Exercise 2

2023-02-12

#1) Saratoga house prices

Pricing Strategy

Main Focus: More preciously prediction for price

For the tax manager who want to know the precious prediction for price, we made more precious model from the data and suggested the points what elemets affect on how much price is.

Data

The description of the dataset in the salatago house;

- price: price (1000s of US dollars)

<Dependent variables(numerical)> - lotSize: size of lot (square feet) - Age: age of house (years) - landValue: value of land (1000s of US dollars) - livingArea: living are (square feet) - pctCollege: percent of neighborhood that graduated college - bedrooms: number of bedrooms - fireplaces: number of fireplaces - bathrooms: number of bathrooms (half bathrooms have no shower or tub) - rooms: number of rooms

<Dependent variables(non-numerical)> - heating: type of heating system - fuel: fuel used for heating - sewer: type of sewer system - waterfront: whether property includes waterfront - newConstruction: whether the property is a new construction - centralAir: whether the house has central air

Documentation of the Saratago House dataset https://r-data.pmagunia.com/dataset/r-dataset-package-mosaicdata-saratogahouses

Model

We used the following steps to make the precious model.

- 1 Split data train/test dataset
- 2 Create squared variables and interaction variables of the numerical data in the SaratogaHouses

we repeated the followign procedures ten times and take an average of rmse

The estimation of the model is

$$\begin{aligned} log(Price) = \beta_0 + \beta_{\nless}[numerical\ variables]^2 + \beta_{\nless}[interaction\ terms\ by\ each\ numerical\ variables] \\ + \beta_{\nless}[non - numerical\ variables(dummytemrs)] \end{aligned}$$

- 3 Linear regression with all variables
- 4 Knn regression with all variables
- 5 Compared the average of rmse of Linear and Knn model to find better fit model
- 6 Summarized the better model and interpreted its meaning

Results

The liner model of RMSE is 0.2822 and The Knn model of RMSE is 0.3061. Please see the detail of the linear reagression in the appendix.

Discussion: Comparison between Linear and LNN model

In this estimation, from the result that rmse of the linear model is smaller than that of knn model, the fitting of the linear model is better than that of the best linear model. We can think this reason is what the liner model that is set up close to the true model.

Conclusion for Tax authority

From the result of the estimation of the linear model(Appendix 1), we can say that elements that increases house prices are more "fireplaces", more "newConstructionNo" at the statistically siginificance. However, more "age", "heatinghot water/steam", "waterfrontNo" make its price decrease at the statistically siginificance.

Appendix

1. Result of the model

```
Call:
lm(formula = log(price) ~ ., data = data_train)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.7497 -0.1405  0.0100  0.1576  1.1371 

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)    
(Intercept)              1.149e+01  2.594e-01  44.320  < 2e-16 ***
lotSize                  1.400e-01  9.121e-02   1.535 0.125100    
age                     -6.528e-03  1.985e-03  -3.288 0.001037 ** 
landValue                2.991e-06  2.378e-06   1.258 0.208710    
livingArea               1.373e-04  1.658e-04   0.828 0.407822    
pctCollege              -2.385e-03  6.711e-03  -0.355 0.722334    
bedrooms                 1.206e-01  9.930e-02   1.215 0.224662    
fireplaces               4.066e-01  1.081e-01   3.761 0.000176 ***
bathrooms                2.879e-01  1.326e-01   2.171 0.030119 *  
rooms                    1.462e-02  3.464e-02   0.422 0.673072    
lotSize.sq               1.467e-03  4.970e-03   0.295 0.767818    
lotSize._.age           -1.063e-03  4.809e-04  -2.211 0.027197 *  
lotSize._.landValue     -7.900e-07  4.299e-07  -1.838 0.066306 .  
lotSize._.livingArea    -2.544e-05  4.040e-05  -0.630 0.528950    
lotSize._.pctCollege     8.655e-04  1.488e-03   0.582 0.560879    
lotSize._.bedrooms       1.467e-02  2.213e-02   0.663 0.507411    
lotSize._.fireplaces    -8.360e-03  3.149e-02  -0.265 0.790681    
lotSize._.bathrooms     -5.440e-02  3.014e-02  -1.805 0.071331 .  
lotSize._.rooms          5.359e-03  9.768e-03   0.549 0.583339    
age.sq                   1.744e-05  5.910e-06   2.951 0.003222 ** 
age._.landValue          1.959e-08  7.786e-09   2.516 0.011983 *  
age._.livingArea        -4.245e-07  8.106e-07  -0.524 0.600590    
age._.pctCollege         7.604e-05  2.970e-05   2.560 0.010585 *  
age._.bedrooms          -1.111e-04  4.943e-04  -0.225 0.822186    
age._.fireplaces         3.312e-04  6.099e-04   0.543 0.587238    
age._.bathrooms          7.385e-04  6.041e-04   1.222 0.221757    
age._.rooms             -2.342e-04  1.869e-04  -1.253 0.210419    
landValue.sq            -9.147e-12  2.599e-12  -3.520 0.000447 ***
landValue._.livingArea  -9.431e-10  7.145e-10  -1.320 0.187081    
landValue._.pctCollege   9.317e-08  3.619e-08   2.575 0.010144 *  
```

```
landValue._.bedrooms    -7.029e-07  4.219e-07  -1.666 0.095931 .
landValue._.fireplaces  -1.186e-06  5.235e-07  -2.267 0.023574 *
landValue._.bathrooms    7.389e-07  5.630e-07   1.312 0.189637
landValue._.rooms        2.372e-08  1.764e-07   0.134 0.893069
livingArea.sq           -3.616e-08  5.054e-08  -0.715 0.474500
livingArea._.pctCollege  3.326e-06  2.451e-06   1.357 0.174924
livingArea._.bedrooms    3.422e-05  4.263e-05   0.803 0.422323
livingArea._.fireplaces -1.989e-05  5.200e-05  -0.382 0.702190
livingArea._.bathrooms   9.046e-05  5.673e-05   1.595 0.111041
livingArea._.rooms      -1.321e-05  2.035e-05  -0.649 0.516440
pctCollege.sq           -4.168e-05  6.088e-05  -0.685 0.493686
pctCollege._.bedrooms    3.026e-04  1.391e-03   0.218 0.827838
pctCollege._.fireplaces -4.274e-03  1.552e-03  -2.754 0.005966 **
pctCollege._.bathrooms  -1.383e-03  1.852e-03  -0.747 0.455277
pctCollege._.rooms      -2.517e-05  5.227e-04  -0.048 0.961603
bedrooms.sq             -3.858e-03  1.592e-02  -0.242 0.808578
bedrooms._.fireplaces   -5.325e-02  2.805e-02  -1.899 0.057841 .
bedrooms._.bathrooms    -6.534e-02  3.109e-02  -2.102 0.035765 *
bedrooms._.rooms        -1.430e-04  1.105e-02  -0.013 0.989677
fireplaces.sq            2.558e-02  2.486e-02   1.029 0.303794
fireplaces._.bathrooms   7.453e-03  3.599e-02   0.207 0.835996
fireplaces._.rooms       6.778e-03  1.080e-02   0.628 0.530341
bathrooms.sq            -3.959e-02  2.735e-02  -1.448 0.147982
bathrooms._.rooms        9.407e-03  1.204e-02   0.781 0.434895
rooms.sq                 2.086e-04  3.692e-03   0.057 0.954952
heatinghot water/steam  -4.657e-02  2.266e-02  -2.055 0.040033 *
heatingelectric          3.426e-02  6.399e-02   0.535 0.592505
fuelelectric            -5.308e-02  6.323e-02  -0.839 0.401376
fueloil                 -7.454e-03  2.733e-02  -0.273 0.785087
sewerpublic/commercial   1.201e-02  2.076e-02   0.579 0.562873
sewernone               -1.179e-01  8.472e-02  -1.392 0.164108
waterfrontNo            -5.851e-01  8.477e-02  -6.903  7.9e-12 ***
newConstructionNo        1.391e-01  4.102e-02   3.390 0.000719 ***
centralAirNo            -1.832e-02  1.831e-02  -1.000 0.317270
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.2678 on 1318 degrees of freedom
Multiple R-squared:  0.645, Adjusted R-squared:  0.6281
F-statistic: 38.02 on 63 and 1318 DF,  p-value: < 2.2e-16
```

2. Classification and retrospective sampling

Results

```
The coefficients of the logit model
        (Intercept)            duration              amount         installment                 age 
              -0.66                0.02                0.00                0.19               -0.02 
    historyterrible          purposeedu purposegoods/repair      purposenewcar      purposeusedcar 
              -2.02                0.91                0.13                0.94               -0.67 

confusion matrix
   yhat
y     0   1
  0 131  11
  1  44  14

out-of-sample accuracy rate
0.725

the result of the null model
  0   1 
142  58 

the null model accuracy rate
0.71
```

Disucussion

What do you notice about the history variable vis-a-vis predicting defaults?

From the coefficient of the logit model, the poor and terrible of the history made the probability of default decrease.

What do you think is going on here?

Intuitively, the poor and terrible of the history made the probability of default increase. So there is something with the bad estimation. We can think this reason is caused by what the default is rare, and so we cannot collect data randomly(the data is not collected through random sampling) that is biased.

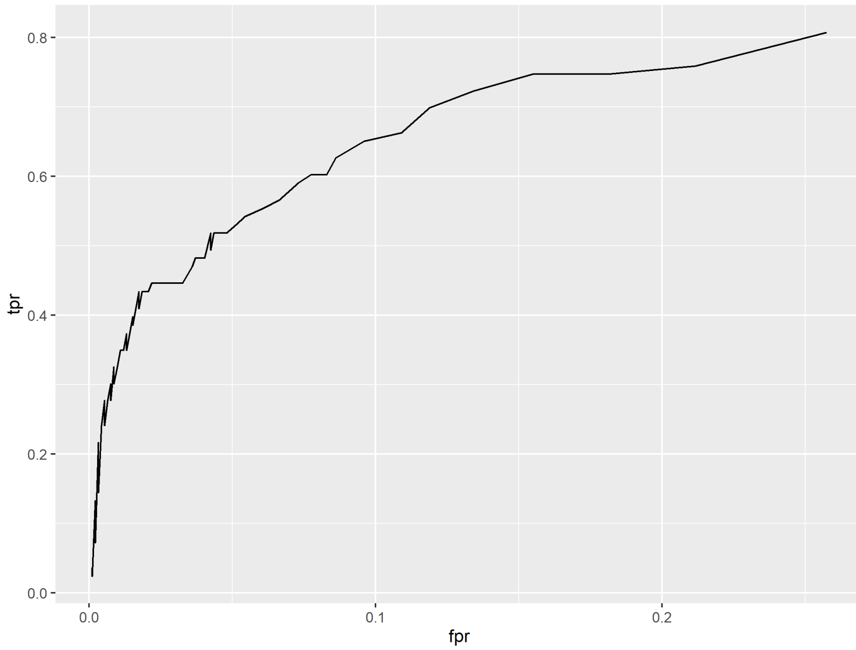
Do you think this data set is appropriate for building a predictive model of defaults

We don't think so. Because the out-of-sample accuracy rate is 0.725 while the null model accuracy rate is 0.71. Therefore, the improvement of the estimation is so low.

Would you recommend any changes to the bank's sampling scheme?

As we said above, the data should be collected randomly that will make biased decrease.

3. Children and hotel reservations



predict	actual
12	14
8	15
11	28
6	19
17	30
10	21
14	25
6	17
10	16
13	25
6	26
5	11
12	16
13	20
11	17
10	16
14	22
11	20
15	26
10	18