COBRA: Contrastive Bi-Modal Representation Algorithm

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Abstract

There are a wide range of applications that involve multi-modal data, such as cross-modal retrieval, visual question-answering, and image captioning. Such applications are primarily dependent on aligned distributions of the different constituent modalities. Existent approaches generate latent embeddings for each modality in a joint fashion by representing them in a common manifold. However, these joint embedding spaces fail to sufficiently reduce the modality gap, which affects the performance in downstream tasks. We hypothesize that these embeddings retain the intra-class relationships but are unable to preserve the inter-class dynamics. In this paper, we present a novel framework COBRA that aims to train two modalities (image and text) in a joint fashion inspired by the Contrastive Predictive Coding (CPC) and Noise Contrastive Estimation (NCE) paradigms which preserve both inter and intra-class relationships. We empirically show that this framework reduces the modality gap significantly and generates a robust and task-agnostic joint-embedding space. We outperform existing work on four diverse downstream tasks spanning across seven benchmark cross-modal datasets.

CCS Concepts

• Computing methodologies → Learning latent representations; • Information systems → Multimedia information systems.

Keywords

Joint embedding spaces, latent representations, contrastive learning, bi-modal data

1 Introduction

Systems built on multi-modal data have been shown to perform better than systems that solely use uni-modal data [5, 45]. Due to this fact, multi-modal data is widely used in and generated by different large scale applications. These applications often utilize this multi-modal data for tasks such as information retrieval [9, 41], classification [44, 52], and question-answering [24, 32]. It is therefore important to represent such multi-modal data in a meaningful and interpretable fashion to enhance the performance of these large-scale applications. Since a majority of such applications focus predominantly on text and image modalities, in this work we only focus on learning joint cross-modal representations for images and text.

However, learning meaningful representations for such multi-modal data is challenging because there exists a distributional shift between these modalities [15, 34]. The lack of consistency in representations across modalities further magnifies this shift. Due to such difficulties, any similarity metric between the representations across modalities is intractable to compute [34]. The reduction of this distributional shift boils down to two challenges: (1) projecting the representations of data belonging to different modalities to a common manifold (also referred to as the joint embedding space), and (2) retaining their semantic relationship with other samples from the same class as well as different classes.

The need for a joint embedding space is emphasized by the inability of uni-modal representations to align well with each other. Over the last few years, literature [15, 26, 33] has been presented where the representations were modeled in the joint embedding space, but reducing the modality gap significantly has posed to be an arduous task. We believe this is due to the fact that current cross-modal representation systems regularize the distance of pairs of representations of those data samples which belong to the same classes (but different modalities) but not of pairs of representations belonging to different classes (can be from the same or different modalities). While current work [15, 33] has focused on conserving the semantic relationship between intra cross-modal data, i.e., belonging to the same class, we surmise that along with this, preserving inter cross-modal interactions will help the model learn a more discriminatory boundary between different classes.

Motivation: We posit that preserving the relationship between representations of samples belonging to different classes, in a modality invariant fashion, can improve the quality of joint cross-modal embedding spaces. We formulate this hypothesis as it introduces a contrastive proximity mechanism between data belonging to different semantic classes. This distancing will allow the model to converge to a better generalizing decision boundary. Similar contrastive learning paradigms based on information gain have been performing very well in the self-supervised learning problem settings [16, 53]. To the best of our knowledge, we are the first to propose a method to learn joint cross-modal embeddings based on contrastive learning paradigms.

Contributions: Our contributions are as follows:

• We propose a novel joint cross-modal embedding framework called COBRA (Contrastive Bi-modal Representation Algorithm) which represents the data across different modalities in a common manifold.

• We employ a new optimization strategy which preserves not only the relationship between different intra cross-modal data samples but also preserves the relationship between inter cross-modal data samples using contrastive learning paradigms (refer Figure 1) inspired by the recent success of similar frameworks in self-supervised learning problems [16, 51, 53].

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We empirically validate our model by achieving state-of-the-art results on four diverse downstream tasks: (1) cross-modal retrieval [15, 54, 66], (2) fine-grained multi-modal sentiment classification [10], (3) multi-modal disaster classification [1, 11], and (4) multi-modal fake news detection [20, 49, 56].

The rest of the paper is structured as follows. Section 2 covers the adjoining work done in the field of cross-modal retrieval systems and multi-modal fusion along with an introduction to the contrastive learning paradigms, which forms the theoretical backbone of our approach. Section 3 presents our proposed methodology. Section 4 provides a description of the benchmark datasets and the metrics used. Section 5 concludes the paper.

2 Related Work

In this section, we discuss the topics that inspire the architecture and loss functions used in COBRA: Cross-modal Correlation, Multi-modal Fusion, Contrastive Learning Paradigms and Noise Contrastive Estimation. We further discuss the tasks used to evaluate COBRA: Cross-modal Retrieval, Multi-modal Fake News Detection and Multi-modal Sentiment Classification.

2.1 Cross-modal Correlation

The initial attempts at using deep architectures for establishing cross-modal correlation relationships were inspired from the traditional methods. Andrew et al. [4] proposed Deep Canonical Correlation Analysis (DCCA) based on the older Canonical Correlation Analysis (CCA) [14]. DCCA works for only two modalities and is able to generate highly correlated (linear) projections. Kan et al. [19] were one of the first to work in the supervised setting and proposed a network that learns a common discriminative subspace using Fisher’s criterion in a neural network. Cross Media Multiple Deep Network (CMDN) [33] and Cross Modal Correlation Learning (CCL) [35] are two networks that utilize the inter and intra modality correlation and learn the common representations of multi-modal data.

2.2 Multi-modal Fusion

Significant amount of work in the domain of multimedia research has been done on fusion techniques for datasets of multiple modalities. The type of fusion performed affects the dynamics of the features produced. Early fusion techniques that are based on simple concatenation [38, 59] do not capture the intra-modal relations well. Later fusion techniques [18, 30] on the other hand prioritize intra-modal learning abilities compromising on cross-modal differentiability. This is because these models make decisions on a weighted average score of individual modality features. To solve both these limitations, Mai et al. [26] proposed an adversarial representation learning and graph fusion network for multi-modal fusion. They employed adversarial techniques to learn a modality-invariant embedding space and used a hierarchical graph neural network to capture multi-modal interactions. Fusion networks have also shown great performance in application specific tasks. Ding et al. [8] proposed a fusion based DNN for predicting popularity on social media. Further, Hong et al. [13] proposed a deep fusion network for the task of image completion.

2.3 Contrastive Learning Paradigms

Contrastive Learning techniques have gained popularity recently because of their success in unsupervised settings. Oord et al. [53] were one of the first one to propose a Contrastive Predictive Coding (CPC) technique that could generate useful representations from high dimensional data universally in an unsupervised fashion. Chen et al. [16] improved upon this and proposed a CPCv2 that performed better results on classification and object detection tasks. Further, Tian et al. [51] developed a compact representation that maximized mutual information between different views of the same scene and hence improved performance on image and video unsupervised learning tasks. Chen et al. [6] proposed a Simple Framework for Contrastive Learning of Visual Representations (SimCLR) that eliminated the requirement of specialized architectures or memory.
banks for contrastive tasks and also gave state-of-the-art results on self-supervised classification tasks.

2.4 Noise Contrastive Estimation

Almost all the contrastive paradigms detailed in the previous section rely on some sort of negative sampling techniques to reduce the complexity of computing representations. Gutmann et al. [12] first proposed NCE as a technique to model discriminations between a true statistical distribution and an artificial noise distribution. By using a non-linear regression to estimate the true distribution via contrastive estimation against randomly drawn noise samples, they showed that it is possible to precisely converge to the optimal parameters of the true distribution within an error bound. Since then, several applications have made use of NCE to estimate sample distributions. Mnih et al. [29] leveraged NCE to learn word embeddings over large vocabulary spaces in a scalable and efficient manner. They showed that this method achieved state-of-the-art results with minimal training time. Rao et al. [40] utilized an NCE based loss to achieve state-of-the-art results for the problem of answer-selection. They did so by modelling the problem as a pointwise classification problem and optimizing the model training by using NCE. More recently, Amrani et al. [3] applied NCE to learn robust density estimates for different modalities. They showed that by applying NCE to approximate the densities of different modality samples, they were able to perform well on diverse downstream tasks like visual question-answering and text-to-video retrieval.

2.5 Cross-modal Retrieval

We focus on the literature based on generating joint embeddings for cross-modal retrieval. Wu et al. [58] proposed a technique to generate embeddings that preserve the semantic structure of the labels in the data. Mithun et al. [27] discuss a framework that utilizes multi-modal cues from videos for video-text retrieval. Mithun et al. [28] leveraged web images and tags to learn a visual-semantic joint embedding. Further, Hu et al. [15] proposed a scalable autoencoder based architecture to learn a smooth and pure label representation space (shared across modalities) for any number of input modalities.

2.6 Multi-modal Fake News Detection

Deep neural networks have shown great potential in detecting multi-modal fake news. Wange et al. [56] discussed a model that learnt event invariant feature representations across modalities using an adversarial network. Khattar et al. [20] proposed Multi-modal Variational Autoencoder (MVAE) network that employed a bi-modal variational autoencoder for fake news classification. Singhal et al. [48] proposed an architecture SpotFake++ that leveraged pre-trained language transformers and convolutional neural networks for detecting fake news.

2.7 Multi-modal Sentiment Classification

Multi-modal sentiment classification is a promising area of research and there have been many attempts at using deep neural networks for this task. Chen et al. [62] developed Tensor Fusion Networks, an end-to-end model which learns both intra-modality and inter-modality dynamics for the task of sentiment classification. Pham et al. [37] proposed Seq2Seq2Sentiment, an unsupervised method for learning joint multi-modal representations using sequence to sequence models. Wang et al. [57] discussed a new fusion method TransModality using transformers in an end-to-end fashion for multi-modal sentiment analysis.
3 Methodology

In this section, we first explain the formulation of our problem statement in terms of the data we use. Then we introduce and explain the architecture of our model, along with the loss functions used. We finally explain our optimization and training strategy.

3.1 Problem Formulation

We have two modalities, i.e. text and image, we denote the $j$-th image sample as $x^i_T \in \mathbb{R}^{d_T}$ and the $j$-th text sample as $x^j_T \in \mathbb{R}^{d_T}$. Here, $d_T$ and $d_T$ represent the dimensionality of the image and text samples respectively. We denote the image dataset as $X_T = (x^0_T, x^1_T, ..., x^{n_T-1}_T)$ and the text dataset as $X_T = (x^0_T, x^1_T, ..., x^{n_T-1}_T)$, where $n_T$ and $n_T$ denote the total number of data samples in the image and text datasets respectively. The corresponding labels for the image and text modalities are represented as follows: $Y_T = \{y^0_T, y^1_T, ..., y^{n_T-1}_T\}$ and $Y_T = \{y^0_T, y^1_T, ..., y^{n_T-1}_T\}$. Assuming there are $C$ distinct semantic classes in our multi-modal dataset, the labels: $y_T^j \in \{0, 1, ..., C-1\}$, $y_T^j \in \{0, 1, ..., n_T-1\}$, and $j \in \{0, 1, ..., n_T-1\}$.

3.2 Model Architecture

The general architecture for our model is given in Figure 2. The aim is to represent the data in a common manifold, such that the class-wise representations are modality invariant and discriminatory. To this end, we use an autoencoder for each modality to generate representations that are high fidelity in nature. We utilize an orthogonal transform layer, which takes as input the hidden space of the projected representations and then projects these representations into a joint space that is modality invariant and discriminates between classes well.

We denote the encoded representation as $z^i_T = f_j(x^i_T, \Theta_j)$ and the reconstructed sample as $\hat{x}^i_T = g_j(z^i_T, \Phi_j)$ where $i \in \{0, n_T-1\}$ and $j \in \{0, 1, ..., n_T-1\}$ for text and image respectively, and where $j \in \{0, 1, ..., n_T-1\}$ for text and image respectively. $f_j$ denotes the encoder of the $j$-th modality parameterised by $\Theta_j$. Similarly, $g_j$ denotes the decoder of the $j$-th modality parameterised by $\Phi_j$. Given the representations $z^i_T$ and $z^j_T$, which have dimensions $Z_T$ and $Z_T$, we project the representations to a joint subspace such that the representation of each semantic class is orthogonal to each other [15]. We call these projections $O^i_T$ and $O^j_T$, both of which have dimension $Z$.

We define the loss function in COBRA as a weighted sum of Reconstruction Loss, Cross-Modal Loss, Supervised Loss, and Contrastive Loss.

3.2.1 Reconstruction Loss

Reconstruction loss has been used in the autoencoder. Given the decoder output $\hat{x}^i_T$ and the input $x^i_T$, we define the reconstruction loss shown in Eq. 1 as:

$$L_R = \sum_{i=0}^{n_T-1} \sum_{j \in \{I,T\}} \| \hat{x}^i_T - x^j_T \|_2$$

3.2.2 Cross-Modal Loss

The projected representations $O^i_T$ and $O^j_T$ align class representations within each modality. The cross-modal loss aims to align representations of the same class across different modalities. Given the projected representations $O^i_T$ and $O^j_T$, we define the cross-modal loss shown in Eq. 2 as:

$$L_M = \sum_{i=0}^{n_T-1} \| O^i_T - O^j_T \|_2^2$$

3.2.3 Supervised Loss

As we try to model an orthogonal latent space having the joint embeddings, we utilize the one-hot labels of the data samples to reinforce those samples belonging to the same class but different modalities to be grouped together in the same subspace. Let $\hat{y}^j_T$ be the one-hot encoded label for the $j$-th sample of the $j$-th modality, and $O^j_T$ be the projected representation, we then define the supervised loss shown in Eq. 3 as:

$$L_S = \sum_{i=0}^{n_T-1} \sum_{j \in \{I,T\}} \| O^i_T - \hat{y}^j_T \|_2^2$$

3.2.4 Contrastive Loss

As stated by Tian et. al. [51], to implement the contrastive loss, the definitions of positive samples and negative samples of representations are of utmost importance. We will first define the positive and negative samples pertaining to our model. Given the projected representations $O^i_T$ and $O^j_T$, a positive pair is defined as the representations of data samples belonging to the same modality and class. A negative pair is defined as the representations of two data samples belonging to same or different modality of different class.

For defining the contrastive loss, we have to define a scoring function that yields high values for positive samples and low values for negative values. We simply take the dot product of the representations in the joint embedding space as our scoring function. Following several recent works [6, 16, 21, 53], our loss function enforces the model to select the positive sample from a fixed sized set $S = \{p, n_1, n_2, ..., n_N\}$ containing one positive and $N$ negative samples. Therefore we formulate our contrastive loss shown in Eq. 4 as:

$$L_C = -E_S \left[ \log \frac{a^T p}{a^T p + \sum_{i=1}^{n_T} a^T n_i} \right]$$

where $a$ is the anchor point, $p$ is its corresponding positive sample, $E$ is an expectation operator over all possible permutations of $S$ and $n_i$ are all the negative samples. The anchor, positive and negative samples are randomly drawn from the current mini-batch. We minimize the above expectation running over all samples. Since fetching negative samples from the entire dataset is computationally infeasible, we sample the negative points only from the current mini-batch in memory.

Since, we sample only a finite sized set of negative samples, the model can miss out on characteristics of the distribution of the joint embeddings. To avoid this we, implement another loss called the Noise Contrastive Estimation (NCE) [12] loss, which is an effective
method for estimating unnormalized models. NCE helps to model the distribution of the negative samples by leveraging a proxy noise distribution. It does so by estimating the probability of a sample coming from a joint distribution rather than it coming from a noise distribution. The noise distribution is assumed to be an uniform distribution. Denoting the joint distribution of positive samples as $p_f$, the noise distribution as $p_n$, the anchor sample as $a$ and every other sample (can be positive or negative) as $s$, the probability of data sample $s$ coming from the joint distribution $p_f$ is:

$$P(X = 1 | s; a) = \frac{p_f(s|a) + Np_n(s|a)}{p_f(s|a)}$$  \hfill (5)

where $N$ is the number of samples from the noise distribution. Now we can estimate Eq. 4 as shown in Eq. 6:

$$L_{c} = -E_{a}[E_{s-p_f(s|a)}[\{P(X = 1 | s; a)] + NE_{s-p_n(s|a)}[1 - P(X = 1 | s; a)] \}$$  \hfill (6)

### 3.3 Optimization and Training Strategy

To train our network, we define a loss which is a weighted sum of the reconstruction loss, cross-modal loss, supervised loss and contrastive loss. The weights are treated as hyperparameters.

$$L = \lambda_g L_r + \lambda_s L_s + \lambda_m L_m + \lambda_c L_c$$  \hfill (7)

The objective function in Eq. 7 is optimized using stochastic gradient descent. The loss is summed over all modalities, and the corresponding gradient is propagated through all the components in the model. This is explained in Algorithm 1. This is done for 200 epochs. The models were implemented and trained with the PyTorch framework on an Nvidia GTX 1050 GPU.

### 4 Experiments

To evaluate our proposed method, we test our model on four different tasks, namely, cross-modal retrieval, multi-modal fake news detection, multi-modal sentiment classification, and multi-modal disaster classification. We compare the performance of our model against state-of-the-art models of corresponding tasks.

In the following sections, we describe the datasets and evaluation metrics adopted, followed by the results achieved on each downstream task mentioned above.

#### 4.1 Cross-Modal Retrieval

In the task of cross-modal retrieval, we use COBRA to retrieve an image given a text query, or a text sample given an image query.

##### 4.1.1 Datasets

For the cross-modal retrieval task, we utilize four different datasets. For Wikipedia, MS-COCO, and NUS-Wide 10k datasets, we convert the images into 4096-dimensional feature vectors using the fc7 layer of VGGnet [47]. In the Wikipedia and MS-COCO dataset, we convert the texts into 300-dimensional feature vectors using Doc2Vec [22]. For the NUS-Wide 10k dataset, we convert the text into 1000-dimensional Bag of Words feature vectors. The PKU-XMedia dataset contains texts represented as 3000-dimensional Bag of Words feature vectors and images represented as 4096-dimensional feature vectors, generated using the fc7 layer of VGGnet [47].

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**Algorithm 1: Flow of the COBRA algorithm**

- **Input**: The image training set $X_I$, the text training set $X_T$, the image label set $Y_I$, the text label set $Y_T$, dimensionality of the joint embedding space $Z$, image batch size $b_I$, text batch size $b_T$, learning rate $\eta$, hyperparameters $\lambda_M, \lambda_C, \lambda_S, \lambda_R$, number of training epochs $N$ and number of iterations (batch count) per epoch $B$

- **Output**: The optimal encoder weights $\Theta_I, \Theta_T$ and optimal decoder weights $\Phi_I, \Phi_T$

1. Initialize $\Theta_I, \Theta_T, \Phi_I, \Phi_T$ randomly
2. for $i=1,2,\ldots,N$
   3. Sample a random text minibatch $m_I$ of size $b_I$
   4. Sample a random image minibatch $m_T$ of size $b_T$
   5. Compute the image and text encoded latent representations $z_I$ and $z_T$
   6. Compute the image and text orthogonal projections $O_I$ and $O_T$
   7. Compute the image and text reconstructions $\hat{x}_I$ and $\hat{x}_T$
   8. Compute the losses: $L_R$ (Eq. 1), $L_M$ (Eq. 2), $L_S$ (Eq. 3), and $L_C$ (Eq. 4, 6)
   9. Compute total loss (Eq. 7):
      $$L = \lambda_s L_s + \lambda_g L_R + \lambda_m L_m + \lambda_c L_c$$
   10. Update model weights using a SGD update rule:
       $$\Theta_I \leftarrow \Theta_I - \eta \frac{dL}{d\Theta_I}; \Theta_T \leftarrow \Theta_T - \eta \frac{dL}{d\Theta_T}; \Phi_I \leftarrow \Phi_I - \eta \frac{dL}{d\Phi_I}; \Phi_T \leftarrow \Phi_T - \eta \frac{dL}{d\Phi_T}$$

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- The Wikipedia dataset [42] contains 2866 text-image pairs, divided into 10 semantic classes, such as warfare, art & architecture and media. As originally done in the work [42], we use a training set of 2173 text-image pairs, a validation set of 231 text-image pairs, and a test set of 462 text-image pairs.
- The PKU-Xmedia dataset [36, 63] contains 5000 text-image pairs, divided into 20 semantic classes. We use a training set of 4000 text-image pairs, a validation set of 500 text-image pairs, and a test set of 500 text-image pairs.
- The MS-COCO dataset [23] contains 82079 text-image pairs, divided into 80 semantic classes. We use a training set of 57455 text-image pairs, a validation set of 14624 text-image pairs, and a test set of 10000 text-image pairs.
- The NUS-Wide 10k dataset [7] contains 10000 text-image pairs, divided into 10 semantic classes. We use a training set of 8000 text-image pairs, a validation set of 1000 text-image pairs, and a test set of 1000 text-image pairs.

#### 4.1.2 Evaluation Metrics

We compare our performance against existing state-of-the-art models based on Mean Average Precision (mAP). For the purpose of our evaluation, we ensure that we use the same features that were used across other existing state-of-the-art models.
Table 1: Performance (mAP) on the Wikipedia Dataset

| Method   | Image → Text | Text → Image | Average |
|----------|--------------|--------------|---------|
| MCCA [43] | 0.202        | 0.189        | 0.195   |
| ml-CCA [39] | 0.388        | 0.336        | 0.372   |
| DDCAE [55] | 0.308        | 0.290        | 0.299   |
| JRL [64]  | 0.343        | 0.376        | 0.330   |
| ACMR [54] | 0.479        | 0.426        | 0.452   |
| CMDN [33] | 0.487        | 0.427        | 0.457   |
| CCL [35]  | 0.504        | 0.457        | 0.481   |
| D-SCMR [66] | 0.521        | 0.478        | 0.499   |
| SDML [15] | 0.522        | 0.488        | 0.505   |
| DAML [60] | 0.559        | 0.481        | 0.520   |
| COBRA    | **0.742**    | **0.739**    | **0.740** |

Table 2: Performance (mAP) on the MS-COCO Dataset

| Method   | Image → Text | Text → Image | Average |
|----------|--------------|--------------|---------|
| MCCA [43] | 0.646        | 0.640        | 0.643   |
| ml-CCA [39] | 0.667        | 0.661        | 0.664   |
| DDCAE [55] | 0.412        | 0.411        | 0.411   |
| ACMR [54] | 0.692        | 0.687        | 0.690   |
| DCCA [4]  | 0.415        | 0.414        | 0.415   |
| GSS-SL [65] | 0.707        | 0.702        | 0.705   |
| SDML [15] | 0.827        | 0.818        | 0.823   |
| COBRA    | **0.854**    | **0.853**    | **0.853** |

4.1.3 Results

We report the highest mAP for Text to Image (TTI) and Image to Text (ITT) retrieval on all four datasets. From the t-SNE plot for Wikipedia given in Figure 3, we observe that COBRA is able to effectively form joint embeddings for different classes across modalities, resulting in superior performances across the aforementioned datasets.

We achieve a 22% improvement over the previous state-of-the-art (DAML [60]) on the Wikipedia dataset (Table 1). We achieve a 3% improvement over the previous state-of-the-art (SDML [15]) on the MS-COCO dataset (Table 2). We achieve a 3.5% improvement over the previous state-of-the-art (SDML [15]) on the PKU-XMedia dataset (Table 3). We achieve a 10.9% improvement over the previous state-of-the-art (ACMR [54]) on the NUS-Wide 10k dataset (Table 4).

The differences in the improvement obtained by COBRA across datasets relative to existing work is due to the fact that multi-class classification normally observes a decrease in performance with an increase in the number of classes. For example, the Wikipedia dataset has only ten classes, whereas the MS-COCO dataset has eighty classes.

4.2 Multi-modal Fake News Detection

In the task of multi-modal fake news detection, we use COBRA to determine whether a given bi-modal query (text and image) corresponds to a real or fake news sample.

Table 3: Performance (mAP) on the PKU-XMedia Dataset

| Method   | Image → Text | Text → Image | Average |
|----------|--------------|--------------|---------|
| MCCA [43] | 0.620        | 0.616        | 0.618   |
| DDCAE [55] | 0.868        | 0.878        | 0.873   |
| JRL [64]  | 0.770        | 0.788        | 0.779   |
| ACMR [54] | 0.882        | 0.885        | 0.883   |
| CMDN [33] | 0.485        | 0.516        | 0.501   |
| DCCA [4]  | 0.869        | 0.871        | 0.870   |
| GSS-SL [65] | 0.875        | 0.878        | 0.876   |
| SDML [15] | 0.899        | 0.917        | 0.908   |
| COBRA    | **0.945**    | **0.941**    | **0.943** |

Table 4: Performance (mAP) on the NUS-Wide 10k dataset

| Method   | Image → Text | Text → Image | Average |
|----------|--------------|--------------|---------|
| MCCA [43] | 0.448        | 0.462        | 0.455   |
| DDCAE [55] | 0.511        | 0.540        | 0.525   |
| JRL [64]  | 0.586        | 0.598        | 0.592   |
| ACMR [54] | 0.588        | 0.599        | 0.593   |
| CMDN [33] | 0.492        | 0.515        | 0.504   |
| CCL [35]  | 0.506        | 0.535        | 0.521   |
| DCCA [4]  | 0.532        | 0.549        | 0.540   |
| SDML [15] | 0.55         | 0.505        | 0.527   |
| DAML [60] | 0.512        | 0.534        | 0.523   |
| COBRA    | **0.703**    | **0.701**    | **0.702** |

4.2.1 Datasets

For the multi-modal fake news detection task, we utilize the Fake-NewsNet Repository [46]. This repository contains two datasets, namely, Politifact and Gossipcop. These datasets contain news content, social context, and dynamic information. We pre-process the data similar to Spotfake+ [48]. For both datasets, we convert images into 4096-dimensional feature vectors using VGGNet [47], and we convert texts into 38400-dimensional feature vectors using XLNet [61]. Each dataset contains two semantic classes, namely, Real and Fake.

- The Politifact dataset contains 1056 text-image pairs. We get 321 Real and 164 Fake text-image pairs after pre-processing. We use a training set of 381 text-image pairs, a validation set of 50 text-image pairs and a test set of 54 text-image pairs.
- The Gossipcop dataset contains 22140 text-image pairs. We get 10259 Real and 2581 Fake text-image pairs after pre-processing. We use a training set of 10010 text-image pairs, a validation set of 1830 text-image pairs, and a test set of 1000 text-image pairs.

4.2.2 Evaluation metrics

We compare our performance against existing state-of-the-art models based on number of correctly classified queries (accuracy). For the purpose of our evaluation, we ensure that we use the same features that were used across other existing state-of-the-art models. To visualize the purity of the joint embedding space for different classes and modality samples, we plot the joint embeddings of COBRA trained on both the Gossipcop and Politifact datasets. We plot
| Method       | Politifact (%) | Gossipcop (%) |
|--------------|----------------|---------------|
| EANN [56]    | 74             | 86            |
| MVAE [20]    | 67.3           | 77.5          |
| SpotFake [49]| 72.1           | 80.7          |
| SpotFake+ [48]| 84.6          | 85.6          |
| COBRA        | **86**         | **86.7**      |

the embeddings (Figure 3) by employing the t-SNE [25] transformation to reduce the high dimensional joint embeddings ($O_l$ and $O_T$) to 3 dimensional data points. The figures clearly exhibit the high discrimination between samples of different classes in the joint embedding space. This provides further empirical validation for the high class divergence across the joint embedding space, irrespective of the modalities of the data points.

4.2.3 Results
We achieve a 1.4% improvement over the previous state-of-the-art (SpotFake+ [48]) on the Politifact dataset (Table 5). We achieve a 1.1% improvement over the previous state-of-the-art (SpotFake+ [48]) on the Gossipcop dataset (Table 5). We believe that better performance of our model could not be achieved because of high class imbalance of these two datasets. Further on observing the t-SNE plots in Figure 3, we discern a high intra-class variability in the Gossipcop dataset.

4.3 Multimodal Fine-grained Sentiment Classification
In the task of multi-modal fine-grained sentiment classification, we use COBRA to classify a given bi-modal query (text and image) into one of ten sentiment categories.

4.3.1 Datasets
For the multi-modal fine-grained sentiment classification task, we analyze the performance of our model on the MeTooMA dataset [10]. This dataset contains 9973 tweets that have been manually annotated into 10 classes, namely, text only informative and image only informative (Relevance), Support, Opposition and Neither (Stance), Directed Hate and Generalized Hate (Hate Speech), Allegation, Refutation and Justification (Dialogue acts), and sarcasm. We convert the images into 4096-dimensional feature vectors using the fc7 layer of VGGnet [47]. We convert the texts into 300-dimensional feature vectors using Doc2Vec [22]. We use a training set of 4500 text-image pairs, a validation set of 1000 text-image pairs and a test set of 1000 text-image pairs.

4.3.2 Evaluation Metrics
We report the number of correctly classified queries (accuracy). To the best of our knowledge, we are the first to test a multi-modal classification model on this dataset. To this end, we evaluate our model against a Text-only and Image-only baseline, and Early Fusion. For the baselines, we use a Fully Connected network.

4.3.3 Results
We obtain an average classification accuracy of 88.32% across all classes on the MeTooMA Dataset. This is a 1.2% improvement over Early Fusion (Table 6). We observe a low increase in Text only and

Figure 3: t-SNE visualizations of the joint embedding spaces of the models trained on Gossipcop, Politifact and Wikipedia datasets. The different colours correspond to the various class labels in the dataset. The circles represent text modality and the squares represent image modality.

Image only informative tasks due to the fact that 53.2% of our training data had text-image pairs with conflicting labels, i.e., from a given text-image pair, the text may be labelled as 'relevant' whereas the corresponding image may be labelled as 'irrelevant'. Furthermore, for classes under the Hate Speech, Sarcasm, and Dialogue Acts categories, we observe that there are less than 600 samples for each class. In categories such as Stance, where the 'Support' class
has over 3000 samples, we observe much larger improvements in performance.

4.4 Multi-modal Disaster Classification

In the task of multi-modal disaster classification, we use COBRA to perform three classification tasks given a bi-modal (text and image) query. The classification tasks are further explained in the dataset section below.

4.4.1 Datasets

For the multi-modal disaster classification task, we utilize the Crisis-MMD dataset [2, 31]. It consists of 16058 tweets and 18082 images that were collected during natural disasters such as hurricanes and floods in the year 2017. There are 3 classification tasks that can be performed on this dataset —

- Informative or Non-Informative classification — this represents whether or not a particular text-image pair from a tweet is informative.
- Humanitarian Categories classification — this includes classes such as affected individuals, vehicle damage, missing or found people, and infrastructure or utility damage. This is once again done for a particular text-image pair from a tweet.
- Damage severity assessment — this includes classes such as severe damage, mild damage and little or no damage. This is once again done for a particular text-image pair from a tweet.

We convert the images into 4096-dimensional feature vectors using the fc7 layer of VGGnet [47]. We convert the texts into 300-dimensional feature vectors using Doc2vec [22]. We use a training set of 2000 text-image pairs, a validation set of 793 text-image pairs for the first 2 classification tasks, a validation set of size 697 for the third classification task, and a test set of 500 text-image pairs.

4.4.2 Evaluation Metrics

We compare our performance against existing state-of-the-art models based on number of correctly classified queries (accuracy).

4.4.3 Results

We obtain the following results on the three tasks (Table 7) —

- Informative or Non-Informative classification — we obtain an accuracy of 93.49%, which is a 1.09 % improvement over Agarwal et al. [1].
- Humanitarian Categories — we obtain an accuracy of 42.25%, which is a 5.45 % improvement over Agarwal et al. [1].
- Damage severity assessment — we obtain an accuracy of 64.58%, which is an 8.38% improvement over Agarwal et al. [1].

We believe this improvement is achieved because of the good quality of the representations obtained from COBRA. The t-SNE plots which further strengthen our claim can be found in the Appendix.

5 Conclusion

In this paper, we propose a novel approach (COBRA) to jointly learn bi-modal representations in an orthogonal space. We show that our proposed method learns better representations which allows the model to generalize the decision boundary in a much more robust fashion. This enables us to achieve state-of-the-art results on four downstream tasks. The representations learnt are high-fidelity in nature, containing sufficient information for reconstruction as well as tasks such as retrieval and classification. Different from other models, COBRA, along with preserving the intra-class relationship of samples in the embedding space, also preserves the inter-class relationship using a Contrastive Learning Paradigm called Noise Contrastive Estimation (NCE). This ensures that the samples belonging to the same class are clustered together, and that the distance between clusters of samples belonging to different classes (irrespective of the modality) is maximized in the joint embedding space. As for the future work, we attempt to extend our method to a self-supervised/semi-supervised problem setting.
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Udandarao et al.
Table 8: Dataset Descriptions - "*/" in the samples column denotes the number of training/validation/test samples used. T1, T2 and T3 for the CrisisMMD dataset refer to the first, second and third classification task respectively.

| Dataset       | Classes | Modality | Samples             | Features          |
|---------------|---------|----------|---------------------|-------------------|
| Wikipedia     | 10      | Image    | 2173/231/462        | 4096-D VGG        |
|               |         | Text     | 2173/231/462        | 300-D Doc2Vec     |
| PKU XMedia    | 20      | Image    | 4000/500/500        | 4096-D VGG        |
|               |         | Text     | 4000/500/500        | 3000-D BoW        |
| NUS-Wide 10k | 10      | Image    | 8000/1000/1000      | 4096-D VGG        |
|               |         | Text     | 8000/1000/1000      | 1000-D BoW        |
| MS-COCO      | 80      | Image    | 57455/14624/10000   | 4096-D VGG        |
|               |         | Text     | 57455/14624/10000   | 300-D Doc2Vec     |
| Politifact    | 2       | Image    | 381/50/54           | 4096-D VGG        |
|               |         | Text     | 381/50/54           | 38400-D XLNet     |
| Gossipcop     | 2       | Image    | 10010/1830/1000     | 4096-D VGG        |
|               |         | Text     | 10010/1830/1000     | 38400-D XLNet     |
| MeTooMA      | 10      | Image    | 4500/1000/1000      | 4096-D VGG        |
|               |         | Text     | 4500/1000/1000      | 300-D Doc2Vec     |
| CrisisMMD    | T1 - 2  | Image    | 2000/793 (T1&T2), 697 (T3)/500 | 4096-D VGG |
|               | T2 - 8  | Text     | 2000/793 (T1&T2), 697 (T3)/500 | 300-D Doc2Vec    |
|               | T3 - 3  |          |                     |                   |

Table 9: Baseline approaches for Multimodal Fine-grained Sentiment Classification

| Baseline Model        | Description                                                                 |
|-----------------------|-----------------------------------------------------------------------------|
| Text-only baseline    | Every text is vectorized using Doc2Vec embeddings and a fully connected network (with relu activations) is used with softmax outputs to perform the classification |
| Image-only baseline   | Every image is vectorized using a pretrained VGG-19 network and a fully connected network (with relu activations) is used with softmax outputs to perform the classification |
| Early Fusion          | Every image-text pair is vectorized (using the previously mentioned networks), concatenated directly, and a fully connected network (with relu activations) is used with softmax outputs to perform the classification |
Figure 4: 3D t-SNE visualizations of the joint embedding spaces of the models trained on Gossipcop, Politifact and Wikipedia datasets. The different colours correspond to the various class labels in the datasets. The circles represent text modality and the squares represent image modality.

Figure 5: 2D t-SNE visualizations of the joint embedding spaces of the models trained on different tasks of CrisisMMD dataset. The different colours correspond to the various class labels in the datasets. The circles represent text modality and the squares represent image modality.