Datasets

The datasets are downloaded from the link https://archive.ics.uci.edu/ml/index.php. The two datasets chosen are Car Evaluation and Adult, same as the ones in Homework 1. The car evaluation dataset was chosen as it was interesting to see the effects of the various parameters across the general population. However, the data size was a little unsatisfactory. The adult dataset was chosen to look at the impact of race and sex on income earned for the same occupation. This dataset also had a relatively large number of records to play around with. For both datasets, the features were limited to be able to run effective experiments.

1) Car Evaluation [1]
   The dataset is derived from a simple hierarchical decision model originally developed for the demonstration of DEX, M. Bohanec, V. Rajkovic: Expert system for decision making. Sistemica 1(1), pp. 145-157, 1990.).
   This dataset will be referred to as dataset 1. This is a multivariate classification dataset. It has 6 attributes with 1728 instances. The 6 attributes are buying, maintenance cost, number of doors, number or persons, luggage boot size and safety. The class values are inaccurate, accurate, good and very good.
2) Adult [1]
   The dataset extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0)).
   This dataset will be referred to as dataset 2. This is a multivariate classification dataset. It has 14 attributes with 48842 instances. The 14 attributes are age, workclass, education, education num, marital status, occupation, relationship, race, sex, capital gain, capital loss, hours per week and native country. The class values are >50K and <=50K.

KMeans

KMeans is a partition based clustering method. The data points get assigned to the centroids that have the smallest distance between them. For the experiment, I used Euclidean distance as the measurement. The KMeans algorithm can represent data in any dimension and thus this metric is used. To determine the optimal number of clusters for the two datasets, I used a combination of Elbow method and average silhouette score. The Elbow method was applied to the distortion.

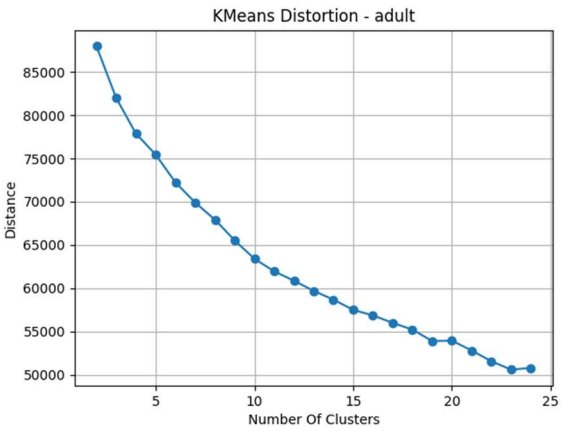
Links used as a reference:

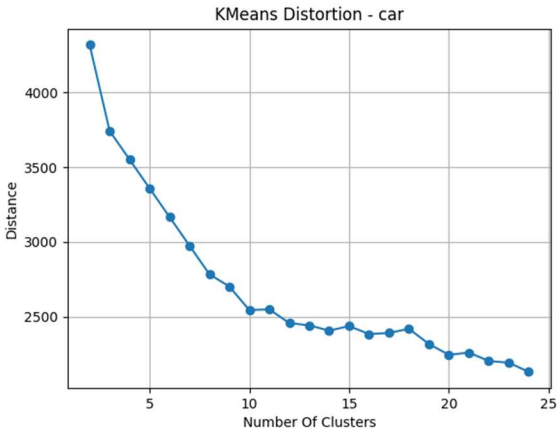
1) https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_analysis.html
2) https://towardsdatascience.com/silhouette-method-better-than-elbow-method-to-find-optimal-clusters-378d62ff6891
3) https://stackoverflow.com/questions/63471999/how-to-plot-clusters-and-centers-from-a-multi-feature-kmeans-model-with-matplot

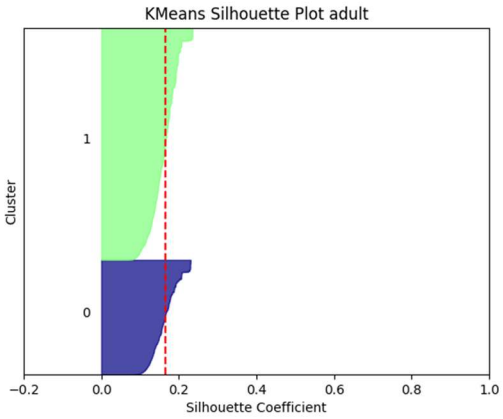
For dataset 1, using the Elbow method, the clusters of interest are 3, 8 and 10. Using the average silhouette score plot, the optimum cluster is found to be 3.

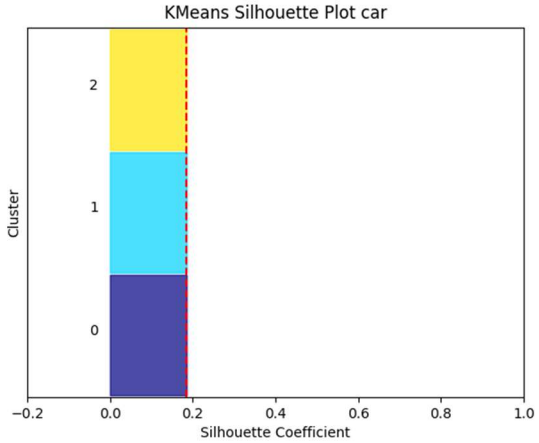
For dataset 2, using the Elbow method, the clusters of interest are 2, 3 and 5. Using the average silhouette score plot, the optimum cluster is found to be 2.

Dataset 2 **Dataset 1**









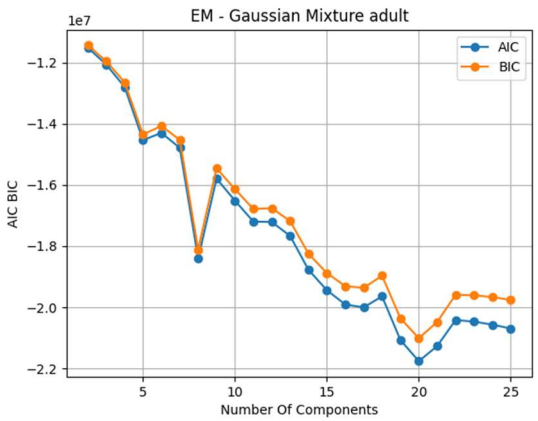
Expectation Maximization

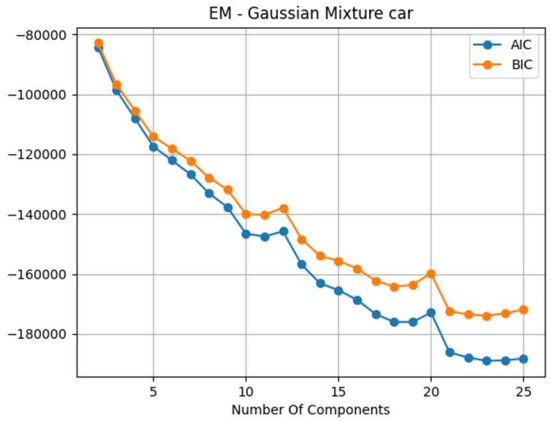
Expectation maximization is an algorithm that estimates the values of latent variables. Here we estimate the density using Gaussian Mixture Model. To determine the optimal number of clusters for the two datasets, I used a combination of Elbow method and average silhouette score. The Elbow method was applied to the AIC and BIC scores.

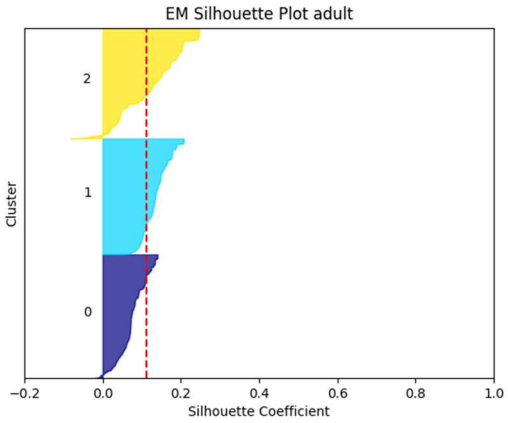
For dataset 1, using the Elbow method, the clusters of interest are 3, 5 and 10. Using the average silhouette score plot, the optimum cluster is found to be 3.

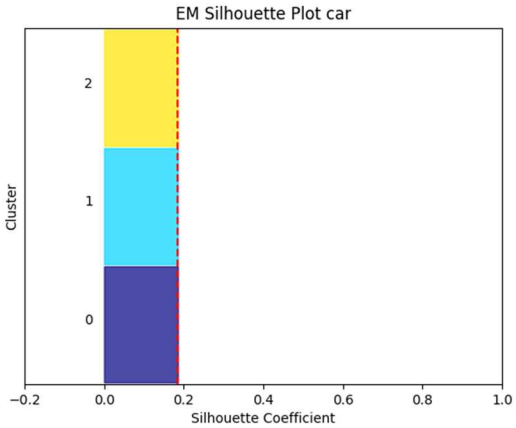
For dataset 2, using the Elbow method, the clusters of interest are 3 and 5. Using the average silhouette score plot, the optimum cluster is found to be 3.

Dataset 2 **Dataset 1**









Principal Component Analysis (PCA)

PCA is a linear dimensionality reduction method that transforms a set of variables into a smaller number of uncorrelated variables, known as principal components, while retaining as much of the variation of the original dataset. The number of components is determined using the explained variance and cumulative variance.

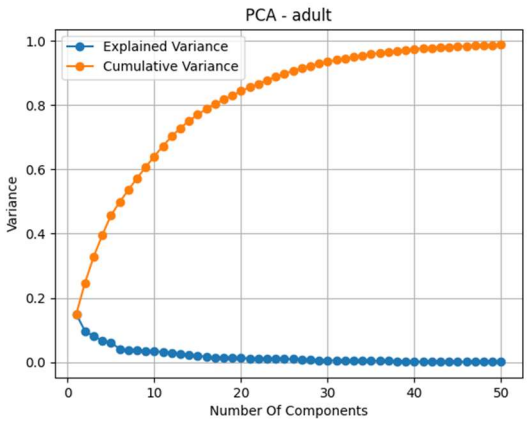
Links used as a reference:

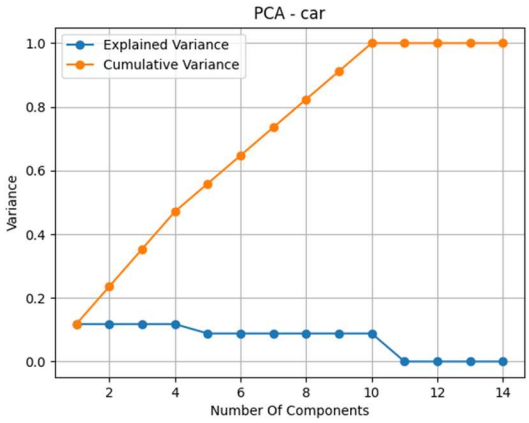
1) https://towardsdatascience.com/principal-component-analysis-pca-with-scikit-learn-1e84a0c731b0
2) https://www.oreilly.com/library/view/hands-on-unsupervised-learning/9781492035633/ch04.html

For dataset 1, the number of components is determined to be 9, where the cumulative variance is around 95%. The scatter plot along the two principal components is shown below.

For dataset 2, the number of components is determined to be 30, where the cumulative variance is around 95%. The scatter plot along the two principal components is shown below.

Dataset 2 **Dataset 1**





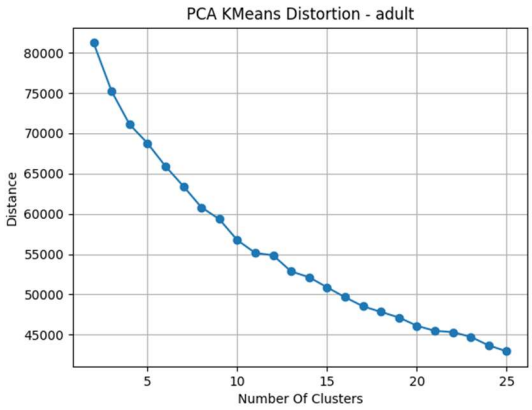
PCA With KMeans:

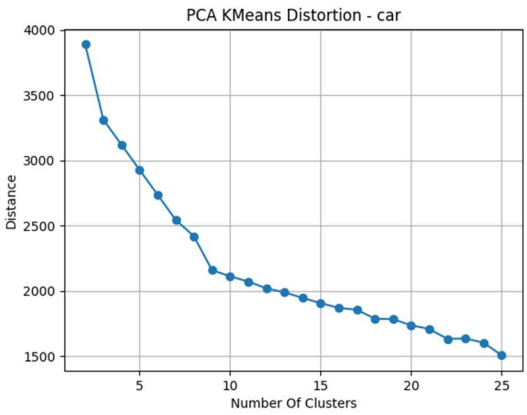
KMeans was run on top of the reduced dataset using PCA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 7 and 9. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 3, 4, 5 and 8. Using the average silhouette score plot, the optimum cluster is found to be 2.

The average silhouette plot for both KMeans and Gaussian Mixture are same which is interesting. Only one of the plots is shown. The plots are generated in the plots folder when running the experiment.



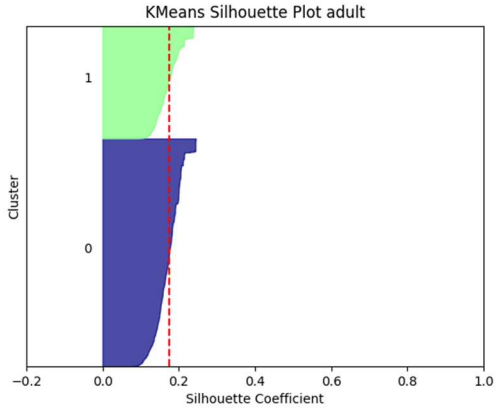


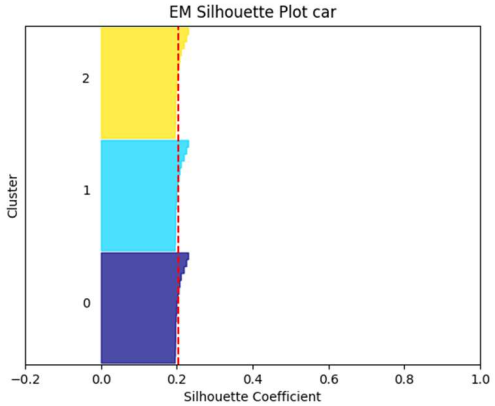
PCA With Expectation Maximization:

Gaussian Mixture was run on top of the reduced dataset using PCA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 4, 6, 7 and 9. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 2, 3, 5 and 7. Using the average silhouette score plot, the optimum cluster is found to be 2.

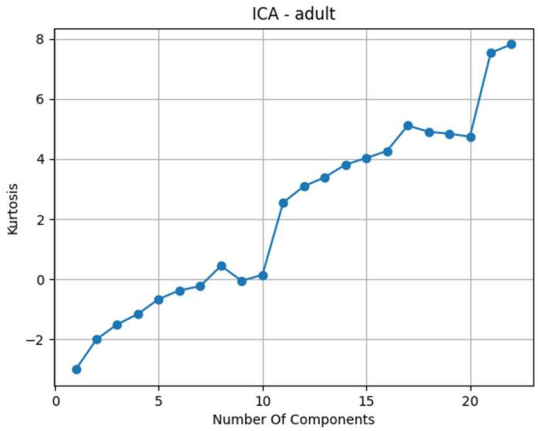




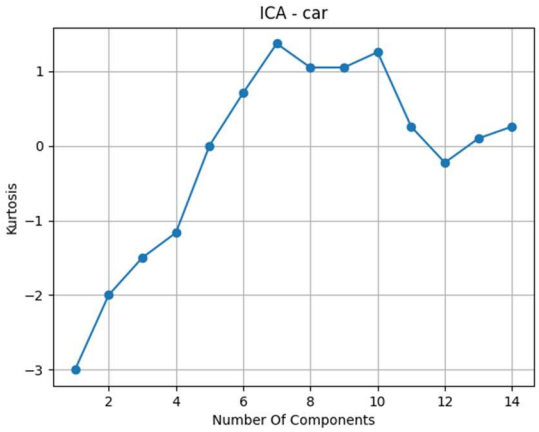
Independent Component Analysis (ICA)

ICA aims to separate information by transforming the input space into a maximally independent basis. Kurtosis is used to determine the number of components. It is a measure that defines how heavily the tails of a distribution differ from the tails of a normal distribution.

Dataset 2



Dataset 1



Links used as a reference:

1) https://www.oreilly.com/library/view/hands-on-unsupervised-learning/9781492035633/ch04.html

For dataset 1, the optimum number is found to be 7.

For dataset 2, the number of components of interest are 8, 10, 11, 21 and 37. The optimum number is found to be 10.

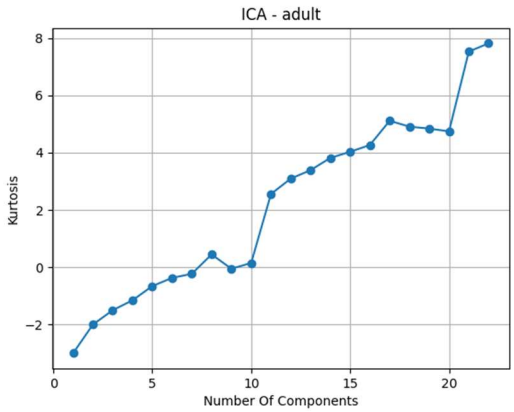
ICA With KMeans:

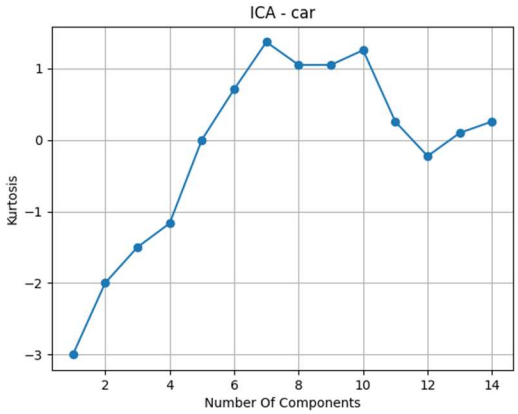
KMeans was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 5 and 6. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 3, 4 and 7. Using the average silhouette score plot, the optimum cluster is found to be 7.

The average silhouette plot for both KMeans and Gaussian Mixture are same which is interesting. Only one of the plots is shown. The plots are generated in the plots folder when running the experiment.





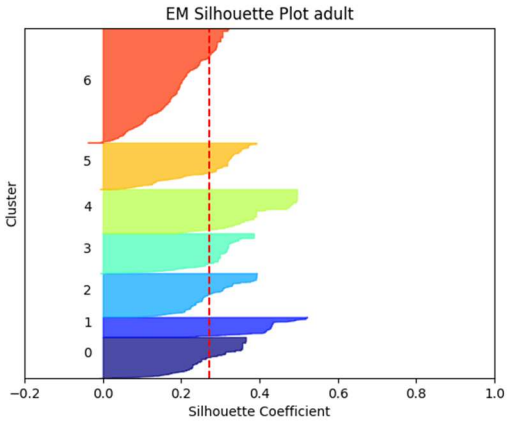
ICA With Expectation Maximization:

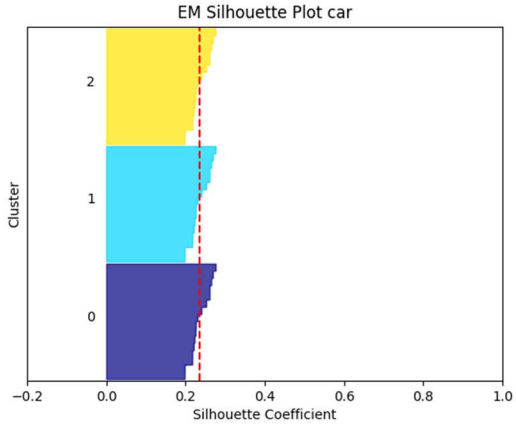
Gaussian Mixture was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 4, 5 and 7. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 3, 4, 6, 7 and 8. Using the average silhouette score plot, the optimum cluster is found to be 7.

The kurtosis plot can be found in the plots folder in the code directory.





Gaussian Random Projection (GRP)

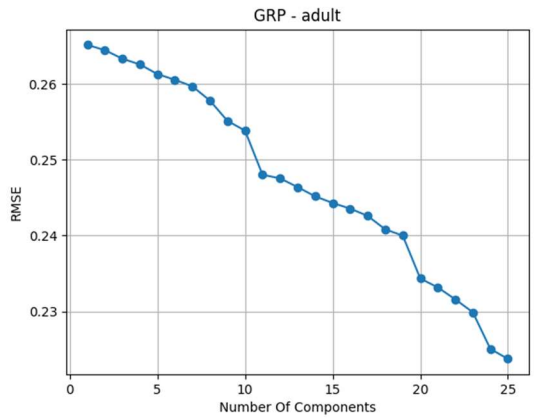
GRP reduces dimensionality by projecting the original input space on a randomly generated matrix where components are draw from a distribution $N(0, \frac{1}{n_{components}})$

The results are compares using the reconstruction loss.

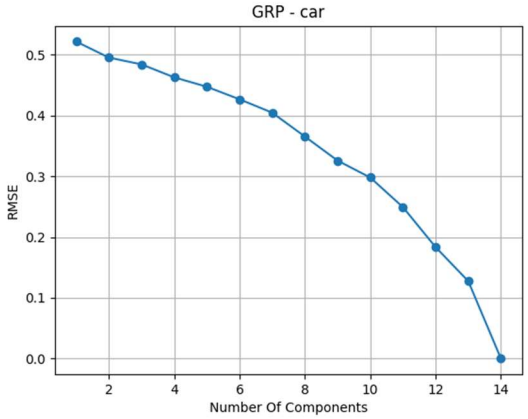
Links used as a reference:

1) https://scikit-learn.org/stable/modules/random_projection.html
2) https://www.oreilly.com/library/view/hands-on-unsupervised-learning/9781492035633/ch04.html
3) https://asifrehan.com/how-to-compute-reconstruction-error-for-random-projection/

Dataset 2



Dataset 1



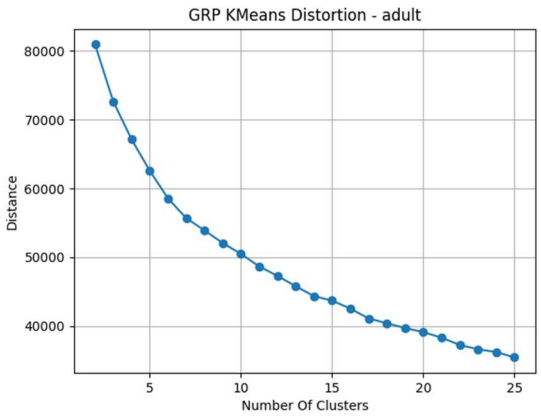
GRP With KMeans:

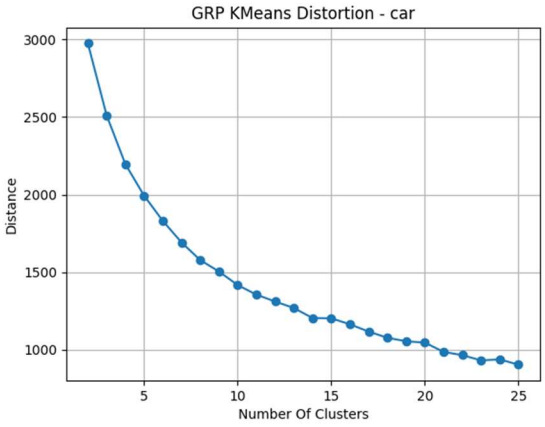
KMeans was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 5, 6 and 7. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 3, 5, 8 and 9. Using the average silhouette score plot, the optimum cluster is found to be 2.

The average silhouette plot for both KMeans and Gaussian Mixture are same which is interesting. Only one of the plots is shown. The plots are generated in the plots folder when running the experiment.





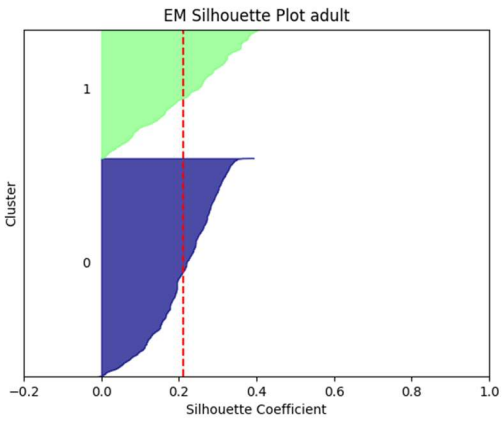
GRP With Expectation Maximization:

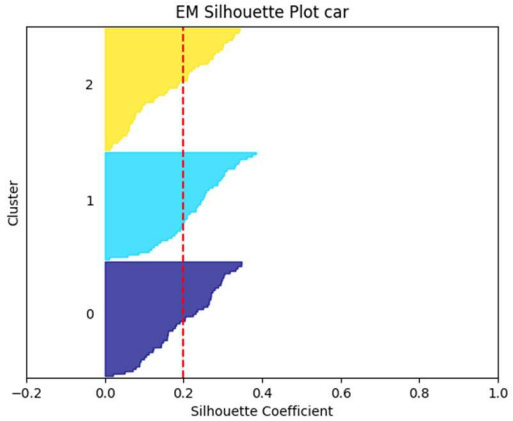
Gaussian Mixture was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 3, 5 and 6. Using the average silhouette score plot, the optimum cluster is found to be 3.

For dataset 2, using the Elbow method, the clusters of interest are 3, 4 and 7. Using the average silhouette score plot, the optimum cluster is found to be 2.

The distortion plot can be found in the plots folder in the code directory.





Mini Batch Dictionary Learning

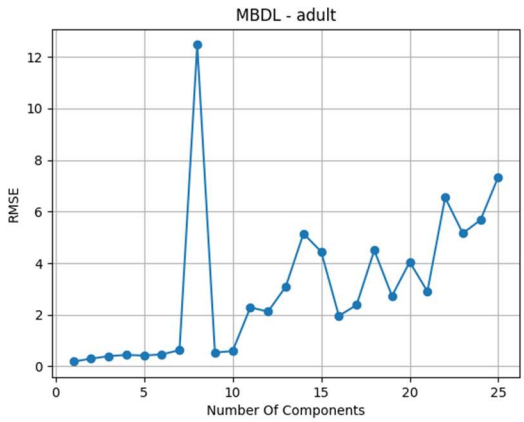
Finds a dictionary that performs well at sparsely encoding the fitted data. The algorithm learns the sparse representation of the data.

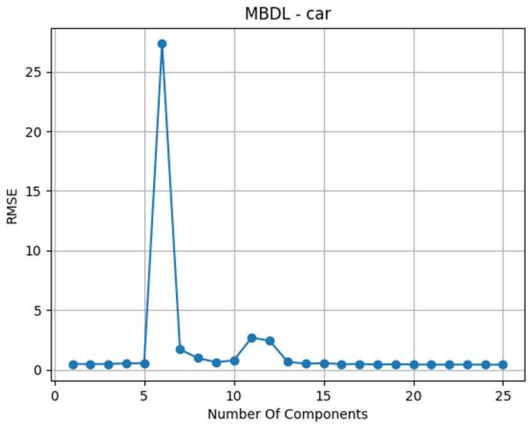
The results are compares using the reconstruction loss.

Links used as a reference:

1) https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.MiniBatchDictionaryLearning.html
2) https://www.oreilly.com/library/view/hands-on-unsupervised-learning/9781492035633/ch04.html
3) https://asifrehan.com/how-to-compute-reconstruction-error-for-random-projection/

Dataset 2 **Dataset 1**





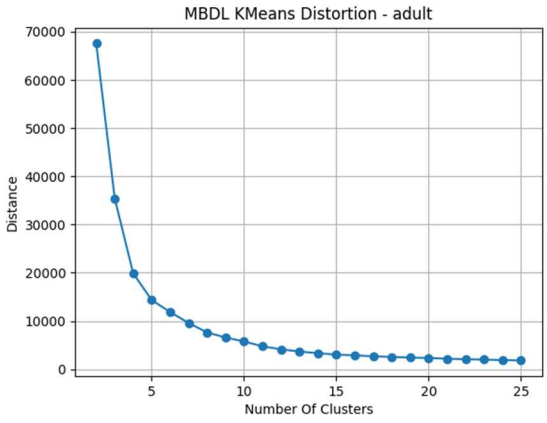
Mini Batch Dictionary Learning With KMeans:

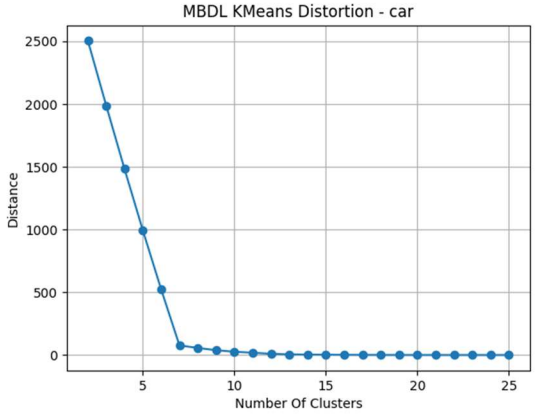
KMeans was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the cluster of interest is 7. Comparing with the average silhouette score plot, the optimum cluster is found to be 7.

For dataset 2, using the Elbow method, the clusters of interest are 3, 4 and 5. Using the average silhouette score plot, the optimum cluster is found to be 2.

The average silhouette plot for both KMeans and Gaussian Mixture are same which is interesting. Only one of the plots is shown. The plots are generated in the plots folder when running the experiment.





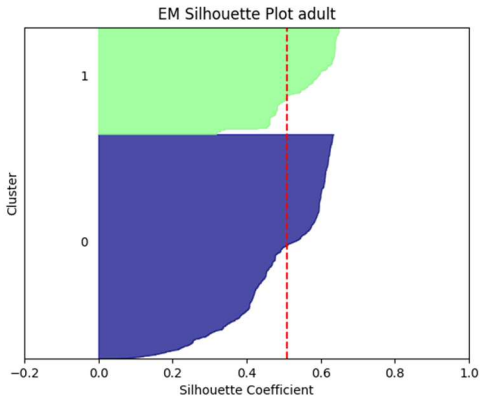
Mini Batch Dictionary Learning With Expectation Maximization:

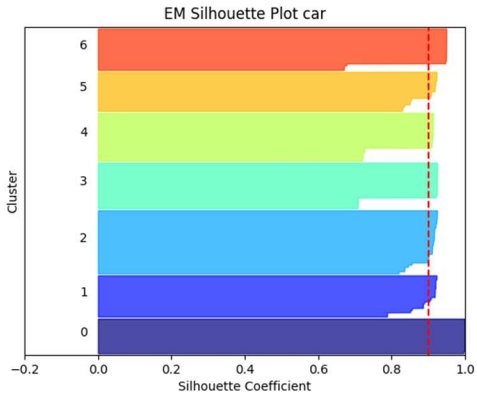
Gaussian Mixture was run on top of the reduced dataset using ICA. The results are shown below.

For dataset 1, using the Elbow method, the clusters of interest are 4, 5, 6 and 7. Using the average silhouette score plot, the optimum cluster is found to be 7.

For dataset 2, using the Elbow method, the clusters of interest are 3, 5, 6 and 10. Using the average silhouette score plot, the optimum cluster is found to be 2.

The reconstruction error plot can be found in the plots folder in the code directory.





Neural Network – MLP Evaluation

Below are the accuracy scores and model times for the experiments using the MLP classifier from scikit learn - neural network.

Algorithm	Accuracy - In Sample	Accuracy - Out Sample	Fit Time	Query Time
Principal Component Analysis	0.789081886	0.653179191	3.029490709	0.002018929
Independent Component Analysis	0.710504549	0.570327553	3.686540842	0.001997471
Gaussian Random Projection	0.779156328	0.755298651	4.129885674	0.00303483
Mini Batch Dictionary Learning	0.669975186	0.524084778	0.798716307	0.001969337
KMeans	0.70306038	0.693641618	0.626730442	0.001999617
Expectation Maximization	0.70306038	0.693641618	2.853698969	0.002007484

Overall GRP has the best accuracy scores though it takes longer than the other methods. Mini batch dictionary learning has the worst performance metrics. However, this could be because of the batch size provided along with the small dataset chosen.

Both clustering methods have similar accuracy scores with the difference being in the model execution times. The scores are likely to improve with dimensionality reduction as it doesn't look like the clustering is optimal for the given features.

References

1) Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.