ABSTRACT
Image perception is one of the most direct ways to provide contextual information about a user concerning his/her surrounding environment; hence images are a suitable proxy for contextual recommendation. We propose a novel representation learning framework for image-based music recommendation that bridges the heterogeneity gap between music and image data; the proposed method is a key component for various contextual recommendation tasks. Preliminary experiments show that for an image-to-song retrieval task, the proposed method retrieves relevant or conceptually similar songs for input images.

KEYWORDS
Heterogeneous Recommendation, Multimedia Recommendation, Image-based Music Recommender System

1 INTRODUCTION
Contextualization is an important feature in many recommender systems [1]. For example, music-streaming services such as Spotify, use the current mood of the user or adapt recommendations depending on the time of the day. Apart from the user mood or time information, image perception is a more direct way to acquire contextual information about the user’s immediate environment due to its rich information. Therefore, images are a better proxy for contextual recommendation. However, the heterogeneity gap between different types of data makes this challenging. In this paper we propose an innovative framework to bridge the heterogeneity gap between music and image data for image-based music recommendation; as such, the proposed method is a key component for various contextual recommendation tasks.

Figure 1 shows the three modules of the proposed framework: 1) a CNN module, 2) a network embedding module, and 3) a retrieval module. The CNN module uses the VGG-19 [3] pre-trained model to obtain the image representations. The network embedding module, inspired by [5], bridges the concepts of songs and images via keywords, and learns the representations of images, songs, and their corresponding keywords based on neighborhood proximity [4, 5]. Finally, the retrieval module yields the recommended songs for an input image given the representations from the CNN and network embedding modules. The experiments show that for the image-to-song retrieval task, given the input image, the proposed method retrieves songs that are relevant or conceptually similar.

2 IMAGE-BASED MUSIC RECOMMENDATION
Figure 1(a) illustrates the three modules of the proposed framework. CNN Module In this framework we apply the VGG-19 pre-trained model, which yielded a 7% top-5 error on the ILSVRC-2012 dataset, to obtain the image representations (hereafter referred to as the CNN-based representations). The network structure of VGG-19 includes 16 convolutional layers and 3 fully-connected layers, with the use of 3 × 3 filters. To generate the 4096-dimensional representation for each image, we extract the representations from the second rather than the third fully-connected layer. In our task, we use weights pre-trained on a 1000-class object recognition task using about 150,000 224 × 224-pixel images.

Network Embedding (NE) Module We use neighborhood proximity [4, 5] in network embedding to capture the relationship between images and songs, and then use this relationship for recommendations. In particular, we construct a heterogeneous tripartite network by connecting the two types of multimedia data with corresponding keywords; hence there are three types of vertices (i.e., images, words, and songs) and two types of edges in the network: (1) Song-keyword edge: connects each song with the keywords in its lyrics; the weight indicates the relevance between the song and the keyword. (2) Image-keyword edge: connects each image with its corresponding keyword; the weight indicates the relevance between the image and the keyword.

In the proposed framework, the vertex representations are learned based on their neighborhood proximity using stochastic gradient descent with edge sampling [4] and negative sampling [2].

Retrieval Module Given an input image, the retrieval module comprises the following three stages:
(1) Image transformation: the CNN module is used to transform the input image into a 4096-dimensional CNN-based representation.

(2) Image retrieval: the most relevant images with respect to the input image are retrieved by calculating the Euclidean distance between their CNN-based representations and those of the pre-trained images.

(3) Song recommendation: the most relevant songs are recommended based on the Euclidean distances between the NE-based representations of songs and the images retrieved in the previous stage.

3 PRELIMINARY EXPERIMENTS

We obtained the music dataset from KKBOX\(^1\), and crawled the lyrics for keyword extraction and network construction for the proposed framework. For the keyword extraction, we used the Jieba toolkit\(^2\) for Chinese word segmentation and extracted 72 frequent keywords from the titles and song lyrics. Moreover, we constructed our image dataset by using search engines to collect images given the 72 selected keywords, and also included in the experimental dataset songs that contained at least one of the keywords, yielding a total of 62,316 songs, 72 keywords, and 33,459 images.

Table 1: Image-to-song retrieval (hit rate@10)

| n       | Proposed model | KM | POP |
|---------|----------------|----|-----|
| 5       | 0.913          | 0.902 | 0.124 |
| 10      | 0.918          | 0.917 | 0.157 |
| 50      | 0.943          | 0.941 | 0.356 |
| 100     | 0.943          | 0.943 | 0.378 |

Table 1 lists the results of an image-to-song retrieval task. For each input image, our framework recommended the top 10 songs obtained from top 2 relevant songs for the top 5 relevant images, whereas the keyword matching (KM) baseline recommended 10 songs directly based on the keyword associated with the input image in songs' lyrics and the popular (POP) baseline recommended 10 songs randomly selected from the top-100 most popular songs. For each of the 72 keywords, we collected the top n conceptually similar words of the extracted keywords from ConceptNet\(^3\) to construct the ground truth: the lyrics of a recommended song containing at least one of the associated keywords or their corresponding conceptually similar words. The result shows that our framework is able to retrieve more literally relevant songs to the input images than the two baselines, KM and POP.

Furthermore, we conducted an user study in which we collected feedback from 10 users, by having each user listen to the top 10 retrieved songs for each of the given 4 input images. Figure 1(b) shows the 4 input images and Table 2 tabulates the results in terms of precision; the performance of our method is superior to all of the baseline methods. For snow-themed images, it is worth mentioning that the lyrics of most of the recommended songs included the concept-related words Christmas and cold; this shows that the proposed method recommends music based on contextual information. To sum up, Tables 1 and 2 indicate that our method is able to retrieve more relevant songs than the baseline methods in terms of both literal and contextual aspects.

Table 2: User feedback for the 4 images (precision@10)

| Theme          | Snow forest | Sky with clouds | Coffee | Ocean |
|----------------|-------------|-----------------|--------|-------|
| (b-1)          | 0.776       | 0.623           | 0.655  | 0.709 |
| (b-2)          | 0.531       | 0.569           | 0.546  | 0.531 |
| (b-3)          | 0.414       | 0.514           | 0.371  | 0.586 |
| (b-4)          | 0.414       | 0.514           | 0.371  | 0.586 |

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4 CONCLUSION AND FUTURE WORK

We present a representation learning framework that bridges the heterogeneity gap between music and image information for image-based music recommendation. Preliminary results demonstrate that the proposed method retrieves more relevant or conceptually similar songs for input images than the baseline methods. In future, we will incorporate user listening behavior into the NE module to construct an image-based and personalized recommender system.

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