Private-Shared Disentangled Multimodal VAE for Learning of Latent Representations

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Abstract

Multi-modal generative models represent an important family of deep models, whose goal is to facilitate representation learning on data with multiple views or modalities. However, current deep multi-modal models focus on the inference of shared representations, while neglecting the important private aspects of data within individual modalities. In this paper, we introduce a disentangled multi-modal variational autoencoder (DMVAE) that utilizes disentangled VAE strategy to separate the private and shared latent spaces of multiple modalities. We demonstrate the utility of DMVAE two image modalities of MNIST and Google Street View House Number (SVHN) datasets as well as image and text modalities from the Oxford-102 Flowers dataset. Our experiments indicate the essence of retaining the private representation as well as the private-shared disentanglement to effectively direct the information across multiple analysis-synthesis conduits.

1. Introduction

Representation learning is a key step in the process of data understanding, where the goal is to distill interpretable factors associated with the data. Representation learning approaches typically focus on data observed in a single modality, such as text, images, or video. Nevertheless, most real world data comes from processes that manifest itself in multiple views or modalities. In computer vision, image-based data is typically accompanied with text description to promote understanding of its latent factors. For example, in Fig. 1a, an image of a flower is augmented with captions describing the detailed characteristics of the flower. To study about the flower, the background of the image is unnecessary but the additional information of text description is helpful. Therefore, accurate modeling of the underlying data representation has to consider both the private aspects of individual modalities as well as what those modalities share, as illustrated in Fig. 1b.

In this paper, we propose a generative variational model that can learn both the private and the shared latent space of each modality, with each latent variable attributed to a disentangled representational factor. The model extends the well-known family of Variational AutoEncoders (VAEs) [10] by introducing separate shared and private spaces, whose representations are induced using pairs of individual modality encoders and decoders. To create the shared representation, we impose consistency of representations using a product-of-experts (PoE) [6] inference network.

Figure 1: (a) Example of bimodal data, where one modality, I, is an image of a flower and the other, T, represents a textual caption describing the flower. (b) Only some of the factors, here aligned with the caption for simplicity, are shared by both modalities in Shared I ∩ T. Other factors are private to individual modalities, grouped in separate Private spaces. By definition, the three spaces are disentangled from each other.
While the shared latent representation can be used to model the compatibility of the two modalities, the representation can also enable cross-reconstruction of one modality from another. We demonstrate that this essential task can and has to be effectively combined in an end-to-end learning framework with the private-shared disentangled VAE, resulting in our novel disentangled multi-modal variational autoencoder (DMVAE).

We apply the DMVAE to two multi-modal representation learning problems. In the first setting, we consider the problem of learning the shared/private generative representations of digit images from two datasets of different styles, where the shared property becomes the digit class and the private property becomes the style of each dataset. In the second setting, we generalize the modality types further into images and text, aiming to model the joint representation of flower appearance and the corresponding captions, which describe the visual characteristics of the flower. We show that DMVAE excels both as an analysis tool as well as the (cross) synthesis generative model.

Our main contributions are as follows.

- We segregate the latent representation space into the union of the private and the shared spaces. We show that the private latent space is critical for modeling the disjoint properties of each modality while the shared latents enable linking and cross-synthesis across domains, as signified in the experiments in Sec. 5.1 and Sec. 5.3.

- We improve the compatibility between modalities by introducing the cross-VAE task (loss), whose aim is the cross-modal reconstruction through the shared latent space. The impact of the cross-VAE direction, induced by the properties of the linked datasets is examined in the ablation study in Sec. 5.3.

- By applying our model to (image, text) as well as (image, image) representation modeling problems, we demonstrate the universal applicability and effectiveness of the the DMVAE framework, across different data types.

2. Related Work

Several lines of related work can be linked to our proposed DMVAE. Our modeling task is intimately related to image-to-image translations problems, the task of translating between different representations of one image, such as the sketch-photographic, summer-winter, etc., views of a visual object or a scene. We begin by reviewing relevant prior work in this area, subsequently extending it to multi-modal learning that can take any input data type.

**Image-to-image translation.** Multiple research efforts have attempted to solve the image-to-image translation problem by framing it as a two-modality matching setup. [23] utilize GAN [5] framework, which takes the image from one modality as the fake sample against another modality. They combine VAE into GAN so that the latent space encodes information about the ground truth outputs, rectifying the mode collapse problem. The diversity of the output that the latent factor can provide is enhanced with the latent regressor GAN, which tries to generate output from randomly drawn latent factors and then attempts to recover the latent code again.

[4] disentangles the latent representation into two parts; the shared between the two modalities and the exclusive within each modality. Using only the shared part of the representation in the image translation, the domain-specific variation is reduced. Furthermore, adding noise with the shared latent factors for generation improves the diversity in translation between images. However, the paired input images are necessary to train these models. [12, 8] show that cross-domain mapping and cross-cycle consistency enable an effective style transfer using unpaired data. They separate a domain-invariant content and a domain-specific attribute (style) latent space using an adversarial loss. [2] separates private and shared networks in each domain utilizing DANN [16] to make it possible for the unlabeled target domain to learn the transferred information from the labeled source more effectively with only the latent codes from the shared network. Although these methods are able to achieve realistic and diverse image translation, they make use of the strong within-image-modality conditioning, which may fail when the modalities exhibit vastly different properties (e.g., text and image).

**Multi-modal Learning.** Several prior works have considered the problem of modeling multi-modal data using gen-
erative VAE-inspired models. JMVAE [19] exploits the joint inference network $q(z|x_1, x_2)$ to learn the interaction of two modalities, $x_1$ and $x_2$. To address the missing modality problem, where some of the data samples are not paired (i.e., do not have both views present), they train inference networks $q(z|x_1)$, $q(z|x_2)$ in addition to the bimodal inference model $q(z|x_1, x_2)$, and then minimize the distance between uni- and multi-modal based latent distribution. JVAE [20] adopts a product-of-expert (PoE) [6] for the joint posterior $q(z|x_1, x_2)$ of multi modalities in the inference network. The approach leverages the unimodal inference networks, whose predictions are constrained and made consistent through the PoE. JVAE trains the model with two-stage process to handle both paired and missing modality data. Due to this fact, the number of required inference networks increases exponentially for more than two modalities. To alleviate the inefficiency of JVAE, MVVAE [21] considers only partial combination of observed modalities. This helps reduce the number of parameters and increase the computational efficiency of learning. [18] applies Mixture-of-Expert (MoE) to jointly learn the shared factors across multi-modalities. Though they introduce the concept of the private and shared information of multi-modalities, it is implicitly conceived. Moreover, the use IVAE for the approximation makes the contribution of MoE vague.

However, the aforementioned prior works based on VAE use a single latent space to represent the multi-modal data. Although [2] attempt to separate the private and shared networks, their method uses deterministic latent features. Moreover, they require target label information to train their model. Within one common latent space under the VAE framework, modality-specific factors could be entangled with the shared factors across all modalities, reducing the ability of these generative models to represent the data and infer the "true" latent factors.

In this paper, we address these challenges by explicitly separating the shared from the disjoint private spaces, using individual inference networks to achieve this goal. This is illustrated in Fig. 2. In subsequent sections, we review the core VAE framework, followed by the details of our DMVAE modeling approach, and the experimental evaluation.

3. Background

Our DMVAE framework builds upon the VAE model of [10]. We first highlight the relevant aspects of VAE-based models, which we then leverage to construct the DMVAE in Sec. 4.

Variational Autoencoder. A variational autoencoder (VAE) [10] implements variational inference for the latent variable via autoencoder structure. The objective of the VAE is to maximize the marginal distribution $p(x) = \int p_\theta(x|z)p(z)dz$ which is, however, intractable. Thus, VAE introduces the evidence lower bound (ELBO) which uses an approximated recognition model $q_\phi(z|x)$ instead of the intractable true posterior. It maximizes $\mathbb{E}_{z \sim q_\phi(z|x)}[\log p_\theta(x|z)]$ while minimizing $KL(q_\phi(z|x), p(z))$.

$$\log p(x) \geq \mathbb{E}_{p(x)}[ELBO(x; \theta, \phi)]$$

$$= \mathbb{E}_{p(x)}[\mathbb{E}_{q_\phi(z|x)}[\log p_\theta(x|z)] - KL(q_\phi(z|x)||p(z))] \quad (1)$$

$q_\phi(z|x)$ and $p_\theta(x|z)$ are represented as encoder and decoder in the network with the learning parameter $\phi$ and $\theta$, respectively. The first term of ELBO (Eq. (1)) is the reconstruction error and the second term plays a role of regularizer not to be far from the prior distribution $p(z)$. We next discuss in more detail the effect of the second term on disentanglement.

4. DMVAE Framework

In this section, we introduce the new DMVAE model. Sec. 4.1 describes the architecture of private and shared latent spaces within the disentangled representation. In Sec. 4.2 and Sec. 4.3, we define the DMVAE inference models, accompanied with the learning objective in Sec. 4.4.

4.1. Private / Shared-Disentangled Multi-Modal VAE

The assumption in this paper is that under the multi-modal description of a concept, the latent space of the concept is divided into a private space of each modality and one shared space across all modalities1. Our goal is to obtain well-separated private and shared spaces. This separation is critical; the shared latent space can only transfer the information common across modalities, but it will fail to model the individual aspects of the modalities. In a generative model, such as the VAE, modeling the private factors is critical as those factors enable both the high fidelity of the data reconstruction as well as the improved separation (disentanglement) of the latent factors across modalities.

Our model is illustrated in Fig. 3 for the case of two modalities. Given paired i.i.d. data $\{(x_1, x_2)\}$, we infer the latents $z_1 \sim q_{\phi_1}(z|x_1), z_2 \sim q_{\phi_2}(z|x_2)$, where $\phi_1, \phi_2$ are the parameters of each individual modal inference network. We assume the latents can be factorized into $z_1 = [z_{p_1}, z_{s_1}]$ and $z_2 = [z_{p_2}, z_{s_2}]$, where $z_{p_1}, z_{p_2}$ represent the private latent of modalities $x_1, x_2$, respectively, and $z_{s_1}, z_{s_2}$ represent the shared latents, which are to model the commonality between the two modalities.

For the desired shared representation in $z_{s_1}, z_{s_2}$ we seek to effectively make $z_{s_1} = z_{s_2}$. We describe how to accomplish this using a PoE-based consistency model in Sec. 4.2, which approximates the shared inference network $p(z_s|x_1, x_2)$.

1 Other more intricate representations of private and shared spaces may arise in the presence of more than two modalities. However, we do not
4.2. Latent Space Inference

First, we define the latent space inference in our model. Given $N$ modalities $\mathbf{x} = (x_1, \ldots, x_N)$, each modality has the posterior distribution $p(z_i|x_i)$, approximated by inference networks $q(z_i|x_i) = q(z_{pi}, z_{si}|x_i)$. Since the shared latent space should reflect the information shared across all modalities, we require that the representation be consistent, i.e., $z_{si} = z_s$ w.p.1, $\forall i$. Consequently, we separate the private inference $q(z_{pi}|x_i)$ from the shared inference network $q(z_s|x)$, defined using the product-of-experts (PoE) model [6], adopted in [20, 21]:

$$q(z_s|x) \propto p(z_s) \prod_{i=1}^{N} q(z_s|x_i).$$

In the case where all inference networks and priors assume conditional Gaussian forms, $p(z) = \mathcal{N}(z|0, I)$ and $q(z|x_i) = \mathcal{N}(z|\mu_i, C_i)$ of i-th Gaussian expert with the covariance $C_i$, the PoE shared inference network will have the closed form of $q(z|x)$ as $\mathcal{N}(z|\mu, C)$ where $C^{-1} = \sum_i C_i^{-1}$ and $\mu = C \sum_i C_i^{-1} \mu_i$.

**Missing-mode Inference.** An important benefit of the PoE-induced shared inference is that the individual modality shared networks can also be used for inference in instances when one (or more) of the modalities is missing. Specifically, as illustrated in the bi-modal case of Fig. 2b, under the $x_2$ missing, the shared latent space would be simply inferred using the remaining modality shared inference network $q(z_s|x_1)$; and vice-versa for missing $x_1$. 

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4.3. Reconstruction Inference

In addition to inferring the latent factors, a key enabler in VAE is the reconstruction inference, or encoding-decoding. Specifically, we seek to infer $p(\tilde{x}|x) = \int p(\tilde{x}, z|x)dz = \int p(\tilde{x}|z)p(z|x)dz = \mathbb{E}_{p(z|x)}[p(\tilde{x}|z)] \approx \mathbb{E}_{q(z|x)}[p(\tilde{x}|z)]$.

The reconstruction inference in multi-modal settings, much like the latent space inference, has to consider the cases of complete and missing modality data. We assume bi-modality without loss of generality. The first case is the self-reconstruction within a single modality, $\mathbb{E}_{q(z_{pi}|x_i)q(z_{si}|x_i)}[p(\tilde{x}_i|z_{pi}, z_s)]$ for $i = 1, 2$. The second form is the joint multi-modal reconstruction, $\mathbb{E}_{q(z_{pi}|x_i)q(z_{si}|x_{i}, x_j)}[p(\tilde{x}_i|z_{pi}, z_s)]$ for $i = 1, 2$. It is also possible to consider the cross-modal reconstruction, e.g., $p(\tilde{x}_2|x_1) = \mathbb{E}_{p(z_{pi}|x_i)q(z_{si}|x_{i}, x_j)}[p(\tilde{x}_2|z_{pi}, z_s)]$, illustrated in Fig. 2b. This instance, where $x_2$ is missing, is facilitated using the prior on the private space of $x_2, p(z_{pi})$.

The different reconstruction inference modes are essential for model learning but also valuable for understanding the model performance. For instance, one may seek to see how successful the multi-modal DMVAE is in learning the shared and private representations in the context of synthesizing one modality from another. We highlight these cross-synthesis experiments in Sec. 5.1 and Sec. 5.2.

4.4. Learning Objective

In general, for each data point $\mathbf{x} = (x_1, x_2, \ldots, x_N)$ and $N$ modalities, the learning objective assumes the form:

$$\sum_i \mathbb{E}_{p(x_i)} \left[ \lambda_i \mathbb{E}_{q_0(z_{pi}|x_i), q_0(z_{si}|x_i)} \log p_0(x_i|z_{pi}, z_s) \right] - KL(q_0(z_{pi}|x_i)||p(z_{pi})) - KL(q_0(z_s|x_i)||p(z_s)) + \sum_j \left( \lambda_j \mathbb{E}_{q_0(z_{pi}|x_i), q_0(z_{si}|x_j)} \log p_0(x_i|z_{pi}, z_s) \right) - KL(q_0(z_{pi}|x_i)||p(z_{pi})) - KL(q_0(z_{si}|x_j)||p(z_s)) \right],$$

where $\lambda_i$ balances the reconstruction across different modalities. The first term models the accuracy of reconstruction with the jointly learned shared latent factor, compensated by the KL-divergence from the prior. The second set of terms assesses the accuracy of the cross-modal reconstruction, $x_i \leftarrow x_j$ for $i \neq j$ and the accuracy of self-reconstruction for $i = j$, again compensated by the divergence.

5. Experiments

We demonstrate the effectiveness of our proposed DMVAE framework on two experimental setup. In Sec. 5.1, we
show how DMVAE can learn the common latent representation given two image modalities of MNIST and street-view house number (SVHN) datasets. We evaluate our model both quantitatively and qualitatively by cross-synthesizing images from one to another modality. Sec. 5.2 further investigates DMVAE on the image and text modalities using the Oxford-102 Flowers dataset. We examine how well the flower image and its descriptions are retrieved between two modalities. Sec. 5.3 evaluates the effectiveness of different model components in an ablation study. The code for our DMVAE model and the experiments in this section is available at https://github.com/iffsid/mmvae.

5.1. Image-Image Modality

As in MMVAE [18], we ground the bi-modal setup by giving one modality as MNIST images and another modality as SVHN images. By assuming that the pair of (MNIST, SVHN) images is constructed according to the digit identity \( \{0, \ldots, 9\} \), we expect the shared information between the MNIST and SVHN modalities to be the digit identity and each private latent space includes styles of the digits, such as width, tilt, background etc. We follow MMVAE to create the paired data.

For MNIST, we assume one dimensional private space while SVHN which has more diverse style requires four dimension for its private latent space. To model the ten class factors as the shared latent representation, we set 10 dimensional shared latent space. The details of the model (encoder/decoder) architectures and the optimization are described in the Supplement.

**Quantitative Evaluation.** In order to assess whether the desired shared latent representations are learned, we generate two kinds of images at test time. The first one is prior-synthesized images. After sampling the shared latent code from the prior distribution, we generate the MNIST and SVHN images based on the same shared space sample. Secondly, given an image of one modality, the shared latent code is extracted and transferred to another modality in order to synthesize an image. For both of the cases, we feed the private latent factors sampled from the prior distribution \( \mathcal{N}(0, 1) \), which promotes the diversity of the generated image. We use the same protocol as in MMVAE to evaluate the cross-synthesized images. To predict the digit class, the

<table>
<thead>
<tr>
<th>Model</th>
<th>Cross(M→S)</th>
<th>Cross(S→M)</th>
<th>Joint</th>
</tr>
</thead>
<tbody>
<tr>
<td>MVAE [21]</td>
<td>9.5</td>
<td>9.3</td>
<td>12.7</td>
</tr>
<tr>
<td>MMVAE [18]</td>
<td>86.4</td>
<td>69.1</td>
<td>42.1</td>
</tr>
<tr>
<td>DMVAE</td>
<td>88.1</td>
<td>83.7</td>
<td>44.7</td>
</tr>
</tbody>
</table>

Figure 4: Cross-synthesis images from the opposite modality. (a) and (b) are results with DMVAE, (c) and (d) are results with MVAE. In each image, the first row is the ground truth images from which the share latent code comes. The following rows are the cross-synthesized images.
Figure 5: Visualization of 2-D embeddings of latent features of MNIST and SVHN, using tSNE. ‘+’ and ‘o’ represent the MNIST and SVHN test data points respectively and each color associates with one of ten digit classes, \{0, 1, ..., 9\}. (a) DMVAE embedding result. (b) MMVAE embedding result.

the following rows are the cross-synthesized images. For DMVAE results Fig. 4a and Fig. 4b, cross-synthesized images require private latent code for the style. We generate 5 different rows of the synthesized images with 5 different private factors which are depicted from the second row. Though the private latent values can be sampled from the Gaussian prior distribution, we pick those latent values that can express "extreme" styles to assess whether the visually distinct style is kept. When SVHN image is synthesized from MNIST image as in Fig. 4b, styles of SVHN such as (dark / bright) (letter / background) color, or overall shadow, or width of digit are reflected in the cross-synthesized images as well as the conditioning MNIST classes are kept. In Fig. 4b, MNIST needs one dimensional private latent factor to be generated using the SVHN shared latent factor. We vary the private latent value from -1 to 3 to generate 5 different rows of the synthesized images. From top to bottom, the synthesized MNIST images show the varied width and slanted styles. Fig. 4c and Fig. 4d illustrate the results of MMVAE with the same ground truth images as in those of DMVAE. As well as the synthesized images cannot reflect the digit identity from the ground truth images clearly, there is no freedom of feeding diverse styles since MMVAE does not separate private latent space aside from the shared latent space.

In order to investigate how the shared latent space encodes each modality, we project the latent features inferred by the encoders, on the test set, into a 2-D space with tSNE. We use 400 randomly selected samples to plot the embedded features. In Fig. 5a, even though our model is trained without class label information, MNIST shared feature and SVHN shared features are gathered nearby according to the digit identity, which indicates DMVAE learns the digit identity only with the paired data. In contrast to DMVAE where MNIST and SVHN data points with the same class are heading for the same direction, MMVAE embeddings are clustered separately per dataset. This represents that DMVAE is able to amplify the role of the shared features by placing the styles aside into the private space, compared to MMVAE baseline.

5.2. Image-Text Modality

We further examine DMVAE on the Oxford-102 Flowers dataset [15], where each flower image is paired with ten captions that describe the visual characteristics of the flower. This dataset consists of 102 classes of 8,189 flower images, split into 62 training, 20 validation, and 20 test classes. Since the categories of the test set are disjoint from those of the training and validation sets, the problem falls within the scope of zero-shot test-time tasks. For the fair comparison with the prior works [1, 13, 22, 17], which utilize the class label of the Flowers dataset during training, we apply the following additional matching loss suggested in [22, 17].

\[
L_M^I = \frac{1}{B} \sum_{m=1}^{B} \sum_{n=1}^{B} p_{m,n} \log \frac{p_{m,n}}{q_{m,n} + \epsilon}, \tag{4}
\]

where \(p_{m,n} = \frac{\exp(\tilde{z}_{ST_m}^T \tilde{z}_{ST_n})}{\sum_{k=1}^{B} \exp(\tilde{z}_{ST_m}^T \tilde{z}_{ST_k})}\) is the probability of matching the \(m\)-th image shared feature to the normalized \(n\)-th text shared feature for \(m, n \in [1, B]\), with \(B\) the batch size; \(\tilde{z}_{ST_m}\) is the \(m\)-th image shared features, and \(\tilde{z}_{ST_n}\) is the normalized \(n\)-th text shared feature, \(\tilde{z}_{ST_n} = \frac{z_{ST_n}}{||z_{ST_n}||}\). \(q_{m,n} = \frac{Y_{m,n}}{\sum_{k=1}^{B} Y_{m,k}}\) is the normalized true matching proba-
bility where $Y_{m,n} = 1$ if the pair is matched and 0 otherwise. $L^M_{mn}$, the matching loss from text shared feature to the normalized image feature is computed in a similar manner. These losses take the advantage of the class label information to construct matched and unmatched pairs within a batch, in order to minimize the compatibility with unmatched pairs.

Given a $224 \times 224 \times 3$ dimensional input image, we first apply pre-trained ResNet-101 to generate $7 \times 7 \times 2048$ dimensional features. After global-average pooling layer, a FC layer is used to extract 64d shared latent feature and 3d private latent feature. For the simplicity of the network, our generative model decodes the 2048d feature, the reconstruction of the feature produced from the global-average pooling layer in the encoder, instead of the ambient image.

For the caption, we first extract the sequence of the word embedding using the BERT [3] tokenizer and the BERT base model, pre-trained on the uncased book corpus and English Wikipedia datasets, where the maximum length of the sequence is 30. A sequence whose length is less than 30 is padded by zeros. Given the 768d caption embedding in the BERT base model, we construct our text inference network using a bidirectional LSTM [7] of hidden dimension 512, followed by a max pooling layer and a FC layer to create the final 64d shared feature and the 3d private feature. For the same reasons as the image modality, the text modality decoder produces 1024d features corresponding to the output of max pooling in the text encoder. We use Adam optimizer [9] with batch size 64.

**Quantitative Evaluation.** As suggested in [1, 13, 22, 17], we evaluate the compatibility of image and text modalities in terms of recognition and retrieval on the shared latent space. The shared features of the text modality are averaged per class for the evaluation in both directions. For image-to-text cross generation, recognition is assessed with the Rank1 score and for text-to-image cross generation, retrieval is measured with AP@50. To compute Rank1, after ranking the cosine similarity between a given query image feature and all per-class-averaged text features, we assert whether the closest text feature shares same label with the query image. To compute AP@50, images are first ranked according to their cosine similarity with a given query text feature, averaged per class, assessing the fraction of the closest 50 images with the same class label as the query text, finally averaged over all classes. Tab. 2 shows the recognition and retrieval evaluation results. DMVAE outperforms competition on the image-to-text cross-recognition while achieving identical performance on text-to-image retrieval task.

**Qualitative Evaluation.** In Fig. 6, each row depicts the top3 retrieved captions given a query image according to the cosine similarity in the shared latent space. All the retrieved captions have the same class label as the query image except for the red colored caption in the last row, where the class is that of the image in the second row. In spite of the incorrectly retrieved caption, we can observe that the description

<table>
<thead>
<tr>
<th>Model</th>
<th>Img2Txt (Rank1)</th>
<th>Txt2Img (AP@50)</th>
</tr>
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<tbody>
<tr>
<td>Word2Vec [14]</td>
<td>54.2</td>
<td>52.1</td>
</tr>
<tr>
<td>GMM+HGLMM [11]</td>
<td>54.8</td>
<td>52.8</td>
</tr>
<tr>
<td>Word CNN [1]</td>
<td>60.7</td>
<td>56.3</td>
</tr>
<tr>
<td>Word CNN-RNN [1]</td>
<td>65.6</td>
<td>59.6</td>
</tr>
<tr>
<td>Triplet [13]</td>
<td>64.3</td>
<td>64.9</td>
</tr>
<tr>
<td>IATV [15]</td>
<td>68.9</td>
<td>69.7</td>
</tr>
<tr>
<td>CMPM+CMPC [22]</td>
<td>68.4</td>
<td>70.1</td>
</tr>
<tr>
<td>TIMAM [17]</td>
<td>70.6</td>
<td>73.7</td>
</tr>
</tbody>
</table>

**Table 2: Recognition and retrieval results on the Oxford-102 Flowers dataset.**

![Figure 6: Given a query image, captions are retrieved. The red colored caption represents the incorrect retrieval.](image)

**Figure 6:** Given a query image, captions are retrieved. The red colored caption represents the incorrect retrieval.

<table>
<thead>
<tr>
<th>Query</th>
<th>Rank1</th>
<th>Rank2</th>
<th>Rank3</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Image" /> this flower has smooth white petals, two which are long and three which are oblong</td>
<td><img src="image" alt="Image" /> a flower with five white petals and a yellow pistil</td>
<td><img src="image" alt="Image" /> this flower has five very smooth white petals with rounded edges</td>
<td></td>
</tr>
<tr>
<td><img src="image" alt="Image" /> this flower has orange upright petals that have pointed tips</td>
<td><img src="image" alt="Image" /> this flower has a lightly multicolored pedicel that holds the upright sharply pointed orange petals</td>
<td><img src="image" alt="Image" /> this flower has knife like orange petals that stick up vertically</td>
<td></td>
</tr>
<tr>
<td><img src="image" alt="Image" /> the petals on this flower are long and droopy with an orange color to them</td>
<td><img src="image" alt="Image" /> the petals are curled, orange, and covered with dark red spots</td>
<td><img src="image" alt="Image" /> a bird shaped flower with shiny orange petals that sprout out of it’s pedicel</td>
<td></td>
</tr>
</tbody>
</table>

![Figure 7: Given a query caption, images are retrieved. The red bounding box on the image represents the incorrect retrieval.](image)

**Figure 7:** Given a query caption, images are retrieved. The red bounding box on the image represents the incorrect retrieval.
Table 3: Ablation study on MNIST and SVHN modalities to analyze each component of DMVAE. pM and pS represent private space of MNIST and private space of SVHN respectively. crVAE indicates the cross-VAE loss.

<table>
<thead>
<tr>
<th>Components</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>pM</td>
<td>pS</td>
</tr>
<tr>
<td>o</td>
<td>o</td>
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<td>o</td>
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6. Conclusion

In this paper, we introduce a novel multi-modal VAE model with separated private and shared spaces. We verify that having a private space per modality as well as the common shared space can significantly impact the representational performance of multimodal VAE models. We also demonstrate that VAE with the cross-reconstruction is important for separation of factors across the two sets of spaces. Application to image-to-image and image-to-text modeling tasks demonstrates the universal properties and effectiveness of DMVAE across different data types.

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