Multimodal Transformer for Parallel Concatenated Variational Autoencoders

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Abstract

In this paper, we propose a multimodal transformer using parallel concatenated architecture. Instead of using patches, we use column stripes for images in R, G, B channels as the transformer input. The column stripes keep the spatial relations of original image. We incorporate the multimodal transformer with variational autoencoder for synthetic cross-modal data generation. The multimodal transformer is designed using multiple compression matrices, and it serves as encoders for Parallel Concatenated Variational AutoEncoders (PC-VAE). The PC-VAE consists of multiple encoders, one latent space, and two decoders. The encoders are based on random Gaussian matrices and don’t need any training. We propose a new loss function based on the interaction information from partial information decomposition. The interaction information evaluates the input cross-modal information and decoder output. The PC-VAE are trained via minimizing the loss function. Experiments are performed to validate the proposed multimodal transformer for PC-VAE.

1 Introduction

Multimodal machine learning studies models to process, generate, or integrate information from multiple modalities [2]. The availability of benchmark multimodal datasets is important for machine learning research. However, some datasets are very limited because of time (e.g., COVID-19 data in early 2020), resources (e.g., art masterpieces), ethics (e.g., colon animals) or the cost of experiments (e.g., space shuttle launching), etc. Synthetic data generated from Variational AutoEncoder (VAE) and Generative Adversarial Network (GAN) are often used to solve the data scarcity problem. In this paper, we focus on multimodal transformer-based VAE.

Multimodal transformer has become a hot research area. It is often related with natural language or text processing. In [35], multimodal transformer was applied to human language with a mixture of natural language, facial gestures, and acoustic behaviors, and addressed issues such as long-range dependencies across modalities and inherent data non-alignment. In [14], a Unified Transformer model was proposed to learn the tasks across different multimodal domains such as natural language understanding and multimodal reasoning. Each input modality was encoded by an encoder and and encoded outcomes were used for the predictions via a shared decoder. In [17], the joint learning of image-to-text and text-to-image generations was studied based on a single multimodal model to target the bi-directional tasks, and a transformer was adopted with a unified architecture for the performance and task-agnostic design. In [45], the multimodal features such as speech prosody, verbal words, and facial expression, were extracted from the video clips for multimodal transformer. In [27], a Multi-Level Multi-Modal Transformer was proposed to process and integrate multiple textual instructions and multiple images. In [15], a multimodal transformer architecture was proposed along with a rich representation for text in images. This approach targets the TextVQA task. In [18],
reasoning about text in images to answer a question was studied using multimodal transformer. In [42], Multimodal Named Entity Recognition was proposed for social media posts. A multimodal interaction module was introduced to get both image-related word representations and word-related visual representations.

In multimodal transformers for general studies, multimodal self-attention in transformer was proposed to make unequal treatment to different modalities and avoid encoding useless information from less important modalities [41]. In [43], multimodal transformer was proposed for image captioning, which simultaneously captures interactions within modality and cross-modality with multimodal reasoning and output accurate captions. In [44], the Factorized Multimodal Transformer was presented for multimodal sequential learning, which could increase the number of self-attentions to better model the multimodal phenomena. This model can extract the information of long-range multimodal dynamics asynchronously. In [45], a History Aware Multimodal Transformer was introduced to help with multimodal decision making via incorporating a long-horizon history. This model used a hierarchical vision transformer to encode all the previous observations. In [46], three important factors were investigated for multimodal transformer that can impact the representations of pretraining data, loss function, and the attention mechanism. In [47], Zhu studied multimodal transformer enhancement using external label and in-domain pretrain. In [37], a new fusion method, TransModality, was introduced to multimodal sentiment analysis.

In the theoretical and behavior studies of multimodal transformer, the behavior of Transformers with modal-incomplete data was studied in [30], and it was observed that transformer models are sensitive to missing modalities and different modal fusion strategies could affect the robustness. In [40], an effective multimodal-driven deep neural network was proposed to perform 3D surface super-resolution in the regular 2D domain. This model jointly consider the normal modalities, depth, and texture. In [41], multimodal representations learning from unlabeled data was introduced using transformer architectures without using convolution. In [6], multimodal Sparse Phased Transformer was studied to reduce the complexity of self-attention and memory footprint. Parameter sharing in each layer and co-attention factorization that share parameters between cross attention blocks was introduced to minimize impact on task performance. To make effective interaction among different modalities, a universal multimodal transformer was introduced to learn joint representations among different modalities [25].

The contributions of this paper include the following.

1. We propose a multimodal transformer for synthetic cross-modal data generation. The multimodal transformer is designed using multiple compression matrices.
2. We propose a new machine learning model, parallel concatenated variational autoencoders (PC-VAE). The multimodal transformer serves as encoders for PC-VAE. The PC-VAE consists of multiple encoders, one latent space, and two decoders (visual and audio).
3. We propose a new vision transformer. Instead of using patches, we use stripes for images in R, G, B channels.
4. We propose a new loss function based on the interaction information from partial information decomposition. The interaction information evaluates the input cross-modal information and decoder output. The PC-VAE are trained via minimizing the interaction information.

2 Related Work

The vision transformer was proposed in [8], which divides an image into multiple patches, and each patch can be processed individually. Recently, ViT [8] achieved very good results with less computational cost. In ViT, an image was split into fixed-size patches, linearly embedded, and then position embeddings were added. The resulting vector was fed to a standard Transformer encoder. To perform classification using ViT, an extra learnable “classification token” was added to the sequence.

In [12], masked autoencoder was proposed using vision transformer to recover the original images even if some patches are masked. It develops an asymmetric encoder-decoder architecture. Its encoder is a Vision Transformer (ViT) [8], and was applied only on visible, unmasked patches. This transformer has been very successful for natural language processing. In [24], a conditional VAE was proposed to generate diverse gestures from speech audio. The conditional VAE was used to model audio-to-motion mapping via decomposing the cross-modal latent code into motion-specific code...
and shared code. Visual and audio contain both common and complementary information. In [11], a cross-modal cycle generative adversarial network was proposed to handle cross-modal visual-audio mutual generation.

In the related works on multimodal transformers for visual and audio information. In [46], audio and visual information was integrated using multimodal fusion mechanism based on a hierarchical transformer, which could capture the dependencies among frame and shots. Multimodal transformer was used to fuse audio-visual modalities on the model level in [16]. After encoding audio and visual modalities, the multi-head attention was applied to produce multimodal emotional intermediate representations from semantic feature space. In [12], deep-learning algorithms for audio-visual detection of user’s expression was studied, and a transformer architecture with encoder layers was proposed to integrate audio-visual features for expressions tracking. In [10], a multidomain multimodal transformer was proposed for video retrieval, which provided multidomain generalisation via combining different video caption datasets. In [22], a parameter sharing scheme based on low-rank approximation was proposed to reduce the number of parameters associated with the audio-visual video representation learning in multimodal transformers. The Transformer was decomposed into modality-specific and modality-shared parts. In [33], multimodal adaptation gate was introduced to accept multimodal nonverbal data during fine-tuning, and the visual and acoustic modalities were studied in this model. In [21], multimodal transformer networks was proposed for end-to-end video-grounded dialogue systems, and a query-aware attention through an auto-encoder was studied to obtain query-related features from non-text information. In [39], a multimodal emotion recognition algorithm during a conversation was studied, and separate models for visual and audio were structured and trained.

In the current VAE, Evidence Lower Bound (ELBO) function is often used as the cost function for VAEs, and ELBO includes Kullback–Leibler (KL) divergence and reconstruction error [19]. The purpose of VAE is to generalize the input and provide generative modeling for the input. In [28], ELBO was used to train the linear VAEs, and comparing to the relative to log marginal likelihood method, this approach does not introduce any additional spurious local maxima. In this paper, we propose a new cost function for synthetic data evaluation and performance metric using interaction information from Partial Information Decomposition (PID).

The loss function has been used for VAE training. Evidence lower bound objective (ELBO) loss function has been widely to train the VAE parameters [19] [29]. In [26], transfer entropy was used as a loss function for VAE training. All the above loss functions are based on a VAE system with same modality and single input and single output system. In our multimodal transformer PC-VAE, the input has multimodality, so we propose a new loss function based on Partial Information Decomposition (PID).

3 Multimodal Transformer for Parallel Concatenated VAEs

3.1 Transformer and Architecture

In the existing vision transformer [8][12], uniformly partitioned patches are used for an image, as illustrated in Fig. 1(a). In this paper, we propose a new vision transformer using stripes from each RGB channel image, as illustrated in Fig. 1(b)(c)(d). Then linear transformation is applied to each stripe in the RGB channel images respectively.

We further extend the transformer to multimodal transformer, which can split any multimodal data to a number of smaller-size single modality data (e.g., images or audio segments). We propose a parallel concatenated architecture for multimodal transformer in PC-VAE, as shown in Fig. 2. It illustrates the PC-VAE with two modalities, image and audio.

The RGB image stripe $x_i$ is a matrix, then we can vectorize it [3], which is the concatenation of its columns, i.e., $vec(x) = [x_1, x_2, \cdots, x_N]^t$. For image stripes, each of the parallel concatenated transformer can be expressed as

$$\mu_i = \Phi_i x_i$$  \hspace{1cm} (1)

where $i = 1, 2, \cdots, L$, and $\Phi_i$ is compression matrix having size $N'_i \times N_1$ and $N'_i < N_1$. $\mu_i$ is the output of compression for image signals, and it has length $N'_i$, versus the original length $N_1$ of $x_i$. In Fig. 2 $\Phi_i$ is Image-matrix (I-matrix) $i$ for image stripes. Then all the $\mu_i$ ($i = 1, 2, \cdots, L$) values are
Figure 1: Different transformer schemes. (a) Existing approach. (b) Transformer for R channel. (c) Transformer for G channel. (d) Transformer for B channel.

Figure 2: The architecture of PC-VAE with multimodal Transformer.

\[ \mu_v = \sum_{i=1}^{L} \mu_i \]  
(2)

Regarding matrix for audio segments in Fig. 2, we can choose different matrix \( \Psi_j \), and

\[ \mu_j = \Psi_j y_j \]  
(3)

where \( y_j \) is audio segment and \( j = 1, 2, \cdots, M \). If the size of matrix \( \Phi_j \) is \( N'_2 \times N_2 \) (\( N'_2 < N_2 \)), then the output \( \mu_j \) has length \( N'_2 \). Then all the \( \mu_j \) \( (j = 1, 2, \cdots, M) \) values are summed together, we get

\[ \mu_a = \sum_{i=1}^{M} \mu_j \]  
(4)
In this paper, we choose the compression matrices $\Phi_i$ and $\Psi_j$ as zero-mean Gaussian random matrix with unit variance. The compression matrix $\Phi_i$ and $\Psi_j$ are generated randomly, but once they are generated, all values in the matrix are frozen during the training and testing process. This is quite different with the current KL-VAE in which the parameters in the encoder neural network need to be tuned in the training process. Our approach saves computation because it doesn’t need any training in the encoders.

Then we can compute the variance $\sigma_v^2$ of all visual signals, and a reparameterization process is performed based on $\mu_v$ and $\sigma_v$,

$$z_v = \mu_v + \sigma_v \epsilon$$

where $\epsilon \sim \mathcal{N}(0, I)$. Similarly, we can use reparameterization process to get $z_a$ based on $\mu_a$ and $\sigma_a$

$$z_a = \mu_a + \sigma_a \epsilon$$

The latent space in Fig. 2 is a vector, and it is obtained based on the serial concatenation of $z_v$ and $z_a$. So the total length of latent space in Fig. 2 is $N_1 + N_2$. The latent space $z$ serves as the input to the PC-VAE two decoders, visual decoder and audio decoder.

The visual and audio decoders are just two convolutional neural networks (CNN). Their inputs are from the latent space $z$, but their outputs are different. The visual decoder has colored image output, and the audio decoder produces audio signals. For different applications, the CNN structures are different.

The benefits of our multimodal transformer includes the following.

1. The vectorization of images are performed in columns, and our vision transformer partitions the images into stripes by columns, which keeps the original spatial relations of pixels.
2. The Gaussian random matrices $\Phi_i$ and $\Psi_j$ are chosen randomly, and they don’t need any selection and training process.
3. All the operations of latent space construction are linear, so it saves computational cost.
4. The inputs to the visual decoder and audio decoder are the same, which makes data processing easier.
5. All the linear transformation in the multimodal transformer and the neural network processing in the decoders are in parallel, which can tremendously increase the processing speed.

### 3.2 Loss Function Using Interaction Information

Partial Information Decomposition (PID) was proposed to evaluate the mutual information between multiple variables [38, 31, 9]. PID can decompose mutual information to unique information, redundant information, and synergetic information. In our cross-modal information generative modeling, the mutual information between input cross-modalities $(X_1, X_2)$ and output modality $Y$ can be decomposed as [38]. The whole region is $I(X_1, X_2; Y)$; the red region is redundant information $R(X_1; X_2)$; the blue region is synergetic information $S(X_1, X_2; Y)$; the green and orange regions are the unique information $U(X_1; Y|X_2)$ and $U(X_2; Y|X_1)$. Mathematically, they can be represented as [38].

$$I(X_1, X_2; Y) = U(X_1; Y|X_2) + U(X_2; Y|X_1) + R(X_1, X_2; Y) + S(X_1, X_2; Y)$$

where $U(X_1; Y|X_2)$ denotes the unique information of $Y$ present only in $X_1$ and not in $X_2$; $U(X_2; Y|X_1)$ denotes the unique information of $Y$ present only in $X_2$ and not in $X_1$; $R(X_1, X_2; Y)$ denotes the redundant information of $Y$ present in both $X_1$ and $X_2$; $S(X_1, X_2; Y)$ is the synergetic information of $Y$ that is not present in $X_1$ or $X_2$ individually, but present in $(X_1, X_2)$ jointly. In Fig. 3 we illustrate the relations of these four parts [38].

$$U(X_1; Y|X_2) = I(X_1; Y|X_2)$$
$$U(X_2; Y|X_1) = I(X_2; Y|X_1)$$
$$R(X_1, X_2; Y) = I(X_1; X_2)$$
$$S(X_1, X_2; Y) = I(X_1, X_2; Y) - I(X_1; Y|X_2) - I(X_2; Y|X_1) - I(X_1; X_2)$$
where \( I(X_1; X_2) \) denotes the mutual information between \( X_1 \) and \( X_2 \), and is defined as [7].

\[
I(X_1; X_2) = \sum_{x_1 \in X_1} \sum_{x_2 \in X_2} p(x_1, x_2) \log \frac{p(x_1, x_2)}{p(x_1)p(x_2)} \tag{12}
\]

It is well known that \( I(X_1; X_2) \) is always nonnegative. \( I(X_1; Y|X_2) \) is conditional mutual information [7]

\[
I(X_1; Y|X_2) = \mathbb{E}_{p(x_1, y|x_2)} p(x_1, y|x_2) \log \frac{p(x_1, y|x_2)}{p(x_1|x_2)p(y|x_2)} \tag{13}
\]

where \( \mathbb{E} \) denotes mathematical expectation.

![Figure 3: An illustration of PID with four parts [38].](image)

PID reflects the relations between the four parts. Williams and Beer further defined Interaction Information (II) [38] [36] [34],

\[
II(X_1, X_2; Y) = I(X_1; Y|X_2) - I(X_1; Y) \tag{14}
\]

Based on chain rule [7],

\[
I(X_1, X_2; Y) = I(X_2; Y) + I(X_1; Y|X_2) \tag{15}
\]

so (14) becomes

\[
II(X_1, X_2; Y) = I(X_1, X_2; Y) - I(X_2; Y) - I(X_1; Y) \tag{16}
\]

\[
= I(X_1, X_2; Y) - [I(X_2; Y|X_1) + I(X_1; X_2)]

- [I(X_1; Y|X_2) + I(X_1; X_2)] \tag{17}
\]

\[
= I(X_1, X_2; Y) - I(X_1; Y|X_2) - I(X_1; Y|X_2) - 2I(X_1; X_2)

= [I(X_1, X_2; Y) - I(X_1; X_2)] - I(X_1; Y|X_2)

- I(X_1; X_2) \tag{18}
\]

\[
= S(X_1, X_2; Y) - I(X_1; X_2) \tag{20}
\]

where the derivation from (16) to (17) is based on the relation [38]

\[
I(X_2; Y) = I(X_2; Y|X_1) + I(X_1; X_2) \tag{21}
\]

and from (19) to (20) is based on the synergetic information in (11).

Result in (20) shows that Interaction Information \( II(X_1, X_2; Y) \) is the difference between Synergetic Information and Redundancy Information. It could have the following two cases:

1. When \( II(X_1, X_2; Y) > 0 \), it means the synergetic information is higher than the redundancy information.

2. When \( II(X_1, X_2; Y) < 0 \), it means the redundancy information is higher than the synergetic information.

We incorporate the interaction information into the synthetic data evaluation and cross modal variational autoencoder training. We try to minimize the interaction information because the smaller interaction information means smaller synergetic information, and the output \( Y \) is more close to the input \( X_1 \) and \( X_2 \).
We propose a new loss function based on the above analysis. Assume the image and audio input to PC-VAE are $X_1$, $X_2$, its output is $Y$, and $X_1$ has the same modality with $Y$ without losing of generality.

\[
L(\theta, \phi, x) = II(X_1, X_2; Y) + E(|| Y - X_1 ||^2) \tag{22}
\]

\[
= I(X_1, X_2; Y) - I(X_2; Y) - I(X_1; Y) + E(|| Y - X_1 ||^2) \tag{23}
\]

It includes two parts, the interaction information and reconstruction loss. We will train the PC-VAE via minimizing this loss function.

4 Experiments

We ran our simulation on PC-VAE for visual-audio generative modeling based on a Subset from University of Rochester Music Performance (URMP) dataset (Sub-URMP) \[4][23]. The Sub-URMP contains images and audios cut from the URMP. A sliding window with time duration 0.5 seconds and a stride 0.1 second was used to obtain the data. The first frame of each video chunk, an image with size $1080 \times 1920$, was used to represent the visual content of the sliding window. The audio files are in WAVE format in stereo channel with a sampling rate of 44 KHz and bit depth of 16 bits \[20].

The training set has 71230 paired samples where each pair has one image and one audio file. The validation set has 9575 paired samples. We chose 50000 paired samples for training, and 8000 paired samples for testing. To make it work more efficiently, we performed down-sampling by 34 for the images, and down-sampled by 10 for the audio files. Since the two channels audio data are identical, we only chose one channel data. Based on this data pre-processing, each image has a size of $32 \times 32 \times 3$ where 3 stands for the RGB channels. The each audio file has a size of 2205 which is a 1-D vector.

In our experiment, the PC-VAE encoder is designed with $L = 6$ for image stripes, and $M = 5$ for audio segments. We chose matrix $\Phi_i$ with the number of columns as $\frac{22 \times 3 \times 3}{L} = 512$, and matrix $\Psi_j$, with the number of columns as $\frac{22 \times 5}{M} = 441$. The number of rows in $\Phi_i$ and $\Psi_j$ could be different in simulations.

The configurations of our PC-VAE two decoders are specified as follows. In the visual decoder, a CNN with 3 ReLu layers and 4 transposed convolutional layers was used. The input layer has size of the latent space length. A ReLu layer comes after a 2-D convolutional layer, and then another 2-D convolutional layer followed the ReLu layer. The four convolutional layers have filter size of $7 \times 64$, $3 \times 32$, and $3 \times 3$ respectively. The stride sizes are 8, 2, 2, and 1 for the above four layers. The output size is $32 \times 32 \times 3$, so that it can match the size of the input image. The audio decoder has similar structure as the visual decoder, except for the last layer where we used a fully connected layer with size 2205 instead of a 2D convolutional layer with size $3 \times 3$.

The performance of the multimodal transformed-based PC-VAE for visual generation was evaluated based on two experiments. 1) when both images and audio are present in the encoder side; 2) cross-modal data generation based on one modality only.

In the first experiment, both image and audio information was available. The visual and audio encoders outputs were combined into the latent space. In Fig. 3, we plot an example image generated by the visual decoder with training for 50 epochs, and the latent space $z$ has length 300 (150 from image stripes and 150 from audio segments). In each pair of images, the left image is the input image, and the right image is an example output from the visual decoder. The output images are very similar to the input image. In Fig. 4, we plot an example image generated by the visual decoder with latent space $z$ has length 400 (200 from image stripes and 200 from audio segments).

In Fig. 5, we plot the loss function in (23) based on the interaction information for the experiment when both visual and audio information were present. Observe that the loss function (23) reduces almost monotonically versus the training epochs.

In the second experiment, the visual information was missing, and only audio information was available in the validation, and the images were generated using audio input. In Fig. 6, we plot an example image generated by the visual decoder with training for 50 epochs, and the latent space has length 200. In each pair of images, the left image is the missing image (blind to the encoder
Figure 4: Images generated using PC-VAE based on visual and audio information using loss function in (23). (a) Latent Space length=300; (b) Latent Space length=400.

Figure 5: Reconstruction errors in multimodal transformer-based PC-VAE for visual generation with loss function in (23).

and decoder), and the right image is an example output from the visual decoder. Observe that visual signal could be generated based on audio signal only. Although we only present one example, the visual decoder could generate any number of images based on one audio input. In Fig. 6b, we plot an example image generated by the visual decoder and the latent space has length 250.

The performance of the PC-VAE for audio generation was evaluated based on two experiments. In the first experiment, the audio information was missing, and only image information was available in the validation, and the audio signals were generated using visual input. In Fig. 7a, we plot an example audio signals generated by the audio decoder with training for 50 epochs, and the latent space has length 200. In each pair of audio signals, the left plot in blue is the missing audio (blind to the encoder and decoder), and the right plot (in red) is an example output from the audio decoder. Of course, the audio decoder could generate any number of audio plot based on one visual input. Observe that audio signal could be generated based on visual signal only. In the second experiment, both visual and audio information were available. In Fig. 7b, we plot an example audio generated by the audio decoder with training for 50 epochs, and the latent space has length 400 (200 from visual latent space and 200 from audio latent space). In each pair of plot (blue and red), the left plot in blue is the input audio, and the right plot is an example output from the audio decoder. Observe that the output audio plots are very similar to the input audio signals, and the audio signals could be generated successfully in both cases.
5 Conclusions

We have proposed a multimodal transformer using parallel architecture for synthetic multimodal data generation. The multimodal transformer is designed using multiple compression matrices. We propose a new vision transformer. Instead of using patches, we use column stripes for images in R, G, B channels. The column stripes keep the spatial relations of original image. We have proposed a new machine learning model, PC-VAE. The multimodal transformer serves as encoders for PC-VAE. The PC-VAE consists of multiple encoders, one latent space, and two decoders (visual and audio). Each matrix in the multimodal transformer is chosen as zero-mean unitary Gaussian random matrix.

We have proposed a new cost function based on the interaction information from partial information decomposition. The interaction information evaluates the input cross-modal information and decoder output. The parallel concatenated variational autoencoders are trained via minimizing the interaction information. Experiments are performed to validate the proposed multimodal transformer for parallel concatenated VAEs.

The multimodal transformed-based PC-VAE has potential to help disabled persons to sense the world using the modality that they are capable to perceive. For example, visual signals could be transformed to audible signals using the PC-VAE, so that a visually-impaired person can sense what other people see. A piece of music may not make any sense to hearing-impaired persons, but PC-VAE can transform it to images or video for them to view.
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