

# CS 7641 Machine Learning

## Assignment 3

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Due Sunday April 1st, 2018 11:59pm

### Introduction

This assignment explores unsupervised learning and dimensionality 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 chosen

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, and other resources are spent.

The second dataset is a home sale price prediction dataset taken from an ongoing Kaggle competition. 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 successfully 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 one's algorithms over time.

## Part 1: Clustering Algorithms

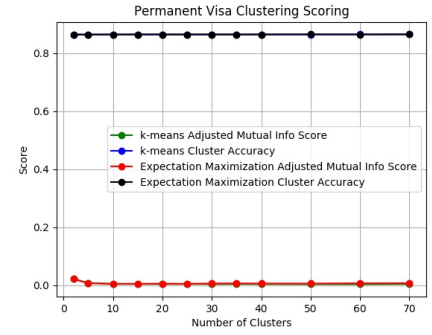
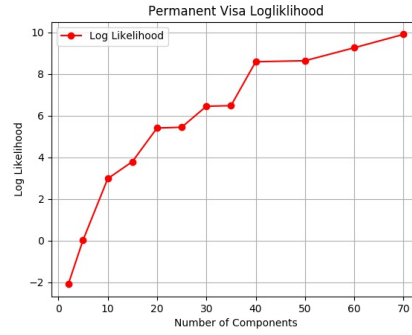
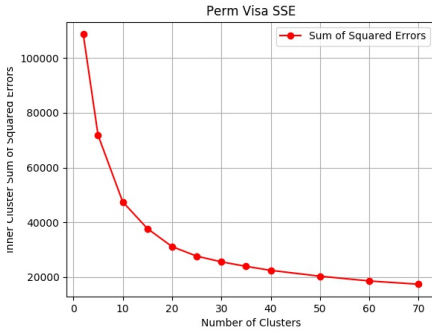
### Introduction

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.

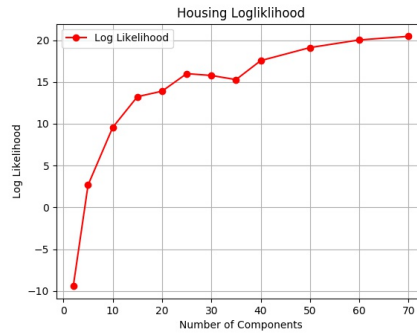
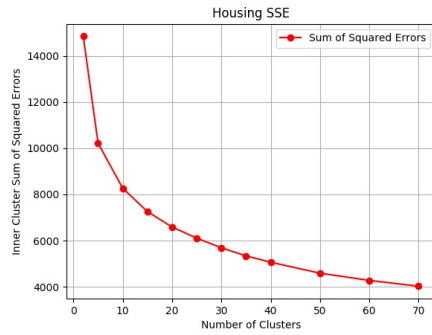
### 1) k-means clustering

#### 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 Likelihood vs. # Components      Perm Visa Scoring for k-means and expectation maximization



Housing Sum of Square Errors for Clusters vs. # Clusters      Housing Log Likelihood vs. # Components      Housing Scoring for k-means and expectation maximization

## k-Means Analysis

Text

Clusters	2	5	10	15	20	25	30	35	40	50	60	70
<b>PERM VISA</b>												
<b>SSE</b>	108717	71834	47453	37701	31090	27611	25517	23874	22410	20267	18532	17331
<b>Log Likelihood</b>	-9.44	2.67	9.57	13.25	13.90	16.01	15.78	15.29	17.56	19.12	20.04	20.47
<b>k-Means AMI</b>	0.022	0.008	0.005	0.005	0.004	0.005	0.004	0.004	0.004	0.004	0.004	0.004
<b>k-Means ACC</b>	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865
<b>EM AMI</b>	0.022	0.007	0.005	0.005	0.006	0.005	0.006	0.007	0.006	0.006	0.007	0.007
<b>EM ACC</b>	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865	0.865
<b>HOUSING</b>												
<b>SSE</b>	14840	10217	8265	7256	6589	6106	5687	5339	5063	4589	4276	4024
<b>k-Means AMI</b>	0.105	0.134	0.120	0.103	0.091	0.080	0.086	0.090	0.086	0.081	0.083	0.081
<b>k-Means ACC</b>	0.628	0.634	0.695	0.702	0.694	0.688	0.695	0.704	0.705	0.715	0.719	0.726
<b>EM AMI</b>	0.010	0.065	0.073	0.073	0.078	0.073	0.081	0.085	0.077	0.078	0.065	0.064
<b>EM ACC</b>	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 likelihood 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

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# Part 2: Dimensionality Reduction Algorithms

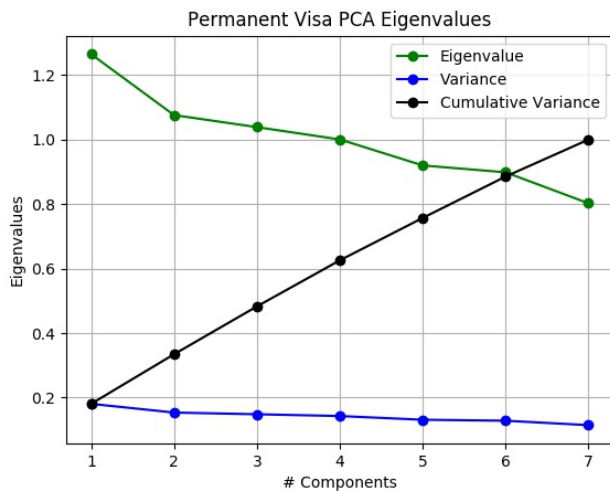
## Introduction

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.

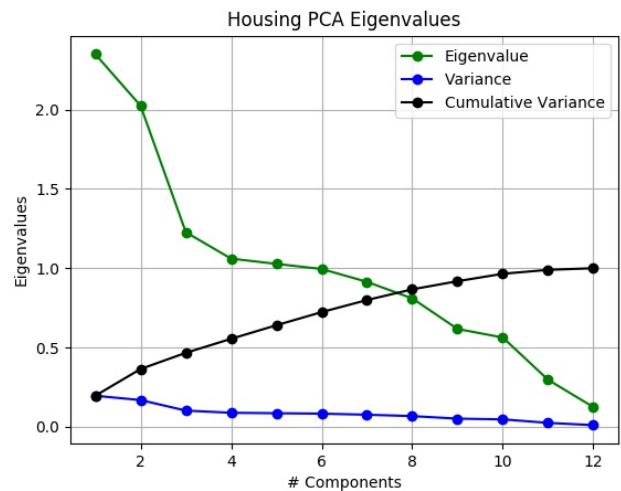
## 1) Principal Components Analysis (PCA)

### Overview

The first dimensionality reduction 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 orthogonal to the preceding component. The resulting eigenvalue matrix from PCA is therefore maximized for covariance.



Permanent Visa Principal Components Analysis



Housing Principal Components Analysis

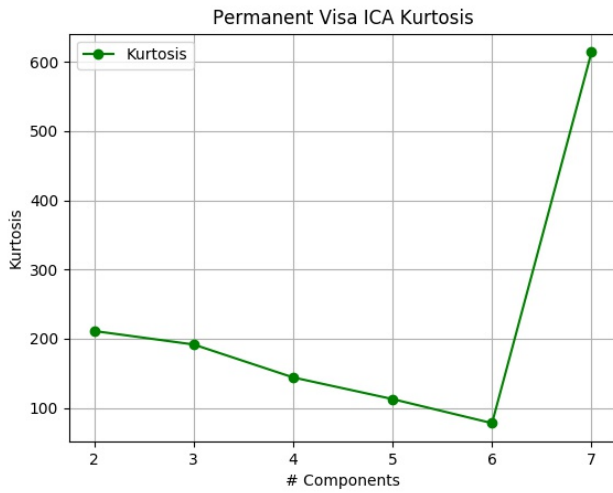
## Analysis

IText

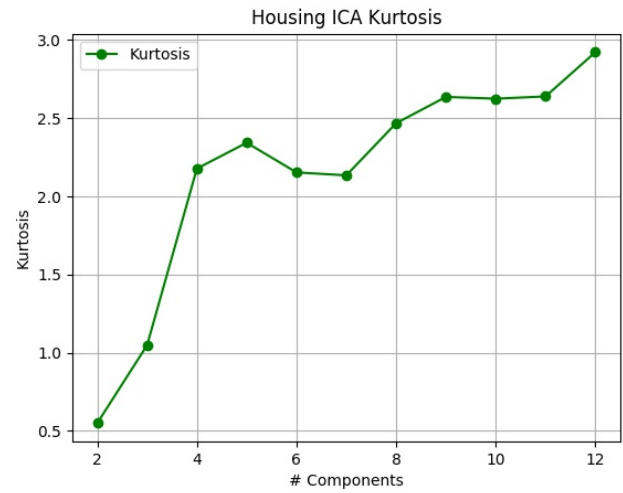
## 2) Independent Components Analysis (ICA)

### Overview

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Permanent Visa Independent Components Analysis



Housing Independent Components Analysis

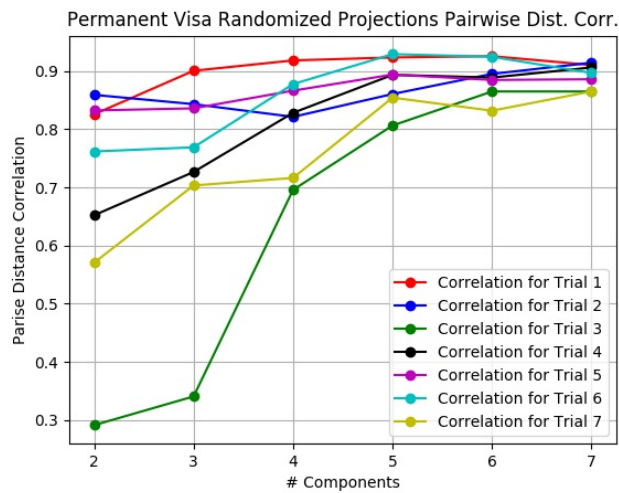
## Analysis

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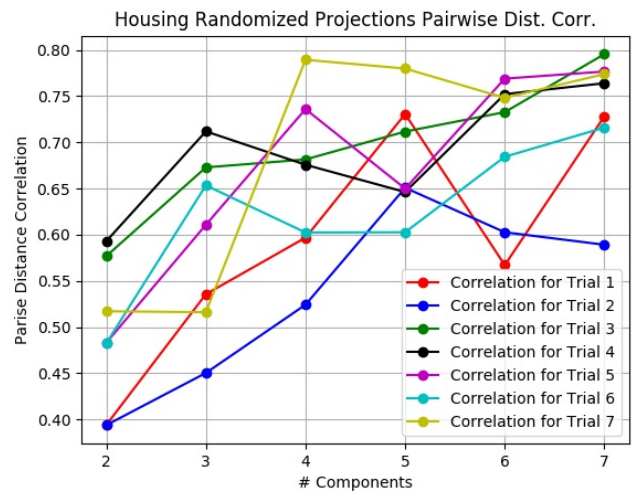
## 3) Randomized Projections

### Overview

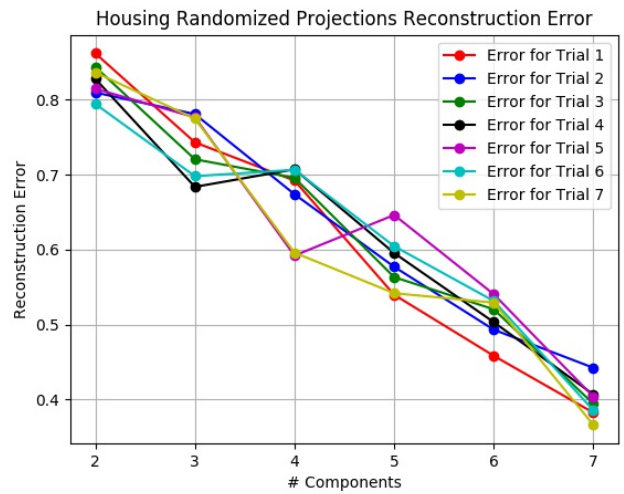
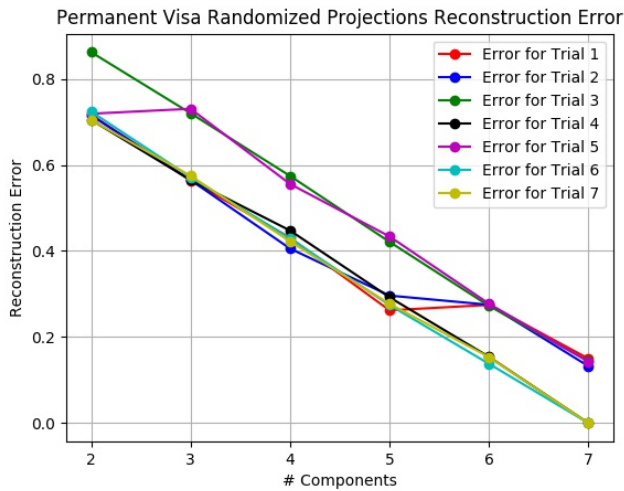
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Permanent Visa Randomized Projections Pairwise Correlation



Housing Randomized Projections Pairwise Correlation



Permanent Visa Randomized Projections Reconstruction Error

Housing Randomized Projections Reconstruction Error

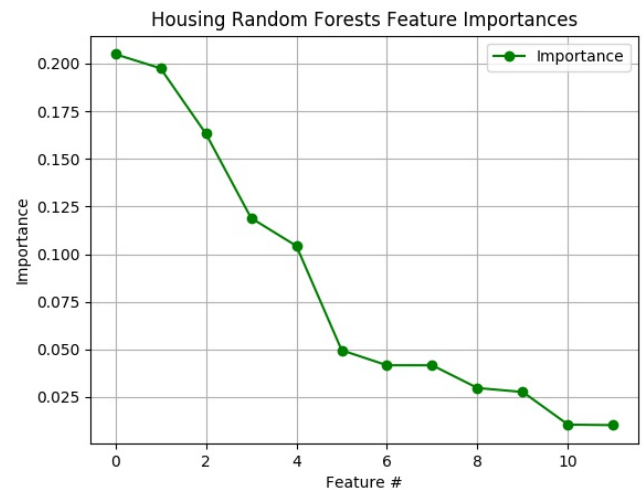
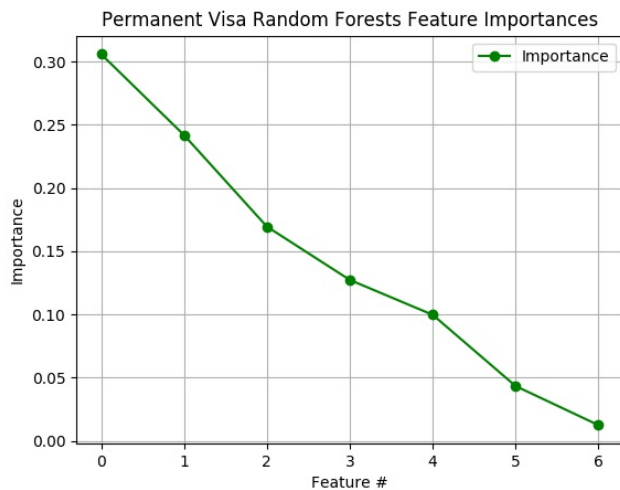
## Analysis

IText

## 4) Random Forests

### Overview

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Permanent Visa Random Forest Feature Importances (Descending Order)

Housing Random Forest Feature Importances (Descending Order)

## Analysis

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## Conclusion

Todo conclusion