capstone_project1

June 22, 2020

0.1 Predicting House Rent

0.2 Introduction:

Brazil Housing is an Public dataset. In this dataset there are total 13 features and 10692 datapoints.

We have house info like city, area, rooms, parking space etc. On this basis we have to predict the "total" rent of house. Here target variable is "total (R$)" column.

0.3 Objective:

In this notebook, we are supposed to clean data,exploratory data analysis , feature engineering, data treatment and application of Machine Learning models to predict the 'total (R$)'.

0.4 Dataset Information:

Brazil Housing is an Public dataset. In this dataset there are total 13 features and 10692 datapoints.

The features columns in the dataset are: 1. city - city located 2. area - area of house 3. rooms - quantity of rooms 4. bathroom - quantity of bathrooms 5. parking spaces - quantity of parking spaces 6. floor - floor 7. animal - acept animals or not 8. furniture - furnish or not 9. hoa - Homeowners association tax 10. property tax - property tax 1. rent amount - rental price 1. fire insurance - fire insurance 1. total - total value

0.5 Important process followed :

- Dataset Preparation and Preprocessing
- Model Training
- Model Testing and Evaluation
- Conclusion

0.5.1 Data preprocessing, Data cleaning, Model Preparation, Model Fitting:

following are the steps: 1. Read the file and explore dataset. 2. Preprocess the data and feature engineering:(Perform an exploratory analysis of the data in order to gain insights and choose the best features) 1. Check the null values from the dataset and handle them appropriately. 2. Remove the insignificant columns from the dataset if necessary. 1. Convert the categorical columns to numerical columns. 1. labelling 2. Perform EDA on the dataset using visualization such as bar plot , Box plot , count plot etc. 2.Split the data into training and testing. 1.train the model with differnt regression techniques. 2. Observe the accuracy of each model and conclude which model gives the maximum accuracy. 1.select model with maximum accuracy and test the data.

Lets start working on dataset

Import required libraries:

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import seaborn as sns
from scipy import stats
from scipy.stats import norm
import warnings
warnings.filterwarnings('ignore',category=DeprecationWarning)
```

[4]:
```
df1=pd.read_csv('brazil_housing.csv')
```

[5]:
```
df1.head()
```

[5]:

	city	area	rooms	bathroom	parking spaces	floor	animal	furniture	hoa (R$)	rent amount (R$)	property tax (R$)	fire insurance (R$)	total (R$)
0	São Paulo	70	2	1	1	7	acept	furnished	2065	3300	211	42	5618
1	São Paulo	320	4	4	0	20	acept	not furnished	1200	4960	1750	63	7973
2	Porto Alegre	80	1	1	1	6	acept	not furnished	1000	2800	0	41	3841
3	Porto Alegre	51	2	1	0	2	acept	not furnished	270	1112	22	17	1421
4	São Paulo	25	1	1	0	1	not acept	not furnished	0	800	25		

```
4                    11          836
```

[6]:
```
df1.shape
```

[6]:
```
(10692, 13)
```

[7]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10692 entries, 0 to 10691
Data columns (total 13 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   city                 10692 non-null  object
 1   area                 10692 non-null  int64
 2   rooms                10692 non-null  int64
 3   bathroom             10692 non-null  int64
 4   parking spaces       10692 non-null  int64
 5   floor                10692 non-null  object
 6   animal               10692 non-null  object
 7   furniture            10692 non-null  object
 8   hoa (R$)             10692 non-null  int64
 9   rent amount (R$)     10692 non-null  int64
 10  property tax (R$)    10692 non-null  int64
 11  fire insurance (R$)  10692 non-null  int64
 12  total (R$)           10692 non-null  int64
dtypes: int64(9), object(4)
memory usage: 1.1+ MB
```

[8]:
```
df1.columns
```

[8]:
```
Index(['city', 'area', 'rooms', 'bathroom', 'parking spaces', 'floor',
       'animal', 'furniture', 'hoa (R$)', 'rent amount (R$)',
       'property tax (R$)', 'fire insurance (R$)', 'total (R$)'],
      dtype='object')
```

[9]:
```
df1.describe()
```

[9]:

	area	rooms	bathroom	parking spaces	hoa (R$)	\
count	10692.000000	10692.000000	10692.000000	10692.000000	1.069200e+04	
mean	149.217920	2.506079	2.236813	1.609147	1.174022e+03	
std	537.016942	1.171266	1.407198	1.589521	1.559231e+04	
min	11.000000	1.000000	1.000000	0.000000	0.000000e+00	
25%	56.000000	2.000000	1.000000	0.000000	1.700000e+02	
50%	90.000000	2.000000	2.000000	1.000000	5.600000e+02	
75%	182.000000	3.000000	3.000000	2.000000	1.237500e+03	
max	46335.000000	13.000000	10.000000	12.000000	1.117000e+06	

```
       rent amount (R$)  property tax (R$)  fire insurance (R$)    total (R$)
count      10692.000000       10692.000000         10692.000000  1.069200e+04
mean        3896.247194         366.704358            53.300879  5.490487e+03
std         3408.545518        3107.832321            47.768031  1.648473e+04
min          450.000000           0.000000             3.000000  4.990000e+02
25%         1530.000000          38.000000            21.000000  2.061750e+03
50%         2661.000000         125.000000            36.000000  3.581500e+03
75%         5000.000000         375.000000            68.000000  6.768000e+03
max        45000.000000      313700.000000           677.000000  1.120000e+06
```

[10]:
```
df1.isnull().sum()
```

[10]:
```
city                  0
area                  0
rooms                 0
bathroom              0
parking spaces        0
floor                 0
animal                0
furniture             0
hoa (R$)              0
rent amount (R$)      0
property tax (R$)     0
fire insurance (R$)   0
total (R$)            0
dtype: int64
```

No Null values *present*

[11]:
```
df1.isnull().describe()
```

[11]:
```
          city   area  rooms bathroom parking spaces  floor animal furniture  \
count   10692  10692  10692    10692          10692  10692  10692     10692
unique      1      1      1        1              1      1      1         1
top     False  False  False    False          False  False  False     False
freq    10692  10692  10692    10692          10692  10692  10692     10692

       hoa (R$) rent amount (R$) property tax (R$) fire insurance (R$)  \
count     10692            10692             10692                10692
unique        1                1                 1                    1
top       False            False             False                False
freq      10692            10692             10692                10692

       total (R$)
count       10692
unique          1
```

```
top         False
freq        10692
```

rename the columns for better of computations

[12]:
```
df1.rename(columns={'hoa (R$)':'hoa','rent amount (R$)':'rent amount','property tax (R$)':'property tax','fire insurance (R$)':'fire insurance','total (R$)':'total'},inplace=True)
```

[13]:
```
df1
```

[13]:

	city	area	rooms	bathroom	parking spaces	floor	animal	furniture	hoa	rent amount	property tax	fire insurance	total
0	São Paulo	70	2	1	1	7	acept	furnished	2065	3300	211	42	5618
1	São Paulo	320	4	4	0	20	acept	not furnished	1200	4960	1750	63	7973
2	Porto Alegre	80	1	1	1	6	acept	not furnished	1000	2800	0	41	3841
3	Porto Alegre	51	2	1	0	2	acept	not furnished	270	1112	22	17	1421
4	São Paulo	25	1	1	0	1	not acept	not furnished	0	800	25	11	836
…	…	…	…	…	…	…	…	…	…	…	…	…	…
10687	Porto Alegre	63	2	1	1	5	not acept	furnished	402	1478	24	22	1926
10688	São Paulo	285	4	4	4	17	acept	not furnished	3100	15000	973	191	19260
10689	Rio de Janeiro	70	3	3	0	8	not acept	furnished	980	6000	332	78	7390
10690	Rio de Janeiro	120	2	2	2	8	acept	furnished	1585	12000	279	155	14020
10691	São Paulo	80	2	1	0	-	acept	not furnished	0	1400	165	22	1587

[10692 rows x 13 columns]

[14]:
```
df1['city'].unique()
```

[14]:
```
array(['São Paulo', 'Porto Alegre', 'Rio de Janeiro', 'Campinas',
       'Belo Horizonte'], dtype=object)
```

lets explore to floor feature

[15]:
```
df1.floor.unique()
```

[15]:
```
array(['7', '20', '6', '2', '1', '-', '4', '3', '10', '11', '24', '9',
       '8', '17', '18', '5', '13', '15', '16', '14', '26', '12', '21',
       '19', '22', '27', '23', '35', '25', '46', '28', '29', '301', '51',
       '32'], dtype=object)
```

Floor column consists of '-' value. to convert it to numerical, we will replace it with 1 (minimum value).

Also we will convert this categorical feature to Numerical feature for computation purpose.

[16]:
```
df1['floor']=df1['floor'].replace('-',1)
df1['floor']=df1['floor'].apply(lambda x:int(x))
```

[17]:
```
df1.floor.unique()
```

[17]:
```
array([  7,  20,   6,   2,   1,   4,   3,  10,  11,  24,   9,   8,  17,
        18,   5,  13,  15,  16,  14,  26,  12,  21,  19,  22,  27,  23,
        35,  25,  46,  28,  29, 301,  51,  32])
```

here, floor has value= 301, which is impossible. This is a outlier.

[18]:
```
df1[df1['floor']==51]
```

[18]:

	city	area	rooms	bathroom	parking spaces	floor	animal	furniture	hoa	rent amount	property tax	fire insurance	total
5694	Campinas	64	2	2	2	51	acept	not furnished	800	1900	129	25	2854

[19]:
```
df1[(df1['city']=='Campinas') & (df1['floor']>20)]
```

[19]:

	city	area	rooms	bathroom	parking spaces	floor	animal	furniture	hoa	rent amount	property tax	fire insurance	total
5694	Campinas	64	2	2	2	51	acept	not furnished	800	1900	129	25	2854

This tells that 'Campinas' city has generally no building with floor value greater than 20. Again this is an outlier.

[20]:
```
df1.floor.value_counts()
```

[20]:
```
1      3542
2       985
3       931
4       748
5       600
6       539
7       497
```

```
8       490
9       369
10      357
11      303
12      257
13      200
14      170
15      147
16      109
17       96
18       75
19       53
20       44
21       42
25       25
23       25
22       24
26       20
24       19
27        8
28        6
29        5
32        2
51        1
301       1
46        1
35        1
Name: floor, dtype: int64
```

[21]:
```
df1[df1['floor']>45]
```

[21]:
```
                city  area  rooms  bathroom  parking spaces  floor animal  \
1654       São Paulo   353      4         5               5     46  acept
2562  Belo Horizonte    80      3         2               2    301  acept
5694        Campinas    64      2         2               2     51  acept

          furniture   hoa  rent amount  property tax  fire insurance  total
1654  not furnished  3000        10000             0             127  13130
2562  not furnished   750         2600           164              35   3549
5694  not furnished   800         1900           129              25   2854
```

This are the outlier with respect to floor feature. lets remove them as follows.

[22]:
```
df1=df1[df1['floor']<45]
```

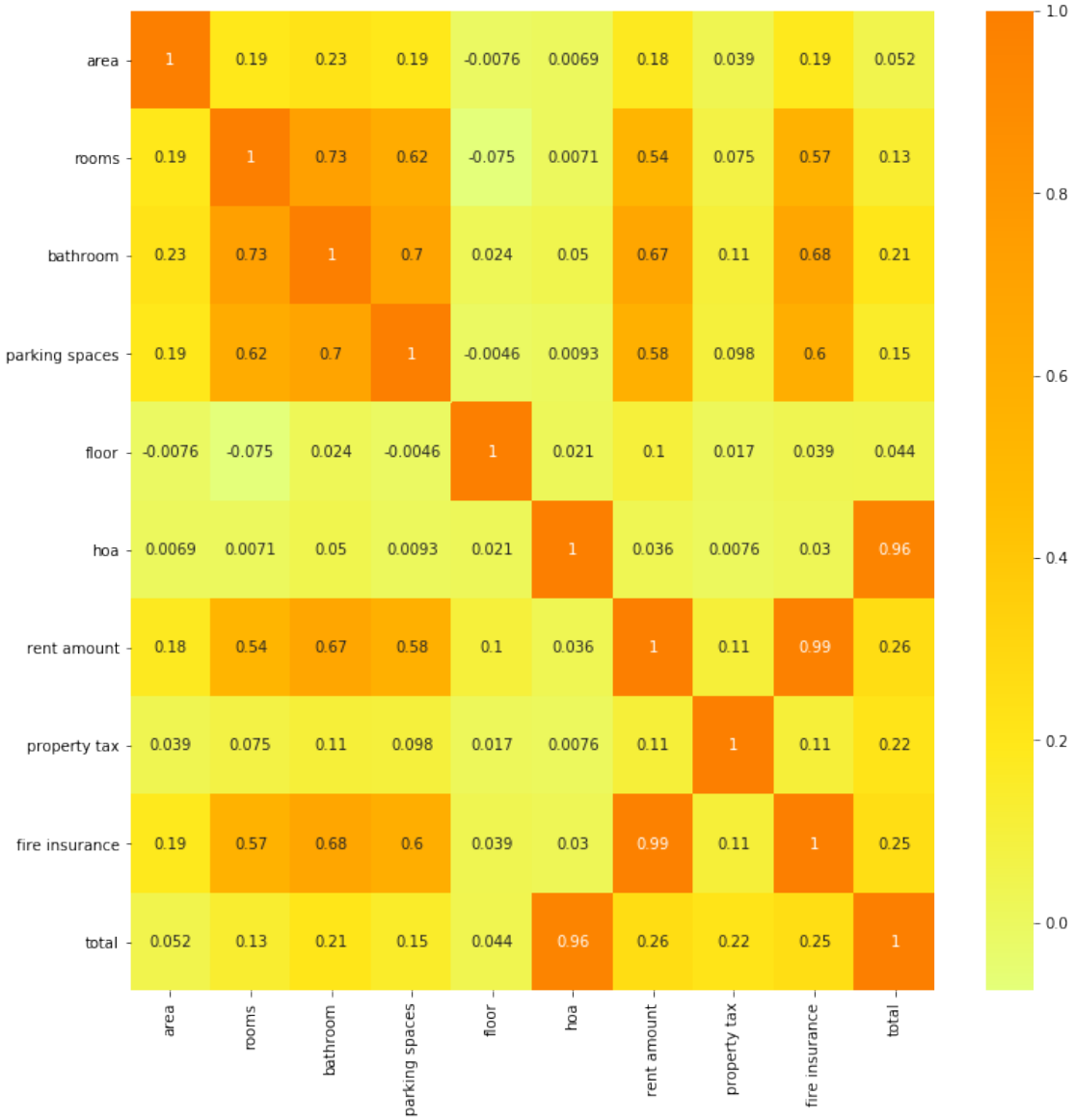
[23]:
```
df1.describe()
```

[23]:
```
                area         rooms      bathroom  parking spaces         floor  \
count  10689.000000  10689.000000  10689.000000    10689.000000  10689.000000
mean     149.213303      2.505941      2.236598        1.608757      5.262419
std      537.087637      1.171322      1.407138        1.589396      5.114125
min       11.000000      1.000000      1.000000        0.000000      1.000000
25%       56.000000      2.000000      1.000000        0.000000      1.000000
50%       90.000000      2.000000      2.000000        1.000000      3.000000
75%      182.000000      3.000000      3.000000        2.000000      8.000000
max    46335.000000     13.000000     10.000000       12.000000     35.000000

                hoa   rent amount   property tax  fire insurance         total
count  1.068900e+04  10689.000000   10689.000000    10689.000000  1.068900e+04
mean   1.173926e+03   3895.984189     366.779867       53.298344  5.490201e+03
std    1.559448e+04   3408.434795    3108.264964       47.768303  1.648684e+04
min    0.000000e+00    450.000000       0.000000        3.000000  4.990000e+02
25%    1.700000e+02   1530.000000      38.000000       21.000000  2.061000e+03
50%    5.600000e+02   2662.000000     125.000000       36.000000  3.582000e+03
75%    1.237000e+03   5000.000000     375.000000       68.000000  6.768000e+03
max    1.117000e+06  45000.000000  313700.000000      677.000000  1.120000e+06
```

[24]:
```
corr=df1.corr()
corr['total']
```

[24]:
```
area              0.051780
rooms             0.134554
bathroom          0.208290
parking spaces    0.148632
floor             0.043958
hoa               0.955031
rent amount       0.264448
property tax      0.218350
fire insurance    0.254869
total             1.000000
Name: total, dtype: float64
```

[25]:
```
fig = plt.figure(figsize=(12,12))
sns.heatmap(corr, cmap = 'Wistia', annot= True);
```



From the above heapmap, once can easily predict that, floor feature is least corelated with total. so lets remove this feature

[26]:
```
df2=df1.drop('floor',axis='columns')
```

[27]:
```
df2.head()
```

[27]:

	city	area	rooms	bathroom	parking spaces	animal	\
0	São Paulo	70	2	1	1	acept	
1	São Paulo	320	4	4	0	acept	
2	Porto Alegre	80	1	1	1	acept	
3	Porto Alegre	51	2	1	0	acept	

```
4     São Paulo    25      1         1               0  not acept

       furniture   hoa  rent amount  property tax  fire insurance  total
0      furnished  2065         3300           211              42   5618
1  not furnished  1200         4960          1750              63   7973
2  not furnished  1000         2800             0              41   3841
3  not furnished   270         1112            22              17   1421
4  not furnished     0          800            25              11    836
```

1 Convert the categorical columns to numerical columns.:

animal is categorical feature.we will convert this categorical feature to Numerical feature by simple labling. 1: acept 0: not acept

[28]:
```
animal_info=pd.DataFrame()
animal_info['name']=df2.animal.unique()
animal_info['label']=[1,0]
animal_info
```

[28]:
```
         name  label
0      acept      1
1  not acept      0
```

[29]:
```
df2['animal']=df2['animal'].replace({'acept':1,'not acept':0})
```

[30]:
```
df2.head()
```

[30]:
```
           city  area  rooms  bathroom  parking spaces  animal      furniture  \
0     São Paulo    70      2         1               1       1      furnished
1     São Paulo   320      4         4               0       1  not furnished
2  Porto Alegre    80      1         1               1       1  not furnished
3  Porto Alegre    51      2         1               0       1  not furnished
4     São Paulo    25      1         1               0       0  not furnished

    hoa  rent amount  property tax  fire insurance  total
0  2065         3300           211              42   5618
1  1200         4960          1750              63   7973
2  1000         2800             0              41   3841
3   270         1112            22              17   1421
4     0          800            25              11    836
```

[31]:
```
df2.animal.describe()
```

[31]:
```
count    10689.000000
mean         0.777715
std          0.415801
```

```
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
Name: animal, dtype: float64
```

furniture is categorical feature.we will convert this categorical feature to Numerical feature by simple labling. 1: furnished 0: not furnished

[32]:
```
furniture_info=pd.DataFrame()
furniture_info['name']=df2.furniture.unique()
furniture_info['label']=[1,0]
furniture_info
```

[32]:
```
            name  label
0      furnished      1
1  not furnished      0
```

[33]:
```
df2['furniture']=df2['furniture'].replace({'furnished':1,'not furnished':0})
```

[34]:
```
city_info=pd.DataFrame(df2['city'].unique())
city_info
```

[34]:
```
                0
0       São Paulo
1    Porto Alegre
2  Rio de Janeiro
3        Campinas
4  Belo Horizonte
```

[35]:
```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
df2['city']=le.fit_transform(df2['city'])
```

[36]:
```
city_info['label']=df2['city'].unique()
```

[37]:
```
city_info
```

[37]:
```
                0  label
0       São Paulo      4
1    Porto Alegre      2
2  Rio de Janeiro      3
3        Campinas      1
4  Belo Horizonte      0
```

we will keep 'city' column for next few steps

[38]:
```
df2.head()
```

[38]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
0	4	70	2	1	1	1	1	2065	
1	4	320	4	4	0	1	0	1200	
2	2	80	1	1	1	1	0	1000	
3	2	51	2	1	0	1	0	270	
4	4	25	1	1	0	0	0	0	

	rent amount	property tax	fire insurance	total
0	3300	211	42	5618
1	4960	1750	63	7973
2	2800	0	41	3841
3	1112	22	17	1421
4	800	25	11	836

[39]:
```
df2.mode()
```

[39]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
0	4	50	3	1	1	1	0	0	

	rent amount	property tax	fire insurance	total
0	2500	0	16	2555

1.1 Lets explore animal feature:

[40]:
```
animal_info
```

[40]:

	name	label
0	acept	1
1	not acept	0

[41]:
```
df2.animal.value_counts()
```

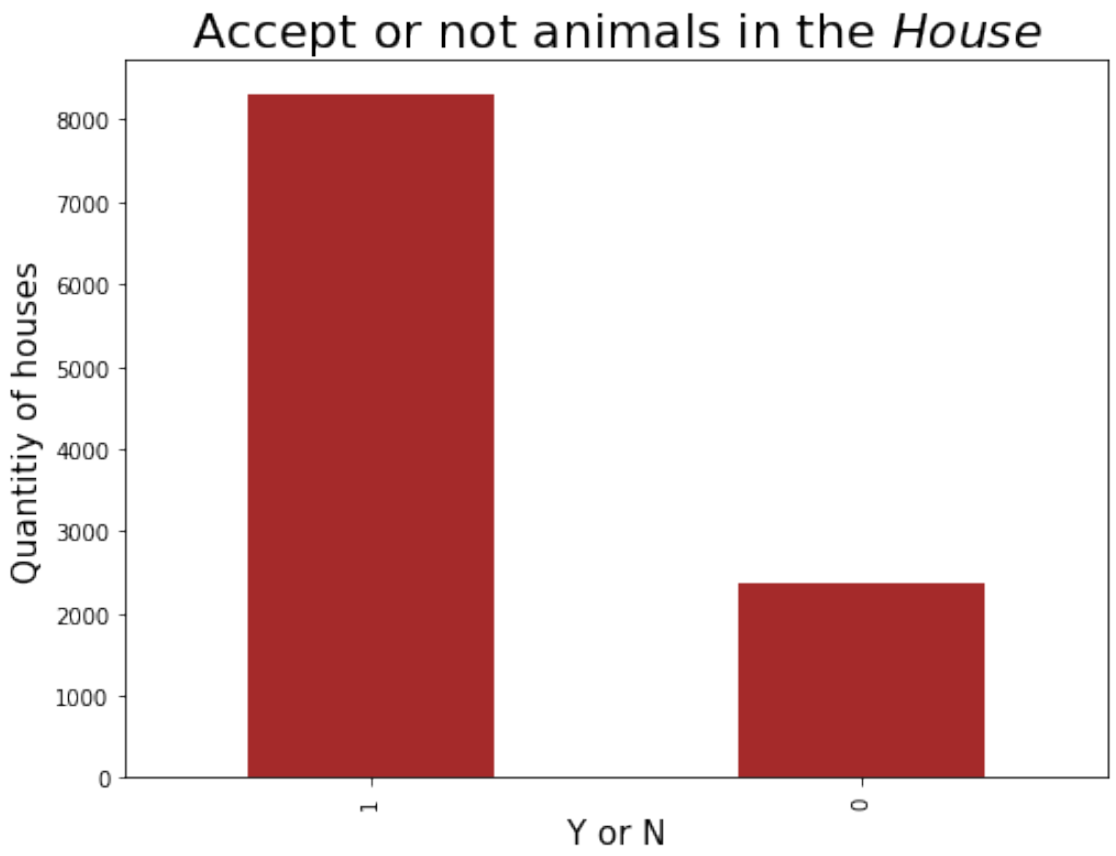
[41]:
```
1    8313
0    2376
Name: animal, dtype: int64
```

[42]:
```
size = [df2.animal.value_counts()]
labels = ['acept', 'not acept']
plt.pie(size, labels = labels, shadow = True, explode = [0, 0.1],radius=1)
plt.legend()
plt.title('Animal Pet Acceptance', fontsize = 20)
plt.show()
plt.tight_layout()
```

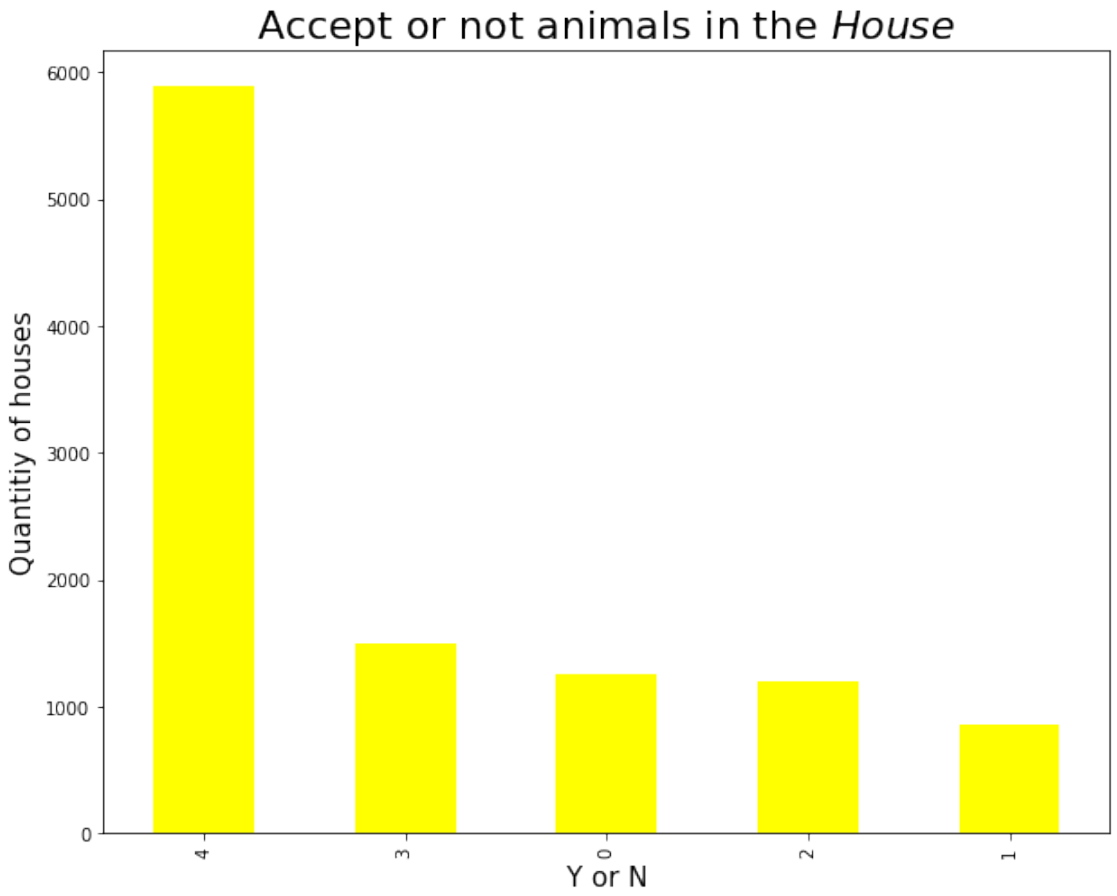
```
/home/rupam/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:3:
MatplotlibDeprecationWarning: Non-1D inputs to pie() are currently squeeze()d,
but this behavior is deprecated since 3.1 and will be removed in 3.3; pass a 1D
array instead.
  This is separate from the ipykernel package so we can avoid doing imports
until
```


```
<Figure size 432x288 with 0 Axes>
```

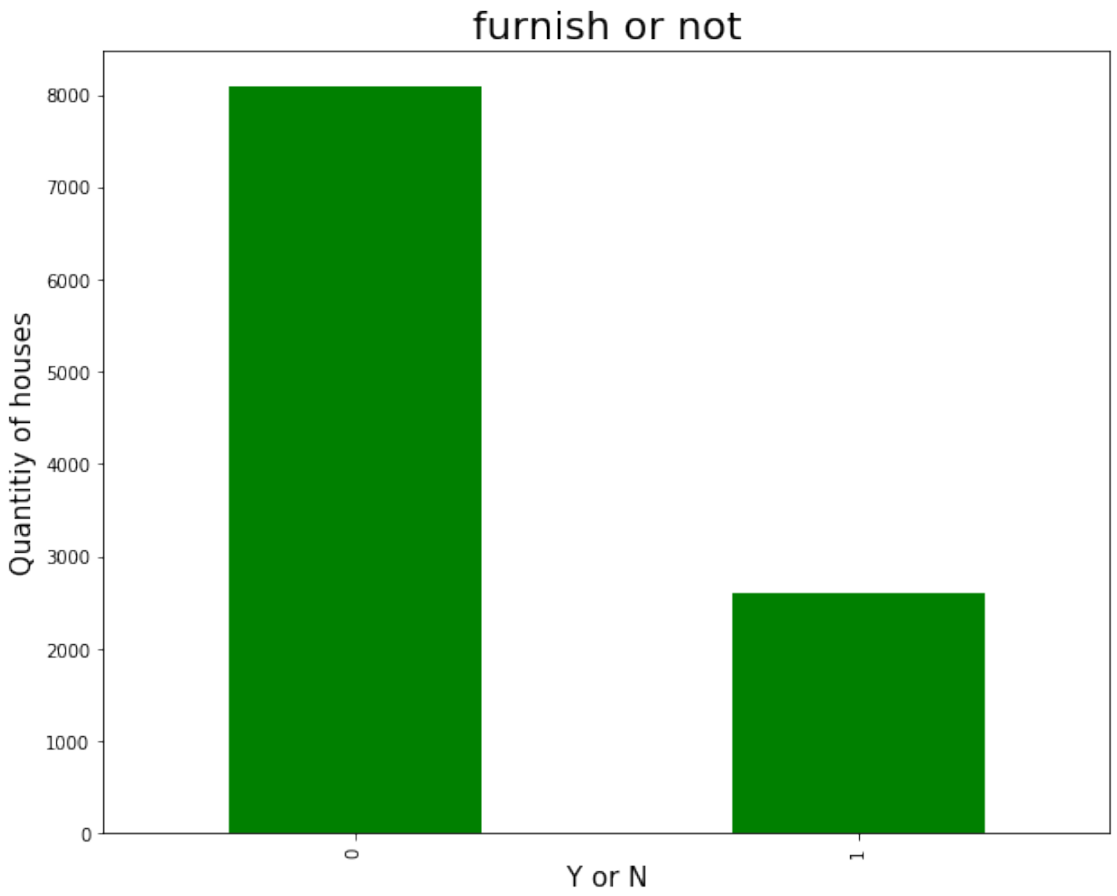
[43]:
```
ax = df2['animal'].value_counts().plot(kind = 'bar',figsize = (8,6),color =␣
↪'brown')
ax.set_title('Accept or not animals in the $House$', fontsize = 22)
ax.set_xlabel('Y or N', fontsize = 15)
ax.set_ylabel('Quantitiy of houses' , fontsize = 15)
plt.show()
```



[44]:
```
ax = df2['city'].value_counts().plot(kind = 'bar',figsize = (10,8),color =␣
↪'yellow')
ax.set_title('Accept or not animals in the $House$', fontsize = 22)
ax.set_xlabel('Y or N', fontsize = 15)
ax.set_ylabel('Quantitiy of houses' , fontsize = 15)
plt.show()
```

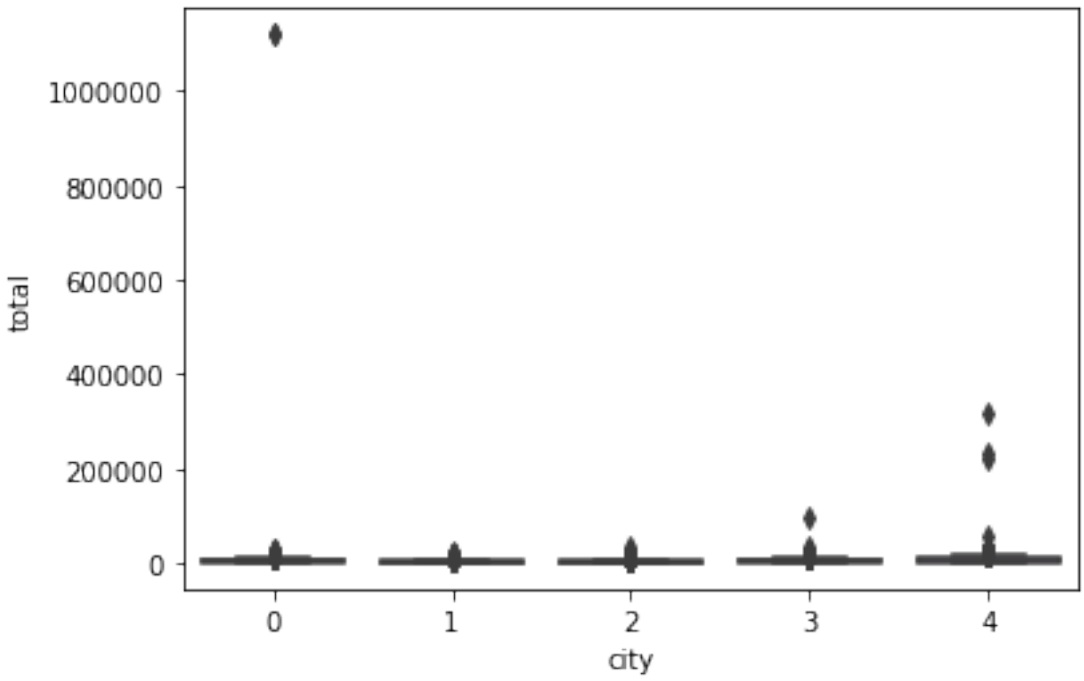


[45]:
```
ax = df2['furniture'].value_counts().plot(kind = 'bar',figsize = (10,8),color =␣
↪'green')
ax.set_title('furnish or not', fontsize = 22)
ax.set_xlabel('Y or N', fontsize = 15)
ax.set_ylabel('Quantitiy of houses' , fontsize = 15)
plt.show()
```



[46]:
```
sns.boxplot(x = 'city', y ='total', data = df2)
```

[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc2f64ac250>
```



This shows the total amount variation in differnt cities. also one can easily observe that our dataset contains various outliers.

lets remove those outlier

[47]:
```
city_group = df2.groupby('city')['total']
type(city_group)
```

[47]:
```
pandas.core.groupby.generic.SeriesGroupBy
```

[48]:
```
Q1 = city_group.quantile(.25)
Q3 = city_group.quantile(.75)
IIQ = Q3 - Q1
lower_limit = Q1 - 1.5* IIQ
upper_limit = Q3 + 1.5* IIQ
```

[49]:
```
Q1
```

[49]:
```
city
0    1610.0
1    1416.0
2    1465.0
3    2067.0
4    2630.0
Name: total, dtype: float64
```

[50]:
```
Q3
```

[50]:
```
city
0    5934.00
1    3632.25
2    3338.00
3    5566.00
4    8590.00
Name: total, dtype: float64
```

[51]:
```
city_group.groups.keys()
```

[51]:
```
dict_keys([0, 1, 2, 3, 4])
```

[52]:
```
new_data = pd.DataFrame()

for city in city_group.groups.keys():
    is_city = df2['city'] == city
    accepted_limit = ((df2['total'] >= lower_limit[city]) &
                      (df2['total'] <= upper_limit[city]))

    select = is_city & accepted_limit
    data_select = df2[select]
    new_data = pd.concat([new_data, data_select])

df3=new_data
```

This is how we have removed outliers.

[53]:
```
new_data.shape
```

[53]:
```
(10092, 12)
```

[54]:
```
df3
```

[54]:

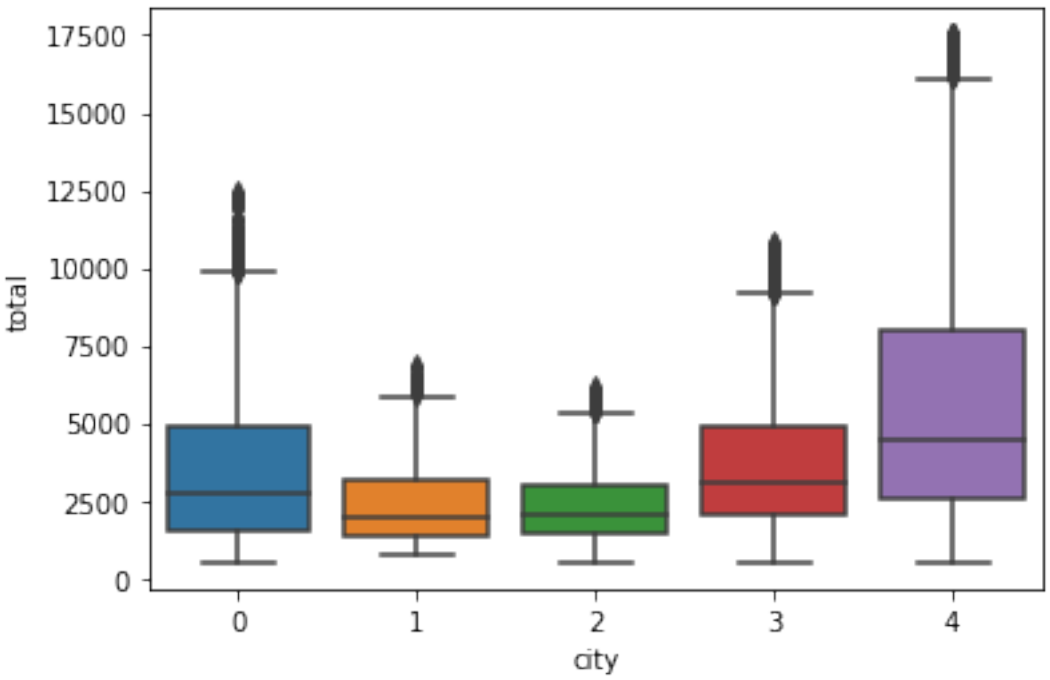
	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
21	0	42	1	1	1	0	1	470	
27	0	64	2	2	1	1	0	352	
37	0	80	3	2	1	1	0	0	
42	0	200	4	2	1	0	0	850	
43	0	45	1	1	1	1	0	500	
…	…	…	…	…	…	…	…	…	
10681	4	230	3	5	3	0	0	3800	
10683	4	280	4	4	2	1	0	4200	
10685	4	83	3	2	2	1	0	888	
10686	4	150	3	3	2	0	1	0	
10691	4	80	2	1	0	1	0	0	

	rent amount	property tax	fire insurance	total
21	2690	172	36	3368
27	1500	80	20	1952
37	11000	425	181	11610
42	2550	9	34	3443
43	1631	192	12	2335
…	…	…	…	…
10681	11000	1100	140	16040
10683	4000	1042	51	9293
10685	7521	221	96	8726
10686	13500	0	172	13670
10691	1400	165	22	1587

[10092 rows x 12 columns]

[55]:
```
sns.boxplot(x = 'city', y ='total', data = df3)
```

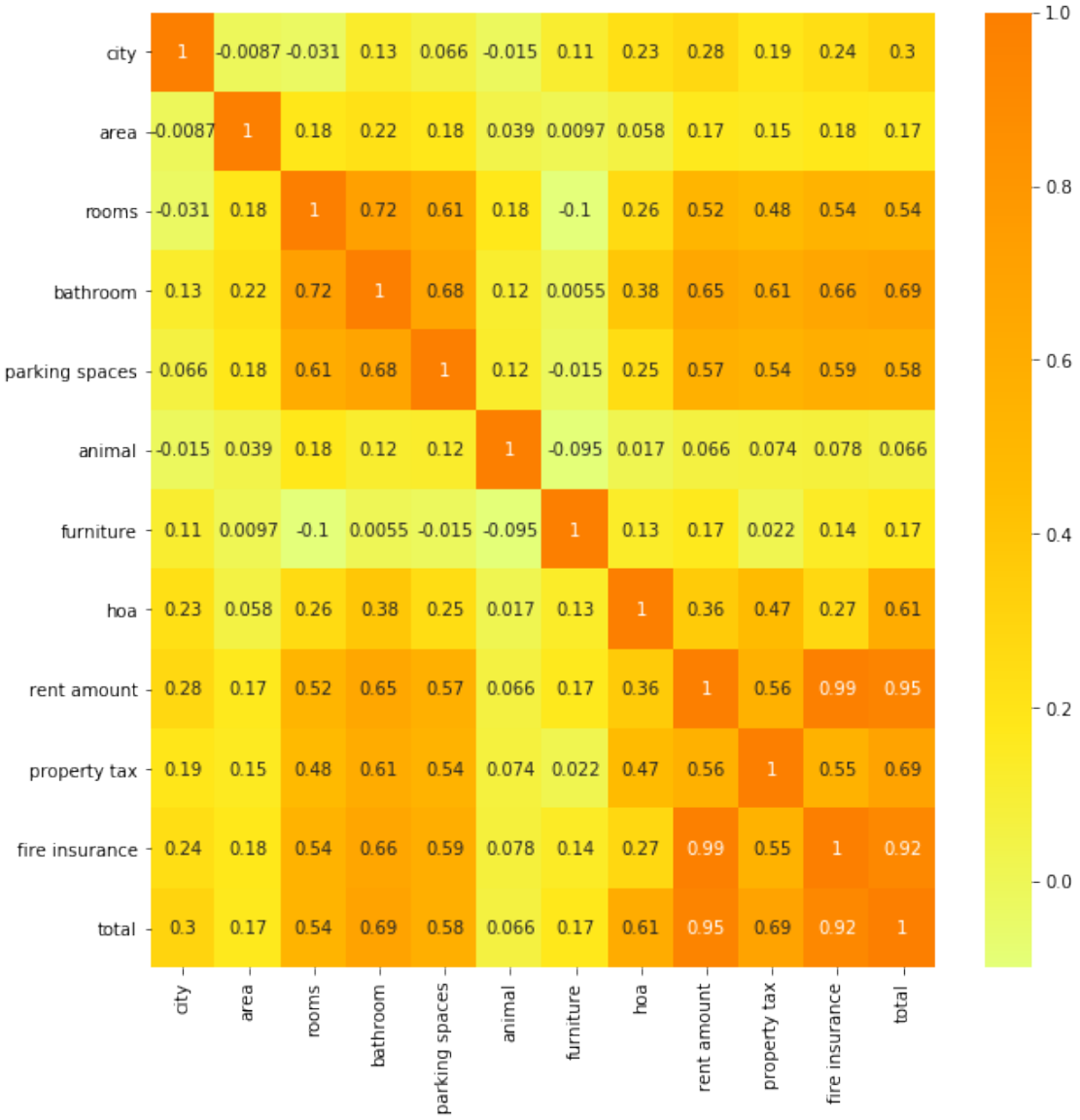
[55]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2f63b5690>



Above, plot is the boxplot for new data after removing outliers with respect to city and total. plot shows that our data is pretty good and one can observe that city named '4' which is São Paulo' has comparitively higher prices which is making it costly city.

[56]:
```
fig = plt.figure(figsize=(10,10))
corr = df3.corr()
```

```
sns.heatmap(corr, cmap = 'Wistia', annot= True);
```



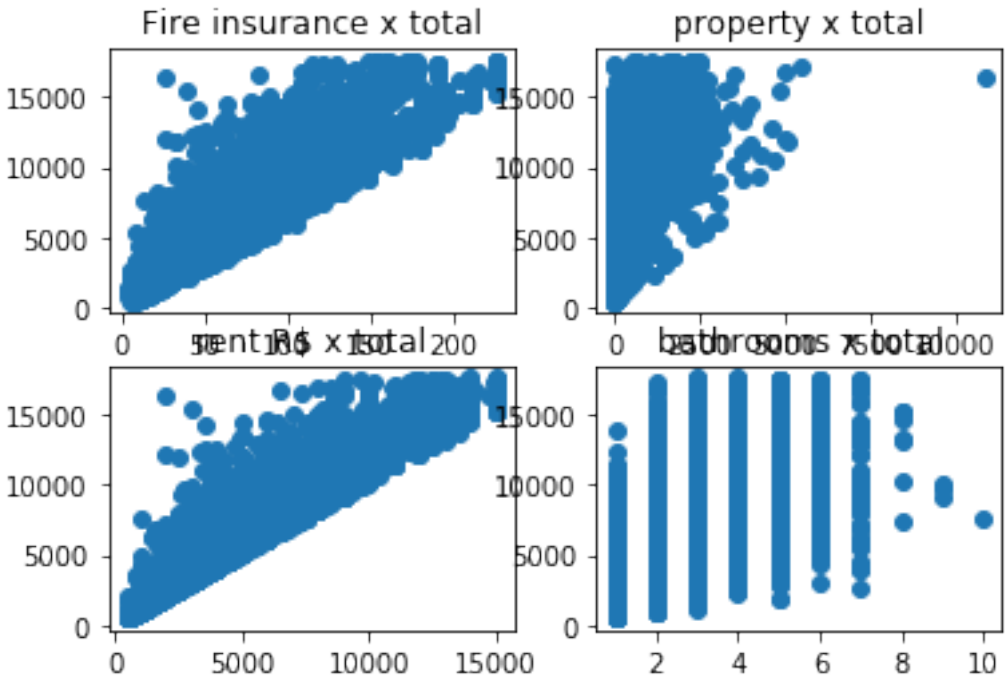
heatmap shows that there is strong relationship between following components:

- fire insurance and rent amount
- fire insurance and total
- total and rent amount
- room and total
- room and bathroom
- hoa and total

lets explore them with graphical view:

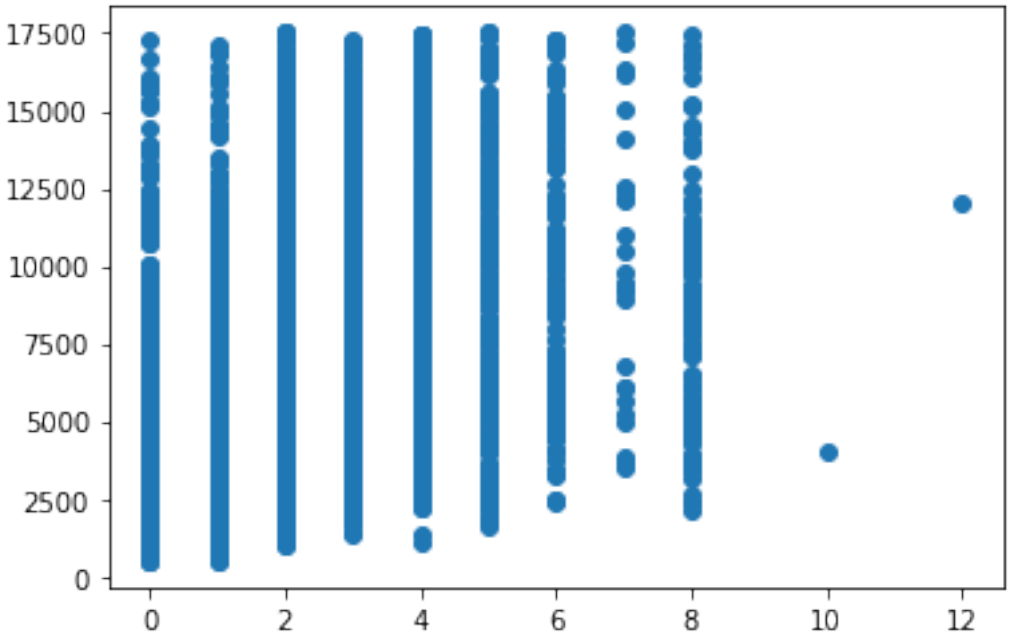
[57]:
```
area = plt.figure()
g1 = area.add_subplot(2,2,1)
g2 = area.add_subplot(2,2,2)
g3 = area.add_subplot(2,2,3)
g4 = area.add_subplot(2,2,4)
g1.scatter(df3['fire insurance'], df3['total'])
g1.set_title('Fire insurance x total')
g2.scatter(df3['property tax'],df3['total'])
g2.set_title('property x total')
g3.scatter(df3['rent amount'],df3['total'])
g3.set_title('rent R$ x total')
g4.scatter(df3['bathroom'],df3['total'])
g4.set_title('bathrooms x total')
```

[57]:
```
Text(0.5, 1.0, 'bathrooms x total')
```



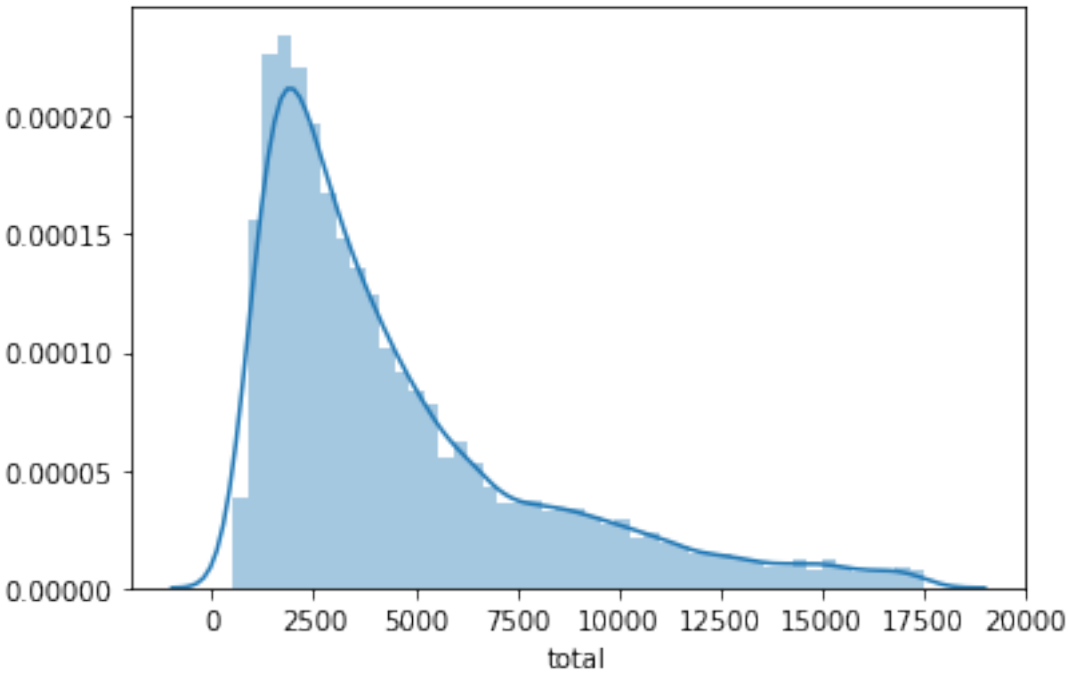
[58]:
```
plt.scatter(df3['parking spaces'], df3['total'])
```

[58]:
```
<matplotlib.collections.PathCollection at 0x7fc2f42ea650>
```



[59]:
```
sns.distplot(df3['total'])
```

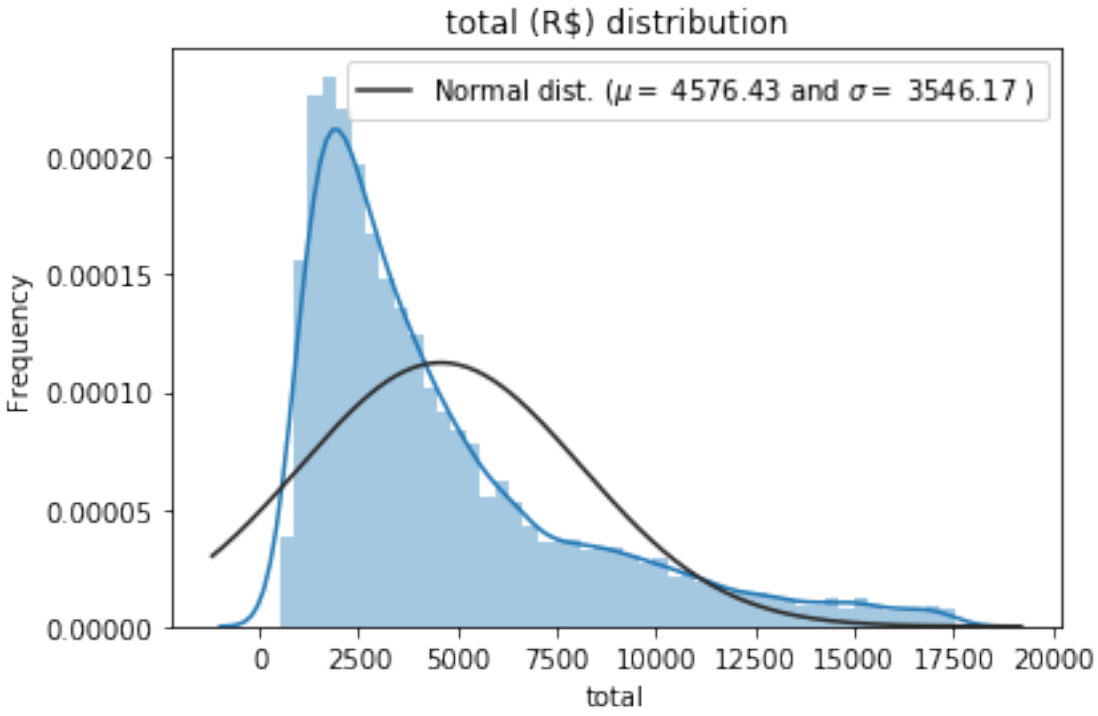
[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2f4242810>



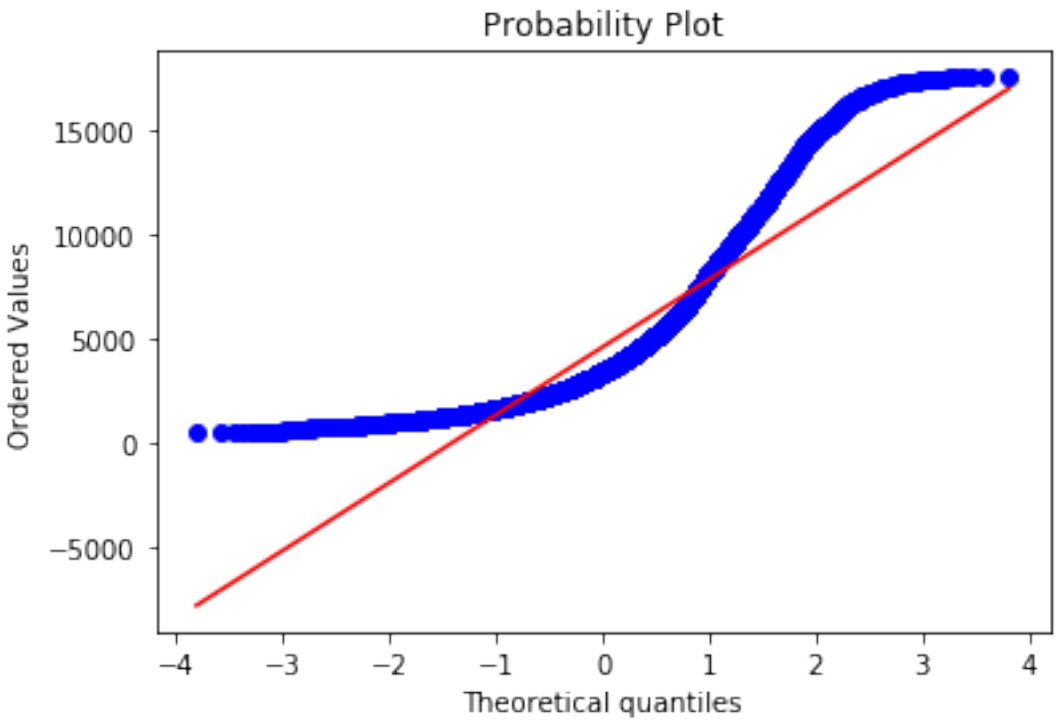
[60]:
```
sns.distplot(df3['total'], fit=norm);

(mu, sigma) = norm.fit(df3['total'])
print( '\n mu = {:.2f} and sigma = {:.2f}\n'.format(mu, sigma))
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu,␣
 ↪sigma)],
            loc='best')
plt.ylabel('Frequency')
plt.title('total (R$) distribution')
```

```
 mu = 4576.43 and sigma = 3546.17
```

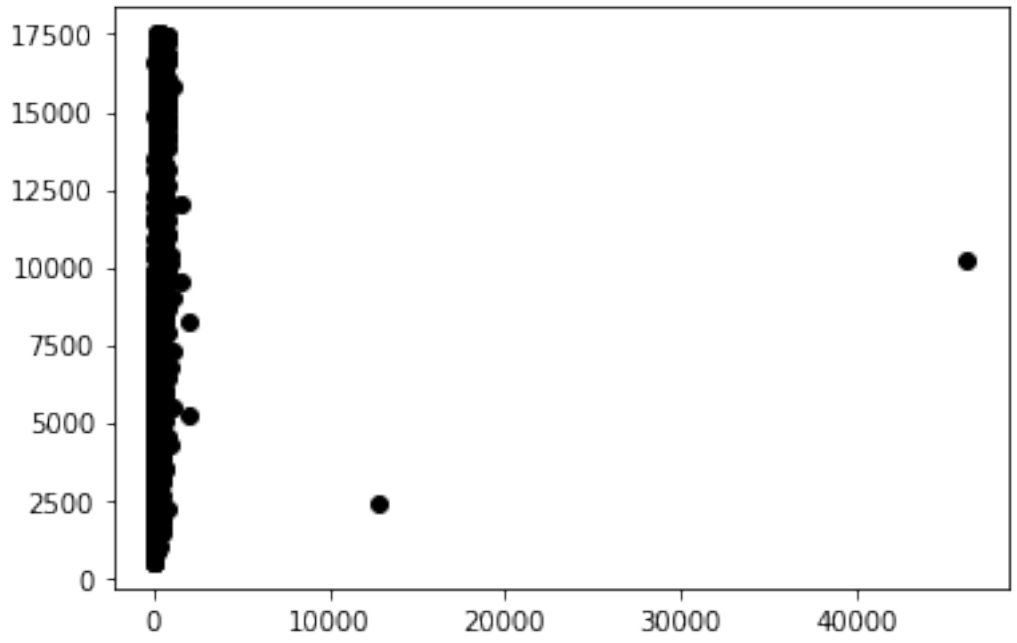
[60]:
```
Text(0.5, 1.0, 'total (R$) distribution')
```



[61]:
```
fig = plt.figure()
stats.probplot(df3['total'], plot=plt)
plt.show()
```



[62]:
```
plt.scatter(y =df3['total'],x = df3.area,c = 'black')
plt.show()
```



[69]:
```
Q1 = df3.quantile(0.25)
Q3 = df3.quantile(0.75)
IQR = Q3- Q1
print(IQR, df3.shape)
```

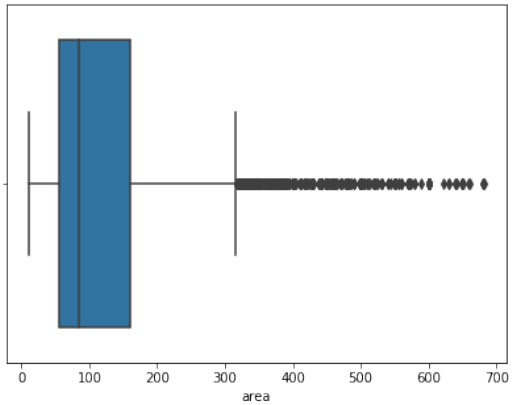
```
city                 2.0
area               105.0
rooms                1.0
bathroom             2.0
parking spaces       2.0
animal               0.0
furniture            0.0
hoa                930.0
rent amount       2848.0
property tax       284.0
fire insurance      39.0
total             3939.0
dtype: float64 (10041, 12)
```

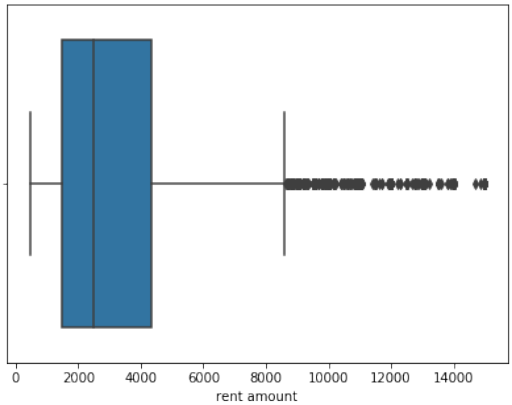
[70]:
```
Q1 = df3['area'].quantile(0.25)
Q3 = df3['area'].quantile(0.75)
IQR = Q3- Q1
```

[71]:
```
df3= df3[~((df3['area'] < (Q1 - 5*IQR)) | (df3['area'] > (Q3 + 5*IQR)))]
df3.shape
```

[71]: (10041, 12)

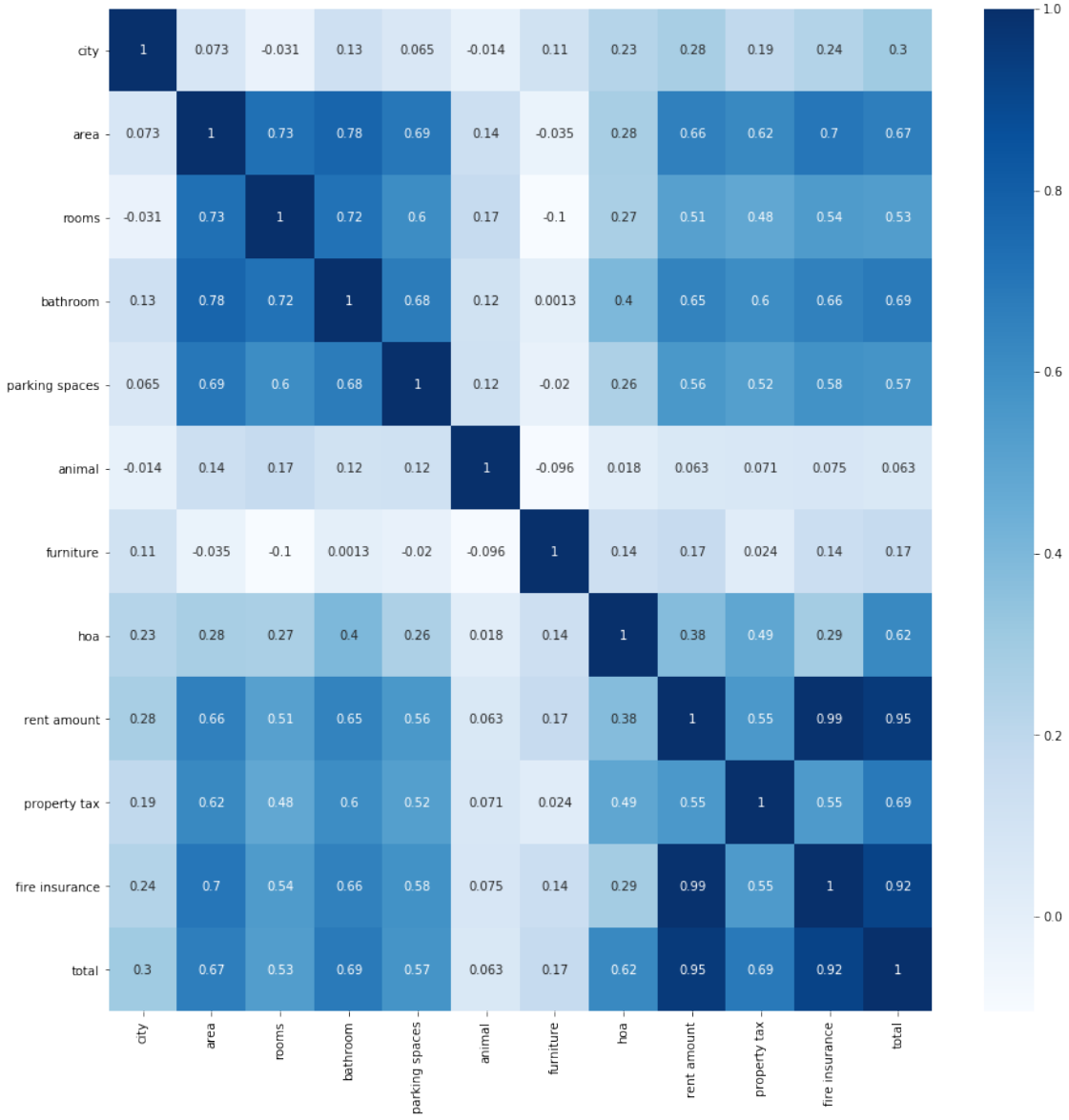
[72]:
```
fig, axs = plt.subplots(ncols=2, figsize=(15,5))
sns.boxplot(x=df3['area'], ax = axs[0])
sns.boxplot(x=df3['rent amount'], ax = axs[1])

plt.show()
```





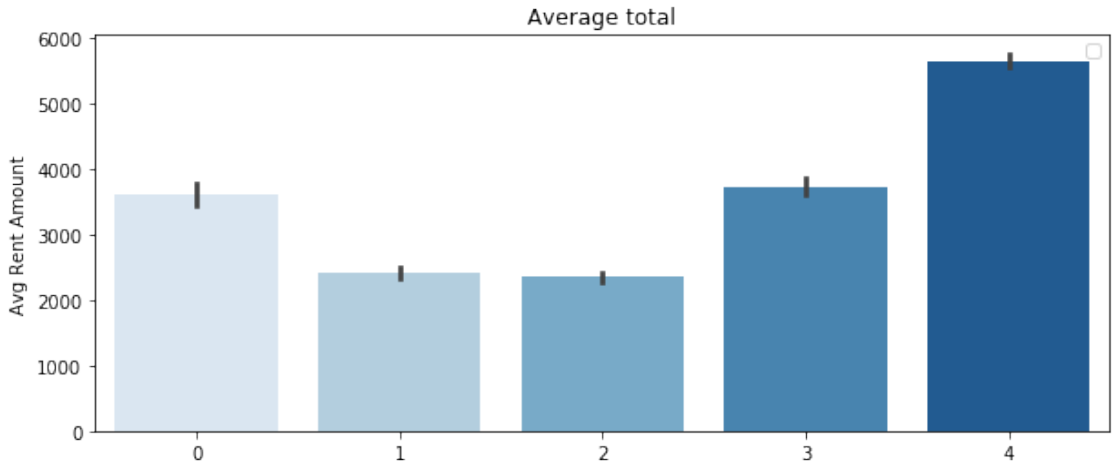
[73]:
```
plt.figure(figsize=(15,15))
c = df3.corr()
sns.heatmap(c,cmap='Blues', annot=True)
```

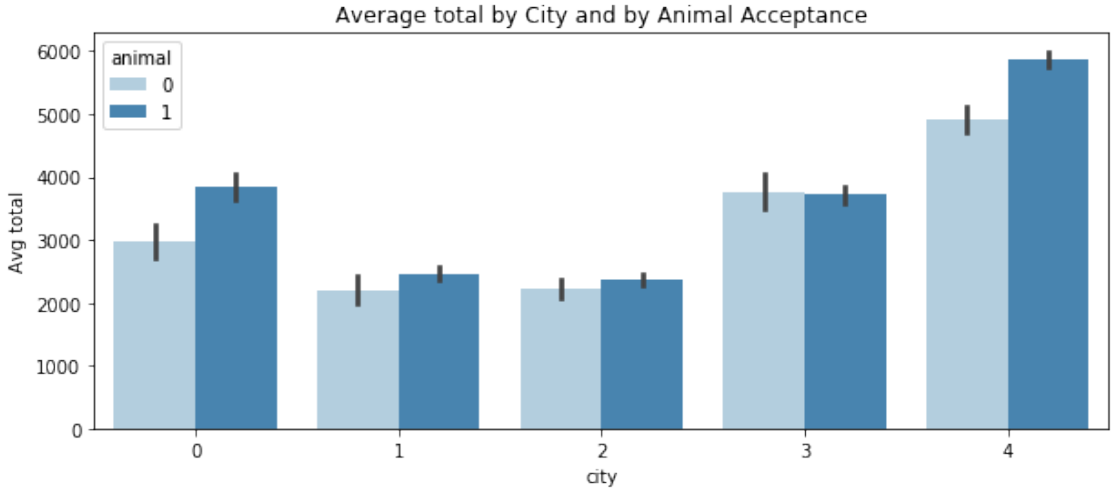
[73]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2f613f990>

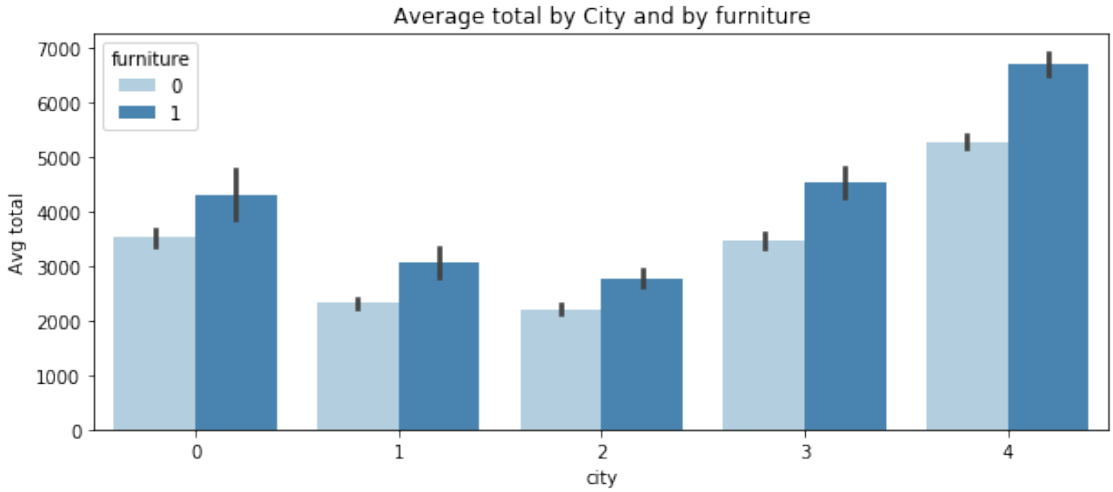


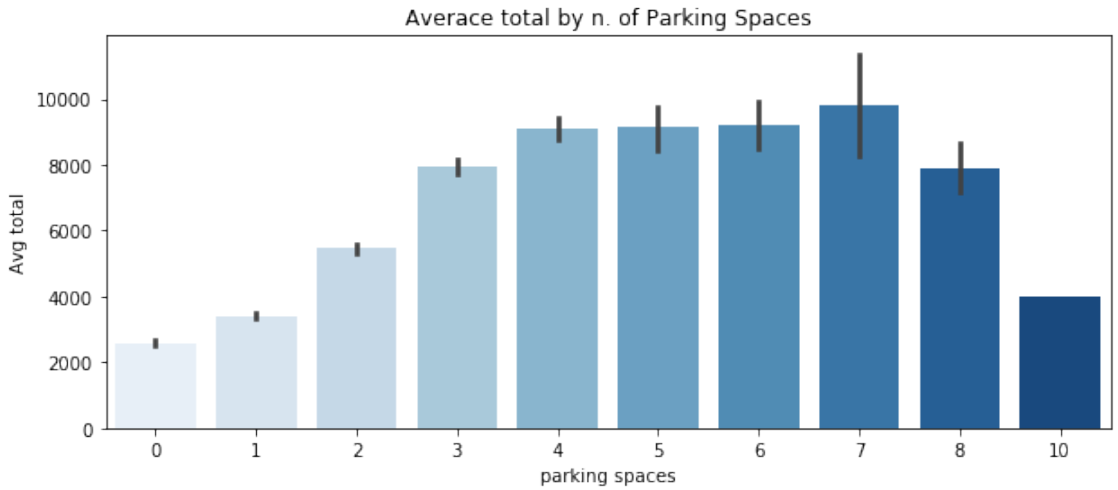
[74]:
```
from numpy import mean

plt.figure(figsize = (10,4))
sns.barplot(data = df3, x='city', y='total', estimator=mean, palette = "Blues")
```

```
plt.ylabel('Avg Rent Amount')
plt.xlabel('')
plt.title('Average total')
plt.legend('')

plt.figure(figsize = (10,4))
sns.barplot(x='city', y='total', data = df3, hue = 'animal', palette='Blues',␣
 ↪estimator = mean)
plt.ylabel('Avg total')
plt.title('Average total by City and by Animal Acceptance')

plt.figure(figsize = (10,4))
sns.barplot(x='city', y='total', data = df3, hue ='furniture', palette='Blues',␣
 ↪estimator = mean)
plt.ylabel('Avg total')
plt.title('Average total by City and by furniture')

plt.figure(figsize = (10,4))
sns.barplot(x='parking spaces', y='total', data = df3, palette='Blues',␣
 ↪estimator=mean)
plt.ylabel('Avg total')
plt.title('Averace total by n. of Parking Spaces')
plt.show()

plt.figure(figsize = (10,4))
sns.barplot(x='city', y='area', data = df3, palette='Blues', estimator = mean)
plt.ylabel('Avg area')
plt.title('Average total by City and by area ')
```

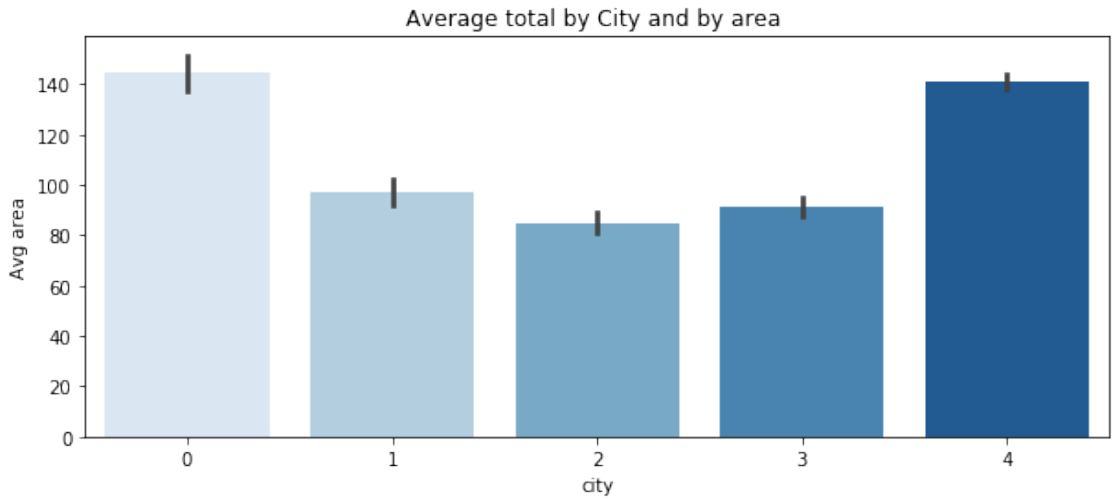



Average total by City and by Animal Acceptance
animal
0
1
Avg total
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
city


Average total by City and by furniture
furniture
0
1
Avg total
7000
6000
5000
4000
3000
2000
1000
0
0
1
2
3
4
city



[74]: Text(0.5, 1.0, 'Average total by City and by area ')



[75]:
```
df4=df3
```

[76]:
```
df4.shape
```

[76]: (10041, 12)

[77]:
```
c=df4.corr()
```

[78]:
```
c['total']
```

[78]:
```
city              0.303727
area              0.671775
rooms             0.533597
bathroom          0.688641
parking spaces    0.573870
animal            0.063146
furniture         0.172157
hoa               0.622417
rent amount       0.954340
property tax      0.689366
fire insurance    0.920206
total             1.000000
Name: total, dtype: float64
```

[79]:
```
df4.describe()
```

[79]:

	city	area	rooms	bathroom	parking spaces
count	10041.000000	10041.000000	10041.000000	10041.000000	10041.000000
mean	2.953789	124.985360	2.419878	2.104472	1.487003
std	1.417048	104.049806	1.123269	1.293156	1.481444
min	0.000000	11.000000	1.000000	1.000000	0.000000
25%	2.000000	55.000000	2.000000	1.000000	0.000000
50%	4.000000	85.000000	2.000000	2.000000	1.000000
75%	4.000000	160.000000	3.000000	3.000000	2.000000
max	4.000000	682.000000	10.000000	10.000000	10.000000

	animal	furniture	hoa	rent amount	property tax
count	10041.000000	10041.000000	10041.000000	10041.000000	10041.000000
mean	0.773529	0.236431	816.390001	3405.876905	270.925007
std	0.418569	0.424911	928.857584	2713.350549	438.489246
min	0.000000	0.000000	0.000000	450.000000	0.000000
25%	1.000000	0.000000	170.000000	1500.000000	34.000000
50%	1.000000	0.000000	540.000000	2500.000000	111.000000
75%	1.000000	0.000000	1100.000000	4348.000000	318.000000
max	1.000000	1.000000	8000.000000	15000.000000	10830.000000

	fire insurance	total
count	10041.000000	10041.000000
mean	46.420078	4539.788567
std	37.868637	3504.765060
min	3.000000	499.000000
25%	20.000000	1997.000000
50%	33.000000	3350.000000
75%	59.000000	5936.000000
max	226.000000	17520.000000

Lets explore area feature:

[80]:
```
df4['area'].mean()
```

[80]:
```
124.985360023902
```

[81]:
```
df4['area'].max()
```

[81]:
```
682
```

[82]:
```
df4['area'].min()
```

[82]:
```
11
```

[83]:
```
df4[df4['area']<15]
```

[83]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
785	4	11	1	1	0	0	1	300	
1588	4	13	1	1	0	1	0	0	
4864	4	13	1	1	0	1	0	0	
6784	4	12	1	1	0	0	0	0	

	rent amount	property tax	fire insurance	total
785	2000	42	26	2368
1588	2200	42	28	2270
4864	2200	5	28	2233
6784	950	50	13	1013

[84]:
```
df4[df4['area']>600]
```

[84]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
570	0	680	7	6	8	1	0	0	
2050	0	622	5	5	6	1	0	0	
3647	0	682	6	7	6	1	0	0	
6996	0	640	6	7	5	1	1	0	
7645	0	659	5	4	6	1	0	0	
1206	4	642	4	7	4	1	0	0	
1276	4	629	4	4	4	1	0	0	
1774	4	640	4	4	4	1	1	5400	
3570	4	650	4	6	6	1	0	0	
4471	4	630	4	6	4	0	0	0	
5257	4	650	4	6	5	1	0	0	
5779	4	680	4	5	8	1	0	0	
6202	4	650	3	7	2	1	0	0	
7906	4	660	4	6	4	1	0	500	
8112	4	651	7	7	8	1	0	0	

	rent amount	property tax	fire insurance	total
570	8000	428	132	8560

```
2050        10000            924              164  11090
3647         5500            428               91   6019
6996         6141            667              101   6909
7645        11000            913              181  12090
1206         9050            250              137   9437
1276        15000           2064              226  17290
1774        10200           1584              130  17310
3570         8500           1600              128  10230
4471        12300           2667              185  15150
5257        10000            834              151  10990
5779         8000            217              121   8338
6202         9900            600              149  10650
7906         6000           4283               91  10870
8112         8500           1595              128  10220
```

[85]:
```
df5=df4
type(df5)
```

[85]:
```
pandas.core.frame.DataFrame
```

consider, Usually room need minimum 15 unit of area and maximum 200 unit. those data values which are beyond this values are certainly outliers. lets explore them and clean the data:

[86]:
```
df5[(df5.area/df5.rooms)<15]
```

[86]:
```
      city  area  rooms  bathroom  parking spaces  animal  furniture  hoa  \
2867     0   100      7         2               1       1          0    0
7770     0    25      2         1               0       0          0    0
325      2    28      2         1               1       1          0    0
20       4   100      7         4               0       1          0    0
785      4    11      1         1               0       0          1  300
1588     4    13      1         1               0       1          0    0
2899     4    41      3         2               1       0          1    0
3935     4    35      5         1               0       1          0    0
4194     4    35      3         2               0       1          0    0
4864     4    13      1         1               0       1          0    0
6784     4    12      1         1               0       0          0    0
7448     4    30      4         4               2       1          1    0
8931     4    24      2         2               1       1          0  993

      rent amount  property tax  fire insurance  total
2867         2800            28              46   2874
7770         2200           104              30   2334
325           600             0              11    611
20           3800           118              58   3976
785          2000            42              26   2368
1588         2200            42              28   2270
```

```
2899         6500             0              83   6583
3935         2500           200              38   2738
4194         1600            84              25   1709
4864         2200             5              28   2233
6784          950            50              13   1013
7448         5000          4247              76   9323
8931         5500           141              70   6704
```

[87]:
```
df5.shape
```

[87]:
```
(10041, 12)
```

[88]:
```
df5
```

[88]:
```
       city  area  rooms  bathroom  parking spaces  animal  furniture   hoa  \
21        0    42      1         1               1       0          1   470
27        0    64      2         2               1       1          0   352
37        0    80      3         2               1       1          0     0
42        0   200      4         2               1       0          0   850
43        0    45      1         1               1       1          0   500
…     …   …    …      …         …               …       …          …   …
10681     4   230      3         5               3       0          0  3800
10683     4   280      4         4               2       1          0  4200
10685     4    83      3         2               2       1          0   888
10686     4   150      3         3               2       0          1     0
10691     4    80      2         1               0       1          0     0

       rent amount  property tax  fire insurance  total
21            2690           172              36   3368
27            1500            80              20   1952
37           11000           425             181  11610
42            2550             9              34   3443
43            1631           192              12   2335
…             …            …                …    …
10681        11000          1100             140  16040
10683         4000          1042              51   9293
10685         7521           221              96   8726
10686        13500             0             172  13670
10691         1400           165              22   1587

[10041 rows x 12 columns]
```

[89]:
```
df5=df5[df5.area/df5.rooms>15]
```

[90]:
```
df5
```

[90]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
21	0	42	1	1	1	0	1	470	
27	0	64	2	2	1	1	0	352	
37	0	80	3	2	1	1	0	0	
42	0	200	4	2	1	0	0	850	
43	0	45	1	1	1	1	0	500	
…	…	…	…	…	…	…	…	…	
10681	4	230	3	5	3	0	0	3800	
10683	4	280	4	4	2	1	0	4200	
10685	4	83	3	2	2	1	0	888	
10686	4	150	3	3	2	0	1	0	
10691	4	80	2	1	0	1	0	0	

	rent amount	property tax	fire insurance	total
21	2690	172	36	3368
27	1500	80	20	1952
37	11000	425	181	11610
42	2550	9	34	3443
43	1631	192	12	2335
…	…	…	…	…
10681	11000	1100	140	16040
10683	4000	1042	51	9293
10685	7521	221	96	8726
10686	13500	0	172	13670
10691	1400	165	22	1587

[10006 rows x 12 columns]

[91]:
```
df5.shape
```

[91]: (10006, 12)

[92]:
```
df5[df5.area/df5.rooms>200]
```

[92]:

	city	area	rooms	bathroom	parking spaces	animal	furniture	hoa	\
592	0	450	2	2	5	1	0	0	
666	0	405	2	3	0	1	0	3500	
10619	0	360	1	1	8	1	0	0	
10661	1	250	1	2	2	1	0	0	
2109	2	225	1	2	0	1	0	0	
1138	3	500	2	5	5	0	0	0	
7226	3	500	2	5	5	0	0	0	
1635	4	418	2	4	3	0	0	5274	
4338	4	440	1	2	4	1	0	1	
6202	4	650	3	7	2	1	0	0	
7794	4	500	2	2	1	1	0	129	
7822	4	270	1	1	0	1	0	0	

```
9012      4   330      1         3               8       1           0     0

       rent amount  property tax  fire insurance  total
592            1512            71              25   1608
666            4000           699              54   8253
10619          2190           167              36   2393
10661          2200           602              34   2836
2109           3500           218              63   3781
1138           1810            54              28   1892
7226           1810            54              28   1892
1635           6875           117              88  12350
4338           9800           584             148  10530
6202           9900           600             149  10650
7794           2140             0              33   2302
7822           1400             0              22   1422
9012           3147             0              48   3195
```

[93]:
```
df5=df5[df5.area/df5.rooms<200]
```

[94]:
```
df5
```

[94]:
```
       city  area  rooms  bathroom  parking spaces  animal  furniture   hoa  \
21        0    42      1         1               1       0          1   470
27        0    64      2         2               1       1          0   352
37        0    80      3         2               1       1          0     0
42        0   200      4         2               1       0          0   850
43        0    45      1         1               1       1          0   500
…     …   …    …      …         …               …       …          …   …
10681     4   230      3         5               3       0          0  3800
10683     4   280      4         4               2       1          0  4200
10685     4    83      3         2               2       1          0   888
10686     4   150      3         3               2       0          1     0
10691     4    80      2         1               0       1          0     0

       rent amount  property tax  fire insurance  total
21             2690           172              36   3368
27             1500            80              20   1952
37            11000           425             181  11610
42             2550             9              34   3443
43             1631           192              12   2335
…              …              …               …    …
10681         11000          1100             140  16040
10683          4000          1042              51   9293
10685          7521           221              96   8726
10686         13500             0             172  13670
10691          1400           165              22   1587
```

```
[9984 rows x 12 columns]
```

[95]:
```
df5.shape
```

[95]:
```
(9984, 12)
```

below is the correlation of differnt features with total from our cleaned data

[96]:
```
c=df5.corr()
c['total']
```

[96]:
```
city              0.304358
area              0.677176
rooms             0.534585
bathroom          0.688942
parking spaces    0.575808
animal            0.062198
furniture         0.172825
hoa               0.622778
rent amount       0.954369
property tax      0.691043
fire insurance    0.920276
total             1.000000
Name: total, dtype: float64
```

[97]:
```
df5=df5.drop(['furniture','animal'],axis='columns')
```

[98]:
```
x=df5.drop('total',axis='columns')
y=df5['total']
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.preprocessing import MinMaxScaler
X_norm = MinMaxScaler().fit_transform(x)
chi_selector = SelectKBest(chi2, k=7)
chi_selector.fit(X_norm, y)
chi_support = chi_selector.get_support()
chi_feature = x.loc[:,chi_support].columns.tolist()
chi_feature
```

[98]:
```
['city',
 'area',
 'bathroom',
 'parking spaces',
 'hoa',
 'rent amount',
 'fire insurance']
```

lets drop some features which are not much important based on the above data

[99]:
```
df6=df5.drop(['parking spaces','property tax'],axis='columns')
```

[100]:
```
df6
```

[100]:

	city	area	rooms	bathroom	hoa	rent amount	fire insurance	total
21	0	42	1	1	470	2690	36	3368
27	0	64	2	2	352	1500	20	1952
37	0	80	3	2	0	11000	181	11610
42	0	200	4	2	850	2550	34	3443
43	0	45	1	1	500	1631	12	2335
…	…	…	…	…	…	…	…	…
10681	4	230	3	5	3800	11000	140	16040
10683	4	280	4	4	4200	4000	51	9293
10685	4	83	3	2	888	7521	96	8726
10686	4	150	3	3	0	13500	172	13670
10691	4	80	2	1	0	1400	22	1587

[9984 rows x 8 columns]

lets save our clean data using pickle into housing data file

[101]:
```
import pickle
with open('housing_data','wb') as file:
    pickle.dump(df6,file)
```

[102]:
```
with open('housing_data','rb') as file:
    mp=pickle.load(file)
```

[103]:
```
mp.head()
```

[103]:

	city	area	rooms	bathroom	hoa	rent amount	fire insurance	total
21	0	42	1	1	470	2690	36	3368
27	0	64	2	2	352	1500	20	1952
37	0	80	3	2	0	11000	181	11610
42	0	200	4	2	850	2550	34	3443
43	0	45	1	1	500	1631	12	2335

lets create X and y for model preparation:

[104]:
```
X=df6.drop('total',axis='columns')
```

[105]:
```
X
```

[105]:

	city	area	rooms	bathroom	hoa	rent amount	fire insurance
21	0	42	1	1	470	2690	36
27	0	64	2	2	352	1500	20
37	0	80	3	2	0	11000	181
42	0	200	4	2	850	2550	34

```
43         0    45       1          1   500          1631               12
…      …   …    …        …    …     …     …             …
10681      4   230       3          5  3800         11000              140
10683      4   280       4          4  4200          4000               51
10685      4    83       3          2   888          7521               96
10686      4   150       3          3     0         13500              172
10691      4    80       2          1     0          1400               22

[9984 rows x 7 columns]
```

[106]:
```
y=df6['total']
```

[107]:
```
y
```

[107]:
```
21         3368
27         1952
37        11610
42         3443
43         2335
          …
10681     16040
10683      9293
10685      8726
10686     13670
10691      1587
Name: total, Length: 9984, dtype: int64
```

2 Split the data into training and testing:

we will keep test size as 20% of data.

[108]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=10)
```

To apply the other algorithms and check the accuracy with differnt parameters we will define python function.we will use cross_val_score to increase accuracy by training data in n_splits.

We will apply following algorithms: * Linear Regression * Logistic Regression * lasso * Desicion tree

[110]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import ShuffleSplit
```

```
from sklearn.model_selection import cross_val_score

def find_best_model_using_gridsearchcv(X,y):
    algos = {
        'linear_regression' : {
            'model': LinearRegression(),
            'params': {
                'normalize': [True, False]
            }
        },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [1,2],
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion' : ['mse','friedman_mse'],
                'splitter': ['best','random']
            }
        }
    }
    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
    for algo_name, config in algos.items():
        gs =  GridSearchCV(config['model'], config['params'], cv=cv,␣
 ↪return_train_score=False)
        gs.fit(X,y)
        scores.append({
            'model': algo_name,
            'best_score': gs.best_score_,
            'best_params': gs.best_params_
        })

    return pd.DataFrame(scores,columns=['model','best_score','best_params'])

find_best_model_using_gridsearchcv(X,y)
```

```
/home/rupam/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_coordinate_descent.py:476: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 275951411.8333465, tolerance: 9853516.58480854
  positive)
/home/rupam/anaconda3/lib/python3.7/site-
```

```
packages/sklearn/linear_model/_coordinate_descent.py:476: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 374136388.79793966, tolerance: 9774515.357298834
  positive)
/home/rupam/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_coordinate_descent.py:476: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 206211140.09103462, tolerance: 9748237.426599275
  positive)
/home/rupam/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_coordinate_descent.py:476: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 347741440.7569927, tolerance: 9698897.641727606
  positive)
/home/rupam/anaconda3/lib/python3.7/site-
packages/sklearn/linear_model/_coordinate_descent.py:476: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations.
Duality gap: 332359096.9796154, tolerance: 9748237.426599275
  positive)
```

[110]:

	model	best_score	best_params
0	linear_regression	0.992011	{'normalize': True}
1	lasso	0.992008	{'alpha': 1, 'selection': 'random'}
2	decision_tree	0.983247	{'criterion': 'mse', 'splitter': 'random'}

This shows that is linear regression is giving maximum accuracy. So we will select it for further process.

Lets predict test model with other data

[111]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression(normalize=True)
model.fit(X_train,y_train)
score=model.score(X_test,y_test)
score
```

[111]:
```
0.9915158263616495
```

2.1 our model has 99.15% of accuracy

[112]:
```
model.coef_
```

[112]:
```
array([ 15.69027   ,   1.6228052 , -23.71711935,  49.48423961,
         1.16527751,   0.94221371,   6.16295272])
```

[113]:
```
model.intercept_
```

[113]:
```
-203.29971031479454
```

[114]:
```
city_info
```

[114]:

	0	label
0	São Paulo	4
1	Porto Alegre	2
2	Rio de Janeiro	3
3	Campinas	1
4	Belo Horizonte	0

following is the function to predict total price

[115]:
```
def predict_price(city,area,rooms,bathroom,hoa,rent_amount,fire_insurance):
    total_price=model.
 ↪predict([[city,area,rooms,bathroom,hoa,rent_amount,fire_insurance]])
    return total_price
```

[116]:
```
predict_price(0,150,4,5,1300,1500,1000)
```

[116]:
```
array([9283.80783762])
```

[117]:
```
predict_price(1,150,4,5,1300,1500,1000)
```

[117]:
```
array([9299.49810761])
```

[118]:
```
predict_price(2,150,4,5,1300,1500,1000)
```

[118]:
```
array([9315.18837761])
```

[119]:
```
predict_price(3,150,4,5,1300,1500,1000)
```

[119]:
```
array([9330.87864761])
```

[120]:
```
predict_price(4,150,4,5,1300,1500,1000)
```

[120]:
```
array([9346.5689176])
```

In above cases we predict price for same data in differnt cities. And as expected, prices are high in city no '4' ie. 'São Paulo'

2.1.1 Conclusion:

Hence, We successfully build a model for predicting total amount for renting house in brazil in differnt cities.