Madrid Real Estate - Linear Regression Project

MDB 2018 - O2 - H

First we import libraries we will need

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:

```
import warnings
warnings.filterwarnings('ignore')
import os
import time
```

We then import the data that was cleaned using Dataiku as per the attached document

In [3]:

```
df = pd.read_csv("./Data/idealista_data_V2_prepared.csv")
```

In [4]:

```
df.head() #We check the head of the dataframe to make sure everything seems ok
```

Out[4]:

	address	bathrooms	country	detailedType_typology	detailedType_subTypology	distance	district	exteric
0	calle de San Restituto, 14	1	es	flat	NaN	5370	Moncloa	True
1	saliente	4	es	chalet	independantHouse	12096	Urbanizaciones	False
2	calle Mallorca, 3	1	es	flat	NaN	1192	Centro	True
3	calle Valmojado, 181	3	es	flat	NaN	5422	Latina	True
4	avenida donostiarra, 21	2	es	flat	NaN	4326	Ciudad Lineal	True

5 rows × 39 columns

In [5]:

```
df.info() #We can see
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4148 entries, 0 to 4147
Data columns (total 39 columns):
address                     4148 non-null object
bathrooms                   4148 non-null int64
country                     4148 non-null object
detailedType_typology       4148 non-null object
detailedType_subTypology    716 non-null object
distance                    4148 non-null int64
district                    4148 non-null object
exterior                    4148 non-null bool
externalReference           2805 non-null object
floor                       4148 non-null int64
has360                      4148 non-null bool
has3DTour                   4148 non-null bool
hasLift                     4148 non-null bool
hasPlan                     4148 non-null bool
hasVideo                    4148 non-null bool
latitude                    4148 non-null float64
longitude                   4148 non-null float64
municipality                4148 non-null object
neighborhood                3990 non-null object
newDevelopment              4148 non-null bool
numPhotos                   4148 non-null int64
operation                   4148 non-null object
hasParkingSpace             1387 non-null object
parkingSpaceIncluded        1387 non-null object
parkingSpacePrice           215 non-null float64
price                       4148 non-null float64
priceByArea                 4148 non-null float64
propertyCode                4148 non-null float64
propertyType                4148 non-null object
province                    4148 non-null object
rooms                       4148 non-null int64
showAddress                 4148 non-null bool
size                        4148 non-null float64
status                      4148 non-null object
suggestedTexts_subtitle     4148 non-null object
suggestedTexts_title        4148 non-null object
thumbnail                   4135 non-null object
url                         4148 non-null object
geopoint                    4148 non-null object
dtypes: bool(8), float64(7), int64(5), object(19)
memory usage: 1.0+ MB
```

We can see that there are a lot of categorical variables. These won't be the best for our regression project so we need to check how many unique categories and how broad they are.

In [6]:

```
for col in df.columns:
    if df[col].dtype == 'O':
        print(col ,'------', df[col].dtype == 'O')
        print(df[col].nunique())
        print("========================")
```

```
address ------ True
2580
========================
country ------ True
1
========================
detailedType_typology ------ True
2
========================
detailedType_subTypology ------ True
6
========================
district ------ True
67
========================
externalReference ------ True
2548
```

```
========================
municipality ------ True
13
========================
neighborhood ------ True
162
========================
operation ------ True
1
========================
hasParkingSpace ------ True
1
========================
parkingSpaceIncluded ------ True
2
========================
propertyType ------ True
5
========================
province ------ True
1
========================
status ------ True
2
========================
suggestedTexts_subtitle ------ True
191
========================
suggestedTexts_title ------ True
2547
========================
thumbnail ------ True
3931
========================
url ------ True
3944
========================
geopoint ------ True
3741
========================
```

We can tell that most categorical variables might be too broad. Others are redundant (only 1)
So we will drop all columns that seem useless and build our regression from there

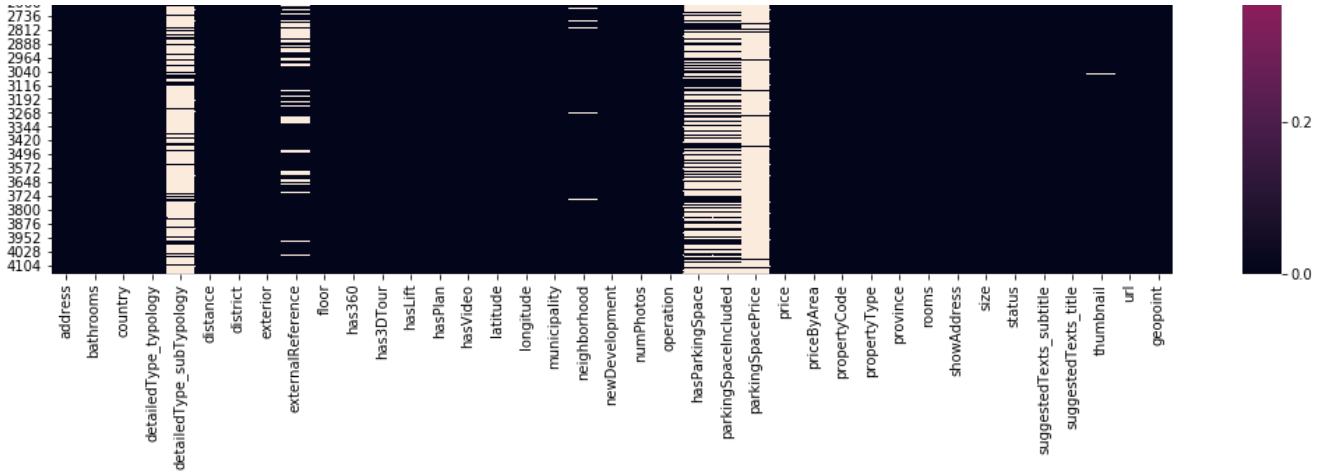
We need to check the categories that have only 1 to make sure that they are not T/F categories with NaN as flags

In [7]:

```
fig, ax = plt.subplots(figsize=(18,10))
sns.heatmap(df.isnull())
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d65e14c630>
```



Seems like sub_Typology, externalReference, hasParkingSpace, parkingSpaceIncluded and parkingSpacePrice have a lot of nulls. The first 2 we might drop as they seem to be almost identifiers, has parking space we could try settin them to false.
and drop the other 2 columns related to parking space

In [8]:

```
df['hasParkingSpace'].isnull().sum()/len(df['hasParkingSpace']) # 66% of the rows are null values, we t
ake a risk using this
```

Out[8]:

```
0.6656219864995179
```

In [9]:

```
df['hasParkingSpace'].fillna(False, inplace=True) #We try imputing as parkins space seems important
```

In [10]:

```
col_drop = []
for col in df.columns:
    if df[col].dtype == 'O' and (df[col].nunique() == 1 or df[col].nunique() >100 or df[col].isnull().s
um()/len(df[col]) > 0.5) :
        col_drop.append(col)
```

In [11]:

```
col_drop.append('parkingSpacePrice') #This column is almost completely empty
col_drop
```

Out[11]:

```
['address',
 'country',
 'detailedType_subTypology',
 'externalReference',
 'neighborhood',
 'operation',
 'parkingSpaceIncluded',
 'province',
 'suggestedTexts_subtitle',
 'suggestedTexts_title',
 'thumbnail',
 'url',
 'geopoint',
 'parkingSpacePrice']
```

In [12]:

```
df.drop(col_drop, axis=1, inplace=True)
```

In [13]:

```
for col in df.columns:
    if df[col].dtype == 'O':
        print(col ,'------', df[col].dtype == 'O')
        print(df[col].nunique())
        print("========================")
```

```
detailedType_typology ------ True
2
========================
district ------ True
67
========================
municipality ------ True
13
========================
propertyType ------ True
5
========================
status ------ True
2
========================
```

We this we take care of wrangling the categorical values

Now we check the rest for null values

In [14]:

```
df.isnull().any().any()
```

Out[14]:

```
False
```

We are now ready to start exploring and finding our model features

In [25]:

```
for col in df.columns:
    if df[col].dtype == 'bool':
        print(col ,'------', df[col].dtype == 'bool')
        print(df[col].nunique())
        print("========================")
```

```
exterior ------ True
2
========================
has360 ------ True
2
========================
has3DTour ------ True
2
========================
hasLift ------ True
2
========================
hasPlan ------ True
2
========================
hasVideo ------ True
2
========================
newDevelopment ------ True
1
========================
hasParkingSpace ------ True
2
========================
showAddress ------ True
2
```

==========

"newDevelopment" is a boolean variable with all Falses so we will also drop it

In [26]:

```
df.drop('newDevelopment', axis=1, inplace=True)
```

Exploratory Data Analisys

In [27]:

```
df.describe()
```

Out[27]:

	bathrooms	distance	floor	latitude	longitude	numPhotos	price	priceByArea	pro
count	4148.000000	4148.000000	4148.000000	4148.000000	4148.000000	4148.000000	4148.000000	4148.000000	4.14
mean	1.706606	4496.768322	3.187801	40.435634	-3.692264	22.273867	1570.477097	16.433703	7.63
std	0.898776	3386.085864	2.772488	0.032076	0.043421	11.602292	813.890293	5.707456	1.81
min	1.000000	22.000000	-1.000000	40.301089	-3.880282	0.000000	400.000000	5.000000	3.02
25%	1.000000	1927.000000	1.000000	40.419253	-3.705716	14.000000	950.000000	13.000000	8.27
50%	2.000000	3418.000000	3.000000	40.432533	-3.690367	21.000000	1300.000000	15.000000	8.32
75%	2.000000	6500.000000	5.000000	40.456387	-3.673120	28.000000	1935.000000	19.000000	8.34
max	9.000000	14944.000000	25.000000	40.545903	-3.536303	94.000000	4000.000000	63.000000	8.34

In [28]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4148 entries, 0 to 4147
Data columns (total 24 columns):
bathrooms                4148 non-null int64
detailedType_typology    4148 non-null object
distance                 4148 non-null int64
district                 4148 non-null object
exterior                 4148 non-null bool
floor                    4148 non-null int64
has360                   4148 non-null bool
has3DTour                4148 non-null bool
hasLift                  4148 non-null bool
hasPlan                  4148 non-null bool
hasVideo                 4148 non-null bool
latitude                 4148 non-null float64
longitude                4148 non-null float64
municipality             4148 non-null object
numPhotos                4148 non-null int64
hasParkingSpace          4148 non-null bool
price                    4148 non-null float64
priceByArea              4148 non-null float64
propertyCode             4148 non-null float64
propertyType             4148 non-null object
rooms                    4148 non-null int64
showAddress              4148 non-null bool
size                     4148 non-null float64
status                   4148 non-null object
dtypes: bool(8), float64(6), int64(5), object(5)
memory usage: 551.0+ KB
```

At a first glance, knowing about renting apartment. There should be a correlation between:
Price and Size

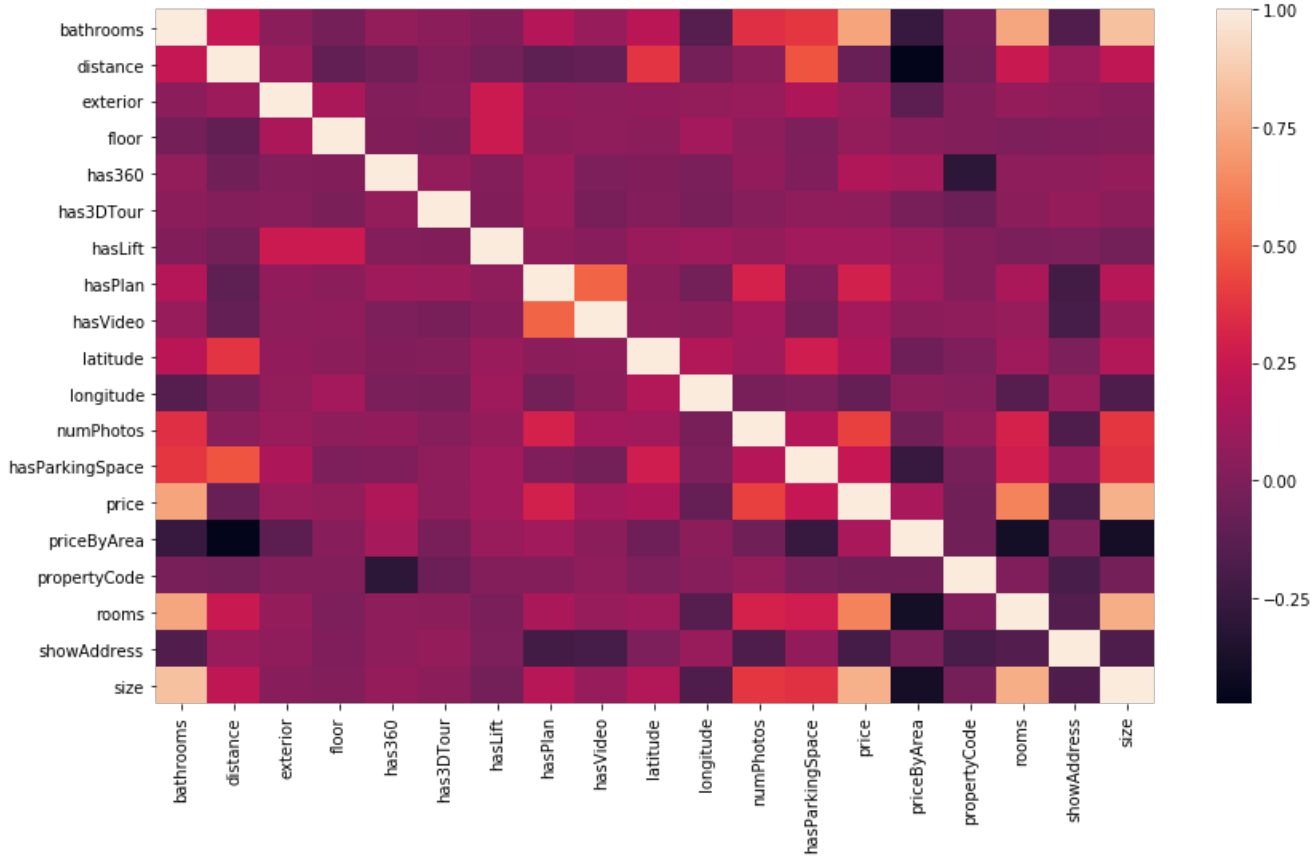
Price and Size
Price and rooms
Price and district
Price and having parking

In [37]:

```
plt.subplots(figsize=(14,8))
sns.heatmap(df.corr())
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d6612b1be0>
```



In [35]:

```
df.corr()['price']
```

Out[35]:

```
bathrooms          0.733046
distance          -0.078170
exterior           0.087460
floor              0.068430
has360             0.170783
has3DTour          0.053712
hasLift            0.113241
hasPlan            0.293408
hasVideo           0.128853
latitude           0.157629
longitude         -0.084138
numPhotos          0.413168
hasParkingSpace    0.236443
price              1.000000
priceByArea        0.138320
propertyCode      -0.051988
rooms              0.615577
showAddress       -0.204833
size               0.776695
Name: price, dtype: float64
```

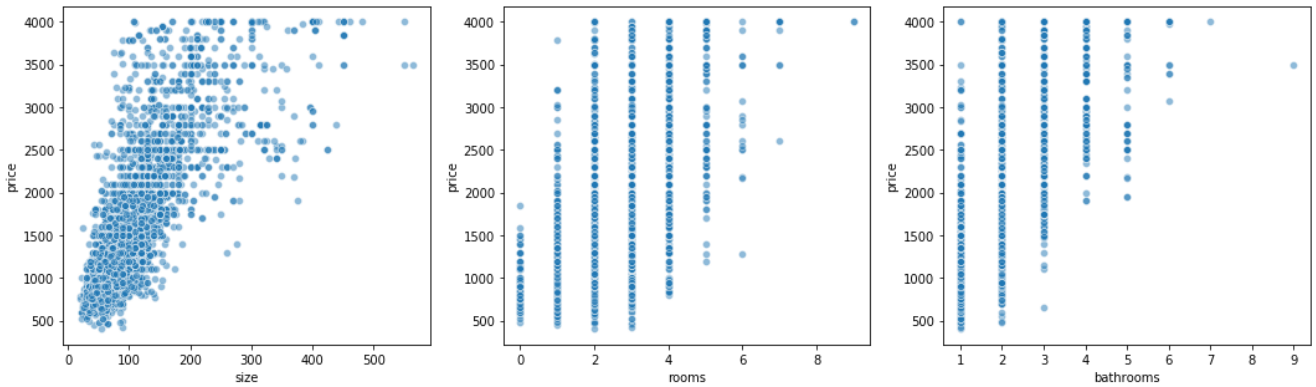
Seems the highest correlations are with bathrooms, hasPlan, numPhotos, rooms and size
This could be because the more expensive places tendo to have more work into them including more information to the platform. The size, rooms and bathrooms are logical correlations

In [43]:

```
fig, ax = plt.subplots(1,3, figsize=(18,5))
sns.scatterplot(x='size', y='price', data=df, ax=ax[0], alpha=0.5)
sns.scatterplot(x='rooms', y='price', data=df, ax=ax[1], alpha=0.5)
sns.scatterplot(x='bathrooms', y='price', data=df, ax=ax[2], alpha=0.5)
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d6615526a0>
```

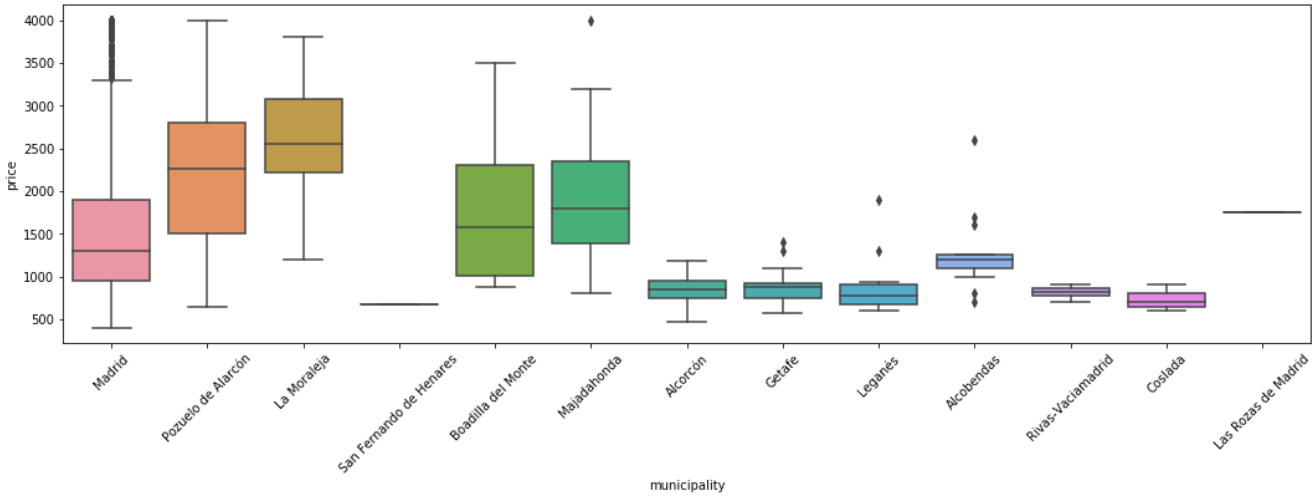


In [50]:

```
fig, ax = plt.subplots(figsize=(18,5))
g = sns.boxplot(x='municipality', y='price', data=df)
g.set_xticklabels(df['municipality'].unique(),rotation=45)
```

Out[50]:

```
[Text(0,0,'Madrid'),
 Text(0,0,'Pozuelo de Alarcón'),
 Text(0,0,'La Moraleja'),
 Text(0,0,'San Fernando de Henares'),
 Text(0,0,'Boadilla del Monte'),
 Text(0,0,'Majadahonda'),
 Text(0,0,'Alcorcón'),
 Text(0,0,'Getafe'),
 Text(0,0,'Leganés'),
 Text(0,0,'Alcobendas'),
 Text(0,0,'Rivas-Vaciamadrid'),
 Text(0,0,'Coslada'),
 Text(0,0,'Las Rozas de Madrid')]
```



We can see that there seems to be a sizeable difference in price between the different municipalities

In [55]:

```
df['district'].nunique()
```

Out[55]:

67

In [66]:

```
9 // 2
```

Out[66]:

4

In [63]:

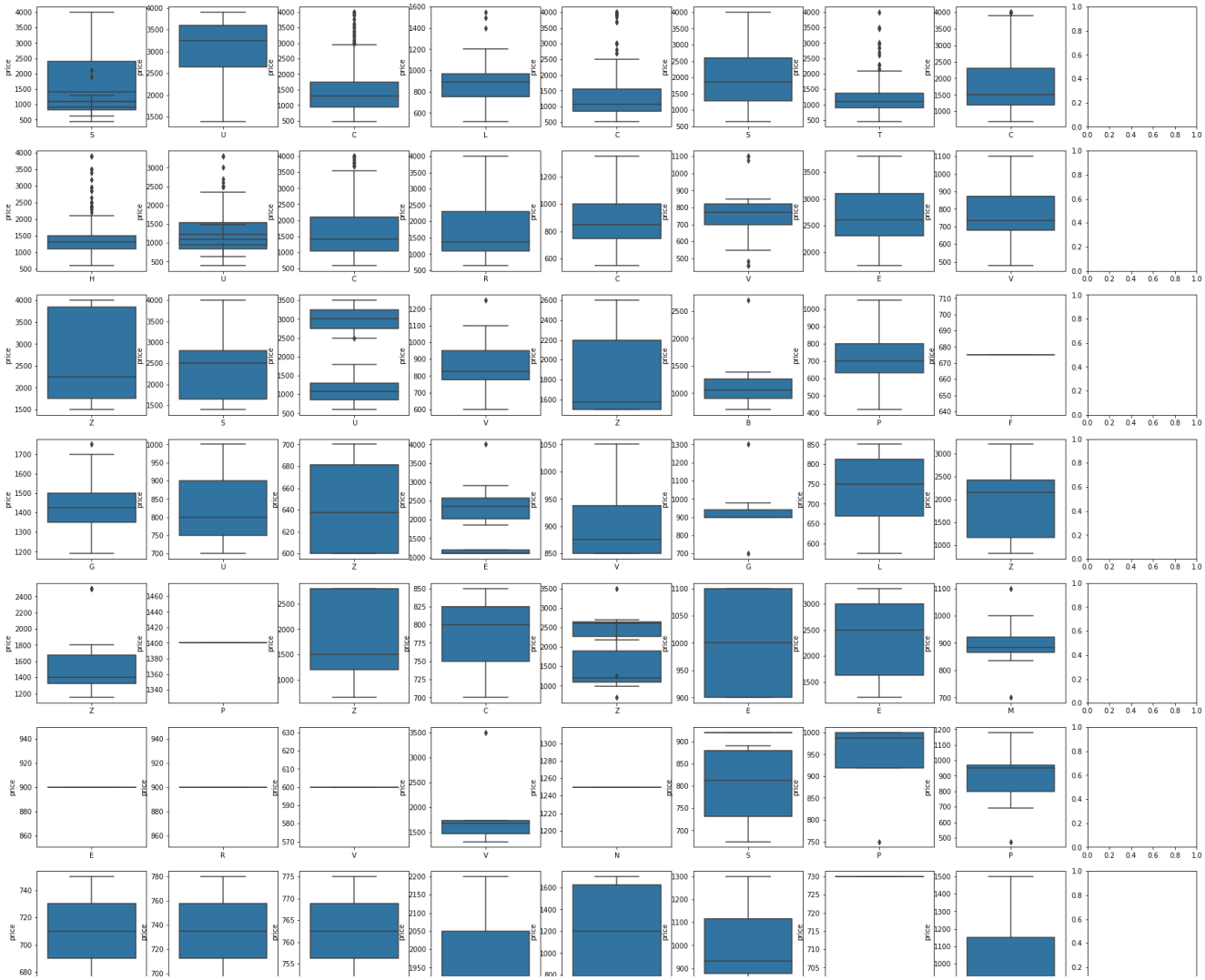
```
9 % 2
```

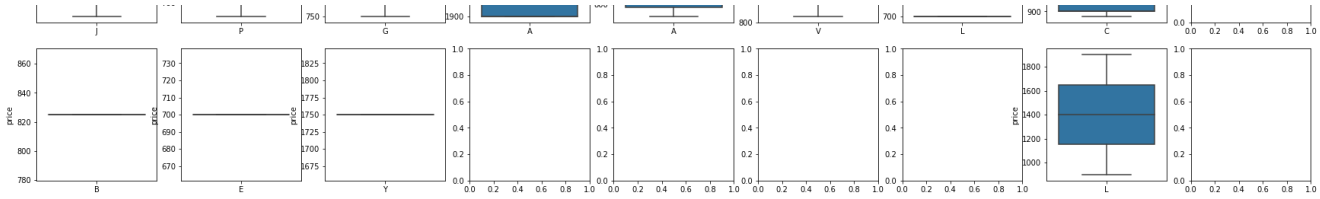
Out[63]:

1

In [69]:

```
fig, ax = plt.subplots(8,9, figsize=(30,30))
for i, district in enumerate(df['district'].unique()):
    row = i // 9
    col = i % 8
    g =sns.boxplot(y='price', data=df[df['district'] == district], ax = ax[row, col])
    g.set_xticklabels(district)
```





We can also see that there is a big difference between the prices of the different districts. So we will have to take theser into accoutn as well for our model

In [72]:

```
df['numPhotos'].describe()
```

Out[72]:

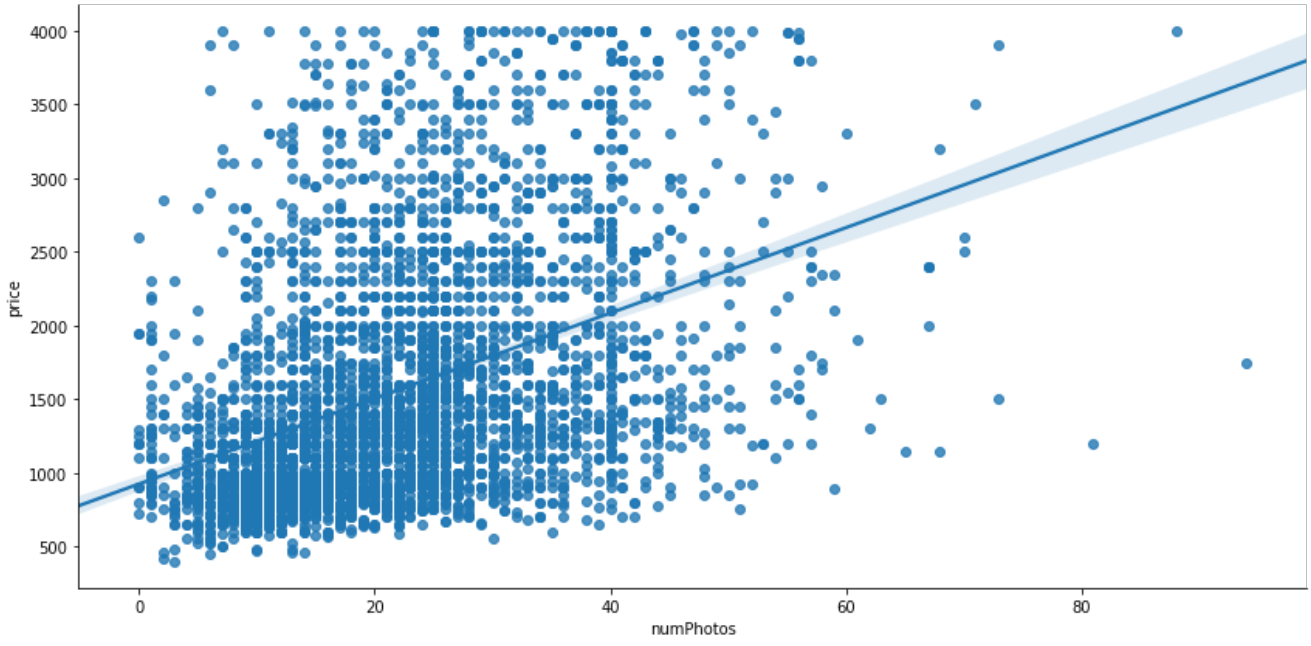
```
count    4148.000000
mean       22.273867
std        11.602292
min         0.000000
25%        14.000000
50%        21.000000
75%        28.000000
max        94.000000
Name: numPhotos, dtype: float64
```

In [86]:

```
sns.lmplot('numPhotos', 'price', data=df, height=6,aspect=2)
```

Out[86]:

```
<seaborn.axisgrid.FacetGrid at 0x1d669b7aac8>
```



There seems to be a positive correlation between the num of photos ina listing and its price.
This could be because the more expensive listincs probably use real estate agent, and to increase exposure they have more pictures. But this could be a spurrious correlation

Model Building

In [87]:

```
from statsmodels.regression.linear_model import OLS
```

In [88]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4148 entries, 0 to 4147
Data columns (total 24 columns):
bathrooms                4148 non-null int64
detailedType_typology    4148 non-null object
distance                 4148 non-null int64
district                 4148 non-null object
exterior                 4148 non-null bool
floor                    4148 non-null int64
has360                   4148 non-null bool
has3DTour                4148 non-null bool
hasLift                  4148 non-null bool
hasPlan                  4148 non-null bool
hasVideo                 4148 non-null bool
latitude                 4148 non-null float64
longitude                4148 non-null float64
municipality             4148 non-null object
numPhotos                4148 non-null int64
hasParkingSpace          4148 non-null bool
price                    4148 non-null float64
priceByArea              4148 non-null float64
propertyCode             4148 non-null float64
propertyType             4148 non-null object
rooms                    4148 non-null int64
showAddress              4148 non-null bool
size                     4148 non-null float64
status                   4148 non-null object
dtypes: bool(8), float64(6), int64(5), object(5)
memory usage: 551.0+ KB
```

We know that we have the most logical correlations between price, size, rooms and bathrooms. But there might alos be a relacion between each other so we will build the model with these to check their significance

In [89]:

```
feats = df[['size','rooms','bathrooms']]
```

In [91]:

```
from sklearn.preprocessing import StandardScaler
```

In [92]:

```
scaler = StandardScaler()
```

In [93]:

```
feats = scaler.fit_transform(feats)
```

In [94]:

```
target = df['price']
```

In [101]:

```
model = OLS(target,feats)
results = model.fit()
```

In [102]:

```
results.summary()
```

Out[102]:

Out[102]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.133
Model:	OLS	**Adj. R-squared:**	0.132
Method:	Least Squares	**F-statistic:**	211.3
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	1.45e-127
Time:	21:55:52	**Log-Likelihood:**	-36610.
No. Observations:	4148	**AIC:**	7.323e+04
Df Residuals:	4145	**BIC:**	7.324e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x1	451.2024	50.958	8.854	0.000	351.297	551.108
x2	-16.9535	41.566	-0.408	0.683	-98.445	64.539
x3	231.9675	48.523	4.781	0.000	136.837	327.098

Omnibus:	848.079	**Durbin-Watson:**	0.145
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2669.183
Skew:	1.036	**Prob(JB):**	0.00
Kurtosis:	6.340	**Cond. No.**	3.98

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Seems like number of rooms is not significant. So we will drop that variable

In [103]:

```
feats = scaler.fit_transform(df[['size','bathrooms']])
```

In [104]:

```
model = OLS(target,feats)
results = model.fit()
results.summary()
```

Out[104]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.133
Model:	OLS	**Adj. R-squared:**	0.132
Method:	Least Squares	**F-statistic:**	317.0
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	7.81e-129
Time:	21:57:12	**Log-Likelihood:**	-36610.
No. Observations:	4148	**AIC:**	7.322e+04
Df Residuals:	4146	**BIC:**	7.324e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**

x1	442.7951	46.599	9.502	0.000	351.437	534.153
x2	226.4561	46.599	4.860	0.000	135.098	317.814

Omnibus:	849.587	**Durbin-Watson:**	0.145
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2645.969
Skew:	1.041	**Prob(JB):**	0.00
Kurtosis:	6.313	**Cond. No.**	3.34

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Seems like they are both significant, but we're getting a low R^2 so we'll try to add some more variables

In [105]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance']])
model = OLS(target,feats)
results = model.fit()
results.summary()
```

Out[105]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.148
Model:	OLS	**Adj. R-squared:**	0.148
Method:	Least Squares	**F-statistic:**	240.3
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	9.56e-144
Time:	21:58:15	**Log-Likelihood:**	-36572.
No. Observations:	4148	**AIC:**	7.315e+04
Df Residuals:	4145	**BIC:**	7.317e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x1	459.7384	46.227	9.945	0.000	369.109	550.368
x2	265.6544	46.406	5.725	0.000	174.675	356.634
x3	-226.8416	26.112	-8.687	0.000	-278.036	-175.647

Omnibus:	866.312	**Durbin-Watson:**	0.122
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2904.474
Skew:	1.037	**Prob(JB):**	0.00
Kurtosis:	6.537	**Cond. No.**	3.44

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

As we set the distance as the center of Madrid, it seems like being far from the center has a negative effect on the rental price. This could probably be used better with the districts but we won't use them yet

In [106]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance', 'numPhotos']])
model = OLS(target,feats)
```

```
results = model.fit()
results.summary()
```

Out[106]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.150
Model:	OLS	**Adj. R-squared:**	0.149
Method:	Least Squares	**F-statistic:**	183.1
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	1.20e-144
Time:	22:00:01	**Log-Likelihood:**	-36567.
No. Observations:	4148	**AIC:**	7.314e+04
Df Residuals:	4144	**BIC:**	7.317e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x1	436.1824	46.785	9.323	0.000	344.459	527.906
x2	253.0694	46.530	5.439	0.000	161.846	344.292
x3	-221.5733	26.139	-8.477	0.000	-272.819	-170.327
x4	86.3701	27.544	3.136	0.002	32.369	140.371

Omnibus:	912.535	**Durbin-Watson:**	0.121
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3054.301
Skew:	1.092	**Prob(JB):**	0.00
Kurtosis:	6.592	**Cond. No.**	3.64

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

So far all our chosen features are significant in their relationship with the target variable 'price'
but we're still only explaining 15% of the variance in y. Some possible correlations to price can be if the place is exterior or not, if it has a lift, if it has a parking spot
and the floor the apartment is on. So we will aggregate all those to our model

In [109]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance', 'numPhotos',
                                 'hasParkingSpace', 'exterior', 'floor','hasLift']])
model = OLS(target,feats,)
results = model.fit()
results.summary()
```

Out[109]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.154
Model:	OLS	**Adj. R-squared:**	0.152
Method:	Least Squares	**F-statistic:**	93.86
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	7.74e-144
Time:	22:41:16	**Log-Likelihood:**	-36559.
No. Observations:	4148	**AIC:**	7.313e+04
Df Residuals:	4140	**BIC:**	7.318e+04

Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	448.5607	47.283	9.487	0.000	355.862	541.260
x2	240.4219	47.009	5.114	0.000	148.259	332.585
x3	-230.3370	29.263	-7.871	0.000	-287.708	-172.966
x4	73.1808	27.729	2.639	0.008	18.817	127.544
x5	19.1471	30.947	0.619	0.536	-41.526	79.820
x6	39.6426	26.653	1.487	0.137	-12.612	91.897
x7	4.8519	26.613	0.182	0.855	-47.324	57.028
x8	79.9169	27.387	2.918	0.004	26.225	133.609

Omnibus:	999.514	**Durbin-Watson:**	0.115
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3196.133
Skew:	1.212	**Prob(JB):**	0.00
Kurtosis:	6.551	**Cond. No.**	3.95

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

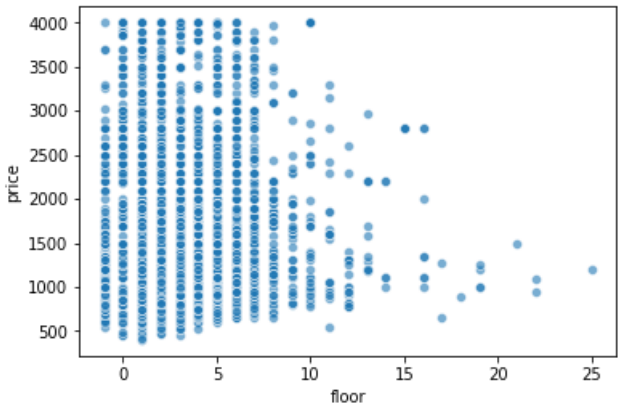
Seems like having a parking space, being exterior and which floor they're on are not significant.
We check the reponse to floor as it might be a non linear relationship

In [112]:

```
sns.scatterplot('floor', 'price', data=df, alpha=0.6)
```

Out[112]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d669a17198>
```



There seems to be almost no relationship

In [114]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance', 'numPhotos',
                                 'hasLift']])
model = OLS(target,feats,)
results = model.fit()
results.summary()
```

Out[114]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.153
Model:	OLS	**Adj. R-squared:**	0.152
Method:	Least Squares	**F-statistic:**	149.6
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	2.00e-146
Time:	22:45:08	**Log-Likelihood:**	-36560.
No. Observations:	4148	**AIC:**	7.313e+04
Df Residuals:	4143	**BIC:**	7.316e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
x1	452.0322	46.911	9.636	0.000	360.062	544.003
x2	241.8610	46.558	5.195	0.000	150.582	333.140
x3	-218.4972	26.112	-8.368	0.000	-269.691	-167.303
x4	77.1545	27.615	2.794	0.005	23.013	131.296
x5	94.0462	25.495	3.689	0.000	44.063	144.030

Omnibus:	984.412	**Durbin-Watson:**	0.116
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3159.656
Skew:	1.193	**Prob(JB):**	0.00
Kurtosis:	6.548	**Cond. No.**	3.65

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

We're back to 100% significance, but we need to test the other boolean values for their correlation
has360
has3DTour
hasLift
hasPlan hasVideo

In [117]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance', 'numPhotos',
                                 'hasLift', 'has360','has3DTour', 'hasLift',
                                'hasPlan', 'hasVideo']])
model = OLS(target,feats,)
results = model.fit()
results.summary()
```

Out[117]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.156
Model:	OLS	**Adj. R-squared:**	0.154
Method:	Least Squares	**F-statistic:**	84.69
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	6.24e-145
Time:	22:52:15	**Log-Likelihood:**	-36554.
No. Observations:	4148	**AIC:**	7.313e+04
Df Residuals:	4139	**BIC:**	7.318e+04
Df Model:	9		

Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	444.0775	46.931	9.462	0.000	352.067	536.088
x2	236.3259	46.548	5.077	0.000	145.067	327.585
x3	-205.9304	26.471	-7.780	0.000	-257.827	-154.033
x4	60.1334	28.445	2.114	0.035	4.365	115.902
x5	45.5612	12.744	3.575	0.000	20.576	70.546
x6	66.6015	25.607	2.601	0.009	16.398	116.805
x7	2.7749	25.535	0.109	0.913	-47.287	52.837
x8	45.5612	12.744	3.575	0.000	20.576	70.546
x9	62.7697	31.462	1.995	0.046	1.086	124.453
x10	-11.3108	29.729	-0.380	0.704	-69.595	46.974

Omnibus:	834.288	**Durbin-Watson:**	0.117
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2433.558
Skew:	1.045	**Prob(JB):**	0.00
Kurtosis:	6.117	**Cond. No.**	7.82e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.59e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

We see a couple of non-significant variables so we take them out

In [124]:

```
feats = scaler.fit_transform(df[['size','bathrooms','distance', 'numPhotos',
                                 'hasLift', 'has360', 'hasLift',
                                'hasPlan']])
model = OLS(target,feats,)
results = model.fit()
results.summary()
```

Out[124]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.155
Model:	OLS	**Adj. R-squared:**	0.154
Method:	Least Squares	**F-statistic:**	108.9
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	6.20e-147
Time:	22:54:49	**Log-Likelihood:**	-36554.
No. Observations:	4148	**AIC:**	7.312e+04
Df Residuals:	4141	**BIC:**	7.317e+04
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	444.2716	46.911	9.471	0.000	352.302	536.242
x2	236.1096	46.535	5.074	0.000	144.877	327.343
x3	-205.4303	26.434	-7.771	0.000	-257.255	-153.605

x3	-205.4303	26.434	-7.771	0.000	-257.255	-153.605
x4	60.4636	28.413	2.128	0.033	4.758	116.169
x5	45.5513	12.741	3.575	0.000	20.573	70.530
x6	67.4951	25.492	2.648	0.008	17.518	117.473
x7	45.5513	12.741	3.575	0.000	20.573	70.530
x8	57.0541	27.045	2.110	0.035	4.032	110.077

Omnibus:	838.014	**Durbin-Watson:**	0.117
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2441.811
Skew:	1.049	**Prob(JB):**	0.00
Kurtosis:	6.118	**Cond. No.**	7.76e+15

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.57e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

There seems to be significant in general, but we're still getting the 15 R2 meaning that
we're not explaining a lot of the Y variance with our X.
This could mean that the largest explanation is in the categorical variables

Variable Importances

One method we can use to find variable importances in our dataset is using a different model
In this case we can use Random Forest to see which variables seem most important to the price

In [159]:

```
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor

from sklearn.model_selection import train_test_split
```

In [125]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4148 entries, 0 to 4147
Data columns (total 24 columns):
bathrooms                4148 non-null int64
detailedType_typology    4148 non-null object
distance                 4148 non-null int64
district                 4148 non-null object
exterior                 4148 non-null bool
floor                    4148 non-null int64
has360                   4148 non-null bool
has3DTour                4148 non-null bool
hasLift                  4148 non-null bool
hasPlan                  4148 non-null bool
hasVideo                 4148 non-null bool
latitude                 4148 non-null float64
longitude                4148 non-null float64
municipality             4148 non-null object
numPhotos                4148 non-null int64
hasParkingSpace          4148 non-null bool
price                    4148 non-null float64
priceByArea              4148 non-null float64
propertyCode             4148 non-null float64
propertyType             4148 non-null object
rooms                    4148 non-null int64
showAddress              4148 non-null bool
size                     4148 non-null float64
status                   4148 non-null object
```

```
status                  4140 non-null object
dtypes: bool(8), float64(6), int64(5), object(5)
memory usage: 551.0+ KB
```

In [126]:

```
feats = df.columns
```

In [194]:

```
X = df.copy()
```

In [195]:

```
X.columns
```

Out[195]:

```
Index(['bathrooms', 'detailedType_typology', 'distance', 'district',
       'exterior', 'floor', 'has360', 'has3DTour', 'hasLift', 'hasPlan',
       'hasVideo', 'latitude', 'longitude', 'municipality', 'numPhotos',
       'hasParkingSpace', 'price', 'priceByArea', 'propertyCode',
       'propertyType', 'rooms', 'showAddress', 'size', 'status'],
      dtype='object')
```

In [196]:

```
X.drop(['latitude','longitude','price','priceByArea','propertyCode','detailedType_typology', 'showAddress'], axis=1, inplace=True)
```

In [153]:

```
y = df['price']
```

In [197]:

```
X = pd.get_dummies(X)
```

In [155]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.32, random_state=101)
```

In [162]:

```
rfr = RandomForestRegressor()
rfr.fit(X_train,y_train)
print("Train: ",rfr.score(X_train,y_train))
print("Test: ",rfr.score(X_test,y_test))
```

```
Train:  0.9651517481891312
Test:  0.8290800242277729
```

In [161]:

```
gbr = GradientBoostingRegressor(n_estimators=200)
gbr.fit(X_train,y_train)
print("Train: ",gbr.score(X_train,y_train))
print("Test: ",gbr.score(X_test,y_test))
```

```
Train:  0.8760118547910274
Test:  0.8446767651624798
```

In [166]:

```
def rf_feat_importance(m, df):
    return pd.DataFrame({'cols': df.columns, 'imp' :
```

```
    return pd.DataFrame({'cols' : df.columns, 'imp' :
    m.feature_importances_}).sort_values('imp',ascending = False)
```

In [167]:

```
fi = rf_feat_importance(rfr, X)
fi[:10]
```

Out[167]:

	cols	imp
12	size	0.684596
1	distance	0.115815
9	numPhotos	0.041142
0	bathrooms	0.028986
3	floor	0.021540
4	has360	0.012062
7	hasPlan	0.011795
54	district_Salamanca	0.011428
11	rooms	0.010786
21	district_Chamartín	0.007974

In [168]:

```
fi = rf_feat_importance(gbr, X)
fi[:10]
```

Out[168]:

	cols	imp
12	size	0.726602
1	distance	0.113933
0	bathrooms	0.057397
9	numPhotos	0.019247
54	district_Salamanca	0.012516
7	hasPlan	0.012164
4	has360	0.009536
21	district_Chamartín	0.008145
11	rooms	0.005917
85	municipality_La Moraleja	0.003539

From these experiments, we can see that size seems to be the most important metric for this algorithm.
Same with distance, bathroom, num Photos, but then Districts start appearing.

We'll run the Linear Model with the dummy variables for district.However at this point the number of features has exploded so we might not be able to interpret the model that easily

Back to Linear Model

In [170]:

```
feats = scaler.fit_transform(X)
model = OLS(target,feats)
results = model.fit()
```

```
results = model.fit()
results.summary()
```

Out[170]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.168
Model:	OLS	**Adj. R-squared:**	0.150
Method:	Least Squares	**F-statistic:**	9.425
Date:	Sat, 22 Dec 2018	**Prob (F-statistic):**	5.60e-107
Time:	23:14:36	**Log-Likelihood:**	-36523.
No. Observations:	4148	**AIC:**	7.322e+04
Df Residuals:	4061	**BIC:**	7.377e+04
Df Model:	87		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	205.4592	51.061	4.024	0.000	105.351	305.567
x2	-221.5089	82.686	-2.679	0.007	-383.619	-59.399
x3	41.8133	29.226	1.431	0.153	-15.486	99.113
x4	-2.2624	28.180	-0.080	0.936	-57.511	52.986
x5	60.9989	25.859	2.359	0.018	10.302	111.696
x6	-5.7410	25.814	-0.222	0.824	-56.351	44.869
x7	37.3628	30.641	1.219	0.223	-22.710	97.435
x8	59.8899	31.918	1.876	0.061	-2.686	122.466
x9	-23.7765	30.235	-0.786	0.432	-83.054	35.501
x10	47.2773	29.019	1.629	0.103	-9.616	104.171
x11	46.5078	32.931	1.412	0.158	-18.055	111.071
x12	44.6386	48.942	0.912	0.362	-51.314	140.591
x13	419.6552	57.875	7.251	0.000	306.189	533.122
x14	8.1160	22.397	0.362	0.717	-35.795	52.027
x15	-48.1808	25.985	-1.854	0.064	-99.126	2.765
x16	-5.6804	24.995	-0.227	0.820	-54.684	43.323
x17	0.4391	28.448	0.015	0.988	-55.335	56.213
x18	4.5490	24.997	0.182	0.856	-44.458	53.556
x19	-48.1944	25.156	-1.916	0.055	-97.514	1.125
x20	4.4471	33.557	0.133	0.895	-61.343	70.237
x21	-17.2766	36.548	-0.473	0.636	-88.930	54.377
x22	35.9604	23.917	1.504	0.133	-10.929	82.850
x23	24.1234	26.916	0.896	0.370	-28.647	76.894
x24	-31.0594	25.758	-1.206	0.228	-81.559	19.440
x25	-3.0022	16.967	-0.177	0.860	-36.267	30.263
x26	1.7570	21.968	0.080	0.936	-41.311	44.825
x27	-11.9293	23.948	-0.498	0.618	-58.880	35.021
x28	-5.0973	31.070	-0.164	0.870	-66.012	55.818
x29	-4.1945	21.931	-0.191	0.848	-47.191	38.802
x30	25.6593	22.776	1.127	0.260	-18.994	70.313
x31	29.5640	18.618	1.588	0.112	-6.937	66.065

x31	29.3640	16.618	1.588	0.112	-6.937	66.665
x32	-6.1367	21.580	-0.284	0.776	-48.445	36.171
x33	-19.1467	32.373	-0.591	0.554	-82.616	44.323
x34	0.7062	12.845	0.055	0.956	-24.476	25.889
x35	2.7233	22.512	0.121	0.904	-41.413	46.860
x36	-6.6724	24.531	-0.272	0.786	-54.767	41.422
x37	6.7817	28.574	0.237	0.812	-49.239	62.802
x38	-5.0060	33.833	-0.148	0.882	-71.336	61.325
x39	4.1834	24.558	0.170	0.865	-43.965	52.331
x40	0.4743	23.792	0.020	0.984	-46.172	47.120
x41	-1.9667	28.420	-0.069	0.945	-57.685	53.752
x42	-42.6482	25.309	-1.685	0.092	-92.268	6.972
x43	-14.0666	31.188	-0.451	0.652	-75.212	47.079
x44	-0.8344	24.144	-0.035	0.972	-48.170	46.501
x45	-34.4332	25.439	-1.354	0.176	-84.308	15.441
x46	1.1207	24.626	0.046	0.964	-47.160	49.402
x47	-24.4176	40.887	-0.597	0.550	-104.578	55.743
x48	-2.7609	28.748	-0.096	0.923	-59.122	53.600
x49	-5.9971	27.128	-0.221	0.825	-59.182	47.188
x50	-12.4050	25.067	-0.495	0.621	-61.550	36.740
x51	-6.4747	31.829	-0.203	0.839	-68.876	55.927
x52	-27.1864	25.389	-1.071	0.284	-76.962	22.589
x53	0.8736	25.585	0.034	0.973	-49.287	51.034
x54	4.0600	22.905	0.177	0.859	-40.846	48.966
x55	97.9534	25.809	3.795	0.000	47.354	148.553
x56	-11.6577	28.962	-0.403	0.687	-68.438	45.123
x57	-0.6736	35.836	-0.019	0.985	-70.933	69.585
x58	-0.4243	23.518	-0.018	0.986	-46.533	45.684
x59	-16.3895	24.558	-0.667	0.505	-64.537	31.758
x60	1.6430	24.161	0.068	0.946	-45.726	49.011
x61	-32.2506	37.380	-0.863	0.388	-105.536	41.035
x62	14.5523	25.509	0.570	0.568	-35.460	64.564
x63	-37.6789	25.243	-1.493	0.136	-87.169	11.811
x64	14.8909	23.173	0.643	0.521	-30.541	60.323
x65	-16.7089	49.905	-0.335	0.738	-114.550	81.132
x66	-10.4519	33.527	-0.312	0.755	-76.182	55.278
x67	-7.7539	31.947	-0.243	0.808	-70.388	54.880
x68	2.2415	21.997	0.102	0.919	-40.884	45.367
x69	-19.5528	26.095	-0.749	0.454	-70.713	31.607
x70	-8.4383	28.920	-0.292	0.770	-65.137	48.260
x71	-19.8399	25.948	-0.765	0.445	-70.712	31.032
x72	-4.3368	12.893	-0.336	0.737	-29.614	20.940
x73	0.1557	35.855	0.004	0.997	-70.140	70.451
x74	-4.6726	23.476	-0.199	0.842	-50.698	41.353
x75	1.5359	26.378	0.058	0.954	-50.180	53.252
x76	-17.1841	24.691	-0.696	0.486	-65.592	31.224

x77	19.7587	28.457	0.694	0.488	-36.033	75.550
x78	-20.4604	23.296	-0.878	0.380	-66.133	25.213
x79	-9.5994	24.520	-0.391	0.695	-57.671	38.473
x80	3.2199	24.642	0.131	0.896	-45.092	51.531
x81	8.1706	13.458	0.607	0.544	-18.214	34.556
x82	13.3744	51.967	0.257	0.797	-88.510	115.259
x83	13.6905	61.630	0.222	0.824	-107.138	134.519
x84	-0.1131	12.766	-0.009	0.993	-25.142	24.915
x85	-4.9602	13.200	-0.376	0.707	-30.840	20.920
x86	36.4178	13.982	2.605	0.009	9.005	63.831
x87	-4.3368	12.893	-0.336	0.737	-29.614	20.940
x88	-5.7289	55.418	-0.103	0.918	-114.378	102.920
x89	-12.4237	26.040	-0.477	0.633	-63.477	38.629
x90	1.6291	30.509	0.053	0.957	-58.186	61.444
x91	-15.8643	13.297	-1.193	0.233	-41.934	10.205
x92	-0.5695	12.929	-0.044	0.965	-25.918	24.778
x93	0.7062	12.845	0.055	0.956	-24.476	25.889
x94	-34.3182	34.718	-0.988	0.323	-102.385	33.748
x95	-1.6480	23.948	-0.069	0.945	-48.599	45.303
x96	3.8175	16.168	0.236	0.813	-27.880	35.515
x97	23.4454	22.284	1.052	0.293	-20.244	67.135
x98	-6.2919	25.285	-0.249	0.803	-55.865	43.281
x99	1.5768	12.909	0.122	0.903	-23.733	26.886
x100	-1.5768	12.909	-0.122	0.903	-26.886	23.733

Omnibus:	1051.243	**Durbin-Watson:**	0.093
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3994.348
Skew:	1.215	**Prob(JB):**	0.00
Kurtosis:	7.148	**Cond. No.**	4.42e+16

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.01e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [180]:

```
for i, col in enumerate(X.columns):
    if col == 'district_Salamanca':
        print(i)
```

```
54
```

We can see that we have a lot of districts that are not significant at all, but at the same time some districts seem to be very significant like being ins Salamanca (feature 55) has an almost 100 Euro premium in rent with almost 0 p-value

Conclusions

We have concluded that as we suspected. The size of the apartment, the ammount of rooms, bathrooms are positively

correlated to the price of rent, and are also very significant to it. The district is alos important, although some districts like Salamanca command a premium while others are less significant. This is logical as some districts won't affect the price as they are not special. That's why those dummy variables seem unimportant.

As we care more about the predictive power of our model, than the inference we get from it. We will swith to using sklearns Linear Models to try and get a better model with a higher R^2 to implement.

Machine Learning

In [183]:

```
from sklearn.linear_model import Lasso, Ridge, LinearRegression
```

In [187]:

```
X2 = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X2, y, test_size=0.3, random_state=101)
```

In [188]:

```
m1 = LinearRegression()
m1.fit(X_train, y_train)
print("Train: ", m1.score(X_train, y_train))
print("Test: ", m1.score(X_test, y_test))
```

```
Train:  0.786660537558906
Test:  -5.849476790004094e+26
```

Well that is weird, this could be because off all the insignificant and dummy variables. We can add some regularization to our model We can start with L2 regularization with Ridge Regression, and if it's not enough we can go for L1 reg with LASSO

In [191]:

```
m2 = Ridge()
m2.fit(X_train, y_train)
print("Train: ", m2.score(X_train, y_train))
print("Test: ", m2.score(X_test, y_test))

m2_coef = pd.DataFrame(m2.coef_, index=X.columns, columns=['coef'])
```

```
Train:  0.7884826245934231
Test:  0.7929662322250918
```

This seems much better. We can also check the coefficients

In [207]:

```
m2_coef[m2_coef['coef'] > 10].sort_values(by='coef', ascending = False)
```

Out[207]:

	coef
size	399.740743
bathrooms	213.527895
district_Salamanca	88.064063
hasPlan	70.350010
has360	54.542340
rooms	52.904398
numPhotos	43.116144
hasParkingSpace	42.934122

	coef
hasLift	41.747064
municipality_La Moraleja	37.461836
district_Chamartín	35.596708
exterior	35.131653
district_Encinar de los Reyes	29.961159
district_El Soto de la Moraleja	27.286602
propertyType_penthouse	26.880869
district_Chamberí	19.967412
district_Zona norte	18.319111
district_Zona Monte el Pilar	17.127174
district_Urbanizaciones	15.101617
municipality_Boadilla del Monte	14.723845
municipality_Alcorcón	14.121536
district_Retiro	10.380535

These coefficients are all from a Scaled Variable, that's why Size seems too big. This can only be interpreted as biggest price "movers"

In [208]:

```
m3 = Lasso()
m3.fit(X_train, y_train)
print("Train: ", m3.score(X_train, y_train))
print("Test: ", m3.score(X_test, y_test))

m3_coef = pd.DataFrame(m3.coef_, index=X.columns, columns=['coef'])
```

```
Train:  0.7883007135327403
Test:  0.794321359881087
```

In [210]:

```
m3_coef[m3_coef['coef'] > 10].sort_values(by='coef', ascending = False)
```

Out[210]:

	coef
size	401.092479
bathrooms	212.619603
district_Salamanca	100.110465
municipality_La Moraleja	79.810637
hasPlan	68.954368
has360	53.861210
rooms	51.793921
district_Chamartín	43.269687
numPhotos	42.832062
hasLift	42.246458
hasParkingSpace	40.222385
exterior	34.505599
district_Chamberí	29.477734
propertyType_penthouse	27.225086

	coef
district_Retiro	17.374733
district_Zona norte	16.944472
district_Zona Monte el Pilar	15.378554
district_Urbanizaciones	14.721274
district_Alcobendas Centro	11.703159
district_Moncloa	10.659123

In [215]:

```
print(sum(m3_coef['coef'] > 0), "coefficients not made '0' by model")
```

```
40 coefficients not made '0' by model
```

The LASSO model made 60 coefficients 0, reducing the chances of the model being wrong because of insignificant variables

In [217]:

```
print("LinReg Score: ", m1.score(X_test, y_test))
print("Ridge Score: ", m2.score(X_test, y_test))
print("Lasso Score: ", m3.score(X_test, y_test))
```

```
LinReg Score:  -5.849476790004094e+26
Ridge Score:  0.7929662322250918
Lasso Score:  0.794321359881087
```

As Lasso Uses less variables and gave us marginally a better score, wwe can then optimize for this one

In [245]:

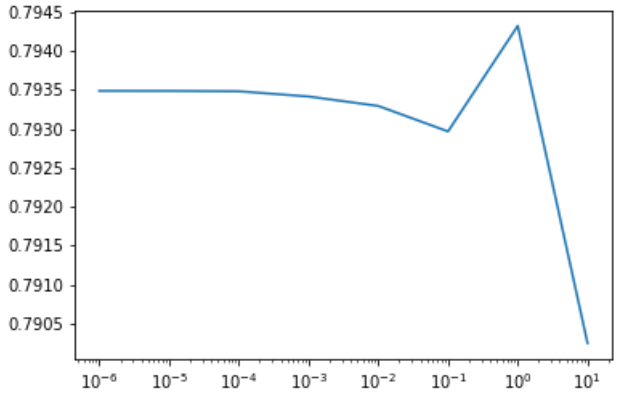
```
loss_values = [0.000001,0.00001,0.0001,0.001,0.01,0.1,1,10]
train_score = []
test_score = []

for i in loss_values:
    m = Lasso(alpha=i)
    m.fit(X_train, y_train)
    train_score.append(m.score(X_train, y_train))
    test_score.append(m.score(X_test, y_test))

models_list = pd.DataFrame(data={'Loss':loss_values, 'Train':train_score, 'Test': test_score})
models_list
```

Out[245]:

	Loss	Train	Test
0	0.000001	0.788483	0.793486
1	0.000010	0.788483	0.793486
2	0.000100	0.788483	0.793481
3	0.001000	0.788483	0.793414
4	0.010000	0.788483	0.793293
5	0.100000	0.788481	0.792966
6	1.000000	0.788301	0.794321
7	10.000000	0.780804	0.790248

In [253]:

```
plt.plot(models_list['Loss'], models_list['Test'])
plt.xscale('log')
```



Seems like the best linear model for this dataset is the Lasso Regression algorithm with an alpha of 1 (default)

Final Conclusions

We found what the main drivers for the price is, and we found that in the case of districts, only some were important and not the other ones. We also had to decide between interpretability getting 15% explained variance in Y with that set. Compared with Predictions power which using sklearn's linear methods got close to 80% in R squared.

As next steps, we will reproduce this model in Dataiku so that we can use the flow to create a train/val/test dataset. And then create some new features with the model as predcited price so we can use residuals to figure out if a listing price is a good deal or not