Variational Fusion for Multimodal Sentiment Analysis

Navonil Majumder[†], Soujanya Poria[‡], Gangeshwar Krishnamurthy^Φ, Niyati Chhaya[▽], Rada Mihalcea^{||}, Alexander Gelbukh[†]

[†]Centro de Investigación en Computación, Instituto Politécnico Nacional, Mexico [‡]Information Systems Technology and Design, SUTD, Singapore ^ΦA*STAR AI Initiative, Institute of High Performance Computing, Singapore [∇]Adobe Research, India

Computer Science & Engineering, University of Michigan, USA

Abstract

Multimodal fusion is considered a key step in multimodal tasks such as sentiment analysis, emotion detection, question answering, and others. Most of the recent work on multimodal fusion does not guarantee the fidelity of the multimodal representation with respect to the unimodal representations. In this paper, we propose a variational autoencoder-based approach for modality fusion that minimizes information loss between unimodal and multimodal representations. We empirically show that this method outperforms the state-of-theart methods by a significant margin on several popular datasets.

1 Introduction

Multimodal sentiment analysis has received significant traction in recent years, due to its ability to understand the opinions expressed in the increasing number of videos available on open platforms such as YouTube, Facebook, Vimeo, and others. This is important, as more and more enterprises tend to make business decisions based on the user sentiment behind their products as expressed through these videos.

Multimodal fusion is considered a key step in multimodal sentiment analysis. Most recent work on multimodal fusion (Poria et al., 2017; Zadeh et al., 2018c) has focused on the strategy of obtaining a multimodal representation from the independent unimodal representations. Our approach takes this strategy one step further, by also requiring that the original unimodal representations be reconstructed from the unified multimodal representation. The motivation behind this is the

intuition that different modalities are an expression of the state of the mind. Hence, if we assume that the fused representation is the mind-state/sentiment/emotion, then in our approach we are ensuring that the fused representation can be mapped back to the unimodal representations, which should improve the quality of the multimodal representation. In this paper, we empirically argue that this is the case by showing that this approach outperforms the state-of-the-art in multimodal fusion.

We employ a variational autoencoder (VAE) (Kingma and Welling, 2014), where the encoder network generates a latent representation from the unimodal representations. Further, the decoder network decodes the unimodal representations from the latent representation to the original unimodal representation. This latent representation is treated as the multimodal representation for the final classification.

2 Related Work

Rozgic et al. (2012) and Wollmer et al. (2013) were the first to fuse acoustic, visual, and text modalities for sentiment and emotion detection. Later, Poria et al. (2015) employed CNN and multi-kernel learning for multimodal sentiment analysis. Further, Poria et al. (2017) used long short-term memory (LSTM) to enable context-dependent multimodal fusion, where the surrounding utterances are taken into account for context.

Recently, for context-free setting where the surrounding utterances are not used as context, Zadeh et al. (2017) used tensor outer-products to

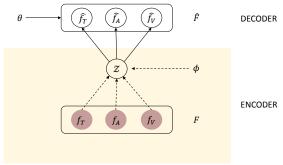


Figure 1: Graphical model of our multimodal fusion scheme.

model intra- and inter-modal interactions. Again, Zadeh et al. (2018a) used multi-view learning for utterance-level multimodal fusion. Further, Zadeh et al. (2018c) employed hybrid LSTM memory components to model intra-modal and cross-modal interactions.

3 Method

Usually humans express their thoughts through three perceivable modalities - textual (speech), acoustic (pitch and other properties of voice), and visual (facial expression). Where most recent works on multimodal fusion treat these unimodal representations independently and employ an encoder network to obtain the fused representation vector, we go one step further by decoding the fused-multimodal representation into the original unimodal representations.

First the utterance-level unimodal features are extracted independently. Then, the modality features are fed to encoder network to sample the fused representation. Further, the fused representation is decoded back to the unimodal representations to ensure the fidelity of the fused representation. This setup is basically an autoencoder. Specifically, we employ a variational autoencoder (VAE) (Kingma and Welling, 2014), as described in Fig. 1, where the latent representation is used as the fused representation.

3.1 Unimodal Feature Extraction

Textual (f_t) , visual (f_v) , and acoustic (f_a) features are extracted using CNN, 3D-CNN (Tran et al., 2015), and OpenSmile (Eyben and Schuller, 2015) respectively, with the methodology described by Poria et al. (2017).

3.2 Encoder

The encoder takes the concatenation of the unimodal features F of an utterance as input, where f_t is textual feature of size D_t , f_a is acoustic feature of size D_a , and f_v is visual feature of size D_v , and infers the latent multimodal representation z of size D_z from the posterior distribution $p_{\theta}(z|F)$, such that

$$F = f_t \oplus f_a \oplus f_v, \tag{1}$$

$$p(F) = \int p_{\theta}(F|z)p(z)dz, \qquad (2)$$

$$p(z) = \mathcal{N}(0, I). \tag{3}$$

Since, the true posterior distribution $p_{\theta}(z|F)$ is intractable, F is fed through two fully-connected layers to generate mean (μ_{enc}) and standard deviation (σ_{enc}) of the approximate posterior normal distribution $q_{\phi}(z|F) = \mathcal{N}(\mu_{enc}, \sigma_{enc})$, which infers the latent representation z:

$$h_1 = \text{ReLU}(W_{h_1}F + b_{h_1}),$$
 (4)

$$\mu_{enc} = W_{\mu} h_1 + b_{\mu},\tag{5}$$

$$\sigma_{enc} = \text{softplus}(W_{\sigma}h_1 + b_{\sigma}),$$
 (6)

where $F \in \mathbb{R}^{D_t + D_a + D_v}$, $W_{h_1} \in \mathbb{R}^{D_h \times (D_t + D_a + D_v)}$, $b_{h_1} \in \mathbb{R}^{D_h}$, $h_1 \in \mathbb{R}^{D_h}$, $W_{\{\mu,\sigma\}} \in \mathbb{R}^{D_z \times D_h}$, $b_{\{\mu,\sigma\}} \in \mathbb{R}^{D_z}$, $\mu_{enc} \in \mathbb{R}^{D_z}$, and $\sigma_{enc} \in \mathbb{R}^{D_z}$.

Sampling Latent (Multimodal) Representation The latent representation $z \sim q_{\phi}(z|F)$ is sampled using the reparameterization trick (Kingma and Welling, 2014) to facilitate backpropagation:

$$z = \mu_{enc} + \epsilon \odot \sigma_{enc}, \tag{7}$$

$$\epsilon \sim \mathcal{N}(0, I),$$
 (8)

where $z \in \mathbb{R}^{D_z}$, $\epsilon \in \mathbb{R}^{D_z}$, and \odot represents hadamard product. This z is considered as the fused multimodal representation.

3.3 Decoder

The decoder reconstructs the input as \hat{F} from the latent representation z with two fully-connected layers as follows:

$$h_3 = \text{softplus}(W_{h_3}z + b_{h_3}), \tag{9}$$

$$\hat{F} = W_{rec}h_3 + b_{rec},\tag{10}$$

where $W_{h_3} \in \mathbb{R}^{D_h \times D_z}$, $b_{h_3} \in \mathbb{R}^{D_h}$, $W_{rec} \in \mathbb{R}^{(D_t + D_a + D_v) \times D_h}$, $b_{rec} \in \mathbb{R}^{(D_t + D_a + D_v)}$, $h_3 \in \mathbb{R}^{D_h}$, and $\hat{F} \in \mathbb{R}^{(D_t + D_a + D_v)}$.

3.4 Classification

We tried two different classification networks:

Logistic Regression (LR) We employ a fully-connected layer with softmax activation where the fused representation z is fed:

$$\mathcal{P} = \operatorname{softmax}(W_{cls}z + b_{cls}), \tag{11}$$

$$\hat{y} = \underset{i}{\operatorname{argmax}} \mathcal{P}[i], \tag{12}$$

where $W_{cls} \in \mathbb{R}^{C \times D_z}$, $b_{cls} \in \mathbb{R}^C$, $\mathcal{P} \in \mathbb{R}^C$ is the vector of class-probabilities, \hat{y} is the predicted class, and C is the number of classes (C = 2 in our case).

Context-Dependent Classifier (bc-LSTM (Poria et al., 2017)) The sequence of fused utterance representations (z_i) in a video is fed to a bidirectional-LSTM (Hochreiter and Schmidhuber, 1997), following Poria et al. (2017), of size D_l for context propagation and then the output of the LSTM is fed to a fully-connected layer with softmax activation for classification:

$$Z = [z_1, z_2, \dots, z_n], \tag{13}$$

$$H = \text{bi-LSTM}(Z), \tag{14}$$

$$H = [h_1, h_2, \dots, h_n],$$
 (15)

$$\mathcal{P}_j = \operatorname{softmax}(W_{cls}h_j + b_{cls}), \tag{16}$$

$$\hat{y}_j = \operatorname*{argmax}_{i} \mathcal{P}_j[i], \tag{17}$$

where Z is the sequence of fused utterance representations in a video with n utterances, H is the context-dependent fused representations of the utterances $(h_i \in \mathbb{R}^{2D_l})$, $W_{cls} \in \mathbb{R}^{C \times 2D_l}$, $b_{cls} \in \mathbb{R}^C$, $\mathcal{P}_j \in \mathbb{R}^C$ is the vector of class-probabilities for utterance j, \hat{y}_j is the predicted class for utterance j, and C is the number of classes (e.g. C = 2 for MOSI dataset (Section 4.1)).

3.5 Training

Latent Representation Inference Following Kingma and Welling (2014), the approximate posterior distribution $q_{\phi}(z|F)$ is tuned close to the true posterior $p_{\theta}(z|F)$ by maximizing the evidence lower bound (ELBO), where

$$\log p(F) \ge \text{ELBO},\tag{18}$$

ELBO =
$$\mathbb{E}_{q_{\phi}(z|F)}[\log p_{\theta}(F|z)]$$

$$-\operatorname{KL}[q_{\phi}(z|F)||p(z)]. \tag{19}$$

The first term of the ELBO, $\mathbb{E}_{q_{\phi}(z|F)}[\log p_{\theta}(F|z)]$, corresponds to the reconstruction loss of input F. The second term,

 $\mathrm{KL}[q_{\phi}(z|F)||p(z)]$, pushes the approximate posterior $q_{\phi}(z|F)$ close to the prior $p(z) = \mathcal{N}(0, I)$ by minimizing the KL-divergence between them.

Classification To train the sentiment classifier (Section 3.4), we minimize the categorical crossentropy (E), defined as

$$E = -\frac{1}{N} \sum_{i=1}^{N} \log \mathcal{P}_i[y_i], \qquad (20)$$

where N is the number of samples, \mathcal{P}_i is the probability distribution for sample i on different classes (for our experiments, we use two classes; positive and negative), and y_i is the target class for sample i.

The networks are optimized using stochastic-gradient-descent-based Adam (Kingma and Ba, 2015) algorithm. Further, the hyperparameters $\{D_h, D_l\}$ and learning-rate are optimized with grid-search (optimal hyperparameters are listed in the supplementary material). The latent representation size D_z is set to 100.

4 Experimental Settings

We evaluate the quality of the multimodal features extracted by VAE¹ using two classifiers (Section 3.4). Hence, the two variants are named VAE+LR and VAE+bc-LSTM in Table 2.

4.1 Datasets

We evaluate our approach on three different datasets.

MOSI (Zadeh et al., 2016) This dataset contains videos of 89 people reviewing various topics in English. The videos are segmented into utterances where each utterance is annotated with sentiment tags (positive/negative). Our train/test splits of the dataset are completely disjoint with respect to speakers. In particular, 1447 and 752 utterances are used for training and test respectively.

MOSEI (Zadeh et al., 2018b) MOSEI dataset contains 22676 utterances from 3229 videos. The videos were crawled from Youtube. There are 1000 unique speakers in the MOSEI dataset. Videos in MOSEI mostly comprise of product and movie reviews. We used 16188, 1874, and 4614 utterances as training, validation, and test folds.

¹implementation available at https://github.com/xxxx/xxxx/ (will be releaved upon acceptance)

respectively. The utterances are labeled with either of the *positive*, *negative*, *and neutral* sentiment categories.

IEMOCAP (Busso et al., 2008) IEMOCAP contains two way conversations among ten speakers, segmented into utterances. The utterances are tagged with one of the six emotion labels *anger*, *happy, sad, neutral, excited, and frustrated.* The first eight speakers of sessions one to four belong to training set and the rest to the test set.

Dataset	Train	Test
MOSEI	16188	4614
IEMOCAP	5810	1623
MOSI	1447	752

Table 1: Utterance count in the train and test sets.

4.2 Baseline Methods

Logistic Regression (LR) The concatenation of the utterance-level unimodal representations is classified using logistic regression as described in Section 3.4. This does not consider the surrounding neighbouring utterances as context.

bc-LSTM (**Poria et al., 2017**) The concatenation of the utterance-level unimodal representations is sequentially fed to the bc-LSTM classifier described in Section 3.4. This is the state-of-theart method.

TFN (Zadeh et al., 2017) This network models both intra-modal and inter-modal interactions through outer product. It does not use the neighbouring utterances as context.

MFN (Zadeh et al., 2018a) This network exploits multi-view learning to fuse modalities. It also does not use neighbouring utterances as context.

MARN (Zadeh et al., 2018c) In this model the intra-modal and cross-modal interactions are modeled with hybrid LSTM memory component.

5 Results and Discussion

Table 2 shows the performance our VAE-based methods, namely VAE+LR and VAE+bc-LSTM, outperform their concatenation fusion counterpart LR and bc-LSTM consistently on all three datasets. Specifically, our context-dependent

Method	MOSI	MOSEI	IEMOCAP
TFN	74.8	53.7	56.8
MARN	74.5	53.2	54.2
MFN	74.2	54.1	53.5
LR	74.6	56.6	53.9
VAE+LR	77.8	57.4	54.4
bc-LSTM	75.1	56.8	57.7
VAE+bc-LSTM	80.4*	58.8 *	59.6*

Table 2: Trimodal (acoustic, visual, and textual) F1-scores of our method against the baselines (results on MOSI and IEMOCAP are based on the dataset split from Poria et al. (2017)); * signifies statistically significant improvement (p < 0.05 with paired t-test) over bc-LSTM.

model, VAE+bc-LSTM, outperforms the context-dependent state-of-the-art method bc-LSTM on all the datasets, by 3.1% on average. Moreover, our context-free model VAE+LR outperforms the other context-free models, namely MFN, MARN, TFN, and LR, on all datasets, by 1.5% on average. Also, due to the contextual information, VAE+bc-LSTM outperforms VAE+LR by 3.1% on average.

This is due to the superior multimodal representation from VAE, that retains enough information from the unimodal representations to allow reconstruction. This leads to highly informative classification. (Supplementary material compares the visualizations of the fused representations)

5.1 Case Study

Comparing the predictions of our model to the baselines reveals that our model is better equipped for catching the instances where the non-verbal cues are essential for classification. For instance, the utterance from IEMOCAP "I still can't live on in six seven and five. It's not possible in Los Angeles. Housing is too expensive." is mis-classified as excited by bc-LSTM, whereas VAE+bc-LSTM correctly classifies it as angry. We posit that in this case the bc-LSTM is confused by the emotionally ambiguous textual modality, whereas the VAE+bc-LSTM taps into the visual modality to observe the frown on the speakers face to make the correct classification. Besides this, we observed several similar cases where VAE+bc-LSTM or VAE+LR correctly classifies based on non-verbal cues, where their non-VAE counterparts could not.

Error Analysis "No. I am just making myself fascinating for you." is response to a question

"you going out somewhere, dear?". This is a sarcastic response. VAE+bc-LSTM falsely predicted the emotion as *excited*, where the ground truth is *angry*. We suspect that our model's failure to identify sarcasm with the aid of multimodality led to this misclassification.

6 Conclusion

In this paper, we presented a comprehensive fusion strategy, based on VAE that outperforms previous methods by a significant margin. The encoder and decoder networks in the VAE are simple fully-connected layers. We plan to improve the performance of our method by employing more sophisticated networks, such as fusion networks like MFN and TFN as the encoders.

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