Experiments

October 2, 2013

1 Synthetic Dataset

`More mathematical formula`

To verify the proposed algorithm, we compared with EM for mixture of Gaussians and spectral algorithm for mixture of spherical Gaussians (Hsu & Kakade, 2013). The assumption in (Hsu & Kakade, 2013) is very restricted, the means of the each Gaussian component should span a k-dimension subpsace, where k is number of components. Meanwhile, each component should be a spherical Gaussian. We also compared with another *nonparametric* spectral algorithms propsed by (Kasahara & Shimotsu, 2010) which uses histgram to approximate the conditional distribution. It could be thought as a special case of our method using delta kernel. It is predictable that their performance is not comparable to others because of the inferior histgram, the error is about 10 times to EM method. So that, we didn't plot it in the figures.

We generated synthetic data from the mixture models in four different settings, i.e., each view with different/same Gaussian/Gamma and Gaussian conditional distributions. In the Gamma/Gaussian mixture, we chose parameters to make the Gamma distribution more skew. For all the setting, we set the covariance of Gaussians be diagonal and the parameters are predefined to make sure they are not covered together in the sense of the ratio of the variance between the classes to the variance within the classes [1]. We also varied the number of observations n, from 50 to $100,000$, and components k in range $[2, 3, 4, 8]$ in experiments to illustrate the convergence property of our algorithm. The mixture proportions are not balanced.. For each n, k in each setting, we randomly sampled 10 sets of instances from the model for training. `Add details of the mixture proportion.`

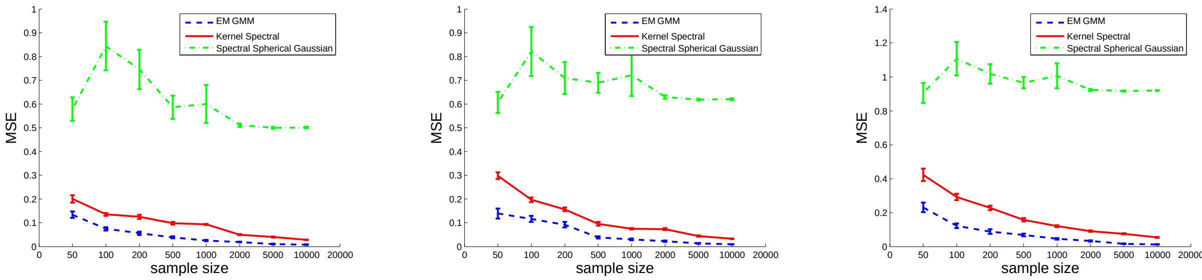
For EM algorithm, since it is not guaranteed to get the global solutions each trial, we repeated it 10 times with random initialization and added regularization term to make sure the covariance parameters is valid. We selected the best kernel bandwidth for each view by evaluated on separated generated datasets. We measured the performance of algorithms by the $l2$-norm to the ground-truth marginal distribution of each view. The results are plotted in Fig. **??**

`Some explanation for the results`

References

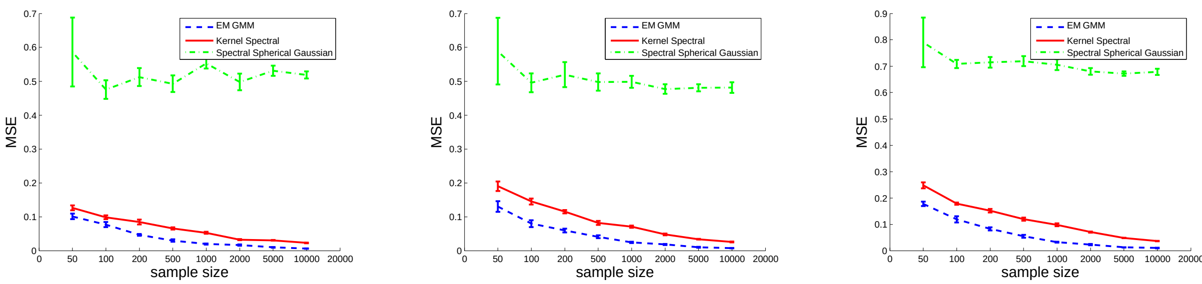
Hsu, Daniel and Kakade, Sham M. Learning mixtures of spherical gaussians: moment methods and spectral decompositions. In *Proceedings of the 4th conference on Innovations in Theoretical*

[1] This is because of the identifiable assumption in (Hsu & Kakade, 2013)



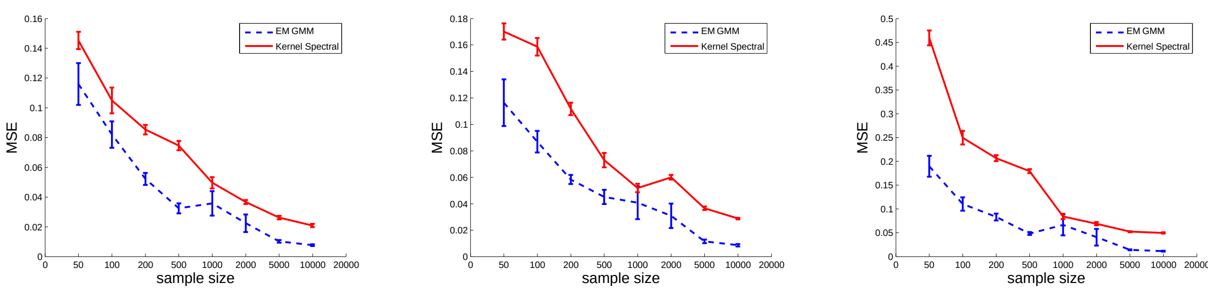
(a) View 1 (b) View 2 (c) View 3

Figure 1: The empirical results on synthetic dataset with different 2 Gaussian components in each view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



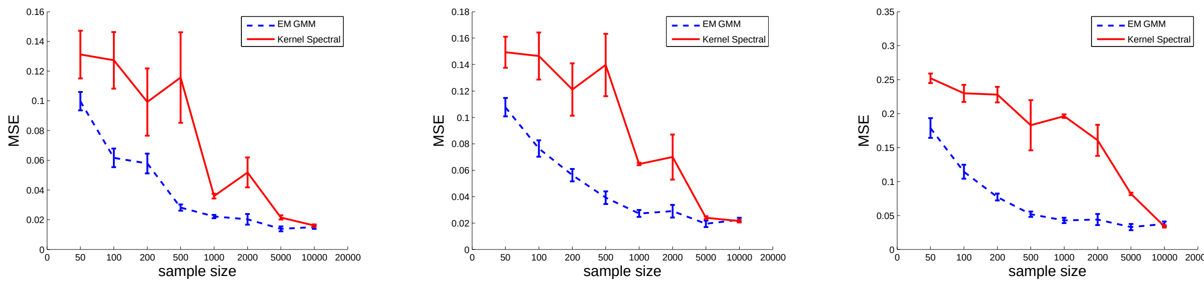
(a) View 1 (b) View 2 (c) View 3

Figure 2: The empirical results on synthetic dataset with different 3 Gaussian components in each view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



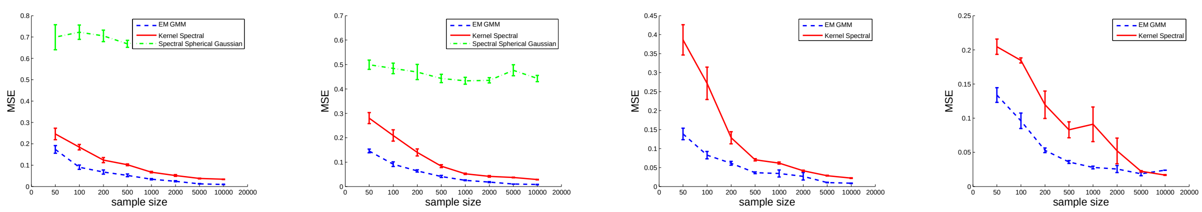
(a) View 1 (b) View 2 (c) View 3

Figure 3: The empirical results on synthetic dataset with different 4 Gaussian components in each view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



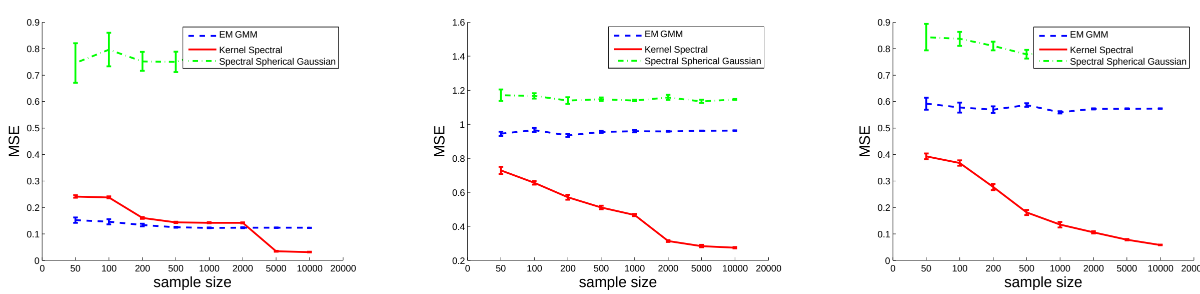
(a) View 1 (b) View 2 (c) View 3

Figure 4: The empirical results on synthetic dataset with different 8 Gaussian components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



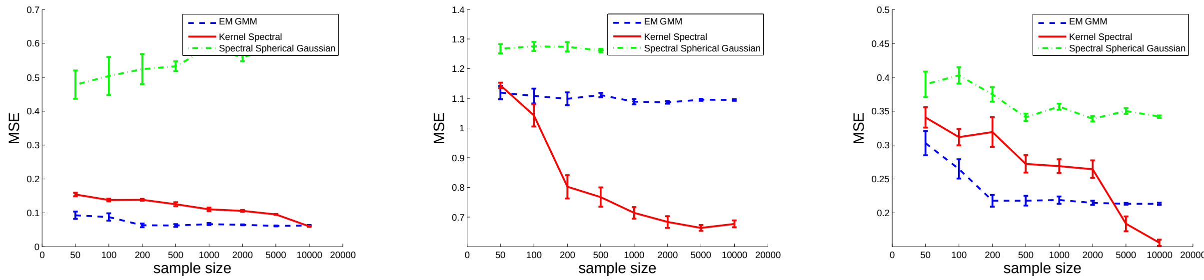
(a) 2 components (b) 3 components (c) 4 components (d) 8 components

Figure 5: The empirical results on synthetic dataset with same Gaussian components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth.



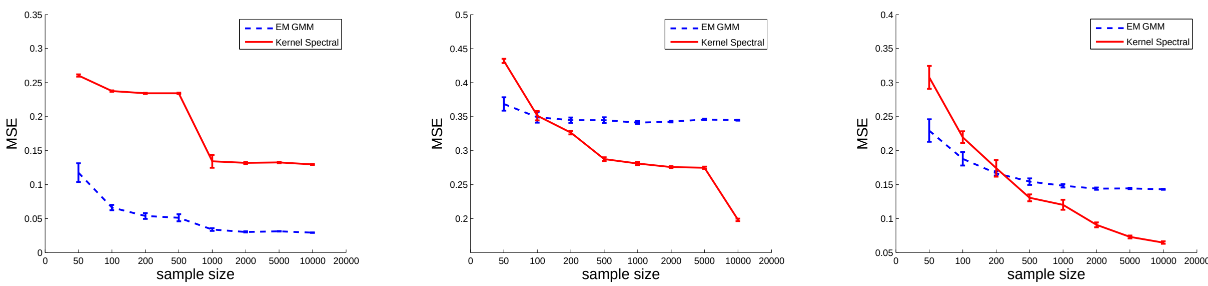
(a) View 1 (b) View 2 (c) View 3

Figure 6: The empirical results on synthetic dataset with different 2 Gaussian/Gamma components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



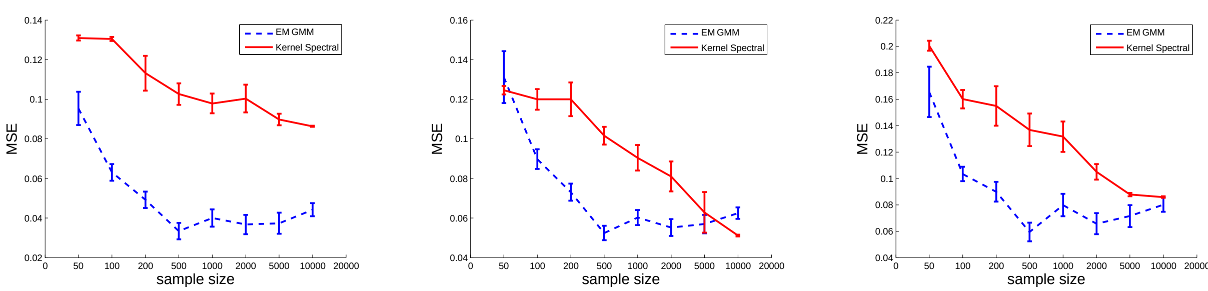
(a) View 1 (b) View 2 (c) View 3

Figure 7: The empirical results on synthetic dataset with different 3 Gaussian/Gamma components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



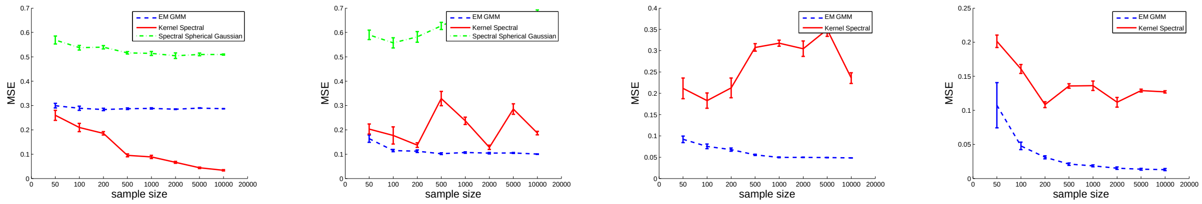
(a) View 1 (b) View 2 (c) View 3

Figure 8: The empirical results on synthetic dataset with different 4 Gaussian/Gamma components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



(a) View 1 (b) View 2 (c) View 3

Figure 9: The empirical results on synthetic dataset with different 8 Gaussian/Gamma components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth for each view.



(a) 2 components (b) 3 components (c) 4 components (d) 8 components

Figure 10: The empirical results on synthetic dataset with same Gaussian/Gamma components in eavh view measured by the $l2$-norm between marginal distribution and ground-truth.

Computer Science, ITCS '13, pp. 11–20, New York, NY, USA, 2013. ACM. ISBN 978-1-4503-1859-4.

Kasahara, Hiroyuki and Shimotsu, Katsumi. Nonparametric identification of multivariate mixtures. *Journal of the Royal Statistical Society - Series B*, 2010.