Revisiting PSM Analysis of College Athletic Success with Machine Learning: LASSO Regression & Gradient Boosting

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Abstract

This study PSM to determine the causal effects of college football success on donations and applications. We replicated their analysis and then used LASSO regression & (possibly) gradient boosting aiming to improve the robustness of the propensity scores.

Introduction

The study uses bookmaker spreads to calculate the propensity scores and found that football success leads to better outcomes. We use LASSO and gradient boosting to aiming improve the PSM estimates and variable selection to see their effects.

Literature Review

- Pairing PSM and gradient boosting significantly enhances predictive accuracy (Kim et al., 2023)
- Gradient boosting is more robust and preferred over other ML methods in finding average treatment effects (Yang, Chuang, Kuan, 2020)
- LASSO regressions have demonstrated their usefulness in subset selection especially in high-dimensional settings (Tibshirani, 1996).
- While LASSO is not as powerful in comparison to other ML methods, combined with PSM it demonstrates extreme robustness (Pirracchio, Petersen, van der Laan, 2015)

Findings

lead2_pscore_wk10_group_12

| OLS Regression Results | | | | |
|---|--|---|---|--|
| Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: | lead2_exp_wins_wk11 OLS Least Squares Mon, 29 Apr 2024 18:15:03 393 357 | R-squared: Adj. R-squared F-statistic: Prob (F-statis Log-Likelihood AIC: BIC: | tic): | 0.174 0.093 nan nan -2.9759 77.95 221.0 |
| Covariance Type: | cluster ========== | | | |
| | | coef | std err | Z |
| lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 lead2_pscore_wk11 | _group_2 _group_3 _group_4 _group_5 _group_6 _group_7 _group_8 _group_9 _group_10 _group_11 | 0.1529 -0.0803 1.6379 0.6030 0.5882 2.1827 0.6534 0.0269 -4.1408 1.9579 -0.4022 -0.6552 OLS Regression | 0.309 1.016 0.810 2.390 0.586 1.576 1.503 2.235 1.815 | -0.260 1.613 0.744 |
| OLS Regression Results | | | | |
| Dep. Variable: Model: Method: Date: Time: No. Observations: Df Residuals: Df Model: Covariance Type: | lead2_exp_wins_wk10 OLS Least Squares Mon, 29 Apr 2024 18:15:03 1136 1123 12 cluster | R-squared: Adj. R-squared: F-statistic: Prob (F-statist Log-Likelihood: AIC: BIC: | ic): | 0.122 0.112 13.71 2.91e-13 -579.68 1185. 1251. |
| | | coef | std err | z |
| const lead2_pscore_wk10_ lead2_pscore_wk10_ lead2_pscore_wk10_ lead2_pscore_wk10_ lead2_pscore_wk10_ lead2_pscore_wk10_ lead2_pscore_wk10_ | _group_2 _group_3 _group_5 _group_9 | 0.6200 -0.2114 -0.0790 -0.0775 0.0691 0.0441 0.0313 | 0.030 0.037 0.046 0.053 0.050 0.094 0.075 | 20.782 -5.694 -1.723 -1.461 1.393 0.471 0.416 |

Figure: LASSO Regression

Machine Learning

While using the machine learning technique of a LASSO regression does yield smaller confidence intervals with less variables, narrowing the subset, it is not statistically different from the original data. This could be explained by less variables around the same mean. More statistical analysis can help explain whether this is an accurate representation.

Conclusions

The study finds that success in college football positively affects alumni donations, application rates, and academic reputation, while also increasing in-state enrollment and SAT scores of incoming students, especially in elite conferences. Our machine learning technique shows that with LASSO while some variables are omitted in the earlier stages it does not change the factors that are overall chosen.

Appendix

1.987



Figure: Appendix/Github