Exercise 2

2023-02-22

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 in the following

$$\begin{aligned} lm1: \quad Price = \beta_0 + \beta^t(&lotSize + age + landValue \\ &+ livingArea + pctCollege + bedrooms + fireplaces + bathrooms + rooms) \end{aligned}$$

lm2

$$\begin{aligned} lm2: \quad Price = \beta_0 + \beta^t(&lotSize^2 + age^2 + landValue^2 + livingArea^2 + \\ &pctCollege^2 + bedrooms^2 + fireplaces^2 + bathrooms^2 + rooms^2 + \\ &lotSize : age + landValue : age + livingArea : age + bedrooms : age) \end{aligned}$$

$$\begin{aligned} lm3: \quad Price = \beta_0 + \beta^t(&lotSize + age + landValue + \\ &livingArea + pctCollege + bedrooms + fireplaces + bathrooms + rooms \\ &+ age : lotSize + landValue : lotSize + livingArea : lotSize + bedrooms : lotSize) \end{aligned}$$

$$
\begin{aligned}
lm4: \quad Price = \beta_0 + \beta^t(&lotSize + age + landValue + livingArea \\
&+ pctCollege + bedrooms + fireplaces + bathrooms + rooms \\
&+ age : bathrooms + landValue : bathrooms + livingArea : bathrooms + bedrooms : bathrooms)
\end{aligned}
$$

$$
lm5: \quad Price = \beta_0 + \beta rt(. - heating - sewer - waterfront - newConstruction)^2
$$

$$
\begin{aligned}
lm6 : Price = \beta_0 + \beta_{\nvDash}()[&numerical\ variables]^2 + \beta_{\nvDash}[interaction\ terms\ by\ each\ numerical\ variables] \\
&+ \beta_{\nvDash}[non - numerical\ variables(dummytemrs)]
\end{aligned}
$$

- 3 Linear regression with some original setting(r1-r5) and all variables(r6)
- 4 Knn regression with all variables
- 5 Compared the average of rmse in the linear model to find the best linear model, also compared it to Knn model to find better fit model
- 6 Summarized the better model and interpreted its meaning

Results

Here linear model 1 (lm1) is the medium model as mentioned in the lecture slide, wherein professor has mentioned that the medium model is price versus all variables above (main effects only). Now using the combination of transformations and by adding the interactions, we have tried to handbuild a model for price that outperforms the medium model that has alreday been discussed in class. From the results obtained so far, we have found that the best model is the linear model 4 (lm4) as it has the lowest RMSE value of 58206.47. This lowest rmse value will vary for another train/ test split, on different run ("Horse Race", as mentioned in question). Here the lm4 model is obtained by interacting the 'bathrooms' variable with all other quantitative variables. The reason for interacting with 'bathrooms' is that bathroom coefficient is not only significant, but also it has the largest coefficient value as shown in the result below in almost all regressions. Here we may mention that in this run, we have found the rmse values of 58752.55, 59075.90, 58607.72, 58206.47, 60105.40, 58650.36, 60401.00 for linear models 1(r1), 2(r2), 3(r3), 4(r4), 5(r5), KNN model and K-CV model respectively. Thus clearly lm4 model is found to be the best model with lowest rmse value.

Also, We tried to do the same regression on the way of K-CV, and then we got the rmse of the linear regression(basic model) is 60543.82, that of linear model 4 is 60480.13, and that of the KNN regression is 61817.15. This results looks like the same as the way of the ten-times average.

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. 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 models and Knnmodel, **Tax authority should use the best linear model** because it has the lowest rmse. Also, taking a look at the summary of the best linear model(Appendix 1), we can get that elements that increases house prices are more "lotSize", more "landValue", more "livingArea", more "bedrooms", more "bathrooms", and more "rooms" at the statistically significance.

Appendix

Summary of the lm4 model(average)

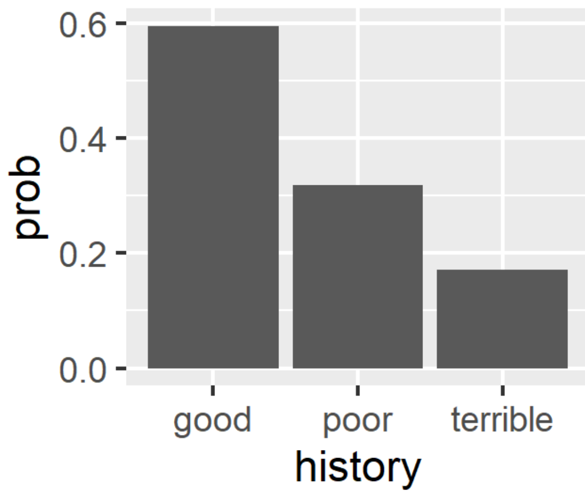
```
Call:
lm(formula = price ~ lotSize + age + landValue + livingArea +
```

```
    pctCollege + bedrooms + fireplaces + bathrooms + rooms +
    age:bathrooms + landValue:bathrooms + livingArea:bathrooms +
    bedrooms:bathrooms, data = saratoga_train)

Residuals:
    Min      1Q  Median      3Q     Max
-264955  -33343   -5024   26653  441867

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)          -1.936e+04  2.053e+04  -0.943 0.345742
lotSize               8.736e+03  2.374e+03   3.680 0.000243 ***
age                  -1.334e+02  1.464e+02  -0.911 0.362408
landValue             1.537e+00  1.691e-01   9.090  < 2e-16 ***
livingArea            2.916e+01  1.092e+01   2.671 0.007661 **
pctCollege            3.143e+01  1.630e+02   0.193 0.847118
bedrooms              1.948e+04  7.994e+03   2.437 0.014926 *
fireplaces            4.307e+03  3.246e+03   1.327 0.184763
bathrooms             4.410e+04  1.013e+04   4.353 1.44e-05 ***
rooms                 2.501e+03  1.069e+03   2.339 0.019464 *
age:bathrooms         1.290e+01  8.153e+01   0.158 0.874311
landValue:bathrooms  -2.759e-01  7.283e-02  -3.789 0.000158 ***
livingArea:bathrooms  2.185e+01  4.584e+00   4.766 2.08e-06 ***
bedrooms:bathrooms   -1.631e+04  3.897e+03  -4.185 3.04e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 57650 on 1368 degrees of freedom
Multiple R-squared:  0.6565,    Adjusted R-squared:  0.6533
F-statistic: 201.2 on 13 and 1368 DF,  p-value: < 2.2e-16
```

2) Classification and retrospective sampling

Results

The graph of the default probability by credit history is



The result of the logit model that we built is

```
      (Intercept)          duration               amount       installment                age
            -0.71              0.03                 0.00              0.22              -0.02
  historyterrible       purposeedu purposegoods/repair     purposenewcar     purposeusedcar
            -1.88              0.72                 0.10              0.85              -0.80
```

```
   yhat
y     0   1
  0 645  55
  1 211  89

accuracy rate
0.734

the result of the null model
  0   1
700 300

the null model accuracy rate
0.70
```

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.

As this evidence, the bar graph has shows that people of the good credit history has the higher default probability. However, this is different from the intuitive result and is not reality.

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 0.734 while the null model accuracy rate is 0.70. Therefore, the improvement of the estimation is so low(only 3.4 percentage point).

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

Model Building

Models

We shows the models that we used in this problems. First, the baseline 1 is

$$children = \beta_0 + \boldsymbol{\beta}\mathbf{X}_{market\ segment,\ adults,\ customer_type,\ is\ repeated\ guest}$$

The baseline 2 is

$$children = \beta_0 + \boldsymbol{\beta}\mathbf{X}_{all\ variables\ excpet\ arriving\ date}$$

The our model is

$$\begin{aligned} children = \beta_0 + \boldsymbol{\beta}\mathbf{X}_{all\ variables\ excpet\ arriving\ date} &+ arriving\ year + arriving\ month \\ &+ average\ daily\ rate \times adults \\ &+\ days\ in\ waiting_list \times adults \\ &+ stays\ in\ weekend_nights \times adults \\ &+ total\ of\ special\ requests \times adults \\ &+ booking\ changes \times average\ daily\ rate \\ &+ booking\ changes \times days\ in\ waiting_list \\ &+ lead\ time \times booking\ changes \\ &+ (lead\ time)^2 \end{aligned}$$

Check

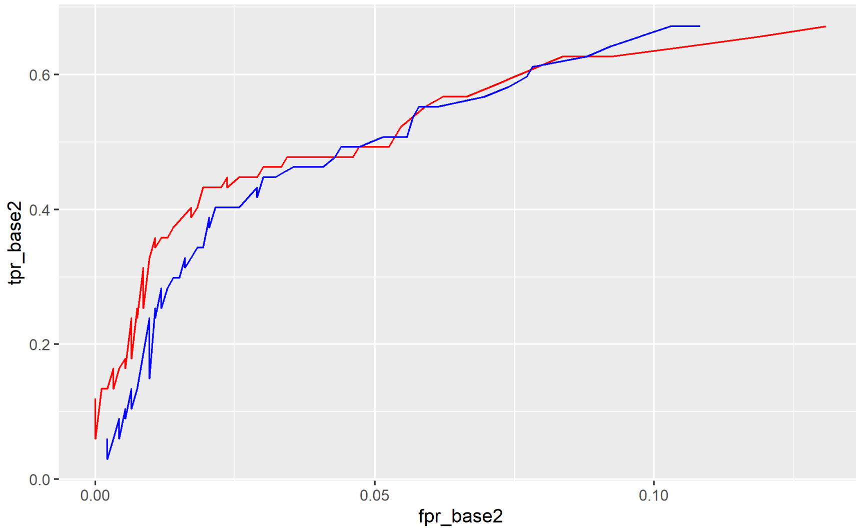
Out-of-sample accuracy rate by each model is

baseline1	baseline2	mymodel
0.9202222	0.9368889	0.9375556

Therefore, the model accuracy of my model is higher than the baseline2 by 0.1% and thn the baseline 1 by 1.7%.

Model validation: step 1

The ROC curve of baseline 2 and my model is



red line: baseline 2, blue line: my model

From the graph, if FPR=0.05 my model has higher tpr than baseline 2, and so my model is better than baseline 2 in this case.

However, in the low FPR, the TPR of baseline 2 is higher than that of my model, and so my model is worse than baseline 2. Also, in the high FPR, the TPR of baseline 2 is lower than that of my model, and so my model is better than baseline 2.

Model validation: step 2

In this case, we assumed a threshold is 50%, and our results is in the following.

predict_base2	predict_model	actual
8	7	14
6	11	21
11	11	14
10	10	19
10	9	19
15	17	21
12	10	26
8	7	26
5	6	19
12	12	24
8	8	18
8	8	17
7	8	17
11	11	17
11	13	24
13	15	21
12	11	20
7	11	12
17	17	25
16	19	28

sum_base2	sum_predict	sum_actual
207	221	402

From the result, the predicting the total number of bookings with children by baseline 2 is 207, that by my model is 221, and that by actual data is 402. The accurancy of the prediction of the our model is around 50%, which is so lower than we expected. However, our model's accurancy of the prediction is higher than the baseline 2's one.