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

from utils import bootcampviztools as bt
from utils import toolbox_ML as tl

from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error,
mean_absolute_percentage_error, root_mean_squared_error
from sklearn.model_selection import GridSearchCV, cross_val_score,
train_test_split

from catboost import CatBoostRegressor
from xgboost import XGBRegressor
```

Project objective

The objective of this project is to create an ML model that allows predicting the sale price of a house taking into account a series of features. To achieve the objective we will perform a supervised regression model.

Extraction and understanding of the data

The data has been obtained from a **Kaggle dataset**: Data link.

The data contains information on the sale of homes in King County, Washington from May 2014 to May 2015. To have the data in a more accessible way when handling them they have been stored in the `Data` folder, as well as other possible versions of the data in which data has been removed or added.

The models that will be used and compared are: **Random Forest Regressor**, **XGBoost Regressor** and **CatBoost Regressor**.

```python
df = pd.read_csv('./data/kc_house_data.csv')
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
```

```
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
None

           id             date      price  bedrooms  bathrooms
sqft_living  \
0  7129300520  20141013T000000 221900.000         3      1.000
1180
1  6414100192  20141209T000000 538000.000         3      2.250
2570
2  5631500400  20150225T000000 180000.000         2      1.000
770
3  2487200875  20141209T000000 604000.000         4      3.000
1960
4  1954400510  20150218T000000 510000.000         3      2.000
1680

   sqft_lot  floors  waterfront  view  ...  grade  sqft_above
sqft_basement  \
0      5650   1.000           0     0  ...      7        1180
0
1      7242   2.000           0     0  ...      7        2170
400
2     10000   1.000           0     0  ...      6         770
0
3      5000   1.000           0     0  ...      7        1050
910
4      8080   1.000           0     0  ...      8        1680
0

   yr_built  yr_renovated  zipcode    lat     long  sqft_living15
sqft_lot15
0      1955             0    98178 47.511 -122.257           1340
5650
1      1951          1991    98125 47.721 -122.319           1690
```

```
7639
2       1933              0    98028 47.738 -122.233          2720
8062
3       1965              0    98136 47.521 -122.393          1360
5000
4       1987              0    98074 47.617 -122.045          1800
7503

[5 rows x 21 columns]
```

```
pd.options.display.float_format = '{:.3f}'.format
df.describe().T
```

```
                  count           mean            std         min  \
id            21613.000 4580301520.865 2876565571.312 1000102.000
price         21613.000     540088.142     367127.196   75000.000
bedrooms      21613.000          3.371          0.930       0.000
bathrooms     21613.000          2.115          0.770       0.000
sqft_living   21613.000       2079.900        918.441     290.000
sqft_lot      21613.000      15106.968      41420.512     520.000
floors        21613.000          1.494          0.540       1.000
waterfront    21613.000          0.008          0.087       0.000
view          21613.000          0.234          0.766       0.000
condition     21613.000          3.409          0.651       1.000
grade         21613.000          7.657          1.175       1.000
sqft_above    21613.000       1788.391        828.091     290.000
sqft_basement 21613.000        291.509        442.575       0.000
yr_built      21613.000       1971.005         29.373    1900.000
yr_renovated  21613.000         84.402        401.679       0.000
zipcode       21613.000      98077.940         53.505   98001.000
lat           21613.000         47.560          0.139      47.156
long          21613.000       -122.214          0.141    -122.519
sqft_living15 21613.000       1986.552        685.391     399.000
sqft_lot15    21613.000      12768.456      27304.180     651.000

                         25%            50%            75%
max
id            2123049194.000 3904930410.000 7308900445.000
9900000190.000
price             321950.000     450000.000     645000.000
7700000.000
bedrooms               3.000          3.000          4.000
33.000
bathrooms              1.750          2.250          2.500
8.000
sqft_living         1427.000       1910.000       2550.000
13540.000
sqft_lot            5040.000       7618.000      10688.000
1651359.000
floors                 1.000          1.500          2.000
```

```
3.500
waterfront              0.000          0.000          0.000
1.000
view                    0.000          0.000          0.000
4.000
condition               3.000          3.000          4.000
5.000
grade                   7.000          7.000          8.000
13.000
sqft_above           1190.000       1560.000       2210.000
9410.000
sqft_basement           0.000          0.000        560.000
4820.000
yr_built             1951.000       1975.000       1997.000
2015.000
yr_renovated            0.000          0.000          0.000
2015.000
zipcode             98033.000      98065.000      98118.000
98199.000
lat                    47.471         47.572         47.678
47.778
long                 -122.328       -122.230       -122.125        -
121.315
sqft_living15        1490.000       1840.000       2360.000
6210.000
sqft_lot15           5100.000       7620.000      10083.000
871200.000
```

It can be seen that the data type of the dataset columns are `int` and `float`, that is, numerical type. The Dataset has a total of 21 columns and a total of 21613 rows (or instances). It does not present null values.

We find an `object` type column: **date**. This column indicates the date on which the sale was made.

As for the description of the `Price` column values we can see that 75% of prices are below $645,000, while the maximum value is found at $7,700,000, something that may indicate outliers values in our Target variable. We can also find this in the `Bathrooms` column where there is a maximum value of 33 bathrooms while 75% are below 4 bathrooms.

The `Waterfront` variable is a binary variable **, since both in its quartiles and at its maximum and minimum the only values we find are 0 and 1.

We are going to make an informative table to be able to understand in a simpler way what each variable represents.

Variable	Type	Description	Notes
ID	int64	Single Housing Identifier	It may not be relevant to analysis

Variable	Type	Description	Notes
date	object	Date of sale of housing	Date format may require conversion
Price	float64	Sales price of house in dollars	OBJECTIVE VARIABLE FOR PRICE PREDICTIO N
Bedrooms	int64	Number of rooms in the house	It can include small bedrooms
Bathrooms	float64	Number of bathrooms in the house	Considered half bathrooms as 0.5 (those who have no shower)
sqft_living	int64	Square meters of habitable housing	Related to the price
sqft_lot	int64	Square meters of the land	Includes garden and other exterior spaces
floors	float64	Number of apartments in the house	It can be decimal if there are mezzanines
Waterfront	int64	1 If the house has a view of the water, 0 if no	Binary categorical variable
view	int64	Housing view score (0-4)	0 Indicates without a view, 4 is the best view
condition	int64	General state of housing (1-5)	1 is bad, 5 is excellent
grade	int64	Construction quality and finishes (1-13)	Based on construction standards
sqft_above	int64	Square meters of the part on the ground	Excludes basement
sqft_basement	int64	Square meters of	0 If you have

Variable	Type	Description	Notes
		basement	no basement
yr_built	int64	Year of housing construction	It can influence the price and status
yr_renovated	int64	Year of the last renewal, 0 if it has never been renewed	It can affect the value of housing
zipcode	int64	Location postal code	It can be used for geospatial analysis
Latin	float64	Latitude of the house	Geographical coordinate
long	float64	Housing length	Geographical coordinate
sqft_living15	int64	Average square meters of nearby homes	Neighborhood value indicator
sqft_lot15	int64	Average square meters in the area	It can influence the price

```
'''Change sale date format'''
df = df.rename({'date':'sale_date'}, axis = 1)
df['sale_date'] = pd.to_datetime(df['sale_date'], yearfirst=True)
```

Cardinality, Missing values and type of variable.

Although we have already made an informative table of each variable above, the following table will provide us with information on the cardinality of the variables, the number of unique values, percentage of Missing values and the type of variable. This information is useful for the analysis of the variables and how to treat them.

```
tl.describe_df(df)

          columna            tipo  %_nulos  valores_unicos  
%_cardinalidad
0              id           int64    0.000           21436  
99.180
1       sale_date  datetime64[ns]    0.000             372  
1.720
2           price         float64    0.000            4028  
18.640
3        bedrooms           int64    0.000              13  
```

```
0.060
4        bathrooms         float64    0.000                30
0.140
5      sqft_living           int64    0.000              1038
4.800
6         sqft_lot           int64    0.000              9782
45.260
7           floors         float64    0.000                 6
0.030
8       waterfront           int64    0.000                 2
0.010
9             view           int64    0.000                 5
0.020
10       condition           int64    0.000                 5
0.020
11           grade           int64    0.000                12
0.060
12      sqft_above           int64    0.000               946
4.380
13   sqft_basement           int64    0.000               306
1.420
14        yr_built           int64    0.000               116
0.540
15    yr_renovated           int64    0.000                70
0.320
16         zipcode           int64    0.000                70
0.320
17             lat         float64    0.000              5034
23.290
18            long         float64    0.000               752
3.480
19   sqft_living15           int64    0.000               777
3.600
20      sqft_lot15           int64    0.000              8689
40.200
```

We can see that there are some categorical variables such as `Waterfront` being this binary and already mentioned above, `Floor` with 6 unique values, `view` with 5 unique values,`Condition` 'with 5 unique values. The features `Bedrooms` and `Grade`, but we will see it later in Features's analysis as categorical.

The ID column does not contain 100% of cardinality, but it is very close. This indicates that there are some indices that are duplicated in the DF, something that is not common since the ID should be a unique identifier.

```
df['id'].duplicated().value_counts()

id
False    21436
```

```
True        177
Name: count, dtype: int64
```

There are a total of 177 IDS that are duplicated (1%).

```
df.loc[df['id'].duplicated(keep=False)].sort_values(by = 'id',
ascending=False).head()
```

```
               id   sale_date       price  bedrooms  bathrooms
sqft_living  \
1085   9834200885 2014-07-17 360000.000         4      2.500
2080
1086   9834200885 2015-04-20 550000.000         4      2.500
2080
15199  9834200305 2014-07-16 350000.000         3      1.000
1790
15200  9834200305 2015-02-10 615000.000         3      1.000
1790
6345   9828200460 2014-06-27 260000.000         2      1.000
700

       sqft_lot  floors  waterfront  view  ...  grade  sqft_above  \
1085       4080   1.000           0     0  ...      7        1040
1086       4080   1.000           0     0  ...      7        1040
15199      3876   1.500           0     0  ...      7        1090
15200      3876   1.500           0     0  ...      7        1090
6345       4800   1.000           0     0  ...      7         700

       sqft_basement  yr_built  yr_renovated  zipcode    lat     long
\
1085            1040      1962             0    98144 47.572 -122.290

1086            1040      1962             0    98144 47.572 -122.290

15199            700      1904             0    98144 47.575 -122.288

15200            700      1904             0    98144 47.575 -122.288

6345               0      1922             0    98122 47.615 -122.300


       sqft_living15  sqft_lot15
1085            1340        4080
1086            1340        4080
15199           1360        4080
15200           1360        4080
6345            1440        4800

[5 rows x 21 columns]
```

Seeing the IDs repeated in the DF we observe that the only columns that change are the sale date and the sale price, this indicates that there are homes that have been sold more than once during this period of time.

To know the number of times that a house has been sold we will create a new column called `sales' that will count the number of times based on how many times the ID is repeated.

```
df['ventas'] = df.groupby('id')['id'].transform('count')
df[df['ventas'] > 1]
df.ventas.value_counts()

ventas
1    21260
2      350
3        3
Name: count, dtype: int64
```

There are a total of 170 houses that have been sold 2 times and there is a house that has been sold a total of 3 times.

As our main objective is to predict the price of a house in an initial way we will keep the first registration of the sale of the house and eliminate the rest since the future sales have been conditioned by the previous price of the same.

```
df = df.drop_duplicates(subset=['id'], keep='first')
df.ventas.value_counts()

ventas
1    21260
2      175
3        1
Name: count, dtype: int64
```

We will use the date of sale of homes as a DATASET index since it will not provide us with greater use for the model. We will erase the ID of the homes since it will not help us for the creation of the model.

```
df = df.set_index('sale_date')
df = df.drop(columns='id', axis = 1)

bedrooms_33 = df[df['bedrooms'] == 33].index
df = df.drop(bedrooms_33)

df_limpio = df.to_csv('./data/df_limpio_modelo.csv')
```

Data analysis

Once we have established a business objective, extracted, understood and cleaned the data, we begin with the analysis of the variables, both of the `target` variable (price in our case) and the rest of the variables.

To start with the analysis we will recover the new dataset with all the changes we have made previously, which is the `data` folder.

- We eliminate the `sales` column since it is no longer necessary.
- We establish again `Sale_date` as our index.

```
df = pd.read_csv("./data/df_limpio_modelo.csv")
df = df.drop(columns='ventas', axis = 1)
df = df.set_index('sale_date')
df.head()
```

```
                price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
sale_date

2014-10-13 221900.000         3      1.000         1180      5650
1.000
2014-12-09 538000.000         3      2.250         2570      7242
2.000
2015-02-25 180000.000         2      1.000          770     10000
1.000
2014-12-09 604000.000         4      3.000         1960      5000
1.000
2015-02-18 510000.000         3      2.000         1680      8080
1.000

            waterfront  view  condition  grade  sqft_above
sqft_basement  \
sale_date

2014-10-13           0     0          3      7        1180
0
2014-12-09           0     0          3      7        2170
400
2015-02-25           0     0          3      6         770
0
2014-12-09           0     0          5      7        1050
910
2015-02-18           0     0          3      8        1680
0

            yr_built  yr_renovated  zipcode    lat     long
sqft_living15  \
sale_date

2014-10-13      1955             0    98178 47.511 -122.257
1340
2014-12-09      1951          1991    98125 47.721 -122.319
1690
2015-02-25      1933             0    98028 47.738 -122.233
2720
```

```
2014-12-09       1965             0     98136 47.521 -122.393
1360
2015-02-18       1987             0     98074 47.617 -122.045
1800

            sqft_lot15
sale_date
2014-10-13        5650
2014-12-09        7639
2015-02-25        8062
2014-12-09        5000
2015-02-18        7503
```

Once we have recovered our dataset, we will divide the data into two groups:

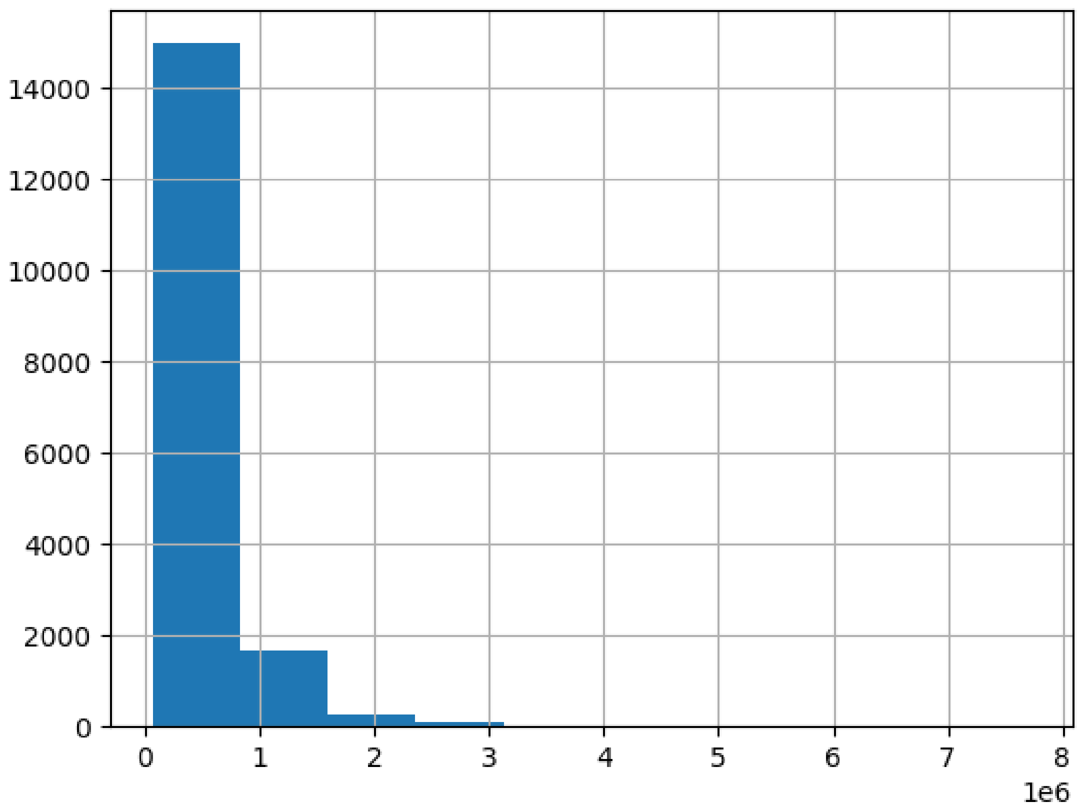
- `Train Set`. This set will help us visualize the data and perform the necessary transformations. It will also be the set with which we will train our model / models.
- `Test Set` test. We will keep this set and use it against the results obtained in our model to know how precise it is.

```
target = "price"

train_set, test_set = train_test_split(df, test_size = 0.2,
random_state = 42)
```

Analysis of the `target` variable

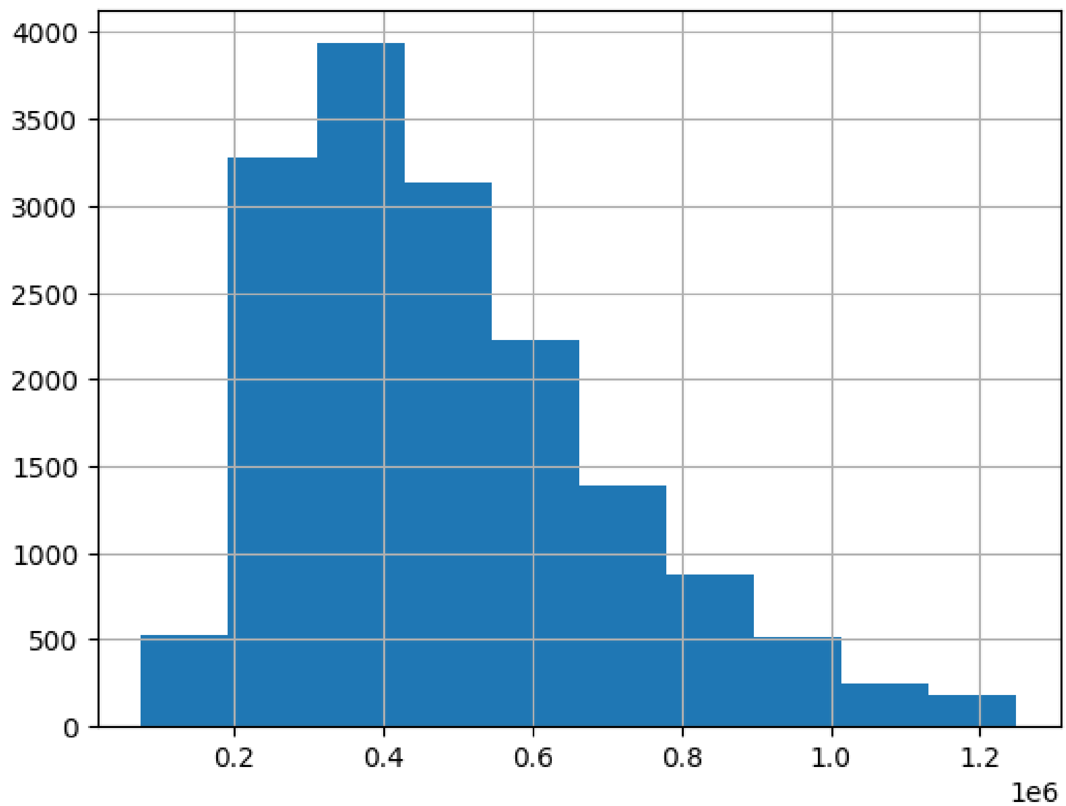
We perform an analysis of our Target variable to know the type of distribution it has.

```
train_set[target].hist();
```



Our Target variable does not follow a normal distribution and presents a tail to the right.

```
precios_bajos = train_set.loc[train_set[target] < 1250000]
precios_bajos[target].hist();
```



It is also observed that most houses have a price between 200,000 and 1,000,000 dollars. There are some houses that exceed these prices, reaching a maximum value of almost 8,000,000 dollars. This is not the ideal distribution for a linear regression model.

Analysis of features

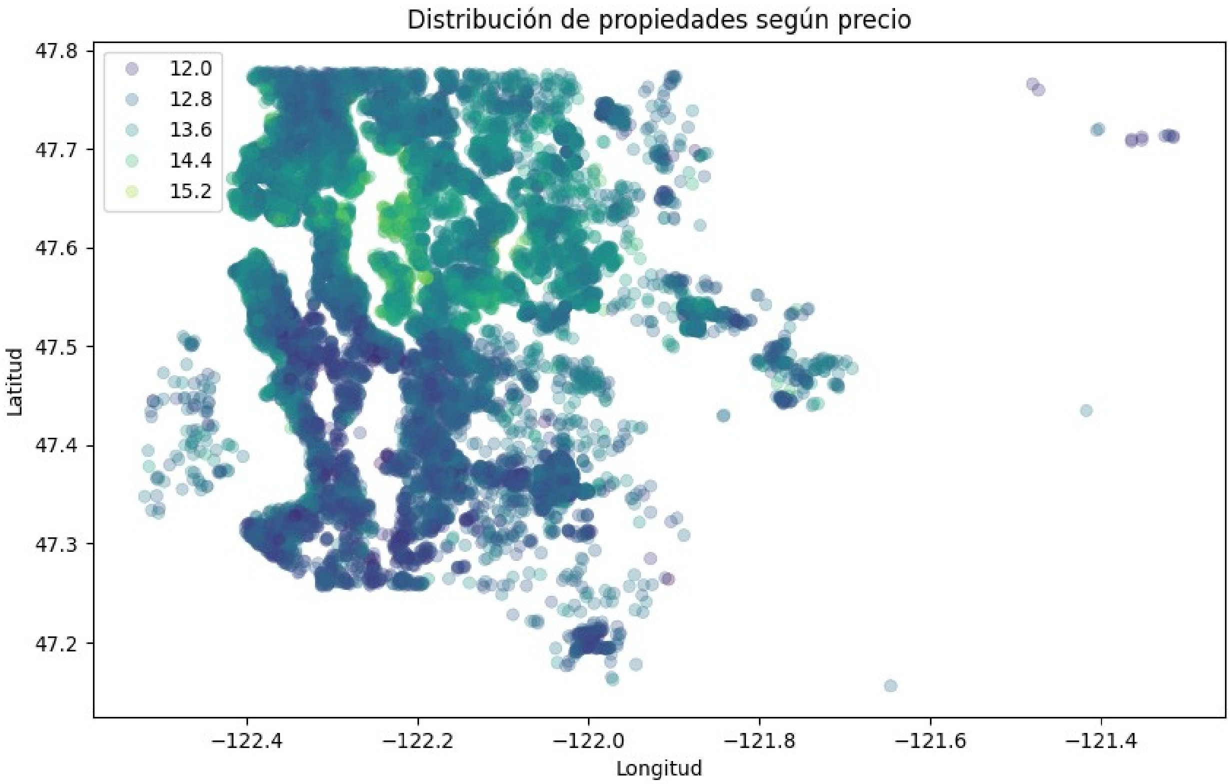
Now we will perform an analysis of the rest of features found in the DataSet. To perform the analysis we will divide the features into two groups:

- Numerical
- Categorical

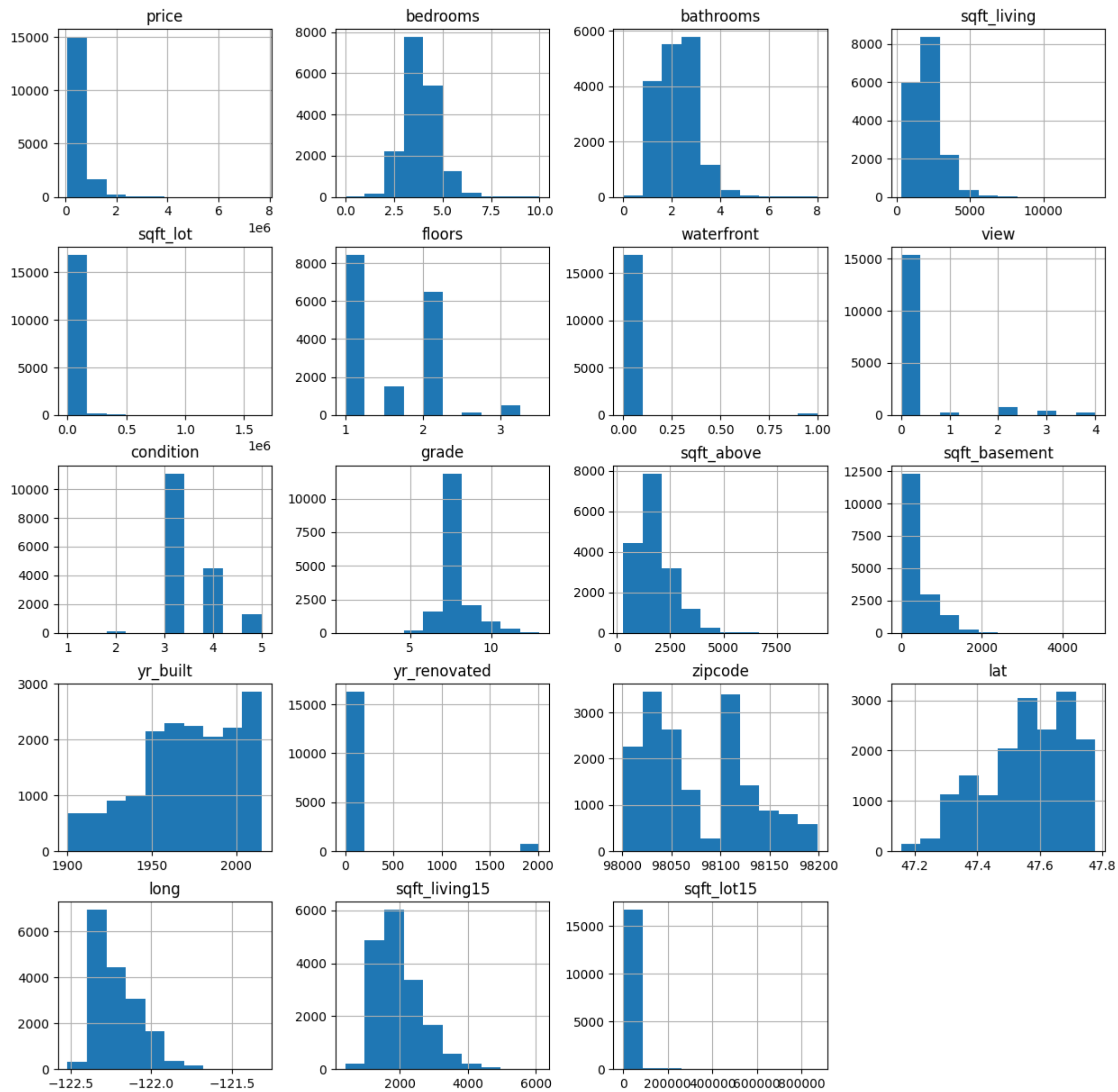
With the data of `Lat` and `Long` we can represent things in a geographical way in a graphic having the price of homes as hue. For this graphic representation, the data has been transformed logarithmically so that they are easier to represent.

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x=train_set['long'], y=train_set['lat'], alpha=0.3,
edgecolor=None, legend=True, hue = np.log(train_set[target]),
palette='viridis')

plt.xlabel("Longitud")
plt.ylabel("Latitud")
plt.title("Distribución de propiedades según precio")
```

```
plt.legend()
plt.show()
```




```
train_set.hist(figsize = (15,15));
```



The feature `yr_renovated` we will consider it as categorical since 95% of the homes have not been reformed, so we can turn it into a binary categorical.

```
features = train_set.columns.to_list()
features.remove(target)

cat_features =
['bedrooms','bathrooms','floors','waterfront','view','condition','grad
e','yr_renovated']
num_features = [col for col in train_set.columns if col not in
cat_features]

num_features
```

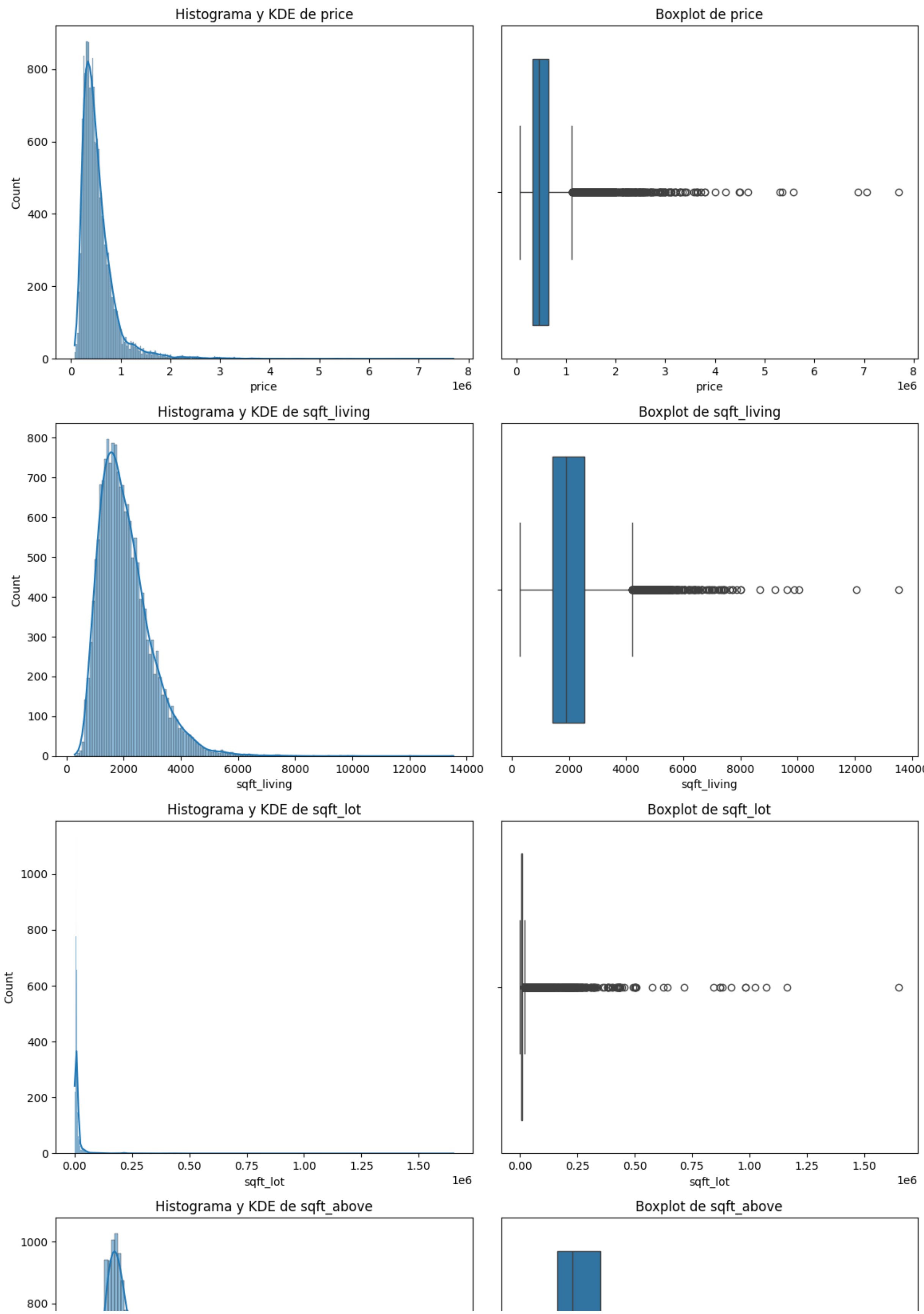
```
['price',
 'sqft_living',
 'sqft_lot',
 'sqft_above',
 'sqft_basement',
 'yr_built',
 'zipcode',
 'lat',
 'long',
 'sqft_living15',
 'sqft_lot15']
```

Analysis of the **numerical features**

First we will perform an EDA analysis of the numerical features to know how their distributions are. To do this, we will represent the data visually through boxploots and density histograms.

```
bt.plot_combined_graphs(df = train_set, columns=num_features,
whisker_width=1.5)
```

```
(11, 2)
```



Histograma y KDE de price
Boxplot de price
Count
price
1e6
Histograma y KDE de sqft_living
Boxplot de sqft_living
sqft_living
Histograma y KDE de sqft_lot
Boxplot de sqft_lot
sqft_lot
Histograma y KDE de sqft_above
Boxplot de sqft_above

In the previous graphics it can be seen that all features except `yr_built`,`Zipcode` and `Lat` have a large number of values **outliers**. It will not be necessary to apply transformations to these variables with outliers since trees -based algorithms know how to manage them. Nor will we apply a transformation to the feature `Long` since it is a geographical measure, just like lat.

Numerical features correlation

We will perform this correlation through the `Pearson` correlation

```
corr = train_set[num_features].corr()
corr[target].sort_values(ascending = False)
```

```
price            1.000
sqft_living      0.705
sqft_above       0.609
sqft_living15    0.586
sqft_basement    0.333
lat              0.303
sqft_lot         0.090
sqft_lot15       0.082
yr_built         0.054
long             0.018
zipcode         -0.057
Name: price, dtype: float64
```

Most features have a good correlation with the price. To keep the best we will establish a criterion that will consist of having a minimum of correlation to be considered relevant to the model.

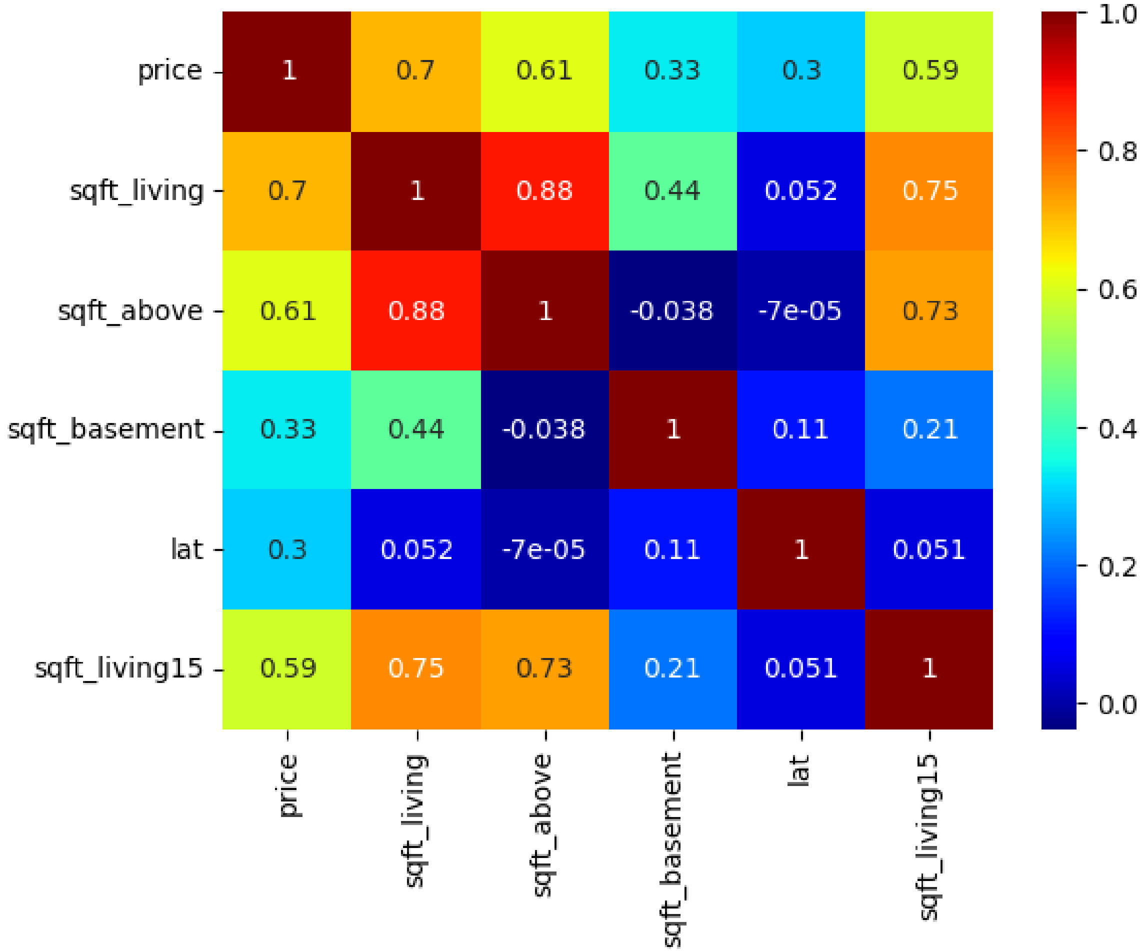
```
pearson_num_features = []
criterio = 0.15
for col in num_features:
    if corr[col][target] > criterio:
        pearson_num_features.append(col)

pearson_num_features
```

```
['price', 'sqft_living', 'sqft_above', 'sqft_basement', 'lat',
'sqft_living15']
```

** Colinerality **

Once these features have been chosen, we will analyze whether they have some kind of collinearity among them. It is important to know if there is a strong correlation between independent features since they can harm the model. To know the correlation between them we will use a **Heatmap**.

```
sns.heatmap(data = corr.loc[pearson_num_features,
pearson_num_features], annot=True, cmap = 'jet');
```

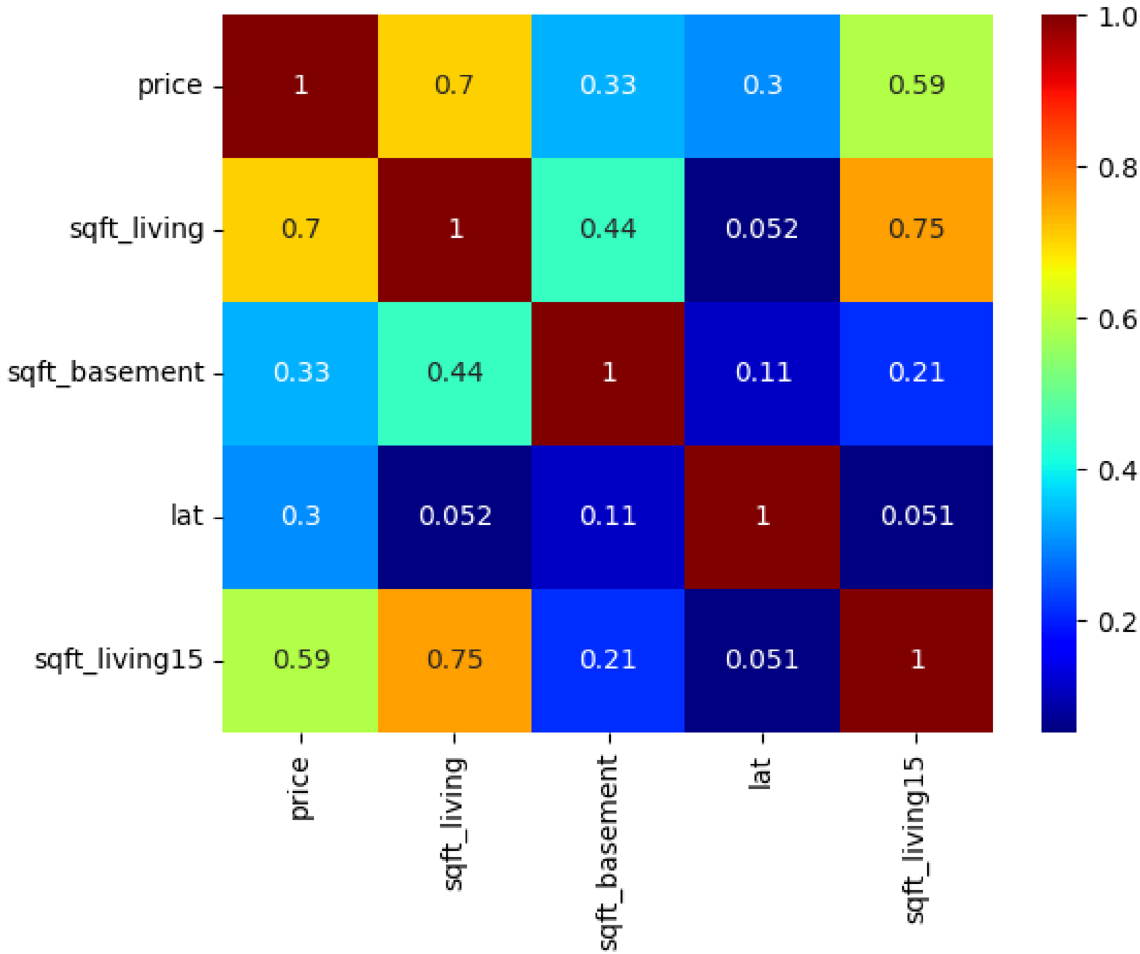


These are the colinealities we find:

- `sqft_above` it has colinerality with: sqft_living (88%), sqft_living15 (73%).
- `sqft_living15` has colinerality with: sqft_living (75%).

We will eliminate from the `sqft_above` list since it is the one that presents the greatest colinerality.

```
pearson_num_features.remove('sqft_above')

sns.heatmap(data = corr.loc[pearson_num_features,
pearson_num_features], annot=True, cmap = 'jet');
```



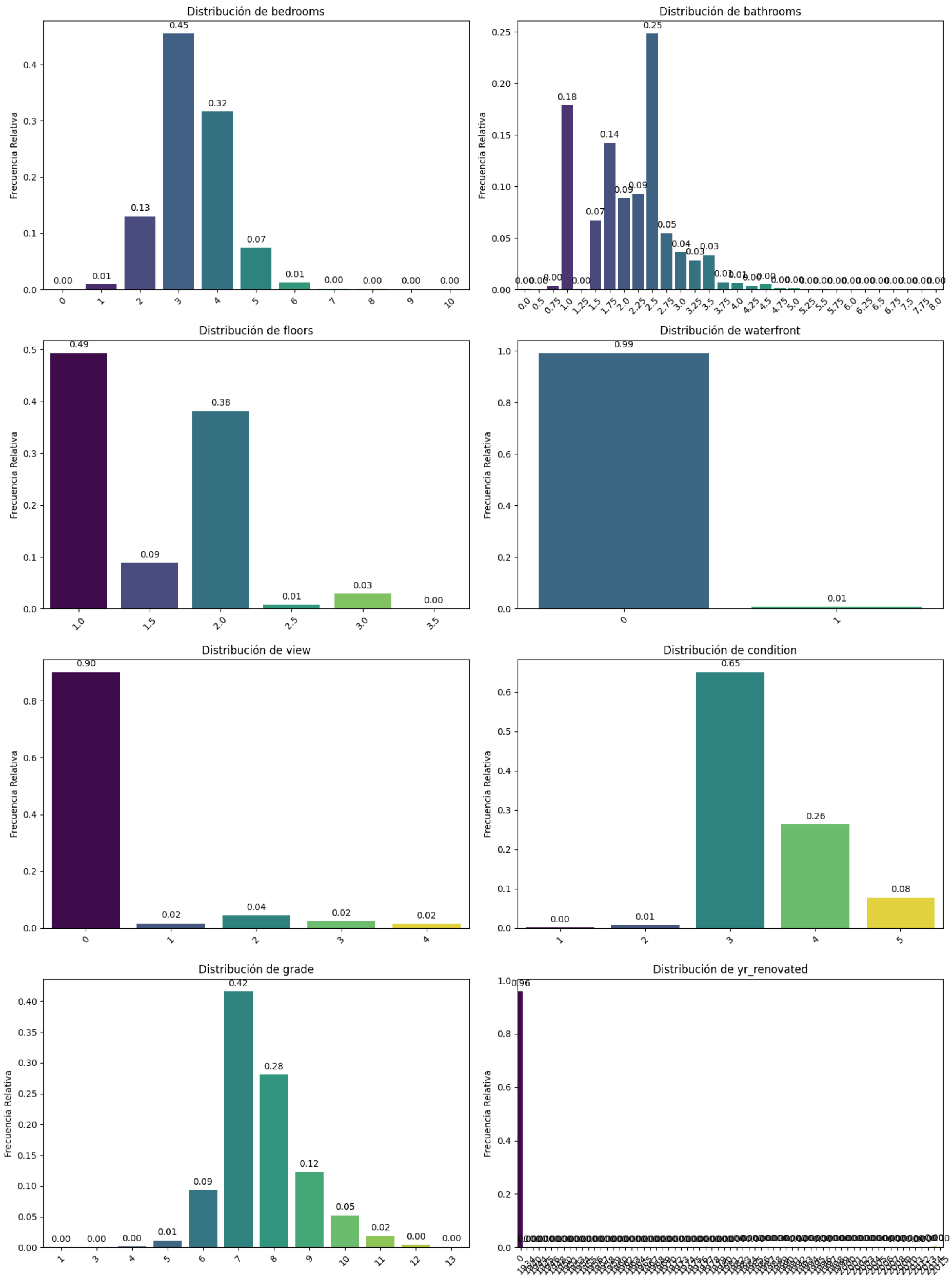
These are the numerical features that we will use for our model.

```
pearson_num_features.remove(target)

pearson_num_features

['sqft_living', 'sqft_basement', 'lat', 'sqft_living15']
```

Analysis of the `categorical features`

Once we have analyzed and selected the numerical features, we will carry out the analysis process for the categorical features of the DATASET. For this we will use different visualizations and correlations other than those used with numericals.

```
bt.pinta_distribucion_categoricas(df = train_set,
columnas_categoricas=cat_features, relativa=True,
mostrar_valores=True)
```


Distribución de bedrooms
Frecuencia Relativa
0.00
0.01
0.13
0.45
0.32
0.07
0.01
0.00
0.00
0.00
0.00
0
1
2
3
4
5
6
7
8
9
10
Distribución de bathrooms
Frecuencia Relativa
0.18
0.07
0.14
0.09
0.09
0.25
0.05
0.04
0.03
0.03
0.0
0.5
0.75
1.0
1.25
1.5
1.75
2.0
2.25
2.5
2.75
3.0
3.25
3.5
3.75
4.0
4.25
4.5
4.75
5.0
5.25
5.5
5.75
6.0
6.25
6.5
6.75
7.5
7.75
8.0
Distribución de floors
Frecuencia Relativa
0.49
0.09
0.38
0.01
0.03
0.00
1.0
1.5
2.0
2.5
3.0
3.5
Distribución de waterfront
Frecuencia Relativa
0.99
0.01
0
1
Distribución de view
Frecuencia Relativa
0.90
0.02
0.04
0.02
0.02
0
1
2
3
4
Distribución de condition
Frecuencia Relativa
0.00
0.01
0.65
0.26
0.08
1
2
3
4
5
Distribución de grade
Frecuencia Relativa
0.00
0.00
0.00
0.01
0.09
0.42
0.28
0.12
0.05
0.02
0.00
0.00
1
3
4
5
6
7
8
9
10
11
12
13
Distribución de yr_renovated
Frecuencia Relativa
0.96

In each categorical variable it can be seen that there is a dominant group that concentrates most values.

- `Waterfront` = 0 (it has no view of the sea) concentrates 99% of the data.
- `Yr_renovated` = 0 (it has not been renewed) concentrates 96% of the data. This variable could be converted to binary: it has been renovated (1) or not (0).
- `view` = 0 (they are not good views) concentrates 90% of the data.
- `Condition` = 3 concentrates 65% of the data.
- `Grade` = 7 concentrates 42% of the data.

** FEATURES correlation **

Once the distribution of features is visualized and analyzed, let's see the correlation they have with the Target variable (Price). To know the correlation of the categorical variables with the target, we will use the `anova` correlation

```
from scipy.stats import f_oneway

anova_results = {}
for col in cat_features:
    grupos = [train_set[target][train_set[col] == valor] for valor in
train_set[col].unique()]
    stats, p_value = f_oneway(*grupos)
    anova_results[col] = p_value

#Para verlo en formato Dataframe
# anova_df = pd.DataFrame(list(anova_results.items()), columns =
["Variable", "p_value"])
anova_results

{'bedrooms': 0.0,
 'bathrooms': 0.0,
 'floors': 7.6218201057e-314,
 'waterfront': 6.27440011047515e-262,
 'view': 0.0,
 'condition': 1.8764452127159177e-18,
 'grade': 0.0,
 'yr_renovated': 1.1694948220099811e-73}
```

All categorical features have a P_Value less than 0.05, so we can reject the null hypothesis and accept that these features have a significant statistical relationship with the target. We will use them in the model.

As for the feature `yr_renovated` we will create a new feature called` renovated both for Train Set and test set that will save the data binaryly: if the house has been reforma (1) or not (0).

```
"""Cambiar la columna 'yr_renovated' a una binaria: Ha sido reformada
(1) o no (0)"""

"""Para train set"""
```

```
train_set['reformada'] = (train_set['yr_renovated'] != 0).astype(int)

"""Para test set"""
test_set['reformada'] = (test_set['yr_renovated'] != 0).astype(int)

cat_features.append('reformada')
cat_features.remove('yr_renovated')
```

We will also transform the feature `Bathroom` in a smaller number of groups to make it easier to understand for the model

```
"""Convertir la feature 'bathroom' en una categórica de 4 grupos"""
"""Para train set"""
train_set.loc[train_set['bathrooms'] <= 1.25, 'bathrooms_cat'] = 0  #
Pocos baños
train_set.loc[(train_set['bathrooms'] > 1.25) &
(train_set['bathrooms'] <= 2.5), 'bathrooms_cat'] = 1  # Estándar
train_set.loc[(train_set['bathrooms'] > 2.5) & (train_set['bathrooms']
<= 3.75), 'bathrooms_cat'] = 2  # Grandes
train_set.loc[train_set['bathrooms'] > 3.75, 'bathrooms_cat'] = 3  #
Lujo

"""Para test set"""
test_set.loc[test_set['bathrooms'] <= 1.25, 'bathrooms_cat'] = 0  #
Pocos baños
test_set.loc[(test_set['bathrooms'] > 1.25) & (test_set['bathrooms']
<= 2.5), 'bathrooms_cat'] = 1  # Estándar
test_set.loc[(test_set['bathrooms'] > 2.5) & (test_set['bathrooms'] <=
3.75), 'bathrooms_cat'] = 2  # Grandes
test_set.loc[test_set['bathrooms'] > 3.75, 'bathrooms_cat'] = 3  #
Lujo

cat_features.append('bathrooms_cat')

cat_features.remove('bathrooms')
```

We join the selected features in the `selected_features` variable as the best based on the correlation they have with both numerical and categorical price

```
selected_features = pearson_num_features + cat_features
```

Creation of the model

Once we have analyzed and selected all features for our model, we will pass with the creation of the Predictor Price model. For this process we will perform a **Cross-Validation** between 3 different models and we will stay with the best metric. Our main metric will be the **RMSE**

```python
"""Train set division"""
x_train = train_set.drop(columns = target, axis = 1)
y_train = train_set[target]

"""Test set division"""
x_test = test_set.drop(columns = target, axis = 1)
y_test = test_set[target]
```

Model comparison

To get the best possible model we will use 3 different models:

- Random Forest Regressor
- XGBoost Regressor
- Catboost Regressor

```python
rf_reg = RandomForestRegressor(random_state=42, max_depth = 10)
xgb_reg = XGBRegressor(random_state = 42, max_depth = 10)
cat_reg = CatBoostRegressor(random_state=42, max_depth=10, verbose=0)
```

Models with all features

First we will perform the Cross-Validation with all the dataset features.

```python
original_features = train_set.columns.to_list()

original_features.remove(target)
original_features.remove('reformada')

original_features.remove('bathrooms_cat')

original_features
```

```
['bedrooms',
 'bathrooms',
 'sqft_living',
 'sqft_lot',
 'floors',
 'waterfront',
 'view',
 'condition',
 'grade',
 'sqft_above',
 'sqft_basement',
 'yr_built',
 'yr_renovated',
 'zipcode',
 'lat',
 'long',
```

```
 'sqft_living15',
 'sqft_lot15']

models = [('RF_reg', rf_reg),
          ('XGB_reg', xgb_reg),
          ('Catboost_reg', cat_reg)]

results = []

for name, model in models:
    print(f"Evaluando el modelo: {name}")

    x_train_model = x_train[original_features]
    x_test_model = x_test[original_features]

    cv_rmse = np.sqrt(-cross_val_score(model, x_train_model, y_train,
cv=5, scoring='neg_mean_squared_error'))

    model.fit(x_train_model, y_train)

    y_pred = model.predict(x_test_model)

    # Cálculo de MAE
    mae = mean_absolute_error(y_test, y_pred)

    # Cálculo de MAPE
    mape = np.mean(np.abs((y_test - y_pred) / y_test))  # Porcentaje
de error medio

    results.append({
        'Model': name,
        'RMSE (Cross-Val)': np.mean(cv_rmse),
        'MAPE': mape,
        'MAE': mae
    })

results_df = pd.DataFrame(results)
print(results_df)
```

```
Evaluando el modelo: RF_reg
Evaluando el modelo: XGB_reg
Evaluando el modelo: Catboost_reg
          Model  RMSE (Cross-Val)  MAPE       MAE
0        RF_reg        138332.690 0.140 72720.786
1       XGB_reg        139517.530 0.127 67816.722
2  Catboost_reg        125092.499 0.116 60225.260
```

Models with selected features

Now we will carry out the same process with the selected features.

```python
selected_features
```

```
['sqft_living',
 'sqft_basement',
 'lat',
 'sqft_living15',
 'bedrooms',
 'floors',
 'waterfront',
 'view',
 'condition',
 'grade',
 'reformada',
 'bathrooms_cat']
```

```python
models = [('RF_reg', rf_reg),
          ('XGB_reg', xgb_reg),
          ('Catboost_reg', cat_reg)]

results = []

for name, model in models:
    print(f"Evaluando el modelo: {name}")

    x_train_model = x_train[selected_features]
    x_test_model = x_test[selected_features]

    cv_rmse = np.sqrt(-cross_val_score(model, x_train_model, y_train,
cv=5, scoring='neg_mean_squared_error'))

    model.fit(x_train_model, y_train)

    y_pred = model.predict(x_test_model)

    # Cálculo de MAE
    mae = mean_absolute_error(y_test, y_pred)

    # Cálculo de MAPE
    mape = np.mean(np.abs((y_test - y_pred) / y_test))  # Porcentaje
de error medio

    results.append({
        'Model': name,
        'RMSE (Cross-Val)': np.mean(cv_rmse),
        'MAPE': mape,
        'MAE': mae
    })

results_df = pd.DataFrame(results)
print(results_df)
```

```
Evaluando el modelo: RF_reg
Evaluando el modelo: XGB_reg
Evaluando el modelo: Catboost_reg
          Model  RMSE (Cross-Val)  MAPE       MAE
0        RF_reg        162706.946 0.162 86516.556
1       XGB_reg        166916.772 0.159 85457.924
2  Catboost_reg        156864.142 0.150 80040.648
```

We get better results in all models using all dataset features. The best model is the `Catboost returns, with an RMSE of 125,092.5 dollars.

Improves the best model with **Gridsearch**

Once we have the best model, we will apply a `Gridsearch` in which we will try different parameters to obtain the best possible result and thus see if it improves.

Grid Search with all features

```
catboost_model = CatBoostRegressor(random_state=42, verbose=0)

param_grid = {
    'iterations': [200, 500, 1000],
    'learning_rate': [0.01, 0.05, 0.1],
    'depth': [4, 6, 8, 10],
}

grid_model = GridSearchCV(estimator=catboost_model,
                          param_grid=param_grid,
                          cv = 5,
                          scoring = 'neg_mean_squared_error')

grid_model.fit(x_train[original_features], y_train)

GridSearchCV(cv=5,
             estimator=<catboost.core.CatBoostRegressor object at
0x000001CD00ED33B0>,
             param_grid={'depth': [4, 6, 8, 10], 'iterations': [200,
500, 1000],
                         'learning_rate': [0.01, 0.05, 0.1]},
             scoring='neg_mean_squared_error')

print("Best parameters:", grid_model.best_params_)
print("Best RMSE:", (-grid_model.best_score_)**0.5)

Best parameters: {'depth': 6, 'iterations': 1000, 'learning_rate':
0.1}
Best RMSE: 119045.6259385073
```

** Predictions against the test set **

```
y_pred = grid_model.predict(x_test[original_features])

rmse = root_mean_squared_error(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

mape = np.mean(np.abs((y_test - y_pred) / y_test)) * 100

print(f"RMSE: {rmse}")
print(f"MAE: {mae}")
print(f"MAPE: {mape}%")
```

```
RMSE: 102675.58008651157
MAE: 60623.42551526358
MAPE: 11.82723183708813%
```

The only metric that has improved RMSE, being this with the Gridsearch of 102,675.58 dollars.

Model recording

Once we have achieved the best model, we will record it in the `models` folder to be able to use it again if necessary. To save the model we will use `Joblib`.

```
import joblib

# Savel model
joblib.dump(grid_model.best_estimator_, 'models/catboost_model.pkl')

# Load model later
loaded_model = joblib.load('catboost_model.pkl')

# Check everything works properly
y_pred_loaded_model = loaded_model.predict(x_test[original_features])
print(f"Predicciones con el modelo cargado:
{y_pred_loaded_model[:5]}")  # Muestra las primeras 5 predicciones
```

```
Predicciones con el modelo cargado: [592986.60890492 285861.78524006
333754.99426148 401826.3219303
 558707.12034682]
```