Camera-Murray-Garg-Thangella_CS109A_Project_Milestone4

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1 CS 109A/AC 209A/STAT 121A Data Science: Airbnb Project

1.1 Milestone #4 - Baseline Model

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1.1.1 Baseline Model

Import libraries

```
In [1]: # import libraries
        import warnings
        import numpy as np
        import pandas as pd
        import matplotlib
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import f1_score
        import random
        from sklearn.linear_model import LogisticRegression

        # suppress warnings
        warnings.filterwarnings ( 'ignore' )
        %matplotlib inline
```

Load the cleansed data We begin by loading the listings dataset we saved after cleansing from milestone #3:
- cleansed_listings.csv.gz - the New York City Airbnb listing data from January 2015 (cleansed)

Note - The baseline model is ignoring seasonality for now. If we can later determine that seasonality plays a large enough part in price prediction, we'll include it in our final model.

```
In [2]: # load listings data into a pandas df
        listingsDF = pd.read_csv (  './datasets/cleansed_listings.tab.gz', sep = '\

        # display the first two rows
        listingsDF.head ( n = 2 )
```

```
Out[2]:                                        name   neighborhood property_type  \
        id
        1069266        Stay like a real New Yorker!   Midtown East     Apartment
        2061725  Option of 2 Beds w Private Bathroom       Bushwick     Apartment

                       room_type  accommodates  bathrooms  bedrooms  beds  bed_type
        id
        1069266  Entire home/apt             2        1.0       1.0   1.0  Real Bed
        2061725     Private room             2        1.0       1.0   2.0  Real Bed

                 square_feet            ...             review_scores_accuracy  \
        id                              ...
        1069266          NaN            ...                                9.0
        2061725          NaN            ...                               10.0

                 review_scores_cleanliness  review_scores_checkin  \
        id
        1069266                        7.0                    9.0
        2061725                       10.0                   10.0

                 review_scores_communication  review_scores_location  \
        id
        1069266                          9.0                    10.0
        2061725                         10.0                     9.0

                 review_scores_value  host_listing_count  months_as_host  \
        id
        1069266                  9.0                   1              21
        2061725                 10.0                   4              24

                 months_since_first_review  months_since_last_review
        id
        1069266                         21                         1
        2061725                         11                         1

        [2 rows x 30 columns]
```

```
In [3]: print ( 'The listings dataframe has {0} listings and {1} columns.' ).format
```

```
The listings dataframe has 19526 listings and 30 columns.
```

The cleansed listings dataframe is the main dataset we'll be using for our baseline prediction. It has 19,526 listings and 31 columns. The columns are listed below.

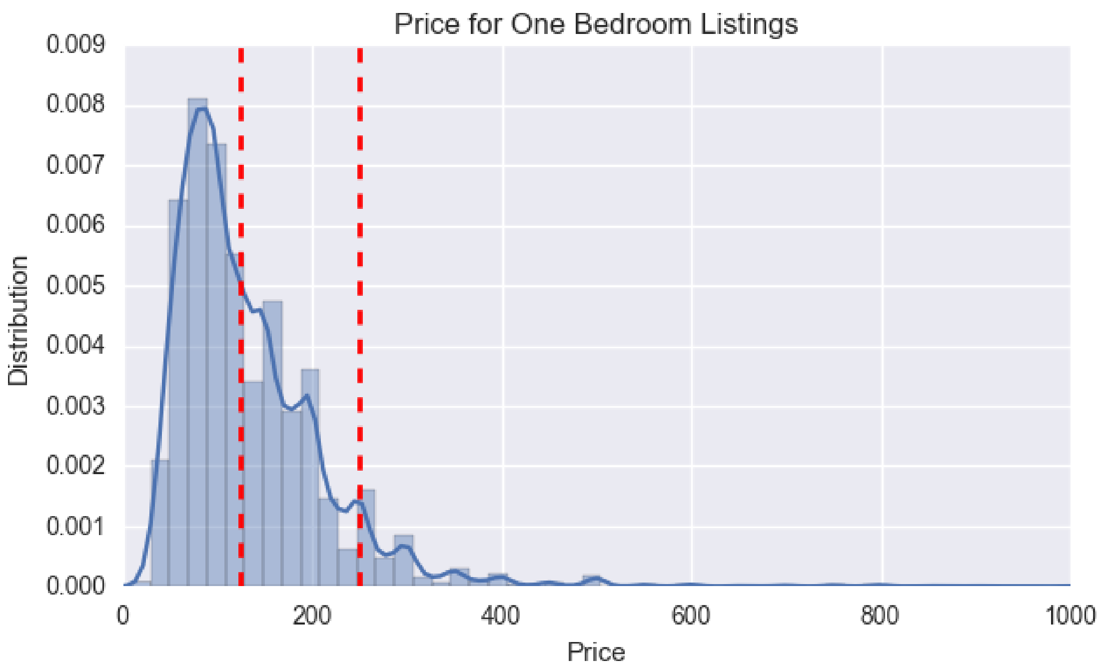
```
In [4]: print listingsDF.columns.values
```

```
['name' 'neighborhood' 'property_type' 'room_type' 'accommodates'
 'bathrooms' 'bedrooms' 'beds' 'bed_type' 'square_feet' 'price'
 'guests_included' 'minimum_nights' 'maximum_nights' 'availability_30'
 'availability_60' 'availability_90' 'availability_365' 'number_of_reviews'
 'review_scores_rating' 'review_scores_accuracy'
 'review_scores_cleanliness' 'review_scores_checkin'
 'review_scores_communication' 'review_scores_location'
 'review_scores_value' 'host_listing_count' 'months_as_host'
 'months_since_first_review' 'months_since_last_review']
```

Keeping in mind that our goal is to provide pricing guidance to new owners who wish to list their property, we've come up with three price groupings based on our data to have a nice balance between the groups **and** user-friendly ranges. As we can see from the distribution below (filtering out the handful of $1000+ listings to improve the visualization) for one bedroom listings, there's a wide range. We'll create a new target variable to identify each listing for one of three categories:
- Low: Up to $125
- Mid: $125 - $250
- High: Over $250

Note: The distribution is different than in milestone #3. We discovered an error we made on the price column while cleansing the data and have since corrected it. Our price ranges have been updated as well.

```
In [5]: # set up visualization
        sns.set ( rc = { "figure.figsize" : ( 7, 4 ) } )

        # plot the histogram of prices - filtering out the extreme highs
        ax = sns.distplot ( listingsDF [ "price" ] [ listingsDF [ "price" ] < 1000

        # set the labels
        ax.set_title  ( "Price for One Bedroom Listings" )
        ax.set_xlabel ( "Price" )
        ax.set_ylabel ( "Distribution" )

        ax.set_xlim ( 0, 1000 )

        # set our price grouping cutoffs
        plt.axvline ( 125, color = 'r', linestyle = 'dashed', linewidth = 2 )
        plt.axvline ( 250, color = 'r', linestyle = 'dashed', linewidth = 2 )

        # display the visualization
        plt.show()
```



Now, let's create a price category column and drop the price column.

```
In [6]: # create the price_category column based on our ranges
        listingsDF [ "price_category" ] = "Low"
        listingsDF [ "price_category" ][ ( listingsDF [ "price" ] >= 125 ) & ( list
        listingsDF [ "price_category" ][ ( listingsDF [ "price" ] >  250 ) ] = "Hig

        # drop the price column
        listingsDF.drop ( [ 'price' ], axis = 1, inplace = True )

        # display the first two rows
        listingsDF.head ( n = 2 )
```

```
Out[6]:                                    name   neighborhood property_type  \
        id
        1069266        Stay like a real New Yorker!   Midtown East     Apartment
        2061725   Option of 2 Beds w Private Bathroom       Bushwick     Apartment

                       room_type  accommodates  bathrooms  bedrooms  beds  bed_type
        id
        1069266  Entire home/apt             2        1.0       1.0   1.0  Real Bec
        2061725     Private room             2        1.0       1.0   2.0  Real Bec

                square_feet       ...        review_scores_cleanliness  \
        id                        ...
        1069266         NaN       ...                              7.0
```

```
2061725          NaN       ...                             10.0

         review_scores_checkin  review_scores_communication  \
id
1069266                    9.0                          9.0
2061725                   10.0                         10.0

         review_scores_location  review_scores_value  host_listing_count  \
id
1069266                    10.0                  9.0                   1
2061725                     9.0                 10.0                   4

         months_as_host  months_since_first_review  months_since_last_revie
id
1069266              21                         21
2061725              24                         11

         price_category
id
1069266             Mid
2061725             Low

[2 rows x 30 columns]
```

Now let's see what the distribution is among the price categories.

In [7]:
```
# set up visualization
sns.set ( rc = { "figure.figsize" : ( 4, 3 ) } )
ax = plt.axes()

# create a barplot of the price categories
ax = sns.barplot ( x = listingsDF.price_category.value_counts().index
                 , y = listingsDF.price_category.value_counts() )

# set the labels
ax.set_title  ( "Price Categories for One Bedroom Listings" )
ax.set_xlabel ( "Price Category" )
ax.set_ylabel ( "Number of Listings" )

# display the visualization
plt.show()
```

We can see from the visualization that we have a reasonable number of listings in each category.

Save the new dataset.

```
In [8]: # save the listings dataframe as a tab-delimited, compressed file
        listingsDF.to_csv ( './datasets/cleansed_listings_with_target.tab.gz', sep
```

Split our dataframe into train and test and separate our predictors from the target.

```
In [17]: # split our dataframe into train and test
         train, test = train_test_split ( listingsDF, train_size = 0.6 )

         # separate x's and y's
         x_train = train.drop ( "price_category", axis = 1 )
         x_test  = test.drop  ( "price_category", axis = 1 )
         y_train = train [ "price_category" ]
         y_test  = test  [ "price_category" ]
```

Establishing a baseline model Before we begin model building, we need to establish a baseline model to compare against our final model. Our goal is to provide pricing guidance to new owners who wish to list their property, we come up with three price groupings based on our data to have a nice balance between the groups and user-friendly ranges.

We'll use the following models for our baselines (note: our baselines are intentionally very simple and don't use logistic regression, LDA, QDA, etc. as outlined in lab 10): - Random selection - Low model (choose "Low" category only) - Mid model (choose "Mid" category only) - High model (choose "High" category only)

These models will be applied to our testing dataset. But first, let's look at the proportion of listings in the test set that fall in to each price category.

```
In [18]: # fetch the number of listings in the test dataset
         num_listings = y_test.shape [ 0 ]

         # print the price category percentages
         print ( 'Percentage of listings with the price category Low: {0:.1f}%, Mic
```

```
Percentage of listings with the price category Low: 54.5%, Mid: 39.5%, High: 6.0%
```

Create a function to score our models.

```
In [11]: # function to compute the accuracy of a given model
         score = lambda model, x_test, y_test: pd.Series ( [ model.score ( x_test,
                                                             model.score ( x_test [
                                                             model.score ( x_test [
                                                             model.score ( x_test [
                                                             f1_score    ( y_test,
                                                             index = [ 'Overall Acc
```

Create functions for our baseline models.

```
In [12]: # model predicting random values
         class random_model ( object ):
             def predict ( self, x ):
                 cats = [ "Low", "Mid", "High" ]
                 return np.random.choice ( cats, len ( x ), replace = True )

             def score ( self, x, y ):
                 y_pred = self.predict ( x )
                 return ( y_pred == y ).sum() * 1. / len ( y )

         # model predicting Low
         class low_model ( object ):
             def predict ( self, x ):
                 return np.array ( [ "Low" ] * len ( x ) )
             def score ( self, x, y ):
                 y_pred = self.predict ( x )
                 return ( y_pred == y ).sum() * 1. / len ( y )

         # model predicting Mid
         class mid_model ( object ):
             def predict ( self, x ):
                 return np.array ( [ "Mid" ] * len ( x ) )
             def score ( self, x, y ):
                 y_pred = self.predict ( x )
                 return ( y_pred == y ).sum() * 1. / len ( y )

         # model predicting High
         class high_model ( object ):
```

```
    def predict ( self, x ):
        return np.array ( [ "High" ] * len ( x ) )
    def score ( self, x, y ):
        y_pred = self.predict ( x )
        return ( y_pred == y ).sum() * 1. / len ( y )
```

Build our models and score.

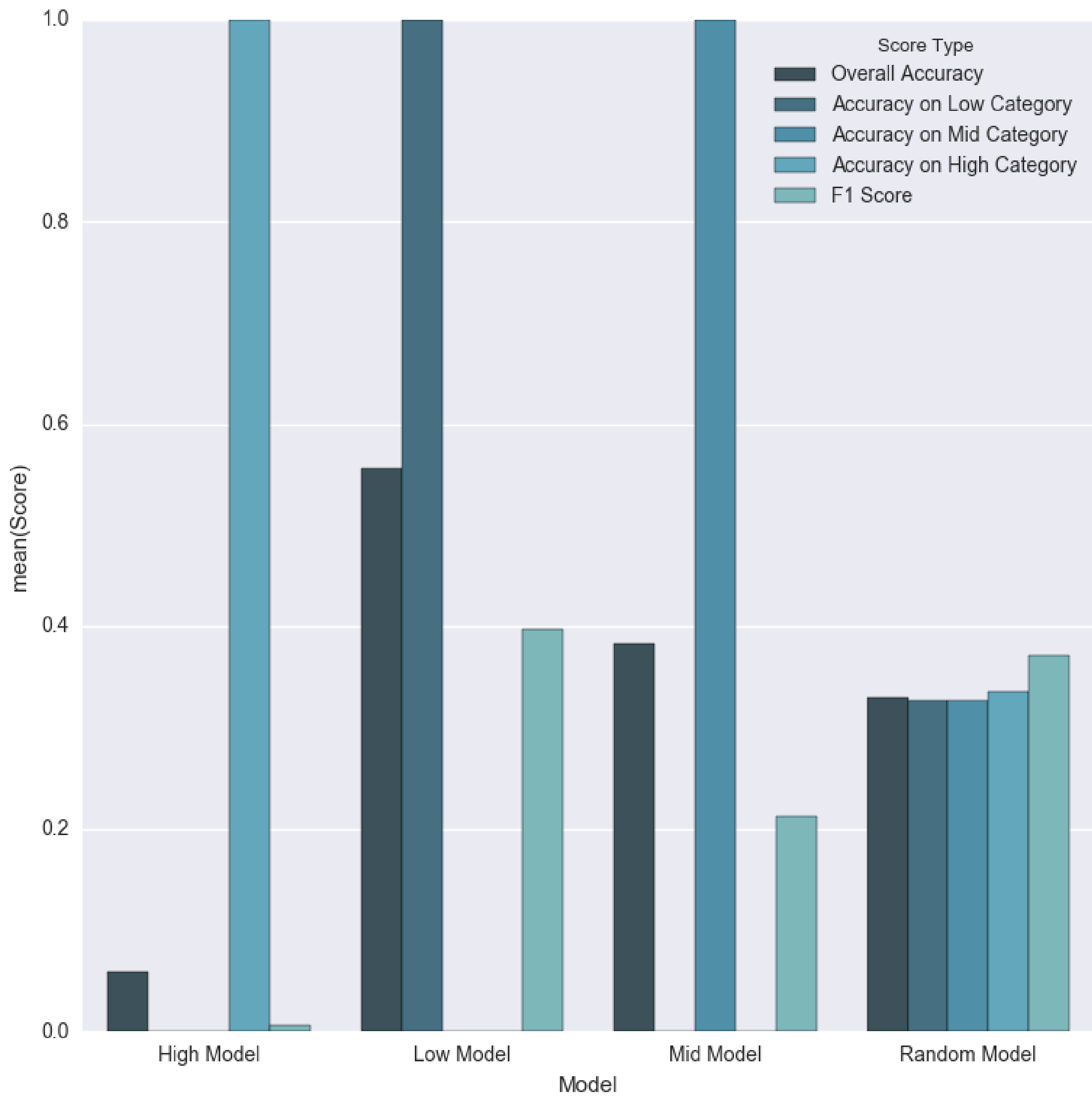
In [13]:
```
# build and score our baseline models
random              = random_model()
random_model_scores = score ( random, x_test, y_test )

low                 = low_model()
low_model_scores    = score ( low, x_test, y_test )

mid                 = mid_model()
mid_model_scores    = score ( mid, x_test, y_test )

high                = high_model()
high_model_scores   = score ( high, x_test, y_test )

# print scores
scoreDF = pd.DataFrame ( { 'Random Model'                : random_model_scor
                           'Low Model'                   : low_model_scores,
                           'Mid Model'                   : mid_model_scores,
                           'High Model'                  : high_model_scores
scoreDF
```

Out[13]:

	High Model	Low Model	Mid Model	Random Model
Overall Accuracy	0.059531	0.556523	0.383946	0.329535
Accuracy on Low Category	0.000000	1.000000	0.000000	0.328042
Accuracy on Mid Category	0.000000	0.000000	1.000000	0.327109
Accuracy on High Category	1.000000	0.000000	0.000000	0.335484
F1 Score	0.006690	0.397961	0.213035	0.372206

Summary

In [14]:
```
# set up visualization
sns.set ( rc = { "figure.figsize" : ( 9, 9 ) } )
sns.set_palette ( palette = "GnBu_d" )
ax = plt.axes()

# create a barplot of the price categories
#ax = sns.barplot ( x = list(scoreDF.columns.values), y = scoreDF.values,
q = pd.concat ( [ pd.DataFrame ( { "Score Type": np.tile ( scoreDF.index.v
ax = sns.barplot ( x = "Model", y = "Score", hue = "Score Type", data = q
```



As mentioned earlier, we chose very simple baselines based on what was done in lab 10 and will pursue more advanced models later in the project. Our baselines perform as expected with the overall accuracy of each price category following the distribution of the test dataset and the random model with very similar accuracies for all score types.