Comparing Exploratory Graphical Analyses and Unique Variable Analysis to Other Dimension Reduction Methods On Machine Learning Algorithms

Sean H. Merritt  
Department of Economics  
Claremont Graduate University  
150 E 10th St, Claremont, CA, 91711  
sean.merritt@cgu.edu

Alexander P. Christensen  
Department of Psychology and Human Development  
Vanderbilt University  
Nashville, TN, 37203  
alexander.christensen@vanderbilt.edu

October 25, 2022

Abstract

Developing interpretable machine learning models has become an increasingly important issue. One way in which data scientists have been able to develop interpretable models has been to use dimension reduction techniques. In this paper, we examine several dimension reduction techniques including two recent approaches developed in the network psychometrics literature called exploratory graph analysis (EGA) and unique variable analysis (UVA). We compared EGA and UVA with two other dimension reduction techniques common in the machine learning literature (principal component analysis and independent component analysis) as well as no reduction to the variables real data. We show that EGA and UVA perform as well as the other reduction techniques or no reduction. Consistent with previous literature, we show that dimension reduction can decrease, increase, or provide the same accuracy as no reduction of variables. Our tentative results find that dimension reduction tends to lead to better performance when used for classification tasks.

Keywords dimension reduction · exploratory graph analysis · PCA · ICA · machine learning · interpretability

1 Introduction

Machine learning has proliferated across science and impacted domains such as biology, chemistry, economics, neuroscience, physics, and psychology. In nearly all scientific domains, new technology has allowed for more data to be collected leading to high-dimensional data. With increasingly complex data, the parameters of the machine learning algorithms exponentially increase leading to issues in interpretability. Solutions to this issue requires either careful feature engineering, feature selection, regularization or some combination of them. In this paper, we focus on feature engineering by way of dimension reduction.

The goal of dimension reduction within machine learning is to reduce the number of variables to a refined set of variables that retain the maximum variance explainable in the whole set that then maximizes prediction. The standard method in machine learning has been to apply Principal Component Analysis (PCA). PCA attempts to find a linear combination of dimensions that are uncorrelated (or orthogonal) and adequately explain the majority of variance between all variables in the dataset. The utility of PCA in machine learning contexts is clear: variables are embedded in
a reduced dimensional space that maximizes their distinct variance from other variables in other dimensions. Given the congruence between the goals of dimension reduction within machine learning and the function of PCA, it’s not surprising that the method has become the go-to choice for machine learning researchers.

Should PCA be the de facto dimension reduction method? Previous work examining the effects of different dimension reduction techniques within machine learning algorithms is sparse. [1] tested PCA and latent discriminant analysis (LDA) against no dimension reduction on cardiotocography data. They found that PCA performed better than no reduction when the number of features was high. Similar work found that PCA tends to perform as well if not outperform no reduction [2, 3]. These studies, however, have been limited to examining classification tasks only and very specific applications (e.g., cardiotocography, internet of things bot detection). Whether PCA should be routinely applied to data before using machine learning algorithms is an open question that we aim to address.

Other commonly used dimension reduction techniques include independent component analysis (ICA). ICA is similar to PCA in that it tries to linearly separate variables into dimensions that are statistically independent rather than uncorrelated. This function is the major difference between their goals: PCA seeks to maximize explained variance in each dimension such that dimensions are uncorrelated whereas ICA seeks to identify underlying dimensions that are statistically independent (whether explained variance maximized is not an assumption). Similar to PCA, there is a strong congruence between the goals of dimension reduction within machine learning and ICA. With statistically independent dimensions, the data are separated into completely unique dimensions. This property ensures that the predicted variance of an outcome is explained uniquely by each dimension. One advantage ICA has over PCA is that it can work well with non-Gaussian data and therefore does not require variables to be normalized. ICA is commonly used in face recognition [4] as well as neuroscience to identify distinct connectivity patterns between regions of the brain [5, 6].

PCA and ICA are perhaps the two most commonly used dimension reduction methods in machine learning. Despite their common usage, few studies have systematically evaluated whether one should be preferred when it comes to classification or regression tasks. Similarly, few studies, to our knowledge, have examined the extent to which dimension reduction improves prediction accuracy relative to no data reductions at all. Beyond PCA and ICA, there are other dimension reduction methods that offer different advantages that could potentially be useful in machine learning frameworks.

Exploratory graph analysis (EGA) and unique variable analysis (UVA) are two methods that have recently emerged in the field of network psychometrics [7]. These techniques build off of graph theory and social network analysis techniques to identify dimensions in multivariate data. EGA in particular has been shown to perform as well as or better than PCA when recovering simulated dimensions in data [8, 9]. UVA in contrast rose out of a need to identify whether variables are redundant with one another and could be reduced to single, unique variables [10]. Given the goal of dimension reduction in machine learning, these two approaches seem potentially useful for reducing high-dimensional data and identifying unique sources of variance (respectively).

In the present study, we compare PCA, ICA, EGA, UVA, and no reduction on 14 different data sets, seven classification tasks and seven regression tasks. The main aims of this paper are to (1) introduce two alternative dimension reduction methods to the machine learning literature, (2) compare these and the other dimension reduction methods against each other as well as no reductions to the data on a variety of data types and tasks, and (3) examine features of data that lead to dimension reduction improving machine learning algorithms prediction over no reduction. The paper is outlined as follows: section two defines and formalizes EGA and UVA, section three explains the data and procedures in detail, section four reports the results, and section five provides our concluding remarks.

2 Psychometric Dimension Reduction

2.1 Exploratory Graph Analysis

Exploratory graph analyses (EGA) begins by representing the relationship among variables with the Gaussian graphical model (GGM) with the graph $G = \{v_i, e_{ij}\}$, where node $v_i$ represents the $i^{th}$ variable and the edge $e_{ij}$ is the partial correlation between variable $v_i$ and $v_j$. Estimating the GGM is usually done using the EBICglasso [11, 12, 13], which applies the graphical least absolute shrinkage and selection operator (GLASSO) [14, 15] to the inverse covariance matrix and uses the extended Bayesian information criterion (EBIC) [16] to select the model.

The EBICglasso has two tunable parameters: lambda ($\lambda$) and gamma ($\gamma$). $\lambda$ controls the sparsity of the network with larger values leading to sparser (fewer edges) networks. Usually, several values (e.g., 100) between a logarithmic range of $\lambda$ are used to estimate networks. The default setting of this range is defined by a minimum-maximum ratio typically set to 0.01 [12]. The $\gamma$ parameter is used in the EBIC, which is used for model selection. $\gamma$ controls how much simpler models (i.e., networks with fewer edges) are preferred to more complex models (i.e., networks with more edges). Larger
γ values lead to denser networks, smaller γ values lead to sparser networks. The default setting for this parameter is typically set to 0.5.

After estimating the GGM, EGA estimates the number of dimensions of the data using a community detection algorithm. Simulation studies have found that the most effective algorithms to detect dimensions are the Walktrap [17] and Louvain [18, 19, 20, 9, 21]. Since the introduction of EGA, several simulation studies have found them to be among the best methods for determining the number of dimensions in different types of data (e.g., binary, continuous, ordinal).

In order to obtain values for each dimensions, so-called "network scores" are computed for each dimension identified by the community detection algorithm. This process starts by first computing network loadings, which statistically similar to factor and component loadings. Network loadings are computed by taking the standardized node strength (sum of each node’s connections) within and between each dimension. Network loadings are calculated following Christensen and Golino [22]:

\[ L_{if} = \sum_{j \in f} |w_{ij}|, \]  

where \( L_{if} \) represents the loading of the node \( i \) on dimension \( f \) and \( j \in f \) are all nodes \( j \) determined to be part of dimension \( f \) (as determined by the community detection algorithm). This measure is standardized by:

\[ \kappa_{L_{if}} = \frac{L_{if}}{\sqrt{\sum L_f}} \]  

These standardized network loadings are represented in an \( i \times f \) matrix, \( \kappa \). Finally, we transform the observed data, \( X \), to the network scores, \( \hat{\theta} \), following Golino et al. [23]:

\[ Q_f = \frac{\kappa_f}{\sqrt{\sum \kappa_i^2 (X_i - \bar{X})^2 / (n-1)}} \]  

and

\[ \hat{\theta}_f = \sum_{f} \left( \frac{Q_{i \in f}}{\sum_{f} Q_{i \in f}} \right) \]  

where \( Q_f \) is the standardized network loadings of dimension \( f \) (\( \kappa_f \)) divided by the standard deviation of the variables with non-zero loadings in dimension \( f \), and \( \hat{\theta}_f \) are the network scores that are computed by summing the product of each variable \( X \) that has a non-zero loading in dimension \( f \) and its corresponding relative loading weight.

### 2.2 Unique Variable Analysis

Another network psychometrics approach that could be valuable in the context of reducing the number of variables used in making predictions with machine learning algorithms is called Unique Variable Analysis (UVA) [10]. The main goal of UVA is to reduce the dataset to a set of unique variables. Rather than the reduction attempting to reduce to a minimal set of variables (like EGA, ICA, and PCA), UVA does not reduce the number of variables unless two or more variables have substantial shared variance.

UVA was developed to solve issues of local dependence in traditional psychometrics. Local dependence is defined as two or more variables that possess potentially redundant information [24]. In the context of a PCA model, local dependence would be reflected in substantial correlation(s) between two (or more) variables’ residuals after extracting the components [25]. For machine learning, UVA’s objective is to maximize the unique variance provided by each feature while minimizing the redundant variance between features.

Like EGA, UVA starts by estimating a Gaussian graphical model using the EBICglasso. With this network, a measure called weighted topological overlap is applied [26]. Weighted topological overlap is defined as the similarity between a pair of nodes’ connections [27, 26]:

\[ \omega_{ij} = \frac{\sum u a_{iu} a_{uj} + a_{ij}}{\min\{k_i, k_j\} + 1 - a_{ij}} \]
where $a_{ij}$ represents the edge weight between node $i$ and $j$, $u$ represents a connection that both node $i$ and $j$ have with some third node $u$, and $k_i$ and $k_j$ are the node strength for node $i$ and node $j$, respectively.

In a recent simulation study examining local dependence, UVA was as accurate or more accurate than the most commonly used local dependence measures in traditional psychometrics [10]. An advantage of UVA is that the dimensional structure of a dataset need not be known in advance. Based on simulation evidence, a threshold of 0.25 offers an optimal balance between false positives and overall accuracy. Using this threshold, UVA combines variables that are greater than or equal to this threshold.

There are many ways to combine variables (including removing all but one of the locally dependent variables) but the simplest is to sum (or average) them. UVA continues to iteratively re-assess whether any local dependence remains, combining variables along the way. Once no local dependence remains (i.e., all weighted topological overlap values are less than 0.25), then the process stops. The result can run the spectrum of data reduction from no reduction (i.e., the original dataset if no local dependence is identified) to dimension reductions equivalent to PCA, ICA, and EGA if local dependence between variable sets correspond to the dimensions identified by these methods. In sum, UVA offers a flexible middle ground between no data reduction and complete data reduction (i.e., reduction equivalent to dimension reduction methods).

Relative to PCA and ICA, EGA and UVA are data driven. Among applied practitioners and data scientists, this quality represents a substantive advantage and reduces the researcher degrees of freedom. UVA has the additional advantage of acting as a middle ground between complete dimension reduction and no data reduction. Since it finds variables that are locally dependent, not all data is reduced and therefore may preserve some information that would be aggregated in other dimension reduction methods.

3 Methods

3.1 Data

To evaluate the effectiveness of the different dimension reduction methods, we trained them on 14 different data sets, seven for regression and seven for classification. We chose to limit the data sets by those that were: tabular data, more than 10 attributes (Mean = 125.8462, Min = 14, Max = 785), and had more than 100 instances (Mean = 14752.08, Min = 120, Max = 70000). Additionally, we sampled data from a variety of domains including business, social sciences, physics, and life sciences. For regression these included: blog feedback [28], communities and crime [29], Facebook metrics [30], online news [31], Parkinson’s telemonitoring [32], superconductivity [33], and skillcraft data [34]. Classification data included: breast cancer diagnosis, divorce [35], heart disease [36], MNIST [37], musical emotion [38], sport articles objectivity [39], and wine data. All of these data, with the exception of the MNIST can be found on the UCI machine learning repository [40]. We accessed a tabular version of the MNIST data via Kaggle.

3.2 Procedure

We started by preproccessing all of our data to remove any missing observations and categorical data (except for the target variables in the classification tasks). We then reduced the variables using PCA, ICA, EGA, and UVA. For the non-reduced data, we used the preprocessed data for fair comparison. We used the R statistical software (version 4.13) [41] with the EGAnet (version 1.2.0) [42] and ica (version 1.0.3) [43] packages. Number of components for PCA and ICA were determined by examining variance explained via a scree plot.

Next, we trained and tuned the hyperparameters of the machine learning models using 75% of each data set with 3-fold cross validation grid search. We used the mean squared error and accuracy for the refitting scores for regression and classification, respectively. Then we tested the data on the other 25% of the data using the best parameters. Finally, to compare the methods we used 5-fold cross validation on the full data set with the best selected parameters. We trained on LASSO and regularized logit for regression and classification, respectively. For both tasks, we used random forests, support vector machine, and XGBoost. All machine learning models were done in Python with the sklearn (version 1.1.2) [44] and XGBoost (version 1.4.2) [45] packages. We compared models with root mean squared error and accuracy.

All R and python scripts and data used in the analyses are available on the GitHub repository.

All R and python scripts and data used in the analyses are available on the GitHub repository.
4 Machine Learning Results

Using analysis of variance, we compared between each method’s performance in regression and classification accuracy. These ANOVAs were followed up using Bonferoni HSD pairwise comparison to determine differences between specific methods.

4.1 Regression

There were moderate significant differences across reduction methods, $F(4, 686) = 8.20, p < .001, \eta^2_p = 0.05$. EGA had significantly higher RMSE than ICA across data ($p < .001, d = 0.53$) but did not differ from PCA ($p = 1.00, d = 0.04$), UVA ($p = 1.00, d = 0.05$), or no reduction ($p = 0.59, d = 0.17$). ICA had significantly lower RMSE than PCA ($p < .001, d = 0.56$), UVA ($p < .001, d = 0.57$, and no reduction ($p = 0.03, d = 0.35$). PCA did not significantly differ from UVA ($p = 1.00, d = 0.01$) and no reduction ($p = 0.38, d = 0.21$). UVA did not significantly differ from no reduction ($p = 0.35, d = 0.22$)

On a more granular level, we examine how each method compared on each data set. There no significant differences in the skillcraft data, $F(4, 92) = 0.34, p = .85, \eta^2_p = 0.01$ or news data, $F(4, 92) = 0.00, p = 1.00, \eta^2_p = 0.00$. The best method and algorithm combination for the blog data was UVA with LASSO ($RMSE = 38.313$) and for the new data was no data reduction with LASSO ($RMSE = 11023.107$).

There were significant differences in the crime data, $F(4, 92) = 10.01, p < .001, \eta^2_p = 0.30$: EGA had lower RMSE than ICA ($p = 0.04, d = 0.90$) and PCA ($p = 0.001, d = 1.26$), ICA had higher RMSE than no reduction ($p < .001, d = 1.38$), PCA had higher RMSE than no reduction ($p < .001, d = 1.74$) and UVA ($p = 0.003, d = 1.17$). The best method and algorithm combination for the crime data was no data reduction with random forest ($RMSE = 0.138$).

There were significant differences in the Facebook data, $F(4, 92) = 13.32, p < .001, \eta^2_p = 0.37$: ICA had lower RMSE than EGA ($p < .001, d = 1.77$), PCA ($p < .001, d = 1.90$), UVA ($p < .001, d = 1.93$), and no reduction ($p = 0.003, d = 1.19$). The best method and algorithm combination for the Facebook data was ICA with random forest ($RMSE = 2.151$).

There were significant differences in the Parkinson’s data, $F(4, 92) = 24.65, p < .001, \eta^2_p = 0.52$: EGA had significantly higher RMSE than ICA ($p < .001, d = 2.03$), UVA ($p < .001, d = 1.85$), and no reduction ($p < .001, d = 2.22$), PCA similarly had significantly higher RMSE than ICA ($p < .001, d = 1.99$), UVA ($p < .001, d = 1.81$), and no reduction ($p < .001, d = 2.18$). The best method and algorithm combination for the Parkinson’s data was UVA with LASSO ($RMSE = 3.680$).

There were significant differences in the superconductor data, $F(4, 92) = 5.70, p < .001, \eta^2_p = 0.20$: ICA had significantly higher RMSE than EGA ($p = 0.01, d = 2.03$), PCA ($p = 0.03, d = 0.93$), UVA ($p = .002, d = 1.21$), and no reduction ($p < .001, d = 1.36$). The best method and algorithm combination for the superconductor data was no data reduction with random forest ($RMSE = 12.680$).

There were significant differences in the skillcraft data, $F(4, 92) = 22.03, p < .001, \eta^2_p = 0.49$: UVA had significantly higher RMSE than EGA ($p < .01, d = 1.81$), ICA ($p < .001, d = 2.00$), PCA ($p < .001, d = 2.40$), and no reduction ($p < .001, d = 2.68$). The best method and algorithm combination for the skillcraft data was no data reduction with random forest ($RMSE = 0.994$).
4.2 Classification

There were small-to-moderate significant differences across reduction methods, $F(4, 686) = 5.48, p < .001, \eta_p^2 = 0.03$. EGA had lower accuracy than ICA ($p = 0.02, d = 0.38$) and PCA ($p < .001, d = 0.48$) but did not differ from UVA ($p = 0.68, d = 1.16$) and no reduction ($p = 0.85, d = 1.12$) across data. ICA did not differ in accuracy from PCA ($p = 0.89, d = 0.11$), UVA ($p = 0.36, d = 0.22$), and no reduction ($p = 0.20, d = 0.26$). PCA was more accurate than UVA ($p = 0.05, d = 0.33$) and no reduction ($p = 0.02, d = 0.37$). UVA did not differ from no reduction ($p = 1.00, d = 0.04$).

On a more granular level, we examine how each method compared on each data set. There no significant differences in the cancer data, $F(4, 92) = 0.23, p = .92, \eta_p^2 = 0.01$. The best method and algorithm combination for the cancer data was EGA and UVA with logit ($\bar{ACC} = 0.970$).

There were significant differences in the divorce data, $F(4, 92) = 3.24, p = .02, \eta_p^2 = 0.12$: ICA was more accurate than no reduction ($p = 0.02, d = 0.97$). Several method and algorithm combinations had perfect accuracy ($\bar{ACC} = 1.000$) for the divorce data: logit with EGA, ICA, PCA, and UVA; random forest with ICA; all methods with SVM; XGBoost with EGA, ICA, and PCA.

There were significant differences in the heart data, $F(4, 92) = 9.38, p < .001, \eta_p^2 = 0.29$: EGA ($p = 0.002, d = 1.21$), ICA ($p < .001, d = 1.31$), and PCA ($p < .001, d = 1.62$) were more accurate than no reduction. ICA ($p = 0.03, d = 0.94$) and PCA ($p = 0.001, d = 1.26$) were more accurate than UVA. The best method and algorithm combination for the heart data was PCA and UVA with random forest ($\bar{ACC} = 0.993$).
There were significant differences in the MNIST data, $F(4, 92) = 95.94, p < .001, \eta_p^2 = 0.81$: EGA had lower accuracy than ICA ($p < .001, d = 4.34$), PCA ($p < .001, d = 4.18$), UVA ($p < .001, d = 5.27$), and no reduction ($p < .001, d = 5.26$). UVA had higher accuracy than ICA ($p = 0.03, d = 0.94$) and PCA ($p = 0.007, d = 1.10$). Similarly, no reduction had higher accuracy than ICA ($p = 0.03, d = 0.92$) and PCA ($p = 0.007, d = 1.09$). The best method and algorithm combination for the MNIST data was ICA with SVM ($\bar{ACC} = 0.982$).

There were significant differences in the music data, $F(4, 92) = 11.09, p < .001, \eta_p^2 = 0.33$: EGA ($p = 0.002, d = 1.23$), ICA ($p = 0.006, d = 1.12$), and PCA ($p < .001, d = 1.49$) had higher accuracy than UVA. Similarly, EGA ($p < .001, d = 1.34$), ICA ($p = 0.002, d = 1.23$), and PCA ($p < .001, d = 1.60$) had higher accuracy than no reduction. The best method and algorithm combination for the music data was EGA with XGBoost ($\bar{ACC} = 1.00$).

There were significant differences in the sports data, $F(4, 92) = 8.51, p < .001, \eta_p^2 = 0.27$: EGA ($p = 0.01, d = 1.04$), ICA ($p = 0.01, d = 1.04$), and PCA ($p = 0.002, d = 1.23$) had higher accuracy than UVA. Similarly, EGA ($p = 0.003, d = 1.19$), ICA ($p = 0.003, d = 1.19$), and PCA ($p < .001, d = 1.38$) had higher accuracy than no reduction. Several method and algorithm combinations had perfect accuracy ($\bar{ACC} = 1.000$) for the sports data: random forest with EGA, ICA, and PCA as well as all methods with XGBoost.

There were significant differences in the wine data, $F(4, 92) = 3.42, p = .01, \eta_p^2 = 0.13$: PCA ($p = 0.05, d = 0.88$) and no reduction ($p = 0.05, d = 0.88$) had higher accuracy than UVA. Several method and algorithm combinations had perfect accuracy ($\bar{ACC} = 1.000$) for the wine data: logit with EGA and PCA; random forest with EGA; SVM with PCA and no reduction; XGBoost with PCA and no reduction.

Figure 2: Classification Results. Error bars are standard errors. y-axis begins at 0.70.
4.3 Comparing Attributes

To better understand when certain reduction methods perform best, we regressed data attributes interacting with each reduction method on the accuracy and RMSE of the data. We standardized the RMSE so as to be comparable across data sets. We tested the number of attributes, number of observations, and the mean kurtosis. We used no reduction as the reference group compared to simple coded dummy variables corresponding to each reduction method (Table 1).

In classification, we find that EGA performed better than no reduction when the number of attributes ($b = 0.001, p < .001$), the sample size ($b = 0.000001, p < .001$), and the average kurtosis ($b = -0.001, p < .001$) increased. ICA was found to perform worse with increase in attributes ($b = -0.001, p < .001$), sample size ($b = -0.000001, p < .001$), and mean kurtosis ($b = -0.000002, p < .001$). UVA and PCA was no different than no reduction on number of attributes, sample size, and kurtosis.

We were not able to replicate these results in the regression data. ICA performed better than no reduction when number of attributes classification ($b = 0.008, p < .01$) and sample size ($b = 0.000001, p < .05$) increased, but not kurtosis ($b = -0.00001, p > .05$). PCA performed worse with increase in attributes ($b = -0.019, p < .01$) and sample size ($b = -0.00002, p < .001$), but not kurtosis ($b = -0.001, p > .05$). UVA performed better with an increase in attributes ($b = 0.005, p < .05$) and EGA performed worse with an increase in kurtosis ($b = -0.00002, p < .001$).

We believe that the results for the classification tasks were skewed by the MNIST data (much larger sample and number attributes and no reduction performed was best). We re-ran these regressions without the MNIST and found that there was no difference between reduction methods and no reduction methods with increasing attributes, sample size, or kurtosis.

5 Conclusion

Feature engineering is one of the first steps toward maximizing prediction in machine learning algorithms. Our work examined the effects of dimension reduction on data features using two techniques common to the machine learning literature, PCA and ICA, and two techniques derived out of the network psychometrics literature, EGA and UVA. Overall, we find EGA and UVA perform just as well as PCA, ICA, and no reduction. The predictive performance of each of these methods, however, varied greatly depending on the data. EGA, PCA, and ICA tended to perform similarly while UVA and no reduction tended to perform similarly. As a general trend, we found the best method and algorithm pairs tended to be EGA, ICA, and PCA for the classification tasks, and UVA and no reduction for the regression tasks.

Beyond task type, we examined this variability of performance in the attributes of the data. We failed replicated [1] results that found that PCA performed better than no reduction when there is more attributes in the data. However, we did find evidence that EGA performed better than no reduction when the number attributes, sample size, and kurtosis increased on classification tasks. Given that we did not find this to be the case in the regression tasks or replicable without the MNIST, it is not likely that these effects were much more than chance. While our general trend found that dimension reduction may be more effective for classification tasks than regression tasks, more research needs to be done. Future research should also examine how different dimension reduction effects results of textual, visual, and audio data.

One surprising result was that ICA did not perform better with greater kurtosis in the data. Given that ICA was designed for non-Gaussian, we might expect to it to perform well on this type of data. On the other hand we would expect EGA and PCA to perform worse given that both are designed with Gaussian based assumptions. We find that EGA performed better than no reduction method with an increasing kurtosis in the data. One caveat to this might be that we used kurtosis instead of negentropy. We might find ICA to perform better where negentropy is higher.

Broadly, dimension reduction appears to perform better than no reduction on classification tasks. One view might be that with simplified data structures there is less noise stemming from unique variance across different data features that make precise classification difficult. Conversely, this same unique variance may improve performance on regression tasks. Indeed, regression performance in the field of personality psychology has seen consistent and robust effects of individual variables, termed personality nuances, outperforming more global traits that are identified by dimension reduction methods [46, 47, 48].

Our results demonstrated that EGA and UVA are robust methods that can be applied in machine learning. They both provide the advantage of reducing researcher degrees of freedom by estimating the number of dimensions and assigning features to those dimensions automatically. EGA is an additional dimension reduction tool that can be added the machine learning practitioner’s toolbox while UVA offers the reduction of features if there are features that may be redundant with one another. An added benefit of modeling variables as a network is that graph theory measures can be applied to multivariate representations of data features that could provide new features that are extracted from the relationships between them [49]. Whether researchers should reduce the number of features of the data using dimension...
Table 1:

|                  | Accuracy | RMSE     |
|------------------|----------|----------|
|                  | (1)      | (2)      | (3)      | (4)      | (5)      | (6)      |
| **EGA**          | −0.018***| −0.015***| −0.015***| 0.502*** | 0.397*** | 0.392*** |
|                  | (0.005)  | (0.005)  | (0.005)  | (0.147)  | (0.103)  | (0.089)  |
| **ICA**          | 0.013*** | 0.007    | 0.007    | −0.518***| −0.307***| −0.240***|
|                  | (0.005)  | (0.005)  | (0.005)  | (0.147)  | (0.103)  | (0.089)  |
| **PCA**          | 0.006    | 0.007    | 0.007    | 0.959*** | 0.383*** | 0.183**  |
|                  | (0.005)  | (0.005)  | (0.005)  | (0.147)  | (0.103)  | (0.089)  |
| **UVA**          | 0.011**  | 0.011**  | 0.011**  | −0.360** | −0.224** | −0.183** |
|                  | (0.005)  | (0.005)  | (0.005)  | (0.147)  | (0.103)  | (0.089)  |
| **Attributes**   | −0.0001***| 0.0000    | 0.0000    | −0.0001***| 0.0000    | 0.0000   |
|                  | (0.0001) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **N**            | 0        | −0.00000***| 0         | −0.00000   | 0        | 0.0000   |
|                  |          | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| **mean_kurt**    |          |          |          | −0.0001***| 0.0000    | 0.0000   |
|                  |          |          |          | (0.0000)  | (0.0000)  | (0.0000) |
| **Algorithm1**   | −0.023***| −0.023***| −0.023***| 0.002     | 0.002     | 0.002    |
|                  | (0.004)  | (0.004)  | (0.004)  | (0.067)  | (0.068)  | (0.069)  |
| **Algorithm2**   | −0.002   | −0.002   | −0.002   | 0.107     | 0.107     | 0.107    |
|                  | (0.004)  | (0.004)  | (0.004)  | (0.067)  | (0.068)  | (0.069)  |
| **Algorithm3**   | −0.0001  | −0.0001  | −0.0001  | −0.030    | −0.030    | −0.030   |
|                  | (0.004)  | (0.004)  | (0.004)  | (0.067)  | (0.068)  | (0.069)  |
| **EGA:Attributes** | 0.0001***|          |          | −0.004    |          |          |
|                  | (0.0002) |          |          | (0.003)  |          |          |
| **ICA:Attributes** | −0.0001***| 0.008**  |          |          |          |          |
|                  | (0.0002) |          |          | (0.003)  |          |          |
| **PCA:Attributes** | 0.0000   | −0.019***|          |          |          |          |
|                  | (0.0002) |          |          | (0.003)  |          |          |
| **UVA:Attributes** | −0.00000 | 0.005*   |          |          |          |          |
|                  | (0.0002) |          |          | (0.003)  |          |          |
| **EGA:N**        |          |          |          | 0.00000***| −0.0001  | −0.0002* |
|                  |          |          |          | (0.0000) | (0.0001) | (0.001)  |
| **ICA:N**        |          |          |          | −0.00000***| 0.000001*|          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **PCA:N**        |          |          |          | 0.00000   | −0.00002***|          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **UVA:N**        |          |          |          | −0.00000  | 0.000001 | 0.00001  |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **EGA:mean_kurt** |          |          |          | 0.000001***| −0.0002* |          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **ICA:mean_kurt** |          |          |          | −0.00002***| 0.0001   |          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **PCA:mean_kurt** |          |          |          | 0.00000   | −0.0001  |          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **UVA:mean_kurt** |          |          |          | −0.00000  | 0.00001  |          |
|                  |          |          |          | (0.0000) | (0.0001) |          |
| **Constant**     | 0.963*** | 0.961*** | 0.961*** | −0.000    | 0.000    | −0.000   |
|                  | (0.002)  | (0.002)  | (0.002)  | (0.073)  | (0.051)  | (0.045)  |
| **Observations** | 600      | 600      | 600      | 600      | 600      | 600      |
| **R²**           | 0.288    | 0.292    | 0.293    | 0.125    | 0.073    | 0.054    |
| **Adjusted R²**  | 0.273    | 0.278    | 0.278    | 0.108    | 0.054    | 0.034    |
| **Residual Std. Error (df = 587)** | 0.051    | 0.051    | 0.051    | 0.941    | 0.969    | 0.979    |
| **F Statistic (df = 12; 587)** | 19.791***| 20.193***| 20.236***| 7.017*** | 3.855*** | 2.772*** |

*Note:*

*p < 0.1; **p < 0.05; ***p < 0.01*
reduction methods is specific to each dataset. We provide evidence that classification tasks can be improved with dimension reduction methods while regression tasks are less affected. The combination of the task type, method and algorithm combination, and attributes of the data all contribute to performance. Untangling these components and their effects on performance remains an important direction for machine learning.
References

[1] G Thippa Reddy, M Praveen Kumar Reddy, Kuruvu Lakshmann, Rajesh Kaluri, Dharmendra Singh Rajput, Gautam Srivastava, and Thar Baker. Analysis of dimensionality reduction techniques on big data. *IEEE Access*, 8:54776–54788, 2020.

[2] Hayretdin Bahşi, Sven Nõmm, and Fabio Benedetto La Torre. Dimensionality reduction for machine learning based iot botnet detection. In *2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, pages 1857–1862. IEEE, 2018.

[3] Jorge Vizárraga, Roberto Casas, Álvaro Marco, and J David Buldain. Dimensionality reduction for smart IoT sensors. *Electronics*, 9(12):2035, 2020.

[4] Marian Stewart Bartlett, Javier R Movellan, and Terrence J Sejnowski. Face recognition by independent component analysis. *IEEE Transactions on neural networks*, 13(6):1450–1464, 2002.

[5] Vince D Calhoun and Tülay Adali. Unmixing fmri with independent component analysis. *IEEE Engineering in Medicine and Biology Magazine*, 25(2):79–90, 2006.

[6] Martin J McKeown and Terrence J Sejnowski. Independent component analysis of fmri data: examining the assumptions. *Human Brain Mapping*, 6(5-6):368–372, 1998.

[7] Sacha Epskamp, Gunter Maris, Lourens J Waldorp, and Denny Borsboom. Network psychometrics. In P Irwing, D Hughes, and T Booth, editors, *The Wiley handbook of psychometric testing, 2 volume set: A multidisciplinary reference on survey, scale and test development*. Wiley, New York, NY, 2018.

[8] Hudson Golino and Sacha Epskamp. Exploratory Graph Analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE*, 12:e0174035, 2017.

[9] Hudson Golino, Dingjing Shi, Alexander P Christensen, Luis Eduardo Garrido, Maria D Nieto, Ritu Sadana, Jotheeswaran Amuthavalli Thiyagarajan, and Agustin Martinez-Molina. Investigating the performance of Exploratory Graph Analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, 25:292–320, 2020.

[10] Alexander P Christensen, Luis Eduardo Garrido, and Hudson Golino. Unique variable analysis: A network psychometrics method to detect local dependence. *PsyArXiv*, 2022.

[11] Sacha Epskamp, Angélique O J Cramer, Lourens J Waldorp, Verena D Schmittmann, and Denny Borsboom. qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, 48:1–18, 2012.

[12] Sacha Epskamp and Eiko I Fried. A tutorial on regularized partial correlation networks. *Psychological Methods*, 23:617–634, 2018.

[13] Rina Foygel and Mathias Drton. Extended Bayesian information criteria for Gaussian graphical models. In J D Lafferty, C K I Williams, J Shawe-Taylor, R S Zemel, and A Culotta, editors, *Advances in neural information processing systems*, pages 604–612, 2010.

[14] Jerome Friedman, Trevor Hastie, and Robert Tibshirani. Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 9:432–441, 2008.

[15] Jerome Friedman, Trevor Hastie, and Robert Tibshirani. *glasso: Graphical lasso – Estimation of Gaussian graphical models*, 2014. R package version 1.8.

[16] Jiahua Chen and Zehua Chen. Extended bayesian information criteria for model selection with large model spaces. *Biometrika*, 95:759–771, 2008.

[17] P Pons and M Latapy. Computing communities in large networks using random walks. *Journal of Graph Algorithms and Applications*, 10:191–218, 2006.

[18] Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008:P10008, 2008.

[19] Alexander P Christensen, Luis Eduardo Garrido, and Hudson Golino. Comparing community detection algorithms in psychological data: A Monte Carlo simulation. *PsyArXiv*, 2021.

[20] Kathleen M Gates, Teague Henry, Doug Steinley, and Damien A Fair. A Monte Carlo evaluation of weighted community detection algorithms. *Frontiers in Neuroinformatics*, 10:45, 2016.

[21] Zhao Yang, René Algesheimer, and Claudio J Tessone. A comparative analysis of community detection algorithms on artificial networks. *Scientific Reports*, 6:30750, 2016.
[22] Alexander P Christensen and Hudson Golino. On the equivalency of factor and network loadings. *Behavior Research Methods*, 53:1563–1580, 2021.

[23] Hudson Golino, Alexander P Christensen, Robert Moulder, Seohyun Kim, and Steven M Boker. Modeling latent topics in social media using dynamic exploratory graph analysis: The case of the right-wing and left-wing trolls in the 2016 us elections. *Psychometrika*, 87(1):156–187, 2022.

[24] Wen-Hung Chen and David Thissen. Local dependence indexes for item pairs using item response theory. *Journal of Educational and Behavioral Statistics*, 22(3):265–289, 1997.

[25] Pere J Ferrando, Ana Hernandez-Dorado, and Urbano Lorenzo-Seva. Detecting correlated residuals in exploratory factor analysis: New proposals and a comparison of procedures. *Structural Equation Modeling: A Multidisciplinary Journal*, pages 1–9, 2022.

[26] Bin Zhang and Steve Horvath. A general framework for weighted gene co-expression network analysis. *Statistical Applications in Genetics and Molecular Biology*, 4:17, 2005.

[27] Erzsébet Ravasz, Anna Lisa Somera, Dale A Mongru, Zoltán N Oltvai, and A-L Barabási. Hierarchical organization of modularity in metabolic networks. *Science*, 297:1551–1555, 2002.

[28] Krisztian Buza. Feedback prediction for blogs. In *Data analysis, machine learning and knowledge discovery*, pages 145–152. Springer, 2014.

[29] Michael Redmond and Alok Baveja. A data-driven software tool for enabling cooperative information sharing among police departments. *European Journal of Operational Research*, 141(3):660–678, 2002.

[30] Sérgio Moro, Paulo Rita, and Bernardo Vala. Predicting social media performance metrics and evaluation of the impact on brand building: A data mining approach. *Journal of Business Research*, 69(9):3341–3351, 2016.

[31] Etham J Thompson, Mark R Blair, Lihan Chen, and Andrew J Henrey. Video game telemetry as a critical tool in the study of complex skill learning. *PLoS ONE*, 8(9):e75129, 2013.

[32] Robert Detrano, Andras Janosi, Walter Steinbrunn, Matthias Pfisterer, Johann-Jakob Schmid, Sarbjit Sandhu, Kern H Guppy, Stella Lee, and Victor Froelicher. International application of a new probability algorithm for the diagnosis of coronary artery disease. *The American Journal of Cardiology*, 64(5):304–310, 1989.

[33] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[34] Joseph J Thompson, Mark R Blair, Lihan Chen, and Andrew J Henrey. Video game telemetry as a critical tool in the study of complex skill learning. *PLoS ONE*, 8(9):e75129, 2013.

[35] Mustafa Kemal Yöntem, ADEM Kemal, Tahsin Ilhan, and Serhat Kılıçarslan. Divorce prediction using correlation based feature selection and artificial neural networks. *Nevşehir Hacı Bektaş Veli Üniversitesi SBE Dergisi*, 9(1):259–273, 2019.

[36] Robert Detrano, Andras Janosi, Walter Steinbrunn, Matthias Pfisterer, Johann-Jakob Schmid, Sarbjit Sandhu, Kern H Guppy, Stella Lee, and Victor Froelicher. International application of a new probability algorithm for the diagnosis of coronary artery disease. *The American Journal of Cardiology*, 64(5):304–310, 1989.

[37] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[38] Mehmet Bilal Er and Ibrahim Berkan Aydilek. Music emotion recognition by using chroma spectrogram and deep visual features. *International Journal of Computational Intelligence Systems*, 12(2):1622–1634, 2019.

[39] Nadine Hajj, Yara Rizk, and Mariette Awad. A subjectivity classification framework for sports articles using improved cortical algorithms. *Neural Computing and Applications*, 31(11):8069–8085, 2019.

[40] Dheeru Dua and C Graff. UCI machine learning repository. university of california, school of information and computer science, irvine, ca (2019), 2019.

[41] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2022.

[42] Hudson Golino and Alexander P Christensen. *EGAnet: Exploratory Graph Analysis– A Framework for Estimating the Number of Dimensions in Multivariate Data Using Network Psychometrics*, 2022. R package version 1.1.1.

[43] Nathaniel E Helwig. *ica: Independent Component Analysis*, 2022. R package version 1.0-3.

[44] Oliver Kramer. Scikit-learn. In *Machine learning for evolution strategies*, pages 45–53. Springer, 2016.

[45] Jason Brownlee. *XGBoost with Python: Gradient boosted trees with XGBoost and scikit-learn*. Machine Learning Mastery, 2016.
[46] René Mõttus. Towards more rigorous personality trait–outcome research. *European Journal of Personality*, 30:292–303, 2016.

[47] René Mõttus, Timothy Bates, D M Condon, D Mroczek, and William Revelle. Leveraging a more nuanced view of personality: Narrow characteristics predict and explain variance in life outcomes. *PsyArXiv*, 2018.

[48] Anne Seeboth and René Mõttus. Successful explanations start with accurate descriptions: Questionnaire items as personality markers for more accurate predictions. *European Journal of Personality*, 32:186–201, 2018.

[49] Patrick K Goh, Michelle M Martel, Payton J Jones, Pevitr S Bansal, Ashley G Eng, Anjeli R Elkins, Melina H Thaxton, and Russell A Barkley. Clarifying relations between ADHD and functional impairment in adulthood: Utilization of network and machine learning approaches. *Assessment*, page 10731911211050921, 2021.