SML: Exercise 2

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Introduction

This report aims to find the best set of predictors for past cumulative grocery sales (in dollars) for Dominick's Finer Foods.

Data

The data set contains seven years of store-level data collected at Dominick's Finer Foods by the University of Chicago Booth School of Business. The data can be found at https://www.chicagobooth.edu/research/kilts/datasets/dominicks. The data set contains 50 variables, which stem from:

1. customer count files, which contain information about in-store traffic;
2. a demographics file, which contains store-specific demographic data;
3. number identification files, which contain product information.

Of the fifty variables, `GROCERY_sum` is used as dependent variable. Furthermore, four categorical variables are dropped; `STORE`, `CITY`, `ZIP` and `SPHINDX`. The remaining variables are potential predictor variables.

Method

To find the optimal set of predictor variables, and there corresponding weights, we use a regression method that penalizes the size of coefficients. The penalty is useful when predictors are collinear, or the number of predictors destabilizes estimation. This data set only consists of 77 observations for 50 variables, hence the number of predictors would destabilize estimation if not penalized.

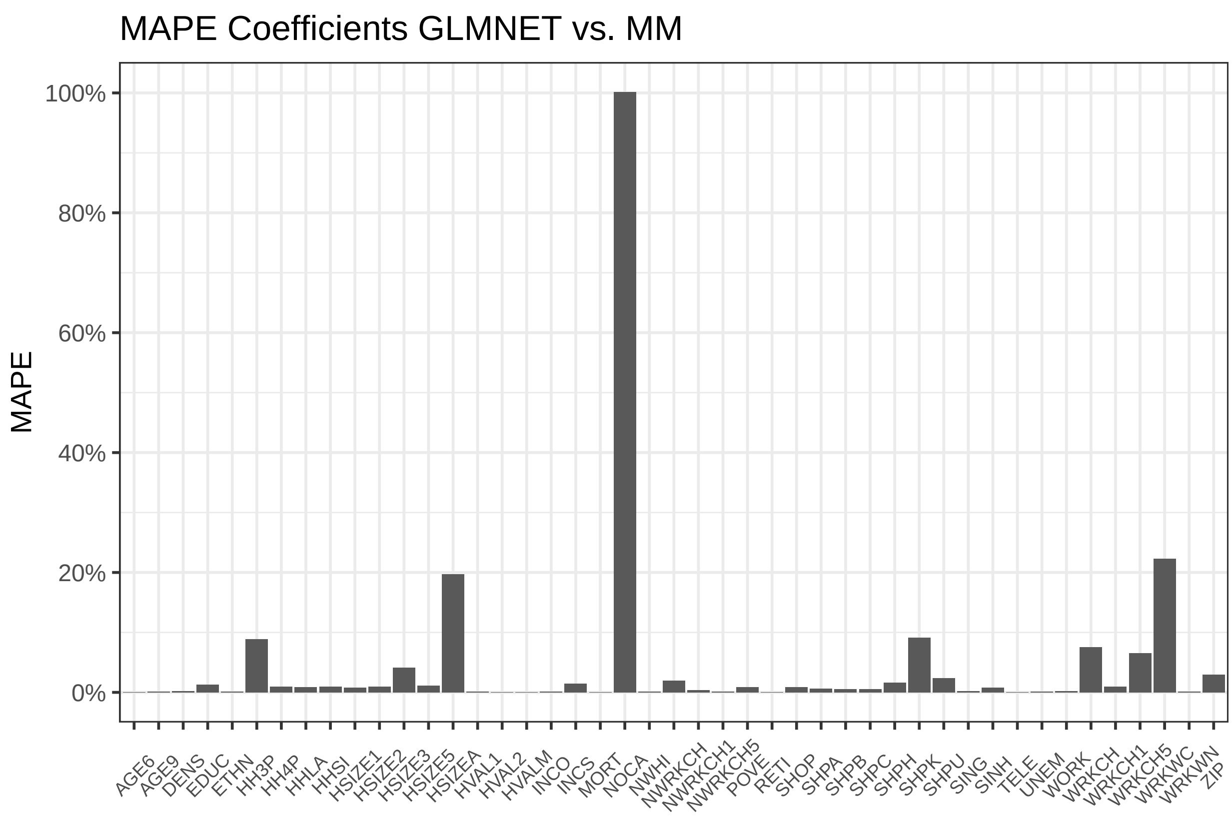
Let $P(\beta)$ denote a general penalty function. Then, the penalized regression equation becomes

$$L(\beta) = (\mathbf{y} - \mathbf{x}\beta)^T(\mathbf{y} - \mathbf{x}\beta) + \lambda P(\beta),$$

where λ is the hyperparameter that determines the strength of the penalty. When $P(\beta) = \beta^2$, the regression is called 'ridge' regression. Similarly, when $P(\beta) = |\beta|$, the regression is called 'LASSO' regression. Finally, any convex combination $P(\beta) = \alpha|\beta| + (1-\alpha)\beta^2$ of the 'ridge' and 'LASSO' penalty, where α denotes the weight on the 'LASSO' penalty, is called 'elastic net' (compare Zou and Hastie 2005).

Results

In an estimation on simulated data, we get the same results for `glmnet` and our implementation based on the MM algorithm. We suspect that the algorithm used in the glmnet package (generalized linear model via penalized maximum likelihood), converges faster and hence delivers more precise estimates than our implementation of the elastic net with the MM algorithm.


MAPE Coefficients GLMNET vs. MM
MAPE
100%
80%
60%
40%
20%
0%
AGE6
AGE9
DENS
EDUC
ETHN
HH3P
HH4P
HHLA
HHSI
HSIZE1
HSIZE2
HSIZE3
HSIZE5
HSIZEA
HVAL1
HVAL2
HVALM
INCO
INCS
MORT
NOCA
NWHI
NWRKCH
NWRKCH1
NWRKCH5
POVE
RETI
SHOP
SHPA
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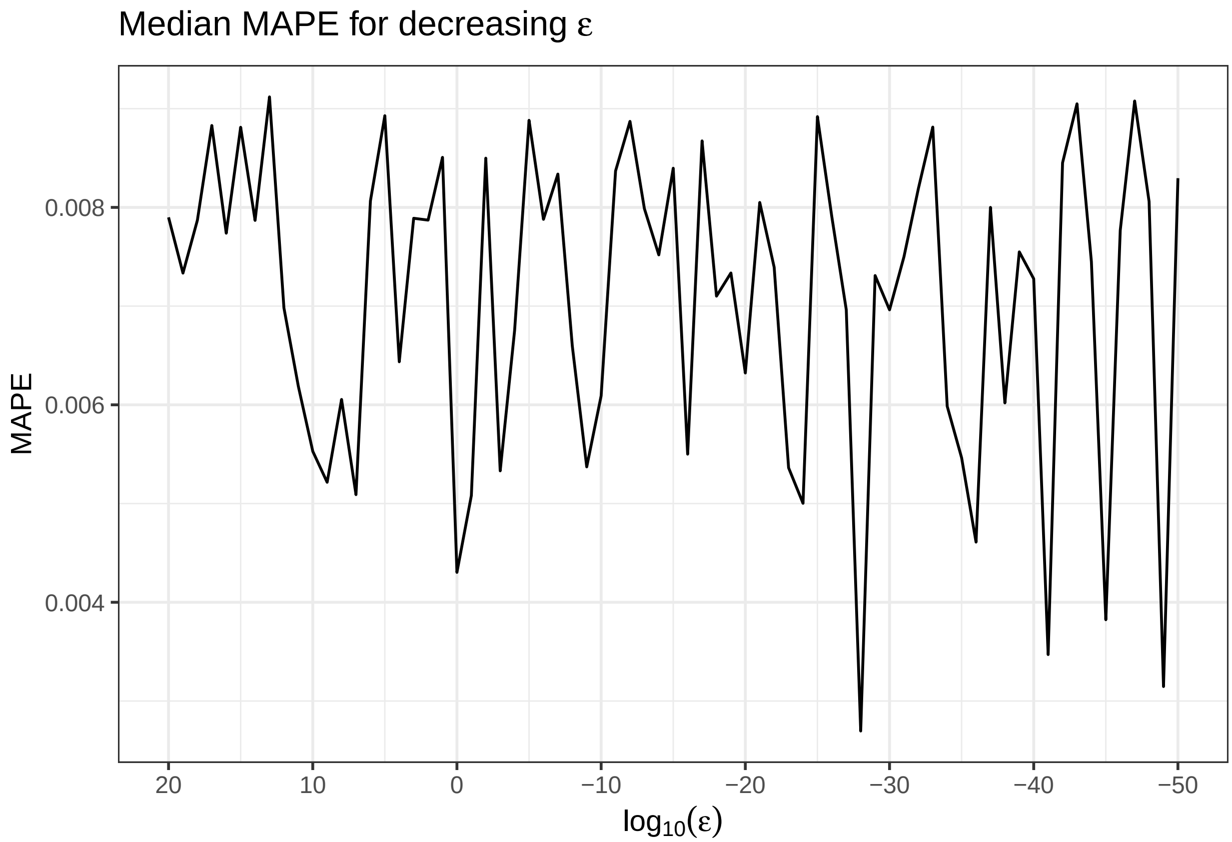

Conclusion and Discussion

References

Code

Zou, Hui, and Trevor Hastie. 2005. "Regularization and Variable Selection via the Elastic Net." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 67 (2): 301–20.