

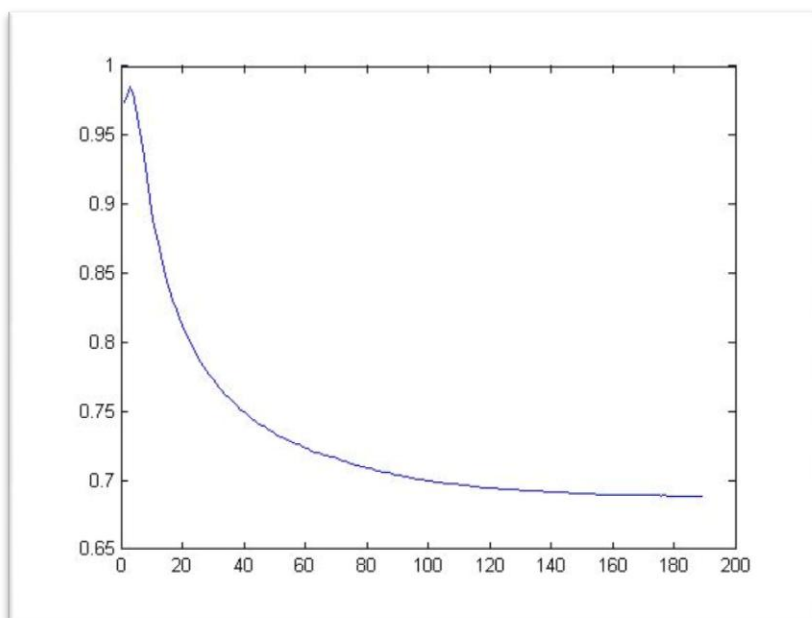
Advanced Statistical Machine Learning and Pattern Recognition

Assignment 1

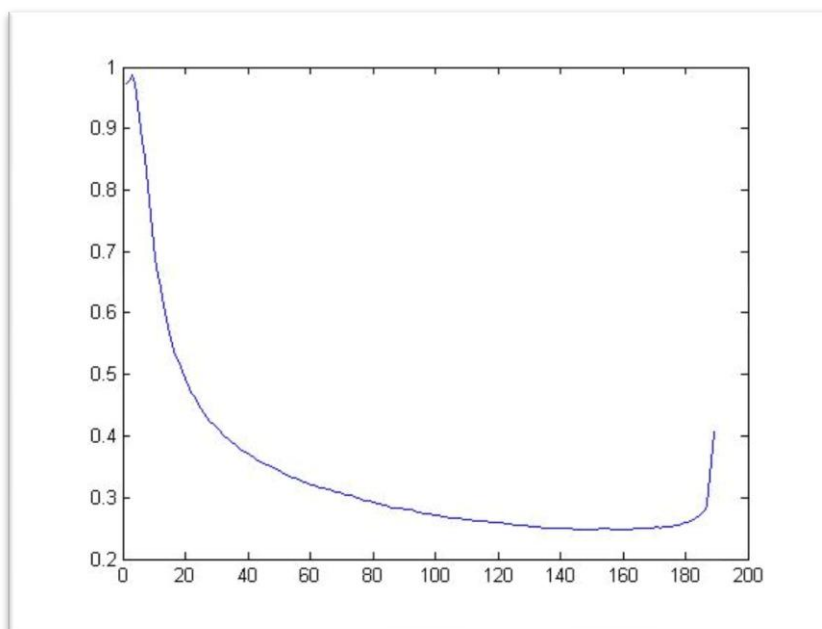
Ioannis Kassinopoulos (ik1410)

Recognition Rates (YALEB)

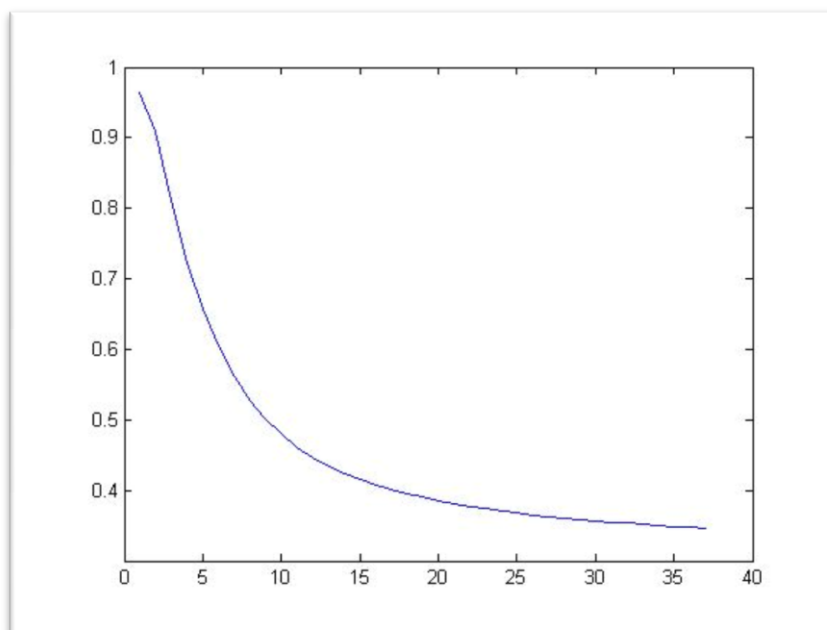
PCA



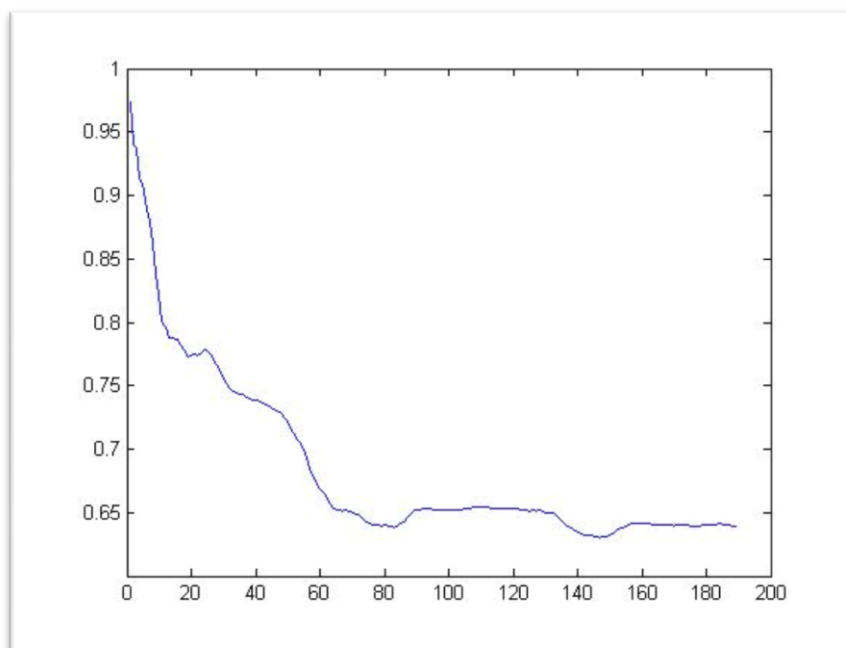
whitened-PCA



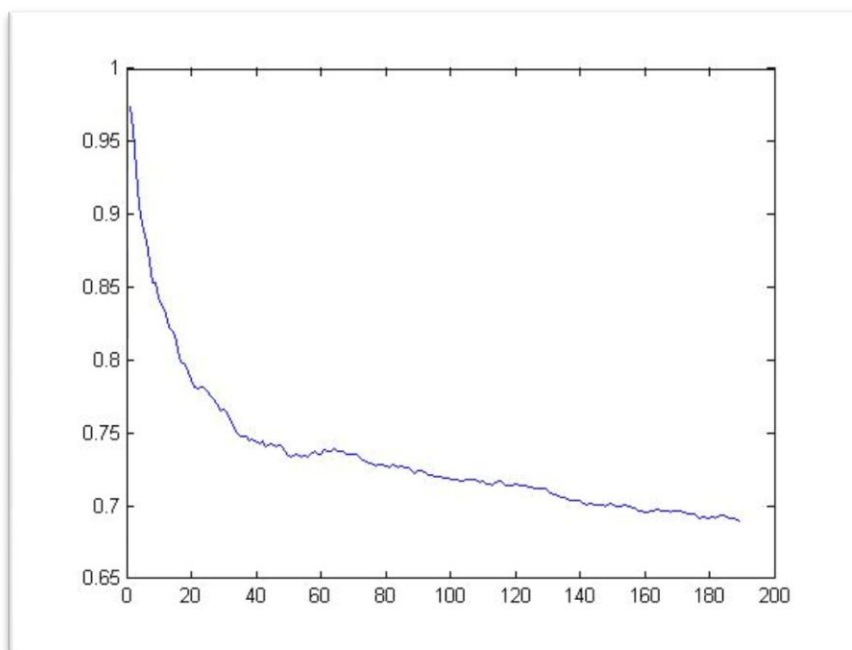
LDA



LPP

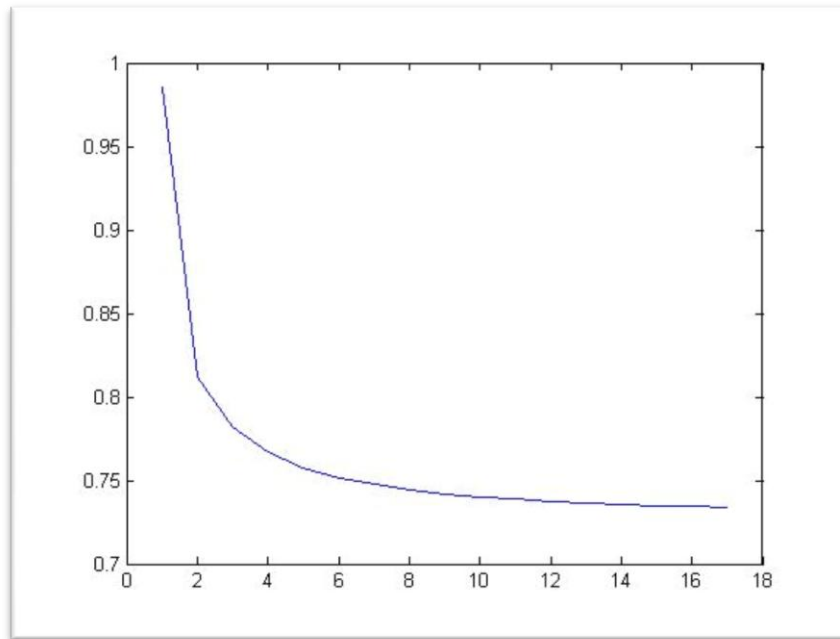


FastICA

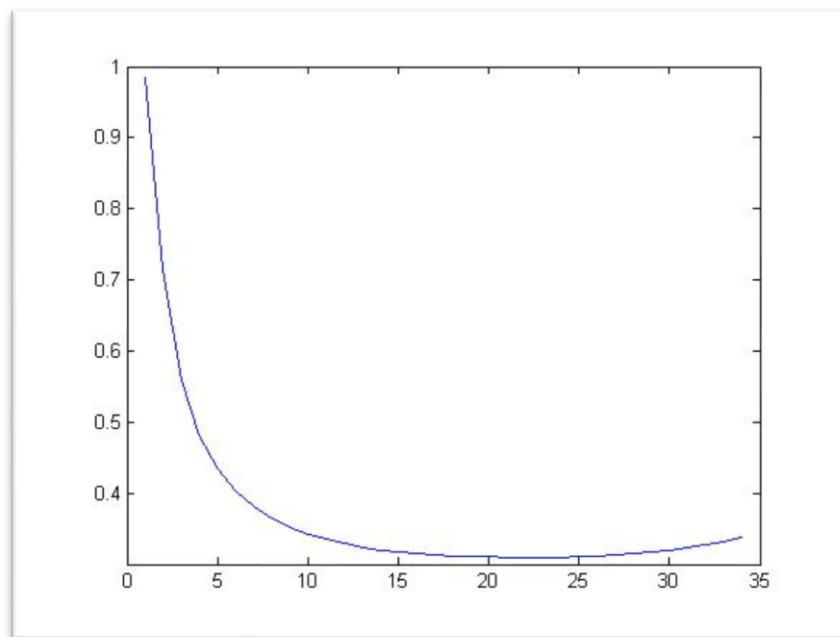


Recognition Rates (PIE)

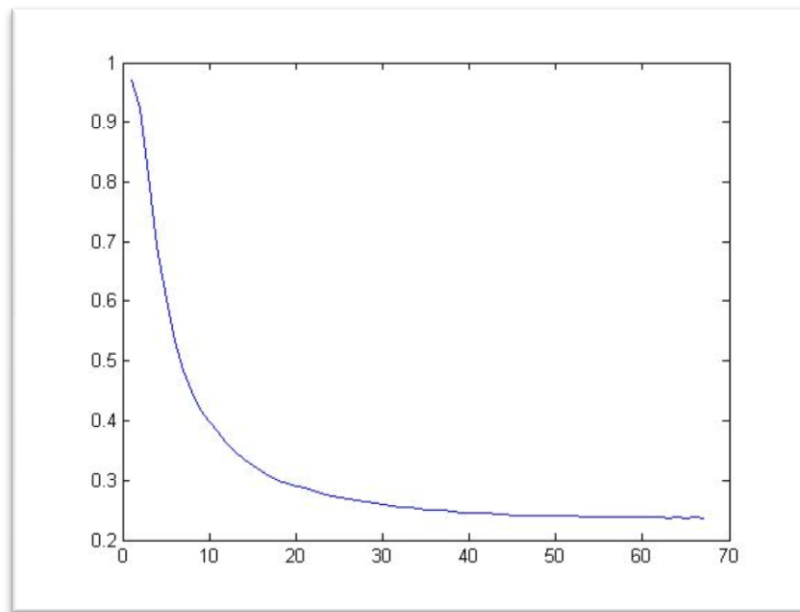
PCA



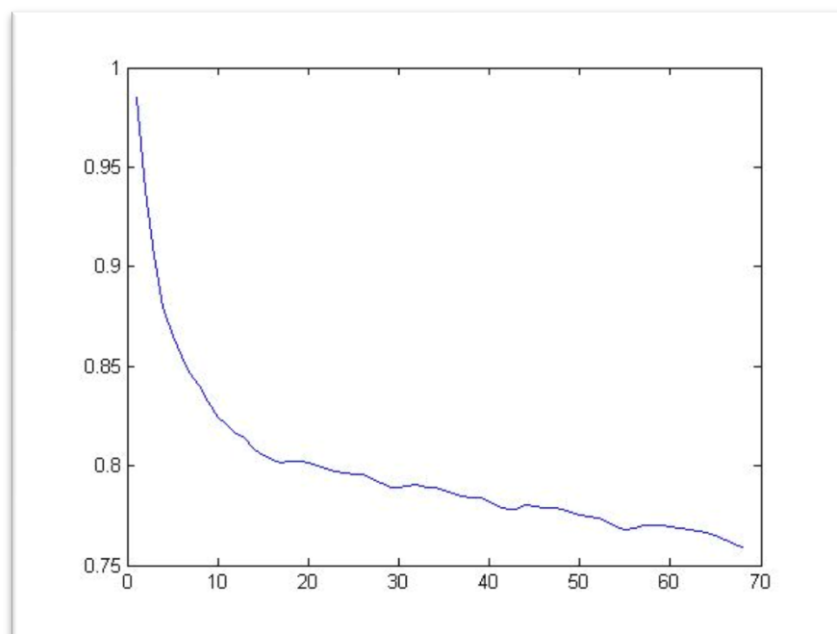
Whitened-PCA



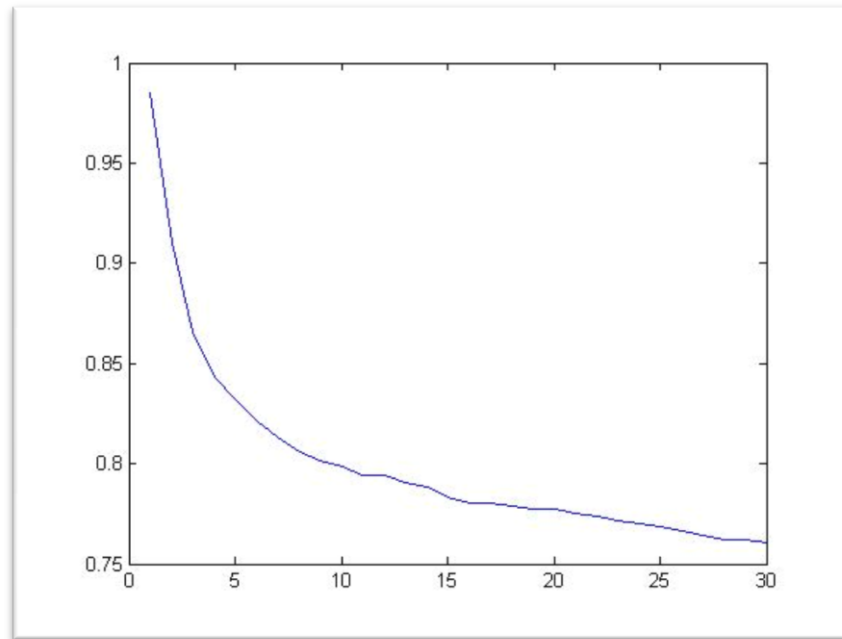
LDA



LPP



FastICA:



Discussion

From the results, we can observe that the most suitable techniques for our purpose are whitened-PCA and LDA. Both give acceptable error rates even for a small number of dimensions. LDA was expected to perform that well since it takes advantage of the labelling information provided and uses it to minimize class variance while maximizing mean variance across the classes. The nature of the technique makes it by definition a well suited dimensionality reduction method for classification. On the other hand I was not expecting whitened-PCA to perform that well especially after observing the relatively low performance of PCA. As we can observe from the results, whitened-PCA yields comparable classification rates to those of LDA even though they are not as consistent. This shows that decorrelating our variables provides the learner with a more meaningful representation. PCA and LPP perform poorly since they don't take into consideration between-class statistics but only global and local variance respectively. ICA also performs poorly, which is expected considering it was originally intended to be used for signal processing and blind source separation assuming statistical independence.

The relationship between dimensionality and performance is obvious from the graphs. As we increase our dimensionality the classification performance increases at a decreasing rate (with the exception of whitened-PCA). It's up to the user and specific to the application the level at which we will allow our dimensionality to increase as there is a trade-off between performance and complexity.