Noise Estimation Using Density Estimation for Self-Supervised Multimodal Learning

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Abstract. One of the key factors of enabling machine learning models to comprehend and solve real-world tasks is to leverage multimodal data. Unfortunately, annotation of multimodal data is challenging and expensive. Recently, self-supervised multimodal methods that combine vision and language were proposed to learn multimodal representations without annotation. However, these methods choose to ignore the presence of high levels of noise and thus yield sub-optimal results. In this work, we show that the problem of noise estimation for multimodal data can be reduced to a multimodal density estimation task. Using multimodal density estimation, we propose a noise estimation building block for multimodal representation learning that is based strictly on the inherent correlation between different modalities. We demonstrate how our noise estimation can be broadly integrated and achieves comparable results to state-of-the-art performance on five different benchmark datasets for two challenging multimodal tasks: Video Question Answering and Text-To-Video Retrieval.

Keywords: Multimodal learning, self-supervised, representation learning, noise estimation

1 Introduction

Multimodal learning is a well established methodology for tackling complex and challenging artificial intelligence tasks such as Visual Question Answering \cite{8,20,12,97,10} and Text-to-Video Retrieval \cite{36,46,99,42,69}. The motivation for gleaning information from multiple correlated data sources comes from how we as humans perceive the world and learn from experience. Using the correlation between speech and vision, a person is able to recognize objects by their names while learning the visual characteristics. Additionally, concepts can be learned separately and a combination can be comprehended automatically, e.g., ‘running’ and ‘beach’ vs. ‘running on the beach’.

Manual annotation of large-scale datasets and specifically multimodal datasets is challenging and expensive. This difficulty results in a shortage which limits the progress of supervised machine learning and has become the key development bottleneck. Recently, to combat costs and effort of annotation, self-supervised
machine learning presents new ways to better utilize the abundant unlabeled data on the web. However, most self-supervised systems aim to learn from a single data modality, which limits their applicability.

In contrast to the above, recently showed that unlabeled instructional videos could be used as training data for a self-supervised multimodal learning system due to the high correlation between the spoken word and the ongoing visuals. Unfortunately, such systems are forced to deal with high noise levels and thus yield sub-optimal results as we will show in Section 4.

In this paper, we propose a novel noise robust multimodal representation learning building block for self-supervised learning. We utilize the inherent correlation between different modalities for efficient multimodal learning in the presence of extreme levels of noise. Specifically, we show that noise estimation can be reduced to a density estimation problem. We define a multimodal similarity function and show that based on this function, noise is correlated with sparsity and vice versa.

Ultimately, we integrate our proposed building block into an embedding model and learn superior joint video-text representations that achieve comparable state-of-the-art performance on five datasets: MSRVTT, LSMDC, MSVD, MSRVTT-QA and MSVD-QA; for two different tasks: Video Question Answering and Text to Video Retrieval.

Contributions. The key contributions of this paper are three fold:

1. We show that the problem of noise estimation for multimodal data can be efficiently reduced to a multimodal density estimation task.
2. We propose a novel building block for noise-robust multimodal representation learning and demonstrate its integration into the max margin ranking loss function.
3. We demonstrate comparable state-of-the-art performance on five datasets for two different challenging multimodal tasks by utilizing our approach for self-supervised multimodal learning with the HowTo100M dataset.

2 Related Work

2.1 Self-Supervised Learning

Self-supervised learning methods strive to learn informative data representations by defining and solving a pretext task. In these pretext tasks, pseudo labels can be generated automatically and compact data representations must be learned in order to solve these tasks. Many pretext tasks were proposed in recent years. Examples for such pretext tasks are: colorizing grayscale images, image jigsaw puzzle, image inpainting, video frame order verification, video frame order recognition, video colorization, video future prediction, audio-visual correspondence, speech-visual correspondence, etc. For an extended review on self-supervised learning in the visual domain see .
In this work, we focus on speech-visual correspondence in unlabeled instructional videos, where speech is converted to text using an automatic speech recognition system. Speech-visual correspondence is considered a difficult pretext task due to extremely noisy pseudo labels, yet it can be a highly advantageous task since it provides semantic information of visual features in the form of natural text. Such valuable information can be utilized to solve many challenging multimodal downstream tasks as we show in Section 4.

2.2 Multimodal Representation Learning

The word *modality* refers to a particular form of sensory perception, such as the visual and auditory modalities. A machine learning task or dataset is said to be *multimodal* when it includes a number of modalities.

Multimodal representation learning frameworks can be divided into three types: (a) joint representation which aims to learn a shared semantic subspace \[63,129,83,51,95\]; (b) an encoder-decoder framework which aims to translate from one modality into another and keep their semantics consistent \[39,84,61,83,58,52,50\]; and (c) coordinated representation which aims to learn separated yet coordinated representations for each modality under some constraints \[93,94,11,28,68,53,22,6,89,82\]. For an extended review on multimodal machine learning see \[5\].

In this work, we focus on coordinated representations that enforce similarity among them. Our goal is to enforce the multimodal representations of similar 'concepts' to be close to each other. E.g., a video of a man running on the beach should be close in representation to the textual representation of 'a man running on the beach' as opposed to 'a man cooking in the kitchen'.

The multimodal representation described above is highly valuable for solving multimodal machine learning tasks. If a machine learning model learns to link between the visuals and text of specific concepts it should be able, for example, to answer natural language questions about visual content, or do cross-modal retrieval more easily (Section 4.2).

2.3 Density Estimation

The aim of density estimation is to estimate the probability density function underlying the data, which is assumed to be *i.i.d*. Existing density estimation algorithms can be divided into two categories: (a) parametric or semi-parametric approaches such as Gaussian Mixture models \[57,114,40,99\] and probabilistic graphical models \[25,20,87\]; and (b) non-parametric approaches such as histograms \[65\], Splines \[72,9\], neural network-based density estimation \[38,31,79,80,78,54\] and Kernel Density Estimation \[66,67,37,77\]. For an extended review on density estimation for high-dimensional data see \[91\].

In this work, we utilize *multimodal* k-Nearest Neighbor density estimation, which is a special case of Kernel Density Estimation. With it, we form a novel noise-robust multimodal representation learning model.
2.4 Learning with Noisy Data

Learning with noisy data can be divided into two approaches: (a) formulating explicit or implicit noise models to characterize the distribution of noisy and true labels using neural networks \([14,21,33,50,56,73]\), graphical models \([96,35]\), etc. and (b) using correction methods. E.g., relabeling the data during training \([59]\), jointly optimizing the model’s parameters and estimating true labels \([76]\), using noise-tolerant loss function \([13,81]\) or noise tolerant training algorithms \([34]\). However, these methods often require a small set of data with clean labels to be available.

In this work, we propose a true label estimation method that does not require availability of clean labels. We base our estimation on the correlation between modalities alone.

3 Method

3.1 Motivation

In multimodal data, a sample is said to be noisy when two or more modalities do not share the same semantic meaning. E.g., a video-text pair that is associated with each other, yet the text is not related to the ongoing visuals. Existing multimodal embedding models are susceptible to such noisy data. I.e., the model is likely to adjust itself to the noise in the data and thus yield sub-optimal results. This scenario is very common in the case of self-supervised multimodal learning and even when learning from unlabeled instructional videos. Although in these instructional videos there is some correlation between caption (speech transcription) and vision, unfortunately often a person is talking about something that is not present visually. E.g., in the HowTo100M dataset \([43]\), the authors manually inspected 400 randomly sampled clip-caption pairs and found that in about 50%, there is not a single object or action mentioned in the caption that is also visually present in the video clip.

To deal with noise, we suggest to utilize the inherent correlation between the different modalities that is based on Definition 1 and Assumption 1. See Fig. 1 for a visualization and a detailed explanation.

**Definition 1.** A correctly (wrongly) associated pair is a clip-caption pair \((v_i, c_i)\) that share (do not share) the same semantic meaning, i.e., the caption describes (does not describe) the ongoing visuals.

**Assumption 1** The probability that \(v_i\) is correctly associated with \(c_i\) is higher when \(v_i\) is close to other video clips that are associated with captions that are close to \(c_i\).

Based on Assumption 1, correctly associated pairs form dense clusters in both modalities that contain pairs that are also associated with each other (see Figure 2a). Thus, by defining a multimodal similarity function (i.e., a similarity measure
Fig. 1. Noise estimation using multimodal density estimation

(a) Multimodal data visualization. Each initial monomodal embedding space contains somewhat dense clusters of 'concepts', where a 'concept' could be a specific object or action (e.g., 'cutting', 'knife', 'check', 'tire', 'oven', etc.). It is likely that correctly associated (Definition 1) pairs form dense clusters in both modalities that contain pairs that are also associated with each other and of the same 'concept' (GREEN, $z_1 - z_6, z_9 - z_{11}$). In contrast, a wrongly associated (Definition 1) pair may still belong to dense clusters in both modalities but those clusters are not likely to contain pairs that are associated with each other (RED, $z_7$ and $z_8$). Best viewed in color.

(b) Multimodal space defined by (1). Each point below ($\{z_i\}_{i=1}^{11}$) represents a single pair from the sub-figure above. The distance between points that is visualized is computed based on (1). Given Assumption 1 in the multimodal space below, correctly associated pairs are correlated with density and vice-versa. Best viewed in color.
between pairs), we can formulate the task of finding correctly associated pairs simply as a multimodal density estimation task. In this formulation, pairs in dense areas will be more likely to be correctly associated, while pairs in sparse areas will be more likely to be wrongly associated (see Figure 2b).

### 3.2 Notation and Problem Formulation

Let \( \{ v_i \in \mathbb{R}^d, c_i \in \mathbb{R}^d \}_{i=1}^M \) denote the set of video-caption pairs, where for each \( i \), the video clip \( v_i \) is associated with the caption sentence \( c_i \), and \( M \) denotes the size of the dataset. Let \( f_v(v_i) : \mathbb{R}^d \rightarrow \mathbb{R}^d \) and \( f_c(c_i) : \mathbb{R}^d \rightarrow \mathbb{R}^d \) denote the embedding functions of \( v_i \) and \( c_i \) respectively. Let \( p_i \in \{0, 1\} \) denote a binary indicator for whether or not a \( (v_i, c_i) \) is correctly associated \( (p_i = 1) \) or wrongly associated \( (p_i = 0) \).

The task of noise robust multimodal representation learning aims to map all of the data modalities to a single embedding space such that for all \( v_i \) that is correctly associated with \( c_i \), \( f_v(v_i) \approx f_c(c_i) \) according to some similarity function.

### 3.3 Noise Estimation Using Multimodal Density Estimation

For ease of notation we will denote the pair \( (v_i, c_i) \) as \( z_i \). Let us define a similarity function between pairs, \( S : \mathbb{R}^{d_v+d_c} \times \mathbb{R}^{d_v+d_c} \rightarrow \mathbb{R} \),

\[
S(z_i, z_j) \doteq \min\{s(v_i, v_j), s(c_i, c_j)\},
\]

where, \( s \) can be, for example, the cosine similarity function \( s(a, b) = \frac{a^\top b}{\|a\|\|b\|} \).

Using (1), a pair \( z_i \) is close to \( z_j \) only if \( v_i \) is close to \( v_j \) and \( c_i \) is close to \( c_j \) as well.

We denote \( \hat{p}_i \) as the estimated probability of \( z_i \) being correctly associated, and compute it using its local k-NN density estimation normalized such that \( \hat{p}_i \in [0, 1] \):

\[
\hat{p}_i \doteq \frac{1}{2} + \frac{1}{2K} \sum_{k=1}^K S(z_i, z_{ik}),
\]

where, \( z_{ik} \) is the k'th nearest neighbor of \( z_i \) and \( S \) is the multimodal similarity function defined in (1).

### 3.4 Soft Max Margin Ranking Loss

Integrating our noise estimation component from above into a max margin ranking loss function \([88,64]\) is straightforward. We weight each pair \( z_i \) with its estimated probability \( \hat{p}_i \) of being correctly associated. We call it Soft Max Margin Ranking:

\[
L_{\text{soft-rank}} = \sum_{i \in P} \left( \hat{p}_i \sum_{j \in N_i} \max\{0, s_{ij} - s_{ii} + \delta\} + \max\{0, s_{ji} - s_{ii} + \delta\} \right),
\]
where, $P$ is the set of noisy associated (positive) pairs, $N_i$ is the set of negative pairs for clip-caption pair $(v_i, c_i)$, $\tilde{p_i}$ is defined in (2), $s_{ij}$ is the similarity score between the embedding of the clip-caption pair $(f_v(v_i), f_c(c_j))$, and $\delta$ is the margin. The first term in the equation above is for matching a video with a negative caption and the second term is for matching a caption with a negative video.

4 Experimental Settings

In Section 4.1 we describe the implementation details of our method and in Section 4.2 we describe the downstream tasks and five datasets in our evaluations.

4.1 Implementation Details

Model. For a fair comparison to the baseline model HTM [43], we use the same class of non-linear embedding functions:

$$f(v) = (W^v_1 v + b^v_1) \circ \sigma(W^v_2 (W^v_1 v + b^v_1) + b^v_2)$$  \hspace{1cm} (4)$$

$$g(c) = (W^c_1 c + b^c_1) \circ \sigma(W^c_2 (W^c_1 c + b^c_1) + b^c_2),$$  \hspace{1cm} (5)

where $W^v_1 \in \mathbb{R}^{d \times d_v}$, $W^v_2 \in \mathbb{R}^{d \times d_v}$, $W^c_1 \in \mathbb{R}^{d \times d_c}$, $W^c_2 \in \mathbb{R}^{d \times d_c}$, $b^v_1, b^v_2, b^c_1, b^c_2 \in \mathbb{R}^d$ are the learnable parameters, $\sigma$ is an element-wise sigmoid activation and $\circ$ is the element-wise multiplication. We use $d_v = 4096$, $d_c = 300$, and $d = 6144$.

Training dataset. We train our model using the HowTo100M [43] narrated video dataset. It consists of more than 1.2M videos accompanied with automatically generated speech transcription. Similarly to [43], we use the provided transcription to create pairs of video-caption defined by each caption time stamp, where each video shorter than 5 seconds is extended symmetrically in time so that the duration is at least 5 seconds. Note that while the original dataset consists of 136M pairs, we only use 1.16M pairs since some of the videos are no longer available for download.

Input caption features. For the word representations, we use the standard GoogleNews pre-trained word2vec embedding model [44]. For the input sentence representations used in Section 3.3 we simply average word representation over each sentence.

Input visual features. We extract 2D features using ImageNet pre-trained Resnet-152 [17] at a rate of 1 frame per second. We extract 3D features using Kinetics [7] pre-trained ResNeXt-101 16-frames [15] at a rate of 24 frames per second. After temporal max pooling we concatenate 2D and 3D features to form a single feature vector per video clip.

Loss. We train our embedding model using the Soft Max Margin loss function described in Section 3.4.

Optimization. We use the ADAM [27] optimizer with a fixed learning rate of $10^{-3}$. 

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**k-NN Computation.** To compute k-NN efficiently over the entire dataset we use Facebook AI Similarity Search (FAISS) [24]. Due to the high correlation between video segments of the same video, in practice we extract $K$ nearest neighbors that originate from different videos, where $K = 4$.

**Time complexity.** Using FAISS [24], computation of the Multimodal Density Estimation described in Section 3.3 is done in less than 15 hours over 10 CPUs. Training the model on the large HowTo100M dataset is done on a single V100 GPU and takes less than 24 hours.

### 4.2 Downstream Tasks

**Video Visual Question Answering (VQA).** The Video VQA task comprises answering questions about videos presented in natural language [3]. Essentially, an instance of VQA includes an input video and a free-form textual query regarding the content in the video, and an expected textual answer. To accommodate this task we fine-tune our learned multimodal representations and evaluate our model on two datasets: MSRVTT-QA and MSVD-QA [97]. These datasets are based on existing video description datasets. See Table 1 for detailed statistics of each dataset.

Most VQA models use a video and question as input, and the answer is presented as the output of an LSTM unit [18] or a softmax layer over a set of predetermined answers. However, these types of architectures do not fully utilize the information which exists in coordinated representations, i.e., the representation of the correct answer might likely be closely embedded to the visual representation, given the question. To better utilize our learned multimodal representations specifically for the VQA task, we use a similar architecture to [19], but for video. We learn two more sets of embeddings on top of the pre-trained embeddings that were learned with the HowTo100M dataset: a question+video embedding, i.e., we embed the question and video to a single feature vector; and an answer embedding. We train the model with a max margin ranking loss function to embed an answer close to its question+video. Inference is performed simply with a nearest neighbor search over the set of predetermined answers in the joint video+question and answer space. This model is very simple compared to most VQA models, yet as we show in Table 4 it is very powerful when built on powerful self-supervised pre-trained joint embeddings.

| Table 1. Video question answering dataset statistics | Dataset | Clip Length [s] | #Clips | #Questions |
|----------------------------------------------------|---------|----------------|--------|-----------|
|                                                    |         |                | Train  | Val       | Test     |
| MSRVTT-QA [97]                                     | 20      | 10,000         | 158,581| 12,278    | 72,821   |
| MSVD-QA [97]                                       | 20      | 1970           | 30,933 | 6,415     | 13,157   |
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**Text-To-Video Retrieval.** Text-To-Video Retrieval includes retrieval of video clips based on textual description [36,46,69]. With a learned joint representation space, retrieval is performed with a nearest neighbor search over the joint embedding space. To evaluate our model we use three different datasets: MSRVTT, MSVD and LSMDC [98,8,62]. We use the standard evaluation metrics: recall at $K$ (R@K) for $K = 1, 5, 10$ and median recall (MR). See Table 2 for detailed statistics of each dataset.

### Table 2. Text-Video retrieval dataset statistics. We use the same test set split as defined by [46,99,42] for a fair comparison

| Dataset   | Clip Length [s] | #Clips | #Sentences |
|-----------|----------------|--------|------------|
|           |                |        | Train      | Val   | Test   |
| MSRVTT   | 20             | 10,000 | 130,260    | 9,940 | 1000   |
| MSVD     | 20             | 1970   | 48820      | 4401  | 3,350  |
| LSMDC    | 5              | 128,085| 101,079    | 7408  | 1000   |

### 5 Results and Analysis

We compare our proposed model against two ablative baselines and multiple task specific state-of-the-art models:

- **HTM-PT [43].** The model (architecture and loss function) used in [43]. This baseline is pre-trained (PT) on the HowTo100M dataset. It is the exact architecture described in Section 4.1 for our model. The only differentiating element is the loss function. [43] use the max margin ranking loss function, while we use our proposed Soft Max Margin ranking loss function. Since the model is also trained identically to our own model it is clear that any gain in performance over this baseline is due to our novel noise estimation based density estimation component.

- **HTM-no-PT [43].** The same model from above, but without pre-training (no-PT) on the HowTo100M dataset. The (under) performance of this baseline on downstream tasks demonstrate the potential gain in performance by utilizing self-supervised speech-visual correspondence training.

- **Task specific state-of-the-art models.** After fine-tuning for downstream tasks we compare our proposed model to state-of-the-art models for each task and each dataset. [12,97,10,20] for VQA, and [36,46,99,42,43,41] for Text-To-Video Retrieval.

Tables 3 and 4 show the result for Text-To-Video Retrieval and Video Question Answering, respectively. Table 5 shows the results for Zero-Shot Text-To-Video Retrieval under ‘unfair’ settings. We summarize key insights below:
Our model consistently outperforms the baselines (HTM-PT, HTM-no-PT \[43\]) in both Visual Question Answering and Text-To-Video Retrieval on five different datasets.

- We set a new state-of-the-art performance for two Visual Question Answering datasets: MSRVTT-QA and MSVD-QA.
- We set a new state-of-the-art performance for Zero-Shot Text-To-Video Retrieval on two datasets: LSMDC and MSVD.
- We set a new state-of-the-art performance for (fine-tuned) Text-To-Video Retrieval on two datasets: MSRVTT and MSVD.
- We demonstrate in Table 5 that our model outperforms or at least matches the performance of HTM-PT \[43\] even given a setting which is a clear disadvantage such as training it without 3D features (i.e., only 2D). This shows: (a) the power of our noise estimation method and its potential; and (b) that by integrating our multimodal density estimation component it is possible to save time and/or computation power when necessary, without any performance degradation.
- Specifically in MSRVTT dataset our 2D-based model actually performs slightly better than our 2D+3D-based model. This result requires further investigation.

### Table 3. Text-To-Video Retrieval. Zero-Shot: training was done only with HowTo100M dataset. Fine-Tuned: model was fine-tuned with the relevant benchmark dataset. For MR the lower the better. *: results for MSRVTT and LSMDC are from \[43\], while results for MSVD have been reproduced. †: CE \[36\] use extra labeled data in the form of pre-trained semantic embeddings which include general features such as motion, appearance, scene features and OCR.

| Method          | MSRVTT | LSMDC | MSVD |
|-----------------|---------|-------|------|
|                 | R@1   | R@5   | R@10 | MR   | R@1   | R@5   | R@10 | MR   | R@1   | R@5   | R@10 | MR   |
| **Zero-Shot**   |        |       |      |      |       |       |      |      |       |       |      |      |
| Random          | 0.1    | 0.5   | 1.0  | 500.0| 0.15  | 0.75  | 1.49  | 335  |
| MIL-NCE \[41\]  | 9.9    | 24.0  | 32.4 | 29.5 | –     | –     | –     | –    |
| HTM-PT* \[43\]  | 7.5    | 21.2  | 29.6 | 38.0 | 4.0   | 9.8   | 14.0  | 137.0| 12.86| 33.06| 45.83| 13.0 |
| Ours            | 8.0    | 21.3  | 29.3 | 33.0 | 4.2   | 11.6  | 17.1  | 119.0| 13.66| 35.7 | 47.74| 12.0 |
| **Fine-Tuned**  |        |       |      |      |       |       |      |      |       |       |      |      |
| CET† \[36\]     | 18.2   | 46.0  | 60.7 | 7.0  | 11.2  | 26.9  | 34.8  | 25.0 | 19.8 | 49.0 | 63.8 | 6.0  |
| JEMC \[42\]     | 7.0    | 20.9  | 28.7 | 38.0 | –     | –     | –     | –    | 20.3 | 47.8 | 61.1 | 6.0  |
| JS Fusion \[29\]| 10.2   | 31.2  | 43.2 | 13.0 | 9.1   | 21.2  | 34.1  | 36   | –    | –    | –    | –    |
| MoEE \[15\]     | 14.2   | 39.2  | 53.8 | 9    | 10.1  | 25.6  | 34.6  | 27   | –    | –    | –    | –    |
| HTM-no-PT* \[43\]| 12.4  | 36.0  | 52.9 | 10.0 | 5.8   | 18.8  | 28.4  | 45.0 | 13.0 | 37.43| 52.41| 10.0 |
| Ours            | 17.4   | 41.6  | 53.6 | 8.0  | 6.4   | 19.8  | 28.4  | 39.0 | 20.3 | 48.97| 63.26| 6.0  |

### 6 Summary

In this work, we showed that the problem of noise estimation in multimodal data can be effectively reduced to a multimodal density estimation task. Based on this
Table 4. Video Question Answering. Results of [20] and [12] have been reproduced in [10].

| Method      | MSRVTT-QA [%] | MSVD-QA [%] |
|-------------|---------------|-------------|
| ST-VQA [20] | 30.09         | 31.3        |
| Co-Mem [12] | 32.0          | 31.7        |
| AMU [97]    | 32.5          | 32.0        |
| HMEMA [10]  | 33.0          | 33.7        |
| HTM-no-PT [43] | 27.05     | 33.8        |
| HTM-PT [43] | 34.38         | 34.83       |
| Ours        | 35.06         | 35.13       |

Table 5. Zero-shot Text-To-Video Retrieval in ‘unfair’ settings. For MR the lower the better. We show below that our model outperforms or at least matches the performance of HTM-PT [43] even given a setting which is a clear disadvantage such as training it without 3D features (no-3D), i.e., only 2D features.

| Method      | MSRVTT | LSMDC | MSVD |
|-------------|--------|-------|------|
| HTM-PT [43] | R@1 7.5 | R@5 21.2 | R@10 29.6 | MR 43.0 |
| HTM-PT [43] no-3D | 6.9 | 19.8 | 27.4 | 43.0 | MR 11.5 |
| Ours (no 3D) | 8.4 | 22.0 | 30.4 | 36.0 | MR 12.74 |

An efficient noise estimation we proposed a novel building block for noise robust multimodal representation learning that can be integrated into many multimodal learning models and improve their performance instantly. We demonstrated how to integrate our building block into the max margin ranking loss function (Soft Max Margin) and it can similarly be integrated into various architectures and losses. We trained Soft Max Margin on the self-supervised proxy task of speech-visual correspondence that is known to be highly noisy. We further evaluated Soft Max Margin on two different downstream tasks: Visual Question Answering and Text-to-Video Retrieval; and achieved comparable state-of-the-art performance on five different datasets. These results emphasize the importance of self-supervised multimodal representation learning for advancing the state of the art in challenging multimodal artificial intelligence tasks.

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