4-12-2024

Examining Regression Assumption Violations in Machine Learning Models Using the Wisconsin Longitudinal Study Dataset

Grace Mooney Anderson
Hope College

Melia Brewer
Hope College

Examining Regression Assumption Violations in Machine Learning Models Using the Wisconsin Longitudinal Study Dataset

Hope College

Grace Mooney Anderson, Melia Brewer, & Robert D. Henry *(faculty mentor)*

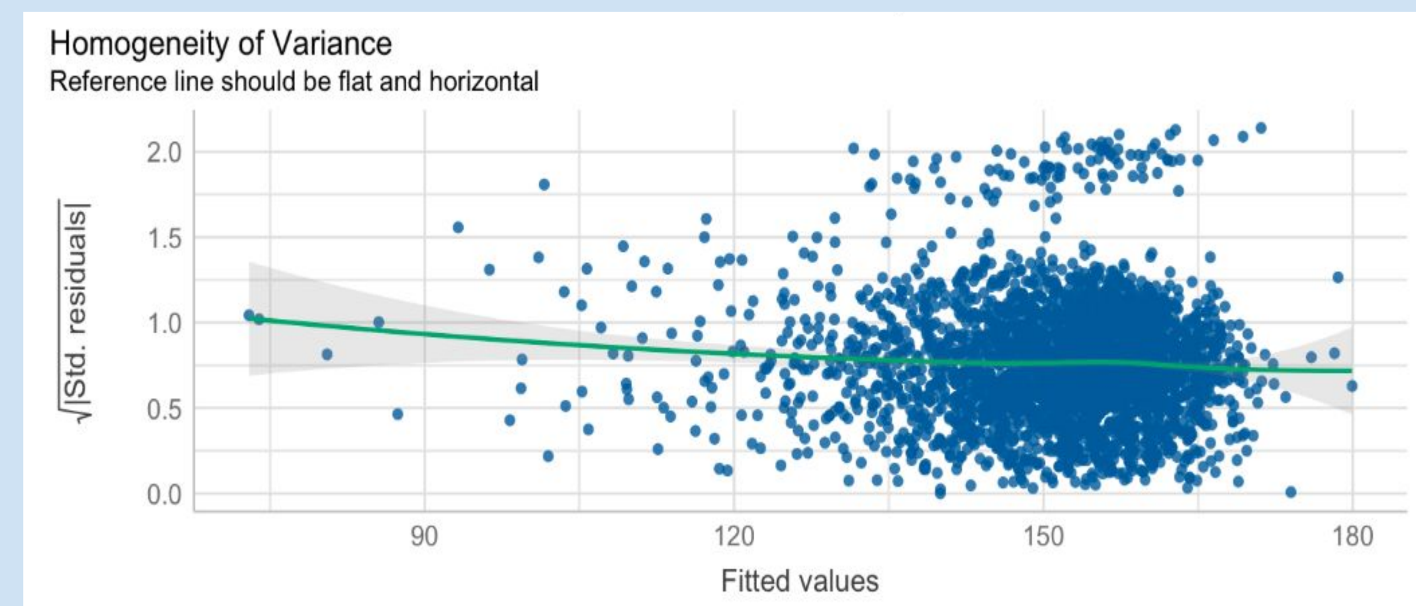
Introduction

- Machine learning (ML) is becoming increasingly relevant in the social sciences
- Many who use ML models do not verify the assumptions of linear regression (Yarkoni & Westfall, 2017)
- We will use a large dataset (*N*>2,000) and replicate the findings of an accompanying study and replicate these findings using ML
- We will then simulate a dataset
- We hypothesized that the reliability of ML is dampened with the presence of these violations
  - For instance, the probability of Type I errors increasing when heteroscedasticity exists

Method

- Utilized data from the Wisconsin Longitudinal Study (WLS)
- Replicated findings from Clark and Lee (2021) which looked into how both early- and later-life variables correlate with later-life subjective well-being using ordinary least squares (OLS) linear regression
- Utilized three supervised learning models:
  - Regularized regression
  - Support vector machine
  - Random forest
- Monte Carlo simulation used with $N = 3000$ and replications ranging from 20-1000 (depending on the model) to create a dataset with five predictors (X1-X5) and one outcome variable (Y)
- Unstandardized coefficients (see Table) significant at $p<.1$
- All analyses were performed in R

Results

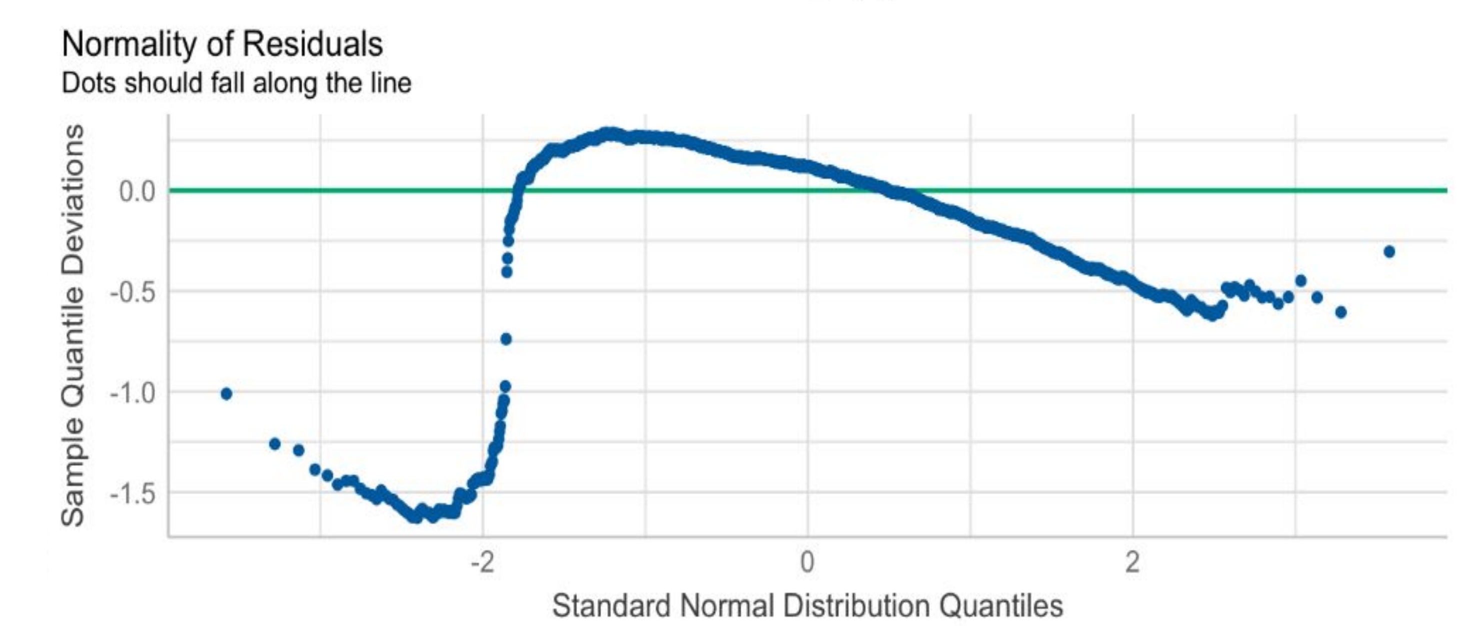


Within the WLS dataset, we found violations of the assumptions of homoscedasticity (above) and normality of residuals (right). All other assumptions were met.

Clark and Lee (2021)	Linear Regression*	Regularized Regression*	Support Vector Machine^	Random Forest^
Mental Health	-0.7	-9.9	100	100
Social Participation	0.6	2.4	17.1	32.8
Education	1.0	1.5	10.1	15.8
Physical Health	25.6	0.2	1.9	5.6
Never Married	-3.3	-0.5	1.4	0.7
IQ	-0.1	-0.1	2.1	36.3
Female	4.7	1.3	0.5	5.1
Number of Siblings	–	-0.3	0.6	19.2
Single Parent Household	–	0.03	0.2	1.5
Mom Age at Birth	–	-0.1	–	23.8
Retired	–	-0.1	–	4.7
Separated	–	0.1	–	3.1
Simulated Dataset	**Linear Regression***	**Regularized Regression***	**Support Vector Machine^**	**Random Forest^**
X1 (0.5)	0.8	0.4	46.6	38.5
X2 (0.6)	0.7	0.5	60.7	25.9
X3 (0.3)	–	0.2	19.1	20.6
X4 (0.1)	–	0.05	5.0	3.5
X5 (0.8)	1.1	0.6	82.5	99.8

* unstandardized coefficients | ^ standardized variable importance (0-100)

Results



Discussion

- Overall, when regression assumptions are violated in ML, the risk for false positive/negative results may be *less* than in the original regression model
- ML may be a useful tool for linear regression assumption violations
- Understanding these implications of assumption violations in ML can significantly improve replicability of models
- More work to be done to understand the implications of these violations for model fit
- Future directions: attempt to "fix" these violations and re-run regression and machine learning models

References

Clark, A.E. & Lee, T. (2021). Early-life correlates of later-life well-being: Evidence from the Wisconsin Longitudinal Study. *Journal of Economic Behavior & Organization*, *181*, 360-368. https://doi.org/10.1016/j.jebo.2017.11.013

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100-1122.