A comparative study for using PCA, LDA, GDA, and Lasso for dimensionality reduction before classification algorithms

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1. Background

- Curse of dimensionality: to many features to process
- Dimensionality reduction can be used to reduce number of features
- Previous studies have shown no one algorithm in universally the best at dimensionality reduction[3][4]

2. Research question What are the effects of PCA, LDA, GDA, and Lasso for dimensionality reduction on classification algorithms?

Refrences

[1]V. Fonti and E. Belitser, "Feature selection using lasso", VU Amsterdam research paper in business analytics, vol. 30, pp. 1–25, 2017.
[2] P. Vu, P. Vu, and D. Xu, "Comparison of pca, Idé and gda for palmprint verification," in 2010 International Conference on Information, Networking and Automation (ICNA), vol. 1, 2010, pp. VI-148-VI-152.
[3] A Babjac, T. Royathy, A. D. Steem, and S. J. Emrich, "A comparison of dimensionality reduction methods for large biological data", New Work, NY, USA: Association for Computing Machinery, 2022. [Online].
[4] A. Martinez and A. Kak, "Pca versus Ida", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 228–233, 2001.

3. Preliminaries

- PCA: find directions of maximal variance[2]
 - LDA: minimize within-class scatter while maximzing between-class scatter[2]
 - GDA,: LDA with different matrices per class and kernel function[2]
- Lasso: Linear model with a penalty function with weight α [1]

5. Results

Table 1: The time it took each of the algorithms the transforms a dataset into a new dataset with less dimensionality



Figure 1: Effect of Number of features left by Lasso on the accuracy of a dataset with a lot of training data

PCA

00.0089

I DA

00.01 38

GDA

49.13.65

	LR				RF		SVM		
	acc<10	best acc	best #features	acc<10	best acc	best #features	acc<10	best acc	best #features
PCA	0.667	0.736	110	0.798	0.809	19	0.670	0.732	110
LDA	0.759	0.759	9	0.798	0.798	9	0.750	0.750	8
GDA	0.745	0.745	7	0.762	0.762	7	0.752	0.752	8
Lasso	0.696	0.773	142	0.793	0.909	53	0.702	0.759	142

0.073 0.650 0.575 0.550 0.575 0.550 0.575 0.500 0.575 0.500 0.575 0.500 0.575 0.500 0.575 0.500 0.500 0.575 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0.5000 0

1 2550

00.01 15

Figure 2: Effect of Number of features left by GDA on the accuracy of a dataset with less training data

	LR			RF			SVM		
	acc<10	best acc	best #features	acc<10	best acc	best #features	acc<10	best acc	best #features
PCA	0.676	0.678	15	0.684	0.685	18	0.676	0.689	39
LDA	0.671	0.671	1	0.550	0.550	2	0.637	0.637	1
GDA	0.671	0.671	1	0.549	0.549	2	0.677	0.677	1
Lasso	0.711	0.712	19	0.698	0.742	19	0.707	0.707	10

Table 2: Statistic about the combinations of classification and dimensionality reduction methods on dataset with lots of training data Table 3: Statistic about the combinations of classification and dimensionality reduction methods on dataset with less training data

4. Metrics

- Transformation time #Features retained
- #Features retained
- Accuracy

6. Conclusion

- -Changes in number of features and classes does not change relative performance of algorithms -Number of features does change relative performance of algorithms
- -LDA in better then GDA (using linear regression)
- -LDA and GDA are better when using LR or SVM and training set is sufficiently large -Lasso and PCA are better when using RF or if the training set becomes small