Learning Audio-Visual Representations with Active Contrastive Coding

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Abstract

Contrastive coding has achieved promising results in self-supervised representation learning. However, there are practical challenges given that obtaining a tight lower bound on mutual information (MI) requires a sample size exponential in MI and thus a large set of negative samples. We can incorporate more samples by building a large queue-based dictionary, but there are theoretical limits to performance improvements even with a large number of negative samples. We hypothesize that random negative sampling leads to a highly redundant dictionary, which could result in representations that are suboptimal for downstream tasks. In this paper, we propose an active contrastive coding approach that builds an actively sampled dictionary with diverse and informative items, which improves the quality of negative samples and achieves substantially improved results on tasks where there is high mutual information in the data, e.g., video classification. Our model achieves state-of-the-art performance on multiple challenging audio and visual downstream benchmarks including UCF101, HMDB51 and ESC50.

1 Introduction

Recent studies have demonstrated promising results on contrastive learning of audio and visual representations (Oord et al., 2018; Hénaff et al., 2019; Schneider et al., 2019; Chen et al., 2020). The self-supervised training process can be understood as building a dynamic dictionary per mini-batch, where “keys” are typically randomly sampled from the data. The encoders are trained to perform dictionary look-up: an encoded “query” should be similar to the value of its matching key and dissimilar to others. This training objective maximizes a lower bound of mutual information (MI) between representations and the data (Hjelm et al., 2018; Arora et al., 2019). However, such lower bounds are tight only for sample sizes exponential in the MI (McAllester & Stratos, 2020), suggesting the importance of building a large and consistent dictionary across mini-batches.

Consequently, He et al. (2020) designed Momentum Contrast (MoCo) that builds a queue-based dictionary with momentum updates. It decouples the dictionary size from the memory capacity of modern GPUs/TPUs, and thus practically achieves a large and consistent dictionary. However, Arora et al. (2019) showed that simply increasing the dictionary size beyond a threshold does not improve (and sometimes can even harm) the performance on downstream tasks. Furthermore, we find that MoCo can suffer when there is high redundancy in the data, because only relevant – and thus limited – parts of the dictionary are updated in each iteration, ultimately leading to a dictionary of redundant items (we show this empirically in Fig.3). We argue that random negative sampling is much responsible for such theoretically and empirically validated issue: a randomly constructed dictionary will contain more “biased keys” (similar keys that belong to the same class) and “ineffective keys” (keys that can be easily discriminated by the current model) than a carefully constructed one. Furthermore, this issue can get aggravated when the dictionary size is large.

In this paper, we focus on learning audio-visual representations of video data by leveraging the natural correspondence between the two modalities, which serves as a useful self-supervisory signal.

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1Fig. 2 blue lines show the probability of sampling unique negatives (instances from different categories) decreases from 37.5% to 30.8% when we increase the batch size from 32 to 128. We compute the probabilities by averaging the number of unique categories across iterations and dividing them by their batch size.
where \( x \) is a “query” We can interpret the contrastive learning objective as a dynamic dictionary look-up process. Given other metrics can also be used, e.g., the log-bilinear form [Oord et al., 2018].

Contrastive Learning. [Gutmann & Hyvärinen, 2010; Oord et al., 2018] learn the representation of data by comparing encoded representations of similar samples with dissimilar samples. This perspective, the optimal solution to equation 1 will enable a dictionary look-up of negative samples by query. The similarity in this case is measured by the dot product between representations, but

\[
\begin{align*}
\min_{\theta_q, \theta_k} \mathbb{E}_{x \sim p_X} \left[ -\log \left( \frac{e^{f(x; \theta_q) \top h(x^+; \theta_k)}}{e^{f(x; \theta_q) \top h(x^+; \theta_k)} + e^{f(x; \theta_q) \top h(x^-; \theta_k)}} \right) \right]
\end{align*}
\]

where \( f(\cdot) \) and \( h(\cdot) \) are feature encoders with learnable parameters \( \theta_q \) and \( \theta_k \), respectively. The samples \( x^+ \) and \( x^- \) are drawn from the same distribution as \( x \in \mathcal{X} \), and are assumed to be similar and dissimilar to \( x \), respectively. Minimizing this objective encourages \( f(\cdot) \) and \( h(\cdot) \) to learn discriminative representations of \( x \) such that \( (x, x^+) \) have a higher similarity than all the other pairs of \( (x, x^-) \). The similarity in this case is measured by the dot product between representations, but other metrics can also be used, e.g., the log-bilinear form [Oord et al., 2018].

We can interpret the contrastive learning objective as a dynamic dictionary look-up process. Given a “query” \( x \), it finds the correct “key” \( x^+ \) among the other irrelevant keys \( x^- \) in a dictionary. In this perspective, the optimal solution to equation 1 will enable a dictionary look-up of \( x^+ \) given a query \( x \). Denoting the query by \( q = f(x) \), the correct key by \( k^+ = h(x^+) \), and the dictionary of \( K \) negative samples by \( \{k_i = h(x_i)\}, i \in [1, K] \), we can express equation 1 in a softmax form,

\[
\begin{align*}
\min_{\theta_q, \theta_k} \mathbb{E}_{x \sim p_X} \left[ -\log \left( \frac{e^{q \cdot k^+ / \tau}}{\sum_{i=0}^{K} e^{q \cdot k_i / \tau}} \right) \right]
\end{align*}
\]

where \( \theta_q \) and \( \theta_k \) are parameters associated with the query and key encoders, respectively, and \( \tau \) is a temperature term that controls the shape of the probability distribution computed by the softmax function.
function. Assuming there is a single positive key $k^+$ in the dictionary, the above objective can be seen as a $(K+1)$-way softmax classifier that aims to classify $q$ as $k^+$.

**Momentum Contrast (MoCo).** The standard approach to contrastive learning builds a dictionary dynamically per mini-batch [Oord et al. 2018; Henaff et al. 2019]; the $(K+1)$ samples correspond to a mini-batch of one positive and $K$ negative samples, which are often randomly chosen from the dataset. This is convenient as we can update the entire model parameters by the standard back-propagation; Fig. 1(a) illustrates this standard approach. However, this approach couples the dictionary size to the mini-batch size, which is capped by the GPU/TPU capacity.

MoCo (He et al. 2020) decouples the dictionary size with the mini-batch size by implementing a queue-based dictionary, i.e., current mini-batch samples are enqueued while the oldest are dequeued. It then applies momentum updates to parameters of a key encoder $\theta_k$ with respect to parameters of a query encoder, $\theta_k \leftarrow m\theta_k + (1-m)\theta_q$, where $m \in [0, 1)$ is a momentum coefficient. Only the parameters $\theta_q$ are updated by back-propagation, while the parameters $\theta_k$ are defined as a moving average of $\theta_m$ with exponential smoothing. These two modifications allow MoCo to build a large and slowly-changing (and thus consistent) dictionary, which lead to substantial improvements on various image recognition tasks including classification, detection, and segmentation (He et al. 2020).

**Theoretical Limitations of Contrastive Learning.** Recent work provides theoretical analysis on the shortcomings of contrastive learning. McAllester & Stratos (2020) show that lower bounds to the MI are only tight for sample size exponential in the MI, suggesting that a large amount of data are required to achieve a tighter lower bound on MI. He et al. (2020) empirically showed that increasing negative samples has shown to improve the learned presentations. However, Arora et al. (2019) showed that such a phenomenon does not always hold: Excessive negative samples can sometimes hurt performance. Also, when the number of negative samples is large, the chance of sampling redundant instances increases, limiting the effectiveness of contrastive learning. One of our main contributions is to address this issue with active sampling of negative instances, which reduces redundancy and improves diversity, leading to improved performance on various downstream tasks.

3 Approach

We present cross-modal active contrastive coding (CM-ACC) to learn audio-visual representations from unlabeled videos. Fig. 1 highlights the main idea of our approach.

3.1 Cross-Modal Contrastive Representation Learning

Let $A = \{a_0, \ldots, a_{N-1}\}$ and $V = \{v_0, \ldots, v_{N-1}\}$ be collections of audio and visual clips, where each pair $(a_i, v_i)$ is taken from the same block of a video and temporally synchronized, for all $i \in [0, N)$. We define query encoders $f_q$ and $f_v$ and key encoders $h_a$ and $h_v$ for audio and visual clips, respectively, with learnable parameters $\{\theta_q, \theta_v\}$ for the query encoders and $\{\theta_a, \theta_v\}$ for the key encoders. These encoders compute representations of audio and visual clips as queries and keys,

$$q^v = f_v(a^{query}), \quad k^a = h_a(v^{key}), \quad q^a = f_a(a^{query}), \quad k^v = h_v(a^{key})$$  \hspace{1cm} (3)

We propose a cross-modal contrastive predictive coding scheme that leverages the natural correspondence between audio and visual channels of video data. At a high-level, our learning objective encourages the representations of audio and visual clips to be similar if they come from the same temporal block of a video. Fig. 1(b) illustrates our cross-modal predictive coding setup.

We train our encoders to perform cross-modal dictionary look-up: Taking as an example the visual-to-audio predictive coding scenario, given a query video clip $a^{query}$, we want to find the corresponding audio clip $a^{key}$ from a dictionary $D_a$. Extending MoCo (He et al. 2020) to our cross-modal setup, we implement a queue-based dictionary $D_a$ that stores keys of audio clips $\{k^a_i\}_{i=1}^K$, where $K$ is the dictionary size. We compute the contrastive loss of equation 2 and backpropagate the gradients only to the visual query encoder $f_v$ and update the parameters $\theta_q$. For the audio encoder $h_a$, we apply the momentum update $\theta_a^k \leftarrow m\theta_a^k + (1-m)\theta_q^a$.

$$\theta_a^k \leftarrow m\theta_a^k + (1-m)\theta_q^a$$  \hspace{1cm} (4)

Note that we have not updated $\theta_q^a$ in this visual-to-audio predictive coding step; we update it during the audio-to-visual predictive coding step (which follows the same process as above with the op-
Figure 1: Our approach (b) extends contrastive coding (a) to the cross-modal scenario and adapts the momentum contrast (MoCo) \cite{he2020momentum} to the dictionary update. Different from all existing work, we propose an active learning idea to the negative sampling.

3.2 Active Sampling of Negative Instances

The quality of negative samples is crucial in contrastive learning. Existing work in contrastive learning typically adopts random negative sampling. However, we want a diverse set of negative samples in our dictionary so that comparisons between positive and negative pairs are most informative. In the supervised setting, this can be done by sampling instances from different categories than the query instance. Unfortunately, in the unsupervised case we do not have access to the labels.

Motivated by active learning \cite{settles2009active}, we propose a novel gradient-based active sampling approach to improve the quality of negative samples. In active learning, the learner chooses samples that seem maximally informative and queries an oracle for labels to obtain an optimal solution with a minimal labeling budget. Adapting this to our setting, we can empower the learner to choose the maximally informative negative samples to construct a dictionary; the main question is how to measure the informativeness of samples without labels.

One way to measure the informativeness is through the lens of uncertainty: If a model is highly uncertain about its prediction of a sample, we can ensure the maximum update to the model by including the sample in a mini-batch (conversely, if the uncertainty is low for all samples in a mini-batch, the model update will be small). In the first-order optimization regime, such as SGD \cite{lecun1998gradient} and its variants, \cite{ash2020active} have shown that gradients of a loss function with respect to the model’s most confident predictions can approximate the uncertainty of samples, demonstrating its effectiveness in active learning where ground-truth labels are assumed to be unknown. They provide a theoretical justification by showing that gradient norms of the last layer of a neural network with respect to pseudo-labels provides a lower bound on gradient norms induced by any other labels. In this work, we use gradients of the last layer to measure the uncertainty and encourage our model to include samples that have the highest gradient magnitudes to constitute a dictionary.

While the uncertainty of each individual samples is important, the diversity of samples is also a critical measure of informativeness. Intuitively, it is possible that a model is highly uncertain about samples from particular semantic categories, but constructing a mini-batch of samples from just those categories can severely bias gradients and ultimately lead to a bad local minima. There are several principled approaches to ensure the diversity of samples, such as submodular optimization \cite{fujisige2005submodular} and Determinantal Point Processes (DPP) \cite{macchi1975some}. Unfortunately, those methods are computationally heavy because of the combinatorial search space \cite{nemhauser1978integer,gilks1995introduction}. In this work, instead of using the expensive solutions,
we opt to the fast solution of [Ash et al., 2020] and use the initialization scheme of the k-MEANS++ seeding algorithm [Arthur & Vassilvitskii, 2007] to sample a diverse set of negatives.

3.3 Cross-Modal Active Contrastive Coding

Algorithm 1 describes our proposed cross-modal active contrastive coding (for comparison, we also provide a version without active sampling in Appendix). At a high-level, we initialize the dictionaries $D_v$ and $D_a$ with $K$ randomly drawn samples from $V$ and $A$, respectively (lines 3-5). For each epoch, we construct “negative candidate pools” $U_v$ and $U_a$ with $N$ random samples from $V$ and $A$, respectively (lines 7-9). For each iteration within an epoch, we actively select the most informative negative samples $S_v$ and $S_a$ from the pools $U_v$ and $U_a$, respectively, and enqueue them into the dictionaries $D_v$ and $D_a$, respectively (lines 11-30). We then perform cross-modal con-
contrastive predictive coding, update the parameters of query encoders $\theta_w^v$ and $\theta_w^a$ via backpropagation, and apply momentum updates to the parameters of key encoders $\theta_k^v$ and $\theta_k^a$ (lines 32–39).

**Active sampling.** Our sampling approach finds the most informative negative instances by considering both *uncertainty* and *diversity*. To measure the uncertainty, we define a pseudo-label space induced by the queries from the other modality, and take the gradient of the last layer of a query encoder network with respect to the most confident prediction, which we call the pseudo-label $\hat{y}$.

For instance, in the case of sampling negative video keys from the pool $U_v$ (lines 14–21), we compute the pseudo-posterior of a video key $v_n \in U_v \setminus D_v$,

$$p(\hat{y}_n^v|v_n, B_a) = \frac{\exp(k_n^v \cdot q_n^a)}{\sum_{i=1}^{M} \exp(k_i^v \cdot q_i^a)} \forall j \in [1, M]$$

where $B_a$ is the current mini-batch of audio queries and defines the pseudo-label space. Note that we consider only the samples in $U_v \setminus D_v$ to rule out samples already in $D_v$. Intuitively, this computes the posterior by the dot-product similarity between $v_n$ and all $q_n^a \in B_a$, producing an $M$-dimensional probability distribution. We then take the most confident class category as the pseudo-label $\hat{y}_n^v$ (line 17) and compute the gradient according to the cross-entropy loss

$$g_{v_n} = \frac{\partial}{\partial \theta_{\text{last}}} \mathcal{L}_{CE}(p(\hat{y}_n^v|v_n, B_a), \hat{y}_n^v) \big|_{\theta=\theta^a}$$

where $\theta_{\text{last}}$ is the parameters of the last layer of $\theta$ (in this case, $\theta^a$ of the audio query encoder $h_a$). Intuitively, the gradient $g_{v_n}$ measures the amount of change (and thus, the uncertainty) $v_n$ will bring to the audio query encoder $h_a$.

One can interpret this as a form of **online hard negative mining**: The gradient is measured with respect to the most probable pseudo-label $\hat{y}_n^v$ induced by the corresponding audio query $q_n^a$. When we compute the contrastive loss, the same audio query will be maximally confused by $v_n$ with its positive key $v^+$ per dot-product similarity, and $v_n$ in this case can serve as a hard negative sample.

Next, we obtain the most diverse and highly uncertain subset $S_v \subseteq U_v \setminus D_v$ using the initialization scheme of $k$-MEANS++ (Arthur & Vassilvitskii 2007) over the gradient embeddings $g_{v_n}$ (line 20). The $k$-MEANS++ initialization scheme finds the seed cluster centroids by iteratively sampling points with a probability in proportion to their squared distances from the nearest centroid that has already been chosen (we provide the exact algorithm in the appendix). Intuitively, this returns a diverse set of instances sampled in a greedy manner, each of which has a high degree of uncertainty measured as its squared distances from other instances that have already been chosen. Finally, we enqueue $S_v$ into $D_v$ and dequeue the oldest batch from $D_v$ (line 21). We repeat this process to sample negative audio keys (lines 23–30); this concludes the active sampling process for $D_v$ and $D_a$.

**Cross-modal contrastive coding.** Given the updated $D_v$ and $D_a$, we perform cross-modal contrastive coding. For visual-to-audio coding, we compute the posteriors of all the video samples $v_i \in B_v$ with respect to the negative samples in the audio dictionary $D_a$

$$p(y_i^v|v_i, a_i, D_a) = \frac{\exp(q_i^a \cdot k_i^a / \tau)}{\sum_{j=0}^{K} \exp(q_j^a \cdot k_j^a / \tau)} \forall i \in [1, M]$$

where the posterior is defined over a cross-modal space with one positive and $K$ negative pairs (line 33). Next, following MoCo (He et al. 2020), we backpropagate the gradient signals only to the query encoders $f_v$ and $f_a$ (lines 36–37), while applying momentum update to the parameters of the key encoders $h_a$ and $h_a$ (lines 38–39). The momentum update allows the dictionaries to change their states slowly, thus making them consistent across iterations.

Note that our momentum update can cause inconsistency in dictionary states because the gradient used to update the query encoders are not directly used to update the corresponding key encoders (see Fig. 1 and lines 38–39 in Alg. 1). To improve the stability during training, we let the gradients flow in a cross-modal fashion (e.g., updating part of $f_v$ and $h_a$ using the same gradient signal from the contrastive loss), by adding one FC layer on top of all encoders and applying momentum update to their parameters. For example, we apply momentum update to the parameters of the FC layer on top of $h_a$ using the parameters of the FC layer from $f_v$. We omit this in Alg. 1 for clarity but show its importance in our ablation experiments (XMoCo (w/o fcl) in Table 1).
4 Related Work

Self-supervised learning has been extensively studied in vision, language, and audio domains, and several approaches have been proposed on designing new pretext task or more efficient learning objectives. One popular idea in the image domain is learning representations by maximizing the MI (Belghazi et al., 2018; Hjelm et al., 2018). In the video domain, several approaches exploited the underlying structure of video data to design efficient pretext tasks, e.g. by adopting ordering (Sermanet et al., 2017; Wang et al., 2019b), temporal consistency (Dwibedi et al., 2019), and spatio-temporal statistics (Xu et al., 2019; Wang et al., 2019a; Han et al., 2019). In the language domain, the transformer-based approaches trained with the masked language model (MLM) objective has been the most successful (Devlin et al., 2019; Liu et al., 2019; Yang et al., 2019).

Riding on the success of BERT (Devlin et al., 2019), several concurrent approaches generalize it to learn visual-linguistic representations (Lu et al., 2019; Li et al., 2020; Su et al., 2019; Tan & Bansal, 2019; Li et al., 2019). CBT (Sun et al., 2019a) and VideoBERT (Sun et al., 2019b) made efforts on adapting BERT-style pretraining for video. However, the MLM loss requires each token in the sequence to be discrete. The current approaches assume visual representations to be fixed and to be given by pretrained visual encoders (fully-supervised), and define the visual MLM objective in terms of visual similarities (e.g. via vector quantization (VQ) or L2 distance metric) between the original and predicted visual representations. Unfortunately, VQ loses fine-grained information and a pretrained visual encoder limits the learning capacity, which are all crucial for downstream tasks.

Besides vision and language signals, several approaches learn audio-visual representations in a self-supervised manner (Owens et al., 2016; Arandjelovic & Zisserman, 2017; Owens & Efros, 2018; Owens et al., 2016). Recently, audio-visual learning has been applied to enable interesting applications beyond recognition tasks, such as sound source localization/separation (Zhao et al., 2018; Arandjelovic & Zisserman, 2018; Gao et al., 2018; Gao & Grauman, 2019a; Ephrat et al., 2018; Gan et al., 2020; Zhao et al., 2019; Yang et al., 2020) and visual-to-sound generation (Hao et al., 2018; Zhou et al., 2018). The work of Owens & Efros (2018), Korbar et al. (2018), and Alwassel et al. (2019) are similar in spirit to our own, but our technical approach differs substantially in the use of active sampling and contrastive learning.

5 Experiments

Implementation detail. Unless otherwise noted, we use 3D-ResNet18 (Hara et al., 2018) as our visual encoders (fv and hv). For audio encoders (fa and ha), we adapt ResNet-18 (He et al., 2016) to audio signals by replacing 2D convolution kernels with 1D kernels. We employ Batch Normalization (BN) (Ioffe & Szegedy, 2015) with the shuffling BN (He et al., 2020) in all our encoders. All models are trained end-to-end with the ADAM optimizer (Kingma & Ba, 2014) with an initial learning rate $\gamma = 10^{-3}$ after a warm-up period of 500 iterations. We use the mini-batch size $M = 128$, dictionary size $K = 30 \times 128$, pool size $N = 300 \times 128$, momentum $m = 0.999$, and temperature $\tau = 0.7$. We used 40 NVIDIA Tesla P100 GPUs for our experiments.

Datasets. We use AudioSet (Gemmeke et al., 2017) and Kinetics-700 (Carreira et al., 2019) as our pretraining data when comparing with state-of-the-art approaches. For Kinetics-700, we use 240K randomly selected videos that contain the audio channel. On AudioSet, we use both a subset of 240K randomly selected videos and the 1.8M full set. For our ablation study, we pretrain our model on Kinetics-Sound (Arandjelovic & Zisserman, 2017) that contains 22K videos from 34 classes of Kinetics that are potentially manifested both visually and audibly. For downstream tasks, we evaluate our models on action recognition using UCF101 (Soomro et al., 2012) and HMDB51 (Kuehne et al., 2011), and on sound classification using ESC50 (Piczak, 2015b). UCF101 contains 13K video clips from 101 action categories, HMDB51 contains 7K video clips from 51 categories, and ESC50 has 2K audio clips from 50 categories. UCF101 and HMDB51 have 3 official train/test splits, while ESC50 has 5 splits. We conduct our ablation study using split-1 of each dataset. We report our average performance over all splits when we compare with prior work.

We preprocess video frames by sampling at 10 FPS and applying random cropping, horizontal flipping, gray-scaling, and temporal jittering. We resize video frames to 3-channel images of $224 \times 224$; we set the clip length to 16 frames during pretraining, and 32 frames during finetuning on downstream tasks. For audio channel, we extract mel-spectrograms from the raw waveform using the
Table 1: Top-1 accuracy of unimodal vs. cross-modal pretraining on downstream tasks.

| #  | Approach          | Pretrain Obj.   | UCF101  | HMDB51  | ESC50   | Gains     |
|----|-------------------|-----------------|---------|---------|---------|-----------|
| ① | Scratch           | -               | 63.3    | 29.7    | 54.3    |           |
| ② | Supervised        | Supervised      | 86.9    | 53.1    | 78.3    |           |
| ③ | SMoCo             | Uni. rand.      | 70.7    | 35.2    | 69.0    |           |
| ④ | XMoCo (w/o fcl)   | Cross rand.     | 72.9 \(\uparrow2.2\) | 37.5 \(\uparrow2.3\) | 70.9 \(\uparrow1.9\) | \(\Delta(4-3)\) |
| ⑤ | XMoCo             | Cross rand.     | 74.1 \(\uparrow1.2\) | 38.7 \(\uparrow1.2\) | 73.0 \(\uparrow2.1\) | \(\Delta(5-4)\) |
| ⑥ | CM-ACC            | Cross active    | 77.2 \(\uparrow3.1\) | 40.6 \(\uparrow1.9\) | 79.2 \(\uparrow6.1\) | \(\Delta(6-5)\) |

Unimodal vs. cross-modal pretraining. To validate the benefits of cross-modal pretraining, we compare it to its unimodal counterparts. We pretrain our model on Kinetics-Sound with a randomly sampled dictionary (similar to MoCo [He et al., 2020]; we call this XMoCo). For the unimodal case, we pretrain two models on visual clips and audio clips, respectively; we call these SMoCo. We also compare ours with a model trained from scratch (Scratch), and a model pretrained on Kinetics-Sound in a fully-supervised manner (Supervised). Lastly, we include XMoCo (w/o fcl) that is identical to XMoCo except that we do not include the additional FC layers on top of encoders. All these models are finetuned end-to-end on each downstream task using the same protocol.

Random vs. active sampling. To validate the benefits of active sampling over random sampling, we compare models pretrained with different sampling approaches on downstream tasks. As shown in Table 1, CM-ACC outperforms the XMoCo, which uses random sampling, by large margins, i.e. 3.1%, 1.5%, and 6.1% on UCF101, HMDB51, and ESC50, respectively (\(\Delta(6-5)\)).

Next, we compare the number of unique categories the sampled instances originally belong to, using the ground-truth labels provided in the dataset. The more categories the samples come from, we get more diverse and less redundant samples. We train these on UCF-101 over 300 iterations with different mini-batch sizes, \(M \in \{32, 64, 128\}\). Fig. 2 shows that active sampling selects more categories than random sampling across all three mini-batch sizes. At \(M = 128\), active sampling
| Method                  | Architecture | Pretrained on (size)          | UCF101 | HMDB51 |
|------------------------|--------------|-------------------------------|--------|--------|
| Scratch                | 3D-ResNet18  | -                             | 46.5   | 17.1   |
| Supervised             | VGG-M-2048   | ImageNet                      | 82.8   | 46.7   |
| ShufflAL (Misra et al., 2016) | CaffeNet   | UCF/HMDB                      | 50.2   | 18.1   |
| DRL (Buchner et al., 2018) | CaffeNet   | UCF/HMDB                      | 58.6   | 25.0   |
| OPN (Lee et al., 2017) | VGG          | UCF/HMDB                      | 59.8   | 23.8   |
| DPC (Han et al., 2019) | 3D-ResNet18  | UCF101                        | 60.6   | -      |
| MotionPred (Wang et al., 2019) | C3D        | Kinetics400 (N/A)             | 61.2   | 33.4   |
| St-Puzzle (Kim et al., 2019) | 3D-ResNet18 | Kinetics400 (N/A)             | 65.8   | 33.7   |
| C3D Order (Xu et al., 2019) | R(2+1)-D-18 | Kinetics400 (N/A)             | 72.4   | 30.9   |
| CBT (Sun et al., 2019) | S3D & BERT   | Kinetics600 (500K)            | 79.5   | 44.6   |
| DPC (Han et al., 2019) | 3D-ResNet34  | Kinetics400 (306K)            | 75.7   | 35.7   |
| SeLaVi (Asano et al., 2020) | R(2+1)-D-18 | Kinetics400 (240K)            | 83.1   | 47.1   |
| AVTS (Korbar et al., 2018) | MC3        | Kinetics400 (240K)            | 85.8   | 56.9   |
| XDC (Alwassel et al., 2019) | R(2+1)-D-18 | Kinetics400 (240K)            | 84.2   | 47.1   |
| AVID (Morgado et al., 2020) | R(2+1)-D-18 | Kinetics400 (240K)            | 87.5   | 60.8   |
| GDT (Patrick et al., 2020) | R(2+1)-D-18 | Kinetics400 (N/A)             | 89.3   | 60.0   |
| AVTS (Korbar et al., 2018) | MC3        | AudioSet (240K)               | 86.4   | -      |
| AVTS (Korbar et al., 2018) | MC3        | AudioSet (1.8M)               | 89.0   | 61.6   |
| XDC (Alwassel et al., 2019) | R(2+1)-D-18 | AudioSet (1.8M)               | 91.2   | 61.0   |
| AVID (Morgado et al., 2020) | R(2+1)-D-18 | AudioSet (1.8M)               | 91.5   | 64.7   |
| GDT (Patrick et al., 2020) | R(2+1)-D-18 | AudioSet (1.8M)               | 92.5   | 66.1   |
| Ours                   | 3D-ResNet18  | UCF101                        | 69.1 (+8.5) | 33.3 (+8.3) |
|                        | 3D-ResNet18  | Kine.-Sound (14K)             | 72.2 (+16.6) | 40.6 (+15.6) |
|                        | 3D-ResNet18  | Kinetics700 (240K)            | 90.2 (+0.9) | 61.8 (+1.0) |
|                        | 3D-ResNet18  | AudioSet (240K)               | 90.7 (+1.4) | 62.3 (+1.5) |
|                        | 3D-ResNet18  | AudioSet (1.8M)               | 94.1 (+1.6) | 66.8 (+0.7) |
|                        | R(2+1)-D-18  | AudioSet (1.8M)               | 93.5 (+1.0) | 67.2 (+1.1) |

Table 2: Comparison of SOTA approaches on action recognition. We specify pretraining dataset and the number of samples used if they are reported in the original papers (N/A: not available).

(With gradient embedding) covers 60-70% of categories on UCF101, which is substantially more diverse than random sampling (30-40%). While both sampling schemes perform similarly in early iterations, active sampling starts choosing more diverse instances as the training progresses; this is because the gradient embeddings becomes more discriminative in terms of the uncertainty measure.

**Feature vs. gradient embedding.** Fig. 2 also compares two ways to do active sampling: using gradient embeddings (Eqn. 6) and feature embeddings (the outputs from $h_a$ and $h_v$) when selecting the seed centroids with $k$-MEANS+++. We see that gradient embeddings results in a more diverse set of negative samples than feature embeddings; this is consistent across all three batch sizes. The gradient embeddings directly measure the uncertainty of each candidate, which is missing from the feature embeddings. This shows the importance of considering both uncertainty and diversity when selecting random samples: the $k$-MEANS++ ensures the diversity in the sample set, but without the uncertainty measure we lose important discriminative information from the candidates.

**Effect of dictionary size.** Fig. 3 (b) shows how the dictionary size affects downstream task performance. Here we pretrain our model on Kinetics-700 and finetune it on UCF-101. Overall, all three approaches benefit from large dictionaries up to a threshold (at about $10^3$), which is consistent with previous empirical findings (He et al., 2020). However, both XMoCo and SMoCo starts deteriorating performance after about $10^4$ (which is consistent with previous theoretical claims of Arora et. al (Arora et al., 2019)), whereas ours do not suffer even after $10^4$. This suggests that there are performance limits by simply increasing the size of a randomly-sampled dictionary, and also shows the benefit of our active sampling approach.

**Comparisons with SOTA.** Table 3 and Table 2 show the comparison of our approach and existing self-supervised approaches. Table 3 shows that our model outperforms the other SOTA self-supervised models. When comparing with models that trained on medium-size data (Kinetics and AudioSet 240K), our model outperform the top performance (A VID (Morgado et al., 2020) 79.1%) by 0.1% and 1.8% on Kinetics and AudioSet 240K, respectively. Our approach also outperforms...
Table 3: Comparison of SOTA approaches on audio event classification.

| Method         | Architecture | Pretrained on (size) | ESC50 |
|----------------|--------------|----------------------|-------|
| Random Forest (Piczak, 2015b) | MLP | ESC50 | 44.3 |
| Piczak ConvNet (Piczak, 2015a) | ConvNet-4 | ESC50 | 64.5 |
| ConvRBM (Sailor et al., 2017) | ConvNet-4 | ESC50 | 86.5 |
| SoundNet (Aytar et al., 2016) | ConvNet-8 | SoundNet (2M+) | 74.2 |
| \(L^3\)-Net (Arandjelovic & Zisserman, 2017) | ConvNet-8 | SoundNet (500K) | 79.3 |
| AVTS (Korbar et al., 2018) | VGG-8 | Kinetics (240K) | 76.7 |
| XDC (Alwassel et al., 2019) | ResNet-18 | Kinetics (240K) | 78.0 |
| AVID (Morgado et al., 2020) | ConvNet-9 | Kinetics (240K) | 79.1 |
| AVTS (Korbar et al., 2018) | VGG-8 | AudioSet (1.8M) | 80.6 |
| XDC (Alwassel et al., 2019) | ResNet-18 | AudioSet (1.8M) | 84.8 |
| AVID (Morgado et al., 2020) | ConvNet-9 | AudioSet (1.8M) | 89.2 |
| GDT (Patrick et al., 2020) | ResNet-9 | AudioSet (1.8M) | 88.5 |
| Ours | ResNet-18 | Kinetics700 (240K) | 79.2 \(+0.1\) |
|       |       | AudioSet (240K) | 80.9 \(+1.8\) |
|       |       | AudioSet (1.8M) | 90.8 \(+1.6\) |

We showed that random sampling could be detrimental to contrastive learning due to the redundancy in negative samples, especially when the sample size is large, and proposed an active sampling approach that yields diverse and informative negative samples. We demonstrated this on learning audio-visual representations from unlabeled videos. When pretrained on AudioSet, our approach outperforms previous state-of-the-art self-supervised approaches on various audio and visual downstream benchmarks. We also show that our active sampling approach significantly improves the performance of contrastive learning over random and online hard negative sampling approaches.
A ADDITIONAL EXPERIMENTS

Effect of mutual information. We investigate the impact of the amount of MI on contrastive learning using the Spatial-MultiOmniglot dataset (Ozair et al. 2019). It contains paired images \((x, y)\) of Omniglot characters (Lake et al. 2015) with each image arranged in an \(m \times n\) grid (each grid cell is 32 × 32 pixels). Let \(l_i\) be the alphabet size for the \(i^{th}\) character in each image, then the MI \(I(x, y) = \sum_{i=1}^{mn} log l_i\). This way, we can easily control the MI by adding or removing characters. We follow the experimental protocol of Ozair et al. (Ozair et al. 2019), keeping the training dataset size fixed at 50K and using the same alphabet sets: Tifinagh (55 characters), Hiragana (52), Gujarati (48), Katakana (47), Bengali (46), Grantha (43), Sanskrit (42), Armenian (41), and Mkhedruli (41).

![Figure 3: The effect of a) mutual information (Spatial-MultiOmniglot) and b) dictionary size on the accuracy of classification (UCF101).](image)

Fig. 3(a) shows the results as the number of characters (and thus the MI) increases. We see that all approaches achieve nearly 99% accuracy with less than 3 characters; this is the case when the exponent of the MI is smaller than the dataset size (50K), i.e., \(e^{I(x, y)} = 55\) with one character, \(e^{I(x, y)} = 2,860\) with 2 characters. However, starting from 3 characters, the performance of the regular MoCo (SMoCo) drops significantly; this is because the exponent of the MI (=137,280 \((55 \times 52 \times 48)\)) is much larger than the dataset size. Although our model also drops performance when the MI is increased, it outperforms the other approaches by a large margin. We also observe that XMoCo outperforms SMoCo in mild conditions (1-5 characters) but performs nearly the same as SMoCo with severe conditions (6-9 characters). This suggests that, while cross-modal prediction helps to learn good representations, it also suffers with the same issue when the MI is large, thus adopting active sampling is beneficial.

Effect of pretraining datasets. We investigate the effects of the pretraining datasets, using Kinetics-Sound (22K), Kinetics (240K), and AudioSet (1.8M). To do this in a controllable manner, we vary pretraining conditions while using the same protocol to finetune the models end-to-end on downstream tasks. Table 4 shows that our model benefits from pretraining on video data, and that the performance improves as we use a large pretraining video dataset (Kinetics and AudioSet) than the relatively smaller dataset (Kinetics-Sound). Notably, our approach even outperforms the fully-supervised pretraining approaches by pretraining on a larger video dataset (1.0%, 3.6%, and 8.5% improvement on UCF101, HMDB51, and ESC50, respectively.)

![Table 4: Top-1 accuracy of CM-ACC pretrained on different datasets vs. fully-supervised counterparts (Supervised).]* notates the results are implemented by ourselves.](image)
Online hard example mining vs. active sampling. Hard negative mining is used in a variety of tasks, such as detection (Li et al., 2020), tracking (Nam & Han, 2016), and retrieval (Faghri et al., 2017; Pang et al., 2019), to improve the quality of prediction models by incorporating negative examples that are more difficult than randomly chosen ones. As mentioned in the main paper, our active sampling approach can also be interpreted as a form of hard negative mining, in that we actively choose negative samples by optimizing for uncertainty and diversity.

In this experiment, we compare our approach to online hard example mining (OHEM) (Shrivastava et al., 2016), which constructs negative samples by explicitly choosing the ones that incur high loss values. Specifically, we compute the pseudo-labels for all keys (negative sample candidates) with a given mini-batch of queries. We then compute the classification loss based on these pseudo labels and select the top $M$ keys with the highest loss values. We pretrain the models on Kinetics-700 (Kay et al., 2017) and report the top-1 accuracy on UCF101 (Soomro et al., 2012) and HMDB51 (Kuehne et al., 2011). We use the same architecture and hyper-parameters; the only difference is the sampling approach.

|               | UCF101          |         | HMDB51          |         |
|---------------|-----------------|---------|-----------------|---------|
|               | $M=32$          | $M=64$  | $M=128$         | $M=32$  | $M=64$  | $M=128$ |
| Random        | 61.9            | 63.1    | 66.9            | 33.1    | 33.8    | 35.8    |
| OHEM          | 50.2 (-11.7)    | 60.8 (-2.3) | 65.7 (-1.2)    | 26.8 (-6.3) | 30.1 (-3.7) | 33.2 (-2.6) |
| Active        | 78.0 (+16.1)    | 78.9 (+15.8) | 79.2 (+12.3)   | 41.2 (+8.1) | 42.3 (+8.5) | 42.6 (+6.8) |

Table 5: Online hard example mining (OHEM) (Shrivastava et al., 2016) vs. our active sampling

Table 5 shows OHEM is generally less effective than both random sampling and our active sampling. Intuitively, OHEM promotes the dictionary to contain the most challenging keys for a given mini-batch of queries. Unfortunately, this causes OHEM to produce a redundant and biased dictionary, e.g., negative samples coming from a particular semantic category. This is shown in the table above: When $M$ (mini-batch size) is small, the performance of OHEM is even worse than random sampling, although the gap between OHEM and random sampling decreases as $M$ increases. We believe this is because OHEM has a higher chance of selecting similar negative instances. When $M$ is large, this issue can be mitigated to some extent, but the performance still falls behind ours by a large margin.

This suggests the importance of having a diverse set of negative samples, which is unique in our approach.

B When would cross-modal contrastive learning fail?

In general, cross-modal video representation learning is based on an assumption that the natural correspondence between audio and visual channels could serve as a useful source of supervision. While intuitive, this assumption may not hold for certain videos in-the-wild, which may cause the model to learn suboptimal representations. To investigate when our approach succeeds and fails, we conduct a post-hoc analysis by using the https://www.overleaf.com/project/5ded2abe1e17bc0001e5d8ground-truth semantic category labels provided in Kinetics-700 (Carreira et al., 2019) (which is not used during pretraining). Specifically, we use our pretrained model to solve the audio-visual contrastive pretext task (Eqn.(7) in the main paper) and keep track of the prediction results (correct/incorrect). We then average the pretext task accuracy over 100 randomly chosen samples for each action category.

Figure 4 shows the top-10 and bottom-5 classes by using both audio (left) and video (right) as the query. We observe that, the top ranked classes for both audio and video are the activities that have highly correlated visual-audio signals. For instance, playing bass guitar, play piano, and play violin are all activities related to music. The correlation of audio-visual signals for these activities are obvious; such highly correlated signals are easier to be learned in a cross-modal manner. On the contrary, the bottom ranked classes are those that have subtle audio-visual correlation, e.g. tossing coin, shaking hand, looking at phone, and hugging. We also investigate the distribution of hard-easy classes with that reported in Kinetics-700 (Carreira et al., 2019) learned by the I3D-RGB model (Carreira & Zisserman, 2017). Interestingly, we find that some hard classes (e.g. karaoke and recording music) are listed in our top ranked classes. We suspect that, when only learned within visual modality, some classes with cluttered or completed
Figure 4: Distribution of Kinetics-700 (Carreira et al., 2019) categories sorted by the prediction accuracy.

spatial information will bring difficulties for classification. While, as our cross-modal approach can leverage information from both auditory and visual information, so our model does not limited by such problems.

C VISUALIZATION OF NEGATIVE INSTANCES

Figure 5 shows negative instances selected by random sampling and active sampling when we use audio clips as the query. We visualize the center frames of the selected video clips. We can see that our approach selects more challenging examples than the random sampling approach. For instance, given a query opening bottle, our approach selected video clips from the same or similar semantic categories, e.g. drinking shot and opening bottle. Given snowboarding, our approach selected more video clips related to categories containing the snow scene, e.g. ice fishing, snow kiting, and toboganing.

Furthermore, we also find that our approach selects more diverse negative samples. For example, given a query snowboarding, active sampling selected video clips from 4 different categories related to the snow scene: (ice fishing, playing ice hockey, snow kiting, and toboganing). In comparison, the random sampling approach yields fewer semantic categories in general. This suggests that our active sampling approach produces more ‘challenging’ and ‘diverse’ negative instances than the random sampling approach.

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Figure 5: Center frames of video clips selected by random sampling and active sampling
Algorithm 2 Cross-Modal Contrastive Coding without Active Sampling

1: Require: Audio-visual clips A, V; dictionary D; encoders f_v, f_a; dictionary size K; mini-batch size M; learning rate γ; momentum m
2: Initialize parameters, \( \theta^v_0, \theta^a_0, \theta^k_0, \theta^{\gamma}_0 \sim \text{Uniform}(0, 1) \)
3: Load a dictionary at random, \( D_a \leftarrow \{v_1, \ldots, v_K\} \sim \text{Random}(V) \)
4: Encode mini-batch samples, \( k^a_i \leftarrow h_a(v_i), \forall v_i \in D_a \)
5: Encode dictionary samples, \( k^a_i \leftarrow h_a(a_i), \forall a_i \in D_a \)
6: for epoch = 1 to #epochs do
    7:     for t = 1 to #mini-batches do
        8:         Encode mini-batch samples, \( B_a \leftarrow \{v_1, \ldots, v_M\} \sim V \)
        9:         Encode mini-batch samples, \( B_a \leftarrow \{a_1, \ldots, a_M\} \sim A \)
     10:     \( \triangleright \) Update dictionaries
     11:     Encode mini-batch samples, \( k^a_i \leftarrow h_a(v_i), \forall v_i \in B_a \)
     12:     Encode mini-batch samples, \( k^a_i \leftarrow h_a(a_i), \forall a_i \in B_a \)
     13:     Update \( D_a \leftarrow \text{ENQUEUE} \left( \text{DEQUEUE}(D_a), B_a \right) \)
     14: Update \( D_a \leftarrow \text{ENQUEUE} \left( \text{DEQUEUE}(D_a), B_a \right) \)
     15:     \( \triangleright \) Cross-modal contrastive predictive coding
     16:     Encode mini-batch samples, \( q^a_i \leftarrow f_a(v_i), \forall v_i \in B_v \)
     17:     Encode mini-batch samples, \( q^a_i \leftarrow f_a(a_i), \forall a_i \in B_a \)
     18: Compute the posterior, \( p(y^a_i | v_i, a_i, D_v) = \frac{\exp(q^a_i k^a_i / \tau)}{\sum_{j=0}^{K} \exp(q^a_i k^a_j / \tau)} \)
     19: Compute the posterior, \( p(y^a_i | a_i, v_i, D_a) = \frac{\exp(q^a_i k^a_i / \tau)}{\sum_{j=0}^{K} \exp(q^a_i k^a_j / \tau)} \)
     20:     \( \triangleright \) Update model parameters
     21: Update \( \theta^v_0 \leftarrow \theta^v_0 - \gamma \sum_{i=1}^{M} q^a_i \big( \log p(y^a_i | v_i, a_i, D_v) \big) \bigg| \theta = \theta^v_0 \)
     22: Update \( \theta^a_0 \leftarrow \theta^a_0 - \gamma \sum_{i=1}^{M} q^a_i \big( \log p(y^a_i | a_i, v_i, D_a) \big) \bigg| \theta = \theta^a_0 \)
     23: Momentum update \( \theta^v_0 \leftarrow \theta^v_0 + (1 - m) \theta^v_0 \)
     24: Momentum update \( \theta^a_0 \leftarrow \theta^a_0 + (1 - m) \theta^a_0 \)
     25: end for
     26: end for
27: return Optimal solution \( \theta^v_0, \theta^a_0, \theta^k_0, \theta^{\gamma}_0 \)

Algorithm 3 k-MEANS++ Seed Cluster Initialization

1: Require: Data X of N samples; number of centroids K
2: Choose one centroid uniformly at random, \( C[0] \leftarrow x \sim \text{Random}(X) \)
3: for \( k = 1 \) to \( K - 1 \) do
    4: \( \triangleright \) Compute a cumulative probability distribution with a probability in proportion to their squared distances from the nearest centroid that has already been chosen
    5: for \( n = 0 \) to \( N - 1 \) do
        6: Compute the squared distance, \( D[n] \leftarrow (\text{min}_d\text{ist}(X[n], C))^2 \)
    7: end for
    8: Compute the cumulative probability distribution, \( P \leftarrow \frac{\text{cumsum}(D)}{\text{sum}(D)} \)
    9: \( \triangleright \) The next centroid is chosen using \( P(X) \) as a weighted probability distribution
10: Choose one centroid at random, \( C[k] \leftarrow x \sim P(X) \)
11: end for
12: return \( C \) containing K centroids
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