, we select 14 pairs to balance sufficient examples while preserving the model's focus on the task prompt (step 2). Finally, we provide the LLM with the visual descriptions or audio labels for which we want to generate new audio descriptions (step 3). We developed this approach by experimenting with samples from

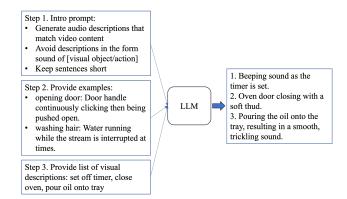


Fig. 2. Given visual-centric descriptions, we propose to use an LLM (ChatGPT) to generate audio descriptions (*step 3*). The LLM is prompted with a task description (*step 1*) and few-shot paired examples of visual-centric and audio descriptions (*step 2*).

EpicMIR, and apply the same strategy directly to EgoMCQ and EpicSounds in Sec. 4.

3.3. Our proposed text-audio retrieval benchmarks

We apply our approach for generating audio descriptions to EpicMIR, EgoMCQ, and EpicSounds. As a result, we obtain three new benchmarks, namely AudioEpicMIR, AudioMCQ, and EpicSoundsRet. We refer to the original visual descriptions/audio class labels for all benchmark datasets as *Aud orig* and to our LLM-generated descriptions as *Aud LLM*.

AudioEpicMIR is curated from the EpicMIR task by extracting the audio tracks of the EpicMIR videos and keeping their original visual descriptions. Additionally, we generate audiocentric descriptions using ChatGPT (GPT-3.5) [1] as the LLM in our methodology, as described in Sec. 3.2.

AudioEgoMCQ is gathered based on the EgoMCQ task. We observe that in this dataset, some of the videos do not have an audio soundtrack at all. Therefore, to generate a text-audio dataset, we need to exclude some of the original text-video pairs. Specifically, for the **intra-video** task, we excluded all text-video pairs when the video corresponding to the text query did not contain sound. For **inter-video**, we additionally replaced clips without audio from the pairs by clips with audio. Finally, we exclude text-video pairs if any of the five videos have a silent soundtrack. This results in 23,121 text-audios pairs. The remaining original visual descriptions contain an average of 8.15 words (with a standard deviation of 3.01). We use our audio description generation approach described in Sec. 3.2 to obtain audio-centric descriptions. As before, we use ChatGPT (GPT-3.5) [1] as the LLM.

EpicSoundsRet differs from EpicMIR and EgoMCQ in that it originally contains *audio class labels*, not *visual descriptions*. For the retrieval task we use the audio class labels as text queries together with the corresponding audio files. We use our LLM prompts out of the box to generate *audio descriptions* for EpicSounds starting from the *audio labels*.

3.4. Determining the audio relevancy using LLMs

We observe that many video clips contain audio that is too noisy or generic to inform the text-audio retrieval process. An example is 'taking clothes from basket' or 'putting clothes in basket' which both have similar associated sounds that are hard to differentiate. This prompts the question, can we identify such audio by looking only at the given visual description? To explore this, we tasked GPT-4 with splitting the original visual text descriptions into three categories according to the relevancy of the sound:

- High: audio is very informative for the visual task, e.g. 'turning on tap', 'washing dishes'.
- Moderate: audio is informative but not enough information is provided in the text description for it to be identifiable, e.g. 'putting a plate down' has a different sound based on if it is placed on a kitchen table or a sofa.
- Low: audio is not likely to be informative, e.g. 'get carrot'.

4. EXPERIMENTS

Evaluation metrics. On AudioEpicMIR and EpicSoundsRet, we report Mean Average Precision (mAP) and normalised Discounted Cumulative Gain (nDCG) [28] following [27]. nDCG measures the relevance of text descriptions in response to a video query by positively acknowledging semantically analogous descriptions in addition to the correct pair. For AudioEgoMCQ, we report the Retrieval@1 score, similar to [21]. We consider the following two tasks. For the more challenging **intra-video** task we are given a text query and aim to find the corresponding clip out of 5 clips selected from the same video. In contrast, the **inter-video** task uses a pool of 5 clips, each selected from a different video.

Models. We use two recent text-audio retrieval models, namely LAION-Clap [10, 29] and WavCaps [18]. Both models were trained and/or finetuned on the audio-centric Audio-Caps [4] and Clotho [30] datasets. We use these models to assess zero-shot egocentric text-audio retrieval capabilities, i.e. without any training on egocentric data.

Zero-shot egocentric text-audio retrieval. We evaluate the audio-centric pre-trained LAION-Clap and WavCaps models directly on the egocentric text-audio retrieval datasets (zeroshot setting) and provide the results on AudioEpicMIR in Tab. 1. We observe that the LLM-generated audio descriptions yield a consistent boost. We hypothesize that this improvement stems both from aligning the style of descriptions more closely with the training distribution for the models and from the inclusion of more audio-centric content. We additionally report results for AudioEgoMCQ in Tab. 2 and Epic-SoundsRet in Tab. 3. For AudioEgoMCQ, we observe that for the intra-video task, using LLM descriptions provides consistent improvements over using the original labels. For the inter-video task we observe that the WavCaps model finetuned on Clotho yields a small decrease in performance as compared to using the original labels. We attribute the varia-

Table 1.Zero-shot text-audio retrieval on AudioEpicMIRwith LLM-generated audio descriptions compared to usingvisual descriptions.WavCaps-AC and WavCaps-Cl were fine-tuned on AudioCaps and Clotho respectively.

| Pre-trained audio model | LLM-generated audio descriptions | 1 | mAP(%) | | | DCG(% |) |
|-------------------------|----------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| | | A->T | T->A | AVG | A->T | T->A | AVG |
| Random | | 5.6 | 6.4 | 6.0 | 10.7 | 12.3 | 11.5 |
| LAION-Clap | \checkmark | 8.9 | 8.4 | 8.6 | 15.3 | 17.0 | 16.2 |
| LAION-Clap | | 10.0 | 9.3 | 9.6 | 17.2 | 18.2 | 17.7 |
| WavCaps-AC | \checkmark | 10.3 | 9.0 | 9.7 | 17.5 | 17.5 | 17.5 |
| WavCaps-AC | | 11.2 | 10.4 | 10.8 | 18.9 | 20.0 | 19.4 |
| WavCaps-Cl | \checkmark | 10.9 | 9.5 | 10.2 | 18.3 | 18.2 | 18.2 |
| WavCaps-Cl | | 11.5 | 10.4 | 10.9 | 19.2 | 20.2 | 19.7 |

 Table 2.
 Zero-shot text-audio retrieval results on AudioE-goMCQ with LLM-generated audio descriptions compared to using visual descriptions. The data is filtered as per Sec. 3.3.

| Pre-trained audio model | LLM-generated audio descriptions | Intra-video(%) | Inter-video(%) |
|-------------------------|----------------------------------|----------------|----------------|
| Random | | 20.0 | 20.0 |
| LAION-Clap | \checkmark | 24.2 | 27.5 |
| LAION-Clap | | 25.2 | 28.9 |
| WavCaps-AC | \checkmark | 24.1 | 30.9 |
| WavCaps-AC | | 25.1 | 31.1 |
| WavCaps-Cl | \checkmark | 24.6 | 32.1 |
| WavCaps-Cl | | 25.6 | <u>31.8</u> |

tion in task performance to the differing text queries and the more visual-centric nature of Clotho descriptions compared to AudioCaps. For EpicSoundsRet, using LLM descriptions gives a significant improvement over using the original audio class labels in most cases.

Evaluating text-audio retrieval on subsets with different audio relevancy. We employ GPT-4 to split the audio tracks in AudioEpicMIR into three subsets as described in Sec. 3.4. The subsets are selected by the LLM based on how difficult it is to identify the audio content solely from the sound. We compare the performance of different models to a random baseline on these newly created subsets in Tab. 4. The random baseline has been obtained by providing randomly sampled text descriptions as the 'correct' descriptions for a given au-

 Table 3.
 Zero-shot text-audio retrieval on EpicSoundsRet

 with LLM-generated audio descriptions compared to using
 audio class labels

| Pre-trained audio model | LLM-generated audio descriptions | mAP(%) | | | nDCG(%) | | |
|-------------------------|-------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| | | A->T | T->A | AVG | A->T | T->A | AVG |
| Random | | 8.7 | 2.8 | 5.7 | 1.8 | 1.9 | 1.9 |
| WavCaps-Cl | \checkmark | 24.3 | 12.0 | 18.1 | 11.0 | 13.6 | 12.3 |
| WavCaps-Cl | | 30.2 | 11.3 | 20.8 | 14.8 | 13.7 | 14.3 |
| LAION-Clap | \checkmark | 28.5 | 8.2 | 18.3 | 16.1 | 9.5 | 12.8 |
| LAION-Clap | | 29.9 | 11.7 | 20.8 | 16.3 | 14.3 | 15.3 |
| WavCaps-AC | \checkmark | 24.3 | 11.9 | 18.2 | 12.4 | 13.8 | 13.1 |
| WavCaps-AC | | 31.2 | 11.9 | 21.5 | 16.9 | 14.3 | 15.6 |

Table 4. Zero-shot text-audio retrieval on different subsets of AudioEpicMIR, split according to the informativeness of audio files as judged by GPT-4. LLM-generated audio descriptions give the best results across all subsets (Aud LLM), compared to using the original visual descriptions (Aud orig). WavCaps-Cl performs best when the audio files are considered to be highly informative.

| AudioEpicMIR subset | Descriptions | | mAP(%) | nDCG(%) | | |
|-------------------------|--------------|------|-------------------------|---------|-------------------------|--|
| ridalo2preisiire saosee | Desemptions | AVG | δ to rand. perf. | AVG | δ to rand. perf. | |
| | Random perf. | 12.8 | - | 24.4 | - | |
| Low | Aud orig | 15.5 | 2.7 | 28.2 | 3.8 | |
| | Aud LLM | 15.6 | 2.8 | 27.9 | 3.5 | |
| | Random perf. | 7.2 | - | 13.0 | - | |
| Moderate | Aud orig | 11.5 | 4.3 | 19.1 | 6.1 | |
| | Aud LLM | 12.4 | 5.2 | 20.2 | 7.2 | |
| | Random perf. | 5.7 | - | 9.7 | - | |
| High | Aud orig | 14.0 | 8.3 | 21.0 | 11.3 | |
| | Aud LLM | 15.2 | 9.5 | 23.7 | 14.0 | |

Table 5. Zero-shot text-audio retrieval on different subsets of AudioEgoMCQ, split according to the informativeness of audio files as judged by GPT-4. WavCaps-Cl performs best for highly informative audio files. Random values for both tasks are 20.0.

| AudioEgoMCQ subset | Descriptions | Intra-video(%) | Inter-video(%) |
|--------------------|--------------|----------------|----------------|
| Low | Aud orig | 21.7 | 28.2 |
| | Aud LLM | 22.6 | 26.9 |
| Moderate | Aud orig | 25.0 | 32.7 |
| | Aud LLM | 26.8 | 34.2 |
| High | Aud orig | 30.3 | 39.0 |
| | Aud LLM | 30.8 | 39.1 |

dio. The audio retrieval model employed is WavCaps-Cl. We observe that for the subset deemed to have 'low' audio relevance, the random performance more than doubles in comparison to the random evaluation on the full test set. This is a result of the subset's pool of text descriptions being fairly repetitive. Hence, to ensure a more equitable comparison of model performance across the subsets, we consider the incremental improvement of each model from its initial random metrics (δ to rand. perf.). The accuracy increases as we go from the 'low' to the 'high' subset. At the same time, the incremental improvement over the random performance is most significant for the 'high' subset. We perform the same experiment on the AudioEgoMCQ subsets and observe that GPT-4 is indeed capable of selecting videos for which the audio is more likely to have informative content (Tab. 5).

5. CONCLUSION

In this study, we introduced three new benchmarks for egocentric text-audio retrieval. We proposed a methodology of generating audio descriptions using an LLM starting from visual-centric descriptions and audio class labels. Lastly, we have shown that we can use guidance from an LLM to filter out noisy audio content extracted from video datasets. We believe these contributions can apply beyond the egocentric setting and hope they will improve text-audio understanding.

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A. SUPPLEMENTARY MATERIAL: A SOUND APPROACH: USING LARGE LANGUAGE MODELS TO GENERATE AUDIO DESCRIPTIONS FOR EGOCENTRIC TEXT-AUDIO RETRIEVAL

In this supplementary material, we will provide further experimental results and details regarding the pre-trained models that we used. In Sec. A.1, we present additional information and analysis of the EpicSoundsRet benchmark based on the EpicSounds [26] dataset. For completeness, we include the prompts for generating audio descriptions in Sec. A.2. In Sec. A.3, we evaluate the impact of additionally using the audio modality for the text-video retrieval task. We provide more insight into the differences between the Clotho and AudioCaps finetuned checkpoints used in our work in Sec. A.4. In Sec. A.5 we briefly expand on the results obtained on the AudioEgoMCQ task whilst in Sec. A.6 we provide more experiments on the AudioEgoMCO benchmark. Lastly, we compare the relative performance differences of the models used for the experiments in the paper on multiple benchmarks in Sec. A.7.

A.1. EpicSounds

In our experiments with the AudioEpicMIR and AudioEgoMCQ benchmarks, we generated *audio descriptions* using LLMs starting from *visual* class labels. For EpicSounds, we have access to *audio* class labels. As a result, our prompts are *not* necessarily optimal when using *audio* class labels as inputs. Nevertheless, despite being created from a set of prompts that might not be ideal, the *audio descriptions* still perform better in the retrieval task compared to the original audio labels as can be seen in Tab. 3 in the main paper.

The WavCaps model finetuned on Clotho performs slightly worse on the text-audio task when using LLM-generated descriptions on EpicSounds than when using the original audio labels. However, we do not see this behaviour when using models finetuned on AudioCaps. This discrepancy likely arises because Clotho descriptions often include substantial visual details in addition to audio content, leading to a significant style difference in our audio-focused descriptions. However, regardless of the model used, LLM-generated descriptions overall yield better results than using class labels, particularly in the audio-to-text retrieval direction.

We employed the same retrieval metrics for AudioEpicMIR and EpicSoundsRet. This required constructing a relevancy matrix (more information on this is available here [31, 27]). This relevancy matrix takes into account that for one given description, multiple audio files can be equally relevant. On AudioEpicMIR, the relevancy matrix would look at all unique text descriptions, and depending on how many nouns and verbs the other descriptions would have in common, it would assign values between 0 and 1 to these similar descriptions. For EpicSoundsRet we start with audio class labels as 'descriptions' and assign a score of 1 to all audios and text descriptions where the text description belongs to the same class. We use the same relevancy matrix to calculate the retrieval scores for the *Aud orig* and *Aud LLM* descriptions. This also applies to AudioEpicMIR.

A.2. Prompts

We use LLMs, specifically GPT3.5, to generate audio descriptions starting from visual class labels. Tab. 6 shows the prompts we used.

Furthermore, we used GPT4 to decide the difficulty of identifying the action associated with a sound. The prompt we used for that is provided in Tab. 7.

A.3. Multimodal text-video retrieval

In this section, we show that text-video retrieval benefits from jointly using the audio and visual modalities. We report textvideo retrieval results on the EpicMIR task in Tab. 8. The joint multimodal evaluation is carried out via late fusion of the outputs of the text-audio and text-video retrieval models. Boosts in performance for the multimodal evaluation compared to the unimodal models (i.e. audio only and visual only) are observed both when using the original descriptions (Joint w. Aud orig) and when using the original descriptions for the visual model together with the LLM-generated ones for the audio model (Joint w. Aud LLM).

Additionally, we investigate how text-video retrieval performs on the same audio relevancy subsets investigated in Tab. 4. Results are provided in Tab. 9 and follow a similar trend as for the audio only experiments. More specifically, the multimodal text-video retrieval performs best on the 'high' subset. We also notice that text-video retrieval when only using the visual modality also exhibits stronger performance on subsets with higher audio relevancy. We hypothesise that this is because the more audio significant actions tend to also be more common, or easier to identify for visual models.

For the text-video retrieval experiments, we used the EgoVLP [21] codebase. More precisely, we take the provided pre-trained EgoVLP [32] model and evaluate it in a zero-shot fashion. This model processes the clips by randomly selecting a number of frames. We set the number of frames to 16 in our experiments. Additionally, we do not use the dual_softmax evaluation approach used in the codebase [32] but instead leverage the standard similarity matrix at evaluation time. This is consistent with how the underlying EgoVLP model was trained [32].

A.4. Leveraging models finetuned on Clotho for tasks with original visual descriptions

The Clotho [30] dataset was collected by providing annotators with audio files and asking them to generate descriptions of the audio sound. However, by looking at descriptions, we **Table 6**. Overview of the methodology for bridging the gap between visual classes/descriptions and video soundtrack descriptions using LLMs. The process includes setting the scene, few-shot prompting with examples, and generating audio descriptions from video descriptions.

| Index | Prompts |
|-------|--|
| 1. | You are an expert in audio and visual description of videos. You have seen the AudioCaps and Clotho datasets and know how to generate relevant audio descriptions using simple terms. You will help me generate audio descriptions that can match the audio content of a video for which the video description is provided. Avoid the use of object or actions that cannot be inferred from the audio signal alone. Try to create proper short sentences when generating the audio descriptions. When multiple audio descriptions can be possible, provide one that best generalises the sounds.Try to avoid generating audio descriptions in the form of 'sound of [visual object/action]' and instead use the actual noise or sound that object/action can make. If unsure, you can provide multiple possible sounds. To help you understand the sort of descriptions I am looking for, in the next prompt I will provide you a few pairs of video descriptions and the corresponding audio descriptions. Then I will ask you to generate audio descriptions given new video descriptions. |
| 2. | Here are some examples in the form of (video description: audio description) and examples are separated by semicolon. ('burping', 'A man giving out a loud burp');('sneezing', 'Someone sneezes');('washing dishes', 'Metal clinking and clanging occur');('washing dishes', 'Water splashing and glasses clanging to- gether then more clanging ending with glass squeaking sound');('opening door', 'Door handle continuously clicking then being pushed open');('spray painting', 'Powerful bursts of spraying');('crying', 'A baby cries and screams');('opening door', 'Hissing then creaking as a door is opened');('applauding', 'A large num- ber of people clap, cheer, and shout');('closing door', 'Metal clings followed by rumbling and metal slid- ing');('whistling', 'A person is whistling a tune');('shearing sheep', 'Sheep bleat quietly');('washing hair', 'Water running while the stream is interrupted at times');('sawing wood', 'Rubbing and sawing of wood'). I want you to learn from them and not generate descriptions for this prompt. |
| 3. | Generate an audio description for each of the following enumerated video descriptions separated by semi- colon. Try to avoid generating audio descriptions in the form of 'sound of [visual object/action]' and instead use the actual noise or sound that object/action can make. If unsure, you can provide multiple possible sounds. Remember the original prompt. Provide your answers in the form [description index. video description: gen- erated audio description]. |

<Add the list of visual labels separated by ; here>

Table 7. Prompts used for employing LLMs in assessing the likelihood of identifying video actions solely through audio tracks.

| Index | Prompts |
|-------|---|
| 1. | You have a lot of experience with video and audio descriptions. You are working with videos that have an associate audio file. You only have descriptions of the visual content. Some videos are highly correlated with the audio content, such as those depicting someone cutting vegetables. Other videos have very generic audios and if only given the audio content, the video content might not be easy to figure out. I want you to tell me if a video description is relevant for the possible associated audio content. I want you to provide your answers in the form of a dictionary where the key is the description I am giving you and the value is the relevance. Relevance should be high if the sound associated is easy to assume. Relevance should be moderate if the associated sounds can be more than one. Relevance should be low if it's unlikely to hear any specific sounds. Process each entry individually. Input descriptions will be given in the form of a list. Do not provide additional comments, just the relevance. |

Table 8. Zero-shot capabilities of text-audio (audio only) and text-video (video only) retrieval models compared to the joint evaluation with late fusion on EpicMIR. * Numbers are obtained using the text-video retrieval model from [21].

| EpicMIR | mAP(%) | | | nDCG(%) | | |
|------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Epiciant | A->T | T->A | AVG | A->T | T->A | AVG |
| Random [21] | 5.7 | 5.6 | 5.7 | 10.8 | 10.9 | 10.9 |
| Audio only (WavCaps-Cl w. Aud LLM) | 11.5 | 10.5 | 11.0 | 19.2 | 20.3 | 19.7 |
| Video only (EgoVLP*) | 24.7 | 18.4 | 21.6 | 27.4 | 24.6 | 26.0 |
| Joint w. Aud orig | <u>25.4</u> | <u>19.3</u> | <u>22.4</u> | <u>28.7</u> | <u>26.0</u> | <u>27.3</u> |
| Joint w. Aud LLM | 25.8 | 19.9 | 22.8 | 29.1 | 26.9 | 28.0 |

Table 9. Zero-shot multimodal text-video retrieval on different subsets of AudioEpicMIR, split according to the informativeness of audio files as judged by GPT-4. LLM-generated audio descriptions give the best results across all subsets (Aud LLM), compared to using the original visual descriptions (Aud orig). The joint model performs best when the audio files are considered to be highly informative.

| AudioEpicMIR subset | Descriptions | | mAP(%) | nDCG(%) | | |
|---------------------|-------------------|------|-------------------------|---------|-------------------------|--|
| r | | AVG | δ to rand. perf. | AVG | δ to rand. perf. | |
| | Random perf. vid. | 12.5 | - | 23.4 | - | |
| Low | Vid orig | 23.3 | 10.8 | 30.8 | 7.4 | |
| LOW | Aud orig | 23.7 | 11.2 | 32.1 | 8.7 | |
| | Aud LLM | 23.4 | 10.9 | 32.1 | 8.7 | |
| | Random perf. vid. | 7.2 | - | 12.2 | - | |
| Moderate | Vid orig | 27.3 | 20.1 | 28.0 | 15.8 | |
| Moderate | Aud orig | 27.7 | 20.5 | 29.1 | 16.9 | |
| | Aud LLM | 28.5 | 21.3 | 29.7 | 17.5 | |
| | Random perf. vid. | 5.8 | - | 9.1 | - | |
| TE-L | Vid orig | 32.9 | 27.1 | 36.0 | 26.9 | |
| High | Aud orig | 33.6 | 27.8 | 37.1 | 28.0 | |
| | Aud LLM | 34.6 | 28.8 | 38.3 | 29.2 | |

observe that the annotators tended to provide plausible visual descriptions of the sounds rather than describe the actual sound. Some examples are "A group is in a carriage that is being drawn by a horse on a paved road." or "A man moves from the basement to upstairs, moving a heavy metal object with him.". Such visual details cannot be inferred just by listening to an audio. Therefore, this dataset matches better our setting of generating audio descriptions starting from visual descriptions since, when no obvious audio description can be generated, the output description often contains a reworded version of the provided visual input. In contrast, AudioCaps descriptions are shorter and more audio focused e.g. "Speech in the distance with a bleating sheep nearby." or "Food and oil sizzling followed by a woman speaking.". Furthermore, the WavCaps model has been finetuned on the Clotho data, which contains 25 times fewer training examples than Audio-Caps. This could mean that the model finetuned on Clotho retains more generality which can be useful in settings with new audio content that the LLM might generate.

A.5. Intra-video vs inter-video results

When using the WavCaps-Cl model, we notice in Tab. 2 that the inter-video task performs slightly better when using orig-

Table 10. Zero-shot text-audio retrieval on different subsets of AudioEgoMCQ, split according to the informativeness of audio files as judged by GPT-4. WavCaps-AC performs best for highly informative audio files. Random values for both tasks are 20.0.

| AudioEgoMCQ subset | Descriptions | Intra-video(%) | Inter-video(%) |
|--------------------|--------------|----------------|----------------|
| Low | Aud orig | 21.0 | 27.0 |
| | Aud LLM | 22.4 | 26.9 |
| Moderate | Aud orig | 26.2 | 32.7 |
| | Aud LLM | 26.6 | 33.2 |
| High | Aud orig | 28.7 | 37.0 |
| | Aud LLM | 29.1 | 37.4 |

inal descriptions compared to using the LLM-generated ones. Based on our analysis, we believe that this is due to the different distribution of text queries between the two tasks (i.e. intra-video and inter-video).

A.6. Evaluation on different subsets of AudioEgoMCQ according to informativeness

We additionally evaluate the WavCaps model finetuned on AudioCaps on the *low*, *moderate*, and *high* subsets of AudioEgoMCQ in Tab. 10. We notice that when using this checkpoint, the inter-video LLM performance is higher on the *moderate* and *high* and just a bit lower on the *low* subset. This is in accordance with results in Tab. 5 where the checkpoint used was finetuned on Clotho. However, when using the AudioCaps finetuned model with LLM descriptions, the decrease on the *low* subset is much lower than when using the Clotho finetuned model. We believe that this is related to Clotho being more visual based as described in A.4. As a result, when using AudioCaps finetuned models, the overall retrieval performance is better for the LLM descriptions than when using Clotho based models.

A.7. Why does WavCaps-Cl give better results on AudioEpicMIR and AudioEgoMCQ whilst the WavCaps-AC model is better on EpicSoundsRet?

We found that the WavCaps model, when finetuned with AudioCaps, performs best for EpicSounds. In contrast, for the other two datasets, the top-performing model is Wav-Caps finetuned on Clotho. This variation in performance is linked to the nature of the input labels provided to the LLM. Specifically, EpicSounds uses only audio inputs, while AudioEpicMIR and AudioEgoMCQ rely solely on visual inputs. LLMs tend to merge the visual and audio information in the same sentence, especially when the input leans more towards visual content. As AudioCaps descriptions primarily focus on audio, whereas Clotho provides a balanced mix of both audio and visual details. Tasks that are more audio-centric benefit significantly from models finetuned on AudioCaps. Conversely, tasks with a visual emphasis favour models finetuned on Clotho, due to their original labels being more visual-centric.