**Project I: Predict the Housing Prices in Ames**

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**1.Dataset Introduction and Analysis Goal**

The dataset we use contains 2930 rows and 83 columns. It is from the Ames Assessor’s Office used to compute predicted house prices. Within the 83 columns, housing price would be the response in my analysis. I would build two prediction models(one linear regression model with Elasticnet penalty and one XGBoost tree model). And the performance target would be RMSEs less than

0.125 for the first 5 training/test splits and

0.135 for the remaining 5 training/test splits.

**2.Pre-Processing Procedure**

**2.1 Missing values**

There are 159 missing values which all from the “Garage\_Yr\_Blt”. By looking through several correlated variables, I found the 159 houses miss “Garage\_Yr\_Blt” because no garages have ever been built for these houses. In this case, I would just impute these missing values with 0.

**2.2 Remove unnecessary variables**

To prevent overfitting, remove some extremely unbalanced categorical variables. And remove “Longitude” and “Latitude” because they are not interpretable.

Removed variables:

"Street","Utilities","Condition\_2","Roof\_Matl","Heating","Pool\_QC", "Misc\_Feature","Low\_Qual\_Fin\_SF","Pool\_Area","Longitude","Latitude"

**2.3 Winsorization**

Apply winsorization on some numerical variable with upper 95% quantile of that variable based on the train data. Because some area-related variables should be capped to better approximated the selling price by a linear relationship.

Winsorized variables:

"Lot\_Frontage","Lot\_Area","Mas\_Vnr\_Area","BsmtFin\_SF\_2", "Bsmt\_Unf\_SF","Total\_Bsmt\_SF","Second\_Flr\_SF","First\_Flr\_SF", "Gr\_Liv\_Area","Garage\_Area","Wood\_Deck\_SF","Open\_Porch\_SF",

"Enclosed\_Porch","Three\_season\_porch","Screen\_Porch","Misc\_Val"

**2.4 Transformed X matrix to a numerical matrix**

To fit XGBoost and linear regression model with elasticnet penalty, I need to transform the design matrix to a numerical matrix. For tree model, we need to generate K binary categorical variables when K>2. The transformed matrix could also be used in linear regression model since the redundant features would not be selected by glmnet function.

To make the fitted model using train data works well in test data, I also need to prune the test data matrix to make its columns names and order the same as train data matrix.

**2.5 Take the log scale of response into calculation**

To prevent infinities and nans popping up in the metric calculations, I would fitted the model to predicted the logarithm of the price. And transform the price back using exponential when output the predicted Sales\_Price.

**3. Building Model and Tuning Parameter**

**3.1 Linear regression model with elasticnet penalty 0.5**

Instead of using Ridge regression or Lasso regression, I choose linear regression with elasticnec penalty because the alpha could be adjusted through 0 to 1. I could tune alpha to fit a model with better prediction. I create a sequence (0.1,...,1) of alpha and calculate the RMSE with different alpha in a loop and pick the alpha which gives the lowest averaged RMSE(over the ten training/test data split).

Below is the table which gives the averaged RMSE of different alpha.

|  |  |
| --- | --- |
| alpha | Averages RMSE |
| 0.1 | 0.1229917 |
| 0.2 | 0.1229840 |
| 0.3 | 0.1228717 |
| 0.4 | 0.1227662 |
| 0.5 | 0.1228138 |
| 0.6 | 0.1231402 |
| 0.7 | 0.1230443 |
| 0.8 | 0.1230642 |
| 0.9 | 0.1232108 |
| 1 | 0.1241447 |

**Table 1 Averaged RMSE for different alpha values**

Note: The lambda value is always the lambda.min which given by the cv.glmnet function in R.

**3.2 XGBoost tree model**

There are several parameters in the xgboost function needed to be tuned.

**Eta**: control the learning rate, It is used to prevent overfitting. Lower value for eta implies larger value for n rounds. Low eta value means model more robust to overfitting but slower to compute. We selected 0.05 by compare the calculated RMSE values.

**Max\_depth**: maximum depth of a tree. Default: 6.

**Subsample**: subsample ratio of the training instance. Setting it to 0.5 means that xgboost randomly collected half of the data instances to grow trees and this will prevent overfitting.

**Nrounds**: max number of boosting iterations. We would use 5000 since we have a relatively small eta.

Below is a table (Table 2) which gives the averaged RMSE of different eta while other 3 parameters are constant.

|  |  |
| --- | --- |
| eta | Averaged RMSE |
| 0.01 | 0.1192660 |
| 0.02 | 0.1200814 |
| 0.03 | 0.1199727 |
| 0.04 | 0.1218123 |
| 0.05 | 0.1225904 |
| 0.06 | 0.1228900 |
| 0.07 | 0.1247862 |
| 0.08 | 0.1245572 |
| 0.09 | 0.1259697 |
| 0.1 | 0.1252217 |

|  |  |  |
| --- | --- | --- |
| Split | RMSE(Elastic penalty) | RMSE(XGBoost) |
| 1 | 0.1228109 | 0.114669 |
| 2 | 0.1196406 | 0.1177595 |
| 3 | 0.1217998 | 0.1149293 |
| 4 | 0.1204003 | 0.116853 |
| 5 | 0.1118636 | 0.1117804 |
| 6 | 0.1332633 | 0.1281007 |
| 7 | 0.1265432 | 0.1328459 |
| 8 | 0.1211565 | 0.1265862 |
| 9 | 0.1298632 | 0.1282488 |
| 10 | 0.1235264 | 0.1275834 |

**Table 2** **Averaged RMSEs for different eta values Table 3 RMSE values for each split**

**4. Performance**

Using the two models I describe above, I calculated the RMSEs of the ten split training/test data. The summary table is above, Table 3.

We can see from the table that all results satisfy the prediction requirements.

**5. Running Time**

With 2019 MacBook Pro, 2.4 GHz Intel Core i5 CPU with 16GB memory. The averaged running time for each split is around 2min and 35 seconds. XGBoost takes up about 2min and 30 seconds while the elastic regression only cost 5 seconds.

**6. Conclusion**

For both linear regression model with elasticnet penalty and XGBoost tree model, not only one parameter combination could satisfy the prediction requirement based on the ten training/test data. To get the lowest RMSE, I choose alpha=0.1 for elasticnet penalty and eta=0.04 for XGBoost. Moreover, since the lower eta value, I need to set a quite high nrounds value, which make the running time for XGBoost model pretty long compared to the linear regression model.

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R document about the xgboost function in xgboost package