AVGZSLNet: Audio-Visual Generalized Zero-Shot Learning by Reconstructing Label Features from Multi-Modal Embeddings

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Abstract

In this paper, we solve for the problem of generalized zero-shot learning in a multi-modal setting, where we have novel classes of audio/video during testing that were not seen during training. We demonstrate that projecting the audio and video embeddings to the class label text feature space allows us to use the semantic relatedness of text embeddings as a means for zero-shot learning. Importantly, our multi-modal zero-shot learning approach works even if a modality is missing at test time. Our approach makes use of a cross-modal decoder which enforces the constraint that the class label text features can be reconstructed from the audio and video embeddings of data points in order to perform better on the multi-modal zero-shot learning task. We further minimize the gap between audio and video embedding distributions using KL-Divergence loss. We test our approach on the zero-shot classification and retrieval tasks, and it performs better than other models in the presence of a single modality as well as in the presence of multiple modalities.

Index Terms: Zero-shot learning, Multiple modalities, Audio, Video, Classification, Retrieval, Deep learning

1. Introduction

Deep learning methods have become extremely popular in language processing as well as computer vision tasks on images, videos, and sounds. Traditional deep learning methods require the network to be trained on massive amounts of data, with each category/class having a large number of data points.

However, in many real-life settings, data may not be available for all classes. In such cases, the standard deep learning training methods will end up making the model overfit to the classes for which it has seen examples during training. Such models will fail miserably in classifying data points from classes for which it has not seen any examples during training. Humans, on the other hand, perform much better in such a setting. Given the description of a category, such as a cat, a person will be fairly successful in identifying pictures of cats. This capacity will be further enhanced if he/she has already seen similar animals such as tiger, leopards. We want deep learning models to have such a capability. Zero-shot learning is an area of machine learning that deals with this problem.

Zero-shot learning involves specialized training of networks in order to enable them to classify unseen classes at test time using only basic class information such as class name, description ¹²³⁴. Zero-shot learning enables networks to learn good semantic representations so that it can transfer the knowledge gained from seen classes to unseen classes. Zero-shot learning settings can assume that the test data belonged only to the unseen classes ⁵. A harder setting is where test data can belong to both seen and unseen classes ⁶. This is because the model will be biased towards the seen classes having been trained extensively on them. This setting is termed as generalized zero-shot learning.

Zero-shot learning has been extensively applied to images and has also been applied to videos, sounds. Very recently, ¹¹ dealt with a multi-modal setup where each data point consisted of a video and corresponding audio. It applies zero-shot learning to this setup and shows how audio information helps to better classify videos under the zero-shot setting, e.g., honking of a car even if it is not visible in the video. It learns a joint projection feature space for class labels, video, and audio data.

We propose an approach to improve zero-shot learning in the audio-visual setting. First, we try to reduce the gap between the data distributions of the audio and video embeddings of the data points using KL-Divergence. This is different from ¹¹, where the method tries to generate the same embedding for both the audio and video data of each data point using mean squared error (MSE) loss. We show through an ablation experiment that KL-Divergence loss helps the network perform better since the resulting audio and video embedding distributions are similar. Second, we use a cross-modal decoder to optimize the audio and video embeddings in such a way that the class label feature can be reconstructed from them. This forces the projection networks to include class-level information in the audio and visual embeddings. A detailed description of our method can be found in Sec. ².

At test time, the test data point modalities (audio or video or both) are projected to our learned embedding space where we perform the nearest neighbor classification. We predict the class label embedding that is closest to the test data point multimodal embedding as the output class. We perform experiments for generalized zero-shot classification and retrieval to show the efficacy of our method. We perform experiments on the AudioSetZSL dataset proposed by ¹¹.

Our contributions are as follows:

• We propose a novel method to improve Audio-Visual Generalized Zero-Shot Learning by using a cross-modal decoder and KL-Divergence loss.
• We experimentally show that our method performs well for both generalized zero-shot audio-visual classification and retrieval.
• We experimentally show that our method performs well even when only audio or video data is present for the test data point.

2. Related Works

Zero-Shot Learning: Zero-shot learning ¹³⁻¹⁰⁻¹¹⁻¹²⁻¹³ involves training a network in a specialized way so that it can reasonably classify unseen classes. A common training approach is to push the feature embeddings of data
close to the semantic embedding of their class. Semantic embedding of their class is obtained by using the class label text [2–4] or description/attributes [5,11,12]. Some methods [12,13,9] use both kind of class information. At test time, the query data can be from the unseen classes only [5] or from both seen and unseen classes. The latter is called generalized zero-shot learning [10]. We perform experiments on this harder setting. CIME [4] performs generalized zero-shot learning on audio-visual data. It tries to map the label, audio, and video features to the same embedding space and then perform the nearest neighbor based classification to predict the classes of query data. It learns weights to combine distances in the audio and video domains for the final classification/retrieval.

**Audio-Visual Learning:** There have been several works that combine audio and video data to improve network performance in various tasks such as audio-visual correspondence learning [14,15,16,17], audio-visual source separation [18,19] and others. [15] uses self-supervision to detect the temporal alignment between audio and video. Features learned from this setting can be applied to several downstream tasks like source localization and action recognition. [20] uses an audio-visual setting to train a model to perform speaker-independent speech source separation. [18] uses self-supervision to perform pixel-level audio source localization.

**Prototype based Few-shot Learning:** Like zero-shot learning, few-shot learning also deals with training models that support unseen classes at test time. But few-shot learning models get access to a few (1 to 5) examples of the unseen class at test time. The most used approach of solving few-shot learning is to use the trained model to produce features for the few labeled examples of the unseen test class and use the features to produce a class prototype. This prototype can then be used to perform nearest neighbor based classification for each query data in order to predict the output class [21,22,23,24,25,26].

In zero-shot learning, the class label text embedding can be thought of as the class prototype. We train the network to try to project each audio/video data to their class prototype.

### 3. Proposed Method

#### 3.1. Problem Setting

During training, each data point $x_i$ consists of audio, video and label text data. Using pretrained networks, features for audio, video and label text are obtained ($a_i, v_i, t_i$ respectively) [1]. The task is to train a network that projects the audio, video and text features to an embedding space where the audio and video embeddings are close to the text embedding of the same class.

$$a_i, v_i, t_i = F_A(a_i), F_V(v_i), F_T(t_i)$$

Where $F_A, F_V, F_T$ are embedding networks for audio, video and text features; and $a_i, v_i, t_i$ are the generated audio, video and text embeddings.

At test time, query data can be from both seen (S) and unseen (U) classes. Query data can have either audio or video or both data available. Text features for all seen $t_s$ and unseen classes $t_u$ are known. The objective is to predict the output class for each query data by using the text embedding of each class and the audio and/or video embedding of the query data.

#### 3.2. Dealing with Distribution Gap

An important task for solving this problem is to bring the audio and video embeddings closer to each other so that at test time, even if only audio or video is present, the model can still be fairly successful in classifying the queries. [1] uses a mean squared error loss on each pair of audio-video embeddings for a data-point. However, we propose to use KL-Divergence instead to reduce the gap between the audio and video embedding distributions. We show in the ablation section that this leads to better results in this setting.

$$L_{KLD} = KLD(A,V)$$

Where $KLD$ is KL-Divergence; $A$ and $V$ refers to the audio and video embedding distributions, respectively.

#### 3.3. Cross-Modal Decoder to reconstruct Label Features

In the zero-shot learning setting, at test time, we want the audio or video embeddings to have a lot of similarity with the class label text embedding. This will be maximized if the audio and video embeddings contain information about the original text features ($x_i^t$). To achieve this, we propose a cross-modal decoder. As shown in Fig 1, a decoder network is added to the model. The decoder is trained to reconstruct the label text features ($x_i^t$) from the text embeddings, audio embeddings, video embeddings and audio embeddings separately.

$$L_{CMD}(a_i, v_i, t_i, x_i^t) = d(F_{DEC}(t_i), x_i^t) + d(F_{DEC}(a_i), x_i^t) + d(F_{DEC}(v_i), x_i^t)$$

Where $F_{DEC}$ is the shared decoder network for text, audio and video; $L_{CMD}$ is the cross-modal decoder loss, $d$ is the distance metric. We use mean square error (MSE) for the distance metric.

In the process of minimizing $L_{CMD}$, the embedding or projection networks learn to extract class information from audio and video features. We experimentally show that this improves the performance of the network.

#### 3.4. Triplet Loss and Attention

In order to help the network bring audio and video embeddings closer to the text embeddings of their classes and push embeddings of different classes further away, we use the triplet losses same as used in [1].

$$L_{TA}(a_p, t_p, a_q, t_q) = |d(a_p, t_p) - d(a_q, t_p) + \delta|_+$$

$$L_{TV}(v_p, t_p, v_q, t_q) = |d(v_p, t_p) - d(v_q, t_p) + \delta|_+$$

Where $a_p, v_p$ and $a_q, v_q$ are audio, video embeddings for a data point belonging to class $p$ and class $q$ respectively; and $\delta$ is the
margin hyper-parameter. $L_{TA}$ and $L_{TV}$ are the triplet loss on audio and video embeddings respectively.

We also learn modality attention weights for audio and video distances for each sample so that the modality with more information dominates our distance calculation, as used in [1].

### 3.5. Method Overview

Our proposed Audio-Visual Generalized Zero-Shot Learning method (AVGZSLNet) is described in full in this section.

During training, for each mini-batch, first, we obtain the embeddings for audio, video, and label text features using the embedding/projection networks (Eq. 1). Next, we calculate the KL-Divergence of audio and video embedding distributions using Eq. 2, the cross-modal decoder loss using Eq. 3 and the triplet loss for audio and video embeddings using Eq. 4 [5]. Next, we find the distances for each training data point from the class label text embeddings in the audio and video domains. We train the attention network to produce the attention weights for the audio and video distances, so as to give more weight to the domain having less entropy, using the process given in [1]. We optimize the networks on these losses.

During testing, we first obtain the label text embedding for all classes using Eq. 1. Then, for each query data point, we first obtain the embeddings for audio, video data using Eq. 1. Next, we calculate the distance of the audio and video embeddings from each class label text embedding. We, then, calculate the attention weight for audio and video distances. We use it to perform a weighted addition of audio and video distances to obtain the final distance between the query and each class label text embedding. Using this distance, we predict the nearest class text embedding as the output class.

The full loss function can be defined as follows:

$$L = \lambda L_{KLD} + \beta \sum_i L_{CMD} + \gamma \sum_{p,q \in U, p \neq q} \left( \alpha_v L_{TV} + \alpha_a L_{TA} \right)$$

(6)

Where \( \lambda, \beta, \gamma \) are hyper-parameters, \( U \) is the set of all seen classes and \( \alpha_v, \alpha_a \) are attention weights for video and audio modality.

### 4. Experiments

#### 4.1. Dataset

We use the AudioSetZSL dataset proposed by [1] to study the task of audio-visual generalized zero-shot learning. It is a subset of AudioSet [27], and it consists of 156,416 video segments, and with each video having only one label.

#### 4.2. Implementation Details

We train the audio network proposed in [28], on the audio data spectrogram in the trainset of AudioSetZSL. We extract the audio features from this network after the seventh convolution layer and obtain a 1024 dimension vector by averaging. We extract the video features from an inflated 3D CNN network pre-trained on the Kinetics action recognition dataset [29]. The video feature is obtained in the same way, i.e., from before the classification layer and averaged to a 1024 dimension vector. For the text features, we use the word2vec network that has been pre-trained on the Wikipedia dataset to obtain 300 dimension features [30]. The projection network for audio and video embeddings are 2 layer fully connected networks. The text embedding network is a 1 layer fully connected network. The output dimension of all the 3 projection networks is 64. All the implementation settings are same as [1].

#### 4.3. Metrics

We use the mean class accuracy (% mAcc) metric for classification and the mean average precision (% mAP) metric for retrieval. We perform classification/retrieval for all classes and then report the performance for seen (S) and unseen (U) classes. We focus on the harmonic mean (HM) of the performances on seen and unseen classes.

#### 4.4. Generalized Zero-Shot Classification

Table 1 shows how our method performs for generalized zero-shot classification. The results for audio-only, video and both (audio and video) data during testing. The audio-video concatenation model needs both audio and video data for testing.

The decoder network in our method is a 2 layer fully connected network with an output dimension of 300, which is the same as the text features from word2vec. Zero-shot classifiers are biased towards the seen classes, so we reduce the scores for seen classes as proposed in [10]. We report the results for our method in 3 settings, i.e., test data is a) only audio or b) only video or c) both. When both audio and video data is available during testing, we get distance values for both audio and video domains. We report the results for 3 ways of combining both the distances, i.e., a) (no attn) selecting either audio/video modality distance based on lower entropy as in [1], b) (eq wt) performing weighted addition of audio and video distances with equal weights for both, c) (w/ attn) using the attention module to predict the weights for audio and video distances [1]. We compare our results with audio-only, video-only, audio-video concatenation, and pre-trained models. The audio-only model consists of a single projection/embedding network projecting audio features to the embedding space, and it trains to push the audio embeddings closer to the corresponding class label embedding. The video-only model is similar, but it uses only video data. The audio-video concatenation model also trains only one projection network, but it uses the audio-video concatenated features as input. It needs both audio and video data to perform training or testing. The pre-trained model uses the features produced by the pre-trained networks (used to extract the initial features for our method) to predict the nearest class. It can use only audio or video features at a time to make these predictions. Generalized Canonical Correlation Analysis [31] is a standard method for maximizing the correlation between example pair-wise data. In this setting, GCCA is used to maximize the correlation between audio, video, and text for every data-point. We report retrieval results for GCCA. All the settings are the same as [1].

| Model | Test Modality | S (%) | U (%) | HM (%) |
|-------|---------------|-------|-------|--------|
| audio only model | audio | 38.35 | 22.22 | |
| CJME | audio | 25.58 | 22.64 | |
| AVGZSLNet (ours) | audio | 29.69 | 23.91 | 34.70 |
| video only model | video | 42.27 | 33.84 | |
| CONSE | video | 48.50 | 77.90 | |
| DEVISE | video | 39.80 | 26.00 | 31.50 |
| SAEL | video | 29.30 | 23.20 | |
| ESZSL | video | 33.80 | 19.00 | 24.30 |
| ALLE | video | 47.90 | 25.00 | 33.00 |
| CJME | video | 41.51 | 28.76 | 33.99 |
| AVGZSLNet (ours) | video | 44.12 | 30.49 | 36.06 |
| CJME (no attn) | audio or video | 31.72 | 26.31 | 28.76 |
| AVGZSLNet (ours) (no attn) | audio or video | 31.51 | 28.34 | 29.84 |
| audio-video concat model | both | 45.83 | 27.91 | 34.70 |
| CJME (eq wt) | both | 30.29 | 30.79 | |
| AVGZSLNet (ours) (eq wt) | both | 33.76 | 33.91 | 33.84 |
| CJME (w/ attn) | both | 41.07 | 29.58 | 34.39 |
| AVGZSLNet (ours) (w/ attn) | both | 44.63 | 31.93 | 37.23 |

Table 1: Generalized zero-shot classification mean class accuracy (% mAcc) achieved with audio or video or both (audio and video) data during testing.
Table 2: Generalized zero-shot retrieval mean average precision (% mAP) achieved with only audio, only video, and both (audio and video) data during testing.

| Model                  | Test | S   | U   | HM |
|------------------------|------|-----|-----|----|
| pre-trained model      | T → A | 3.83| 1.66| 2.37|
| GCCA [1]               | T → A | 49.84| 2.39| 4.56|
| audio only model       | T → A | 43.16| 3.34| 6.20|
| CJME [1]               | T → A | 48.24| 3.32| 6.21|
| AVGZSLNet (ours)       | T → A | 48.54| 3.65| 6.79|

| pre-trained model      | T → V | 3.83| 2.53| 3.05|
| GCCA [1]               | T → V | 57.67| 3.54| 6.67|
| video only model       | T → V | 48.62| 5.25| 9.47|
| CJME [1]               | T → V | 59.39| 5.55| 10.15|
| AVGZSLNet (ours)       | T → V | 58.39| 6.34| 11.44|

| CJME (no attn) [1]     | T → A or V | 65.74| 5.09| 9.45|
| AVGZSLNet (ours) (no attn) | T → A or V | 65.94| 5.55| 10.24|
| CJME (eq wt.) [1]      | T → AV | 65.45| 5.40| 9.97|
| AVGZSLNet (ours) (eq wt.) | T → AV | 66.39| 6.34| 11.57|
| CJME (w/ attn) [1]     | T → AV | 62.97| 6.67| 10.41|
| AVGZSLNet (ours) (w/ attn) | T → AV | 63.58| 6.57| 11.90|

Table 3: Generalized zero-shot crossmodal retrieval % mAP.

| Model                  | Test | S   | U   | HM |
|------------------------|------|-----|-----|----|
| pre-trained model      | audio → video | 5.81| 2.37| 2.80|
| GCCA [1]               | audio → video | 22.12| 3.65| 6.26|
| CJME [1]               | audio → video | 26.87| 4.31| 7.43|
| AVGZSLNet (ours)       | audio → video | 26.63| 4.44| 7.61|

| pre-trained model      | video → audio | 5.22| 2.57| 3.19|
| GCCA [1]               | video → audio | 26.68| 2.98| 5.26|
| CJME [1]               | video → audio | 29.33| 4.35| 7.58|
| AVGZSLNet (ours)       | video → audio | 29.56| 4.45| 7.74|

4.5. Generalized Zero-Shot Retrieval

Table 2 shows generalized zero-shot retrieval results from class label text, i.e., retrieving samples (audio A or video V or both AV) from the dataset in the order of how close they are to the class labels T in the embedding space. The results for the audio-only, video-only, pre-trained, CONSE, DEVISE, SADE, ESZSL, ALE, CJME models have been taken from [1]. The results for the unseen classes for all cases are very low. [1] attributes this to the bias of the trained models towards seen classes in generalized zero-shot learning. This is corrected in classification by reducing the scores of the seen classes. This correction cannot be done here as there is no concept of class or scores in retrieval.

From Table 2 we can see that when performing retrieval from class label text embedding using only audio or only video embedding, our method AVGZSLNet performs better than CJME [1], pre-trained model and GCCA. Our model AVGZSLNet with attention performs better by about 1.5% than the best CJME model with attention. It also beats CJME without attention and CJME with equal weights given to both audio and video distances. Fig. 2 shows the qualitative results for generalized zero-shot retrieval from class label text on the AudioSetZSL. This shows the efficacy of our method.

Crossmodal retrieval: Table 3 shows the results for generalized crossmodal zero-shot retrieval from audio to video and from video to audio. Our method performs better than CJME, pre-trained model, and GCCA. This shows that our method is better at reducing the gap between the audio and video features of the same class.

5. Ablation

We perform ablation to verify the contribution of the cross-modal decoder and the KL-Divergence loss in the performance of our method. Table 4 shows that both the losses lead to improvements in performance over CJME. After using KL-Divergence loss to reduce the gap between audio and video embedding distributions, the network performance increases significantly over CJME (35.83 vs. 34.39). The addition of the cross-modal decoder to incorporate class label information in the multi-modal features leads to a further increase in performance (37.23 vs. 34.39).

6. Conclusion

We proposed a method for audio-visual generalized zero-shot learning in a multi-modal setting using a cross-modal decoder to improve the performance. We also minimize the gap between audio and video embedding distributions using KL-Divergence loss. We experimentally showed how our method performed well on audio-visual generalized zero-shot classification and retrieval. Through ablation experiments, we validated the choice of the losses that we proposed. Therefore, we can conclude that our method AVGZSLNet improves audio-visual generalized zero-shot learning.
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