CS 7641 Machine Learning
Assignment 3

Philip Bale
pbale3

Due Sunday April 1st, 2018 11:59pm

Introduction

This assignment explores unsupervised learning and dimensitonality reduction. It begins by examining clustering algorithms, specifically k-means and expectation maximization. It then proceeds to cover four dimensionality reduction algorithms: principal components analysis, individual components analysis, randomized projections, and random forests. After running these six algorithms on the original datasets and observing the results, the results are then piped into a neural network learner for further examination.

Datasets

The datasets chosen were the same datasets chosen for assignment 1. The first dataset is the US permanent visa dataset. This dataset is interesting due to its potential to aid in the visa application process from a cost and time savings potential. It could also enable confidence in those interested in applying for a US permanent visa but doubting their chances of acceptance. At the end of the day, the goal is it to try to determine the application result before time, money, nd other resources are spent. As before, 6 features are used.

The second dataset is a home sale price prediction dataset taken from an ongoing Kaggle competiton. This dataset is interesting for two primary reasons: real-world applicability and participating in a Kaggle challenge. First, modeling home prices is both a difficult and lucrative task. If one can succesfully model home sale prices on large sets of data, he/she can make large amounts of money investing in real estate when he/she detects outliers in listed price vs. what it is expected to sell for. This applies to flipping, investing, and remodeling. Second, the dataset is part of an ongoing Kaggle competition that does not have a winning solution yet. By taking part of the competition, the dataset presents the opportunity to work towards a winning solution and advance ones algorithms over time. As before, 11 features are used.

Part 1: Clustering Algorithms

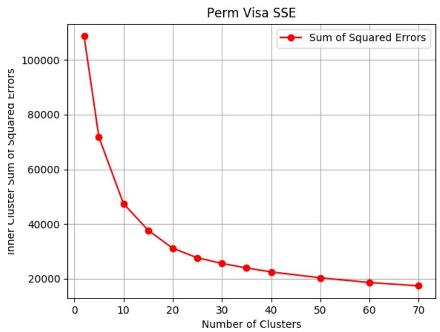
Introduction

K-means clustering is the first algorithm applied to the datasets and expectation maximization is the second. Both algorithms work by clustering: gathering groups of instances together based upon their features. The rationale is that similar instances will likely be labeled the same way–such as identical visa applications obtaining the same outcome.

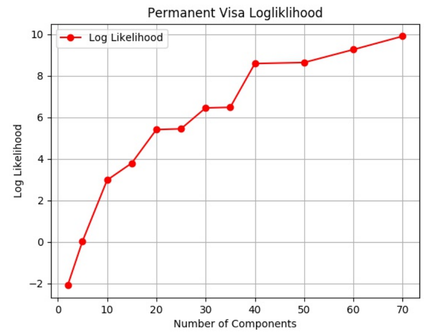
1) k-means clustering

Overview

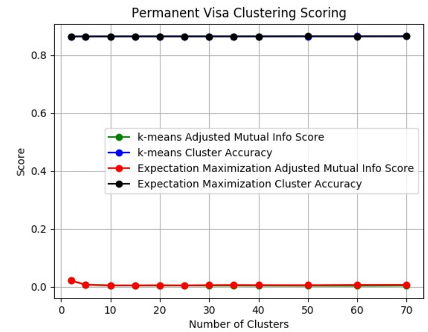
K-means works by clustering n instances into k-clusters of similarity using least-squares Euclidean distance between the instances. In practice, the algorithm converges on 'mean' for each cluster that is representative of the members of that cluster. A variety of cluster sizes were tested to find the best parameters possible.



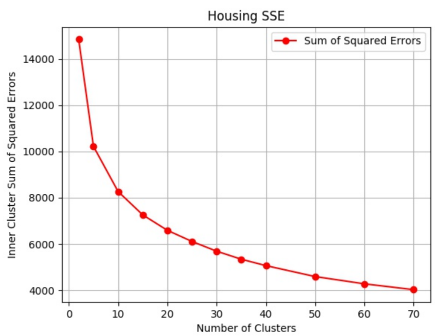
Perm Visa Sum of Square Errors for Clusters vs. # Clusters



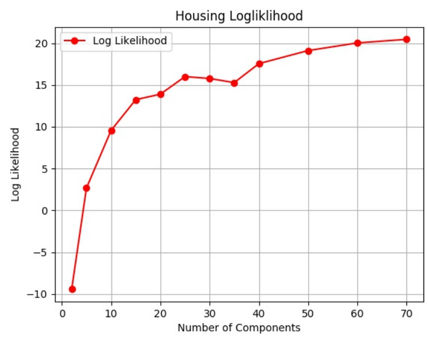
Perm Visa Log Liklihood vs. # Components



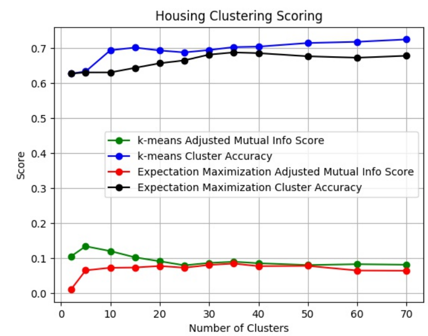
Perm Visa Scoring for k-means and expectation maximization



Housing Sum of Square Errors for Clusters vs. # Clusters



Housing Log Liklihood vs. # Components



Housing Scoring for k-means and expectation maximization

k-Means Analysis

Observing the graphs above, it is clear to see that varying the number of clusters used has a clear impact on the performance of k-Means clustering. For both datasets, as the number of clusters increases, the clusters are more able to represent the data. Logically, there are instances where increasing number of clusters will decrease the accuracy instead of increasing it, such as when just starting out and before convergence (using Euclidean distance for converge properties).

The first measurement used to determine the effectiveness is the sum of square errors (SSE). The SSE measures how far away an instance data point is from the mean of its cluster. As the number of clusters increases, the SSE noticably drops and then converges. This makes sense because at a certain point, adding more clusters is overfitting and not necessary to get the all training data into its best possible fit.

From the scoring data, it is shown that the permanent visa data, performs remarkably well with a small number of clusters and does not show any noticable improvement by increasing clusters. This is due to the fact that the permanent visa data is extremely homogenous and does not contain many outliers at all. On the other hand, the housing price data is much more susceptible to changes in number of clusters. As the number of clusters increases, the testing data gradually increases in accuracy before leveling off. Since the housing data is much more varied and complex, there are intricacies of the data that require more clusters to capture well.

Clusters	2	5	10	15	20	25	30	35	40	50	60	70
PERM VISA												
SSE	108717	71834	47453	37701	31090	27611	25517	23874	22410	20267	18532	17331
Log Liklihood	-9.44	2.67	9.57	13.25	13.90	16.01	15.78	15.29	17.56	19.12	20.04	20.47
k-Means AMI	0.022	0.008	0.005	0.005	0.004	0.005	0.004	0.004	0.004	0.004	0.004	0.004
k-Means ACC	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865
EM AMI	0.022	0.007	0.005	0.005	0.006	0.005	0.006	0.007	0.006	0.006	0.007	0.007
EM ACC	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865
HOUSING												
SSE	14840	10217	8265	7256	6589	6106	5687	5339	5063	4589	4276	4024
Log Liklihood	-2.09	0.03	2.97	3.79	5.41	5.44	6.45	6.48	8.59	8.63	9.26	9.90
k-Means AMI	0.105	0.134	0.120	0.103	0.091	0.080	0.086	0.090	0.086	0.081	0.083	0.081
k-Means ACC	0.628	0.634	0.695	0.702	0.694	0.688	0.695	0.704	0.705	0.715	0.719	0.726
EM AMI	0.010	0.065	0.073	0.073	0.078	0.073	0.081	0.085	0.077	0.078	0.065	0.064
EM ACC	0.628	0.631	0.631	0.644	0.657	0.666	0.682	0.688	0.686	0.677	0.673	0.679

Table of Housing Data Results for Cluster

2) Expectation Maximization

Overview

Expectation Maximization is the second algorithm applied to the datasets and, similar to k-means, is a clustering algorithm. Expectation Maximization works by iteratively finding the maximum liklihood of parameters leading to a labeling of an instance despite possibly not having all data or parameters. For our examples, we used Scikit-learn's Gaussian mixture models to implement the Expectation Maximization algorithm. A varying number of mixture components (or number of distributions) were used to determine the best possible parameters for the clustering.

Expectation Maximization Analysis

Expectation maximization performed only slightly worse than k-means on the datasets. Insterad of using a sum of square errors calculation, a log liklihood is calculated to effectively determine the probability of succesful labeling. Interestingly, the housing dataset converges quite quickly to a near-peak log liklihood where as the permanent visa dataset takes a bit longer. This makes sense, as the permanent visa dataset is much larger and while an indicitor of classification performance and determining factor for component count, it does not gaurantee how well the algorithm will perform using such settings.

In terms of scoring, while k-means performed slightly better, it isn't by much for the housing dataset–and it was insignificantly better for the permanent visa dataset. The adjusted mutual info score, which helps to determine the differences between clusters while accounting for chance, also performs similarly for expectation maximization compared to k-means. Overall, while k-means performed better in our trials, it is reasonable to believe datasets exist that would fare better using expectation maximization.

Part 2: Dimensionality Reduction Algorithms

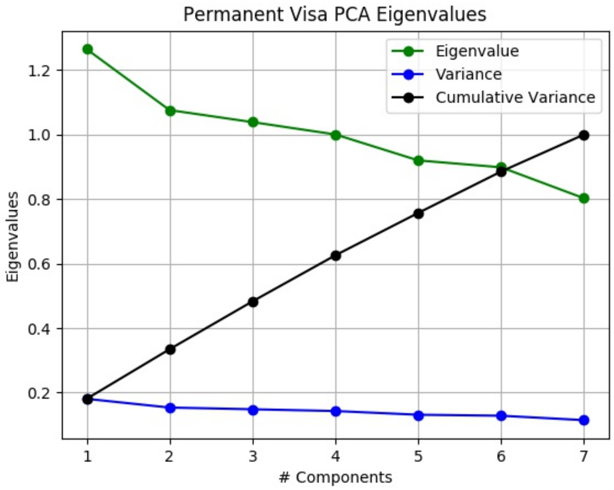
Introduction

Part 2 deals with dimensionality reduction algorithms. The four algorithms used are principal components analysis, individual components analysis, randomized projections, and random forests. After running the algorithms on both datasets, an analysis is provided on the results. Later, we will take the results of the dimensionality reduction algorithms and use them as inputs to a neural network.

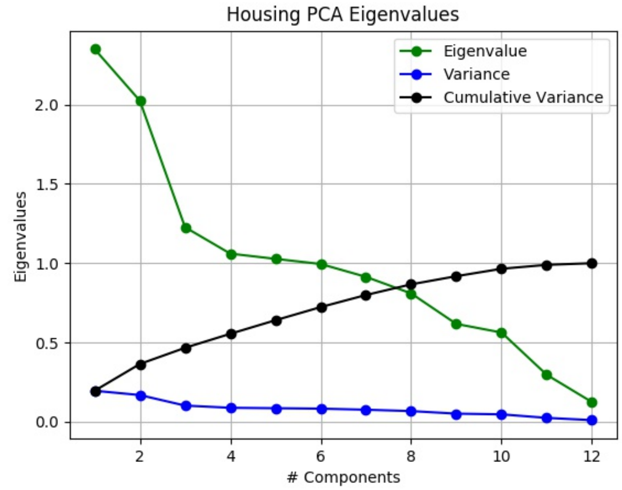
1) Principal Components Analysis (PCA)

Overview

The first dimenstionality reductation algorithm, Principal component analysis is a statistics approach to finding vectors that maximize variance and thus help to determine components that are correlated. Each subsequent component is found with the intent to be orthoganal to the preceding component. The resulting eigenvalue matrix from PCA is therefore maximized for covariance.



Permanent Visa Principal Components Analysis



Housing Principal Components Analysis

Analysis

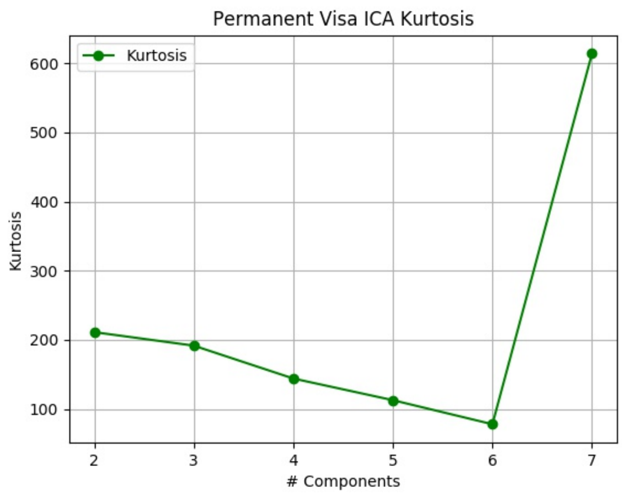
Principal component analysis seeks to reduce the number of dimensions in the data without sacrificing data quality. The prinicipal component analysis results show that both the eigenvalues and the variance decrease for both datasets as the number of components is increases. For the permanent visa dataset, the size of the eigenvalues is consistant with a slight continous decrease. In the case that there was a sharp decrease and then level off, it would indicate that there are features that are potentially unnecessary and removable. Since the level off is gradual, it indicates that each feature is important to representing the initial data. While the housing dataset has a sharp very initial drop, it then has a continous downwards trend for its eigenvalues, also indicating that removing too many features may not be a wise thing to do.

The variance graphs also provide interesting views into the ability of PCA to reduce dimensionality without sacrificing data quality. While the housing dataset indiciates a higher variance between different features, the permanent visa dataset proves to be more evenly distributed. Since we are trying to maximize variance between the different components (so that we most accurately represent the higher dimension data), we want to choose a number of components that demonstrates such. For the permanent visa dataset, that number appears to be around 5 components and for the housing dataset it apepars to be around 9 components.

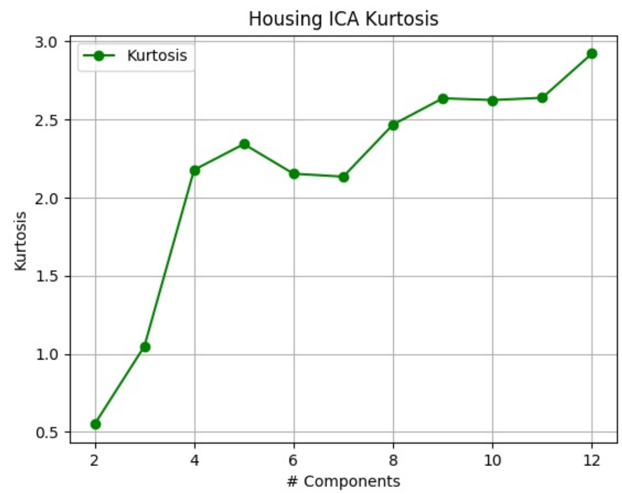
2) Independent Components Analysis (ICA)

Overview

The second dimensionality reduction algorithm, independent components analysis, is an approach to separating a mixture of a data into appropriate subcomponents. As discussed in lecture, a good example of what ICA is used for is the cocktail problem; where one needs to separate various sounds into their sources: a tv show, humans, car noises, etc. Kurtosis is used as a measurement of how gaussian the derived components are.



Permanent Visa Independent Components Analysis



Housing Independent Components Analysis

Analysis

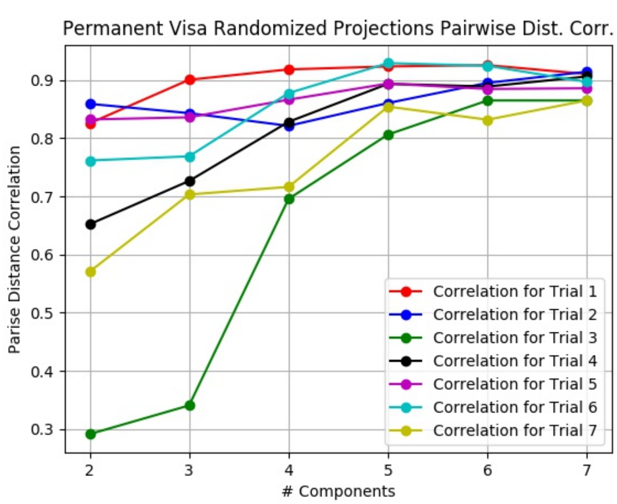
While PCA sought to maximize variance, ICA seeks to separate mixed data into subcomponents. As a dimensionality aglorithm, independent components analysis also wants to minimize dimesionality while preserving data quality. Using the kurtosis measurement, we are able to measure the spikiness of the data distribution. It's important to note that kurtosis is sensitive to outliers and therefore not always robust to measuring gaussianity.

The parameter to tune was number of components (dimensions). Similar to PCA, it is observed that the permanent visa dataset is significantly more homogenous then the housing dataset. It also suggest that 5 dimensions be kept for the permanent visa dataset and approximately 5-9 for the housing dataset.

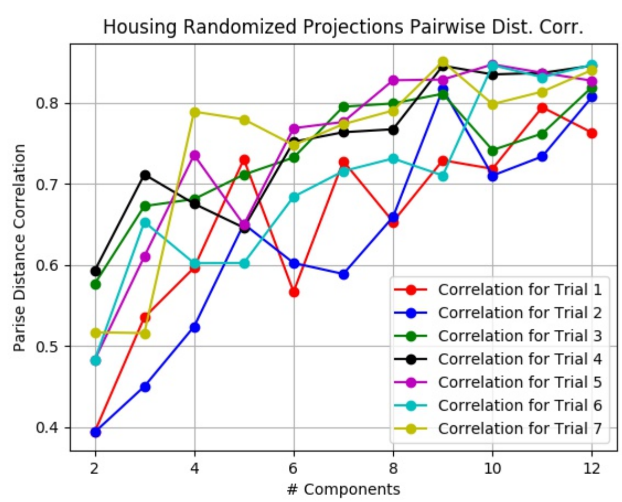
3) Randomized Projections

Overview

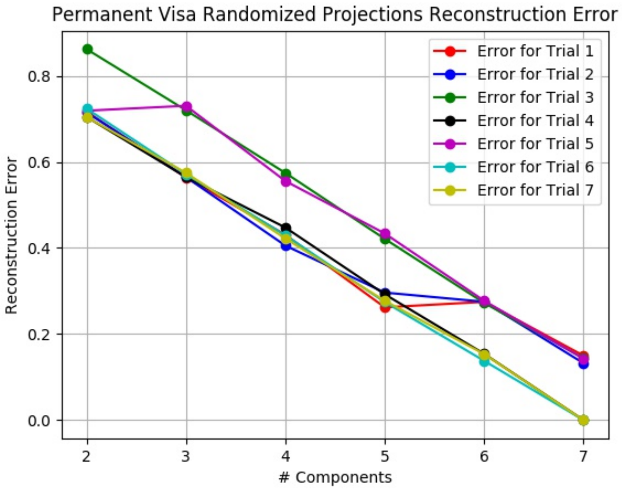
The third dimensionality reduction algorithm, randomized projections, is an approach that randomly generates a projection matrix that attempts to create a lower dimension representation of the data that is approximately accurate to its original state. By varying the number of components to project, we can run varoius tests on how well the lower dimension data captures the original.



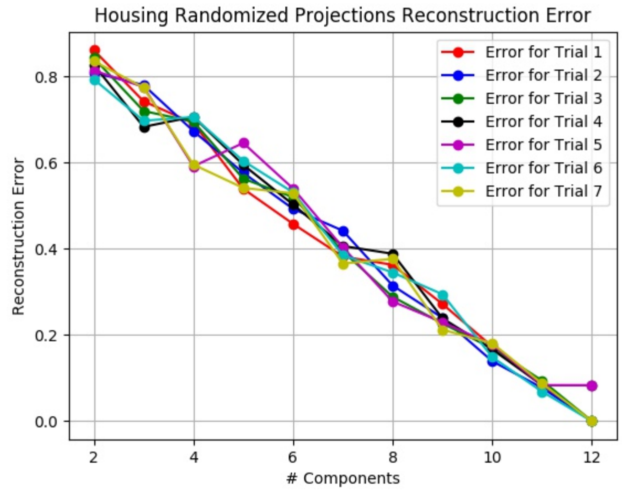
Permanent Visa Randomized Projections Pairwise Correlation



Housing Randomized Projections Pairwise Correlation



Permanent Visa Randomized Projections Reconstruction Error



Housing Randomized Projections Reconstruction Error

Analysis

Randomized projections, of all the dimesionality reduction algorithms, was the most susceptible to variation in performance due to its random nature. In such, various trials were run, each varying the random state and maintaining that same random state for a variety of number of components. We ran 10 trials for each dataset (and kept the most relevant 7).

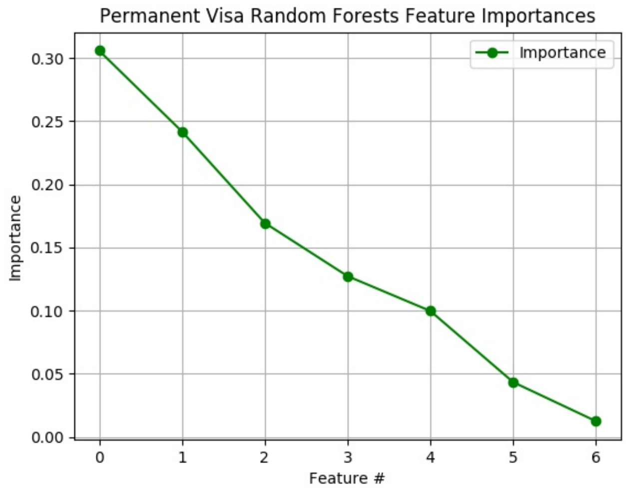
The first measure used to determine the appropriate number of dimensions to reduce to was pairwise distance between the original and reduced data. From the graphs, it is easy to see that the distance (akin to difference in the instances) converges around 5 components for the permanent visa dataset and 9-10 for the housing dataset.

The second, measurement used was reconstruction error. For both datasets, the reconstuction error decreases signficiantly as the number of dimensions is increased. This makes sense as the more dimensions available, the more easily the initial data can be reconstructed. While reconstruction error doesn't give us a clear indicator as to how well a learner will perform on the deconstructed data, it does give insight into how much data is thrown away at each reduction of dimension.

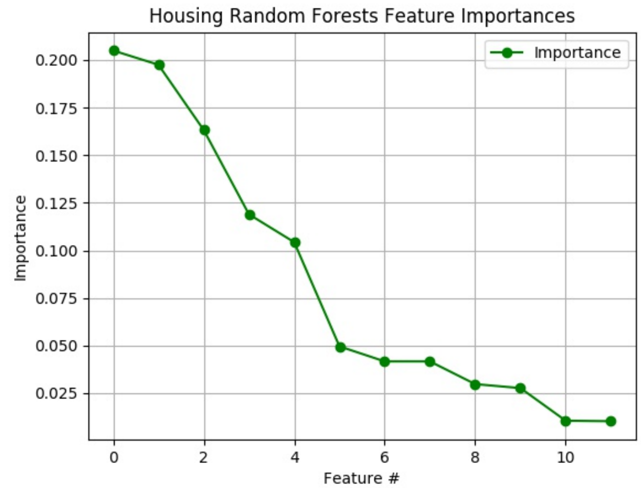
4) Random Forest Feature Selection

Overview

The fourth, and last, dimensionality reduction algorithm, random forest feature selection, is an approach that uses an ensemble of decision trees conditioned on different features. By training the decision tree and observing the impact of each feature by its ability to classify data correctly, we can select the most important features and disregard unimporant features.



Permanent Visa Random Forest Feature Importances (Descending Order)



Housing Random Forest Feature Importances (Descending Order)

Analysis

The last dimensionality reduction algorithm produces results consistent with the others. The number of estimators used was 100 to give a robust learner and all class weights were treated equally. To keep trials consistent, the same random state, number of estimators, and initial class weights were used for each trial of the random forest feature selector.

For the permanent visa dataset, approximately 5 of the features have high importance in terms of a random forest classying data correctly, whereas approximately 9 of the features have high importance for the housing dataset. Interestingly enough, the feature importance graph for the housing dataset indicates that there is a quick dropoff between 5 features in terms of importance. These findings are consistent with the results of the other dimensionality reduction algorithms.

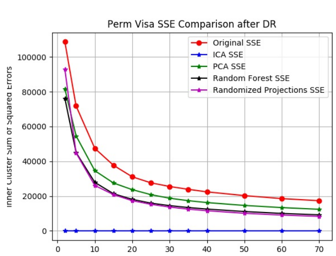
By using the various algorithms in tandem, it gives us confidence to safely pick a dimensionality of 5 for the permanent visa dataset and 9 for the housing dataset.

Part 3: Dimensionality Reduction and Clustering

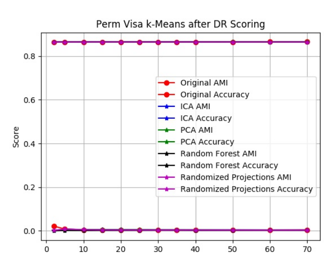
Overview

In this section, clustering algorithms are run on the results of the dimensionality reduction algorithms and then compared. All dimentionality reduction and all clustering algorithms from above are used.

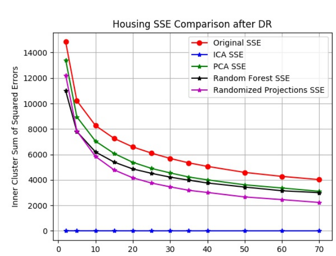
k-Means after Dimensionality Reduction



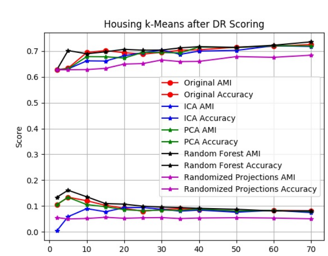
Perm Visa SSE



Perm Visa Scoring



Housing SSE



Housing Scoring

Analysis

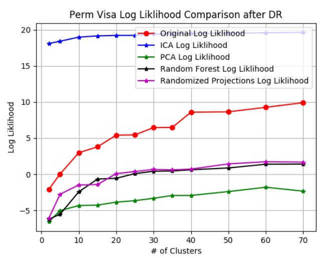
Above, graphs were computed showing the baseline clustering from Part 1, as well as clustering after each of the dimensionality reductions. Based on the results of part 2, a dimension of 5 was used for the permanent visa dataset and 9 for the housing dataset.

As is immediately apparent, the types of clusters generated vary greatly based on the dimensionality reduction algorithm used. A great way of seeing this is the sum of squared errors for each number of clusters. Each algorithm calculated a different SSE–while part of this can be attributed to the random start of the cluster centers, they do not converge to the same error rates (and thus locations for the testing data).

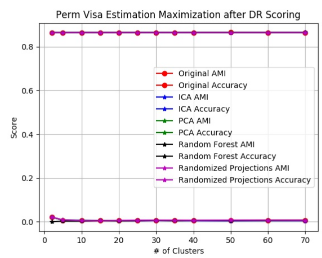
When looking at the scoring graph, it is observed that k-Means performs roughly consistently after each of the dimensionality algorithms. Other than Randomized projections, which performs slightly worse than the other, the algorithms tend to converge in both accuracy and adjusted mutual information. Similar to before, however, the permanent visa dataset is easily classified and does vary significantly depending on the algorithm used.

For the housing dataset, it becomes clear that random forest feature selection provides the best manner of selecting features. In a way, this makes sense as the random forest feature selector is a robust, generic way of viewing which features contribute the most to classification.

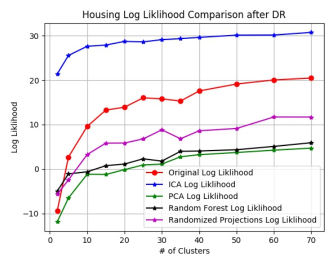
Expectation Maximization after Dimensionality Reduction



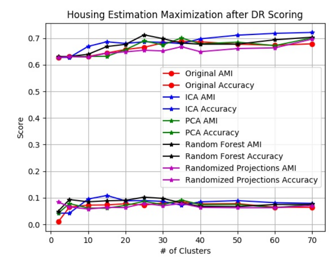
Perm Visa Log Liklihood



Perm Visa Scoring



Housing Log Liklihood



Housing Scoring

Analysis

Similar to k-Means, based on part 2, 5 and 9 were the dimension parameters used for expectation maximization.

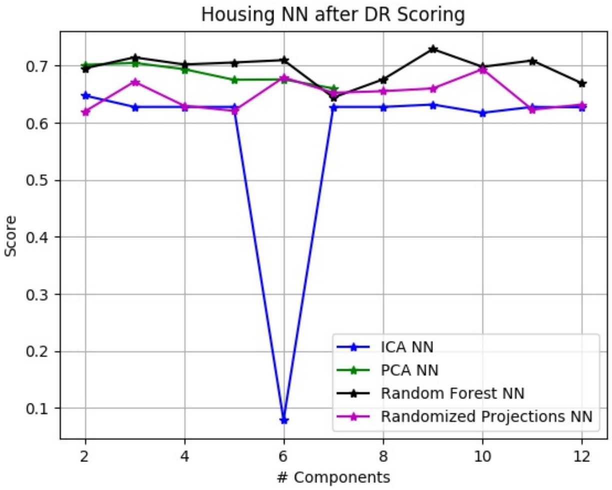
Again, the clusters generated vary signficiantly based on the dimensionality reduction algorithm used. This can be observed through the log liklihood calculations plotted above for each dimensionality reduction algorithm and baseline expectation algorithm. In EM, the log liklihood represents the liklihood of the data being correctly classified. After dimensionality reducing, the number of clusters generally increases this liklihood for both datasets.

Performance results, again, were similar to the k-Means analysis above. One noticeable difference, however, was that ICA proved to be the most succesful algorithm for the more complex housing dataset. While random forests still performed well, they did not stand out as before. Since expectation maximization tries to maximize likilhood and ICA seeks to separate mixed data, this is a viable outcome for scoring. On average, expectation maximization performs slightly worse across algorithms than k-Means, however.

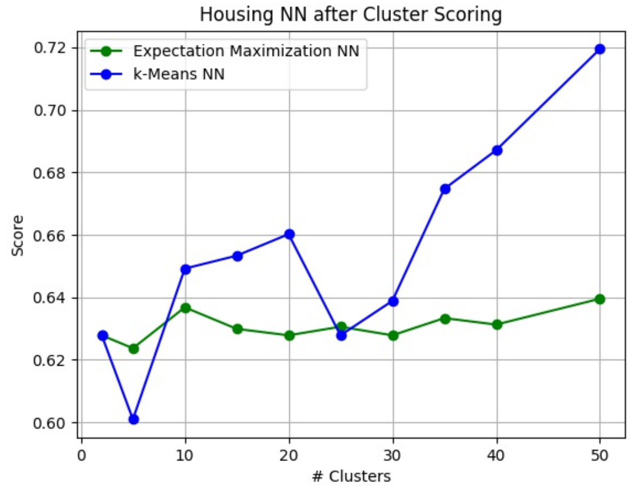
Part 4/5: Dimensionality Reduction, Clustering, and Neural Networks

Overview

In this section, similar to part 3, neural networks are run on the results of the dimensionality reduction algorithms and the clustering algorithms, and then compared.



Housing NN after dimenstionality reduction



Housing NN after clustering

Dimensionality Reduction + NN Analysis

Clustering + NN Analysis

Conclusion

Todo conclusion