SELF-WEIGHTED MULTIVIEW METRIC LEARNING BY MAXIMIZING THE CROSS CORRELATIONS

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ABSTRACT
With the development of multimedia time, one sample can always be described from multiple views which contain compatible and complementary information. Most algorithms cannot take information from multiple views into considerations and fail to achieve desirable performance in most situations. For many applications, such as image retrieval, face recognition, etc., an appropriate distance metric can better reflect the similarities between various samples. Therefore, how to construct a good distance metric learning methods which can deal with multiview data has been an important topic during the last decade.

In this paper, we proposed a novel algorithm named Self-weighted Multiview Metric Learning (SM²L) which can finish this task by maximizing the cross correlations between different views. Furthermore, because multiple views have different contributions to the learning procedure of SM²L, we adopt a self-weighted learning framework to assign multiple views with different weights. Various experiments on benchmark datasets can verify the performance of our proposed method.

Index Terms— Multiview learning, Metric learning, Self-weighted

1. INTRODUCTION
With the coming of information period, massive data has been generated from various fields to meet the requirement of different people. It is a common phenomena that one same sample can always be described by different tools (or techniques). For example, an image can be represented by several descriptors, such as Local Binary Patterns (LBP) [1], Histogram of Oriented Gradient (Hog) [2] and Locality-constrained Linear Coding (LLC) [3]. Because these descriptors contain different which is compatible and complementary, how to exploit the multiview data to further improve the performance of various applications [4] [5] [6] is of vital importance but challenging.

For many applications, such as image retrieval [7], face recognition [8], etc. [9] [10], learning an appropriate distance metric can help these applications to measure the similarities between samples precisely. Xing et al. [11] proposed a convex optimization function, which minimizes the distances between samples from the same class. Meanwhile, they introduced two constraints to obtain a better metric. Weinberger et al. [12] introduced a DML method named Large Margin Nearest Neighbor (LMNN), which refers the thoughts of SMVs [13]. Information-Theoretic Metric Learning (ITML) [14] is another well-known DML methods which combines information theory [15] with distance metric learning (DML) and achieves good performances. Neighborhood components analysis (NCA) [16] trains a distance metric by maximizes the probabilities of that samples and their stochastic neighbors are from the same class. Even though these algorithms have wide influences on this field, most DML methods cannot deal with multiview data simultaneously and waste a lot of important information.

In order to deal with the problem above, multiview learning [17] [18] has been studied recently. Kumar et al. [19] developed a co-regularized framework to minimize the distinctions between all views. All views are forced to learn from each other via the proposed framework. Xia et al. [20] extended spectral embedding into multiview mode and proposed a self-weighted method to calculate the weights of all views. Canonical correlation analysis (CCA) [21] is another good multiview method which is an extension of Principal component analysis (PCA) [22] and constructs the low-dimensional subspace by maximizing the cross correlations of each two views. Zhai et al. [23] combined global consistency with local smoothness and obtained a multiview metric learning method. Futhermore, some dimension reduction techniques can also be utilized as DML methods, such as PCA [22] and LDA [24]. Till now, most distance metric learning methods cannot deal with multiview data and obtain better performances. It is essential for researchers to conduct more studies on this field [25].

In this paper, we propose a novel multiview metric learning methods named Self-weighted Multiview Metric Learning (SM²L) which can fully exploit multiview data to measure similarities between different samples. The proposed SM²L first introduced the maximum margin criterion for all views to maximize the distances between samples from different classes in each view. Then, in order to force all views to learn from each other, SM²L aims to maximize the cross correlations between the multiview features of one same sam-
ple. Finally, because multiple views have different impacts on the construction process of distance metric, SM$^2$L equips multiple views with different weights which can be learned automatically.

This paper is organized as follows: in section 2, we introduced some basic knowledge and some related works. In section 3, we introduced the construction procedure of our proposed SM$^2$L in detail and the solving procedure of it. In section 4, we conducted several experiments to show the excellent performance of our proposed method. And section 5 made a conclusion in detail.

2. RELATED WORKS

In this section, we introduced some related algorithms which were referred in our proposed SM$^2$L.

2.1. Basic Knowledge

Assume we are given a set of multiview data $X = \{X^v \in \mathbb{R}^{D_v \times n}, v = 1, \cdots, m\}$ which consists of $n$ samples from $m$ views, where $X^v = \{x^v_1, x^v_2, \cdots, x^v_n\} \in \mathbb{R}^{D_v \times n}$ contains all features from the $v$th view. For any two features $x_i^v$ and $x_j^v$ in the $v$th view, their Mahalanobis distance can be computed as:

$$d_{A^v}(x_i^v, x_j^v) = \sqrt{(x_i^v - x_j^v)^T A^v (x_i^v - x_j^v)}$$

Where $A^v$ is the distance metric matrix for the $v$th view. $d_{A^v}(x_i^v, x_j^v)$ represents the distance between $x_i^v$ and $x_j^v$. Because $A^v$ is a semi-definite matrix, it can be decomposed into $A^v = W^v (W^v)^T$, $W^v \in \mathbb{R}^{D_v \times D_v}$ and $d_v \leq D_v$ using eigenvalue decomposition.

For multiview distance metric learning, it’s essential for all views to learn from each other to improve the quality of distance metric for each view. And for any distance metric, it should satisfy these four properties as follows:

1) triangular inequality: $d_{A^v}(x_i^v, x_j^v) \leq d_{A^v}(x_i^v, x_k^v) + d_{A^v}(x_k^v, x_j^v)$;

2) non-negativity: $d_{A^v}(x_i^v, x_j^v) \geq 0$;

3) symmetry: $d_{A^v}(x_i^v, x_j^v) = d_{A^v}(x_j^v, x_i^v)$;

4) distinguishability: $d_{A^v}(x_i^v, x_j^v) = 0 \iff x_i^v = x_j^v$.

2.2. Related Algorithms

In this section, we introduced the construction procedure of our proposed SM$^2$L.

2.2.1. Multiview Spectral Embedding

Multiview Spectral Embedding (MSE) [20] is a well-known multi-view dimension reduction method which can assign all views with appropriate weights automatically. It encodes different features from multiple views to achieve a physically meaningful embedding. Furthermore, MSE integrates laplacian graphs from multiple views via global coordinate alignment, which helps all views to learn from each other. And the objective function of MSE has been shown as follows:

$$\arg\min_{\alpha, Y} \sum_{v=1}^{m} \alpha_v tr\left((Y L^v)^T (Y^T)ight)$$

s.t. $YY^T = I; \sum_{v=1}^{m} \alpha_v = 1, \alpha_v \geq 0$

$\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_m]$ is a set of coefficients which can reflect the importance of different views. $L^v$ is the laplacian graph for features in the $v$th view. It reflects the neighborhood relationship between features in the $v$th view. And $Y$ is the common low-dimensional representation for the original multi-view data. In order to obtain the optimal $Y$, MSE develops an iterative optimization procedure to update $\alpha$ and $Y$ alternately. However, MSE is not a multiview metric learning method which cannot measure similarities between multiview data.

2.2.2. Generalized Multi-view Analysis

Sharma et al. [26] proposed a multiview learning method to construct subspace for the task of classification [27]. They extended linear discriminant analysis (LDA) [24] into multiview mode by maximizing the cross correlations between each two views as follows:

$$\arg\max_{P_1, P_2, \cdots, P_m} \sum_{i=1}^{m} \alpha_i tr\left((P_i)^T S^i_k (P_i)^Tight)$$

$$+ \sum_{i<j} \lambda_{ij} tr\left((P_i)^T X (X)^T P_jight)$$

s.t. $\sum_{i=1}^{m} \gamma_i tr\left((P_i)^T S^i_w (P_i)ight) = I_p$

Where $P_i$ represents the projection matrix for features in the $i$th view, $S^i_k$ is the between-class scatter matrix while $S^i_w$ is the within-class scatter one. $\alpha_i$ and $\gamma_i$ are the weights for between and within-class degree the $i$th view. And $\lambda_{ij}$ is the regularized parameter. Even though Eq 3 maximize the cross correlations between each two views, they cannot assign all views with different weights automatically, which causes too many parameters need to be set during the experiments.

3. THE PROPOSED SM$^2$L

In this paper, we describe the construction procedure of SM$^2$L in detail as fig 3. SM$^2$L first adopts maximize maximum margin criterion to help all views to construct distance metric matrix by maximize the distances between features from different classes. Then, SM$^2$L forces all views to learn from each other by maximizing the cross correlations between each two
views. Finally, SM$^2$L assigns all views with different weights automatically to fully exploit the information of multiview data.

### 3.1. The Construction Procedure of SM$^2$L

For multiview data $X = \{X^v \in \mathbb{R}^{D_v \times n}, v = 1, \ldots, m\}$ together with pairwise constraints $S$ and $D$ as follows:

- $S: \forall(x_i^v, x_j^v) \in S$, $x_i^v, x_j^v \in$ same class
- $D: \forall(x_i^v, x_j^v) \in D$, $x_i^v, x_j^v \in$ different classes

Then, according to the constraints above, SM$^2$L aims to maximize the distances between features from different classes while minimizing the distances between features in the same class as follows:

$$\arg\max_{A^v} \sum_{v=1}^{m} \left( \frac{d^2_{A^v}(x_i^v, x_j^v)}{N_D} - \frac{d^2_{A^v}(x_i^v, x_j^v)}{N_S} \right) \quad (4)$$

Where $N_S$ and $N_D$ are the numbers of pairwise constraints in $S$ and $D$. It is clearly that Eq.4 maximizes the distances between features from the different classes for all views. Due to Eq.4 and $A^v = W^v(W^v)^T$, Eq.4 can be further transformed as follows:

$$\arg\max_{W^v_1, \ldots, W^v_m} \sum_{v=1}^{m} tr \left\{ (W^v)^T \sum_{(x_i^v, x_j^v) \in D} \frac{(x_i^v - x_j^v)(x_i^v - x_j^v)^T}{N_D} W^v \right\}$$

$$- (W^v)^T \sum_{(x_i^v, x_j^v) \in S} \frac{(x_i^v - x_j^v)(x_i^v - x_j^v)^T}{N_S} W^v \} \quad (5)$$

And Eq.5 equals to

$$\arg\max_{W^v_1, \ldots, W^v_m} \sum_{v=1}^{m} tr \left\{ (W^v)^T (M_D - M_S) W^v \right\} \quad (6)$$

s.t. $(W^v)^T W^v = I, v = 1, 2, \ldots, m$.

Where $M_D = \sum_{(x_i^v, x_j^v) \in D} \frac{(x_i^v - x_j^v)(x_i^v - x_j^v)^T}{N_D}$ and $M_S = \sum_{(x_i^v, x_j^v) \in S} \frac{(x_i^v - x_j^v)(x_i^v - x_j^v)^T}{N_S}$. Therefore, the construction of $A^v$ is equal to find the optimal $W^v$.

However, Eq.5 cannot integrate information from multiple views. In order to fully take multiview data into consideration, SM$^2$L adopts the idea from [26] and maximizes the cross correlations between each pair of views as follows:

$$\arg\max_{W^v_1, \ldots, W^v_m} \sum_{v=1}^{m} tr \left\{ (W^v)^T (M_D - M_S) W^v \right\} + \sum_{v \neq w} \lambda_{vw} tr \left\{ ((W^v)^T X^v(X^w)^T W^w \right\} \quad (7)$$

s.t. $(W^v)^T W^v = I, v = 1, 2, \ldots, m$

Through Eq.7 all views can learn from each other to further improve the performance of distance metric learning. However, because multiple views have different impacts on the construction of their distance metric matrix, it is essential for SM$^2$L to learn the weights of these views automatically. Therefore, the objective function of SM$^2$L can be organized as follows:

$$\max \mathcal{G}(\alpha, W^1, W^2, \ldots, W^m) = \sum_{v=1}^{m} \alpha_v tr \left( (W^v)^T (M_D - M_S) W^v \right)$$

$$+ \sum_{v \neq w} \frac{\alpha_v + \alpha_w}{\eta_{vw}} tr \left( (W^v)^T X^v(X^w)^T W^w \right) \quad (8)$$

s.t. $(W^v)^T W^v = I, v = 1, 2, \ldots, m$.

Where $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_m]$ consists of weights of multiple views. $r > 1$ ensures that all views have impacts on the construction of distance metric matrix. Therefore, once the optimal $W^v$ is obtained for the $v$th view, the distance metric matrix can be calculated by $A^v = W^v(W^v)^T$.

### 3.2. The Solving Procedure of SM$^2$L

In this section, we introduce the solving procedure of SM$^2$L in detail. Because it is difficult to obtain $\alpha$ and $W^1, W^2, \ldots, W^m$ simultaneously, SM$^2$L adopts alternately iteration to update the variables separately.

**Update $W^1, W^2, \ldots, W^m$:** SM$^2$L keeps $\alpha$ unchanged to update $W^v, v = 1, 2, \ldots, m$ solely. It has been verified in [26] that the optimization procedure for $W^1, W^2, \ldots, W^m$ is a generalized eigenvalue decomposition problem. The solving procedure of SM$^2$L is similar with that in [26].

**Update $\alpha$:** After $W^1, W^2, \ldots, W^m$ are obtained, how to calculate $\alpha$ is a main problem. By using a Lagrange multiplier $\lambda$ to take the constraint $\sum_{v=1}^{m} \alpha_v = 1$ into consideration, we get the Lagrange function as:

$$\mathcal{L}(\alpha, \lambda) = \mathcal{G}(\alpha, W^1, W^2, \ldots, W^m) - \lambda \left( \sum_{v=1}^{m} \alpha_v - 1 \right) \quad (9)$$

By setting the derivative of $\mathcal{L}(\alpha, \lambda)$ with respect to $\alpha_v$ and $\lambda$ to zero, we can get:

$$\frac{\partial \mathcal{L}(\alpha, \lambda)}{\partial \alpha_v} = \frac{\partial \mathcal{G}(\alpha, W^1, W^2, \ldots, W^m)}{\partial \alpha_v} - \lambda = 0, v = 1, 2, \ldots, m$$

$$\frac{\partial \mathcal{L}(\alpha, \lambda)}{\partial \lambda} = \sum_{v=1}^{m} \alpha_v - 1 = 0$$

Through Eq.9 we can get $\alpha_v$:

$$\alpha_v = \frac{1}{\lambda} \left( \frac{1}{\lambda} \left[ \frac{1}{\lambda} \left( (U^v)^T J^v U^v \right)^{1/(r-1)} \right] \right)^{1/(r-1)} \quad (10)$$
where

$$J^v = tr\left((W^v)^T (M_D - M_S) W^v\right) + \frac{1}{2\eta} tr\left((W^v)^T X^v(X^w)^T W^w\right)$$ (12)

And we can update $\alpha_v, v = 1, 2, \ldots, m$ according to Eq(11) SM2L iterative $\alpha$ and $W^1, W^2, \ldots, W^m$ alternately. And the iteration stops once the obtained $W^1, W^2, \ldots, W^m$ converge.

### 4. EXPERIMENT

In this section, we conducted various experiments on benchmark datasets. And the experiments have verified that our proposed SM2L can achieve good performances.

#### 4.1. Datasets and Comparing Methods

In this section, we introduced the utilized datasets and the comparing methods in detail. There are 3 datasets utilized in our experiments, including 3Sources, Cora, WebKB. All these datasets are benchmark multiview datasets.

3Sources is a benchmark multiview dataset and consists of 3 well-known online news sources: BBC, Reuters and the Guardian. Each source was utilized as one single view and this dataset selected 169 stories as samples. Cora contains 2708 publications which come from 7 classes. Contents and cites are utilized as 2 views in Cora dataset. WebKB contains 4 subsets of documents over 6 categories. All samples in WebKB consists features from 3 views in one page, including the text on it, the anchor text on the hyperlink pointing to it and the text in its title.

In order to show the excellent performance of SM2L, we compare it with several distance metric learning methods in the experiments, including ITML [14], CMM [28], LMNN [12] and MML [29]. ITML, CMM and LMNN are 3 famous single view DML methods. They cannot utilized features from multiple views at the same time. Therefore, we trained them on these views and shown the best performances. Both MML and our proposed SM2L are multiview DML methods.

#### 4.2. Experiment Results

In this section, we conducted experiments on the benchmark datasets which has been described above and shown the results carefully. In our experiments, all methods are trained or tested using the same training or testing samples.

For 3Sources dataset, our experiment randomly select 120 and 80 samples as training ones while the other ones are assigned as testing ones. All DML methods trained their distance metric matrix after the training phase, the experiment adopts 1NN classification on the testing samples. All the DML methods are conducted 10 times and the mean and max classification accuracies are shown as Table 2.

It is clearly that SM2L can achieve best performances on 3Sources dataset. As single view DML methods, ITML, CMM and LMNN cannot achieve satisfactory performances.
Because MML and SM²L are multiview metric learning methods, they are better than those 3 single view ones. Because multiview algorithms take more information into considerations, they are better in most situations.

For Cora dataset, our experiment randomly select 1900 and 1400 samples as training ones while the other ones are assigned as testing ones. All DML methods trained their distance metric matrix after the training phase, the experiment adopts 1NN classification on the testing samples. All the DML methods are conducted 10 times and the mean and max classification accuracies are shown as Table 2.

SM²L can achieve best performances on Cora dataset. Meanwhile, MML is another good distance metric learning for multiview data. For those 3 single view methods, LMNN and CMM are better than ITML.

For 4 subsets of WebKB, we randomly select 70% samples as training ones while the other(about 30%) are selected as testing ones. All DML methods trained their distance metric matrix after the training phase, the experiment adopts 1NN classification on the testing samples. All the DML methods are conducted 10 times and the mean and max classification accuracies are shown as Table 3.

It can be found in Table 3 that SM²L can achieve best performances in most situations. For 4 subsets of WebKB, because MML and SM²L are multiview methods which can full exploit multiview data, they are better than those 3 single view methods. For those 3 single view methods, LMNN is the best one for WebKB.

5. CONCLUSION

In this paper, we propose a novel multiview distance metric learning method named Self-weighted Multiview Metric Learning (SM²L). The proposed SM²L utilized maximum margin criterion to maximize the distances between multiview features from different classes while minimize the distances between multiview features from the same ones. Furthermore, SM²L integrates information from all views maximizing the cross correlations between each 2 views. Finally, we show the solving procedure of SM²L in detail. The experiment results have shown the superiority of SM²L.

6. REFERENCES

[1] Timo Ojala, Matti Pietikäinen, and Topi Mäenpää, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” IEEE Transactions on Pattern Analysis & Machine Intelligence, , no. 7, pp. 971–987, 2002.

[2] Rui Hu and John Collomosse, “A performance evaluation of gradient field hog descriptor for sketch based image retrieval,” Computer Vision and Image Understanding, vol. 117, no. 7, pp. 790–806, 2013.

[3] Jinjun Wang, Jianchao Yang, Kai Yu, Fengjun Lv, Thomas Huang, and Yihong Gong, “Locality-constrained linear coding for image classification,” 2010.

[4] Lin Wu, Yang Wang, Junbin Gao, and Xue Li, “Deep adaptive feature embedding with local sample distributions for person re-identification,” Pattern Recognition, vol. 73, pp. 275–288, 2018.

[5] Lin Wu, Yang Wang, Ling Shao, and Meng Wang, “3d personvlad: Learning deep global representations for video-based person reidentification,” IEEE transactions on neural networks and learning systems, 2019.

[6] Lin Wu, Yang Wang, Junbin Gao, and Xue Li, “Where-and-when to look: Deep siamese attention networks for
video-based person re-identification,” IEEE Transactions on Multimedia, 2018.

[7] Yang Wang, Xuemin Lin, Lin Wu, and Wenjie Zhang, “Effective multi-query expansions: Collaborative deep networks for robust landmark retrieval,” IEEE Transactions on Image Processing, vol. 26, no. 3, pp. 1393–1404, 2017.

[8] Huibing Wang, Lin Feng, Jing Zhang, and Yang Liu, “Semantic discriminative metric learning for image similarity measurement,” IEEE Transactions on Multimedia, vol. 18, no. 8, pp. 1579–1589, 2016.

[9] Lin Feng, Huibing Wang, Bo Jin, Haohao Li, Mingliang Xue, and Le Wang, “Learning a distance metric by balancing kl-divergence for imbalanced datasets,” IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 49, no. 9, pp. 1–12, 2018.

[10] Yang Wang, Xuemin Lin, Lin Wu, and Wenjie Zhang, “Effective multi-query expansions: Robust landmark retrieval,” in Proceedings of the 23rd ACM international conference on Multimedia. ACM, 2015, pp. 79–88.

[11] Eric P Xing, Michael I Jordan, Stuart J Russell, and Andrew Y Ng, “Distance metric learning with application to clustering with side-information,” in Advances in neural information processing systems, 2003, pp. 521–528.

[12] Kilian Q Weinberger, John Blitzer, and Lawrence K Saul, “Distance metric learning for large margin nearest neighbor classification,” in Advances in neural information processing systems, 2006, pp. 521–528.

[13] Thorsten Joachims, “Training linear svms in linear time,” in Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2006, pp. 217–226.

[14] Jason V Davis, Brian Kulis, Prateek Jain, Suvrit Sra, and Inderjit S Dhillon, “Information-theoretic metric learning,” in Proceedings of the 24th international conference on Machine learning. ACM, 2007, pp. 209–216.

[15] Thomas M Cover and Joy A Thomas, Elements of information theory, John Wiley & Sons, 2012.

[16] Jacob Goldberger, Geoffrey E Hinton, Sam T Roweis, and Ruslan R Salakhutdinov, “Neighbourhood components analysis,” in Advances in neural information processing systems, 2005, pp. 513–520.

[17] Yang Wang, Xuemin Lin, Lin Wu, Wenjie Zhang, Qing Zhang, and Xiaodi Huang, “Robust subspace clustering for multi-view data by exploiting correlation consensus,” IEEE Transactions on Image Processing, vol. 24, no. 11, pp. 3939–3949, 2015.

[18] Yang Wang, Lin Wu, Xuemin Lin, and Junbin Gao, “Multiview spectral clustering via structured low-rank matrix factorization,” IEEE transactions on neural networks and learning systems, vol. 29, no. 10, pp. 4833–4843, 2018.

[19] Abhishek Kumar, Piyush Rai, and Hal Daume, “Co-regularized multi-view spectral clustering,” in Advances in neural information processing systems, 2011, pp. 1413–1421.

[20] Tian Xia, Dacheng Tao, Tao Mei, and Yongdong Zhang, “Multiview spectral embedding,” IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 40, no. 6, pp. 1438–1446, 2010.

[21] David R Hardoon, Sandor Szedmak, and John Shawe-Taylor, “Canonical correlation analysis: An overview with application to learning methods,” Neural computation, vol. 16, no. 12, pp. 2639–2664, 2004.

[22] Ian Jolliffe, Principal component analysis, Springer, 2011.

[23] Deming Zhai, Hong Chang, Shiguang Shan, Xilin Chen, and Wen Gao, “Multiview metric learning with global consistency and local smoothness,” ACM Transactions on Intelligent Systems and Technology (TIST), vol. 3, no. 3, pp. 53, 2012.

[24] Sebastian Mika, Gunnar Ratsch, Jason Weston, Bernhard Scholkopf, and Klaus-Robert Mullers, “Fisher discriminant analysis with kernels,” in Neural networks for signal processing IX: Proceedings of the 1999 IEEE signal processing society workshop (cat. no. 98th8468). Ieee, 1999, pp. 41–48.

[25] Yang Wang, Wenjie Zhang, Lin Wu, Xuemin Lin, Meng Fang, and Shirui Pan, “Iterative views agreement: An iterative low-rank based structured optimization method to multi-view spectral clustering,” in International Joint Conference on Artificial Intelligence, 2016, pp. 2153–2159.

[26] Abhishek Sharma, Abhishek Kumar, Hal Daume, and David W Jacobs, “Generalized multview analysis: A discriminative latent space,” in 2012 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2012, pp. 2160–2167.

[27] Fei Wang, “Semisupervised metric learning by maximizing constraint margin,” in 2011 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2011, pp. 2170–2177.

[28] Lin Wu, Yang Wang, and Ling Shao, “Cycle-consistent deep generative hashing for cross-modal retrieval,” IEEE Transactions on Image Processing, vol. 28, no. 4, pp. 1602–1612, 2019.

[29] Fei Wang, “Semisupervised metric learning by maximizing constraint margin,” IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 41, no. 4, pp. 931–939, 2011.
[29] Huibing Wang, Lin Feng, Xiangzhu Meng, Zhaofeng Chen, Laihang Yu, and Hongwei Zhang, “Multi-view metric learning based on kl-divergence for similarity measurement,” *Neurocomputing*, vol. 238, pp. 269–276, 2017.