TESTE TÉCNICO DATA SCIENCE -- COGNITIVO-AI

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Análise exploratória para avaliar a consistência dos dados e identificar possíveis variáveis que impactam sua variável resposta.

Opção: Modelagem para classificação do room type (feature ‘room_type’) com a utilização do Python:

O trabalho é composto das seguintes fases:

1) Análise dos dados

- Verificação de atributos faltantes,
- Verificação da necessidade de normalização ou padronização.
- Verificação da necessidade de transformação para valores numéricos (one-hot-encoding), se precisar.
- Analise das classes
- Verificação da necessidade de balanceamento das classes

2) Modelagem:

- Avaliação de resultados com base sem e com balanceamento
- Aplicação dos classificadores Decision Tree, Bagging, Boosting e o Random Forest (RF)
- Aplicação de rede neural (código disponível no arquivo Cognitivo-ai RNN.ipynb - feito no Colab ambiente Google)

3) Conclusão:

- vide arquivo README.MD

1) Análise dos dados

In [1]:
```
##-- Importação dos pacotes
import numpy as np
from scipy.stats import norm
import matplotlib.pyplot as plt
import pandas as pd
from scipy import stats
from patsy import dmatrices
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [2]:
```
##-- Leitura do aquivo
df = pd.read_csv("E:/CV/Processo Seletivo/Cognitivo-ai/listings.csv")

print (df.shape[0])
df.tail()
```

```
26615
```

Out[2]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_n
26610	48269503	Quarto inteiro no Recreio dos Bandeirantes.	389246322	Vivian	NaN	Recreio dos Bandeirantes	-23.01452	-43.46005	Private room	94	
26611	48269534	Casa grande mobiliada, 2 quartos em Jacarepaguá.	122122028	Victor	NaN	Cidade de Deus	-22.95078	-43.35997	Entire home/apt	141	
26612	48270411	BR-RJ020 Casa Niemeyer vista deslumbrante	13773093	Raphael	NaN	São Conrado	-22.99825	-43.25133	Entire home/apt	2500	
26613	48270514	Casa Tijuca - Curtir e aproveitar o Rio	23737846	Lucas	NaN	Tijuca	-22.92816	-43.24319	Entire home/apt	160	
26614	48276004	Rio Spot Homes D040	13580277	Marcio	NaN	Copacabana	-22.96482	-43.17428	Entire home/apt	316	

In [3]:
```
#-- Verifica os tipos dos atributos
df.dtypes
```

Out[3]:
```
id                                 int64
name                              object
host_id                            int64
host_name                         object
neighbourhood_group              float64
neighbourhood                     object
latitude                         float64
longitude                        float64
room_type                         object
price                              int64
minimum_nights                     int64
number_of_reviews                  int64
last_review                       object
reviews_per_month                float64
calculated_host_listings_count     int64
availability_365                   int64
dtype: object
```

In [4]:
```
df.describe()
```

Out[4]:

	id	host_id	neighbourhood_group	latitude	longitude	price	minimum_nights	number_of_reviews	revie
count	2.661500e+04	2.661500e+04	0.0	26615.000000	26615.000000	26615.000000	26615.000000	26615.000000	
mean	2.526448e+07	1.006657e+08	NaN	-22.965837	-43.248533	742.589254	4.725268	12.146308	
std	1.573416e+07	1.090670e+08	NaN	0.034971	0.096296	5368.868834	19.102522	29.722813	
min	1.787800e+04	3.607000e+03	NaN	-23.072920	-43.704790	0.000000	1.000000	0.000000	
25%	1.220219e+07	1.431500e+07	NaN	-22.984570	-43.304090	157.000000	1.000000	0.000000	
50%	2.374090e+07	6.026326e+07	NaN	-22.971700	-43.196210	280.000000	2.000000	2.000000	
75%	4.089613e+07	1.546962e+08	NaN	-22.951575	-43.186300	550.000000	4.000000	9.000000	
max	4.827600e+07	3.892463e+08	NaN	-22.749820	-43.104860	625216.000000	1000.000000	446.000000	

In [5]:
```
#-- Verifica se possui dados duplicados
data = df.drop_duplicates(keep='first')
data.describe()
```

Out[5]:

	id	host_id	neighbourhood_group	latitude	longitude	price	minimum_nights	number_of_reviews	reviev
count	2.661500e+04	2.661500e+04	0.0	26615.000000	26615.000000	26615.000000	26615.000000	26615.000000	
mean	2.526448e+07	1.006657e+08	NaN	-22.965837	-43.248533	742.589254	4.725268	12.146308	
std	1.573416e+07	1.090670e+08	NaN	0.034971	0.096296	5368.868834	19.102522	29.722813	
min	1.787800e+04	3.607000e+03	NaN	-23.072920	-43.704790	0.000000	1.000000	0.000000	
25%	1.220219e+07	1.431500e+07	NaN	-22.984570	-43.304090	157.000000	1.000000	0.000000	
50%	2.374090e+07	6.026326e+07	NaN	-22.971700	-43.196210	280.000000	2.000000	2.000000	
75%	4.089613e+07	1.546962e+08	NaN	-22.951575	-43.186300	550.000000	4.000000	9.000000	
max	4.827600e+07	3.892463e+08	NaN	-22.749820	-43.104860	625216.000000	1000.000000	446.000000	

>> Não possui dados duplicados

In [6]:
```
data['neighbourhood_cod'] = data['neighbourhood'].astype("category").cat.codes
data['room_type_tgt'] = data['room_type'].astype("category").cat.codes
```

In [7]:
```
data.head()
```

Out[7]:

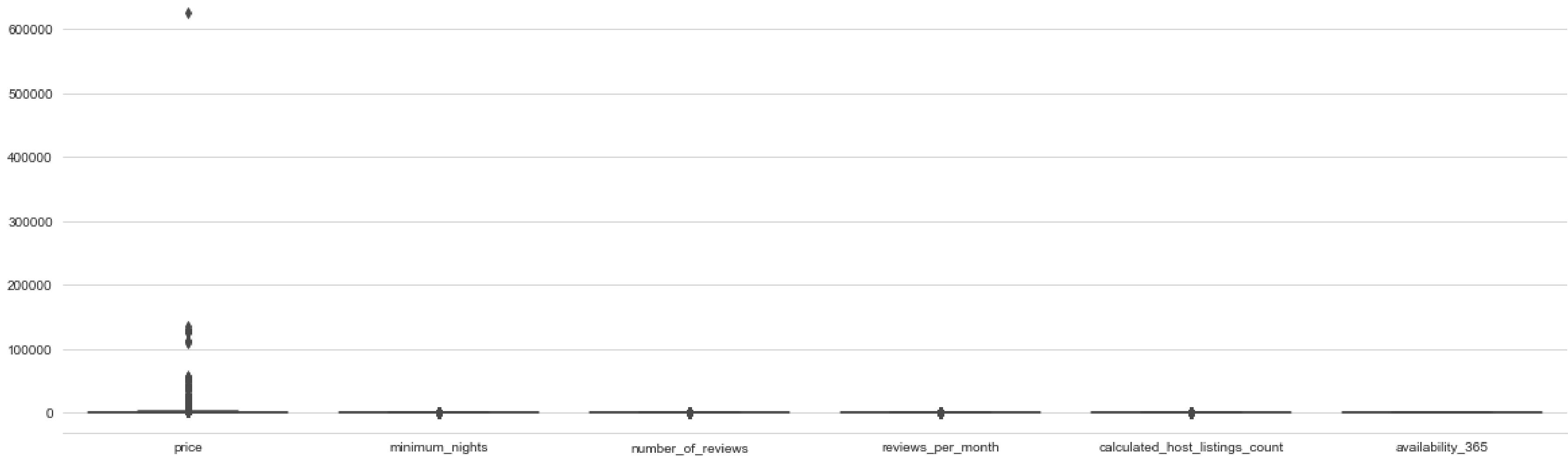
	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	nu
0	17878	Very Nice 2Br in Copacabana w. balcony, fast WiFi	68997	Matthias	NaN	Copacabana	-22.96592	-43.17896	Entire home/apt	221	5	
1	24480	Nice and cozy near Ipanema Beach	99249	Goya	NaN	Ipanema	-22.98570	-43.20193	Entire home/apt	307	3	
2	25026	Beautiful Modern Decorated Studio in Copa	3746246	Ghizlane	NaN	Copacabana	-22.97712	-43.19045	Entire home/apt	160	7	
3	35636	Cosy flat close to Ipanema beach	153232	Patricia	NaN	Ipanema	-22.98816	-43.19359	Entire home/apt	273	2	
4	35764	COPACABANA SEA BREEZE - RIO - 20 X Superhost	153691	Patricia Miranda & Paulo	NaN	Copacabana	-22.98127	-43.19046	Entire home/apt	135	3	

In [8]:
```
##-- Lista códigos do bairro
bairro_s = data['neighbourhood'].unique()
bairro_n = data['neighbourhood_cod'].unique()

map_bairro = dict(zip(bairro_s, bairro_n))
print("\nDicionário bairro:")
print(map_bairro)

##-- Lista tipos de quarto
room_type_s = data['room_type'].unique()
room_type_n = data['room_type_tgt'].unique()

map_room = dict(zip(room_type_s, room_type_n))
print("\nDicionário tipo de quarto:")
print(map_room)
```

```
Dicionário bairro:
{'Copacabana': 32, 'Ipanema': 62, 'Barra da Tijuca': 8, 'Flamengo': 44, 'Santa Teresa': 119, 'Gávea': 56, 'Leblon': 7
4, 'Jacarepaguá': 65, 'Campo Grande': 20, 'Laranjeiras': 73, 'Humaitá': 59, 'São Conrado': 126, 'Botafogo': 14, 'Cent
ro': 25, 'Vidigal': 141, 'Santo Cristo': 120, 'Itanhangá': 64, 'São Cristóvão': 127, 'Maracanã': 81, 'Glória': 51, 'T
ijuca': 132, 'Lagoa': 72, 'São Francisco Xavier': 128, 'Catete': 22, 'Pitangueiras': 101, 'Marechal Hermes': 82, 'Jar
dim Botânico': 67, 'Senador Camará': 123, 'Irajá': 63, 'Vargem Grande': 136, 'Recreio dos Bandeirantes': 109, 'Leme':
75, 'Anil': 5, 'Vargem Pequena': 137, 'Estácio': 43, 'Cosme Velho': 34, 'Gardênia Azul': 49, 'Taquara': 130, 'Bangu':
7, 'Urca': 135, 'Grajaú': 52, 'Joá': 71, 'Alto da Boa Vista': 2, 'Penha Circular': 98, 'Vila Isabel': 143, 'Jardim Su
lacap': 70, 'Praça da Bandeira': 105, 'Encantado': 39, 'Rio Comprido': 113, 'Lins de Vasconcelos': 76, 'Cosmos': 35,
'Santíssimo': 121, 'Gamboa': 48, 'Bonsucesso': 13, 'Camorim': 18, 'Piedade': 99, 'Vila da Penha': 147, 'Olaria': 87,
'Vila Valqueire': 146, 'Cidade de Deus': 28, 'Riachuelo': 110, 'Barra de Guaratiba': 9, 'Praça Seca': 104, 'Padre Mig
uel': 90, 'Méier': 86, 'Tauá': 131, 'Curicica': 36, 'Rocinha': 116, 'Engenho Novo': 40, 'Andaraí': 4, 'Santa Cruz': 1
18, 'Inhoaíba': 61, 'Guaratiba': 55, 'Cidade Nova': 26, 'Freguesia (Jacarepaguá)': 46, 'Mangueira': 79, 'Cachambi': 1
6, 'Pedra de Guaratiba': 96, 'Portuguesa': 102, 'Campinho': 19, 'Cavalcanti': 24, 'Freguesia (Ilha)': 45, 'Higienópol
is': 57, 'Bento Ribeiro': 12, 'Engenho de Dentro': 42, 'Todos os Santos': 133, 'Paciência': 89, 'Maria da Graça': 83,
'Sampaio': 117, 'Cordovil': 33, 'Rocha Miranda': 115, 'Jacaré': 66, 'Barros Filho': 10, 'Engenho da Rainha': 41, 'Saú
de': 122, 'Benfica': 11, 'Ricardo de Albuquerque': 112, 'Del Castilho': 37, 'Parada de Lucas': 92, 'Rocha': 114, 'Pav
una': 94, 'Penha': 97, 'Vicente de Carvalho': 140, 'Jardim Guanabara': 69, 'Quintino Bocaiúva': 106, 'Brás de Pina':
15, 'Pilares': 100, 'Pechincha': 95, 'Madureira': 77, 'Tanque': 129, 'Inhaúma': 60, 'Gericinó': 50, 'Abolição': 0, 'V
ila Militar': 145, 'Parque Anchieta': 93, 'Ramos': 107, 'Catumbi': 23, 'Realengo': 108, 'Jardim Carioca': 68, 'Paquet
á': 91, 'Cocotá': 29, 'Bancários': 6, 'Anchieta': 3, 'Moneró': 85, 'Vista Alegre': 148, 'Guadalupe': 54, 'Tomás Coelh
o': 134, 'Deodoro': 38, 'Cacuia': 17, 'Ribeira': 111, 'Osvaldo Cruz': 88, 'Vaz Lobo': 139, 'Sepetiba': 125, 'Praia da
Bandeira': 103, 'Complexo do Alemão': 31, 'Vila Kosmos': 144, 'Vasco da Gama': 138, 'Água Santa': 150, 'Cascadura': 2
1, 'Vigário Geral': 142, 'Cidade Universitária': 27, 'Grumari': 53, 'Senador Vasconcelos': 124, 'Manguinhos': 80, 'Ga
leão': 47, 'Coelho Neto': 30, 'Honório Gurgel': 58, 'Acari': 1, 'Zumbi': 149, 'Maré': 84, 'Magalhães Bastos': 78}

Dicionário tipo de quarto:
{'Entire home/apt': 0, 'Private room': 2, 'Shared room': 3, 'Hotel room': 1}
```

In [9]:
```
data_out = data[['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month', 'calculated_host_listings_count'
, 'availability_365', 'room_type_tgt']]
xdata = data_out.copy()
xdata.drop(columns=['room_type_tgt'], inplace=True)
```

In [10]:
```
#-- Verificar outliers das variáveis
import seaborn as sns
sns.set_style("whitegrid")
f = plt.figure(figsize=(20,6))
f.tight_layout()
sns.boxplot(data=xdata, palette="deep")
sns.despine(left=True)
```



-- A variável 'price' sugere outliers. Deve-se investigar e retirar possíveis outliers.

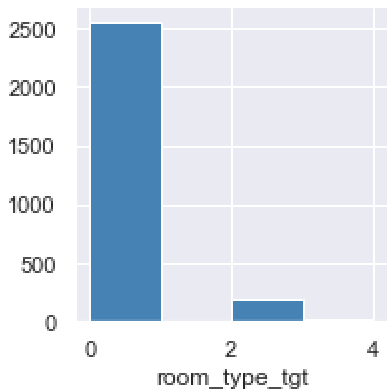
In [11]:
```
#-- Identificar e retirar os Outliers
#-- Identificar e retirar os Outliers
#-- Verifica outliers

def remove_nans_outliers(df, attributes, out_in=0):

    dfn = df.copy()

    for var in attributes:
        # verifica se variável é numerica
        if np.issubdtype(df[var].dtype, np.number):
            Q1 = df[var].quantile(0.25)
            Q2 = df[var].quantile(0.5)
            Q3 = df[var].quantile(0.75)
            IQR = Q3 - Q1

        if out_in==0 :
            # apenas inliers segundo IQR
            dfn = df.loc[(df[var] >= Q1-(IQR*1.5)) & (df[var] <= Q3+(IQR*1.5)), :]
        else:
            # apenas outliers segundo IQR
            dfn = df.loc[(df[var] < Q1-(IQR*1.5)) | (df[var] > Q3+(IQR*1.5)), :]

        dfn = dfn.loc[dfn[var].notnull(),:]

    return dfn

attributes = ['price']
data_n = remove_nans_outliers(data, attributes, 0)
data_out = remove_nans_outliers(data, attributes, 1)

print("Antes: %d, Depois remocao outliers: %d" % (data.shape[0], data_n.shape[0]))
print("Outliers: ", data_out.shape[0])
```

```
Antes: 26615, Depois remocao outliers: 23845
Outliers:  2770
```

In [12]:
```
##-- Verificação da distribuição das classes (room_type) para os outliers
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="darkgrid")

f = plt.figure(figsize=(20,6))
f.tight_layout()
g = sns.FacetGrid(data_out,  margin_titles=True)
bins = np.linspace(0, 4, 5)
g.map(plt.hist, 'room_type_tgt', color="steelblue", bins=bins)
roomtype = data_out.groupby('room_type_tgt')
print (roomtype['room_type_tgt'].count())
```

```
room_type_tgt
0    2550
1       3
2     199
3      18
Name: room_type_tgt, dtype: int64
```

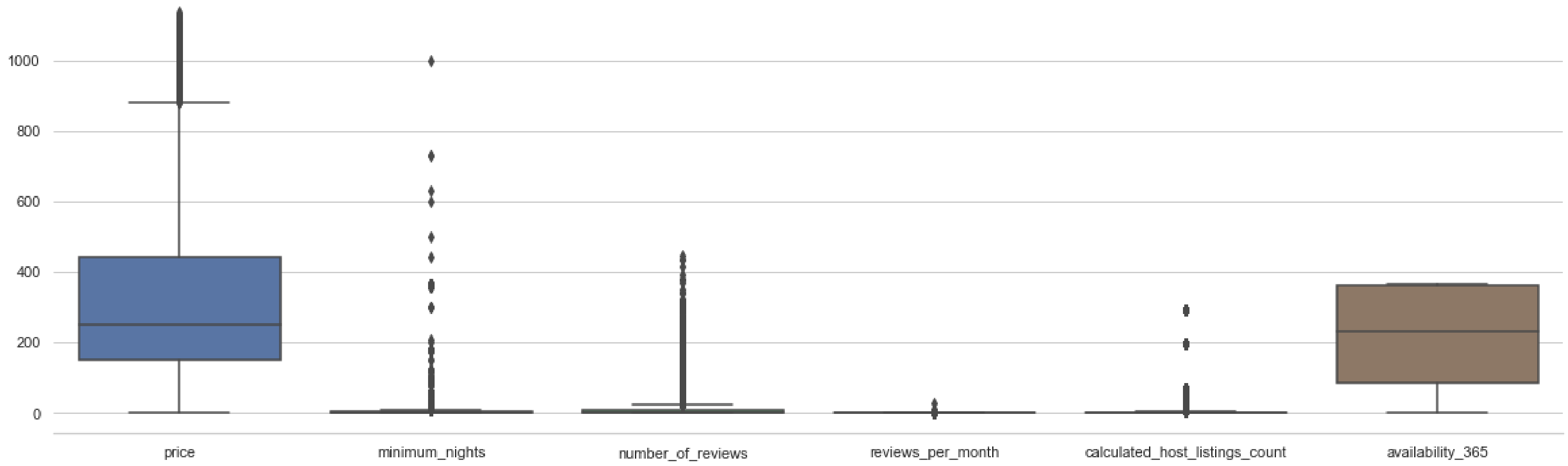
```
<Figure size 1440x432 with 0 Axes>
```



-- Verifica-se a predominância do tipo 'Entire home/apt' dentre os outliers.

-- Segue estudo das variáveis sem outliers.

In [13]:
```
#-- Variáveis sem outliers
import seaborn as sns

xdata = data_n[['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month', 'calculated_host_listings_count',
'availability_365']]

sns.set_style("whitegrid")
f = plt.figure(figsize=(20,6))
f.tight_layout()
sns.boxplot(data=xdata, palette="deep")
sns.despine(left=True)
```



In [14]:
```
##-- Dataset que será considerado para a modelagem
data_n.head()
```

Out[14]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	nı
0	17878	Very Nice 2Br in Copacabana w. balcony, fast WiFi	68997	Matthias	NaN	Copacabana	-22.96592	-43.17896	Entire home/apt	221	5	
1	24480	Nice and cozy near Ipanema Beach	99249	Goya	NaN	Ipanema	-22.98570	-43.20193	Entire home/apt	307	3	
2	25026	Beautiful Modern Decorated Studio in Copa	3746246	Ghizlane	NaN	Copacabana	-22.97712	-43.19045	Entire home/apt	160	7	
3	35636	Cosy flat close to Ipanema beach	153232	Patricia	NaN	Ipanema	-22.98816	-43.19359	Entire home/apt	273	2	
4	35764	COPACABANA SEA BREEZE - RIO - 20 X Superhost	153691	Patricia Miranda & Paulo	NaN	Copacabana	-22.98127	-43.19046	Entire home/apt	135	3	

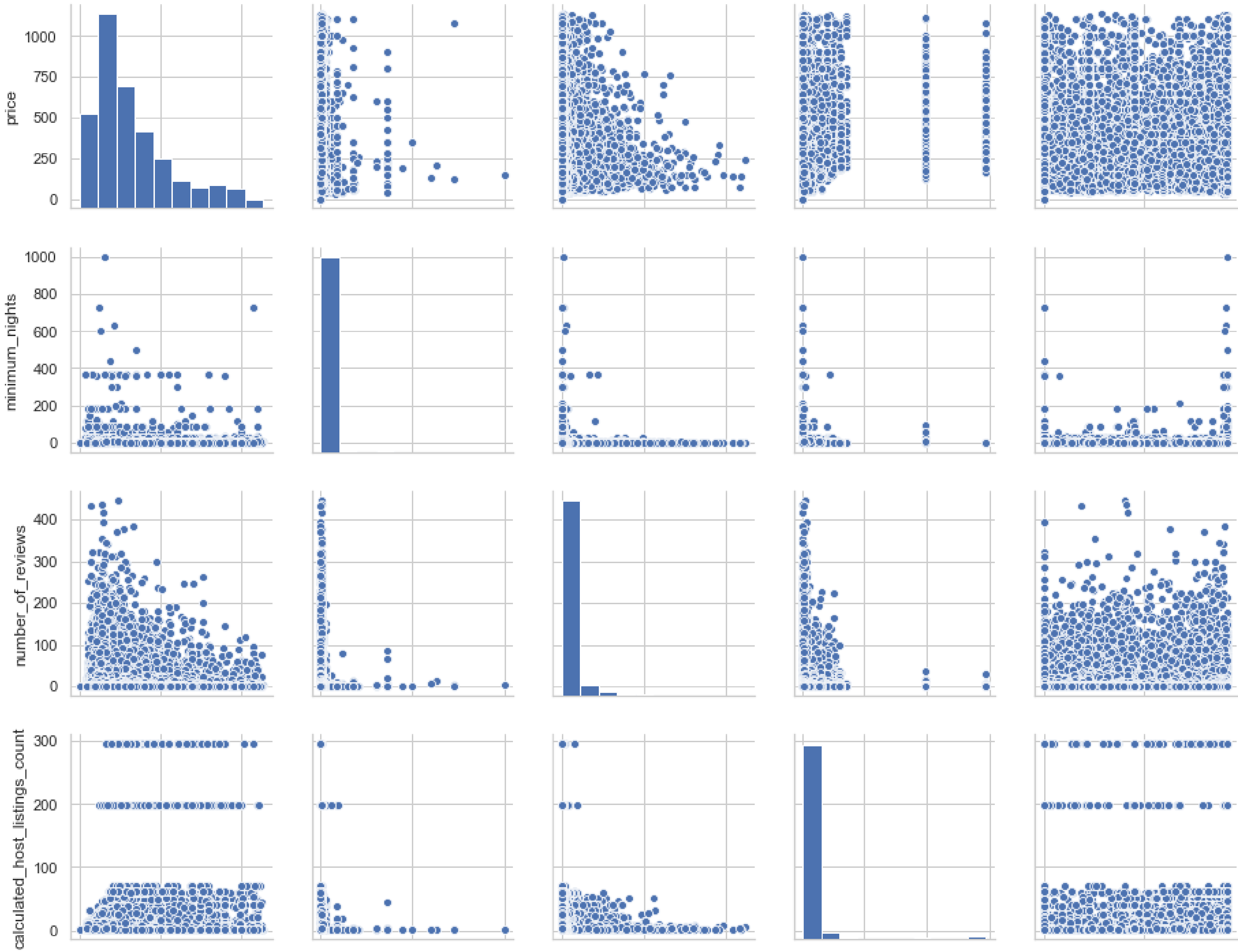
-- O dataset "data_n" sem outliers será considerado para construção dos modelos. O atributo 'reviews_per_month' foi exluido para a modelagem por possuir aproximadamente 40% de seus valores nulos.

-- Verificação de correlações entre as variáveis

In [15]:
```
##-- verificar correlação entre as variáveis
cabec_corr =['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365']
data_set = data_n[cabec_corr]
```

In [16]:
```
import seaborn as sns
sns.pairplot(data_set)
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x185eea34348>


price
minimum_nights
number_of_reviews
calculated_host_listings_count

In [17]:
```
data_set.corr()
```

Out[17]:

	price	minimum_nights	number_of_reviews	calculated_host_listings_count	availability_365
price	1.000000	0.020744	-0.144194	0.069146	0.067785
minimum_nights	0.020744	1.000000	-0.030546	-0.023039	0.020406
number_of_reviews	-0.144194	-0.030546	1.000000	-0.059971	-0.068888
calculated_host_listings_count	0.069146	-0.023039	-0.059971	1.000000	0.052607
availability_365	0.067785	0.020406	-0.068888	0.052607	1.000000

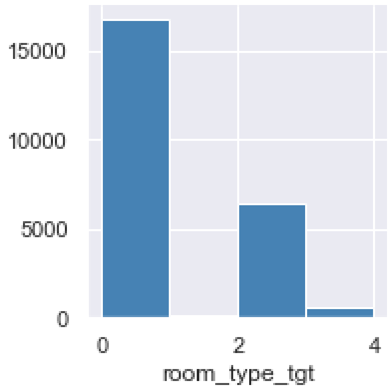
-- Verifica-se baixa correlação entre as variáveis. Portanto, não haverá eliminação de variáveis .

-- Verificação da distribuição das classes da variável target: room_type

In [18]:
```
#-- Verificar a distribuição da variável target: room_type
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="darkgrid")

f = plt.figure(figsize=(20,6))
f.tight_layout()
g = sns.FacetGrid(data_n,  margin_titles=True)
bins = np.linspace(0, 4, 5)
g.map(plt.hist, 'room_type_tgt', color="steelblue", bins=bins)
roomtype = data_n.groupby('room_type_tgt')
print (roomtype['room_type_tgt'].count())
```

```
room_type_tgt
0    16735
1       96
2     6420
3      594
Name: room_type_tgt, dtype: int64
```

```
<Figure size 1440x432 with 0 Axes>
```



In [19]:
```
data_n.describe()
```

Out[19]:

	id	host_id	neighbourhood_group	latitude	longitude	price	minimum_nights	number_of_reviews	review
count	2.384500e+04	2.384500e+04	0.0	23845.000000	23845.000000	23845.000000	23845.000000	23845.000000	
mean	2.588098e+07	1.037807e+08	NaN	-22.964649	-43.245371	328.967331	4.509709	13.292137	
std	1.569127e+07	1.106689e+08	NaN	0.035233	0.095197	245.505500	18.910774	31.044277	
min	1.787800e+04	3.607000e+03	NaN	-23.072920	-43.704790	0.000000	1.000000	0.000000	
25%	1.285540e+07	1.448296e+07	NaN	-22.984120	-43.287460	150.000000	1.000000	0.000000	
50%	2.694611e+07	6.211486e+07	NaN	-22.970790	-43.194550	250.000000	2.000000	2.000000	
75%	4.107804e+07	1.620224e+08	NaN	-22.949010	-43.185690	443.000000	4.000000	10.000000	
max	4.827600e+07	3.892463e+08	NaN	-22.749820	-43.104860	1139.000000	1000.000000	446.000000	

In [20]:
```
cabec_pca = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'ne
ighbourhood_cod', 'room_type_tgt']
data_set = data_n[cabec_pca]

data_set = data_set.to_numpy()
nrow,ncol = data_set.shape
print (data_set.shape)
```

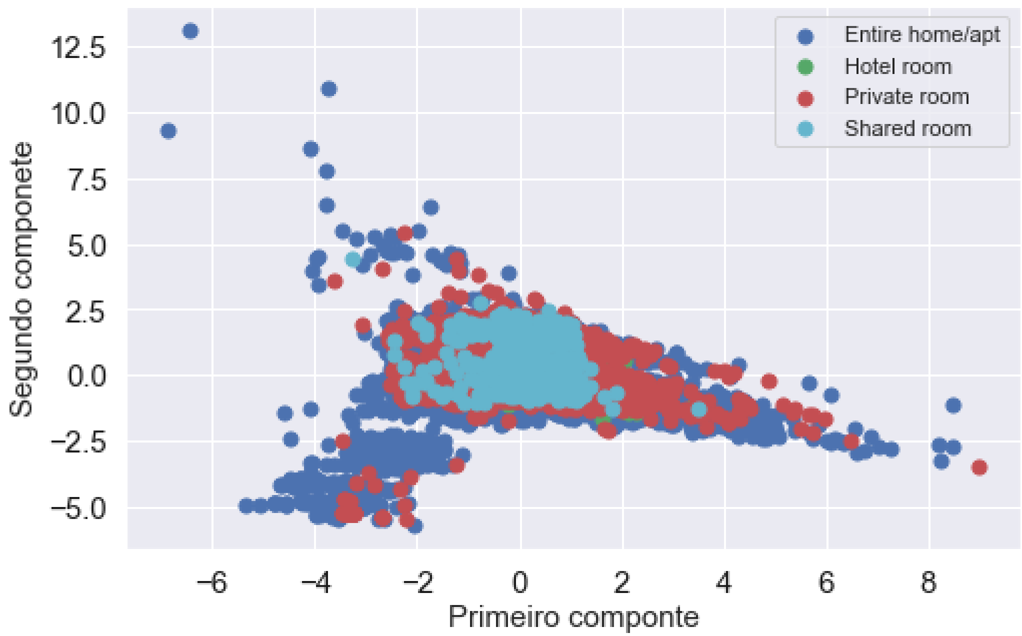
```
(23845, 7)
```

In [21]:
```
import random
random.seed(42) # define the seed (important to reproduce the results)

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

In [22]:
```
y = data_set[:,-1]
X = data_set[:,0:ncol-1]
print(X.shape)
scaler = StandardScaler().fit(X)
X = scaler.transform(X)
```

```
(23845, 6)
```

In [23]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X)

classes = np.unique(y)

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
aux = 0
plt.figure(figsize=(8,5))
for c in classes:
    lb = c
    nodes = np.where(y == c)
    if lb == 0 :
        lb = 'Entire home/apt'
    elif lb == 1 :
        lb = 'Hotel room'
    elif lb == 2 :
        lb = 'Private room'
    else:
        lb = 'Shared room'

    plt.scatter(pca_result[nodes,0], pca_result[nodes,1], s=50, color = colors[aux], label = lb)
    aux = aux + 1
plt.legend()
plt.xlabel("Primeiro componte", fontsize=15)
plt.ylabel("Segundo componete", fontsize=15)
plt.xticks(color='k', size=15)
plt.yticks(color='k', size=15)
plt.show(True)
```



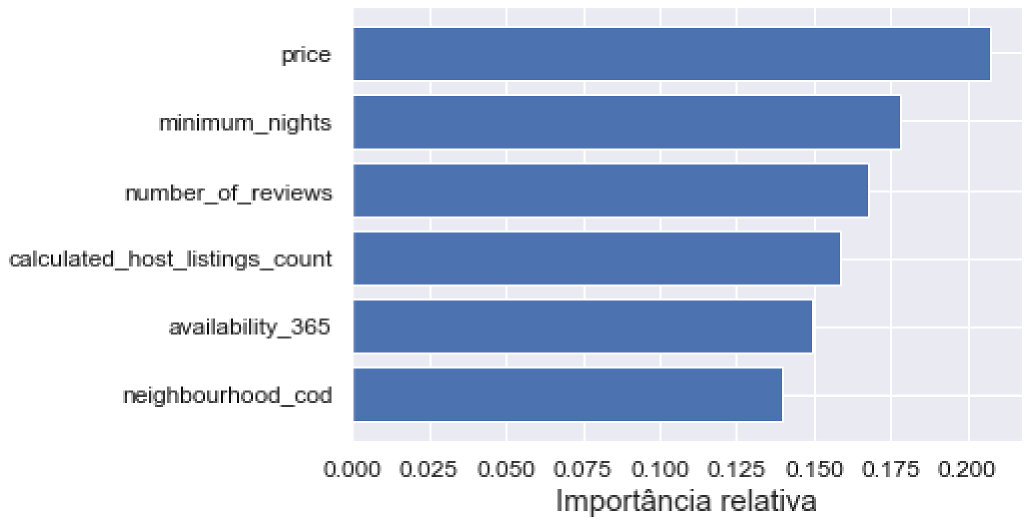
-- Observa-se sobreposição de lasses. Para haja classificação adequada por algum método de classificação supervisionado devem ser mitigadas: a) informações complementares para identificação do tipo de quarto; b) se o processo de classificação dos tipos de quarto pelo AirBnb é insuficiente (deveriam haver mais tipos); c) existência de tendências ao tipo 'Entire home/apt" no cadastramento.

-- A análise sugere o tratamento do desbalanceamento das classes.

2) Modelagem

-- Modelagem sem balanceamento das classes

In [24]:
```
pca = PCA()

pca_result = pca.fit_transform(X)
var_exp = pca.explained_variance_ratio_

importances = var_exp
# attributes >> valores salvos na leitura do aquivo
indices = np.argsort(importances)
attributes_rank = []
for i in indices:
    attributes_rank.append(cabec_pca[i])
#plt.title('Valor da informação das variáveis', fontsize=15)
plt.tight_layout()
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), attributes_rank, fontsize=25)
plt.xlabel('Importância relativa',fontsize=15)
plt.xticks(color='k', size=12)
plt.yticks(color='k', size=12)

plt.show()
```



-- Considerado o valor de informação das variáveis atravéis dos componentes oricnipais, para a modelagem de classificação serão consideradas as seguintes variáveis: 'price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365' e 'neighbourhood_cod'.

In [25]:

```
cabec_pca = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'ne
ighbourhood_cod', 'room_type_tgt']
data_set = data_n[cabec_pca]

data_set = data_set.to_numpy()
nrow,ncol = data_set.shape
print (data_set.shape)
```

```
(23845, 7)
```

In [26]:

```
random.seed(42) # define the seed (important to reproduce the results)

y = data_set[:,-1]
X = data_set[:,0:ncol-1]
print(X.shape)
scaler = StandardScaler().fit(X)
X = scaler.transform(X)
```

```
(23845, 6)
```

In [27]:

```
from sklearn import tree
from sklearn.ensemble import BaggingClassifier
from sklearn.datasets import make_classification
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier


#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics

models = [
        ('Tree Gini', tree.DecisionTreeClassifier(criterion = 'gini', random_state = 101)),
        ('Tree Entropy', tree.DecisionTreeClassifier(criterion = 'entropy',random_state = 101)),
        ('Bagging', BaggingClassifier(base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy', random_state = 
101),
                          n_estimators=10)) ,
        ('Boosting', AdaBoostClassifier(n_estimators=10,learning_rate=1,
                         base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy'))),
        ('Random Forest', RandomForestClassifier(n_estimators=100, bootstrap=True, class_weight=None, criterion='gini'
,
            max_depth=None, max_features='auto', 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_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False))
    ]

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


p = 0.2 # fraction of elements in the training set
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size = p, random_state = 42)

for name, model in models:
    model.fit (x_train, y_train)
    print ('Accuracy ({}): \t{}'.format (name, model.score(x_test,y_test)))
```

```
Accuracy (Tree Gini):	0.7471167959739987
Accuracy (Tree Entropy):	0.7462780457118893
Accuracy (Bagging):	0.799119312224785
Accuracy (Boosting):	0.7932480603900188
Accuracy (Random Forest):	0.8117005661564269
```

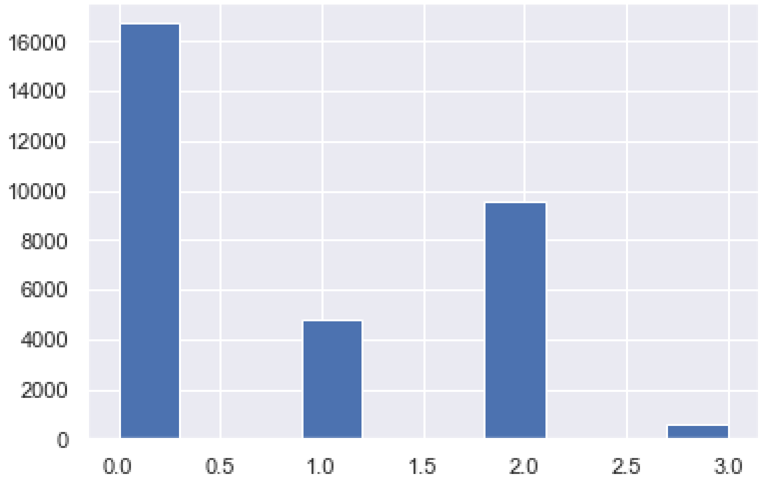
-- O classificador Random Forest (com o critério 'Gini') obeteve melhor acurácia (81%).

-- Modelagem com tratamento de Balanceamento das classes

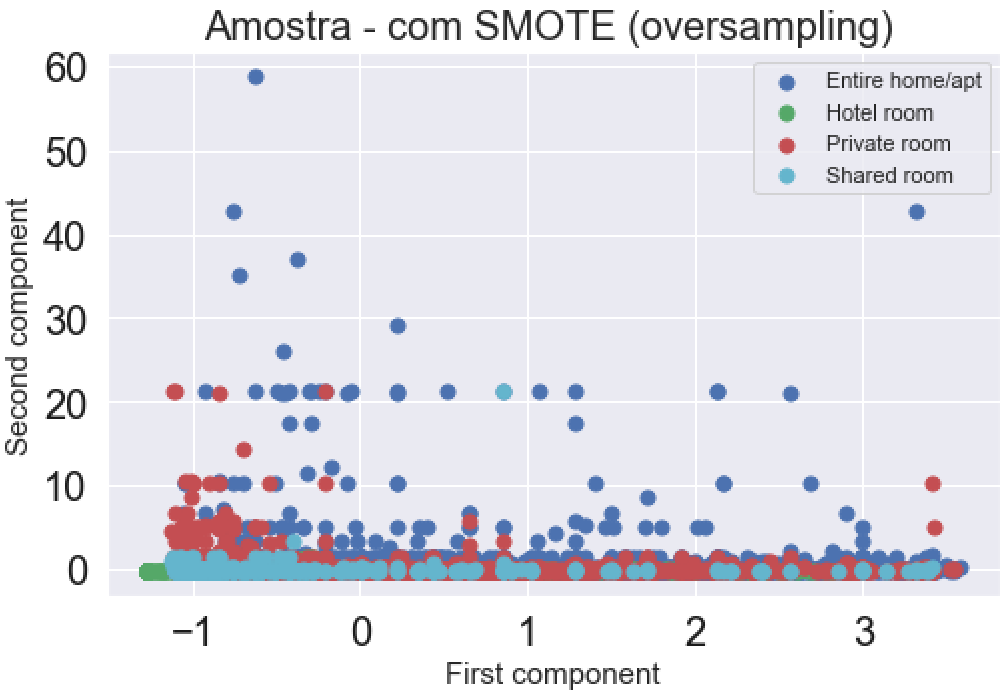
-- Geração das bases balanceladas

In [28]:
```
from imblearn import over_sampling
from imblearn import under_sampling
from imblearn import combine
from imblearn.combine import SMOTEENN
```

In [29]:
```
##-- Synthetic Minority Over-sampling Technique (SMOTE)
strategy = {1: int(X.shape[0]* 0.2), 2: int(X.shape[0]* 0.4)}
oversamp = over_sampling.SMOTE(random_state=42, sampling_strategy=strategy, k_neighbors=5 ) # sampling_strategy pode s
er usado para casos binários
Xo, Yo = oversamp.fit_resample(X, y)
h = plt.hist(Yo)
```



In [30]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
pca = PCA(n_components=2)

scaler = StandardScaler().fit(Xo)
pca_result = scaler.transform(Xo)

classes = np.unique(Yo)

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
aux = 0
plt.figure(figsize=(8,5))
for c in classes:
    nodes = np.where(Yo == c)
    lb = c

    if lb == 0 :
        lb = 'Entire home/apt'
    elif lb == 1 :
        lb = 'Hotel room'
    elif lb == 2 :
        lb = 'Private room'
    else:
        lb = 'Shared room'
    plt.scatter(pca_result[nodes,0], pca_result[nodes,1], s=50, color = colors[aux], label = lb)
    aux = aux + 1
plt.legend()
plt.xlabel("First component", fontsize=15)
plt.ylabel("Second component", fontsize=15)
plt.xticks(color='k', size=20)
plt.yticks(color='k', size=20)
plt.title('Amostra - com SMOTE (oversampling) ', fontsize=20)
plt.show(True)
```



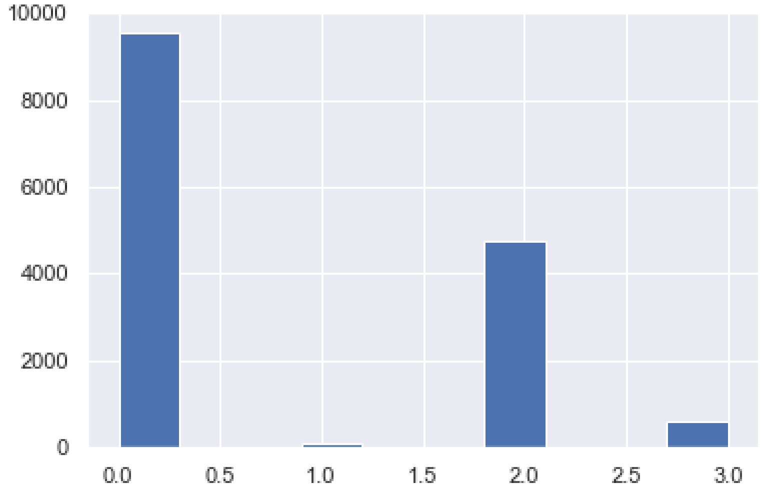
Amostra - com SMOTE (oversampling)
Entire home/apt
Hotel room
Private room
Shared room
Second component
First component
60
50
40
30
20
10
0
−1
0
1
2
3

In [31]:
```
models = [
        ('Tree Gini', tree.DecisionTreeClassifier(criterion = 'gini', random_state = 101)),
        ('Tree Entropy', tree.DecisionTreeClassifier(criterion = 'entropy',random_state = 101)),
        ('Bagging', BaggingClassifier(base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy', random_state = 
101),
                          n_estimators=10)) ,
        ('Boosting', AdaBoostClassifier(n_estimators=10,learning_rate=1,
                         base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy'))),
        ('Random Forest', RandomForestClassifier(n_estimators=100, bootstrap=True, class_weight=None, criterion='gini'
,
            max_depth=None, max_features='auto', 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_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False))
    ]

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

p = 0.2 # fraction of elements in the training set
x_train, x_test, y_train, y_test = train_test_split(Xo, Yo, test_size = p, random_state = 42)

for name, model in models:
    model.fit (x_train, y_train)
    print ('Accuracy ({}): \t{}'.format (name, model.score(x_test,y_test)))
```

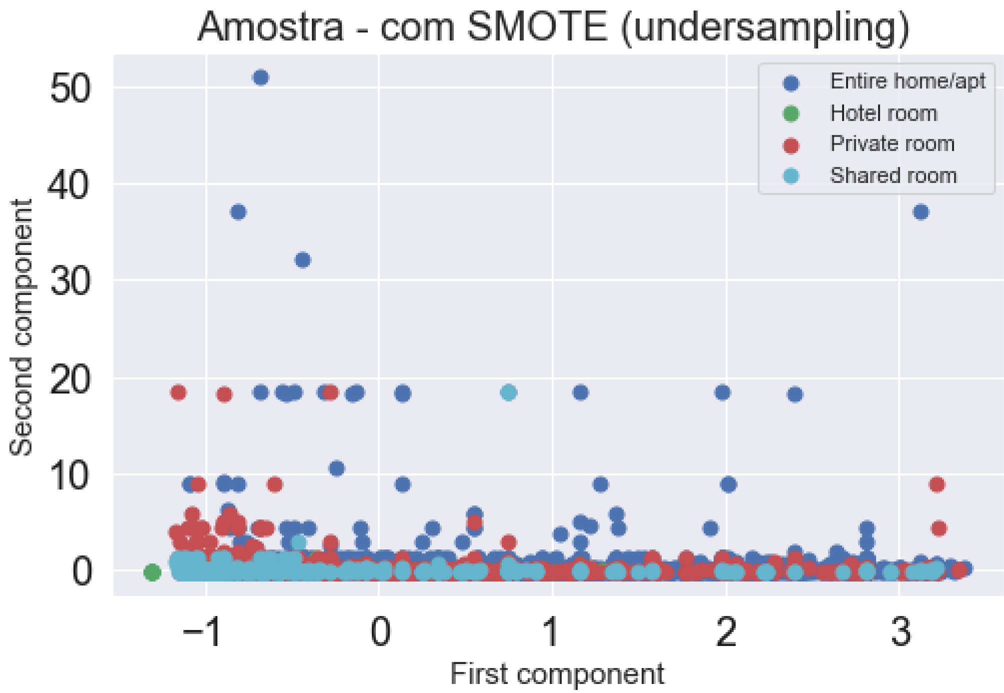
```
Accuracy (Tree Gini):	0.7833438685208597
Accuracy (Tree Entropy):	0.7835018963337548
Accuracy (Bagging):	0.8320164348925411
Accuracy (Boosting):	0.8154235145385588
Accuracy (Random Forest):	0.8484513274336283
```

-- Over-sampling (SMOTE): As acurácias dos classificadores referentes à base balanceada foram melhores que as da base normal (sem balanceamento)

In [32]:
```
##-- Synthetic Minority Under-sampling Technique

strategy = {0: int(X.shape[0]* 0.4), 2: int(X.shape[0]* 0.2)}

undersamp = under_sampling.RandomUnderSampler(random_state=42,  sampling_strategy=strategy)
Xu, Yu = undersamp.fit_resample(X, y)
h = plt.hist(Yu)
```



In [33]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
pca = PCA(n_components=2)

scaler = StandardScaler().fit(Xu)
pca_result = scaler.transform(Xu)

classes = np.unique(Yu)

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
aux = 0
plt.figure(figsize=(8,5))
for c in classes:
    lb = c

    if lb == 0 :
        lb = 'Entire home/apt'
    elif lb == 1 :
        lb = 'Hotel room'
    elif lb == 2 :
        lb = 'Private room'
    else:
        lb = 'Shared room'
    nodes = np.where(Yu == c)
    plt.scatter(pca_result[nodes,0], pca_result[nodes,1], s=50, color = colors[aux], label = lb)
    aux = aux + 1
plt.legend()
plt.xlabel("First component", fontsize=15)
plt.ylabel("Second component", fontsize=15)
plt.xticks(color='k', size=20)
plt.yticks(color='k', size=20)
plt.title('Amostra - com SMOTE (undersampling) ', fontsize=20)
plt.show(True)
```


Amostra - com SMOTE (undersampling)
Entire home/apt
Hotel room
Private room
Shared room
Second component
First component
50
40
30
20
10
0
−1
0
1
2
3

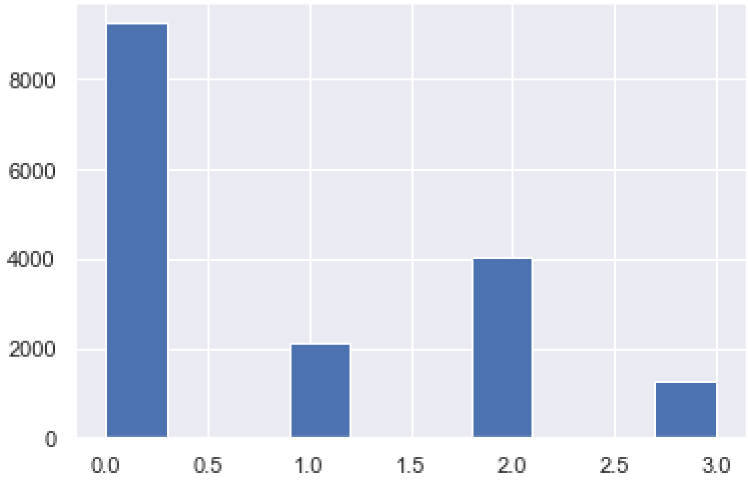
In [34]:
```
models = [
        ('Tree Gini', tree.DecisionTreeClassifier(criterion = 'gini', random_state = 101)),
        ('Tree Entropy', tree.DecisionTreeClassifier(criterion = 'entropy',random_state = 101)),
        ('Bagging', BaggingClassifier(base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy', random_state =
101),
                          n_estimators=10)) ,
        ('Boosting', AdaBoostClassifier(n_estimators=10,learning_rate=1,
                         base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy'))),
        ('Random Forest', RandomForestClassifier(n_estimators=100, bootstrap=True, class_weight=None, criterion='gini'
,
            max_depth=None, max_features='auto', 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_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False))
    ]

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

p = 0.2 # fraction of elements in the training set
x_train, x_test, y_train, y_test = train_test_split(Xu, Yu, test_size = p, random_state = 42)

for name, model in models:
    model.fit (x_train, y_train)
    print ('Accuracy ({}): \t{}'.format (name, model.score(x_test,y_test)))
```

```
Accuracy (Tree Gini):	0.686
Accuracy (Tree Entropy):	0.691
Accuracy (Bagging):	0.7493333333333333
Accuracy (Boosting):	0.7323333333333333
Accuracy (Random Forest):	0.7626666666666667
```

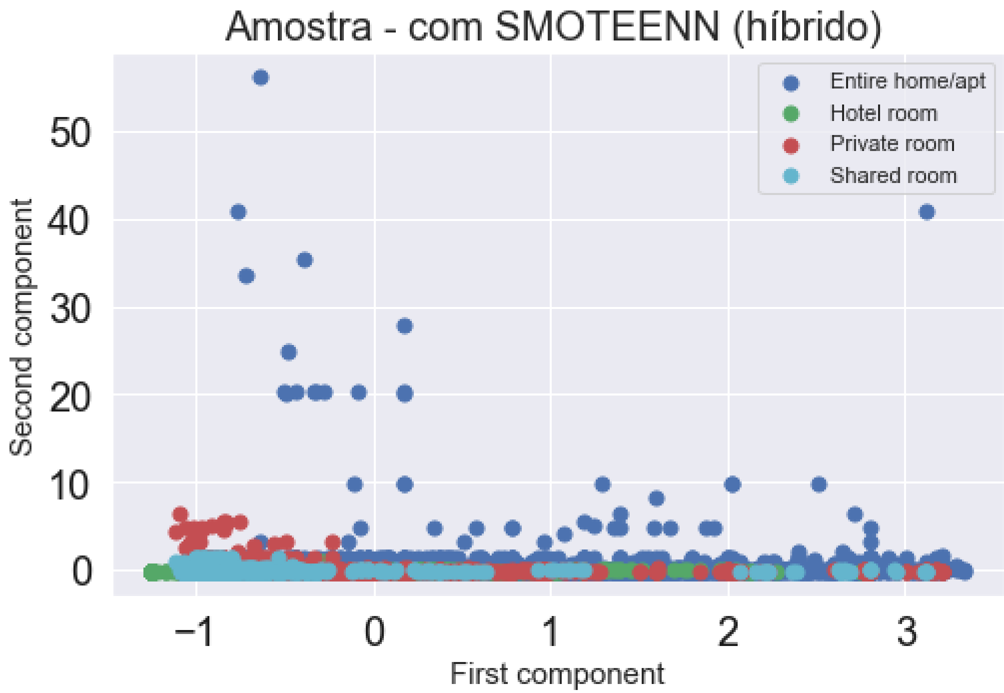
-- Under-sampling: As acurácias dos classificadores foram piores que as da base normal (sem balanceamento) e ao da base balanceada Over-sampling (SMOTE).

In [35]:

```
##-- SMOTEENN

strategy = {1: int(X.shape[0]* 0.1), 2: int(X.shape[0]* 0.4), 3: int(X.shape[0]* 0.1)}

overunder = combine.SMOTEENN(random_state=42,  sampling_strategy=strategy)
Xc, Yc = overunder.fit_resample(X, y)

h = plt.hist(Yc)
```



In [36]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
pca = PCA(n_components=2)

scaler = StandardScaler().fit(Xc)
pca_result = scaler.transform(Xc)

classes = np.unique(Yc)

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'w']
aux = 0
plt.figure(figsize=(8,5))
for c in classes:
    lb = c

    if lb == 0 :
        lb = 'Entire home/apt'
    elif lb == 1 :
        lb = 'Hotel room'
    elif lb == 2 :
        lb = 'Private room'
    else:
        lb = 'Shared room'
    nodes = np.where(Yc == c)
    plt.scatter(pca_result[nodes,0], pca_result[nodes,1], s=50, color = colors[aux], label = lb)
    aux = aux + 1
plt.legend()
plt.xlabel("First component", fontsize=15)
plt.ylabel("Second component", fontsize=15)
plt.xticks(color='k', size=20)
plt.yticks(color='k', size=20)
plt.title('Amostra - com SMOTEENN (híbrido) ', fontsize=20)
plt.show(True)
```


Amostra - com SMOTEENN (híbrido)
Entire home/apt
Hotel room
Private room
Shared room
Second component
First component
0
10
20
30
40
50
−1
0
1
2
3

In [37]:
```
models = [
        ('Tree Gini', tree.DecisionTreeClassifier(criterion = 'gini', random_state = 101)),
        ('Tree Entropy', tree.DecisionTreeClassifier(criterion = 'entropy',random_state = 101)),
        ('Bagging', BaggingClassifier(base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy', random_state = 
101),
                          n_estimators=10)) ,
        ('Boosting', AdaBoostClassifier(n_estimators=10,learning_rate=1,
                         base_estimator=tree.DecisionTreeClassifier(criterion = 'entropy'))),
        ('Random Forest', RandomForestClassifier(n_estimators=100, bootstrap=True, class_weight=None, criterion='gini'
,
            max_depth=None, max_features='auto', 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_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False))
    ]

import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

p = 0.2 # fraction of elements in the training set
x_train, x_test, y_train, y_test = train_test_split(Xc, Yc, test_size = p, random_state = 42)

for name, model in models:
    model.fit (x_train, y_train)
    print ('Accuracy ({}): \t{}'.format (name, model.score(x_test,y_test)))
```

```
Accuracy (Tree Gini):   0.9219497607655502
Accuracy (Tree Entropy):        0.9156698564593302
Accuracy (Bagging):     0.9383971291866029
Accuracy (Boosting):    0.9174641148325359
Accuracy (Random Forest):       0.9572368421052632
```

-- SMOTEENN (híbrido): As acurácias dos classificadores foram melhores que as da base normal (sem balanceamento) e as das bases balanceadas Over-sampling (SMOTE) e Under-sampling.

Salvar bases

In [38]:
```
##-- Salva base de dados sem balanceamento
cabec = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'neighb
ourhood_cod', 'room_type_tgt']

bd_SemBalanceamento = data_n[cabec]
bd_SemBalanceamento.to_pickle('E:/CV\Processo Seletivo/Cognitivo-ai/bd_SemBalanceamento.pkl')
```

In [39]:
```
##-- Salva cadastro balanceado - bd_oversampling
cabec = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'neighb
ourhood_cod']

bd_oversampling = pd.DataFrame(Xo, columns=cabec)
bd_oversampling['room_type_tgt']= Yo
bd_oversampling.to_pickle('E:/CV\Processo Seletivo/Cognitivo-ai/bd_oversampling.pkl')
```

In [40]:
```
##-- Salva cadastro balanceado - bd_undersampling
cabec = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'neighb
ourhood_cod']

bd_undersampling = pd.DataFrame(Xu, columns=cabec)
bd_undersampling['room_type_tgt']= Yu
bd_undersampling.to_pickle('E:/CV\Processo Seletivo/Cognitivo-ai/bd_undersampling.pkl')
```

In [41]:
```
##-- Salva cadastro balanceado - bd_SMOTEENN_Comb
cabec = ['price', 'minimum_nights', 'number_of_reviews', 'calculated_host_listings_count', 'availability_365', 'neighb
ourhood_cod']

bd_SMOTEENN_Comb = pd.DataFrame(Xc, columns=cabec)
bd_SMOTEENN_Comb['room_type_tgt']= Yc
bd_SMOTEENN_Comb.to_pickle('E:/CV\Processo Seletivo/Cognitivo-ai/bd_SMOTEENN_Comb.pkl')
```

In [ ]: