JOINT LEARNING OF SELF-REPRESENTATION AND INDICATOR FOR MULTI-VIEW IMAGE CLUSTERING

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Problem Definition

Given a set of images with multiple views, Multi-View Clustering (MVC) is to partition the image set into clusters by exploiting the complementary information among the views.

Motivation

Previous subspace learning based MVC clustering methods suffer two limitations:

- Affinity matrix learning and cluster indicator prediction are accomplished separately, resulting that they are hardly optimal for.
- The desired discrete clustering indicator is approximated by continuous value for the convenience in model solving, which degrades MVC performance.

Contributions

- An unified model for multi-view image clustering that jointly learn the self-representation, continue cluster indicator and discrete cluster indicator.

Approach

Model

self-representation in each view

$$\arg\min_{Z_v,E_v,F,P,Q} \sum_{v=1}^{V} \left\{ \begin{array}{l} \|X_v - X_v Z_v - E_v\|_F^2 + \lambda_1 \|E_v\|_1 \\ +\lambda_2 Tr(P^T L_v P) + \lambda_3 \|F - PQ\|_F^2 \end{array} \right\}$$

$$\text{s.t. } Z_v(i,i) = 0, P^T P = I, Q^T Q = I, F \in I_{dx}$$

continuous indicator

continuous indicator to discrete indicators

Solution

Update Z $$\arg\min_{Z} \; \|X - XZ - E\|_F^2 + \lambda_2 Tr(P^T L P) \quad \text{s.t.} \quad Z_{ii} = 0$$

Update E $$\arg\min_{E_i} \|(X - XZ)_i - E_i\|_F^2 + \lambda_1 \|E_i\|_1$$

Update P $$\arg\min_{P} \lambda_2 Tr(P^T L P) + \lambda_3 \|F - PQ\|_F^2, \; \text{s.t.} P^T P = I$$

Update Q $$\arg\min_{Q} \lambda_3 \|F - PQ\|_F^2, \quad \text{s.t. } Q^T Q = I$$

Update F $$\arg\max_{F} \; \lambda_3 Tr(F^T PQ), \quad \text{s.t. } F \in I_{dx}$$

Results

Table 1: Clustering performances on ORL dataset (meanstandard deviation).

	Method	NMI	ACC	ARI	F	P	Re
single	SPCbest	0.884(0.002)	0.726(0.025)	0.655(0.005)	0.664(0.005)	0.610(0.006)	0.728(0.005)
single	SSCbest	0.893(0.007)	0.765(0.008)	0.694(0.013)	0.682(0.012)	0.673(0.007)	0.764(0.005)
single	S3Cbest	0.902(0.012)	0.784(0.009)	0.705(0.019)	0.698(0.018)	0.688(0.012)	0.791(0.011)
Multiple	Min-Dis	0.876(0.002)	0.748(0.051)	0.654(0.004)	0.663(0.004)	0.615(0.004)	0.718(0.003)
Multiple	RMSC	0.872(0.012)	0.723(0.025)	0.644(0.029)	0.654(0.028)	0.607(0.033)	0.709(0.027)
Multiple	ConReg	0.883(0.003)	0.734(0.031)	0.668(0.032)	0.676(0.035)	0.628(0.041)	0.731(0.030)
Multiple	LTMSC	0.930(0.002)	0.795(0.007)	0.750(0.003)	0.768(0.007)	0.766(0.009)	0.837(0.004)
Multiple	DiMSC	0.940(0.003)	0.838(0.001)	0.802(0.000)	0.807(0.003)	0.764(0.012)	0.856(0.004)
Multiple	ECMSC	0.947(0.009)	0.854(0.011)	0.810(0.012)	0.821(0.015)	0.783(0.008)	0.859(0.012)
Multiple	CSMSC	0.942(0.005)	0.868(0.012)	0.827(0.002)	0.831(0.001)	0.860(0.002)	0.804(0.003)
Proposed	Ours	0.943(0.005)	0.886(0.016)	0.831(0.019)	0.835(0.019)	0.804(0.023)	0.868(0.018)

Table 2: Clustering performances on ORL dataset (meanstandard deviation).

	Method	NMI	ACC	ARI	F	P	Re
single	SPCbest	0.654(0.009)	0.616(0.030)	0.440(0.011)	0.475(0.011)	0.457(0.011)	0.495(0.010)
single	SSCbest	0.671(0.011)	0.627(0.000)	0.475(0.004)	0.517(0.007)	0.509(0.003)	0.547(0.004)
single	S3Cbest	0.678(0.013)	0.634(0.016)	0.471(0.005)	0.508(0.012)	0.512(0.005)	0.568(0.025)
Multiple	Min-Dis	0.645(0.005)	0.615(0.043)	0.433(0.006)	0.470(0.006)	0.446(0.005)	0.496(0.006)
Multiple	RMSC	0.684(0.033)	0.642(0.036)	0.485(0.046)	0.517(0.043)	0.500(0.043)	0.535(0.044)
Multiple	ConReg	0.673(0.023)	0.611(0.035)	0.466(0.032)	0.501(0.030)	0.476(0.032)	0.532(0.029)
Multiple	LTMSC	0.765(0.008)	0.741(0.002)	0.570(0.004)	0.598(0.006)	0.569(0.004)	0.629(0.005)
Multiple	DiMSC	0.727(0.010)	0.709(0.003)	0.535(0.001)	0.564(0.002)	0.543(0.001)	0.586(0.003)
Multiple	ECMSC	0.773(0.010)	0.771(0.014)	0.590(0.014)	0.617(0.012)	0.584(0.013)	0.653(0.013)
Multiple	CSMSC	0.784(0.001)	0.752(0.001)	0.615(0.005)	0.640(0.004)	0.673(0.002)	0.610(0.006)
Proposed	Ours	0.782(0.005)	0.792(0.026)	0.620(0.008)	0.644(0.007)	0.616(0.009)	0.661(0.006)

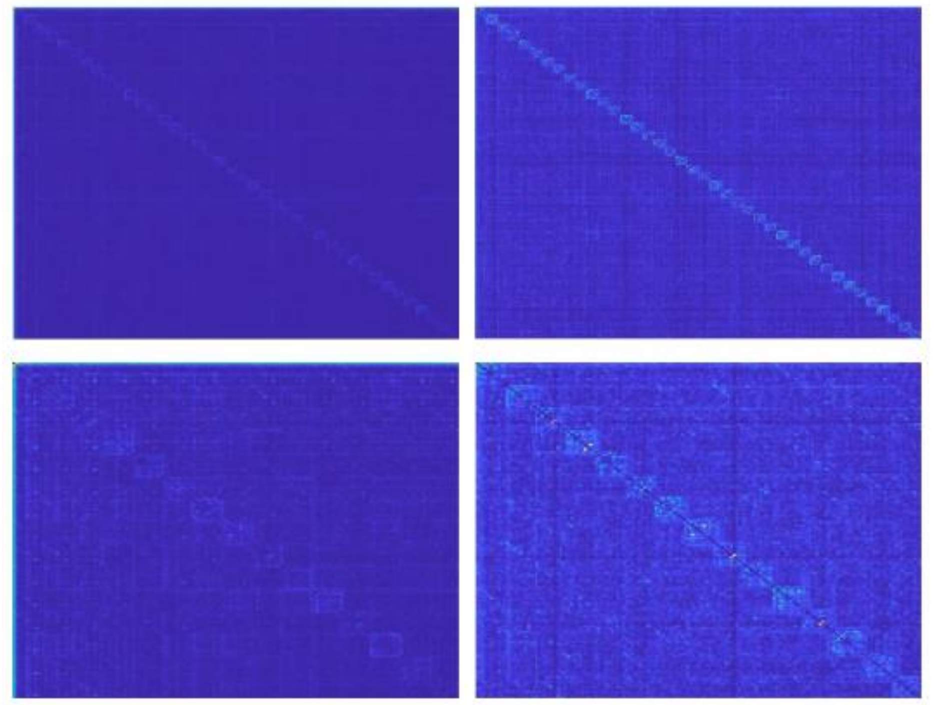
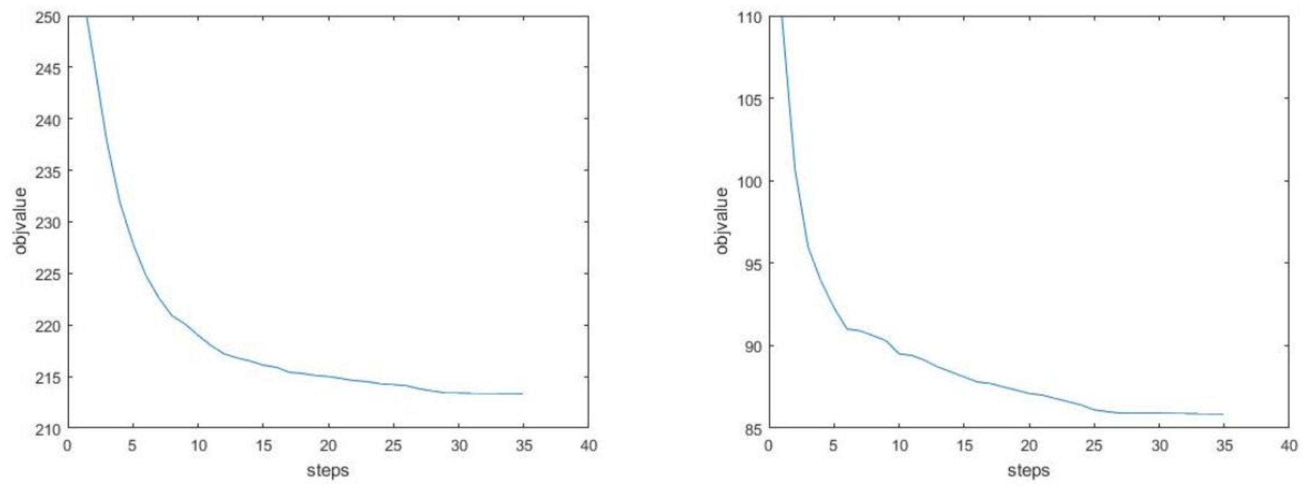


Fig. 1: Affinity matrix visualization on ORL (top) and Yale (bottom). From left to right: The affinity matrix without joint learning and the affinity matrix of our method.



(a) ORL (b) Yale

Fig. 2: Convergence curve of our method on ORL and Yale.