Mathematics Performance in Secondary Education

Yao-Chih Hsu, Xuan-Chun Wang, and Wen-Lee Sin

June 12, 2025



Outline

- Introduction
- 2 Data Visualization
- 3 Dimensionality Reduction
- 4 Regression
- Conclusion
- 6 References



Introduction

Introduction

• Dataset: *Math-Students Performance Data* from Kaggle (Shamim, 2025).



Introduction

Introduction

- Dataset: *Math-Students Performance Data* from Kaggle (Shamim, 2025).
- Variables G1, G2, G3, and absences were provided by the school.
- Remaining variables were collected via questionnaires and are mostly categorical.



Introduction

Analyze G3 to identify influential variables.



Data Grouping

We grouped the data into the following:

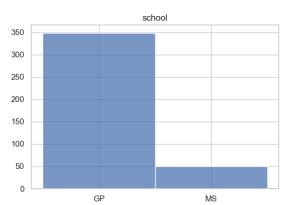
Groups	Variables				
support	schoolsup, famsup, paid				
family	address, famsize, Pstatus, guardian,				
	traveltime, famrel				
parents	Medu, Fedu, Mjob, Fjob				
performance	failures, studytime, absences				
alcohol	Dalc, Walc, health				
after_class	activities, freetime, goout				
school_choice	reason, nursery, higher				
score	G1, G2, G3				

The variables not yet assigned to any group are:

sex, age, internet, romantic.

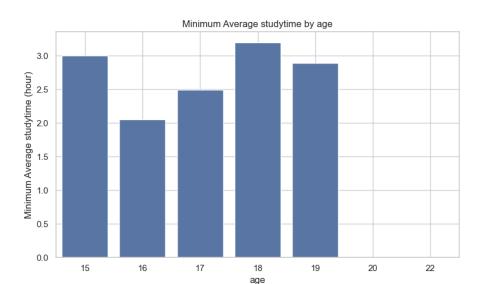


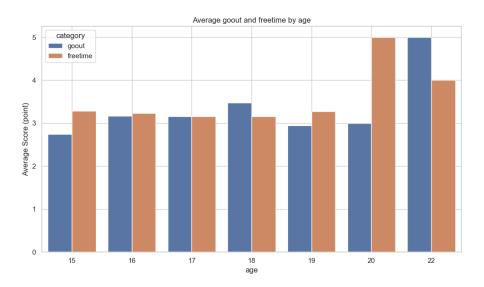
Data Visualization



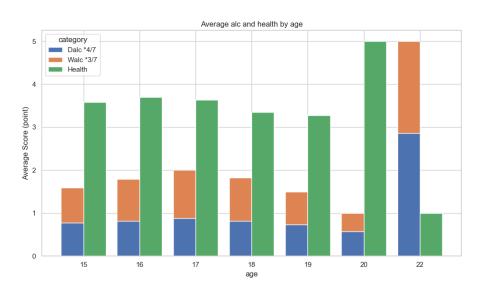
GP (Gabriel Pereira) MS (Mousinho da Silveira)

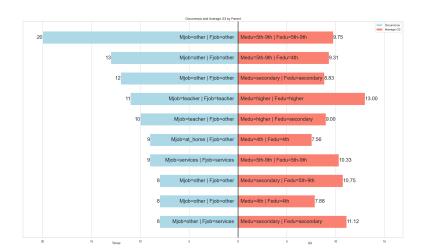


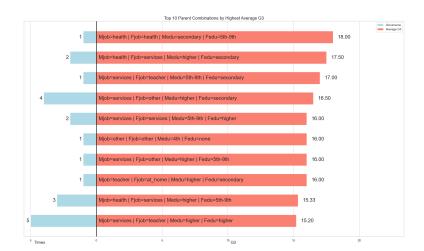




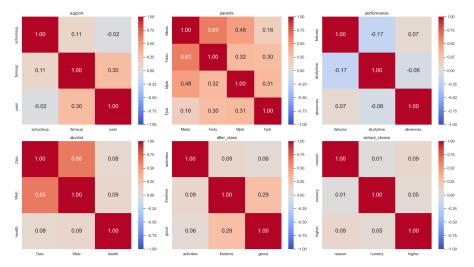




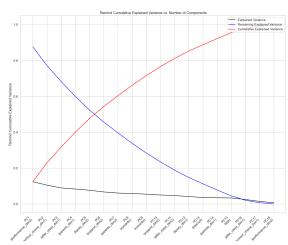




Multidimensional Scaling



PCA





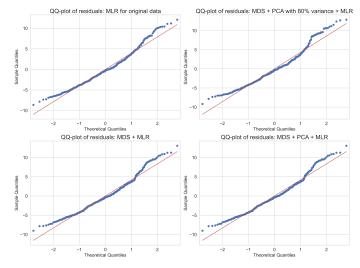
Variables of MLR

We compared four models:

- Original + MLR
- MDS + MLR
- MDS + PCA + MLR
- MDS + PCA 80% + MLR

The variables in the dataset transformed by MDS are as follows:

Q-Q plots of MLR

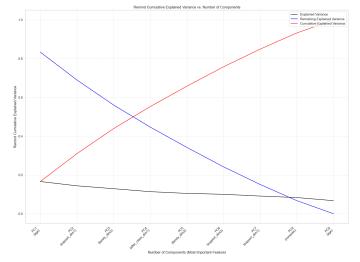


Variables of Reduced MLR

Models	Selected Features		
	failures, goout,		
	parents_dim1, after_class_dim1		
Original + MDS	family_dim2, romantic		
+ Stepwise + MLR	<pre>support_dim2, after_class_dim2</pre>		
	support_dim1, age		
	performance_dim1		
	parents_dim1, after_class_dim1		
MDS + PCA	family_dim2, romantic		
+ Stepwise + MLR	<pre>support_dim2, after_class_dim2</pre>		
	support_dim1, age		
	performance_dim1		

Table 1: Selected Features by Different Methods





PC1 (school_choice_dim1)
PC2 (after_class_dim1)

PC1 (parent_dim2)
PC2 (romantic)



Conclusion

Models	R ²	Adj. R ²	MSE	P-value	AIC
MLR for original data	0.27	0.19	62.58	0.9157	2015.10
MDS + MLR	0.19	0.14	77.58	0.7494	2023.96
MDS + PCA + MLR	0.19	0.14	77.58	0.6143	2023.96
MDS + PCA with 80% variance + MLR	0.14	0.11	92.69	0.9442	2031.05
Original data $+$ MDS $+$ Stepwise $+$ MLR	0.20	0.19	293.55	0.0367	1993.82
MDS + PCA + Stepwise + MLR	0.17	0.15	140.12	0.5113	2013.68
Paper Proposed	0.17	0.16	216.03	0.4624	2005.069

Table 2: Comparison of model performance metrics

The variables selected by the paper: absences, schoolsup, higher, failures, Mjob

Conclusion

Model	TOP1	TOP2	TOP3
MLR for original data	failures	schoolsup	paid
MDS + MLR	romantic	support_dim2	support_dim1
MDS + PCA + MLR	romantic	support_dim2	age
MDS + PCA with 80% variance + MLR	romantic	support_dim2	parents_dim1
Original data + MDS + Stepwise + MLR	Mjob_at_home	failures	Mjob_other
MDS + PCA + Stepwise + MLR	age	support_dim1	family_dim2
Paper Proposed	higher	schoolsup	failures

Table 3: Most important feature to each model

Conclusion

The variables we selected are:

Mjob, failures



- Cortez, P. (2008). Student Performance [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C5TG7T
- Cortez, P., & Silva, A. M. (2008). Using data mining to predict secondary school student performance.
- Shamim, A. (2025). *Math students performance data*. Kaggle. https://www.kaggle.com/datasets/adilshamim8/math-students



Thanks for listening!

