An Analysis of Dimensionality Expansion Performed on Quantum and Classical Support Vector Machines

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Abstract

Ever since the discovery of the Support Vector Machine (SVM) algorithm, SVMs have been among one of the best supervised machine learning algorithms to classify linear and non-linear data. Unfortunately, SVMs possess kernel limitations when introduced to higher dimensional data and while working with problems containing large features.

With the introduction of quantum computation and quantum machine learning, researchers have successfully implemented a Quantum Support Vector Machine (QSVM) onto a quantum computer. Doing so has allowed classical data to be transferred into quantum states, taking advantage of the large dimensionality of quantum Hilbert space.

To study the effectiveness and accuracy of dimensionality expansion in QSVMs as opposed to SVMs, we processed dimensionally reduced data into SVMs and QSVMs. Using evaluation metrics and techniques the processed datasets are compared and analyzed.

Keywords: *Quantum Computing, Quantum Machine Learning, Quantum Support Vector Machine, Support Vector Machine, Dimensionality Expansion.*

Summary of Project: (remove this when done report)
In this project, we analyze and compare the classification accuracy of support vector machines (SVM) and quantum support vector machines (QSVM).We first artificially reduce a high-dimension dataset through performing different dimensionality reduction methods such as Principal Component Analysis (PCA). The reduced dataset is then processed by an SVM and QSVM, in-creasing the dimensionality of the data. The new processed datasets from the SVM and QSVM are then analyzed and compared using balanced accuracy and Area Under the Receiver Operating Characteristics (AUROC) techniques.

1 Introduction

[2-5] Hardaker, Richardson, Lien, and Schumann (2004)

2 Background

2.1 Dimensionality Reduction Techniques (Need 5-6)

2.1.1 Principal Component Analysis

2.1.2 Autoencoder

2.1.3 Latent Dirichlet Allocation

2.1.4 Independent Component Analysis

2.1.5 Subsubsection 5

2.1.6 Subsubsection 6

2.2 Support Vector Machines

2.3 Quantum Support Vector Machines

2.4 Evaluation Metrics

2.4.1 Balanced Accuracy

2.4.2 Area Under the Receiver Operating Characteristics

(Chavas & Shi, 2015)

3 Methodology

[12-13]

4 Results

4.1 Subsection

[14]

5 Discussion

5.1 Subsection

[14]

6 Conclusions

[14]

References

Chavas, J.-P., & Shi, G. (2015). An Economic Analysis of Risk, Management, and Agricultural Technology. *Journal of Agricultural and Resource Economics*, *40*(1), 63–79.

Hardaker, J. B., Richardson, J. W., Lien, G., & Schumann, K. D. (2004, 6). Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *The Australian Journal of Agricultural and Resource Economics*, *48*(2), 253–270. doi: 10.1111/j.1467-8489.2004.00239.x

Table 1: Example table of descriptive statistics of the main variables.

Variables	Categories	Unit	Rep	Mean	St. Dev.	Min	Max
Variable 1	Category A	$	8	0	0	0	0
	Category B	lb	8	22,411.20	6,325.90	13,819	31,201
	Category C	$	8	5,869.60	4,609.90	-464.1	12,744.10
Variable 2	Category A	$	8	1,777.40	144.5	1,642.30	1,912.60
	Category B	lb	8	21,444.80	5,146.90	15,096	28,032
	Category C	$	8	4,138.50	2,644.10	22.2	7,932.70
Variable 3	Category A	$	8	2,346.80	190.8	2,168.30	2,525.20
	Category B	lb	8	18,343.30	2,460.70	15,269.00	21,524.10
	Category C	$	8	3,699.20	2,549.80	1,299.10	8,709.80
Variable 4	Category A	$	8	2,288.80	186.1	2,114.80	2,462.90
	Category B	lb	8	23,450.40	4,172.50	20,045.00	32,363.00
	Category C	$	8	6,619.80	1,918.40	4,479.70	10,633.90
	CASE #1			14	6.61	6.9	27.9
	CASE #2			22.8	7.73	10.2	31.4

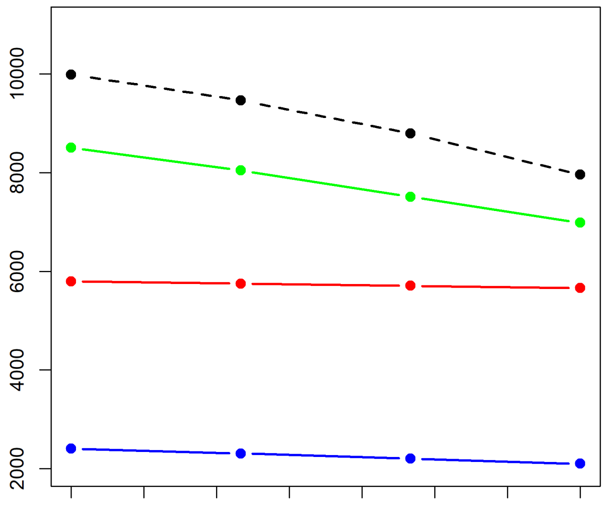

Figure 1: Example figure.