# Airbnb Price Prediction Using Machine Learning

Linlin Li

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Link

## 1 Background

Airbnb is an online marketplace for vacation rentals that provides arrangements for lodging, primarily homestays, or tourism experiences. Homeowners can put their property online so that guests can pay to stay in them. The platform does not own any of the properties and does not host events. It acts as a broker and collects commissions from each booking. Although Airbnb and other websites may provide some general guidance, the price of each property is determined by its host. Appropriate prices are needed, because too high a price will result in a low booking rate, and too low a price will result in a loss of potential revenue. When determining the price, many factors should be considered, such as location, capacity, room type, etc.

In this project, I am going to look at Airbnb listings in Buenos Aires and trying to provide some exploratory analysis around predicting listing prices. First, I will use Exploratory Data Analysis (EDA) to get to know the data. This will help me get an initial sense of which variables are associated with price, and which variables to include in the model. Using the important variables identified in EDA, I will try several classification models attempting to predict the price. Finally, I will evaluate the performance of the model.

## 2 Exploratory Analysis

To begin with the EDA, first I got a summary of the variables using `pandas_profiling` [1] . For the full details, feel free to check the Appendix A. There are 9681 listings in the training set, which contains 24 features. The following are my findings:

- There are no missing values in the training set.
- `is_business_travel_ready` is the same for all observations, so it cannot provide any information for the price. I choose to remove it.
- There are many binary variables. I will convert them into dummy variables after EDA.
- `host_since` is a datetime column and should be converted into metric that measures the number of days the host has been on Airbnb. I used November 5th, 2020 to calculate this metric and named it `host_days_active`. Similarly, `last_review` is converted to `time_since_last_review`.
- `require_guest_phone_verification` and `require_guest_profile_picture` are highly correlated.

- `number_of_reviews` and `reviews_per_month` are highly correlated. This is reasonable because the latter is the "average value" of the former.

- `bedrooms`, `beds` and `bathrooms` are highly correlated. The number of beds has traditionally been a more high priority search parameter on Airbnb, as it is more relevant for the number of people accommodated than the number of bedrooms (and is still the second highest priority parameter when searching on the site. In addition, `guests_included` is correlated with these three variables.

## 2.1 Investigating Binary Variables

Next, I noted that a large amount of the variables are binary. I investigated the association with price via stacked bar plots.

Figure 1: Stacked bar plots between price and some binary variables

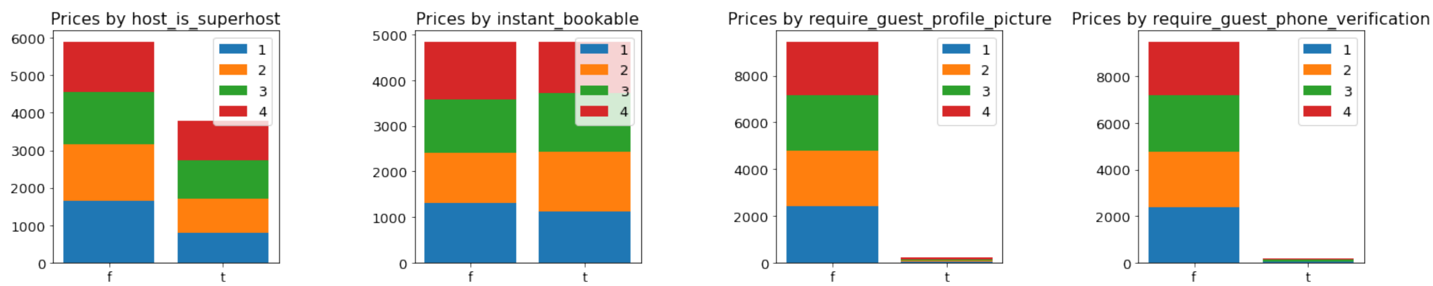



Figure 1 provide a great visualization on how a given binary variable is associated with changes in price. I saw the following findings from the graph:

- `host_is_superhost` seems to be a potential predictor because the distribution of price is different between the two categories of `host_is_superhost`.

- The difference in the distribution of price in the two categories of `instant_bookable` seems to be trivial, maybe `instant_bookable` cannot provide much information about price. I will drop it after EDA.

- The distribution of price for `require_guest_phone_verification` and `require_guest_profile_picture` are very similar. Since these two variables are highly correlated, we can simply drop one of them. I choose to drop `require_guest_profile_picture` after EDA because I think phone verification is more strict.

## 2.2 Investigating Categorical Variables

Several variables have multiple categories (`room_type`, `bed_type` and `cancellation_policy`). I can also visualize these with stacked bar plots, there will just be more bars than a binary variable.

Figure 2: Stacked bar plots between price and some categorical variables

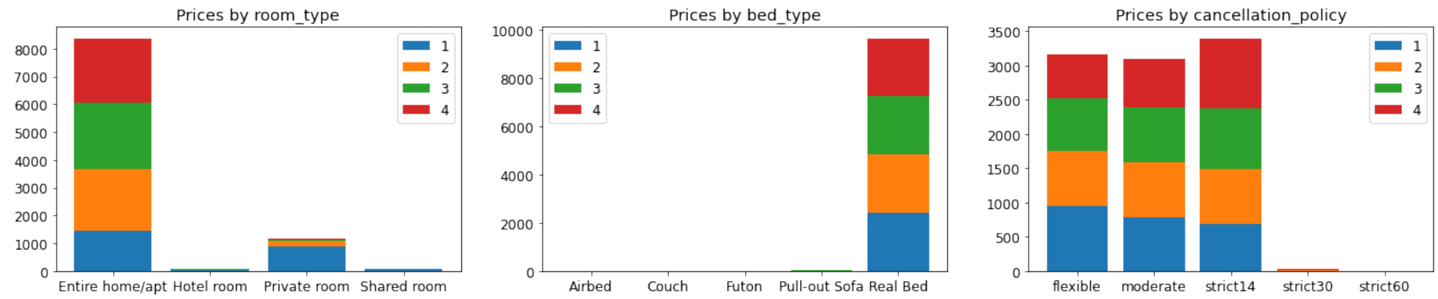



Figure 2 provide a great visualization on how a given categorical variable is associated with changes in price.

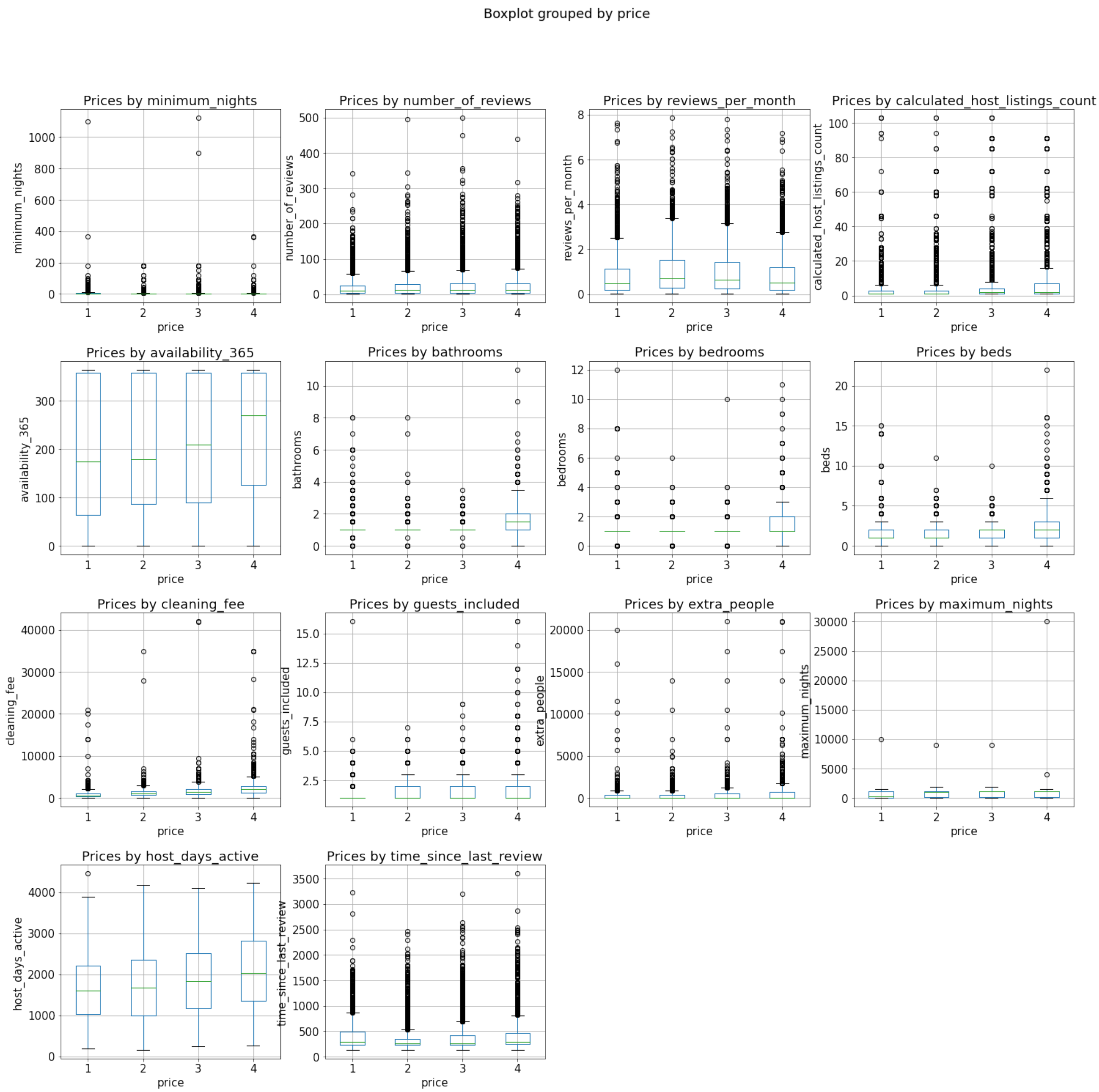
- Several of the categories for variables have very small sample sizes (`bed_type` and `cancellation_policy`).
  - For `cancellation_policy`, 'super_strict_30' and 'super_strict_60' only appear in 26 and 3 listings respectively, which are very small in the training set. Since the super strict options are only available to long-term Airbnb hosts and is invitation only, it is clear that the super strict options are stricter than 'strict_14_with_grace_period'. As the number of 'super strict' is too small, I will combine it with 'strict_14_with_grace_period' after EDA.
  - Similarly, for `bed_type`, I will combine 'Couch' and 'Airbed' into 'other' after EDA.
- It would make sense that `room_type` could be an important factor; perhaps certain rooms types are more private and therefore more expensive.
- The association between `cancellation_policy` and price does not seem so close, which is a bit counterintuitive, because customers tend to pay higher prices when choosing a more flexible policy.
- For `neighbourhood`, I also combine those classes with particularly small sample sizes ($< 7$) with 'other'.

### 2.3 Investigating Numerical Variables

Finally, certain variables are continuous in nature. We can investigate the relationship with price via boxplots. Figure 3 provide a great visualization on how a given numerical variable is associated with changes in price.

- `minimum_nights` and `maximum_nights` seem to provide very little information about price.
- It seems that `bathrooms`, `bedrooms`, `cleaning_fee`, `guests_included`, `availability_365`, `cleaning_fee`, and `calculated_host_listings_count` are influencing factors.

Figure 3: Boxplots between price and some numerical variables




# 3 Data Splits

After performing EDA, I divided the training set into two parts: about 70% of the training set (6776 records) was used for training, and the remaining 30% of the training set (2905 records) was reserved for testing the out-of-sample performance.

In the hyperparameter selection part, I used 10-fold cross-validation on my training set (6776 records) and divided it into 10 folds. Each time I set aside 1 fold for testing and trained the classifier on the other 9 folds and evaluated the categorization accuracy on the 1 fold. After adjusting the hyperparameters, I computed the out-of-sample accuracy of each of my models on my test set (2905 records).

## 4 Models

After cleaning and dropping columns, the available features in the model are:

- Room type
- Minimum and maximum nights stay
- Total number of reviews
- Average number of reviews left by guest each month
- How many listings the host is responsible for in total
- Number of days available to book in the next 365 days
- Whether or not a host is a superhost, has their identity verified (e.g. by verifying a phone number)
- The number of bathrooms, bedrooms, and beds
- Type of bed
- Cleaning fee and extra person fee
- The number of guests included in the booking fee
- The type of cancellation policy
- How many days the host has been listing on Airbnb
- Amount of time since the most recent reviews
- Neighborhood

The continuous variables were standardized using `scikit-learn`'s `StandardScaler()`. Categorical features were encoded into indicator variables using `pandas.get_dummies()`.

In order to have a basic sense of which algorithms to go. I first tried many baseline classification models using `compare_models()` from `PyCaret` [2], which is an end-to-end machine learning and model management tool that automates machine learning workflows and accelerate the experiment cycle exponentially. Due to limited time and computating resources, I used the default setting of `compare_models()`, where some models that require a long running time are prevented for comparison. Table 1 displays the results of models with default hyperparameters using 10-fold cross-validation on my training set (6776 records).

Random forest and some boosting algorithms seem to perform better than others. Thanks to the high-quality libraries available online, these algorithms are easy to train and use for prediction. In the next section, I will try these algorithms, and tune their hyperparameters.

| | Model | Accuracy | AUC | Recall | Prec. | F1 | TT (Sec) |
|---|---|---|---|---|---|---|---|
| **rf** | Random Forest Classifier | 0.5403 | 0.7933 | 0.5420 | 0.5485 | 0.5432 | 0.2170 |
| **lightgbm** | Light Gradient Boosting Machine | 0.5331 | 0.7919 | 0.5346 | 0.5410 | 0.5359 | 0.1160 |
| **catboost** | CatBoost Classifier | 0.5319 | 0.7894 | 0.5337 | 0.5366 | 0.5334 | 3.9600 |
| **xgboost** | Extreme Gradient Boosting | 0.5298 | 0.7888 | 0.5310 | 0.5381 | 0.5328 | 1.4750 |
| **gbc** | Gradient Boosting Classifier | 0.5283 | 0.7844 | 0.5301 | 0.5396 | 0.5323 | 0.6360 |
| **et** | Extra Trees Classifier | 0.5252 | 0.7753 | 0.5270 | 0.5309 | 0.5271 | 0.1610 |
| **ada** | Ada Boost Classifier | 0.4993 | 0.7371 | 0.5012 | 0.5045 | 0.5009 | 0.0630 |
| **lr** | Logistic Regression | 0.4907 | 0.7564 | 0.4929 | 0.5011 | 0.4942 | 0.1970 |
| **lda** | Linear Discriminant Analysis | 0.4824 | 0.7474 | 0.4836 | 0.5232 | 0.4921 | 0.0200 |
| **ridge** | Ridge Classifier | 0.4777 | 0.0000 | 0.4805 | 0.4832 | 0.4780 | 0.0750 |
| **knn** | K Neighbors Classifier | 0.4604 | 0.7026 | 0.4616 | 0.4720 | 0.4618 | 0.2630 |
| **dt** | Decision Tree Classifier | 0.4451 | 0.6294 | 0.4463 | 0.4476 | 0.4452 | 0.0840 |
| **svm** | SVM - Linear Kernel | 0.4418 | 0.0000 | 0.4438 | 0.4474 | 0.4184 | 0.1200 |

Table 1: Baseline classification models. Results are based on 10-fold cross-validation on my training set (6776 records). Table is sorted by accuracy. Certain models are prevented for comparison because of their longer run-time.

# 5 Training

## 5.1 Random Forest Classifier

In the random forest classifier, each tree in the ensemble is built from a sample drawn with replacement (i.e., a bootstrap sample) from the training set [3]. When splitting each node during the construction of a tree, the best split is found from a random subset of variables [3]. The purpose of these two sources of randomness is to decrease the variance of the forest estimator [3]. Random forests achieve a reduced variance by combining diverse trees, sometimes at the cost of a slight increase in bias [3]. The `scikit-learn` implementation combines classifiers by averaging their probabilistic prediction, instead of letting each classifier vote for a single class [4].

It took about 6.58 seconds (wall time) to train a random forest classifier on the whole training set (9681 records).

## 5.2 Gradient Boosting Classifier

In boosting, the individual models are not built on completely random subsets of data and features but sequentially by putting more weight on instances with wrong predictions and high errors [5]. In each round of training, the weak learner is built and its predictions are compared to the correct outcome that we expect [5]. The distance between prediction and truth represents the error rate of our model, which can be used to calculate the gradient [5]. The gradient can be used to find the direction in which to change the model parameters in order to (maximally) reduce the error in the next round of training by “descending the gradient” [5].

In Gradient Boosting, we are combining the predictions of multiple models, we are not optimizing the model parameters directly but the boosted model predictions [5].

It took about 26.6 seconds (wall time) to train a gradient boosting classifier on the whole training set (9681 records).

### 5.3 XGBoost Classifier

XGBoost, also called Extreme Gradient Boosting, is a specific implementation of the Gradient Boosting method which uses more accurate approximations to find the best tree model [6]. While regular gradient boosting uses the loss function of the base model (e.g. decision tree) as a proxy for minimizing the error of the overall model, XGBoost uses the second-order derivative as an approximation, which tends to provide more information about the gradients [6].

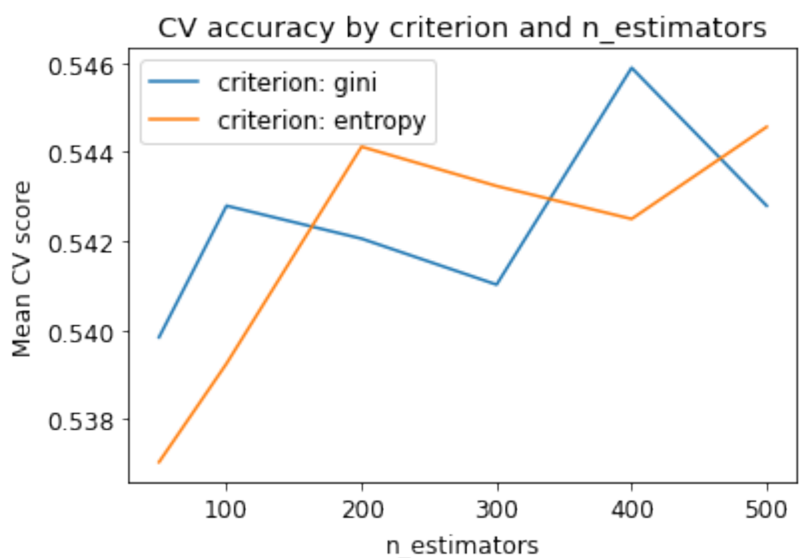
It took about 11.3 seconds (wall time) to train a XGBoost classifier on the whole training set (9681 records).

## 6 Hyperparameter Selection

### 6.1 Random Forest Classifier

In the random forest model, I tried to tune "criterion" and "n_estimators". I used grid search to get the accuracy using 10-fold cross-validation on my training set (6776 records). Figure 4 shows the cross-validation accuracy on my training set and these two hyperparameters.

Figure 4: Cross-validation accuracy using Random Forest Classifier on my training set (6776 records).

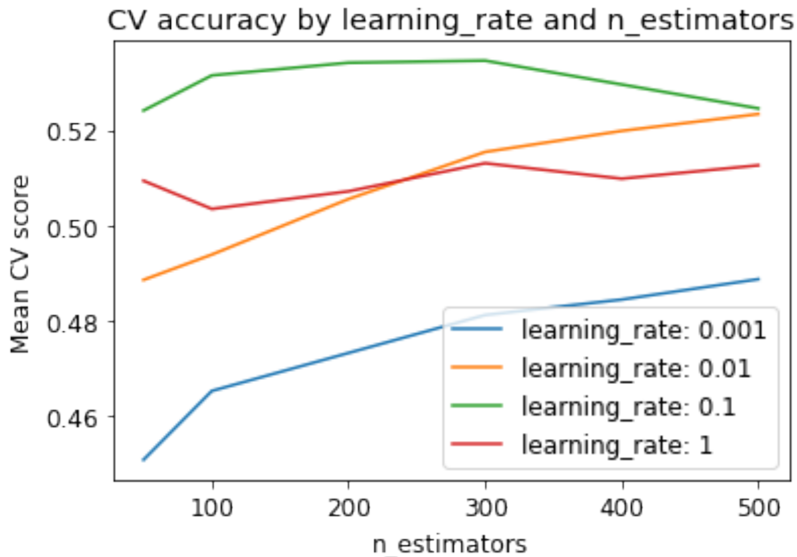



As can be seen in Figure 4, the best combinations of these two hyperparameters is "criterion = 'gini' " and "n_estimators=400".

### 6.2 Gradient Boosting Classifier

In the gradient boosting model, I tried to tune "learning_rate" and "n_estimators". I used grid search to get the accuracy using 10-fold cross-validation on my training set (6776 records). Figure 5 shows the cross-validation accuracy on my training set and these two hyperparameters.

Figure 5: Cross-validation accuracy using Gradient Boosting Classifier on my training set (6776 records).

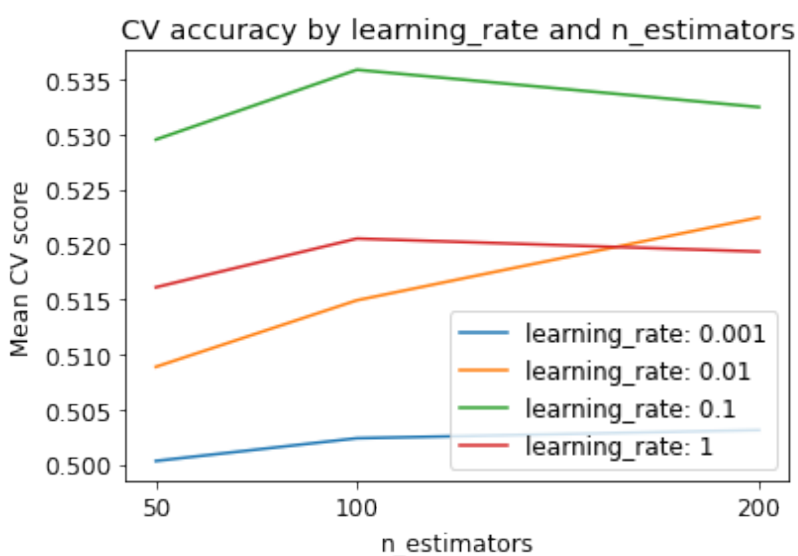



As can be seen in Figure 5, the best combinations of these two hyperparameters is "learning_rate = 0.1 " and "n_estimators=300".

### 6.3 XGBoost Classifier

In the XGBoost model, I tried to tune "learning_rate" and "n_estimators". However, due to limited computing resources, I cannot directly use grid search to get the results using 10-fold cross-validation on my training set (6776 records). In this case, I tried to manually calculated the 10-fold cross-validation accuracy for each combinations of hyperparameters. Figure 6 shows the cross-validation accuracy on my training set and these two hyperparameters.

Figure 6: Cross-validation accuracy using XGBoost Classifier on my training set (6776 records).



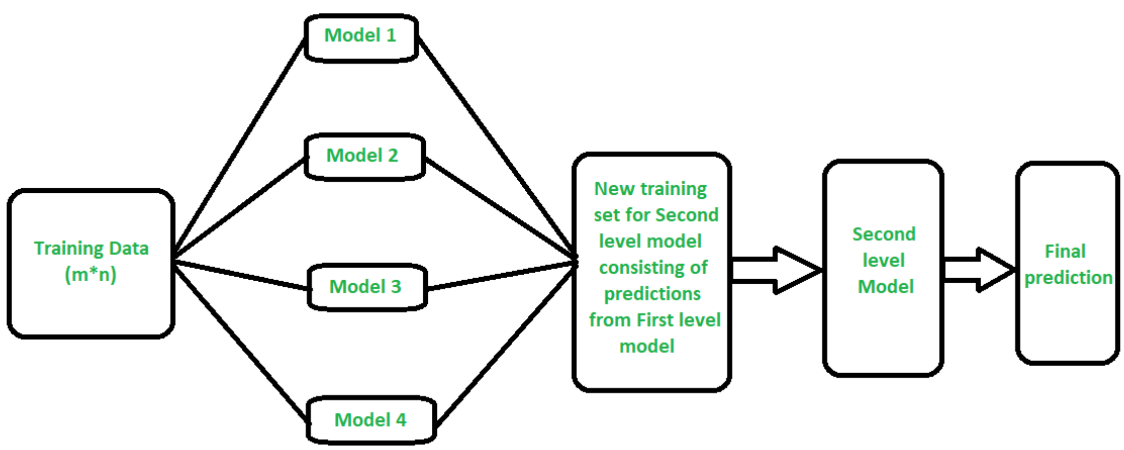
As can be seen in Figure 6, the best combinations of these two hyperparameters is “learning_rate = 0.1 ” and “n_estimators=100”.

# 7 Stacked Models

One possible way to improve the predictive accuracy is to combine different models. Stacking (sometimes called “stacked generalization”) involves training a new learning algorithm to combine the predictions of several base learners [7]. First, the base learners are trained using the available training data, then a combiner or meta algorithm, called the super learner, is trained to make a final prediction based on the predictions of the base learners [7]. Figure 7 shows the struc Such stacked ensemble often outperforms any of the individual base learners (e.g., a single random forest) and has been shown to represent an asymptotically optimal system for learning [8].

I tried to stack the predictions from the top 7 classifiers in Table 1 up to get a final prediction using a linear model as the combiner. All of these 7 classifiers form the base layer of the stack, and their predictions are used as input to the meta model. It is very convenient to do this by `stack_models()` in `PyCaret`. Similarly, the output of this function is the result of the stacked models using 10-fold cross-validation.

Figure 7: Stacked Models




# 8 Errors and Mistakes

This competition is not that easy as it seems to be. For me, feature selection is the hardest part. In the original dataset, there are 24 features (except the response), including DateTime features, categorical features, and numeric features. Additionally, some features are highly correlated, which increases the demand for feature selection and increases the difficulty for modeling. If I delete too many features, I will lose too much information about prices; if I keep too many unnecessary features, the predictive accuracy may not be satisfactory.

# 9 Predictive Accuracy

My Kaggle username is Linlin Li. Table 2 displays the performance of my models.

| | Models | CV Accuracy | Out-of-sample Accuracy | Test Accuracy* |
|---|---|---|---|---|
| **rf** | Random Forest Classifier | 0.5494 | 0.5491 | 0.5643 |
| **gbc** | Gradient Boosting Classifier | 0.5331 | 0.547 | 0.5402 |
| **xgboost** | Extreme Gradient Boosting | 0.5342 | 0.5497 | 0.545 |
| **stacked5** | Stacked model of 5 base learners | 0.5502 | 0.559 | 0.5619 |
| **stacked7** | Stacked model of 7 base learners | 0.55 | 0.5608 | 0.5788 |
| **stacked10** | Stacked model of 10 base learners | 0.5561 | 0.5597 | 0.5691 |

Table 2: Categorization accuracy of models on the training set and the test set. Out-of-sample accuracy was obtained on my test set (2905 records). Note that test accuracy was obtained from Kaggle (based on 30% of test set). For each model, I've submitted several versions to Kaggle and the results here in test accuracy are the best among each model.

From Table 2, "stacked7" is probably my best model, which performs slightly better than other models on both my test set and the test set on Kaggle. We can visualize its performance on the out-of-sample data (2905 records) in Figure 8 and 9.

From the confusion matrix (Figure 8) of the model, we can see that the overall performance of the model seems to be good. And it performs better on class 1 and 4 than on class 2 and 3.

In a multi-class model, we can plot $K$ number of ROC Curves for $K$ number classes using One vs ALL methodology. For Example, if you have three classes named X, Y, and Z, you will have one ROC for X classified against Y and Z, another ROC for Y classified against X and Z, and the third one of Z classified against Y and X. As shown in Figure 9, AUC for each class is at least 0.73, which is much greater than 0.5, which means that there is at least 73% chance that the model will be able to distinguish each class from the other classes.

Figure 8: Confusion matrix of the stacked model of 7 base learners on my test data (2905 records).

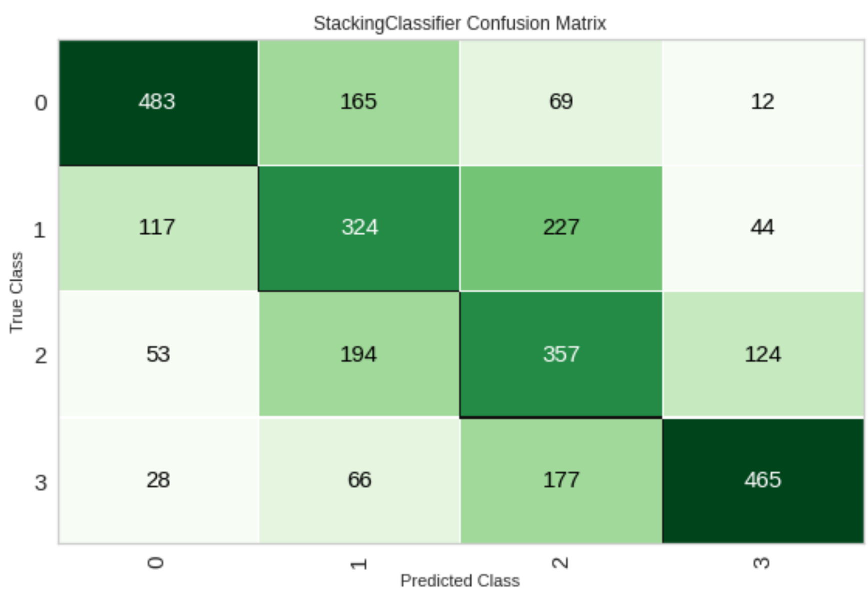
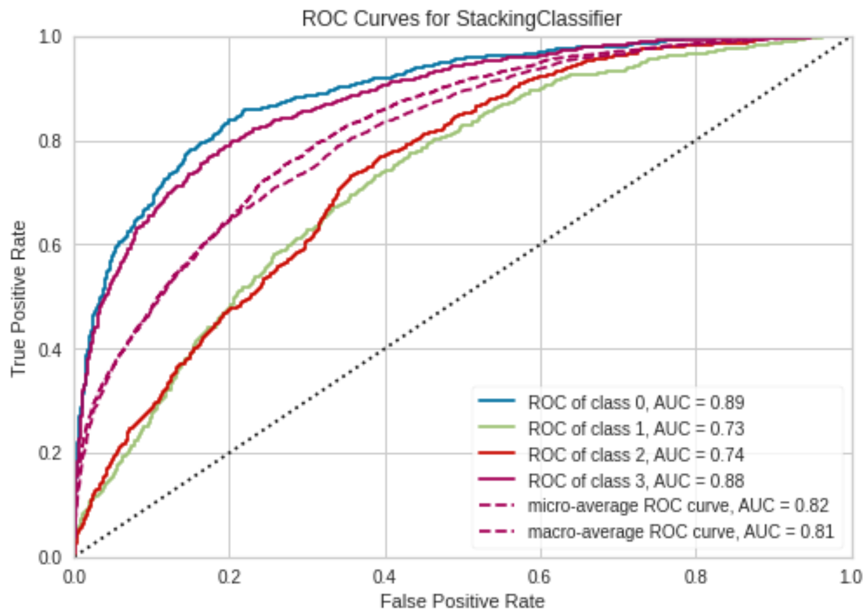


Figure 9: AUC curve for the stacked model of 7 base learners on my test data (2905 records).




# References


[1] Simon Brugman. pandas-profiling: Exploratory Data Analysis for Python. https://github.com/pandas-profiling/pandas-profiling, 2019. Version: 2.X, Accessed: November 5, 2020.

[2] Moez Ali. *PyCaret: An open source, low-code machine learning library in Python*, July 2020. PyCaret version 2.1.

[3] Tin Kam Ho. The random subspace method for constructing decision forests. *IEEE transactions on pattern analysis and machine intelligence*, 20(8):832–844, 1998.

[4] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[5] Jerome H Friedman. Stochastic gradient boosting. *Computational statistics & data analysis*, 38(4):367–378, 2002.

[6] Tianqi Chen, Tong He, Michael Benesty, Vadim Khotilovich, and Yuan Tang. Xgboost: extreme gradient boosting. *R package version 0.4-2*, pages 1–4, 2015.

[7] Brad Boehmke and Brandon M Greenwell. *Hands-on machine learning with R*. CRC Press, 2019.

[8] Mark J Van der Laan, Eric C Polley, and Alan E Hubbard. Super learner. *Statistical applications in genetics and molecular biology*, 6(1), 2007.


# A Code

# Airbnb Price Prediction Using Machine Learning


### Linlin Li


## Load Data

In [1]:
```
!pip install --quiet pandas_profiling
```

In [2]:
```
!pip install --quiet xgboost
```

In [3]:
```
! python3 -m pip install --quiet scikit-optimize
```

In [4]:
```
! python3 -m pip install --quiet pycaret
```

In [5]:
```
! pip install --quiet shap
```

In [6]:
```
import pandas as pd
import numpy as np
import pandas_profiling as pp
import seaborn as sns
import matplotlib.pyplot as plt
from datetime import datetime
import xgboost
from sklearn.preprocessing import StandardScaler, OneHotEncoder, Label
Encoder
from sklearn.model_selection import cross_validate, train_test_split,
cross_val_score, GridSearchCV, KFold
from sklearn.pipeline import Pipeline, FeatureUnion, make_pipeline
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.ensemble import RandomForestClassifier, GradientBoostingC
lassifier
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from skopt import BayesSearchCV
from skopt.space import Real, Categorical, Integer
from skopt.plots import plot_objective, plot_histogram
from xgboost import XGBClassifier
from pycaret.classification import *
```

In [7]:
```
train = pd.read_csv('data/train.csv', index_col = 0)
```

# Exploratory Data Analysis

In [8]:
```
profile = pp.ProfileReport(train)
```

In [9]:
```
profile.to_file("Initial_EDA.html")
```

In [10]:
```
## `is_business_travel_ready` is the same for all observations
print('is_business_travel_ready :', np.unique(train['is_business_trave
l_ready']))
train_df = train.drop(['is_business_travel_ready'], 1)
```

```
is_business_travel_ready : ['f']
```

In [11]:
```
print('\n minimum_nights > 10:', np.sum(train['minimum_nights']< 10) /
len(train['minimum_nights']))

print('\n maximum_nights < 365:', np.sum(train['maximum_nights']> 365)
/ len(train['maximum_nights']))

print('\n bed_type: \n', train['bed_type'].value_counts())

print('\n require_guest_profile_picture: \n', train['require_guest_pro
file_picture'].value_counts())

print('\n require_guest_phone_verification: \n', train['require_guest_
phone_verification'].value_counts())
```

```
 minimum_nights > 10: 0.9125090383224873

 maximum_nights < 365: 0.5195744241297386

 bed_type:
 Real Bed         9641
Pull-out Sofa      23
Futon              12
Couch               3
Airbed              2
Name: bed_type, dtype: int64

 require_guest_profile_picture:
 f    9454
t     227
Name: require_guest_profile_picture, dtype: int64

 require_guest_phone_verification:
 f    9493
t     188
Name: require_guest_phone_verification, dtype: int64
```

- There are no missing values in the training set.
- `is_business_travel_ready` is the same for all observations, so it cannot provide any information for the price. I choose to remove it.
- The distributions of `minimum_nights` and `maximum_nights` are highly skewed. There are over 90% of Airbnb properties whose minimum nights stay is less than 10 days. However, there are over 50% of Airbnb properties whose maximum nights stay is more than a year.
- Over 99% of `bed_type` is the same, indicating that this feature may not provide much information about the price.
- Over 97% of `require_guest_profile_picture` is the same, indicating that this feature may not provide much information about the price.
- Over 98% of `require_guest_phone_verification` is the same, indicating that this feature may not provide much information about the price.
- `require_guest_profile_picture` and `require_guest_phone_verification` are highly correlated. Because owners who need verification are often more cautious, those require phone verification are likely to require photo verification at the same time.
- `bedrooms` , `beds` and `bathrooms` are highly correlated. The number of beds has traditionally been a more high priority search parameter on Airbnb, as it is more relevant for the number of people accommodated than the number of bedrooms (and is still the second highest priority parameter when searching on the site. In addition, `guests_included` is correlated with these three variables.
- `number_of_reviews` and `reviews_per_month` are highly correlated. This is reasonable because the latter is the "average value" of the former.
- Surprisingly, `maximum_nights` and `room_type` are highly correlated. Maybe it's because customers prefer to stay in private rooms longer.
- From the correlation plots, it seems that `room_type` , `bathrooms` , `bedrooms` , `beds` , `cleaning_fee` , `guests_included` , and `neighbourhood` are influencing factors.

# Data Preprocessing

### `host_since`

This is a datetime column and should be converted into a metric that measures the number of days the host has been on the platform. I used today (November 5, 2020) to calculate this metric.

In [12]:
```
train_df.host_since
```

Out[12]:
```
id
727        8/1/13
6274      2/14/14
6025     10/19/17
8931       2/1/19
7524      1/24/15
           ...
11933     6/26/19
10678     6/12/11
13466     5/26/14
2931       5/4/16
6378      3/21/16
Name: host_since, Length: 9681, dtype: object
```

In [13]:
```
# convert to datetime
train_df.host_since = pd.to_datetime(train_df.host_since)

# calculate the number of days between the date that the host first jo
ined Airbnb and today
train_df['host_days_active'] = (datetime(2020, 11, 5) - train_df.host_
since).astype('timedelta64[D]')
train_df = train_df.drop('host_since', 1)
```

**last_review**

In [14]:
```
# convert to datetime
train_df.last_review = pd.to_datetime(train_df.last_review)

# Calculate the number of days between the last review and today
train_df['time_since_last_review'] = (datetime(2020, 11, 5) - train_df
.last_review).astype('timedelta64[D]')
train_df = train_df.drop('last_review', 1)
```

**cancellation_policy**

In [15]:
```
train_df['cancellation_policy'].value_counts()
```

Out[15]:
```
strict_14_with_grace_period    3396
flexible                       3160
moderate                       3096
super_strict_30                  26
super_strict_60                   3
Name: cancellation_policy, dtype: int64
```

Since the super strict options are only available to long-term Airbnb hosts and is invitation only, it is clear that the super strict options are stricter than "strict_14_with_grace_period". As the number of "super strict" is too small, I choose to combine it with "strict_14_with_grace_period" after EDA.

### `bed_type`

In [16]:
```
train_df['bed_type'].value_counts()
```

Out[16]:
```
Real Bed         9641
Pull-out Sofa      23
Futon              12
Couch               3
Airbed              2
Name: bed_type, dtype: int64
```

Similarly, I will convert `Couch` and `Airbed` into `other` after EDA.

### `require_guest_phone_verification` and `require_guest_profile_picture`

In [17]:
```
train_df.groupby(by = 'require_guest_profile_picture').agg({'price': [
'mean', 'median']})
```

Out[17]:

| | price | |
|---|---|---|
| | mean | median |
| require_guest_profile_picture | | |
| f | 2.486461 | 2 |
| t | 2.889868 | 3 |

In [18]:
```
train_df.groupby(by = 'require_guest_phone_verification').agg({'price'
: ['mean', 'median']})
```

Out[18]:

| | price | |
|---|---|---|
| | mean | median |
| require_guest_phone_verification | | |
| f | 2.488781 | 2 |
| t | 2.856383 | 3 |

Since `require_guest_phone_verification` and `require_guest_profile_picture` are highly correlated, and the mean and median prices for these two variables are very similar, we can simply drop one of them. I might drop `require_guest_profile_picture` after EDA because I think phone verification is more strict.

# Data Visualization

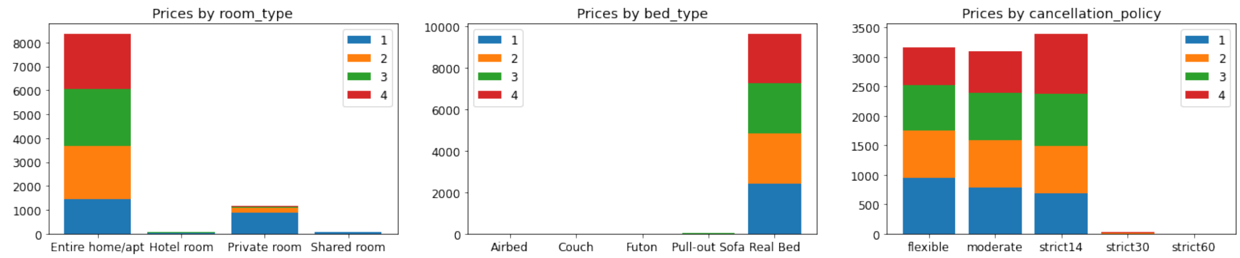
### Binary Variable

In [19]:
```
def plot_categorical(par_name, ax, rename = None):
    df = train_df.groupby(by = ['price', par_name]).count().unstack(fill_value=0).stack().mean(axis=1)
    ind = df.unstack().columns

    p1 = ax.bar(ind, np.array(df.iloc[len(ind)*0:len(ind)*0+len(ind)]))
    p2 = ax.bar(ind, np.array(df.iloc[len(ind)*1:len(ind)*1+len(ind)]), bottom=np.array(df.iloc[len(ind)*0:len(ind)*0+len(ind)]))
    p3 = ax.bar(ind, np.array(df.iloc[len(ind)*2:len(ind)*2+len(ind)]), bottom=np.array(df.iloc[len(ind)*1:len(ind)*1+len(ind)]) + np.array(df.iloc[len(ind)*0:len(ind)*0+len(ind)]))
    p4 = ax.bar(ind, np.array(df.iloc[len(ind)*3:len(ind)*3+len(ind)]), bottom=np.array(df.iloc[len(ind)*2:len(ind)*2+len(ind)]) + np.array(df.iloc[len(ind)*1:len(ind)*1+len(ind)]) + np.array(df.iloc[len(ind)*0:len(ind)*0+len(ind)]))

    ax.set_title(f'Prices by {par_name}')
    ax.set_xticks(ind)
    if rename is None:
        ax.set_xticklabels(df.iloc[len(ind)*i:len(ind)*i+len(ind)].unstack().columns)
    else:
        ax.set_xticklabels(rename)
    ax.legend((p1[0], p2[0], p3[0], p4[0]), df.unstack().index)
```

In [20]:
```
binary = ['host_is_superhost', 'instant_bookable', 'require_guest_profile_picture', 'require_guest_phone_verification']

plt.rcParams.update({'font.size': 13})
fig, axs = plt.subplots(nrows=1, ncols=len(binary), figsize=(22, 4))
plt.subplots_adjust(left=None, bottom=None, right=None, top=None,
                wspace=0.6)
for i in range(len(binary)):
    plot_categorical(binary[i], axs[i])
```


## Categorical Variable

In [21]:
```
categorical = ['room_type', 'bed_type', 'cancellation_policy']

plt.rcParams.update({'font.size': 12})
fig, axs = plt.subplots(nrows=1, ncols=len(categorical), figsize=(22,
4))
for i in range(len(categorical)):
    if i == 2:
        plot_categorical(categorical[i], axs[i], rename = ['flexible',
'moderate', 'strict14', 'strict30', 'strict60'])
    else:
        plot_categorical(categorical[i], axs[i])
```




**neighbourhood**

In [22]:
```
train_df['neighbourhood'].value_counts()
```

Out[22]:
```
Palermo                  3302
Recoleta                 1661
San Nicolás               595
Retiro                    495
Belgrano                  416
Monserrat                 390
San Telmo                 389
Almagro                   379
Balvanera                 365
Villa Crespo              310
Colegiales                183
Núñez                     175
Chacarita                 168
Caballito                 143
Puerto Madero             112
Villa Urquiza              84
Barracas                   58
Constitución               57
Saavedra                   41
La Boca                    39
Boedo                      35
Flores                     30
Coghlan                    28
Villa Ortúzar              26
Parque Patricios           24
Villa Devoto               22
San Cristóbal              19
Villa del Parque           19
Parque Chacabuco           18
Parque Chas                17
Agronomía                  15
Villa General Mitre        10
Villa Pueyrredón            9
Liniers                     8
Vélez Sársfield             6
Villa Luro                  6
Floresta                    6
Villa Santa Rita            4
La Paternal                 4
Mataderos                   3
Nueva Pompeya               2
Monte Castro                2
Parque Avellaneda           2
Villa Real                  2
Versalles                   2
Name: neighbourhood, dtype: int64
```

In [23]:
```
train_df.groupby(by = 'neighbourhood').agg({'price': ['mean', 'median'
, 'std']})
```

Out[23]:

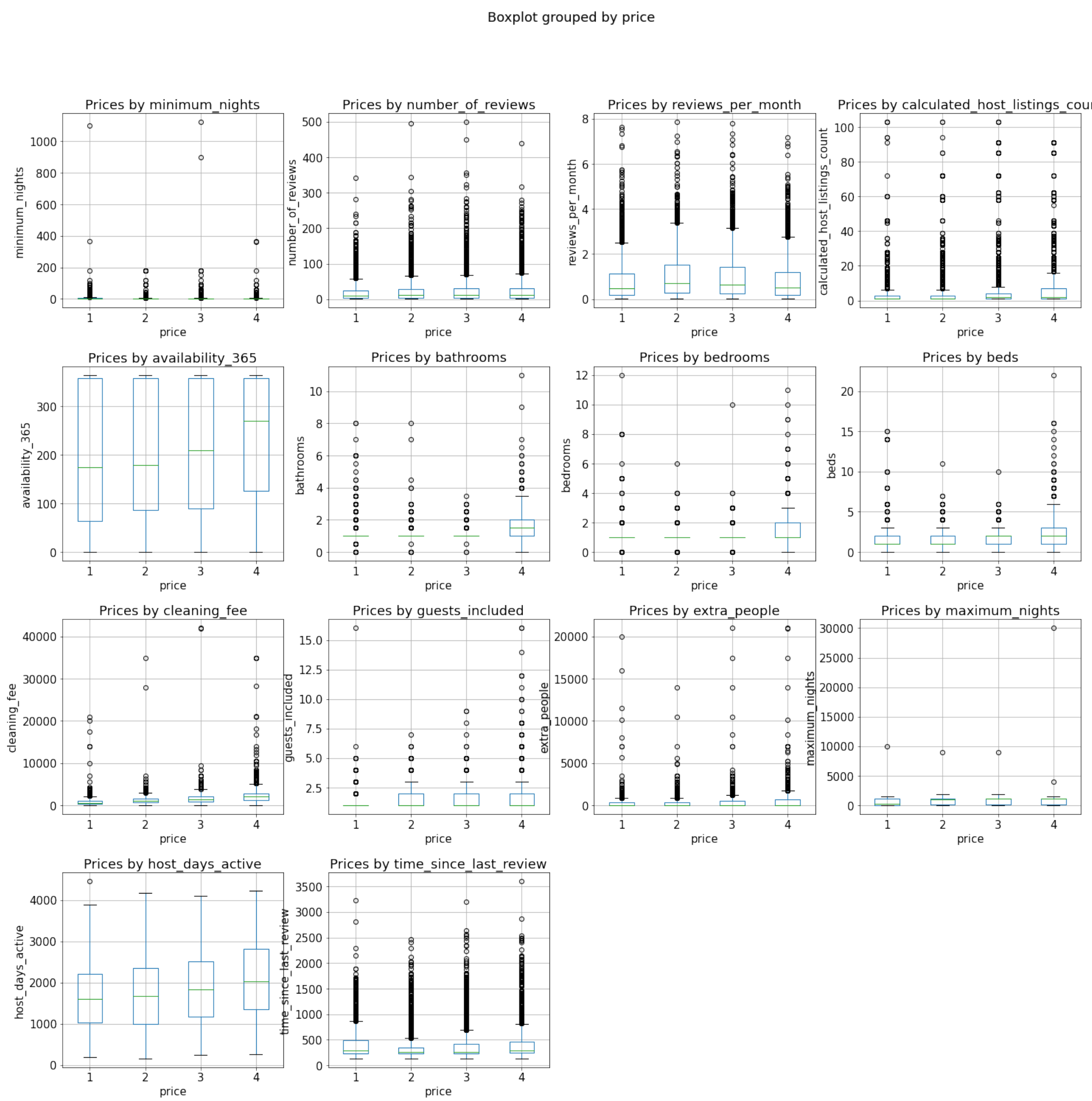
| | price | | |
|---|---|---|---|
| | mean | median | std |
| neighbourhood | | | |
| **Agronomía** | 2.066667 | 2.0 | 0.961150 |
| **Almagro** | 1.849604 | 2.0 | 0.968317 |
| **Balvanera** | 1.939726 | 2.0 | 1.003666 |
| **Barracas** | 2.120690 | 2.0 | 1.185846 |
| **Belgrano** | 2.413462 | 2.0 | 1.124625 |
| **Boedo** | 1.685714 | 1.0 | 0.900047 |
| **Caballito** | 1.860140 | 2.0 | 0.946464 |
| **Chacarita** | 2.303571 | 2.0 | 1.109345 |
| **Coghlan** | 2.035714 | 2.0 | 0.961563 |
| **Colegiales** | 2.371585 | 2.0 | 1.070925 |
| **Constitución** | 1.877193 | 2.0 | 0.825274 |
| **Flores** | 1.533333 | 1.0 | 0.899553 |
| **Floresta** | 2.333333 | 2.0 | 1.366260 |
| **La Boca** | 2.000000 | 2.0 | 1.076055 |
| **La Paternal** | 1.750000 | 1.0 | 1.500000 |
| **Liniers** | 1.750000 | 1.5 | 0.886405 |
| **Mataderos** | 1.333333 | 1.0 | 0.577350 |
| **Monserrat** | 2.243590 | 2.0 | 1.091989 |
| **Monte Castro** | 1.000000 | 1.0 | 0.000000 |
| **Nueva Pompeya** | 2.500000 | 2.5 | 2.121320 |
| **Núñez** | 2.302857 | 2.0 | 1.069291 |
| **Palermo** | 2.792550 | 3.0 | 1.056550 |
| **Parque Avellaneda** | 1.000000 | 1.0 | 0.000000 |
| **Parque Chacabuco** | 1.888889 | 1.0 | 1.182663 |
| **Parque Chas** | 1.588235 | 1.0 | 1.003670 |
| **Parque Patricios** | 1.666667 | 1.0 | 0.916831 |
| **Puerto Madero** | 3.553571 | 4.0 | 0.878566 |
| **Recoleta** | 2.685129 | 3.0 | 1.094434 |

| | | | |
|---|---|---|---|
| **Retiro** | 2.602020 | 3.0 | 1.084112 |
| **Saavedra** | 1.926829 | 2.0 | 1.009709 |
| **San Cristóbal** | 2.052632 | 2.0 | 1.177270 |
| **San Nicolás** | 2.265546 | 2.0 | 1.046112 |
| **San Telmo** | 2.421594 | 2.0 | 1.103951 |
| **Versalles** | 2.500000 | 2.5 | 0.707107 |
| **Villa Crespo** | 1.951613 | 2.0 | 0.982491 |
| **Villa Devoto** | 2.090909 | 1.5 | 1.269011 |
| **Villa General Mitre** | 1.200000 | 1.0 | 0.421637 |
| **Villa Luro** | 1.166667 | 1.0 | 0.408248 |
| **Villa Ortúzar** | 1.500000 | 1.0 | 0.905539 |
| **Villa Pueyrredón** | 2.000000 | 2.0 | 1.000000 |
| **Villa Real** | 2.000000 | 2.0 | 1.414214 |
| **Villa Santa Rita** | 1.750000 | 1.5 | 0.957427 |
| **Villa Urquiza** | 2.000000 | 2.0 | 0.905139 |
| **Villa del Parque** | 1.947368 | 2.0 | 0.970320 |
| **Vélez Sársfield** | 2.000000 | 1.5 | 1.264911 |

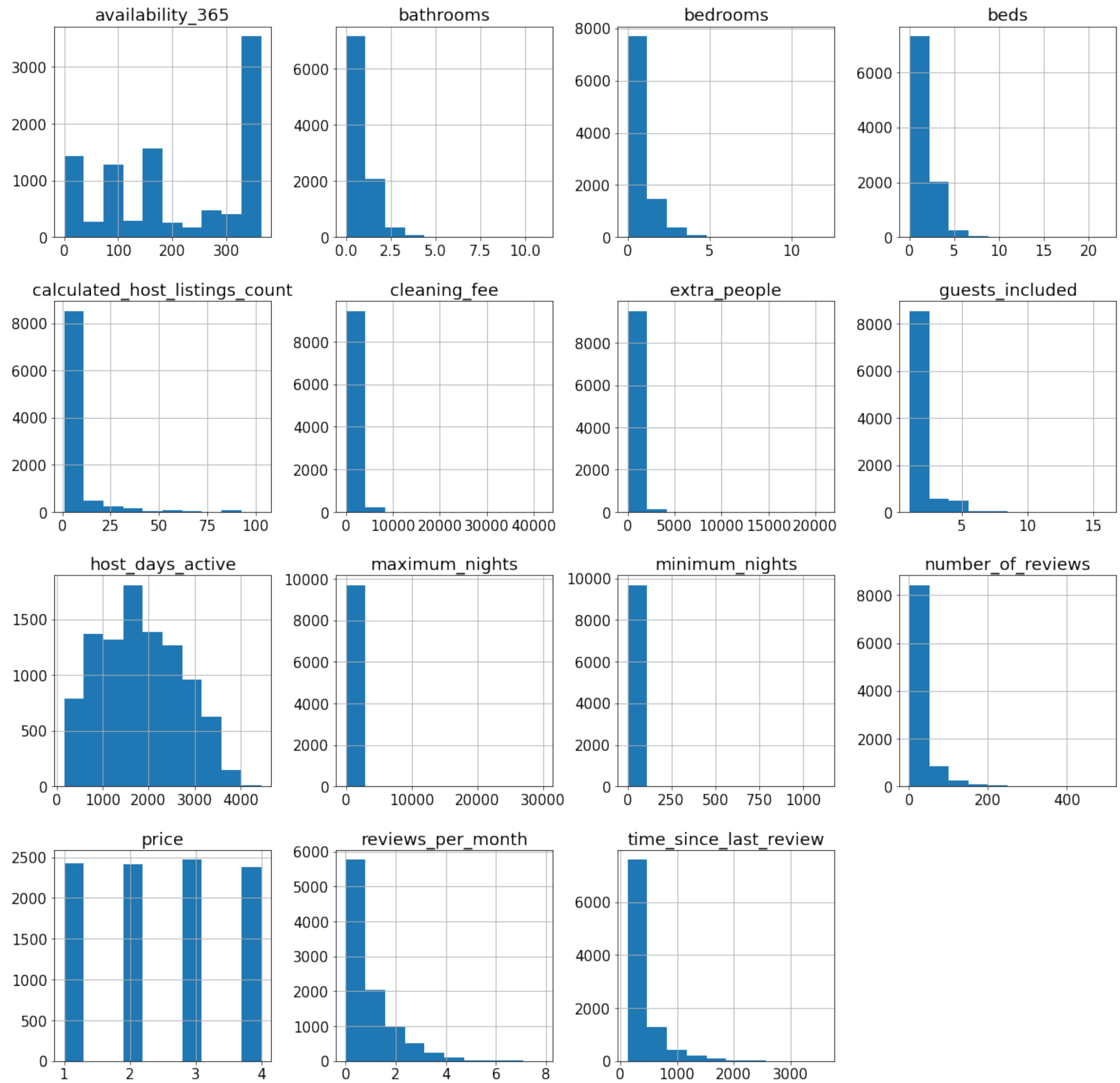
## Numerical variable

In [24]:
```
def plot_numerical(par_name, ax):
    df=train_df[['price', par_name]]

    df.boxplot(column = par_name, by = 'price', ax = ax)
    title_boxplot = f'Prices by {par_name}'
    ax.set_title(title_boxplot)
    ax.set_ylabel(par_name)
```

In [25]:
```
numerical = np.delete(np.array(train_df._get_numeric_data().columns),
                      np.where(np.array(train_df._get_numeric_data().columns) == 'price'))

plt.rcParams.update({'font.size': 15})
fig, axs = plt.subplots(nrows=4, ncols=len(numerical) // 4 + 1, figsize=(24, 24))
fig.suptitle('My Own Title',backgroundcolor='white', color='black')
plt.subplots_adjust(left=None, bottom=None, right=None, top=None,
                    wspace=0.6, hspace=0.3)
axs[3,2].set_axis_off()
axs[3,3].set_axis_off()
for i in range(len(numerical)):
    plot_numerical(numerical[i], axs[i // 4, i % 4])
```



In [26]:
```
## the distribution for the numeric features
train_df._get_numeric_data().hist(figsize=(20,20));
```




# Prepare the data for modeling

In [27]:
```
## bed_type
bed_others = ['Couch', 'Airbed']
bed_keep = list(set(train_df.bed_type) - set(bed_others))
train_df.loc[~train_df.bed_type.isin(bed_keep), 'bed_type'] = 'other'

## neighbourhood
#other = ['Vélez Sársfield', 'Villa Real', 'Mataderos']
#train_df = train_df.loc[~train_df.neighbourhood.isin(other)]
other = ['Vélez Sársfield', 'Floresta', 'Villa Luro', 'La Paternal', '
Villa Santa Rita', 'Mataderos', 'Villa Real', 'Monte Castro', 'Versall
es', 'Parque Avellaneda',  'Nueva Pompeya']
keep = list(set(train_df.neighbourhood) - set(other))
train_df.loc[~train_df.neighbourhood.isin(keep), 'neighbourhood'] = 'o
ther'

# Replacing cancellation_policy categories
train_df.cancellation_policy.replace({
    'super_strict_30': 'strict_14_with_grace_period',
    'super_strict_60': 'strict_14_with_grace_period'
    }, inplace=True)

## require_guest_profile_picture
train_df = train_df.drop(['require_guest_profile_picture'], 1)

## instant_bookable
train_df = train_df.drop('instant_bookable', 1)

## number_of_reviews
#train_df = train_df.drop('number_of_reviews', 1)
```

## check data type

In [28]:
```
len(train_df.columns)
```

Out[28]: 21

In [29]:
```
train_df.dtypes
```

Out[29]:
```
neighbourhood                          object
room_type                              object
minimum_nights                          int64
number_of_reviews                       int64
reviews_per_month                     float64
calculated_host_listings_count          int64
availability_365                        int64
host_is_superhost                      object
bathrooms                             float64
bedrooms                                int64
beds                                    int64
bed_type                               object
cleaning_fee                            int64
guests_included                         int64
extra_people                            int64
maximum_nights                          int64
cancellation_policy                    object
require_guest_phone_verification       object
price                                   int64
host_days_active                      float64
time_since_last_review                float64
dtype: object
```

# Modeling

In [30]:
```
X = train_df.drop('price', axis=1)
y = train_df.price
```

### Seperate train and test data

In [31]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random_state = 0)
```

### Standardize data

The data has both numeric and categorical variables, and I want to standardize the numeric variables but leave the dummies as they are.

In [32]:
```
numeric = np.array(X_train._get_numeric_data().columns)
categorical = np.delete(X_train.columns, np.isin(np.array(X_train.colu
mns), numeric))

## standardize numeric features -- on my training set
X_train_categorical = pd.get_dummies(X_train[categorical])
scaler = StandardScaler()
X_train_numeric = pd.DataFrame(data=scaler.fit_transform(X_train[numer
ic]), columns=numeric, index = X_train_categorical.index)
X_train_std = pd.concat([X_train_numeric, X_train_categorical], axis=1
, sort=False)

## standardize numeric features -- on my test set
X_test_categorical = pd.get_dummies(X_test[categorical])
X_test_numeric = pd.DataFrame(data=scaler.transform(X_test[numeric]),
columns=numeric, index = X_test_categorical.index)
X_test_std = pd.concat([X_test_numeric, X_test_categorical], axis=1, s
ort=False)
```

In [33]:
```
## standardize numeric features -- on the whole training set
X_categorical = pd.get_dummies(X[categorical])
X_numeric = pd.DataFrame(data=scaler.transform(X[numeric]), columns=nu
meric, index = X_categorical.index)
X_std = pd.concat([X_numeric, X_categorical], axis=1, sort=False)
```

## Try many classification models using `pycaret`

`pycaret` presents a nice API that automates most of the boilerplate work in setting up a machine learning pipeline.

In [34]:
```
# load data
data = X_train_std.copy()
data['price'] = y_train

test = X_test_std.copy()
test['price'] = y_test
```

In [35]:
```
clfs = setup(
    data = data,
    target = 'price',
    silent=True,
    session_id=0, ## random_state
    preprocess = False, ## I have done data preprocessing
    fold_strategy = 'kfold',
    test_data = test,
);
```

| | Description | Value |
|---|---|---|
| **0** | session_id | 0 |
| **1** | Target | price |
| **2** | Target Type | Multiclass |
| **3** | Label Encoded | 1: 0, 2: 1, 3: 2, 4: 3 |
| **4** | Original Data | (6776, 65) |
| **5** | Missing Values | False |
| **6** | Numeric Features | 64 |
| **7** | Categorical Features | 0 |
| **8** | Transformed Train Set | (6776, 64) |
| **9** | Transformed Test Set | (2905, 64) |
| **10** | Shuffle Train-Test | True |
| **11** | Stratify Train-Test | False |
| **12** | Fold Generator | KFold |
| **13** | Fold Number | 10 |
| **14** | CPU Jobs | -1 |
| **15** | Use GPU | False |
| **16** | Log Experiment | False |
| **17** | Experiment Name | clf-default-name |
| **18** | USI | d774 |
| **19** | Fix Imbalance | False |
| **20** | Fix Imbalance Method | SMOTE |

The first step is to train all the models in the model library (sklearn, etc.) using default hyperparameters and evaluates performance metrics using cross validation. It returns the trained model object. Here, I use "Accuracy" as evaluation metric.

The output of the function is a table showing averaged score of all models across the folds. By default, the number of folds is set to 10. The table is sorted (highest to lowest) by the metric of choice.

```
In [36]: top = compare_models(sort = 'Accuracy', n_select = 10)
```

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC | TT (Sec) |
|---|---|---|---|---|---|---|---|---|---|
| **rf** | Random Forest Classifier | 0.5403 | 0.7933 | 0.5420 | 0.5485 | 0.5432 | 0.3862 | 0.3868 | 0.2170 |
| **lightgbm** | Light Gradient Boosting Machine | 0.5331 | 0.7919 | 0.5346 | 0.5410 | 0.5359 | 0.3765 | 0.3771 | 0.1160 |
| **catboost** | CatBoost Classifier | 0.5319 | 0.7894 | 0.5337 | 0.5366 | 0.5334 | 0.3750 | 0.3754 | 3.9600 |
| **xgboost** | Extreme Gradient Boosting | 0.5298 | 0.7888 | 0.5310 | 0.5381 | 0.5328 | 0.3721 | 0.3726 | 1.4750 |
| **gbc** | Gradient Boosting Classifier | 0.5283 | 0.7844 | 0.5301 | 0.5396 | 0.5323 | 0.3702 | 0.3710 | 0.6360 |
| **et** | Extra Trees Classifier | 0.5252 | 0.7753 | 0.5270 | 0.5309 | 0.5271 | 0.3663 | 0.3667 | 0.1610 |
| **ada** | Ada Boost Classifier | 0.4993 | 0.7371 | 0.5012 | 0.5045 | 0.5009 | 0.3315 | 0.3320 | 0.0630 |
| **lr** | Logistic Regression | 0.4907 | 0.7564 | 0.4929 | 0.5011 | 0.4942 | 0.3202 | 0.3209 | 0.1970 |
| **lda** | Linear Discriminant Analysis | 0.4824 | 0.7474 | 0.4836 | 0.5232 | 0.4921 | 0.3084 | 0.3124 | 0.0200 |
| **ridge** | Ridge Classifier | 0.4777 | 0.0000 | 0.4805 | 0.4832 | 0.4780 | 0.3034 | 0.3043 | 0.0750 |
| **knn** | K Neighbors Classifier | 0.4604 | 0.7026 | 0.4616 | 0.4720 | 0.4618 | 0.2798 | 0.2814 | 0.2630 |
| **dt** | Decision Tree Classifier | 0.4451 | 0.6294 | 0.4463 | 0.4476 | 0.4452 | 0.2592 | 0.2597 | 0.0840 |
| **svm** | SVM - Linear Kernel | 0.4418 | 0.0000 | 0.4438 | 0.4474 | 0.4184 | 0.2557 | 0.2667 | 0.1200 |
| **nb** | Naive Bayes | 0.2844 | 0.6482 | 0.2910 | 0.3416 | 0.1864 | 0.0525 | 0.0866 | 0.0770 |
| **qda** | Quadratic Discriminant Analysis | 0.2686 | 0.5163 | 0.2751 | 0.2694 | 0.2440 | 0.0324 | 0.0357 | 0.0150 |

## Check each model

### RF

In [37]:
```
rfc = RandomForestClassifier()
```

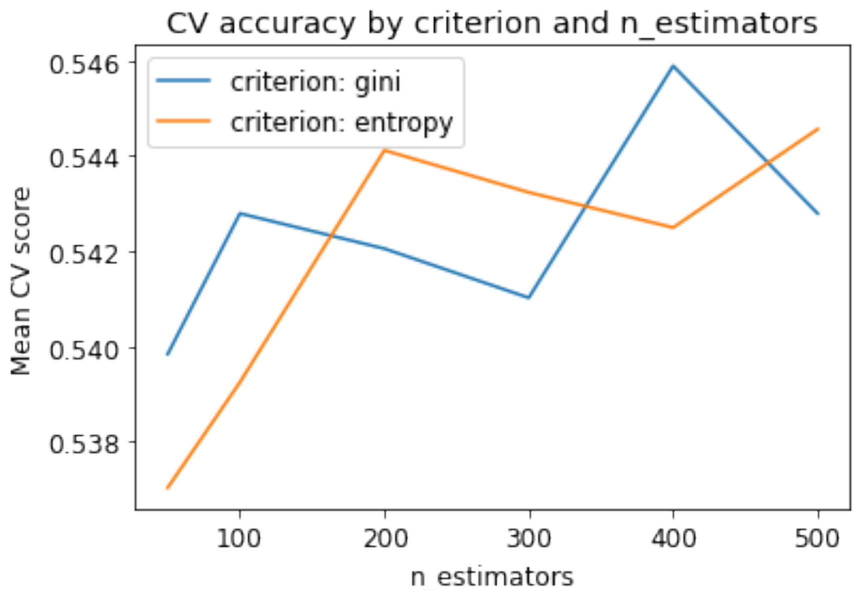
In [38]:
```
params1 = {
    'criterion': ['gini', 'entropy'],
    'n_estimators': [50, 100, 200, 300, 400, 500],
}

print('the number of parameter combinations: ', np.prod(list(map(len,
params1.values()))))
```

```
the number of parameter combinations:  12
```

In [39]:
```
clf_gs = GridSearchCV(
    rfc,
    params1,
    n_jobs=-1,
    cv = 10,
)
clf_gs.fit(X_train_std, y_train)
```

Out[39]:
```
GridSearchCV(cv=10, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_al
pha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_
depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,

min_impurity_decrease=0.0,

min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,

min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jo
bs=None,
                                              oob_score=False,
                                              random_state=None, ver
bose=0,
                                              warm_start=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'n_estimators': [50, 100, 200, 300, 400, 50
0]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score
=False,
             scoring=None, verbose=0)
```

In [40]:
```
plt.rcParams.update({'font.size': 12})
scores = clf_gs.cv_results_['mean_test_score']
scores = np.array(scores).reshape(len(params1['criterion']), len(param
s1['n_estimators']))

for ind, i in enumerate(params1['criterion']):
    plt.plot(params1['n_estimators'], scores[ind], label='criterion: '
+ str(i))
plt.legend()
plt.xlabel('n_estimators')
plt.ylabel('Mean CV score')
plt.title('CV accuracy by criterion and n_estimators')
plt.show()
```




In [41]:
```
clf_gs.best_estimator_
```

Out[41]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=N
one,
                       criterion='gini', max_depth=None, max_feature
s='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=40
0,
                       n_jobs=None, oob_score=False, random_state=No
ne,
                       verbose=0, warm_start=False)
```

In [42]:
```
optimised_random_forest = clf_gs.best_estimator_
print("CV Accuracy: %.2f%%" % (np.mean(cross_val_score(optimised_rando
m_forest, X_train_std, y_train, cv=10)) * 100.0))
print("Out-of-sample Accuracy: %.2f%%" % (optimised_random_forest.scor
e(X_test_std, y_test) * 100.0))
```

```
CV Accuracy: 54.94%
Out-of-sample Accuracy: 54.91%
```

### *Fit the classifier on the whole training set*

In [43]:
```
%%time
optimised_random_forest.fit(X_std, y)
```

```
CPU times: user 6.56 s, sys: 17.1 ms, total: 6.58 s
Wall time: 6.58 s
```

Out[43]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=N
one,
                       criterion='gini', max_depth=None, max_feature
s='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split
=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=40
0,
                       n_jobs=None, oob_score=False, random_state=No
ne,
                       verbose=0, warm_start=False)
```

### Gradient Boosting Classifier

In [44]:
```
bc = GradientBoostingClassifier()
```

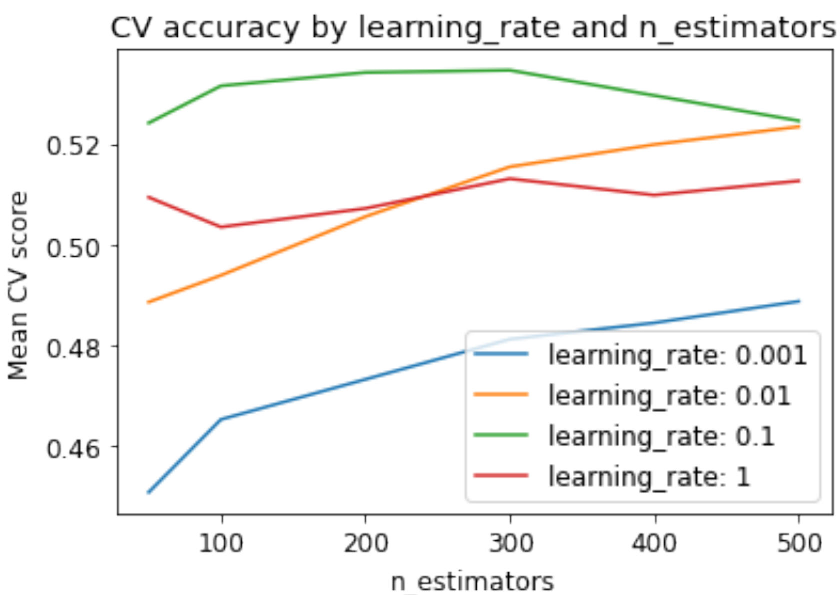
In [45]:
```
params2 = {
    'learning_rate': [0.001, 0.01, 0.1, 1],
    'n_estimators': [50, 100, 200, 300, 400, 500],
}

print('the number of parameter combinations: ', np.prod(list(map(len,
params2.values()))))
```

```
the number of parameter combinations:  24
```

In [46]:
```
clf_gs = GridSearchCV(
    bc,
    params2,
    n_jobs=-1,
    cv = 10,
)
clf_gs.fit(X_train_std, y_train)
```

Out[46]:
```
GridSearchCV(cv=10, error_score=nan,
             estimator=GradientBoostingClassifier(ccp_alpha=0.0,

criterion='friedman_mse',
                                                  init=None, learnin
g_rate=0.1,
                                                  loss='deviance', m
ax_depth=3,
                                                  max_features=None,

max_leaf_nodes=None,

min_impurity_decrease=0.0,

min_impurity_split=None,

min_samples_leaf=1,

min_samples_split=2,

min_weight_fraction_leaf=0.0,
                                                  n_estimators=100,

n_iter_no_change=None,

presort='deprecated',
                                                  random_state=None,
                                                  subsample=1.0, tol
=0.0001,

validation_fraction=0.1,
                                                  verbose=0, warm_st
art=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'learning_rate': [0.001, 0.01, 0.1, 1],
                         'n_estimators': [50, 100, 200, 300, 400, 50
0]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score
=False,
             scoring=None, verbose=0)
```

In [47]:
```
scores = clf_gs.cv_results_['mean_test_score']
scores = np.array(scores).reshape(len(params2['learning_rate']), len(p
arams2['n_estimators']))

for ind, i in enumerate(params2['learning_rate']):
    plt.plot(params2['n_estimators'], scores[ind], label='learning_rat
e: ' + str(i))
plt.legend()
plt.xlabel('n_estimators')
plt.ylabel('Mean CV score')
plt.title('CV accuracy by learning_rate and n_estimators')
plt.show()
```




In [48]:
```
clf_gs.best_estimator_
```

Out[48]:
```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse',
init=None,
                           learning_rate=0.1, loss='deviance', max_d
epth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_s
plit=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimator
s=300,
                           n_iter_no_change=None, presort='deprecate
d',
                           random_state=None, subsample=1.0, tol=0.0
001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

In [49]:
```
optimised_gradient_boosting = clf_gs.best_estimator_
print("CV Accuracy: %.2f%%" % (np.mean(cross_val_score(optimised_gradi
ent_boosting, X_train_std, y_train, cv=10)) * 100.0))
print("Out-of-sample Accuracy: %.2f%%" % (optimised_gradient_boosting.
score(X_test_std, y_test) * 100.0))
```

```
CV Accuracy: 53.31%
Out-of-sample Accuracy: 54.70%
```

***Fit the classifier on the whole training set***

In [50]:
```
%%time
optimised_gradient_boosting.fit(X_std, y)
```

```
CPU times: user 26.6 s, sys: 0 ns, total: 26.6 s
Wall time: 26.6 s
```

Out[50]:
```
GradientBoostingClassifier(ccp_alpha=0.0, criterion='friedman_mse',
init=None,
                           learning_rate=0.1, loss='deviance', max_d
epth=3,
                           max_features=None, max_leaf_nodes=None,
                           min_impurity_decrease=0.0, min_impurity_s
plit=None,
                           min_samples_leaf=1, min_samples_split=2,
                           min_weight_fraction_leaf=0.0, n_estimator
s=300,
                           n_iter_no_change=None, presort='deprecate
d',
                           random_state=None, subsample=1.0, tol=0.0
001,
                           validation_fraction=0.1, verbose=0,
                           warm_start=False)
```

**XGBoost**

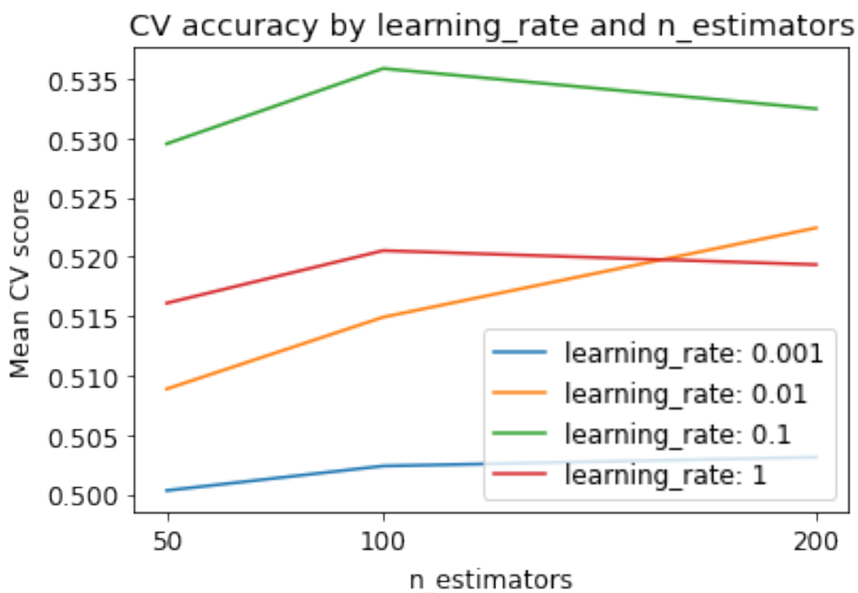
In [51]:
```
xgbc = XGBClassifier()
```

In [52]:
```
params3 = {
    'learning_rate': [0.001, 0.01, 0.1, 1],
    'n_estimators': [50, 100, 200],
}

print('the number of parameter combinations: ', np.prod(list(map(len,
params3.values()))))
```

```
the number of parameter combinations:  12
```

In [53]:
```
scores = []
kf = KFold(n_splits=10)
for i in range(np.prod(list(map(len, params3.values())))):
    s = []
    for train_index, test_index in kf.split(X_train_std):
        classifier = XGBClassifier(n_estimators = params3['n_estimator
s'][i % 3], learning_rate = params3['learning_rate'][i // 3])
        XX_train, XX_test = X_train_std.iloc[train_index, :], X_train_
std.iloc[test_index, :]
        yy_train, yy_test = y_train.iloc[train_index], y_train.iloc[te
st_index]
        classifier.fit(XX_train, yy_train)
        s.append(classifier.score(XX_test, yy_test))
    scores.append(np.mean(s))
```

In [54]:
```
scores = np.array(scores).reshape(len(params3['learning_rate']), len(p
arams3['n_estimators']))

for ind, i in enumerate(params3['learning_rate']):
    plt.plot(params3['n_estimators'], scores[ind], label='learning_rat
e: ' + str(i))
plt.legend()
plt.xlabel('n_estimators')
plt.ylabel('Mean CV score')
plt.title('CV accuracy by learning_rate and n_estimators')
plt.xticks(params3['n_estimators'], params3['n_estimators'])
plt.show()
```




In [55]:
```
optimised_xgbc = XGBClassifier(n_estimators = 100, learning_rate = 0.1
)
print("CV Accuracy: %.2f%%" % (np.mean(cross_val_score(optimised_xgbc,
X_train_std, y_train, cv=10)) * 100.0))
print("Out-of-sample Accuracy: %.2f%%" % (optimised_xgbc.fit(X_train_s
td, y_train).score(X_test_std, y_test) * 100.0))
```

```
CV Accuracy: 53.42%
Out-of-sample Accuracy: 54.97%
```

***Fit the classifier on the whole training set***

In [56]:
```
%%time
optimised_xgbc.fit(X_std, y)
```

```
CPU times: user 11.3 s, sys: 0 ns, total: 11.3 s
Wall time: 11.3 s
```

Out[56]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_i
d=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=
'()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=
0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=
None)
```

## Stacked models

In [57]:
```
## stack 5 base learners to for a stacked model 'stacked5'
### the default meta_model is linear
stack_clf5 = stack_models(top[:5])
## predict on my test data
predict_model(stack_clf5);
```

| | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|
| **0** | 0.5531 | 0.8012 | 0.5638 | 0.5564 | 0.5532 | 0.4026 | 0.4034 |
| **1** | 0.5855 | 0.8278 | 0.5859 | 0.6003 | 0.5905 | 0.4467 | 0.4480 |
| **2** | 0.5487 | 0.7997 | 0.5524 | 0.5560 | 0.5517 | 0.3970 | 0.3973 |
| **3** | 0.5634 | 0.8067 | 0.5610 | 0.5798 | 0.5697 | 0.4184 | 0.4194 |
| **4** | 0.5442 | 0.8015 | 0.5432 | 0.5565 | 0.5478 | 0.3908 | 0.3923 |
| **5** | 0.5310 | 0.7941 | 0.5330 | 0.5440 | 0.5359 | 0.3724 | 0.3731 |
| **6** | 0.5081 | 0.7776 | 0.5116 | 0.5162 | 0.5113 | 0.3434 | 0.3438 |
| **7** | 0.5377 | 0.8051 | 0.5380 | 0.5438 | 0.5399 | 0.3827 | 0.3832 |
| **8** | 0.5628 | 0.8084 | 0.5615 | 0.5706 | 0.5656 | 0.4174 | 0.4179 |
| **9** | 0.5672 | 0.8122 | 0.5678 | 0.5706 | 0.5683 | 0.4221 | 0.4225 |
| **Mean** | 0.5502 | 0.8034 | 0.5518 | 0.5594 | 0.5534 | 0.3994 | 0.4001 |
| **SD** | 0.0205 | 0.0122 | 0.0199 | 0.0217 | 0.0208 | 0.0277 | 0.0278 |

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|---|
| **0** | Stacking Classifier | 0.5590 | 0.8080 | 0.5583 | 0.5720 | 0.5641 | 0.4122 | 0.4128 |

In [58]:
```
## stack 5 base learners to for a stacked model 'stacked7'
### the default meta_model is linear
stack_clf7 = stack_models(top[:7])
## predict on my test data
predict_model(stack_clf7);
```

| | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|
| **0** | 0.5619 | 0.8011 | 0.5716 | 0.5675 | 0.5629 | 0.4141 | 0.4150 |
| **1** | 0.5782 | 0.8301 | 0.5784 | 0.5958 | 0.5839 | 0.4369 | 0.4386 |
| **2** | 0.5442 | 0.8012 | 0.5483 | 0.5540 | 0.5480 | 0.3912 | 0.3916 |
| **3** | 0.5752 | 0.8075 | 0.5724 | 0.5895 | 0.5809 | 0.4340 | 0.4348 |
| **4** | 0.5324 | 0.8027 | 0.5323 | 0.5419 | 0.5355 | 0.3752 | 0.3762 |
| **5** | 0.5339 | 0.7973 | 0.5369 | 0.5483 | 0.5390 | 0.3766 | 0.3775 |
| **6** | 0.5037 | 0.7782 | 0.5072 | 0.5087 | 0.5058 | 0.3377 | 0.3378 |
| **7** | 0.5391 | 0.8046 | 0.5392 | 0.5450 | 0.5415 | 0.3844 | 0.3846 |
| **8** | 0.5628 | 0.8084 | 0.5617 | 0.5704 | 0.5655 | 0.4173 | 0.4179 |
| **9** | 0.5687 | 0.8128 | 0.5707 | 0.5694 | 0.5682 | 0.4241 | 0.4247 |
| **Mean** | 0.5500 | 0.8044 | 0.5519 | 0.5590 | 0.5531 | 0.3992 | 0.3999 |
| **SD** | 0.0222 | 0.0123 | 0.0218 | 0.0240 | 0.0226 | 0.0299 | 0.0302 |

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|---|
| **0** | Stacking Classifier | 0.5608 | 0.8097 | 0.5599 | 0.5744 | 0.5661 | 0.4144 | 0.4152 |

In [59]:
```
## stack 5 base learners to for a stacked model 'stacked10'
### the default meta_model is linear
stack_clf10 = stack_models(top[:10])
## predict on my test data
predict_model(stack_clf10);
```

| | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|
| **0** | 0.5678 | 0.8023 | 0.5772 | 0.5741 | 0.5688 | 0.4222 | 0.4234 |
| **1** | 0.5870 | 0.8294 | 0.5873 | 0.6010 | 0.5921 | 0.4486 | 0.4497 |
| **2** | 0.5546 | 0.8026 | 0.5585 | 0.5637 | 0.5579 | 0.4050 | 0.4056 |
| **3** | 0.5752 | 0.8058 | 0.5720 | 0.5895 | 0.5809 | 0.4338 | 0.4345 |
| **4** | 0.5369 | 0.8037 | 0.5360 | 0.5461 | 0.5394 | 0.3810 | 0.3821 |
| **5** | 0.5442 | 0.8000 | 0.5489 | 0.5570 | 0.5486 | 0.3905 | 0.3914 |
| **6** | 0.5111 | 0.7809 | 0.5146 | 0.5185 | 0.5140 | 0.3474 | 0.3477 |
| **7** | 0.5391 | 0.8044 | 0.5383 | 0.5433 | 0.5409 | 0.3841 | 0.3842 |
| **8** | 0.5672 | 0.8096 | 0.5661 | 0.5740 | 0.5697 | 0.4232 | 0.4236 |
| **9** | 0.5775 | 0.8151 | 0.5792 | 0.5784 | 0.5774 | 0.4358 | 0.4361 |
| **Mean** | 0.5561 | 0.8054 | 0.5578 | 0.5646 | 0.5590 | 0.4072 | 0.4078 |
| **SD** | 0.0221 | 0.0116 | 0.0219 | 0.0230 | 0.0223 | 0.0297 | 0.0298 |

| | Model | Accuracy | AUC | Recall | Prec. | F1 | Kappa | MCC |
|---|---|---|---|---|---|---|---|---|
| **0** | Stacking Classifier | 0.5597 | 0.8102 | 0.5589 | 0.5712 | 0.5643 | 0.4131 | 0.4136 |

# Predict on the test set

In [60]:
```
test = pd.read_csv('data/test.csv', index_col = 0)
```

In [61]:
```
## remove `is_business_travel_ready`
test_df = test.drop(['is_business_travel_ready'], 1)

# host_since
test_df.host_since = pd.to_datetime(test_df.host_since)
test_df['host_days_active'] = (datetime(2020, 11, 5) - test_df.host_si
nce).astype('timedelta64[D]')
test_df = test_df.drop('host_since', 1)

# last_review
test_df.last_review = pd.to_datetime(test_df.last_review)
test_df['time_since_last_review'] = (datetime(2020, 11, 5) -test_df.la
st_review).astype('timedelta64[D]')
test_df = test_df.drop('last_review', 1)

# cancellation_policy
test_df['cancellation_policy'].value_counts()
test_df.cancellation_policy.replace({
    'super_strict_30': 'strict_14_with_grace_period',
    'super_strict_60': 'strict_14_with_grace_period'
    }, inplace=True)

## bed_type
test_df.loc[~test_df.bed_type.isin(bed_keep), 'bed_type'] = 'other'

## neighbourhood
test_df.loc[~test_df.neighbourhood.isin(keep), 'neighbourhood'] = 'oth
er'

## require_guest_profile_picture
test_df = test_df.drop(['require_guest_profile_picture'], 1)

## instant_bookable
test_df = test_df.drop('instant_bookable', 1)

## number_of_reviews
#test_df = test_df.drop('number_of_reviews', 1)
```

In [62]:
```
XXX_test = test_df
```

In [63]:
```
## standardize data
XX_test_categorical = pd.get_dummies(XXX_test[categorical])
scaler = StandardScaler()
XX_test_numeric_std = pd.DataFrame(data=scaler.fit_transform(XXX_test[
numeric]), columns=numeric, index = XX_test_categorical.index)
XX_test_std = pd.concat([XX_test_numeric_std, XX_test_categorical], ax
is=1, sort=False)
```

In [64]:
```
## check number of features
len(XX_test_std.columns), len(X_std.columns)
```

Out[64]:
```
(64, 64)
```

In [ ]:

In [65]:
```
y_pred0 = optimised_random_forest.predict(XX_test_std)
```

In [66]:
```
y_pred1 = optimised_gradient_boosting.predict(XX_test_std)
```

In [67]:
```
y_pred2 = optimised_xgbc.predict(XX_test_std)
```

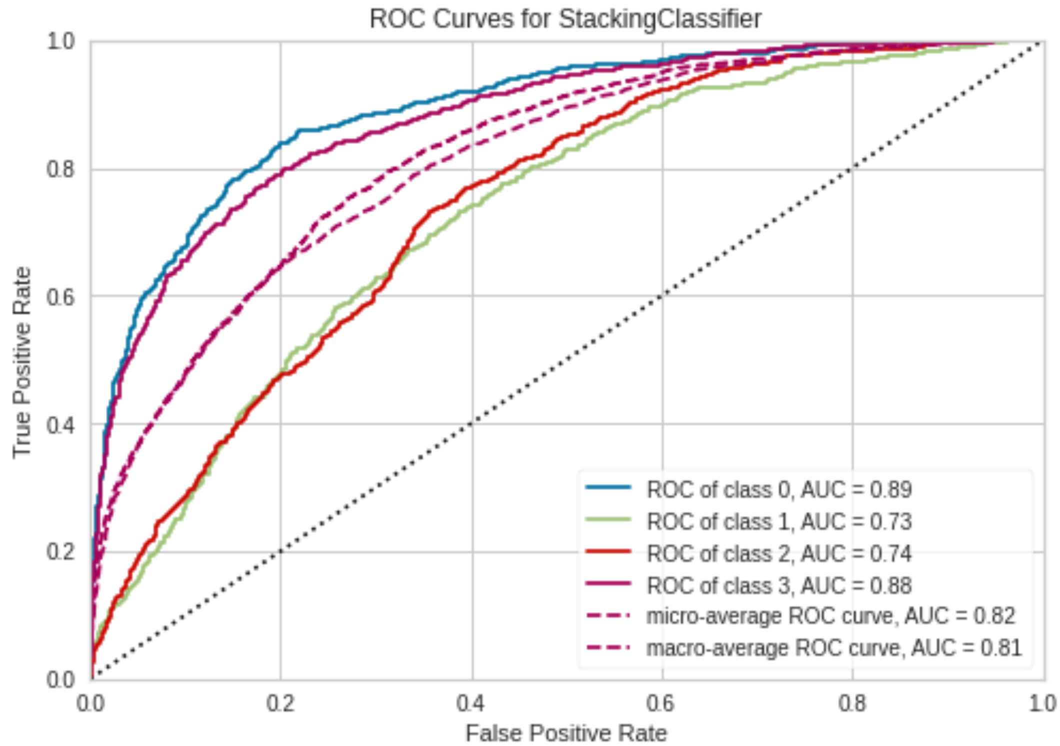
In [68]:
```
y_pred3 = predict_model(stack_clf5, data = XX_test_std)['Label']
```

In [69]:
```
y_pred4 = [p for p in predict_model(stack_clf7, data = XX_test_std)['L
abel']]
```

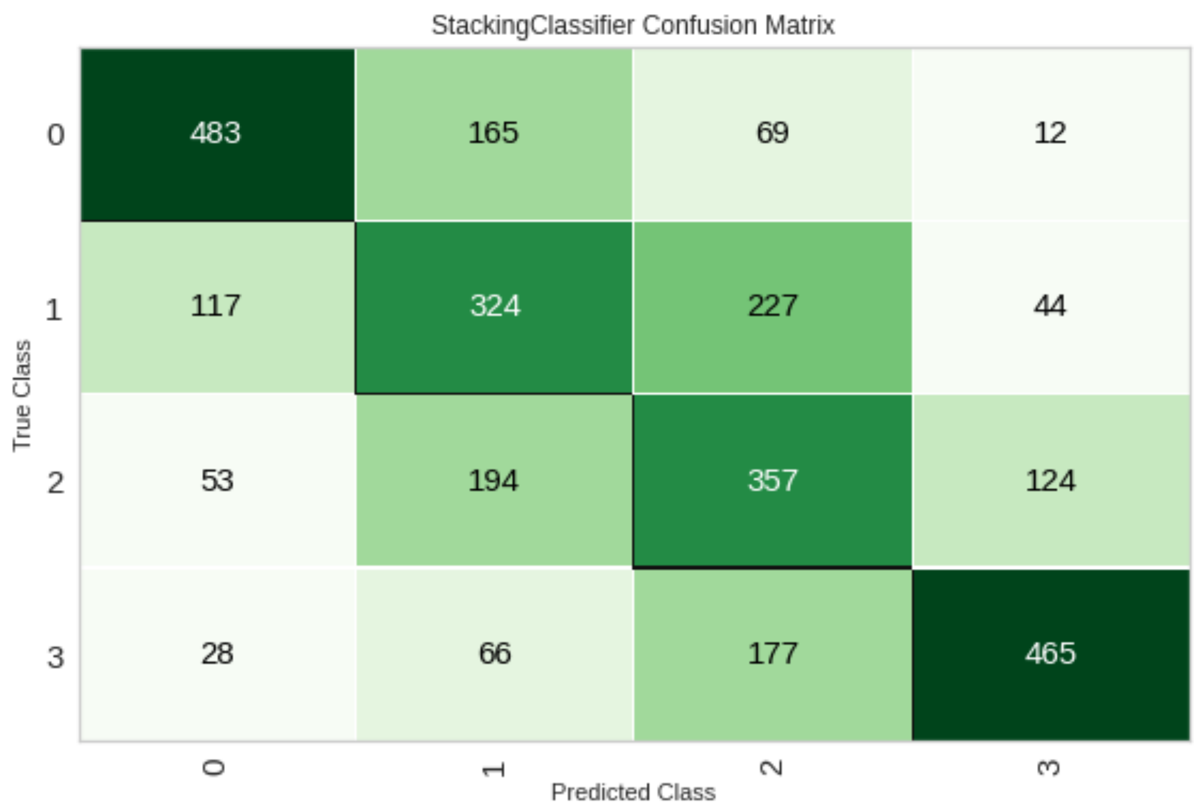
In [70]:
```
y_pred5 = [p for p in predict_model(stack_clf10, data = XX_test_std)['
Label']]
```

## Plot and Evaluate the model

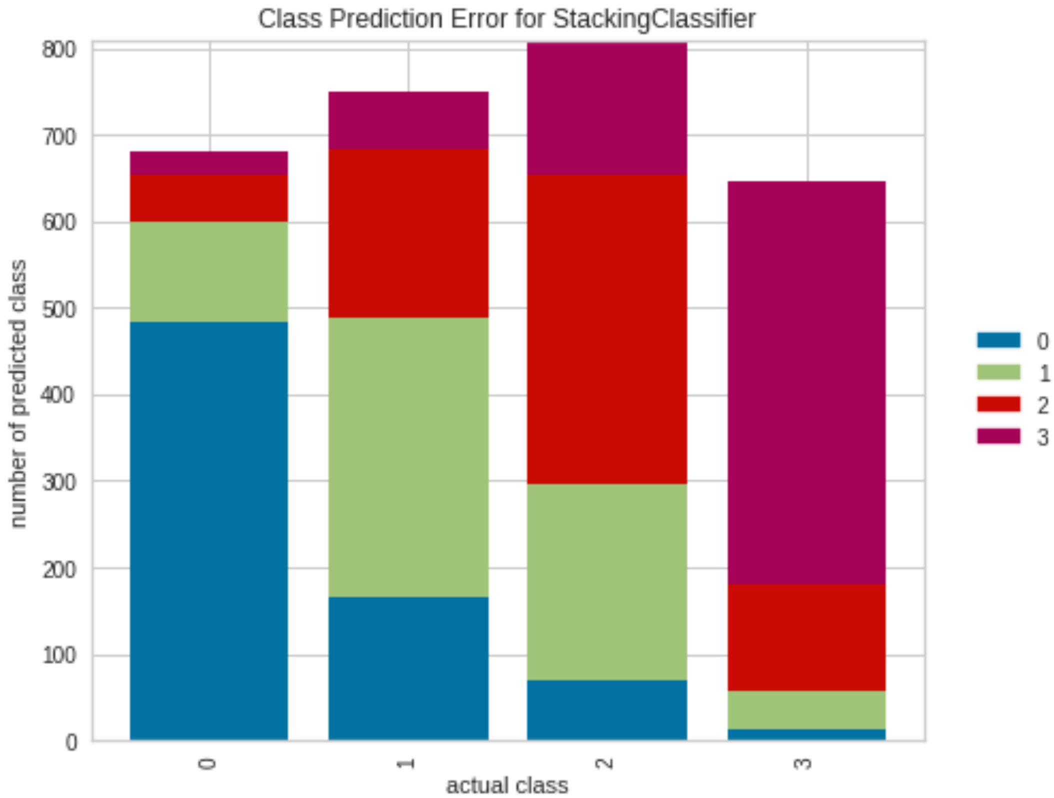
In [71]:
```
plot_model(stack_clf7)
```



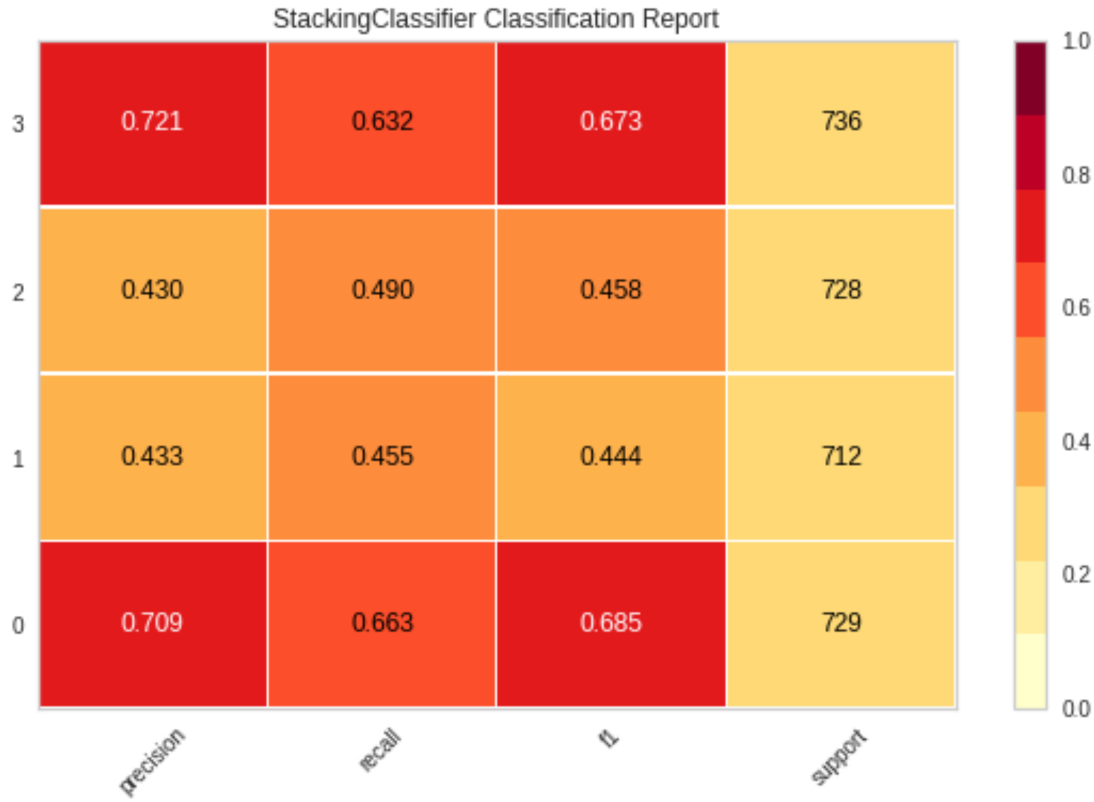

In [72]:
```
plot_model(stack_clf7, 'confusion_matrix')
```



In [73]:
```
plot_model(stack_clf7, 'error')
```



In [74]:
```
plot_model(stack_clf7, 'class_report')
```




In [ ]:
```

```

# Save predictions

In [75]:
```
sample = pd.read_csv('data/sample_submission.csv', index_col = 0)
```

In [76]:
```
sample.price = y_pred0
sample.to_csv('best_rf.csv', index = True)
```

In [77]:
```
sample.price = y_pred1
sample.to_csv('best_gbc.csv', index = True)
```

In [78]:
```
sample.price = y_pred2
sample.to_csv('best_xgbc.csv', index = True)
```

In [79]:
```
sample.price = y_pred3
sample.to_csv('stack5.csv', index = True)
```

In [80]:
```
sample.price = y_pred4
sample.to_csv('stack7.csv', index = True)
```

In [81]:
```
sample.price = y_pred5
sample.to_csv('stack10.csv', index = True)
```

In [ ]:
```
```