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Unsupervised feature selection via joint local learning and group sparse regression

Key words: Unsupervised; Local learning; Group sparse regression; Feature selection

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Motivation

1. Due to the inevitable redundancies and noise in a dataset, the intrinsic data distribution is not best revealed when using all features.

2. Distribution analysis should be simultaneously conducted with the feature selection procedure to best reveal the true data distribution.

Major results (1/5)

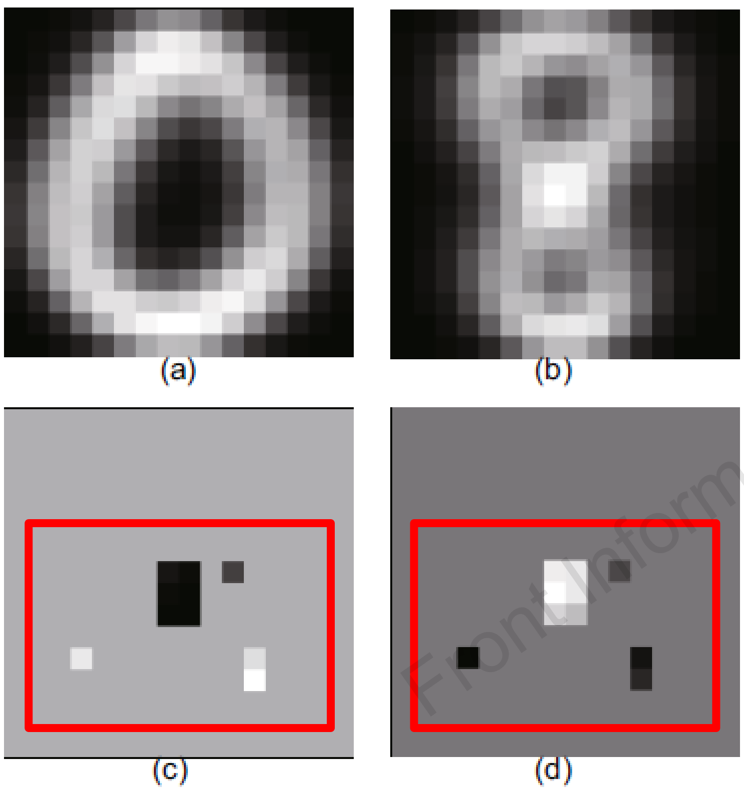


Fig. 1 Visualized feature selection results for USPS08: (a) mean image of digit zero; (b) mean image of digit eight; (c) top 10 features of zero; (d) top 10 features of eight

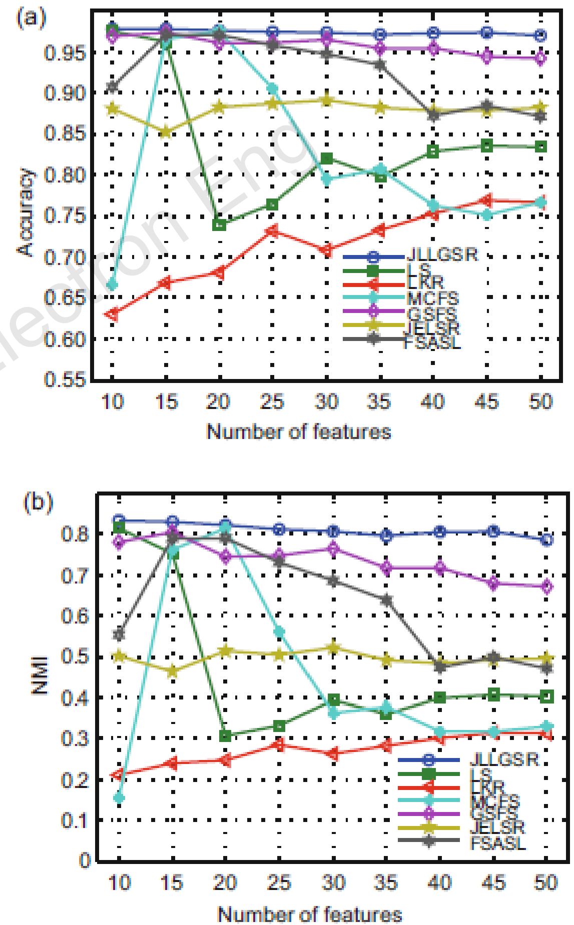


Fig. 2 Clustering results using features ranging from 10 to 50 in USPS08: (a) clustering accuracy; (b) normalized mutual information

Major results (2/5)

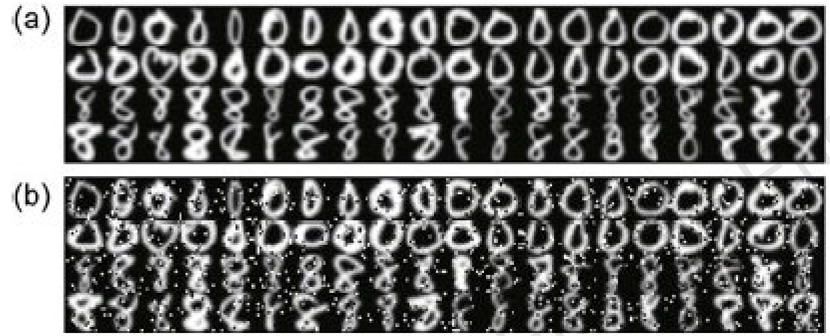


Fig. 3 Original images and images with noise in USPS08: (a) original images; (b) images with 10% salt & pepper noise

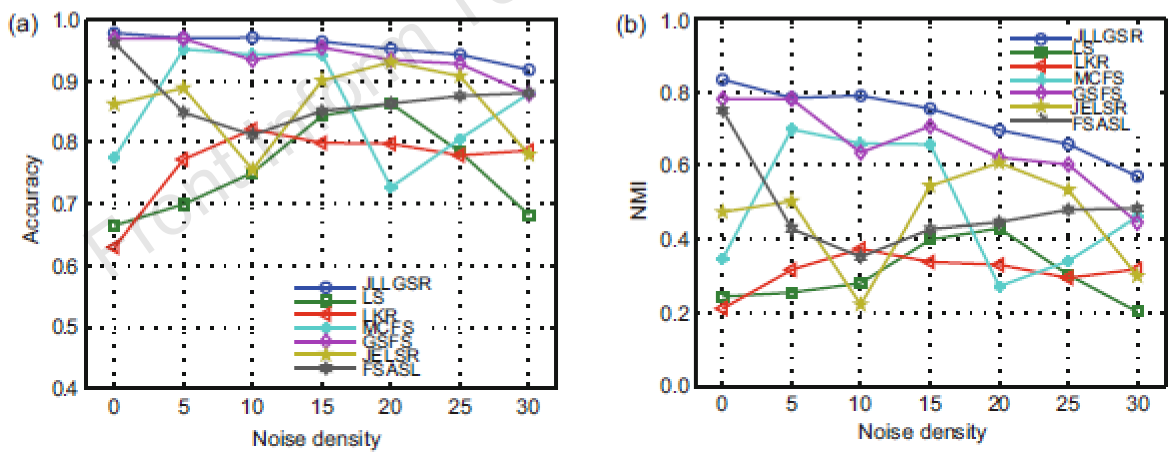


Fig. 4 Clustering results with noise density ranging from 0% to 30% for USPS08: (a) lustering accuracy; (b) normalized mutual information

Major results (3/5)

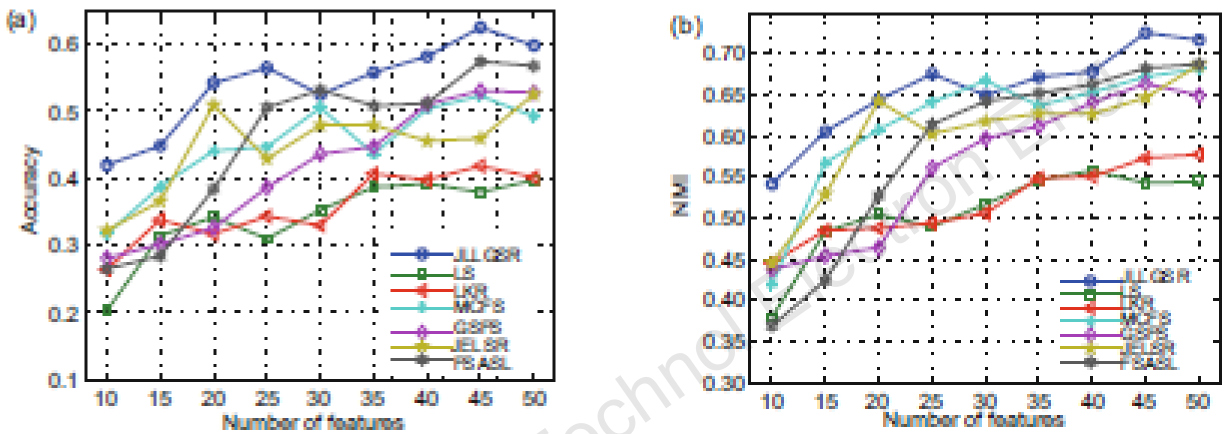


Fig. 5 Clustering results using features ranging from 10 to 50 in ISOLET4: (a) clustering accuracy; (b) normalized mutual information

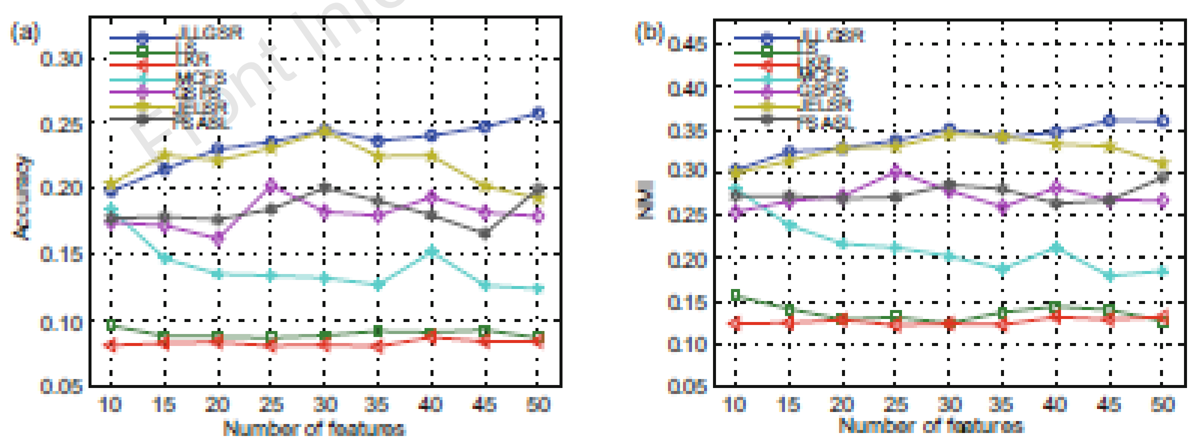


Fig. 6 Clustering results using features ranging from 10 to 50 in YaleB: (a) clustering accuracy; (b) normalized mutual information

Major results (4/5)

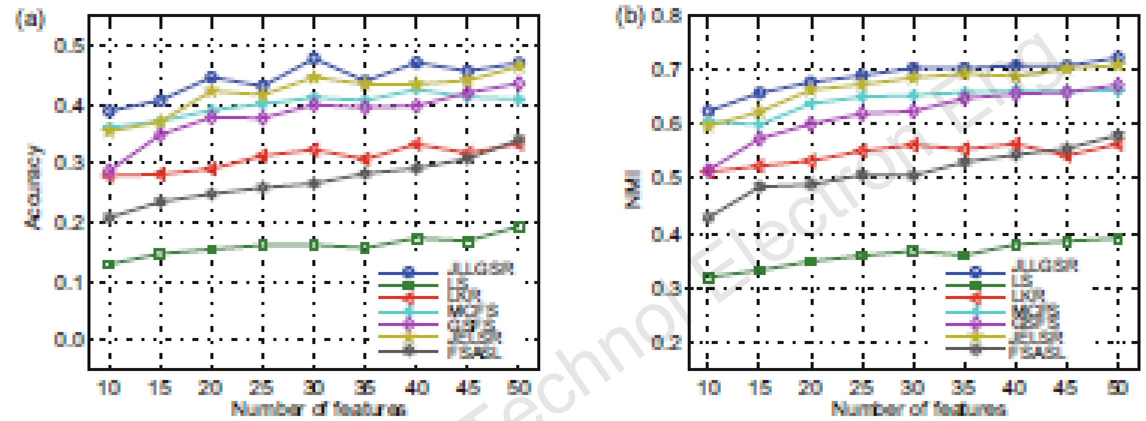


Fig. 7 Clustering results using features ranging from 10 to 50 in COIL100: (a) clustering accuracy; (b) normalized mutual information

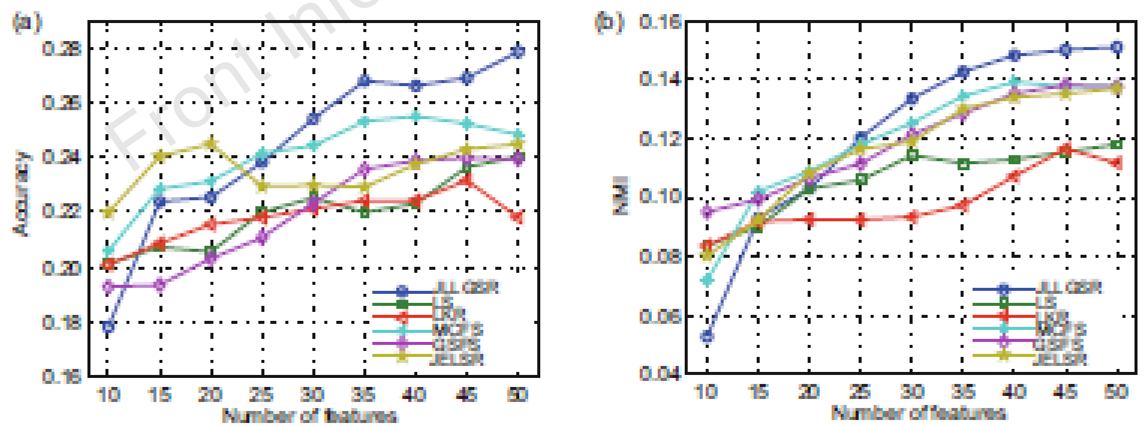
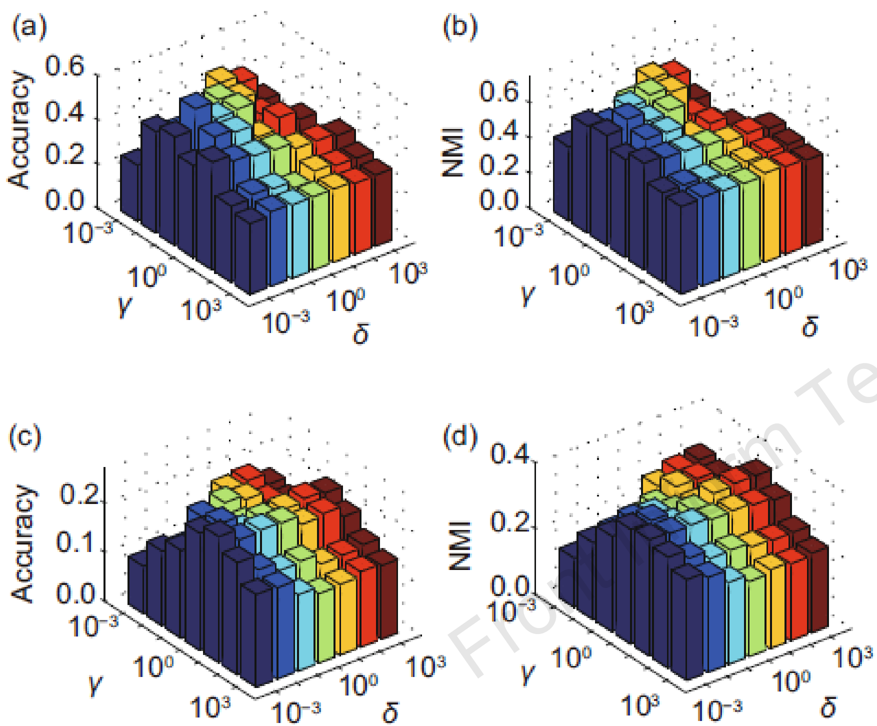


Fig. 8 Clustering results using features ranging from 10 to 50 in CIFAR10: (a) clustering accuracy; (b) normalized mutual information

Major results (5/5)



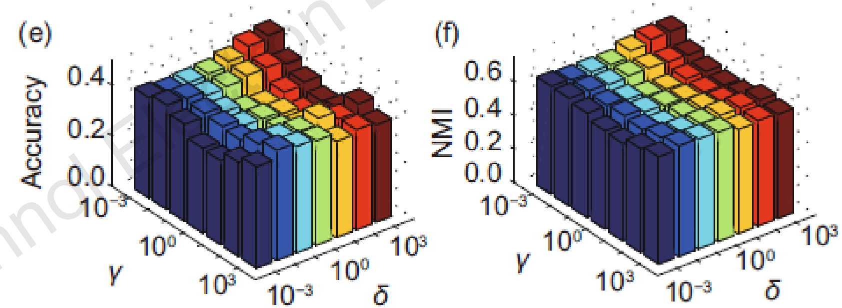


Fig. 10 Clustering accuracy and normalized mutual information (NMI) with the regularization parameters γ and δ ranging from 10^{-3} to 10^{3} from ISOLET4, YaleB, and COIL100: (a) accuracy in ISOLET4; (b) NMI in ISOLET4; (c) accuracy in YaleB; (d) NMI in YaleB; (e) accuracy in COIL100; (f) NMI in COIL100

Conclusions

1. JLLGSR is the first algorithm that incorporates local learning based clustering with group sparse regression in a single model, which makes JLLGSR capable of correcting the cluster structure with selected features and reducing the impact of noise and redundancies.

2. Compared with multi-cluster feature selection (MCFS), GSFS-llc, and joint embedding learning and sparse regression (JELSR), a new bias term has been introduced in the sparse regression model to help improve the generalization capability of JLLGSR.

3. An alternative and iterative optimization algorithm has been exploited to perform the proposed method efficiently, along with its convergence and computational complexity analysis.