ECO395MHomework2

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2024-02-23

#Q1 ## finding best linear model

lm2 = base modeal (made in class)

lm_a = get rid of insignificant variables fireplaces, fuel from lm2

lm_b = lm_a + landvalue*newconstruction

lm-c = lm_b + lotSize*landValue

lm_d = lm_b + lotSize*livingArea

lm_e = lm_b + landValue*livingArea

```
##      Avg of RMSE
## lm2     66996.76
## lm_a    66914.39
## lm_b    58980.29
## lm_c    59045.89
## lm_d    58993.85
## lm_e    59076.98
```

We can see above that our model lm_b outperforms lm2 which was the "medium" model discussed in class. This new model removes the fireplace and fuel variables from lm2 and includes the interaction effect between new construction and land value as well as the interaction between land value and lot size. This model will be compared to a K nearest neighbors regression model for price with appropriately scales variables that has an optimal k value that is provided below. The K nearest neighbor regression regressed on all variables except for pctCollege, sewer, waterfront, fireplaces, or fuel.

```
## [1] 66
```

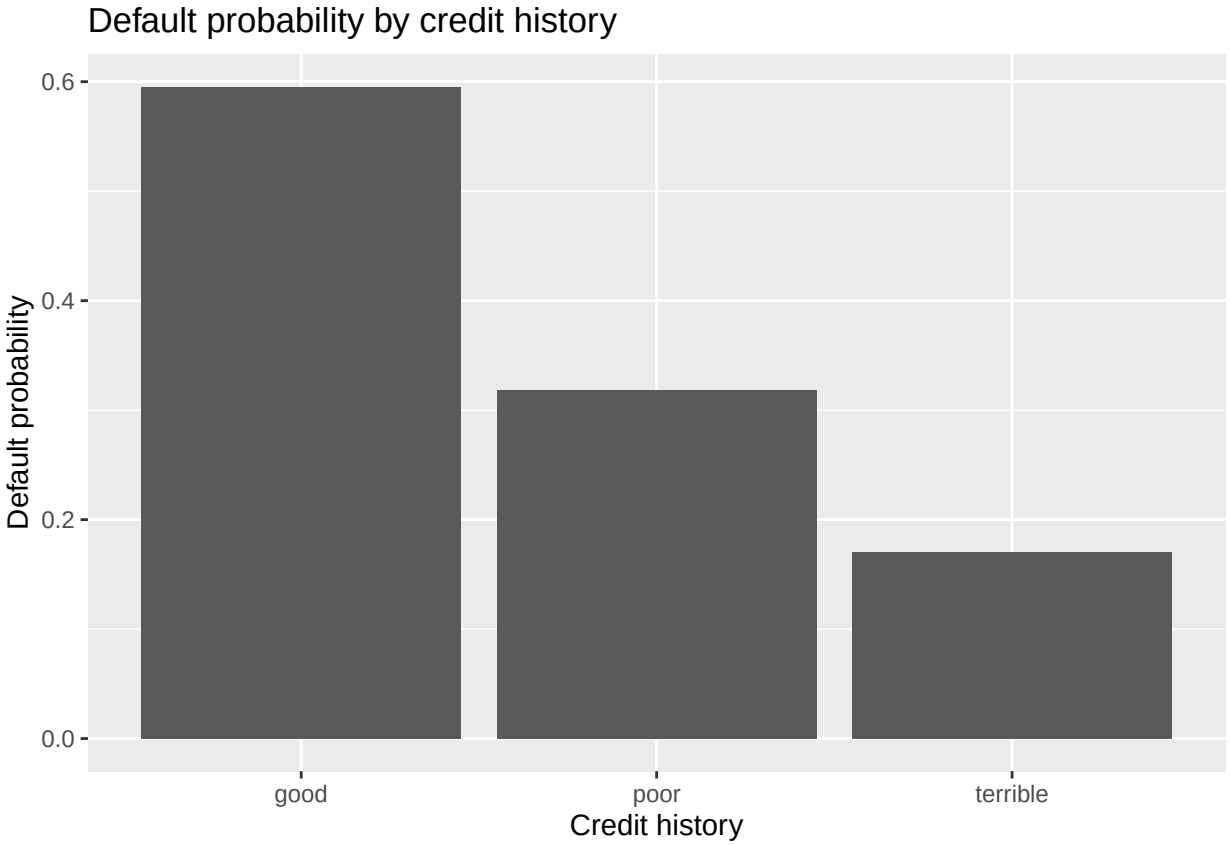
In our comparison we look at the average of the out-of-sample root mean squared error after running both the knn regression and linear model through 50 train-test-splits.

```
##              Avg of RMSE
## KNN             75238.30
## Linear model    58843.64
```

As we can see,The linear model certainly, on average, outperformed the KNN regression in terms of average root mean squared error. We have learned from this case study that for a particular price-modeling strategy, it is important to include potentially relevant interaction effects involving the value of the land that the property is situated on. This effect changes when its new construction or when the lot is a different size. We can also see that the KNN regression has weaker performance than the in class "medium" model. this this is

likely due to the difference between the meaning of an increase or decreases in units varies greatly depending on the variable in question, even though the data is demeaned and scaled. For example, an increase in bathrooms has a very different effect inthe change in house price than the increase in the square footing which may include the bathroom size. Due to this inconsistency, looking in a n-dimensional space for the values that are numerically closer to each other overall may not provide an accurate descriptor of similar houses. However this differences in partial effects would be picked up as the coefficients in the linear model.

Q2: Classification and retrospective sampling




```
##         (Intercept)            duration              amount         installment
##       -7.075258e-01        2.525834e-02        9.596288e-05        2.216019e-01
##                 age         historypoor     historyterrible           purposeedu
##       -2.018401e-02       -1.107586e+00       -1.884675e+00        7.247898e-01
## purposegoods/repair       purposenewcar      purposeusedcar       foreigngerman
##        1.049037e-01        8.544560e-01       -7.959260e-01       -1.264676e+00
```

We have provided above, a par plot measuring the probability of defaulting on the loans for each section of credit history as well as logistic regression that predicts the default probability using the variables duration, amount, installment, age, history, purpose, and foreign. Interestingly, and counter intuitively, we would predict in the logistic regression that, holing all else the same, that we expect someone moving from good credit history to bad or terrible credit history would decrease the chances of defaulting. Similarly, we see in the bar plot, the better the credit history, the higher the chances of defaulting are. This should likely not be the case as a better credit history means the borrower consistently pays off debt in time. Therefore, this would not be a good model to predict defaults in screening prospective loan customers. We believe that this

contradiction has resulted from the experiment design process. Because there are so few defaults, artificially inflating the proportion of defaults in the data set is likely changes the proportions of the good credit history category using a data collection process that is not random. A better representation of default probabilities would result from random sampling of all loans offered rather than oversampling defaults. The bank need need to include more data in random sampling set if there are such few defaults at this bank. Collecting too little data may result in no defaults in the set.

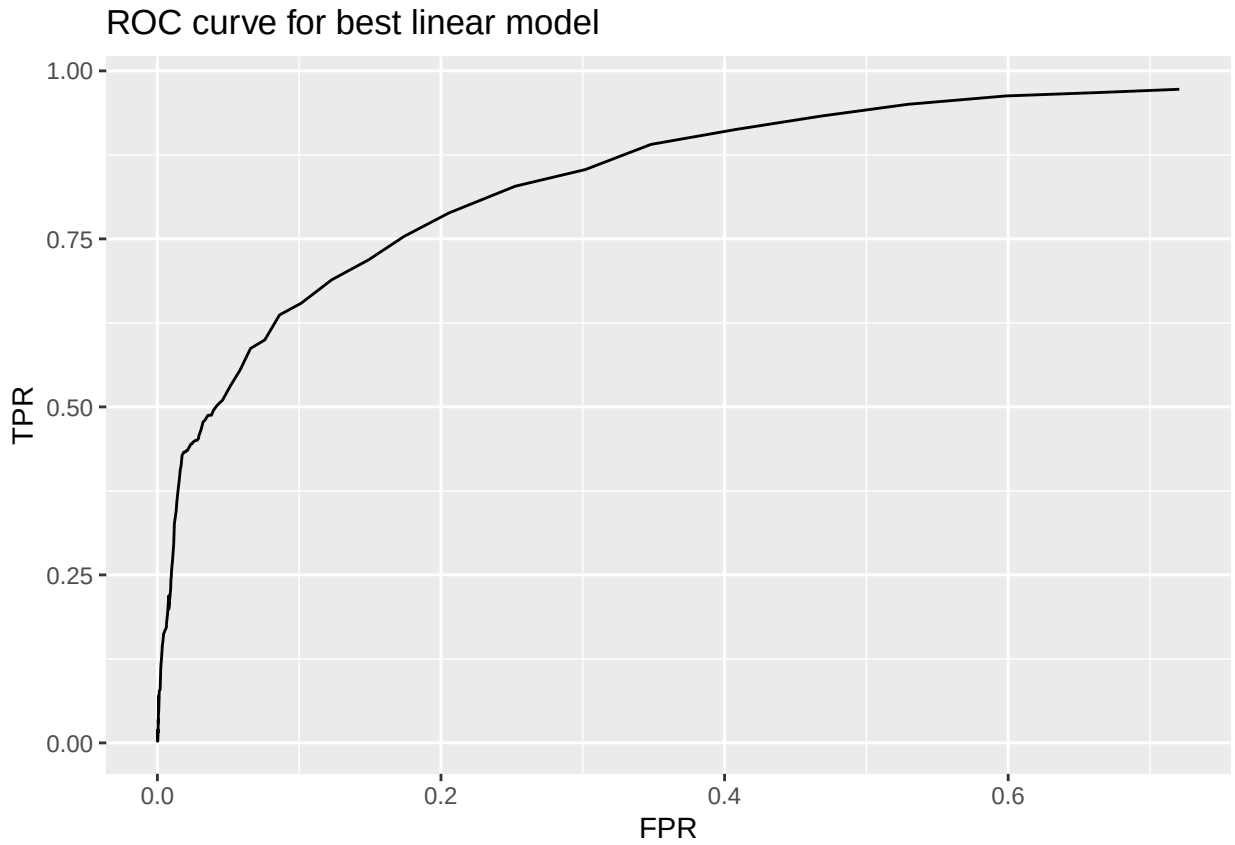
Q3 Children and hotel reservations

Model building

```
##       out-of-sample accuracy rate
## base1                   0.9185311
## base2                   0.9343111
## best                    0.9358178
```

Above are the averages of out-of-sample accuracy rates across 50 train-test-splits for the two base models and a third model which is the 2nd model plus the interaction effects of adults on room_type and special_requests, also, the interaction effect of booking changes with meal. We see that we are able to correctly identify if a child will arrive with the parents about 93.6% of the time.

Model validation: step 1



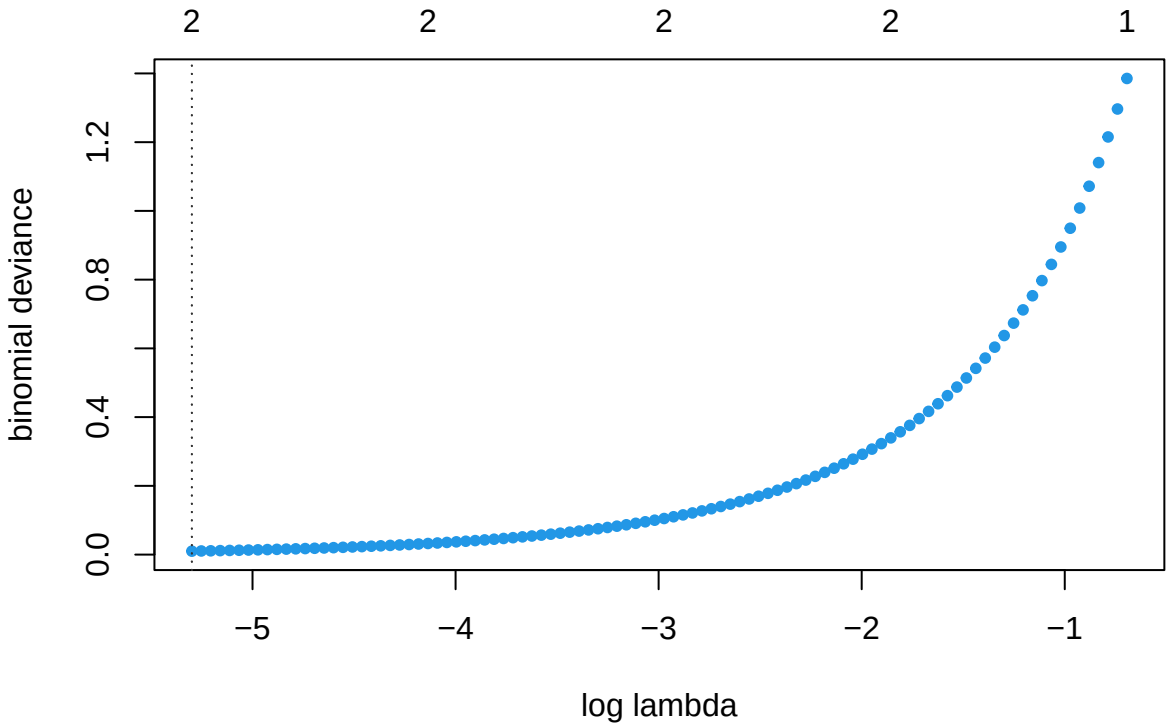
Using the third model mentioned previously, here we see the ROC curve on the validation data set as we vary the classification threshold from 0 in the bottom left to 1 in the top right.

Model validation: step 2

```
##    fold total_count exp_children actual_children
## 1     1         250         21.0              23
## 2     2         250         21.6              22
## 3     3         250         26.1              27
## 4     4         250         22.9              19
## 5     5         250         17.1              18
## 6     6         250         17.6              16
## 7     7         250         21.2              19
## 8     8         250         19.0              22
## 9     9         250         22.5              24
## 10   10         250         23.6              25
## 11   11         250         18.8              17
## 12   12         250         21.4              20
## 13   13         250         19.1              16
## 14   14         250         23.8              24
## 15   15         250         19.5              20
## 16   16         250         21.7              21
## 17   17         250         20.6              17
## 18   18         250         16.9              16
## 19   19         250         22.3              24
## 20   20         249         21.3              12
```

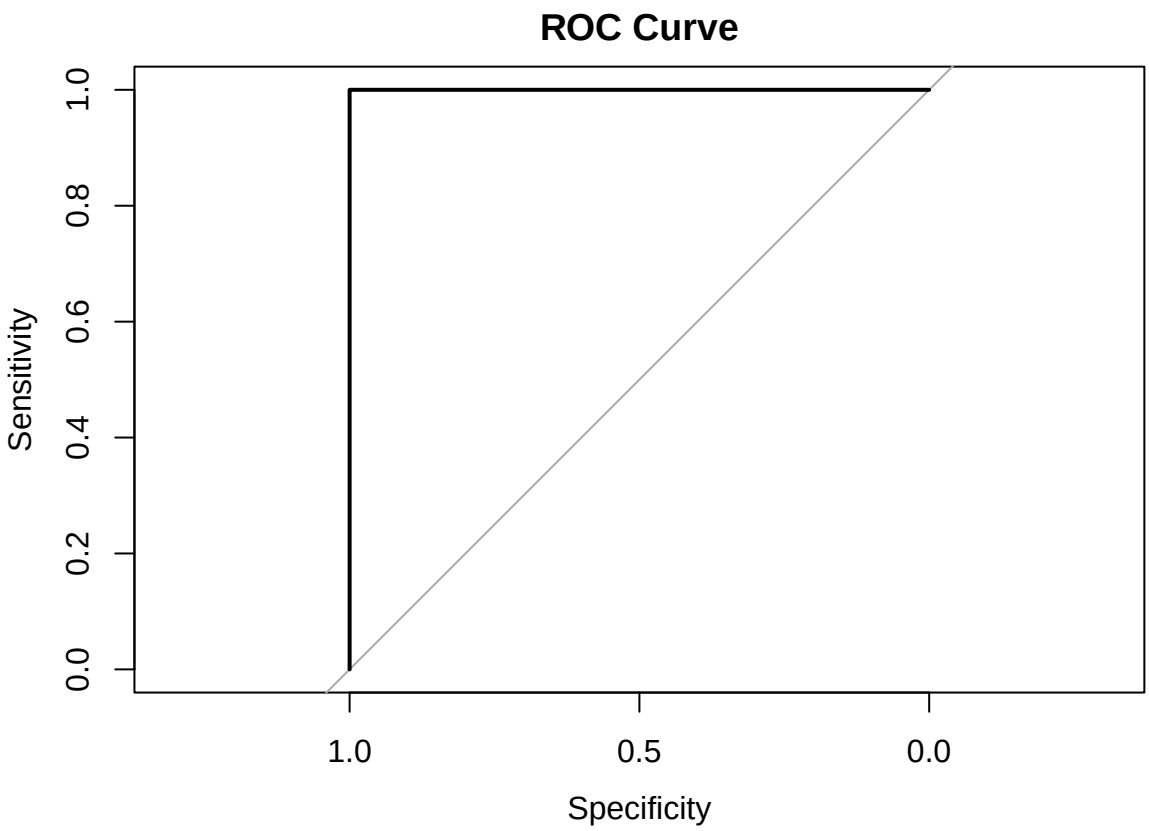
As we can see in the table above, for each of the 20 folds of the data we have the expected number of children and the actual number. In some of the folds we get very close (within 0.1 child in folds 5 and 9) and other times a little bit further way (about 5 off in fold 3). Within each of the 20 folds it seems that we don't have our 93.6% accuracy when we use the same data set to train and test in. However, the fact that we are within 5 children every time, it seems this model would be quite helpful in predicting the total number of bookings with children especially because of how quickly this runs, it could provide some helpful insight for a hotel manager when it comes to resource allocation for each day.

Q4 Mushroom classification




```
## [1] 0.00499739
```

The plot above showcases how the deviance changes as lambda changes. We see that the lambda value that minimizes the deviance is presented just below the plot at around 0.005. Using this optimal lambda, we plot the ROC curve to evaluate the out-of-sample performance of our model. We also provide the optimal threshold to set.




```
##   threshold
## 1 0.5001534
```

Notice that the ROC curve makes a perfect right angle. This perfect AUC score suggests that the model is highly capable of distinguishing between poisonous and edible mushrooms, with minimal error. The probability threshold is suggested to be 0.5001403. We then use the threshold in making our predictions and the following confusion matrix computes the amount of predictions that were made correctly and incorrectly. As the ROC plot would suggest, there are no incorrect predictions.

```
##           Actual
## Predicted   0   1
##         0 771   0
##         1   0 853
```

```
## [1] "False Positive Rate: 0"
```

```
## [1] "True Positive Rate: 1"
```

Based on this confusion matrix, the FPR is 0 (as there are 0 false positives) and the TPR is 1 (as there are no false negatives). These values indicate that the model is achieving perfect classification performance. It is exceptionally effective at identifying poisonous mushrooms without mistakenly classifying edible ones as poisonous, but perfect performance can also sometimes indicate over fitting.