Cross-modal Music Emotion Recognition Using Composite Loss-based Embeddings

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Abstract—Most music emotion recognition approaches use one-way classification or regression that estimates a general emotional category from a distribution of music samples, but without considering emotional variations (e.g., happiness can be further categorised into much, moderate or little happiness). We propose a cross-modal music emotion recognition approach that associates music samples with emotions in a common embedding space by considering both general emotional categories and fine-grained discrimination within each category. Since the association of music samples with emotions is uncertain due to subjective human perceptions, we compute composite loss-based embeddings obtained to maximise two statistical characteristics, one being the correlation between music samples and emotions based on canonical correlation analysis, and the other being a probabilistic similarity between a music sample and an emotion with KL-divergence. The experiments on two benchmark datasets demonstrate the effectiveness of our cross-modal approach, the composite loss and learned acoustic features. In addition, detailed analysis shows that our approach can accomplish robust cross-modal music emotion recognition that not only identifies music samples matching with a specific emotion but also detects emotions expressed in a certain music sample.

Index Terms—Music emotion recognition, Cross-modal recognition, Embeddings, Canonical correlation analysis, Kullback-Leibler divergence

1 INTRODUCTION

Music is a powerful means to evoke human emotions. Analysing the interactions between them is thus important in affective computing, and is one of main focuses of Music Emotion Recognition (MER) which attempts to automatically identify the emotion matching a specific music [1]. MER is useful for many potential applications such as music recommendation and playlist generation for streaming services, and even music therapy in biomedicine [2].

MER is performed differently depending on how emotions are modelised. Two main approaches currently co-exist: categorical and continuous. The former commonly addresses classification of the six ‘general’ emotional categories defined in Ekman’s theory (i.e., happiness, sadness, anger, fear, disgust and surprise) [3]. On the other hand, the continuous approach focuses on regression to suggest ‘specific’ emotional intensities based on Russell’s circumplex model that decomposes emotions along several axes, such as arousal (level of energy) and valence (level of pleasantness) [4]. Both of the categorical and continuous approaches have their pros and cons. While the former can clearly identify general emotions in music, it is impossible to take into account the richness and variations of human emotions. For example, there are several degrees of happiness like much, moderate and little happiness, that cannot be distinguished from each other with the categorical approach. On the other hand, the continuous approach can express fine-grained human emotions in a vector space defined by the arousal and valence axes. However, it is difficult to identify general emotions because dissimilar emotions such as ‘fear’ and ‘anger’ are located close to each other in the arousal-valence space [5]. Therefore, neither categorical nor continuous approach has become preponderant over the other in the literature, despite the benefits of each approach being essential for MER.

In this paper, we propose a Cross-modal Music Emotion Recognition (CMER) approach that can directly analyse the similarity between music and emotion in a common space called an embedding space. In what follows, the term embedding designates the vector representation of a music sample or an emotion in the embedding space. Top-left and bottom-left of Fig. 1 illustrate the aforementioned categorical and continuous approaches that estimate discrete general emotions and specific continuous emotions, respectively. In comparison, the right part of Fig. 1 shows a standard CMER approach that projects music samples and emotions into an embedding space. CMER can identify general emotions because similar emotions are gathered close to each other in terms of their embeddings. It can be noted that music samples and the specific emotions which are highly associated to them are projected in proximity, that is, their fine-grained relations are preserved in the embedding space. This way, CMER can treat both of general and specific emotions.

In addition, emotional intensities are inherently uncertain because they are subjectively annotated according to human perceptions which are highly influenced by many factors such as age, personality, cultural background and surrounding conditions [1], [6]. Most of existing MER ap-
proaches ignore this emotional uncertainty using potentially inaccurate emotional intensities as labels. The emotional uncertainty could cause embeddings to be inaccurate and thus negatively impact the recognition performances.

To deal with the emotional uncertainty, we develop an approach, called CMER using Composite Loss (CMER-CL) that trains music and emotion embeddings with a compound loss examining two statistical characteristics. Firstly, it can be assumed that even if emotional intensities differ from user to user, they remain nevertheless correlated when listening to the same music sample. Thus, Canonical Correlation Analysis (CCA) is used to devise a correlation-based loss [7]. This loss enables us to deal with inter-subject variations in emotional intensities by maximising the correlation between music samples and their associated emotions in an embedding space, so as to find their ‘relative’ connection. That is, the embedding space characterises how acoustic features change according to an increase/decrease in arousal/valence intensities and vice versa. Secondly, music samples yielding very different acoustic features can evoke similar emotions. For instance, happiness can be expressed in different genres like rock, blues and jazz. This kind of large intra-class variation in acoustic features for one emotional category makes projecting a music sample or an emotion into a single point (as shown in Fig. 1) suboptimal. Thus, we additionally project each of music samples and emotions as a probability distribution in another embedding space [8], [9]. This idea is implemented by defining a distribution-based loss that measures the Kullback-Leibler (KL) divergence between the probability distribution for a music sample and the one for an emotion in the embedding space.

Our composite loss consisting of the correlation- and distribution-based losses is necessary for managing the aforementioned inter-subject and intra-class variations resulting from the emotional uncertainty. Only using the correlation-based loss cannot cover the large intra-class variation of acoustic features, while the inter-subject variation of emotional intensities cannot be handled only with the distribution-based loss. The experimental results in Section 4.4 validate the necessity of combining the correlation- and distribution-based losses.

To sum up, this paper contains the following three main contributions: Firstly, we propose CMER-CL that can work with both general and specific emotions since it uses the continuous model of emotions to obtain embeddings of emotions, and the embedding space maintains not only associated music samples and emotions close to each other but also non-associated ones far away. Thus, the embedding space serves as a bridge between music samples and emotions and offers bidirectional music emotion recognition as a by-product of CMER-CL. In other words, we can perform not only Music to Emotion (M2E) to detect emotions expressed in specific music samples but also Emotion to Music (E2M) to identify music samples matching a specific emotion. Secondly, we propose a new composite loss combining the CCA and KL-divergence losses to take into account the emotional uncertainty. Finally, we perform extensive experiments on two benchmark datasets, MediaEval Database for Emotional Analysis in Music (DEAM) [10] and PMEmo [11]. We demonstrate the effectiveness of CMER-CL over one-way baselines, of the composite loss over other alternatives and of the features learned by CMER-CL relatively to the state-of-the-art MER methods. In addition, detailed analysis of CMER-CL results reveals that reasonable recognition is robustly attained even in cases of mis-recognition.

2 RELATED WORK

This section provides a short review of existing MER approaches by dividing them into M2E and E2M. We first review existing M2E approaches by classifying them into three categories: “feature engineering” that hand-crafts emotion-related acoustic features, “feature learning” based on deep learning that automatically learns emotion-related features, and “relation modelling” to extract the relationship between emotional intensities and acoustic features obtained by feature engineering or learning. We then discuss past work dealing with E2M. Through this review, we clarify the novelties of the proposed CMER-CL.

Feature engineering for M2E: Several libraries like MIR-toolbox [12] and openSMILE [13] are currently available to extract fundamental acoustic features such as Zero-Crossing Rate (ZCR), Root-Mean-Square (RMS) energy, Mel-Frequency Cepstral Coefficients (MFCCs), Short-Time Fourier Transform (STFT), etc. However, acoustic signal analysis alone might not be enough to account for all required acoustic characteristics [5]. As a result, a large focus of M2E approaches has been put on feature engineering. Panda et al. [14] distinguished several types of emotion-related acoustic features including spectral features (low-level feature), rhythm clarity (perceptual feature) and genre (high-level semantic feature). Ren et al. [15] proposed acoustic features consisting of modulation spectral analysis of MFCCs, short-term timbre features and long-term joint frequency features computed from a two-dimensional representation of acoustic and modulation frequencies [16]. Mo and Niu [17] presented an acoustic feature extraction technique that combines three signal processing algorithms, the orthogonal matching pursuit, Gabor functions, and the Wigner distribution function, to provide an adaptive time-varying description of music signals with a higher spatial and temporal resolution. Panda et al. [18] proposed algorithms to extract acoustic features related to musical texture and expressive performance techniques (e.g., vibrato, tremolo and glissando). Cho et al. [19] presented acoustic
features by considering temporal sequences of chords (harmonic set of musical notes).

The aforementioned work mainly focuses on designing acoustic features and feature selection to effectively estimate an emotion from a music sample, but it can be claimed that feature engineering does not inherently take into account the emotional uncertainty unlike our CMER-CL approach.

**Feature Learning for M2E**: The advantage of feature learning is the ability to capture high-level features from raw data or hand-crafted (low-level) features. Schmidt et al. [20] applied regression-based Deep Belief Networks (DBNs) [21] to predict arousal/valence directly from spectra obtained by STFT. Weninger et al. [22] evaluated the usefulness of a Long Short-Term Memory (LSTM) to estimate arousal/valence levels from hand-crafted acoustic features [23]. Li et al. [24] proposed a Deep Bidirectional LSTM to predict arousal/valence from low-level acoustic features. Malik et al. [25] demonstrated the effectiveness of stacking a Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) to predict arousal/valence from acoustic features exclusively based on log mel-band energy. Dong et al. [26] developed a Bidirectional Recurrent Sparse Network (BCRSN) that uses the spectrogram of audio signals and reduces computational complexity by converting the continuous arousal/valence prediction process to multiple binary classification problems. Sarkar et al. [27] applied a CNN taking log-mel spectrogram as input to the four-class classification problem defined by Russell’s model quadrants [4]. Hizlisoy et al. [2] proposed a Convolutional Long short-term memory Deep Neural Network (CLDNN) for the classification of three quadrants excluding low arousal - high valence from Russell’s model quadrants [4]. Choi et al. [28] presented a transfer learning approach where a CNN taking mel-spectrograms as input is firstly trained for a music tagging task, and then transferred and fine-tuned for six other tasks such as music genre classification, speech/music classification, emotion prediction etc.

The aforementioned approaches do not take into account the emotional uncertainty. On the other hand, our CMER-CL approach uses high-level acoustic features learned by a pre-trained VGGish model [29], and takes advantage of the composite loss to deal with the emotional uncertainty.

**Relation modelling for M2E**: Past work has also investigated relationships between music samples and emotions. Yang et al. [30] built a group-wise MER scheme (GWMER) which divides users into various groups based on user information such as generation, gender, occupation and personality, and trains a Support Vector Regression (SVR) for the prediction of arousal/valence for each group. GWMER can this way partially address the problem that continuous emotions are more affected by subjective issue than discrete emotions when annotating. Yang and Chen [31] presented a ranking-based neural network model that ranks a collection of music samples by emotion and determines the emotional intensity of each music sample. Yang and Chen [32] and Chin et al. [33] developed probabilistic approaches to deal with the emotional uncertainty by estimating the distribution of emotional intensities from hand-crafted acoustic features. Markov and Matsui [34] showed that modelling with Gaussian Processes (GP) was more powerful than SVR for arousal/valence regression with hand-crafted acoustic features. Fukayama and Goto [35] evaluated the effectiveness of aggregating multiple GP regressions, each trained with different acoustic features. Wang et al. [36] presented Acoustic Emotion Gaussians (AEGs) that treat the emotional uncertainty by modelling hand-crafted acoustic features as a parametric probability distribution (soft assignment) instead of a single point (hard assignment). Wang et al. [37] proposed a Histogram Density Mixture (HDM) model that quantises the arousal/valence space into cells and extracts latent histograms representing characteristic emotion distributions over cells based on hand-crafted acoustic features. Han et al. [38] proposed a geometric approach to classify each example into specific regions of the arousal/valence space by estimating its distance and angle from the origin. Wang et al. [39] developed a MER system for 34 emotional categories based on Hierarchical Dirichlet Process Mixture Model (HDPMM) that links emotion classes using the property of sharing components in the HDPMM.

To the best of our knowledge, relation modelling approaches have so far exclusively relied on feature engineering, and not yet been used with high-level features obtained by feature learning. On the other hand, our CMER-CL approach uses high-level acoustic features based on VGGish, and projects emotional intensities into an embedding space, which enables us to extract high-level feature representations for emotions.

**E2M**: E2M has not been explored as extensively as M2E in the literature. Kuo et al. [40] developed a model for emotion-based film-music recommendation using a music affinity graph which represents the relationship between the associated acoustic features and query emotions. Ruxanda et al. [41] developed an algorithm for dimensionality reduction of emotion-related acoustic features to effectively identify high-dimensional acoustic features for an emotion. Deng et al. [42] proposed an E2M approach based on the assumption that emotions expressed in music listened to in the past have an influence on the user at present. Yang et al. [43] developed an emotion-based music recognition system that firstly predicts the arousal and valence of each music sample using an M2E model, and then identifies music samples by calculating distances between predicted emotions and user’s input emotion.

One main reason for the scarcity of E2M research is that the existing acoustic features associated with emotions are high dimensional [41], and thus not easy to predict directly from emotions using regression. In addition, the aforementioned E2M approaches use raw emotional intensities to link music and emotion, and are therefore potentially affected by the emotional uncertainty. Alternatively, our CMER-CL approach based on the CCA and KL-divergence losses can take into account the emotional uncertainty.

**Cross-modal recognition**: Cross-modal recognition approaches using embeddings have attracted much attention as techniques that can perform effective bidirectional recognition between different modalities (e.g., image, text and audio). Related to audio processing, some researchers explored cross-modal recognition between audio and image [44], [45] as well as between audio and text (lyrics) [46]. But, to the best of our knowledge, no existing work addresses cross-modal recognition between audio and emotion except our previous study [47], where MultiLayer Perceptrons (MLPs)
trained with the CCA loss are used to compute embeddings of music samples and emotions. This paper is an extension of our previous study by adopting RNNs in addition to MLPs, devising a composite loss that combines the CCA and KL-divergence losses, and conducting significantly deeper analysis of experimental results.

3 CMER-CL APPROACH

Fig. 2 shows an overview of our CMER-CL approach. First, a music sample is converted into a sequence of acoustic features \( X^{(m)} = x^{(m)}_1, \ldots, x^{(m)}_{T_m} \) of length \( T_m \). Here, \( x^{(m)}_t \in \mathbb{R}^{D^{(m)}} \) is a \( D^{(m)} \)-dimensional feature vector at time \( t \) for \( 1 \leq t \leq T_m \). In our implementation, VGGish produced by Google [29] is used to segment every music sample with a sampling rate of 44.1kHz into segments of 0.96 seconds, and then \( x^{(m)}_t \) is extracted as a 128-dimensional vector (i.e., \( D^{(m)} = 128 \)) from each segment.

The emotion associated with the music sample is represented as a sequence \( X^{(e)} = x^{(e)}_1, \ldots, x^{(e)}_{T_e} \) of length \( T_e \) where \( x^{(e)}_t \in \mathbb{R}^{D^{(e)}} \) is a \( D^{(e)} \)-dimensional feature vector containing characteristics of the emotion at time \( t \) for \( 1 \leq t \leq T_e \). In our setting, \( x^{(e)}_t \) is defined as a two-dimensional vector (i.e., \( D^{(e)} = 2 \)) indicating arousal and valence intensities recorded with a sampling rate of 2Hz. Unlike \( X^{(m)} \), we do not perform feature extraction on the raw arousal/valence intensities and use the latter directly as \( X^{(e)} \). This is because we consider that only two types of intensities recorded with a low sampling rate have relatively simple characteristics. Note that \( X^{(e)} \) is called an "arousal/valence sequence" in the following discussions.

It is cumbersome to directly project \( X^{(m)} \) and \( X^{(e)} \) into an embedding space because they are sequences of different lengths \( T_m \) and \( T_e \). Thus, as shown in Fig. 2 (a) and (b), music and emotion encoders are used to transform \( X^{(m)} \) and \( X^{(e)} \) into vectors \( \phi^{(m)} \in \mathbb{R}^{D^{(cca)}} \) and \( \phi^{(e)} \in \mathbb{R}^{D^{(cca)}} \), respectively. Each of \( \phi^{(m)} \) and \( \phi^{(e)} \) is a high-level feature that effectively summarises the features in \( X^{(m)} \) or \( X^{(e)} \) and their temporal relations. We use either an MLP or RNN based on bidirectional Gated Recurrent Unit (GRU) [48], [49] as music and emotion encoders as described in Section 3.1.

Then, \( \phi^{(m)} \) and \( \phi^{(e)} \) are projected into an embedding space \( C^{(cca)} \) of dimensionality \( D^{(cca)} \) using different Fully Connected (FC) layers with linear activation. The embeddings for \( \phi^{(m)} \) and \( \phi^{(e)} \) in \( C^{(cca)} \) are denoted by \( \phi^{(m)} \in \mathbb{R}^{D^{(cca)}} \) and \( \phi^{(e)} \in \mathbb{R}^{D^{(cca)}} \), respectively. In addition, two branches of FC layers are used to transform \( \phi^{(m)} \) into a mean vector \( \mu^{(m)} \in \mathbb{R}^{D^{(kl)}} \) and a covariance matrix \( \Sigma^{(m)} \in \mathbb{R}^{D^{(kl)} \times D^{(kl)}} \). This defines an additional embedding for \( \phi^{(m)} \) as a multivariate Gaussian distribution \( \mathcal{N}(\mu^{(m)}, \Sigma^{(m)}) \) in another embedding space \( C^{(kl)} \) of dimensionality \( D^{(kl)} \).

Considering the expensive computational cost to process multivariate Gaussian distributions, we assume that each dimension is independent based on the standard practice of the literature [50], [51]. Thus, \( \mathcal{N}(\mu^{(m)}, \Sigma^{(m)}) \) is reduced to \( \mathcal{N}(\mu^{(m)}, \sigma^{(m)}) \) by replacing \( \Sigma^{(m)} \) with the variance vector \( \sigma^{(m)} \in \mathbb{R}^{D^{(kl)}} \) representing the variance in each dimension. Similarly, \( \phi^{(e)} \) is converted into \( \mathcal{N}(\mu^{(e)}, \sigma^{(e)}) \) in \( C^{(kl)} \) using two branches of FC layers. Under the above-mentioned setting, CMER-CL trains the music and emotion encoders and the six branches of FC layers by jointly minimising the CCA loss between \( \phi^{(m)} \) and \( \phi^{(e)} \) and the KL-divergence loss between \( \mathcal{N}(\mu^{(m)}, \sigma^{(m)}) \) and \( \mathcal{N}(\mu^{(e)}, \sigma^{(e)}) \), as illustrated in Fig. 2 (c).

The following sections describe encoding of music samples and emotions, and more details of the training process. The dimensionalities \( D^{(m)}_v, D^{(e)}_v, D^{(cca)}_v \) and \( D^{(kl)}_v \) are hyper-parameters of CMER-CL whose specific values are provided in Section 4.3.

3.1 Music and emotion encoders

For the music encoder, two types of neural networks were tested: an MLP and an RNN using bidirectional GRU [48], [49]. When the former is used, a mean feature vector \( \bar{x}^{(m)} \) is computed by averaging \( x^{(m)}_1, \ldots, x^{(m)}_{T_m} \) in \( X^{(m)} \), and fed into the MLP which performs several non-linear transformations on \( \bar{x}^{(m)} \) to output \( v^{(m)} \). The RNN using bidirectional GRU computes two types of \( \bar{h}^{(m)} \)-dimensional hidden states \( \bar{h}^{(m)}_t \in \mathbb{R}^{D^{(h)}} \) and \( \bar{h}^{(m)}_t \in \mathbb{R}^{D^{(h)}} \) that represent temporal characteristics of \( X^{(m)} \) in the forward and backward directions, respectively. Roughly speaking, \( \bar{h}^{(m)}_t \) is computed by recursively aggregating \( x^{(m)}_t \) at the current time \( t \) and \( \bar{h}^{(m)}_{t-1} \) obtained at the previous time \( t - 1 \). Letting \( f \) be a function for the recursive aggregation, \( \bar{h}^{(m)}_t \) is described as \( \bar{h}^{(m)}_t = f(x^{(m)}_t, \bar{h}^{(m)}_{t-1}) \) [48]. In contrast, \( \bar{h}^{(m)}_t \) in the backward direction is computed by aggregating \( x^{(m)}_t \) and \( \bar{h}^{(m)}_{t+1} \) at the next time \( t + 1 \), that is,
The vector obtained by concatenating \( \vec{h}_T(m) \) and \( \vec{h}_I(m) \) is a high-level feature expressing bidirectional temporal characteristics in \( X(m) \), and is fed into the FC layers to produce a higher-level feature as \( v(m) \).

Our preliminary experiments showed the effectiveness of an RNN using bidirectional GRU as the emotion encoder regardless of datasets. Therefore, a feature vector \( v(e) \) for an arousal/valence sequence \( X(e) \) is extracted the same way as \( v(m) \) when an RNN is used as the music encoder. Finally, the specific values of hyper-parameters like \( D_h(m) \), \( D_h(e) \) for the RNN-based emotion encoder, and the configuration of FC layers are provided in Section 4.3.

3.2 Training with the composite loss

Let \( \mathcal{X} = \{\{X_n(m), X_n(e)\}\}_{n=1}^N \) be a batch consisting of \( N \) pairs of an acoustic feature sequence and an arousal/valence sequence for associated music samples and emotions. And, \( \mathcal{V} = \{\{v(m)_n, v(e)_n\}\}_{n=1}^N \) is a set of feature pairs obtained by feeding \( \{X_n(m), X_n(e)\} \in \mathcal{X} \) to the music and emotion encoders. The CCA loss \( CCA(F) \) is computed by converting \( \mathcal{V} \) into a set of embeddings \( F = \{\phi(m)_n, \phi(e)_n\}\}_{n=1}^N \). In addition, the KL-divergence loss \( KL(\mathcal{G}) \) is calculated by transforming \( \mathcal{V} \) into a set of pairs of multivariate Gaussian distributions \( \mathcal{G} = \{\mathcal{N}(\mu(m)_n, \sigma(m)_n), \mathcal{N}(\mu(e)_n, \sigma(e)_n)\}\}_{n=1}^N \). Our composite loss \( CL(F, \mathcal{G}) \) combines \( CCA(F) \) and \( KL(\mathcal{G}) \) as follows:

\[
CL(F, \mathcal{G}) = \lambda \cdot CCA(F) + (1 - \lambda) \cdot KL(\mathcal{G}) \tag{1}
\]

where \( \lambda \in [0, 1] \) is a weight parameter to balance \( CCA(F) \) and \( KL(\mathcal{G}) \). Details of \( CCA(F) \) and \( KL(\mathcal{G}) \) are described in the following Sections 3.2.1 and 3.2.2.

3.2.1 Correlation-based embedding with CCA

The CCA loss is employed to construct an embedding space \( C(\text{cca}) \) where \( \{\phi(m)_n\}_{n=1}^N \) and \( \{\phi(e)_n\}_{n=1}^N \) are strongly correlated. More specifically, for each dimension of \( C(\text{cca}) \), music and emotion embeddings are linearly correlated with each other irrespective of their actual values. This linear correlation indicates what change in acoustic features (or emotions) would be associated to the corresponding change in emotions (or acoustic features) for each of these dimensions. This allows us to characterise the relationship between music samples and emotions in a way that is independent from actual emotion intensities attributed by individuals, which is useful for addressing inter-subject variations described in Section 1. To extract embeddings capturing complex correlations between music samples and emotions, FC layers are firstly used to refine \( v(m)_n \) and \( v(e)_n \) into a \( D_z(m) \)-dimensional vector \( z(m)_n \in \mathbb{R}^{D_z(m)} \) and a \( D_z(e) \)-dimensional vector \( z(e)_n \in \mathbb{R}^{D_z(e)} \), respectively. The CCA loss is computed on \( z(m)_n \) and \( z(e)_n \).

Let \( z(m)_n \) be a random vector that is sampled from the probability distribution estimated using a set of \( N \) samples \( \{z(m)_n\}_{n=1}^N \), and \( z(e)_n \) be a random vector from the probability distribution estimated using \( \{z(e)_n\}_{n=1}^N \). In addition, let us assume that \( w(m) \in \mathbb{R}^{D_z(m)} \) and \( w(e) \in \mathbb{R}^{D_z(e)} \) are \( D_z(m) \)- and \( D_z(e) \)-dimensional weight vectors to project \( z(m) \) and \( z(e) \) into scalars, respectively. CCA optimises \( w(m) \) and \( w(e) \) so as to maximise the following correlation between \( w(m)^T z(m)_n \) and \( w(e)^T z(e)_n \) [7]:

\[
\rho(w(m)^T z(m)_n, w(e)^T z(e)_n) = \frac{w(m)^T \Sigma_{(me)} w(e)}{\sqrt{w(m)^T \Sigma_{(mm)} w(m)^T} \sqrt{w(e)^T \Sigma_{(ee)} w(e)}} \tag{2}
\]

where \( \Sigma_{(me)} \in \mathbb{R}^{D_z(m) \times D_z(e)} \) is the cross-covariance matrix computed from \( \{z(m)_n, z(e)_n\}_{n=1}^N \) and \( \Sigma_{(mm)} \in \mathbb{R}^{D_z(m) \times D_z(m)} \) and \( \Sigma_{(ee)} \in \mathbb{R}^{D_z(e) \times D_z(e)} \) are the covariance matrices for \( \{z(m)_n\}_{n=1}^N \) and \( \{z(e)_n\}_{n=1}^N \), respectively. In Eq. (2) the quantity to maximise is invariant in scaling of \( w(m) \) and \( w(e) \), so it is possible to focus on the problem where the denominator is equal to 1. In other words, the objective of CCA is to maximise the numerator in Eq. (2) subject to the constraints \( w(m)^T \Sigma_{(mm)} w(m) = 1 \) and \( w(e)^T \Sigma_{(ee)} w(e) = 1 \).

The CCA approach described above can be re-applied independently on each dimension of \( C(\text{cca}) \). For this, \( D(\text{cca}) \) pairs of weight vectors \( \{(w_d^m, w_d^e)\}_{d=1}^D \) are found to maximise the sum of correlations between \( w_d^m)^T z(m)_n \) and \( w_d^e)^T z(e)_n \). In other words, letting \( W(m)_d \in \mathbb{R}^{D_z(m) \times D(\text{cca})} \) be a matrix where each column is \( w_d^m \), \( \text{CCA}(\text{m}) \) forms a \( (\text{cca}) \)-dimensional embedding \( \phi(m)_n \). Similarly, \( W(e)_d \in \mathbb{R}^{D_z(e) \times D(\text{cca})} \) where each column is \( w_d^e \) is defined to create \( \phi(e)_n = W(e)^T z(e)_n \). From this perspective, the general CCA maximises the sum of correlations each computed for one dimension of \( \phi(m) \) and \( \phi(e) \). Past work has shown that the batch optimisation of \( \{(w_d^m, w_d^e)\}_{d=1}^D \) can be done by solving the following constrained optimisation problem [7]:

\[
\min \text{CCA}(F) = -\text{tr}(W(m)_d^T \Sigma_{(mm)} W(m)_d) = W(e)^T \Sigma_{(ee)} W(e) = I \tag{3}
\]

where the trace operation (tr) is used to sum up the correlations on each dimension of \( \phi(m) \) and \( \phi(e) \). After obtaining the optimal \( W(m)_d \) and \( W(e)_d \), the correlation-based embedding for \( z(m)_n \) of a music sample and the one for \( z(e)_n \) of an emotion are computed as \( \phi(m)_n = W(m)^T z(m)_n \) and \( \phi(e)_n = W(e)^T z(e)_n \), respectively.

3.2.2 Distribution-based embedding with KL-divergence

The CCA loss analyses only the relation (correlation) between music samples and their associated emotions, but neither the relation of a music sample to non-associated emotions nor the relation of an emotion to non-associated music samples. In addition, \( \phi(m)_n \) and \( \phi(e)_n \) are points in \( C(\text{cca}) \) which is unsuitable for managing the large intra-class variation of acoustic features, as discussed in Section 1. To address these issues, the KL-divergence loss \( KL(\mathcal{G}) \) is used to build an embedding space \( C(\mathcal{G}) \) that attempts to fulfil the following conditions: 1) a music sample and its associated emotion are projected as multivariate Gaussian distributions \( \mathcal{N}(\mu(m)_n, \sigma(m)_n^2) \) and \( \mathcal{N}(\mu(e)_n, \sigma(e)_n^2) \) which are similar to each other; 2) a music sample and its non-associated emotion are projected as dissimilar distributions \( \mathcal{N}(\mu(m)_n, \sigma(m)_n^2) \) and \( \mathcal{N}(\mu(e)_n, \sigma(e)_n^2) \) (\( n \neq n' \)). Similarly, an emotion and its non-associated music sample are transformed into dissimilar distributions \( \mathcal{N}(\mu(e)_n, \sigma(e)_n^2) \) and \( \mathcal{N}(\mu(m)_n, \sigma(m)_n^2) \).
For simplicity, \( N(\mu(m), \sigma_n(m)) \) and \( N(\mu(e), \sigma_n(e)) \) are abbreviated into \( N_{n(m)} \) and \( N_{n(e)} \), respectively. In addition, we use the term positive pair to indicate a pair of \( N_{n(m)} \) and \( N_{n(e)} \) obtained for a music sample and its associated emotion. On the other hand, a negative pair expresses a pair of \( N_{n(m)} \) and \( N_{n(e)} \) or a pair of \( N_{n(m)} \) and \( N_{n(e)} \), consisting of non-associated music sample and emotion. Note that by following the standard of cross-modal retrieval [8], [52], we consider that a music sample and an emotion whose indices are the same form a positive pair, and any other pair is a negative pair.

The aforementioned conditions for \( C_{kl} \) can be formulated using a triplet \( (N_{n(m)}, N_{n(e)}, N_{n(m)}) \):

\[
\psi(N_{n(m)}, N_{n(e)}) \leq \alpha + \psi(N_{n(m)}, N_{n(e)}),
\]

where \( \psi(\cdot, \cdot) \) represents a distance between two distributions. Additionally, \( \alpha > 0 \) is a margin hyper-parameter which determines how far the difference between the distance for the positive pair \( N_{n(m)} \) and the one for the negative pair \( N_{n(m)} \) is allowed to be. Eq. (4) uses \( N_{n(m)} \) as an anchor and checks whether its distance to \( N_{n(e)} \) is sufficiently smaller than its distance to \( N_{n(e)} \). Similarly, another triplet \( (N_{n(m)}, N_{n(e)}, N_{n(m)}) \) can define the distance condition using \( N_{n(e)} \) as an anchor:

\[
\psi(N_{n(e)}, N_{n(m)}) \leq \alpha + \psi(N_{n(e)}, N_{n(m)}).
\]

For each positive pair \( (N_{n(m)}, N_{n(e)}) \) in \( G \), \( KL(G) \) examines the distance conditions in Eqs. 4 and 5. Specifically, the following ranking loss \( r(N_{n(m)}, N_{n(e)}) \) is defined by combining two hinge losses as follows:

\[
r(N_{n(m)}, N_{n(e)}) = \sum_{n' \neq n} \left[ \max\left\{ 0, \psi(N_{n(m)}, N_{n(e)}) - \alpha - \psi(N_{n(m)}, N_{n(e)}) \right\} \right]
+ \sum_{n' \neq n} \left[ \max\left\{ 0, \psi(N_{n(e)}, N_{n(m)}) - \alpha - \psi(N_{n(e)}, N_{n(m)}) \right\} \right],
\]

where the first term becomes zero if all the negative pairs defined using \( N_{n(m)} \) as an anchor lead to distances that are greater than the distance between the positive pair by more than \( \alpha \). The second term also checks a similar distance condition using \( N_{n(e)} \) as an anchor. This way \( r(N_{n(m)}, N_{n(e)}) \) indicates how small \( \psi(N_{n(m)}, N_{n(e)}) \) is relative to \( \psi(N_{n(m)}, N_{n(e)}) \) and \( \psi(N_{n(m)}, N_{n(e)}) \) defined for all the negative pairs.

To compute \( r(N_{n(m)}, N_{n(e)}) \), the KL-divergence is employed as a distance \( \psi(\cdot, \cdot) \) between two multivariate Gaussian distributions \( N(\mu_1, \sigma_1) \) and \( N(\mu_2, \sigma_2) \) in \( C_{kl} \) of dimensionality \( D_{kl} \), and is computed as follows:

\[
\psi(N(\mu_1, \sigma_1), N(\mu_2, \sigma_2)) =
\frac{1}{2} \left\{ \sum_{d=1}^{D_{kl}} \frac{\sigma_{1,d}^\prime}{\sigma_{2,d}} - D_{kl} + \ln \frac{\prod_{d=1}^{D_{kl}} \sigma_{2,d}}{\prod_{d=1}^{D_{kl}} \sigma_{1,d}} + \sum_{d=1}^{D_{kl}} \frac{(\mu_{2,d} - \mu_{1,d})^2}{\sigma_{2,d}^2} \right\},
\]

where \( \mu_1 \) and \( \sigma_1 \) are expanded as \( (\mu_{1,1}, \cdots, \mu_{1,D_{kl}})^T \) and \( (\sigma_{1,1}, \cdots, \sigma_{1,D_{kl}})^T \), respectively. Similarly, \( \mu_2 \) and \( \sigma_2 \) are also expanded.

Finally, \( KL(G) \) is defined as the sum of \( r(N_{n(m)}, N_{n(e)}) \) for all the positive pairs in \( G \). Hence, the minimisation of \( KL(G) \) can lead both music and emotion encoders and FC layers to learn parameters so that the KL-divergence between each positive pair is minimised while maximising the KL-divergence between each negative pair.

### 3.3 Testing CMER-CL in M2E and E2M

We evaluate CMER-CL in the framework of M2E and E2M that are formulated as a retrieval task. In M2E, letting \( q \) denote a query music sample, \( J \) test emotions are analysed to identify the one associated with the query music sample. The trained music model consisting in the music encoder and three branches of FC layers, is used to encode the query music sample into its correlation-based embedding \( \phi_q(m) \) and distribution-based embedding \( \lambda_q(m) \). On the other hand, the trained emotion model consisting in the emotion encoder and three branches of FC layers, is used to convert the \( j \)th test emotion \( (1 \leq j \leq J) \) into its correlation-based embedding \( \phi_j(e) \) and distribution-based embedding \( \lambda_j(e) \). The similarity between the query music sample and the \( j \)th test emotion is computed as the weighted sum of the correlation-based similarity between \( \phi_q(m) \) and \( \phi_j(e) \) and the negative KL-divergence between \( \lambda_q(m) \) and \( \lambda_j(e) \), which are weighted by \( \lambda \) and \( 1 - \lambda \) based on Eq. (1), respectively. Then, \( J \) test emotions are sorted by decreasing similarities to the query music sample. The performance of M2E is evaluated by examining whether the test emotion associated with the query music sample is ranked at a high position or not.

Finally, for M2E, the correlation-based similarity \( \rho_{\text{sim}}(\phi_q(m), \phi_j(e)) \) between \( \phi_q(m) = (\phi_{q,1}, \cdots, \phi_{q,D_{(cma)}})^T \) and \( \phi_j(e) = (\phi_{j,1}, \cdots, \phi_{j,D_{(cma)}})^T \) can be defined as follows: As a reminder, the CCA loss is designed to maximise the correlation on each of \( D_{(cma)} \) dimensions independently. The higher the correlation \( \rho_d \) on the \( d \)th dimension \((1 \leq d \leq D_{(cma)}) \) is, the more linearly aligned embedding values for music samples and emotions in training data (i.e., \( \{\phi_{q,d} = w_q^d(z_n)\}_{n=1}^N \) and \( \{\phi_{j,d} = w_j^d(z_n)\}_{n=1}^N \)) are. Based on this, linear regression is performed to extract the approximation line \( g_d(\cdot) \) that takes as input \( \phi_q(m) \) being the embedding value for the query music sample on the \( d \)th dimension and outputs \( g_d(\phi_q,d) \) being an approximate embedding value for the associated emotion. Thus, the negative of the absolute difference between \( g_d(\phi_q,d) \) and the embedding value \( \phi_j(e) \) for the test emotion is defined as its similarity to the query music sample on the \( d \)th dimension. By summing up such similarities on all the \( D_{(cma)} \) dimensions, \( \rho_{\text{sim}}(\phi_q(m), \phi_j(e)) \) is computed as follows:

\[
\rho_{\text{sim}}(\phi_q(m), \phi_j(e)) = - \sum_{d \in \{d|1 \leq d \leq D, \rho_d \geq P\}} \rho_d \left| g_d(\phi_q,m) - \phi_j(e) \right|,
\]
Similarly to M2E, E2M is performed by encoding a query emotion and test music samples with the trained emotion and music models, respectively. Then, test music samples are sorted by computing their correlation-based similarities and negative KL-divergences to the query emotion. The former are computed by extracting approximation lines, each of which uses the embedding value for the query emotion on one dimension to approximate an embedding value for the associated music sample. The rank of the music sample associated with the query emotion is checked to measure the performance of E2M.

4 Experiments

In this section, we evaluate CMER-CL on two datasets: MediaEval Database for Emotional Analysis in Music (DEAM) [10] and PMEmo [11]. We first present an overview and pre-processing on each dataset, the evaluation metrics, and the implementation details. Then, we present the results of three experiments. The first is an ablation study to validate the composite loss, the second compares CMER-CL to one-way regression baselines, and the last examines the generality of CMER-CL by comparing it to the state-of-the-art MER methods.

4.1 Datasets

DEAM [10] provides 1802 music samples that are free audio source records, and their corresponding arousal/valence sequences where arousal and valence intensities lie in $[-10, 10]$. Each music sample was annotated with arousal and valence intensities every 0.5 seconds by at least 5 subjects through Amazon Mechanical Turk. These intensities were projected into the range $[-1, 1]$ for each subject.

DEAM contains 1744 45-second-long music samples and 58 samples that have durations longer than 45 seconds. The authors of DEAM decided to discard the first 15 seconds of annotations after observing high instabilities due to a high variance in how music samples start. Because of this and the fact that most music samples last only 45 seconds, each music sample is normalised to have a length of 30 seconds by taking the segment starting at 15 seconds and ending at 45 seconds. In addition, for each of arousal and valence, an “average sequence” is created by computing the average value over all subjects at each time. The average sequences for arousal and valence are then concatenated into an arousal/valence sequence $X^{(a)}$. Finally, the 30-second segment corresponding to the paired music sample is extracted.

PMEmo [11] (more specifically PMEmo2019) contains 794 music samples which are the chorus parts of high quality popular pop-songs gathered from the Billboard Hot 100, the iTunes Top 100 Songs (USA) and the UK Top 40 Singles Chart. Each music sample is annotated with arousal and valence intensities between 1 (low) and 9 (high) every 0.5 seconds, and then projected into the range $[0, 1]$. Similarly to DEAM, the first 15 seconds of annotations were discarded by taking into account a large variance in beginnings of music samples. Unlike DEAM, music samples and associated arousal/valence sequences in PMEmo have variable lengths ranging from 0.08 to 73.24 seconds. We decided to select music samples with a total length of at least 7.0 seconds to evaluate in total 701 pairs of a music sample and its associated arousal/valence sequence, which is created by averaging arousal and valence intensities over all subjects at each time.

4.2 Evaluation metrics

Each dataset is split into training and test partitions with a proportion of 8 : 2. Specifically, DEAM is split into training and test partitions containing 1441 and 361 pairs of a music sample and an emotion, respectively. Training and test partitions of PMEmo include 560 and 141 pairs, respectively. A model trained on a training partition is evaluated on the corresponding test partition in the framework of M2E and E2M. Assuming $Q$ pairs of a music sample and an emotion in the test partition, M2E is run $Q$ times using each of $Q$ music samples as a query. Then, $Q$ emotions are sorted in decreasing order of their similarities to the query, and the performance is evaluated by checking the rank of the emotion associated with the query music sample. Similarly, E2M is executed $Q$ times by adopting each of $Q$ emotions as a query and examining the rank of its associated music sample.

In this framework, only one sample (i.e., emotion or music sample) is associated with a query (i.e., query music sample or query emotion). A Mean Reciprocal Rank (MRR) [46] is calculated based on $r_q$ that is the rank of the sample associated with a query $q$ in the sorted list of samples. The MRR is defined as the average of reciprocals of all $r_q$ over $Q$ queries, that is, \[ MRR = \frac{1}{Q} \sum_{q=1}^{Q} \frac{1}{r_q}. \] However, the MRR is biased in the sense that it puts much higher priorities on samples ranked at high positions than those at low positions. For example, $r_q = 1$ leads to a reciprocal of 1 while it is 0.05 for $r_q = 20$. In our case, samples associated with queries are rarely ranked in the very top positions, so only using the MRR makes the performance evaluation unclear. Thus, we additionally employ an Average Rank (AR) that is the average of all $r_q$ over $Q$ queries, namely \[ AR = \frac{1}{Q} \sum_{q=1}^{Q} r_q. \] Using the AR, samples can be equally evaluated regardless of their ranks. Although the median of all $r_q$ is one popular evaluation measure for cross-modal retrieval [52], we use their average to be consistent with the calculation of the MRR. To sum up, our evaluation is based on the MRR and AR that respectively become higher and lower as a better performance is obtained. Finally, all models in each configuration are run 10 times. In each of them, all the parameters in CMER-CL (i.e., parameters of music and emotion encoders and six branches of FC layers in Fig. 2) are randomly initialised, and a dataset is randomly split into training and test partitions with a proportion of 8 : 2. The mean and standard-deviation of MRRs and ARs obtained in 10 runs are reported.

4.3 Implementation details

We tested various combinations of an MLP and RNN for music and emotion encoders on DEAM and PMEmo. To simplify the selection of encoder models, MLPs (or RNNs)
with the same architecture were used regardless of encoder types. We found that for the music encoder, an MLP and RNN performed the best on DEAM and PMEmo, respectively. For the emotion encoder, RNNs are the best on both datasets.

The numbers of layers and units per layer of the MLP and RNNs were chosen by grid search. The MLP consists of five FC layers, each of which performs a non-linear transformation based on units using softplus $\sigma(x) = \log(1 + e^x)$ as their activation function. The number of units in each layer is 256 for the first layer, 512 for the second and third layers, and 1024 units for the fourth and fifth layers. That is, $D^{(m)}_n = 1024$ when the encoder is an MLP. A dropout layer with a dropout rate of 0.5 is inserted between two consecutive layers.

Each RNN based on bidirectional GRU has a single layer with a 512-dimensional hidden state (i.e., $D^{(h)}_0 = D^{(e)}_0 = 512$), and finally outputs a 1024-dimensional vector by concatenating the hidden states obtained in the forward and backward directions. This vector is subsequently passed to an MLP consisting of five FC layers where units use softplus as their activation function. The number of units per FC layer was chosen as 512 for the first three ones, and 1024 for the two last ones (i.e., $D^{(m)}_0 = D^{(e)}_0 = 1024$). A dropout layer with a dropout rate of 0.5 is also added behind all layers except the RNN layer and the output layer.

Regarding the embedding spaces based on the CCA and KL-divergence losses, their dimensionalities are set to $D^{(cos)} = D^{(kl)} = 1024$. Based on our experiments, we recommend to set the threshold for the correlation-based similarity $P$, the margin in the KL-divergence loss $\alpha$ and the combination weight for the composite loss $\lambda$ to default values of $(P, \alpha, \lambda) = (0.4, 1.0, 0.5)$ when testing our approach on a new dataset. It is nevertheless possible to optimise these values on a specific dataset by following the optimisation strategy detailed in our supplemental document. The results in the next subsections were obtained using the optimal hyper-parameters $(P, \alpha, \lambda) = (0.5, 1.0, 0.6)$ on DEAM and $(P, \alpha, \lambda) = (0.7, 2.0, 0.5)$ on PMEmo.

Our CMER-CL model is trained using Adam [53] as the optimiser with an initial learning rate of $1^{-5}$. The model was trained for 5001 and 10001 epochs on DEAM and PMEmo, respectively. We implemented all the codes using TensorFlow library (version 1.15) on a machine equipped with Intel i9-9900K CPU, 64GB RAM, NVIDIA RTX 2080Ti GPU and CUDA version 10.0.

### 4.4 Evaluation of the composite loss

To evaluate the effectiveness of our proposed composite loss (Composite), we compare its performance to the ones individually obtained only using the CCA loss (CCA-Loss) or KL-divergence loss (KL-Loss). In addition, to examine the effectiveness of projecting music samples and emotions as probability distributions, we implement the most popular embedding approach that projects them as points based on their cosine similarities in an embedding space [52]. For this approach, all the configurations of our CMER-CL model are the same except that $\psi^{(m)}$ and $\psi^{(e)}$ from the music and emotion encoders are projected into vectors instead of multivariate Gaussian distributions, and $\psi(\cdot, \cdot)$ in Eq. (6) is replaced with the negative of their cosine similarity. We report both the performance only using the loss based on cosine similarities (Cos-Loss) and the one obtained by the composite loss combining CCA-Loss and Cos-Loss (Composite-C).

The results in the next subsections were obtained using the five losses described previously. For both DEAM and PMEmo, the MRRs and ARs using KL-Loss are better than those using CCA-Loss. This may be due to the fact that CCA-Loss alone only considers the correlation between music samples and emotions, and does not necessarily make sure that music samples and emotions in positive pairs are placed close to each other in the embedding space. On the other hand, KL-Loss assigns music samples and emotions in positive pairs to similar multivariate Gaussian distributions while distinguishing the ones in negative pairs by dissimilar distributions. Furthermore, the performances are significantly improved when using Composite compared to using only KL-Loss or CCA-Loss. This verifies the effectiveness of Composite that simultaneously considers CCA-Loss and KL-Loss. Also, the fact that KL-Loss outperforms Cos-Loss and Composite outperforms Composite-C on both DEAM and PMEmo datasets indicates the effectiveness of distribution-based embeddings compared to point-based ones.

Finally, it can be noted that the performances on PMEmo are significantly better than those on DEAM. This could be attributed to the fact that music samples in PMEmo are more standardised, for instance by including only chorus parts of pop songs, which leads the music encoder to find more specialised feature. In other words, the higher diversity in music samples on DEAM makes CMER on this dataset likely to be more difficult.

### 4.5 Comparison with the baseline models

To the best of our knowledge, no existing cross-modal MER method that can be directly compared to CMER-CL has been...
proposed yet. In addition, all the existing approaches using continuous emotion modelling only perform M2E based on a regression approach to predict real-valued characteristics of the arousal/valence sequence (e.g., the average arousal or valence) for a given music sample [20], [22], [24], [25], [26], [30], [31], [32], [34], [35], [36], [37]. Moreover, no existing method can handle E2M to predict acoustic features of the music sample for a given arousal/valence sequence. Considering the aforementioned state of the current MER research, we define the following regression-based baselines to show the effectiveness of CMER-CL.

**M2E baselines:** Two M2E baselines RegBiGRU-M2E and RegMLP-M2E train a regression model that analyses a query music sample and outputs a two-dimensional emotion vector $\overline{x}^{(e)}$ representing the average arousal and valence for this query music sample. In particular, RegBiGRU-M2E predicts $\overline{x}^{(e)}$ by applying an RNN based on bidirectional GRU to a sequence of acoustic features $X^{(m)}$, while RegMLP-M2E employs an MLP that uses the mean $\overline{x}^{(m)}$ of features in $X^{(m)}$ to compute $\overline{x}^{(e)}$. Both baselines are trained to minimise the Mean Absolute Error (MAE) between the actual arousal/valence sequence $\overline{x}^{(e)}$ computed from the ground-truth mean emotion $\overline{x}^{(e)}$ computed from the actual arousal/valence sequence $\overline{x}^{(e)}$.

In the evaluation, given the $q$th test music sample as a query, we evaluate the trained model by predicting its mean emotion $\overline{x}_q^{(e)}$ and checking whether $\overline{x}_q^{(e)}$ is similar to the ground-truth mean emotion $\overline{x}_q^{(e)}$. To this end, we compute the similarities of $\overline{x}_q^{(e)}$ to the ground-truth mean emotions $\left\{\overline{x}_q^{(e)}\right\}_{t=1}^Q$ for all the $Q$ test music samples. The Absolute Error (AE) between $\overline{x}_q^{(e)}$ and $\overline{x}_q^{(e)}$ is used as their dissimilarity. Then, the ground-truth mean emotions are sorted in ascending order of their AEs to get the rank $r_q$ of $\overline{x}_q^{(e)}$. Finally, $r_q$ is used to calculate an MRR and AR.

**E2M baselines:** Similarly to the M2E baselines, an RNN based on bidirectional GRU (RegBiGRU-E2M) and an MLP model (RegMLP-E2M) are used as E2M baselines to predict a mean acoustic feature $\overline{x}^{(m)}$. RegBiGRU-E2M and RegMLP-E2M take as input an arousal/valence sequence $X^{(e)}$ and the mean vector $\overline{x}^{(e)}$ of $X^{(e)}$, respectively. RegBiGRU-E2M and RegMLP-E2M are trained to minimise the MAE between $\overline{x}^{(m)}$ and the ground-truth mean acoustic feature $\overline{x}^{(m)}$ computed from a sequence of acoustic features $X^{(m)}$. Like M2E, an MRR and AR is computed by predicting $\overline{x}_q^{(m)}$ for the $q$th test emotion, measuring the AEs of $\overline{x}_q^{(m)}$ to the ground-truth mean acoustic features $\left\{\overline{x}_q^{(m)}\right\}_{t=1}^Q$ for all the $Q$ music samples, and check the rank $r_q$ of $\overline{x}_q^{(m)}$.

The baseline models were tuned by grid search to find the hyper-parameters leading to the best performances on each dataset. Details about this hyper-parameter tuning can be found in the supplemental document. Table 2 shows the comparison between the above-mentioned baselines and CMER-CL (referred to as Composite in Table 1). CMER-CL significantly outperforms the baselines based on one-way regression of emotion or acoustic features. This highlights the superiority of cross-modal over one-way regression.

### 4.6 Comparison to the MER state-of-the-art

To evaluate the features learnt by CMER-CL, we performed a comparison of the latter against the state-of-the-art on DEAM and PMEmo. To the best of our knowledge, the CMER problem remains still unexplored in the literature, which makes it difficult to find a past study with which our results can be directly compared. Therefore, we carry out the evaluation on the significantly more popular task of MER.

The MER literature is fairly scattered, with each study carrying out experiments on different datasets, choosing different evaluation metrics and strategies. Our experiments on both DEAM and PMEmo were carried out based on the most commonly used setting, that is, a K-fold cross validation evaluated either using the Root Mean Squared Error (RMSE), the Pearson correlation coefficient $R$ or the coefficient of determination $R^2$.

Our CMER-CL model is trained for $K=10$ folds using the default values of $\alpha = 1$ and $\lambda = 0.5$ (P is only required for a retrieval problem, not a regression one). After training the whole of our CMER-CL model, three vectors obtained from the music model (i.e., $\phi^{(m)}$, $\mu^{(m)}$ and $\sigma^{(m)}$ in Fig. 2) are used to train a soft-margin Support Vector Regression model (C-SVR) with Radial Basis Function (RBF) kernel that attempts to predict the arousal and valence intensities associated with a music sample that is input to the music model. Three different configurations for the input to C-SVR are tested: $\phi^{(m)}$ used alone (also referred to as CMER-CL (ccl)), $\mu^{(m)}$ and $\sigma^{(m)}$ concatenated together (CMER-CL (k)), and all the three vectors concatenated together (CMER-CL (all)). On DEAM, the target to predict was chosen as the mean emotion vector of an arousal/valence sequence $X^{(e)}$, while predicting the last emotion vector of value of $X^{(e)}$ on PMEmo. The hyper-parameters of the C-SVR (soft-margin and kernel parameters) were optimised by maximising the average $R^2$ after grid search.

Table 3 shows the results obtained for arousal and valence prediction on DEAM and PMEmo. The learnt features $\phi^{(m)}$, $\mu^{(m)}$ and $\sigma^{(m)}$ can compete with the state-of-the-art for MER. This indicates that our CMER-CL model can still yield proper MER performances. Curiously, $\phi^{(m)}$, $\mu^{(m)}$ and $\sigma^{(m)}$ yield average results for arousal prediction, and notably good ones for valence prediction which is commonly considered as the most difficult of the two problems. All the three tested combinations of $\phi^{(m)}$, $\mu^{(m)}$ and $\sigma^{(m)}$ return
5 Detailed analysis

MRRs and ARs are global metrics that only depend on the rank \( r_q \) of the music sample or emotion associated with a query. It is also desirable to check the relevances of the top-ranked music samples (or emotions) to the query. For this, we compute an average cosine similarity that averages the cosine similarities between the mean acoustic feature of the query music sample and the ones associated with the top 5% emotions detected by CMER-CL in M2E, or between the mean emotion of the query emotion and the ones associated with the top 5% music samples in E2M. A high average cosine similarity means that CMER-CL can recognise music samples that express emotions similar to a query emotion, or emotions expressed in music samples which are acoustically similar to a query music sample.

In what follows, we in particular present the analysis for E2M since the mean emotion for each music sample is two-dimensional and can be interpreted easily. It should be noted that arousal/valence intensities are in \([-1, 1]\) and \([0, 1]\) for DEAM and PMEmo respectively, meaning that average cosine similarities range between -1 and 1 on DEAM, and 0 and 1 on PMEmo. Fig. 3 shows the average cosine similarities for DEAM and PMEmo. In the bar graphs in the left side of Fig. 3 (a) and (b), each query emotion on the horizontal axis is sorted based on the rank \( r_q \) of its associated music sample. That is, the more to the left a query emotion is, the higher its ground truth music sample was ranked for E2M, meaning that the music sample associated with the query emotion was well recognised.

As shown in the bar graphs of Fig. 3 (a) and (b), average cosine similarities obtained on both DEAM and PMEmo are fairly high (close to 1), showing that the top 5% recognised music samples are relevant to most query emotions regardless of the ranks of their ground-truth music samples. More specifically, the median of these average cosine similarities is 0.873 for DEAM and 0.994 for PMEmo (the reason for the very high average cosine similarities on PMEmo is provided in the supplemental document). In addition, the box plots in the right side of Fig. 3 (a) and (b) show the variations in the average cosine similarities. Here, at least 75 percent of all the average cosine similarities are higher than the 25th percentile (first quartile). The fact that the 25th percentile for DEAM and PMEmo are 0.692 and 0.989 respectively, indicates that CMER-CL is able to robustly recognise music samples associated to highly similar emotions to a query emotion. In other words, even if the music sample associated to a query emotion was ranked at a low position, the top 5% music samples recognised by CMER-CL still exhibit emotions close to the query emotion. Nevertheless, average cosine similarities for some query emotions in DEAM are low, indicating room for improvement in the future.

A similar study by computing the average cosine similarity between the acoustic feature of a query music sample and those of music samples associated with the top 5% emotions in M2E showed similarly good performances. Figures showing such average cosine similarities can be found in the supplemental document, and the medians of average cosine similarities on DEAM and PMEmo are 0.753 and
6 Conclusion and Future Work

In this paper, we introduced a Cross-modal Music Emotion Recognition using Composite Loss (CMER-CL) approach that projects music samples and emotions into embedding spaces, in order to consider both general emotional categories and fine-grained discrimination within each category. In particular, to deal with the emotional uncertainty, CMER-CL uses the composite loss consisting of the CCA loss to maximise the correlation between music samples and their associated emotions in an embedding space, and the KL-divergence loss to project them as similar multivariate Gaussian distributions in another embedding space. The experimental results on DEAM and PMEmo validate the effectiveness of the composite loss, cross-modal approach and features learned by CMER-CL. In addition, detailed analysis on CMER-CL’s results demonstrates that it can robustly recognise reasonable music samples (or emotions) even when failing to identify the ground-truth ones.

To further improve the performance of CMER-CL, we aim to extend the music and emotion encoders by pre-training them with self-supervised learning [58] which can learn underlying feature representations using unlabelled data. We also plan to adopt a self-attention layer [59] which can capture long-term dependencies of features and have been reported to be superior to RNNs in various areas.

Finally, the codes (and the instruction of data usage) used in this paper are available on our GitLab repository4, in order for other researchers to reproduce the results and extend the current CMER-CL more easily.

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Cross-modal Music Emotion Recognition Using Composite Loss-based Embeddings (SUPPLEMENTAL DOCUMENT)

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Abstract—This supplemental document of our paper titled Cross-modal Music Emotion Recognition Using Composite Loss-based Embeddings presents experimental details that are excluded from the main body of our paper due to space limitations. In particular, we describe hyper-parameter tuning for our proposed approach, named Cross-modal Music-Emotion Recognition using Composite Loss (CMER-CL), as well as the comparison approaches like Cos-Loss, Composite-C and baselines involved in the comparative studies in Sections 4.2 and 4.3 of our paper. Furthermore, additional insights and results are provided for the detailed analysis in Section 5 of our paper. Finally, the computational cost of CMER-CL is discussed.

1 HYPER-PARAMETER TUNING FOR CMER-CL

This section presents how to tune CMER-CL’s hyper-parameters, especially $P \in [0,1]$ used in the correlation-based similarity to filter out useless dimensions characterised by weak correlations between music samples and their associated emotions, $\alpha \in \mathbb{R}^+$ used in the KL-divergence loss to handle the margin between associated music-emotion pairs and non-associated ones, and $\lambda \in [0,1]$ to control the combination weights of the CCA and KL-divergence losses. Only using either of these losses, an embedding space can be constructed to perform M2E (Music to Emotion) to recognise the emotion expressed in a query music sample, and E2M (Emotion to Music) to identify the music sample matching with a query emotion. Thus, $P$ is firstly tuned based on the performances of M2E and E2M only using the CCA loss. Similarly, $\alpha$ is tuned by carrying out M2E and E2M only with the KL-divergence loss. Finally, $\lambda$ is tuned based on M2E and E2M by combining the CCA and KL-divergence losses that are configured by the separately optimised $P$ and $\alpha$, respectively.

1.1 Tuning $P$

Fig. 1 shows various performances obtained only using the CCA loss configured by different values of $P$. As is the case with our paper, a performance is measured by a Mean Reciprocal Rank (MRR) and an Average Rank (AR). A good performance is indicated by a high MRR and a low AR. In other words, if $P$ is large, only a small number of dimensions characterised by correlations higher than it are used to compute correlation-based similarities. For each dataset, the optimal value of $P$ is selected as the one that yields the best “overall” performance by considering both M2E and E2M performances. We provide an example of how to select the optimal $P$ value on DEAM by referring to Fig. 1. As seen from this figure, although $P = 0.2$ yields the highest median of MRRs in M2E, $P = 0.5$ and 0.6 both lead to the highest median of MRRs in E2M and the lowest embedding space based on the CCA loss independent of the choice of $P$, 10 spaces are firstly constructed by random initialisation of all parameters in CMER-CL (i.e., parameters of music and emotion encoders and the ones of six branches of FC layers in Fig. 2 of our paper), and random splitting of a dataset into training and test partitions with a proportion fixed to $8:2$. Then, every value of $P$ is used to filter out useless dimensions in each of these 10 embedding spaces to get 10 performances.

To determine a range of values to be tested for $P$, we check the maximum correlations among 1024 dimensions of each embedding space. In particular, among the 10 embedding spaces constructed for each dataset, the maximum correlation is 0.783 for DEAM and 0.719 for PMEmo, respectively. We test values between 0 and the maximum correlation with increments of 0.1 for $P$.

In each graph of Fig. 1, the larger $P$ is, the smaller the number of dimensions used in the correlation-based similarity is. In other words, if $P$ is large, only a small number of dimensions characterised by correlations higher than it are used to compute correlation-based similarities. For each dataset, the optimal value of $P$ is selected as the one that yields the best “overall” performance by considering both M2E and E2M performances. We provide an example of how to select the optimal $P$ value on DEAM by referring to Fig. 1. As seen from this figure, although $P = 0.2$ yields the highest median of MRRs in M2E, $P = 0.5$ and 0.6 both lead to the highest median of MRRs in E2M and the lowest

1. Since the KL-divergence loss is always zero in this setting, the four branches of FC layers to produce mean and variance vectors of multivariate Gaussian distributions are not trained.

2. When the composite loss is used, the maximum correlations for 10 CCA-based embedding spaces increase to 0.856-0.857 and 0.9995-0.9997 for DEAM and PMEmo, respectively. This is possibly due to more generalised music and emotion encoders being trained by exploiting both the CCA and KL-divergence losses, which leads to higher-quality embedding spaces. Thus, better CMER-CL’s performances than those reported in this paper might be obtained by carrying out grid search on $P$, $\alpha$ and $\lambda$. But, due to its expensive computational cost, we opt to separately tune these hyper-parameters in this paper.

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medians of ARs in both M2E and E2M. Thus, \( P = 0.5 \) or 0.6 can be considered as optimal on DEAM. In this case in particular, \( P = 0.5 \) is selected after observing that its neighbouring value \( P = 0.4 \) yields higher performances than \( P = 0.7 \) neighbouring \( P = 0.6 \). For PMEmo, \( P = 0.7 \) is chosen because of its significantly higher performances on E2M compared to the other \( P \) values. It can be noted that the performances of CCA-Loss in the comparative study in Section 4.4 of our paper are nothing but the ones that are obtained only using the CCA loss based on the aforementioned optimal \( P \) values.

### 1.2 Tuning \( \alpha \)

Unlike \( P \) that is bounded, the margin \( \alpha \) can theoretically take any positive value. We decided to test values between 0 and 1.5 with increments of 0.1, and powers of 2 between 2 and 128. Using the same box plot format as Figs. 1, 2 and 3, Fig. 4 displays various of the former. The marginal difference in hyper-parameter

### 2 Hyper-parameter Tuning for Composite-C

In this section, we tune hyper-parameters of the two comparison methods, Cos-loss and Composite-C, used in the comparative study in Section 4.4 of our paper. Cos-Loss performs point-based embeddings using the loss based on cosine similarities between music samples and emotions [1], and is used to examine the effectiveness of our proposed KL-Loss implementing distribution-based embeddings. Both of Cos-Loss and KL-Loss construct an embedding space in the same ranking loss framework that involves \( \alpha \) to control the margin between associated music-emotion pairs and non-associated ones. Thus, \( \alpha \) for Cos-Loss is tuned in the same manner as \( \alpha \) for KL-Loss in Section 1.2.

Similarly to Composite, Composite-C is characterised by \( \lambda \) that handles the combination weights of CCA-Loss and Cos-Loss. However, while Cos-Loss is based on normalised cosine similarities ranging from -1 to 1, KL-divergences used in KL-Loss lie in a much wider range like on average about 5.1 for DEAM and 423.7 for PMEmo. It should be noted that \( \lambda \) impacts the range of correlation-based similarities because it determines the number of dimension-wise similarities counted to compute an overall similarity, as seen from Eq. (8) in our paper. Thus, both \( P \) and \( \lambda \) can be tuned to balance the combination of CCA-Loss and Cos-Loss, and the \( P \) values found in Fig. 1 for Composite may not be suitable for Composite-C. Consequently, after selecting the optimal \( \alpha \) for Cos-Loss, grid search on \( P \) and \( \lambda \) is carried out to avoid missing an effective combination of CCA-Loss and Cos-Loss for Composite-C. This grid search for Composite-C is more exhaustive and favourable than the separate optimisation of \( P \) and \( \lambda \) employed for Composite.

#### 2.1 Tuning \( \alpha \) of Cos-Loss

The same values as in Section 1.2 were tested to tune \( \alpha \) for Cos-Loss, i.e., values between 0 and 1.5 with increments of 0.1, and powers of 2 between 2 and 128. Using the same box plot format as Figs. 1, 2 and 3, Fig. 4 displays various

| Table 1: Performance comparison between CMER-CL using the optimal hyper-parameter values (Composite) and CMER-CL using the default ones (Composite-d) |
|---|---|---|---|
| ModelType | M2E | E2M | MRR | AR | MRR | AR |
| Composite | 0.541 ± 0.052 | 3.8 ± 0.6 | 0.542 ± 0.051 | 3.8 ± 0.5 |
| Composite-d | 0.539 ± 0.037 | 4.0 ± 0.5 | 0.497 ± 0.037 | 4.5 ± 0.6 |
Fig. 1. Transitions of performances (MRRs and ARs) obtained only using the CCA loss that is configured by different values of $P$. The optimal $P$ value is selected as 0.5 and 0.7 for DEAM and PMEmo, respectively.
Fig. 2. Transitions of performances (MRRs and ARs) obtained only using the KL-divergence loss that is configured by different values of $\alpha$. The optimal $\alpha$ value is selected as 1.0 and 2.0 for DEAM and PMEmo, respectively.
Fig. 3. Transitions of CMER-CL performances (MRRs and ARs) obtained by different $\lambda$ values, each of which is used to combine the CCA and KL-divergence losses configured by the optimal $P$ and $\lambda$ values found from Figs. 1 and 2, respectively. The optimal $\lambda$ value is selected as 0.6 and 0.5 for DEAM and PMEmo, respectively.
performances on DEAM and PMEmo only using \textit{Cos-Loss} configured by different values of $\alpha$. By following the aforementioned criteria addressing the best overall performance on M2E and E2M, $\alpha = 0.3$ for DEAM and $\alpha = 0.1$ for PMEmo are chosen as the optimal values. The performances of \textit{Cos-Loss} configured with these $\alpha$ values are used in the comparative study in Section 4.4 of our paper.

2.2 Tuning $P$ and $\lambda$ of Composite-C by Grid Search

Fig. 5 presents grid search results on different pairs of $P$ and $\lambda$ values, where $P$ ranges between 0 and the maximum correlation on the considered dataset with an increment of 0.1 and $\lambda \in \{0.1, \cdots 0.9\}$. Each bar in a three-dimensional bar graph indicates the mean of 10 performances (i.e., MRRs or ARs) obtained using a pair of the $P$ and $\lambda$ values. Like the hyper-parameter tuning previously described, these 10 performances are acquired by random initialisation of all parameters in Composite-C and random $8:2$ split of a dataset into training and test partitions. In addition, the computational cost of grid search can be reduced by considering that $P$ is only related to the test process as described in Section 1.1. More specifically, after training 10 Composite-C models (i.e., music and emotion encoders, and embedding spaces based on CCA-Loss and Cos-Loss) using the $\alpha$ value optimised in the previous section and a specific $\lambda$ value, their test processes are repeatedly run to obtain 10 performances for each of the different $P$ values. Note that to make visual interpretation of the results easier, the axes of $\lambda$ and $P$ are depicted in the horizontal and depth directions for the MRR histograms, while the directions of these axes are swapped for the AR histograms in Fig. 5.

As indicated by the red arrows in Fig. 5, the best overall performance is attained using $P = 0.9$ and $\lambda = 0.7$ for DEAM and $P = 0.9$ and $\lambda = 0.1$ for PMEmo. The performances obtained using these optimal $P$ and $\lambda$ are reported as the ones of Composite-C in the comparative study in Section 4.4 of our paper. The fact that the Composite-C performances are significantly worse than the ones of Composite verifies the effectiveness of our proposed CMER-CL based on distribution-based embeddings.

3 Tuning baselines

We explain how to tune the hyper-parameters of the regression-based baselines, RegMLP-M2E, RegMLP-E2M, RegBiGRU-M2E and RegBiGRU-E2M, used in Section 4.5 of our paper. RegMLP-M2E and RegMLP-E2M employ an MLP, and RegBiGRU-M2E and RegBiGRU-E2M adopt an RNN based on bidirectional GRU. The inputs of RegBiGRU-M2E and RegMLP-M2E are a sequence $X^{(m)}$ of 128-dimensional acoustic features extracted by VGGish, and their mean $\bar{x}^{(m)}$, respectively. The outputs of these baselines are a 2-dimensional emotion vector $\bar{\hat{e}}^{(e)}$ that is a prediction of the average arousal and valence for the music sample corresponding to $X^{(m)}$ or $\bar{x}^{(m)}$. In contrast, RegBiGRU-E2M and RegMLP-E2M take as input an arousal/valence sequence $X^{(e)}$ of two-dimensional emotion vectors, and their mean $\bar{\hat{e}}^{(e)}$, respectively. These baselines output a 128-dimensional acoustic feature $\bar{\hat{x}}^{(m)}$ as a prediction of the mean acoustic feature for the music sample associated with $X^{(e)}$ or $\bar{\hat{e}}^{(e)}$. Below, we describe hyper-parameter tuning for hidden layers used between the above-mentioned inputs and outputs.

Using the same music and emotion encoder architectures as the ones optimised for CMER-CL (as reported in Section 4.3 of our paper) did not yield satisfactory performances for the regression-based baselines. More specifically, the M2E baseline obtained an MRR of $0.035 \pm 0.001$ and AR of $109.9 \pm 0.3$ on DEAM, and an MRR of $0.071 \pm 0.004$ and AR of $46.5 \pm 0.7$ on PMEmo. The E2M baseline yielded an MRR of $0.018 \pm 2e^{-6}$ and AR of $181.0 \pm 0.006$ on DEAM, and an MRR of $0.057 \pm 0.003$ and AR of $65.9 \pm 1.2$ on PMEmo. These performances are orders of magnitude worse than the ones of CMER-CL reported in our paper. For this reason, we attempted to improve the performances of the baselines by further tuning their hyper-parameters.

We focus especially on the number of hidden layers and the number of units per hidden layer, and carry out grid search on them. More specifically, we tested configurations involving a number of layers between one and five, and a number of units per layer in $\{16, 32, 64, 128, 256, 512\}$. That is, when using one, two, three, four and five hidden layers, the numbers of possible architectures are $6^1$, $6^2$, $6^3$, $6^4$ and $6^5$, respectively. Thus, our grid search examines in total 9330 architectures. Note that for RegBiGRU-M2E and RegBiGRU-E2M, the first hidden layer is defined as a bidirectional GRU layer while the others are defined as FC layers. For RegMLP-M2E and RegMLP-E2M, all the hidden layers are defined as FC layers. The activation function of units in FC layers is always softplus, and a dropout rate of 0.5 is applied to FC layers that have 256 or 512 units. For a bidirectional GRU layer, the activation functions are used as specified in [2], and no dropout is employed. Furthermore, the MRR of each architecture is monitored every 100 epochs until 10000 epochs, and the model trained during the epoch that yielded the highest MRR is selected for this architecture. One exception is that this performance monitoring is continued until 50000 epochs unless the training converges after 10000 epochs. Like this, the setting of training the baselines is very favourable, considering that the performance of CMER-CL (i.e., Composite) is evaluated only after the last epoch (5001 and 10001 epochs for DEAM and PMEmo, respectively).

Finally, the architecture with the highest MRR after grid search is always used for the comparison with CMER-CL for all baselines, with one exception. In some configurations, an architecture might yield a slightly lower MRR than the highest one, but also a significantly better (lower) AR. It can be considered that the architecture with the highest MRR is relatively subject to overfitting, in which for some queries (i.e., query music samples or query emotions), their associated samples (i.e., emotions or music samples) are ranked at very high positions, while the ranks of samples associated with other queries are very low. In these configurations, we manually select the architecture with the notably better AR among the ones returning the five highest MRRs.

Table 2 shows the selected architecture for each of RegMLP-M2E, RegMLP-E2M, RegBiGRU-M2E and RegBiGRU-E2M on DEAM and PMEmo. As seen from Table 2 of our paper, these baselines are significantly outperformed by CMER-CL despite the comprehensive and careful hyper-parameter tuning strategy. This verifies the effective-
Fig. 4. Transition of Composite-C’s performances (MRRs and ARs) obtained using Cos-Loss configured by different values of $\alpha$. The optimal $\alpha$ value is selected as $0.3$ and $0.1$ for DEAM and PMEmo, respectively.
Fig. 5. Transitions of performances (MRRs and ARs) obtained by different pairs of $P$ and $\lambda$ values. Here, $\alpha$ of Cos-Loss is set to the optimal values found from Fig. 4. As indicated by the red arrows, the optimal pair of $P$ and $\lambda$ values is selected as $(P = 0.9, \lambda = 0.7)$ and $(P = 0.9, \lambda = 0.1)$ for DEAM and PMEmo, respectively.
ness of CMER-CL’s cross-modal embedding approach.

### TABLE 2

Hyper-parameters of the baselines after grid search.

| Model name       | Epochs | Number of units per hidden layer |
|------------------|--------|----------------------------------|
| **DEAM**         |        |                                  |
| RegMLP-M2E       | 8300   | [128, 64, 16, 128, 512]          |
| RegMLP-E2M       | 19200  | [32]                             |
| RegBiGRU-M2E     | 2000   | [512, 64, 32, 16, 32]            |
| RegBiGRU-E2M     | 9200   | [128, 128, 32, 128, 128]         |
| **PMEmo**        |        |                                  |
| RegMLP-M2E       | 5500   | [16]                             |
| RegMLP-E2M       | 9900   | [32, 128, 128]                   |
| RegBiGRU-M2E     | 7500   | [512, 32, 32]                    |
| RegBiGRU-E2M     | 3400   | [512]                            |

4 Detailed analysis results for M2E

Fig. 6 shows the average cosine similarities computed for M2E on DEAM and PMEmo. Cosine similarities are computed between the mean acoustic feature of a query music sample, and the one of the music sample associated to each emotion ranked in the top 5% by CMER-CL. A high average cosine similarity means that CMER-CL recognises emotions expressed in music samples that are acoustically similar to a query music sample. In other words, even if CMER-CL fails to properly recognise the ground-truth emotion associated with the query music sample, emotions reasonably relevant to the query are still recognised because they are associated with acoustically similar music samples to the query.

Just like Fig. 3 in our paper, the bar graphs in the left part of Fig. 6 (a) and (b) are drawn by sorting query music samples in ascending order of the ranks $r_q$ of their associated ground-truth emotions. The more to the left a query music sample is located, the higher its associated emotion is ranked by CMER-CL. It should be noted that the median of pairwise cosine similarities among acoustic features of music samples is 0.674 and 0.800 on DEAM and PMEmo, respectively. Each of these numbers can be interpreted as the cosine similarity between acoustic features of two randomly selected music samples. The bar graphs and box plots in Fig. 6 show that the median of average cosine similarities is 0.753 and 0.837 on DEAM and PMEmo, respectively. These medians are significantly higher than the median of pairwise cosine similarities, which validates the meaningfulness of CMER-CL’s M2E results. In addition, as shown by the box plots in Fig. 6, the 25th percentile (first quartile) of average cosine similarities on DEAM and PMEmo are 0.709 and 0.810, respectively. The fact that even these 25th percentiles are higher than the medians of pairwise cosine similarities, indicates that in most cases CMER-CL’s M2E works better than randomly selecting an emotion for a query music sample.

5 About the detailed analysis for E2M on PMEmo

Fig. 3 (b) of our paper shows that the average cosine similarities in E2M on PMEmo are very high, with a median of 0.994 close to the maximum value of 1. Below, we discuss about the reason for this. Fig. 7 depicts the distribution of 141 test emotions each of which is represented by the two-dimensional mean emotion vector $\bar{x}^{(e)}$ of an arousal/valence sequence $X^{(e)}$. Here, arousal and valence intensities in PMEmo are in $[0, 1]$, so all the emotions are distributed only in the first quadrant. Furthermore, the variance of this distribution is small in particular, as illustrated in Fig. 7. As a result, the average of pairwise cosine similarities among these emotions is $0.9884 \pm 0.0196$, and even the smallest pairwise cosine similarity characterised by the emotions marked by the crosses in Fig. 7 is 0.7846.

It should be noted that if emotions in Fig. 7 could be moved so that their origin is $(0, 0)$, the range of average cosine similarities would be much wider and detailed analysis based on them would be much clearer. However, it is difficult to precisely locate the origin of the arousal/valence space in Fig. 7. For example, z-normalisation can be carried...
out so that emotions have zero mean and unit variance, but there is no guarantee that the resulting zero vector corresponds to the origin. Cosine similarities significantly rely on the location of the origin because they measure similarities between the angles of two vectors. In addition, considering Russell’s circumplex model where emotions are circularly located in the arousal/valence space [3], an angle-based similarity measure like cosine similarity is preferred to other types of measures like Euclidean distance. Thus, reliable analysis is impossible when the exact location of the origin is unknown. For this reason, our detailed analysis on PMEmo is performed using the original arousal and valence intensities without any modification.

6 Computational Costs of CMER-CL

Finally, we discuss about the computational costs of CMER-CL by referring to Table 3. Each number in this table indicates the average runtime of 10 runs to train or test a CMER-CL model with random initialisation of all parameters and random 8 : 2 split of a dataset into training and test partitions. The runtime for testing the CMER-CL model is the average elapsed time to get an M2E (or E2M) result given a query music sample (or query emotion). The hyperparameters of the CMER-CL model are set to the optimal values found in Section 1. Furthermore, the runtimes in Table 3 are measured using a PC equipped with Intel i9-7900X CPU, 128GB RAM and NVIDIA RTX 2080Ti GPU. The codes are written using TensorFlow library (version 1.15) based on CUDA version 11.2.

As seen from the first column in Table 3, training a CMER-CL model on PMEmo takes significantly longer time than training it on DEAM, even though the training partition of PMEmo only contains 561 music-emotion pairs. One main reason is that both of the music and emotion encoders for PMEmo are defined as RNNs that need to process the acoustic feature or emotion vector sequentially in time. To improve the scalability of CMER-CL, we plan to define the music and emotion encoders as self-attention models that can perform batch processing of acoustic features or emotion vectors at all the times [4].

The second and last columns in Table 3 show the very short runtimes of CMER-CL’s test process. This is due to the fact that the test partitions of DEAM and PMEmo only contain 361 and 141 samples (i.e., music samples for E2M or emotions for M2E), respectively. Nevertheless, since the runtime of CMER-CL’s test process scales linearly with the number of samples, the test process would still be expected to finish within seconds even with a number of samples three orders of magnitude higher than the currently tested numbers.

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TABLE 3

|       | DEAM    | PMEmo   |
|-------|---------|---------|
|       | Training | Test (M2E) | Test (E2M) | Training | Test (M2E) | Test (E2M) |
|       | 2118.45 sec | 0.0046 sec | 0.0045 sec | 9472.44 sec | 0.0025 sec | 0.0019 sec |

3. The codes are available at https://mu-lab.info/naoki_takashima/cmer-cl