MultiDEC: Multi-Modal Clustering of Image-Caption Pairs

Sean T. Yang,
University of Washington
ttyang38@uw.edu,

Kuan-Hao Huang,
University of California, Los Angeles
khhuang@cs.ucla.edu,

Bill Howe,
University of Washington
billhowe@cs.washington.edu

Abstract

In this paper, we propose a method for clustering image-captions pairs by simultaneously learning image representations and text representations that are constrained to exhibit similar distributions. These image-caption pairs arise frequently in high-value applications where structured training data is expensive to produce but free-text descriptions are common. MultiDEC initializes parameters with stacked autoencoders, then iteratively minimizes the Kullback-Leibler divergence between the distribution of the images (and text) to that of a combined joint target distribution. We regularize by penalizing non-uniform distributions across clusters. The representations that minimize this objective produce clusters that outperform both single-view and multi-view techniques on large benchmark image-caption datasets.

1 Introduction

In many science and engineering applications, images are equipped with free-text descriptions, but structured training labels are difficult to acquire. For example, the figures in the scientific literature are an important source of information (Sethi et al. 2018; Lee et al. 2017), but no training data exists to help models learn to recognize particular types of figures. These figures are, however, equipped with a caption describing the content or purpose of the figure, and these captions can be used as a source of (noisy) supervision.

Grechkin et al. used distant supervision and co-learning to jointly train an image classifier and a text classifier, and showed that this approach offered improved performance (Grechkin, Poon, and Howe 2018). However, this approach relied on an ontology as a source of class labels. No consensus on an ontology exists in specialized domains, and any ontology that does exist will change frequently, requiring re-training. Our goal is to perform unsupervised learning using only the image-text pairs as input.

A conventional approach is to cluster the images alone, ignoring the associated text. Unsupervised image clustering has received significant research attention in computer vision recently (Xie, Girshick, and Farhadi 2016; Yang et al. 2017; Yang, Parikh, and Batra 2016). However, as we will show, these single-view approaches fail to produce semantically meaningful clusters on benchmark datasets. Another conventional solution is to cluster the corresponding captions using NLP techniques, ignoring the content of the images. However, the free-text descriptions are not a reliable representation of the content of the image, resulting in incorrect assignments.

Current multi-modal image-text models focus on matching images and corresponding captions for information retrieval tasks (Karpathy and Fei-Fei 2015; Dorfer et al. 2018; Carvalho et al. 2018), but there is less work on unsupervised learning for both images and text. Jin et al. (Jin et al. 2015) solved a similar problem where they utilized Canonical Correlation Analysis (CCA) to characterize correlations between image and text. However, the textual information for the model were explicit tag rather than long-form free-text descriptions. Unlike tags, free-text descriptions are extremely noisy: they always contain significant irrelevant information, and may not even describe the content of the image.

We propose MultiDEC, a clustering algorithm for image-text pairs that considers both visual features and text features and simultaneously learns representations and cluster assignments for images. MultiDEC extends prior work on Deep Embedded Clustering (DEC) (Xie, Girshick, and Farhadi 2016), which is a method that simultaneously learns feature representations and cluster assignments using deep neural networks. DEC learns a mapping function from the data space to a lower-dimensional feature space in which it iteratively optimizes Kullback-Leibler divergence between embedded data distribution and a computed target distribution. DEC has shown success on clustering several benchmark datasets including both images and text (separately).

Despite its utility, in our experiments DEC may generate empty clusters or assigns clusters to outlier data points, which is a common problem in clustering tasks (Dizaji et al. 2017; Caron et al. 2018). We address the problem of empty clusters by introducing a regularization term to force the model to find a solution with a more balanced assignment.

We utilize a pair of DEC models to take data from image and text. Derived from the target distribution in (Xie, Girshick, and Farhadi 2016), we propose a joint distribution for both the embedded image features and the text features. MultiDEC simultaneously learns the image representation by iterating between computing the joint target distribution and minimizing KL divergence between the embed-
Multi-View Image-Text Learning Joint embedding of image and text models have been increasingly popular in applications including image captioning [Mao et al. 2015], Xu et al. 2015 [Karpathy and Fei-Fei 2015], question answering [Antol et al. 2015], and information retrieval [Karpathy and Fei-Fei 2015, Dorfer et al. 2018, Carvalho et al. 2018]. DeVise [Frome et al. 2013] is the first method to generate visual-semantic embeddings that linearly transform a visual embedding from a pre-trained deep neural network into the embedding space of textual representation. The method begins with a pre-trained language model, then optimizes the visual-semantic model with a combination of dot-product similarity and hinge rank loss as the loss function. After DeVise, several visual semantic models have been developed by optimizing bi-directional pairwise ranking loss [Kiros, Salakhutdinov, and Zemel 2014, Wang, Li, and Lazebnik 2016] and maximum mean discrepancy loss [Tsai, Huang, and Salakhutdinov 2017]. Maximizing CCA (Canonical Correlation Analysis) [Hardoon, Szedmak, and Shawe-Taylor 2004] is also a common way to acquire cross-modal representation. Yan et al. [Yan and Mikolajczyk 2015] address the problem of matching images and text in a joint latent space learned with deep canonical correlation analysis. Dorfer et al. [Dorfer et al. 2018] develop a canonical correlation analysis layer and then apply pairwise ranking loss to learn a common representation of image and text for information retrieval tasks. However, most image-text multi-modal studies focus on matching image and text. Few methods study the problem of unsupervised clustering of image-text pairs.

Jin et al. addressed a related problem where they aim to cluster images by integrating the multimodal feature generation with the Locality Linear Coding (LLC) and co-occurrence association network, multimodal feature fusion with CCA, and accelerated hierarchical k-means clustering (Jin et al. 2015). However, the text data they handled are tags instead of longer, noisy, and unreliable free-text descriptions as we do in MultiDEC. Grechkin et al. proposed EZLearn [Grechkin, Poon, and Howe 2018], a co-training framework which takes image-text data and an ontology to classify images using labels from the ontology. This model requires prior knowledge of the data in order to derive an ontology; this prior knowledge is not always available, and can significantly bias the results toward the clusters implied by the ontology.

3 Method

Figure 1 shows an overview of our method. MultiDEC clusters data by simultaneously learning DNN parameters $\theta_X$ and $\theta_T$ that map data points $X$ and $T$ to $Z$ and $Z'$ and a set of centroids $\mu_j$ and $\mu'_j$ in the latent space $Z$ and $Z'$, respectively. Following [Xie, Girshick, and Farhadi 2016], our method includes two phases: (1) Parameter initialization. We initialize $\theta_X$ and $\theta_T$ with two stacked autoencoders to learn meaningful representations from both views and apply K-means to obtain initial centroids. (2) Clustering. MultiDEC updates the DNN parameters and centroids by iterating between computing joint auxiliary target distribution and minimizing the Kullback-Leibler (KL) divergence to the calculated target distribution. Details regarding each phase will be elaborated as below.
Figure 1: Overview of our method. MultiDEC includes two phases: parameter initialization and clustering. DNN parameters and centroids are initialized using a stacked reconstructing autoencoder and K-means on the embedded data points. In the clustering phase, parameters and centroids are updated by iterating between computing a joint target distribution and minimizing KL divergence. This figure is best viewed in color.

Parameter Initialization We initialize DNN parameters with two stacked autoencoders (SAE). A stacked autoencoder has shown success in generating semantically meaningful representation in several studies (e.g., (Vincent et al. 2010; Le 2013; Xie, Girshick, and Farhadi 2016)). We utilize a symmetric stacked autoencoder to learn the initial DNN parameters for each view by minimizing mean square error loss between the output and the input. After training the autoencoder, we discard the decoder, pass data X and T through trained encoder and apply K-means to the embeddings on Z and Z’ to obtain initial centroids μj and μ′j.

With the initialization of DNN parameters and centroids, MultiDEC updates the parameters and the centroids by iterating between computing a joint target distribution and minimizing a (regularized) KL divergence of both data views to it. In the first step, we compute soft assignments (i.e., a distribution over cluster assignments) for both views. Following Xie et al., we set α to 1 because we are not able to tune it in an unsupervised manner.

KL Divergence Minimization Xie et al. trained DEC by minimizing the KL divergence between the soft assignment qij and a target distribution pij (presented below in Eq. 3), with a goal of purifying the clusters by learning from high confidence assignments:

\[ L = KL(p||q) = \frac{1}{N} \sum_{i} \sum_{j} p_{ij} \log \frac{p_{ij}}{q_{ij}} \]  

where \( h_j = P(y = j) = \frac{1}{N} \sum_{i} p_{ij} \)

Aligning Image Clusters and Text Clusters After calculating the soft assignments for both views, we need to align the two sets of k clusters. This cluster alignment is obtained from the highest probability cluster (i.e., image i is assigned to cluster \( \text{arg max}_j q_{ij} \)). Next, to align image clusters and text clusters, we use the Hungarian algorithm to find the minimum cost assignment. We create a \( k \times k \) confusion matrix where an entry \((m, n)\) represents the number of data points being assigned to \( m \)-th image cluster and \( n \)-th text cluster. We then subtract the maximum value of the matrix from the value of each cell to obtain the "cost." The Hungarian algorithm is then applied to the cost matrix.

Soft Assignment Following Xie et al. (Xie, Girshick, and Farhadi 2016), we model the probability of data point \( i \) being assigned to cluster \( j \) using the Student’s t-distribution (Maaten and Hinton 2008), producing a distribution \( q_{ij} \) for images and \( r_{ij} \) for text.

\[ q_{ij} = \frac{1 + \|z_i - \mu_j\|^2 / \alpha}{\sum_{j'} (1 + \|z_i - \mu_{j'}\|^2 / \alpha)^{-\frac{\nu+1}{2}}} \]  
\[ r_{ij} = \frac{1 + \|z_i' - \mu_{j'}\|^2 / \alpha}{\sum_{j'} (1 + \|z_i' - \mu_{j'}\|^2 / \alpha)^{-\frac{\nu+1}{2}}} \]  

where \( q_{ij} \) and \( r_{ij} \) are the soft assignments for image view and text view, respectively, and \( \alpha \) is the number of degrees of freedom of the Student’s t-distribution. \( z_i \) is the embedding on latent space \( Z \) of data \( x_i \), which can be described as \( z_i = f_{θX}(x_i) \). \( z_i' \) is the embedding on latent space \( Z' \) of data \( t_i \), which can be illustrated as \( z_i' = g_{θZ}(t_i) \).
| Dataset        | # Points | # Categories | average # words | % of largest Class | % of smallest Class |
|---------------|----------|--------------|----------------|-------------------|-------------------|
| Coco-cross    | 7429     | 10           | 50.3           | 23.2%             | 1.6%              |
| Coco-all      | 23189    | 43           | 50.4           | 7.4%              | 0.4%              |
| Pascal        | 1000     | 20           | 48.9           | 5.0%              | 5.0%              |
| RGB-D         | 1449     | 13           | 38.5           | 26.4%             | 1.7%              |

Table 1: Dataset statistics.

**Joint Target Distribution**  
Xie et al. proposes a target distribution \( Xie, Girshick, and Farhadi 2016 \) which aims to improve cluster purity and to emphasize data points with high assignment confidence:

\[
p_{ij} = \frac{q_{ij}/\beta_j}{\sum_j q_{ij}/\beta_j} 
\]

(8)

where \( \beta_j = \sum_i q_{ij} \).

To fit the model with multi-view problem setting, we propose a joint target distribution:

\[
p_{ij} = \frac{q_{ij}/\beta_j}{2 \times \sum_j q_{ij}/\beta_j} + \frac{r_{ij}/\sigma_j}{2 \times \sum_j r_{ij}/\sigma_j} 
\]

(9)

where \( \beta_j = \sum_i q_{ij} \) and \( \sigma_j = \sum_i r_{ij} \) are soft cluster frequencies for image view and text view, respectively. With this joint target distribution, MultiDEC is able to take both sources of information into account during training.

Some images do not have associated text; we want the model to be robust to this situation. Missing text causes the second term in equation (9) to be 0 and the data points with text would have higher value of \( p_{ij} \) and contribute a larger gradient to the model. We will discuss this issue in more detail in Section 5.

4 Experiments

We evaluate our method with four datasets and compare to several single-view and multi-view algorithms. In these experiments, we aim to verify the effectiveness of MultiDEC on real datasets, validate that MultiDEC outperforms single-view methods and state-of-the-art multi-view methods.

4.1 Datasets

To evaluate our method, we use datasets that have images with corresponding captions as well as ground-truth labels to define the clusters. Our proposed model is tested with four datasets from three different sources and compared against several single-view and multi-view algorithms. We summarize the results in Table 1.

- **Coco-cross** \( Lin et al. 2014 \): MSCOCO is a large-scale object detection, segmentation, and captioning dataset. There are five sentences of captions per image. There are 80 object categories and all these categories belong to 10 supercategories. Every image includes at least one object. We discard images containing multiple objects. For this subset, we pick the category with the largest number of images in each supercategory, which are stop sign, airplane, suitcase, pizza, cell phone, person, giraffe, kite, toilet, and clock. There are 7,429 data points from these 10 categories in total.

- **Coco-all** \( Lin et al. 2014 \): For this subset of MSCOCO, similar to Coco-cross, we remove images with more than one object, while we keep all categories that include more than 100 images. We are able to compile a dataset with 23,189 images from 43 categories.

- **Pascal** \( Rashtchian et al. 2010 \): This dataset contains 1,000 images with 20 categories, 50 images each category. Every image comes with 5 sentences caption.

- **SentencesNYUv2 (RGB-D)** \( Nathan Silberman and Fergus 2012, Kong et al. 2014 \): This dataset includes 1449 images with 13 indoor scenes. Every image is captioned with a paragraph which describes the content of the image. Compared to Coco and Pascal datasets, the captions in this dataset are less specific to the categories and significantly less reliable as a source of information.

We use ResNet-50 \( He et al. 2016 \), pretrained on 1.2M ImageNet \( Deng et al. 2009 \) corpus, for extracting 2048 dimensional image features and doc2vec \( Le and Mikolov 2014 \), which is pre-trained on Wikipedia via skip-gram, to embed captions and obtain text features. Recent studies have shown image features embedded by ImageNet pretrained models improve general image clustering tasks and ResNet-50 features are superior than representation extracted from other state-of-the-art CNN architectures \( Guerin et al. 2017, Guerin and Boots 2018 \). Doc2vec also has shown to produce effective representations for long text paragraphs \( Lau and Baldwin 2016 \).

4.2 Competitive Methods

We compare our method to a variety of single-view and multi-view methods.

**Single-view methods**  
We run two single-view methods to serve as baseline comparison.

- **K-means (KM)** \( Lloyd 1982 \): We applied K-means on both image ResNet-50 features and text doc2vec features to provide a general assessment of the input feature. To reduce the high number of dimensions that can cause clustering algorithms to produce empty clusters \( Bellman 1961, Steinbach, Ertöz, and Kumar 2004 \), we reduce the dimension of the 2048-d ResNet-50 image features to 50-d by Principal Component Analysis (PCA) \( Jolliffe 2011 \).

- **Deep Embedded Clustering (DEC)** \( Xie, Girshick, and Farhadi 2016 \): DEC simultaneously learns feature representations and cluster assignments of the data by minimizing KL divergence between data distribution and an auxiliary target distribution. We then apply K-means to output. We show results for both text and image inputs.
Multi-view methods  We evaluate three state-of-the-art multi-view methods. Current methods for matching image and text models are based on minimizing ranking loss or maximizing CCA between text and image.

- **Unifying Visual-Semantic Embeddings (VSE) + K-means** (Kiros, Salakhutdinov, and Zemel 2014): Kiros et al. proposed a pipeline which unifies joint image-text embedding models by minimizing pairwise ranking loss. The joint embedding is a 1024 dimensional space, so we apply PCA and reduce the dimension of the embedding to 50-d. K-means is further implemented to acquire the cluster centroids on the reduced dimensional embedding.

- **Deep Canonical Correlation Analysis (DCCA) + K-means** (Andrew et al. 2013; Wang et al. 2015): This model includes a Canonical Correlation Analysis layer which combines pairwise ranking loss with the optimal projections of CCA. K-means is then applied to the learned embeddings.

- **Canonical Correlation Layer Optimized with Pairwise Ranking Loss (CCAL-L\_rank) + K-means** (Dorfer et al. 2018): This model includes a Canonical Correlation Analysis layer which combines pairwise ranking loss with the optimal projections of CCA. K-means is then applied to the learned embeddings.

4.3 Evaluation Metrics

All experiments are evaluated by three standard clustering metrics: clustering accuracy (ACC), normalized mutual information (NMI), and adjusted rand index (ARI). For all metrics, higher numbers indicate better performance.

We use hyperparameter settings following Xie et al. (Xie, Girshick, and Farhadi 2016). For baseline algorithms, we use the same setting in their corresponding paper. All the results are the average of 10 trials.

4.4 Experimental Results

Table 4.1 displays the quantitative results for different methods. MultiDEC outperforms other DNN models on this dataset. However, MultiDEC still surpasses other DNN models on this dataset.

Table 3: Clustering performance of several single-view and multi-view algorithms on four datasets. The results reported are the average of 10 iterations. MultiDEC outperforms the comparing methods on three datasets by a large margin. The insufficient performance from DNN models on Pascal dataset might be caused by insufficient amount of data.

5 Discussion

In this section, we discuss additional experiments to expand on MultiDEC’s effectiveness.

5.1 Qualitative Comparison

The cluster metrics are difficult to interpret, so we are interested in exploring a qualitative comparison between MultiDEC and the best single-view and multi-view competitors, DEC and CCA, respectively. Figure 2 is a visualization of the latent space of MultiDEC to illustrate its effectiveness in producing coherent clusters. We use t-SNE to visualize the embeddings from the latent space with perplexity = 30. The positions and shapes of the clusters are not meaningful due to the operation of t-SNE. Both DEC and MultiDEC are able to generate distinct clusters, but DEC appears to have many more false assignments. For example, DEC can struggle to generate distinct clusters, but DEC appears to have many more false assignments. For example, DEC can struggle to generate distinct clusters, but DEC appears to have many more false assignments.

We further compare three algorithms by inspecting examples of the clusters. Figure 3 shows the top five images with highest confidence from each cluster from the Coco-cross dataset.
Figure 2: Qualitative visualization of the latent representation of MultiDEC, DEC, and CCA. (Color encoding is based on groundtruth labels.) We can observe that MultiDEC successfully separates overlapped data points in original latent space and generates semantic meaningful clusters. DEC has trouble with separating kite from airplane and giraffe from pizza. While CCA is able to gather semantic similar images, but the latent space is still difficult for clustering analysis with unclear boundaries between clusters.

Figure 3: The 5 highest-confidence images in each cluster from MultiDEC (left), DEC (middle), and CCA (right). MultiDEC clusters appear qualitatively better. For example, airplanes and kites, two visually and semantically similar concepts, are clearly distinguished, while DEC appears to struggle to distinguish giraffes and pizza. Clock examples separated into two clusters: clocks on towers (cluster #2) and indoors clocks (cluster #9). As we saw in Figure 2, the cluster boundaries are indistinct in CCA latent space, and the qualitative results shown in Figure 3 corroborate this result. We can see several different clusters include similar objects; for example, both cluster #1 and cluster #9 include airplanes and cluster #0 and cluster #7 include giraffes.

5.2 Model Robustness

Model Sensitivity to Text Features We use learned embeddings for text as input to the model. To examine the model’s sensitivity to the quality of the input text representations, we experiment with two other baseline text representations, TF-IDF and FastText (Bojanowski et al. 2017). TF-IDF ignores all co-occurrence relationships, and therefore has significantly less semantic content, so we expect performance to be worse. We produce a 2000-d vector for text features for each data point. FastText is a word embed-
Table 3: Experiment results on model sensitivity to text features vectors. MultiDEC remains similar performance among different text embedding algorithms.

| Input Text Features | Coco-cross | Coco-all | Pascal | RGB-D |
|---------------------|------------|----------|--------|-------|
| Doc2Vec             | 0.822      | 0.668    | 0.499  | 0.521 |
| TF-IDF              | 0.801      | 0.685    | 0.556  | 0.519 |
| FastText            | 0.868      | 0.674    | 0.481  | 0.449 |

Figure 4: Experiment results on model robustness to missing text. The clustering accuracy holds even with very little data, which verify our hypothesis in method section.

Robustness to Missing Text Incomplete views are a very common problem in multi-view clustering (Xu, Tao, and Xu [2015]). In realistic settings, not all images will be equipped with text descriptions, and we want MultiDEC to degrade gracefully in these situations. To analyze the robustness of MultiDEC when text descriptions are missing, we remove text from a random set of images at varying rates. We expect that performance will degrade as we remove text labels — if it did not, then MultiDEC would not be making use of the information in the text labels. The results are shown in Figure 5 and we see that performance does indeed degrade, but not by a significant amount. This result shows that the joint target distribution can work with either or both sources of information (Equation 9). Images with missing text have smaller value of $p_{ij}$ because the second term in equation (9) is ignored, while images with captions have larger value of $p_{ij}$ and contribute larger gradient to the model. We also ran an experiment to test the robustness to noisy text by scrambling the image-text pairs, such that a given percentage of the images would be associated with the text of a different image. This change is more adversarial than missing text, as the incorrect labels could train the model to learn incorrect signals. (Figure 5). The performance of MultiDEC remains steady until almost 60% of the text is perturbed, indicating that MultiDEC is robust to incorrect labels.

Figure 5: MultiDEC performance when swapping the text labels for a random portion of the image-text pairs. The model performance remains high until over 60% of the input text are scrambled.

6 Conclusion

We present MultiDEC, a method that learns representations from multi-modal image-Text pairs for clustering analysis. MultiDEC consists a pair of DEC models to take data from image and text, and works by iteratively computing a proposed joint target distribution and minimizing KL divergence between the embedded data distribution to the computed joint target distribution. We also address the issue of empty cluster by adding a regularized term to our KL divergence loss. MultiDEC demonstrates superior performance on various datasets and outperforms single view algorithms and state-of-the-art multi-view models. We further examine the robustness of MultiDEC to input text features, missing and noisy text. Our experimental results indicate that MultiDEC is a promising model for image-text pair clustering.

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