Cross-Modal Discrete Representation Learning

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Abstract

Recent advances in representation learning have demonstrated an ability to represent information from different modalities such as video, text, and audio in a single high-level embedding vector. In this work we present a self-supervised learning framework that is able to learn a representation that captures finer levels of granularity across different modalities such as concepts or events represented by visual objects or spoken words. Our framework relies on a discretized embedding space created via vector quantization that is shared across different modalities. Beyond the shared embedding space, we propose a Cross-Modal Code Matching objective that forces the representations from different views (modalities) to have a similar distribution over the discrete embedding space such that cross-modal objects/actions localization can be performed without direct supervision. In our experiments we show that the proposed discretized multi-modal fine-grained representation (e.g., pixel/word/frame) can complement high-level summary representations (e.g., video/sentence/waveform) for improved performance on cross-modal retrieval tasks. We also observe that the discretized representation uses individual clusters to represent the same semantic concept across modalities.

1 Introduction

Toddlers acquire much of their knowledge through grounded learning – visual concepts can be acquired through language, and language acquisition emerges through visual interaction. Inspired by this type of grounded learning, a rich body of representation learning research [15, 28, 1, 31, 27] has been exploring the potential to learn from multi-modal data such as video-text, video-audio, and image-audio pairs. These works typically focus on learning a joint embedding space between different modalities, in which high-level summary representations are extracted as embedding vectors. These embedding vectors often represent entire video clips, spoken utterances, or sentences as single vectors, and can be useful on tasks such as cross-modal data retrieval, e.g., finding the most similar visual scene according to a spoken language description. The predominant approach to learning these embedding vectors is to use modality-independent encoders, and while this has been successful for downstream retrieval tasks, it makes it difficult to compare the activations of the encoders from different modalities. Further, the space of continuous embedding vectors is unbounded, which makes interpreting the learned representations challenging.

To this end, we propose to jointly learn high-level embedding vector representations with a fine-grained discrete embedding space that is shared across different modalities. The discrete embedding space enables model interpretability since there are a finite number of embedding vectors which are shared across modalities. Besides the shared embedding space, we propose a Cross-Modal Code

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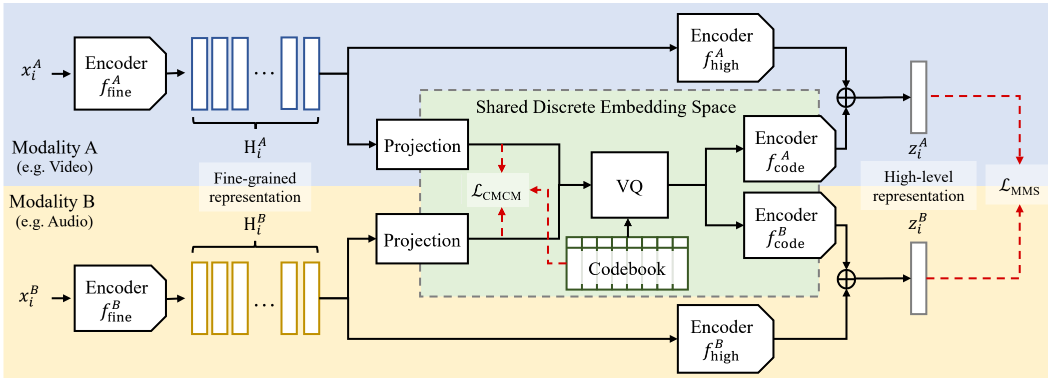

Figure 1: An overview of the proposed framework. The proposed shared discrete embedding space (green region, described in Section 2.2) is based on a cross-modal representation learning paradigm (blue and yellow regions, described in Section 2.1). The proposed Cross-Modal Code Matching $\mathcal{L}_{\text{CMCM}}$ objective is detailed in Section 2.3 and Figure 2.

Matching (CMCM) objective that guides the embedding space to capture cross-modal correspondences of concepts, actions, and words. This not only improves downstream performance on retrieval, but also allows us to better interpret what the model recognized through cross-modal grounded learning.

To verify the effectiveness of our proposed learning framework, we conducted experiments in several cross-modal domains, including video-text, video-audio, and image-audio. We found consistent improvements over baseline models, verifying that the gain was not restricted to the particular choice of network architecture, input modalities, or dataset. We also demonstrate the interpretability of the fine-grained discrete representations by showing the cross-modal relations between the embedding vectors and semantic concepts appearing in the input modalities. Our approach also enables cross-modal concept localization without requiring any labels during training.

2 Methodology

Figure 1 provides an overview of the proposed framework. We begin by describing the two-branch cross-modal representation learning paradigm in Section 2.1 (the blue and yellow regions). Next, we introduce our shared discrete embedding space in Section 2.2 (the green region). Finally, in Section 2.3 and Figure 2, we introduce the Cross-Modal Code Matching objective which guides the model to learn semantically meaningful representations through the shared discrete embedding space.

2.1 Cross-Modal Learning Paradigm

Given a set of data $\mathcal{X} = \{(x_i^A, x_i^B)\}_{i=1}^N$ of size N where each instance x_i is instantiated in different modalities A and B (e.g. video and its corresponding caption), the goal is to derive high-level representative vectors (z_i^A, z_i^B) for each instance (x_i^A, x_i^B) that capture the cross-modal relation measured by a choice of similarity function $S(\cdot,\cdot)$.

For a specific modality $M \in \{A, B\}$, a common first step is to encode raw data x_i^M into a sequence of "fine-grained" latent features H_i^M with a modality-specific neural network f^M_{fine}, i.e. $H_i^M = f^M_{\text{fine}}(x_i^M)$. The fine-grained representations H_i^M can express different kinds of raw data, such as video, audio, or sentences, as a sequence of vectors $\{h^M_{i,1}, ..., h^M_{i,L}\}$ of length L. In the second step, a "high-level" representation z_i^M can be derived by summarizing the fine-grained latent features H_i^M with another encoding function f^M_{high} that reduces the sequence into a single vector, i.e. $z_i^M = f^M_{\text{high}}(H_i^M)$.

For example, with modality A being video, raw data x_i^A can be treated as a sequence along time and space and encoded into fine-grained representations $H_i^A = \{h^A_{i,l}\}_{l=1}^L$ by choosing f^A_{fine} to be a Residual Network [18]. For the second step, a natural choice for f^A_{high} to derive the high-level representation z_i^A would be a mean pooling function over the time and spatial axes (arranged along l).

With the sets of high-level representations $\{z_i^A\}_{i=1}^N$ and $\{z_j^B\}_{j=1}^N$ from different modalities, we can measure the cross-modal relation between any pair of representations (z_i^A, z_j^B) with some similarity function[1] $S(\cdot,\cdot)$. The final step in this paradigm is to adopt an objective function that maximizes the similarity score between "positive" pairs (where $i=j$, and thus the true pairs) and minimizes the similarity score between "negative" pairs (where $i \neq j$, and thus imposter pairs).

While different objective functions, such as Semi-Hard Negative Mining [40] (SHN) and Noise Constrastive Estimation [11] (NCE), have been studied in prior work, we focused on the Masked Margin Softmax [19] (MMS) loss

$$\mathcal{L}_{\text{MMS}} = -\frac{1}{N}\sum_{i=1}^{N}\log\frac{e^{S(z_i^A, z_i^B)-M}}{e^{S(z_i^A, z_i^B)-M} + \sum_{j=1}^{N} I_{i\neq j} e^{S(z_i^A, z_j^B)}}, \tag{1}$$

where the margin M is a hyperparameter to encourage a higher similarity for positive pairs. The MMS loss $\mathcal{L}_{\text{MMS}}$ can be seen as an application of the InfoNCE [33] loss with a margin.

The effectiveness of the described cross-modal learning paradigm has been shown by recent works that achieved state-of-the-art results on benchmark datasets in different cross-modal scenarios such as video-text [27], video-audio [31, 38], and image-text [36, 39].

2.2 Shared Discrete Embedding Space

While the high-level representations (z_i^A, z_i^B) given by the cross-modal learning paradigm benefit end tasks such as data retrieval, the representations cannot be easily interpreted by humans. To obtain fine-grained representations that are more interpretable, we introduce a Vector Quantization [34] (VQ) mechanism after obtaining the H_i^M representations. Formally, with an auxiliary embedding table $E = \{e_1, e_2, ..., e_V\}$ of size V, which we refer to as the *codebook*, vector quantization is performed on each fine-grained representation $h_{i,l}^M \in H_i^M$ of modality $M \in \{A, B\}$ with

$$\bar{h}_{i,l}^M = f^M(h_{i,l}^M) + \text{sg}(e_v - f^M(h_{i,l}^M)), \tag{2}$$

where f^M is a modality specific projection network to project the input to the shared embedding space, $v = \arg\min_{k\in V} \|h_{i,l}^M - e_k\|_2$, and $\text{sg}(\cdot)$ is the stop-gradient operator proposed in straight-through gradient estimation [3] that treats the input as constant during backpropagation. In other words, each vector $h_{i,l}^M$ will be replaced by its nearest neighbor e_v, which we refer to as the *codeword*, in the codebook E. The codebook is randomly initialized and updated with the exponential moving average [34] given the fine-grained representations (more details in Section A of the Appendix).

We trained the shared embedding space jointly with the rest of the framework by modifying the high-level representations z_i^M to include the discretized fine-grained representations as

$$z_i^M = f_{\text{high}}^M(H_i^M) + f_{\text{code}}^M(\bar{H}_i^M), \tag{3}$$

where f_{code}^M is, similar to f_{high}^M, the encoding function for summarizing the sequence of quantized fine-grained representations (e.g., an average pooling function over l). Having such a discrete embedding space allows humans to better interpret the learned embeddings since they are shared across modalities and there are a finite number of them.

2.3 Cross-Modal Code Matching

Ideally, the codebook should be shared across different modalities since the quantization method is independent to the input modality. However, as we demonstrate in Section E of the Appendix, the model will learn to partition the codebook into modality-specific subspaces due to the significant difference between fine-grained representations from different modalities. To learn a shared embedding space that is invariant to input modality, we propose the Cross-Modal Code Matching objective which encourages the model to focus more on the semantic aspect of the input, as illustrated in Figure 2.

For each vector $h_{i,l}^M$ in the fine-grained representation sequence H_i^M encoded from an instance x_i^M of modality M, we first define the probability of $h_{i,l}^M$ belonging to the codeword e_v as the Softmin function of their Euclidean distance, that is

$$P(e_v|h_{i,l}^M) = \frac{\exp(-\|f^M(h_{i,l}^M) - e_v\|_2)}{\sum_{k\in V}\exp(-\|f^M(h_{i,l}^M) - e_k\|_2)}. \tag{4}$$

[1] While we used dot product throughtout this work, we also found euclidean distance works well in practice.

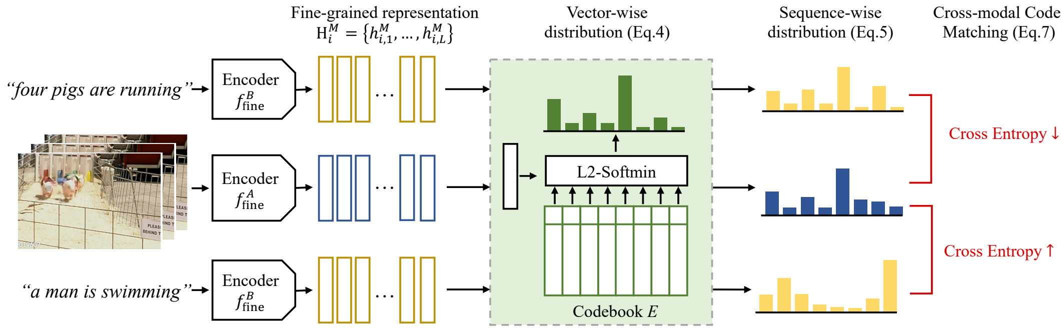

Figure 2: Our proposed Cross-Modal Code Matching objective (described in Section 2.3), which encourages the model to use similar codewords for matching cross-modal pairs.

Note that this definition assigns higher a probability to codewords that are closer to the fine-grained representation, where the closest codeword is used to perform vector quantization. We can then define the sequence-level probability distribution over the codebook as the average of the fine-grained distribution, that is

$$P(e_v|H_i^M) = \frac{1}{L}\sum_l P(e_v|h_{i,l}^M). \tag{5}$$

This distribution is essentially the normalized frequency of codeword usage for a given sequence of fine-grained representations. Next, for a pair of cross-modal data (x_i^A, x_j^B), we define their *code similarity* as the negative symmetric cross entropy of probability distribution over the codebook

$$S_{\text{code}}(x_i^A, x_j^B) = \sum_v P(e_v|H_i^A) \log P(e_v|H_j^B) + \sum_v P(e_v|H_j^B) \log P(e_v|H_i^A), \tag{6}$$

Finally, we propose the *Cross-Modal Code Matching (CMCM)* objective using code similarity as

$$\mathcal{L}_{\text{CMCM}} = -\frac{1}{N}\sum_{i=1}^{N} \log \frac{e^{S_{\text{code}}(x_i^A, x_i^B)}}{e^{S_{\text{code}}(x_i^A, x_i^B)} + \sum_{j\neq i} e^{S_{\text{code}}(x_i^A, x_j^B)}}. \tag{7}$$

Intuitively, the proposed objective encourages the model to represent the input (x_i^A, x_j^B) with similar codewords for positive pairs ($i = j$) and non-matching codewords for negative pairs ($i \neq j$). As a consequence, each codeword is expected to be a modality invariant representation of a more fine-grained concept, action, or word that can be discovered from cross-modal data. For example, a codeword could correspond to both the visual scene of a man juggling, and also the spoken word "juggling," as we demonstrate in our experimental results in Table 2 and Figure 4.

The full objective of our proposed cross-modal representation learning framework is the combination of objectives at different levels

$$\mathcal{L} = \mathcal{L}_{\text{MMS}} + \alpha\mathcal{L}_{\text{CMCM}}, \tag{8}$$

where α controls the weight between the two terms. Empirically, we found $\alpha = 0.1$ worked well across different settings.

3 Related work

Methods fitting into the cross-modal learning paradigm. As described in Section 2.1, many of the existing methods for cross-modal learning fit into the paradigm where encoders are modality-independent. This paradigm has been shown to be effective by achieving state-of-the-art retrieval performance on benchmark datasets with the modality pairs that we considered in this work: video-text [2, 27], video-audio [31, 38], and image-audio [15, 14]. While these prior works relied on different pre-training datasets, model architectures, and objective functions, they all leverage modality-independent encoders. One of the most important features of this paradigm is the fixed inference time for retrieval. Since the encoders are modality-independent, embedding vectors for samples in a given modality can be computed without using any samples from the other modality. Thus retrieval only involves computing the dot product between embedding vectors from two different modalities. As a consequence, these models are more flexible for large-scale retrieval, and the embedding vectors from each modality can be used independently for other downstream tasks.

Other cross-modal learning frameworks. In contrast to the aforementioned works, some methods leverage cross-modal relations within the encoders instead of using modality-independent encoders. This has been done with both cross-modal encoders [21, 27] and cross-modal attention mechanisms [29, 26, 25, 10]. However, the cross-modal interactions increase the complexity for retrieval since every instance of a specific modality must be used as input with every instance of another modality to obtain the embedding vectors. With m and n samples in the modalities respectively, this increases the complexity from the modality-independent approach from $\mathcal{O}(m+n)$ to $\mathcal{O}(mn)$. Further, it also makes analysis of the embedding vectors from any individual modality challenging and inhibits single-modality downstream tasks. Our proposed framework builds on the modality-independent approach to enable light-weight retrieval, but it also enables cross-modal interaction through our proposed codebook and Cross-Modal Code Matching objective.

Uncovering semantic-level correspondences. Image-audio models have been shown to discover spoken words and visual objects without supervision through retrieval tasks [41, 12, 17, 20], and the audio embedding vectors have been shown to cluster into word-like speech units [13, 43, 14]. Some work has studied the ability of video-audio models to relate spoken words to visual objects and actions in videos [4, 38]. However, none of these models incorporated a shared embedding space that enabled modality-invariant representations. VQ units have been used in the audio encoder of an image-audio model [14], which allowed it to capture the hierarchical structure of spoken language. While our proposed framework is similar in that it also discretizes the audio sequence with VQ units, our work differs significantly by capturing the cross-modal interactions between visual and audio inputs in the shared embedding space rather than solely capturing the tree structure of speech. Further, besides image-audio data, our proposed framework can handle video-audio and video-text data. Finally, modality invariant audio-visual representations have been explored using variational autoencoders [22, 47], while we propose modality invariant representations for different cross-modal domains using a shared discrete embedding space.

4 Experiments

4.1 Setup

To demonstrate the generalizability of the proposed method, we tested our framework on different cross-modal datasets and baseline models that fit into the cross-modal learning paradigm. All setups are listed below and summarized in Table 4 of the Appendix. For training the proposed model, we randomly initialized all the modules related to the discrete shared embedding space and trained them jointly with the rest of the framework (see Figure 1). Unless otherwise specified, (1) we "warm-started" our proposed framework by initializing it with the modality-specific encoders (namely, f^M_{fine} and f^M_{high}) from the baseline models; (2) both the projection network f^M and the encoder network f^M_{code} are single linear layers; (3) the codebook size is set to 1024. Please refer to Section B in the Appendix for more implementation details and computational costs.

Video-Text: MSR-VTT [44] contains 10k video clips with length varying from 10 to 32 seconds. While each video is provided with 20 related captions for training, we followed the evaluation protocol from previous works [27, 10, 45] to use the `training-9k` / `test 1k-A` splits for training and testing respectively. CLIP4Clip [27], the current state-of-the-art on MSR-VTT, is selected as the baseline model. Following the cross-modal learning paradigm described in Section 2.1, CLIP4Clip is composed of a pair of encoders: a Visual Transformer [8] and a Text Transformer [42]. Both encoders are initialized from the CLIP model [36], which is pre-trained on the text-image dataset WIT [36] and optimized in the end-to-end manner from pixel/text input. For training the proposed framework on top of CLIP4Clip, we freeze the transformers from CLIP4Clip and update only the modules related to the discrete shared embedding space. Both the projection network f^M (see Eq. 2) and the encoder network f^M_{code} (see Eq. 3) are 4D-Convolutions for video with a depth of 3 and BiLSTMs for text, also with a depth of 3. While CLIP4Clip provided different options for the high-level visual encoder f^M_{high}, we adopted the vanilla mean-pooling model. Following CLIP4Clip, the shared embedding space has a dimension of 512.

Video-Audio: S-MiT [31] contains over 500k pairs of 3-second video and corresponding spoken audio captions averaging 8 seconds. We followed the official protocol to train on the training set of 500k pairs, use the validation set of 10k pairs for development and analysis, and report the retrieval result on a 1k search space over 5 runs randomly sampled from a held-out test set. We selected the same baseline model used on the dataset [31], which contains a visual encoder composed of a

Table 1: Cross-Modal retrieval results on MSR-VTT, S-MiT, and Places.

Modality *A-B* / Dataset — Method	Visual Retrieval ($B \rightarrow A$) R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓	Language Retrieval ($A \rightarrow B$) R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓
Video-Text / MSR-VTT [44]								
Frozen-in-Time [2]	31.0	59.5	70.5	-	-	-	-	-
CLIP4Clip-meanP [27]	43.1	70.4	80.8	16.2	-	-	-	-
CLIP4Clip-tightT [27]	40.2	71.5	80.5	**13.4**	-	-	-	-
Our Baseline†	42.6	71.2	80.8	15.5	**43.0**	70.9	80.9	12.5
Proposed	**43.4**	**72.3**	**81.2**	14.8	42.5	**71.2**	**81.1**	**12.0**
Video-Audio / S-MiT [31]								
S-MiT [31]	32.1	58.9	68.6	-	32.3	57.9	68.1	-
Our Baseline†	30.2	57.3	68.5	41.9	29.7	57.2	68.7	28.5
Proposed	**34.3**	**61.3**	**72.0**	**33.5**	**34.0**	**61.6**	**71.7**	**22.5**
Image-Audio / Places [17]								
ResDAVEnet [16]*	30.9	63.6	74.2	20.2	26.4	58.5	71.2	21.6
ResDAVEnet-VQ [14]*	34.9	70.2	79.4	15.0	32.7	65.6	77.0	18.0
Our Baseline†	43.8	74.1	82.4	15.8	40.4	73.3	82.5	10.9
Proposed	**46.5**	**77.4**	**85.8**	**13.7**	**45.4**	**77.7**	**85.9**	**8.9**

† Existing model reproduced with $\mathcal{L}_{\text{MMS}}$ for fair comparison, see Table 4 in the Appendix for more detail.
* Results obtained by running the official code and pre-trained models, see Appendix for more details.

ResNet-152 pre-trained on ImageNet [7] and TSM ResNet-50 [23] pre-trained on M-MiT [32]. The audio encoder is a randomly initialized 1D-ResNet [16] designed specifically for spectrograms. The shared embedding space has the dimension of 4096, matching the encoders in the baseline model.

Image-Audio: Places [17] contains over 400k pairs of images from the Places 205 dataset [46] and corresponding spoken audio captions averaging 10 seconds. We followed the previous works [15, 16, 14] to use the training set of 400k pairs and report results on the validation set of 1k pairs. We select ResDAVEnet [16] as the baseline model where the visual encoder is a ResNet-50 pre-trained on ImageNet [7] and the audio encoder is a randomly initialized 1D-ResNet [16] designed specifically for spectrograms. The shared embedding space has the dimension of 1024.

4.2 Cross-Modal Retrieval

Data retrieval is one of the most common evaluations for cross-modal representation learning. For example, in video retrieval with input query text, videos in the search space will be ranked by the similarity between the representation of each video and the query. We report the standard retrieval metrics recall at rank K (R@K) and median rank (MdR) in Table 1. We show the performance on both visual retrieval, where input language queries are used to retrieve videos or images, and language retrieval, where input visual queries are used to retrieve spoken or text captions.

Video-Text Retrieval. On the benchmark MSR-VTT dataset, we compared our proposed method against recent works achieving state-of-the-art [2, 24, 27] and provide a full comparison against more prior work [26, 38, 10, 35, 9, 5] in Section C of the Appendix. Frozen-in-Time [2] and CLIP4Clip [27] are similar methods that employ a Visual Transformer [8] to encode video as sequence of images. The key differences between them is the choice of summarizing function (i.e. f^M_{high}) for video and the pre-training procedure. We also note that the CLIP4Clip with tight transformer encoder [27] (CLIP4Clip-tightT) relied on cross-modal reference via self-attention encoders to derive representations, which has a higher time complexity as mentioned in Section 3. With the shared codebook and Cross-Modal Code Matching objection, our proposed framework also enables cross-modal reference and gives an improvement over the baseline model without increasing the time complexity.

Video-Audio Retrieval. Video-Audio retrieval on S-MiT [31] is a challenging task since videos are paired with raw speech audio, which is untranscribed, unsegmented, and can contain background noise and speaker variation. However, our proposed framework that leverages cross-modal connections

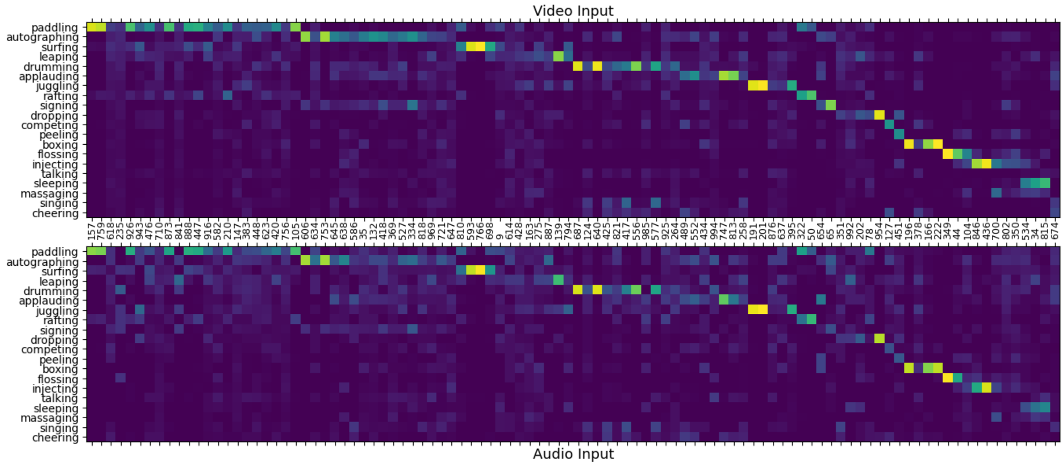

Figure 3: Conditional probability matrix illustrating $P(\text{action}|\text{codeword})$ on the S-MiT development set. Y-axis is action label, showing only the top 20 most frequent labels for simplicity. X-axis is the indices of the top 100 most frequent codewords.

between visual actions and spoken words is able to improve the baseline model by a margin. We further analyze our framework's ability to relate visual actions and spoken words in Section 4.3.

Image-Audio Retrieval. We compare our proposed method against the recent models [16, 14] achieving state-of-the-art and provide a full comparison to previous methods [15, 13, 17] in Section D of the Appendix. Comparing the baseline model, ResDAVEnet [16], and the current state-of-the-art ResDAVEnet-VQ [14], the latter model introduces VQ units into the audio encoder, allowing it to model the hierarchical structure of speech and achieve better retrieval results. With our framework, we introduce our shared VQ embedding space into the ResDAVEnet model to capture cross-modal interactions. This improves the performance over both ResDAVEnet and ResDAVEnet-VQ.

Overall, our proposed method enables consistent improvements regardless of the data modalities and baseline architectures, demonstrating its effectiveness and generalizability.

4.3 Discrete Representation Analysis

One of the important motivations of introducing the discrete cross-modal embedding space is better model interpretability. In this section, we take a closer look into the codewords learned through our proposed framework. For the evaluation, we chose the video-audio setup on S-MiT [31]. We used video-audio pairs from the development set, where each pair is labeled with an action out of 332 categories. Note that we only used labels for analysis, labels are never used for training.

Conditional Probability of Action Labels Given Codeword. First, we compute the conditional probability distributions of action labels given the codewords over the video inputs. Each video input is fixed-length and represented by 27 codewords (3 frames each represented by 3×3 codewords), and we labeled all these codewords with the video's action label. By accumulating codeword labels through the whole development set, we can compute the conditional probability of each action given any codeword, i.e. $P(\text{action}|\text{codeword})$. Results are visualized in the upper part of Figure 3. Similarly, we computed the conditional probabilities based on the audio input where each utterance is represented by up to 32 codewords depending on the utterance length. We selected the most frequent codewords used by the video inputs and plot the conditional probabilities based on the audio input in the lower part of Figure 3. We can observe that both matrices have similar patterns, i.e., when a codeword is activated, there is a high chance of a specific action appearing in the input regardless if it is video or audio. This suggests that our model is able to learn cross-modal representations for actions grounded by either visual or spoken language input. The codewords are not only modality invariant, but more importantly, they also capture the semantic relations of the labels. e.g., codewords with the highest chance to represent "autographing" typically have the second highest chance of representing "signing"; codewords for "surfing" are less likely to represent other actions as all of them are very different from "surfing". We also note that without the Cross-Modal Code Matching objective,

Table 2: Correspondence between codewords, visual actions, and spoken words. Ranking is based on the precision (Prc.) of the top hypothesis of the visual action label. Occurrence (Occ.) indicates the number of times the codeword was activated throughout the development set. Around 750 codewords were activated on the development set. An extended table is available in Section F of the Appendix.

Rank	Code	Occ.	Visual Action				Spoken word			
			Top Hypothesis		Second Hypothesis		Top Hypothesis		Second Hypothesis	
			Label	Prc.	Label	Prc.	Word	F1	Word	F1
1	201	147	juggling	97.5	kicking	1.2	juggling	36.7	juggles	8.3
2	349	112	flossing	96.0	licking	0.7	floss	15.8	flossing	14.0
3	145	49	surfing	95.6	snowing	2.9	surfboard	23.7	waves	7.3
4	29	64	tattooing	94.6	injecting	2.2	tattoo	15.8	tattooed	4.2
5	233	25	ironing	93.8	hammering	6.2	ironing	20.5	iron	4.7
					...					
32	500	89	dialing	60.0	texting	10.0	dialing	13.8	phone	9.8
33	536	28	cheering	60.0	shouting	10.0	cheerleaders	26.8	cheerleading	10.3
34	50	203	rafting	58.6	paddling	25.7	rafting	16.7	raft	8.5
35	664	78	dunking	58.0	leaping	9.1	basketball	11.0	dunking	5.2
					...					
742	733	188	discussing	6.5	applauding	4.6	men	7.3	two	6.4
743	542	58	baking	6.5	peeling	5.2	cupcake	9.2	peanut	6.2

(a) codeword # 201 (b) codeword # 664

Figure 4: Codeword cross-modal localization. Input regions that are encoded by the codeword (selected from Table 2) are highlighted in red.

semantically related video and audio inputs no longer use the same codewords, which we illustrate in Section E of the Appendix.

Cross-Modal Correspondences. Next, we analyze the connections captured by the codewords between action labels and spoken words. With the same label accumulation method described previously, we compute the precision of action prediction with codewords (i.e. $\frac{\text{code-action co-occurrence}}{\text{code occurrence}}$). For the audio, we used word-level transcriptions (from Google's speech-to-text API) to assign a spoken word to each codeword when it is activated by the input utterance. This results in a hypothesis set including around 7k words for each codeword, and we listed the top 2 hypotheses for each codeword with the highest F1 score (instead of precision to avoid domination of high-frequency words). Results are listed in Table 2. For the codewords that have the highest precision on predicting the action label, we found the top hypotheses for spoken words are often the action label itself. E.g., the codeword (rank 1st) for the visual action "juggling" maps to the spoken word "juggling" perfectly. As precision on visual action prediction decreases, we observed fewer perfect mappings, but the spoken word hypotheses remained semantically related to the visual action hypotheses. E.g., the codeword (rank 35th) for the visual action "dunking" with lower precision now maps to the spoken word "basketball." Surprisingly, even the codewords with the lowest precision capture relationships between visual actions and spoken words to some extent. E.g., codeword (rank 743th) that is most related to the action "baking" has the top and second word hypotheses "cupcake" and "peanut."

Codeword Localization. Finally, to visualize the relation between codewords and the input data, we localize the segments of both the video and audio input that are assigned to certain codewords.

Table 3: Ablation study performed on Places [17], scores are averaged over audio and image retrieval.

	Method	Averaged 2-way Retrieval			
		R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓
(a)	Proposed	46.0	77.6	85.9	11.3
(b)	codebook size = 512	46.2	77.4	85.2	11.5
(c)	codebook size = 2048	46.1	76.6	84.7	12.1
(d)	$\alpha = 1.0$	45.6	76.6	85.5	11.6
(e)	$\alpha = 0.0$ (w/o Cross-Modal Code Matching)	45.2	75.5	84.2	12.8
(f)	w/o VQ & w/o Cross-Modal Code Matching	45.7	75.9	84.7	12.6
(g)	w/o warm-start	41.6	73.4	82.5	16.0
(h)	w/o continuous representation ($f^M_{\text{high}}(H^M_i)$)	29.0	63.0	74.7	19.4
(i)	Our Baseline	42.1	73.7	82.5	13.4

This is possible because quantization in our shared embedding space is done at the fine-grained level, so that the time and spatial axes are preserved. Examples are shown in Figure 4, where the regions assigned to the given code are highlighted. Interestingly, we see the codewords being aligned to both the visual actions and the corresponding spoken words. This supports our claim of having a more interpretable representation at the fine-grained level.

4.4 Ablation Study

To justify our framework design and choice of hyperparameters, we conducted an ablation study on the image-audio setting and report the results in Table 3.

Impact of the shared embedding space. For the codebook size, 1024 codewords worked well across different datasets. Halving and doubling the number of codewords (row(b) & (c)) both decreased the performance slightly. For the weight α of the proposed Cross-Modal Code Matching objective, we found that values in the range $(0, 1]$ generally work while 0.1 works the best (row(a) v.s. row(d)). Removing the proposed Cross-Modal Code Matching objective (setting $\alpha = 0$, row(e)), however, hurts the performance. Furthermore, without the objective, the codebook no longer captures cross-modal correspondences, as illustrated in Section E of the Appendix. We also observed that disabling the VQ layer together with the Cross-Modal Code Matching objective slightly recovers performance (row(f) v.s. row(e)). All of these observations serve as evidence that the proposed discrete embedding space is most beneficial to the retrieval task with the guidance from the Cross-Modal Code Matching objective.

Importance of baseline models in the cross-modal learning paradigm. As mentioned in Section 4.1, the discrete shared embedding space is learned with “warm-starting” from a baseline model. We note that warm-starting is important for getting more refined representations that yield better retrieval results (row(a) v.s. row(g)). Without warm-starting, our framework can only perform similar to the baseline (row(g) v.s. row(i)). This finding aligns with previous work [14] that used VQ layers in the audio encoder and used warm-starting to learn acoustic units. Moreover, removing the continuous representations (row(h)) originally used in the cross-modal learning paradigm and using only the codeword representations significantly decreases performance. This exposes the trade-off between interpretability and end-task performance by imposing a discrete embedding space. Hence, we choose to integrate both discrete and continuous embedding space for retrieval as in Eq. 3.

5 Conclusion

In this paper, we proposed a framework for cross-modal representation learning with a discrete embedding space that is shared amongst different modalities and enables model interpretability. We also propose a Cross-Modal Code Matching objective that encourages models to represent cross-model semantic concepts in the embedding space. Combining our discrete embedding space and objective with existing cross-modal representation learning models improves retrieval performance on video-text, video-audio, and image-audio datasets. We also analyze the shared embedding space and find that semantically related video and audio inputs tend to use the same codewords.

Limitations. As described in Section 2.1, the present work relies on the existing cross-modal learning paradigm with modality-independent encoders. Although our proposed method is shown to be effective, further work is required to generalize our method to other cross-modal learning frameworks which are more computationally complex. In addition, recent work [1, 38] demonstrates the benefits of learning from three or more modalities. While the proposed method can theoretically be extended to more modalities, further work is required to handle practical bottlenecks such as the growth in time complexity for the Cross-Modal Code Matching objective with respect to the number of modalities.

Potential Negative Societal Impacts. Our proposed method is self-supervised and does not use any labels during training. It will therefore learn any biases present in the data. However, we expect that our discrete embedding space will help improve interpretability and could help humans discover the biases present in training data before deploying models to any real-world applications.

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Appendix

A Codebook Update Policy

The codebook with d-dimensional codewords is initialized with

$$\begin{aligned} N_v^{(0)} &= 1 \\ m_v^{(0)} &\sim \mathcal{N}_d(0,1) \\ e_v^{(0)} &= m_v^{(0)}, \end{aligned} \tag{9}$$

and updated with each codeword e_v being the exponential moving average (EMA) of all the fine-grained representations $H = \left\{ f^M(h_{i,l}^M) \,\middle|\, \bar{h}_{i,l}^M = e_v \right\}$ that was replaced by e_v for every training step t:

$$\begin{aligned} N_v^{(t)} &\leftarrow \gamma\, N_v^{(t-1)} + (1-\gamma)\ |H| \\ m_v^{(t)} &\leftarrow \gamma\, m_v^{(t-1)} + (1-\gamma)\ \sum_{h \in H} h \\ e_v^{(t)} &\leftarrow \frac{m_v^{(t)}}{N_v^{(t)}}, \end{aligned} \tag{10}$$

where the decay factor γ is set to 0.99 throughout this work. To improve the overall usage of the codebook, the input fine-grained representations are modality-wise batch normalized. In addition, codewords that are not activated (i.e. $|H| = 0$) for 100 consecutive steps are re-initialized during codebook update. The reset value is randomly chosen from activated codewords.

B Implementation Details

For each dataset and modality pair considered in this work, we selected baseline models that follow the cross-modal learning paradigm (as described in Section 2.1). Baseline models with different fine-grained and high-level encoders (f^M_{fine} and f^M_{high}) are summarized in Table 4. The links to the official implementation of these baseline models are also provided in the table. For a fair comparison, we retrained the models with the $\mathcal{L}_{\text{MMS}}$ (margin set to 1e-3) as our baseline models.

Table 4: Experiment setup on MSR-VTT, S-MiT, and Places.

Setup	Modality	Encoders from baseline model	
Dataset	A	f^A_{fine}	f^A_{high}
- Baseline model	B	f^B_{fine}	f^B_{high}
MSR-VTT [44]	video	Vision Transformer[4] [8]	Avg. Pooling + Linear
- CLIP4Clip[1] [27]	text	Transformer[4] [42, 37]	`[EOT]` token + Linear
S-MiT [31]	video	ResNet-152[5] [18] + TSM[6] [23]	Max Pooling + GLU [6]
- AVLnet[2] [38]	audio	Spectrogram+1D-ResNet [16]	Avg. Pooling + GLU [6]
Places [17]	image	ResNet-50[5] [18]	Avg. Pooling + GLU [6]
- ResDAVEnet[3] [16]	audio	Spectrogram+1D-ResNet [16]	Avg. Pooling + GLU [6]

[1] https://github.com/ArrowLuo/CLIP4Clip
[2] https://github.com/roudimit/AVLnet (under BSD license)
[3] https://github.com/wnhsu/ResDAVEnet-VQ (under BSD license)
[4] Initialized from CLIP model pretrained on WebImageText dataset [36].
[5] Pretrained on ImageNet [7].
[6] Pretrained on Multi-MiT [32].

MSR-VTT. For our baseline model, we did not reproduce CLIP4Clip's post-pretraining stage, which trained CLIP4Clip on the subset of HowTo100M [30] before adapting to MSR-VTT, since this stage is not necessary for the best results on MSR-VTT and the subset is not released. We used all of the hyper-parameters of the official implementation except the batch size is reduced from 128 to 64 to meet our hardware restriction. To train the shared discrete embedding space, we warm-started from the baseline model with a learning rate of 1e-5. Each video is encoded into 8 codewords ($2 \times 2 \times 2$ for time, height, width) and each subword unit in the sentence is encoded into 1 codeword. The baseline model is trained for 12 hours on 8 2080Ti GPUs; and it takes an additional 6 hours to train the proposed framework.

S-MiT. The input audio feature is a 40 dimensional mel-spectrogram with a window size of 25 ms and a hop size of 10 ms. The baseline is trained with a batch size of 2048 and a learning rate of 1e-3. To train the shared discrete embedding space, we warm-started from the baseline model with a learning rate of 1e-4. Each video is encoded into 27 codewords ($3 \times 3 \times 3$ for time, height, width) and every 16 consecutive frames from the spectrogram is encoded into 1 codeword. The baseline model is trained for 4 hours on 4 V100 GPUs; and it takes an additional 1 hour to train the proposed framework. For both baseline model and our proposed model, we followed the previous work [31] to perform a second round training with a learning rate of 1e-5 and a batch size of 128. The second round training fine-tunes the TSM video encoder (which is frozen in the first round training) on S-MiT jointly with the rest of the components, which takes 2 days on 8 Titan RTX GPUs.

Places. The input audio feature is a 40 dimentional mel-spectrogram with a window size of 25 ms and a hop size of 10 ms. The baseline is trained with a batch size of 256 and a learning rate of 1e-3. To train the shared discrete embedding space, we warm-started from the baseline model with a learning rate of 1e-4. Each image is encoded into 49 codewords (7×7 for height, width) and every 16 consecutive frames from the spectrogram is encoded into 1 codeword. The baseline model is trained for 36 hours on 1 V100 GPU; and it takes an additional 4 hours to train the proposed framework.

C MSR-VTT Video Retreival Full Comparison

Table 5: Full comparison against prior works on MSR-VTT text-to-video retrieval.

Method	Video Retrieval (Text → Video)			
	R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓
Collaborative Experts [26]	20.9	48.8	62.4	28.2
Multi-Modal Transformer [10]	26.6	57.1	69.6	24.0
Support-Set Bottlenecks [35]	30.1	58.5	69.3	-
Multidomain Multimodal Transformer [9]	38.9	69.0	79.7	16.5
Frozen-in-Time [2]	31.0	59.5	70.5	-
Hierarchical Transformer with Momentum Contrast [24]	30.7	60.9	73.2	-
TeachText [5]	29.6	61.6	74.2	-
CLIP4Clip-meanPooling [27]	43.1	70.4	80.8	16.2
CLIP4Clip-seqLSTM [27]	42.5	70.8	80.7	16.7
CLIP4Clip-seqTransformer [27]	44.5	71.4	81.6	15.3
CLIP4Clip-tightTransformer [27]	40.2	71.5	80.5	13.4
Our Baseline (based on CLIP4Clip-meanPooling)	42.6	71.2	80.8	15.5
Proposed	43.4	72.3	81.2	14.8

In addition to the comparison against recent state-of-the-art methods in Table 1 for video retrieval on MSR-VTT, in Table 5 we show the complete comparison to prior work and summarize the models here. Collaborative Experts [26] leverages "expert" features that can be obtained from the raw video from different off-the-shelf models (such as object detection, scene classification, and speech recognition models) to build representations. Instead of summarizing the expert features into a compact video representation and computing similarity with the text representation, the Multi-Modal Transformer [10] computes similarity between different expert features and the text representation with a proposed variation of the Transformer [42]. Based on the Multi-Modal Transformer, Multidomain Multi-Modal Transformer [9] explored an additional motion feature and the combination of different training datasets to further improve the result. Support-Set Bottlenecks [35] studies the benefit that cross-instance captioning can bring by generating text based on the combination of all representations of similar videos. Similar to our framework, Hierarchical Transformer with Momentum Contrast [24] divided representations from different layer of the encoders into fine-grained (which they referred to feature-level) and high-level (which they reffered to semantic-level) representations. While our work focused on learning discrete representations in the fine-grained embedding space, they performed momentum-based representation matching across the two levels that encourages the two embedding spaces to be more similar. TeachText [5] leverages distillation learning where multiple captions describing the same video can be considered by different teacher models that jointly guide the student network. Frozen-in-Time [2] and CLIP4Clip [27] both found the recent proposed Visual Transformer [8] can significantly improve retrieval results while they differ in the choice of summarizing function for video (i.e. f^M_{high}) and the pre-training procedure. Moreover, CLIP4Clip also introduces different choice of the summarizing function f^M_{high} including RNNs (CLIP4Clip-seqLSTM) and Transformers (CLIP4Clip-seqTransformer) that replaces the mean-pooling function (CLIP4Clip-meanPooling) at the cost of higher time complexity and computational cost. Note that while our work is based on the vanilla mean-pooling function, we achieved comparable or better performance with the proposed discrete embedding representations. As described in Section 3, CLIP4Clip also introduced a cross-modal transformer network (CLIP4Clip-tightTransformer) that allows cross-modal reference for deriving representations.

D Places Image Retrieval Full Comparison

Table 6: Full comparison against prior works on Places image and spoken caption retrieval.

	Audio to Image				Image to Audio			
	R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓	R@1 ↑	R@5 ↑	R@10 ↑	MnR ↓
Harwath et al. [17]‡	14.8	40.3	54.8	–	12.1	33.5	46.3	–
Harwath et al. [13]‡	16.1	40.4	56.4	–	13.0	37.8	54.2	–
DAVEnet [15]	20.0	46.9	60.4	–	12.7	37.5	52.8	–
ResDAVEnet [16]*	30.9	63.6	74.2	20.2	26.4	58.5	71.2	21.6
ResDAVEnet-VQ [14]*	34.9	70.2	79.4	15.0	32.7	65.6	77.0	18.0
Our Baseline†	43.8	74.1	82.4	15.8	40.4	73.3	82.5	10.9
Proposed	**46.5**	**77.4**	**85.8**	**13.7**	**45.4**	**77.7**	**85.9**	**8.9**

‡ Results found in [15].
† Existing model reproduced with $\mathcal{L}_{\text{MMS}}$ for fair comparison.
* Results obtained by running the official code and pre-trained models.

We show the full comparison to prior work on Places-400k in Table 6. The previous methods [13, 17, 15] use less complex audio and image encoders with fewer parameters.

E Results Without Cross-Modal Code Matching

To demonstrate the importance of our proposed Cross-Modal Code Matching objective, Figure 5 illustrates the conditional probability matrix (described in Section 4.3 and Figure 3) when the proposed objective is deactived (setting $\alpha = 0$). Unsurprisingly, we see that the correlation between codewords and action labels are gone, indicating that the assignment of codewords are now dominated by the input modality instead of the underlying action label. This can also be verified by visualizing the discrete embedding space in a lower dimension as plotted in Figure 6. This evidence suggests that the proposed Cross-Modal Code Matching Objective is effective for learning modality-invariant representations.

F Additional Codeword Correspondence and Localization Examples

An extension of Table 2 showing the correspondence between codewords, visual actions, and spoken words are provided in Table 7. We also provide more examples for codeword localization in Figure 7.

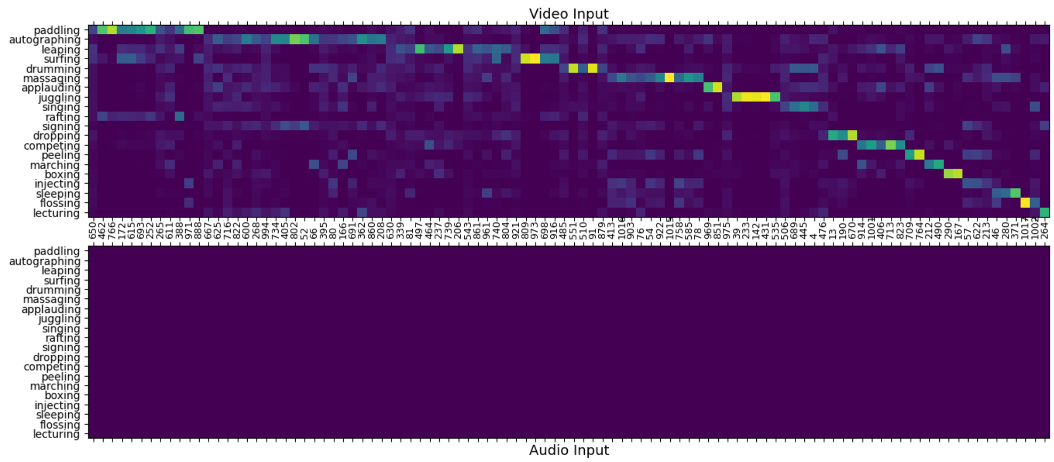
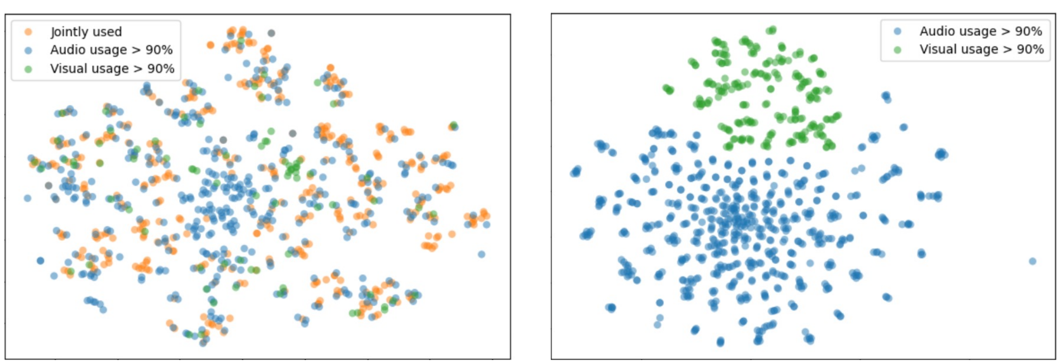
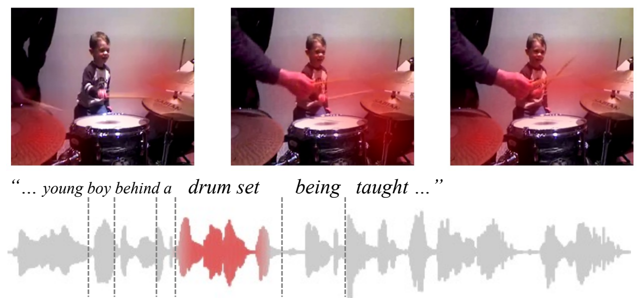


Figure 5: Conditional probability matrix between codewords and action labels learned by our proposed method when the Cross-Modal Code Matching objective is excluded.

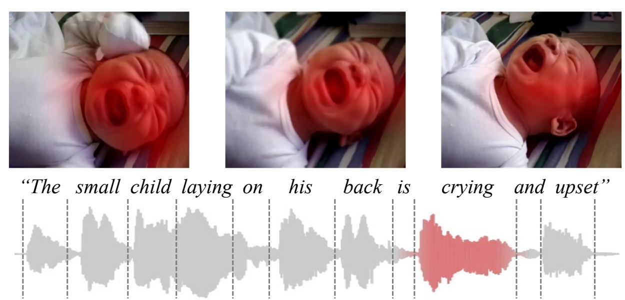


(a) With Cross-modal Code Matching (b) Without Cross-modal Code Matching

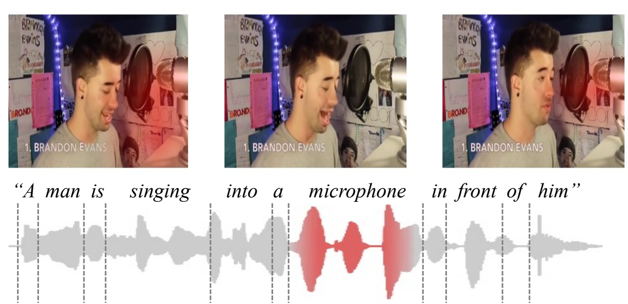
Figure 6: T-SNE visualization of the codebook with and without the proposed Cross-Modal Code Matching Objective. Each point corresponds to a codeword colored with respect to the input modality that utilized it the most. Codewords without high (> 90%) usage from single modality are labeled as "jointly used".



(a) codeword # 687



(b) codeword # 327



(d) codeword # 36

Figure 7: More examples for codeword cross-modal localization.

Table 7: Correspondence between codewords, visual actions, and spoken words (Extended Table 2). The second hypothesis and the occurrence are omitted for simplicity. All codewords activated on S-MiT's development set are listed.

Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1	Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1
1	201	juggling	97.5	juggling	36.7	61	940	landing	44.9	airplane	19.6
2	349	flossing	96.0	floss	15.8	62	262	sewing	44.7	sewing	13.2
3	145	surfing	95.6	surfboard	23.7	63	532	autographing	44.4	selfie	22.2
4	29	tattooing	94.6	tattoo	15.8	64	928	stirring	44.1	boiling	27.3
5	233	ironing	93.8	ironing	20.5	65	747	applauding	43.8	clapping	23.8
6	766	surfing	93.2	surfing	22.1	66	447	paddling	43.1	boat	8.3
7	191	juggling	90.2	juggling	29.1	67	823	skipping	43.0	jump	17.1
8	753	autographing	85.0	autographs	26.4	68	308	shaving	42.5	comb	10.0
9	606	autographing	83.7	signing	16.2	69	518	skiing	41.8	skiing	11.4
10	640	drumming	81.6	drums	19.5	70	860	bulldozing	41.7	bulldozer	25.7
11	436	injecting	81.6	injected	13.2	71	61	extinguishing	41.3	sting	9.1
12	109	peeling	80.9	peeling	21.2	72	296	combing	40.9	brushes	5.9
13	551	shaving	80.2	shaving	18.0	73	435	screwing	40.8	drill	25.0
14	137	paddling	80.0	canoe	25.8	74	705	surfing	40.6	ocean	27.0
15	327	crying	78.8	crying	29.5	75	760	hammering	40.0	hammering	23.3
16	593	surfing	77.7	surfboard	10.9	76	926	paddling	40.0	lake	6.8
17	687	drumming	77.3	drums	14.4	77	888	paddling	39.6	lake	7.4
18	883	tattooing	77.2	tattoo	13.6	78	169	dunking	39.3	nba	7.5
19	1000	inflating	74.5	inflatable	12.8	79	681	manicuring	38.7	nails	13.2
20	222	boxing	71.3	boxing	13.2	80	685	signing	38.6	writing	8.3
21	243	shredding	70.0	shredding	28.6	81	631	paddling	38.5	clouds	12.2
22	157	paddling	69.9	kayak	21.3	82	800	dropping	38.3	beans	12.9
23	427	boxing	69.8	boxers	16.2	83	556	drumming	38.3	marching	11.6
24	774	surfing	69.2	waves	23.0	84	758	wrapping	38.1	wrapping	22.2
25	613	manicuring	67.9	nails	24.5	85	368	texting	38.0	texting	16.7
26	952	leaping	66.0	dolphins	10.7	86	625	combing	37.9	hair	4.9
27	196	boxing	64.1	boxer	13.9	87	166	boxing	37.8	boxing	7.2
28	706	sailing	63.4	sailboat	18.8	88	539	paddling	37.5	helmet	13.0
29	58	shaving	62.8	shaving	10.9	89	139	leaping	37.5	jumping	16.6
30	759	paddling	60.7	paddling	12.4	90	123	drumming	37.1	playing	8.7
31	868	boxing	60.0	boxer	11.2	91	577	drumming	37.0	musical	8.1
32	500	dialing	60.0	dialing	13.8	92	780	screwing	36.9	drill	15.8
33	536	cheering	60.0	cheerleaders	26.8	93	621	leaping	36.6	jumps	9.7
34	50	rafting	58.6	rafting	16.7	94	154	boxing	36.0	referee	14.7
35	664	dunking	58.0	basketball	11.0	95	415	grilling	35.7	grill	15.7
36	103	autographing	57.8	carpet	8.2	96	345	autographing	35.5	pictures	19.3
37	990	wrestling	56.1	wrestling	25.9	97	694	sailing	34.9	sailing	7.0
38	880	sleeping	56.0	sleeping	21.1	98	973	leaping	34.4	tale	8.0
39	48	paddling	55.1	rowing	18.2	99	957	shrugging	34.4	lifting	10.3
40	292	skiing	54.2	skiing	20.0	100	713	paddling	34.3	sunset	25.3
41	602	ironing	52.5	ironing	7.1	101	697	injecting	34.1	doctor	18.8
42	954	dropping	52.4	dropped	8.2	102	431	peeling	33.9	apple	20.0
43	735	applauding	52.1	clapping	23.4	103	164	typing	33.8	laptop	20.6
44	816	autographing	51.0	carpet	22.5	104	776	juggling	33.6	balls	16.5
45	516	swinging	50.0	swing	20.4	105	73	shrugging	32.9	weight	14.6
46	421	carving	50.0	carving	27.2	106	846	injecting	32.8	gloves	7.8
47	168	drumming	49.3	marching	17.5	107	395	juggling	32.7	balls	10.1
48	561	flossing	48.0	mouse	10.0	108	273	dusting	32.6	clean	11.5
49	970	marrying	47.8	bride	22.2	109	737	paddling	32.5	mountains	14.0
50	610	dunking	47.4	basketball	19.5	110	291	coughing	32.4	sneezes	15.6
51	105	paddling	47.2	river	23.7	111	375	colliding	32.4	crashing	14.5
52	150	waxing	47.2	wax	20.3	112	693	sleeping	32.3	baby	28.9
53	92	howling	46.7	barking	15.1	113	111	baking	32.3	baker	13.8
54	929	typing	46.3	typing	22.4	114	805	massaging	32.0	squatted	8.7
55	844	drumming	46.2	band	14.5	115	134	autographing	31.7	obama	7.5
56	497	cheering	45.8	cheerleaders	34.8	116	923	wrapping	31.6	tape	16.7
57	322	paddling	45.8	kayak	7.2	117	698	surfing	31.5	beach	9.8
58	672	boxing	45.6	fighting	28.8	118	362	paddling	31.5	water	8.2
59	97	barbecuing	45.6	grill	26.4	119	505	drumming	31.0	guitar	13.1
60	216	inflating	45.3	balloon	10.3	120	215	shaving	31.0	vent	12.1

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1	Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1
121	642	autographing	30.8	sign	9.9	181	646	autographing	23.5	taking	11.6
122	828	paddling	30.6	river	3.6	182	423	applauding	23.5	crowd	11.1
123	6	leaping	30.3	monkey	31.4	183	699	racing	23.4	motorcycle	16.5
124	974	sprinkling	30.0	sprinkler	26.7	184	651	paddling	23.4	sky	4.5
125	44	flossing	29.9	teeth	3.0	185	414	drenching	23.3	rain	16.9
126	342	drumming	29.9	playing	7.7	186	55	racing	23.3	race	12.0
127	108	boxing	29.8	practicing	24.1	187	718	drumming	23.2	costume	9.2
128	784	pedaling	29.7	bikes	13.1	188	439	pedaling	23.1	cyclist	12.6
129	266	barbecuing	29.7	meat	22.5	189	19	clipping	23.1	tractor	22.2
130	991	drumming	29.6	guitar	11.0	190	255	paddling	23.1	water	3.6
131	597	signing	29.3	writing	4.7	191	701	lecturing	23.0	preacher	16.3
132	817	welding	29.1	steel	11.6	192	444	autographing	22.9	protesters	7.4
133	673	typing	29.1	laptop	12.3	193	859	singing	22.9	performer	5.6
134	113	dialing	29.0	telephone	11.7	194	18	applauding	22.9	cheering	16.2
135	470	sawing	28.9	saw	10.5	195	371	barbecuing	22.9	fire	10.1
136	657	landing	28.7	airplane	11.7	196	315	peeling	22.8	orange	19.9
137	440	surfing	28.6	cap	6.1	197	271	racing	22.7	race	11.1
138	404	rinsing	28.6	scrubbing	13.3	198	955	leaping	22.6	seagulls	24.2
139	0	applauding	28.6	protesting	13.8	199	584	boxing	22.6	bag	23.7
140	950	paddling	28.2	water	9.7	200	555	pitching	22.5	baseball	19.6
141	430	hiking	27.8	hikers	13.8	201	286	piloting	22.5	helicopter	12.5
142	762	leaping	27.8	diving	12.0	202	569	paddling	22.3	down	17.6
143	504	bowing	27.3	praying	19.0	203	692	paddling	22.2	train	31.4
144	295	paddling	27.2	bridge	26.4	204	682	paddling	22.1	trees	16.3
145	579	dunking	27.2	ball	10.5	205	116	slicing	22.0	cutting	22.4
146	380	leaping	26.7	deer	29.3	206	442	dropping	22.0	wipers	16.3
147	152	sleeping	26.7	laying	14.3	207	324	skiing	22.0	skis	4.1
148	603	leaping	26.5	slipping	4.7	208	924	flooding	21.9	flooded	16.3
149	838	dusting	26.5	vacuum	14.3	209	826	bulldozing	21.6	tractor	7.0
150	825	scooping	25.9	spilled	16.7	210	422	falling	21.4	waterfall	19.4
151	64	pedaling	25.9	bicycles	8.5	211	931	bulldozing	21.4	bulldozer	18.2
152	455	erupting	25.6	smoke	20.6	212	259	wrestling	21.3	cuddling	8.0
153	429	competing	25.5	field	13.0	213	475	leaping	21.2	dance	6.1
154	989	competing	25.5	football	19.0	214	905	jumping	21.2	horse	29.1
155	223	competing	25.4	soccer	25.0	215	806	jogging	21.2	jogging	14.3
156	51	bowling	25.4	dome	8.2	216	813	applauding	21.1	waving	15.9
157	379	slicing	25.4	slicing	12.2	217	538	paddling	21.0	water	6.7
158	911	paddling	25.4	aerial	28.0	218	101	massaging	20.9	dog	13.5
159	364	leaping	25.4	bed	18.6	219	482	swinging	20.9	swinging	7.9
160	483	paddling	25.3	flowing	5.7	220	680	leaping	20.9	air	24.1
161	634	autographing	25.0	graduation	4.4	221	1018	dialing	20.7	tapping	44.4
162	884	leaping	25.0	trampoline	8.8	222	665	shaving	20.7	hair	4.1
163	485	stirring	25.0	pan	20.3	223	417	drumming	20.6	stage	8.1
164	540	boxing	25.0	jacks	6.7	224	165	mowing	20.6	lawn	16.5
165	13	paddling	25.0	boat	18.1	225	194	flossing	20.6	scoop	6.9
166	873	paddling	25.0	mountains	8.9	226	200	smashing	20.5	smashed	12.2
167	909	autographing	24.3	book	14.0	227	453	carving	20.4	wood	17.5
168	638	autographing	24.3	either	3.3	228	57	child+singing	20.2	singing	18.5
169	963	plugging	24.3	plug	11.8	229	420	paddling	20.0	forest	13.3
170	131	paddling	24.2	yellow	26.5	230	918	massaging	19.8	laying	13.5
171	799	welding	24.2	construction	27.9	231	810	paddling	19.8	dolphin	2.9
172	486	hammering	24.1	hammering	6.0	232	520	sailing	19.7	boats	5.8
173	465	competing	24.0	teams	11.9	233	190	knitting	19.6	string	10.9
174	67	lecturing	24.0	conference	9.8	234	1016	mopping	19.6	mopping	15.1
175	325	texting	24.0	phone	12.7	235	317	dunking	19.4	basket	18.9
176	1001	competing	23.9	soccer	8.1	236	827	paddling	19.3	ski	8.7
177	242	competing	23.9	football	6.7	237	24	leaping	19.2	dancing	10.2
178	714	calling	23.7	telephone	6.7	238	1019	dropping	19.1	falls	12.1
179	89	competing	23.6	soccer	17.7	239	997	sleeping	19.0	baby	8.3
180	1013	paddling	23.5	forest	19.1	240	77	peeling	19.0	makeup	17.0

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1	Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1
241	126	leaping	18.9	exercising	18.8	301	459	paddling	16.3	view	9.1
242	449	leaping	18.9	tree	17.6	302	323	shaving	16.3	head	19.8
243	187	surfing	18.9	riding	12.3	303	522	dunking	16.3	court	12.5
244	117	raining	18.8	traffic	21.7	304	773	storming	16.2	storm	9.8
245	671	paddling	18.8	city	13.8	305	748	autographing	16.2	sidewalk	14.3
246	736	autographing	18.7	howling	4.9	306	299	punting	16.2	kicks	7.3
247	251	surfing	18.5	scuba	7.0	307	981	paddling	16.2	jacket	14.1
248	491	raining	18.4	simpsons	8.5	308	627	singing	16.2	dark	14.4
249	1	burying	18.4	dirt	19.3	309	239	fishing	16.2	fishing	21.5
250	188	autographing	18.4	beard	8.8	310	41	leaping	16.1	slow	26.0
251	742	pedaling	18.3	bike	22.0	311	479	leaping	16.1	kids	6.8
252	531	chewing	18.2	eats	12.5	312	348	reaching	16.0	slipping	7.7
253	130	applauding	18.1	crowd	7.4	313	63	dropping	16.0	leaves	18.2
254	246	clinging	18.0	bird	31.2	314	892	applauding	16.0	flag	13.6
255	318	dialing	17.9	phone	6.8	315	558	stirring	16.0	cooking	9.9
256	329	extinguishing	17.9	fire	14.5	316	691	paddling	16.0	background	19.0
257	387	barbecuing	17.9	sausages	10.7	317	319	leaping	15.9	up	3.8
258	993	autographing	17.9	movie	7.6	318	845	stirring	15.8	blade	6.7
259	961	paddling	17.9	rushing	8.3	319	801	paddling	15.8	mask	14.7
260	921	surfing	17.8	beach	15.0	320	726	swimming	15.8	swimming	12.2
261	208	cheering	17.8	stadium	15.0	321	458	shrugging	15.8	karate	3.5
262	650	leaping	17.8	jumps	6.4	322	912	applauding	15.7	old	11.0
263	388	dropping	17.8	float	5.6	323	648	peeling	15.7	kitchen	13.8
264	78	paddling	17.8	walnut	6.5	324	572	dialing	15.5	block	3.2
265	332	dropping	17.7	falling	8.8	325	330	paddling	15.5	waterfall	3.3
266	244	lecturing	17.6	giving	7.3	326	211	leaping	15.5	cat	17.9
267	948	paddling	17.6	across	8.9	327	752	paddling	15.5	trail	6.7
268	1008	surfing	17.6	scuba	4.1	328	34	sleeping	15.5	bed	8.6
269	554	sewing	17.6	machine	12.2	329	792	autographing	15.5	sitting	3.5
270	604	leaping	17.6	fish	25.2	330	588	sowing	15.4	farmer	10.5
271	587	saluting	17.5	soldier	12.0	331	869	pouring	15.4	poured	20.5
272	509	discussing	17.5	office	23.5	332	840	leaping	15.4	pool	11.3
273	720	competing	17.5	track	24.2	333	407	measuring	15.4	drawing	8.5
274	1022	shrugging	17.5	gym	18.1	334	667	welding	15.4	metal	17.6
275	987	autographing	17.4	baseball	21.3	335	661	colliding	15.4	hockey	25.0
276	294	drumming	17.4	stick	16.9	336	560	flossing	15.4	animation	14.0
277	552	applauding	17.4	crowd	18.4	337	149	lecturing	15.4	graphs	8.7
278	995	draining	17.4	waterfall	14.3	338	175	autographing	15.3	walking	7.1
279	284	drumming	17.3	concert	29.3	339	815	sleeping	15.3	baby	17.5
280	808	draining	17.3	water	5.8	340	608	autographing	15.3	people	6.1
281	977	snowing	17.2	snowy	10.3	341	795	leaping	15.2	animals	13.6
282	495	unloading	17.1	time-lapse	21.7	342	755	peeling	15.2	kitchen	12.0
283	184	autographing	17.1	hat	16.8	343	138	juggling	15.2	shirtless	18.2
284	210	paddling	17.1	rocks	14.1	344	496	hanging	15.2	hanging	17.9
285	120	boxing	17.0	shorts	13.7	345	641	competing	15.1	marching	4.4
286	914	paddling	17.0	two	8.3	346	2	drumming	15.0	stage	16.7
287	263	dropping	16.9	fruits	8.1	347	916	paddling	15.0	sunny	3.4
288	245	competing	16.9	kicking	7.6	348	393	chewing	15.0	eating	15.4
289	639	autographing	16.8	dress	8.8	349	609	autographing	15.0	talking	2.5
290	739	autographing	16.7	greenfield	9.8	350	269	draining	15.0	water	12.2
291	704	leaping	16.7	dance	15.0	351	731	flossing	15.0	demonstrating	9.0
292	562	splashing	16.7	splashes	19.0	352	513	dialing	14.9	finger	10.0
293	658	splashing	16.7	bottle	24.6	353	382	paddling	14.9	sky	7.0
294	629	sleeping	16.7	reports	14.8	354	645	autographing	14.8	people	3.3
295	1014	massaging	16.6	getting	10.3	355	553	juggling	14.8	spinning	13.8
296	503	pedaling	16.5	jogging	7.2	356	490	spitting	14.8	drink	19.5
297	686	paddling	16.4	nuts	3.6	357	807	crushing	14.7	crushed	13.6
298	734	singing	16.4	singing	15.9	358	412	autographing	14.7	player	9.1
299	334	autographing	16.3	papers	6.8	359	900	leaping	14.7	branch	23.8
300	788	signing	16.3	reading	8.7	360	622	paddling	14.5	rocks	15.9

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1	Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1
361	623	paddling	14.5	yellow	8.7	421	282	dropping	12.7	backdrop	8.9
362	462	leaping	14.5	dancing	18.5	422	443	frying	12.7	food	15.1
363	65	autographing	14.5	pen	5.0	423	676	rinsing	12.7	bath	28.6
364	480	leaping	14.5	greetings	7.5	424	578	grilling	12.6	meat	3.8
365	376	paddling	14.5	large	22.9	425	994	autographing	12.5	bitter	7.7
366	730	paddling	14.4	camera	7.2	426	391	locking	12.5	staircase	8.0
367	213	paddling	14.4	red	16.0	427	155	massaging	12.5	brown	18.1
368	460	trimming	14.3	tomatoes	15.8	428	920	competing	12.5	player	14.6
369	861	dusting	14.3	swiffer	10.0	429	204	autographing	12.5	conference	3.4
370	537	leaping	14.3	daughter	15.4	430	959	manicuring	12.5	purplish	13.8
371	933	towing	14.3	truck	26.5	431	896	bandaging	12.5	tape	4.8
372	636	paddling	14.3	trees	15.9	432	820	peeling	12.4	cutting	5.6
373	336	juggling	14.2	fire	15.2	433	835	drumming	12.4	circle	12.5
374	794	juggling	14.2	boy	3.2	434	202	dropping	12.4	surface	3.7
375	283	piloting	14.1	statue	9.4	435	983	rinsing	12.3	scrubbing	5.6
376	20	singing	14.1	camera	5.8	436	519	autographing	12.3	camera	7.4
377	419	leaping	14.0	flying	13.2	437	945	lecturing	12.3	talking	6.2
378	507	racing	14.0	track	10.1	438	754	paddling	12.3	man	8.6
379	445	driving	14.0	cars	8.8	439	601	dropping	12.2	coffee	17.9
380	11	crouching	14.0	kneeling	28.1	440	140	lecturing	12.2	suit	12.1
381	74	autographing	13.9	blond	26.1	441	87	fueling	12.2	pickup	8.3
382	901	singing	13.9	girl	13.1	442	408	paddling	12.2	blue	7.0
383	313	leaping	13.9	toys	21.6	443	333	draining	12.2	coming	17.4
384	346	packing	13.8	conveyor	18.2	444	979	lecturing	12.1	podium	8.4
385	508	paddling	13.8	person	15.3	445	871	falling	12.1	waterfall	10.7
386	267	saluting	13.8	soldiers	12.8	446	53	paddling	12.1	seen	7.5
387	452	drumming	13.8	stage	18.0	447	32	paddling	12.1	jeans	1.7
388	944	massaging	13.8	back	6.0	448	488	pedaling	12.1	bike	5.3
389	595	juggling	13.8	throws	6.3	449	839	pushing	12.1	pushing	20.8
390	224	paddling	13.8	day	4.3	450	378	dunking	12.1	court	3.7
391	619	shredding	13.8	machinery	7.0	451	489	applauding	12.1	crowd	4.0
392	512	juggling	13.7	t-shirt	7.2	452	999	leaping	12.1	children	4.6
393	160	autographing	13.7	paper	11.7	453	339	skating	12.1	skateboarding	22.0
394	390	pouring	13.7	liquid	21.1	454	653	dropping	12.1	slow	6.0
395	394	paddling	13.7	car	5.3	455	225	autographing	12.1	city	6.3
396	541	flossing	13.6	fancy	8.9	456	30	leaping	12.0	dog	19.8
397	396	massaging	13.6	electronical	6.6	457	654	applauding	12.0	old	12.1
398	321	standing	13.4	performing	9.8	458	102	tattooing	12.0	drawing	10.9
399	432	weeding	13.4	garden	16.3	459	662	autographing	12.0	older	14.0
400	71	bulldozing	13.3	tractor	13.7	460	219	talking	12.0	turned	5.5
401	596	drenching	13.3	window	30.0	461	99	dropping	12.0	cartoon	13.3
402	177	autographing	13.3	broadcast	2.3	462	669	shaving	11.9	legs	11.4
403	10	dialing	13.3	jack	13.6	463	962	dropping	11.9	winds	7.4
404	527	autographing	13.3	street	5.2	464	205	sleeping	11.9	child	10.5
405	837	drenching	13.3	rain	9.6	465	936	dropping	11.9	image	15.2
406	293	leaping	13.3	fly	5.8	466	728	applauding	11.9	rally	12.5
407	867	dropping	13.3	bunch	3.7	467	804	leaping	11.9	field	12.0
408	426	weeding	13.3	gardening	11.1	468	529	leaping	11.9	dog	4.9
409	280	leaping	13.3	dog	20.5	469	971	hitchhiking	11.8	road	19.4
410	331	autographing	13.1	contract	4.4	470	666	applauding	11.8	smiling	13.7
411	523	leaping	13.1	dancing	8.8	471	797	applauding	11.7	black-n-white	11.6
412	741	singing	13.0	microphone	12.5	472	425	drumming	11.7	filming	3.1
413	744	barbecuing	13.0	chef	19.5	473	663	peeling	11.6	waist	5.3
414	724	sawing	13.0	tree	5.6	474	471	applauding	11.6	hands	10.8
415	277	juggling	13.0	motion	3.9	475	711	leaping	11.5	children	7.8
416	16	dialing	12.9	device	4.9	476	611	sleeping	11.5	dog	8.1
417	984	destroying	12.9	tower	11.4	477	715	paddling	11.5	blue	7.8
418	917	dragging	12.9	pulling	20.1	478	36	singing	11.5	microphone	24.7
419	729	leaping	12.8	running	7.2	479	700	tattooing	11.4	someone's	3.2
420	365	autographing	12.8	walk	7.5	480	1017	applauding	11.4	standing	6.1

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1	Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1
481	887	autographing	11.4	sidewalk	4.7	541	982	mopping	9.8	floor	16.7
482	829	leaping	11.4	cat	14.5	542	115	autographing	9.7	yelling	7.6
483	162	lecturing	11.4	speaking	7.3	543	179	sleeping	9.7	tiger	13.2
484	852	swimming	11.3	pool	15.4	544	877	autographing	9.7	at	1.6
485	353	paddling	11.2	trickling	2.1	545	84	paddling	9.7	going	7.8
486	998	paddling	11.2	green	22.4	546	132	autographing	9.7	people	2.7
487	565	manicuring	11.2	painting	8.6	547	902	autographing	9.7	another	2.6
488	129	drumming	11.2	night	25.9	548	383	paddling	9.6	buildings	4.8
489	21	paddling	11.2	going	7.6	549	124	drumming	9.6	silhouette	3.7
490	690	autographing	11.2	blond	7.2	550	986	paddling	9.6	sliding	14.0
491	214	slipping	11.1	snow	11.0	551	253	applauding	9.5	tennis	5.7
492	454	paddling	11.1	bridge	5.6	552	761	autographing	9.5	ground	5.4
493	320	unpacking	11.1	boxes	18.2	553	925	rafting	9.5	group	13.9
494	261	paddling	11.1	down	3.4	554	90	drumming	9.4	wearing	10.2
495	864	sleeping	11.1	father	7.1	555	583	autographing	9.4	standing	7.9
496	411	burying	11.0	hole	16.0	556	725	hammering	9.4	blacksmith	11.1
497	127	competing	11.0	field	5.2	557	976	peeling	9.4	closing	12.9
498	580	child+singing	10.8	girl	10.7	558	922	drenching	9.4	driving	16.8
499	849	paddling	10.8	slowly	8.4	559	198	singing	9.4	tide	9.1
500	285	autographing	10.7	dress	8.1	560	144	screwing	9.4	machine	7.3
501	721	autographing	10.7	middle-aged	2.6	561	607	extinguishing	9.4	spraying	22.7
502	88	leaping	10.7	wall	10.1	562	195	racing	9.4	cars	23.0
503	769	autographing	10.6	table	10.2	563	913	drumming	9.3	sitting	6.6
504	91	autographing	10.6	she	8.1	564	366	bulldozing	9.3	trainer	2.6
505	119	jumping	10.6	rope	8.8	565	703	leaping	9.3	cats	4.3
506	448	paddling	10.6	hat	8.3	566	367	autographing	9.3	holding	6.8
507	831	skating	10.5	park	20.6	567	377	autographing	9.3	hallway	11.8
508	906	leaping	10.5	store	9.6	568	173	raining	9.2	cartoon	25.4
509	344	discussing	10.5	restaurant	25.7	569	86	competing	9.2	field	13.1
510	847	cheering	10.5	competition	4.3	570	328	autographing	9.2	walking	13.2
511	357	shaving	10.4	his	5.3	571	258	leaping	9.2	kids	7.1
512	904	running	10.4	running	13.1	572	487	autographing	9.2	giving	1.5
513	193	paddling	10.4	someone	16.2	573	385	ironing	9.2	clothes	15.8
514	192	applauding	10.3	motocross	6.2	574	598	raining	9.1	cartoon	17.6
515	230	autographing	10.3	looking	10.8	575	128	surfing	9.1	standstill	9.8
516	534	sleeping	10.3	bag	4.5	576	851	lecturing	9.1	upside	12.5
517	550	peeling	10.2	bowl	15.7	577	649	pouring	9.1	concrete	11.1
518	159	autographing	10.2	ward	4.3	578	695	sleeping	9.1	couch	12.8
519	314	leaping	10.2	mixed-race	4.0	579	70	autographing	9.1	people	4.4
520	709	leaping	10.1	animals	4.8	580	197	yawning	9.1	couch	30.6
521	95	sprinkling	10.1	sprinkler	10.8	581	446	applauding	9.0	many	8.8
522	227	sleeping	10.1	oh	2.7	582	351	singing	9.0	bright	3.2
523	935	applauding	10.1	perch	12.5	583	287	paddling	9.0	bird	15.2
524	176	typing	10.1	office	5.3	584	821	drumming	9.0	kayakers	3.8
525	1011	drumming	10.0	boy	17.0	585	310	applauding	9.0	smiling	12.9
526	683	competing	10.0	game	7.1	586	203	paddling	8.9	video	3.7
527	185	knitting	10.0	stitching	8.2	587	624	crushing	8.9	greenfield	20.3
528	289	dropping	10.0	ground	16.5	588	696	autographing	8.9	man	9.7
529	899	reaching	10.0	church	20.8	589	514	paddling	8.9	behind	2.8
530	767	playing	10.0	overwatch	6.7	590	886	falling	8.9	shine	5.6
531	796	paddling	10.0	base	3.7	591	451	peeling	8.9	carrots	5.2
532	161	discussing	9.9	family	10.8	592	953	autographing	8.8	outside	12.5
533	782	leaping	9.9	doing	12.9	593	975	paddling	8.8	building	1.8
534	850	autographing	9.9	american	1.9	594	643	carving	8.8	working	12.4
535	620	leaping	9.8	bridge	4.1	595	418	autographing	8.8	suit	13.1
536	992	leaping	9.8	point-of-view	6.9	596	481	autographing	8.7	woman	9.1
537	547	grilling	9.8	crawling	17.3	597	756	paddling	8.7	wearing	3.2
538	891	paddling	9.8	on	2.5	598	670	signing	8.7	table	7.2
539	340	dusting	9.8	clean.	5.2	599	785	autographing	8.7	standing	2.1
540	659	storming	9.8	yard	18.2	600	787	drumming	8.7	sitting	7.5

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1	Rank	Code	Visual Action Top Hypothesis label	Visual Action Top Hypothesis Prc.	Spoken word Top Hypothesis word	Spoken word Top Hypothesis F1
601	723	autographing	8.7	something	6.1	661	980	kicking	7.7	shooting	12.5
602	719	talking	8.7	toddler	17.9	662	238	sleeping	7.7	squirrel	12.8
603	209	autographing	8.7	hair	8.4	663	360	injecting	7.7	person	2.9
604	521	rafting	8.7	people	8.4	664	853	camping	7.7	tent	8.9
605	98	applauding	8.6	stand	6.2	665	652	autographing	7.6	single	1.5
606	969	leaping	8.6	kids	7.2	666	893	watering	7.6	watering	8.4
607	770	flossing	8.6	explaining	7.5	667	546	piloting	7.6	lyrics	3.4
608	616	leaping	8.5	snow	20.0	668	674	applauding	7.6	night	8.4
609	410	erupting	8.5	explodes	7.5	669	881	autographing	7.5	table	7.6
610	12	paddling	8.5	distance	13.6	670	236	hammering	7.5	wooden	9.5
611	750	flossing	8.5	drinking	8.5	671	778	leaping	7.5	house	8.7
612	1009	autographing	8.5	street	17.1	672	260	flossing	7.5	smiling	19.2
613	463	slicing	8.5	pieces	11.7	673	399	paddling	7.5	of	6.5
614	843	autographing	8.5	speaking	4.8	674	146	autographing	7.5	language	4.9
615	772	paddling	8.5	workers	12.7	675	745	autographing	7.5	sitting	10.0
616	781	leaping	8.5	involving	7.4	676	207	paddling	7.5	man	12.5
617	757	flossing	8.4	caption	10.4	677	732	smelling	7.5	flowers	36.6
618	793	pointing	8.3	gameplay	16.7	678	647	autographing	7.4	smashes	3.3
619	403	racing	8.3	car	5.3	679	894	splashing	7.4	plastic	9.2
620	988	clipping	8.3	shoe	8.3	680	416	drumming	7.4	group	9.8
621	502	paddling	8.3	going	1.5	681	492	autographing	7.4	fans	1.4
622	343	paddling	8.3	over	2.7	682	467	drumming	7.4	child	8.0
623	450	shaving	8.3	chef	5.2	683	573	wrapping	7.4	box	9.8
624	765	paddling	8.2	gymnast	4.8	684	381	autographing	7.4	he	3.0
625	476	paddling	8.2	trees	8.4	685	855	autographing	7.3	gentleman	2.6
626	818	autographing	8.2	vest	3.3	686	939	peeling	7.3	close	7.0
627	746	autographing	8.2	street	13.7	687	494	peeling	7.3	hands	4.9
628	122	applauding	8.2	people	7.8	688	575	paddling	7.3	a	6.0
629	275	leaping	8.2	workout	4.2	689	581	smashing	7.3	building	21.9
630	592	hammering	8.2	piles	3.9	690	142	stopping	7.3	characters	11.4
631	1003	leaping	8.2	around	5.9	691	599	autographing	7.3	two	5.6
632	7	paddling	8.1	and	3.2	692	309	paddling	7.2	shooting	4.8
633	257	raining	8.1	blown	20.7	693	264	drumming	7.2	bedroom	3.6
634	170	leaping	8.1	running	5.5	694	919	autographing	7.2	hands	12.4
635	341	flossing	8.1	how	6.1	695	47	autographing	7.2	woman	6.4
636	354	sewing	8.1	machine	14.2	696	570	paddling	7.1	we	2.0
637	600	paddling	8.1	each	6.1	697	965	paddling	7.1	red	3.4
638	677	rolling	8.1	cooks	6.9	698	361	autographing	7.1	upright	3.6
639	133	sleeping	8.1	string	7.3	699	934	peeling	7.1	putting	7.9
640	678	leaping	8.0	tree	7.5	700	594	sitting	7.1	inject	8.0
641	466	injecting	8.0	close	18.2	701	186	draining	7.1	house	20.9
642	1006	stirring	8.0	pot	5.2	702	809	paddling	7.1	man	11.0
643	212	crying	8.0	helping	7.0	703	783	paddling	7.1	with	1.6
644	889	autographing	8.0	young	4.0	704	151	autographing	7.0	store	6.5
645	437	manicuring	7.9	fingers	8.3	705	474	paddling	7.0	person	9.2
646	468	jumping	7.9	motorcycle	9.9	706	1021	paddling	7.0	decorated	8.9
647	633	applauding	7.9	show	7.9	707	359	paddling	7.0	picture	5.7
648	59	drumming	7.9	watching	14.2	708	740	applauding	6.9	people	6.1
649	814	peeling	7.9	someone	4.7	709	614	autographing	6.9	knick-knack	5.3
650	441	leaping	7.9	jeans	14.1	710	237	leaping	6.9	inflating	6.7
651	775	inflating	7.9	chair	16.5	711	567	autographing	6.9	and	2.8
652	46	autographing	7.9	woman	23.8	712	135	signing	6.9	sitting	6.6
653	824	autographing	7.9	field	2.3	713	506	drumming	6.9	guys	7.3
654	968	dusting	7.9	floor	5.4	714	28	autographing	6.9	hey	7.0
655	544	reaching	7.8	climbing	13.0	715	456	applauding	6.9	animated	4.9
656	389	autographing	7.8	front	14.3	716	768	autographing	6.9	holding	7.4
657	819	lecturing	7.8	laughing	18.1	717	879	leaping	6.9	exercising	5.1
658	498	shaving	7.8	pink	18.5	718	628	drumming	6.9	men	10.4
659	9	paddling	7.7	green	5.2	719	80	discussing	6.9	women	8.6
660	927	singing	7.7	saying	13.9	720	586	applauding	6.8	haired	7.7

Table 6: continued

Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1	Rank	Code	Visual Action Top Hypothesis label	Prc.	Spoken word Top Hypothesis word	F1
721	1004	pouring	6.8	color	6.8	734	167	peeling	6.7	into	3.5
722	72	injecting	6.8	mixing	4.7	735	428	leaping	6.7	doing	2.2
723	876	autographing	6.8	arena	3.8	736	300	paddling	6.6	is	2.3
724	878	gambling	6.8	game	9.4	737	786	paddling	6.6	background	1.7
725	114	paddling	6.8	man	15.7	738	272	leaping	6.6	truck	8.5
726	764	raising	6.8	trash	10.0	739	297	applauding	6.6	rustic	4.5
727	326	leaping	6.8	zooming	3.1	740	303	paddling	6.6	down	1.0
728	217	surfing	6.8	surfer	2.0	741	93	paddling	6.5	car	3.3
729	107	pouring	6.8	bottle	5.8	742	542	baking	6.5	cupcake	9.2
730	749	injecting	6.7	person’s	2.2	743	733	discussing	6.5	men	7.3
731	612	autographing	6.7	disgust	4.8	744	23	leaping	6.5	cross	5.5
732	834	autographing	6.7	outside	12.7	745	104	injecting	6.5	beard	2.6
733	655	marrying	6.7	couple	7.5	746	279	leaping	6.5	garden	4.4