Collabroative weighted multi-view feature extraction
(CWMvFS)

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Chapter

1 Introduction

1.1 Multiview Learning

Multi-view learning is an emerging direction in machine learning which considers learning with multiple views to improve the generalization performance. Multi-view learning is also known as data fusion or data integration from multiple feature sets.

1.2 LCR

local collaborative representative (LCR) method is utilized to preserve the local correlation in between-view and within-view respectively. Furthermore, it realizes that less similar view pairs should share more consistency and complementary information

1.3 CWMvFE

CWMvFE preserves the local correlation in multi-view, including local correlation in both between-view and within-view, but also explores the differences in similarities between different view pairs. Experiments on four image data sets demonstrate that CWMvFE has better performance than other related methods

Chapter 2

Mathematical Formulation

2.1 Formulation

Let us examine MCCA characterized by (8) and (9). First, MCCA only explores the correlations between different views, but neglects to explore the manifold structure of the single-view itself. Second, MCCA ignores the discriminant information between different view pairs, because it assigns the same weight to different view pairs. Thus, we propose a novel method CWMvFE for multi-view feature extraction with the data matrices (1). CWMvFE is based on locality collaborative representation and Jensen Shannon divergence. It not only considers locality correlation information in single-view and multi-view, but also explores similarity between any different view pairs. Thus corresponding to (8) and (9), our optimization problem of CWMvFE can be written as:

$$\min_{P_1,\ldots,P_V} \sum_{\substack{A,B=1\\A\neq B}}^{V} \sum_{i=1}^{N} \|P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot}) - P_B^T(x_i^B - \widetilde{X}^i_B s^B_{i,\cdot})\|_2^2 JS(A \parallel B) \tag{19}$$

where the matrix $\widetilde{X}^i_v = [x^v_{i,1}, \ldots, x^v_{i,k}]$, $v = A, B$ is constructed by $k-$nearest neighborhood samples of x_i^v, and $s^v_{i,\cdot}$ is calculated by (14). $JS(A \parallel B)$ is weight value to measure the similarity between any view pairs, which is calculated by (18). CWMvFE embodies the ideal that less similar view pairs should share more complementary information with each other. The objective function can be expanded as:

$$\begin{aligned}
&\sum_{\substack{A,B=1\\A\neq B}}^{V} \sum_{i=1}^{N} \|P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot}) - P_B^T(x_i^B - \widetilde{X}^i_B s^B_{i,\cdot})\|_2^2 JS(A \parallel B)\\
&= \sum_{\substack{A,B=1\\A\neq B}}^{V} \sum_{i=1}^{N} \Big\{ \|P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot})\|_2^2 + \|P_B^T(x_i^B - \widetilde{X}^i_B s^B_{i,\cdot})\|_2^2\\
&\quad -2P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot})(x_i^B - \widetilde{X}^i_B s^B_{i,\cdot})^T P_B \Big\} JS(A \parallel B)\\
&= 2\sum_{\substack{A,B=1\\A\neq B}}^{V} \sum_{i=1}^{N} JS(A \parallel B) P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot})(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot})^T P_A\\
&\quad - 2\sum_{\substack{A,B=1\\A\neq B}}^{V} \sum_{i=1}^{N} JS(A \parallel B) P_A^T(x_i^A - \widetilde{X}^i_A s^A_{i,\cdot})(x_i^B - \widetilde{X}^i_B s^B_{i,\cdot})^T P_B
\end{aligned}$$

$$= 2 \sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_A^T P_A$$
$$- 2 \sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_B^T P_B \tag{20}$$

where $\mathcal{X}_A = [x_1^A - \widetilde{X}_A^1 s_{1,\cdot}^A, \ldots, x_N^A - \widetilde{X}_A^N s_{N,\cdot}^A]$ and $\mathcal{X}_B = [x_1^B - \widetilde{X}_B^1 s_{1,\cdot}^B, \ldots, x_N^B - \widetilde{X}_B^N s_{N,\cdot}^B]$. Let us examine the last line in (20). It can be easily proven that the first term $\sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_A^T P_A$ explores locality collaborative correlations from the single-view itself, which is similar to CRP (Lv et al., 2017; Huang et al., 2018a). And the second term $\sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_B^T P_B$ is concerned with local canonical correlations information from multi-views. In order to get more generalized flexibility, a parameter $\gamma > 0$ is introduced to balance the above two terms. Thus, the final optimization problem of our CWMvFE is constructed as the following:

$$\max_{P_1,\ldots,P_V} tr\Big(\sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_B^T P_B$$
$$-\gamma \sum_{\substack{A,B=1\\A\neq B}}^{V} JS(A \parallel B) P_A^T \mathcal{X}_A \mathcal{X}_A^T P_A \Big)$$
$$s.t. \quad P_A^T P_A = I, A = 1, \ldots, V \tag{21}$$

where $I \in R^{d\times d}$ is identity matrix. $\gamma > 0$ is the parameter. The problem (21) is equivalent to the following generalized eigenvalue problem:

$$\begin{bmatrix} -\gamma \mathcal{X}_1 \mathcal{X}_1^T \sum_{B=2}^{V} JS(1 \parallel B) & \mathcal{X}_1 \mathcal{X}_2^T JS(1 \parallel 2) & \cdots & \mathcal{X}_1 \mathcal{X}_V^T JS(1 \parallel V) \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{X}_V \mathcal{X}_1^T JS(V \parallel 1) & \mathcal{X}_V \mathcal{X}_2^T JS(V \parallel 2) & \vdots & -\gamma \mathcal{X}_V \mathcal{X}_V^T \sum_{B=1}^{V-1} JS(V \parallel B) \end{bmatrix}$$
$$\begin{bmatrix} P_1 \\ \vdots \\ P_V \end{bmatrix} = \lambda \begin{bmatrix} I & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \vdots & I \end{bmatrix} \begin{bmatrix} P_1 \\ \vdots \\ P_V \end{bmatrix} \tag{22}$$

The projection matrix $P_A = [p_1^A, \ldots, p_d^A], A = 1, \ldots, V$, can be obtained by the eigenvectors associated with the d largest eigenvalues.

Chapter 3

Algorithm

Chapter 4
Documentation of API

4.1 Package organization

4.2 Methods

Chapter 5

Example 5.1

Example 1

from sklearn.cross decomposition import CCA X = [[0., 0., 1.], [1.,0.,0.], [2.,2.,2.], [3.,5.,4.]] Y = [[0.1, -0.2], [0.9, 1.1], [6.2, 5.9], [11.9, 12.3]] cca = CCA(n components=1) cca.fit(X, Y) X c, Y c = cca.transform(X, Y)

5.2 Example

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Chapter 6
Learning Outcome

6.1 ...... ❮ ..... ❮ .....
6.2 ..... ❮ ..... ❮ .....

Appendix A
References

https://moodle.sgsits.ac.in/mod/folder/view.php?id=2102

https://sci-hub.se/https://www.sciencedirect.com/science/article/abs/pii/S0952197620300336

Bibliography

Aleix, M., Robert, B., 1998. The AR Face Database. CVC Technical Report, 24.
Andrew, G., Arora, R., Bilmes, J., Livescu, K., 2013. Deep canonical correlation analysis. In: International Conference on International Conference on Machine Learning. pp. 1–9.

Cai, Y., Jiao, Y.Y., Zhuge, W.Z., Tao, H., Hou, C.Q., 2018. Partial multi-view spectral clustering. Neurocomputing 311, 316–324.

Cao, G., Iosifidis, A., Chen, K., Gabbouj, M., 2018. Generalized multi-view embedding for visual recognition and cross-modal retrieval. IEEE Trans. Cybern. 48 (9), 2542–2555.

Cao, G., Iosifidis, A., Gabbouj, M., 2017. Multi-view nonparametric discriminant analysis for image retrieval and recognition. IEEE Signal Process. Lett. 24 (10), 1537–1541.

Dalal, N., Triggs, B., 2005. Histograms of oriented gradients for human detection. In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Vol. 1. pp. 886–893.

Ferdinando, S., Andy, H., 1994. Parameterisation of a stochastic model for human face identification. In: Proceedings of 2nd IEEE Workshop on Applications of Computer Vision.

Gao, L., Qi, L., Guan, L., 2015. Sparsity preserving multiple canonical correlation analysis with visual emotion recognition to multi-feature fusion. In: IEEE International Conference on Image Processing. pp. 2710–2714.

Guo, S., Shi, X., 2018. An improved spatiogram similarity measure for object tracking. Pattern Recognit. Image Anal. 28 (1), 79–86.

Hardoon, D.R., Szedmak, S.R., Shawe-taylor, J.R., 2004. Canonical correlation analysis: An overview with application to learning methods. Neural Comput. 16 (12), 2639–2664.

Huang, P., Li, T., Gao, G., Yao, Y., Yang, G., 2018a. Collaborative representation based

local discriminant projection for feature extraction. Digit. Signal Process. 76, 84–93
Huang, S., Ren, Y., Xu, Z., 2018b. Robust multi-view data clustering with multi-view capped-norm K-means. Neurocomputing 311, 197–208.

Jan, R., John, S.T., 2010. Multi-View Canonical Correlation Analysis. Taylor, pp. 1–4.
Juuti, M., Corona, F., Karhunen, J., 2018. Stochastic discriminant analysis for linear supervised dimension reduction. Neurocomputing 291, 136–150.

Kan, M., Shan, S., Zhang, H., Lao, S., Chen, X., 2016. Multi-view discriminant analysis. IEEE Trans. Pattern Anal. Mach. Intell. 26 (1), 188–195.

Kumar, S., Bhuyan, M.K., Chakraborty, B.K., 2016. Uncorrelated multiview discriminant locality preserving projection analysis for multiview facial expression recognition.

In: Proceedings of the Tenth Indian Conference on Computer Vision, Graphics and Image Processing. pp. 86:1–86:8.

Li, B., Guo, W., Zhang, X., 2018. A global manifold margin learning method for data feature extraction and classification. Eng. Appl. Artif. Intell. 75, 94–101.

Lim, C., Woo, W., Dlay, S., Wu, D., Gao, B., 2019. Deep multiview heartwave authentication. IEEE Trans. Ind. Inf. 15 (21), 777–786.

Lv, M., Hou, Q., Deng, N., Jing, L., 2017. Collaborative discriminative manifold embedding for hyperspectral imagery. IEEE Geosci. Remote Sens. Lett. 14 (4), 569–573.

Nene, S., Nayar, S., Murase, H., 1996. Columbia object image library.
Ojala, T., Pietikäinen, M., Mäenpää, T., 2002. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal. Mach. Intell. 24 (7), 971–987.

Passalis, N., Tefas, A., 2018. Dimensionality reduction using similarity-induced embeddings. IEEE Trans. Neural Netw. Learn. Syst. 29 (8), 3429–3441.

Sharifzadeh, S., Ghodsi, A., Clemmensen, L.H., Ersboll, B., 2017. Sparse supervised principal component analysis (SSPCA) for dimension reduction and variable selection. Eng. Appl. Artif. Intell. 65, 168–177.

Sun, T., Chen, S., 2007. Locality preserving CCA with applications to data visualization and pose estimation. Image Vis. Comput. 25 (5), 531–543.

Sun, T., Chen, S., Yang, J., Shi, P., 2008. A novel method of combined feature extraction for recognition. In: Eighth IEEE International Conference on Data Mining. pp. 1043–1049.

Sun, S., Xie, X., Yang, M., 2016. Multiview uncorrelated discriminant analysis. IEEE Trans. Cybern. 46 (12), 3272–3284.

Tang, J., Tian, Y., Zhang, P., Liu, X., 2018. Multiview privileged support vector machines. IEEE Trans. Neural Netw. Learn. Syst. 29 (8), 3463–3477.

Turk, M., Pentland, A., 2007. Eigenfaces for recognization. J. Cogn. Neurosci. 3, 71–86.
Wang, H., Feng, L., Yu, L., Zhang, J., 2016. Multi-view sparsity preserving projection for dimension reduction. Neurocomputing 216, 286–295.

Wang, F., Zhang, D., 2013. A new locality-preserving canonical correlation analysis algorithm for multi-view dimensionality reduction. Neural Process. Lett. 37 (2), 135–146.

Wang, J., Zhao, R., Wang, Y., Zheng, C., Kong, J., Yi, Y., 2017. Locality constrained graph optimization for dimensionality reduction. Neurocomputing 245, 55–67.

Wold, S., Ruhe, A., Wold, H., Dunn, W., 1984. The collinearity problem in linear regression. the partial least squares (PLS) approach to generalized inverses. SIAM J. Sci. Stat. Comput. 5 (3), 735–743.

Xia, T., Tao, D., Mei, T., Zhang, D., 2010. Mutilview spectral embedding. IEEE Trans. Syst. Man Cybern. 40 (6), 1438–1447.

Yang, W., Wang, Z., Sun, C., 2015. A collaborative representation based projections method for feature extraction. Pattern Recognit. 48 (1), 20–27.

You, C., Palade, V., Wu, X., 2019. Low-rank robust structure representation in latent space. Eng. Appl. Artif. Intell. 77, 117–124.

Zhai, X., Peng, Y., Xiao, J., 2014. Learning cross-media joint representation with sparse and semisupervised regularization. IEEE Trans. Circuits Syst. Video Technol. 24 (6), 965–978.

Zhang, C.Q., Fu, H.Z., Zhu, P.F., Cao, X.C., 2016. Flexible multi-view dimensionality co-reduction. IEEE Trans. Image Process. 26 (2), 648–659.

Zhang, L., Zhao, Y., Zhu, Z., Wei, S., Wu, X., 2014. Mining semantically consistent patterns for cross-view data. IEEE Trans. Knowl. Data Eng. 26 (11), 2745–2758.

Zhao, X., Wang, X., Wang, H., 2017. Multi-view dimensionality reduction via subspace structure agreement. Multimedia Tools Appl. 76 (16), 17437–17460.

Zhu, Y., Wang, Z., Gao, D., Li, D., 2017. GMFLLM: A general manifold framework unifying three classic models for dimensionality reduction. Eng. Appl. Artif. Intell. 65, 421–432.