Airbnb Price Prediction Using Machine Learning

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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

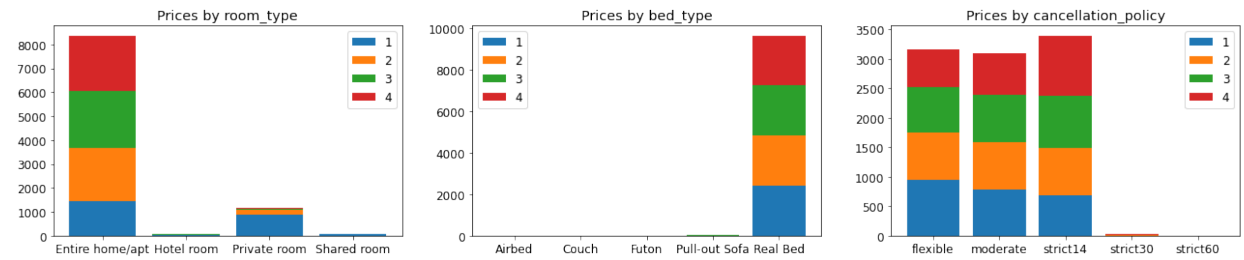
Binary Variable

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]:

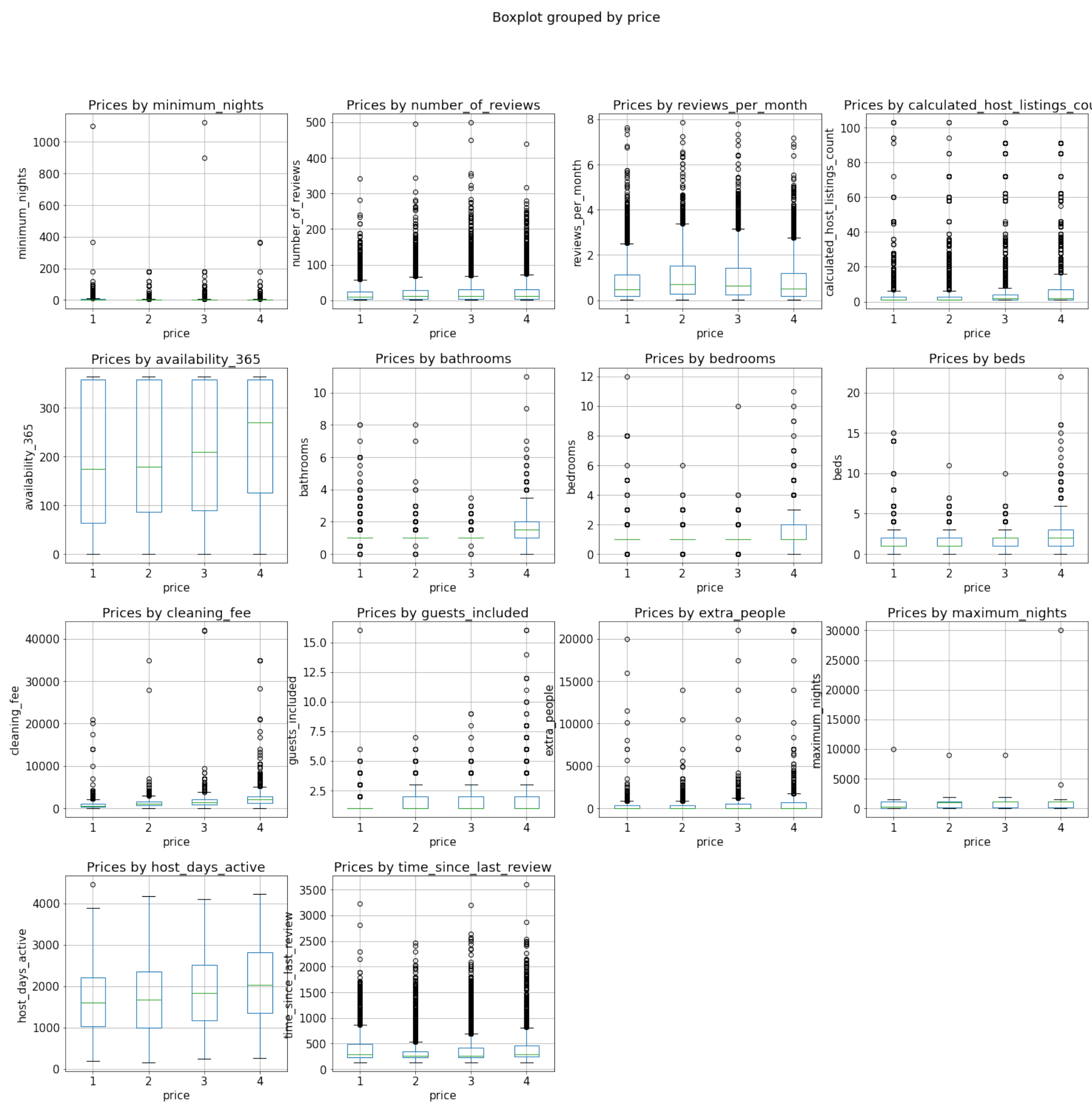
	price		
	mean	median	std
neighbourhood			
Agronomía	2.066667	2.0	0.961150
Almagro	1.849604	2.0	0.968317
Balvanera	1.939726	2.0	1.003666
Barracas	2.120690	2.0	1.185846
Belgrano	2.413462	2.0	1.124625
Boedo	1.685714	1.0	0.900047
Caballito	1.860140	2.0	0.946464
Chacarita	2.303571	2.0	1.109345
Coghlan	2.035714	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

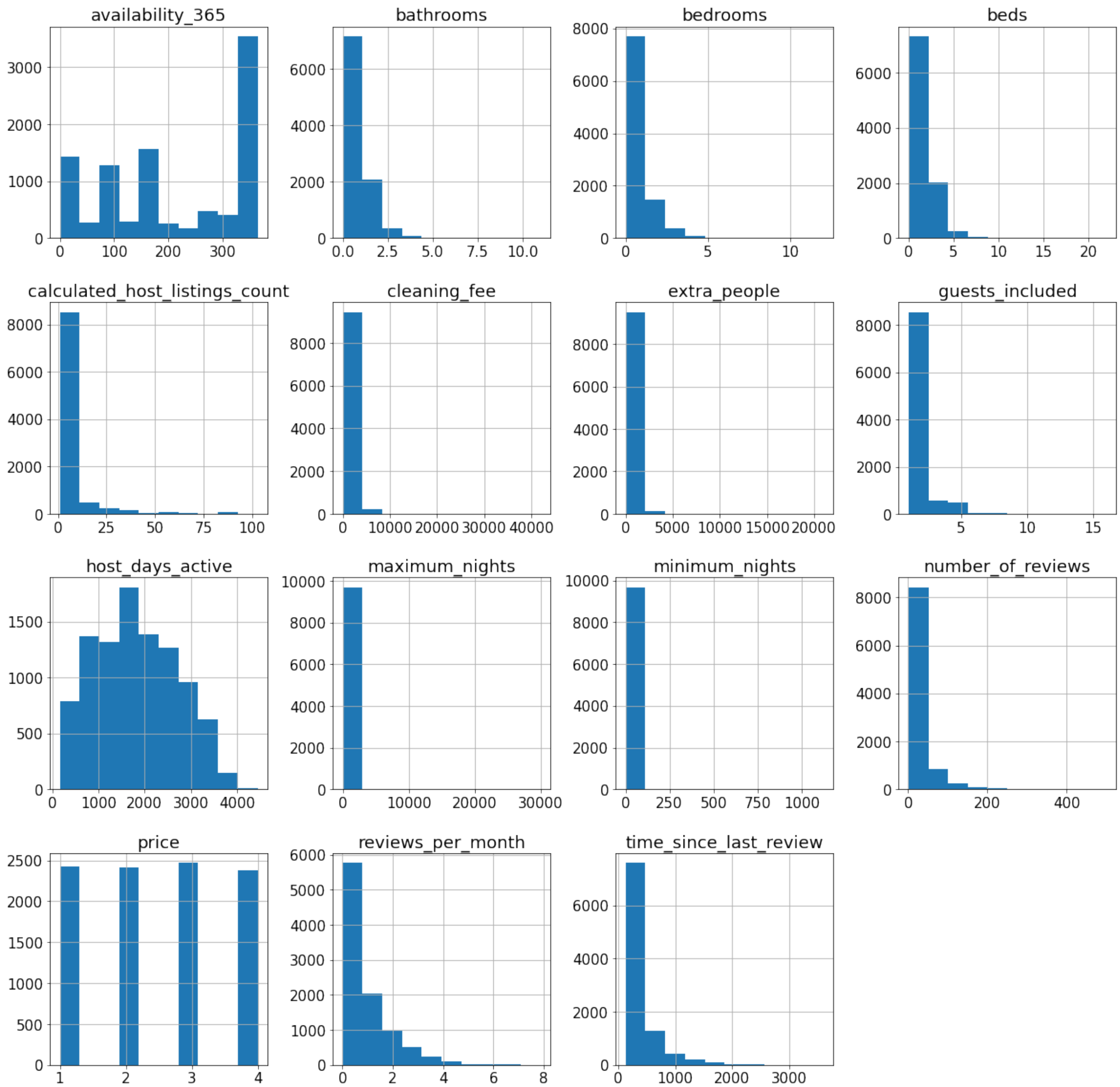
Numerical variable

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().c
olumns) == 'price'))

plt.rcParams.update({'font.size': 15})
fig, axs = plt.subplots(nrows=4, ncols=len(numerical) // 4 + 1, figsiz
e=(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()
```

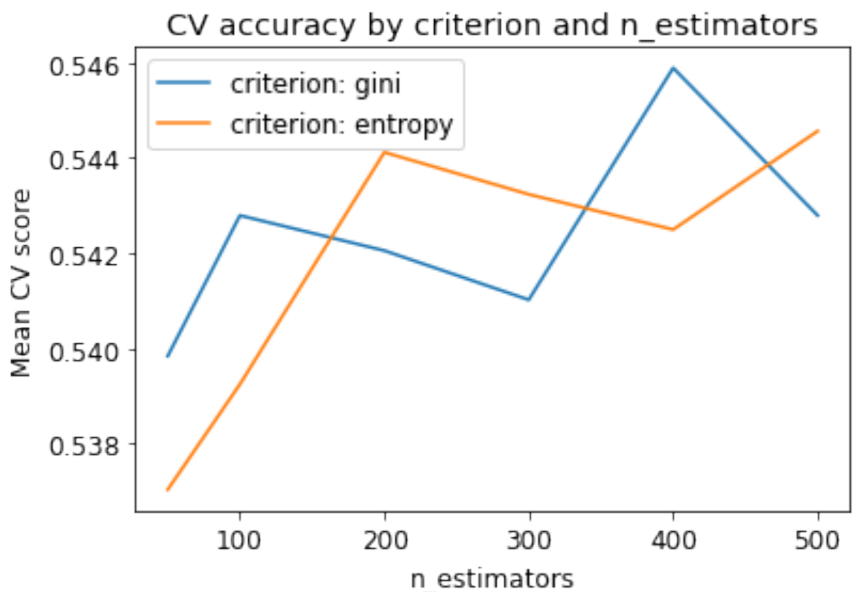
In [38]:
```
params1 = {
    'criterion': ['gini', 'entropy'],
    'n_estimators': [50, 100, 200, 300, 400, 500],
}

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_random_forest, X_train_std, y_train, cv=10)) * 100.0))
print("Out-of-sample Accuracy: %.2f%%" % (optimised_random_forest.score(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=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=400,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

Gradient Boosting Classifier

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

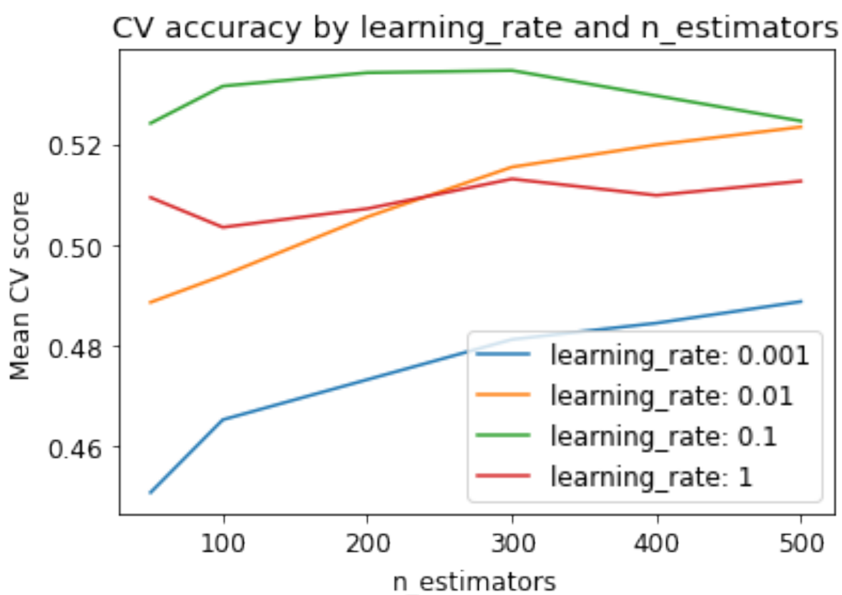
In [45]:
```
params2 = {
    'learning_rate': [0.001, 0.01, 0.1, 1],
    'n_estimators': [50, 100, 200, 300, 400, 500],
}

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

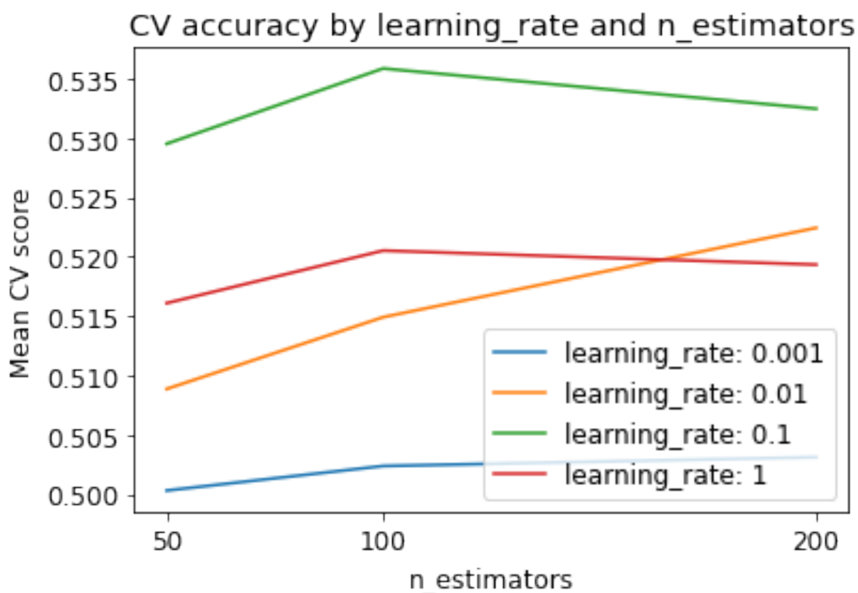
In [51]:
```
xgbc = XGBClassifier()
```

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_estimators'][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[test_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_since).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.last_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'] = 'other'

## 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], axis=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)
```

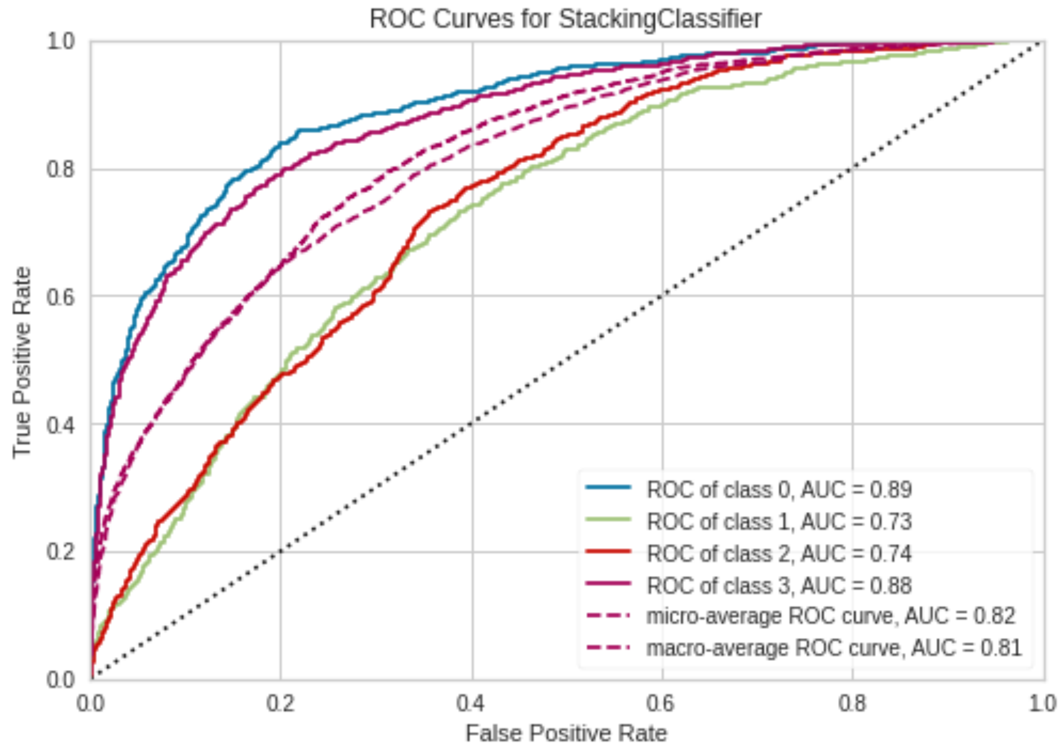
In [68]:
```
y_pred3 = predict_model(stack_clf5, data = XX_test_std)['Label']
```

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

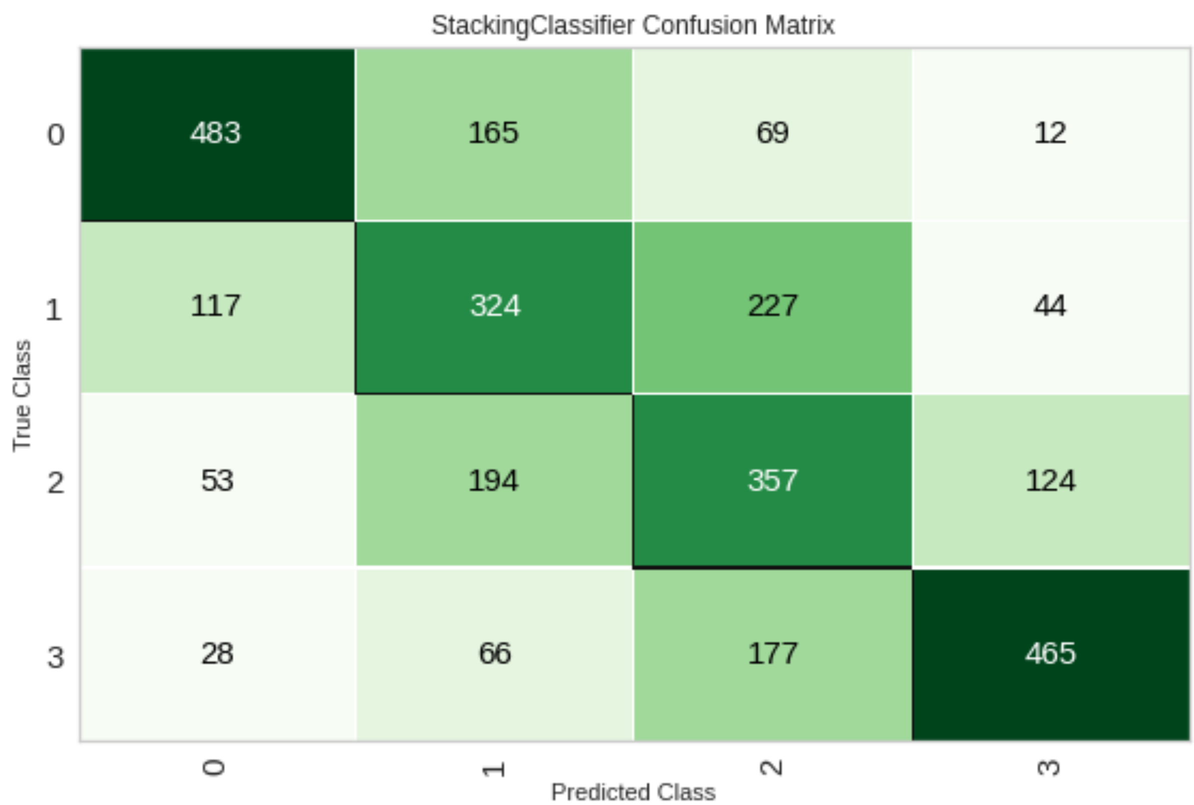
In [70]:
```
y_pred5 = [p for p in predict_model(stack_clf10, data = XX_test_std)['
Label']]
```

Plot and Evaluate the model

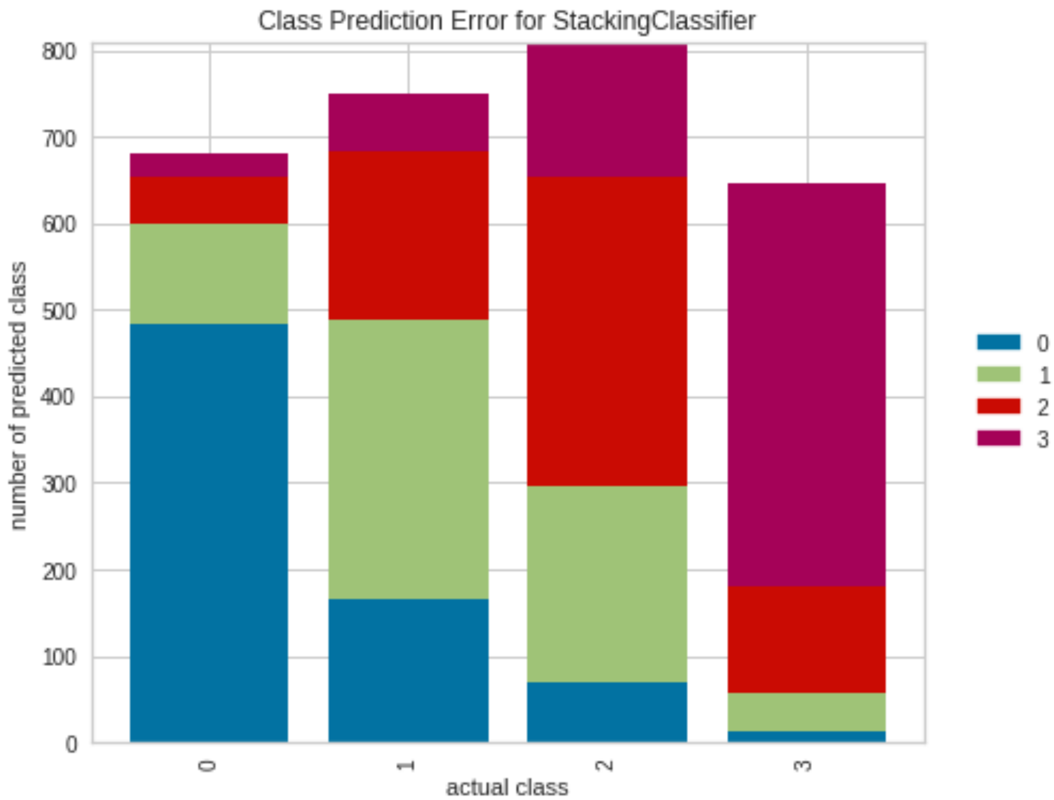
In [71]:
```
plot_model(stack_clf7)
```



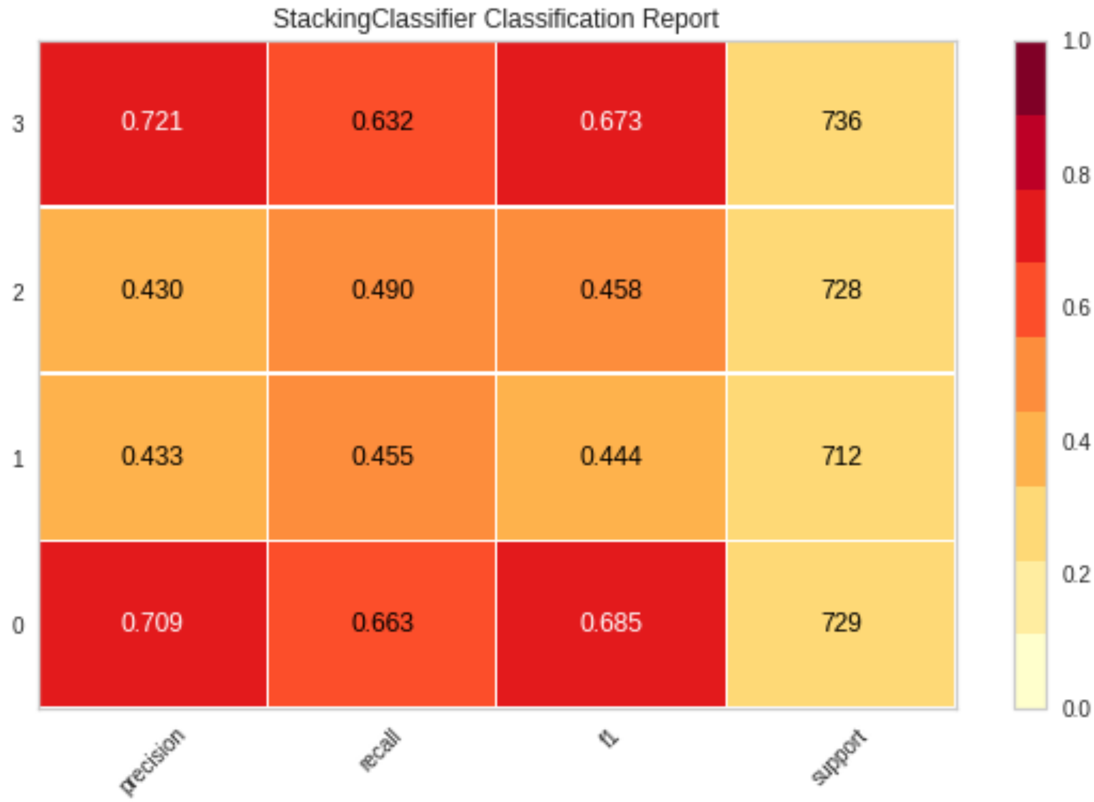
In [72]:
```
plot_model(stack_clf7, 'confusion_matrix')
```



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 [ ]:
```

```