

# Exercise 2

2023-02-12

## 1) Saratoga house prices

### Pricing Strategy

#### Main Focus: More precisely prediction for price

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

#### Data

The description of the dataset in the saratoga 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 area (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 Saratoga House dataset <https://r-data.pmagunia.com/dataset/r-dataset-package-mosaicdata-saratogahouses>

#### Model

We used the following steps to make the precise model.

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

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

The estimation of the model is

$$\log(\text{Price}) = \beta_0 + \beta_{\text{num}}[\text{numerical variables}]^2 + \beta_{\text{int}}[\text{interaction terms by each numerical variables}] + \beta_{\text{non-num}}[\text{non-numerical variables(dummy terms)}]$$

- 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 regression 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 significance. However, more “age”, “heatinghot water/steam”, “waterfrontNo” make its price decrease at the statistically significance.

## 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

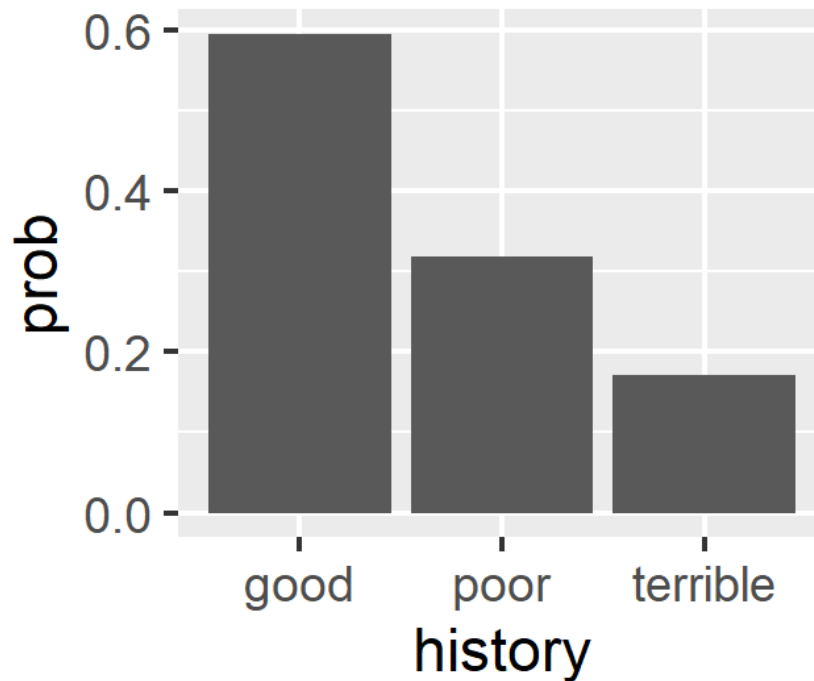
Multiple R-squared: 0.645, Adjusted R-squared: 0.6281

F-statistic: 38.02 on 63 and 1318 DF, p-value: < 2.2e-16

## 2) Classification and retrospective sampling

### Results

The graph of the default probability by credit history is



The result of the logit model that we built is

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

#### Model Building

##### Models

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

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

The baseline 2 is

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

The our model is

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

##### Check

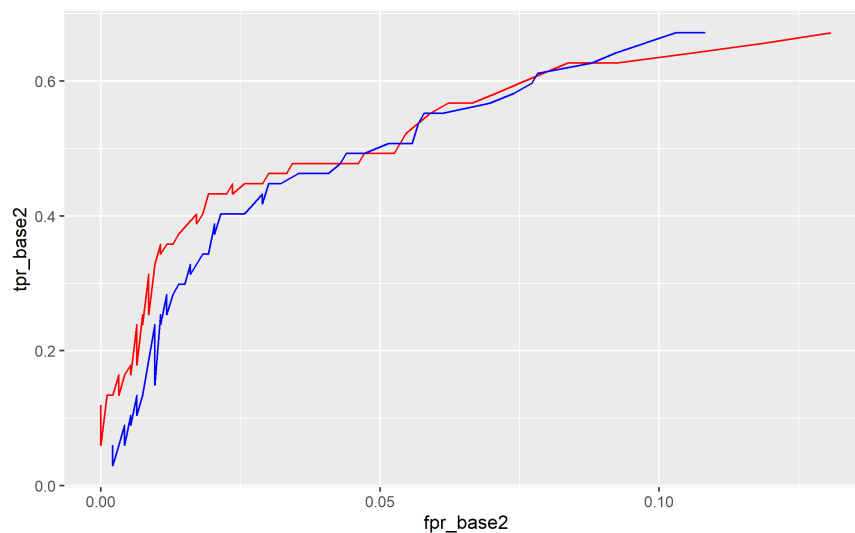
Out-of-sample accuracy rate by each model is

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 accuracy of the prediction of the our model is around 50%, which is so lower than we expected. However, our model's accuracy of the prediction is higher than the baseline 2's one.