Data Science Final Project

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1. Introduction

Research question and hypothesis

Princeton has many diverse houses ranging in size, location, age, and many other factors. With this comes a huge range of house prices. But how do the characteristics of a house determine its price? Our research studies how factors such as the number of bedrooms, location, and the year built affect the price of the house. More precisely, we try to predict `soldPrice`, the price at which a house is sold, using the following possible predictors:

- nbhd (neighborhood)
- bed (number of bedrooms)
- fullBath (number of full baths)
- halfBath (number of half baths)
- style (style)
- age (yearSold minus yearBuilt)
- marketDays (days the house was on market)
- yearSold, daySold, monthSold (date at which the house was sold)

Based off our own experience, we predict that neighborhood/address and the year built have a significant impact on the price of the house.

Data description

Beatrice Bloom, a Princeton Residential Specialist, provides many great resources about the Princeton housing market including a table of houses sold in Princeton since 2011. This data can be found here. We intend to use this data to answer our question. The data is stored in `./data/pton-market-data.csv` in the Github repo.

For a simple exploratory data analysis, we used `group_by` and `summarize` to find the top-10 styles and neighborhoods with the highest price. The results are shown in Table 1.

2. Regression Analysis

Description of models

The final model we adopted was Lasso (short for "Least Absolute Shrinkage and Selection Operator"), a generalization of usual linear regression. We chose this model because among all models we tried (see Table 2), Lasso has the lowest variance of errors (an RMSE of roughly 0.453 million dollars), and a decent R-squared value of 0.522.

Lasso tries to enhance prediction accuracy and model interpretability by performing both variable selection (selecting which predictors to take into account) and shrinkage (shrinking coefficients of less important predictors). For usual linear models, we often try to minimize the sum of squares $\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{i,j}\beta_j)^2$.

Table 1: Top ten styles and neighborhoods with highest meanPrice

style	meanPrice	nbhd	meanPrice
Georgian	2338700	Pretty Brook Area	1270498.3
Transitional	2188875	Institute Area	985201.3
Manor	1736780	Western Section	883958.9
French	1496095	The Glen	883113.5
Mid-Century Modern	1484571	Hun Area	871096.2
Craftsman	1385000	Princeton Ridge	772319.6
Tudor	1155930	Battlefield Area	762876.4
Cape Cod	1132179	Riverside	761638.1
Farmhouse	1105813	Rosedale Area	757956.3
Normandy	992742	Ettl Farm	752933.8

For Lasso, we impose a penalty for more complex models: what we minimize is the sum $\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{i,j}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$. Here, $\lambda \geq 0$ is a parameter that we can tune to best fit our scenario.

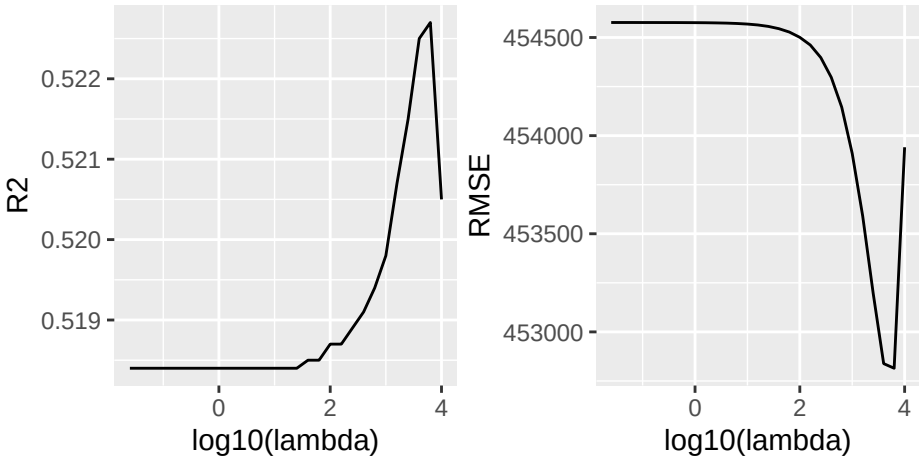
As usual, Lasso assumes that the response variable y follows a linear relation with the predictor variables $y = X\beta + \epsilon$, where ϵ is Normally distributed with mean 0.

Table 2: Performance of all models we tried

	R2	RMSE
full lm	0.5448	454579.1
forward	0.5449	454880.4
backward	0.5449	454880.4
ridge	0.5170	455475.4
lasso	0.5227	452814.7
elastic net	0.5192	454296.0
pcr	0.5996	507588.0

Model output

We calculated the average R-squared and RMSE values using tenfold cross validation. The following graphs plot R-squared and RMSE values against lambda, the parameter in the Lasso model.



As we can see, the best lambda occurs roughly at $10^{3.8} \approx 6309$. Using this lambda, we obtained the R-squared and RMSE values for Lasso in Table 2.

Interprtation of coefficients

Discussion and Limitations

Assumptions possibly not met, curse of dimensionality, did not incorporate census data

Conclusion

Additional Work

Introduce the other models we tried