An Overview of Cross-media Retrieval: Concepts, Methodologies, Benchmarks and Challenges
Yuxin Peng, Xin Huang, and Yunzhen Zhao

Abstract—Multimedia retrieval plays an indispensable role in big data utilization. Past efforts mainly focused on single-media retrieval. However, the requirements of users are highly flexible, such as retrieving the relevant audio clips with one query of image. So challenges stemming from the “media gap”, which means that representations of different media types are inconsistent, have attracted increasing attention. Cross-media retrieval is designed for the scenarios where the queries and retrieval results are of different media types. As a relatively new research topic, its concepts, methodologies and benchmarks are still not clear in the literatures. To address these issues, we review more than 100 references, give an overview including the concepts, methodologies, major challenges and open issues, as well as build up the benchmarks including datasets and experimental results. Researchers can directly adopt the benchmarks to promptly evaluate their proposed methods. This will help them to focus on algorithm design, rather than the time-consuming compared methods and results. It is noted that we have constructed a new dataset XMedia, which is the first publicly available dataset with up to five media types (text, image, video, audio and 3D model). We believe this overview will attract more researchers to focus on cross-media retrieval and be helpful to them.

Index Terms—Cross-media retrieval, overview, concepts, methodologies, benchmarks, challenges.

I. INTRODUCTION

WITH the rapid growth of multimedia data such as text, image, video, audio and 3D model, cross-media retrieval is becoming increasingly attractive, through which users can get the results with various media types by submitting one query of any media type. For instance, on a visit to the Gate Bridge, users can submit a photo of it, and retrieve relevant results including text descriptions, images, videos, audio clips and 3D models.

The research of multimedia retrieval has lasted for several decades [1]. However, past efforts generally focused on single-media retrieval, where the queries and retrieval results belong to the same media type. Beyond the case of single-media retrieval, some methods have been proposed to deal with more than one media type. Such methods aim to combine multiple media types together in a retrieval process as [2], [3], but the queries and retrieval results must share the same media combination. For example, users can retrieve image/text pairs by an image/text pair. Although these methods involve multiple media types, they are not designed for performing retrieval across different media types, and cross-media similarities cannot be directly measured, such as the similarity between an image and an audio clip. Nowadays, as digital media content is generated and found everywhere, requirements of users are highly flexible such as retrieving the relevant audio clips with one query of image. Such retrieval paradigm is called cross-media retrieval, which has been drawing extensive interests. It is more useful and flexible than single-media retrieval because users can retrieve whatever they want by submitting whatever they have [4].

The key challenge of cross-media retrieval is the issue of “media gap”, which means that representations of different media types are inconsistent and lie in different feature spaces, so it is extremely challenging to measure similarities among them. There have been many methods proposed for addressing this issue by analyzing the rich correlations contained in cross-media data. For example, current mainstream methods are designed to learn an intermediate common space for features of different media types, and measure the similarities among them in one common space, which are called common space learning methods. Meanwhile, cross-media similarity measurement methods are proposed to directly compute the cross-media similarities by analyzing the known data relationships without obtaining an explicit common space. A brief illustration of cross-media retrieval is shown in Figure 1. Most of the existing methods are designed for retrieval of only two media types (mainly image and text), but cross-media retrieval emphasizes the diversity of media types. Hence, there still remains a problem of incorporating other media types into the unified framework, such as video, audio and 3D model.

As our research on cross-media retrieval has lasted for several years [5]–[12], we find some key issues on concepts, methodologies and benchmarks are still not clear in the literatures. To address these problems, we review more than 100 references and aim to:

- Summarize existing works and methodologies to present an overview, which will facilitate the research of cross-media retrieval.
- Build up the benchmarks, including datasets and experimental results. This will help researchers to focus on algorithm design, rather than the time-consuming compared methods and results, since they can directly adopt the benchmarks to promptly evaluate their proposed methods.
- Provide a new dataset XMedia for comprehensive evaluations of cross-media retrieval. It is the first publicly available dataset consisting of up to five media types (text, image, video, audio and 3D model).
- Present the main challenges and open issues, which
are important and meaningful for the further research directions of cross-media retrieval.

The rest of this paper is organized as follows: Section II presents the definition of cross-media retrieval. Sections III, IV and V introduce the representative works of common space learning, cross-media similarity measurement and other methods, which are shown in Table I. Section VI summarizes the widely-used datasets for cross-media retrieval, and Section VII presents the experimental results on these datasets. Section VIII presents the open issues and challenges, and finally Section IX concludes this paper.

II. DEFINITION OF CROSS-MEDIA RETRIEVAL

For clarity, we take two media types $X$ and $Y$ as examples to give the formulation of definition for cross-media retrieval. The training data is denoted as $D_{tr} = \{X_{tr}, Y_{tr}\}$, in which $X_{tr} = \{x_{p}\}_{p=1}^{n_{tr}}$, where $n_{tr}$ denotes the number of media instances for training, and $x_{p}$ denotes the $p$-th media instance. Similarly, we denote $Y_{tr} = \{y_{p}\}_{p=1}^{n_{tr}}$. There exist co-existence relationships between $x_{p}$ and $y_{p}$, which mean that instances of different media types exist together to describe relevant semantics. Semantic category labels for training data can be provided and denoted as $[c_{p}^{X}]_{p=1}^{n_{tr}}$ and $[c_{p}^{Y}]_{p=1}^{n_{tr}}$, which indicate the semantic categories that media instances belong to. The testing data is denoted as $D_{te} = \{X_{te}, Y_{te}\}$, in which $X_{te} = \{x_{q}\}_{q=1}^{n_{te}}$, and $Y_{te} = \{y_{q}\}_{q=1}^{n_{te}}$. The goal is to compute cross-media similarities $sim(x_{q}, y_{p})$, and retrieve relevant instances of different media types in testing data for one query of any media type. Unsupervised methods take the setting that all training data is unlabeled, semi-supervised methods take the setting that only a subset of the training data is labeled, while fully supervised methods take the setting that all of the training data is labeled.

Some works involve analyzing the correlation between different media types, mainly image and text, but they are quite different from cross-media retrieval. For example, image annotation methods such as [13] aim to obtain the probabilities that the tags are assigned to images, while in cross-media retrieval, text refers to sentences or paragraph descriptions rather than only tags. Models of image/video caption such as [14], [15] are mainly designed for generating the text descriptions of image/video, while cross-media retrieval aims to find the most relevant texts in the existing data for image/video in the existing data and vice versa. Another important difference between them is that image/video caption only focuses on image/video and text, which is not easy to be extended to other media types, while cross-media retrieval is the retrieval across all media types such as text, image, video, audio and 3D model. In addition, there are some transfer learning works involving different media types such as [16], but transfer learning and cross-media retrieval differ in two aspects: (1) Transfer learning is a learning framework with a broad coverage of methods and applications, which allows the domains, tasks,
and distributions used in training and testing to be different [17]. However, cross-media retrieval is a specific information retrieval task across different media types, and its characteristic challenge and focus are the issue of “media gap”. (2) “Transfer learning aims to extract the knowledge from one or more source tasks and applies the knowledge to a target task” [17], and there exist distinct source and target domains. But different media types are treated equally in cross-media retrieval, and there are usually no distinct source and target domains, or source and target tasks.

III. Common Space Learning

Common space learning based methods are currently the mainstream in cross-media retrieval. They follow the idea that data sharing the same semantics has latent correlations, which makes it possible to construct a common space. Taking the Golden Gate Bridge as an example, all of the text descriptions, images, videos, audio clips and 3D models about it describe similar semantics. Consequently, they can be close to each other in a common high-level semantic space. These methods aim to learn such a common space, and explicitly project data of different media types to this space for similarity measurement.

We mainly introduce seven categories of existing methods as subsections A-G. Among them, (A) traditional statistical correlation analysis methods are the basic paradigm and foundation of common space learning methods, which mainly learn linear projection matrices for common space by optimizing the statistical values. Other categories are classified according to the characteristics on different aspects:

- **On basic model.** (B) DNN-based methods take deep neural network as the basic model and aim to make use of its strong abstraction ability for cross-media correlation learning.
- **On correlation modeling.** (C) cross-media graph regularization methods adopt the graph model to represent the complex cross-media correlations, (D) metric learning methods view the cross-media correlations as a set of similar/dissimilar constraints, and (E) learning to rank methods focus on cross-media ranking information as their optimization objective.
- **On property of common space.** (F) dictionary learning methods generate dictionaries and the learned common space is for sparse coefficient of cross-media data, and (G) cross-media hashing methods aim to learn a common Hamming space to accelerate retrieval.

Because these categories are classified according to different aspects, there exist a few overlaps among these categories. For example, the work of [7] can be classified as both a metric learning and graph regularization method.

A. Traditional Statistical Correlation Analysis Methods

Traditional statistical correlation analysis methods are the basic paradigm and foundation of common space learning methods, which mainly learn linear projection matrices by optimizing the statistical values. Canonical correlation analysis (CCA) [18] is one of the most representative works as introduced in [19]. The cross-media data is often organized as sets of paired data with different media types such as image/text pairs. CCA is a possible solution for such case, which learns a subspace that maximizes the pairwise correlations between two sets of heterogeneous data. As an early classical work, CCA is also used in some recent works such as [20], [21]. CCA and its variants such as [22]–[26], are the most popular baseline methods for cross-media retrieval.

CCA itself is unsupervised and does not use semantic category labels, but researchers have also attempted to extend CCA for incorporating semantic information. Rasiwasia et al. [27] propose to first apply CCA to get the common space of image and text, and then achieve the semantic abstraction by logistic regression. Costa et al. [28] then further verify the effectiveness of combining CCA with semantic category labels. GMA [29] also obtains the improvement on accuracy, which is a supervised extension of CCA. Multi-view CCA [25] is proposed to take high-level semantics as the third view of CCA, and multi-label CCA [26] is designed to deal with the scenarios where cross-media data has multiple labels. These methods achieve considerable progress, which indicates that semantic information is helpful to improve the accuracy of cross-media retrieval. Besides CCA, there are also alternative methods of traditional statistical correlation analysis. For example, cross-modal factor analysis (CFA) [30] is proposed to minimize the Frobenius norm between pairwise data in the common space. As the basic paradigms of cross-media common space learning, these methods are relatively efficient for training and easy to be implemented. However, it is difficult to fully model the complex correlations of cross-media data in the real world only by linear projections. In addition, most of these methods can only model two media types, but cross-media retrieval usually involves more than two media types.

B. DNN-based Methods

With the great advance of deep learning, deep neural network (DNN) has shown its potential in different multimedia applications such as object recognition [31] and text generation [32]. With considerable power of learning non-linear relationships, DNN is also used to perform common space learning for data of different media types. Ngiam et al. [33] apply an extension of restricted Boltzmann machine (RBM) to the common space learning and propose bimodal deep autoencoder, in which inputs of two different media types pass through a shared code layer, in order to learn the cross-media correlations as well as preserve the reconstruction information. Following this idea, some similar deep architectures are proposed and achieve progress in cross-media retrieval. For example, Srivastava et al. [34] adopt two separate deep Boltzmann machine (DBM) to model the distribution over the features of different media types, and the two models are combined by an additional layer on the top of them as the joint representation layer, which can learn the common space by computing joint distribution.

There are also some attempts to combine DNN with CCA as deep canonical correlation analysis (DCCA) [24], [35]. DCCA
can be viewed as a non-linear extension of CCA, and used to learn the complex non-linear transformations for two media types. Different from the previous works [33], [34] which build one network with a shared layer for different media types, there are two separate subnetworks in DCCA, and the total correlation is maximized by the correlation constraints between the code layers. Feng et al. [36] propose three architectures for common space learning: correspondence autoencoder, correspondence cross-modal autoencoder and correspondence full-modal autoencoder. All of them have similar architectures consisting of two subnetworks coupled at the code layers, and jointly consider the reconstruction errors and the correlation loss. Some works also consist of two autoencoders, such as independent component multimodal autoencoder (ICMAE) [37] and deep canonically correlated autoencoders (DCCAE) [38]. ICMAE focuses on attribute discovery by learning the shared representation across visual and textual modalities, and DCCAE is optimized by the integration of reconstruction errors and canonical correlations. Peng et al. [12] propose cross-media multiple deep networks (CMDN), which is a hierarchical architecture with multiple deep networks. CMDN jointly preserves the intra-media and inter-media information to generate two kinds of complementary separate representations for each media type, and then hierarchically combines them to learn the common space via a stacked learning style, which improves the retrieval accuracy. In addition, in the work of [39], clicks of users are exploited as side information for cross-media common space learning. A large part of the aforementioned methods are non-convolutional and take hand-crafted features as inputs as [12], [36]. Wei et al. [40] propose deep-SM to exploit convolutional neural network (CNN) with deep semantic matching, which demonstrates the power of the CNN features in cross-media retrieval. He et al. [41] propose a deep and bidirectional representation learning model, with two convolution-based networks modeling the matched and unmatched image/text pairs simultaneously for training.

The deep architectures used in cross-media retrieval mainly include two ways. The first way can be viewed as one network, and inputs of different media types pass through the same shared layer [33], [34], while the second way consists of subnetworks coupled by correlation constraints at the code layers [36], [42]. These methods take DNN as the basic model, so have the advantage of abstraction ability for dealing with complex cross-media correlations. However, training data usually plays a key role for the performance of DNN model, and large-scale labeled cross-media datasets are much harder to collect than single-media datasets. It is noted that most of the above works have the limitation of taking only two media types as inputs, although there exist some recent works for more than two kinds of inputs such as [43] which takes five input types. Jointly learning common space for more than two media types can improve the flexibility of cross-media retrieval, which is an important challenge for future research.

Except for the above works, other deep architectures have also been designed for multimedia applications such as image/video caption and text to image synthesis [14], [15], [44], [45]. For example, recurrent neural network (RNN) and long short-term memory (LSTM) [14], [15] have been applied to image/video caption, which can generate text descriptions for visual content. Generative adversarial networks (GANs) [46] are proposed by Goodfellow et al., which estimate generative models via an adversarial process by simultaneously training two models: a generative model and a discriminative model. The basic idea of GANs is to set up a game between two players, and pit two adversaries against each other. Each player is represented by a differentiable function, which are typically implemented as deep neural networks according to [47]. Reed et al. [44] develop a GANs formulation to convert the visual concepts from characters to pixels. Later, they propose generative adversarial what-where network (GAWWN) [45] to synthesize images by giving the locations of the content to draw. These methods are not directly designed for cross-media retrieval, but their ideas and models are valuable to it.

C. Cross-media Graph Regularization Methods

Graph regularization [48] is widely used in semi-supervised learning, which considers semi-supervised learning problem in the view of labeling a partially labeled graph. The edge weights denote the affinities of data in the graph, and the aim is to predict the labels of unlabeled vertices. Graph regularization can enrich the training set and make the solution smooth. Zhai et al. [7] propose joint graph regularized heterogeneous metric learning (JGRHML). They incorporate graph regularization into the cross-media retrieval problem, which uses data in the learned metric space for constructing the joint graph regularization term. Then they propose joint representation learning (JRL) method [10] with the ability of jointly considering correlations and semantic information in a unified framework for up to five media types. Specifically, they construct a separate graph for each media type, in which the edge weights denote affinities of labeled and unlabeled data of the same media type. With graph regularization, JRL enriches the training set and learns a projection matrix for each media type jointly. As JRL separately constructs different graphs for different media types, Peng et al. [11] further propose to construct a unified hypergraph for all media types in the common space, thus different media types can boost each other. Another important improvement of [11] is to utilize fine-grained information by media instance segmentation, which helps to exploit multi-level correlations of cross-media data. Graph regularization is also an important part in some recent works such as [49]–[51], where a cross-media graph regularization term is used to preserve the intra-media and inter-media similarity relationships.

Graph regularization is effective for cross-media correlation learning because it can describe various correlations of cross-media data, such as semantic relevance, intra-media similarities and inter-media similarities. Besides, graph regularization can naturally model more than two media types in a unified framework [11]. However, the graph construction process usually leads to high time and space complexity, especially in real-world scenarios with large-scale cross-media data.

D. Metric Learning Methods

Metric learning methods are designed to learn transformations of input features from the given similar/dissimilar
information to achieve better metric results, which are widely used in single-media retrieval [52], [53]. It is natural to view cross-media data as the extension of multi-view single-media data, so researchers attempt to apply metric learning to cross-media retrieval directly. Intuitively, we can learn two transformations for two media types, and let similar instances be close and dissimilar instances be apart [54]. JGRHML [7] is a representative work of cross-media metric learning, which has also been discussed in Section III-C. Besides the similar/dissimilar information, JGRHML introduces a joint graph regularization term for the metric learning. Different media types are complementary in the joint graph regularization and optimizing them jointly can make the solution smooth. Metric learning preserves the semantic similar/dissimilar information during the common space learning, which is important for semantic retrieval of cross-media data. However, the main limitation of existing metric learning methods for cross-media retrieval such as [7], [54] is that they depend on the supervision information, and are not applicable when supervision information is unavailable.

E. Learning to Rank Methods

Learning to rank methods take the ranking information as training data, and directly optimize the ranking of retrieved results, instead of the similarities between pairwise data. Early works of learning to rank focus on single-media retrieval, but some works such as [55] indicate that they can be extended to cross-language retrieval. In the work of [56], a discriminative model is proposed to learn mappings from the image space to the text space, but only uni-directional ranking (text→image) is involved. For bi-directional ranking methods (specifically text→image and image→text ranking information), Wu et al. [57] propose bi-directional cross-media semantic representation model (Bi-CMSRM) to optimize the bi-directional listwise ranking loss. To incorporate the fine-grained information, Jiang et al. [58] first project visual objects and text words into the local common space, and then project them into the global common space in a compositional way with ranking information. In addition, Wu et al. [59] take a conditional random field for shared topic learning, and then perform latent joint representation learning with ranking function. Learning to rank is designed for directly benefiting the final retrieval performance, and can serve as the optimization objective for cross-media retrieval. Existing methods mainly involve only two media types such as [56], [57], [59], and when the number of media types increases, there remains a problem on how to incorporate the ranking information of more than two media types into a unified framework.

F. Dictionary Learning Methods

Dictionary learning methods hold the view that data consists of two parts: dictionaries and sparse coefficients. The idea can also be incorporated into cross-media retrieval: decomposing data into the media-specific part for each media, and the common part for cross-modal correlations. Monaci et al. [60] propose to learn the multi-modal dictionaries for recovering meaningful synchronous patterns from audio and visual signals. The key idea of this method is to learn the joint audiovisual dictionaries, so as to find the temporal correlations across different modalities. However, since it only takes the synchronous temporal signals as inputs, it is not a cross-media retrieval method. Jia et al. [61] propose to learn one dictionary for each modality, while the weights of these dictionaries are the same. In this work, data is clearly decomposed into two parts: the private dictionaries and the shared coefficients. Zhu et al. [62] propose cross-modality submodular dictionary learning (CmSDL), which learns a modality-adaptive dictionary pair and an isomorphic space for cross-media representation.

Coupled dictionary learning [63] is an effective way to jointly construct the private dictionaries for two views. Zhu et al. [64] propose to extend single-media coupled dictionary learning to cross-media retrieval, assuming that there exist linear mappings among sparse coefficients of different media types. Data of one media type can be mapped into the space of another media type via these sparse coefficient mappings. In conclusion, dictionary learning methods model cross-media retrieval problem in a factorization way, and the common space is for sparse coefficients. Based on this idea, they have different views of methods, such as a unique sparse coefficient for all media types [61] and a set of projections among sparse coefficients of different media types [64]. It is easier to capture cross-media correlations from the sparse coefficients of different media types due to the high sparsity. However, it is a challenge to solve the optimization problem with mass calculation of dictionary learning on large-scale cross-media data.

G. Cross-media Hashing Methods

 Nowadays, the amount of multimedia data is growing dramatically, which requires high efficiency of retrieval system. Hashing methods are designed for accelerating retrieval process, and widely used in various retrieval applications. However, most of them only involve a single media type such as image [65]. For example, Tang et al. [66] propose to learn image hashing functions with discriminative information of the local neighborhood structure, and exploit the neighbors of samples in the original space to improve the retrieval accuracy. Cross-media hashing aims to generate the hash codes for more than one media type, and project the cross-media data into a common Hamming space. There have been some works extending single-media hashing to the retrieval of data with multiple views or information sources such as [67], [68]. They are not designed specifically for cross-media retrieval, but these methods and ideas can be easily applied to it. For example, to model the multiple information sources, Zhang et al. [68] propose composite hashing with multiple information sources (CHMIS), and the idea is to preserve both the similarities in the original spaces and the correlations between multiple information sources. Similarly, the idea of preserving both inter-media and intra-media similarities is a key principle in some later works of cross-media retrieval [49], [69]–[71]. For instance, Wu et al. [49] first apply hypergraph to model intra-media and inter-media similarities, and then learn
multi-modal dictionaries for generating hashing codes. The discriminative capability of hash codes has also been taken into consideration [72], which helps to learn the hash codes under supervised condition. More recently, Long et al. [73] propose to learn common space projection and composite quantizers in a seamless scheme, while most existing works view continuous common space learning and binary codes generation as two separate stages.

Besides, cross-media hashing methods are various such as [74]–[83]. The models vary from eigen-decomposition and boosting [74] to the probabilistic generative model [71], and even the deep architectures [78], [82]. The aforementioned cross-media hashing methods mainly consider similar factors such as inter-media similarities, intra-media similarities and semantic discriminative capability. It is noted that cross-media hashing methods are learning-based, because they learn from the cross-media correlations to bridge the “media gap”. Cross-media hashing methods aims to find the common space projections for different media types by aligning their underlying manifold representations.

IV. CROSS-MEDIA SIMILARITY MEASUREMENT

Cross-media similarity measurement methods aim to measure similarities of heterogeneous data directly, without explicitly projecting media instances from their separate spaces to a common space. For the absence of common space, cross-media similarities cannot be computed directly by distance measuring or normal classifiers. An intuitive way is to use the known media instances and correlations in datasets as the basis to bridge the “media gap”.

Existing methods for cross-media similarity measurement usually take the idea of using edges in graphs for representing the relationships among media instances and multimedia documents (MMDs). According to the different focuses of methods, we further classify them into two categories as subsections: (A) Graph-based methods focus on the construction of graphs, and (B) neighbor analysis methods mainly consider how to exploit the neighbor relationships of data for similarity measurement. These two categories have overlaps in algorithm process, because the neighbor relationships may be analyzed in a constructed graph.

A. Graph-based Methods

The basic idea of graph-based methods is to view the cross-media data as vertices in one or more graphs, and the edges are constructed by the correlations of cross-media data. Single-media content similarities, co-existence relationships and semantic category labels can be jointly used for graph construction. Through a process such as similarity propagation [90] and constraint fusion [91], the retrieval results can be obtained. These methods often focus on the situations when the relevance in MMDs is available, which contain data with multiple media types of the same semantics [92]. The co-existence relationships of data in MMDs provide important hints to bridge different media types. For example, a graph indicating the similarities of MMDs plays an important role in [4], [93], and the cross-media retrieval is based on MMD affinities in this graph.

Tong et al. [91] construct an independent graph for each media type. These graphs are further combined by linear fusion or sequential fusion, and then the similarity measurement of cross-media data is conducted. Different from [91], Zhuang et al. [90] construct a uniform cross-media correlation graph, which integrates all media types. The edge weights are determined by the similarities of single-media data and co-existence relationships. Besides, the links among MMDs on web pages
have also been taken into account in the work of [94]. Yang et al. [95] propose a two-level graph construction strategy. They first construct two types of graphs: one graph for each media type, and the other for all MMDs. Then the characteristics of media instances propagate along the MMD semantic graph and the MMD semantic space is constructed to perform cross-media retrieval. While existing methods mostly consider only the positive correlations in similarity propagation, Zhai et al. [6] propose to propagate both the positive and negative correlations among data of different media types in graphs, and improve the retrieval accuracy.

The key idea of graph-based similarity measurement methods is to construct one or more graphs, and represent cross-media correlations on the level of media instances or MMDs. It is helpful to incorporate various types of correlation information by graph construction. However, graph-based methods are time and space consuming due to the process of graph construction. In addition, existing works are often devoted to scenarios where the relevance in MMDs is available, and relevance feedback usually acts as a key factor in these works such as [4], [90], [93]. On the one hand, when the above relevance is unavailable, it would be difficult to perform cross-media retrieval, especially when the queries are out of the datasets. On the other hand, in real-world applications, the relationships of MMDs are usually noisy and incomplete, which is also a key challenge for these methods.

B. Neighbor Analysis Methods

Generally speaking, neighbor analysis methods are usually based on graph construction because the neighbors may be analyzed in a given graph [90], [95]. In this paper, graph-based methods mainly involve the process of graph construction, while neighbor analysis methods focus on using the neighbor relationships for similarity measurement.

Clinchant et al. [2] introduce a multimedia fusion strategy named transmedia fusion for cross-media retrieval. For instance, there exists a dataset containing image/text pairs, and users retrieve the relevant texts by queries of images. Given one query of image, its nearest neighbors will be retrieved according to single-media content similarities, and then the text descriptions of these nearest neighbors are regarded as the relevant texts. Zhai et al. [5] propose to compute cross-media similarities by the probabilities of two media instances belonging to the same semantic category, which are calculated by analyzing the homogeneous nearest neighbors of each media instance. Ma et al. [8] propose to compute cross-media similarities in the perspective of clusters. In their work, clustering algorithm is first applied to each media type, and then the similarities among clusters are obtained according to the data co-existence relationships. The queries will be assigned to clusters with different weights according to the single-media content similarities, and then retrieval results can be obtained by computing the similarities among clusters.

Neighbor analysis methods find the nearest neighbors in datasets with the queries to get the retrieval results. These neighbors can be used as expanded queries, and serve as the bridges for dealing with queries out of the datasets. In addition, some methods such as [5] do not rely on MMDs, so they are flexible. However, because the neighbor analysis methods may be actually based on graph construction, they have the same problem of high time and space complexity. It is also difficult to ensure the relevant relationships of neighbors, so the performance is not stable.

V. Other Methods for Cross-Media Retrieval

Besides common space learning and cross-media similarity measurement methods, we introduce two categories of other cross-media methods as subsections: (A) Relevant feedback analysis is an auxiliary method for providing more information on user intent to promote the performance of retrieval. (B) Multimodal topic model views cross-media data in the topic level, and the cross-media similarities are usually obtained by computing the conditional probability.

A. Relevance Feedback Analysis

To bridge the vast “media gap”, the relevance feedback (RF) is beneficial to provide more accurate information and facilitate the retrieval accuracy. It is worth noting that RF is widely used in cross-media similarity measurement, and the effectiveness has been validated in some works [4], [93], [95]. RF includes two types: short-term feedback and long-term feedback. Short-term feedback only involves RF information provided by the current user, while long-term feedback takes RF information provided by all users into account. For short-term feedback, in the works of [4], [95], when the queries are out of the datasets, the system will show the nearest neighbors in the dataset with the queries, and users should label them as the positive or negative samples. Then the similarities will be refined according to the feedback. For long-term feedback, Yang et al. [93] propose to convert long-term feedback information into pairwise similar/dissimilar constraints to refine the vector representation of data. Zhuang et al. [90] exploit both long-term and short-term feedback. As for long-term feedback, they first investigate the global structure of all feedback and then refine the uniform cross-media correlation graph. For short-term feedback, they simply use the positive samples as expanded queries. RF is an auxiliary technique to improve the retrieval accuracy in an interactive way, but with the cost of human labor.

B. Multimodal Topic Model

Inspired by topic models such as latent dirichlet allocation (LDA) [96] in text processing, researchers have extended topic models to the multimodal retrieval. These models are often designed for applications such as image annotation, involving images and their corresponding tags. Correspondence LDA (Corr-LDA) [97] is a classical multimodal extension of LDA for image annotation. Specifically, it first generates image region descriptions and then generates the caption. However, it takes a strict assumption that each image topic must have a corresponding text topic. To address this problem, topic-regression multi-modal LDA (tr-mmLDA) [98] uses two separate topic models for image and text, and finally applies
a regression module to correlate the two hidden topic sets. Nevertheless, it still takes a strong assumption that each word in the text has a visual interpretation. To further make the topic models flexible and perform cross-media retrieval, Jia et al. [99] propose multi-modal document random field (MDRF) method, which can be viewed as a Markov random field over LDA topic models. Wang et al. [100] propose a downstream supervised topic model, and build a joint cross-modal probabilistic graphical model to discover the mutually consistent semantic topics. Multimodal topic model aims to analyze the cross-media correlations in the topic level. However, these existing methods often take strong assumptions on the distribution of cross-media topics, such as the existence of the same topic proportions or pairwise topic correspondences between different media types, which are not satisfied in real-world application.

VI. CROSS-MEDIA RETRIEVAL DATASET

Datasets are important for the evaluation of cross-media retrieval methods. We study all references of this paper and summarize the frequencies of several popular datasets in Table II. It is shown that Wikipedia and NUS-WIDE datasets are the most widely-used cross-media retrieval datasets. Pascal VOC datasets are a series of important datasets for cross-media retrieval, and also the basis of Pascal Sentence dataset. Pascal VOC 2007 dataset is the most popular one among Pascal VOC datasets. In addition, XMedia dataset is the first cross-media dataset that contains up to five media types. We first introduce Wikipedia and XMedia datasets which are specifically designed for cross-media retrieval, then the rest NUS-WIDE and Pascal VOC 2007 datasets. Besides, we also introduce a large-scale click-based dataset Clickture.

Wikipedia Dataset. Wikipedia dataset [27] is the most widely-used dataset for cross-media retrieval. It is based on “featured articles” in Wikipedia, which is a continually updated article collection. There are totally 29 categories in “featured articles”, but only 10 most populated categories are actually considered. Each article is split into several sections according to its section headings, and this dataset is finally generated as a set of 2,866 image/text pairs. Wikipedia dataset is an important benchmark dataset for cross-media retrieval. However, this dataset is small-scale and only involves two media types (image and text). The categories in this dataset are of high-level semantics to be difficultly distinguished, such as warfare and history, leading to confusions for retrieval evaluation. On the one hand, there are some semantic overlaps among these categories. For example, a war (should belong to warfare category) is usually also a historical event (should belong to history category). On the other hand, even data belonging to the same category may differ greatly on semantics from each other.

XMedia Dataset. For comprehensive and fair evaluation, we have constructed a new cross-media dataset XMedia. We choose 20 categories such as insect, bird, wind, dog, tiger, explosion and elephant. These categories are specific objects that can avoid the confusions and overlaps. For each category, we collect the data of five media types: 250 texts, 250 images, 25 videos, 50 audio clips and 25 3D models, so there are 600 media instances for each category and the total number of media instances is 12,000. All of the media instances are crawled from famous websites: Wikipedia, Flickr, YouTube, 3D Warehouse and Princeton 3D model search engine. XMedia dataset is the first cross-media dataset with up to five media types (text, image, video, audio and 3D model), and has been used in our works [7], [10], [11] to evaluate the effectiveness of cross-media retrieval. XMedia dataset is publicly available and can be accessed through the link: http://www.icst.pku.edu.cn/mipl/XMedia.

NUS-WIDE Dataset. NUS-WIDE dataset [101] is a web image dataset including images and their associated tags. The images and tags are all randomly crawled from Flickr through its public API. With the duplicated images removed, there are 269,648 images in NUS-WIDE dataset of 81 concepts. Totally 425,059 unique tags are originally associated with these images. However, to further improve the quality of tags, those tags that appear no more than 100 times and do not exist in WordNet [102] are removed. So finally 5,018 unique tags are included in this dataset.

Pascal VOC 2007 Dataset. Pascal visual object classes (VOC) challenge [103] is a benchmark in visual object category detection and recognition. Pascal VOC 2007 is the most popular Pascal VOC dataset, which consists of 9,963 images divided into 20 categories. The image annotations serve as the text for cross-media retrieval, and are defined over a vocabulary of 804 keywords.

Clickture Dataset. Clickture dataset [104] is a large-scale click-based image dataset, which is collected from one-year click-through data of a commercial image search engine. The full Clickture dataset consists of 40 million images and 73.6 million text queries. It also has a subset Clickture-Lite with 1.0 million images and 11.7 million text queries. Following recent works as [39], [105], we take Clickture-Lite for experimental evaluation. The training set consists of 23.1 million query-image-click triads, where “click” is an integer indicating the relevance between the image and query, and the testing set has 79,926 query-image pairs generated from 1,000 text queries. Among the above datasets, Wikipedia and XMedia datasets are specifically designed for cross-media retrieval. NUS-WIDE and Pascal VOC 2007 datasets are image/tag datasets, which are initially designed for the evaluation of other applications such as image annotation and classification. There are only tags in these two datasets as text, instead of sentences or paragraph descriptions as Wikipedia and XMedia datasets. Clickture dataset is the largest among these datasets, but it provides no category labels as supervision information.

VII. EXPERIMENTS

A. Feature Extraction and Dataset Split

This subsection presents the feature extraction strategy and split of training/testing set in the experiments. For Wikipedia, XMedia and Clickture datasets, we take the same strategy as [27] to generate both text and image representations, and the representations of video, audio and 3D model are the same as [10]. In detail, texts are represented by the histograms of a
10-topic LDA model, and images are represented by the bag-of-visual-words (BoVW) histograms of a SIFT codebook with 128 codewords. Videos are segmented into several video shots first, and then the 128-dimensional BoVW histogram features are extracted for video keyframes. Audio clips are represented by the 29-dimensional MFCC features, and 3D models are represented by the concatenated 4,700-dimensional vectors of a LightField descriptor set. For NUS-WIDE dataset, we use the 1,000-dimensional word frequency features and for texts, and the 500-dimensional BoVW features for images provided by Chua et al. [101]. For Pascal VOC 2007 dataset, we use publicly available features for the experiments, which is the same as [85] where the 399-dimensional word frequency features are used for texts, and the 512-dimensional GIST features are used for images. The above feature extraction strategy is adopted for all compared methods in the experiments except DCMIT [35], because its architecture contains networks taking the original images and texts as inputs. However, DCMIT does not involve corresponding networks for video, audio and 3D model, so for these 3 media types we use the same extracted features as all the other compared methods.

For Wikipedia dataset, 2,173 image/text pairs are used for training and 693 image/text pairs are used for testing. For XMedia dataset, the ratio of training and testing set is 4:1 for all the five media types, so we have a training set of 9,600 instances and a testing set of 2,400 instances. For NUS-WIDE dataset, we select image/text pairs that exclusively belong to one of the 10 largest categories from valid URLs. As a result, the size of training set is 38,620 and the testing set has a total size of 38,955. Pascal VOC 2007 dataset is split into a training set with 5,011 image/text pairs and a testing set with 4,952 image/text pairs. Images with only one object are selected for the experiments and finally there are 2,808 image/text pairs in the training set and 2,841 image/text pairs in the testing set. For Clickture dataset, there are 11.7 million distinct queries and 1.0 million unique images for training, and 79,926 query-image pairs generated from 1,000 queries for testing.

B. Evaluation Metrics and Compared Methods

Two retrieval tasks are conducted for objective evaluation on cross-media retrieval:

- **Multi-modality cross-media retrieval.** By submitting a query example of any media type, all media types will be retrieved.
- **Bi-modality cross-media retrieval.** By submitting a query example of any media type, the other media type will be retrieved.

On all datasets except for Clickture dataset, both the tasks are performed, and the retrieval results are evaluated by mean average precision (MAP) scores, which are widely adopted in information retrieval. MAP score for a set of queries is the mean of the average precision (AP) for each query. Besides, we also adopt precision-recall curves (PR curves) and running time for comprehensive evaluations. Due to the length limitation of this paper, we show the PR curves and running time on our website: http://www.icst.pku.edu.cn/mipl/XMedia. Clickture dataset does not provide category labels for evaluation with MAP and PR curves. Instead, it consists of many text queries, and for each text query there are multiple images along with the relevance between images and the query, which are uni-directional ground truth. Following [39], [105], we conduct the text-based image retrieval task for each text query, and take discounted cumulative gain for top 25 results (DCG@25) as evaluation metric. The compared methods in the experiments include: BITR [20], CCA [18], CCA+SMN [27], CFA [30], CMCP [6], DCMIT [35], HSNN [5], JGRHML [7], JRL [10], LGCFL [85], ml-CCA [26], mv-CCA [25] and S²UPG [11]. All these methods are evaluated on Wikipedia, XMedia, NUS-WIDE and Pascal VOC 2007 datasets. However, because Clickture dataset provides no category labels for supervised training, only unsupervised methods (BITR, CCA, CFA, DCMIT) are evaluated on this dataset.

C. Experimental Results

Table III shows MAP scores of multi-modality cross-media retrieval. We observe that the methods proposed with semantic information such as CCA+SMN, HSNN, LGCFL, ml-CCA, mv-CCA and JGRHML achieve better results than CCA, CFA and BITR, which only consider the pairwise correlations. DCMIT performs better than CCA due to the use of DNN. CMCP and JRL achieve better results, for the reason that CMCP considers not only the positive but also the negative correlations among different media types, and JRL incorporates the sparse and semi-supervised regularizations to enrich the training set as well as make the solution smooth. S²UPG achieves the best results because it adopts the media patches to model fine-grained correlations, and the unified hypergraph can jointly model data from all media types, so as to fully exploit the correlations among them.

Table IV shows the MAP scores of bi-modality cross-media retrieval. Generally speaking, CMCP, HSNN, JGRHML, JRL and S²UPG get much better results than other methods such as BITR, CCA and CCA+SMN. The trends among them are different from the results on multi-modality cross-media retrieval. For example, the results of CMCP, JGRHML and JRL are close to each other on bi-modality cross-media retrieval, while JRL clearly outperforms CMCP and JGRHML on multimodality cross-media retrieval. S²UPG still achieves the best results, because the fine-grained information of different media types can be modeled into one unified hypergraph to make them boost each other. It is noted that because Clickture dataset provides no category labels for supervised training, we perform unsupervised methods to verify their effectiveness, and the results are shown in Table V. The overall trends among

| Dataset       | Wikipedia | NUS-WIDE | Pascal VOC 2007 | Pascal Sentence | MIR-Flickr | Corel | LabelMe | XMedia |
|---------------|-----------|----------|-----------------|----------------|------------|-------|---------|--------|
| Frequency     | 38        | 30       | 9               | 9              | 7          | 6     | 5       | 3      |
different methods on Clickture dataset are similar with other datasets.

We also conduct experiments on Wikipedia, XMedia and Clickture datasets with the BoW features for texts, and the CNN features for images and videos, to show the performance with different features. We use the 4,096-dimensional CNN features extracted by the fc7 layer of AlexNet, and the 3,000-dimensional BoW text features. Due to page limitation, we just present the average of all MAP scores for cross-modality and bi-modality cross-media retrieval tasks on Wikipedia dataset in Table VI, and the detailed results along with results on other datasets can be found on our website: http://www.icst.pku.edu.cn/mipl/XMedia. Table VI shows that features have significant impacts on the retrieval accuracy. Generally speaking, CNN features significantly improve the performance of most compared methods, while the performance of BoW features is not stable.

**TABLE VIII: Challenges and Open Issues**

**Dataset Construction and Benchmark Standardization**

Datasets are very important for experimental evaluation, but as discussed in Section VI, nowadays there are only a few datasets publicly available for cross-media retrieval. Existing datasets still have shortcomings on the size, the number of media types, the rationality of categories, etc. For example, the sizes of Wikipedia and XMedia datasets are small, and Wikipedia dataset consists of only two media types (image and text). To construct high-quality datasets, specific problems should be considered such as: What categories should be included in the datasets? How many media types should be involved? How large should the dataset be? These questions are important for evaluation on the datasets. For instance, as discussed in Section VI, the high-level semantic categories of Wikipedia dataset may lead to semantic overlaps and confusions, which limits the objectivity of evaluation.

To address the above problems, we are constructing a new dataset named XMediaNet, which consists of five media types (text, image, video, audio, and 3D model). We select 200 categories from WordNet [102] for ensuring the category hierarchy. These categories consist of two main parts: animals and artifacts. There are 48 kinds of animals such as elephant, owl, bee and frog as well as 152 kinds of artifacts such as violin, airplane, shotgun and camera. The total number of media instances will exceed 100,000, and they are crawled from famous websites as Wikipedia, Flickr, YouTube, Findsounds, Freesound and Yobi3D. Once the dataset is ready, we will release it on our website: http://www.icst.pku.edu.cn/mipl/XMedia. We will also provide the experimental results on widely-used datasets, and encourage researchers to submit their results for building up a comprehensive dataset.
continuously updated benchmark (as the website of LFW face dataset [106] at http://vis-www.cs.umass.edu/lfw, and the website of ImageNet dataset [107] at http://www.image-net.org). Researchers can directly adopt the experimental results to evaluate their own methods, which will help them focus on algorithm design, rather than the time-consuming compared methods and results, thus greatly facilitate the development of cross-media retrieval.

**Improvement of Accuracy and Efficiency.** The effective yet efficient methods are still required for cross-media retrieval. First, the accuracy needs to be improved. On the one hand, existing methods still have potential to be improved. For example, graph-based methods of cross-media similarity measurement may use more context information for the effective graph construction such as link relationships. On the other hand, the discriminative power of single-media features is also important. For instance, in the experiments of Section VII, state-of-the-art methods generally adopt the low-dimensional features (e.g., 128-dimensional BoVW histogram features for image and 10-dimensional LDA features for text as in [10], [11], [27]). As discussed in Section VII-C, when more discriminative features are adopted such as CNN features for image, the retrieval accuracy will be improved. Second, the efficiency is also an important factor for evaluations and applications. Cross-media retrieval datasets are still small-scale and limited on the number of media types up to now. Although there have been some hashing methods for cross-media retrieval as [69]–[71], the issue of efficiency has not been paid enough attention to. In the future, with the release of our large-scale XMediaNet dataset, it will be more convenient for researchers to evaluate the efficiency of their methods, which will facilitate the development of practical applications for cross-media retrieval.

**Applications of Deep Neural Network.** DNN is designed to simulate the neuronal structure of human brain which can naturally deal with the correlations of different media types, so it is worth a try to exploit DNN for bridging the “media gap”. Actually, there have been some attempts (such as the aforementioned methods [34], [37] in Section III-B), but they are relatively straightforward applications of DNN, which mostly take the single-media features as raw inputs, and perform common space learning for them by extending existing models such as autoencoders. Although DNN-based methods have achieved considerable progress on cross-media retrieval [12], there is still potential for further improvement. The applications of DNN remain research hotspots on cross-media retrieval, as is the case with single-media retrieval. On the one hand, existing methods mainly take the single-media features as inputs, so they heavily depend on the effectiveness of features. Research efforts may be devoted to designing end-to-end architectures for cross-media retrieval, which take the original media instances as inputs (e.g., the original images and audio clips), and directly get the retrieval results with DNN. Some special networks for specific media types (e.g., R-CNN for object region detection [58]) could also be incorporated into the unified framework of cross-media retrieval. On the other hand, most of the existing methods are designed for only two media types. In the future works, researchers could focus on jointly analyzing more than two media types, which will make the applications of DNN in cross-media retrieval more flexible and effective.

**Exploitation of Context Correlation Information.** The main challenge of cross-media retrieval is still the heterogeneous forms of different media types. Existing methods attempt to bridge the “media gap”, but only achieve limited improvement and the retrieval results are not accurate when dealing with the real-world cross-media data. The cross-media correlations are often with the context information. For example, if an image and an audio clip are from two web pages with link relationship, they are likely to be relevant to each other. Many existing methods (e.g., CCA, CFA and JRL) only take the co-existence relationships and semantic category labels as training information, but ignore rich context information. Actually, cross-media data on the Internet usually does not exist separately, and has important context information such as link relationships. Such context information is relatively accurate, and provides important hints to improve the accuracy of cross-media retrieval. The web data is also usually divergent, so it is important to exploit the context information for complex practical applications. We believe that researchers will pay more attention to rich context information to boost the performance of cross-media retrieval in the future works.

**Practical Applications of Cross-media Retrieval.** With the constant improvement on both effectiveness and efficiency, practical applications of cross-media retrieval will become possible. These applications can provide more flexible and convenient ways to retrieve from the large-scale cross-media data, and users will like to adopt the cross-media search engine which is capable of retrieving various media types as text, image, video, audio, and 3D model with one query of any media type. In addition, other possible application scenarios include the enterprises involving the cross-media data, such as TV stations, media corporations, digital libraries and publishing companies. Both Internet and relevant enterprises will have the huge requirements of cross-media retrieval.

**IX. Conclusion**

Cross-media retrieval is an important research topic which aims to deal with the “media gap” for performing retrieval across different media types. This paper has reviewed more
than 100 references to present an overview of cross-media retrieval, for building up the evaluation benchmarks, as well as facilitating the relevant research. Existing methods have been introduced mainly including the common space learning and cross-media similarity measurement methods. Common space learning methods efficiently learn a common space for different media types to perform retrieval, while cross-media similarity measurement methods directly measure cross-media similarities without a common space. The widely-used cross-media retrieval datasets have also been introduced, including Wikipedia, XMedia, NUS-WIDE, Pascal VOC 2007 and Clickture Datasets. Among these datasets, XMedia which we have constructed is the first dataset with five media types for comprehensive and fair evaluation. We are further constructing a new dataset XMediaNet with five media types and more than 100,000 instances. The cross-media benchmarks, such as datasets, compared methods, evaluation metrics and experimental results have been given, and we have established a continuously updated website to present them. Based on the discussed aspects, the main challenges and open issues have also been presented in the future works. We hope these could attract more researchers to focus on cross-media retrieval, and promote the relevant research and applications.

References
[1] M. S. Lew, N. Sebe, C. Djeraba, and R. Jain, “Content-based multimedia information retrieval: State of the art and challenges,” ACM Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP), vol. 2, no. 1, pp. 1–19, 2006.
[2] S. Clinchant, J. Ah-Pine, and G. Csurka, “Semantic combination of textual and visual information in multimedia retrieval,” in ACM International Conference on Multimedia Retrieval (ICMR), no. 44, 2011.
[3] Y. Liu, W.-L. Zhao, C.-W. Ngo, C.-S. Xu, and H.-Q. Lu, “Coherent bag-of-audio words model for efficient large-scale video copy detection,” in ACM International Conference on Image and Video Retrieval (CIVR), 2010, pp. 89–96.
[4] Y. Yang, D. Xu, F. Nie, J. Luo, and Y. Zhuang, “Ranking with local regression and global alignment for cross media retrieval,” in ACM International Conference on Multimedia (ACM MM), 2009, pp. 175–184.
[5] X. Zhai, Y. Peng, and J. Xiao, “Effective heterogeneous similarity measure with nearest neighbors for cross-media retrieval,” in International Conference on Multimedia Modeling (MMM), 2012, pp. 312–322.
[6] X. Zhai, Y. Peng, and J. Xiao, “Cross-modality correlation propagation for cross-media retrieval,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2012, pp. 2337–2340.
[7] X. Zhai, Y. Peng, and J. Xiao, “Heterogeneous metric learning with joint graph regularization for cross-media retrieval,” in AAAI Conference on Artificial Intelligence (AAAI), 2013, pp. 1198–1204.
[8] D. Ma, X. Zhai, and Y. Peng, “Cross-media retrieval by cluster-based correlation analysis,” in IEEE International Conference on Image Processing (ICIP), 2013, pp. 3986–3990.
[9] X. Zhai, Y. Peng, and J. Xiao, “Cross-media retrieval by intra-media and inter-media correlation mining,” Multimedia System, vol. 19, no. 5, pp. 395–406, 2013.
[10] X. Zhai, Y. Peng, and J. Xiao, “Learning cross-media joint representation with sparse and semi-supervised regularization,” IEEE Transactions on Circuits and Systems for Video Technology (TCSVT), vol. 24, no. 6, pp. 965–978, 2014.
[11] Y. Peng, X. Zhai, Y. Zhao, and X. Huang, “Semi-supervised cross-media feature learning with unified patch graph regularization,” IEEE Transactions on Circuits and Systems for Video Technology (TCSVT), vol. 26, no. 3, pp. 383–396, 2016.
[12] Y. Peng, X. Huang, and J. Qi, “Cross-media shared representation by hierarchical learning with multiple deep networks,” in International Joint Conference on Artificial Intelligence (IJCAI), 2016, pp. 3846–3853.
[13] J. Jeon, V. Lavrenko, and R. Manmatha, “Automatic image annotation and retrieval using cross-media relevance measures,” in International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2003, pp. 119–126.
[14] J. Mao, W. Xu, Y. Yang, J. Wang, and A. L. Yuille, “Deep captioning with multimodal recurrent neural networks (m-rnn),” 2014, arXiv:1412.6632.
[15] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, “Show and tell: A neural image caption generator,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 3156–3164.
[16] J. Tang, X. Shu, Z. Li, G. Qi, and J. Wang, “Generalized deep transfer networks for knowledge propagation in heterogeneous domains,” ACM Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP), vol. 12, no. 4s, pp. 68:1–68:22, 2016.
[17] S. J. Pan and Q. Yang, “A survey on transfer learning,” IEEE Transactions on Knowledge and Data Engineering (TKDE), vol. 22, no. 10, pp. 1345–1359, 2010.
[18] H. Hotelling, “Relations between two sets of variates,” Biometrika, vol. 28, no. 3/4, pp. 321–377, 1936.
[19] D. R. Hardoon, S. Szedmák, and J. Shawe-Taylor, “Canonical correlation analysis: An overview with application to learning methods,” Neural Computation, vol. 16, no. 12, pp. 2639–2664, 2004.
[20] Y. Verma and C. V. Jawahar, “lm2text and text2im: Associating images and texts for cross-modal retrieval,” in British Machine Vision Conference (BMVC), 2014.
[21] B. Klein, G. Lev, G. Sadeh, and L. Wolf, “Associating neural word embeddings with deep image representations using Fisher vectors,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 4437–4446.
[22] S. Akaho, “A kernel method for canonical correlation analysis,” 2006, arXiv:cs/0609071.
[23] N. Rasiwasia, D. Mahajan, V. Mahadevan, and G. Aggarwal, “Cluster canonical correlation analysis,” in International Conference on Artificial Intelligence and Statistics (AISTATS), 2014, pp. 823–831.
[24] G. Andrew, R. Arora, J. Bilmes, and K. Livescu, “Deep canonical correlation analysis,” in International Conference on Machine Learning (ICML), 2010, pp. 3348–3355.
[25] Y. Gong, Q. Ke, M. Isard, and S. Lazebnik, “A multi-view embedding space for modeling internet images, tags, and their semantics,” International Journal of Computer Vision (IJCV), vol. 106, no. 2, pp. 210–233, 2014.
[26] V. Ranjan, N. Rasiwasia, and C. V. Jawahar, “Multi-label cross-modal retrieval,” in 2015 IEEE International Conference on Computer Vision (ICCV), 2015, pp. 4094–4102.
[27] N. Rasiwasia, J. Costa Pereira, E. Coviello, G. Doyle, G. R. Lanckriet, R. Levy, and N. Vasconcelos, “A new approach to cross-modal multimedia retrieval,” in ACM International Conference on Multimedia (ACM MM), 2010, pp. 251–260.
[28] J. Costa Pereira, E. Coviello, G. Doyle, N. Rasiwasia, G. R. Lanckriet, R. Levy, and N. Vasconcelos, “On the role of correlation and abstraction in cross-modal multimedia retrieval,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 36, no. 3, pp. 521–535, 2014.
[29] A. Sharma, A. Kumar, H. Daume III, and D. W. Jacobs, “Generalized multiview analysis: A discriminative latent space,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2012, pp. 2160–2167.
[30] D. Li, N. Dimitrova, M. Li, and I. K. Sethi, “Multimedia content processing through cross-modal association,” in ACM International Conference on Multimedia (ACM MM), 2003, pp. 604–611.
[31] A. Frome, G. S. Corrado, J. Shlens, S. Bengio, J. Dean, M. A. Ranzato, and T. Mikolov, “Devise: A deep visual-semantic embedding model,” in Advances in Neural Information Processing Systems (NIPS), 2013, pp. 2121–2129.
[32] R. Kiros, R. Salakhutdinov, and R. Zemel, “Multimodal neural language models,” in International Conference on Machine Learning (ICML), 2014, pp. 595–603.
[33] J. Ngiam, A. Khosla, M. Kim, J. Nam, H. Lee, and A. Y. Ng, “Multimodal deep learning,” in International Conference on Machine Learning (ICML), 2011, pp. 689–696.
[34] N. Srivastava and R. Salakhutdinov, “Multimodal learning with deep boltzmann machines,” in Advances in Neural Information Processing Systems (NIPS), 2012, pp. 2222–2230.
[35] F. Yan and K. Mikolajczyk, “Deep correlation for matching images and text,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 3441–3450.
F. Feng, X. Wang, and R. Li, “Cross-modal retrieval with correspondence autoencoder,” in ACM International Conference on Multimedia (ACM MM), 2014, pp. 7–16.

H. Zhang, Y. Yang, H. Luan, S. Yang, and T.-S. Chua, “Start from scratch: Towards automatically identifying, modeling, and naming visual attributes,” in ACM International Conference on Multimedia (ACM MM), 2014, pp. 187–196.

W. Wang, R. Arora, K. Livescu, and J. A. Bilmes, “On deep multi-view representation learning,” in International Conference on Machine Learning (ICML), 2015, pp. 1083–1092.

F. Wu, X. Lu, J. Song, S. Yan, Z. M. Zhang, Y. Rui, and Y. Zhuang, “Learning of multimodal representations with random walks on the click graph,” in IEEE Transactions on Image Processing (TIP), vol. 25, no. 2, pp. 630–642, 2016.

Y. Wei, Y. Zhao, C. Lu, S. Wei, L. Liu, Z. Zhu, and S. Yan, “Cross-modal retrieval with CNN visual features: A new baseline,” in IEEE Transactions on Cybernetics (TCYB), vol. 47, no. 2, pp. 449–460, 2017.

Y. He, S. Xiang, C. Kang, J. Wang, and C. Pan, “Cross-modal retrieval via deep and bidirectional representation learning,” IEEE Transactions on Multimedia (TMM), vol. 18, no. 7, pp. 1363–1377, 2016.

W. Wang, B. C. Ooit, X. Yang, D. Zhang, and Y. Zhuang, “Effective multimodal retrieval based on stacked autoencoders,” in International Conference on Very Large Data Bases (VLDB), 2014, pp. 649–660.

L. Castrejon, Y. Aytar, C. Vondrick, H. Pirsiavash, and A. Torralba, “Learning aligned cross-modal representations from weakly aligned data,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 2940–2949.

S. E. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee, “Generative adversarial text to image synthesis,” in International Conference on Machine Learning (ICML), 2016, pp. 1060–1069.

S. E. Reed, Z. Akata, S. Mohan, S. Tenka, B. Schiele, and H. Lee, “Learning what and where to draw,” in Advances in Neural Information Processing Systems (NIPS), 2016, pp. 217–225.

I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. C. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in Neural Information Processing Systems (NIPS), 2014, pp. 2672–2680.

I. J. Goodfellow, “NIPS 2016 tutorial: Generative adversarial networks,” 2017, arXiv: 1701.00160.

M. Belkin, I. Matveeva, and P. Niyogi, “Regularization and semisupervised learning on large graphs,” Learning theory. Springer Berlin Heidelberg, pp. 624–638, 2004.

F. Wu, Z. Yu, Y. Yang, S. Tang, Y. Zhang, and Y. Zhuang, “Sparse multi-modal hashing,” IEEE Transactions on Image Processing (TIP), vol. 16, no. 2, pp. 427–439, 2014.

K. Wang, R. He, L. Wang, W. Wang, and T. Tan, “Joint feature selection and subspace learning for cross-modal retrieval,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 38, no. 10, pp. 2010–2023, 2015.

J. Liang, Z. Li, D. Cao, R. He, and J. Wang, “Self-paced cross-modal subspace matching,” in International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2016, pp. 569–578.

N. Quadrianto and C. H. Lampert, “Learning multi-view neighborhood preserving projections,” in International Conference on Machine Learning (ICML), 2011, pp. 425–432.

B. McFee and G. Lanckriet, “Metric learning to rank,” in International Conference on Machine Learning (ICML), 2010, pp. 775–782.

W. Wu, J. Xu, and H. Li, “Learning similarity function between objects in heterogeneous spaces,” in Microsoft Research Technique Report, 2010.

B. Bai, J. Weston, D. Grangier, R. Collobert, K. Sadamasa, Y. Qi, O. Chapelle, and K. Weinberger, “Learning to rank with (a lot of) word features,” Information Retrieval, vol. 13, no. 3, pp. 291–314, 2010.

D. Grangier and S. Bengio, “A discriminative kernel-based approach to rank images from text queries,” IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 30, no. 8, pp. 1371–1384, 2008.

F. Wu, X. Lu, Z. Zhang, S. Yan, Y. Rui, and Y. Zhuang, “Cross-media semantic representation via bi-directional learning to rank,” in ACM International Conference on Multimedia (ACM MM), 2013, pp. 877–886.

Y. He, S. Xiang, F. Wu, X. Lu, Z. Zhao, W. Lu, S. Tang, and Y. Zhuang, “Deep compositional cross-modal learning to rank via local-global alignment,” in ACM International Conference on Multimedia (ACM MM), 2015, pp. 69–78.

F. Wu, X. Jiang, X. Li, S. Tang, W. Lu, Z. Zhang, and Y. Zhuang, “Cross-modal learning to rank via latent joint representation,” in IEEE Transactions on Image Processing (TIP), vol. 24, no. 5, pp. 1497–1509, 2015.

G. Monaci, P. Jost, P. Vanderheynst, B. Mailhe, S. Lesage, and R. Gribonval, “Learning multi-modal dictionaries,” IEEE Transactions on Image Processing (TIP), vol. 16, no. 9, pp. 2272–2283, 2007.

Y. Jia, M. Salzmann, and T. Darrell, “Factorized latent spaces with structured sparsity,” in Advances in Neural Information Processing Systems (NIPS), 2010, pp. 982–990.

F. Zhu, L. Shao, and M. Yu, “Cross-modality submodular dictionary learning for information retrieval,” in ACM International Conference on Conference on Information and Knowledge Management (CIKM), 2014, pp. 1479–1488.

S. Wang, L. Zhang, Y. Liang, and Q. Pan, “Semi-coupled dictionary learning with applications to image super-resolution and photo-sketch synthesis,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2012, pp. 2216–2223.

Y. Zhuang, Y. Wang, F. Wu, Y. Zhang, and W. Lu, “Supervised coupled dictionary learning with group structures for multi-modal retrieval,” in AAAI Conference on Artificial Intelligence (AAA1), 2013, pp. 1070–1076.

J. Wang, W. Liu, S. Kumar, and S. Chang, “Learning to hash for indexing big data - A survey,” Proceedings of the IEEE, vol. 104, no. 1, pp. 34–57, 2016.

J. Tang, Z. Li, M. Wang, and R. Zhao, “Neighborhood discriminant hashing for large-scale image retrieval,” IEEE Transactions on Image Processing (TIP), vol. 24, no. 9, pp. 2827–2840, 2015.

S. Kumar and R. Udupa, “Learning hash functions for cross-view similarity search,” in International Joint Conference on Artificial Intelligence (IJCAI), 2011, pp. 1360–1365.

D. Zhang, F. Wang, and L. Si, “Composite hashing with multiple information sources,” in International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2011, pp. 225–234.

Y. Zhen and D.-Y. Yeung, “Co-regularized hashing for multimodal data,” in Advances in Neural Information Processing Systems (NIPS), 2012, pp. 1376–1384.

Y. Hu, Z. Jin, H. Ren, D. Cai, and X. He, “Iterative multi-view hashing for cross media indexing,” in ACM International Conference on Multimedia (ACM MM), 2014, pp. 527–536.

Y. Zhen and D.-Y. Yeung, “A probabilistic model for multimodal hash function learning,” in ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (SIGKDD), 2012, pp. 940–948.

Z. Yu, F. Wu, Y. Yang, Q. Tian, J. Luo, and Y. Zhuang, “Discriminative coupled dictionary hashing for fast cross-media retrieval,” in International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2014, pp. 395–404.

M. Long, Y. Cao, J. Wang, and P. S. Yu, “Composite correlation quantization for efficient multimodal retrieval,” in International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR), 2016, pp. 579–588.

M. M. Bronstein, A. M. Bronstein, F. Michel, and N. Paragios, “Data fusion through cross-modality metric learning using similarity-sensitive hashing,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2010, pp. 3594–3601.

M. Rastegari, J. Choi, S. Fakhrzaei, D. Hal, and L. Davis, “Predictable dual-view hashing,” in International Conference on Machine Learning (ICML), 2013, pp. 1328–1336.

G. Ding, Y. Guo, and J. Zhou, “Collective matrix factorization hashing for multimodal data,” in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014, pp. 2083–2090.

D. Zhai, H. Chang, Y. Zhen, X. Liu, X. Chen, and W. Gao, “Parametric local multimodal hashing for cross-view similarity search,” in International Joint Conference on Artificial Intelligence (IJCAI), 2013, pp. 2754–2760.

Y. Zhuang, Z. Yu, W. Wang, F. Wu, S. Tang, and J. Shao, “Cross-media hashing with neural networks,” in ACM International Conference on Multimedia (ACM MM), 2014, pp. 901–904.

Q. Wang, L. Si, and B. Shen, “Learning to hash on partial multimodal data,” in International Joint Conference on Artificial Intelligence (IJCAI), 2015, pp. 3980–3986.
Yuxin Peng is the professor of Institute of Computer Science and Technology (ICST), Peking University, and the chief scientist of 863 Program (National Hi-Tech Research and Development Program of China). He received the Ph.D. degree in computer application technology from Peking University in Jul. 2003. After that, he worked as an assistant professor in ICST, Peking University. He was promoted to associate professor and professor in Peking University in Aug. 2005 and Aug. 2010 respectively. In 2006, he was authorized by the “Program for New Star in Science and Technology of Beijing” and the “Program for New Century Excellent Talents in University (NCET)”. He has published over 100 papers in refereed international journals and conference proceedings, including IJCV, TIP, TCSVT, TMM, PR, ACM MM, ICCV, CVPR, IJCAI, AAAI, etc. He led his team to participate in TRECVID (TREC Video Retrieval Evaluation) many times. In TRECVID 2009, his team won four first places on 4 sub-tasks of the High-Level Feature Extraction (HLFE) task and Search task. In TRECVID 2012, his team gained four first places on all 4 sub-tasks of the Instance Search (INS) task and Known-Item Search (KIS) task. In TRECVID 2014, his team gained the first place in the Interactive Instance Search task. His team also gained both two first places in the INS task of TRECVID 2015 and 2016. Besides, he won the first prize of Beijing Science and Technology Award for Technological Invention in 2016 (ranking first). He has applied 34 patents, and obtained 15 of them. His current research interests mainly include cross-media analysis and reasoning, image and video analysis and retrieval, and computer vision.

Xin Huang received the B.S. degree in computer science and technology from Peking University in Jul. 2014. He is currently pursuing the Ph.D. degree in the Institute of Computer Science and Technology (ICST), Peking University. His research interests include cross-media analysis and reasoning, and machine learning.

Yunzhou Zhao received the B.S. degree in mathematical science from Peking University in Jul. 2014. He is currently pursuing the M.S. degree in the Institute of Computer Science and Technology (ICST), Peking University. His current research interests include cross-media retrieval and machine learning.