In [ ]:

```
!pip install pandas-profiling==3.2.0
!pip install markupsafe==2.0.1
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/
public/simple/
Requirement already satisfied: pandas-profiling==3.2.0 in /usr/local/lib/python3.7/d
ist-packages (3.2.0)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.7/dist-package
s (from pandas-profiling==3.2.0) (1.7.3)
Requirement already satisfied: multimethod>=1.4 in /usr/local/lib/python3.7/dist-pac
kages (from pandas-profiling==3.2.0) (1.8)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dist-packag
es (from pandas-profiling==3.2.0) (1.21.6)
Requirement already satisfied: joblib~=1.1.0 in /usr/local/lib/python3.7/dist-packag
es (from pandas-profiling==3.2.0) (1.1.0)
Requirement already satisfied: visions[type_image_path]==0.7.4 in /usr/local/lib/pyt
hon3.7/dist-packages (from pandas-profiling==3.2.0) (0.7.4)
Requirement already satisfied: jinja2>=2.11.1 in /usr/local/lib/python3.7/dist-packa
ges (from pandas-profiling==3.2.0) (2.11.3)
Requirement already satisfied: requests>=2.24.0 in /usr/local/lib/python3.7/dist-pac
kages (from pandas-profiling==3.2.0) (2.28.1)
Requirement already satisfied: tqdm>=4.48.2 in /usr/local/lib/python3.7/dist-package
s (from pandas-profiling==3.2.0) (4.64.0)
Requirement already satisfied: htmlmin>=0.1.12 in /usr/local/lib/python3.7/dist-pack
ages (from pandas-profiling==3.2.0) (0.1.12)
Requirement already satisfied: seaborn>=0.10.1 in /usr/local/lib/python3.7/dist-pack
ages (from pandas-profiling==3.2.0) (0.11.2)
Collecting markupsafe~=2.1.1
  Using cached MarkupSafe-2.1.1-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_6
4.whl (25 kB)
Requirement already satisfied: tangled-up-in-unicode==0.2.0 in /usr/local/lib/python
3.7/dist-packages (from pandas-profiling==3.2.0) (0.2.0)
Requirement already satisfied: matplotlib>=3.2.0 in /usr/local/lib/python3.7/dist-pa
ckages (from pandas-profiling==3.2.0) (3.2.2)
Requirement already satisfied: pydantic>=1.8.1 in /usr/local/lib/python3.7/dist-pack
ages (from pandas-profiling==3.2.0) (1.9.1)
Requirement already satisfied: PyYAML>=5.0.0 in /usr/local/lib/python3.7/dist-packag
es (from pandas-profiling==3.2.0) (6.0)
Requirement already satisfied: missingno>=0.4.2 in /usr/local/lib/python3.7/dist-pac
kages (from pandas-profiling==3.2.0) (0.5.1)
Requirement already satisfied: phik>=0.11.1 in /usr/local/lib/python3.7/dist-package
s (from pandas-profiling==3.2.0) (0.12.2)
Requirement already satisfied: pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.3 in /us
r/local/lib/python3.7/dist-packages (from pandas-profiling==3.2.0) (1.3.5)
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.7/dist-packag
es (from visions[type_image_path]==0.7.4->pandas-profiling==3.2.0) (22.1.0)
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.7/dist-packag
es (from visions[type_image_path]==0.7.4->pandas-profiling==3.2.0) (2.6.3)
Requirement already satisfied: imagehash in /usr/local/lib/python3.7/dist-packages
(from visions[type_image_path]==0.7.4->pandas-profiling==3.2.0) (4.2.1)
Requirement already satisfied: Pillow in /usr/local/lib/python3.7/dist-packages (fro
m visions[type_image_path]==0.7.4->pandas-profiling==3.2.0) (7.1.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-pa
ckages (from matplotlib>=3.2.0->pandas-profiling==3.2.0) (1.4.4)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/loca
l/lib/python3.7/dist-packages (from matplotlib>=3.2.0->pandas-profiling==3.2.0) (3.
0.9)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist
-packages (from matplotlib>=3.2.0->pandas-profiling==3.2.0) (2.8.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-package
s (from matplotlib>=3.2.0->pandas-profiling==3.2.0) (0.11.0)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-pa
```

```
ckages (from kiwisolver>=1.0.1->matplotlib>=3.2.0->pandas-profiling==3.2.0) (4.1.1)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-package
s (from pandas!=1.0.0,!=1.0.1,!=1.0.2,!=1.1.0,>=0.25.3->pandas-profiling==3.2.0) (20
22.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (f
rom python-dateutil>=2.1->matplotlib>=3.2.0->pandas-profiling==3.2.0) (1.15.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.7/dis
t-packages (from requests>=2.24.0->pandas-profiling==3.2.0) (1.24.3)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.7/dist-package
s (from requests>=2.24.0->pandas-profiling==3.2.0) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-p
ackages (from requests>=2.24.0->pandas-profiling==3.2.0) (2022.6.15)
Requirement already satisfied: charset-normalizer<3,>=2 in /usr/local/lib/python3.7/
dist-packages (from requests>=2.24.0->pandas-profiling==3.2.0) (2.1.0)
Requirement already satisfied: PyWavelets in /usr/local/lib/python3.7/dist-packages
(from imagehash->visions[type_image_path]==0.7.4->pandas-profiling==3.2.0) (1.3.0)
Installing collected packages: markupsafe
  Attempting uninstall: markupsafe
    Found existing installation: MarkupSafe 2.0.1
    Uninstalling MarkupSafe-2.0.1:
      Successfully uninstalled MarkupSafe-2.0.1
Successfully installed markupsafe-2.1.1

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/
public/simple/
Collecting markupsafe==2.0.1
  Using cached MarkupSafe-2.0.1-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.ma
nylinux_2_12_x86_64.manylinux2010_x86_64.whl (31 kB)
Installing collected packages: markupsafe
  Attempting uninstall: markupsafe
    Found existing installation: MarkupSafe 2.1.1
    Uninstalling MarkupSafe-2.1.1:
      Successfully uninstalled MarkupSafe-2.1.1
ERROR: pip's dependency resolver does not currently take into account all the packag
es that are installed. This behaviour is the source of the following dependency conf
licts.
pandas-profiling 3.2.0 requires markupsafe~=2.1.1, but you have markupsafe 2.0.1 whi
ch is incompatible.
Successfully installed markupsafe-2.0.1
```

In [ ]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all
from pandas_profiling import ProfileReport
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from scipy.stats import kruskal
import seaborn as sns
import matplotlib.pyplot as plt
from numpy import array
from sklearn.model_selection import KFold


%matplotlib inline

sns.set()
```

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Dataset 1 - https://www.kaggle.com/datasets/saisaathvik/l rent-prices-of-metropolitan-cities-in-india

In [ ]:

```
df = pd.read_csv("/content/drive/MyDrive/experimental/_All_Cities_Cleaned.csv.zip",
df.head()
```

Out[ ]:

	seller_type	bedroom	layout_type	property_type	locality	price	area	furnish_type	ba
0	OWNER	2.0	BHK	Apartment	Bodakdev	20000.0	1450.0	Furnished	
1	OWNER	1.0	RK	Studio Apartment	CG Road	7350.0	210.0	Semi-Furnished	
2	OWNER	3.0	BHK	Apartment	Jodhpur	22000.0	1900.0	Unfurnished	
3	OWNER	2.0	BHK	Independent House	Sanand	13000.0	1285.0	Semi-Furnished	
4	OWNER	2.0	BHK	Independent House	Navrangpura	18000.0	1600.0	Furnished	

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193011 entries, 0 to 193010
Data columns (total 10 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   seller_type    193011 non-null  object 
 1   bedroom        193011 non-null  float64
 2   layout_type    193011 non-null  object 
 3   property_type  193011 non-null  object 
 4   locality       193011 non-null  object 
 5   price          193011 non-null  float64
 6   area           193011 non-null  float64
 7   furnish_type   193011 non-null  object 
 8   bathroom       193011 non-null  float64
 9   city           193011 non-null  object 
dtypes: float64(4), object(6)
memory usage: 14.7+ MB
```

In [ ]:

```
profile = ProfileReport(df, title="Pandas Profiling Report")
```

In [ ]:

```
profile.to_notebook_iframe()
```

Overview

Dataset statistics

Number of variables	10
Number of observations	193011
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	34268
Duplicate rows (%)	17.8%
Total size in memory	14.7 MiB
Average record size in memory	80.0 B

Variable types

Categorical	6
Numeric	4

Alerts

Dataset has 34268 (17.8%) duplicate rows	**Duplicates**
`locality` has a high cardinality: 4146 distinct values	**High cardinality**
`bedroom` is highly correlated with `price` and 2 other fields (price, area, bathroom)	**High correlation**

In [ ]:

```
# muitos outliers
sns.boxplot(df["price"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
s the following variable as a keyword arg: x. From version 0.12, the only valid posi
tional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  FutureWarning
```

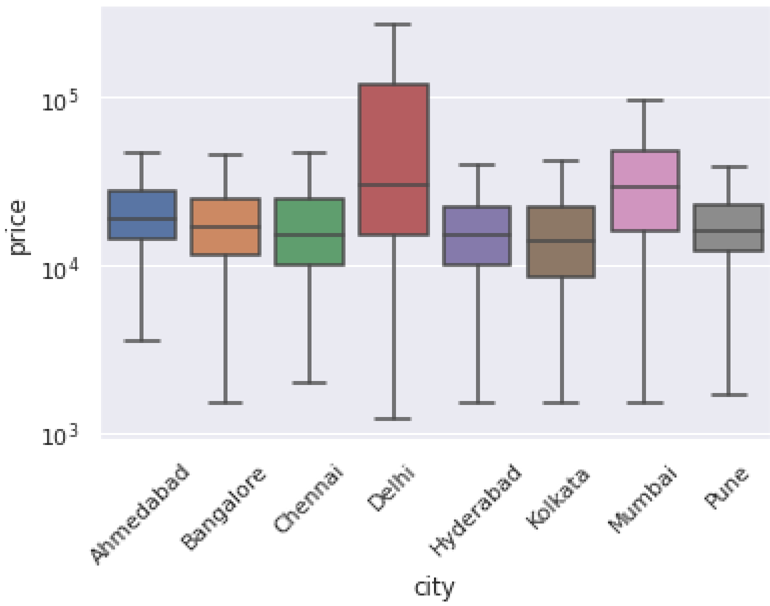
Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff2e8cb4e10>
```

In [ ]:

```
# aparentemente a cidade influencia no preço
ax = sns.boxplot(data=df,
            x = df["city"],
            y = df["price"],
            showfliers = False,
            )
plt.xticks(rotation=45)
ax.set(yscale="log")
```

Out[ ]: [None]



In [ ]:

```
# transformar os dados, ajuda com outliers e etc
df["price_log"] = np.log(df["price"])
df["area_log"] = np.log(df["area"])
```

In [ ]:

```
# onehot
df = pd.get_dummies(df.drop("locality", axis=1), drop_first=True)
#df = df[["bedroom", "price", "area", "bathroom"]]
df.head()
```

Out[ ]:

bedroom	price	area	bathroom	price_log	area_log	seller_type_BUILDER	seller_type_OWNE

	bedroom	price	area	bathroom	price_log	area_log	seller_type_BUILDER	seller_type_OWNE
0	2.0	20000.0	1450.0	2.0	9.903488	7.279319	0	
1	1.0	7350.0	210.0	1.0	8.902456	5.347108	0	
2	3.0	22000.0	1900.0	3.0	9.998798	7.549609	0	
3	2.0	13000.0	1285.0	2.0	9.472705	7.158514	0	
4	2.0	18000.0	1600.0	2.0	9.798127	7.377759	0	

5 rows × 23 columns

In [ ]:

```
X = df.drop(["price", "price_log"], axis=1)
y = df["price_log"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)
```

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

rf.fit(X_train, y_train)
lm.fit(X_train, y_train)
lasso.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_pred_lm = lm.predict(X_test)
y_pred_lasso = lasso.predict(X_test)

print("MSE RF: ", mean_squared_error(y_test, y_pred_rf))
print("MSE LM: ", mean_squared_error(y_test, y_pred_lm))
print("MSE LASSO: ", mean_squared_error(y_test, y_pred_lasso))

print("R2 RF: ", r2_score(y_test, y_pred_rf))
print("R2 LM: ", r2_score(y_test, y_pred_lm))
print("R2 LASSO: ", r2_score(y_test, y_pred_lasso))

print("RMSE RF: ", mean_squared_error(y_test, y_pred_rf, squared=False))
print("RMSE LM: ", mean_squared_error(y_test, y_pred_lm, squared=False))
print("RMSE LASSO: ", mean_squared_error(y_test, y_pred_lasso, squared=False))
```

```
MSE RF:  0.14447997640618462
MSE LM:  0.21942260490186888
MSE LASSO:  0.4028687329520718
R2 RF:  0.8322846779365841
R2 LM:  0.7452897365815508
R2 LASSO:  0.5323417059096036
RMSE RF:  0.38010521754664806
RMSE LM:  0.4684256663568606
RMSE LASSO:  0.6347194127739215
```

In [ ]:

```
from sklearn.metrics import mean_squared_error, r2_score

def train_test_model(model, data, dataset, model_name):
  kfold = KFold(n_splits=5)
  Y = data["target"]
  X = data.drop("target", axis=1)

  count = 0
  index = {}

  # kfold com 5 folds
  for train_index, test_index in kfold.split(data):

    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = Y.iloc[train_index], Y.iloc[test_index]

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    count += 1

    index[model_name + str(dataset) + "_" + str(count)] = mean_squared_error(y_test,
  return index
```

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

data = df.drop(["price", "price_log"], axis=1)
data["target"] = df["price_log"]

data1 = train_test_model(lm, data, 1, "linearModel")
```

In [ ]:

```
data1.update(train_test_model(rf, data, 1, "randomForest"))
```

In [ ]:

```
data1
```

Out[ ]:

```
{'linearModel1_1': 0.26057262002426623,
 'linearModel1_2': 0.32360692100888855,
 'linearModel1_3': 0.26789677324267563,
 'linearModel1_4': 0.33518885055800735,
 'linearModel1_5': 0.3215892438602057,
 'randomForest1_1': 0.17708090175036023,
 'randomForest1_2': 0.1778795651543115,
 'randomForest1_3': 0.23681970741927452,
 'randomForest1_4': 0.35695374099579,
 'randomForest1_5': 0.2586996399949596}
```

In [ ]:

```
data1.update(train_test_model(lasso, data, 1, "lasso"))
```

In [ ]:

```
data1
```

Out[ ]:

```
{'lasso1_1': 0.3109808467574476,
 'lasso1_2': 0.3516004718101653,
 'lasso1_3': 0.482183225146634,
```

```
 'lasso1_4': 0.707694131563812,
 'lasso1_5': 0.31954255398438325,
 'linearModel1_1': 0.26057262002426623,
 'linearModel1_2': 0.32360692100888855,
 'linearModel1_3': 0.26789677324267563,
 'linearModel1_4': 0.33518885055800735,
 'linearModel1_5': 0.3215892438602057,
 'randomForest1_1': 0.17708090175036023,
 'randomForest1_2': 0.1778795651543115,
 'randomForest1_3': 0.23681970741927452,
 'randomForest1_4': 0.35695374099579,
 'randomForest1_5': 0.2586996399949596}
```

Dataset 2 - House prices https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data

In [ ]:

```
df = pd.read_csv("/content/drive/MyDrive/experimental/train.csv")
df.head()
```

Out[ ]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

5 rows × 81 columns

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
```

```
18  OverallCond    1460 non-null   int64
19  YearBuilt      1460 non-null   int64
20  YearRemodAdd   1460 non-null   int64
21  RoofStyle      1460 non-null   object
22  RoofMatl       1460 non-null   object
23  Exterior1st    1460 non-null   object
24  Exterior2nd    1460 non-null   object
25  MasVnrType     1452 non-null   object
26  MasVnrArea     1452 non-null   float64
27  ExterQual      1460 non-null   object
28  ExterCond      1460 non-null   object
29  Foundation     1460 non-null   object
30  BsmtQual       1423 non-null   object
31  BsmtCond       1423 non-null   object
32  BsmtExposure   1422 non-null   object
33  BsmtFinType1   1423 non-null   object
34  BsmtFinSF1     1460 non-null   int64
35  BsmtFinType2   1422 non-null   object
36  BsmtFinSF2     1460 non-null   int64
37  BsmtUnfSF      1460 non-null   int64
38  TotalBsmtSF    1460 non-null   int64
39  Heating        1460 non-null   object
40  HeatingQC      1460 non-null   object
41  CentralAir     1460 non-null   object
42  Electrical     1459 non-null   object
43  1stFlrSF       1460 non-null   int64
44  2ndFlrSF       1460 non-null   int64
45  LowQualFinSF   1460 non-null   int64
46  GrLivArea      1460 non-null   int64
47  BsmtFullBath   1460 non-null   int64
48  BsmtHalfBath   1460 non-null   int64
49  FullBath       1460 non-null   int64
50  HalfBath       1460 non-null   int64
51  BedroomAbvGr   1460 non-null   int64
52  KitchenAbvGr   1460 non-null   int64
53  KitchenQual    1460 non-null   object
54  TotRmsAbvGrd   1460 non-null   int64
55  Functional     1460 non-null   object
56  Fireplaces     1460 non-null   int64
57  FireplaceQu    770 non-null    object
58  GarageType     1379 non-null   object
59  GarageYrBlt    1379 non-null   float64
60  GarageFinish   1379 non-null   object
61  GarageCars     1460 non-null   int64
62  GarageArea     1460 non-null   int64
63  GarageQual     1379 non-null   object
64  GarageCond     1379 non-null   object
65  PavedDrive     1460 non-null   object
66  WoodDeckSF     1460 non-null   int64
67  OpenPorchSF    1460 non-null   int64
68  EnclosedPorch  1460 non-null   int64
69  3SsnPorch      1460 non-null   int64
70  ScreenPorch    1460 non-null   int64
71  PoolArea       1460 non-null   int64
72  PoolQC         7 non-null      object
73  Fence          281 non-null    object
74  MiscFeature    54 non-null     object
75  MiscVal        1460 non-null   int64
76  MoSold         1460 non-null   int64
77  YrSold         1460 non-null   int64
78  SaleType       1460 non-null   object
79  SaleCondition  1460 non-null   object
80  SalePrice      1460 non-null   int64
```

```
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

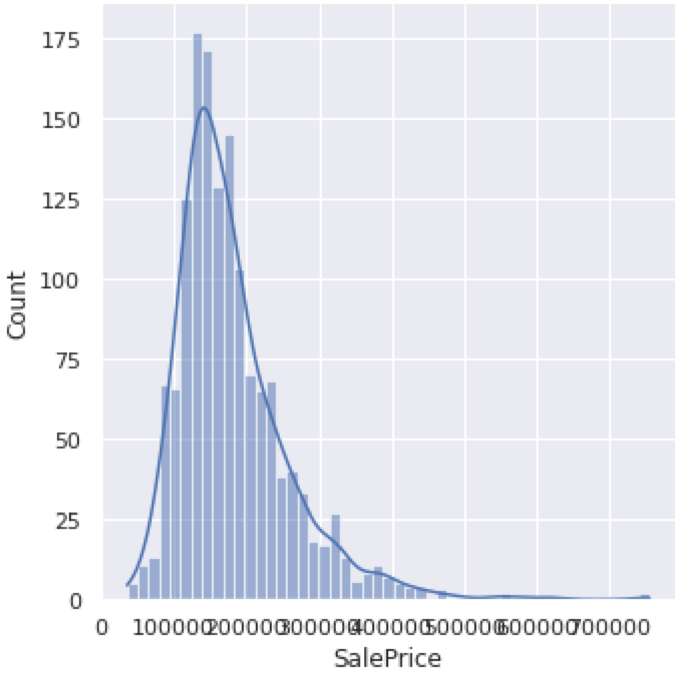
Analise Exploratória. Código base em: https://www.kaggle.com/code/lavanyashukla01/how-i-made-top-0-3-on-a-kaggle-competition

In [ ]:

```
sns.displot(df['SalePrice'], kde=True)
```

Out[ ]:

```
<seaborn.axisgrid.FacetGrid at 0x7ff2ec6edf50>
```



Não segue uma distribuição normal. Distroção positiva. Aparentemente sofre com curtose.

In [ ]:

```
print("Skewness: %f" % df['SalePrice'].skew())
print("Kurtosis: %f" % df['SalePrice'].kurt())
```

```
Skewness: 1.882876
Kurtosis: 6.536282
```

In [ ]:

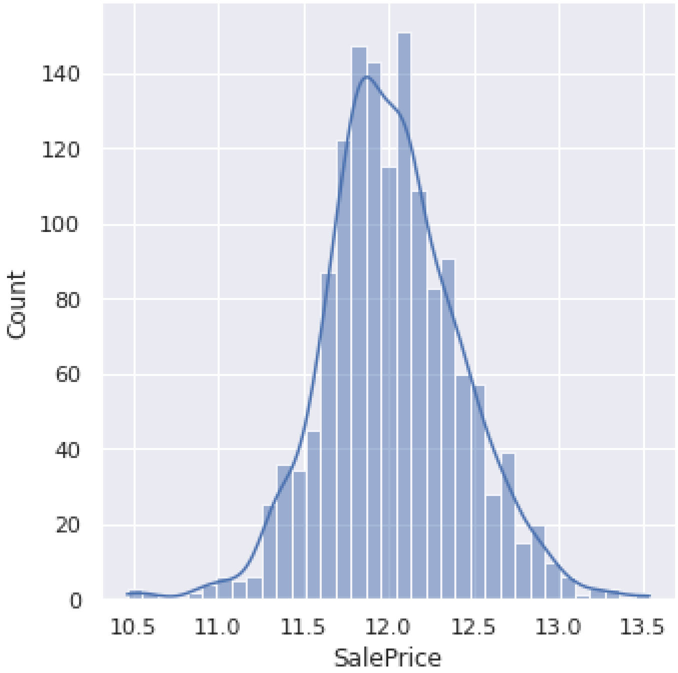
```
df["SalePrice"] = np.log(df["SalePrice"])
```

In [ ]:

```
sns.displot(df['SalePrice'], kde=True)
```

Out[ ]:

```
<seaborn.axisgrid.FacetGrid at 0x7ff2ec1d26d0>
```



Analisando algumas variáveis

In [ ]:

```
numeric_dtypes = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
numeric = []
for i in df.columns:
  if df[i].dtype in numeric_dtypes:
    numeric.append(i)

#sns.pairplot(df[numeric])
```

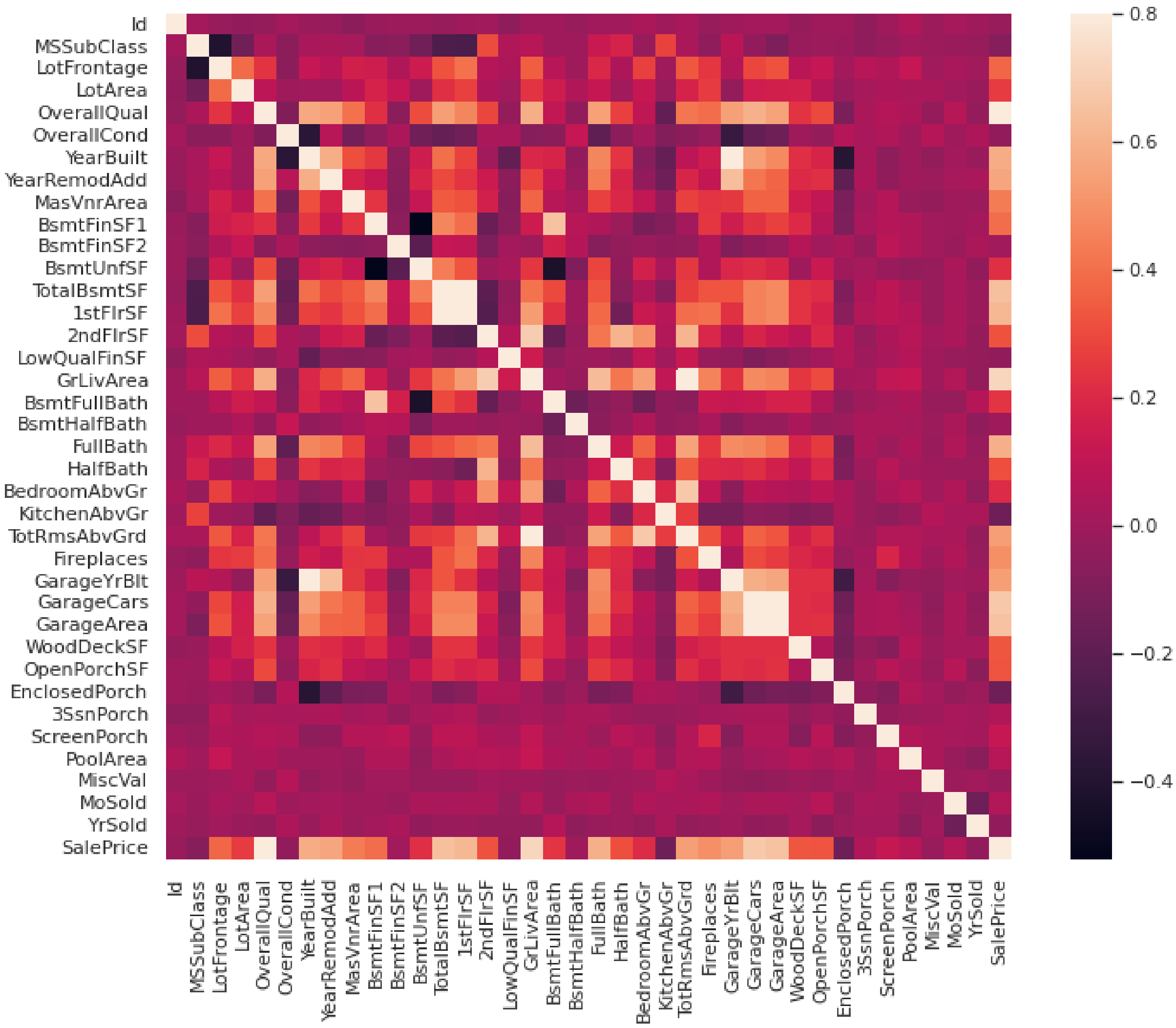
In [ ]:

```
# Remover outliers
df.drop(df[(df['OverallQual']<5) & (df['SalePrice']>200000)].index, inplace=True)
df.drop(df[(df['GrLivArea']>4500) & (df['SalePrice']<300000)].index, inplace=True)
df.reset_index(drop=True, inplace=True)
```

Relação com variáveis númericas

In [ ]:

```
corrmat = df.corr()
f, ax = plt.subplots(figsize=(12, 9))
sns.heatmap(corrmat, vmax=.8, square=True);
```



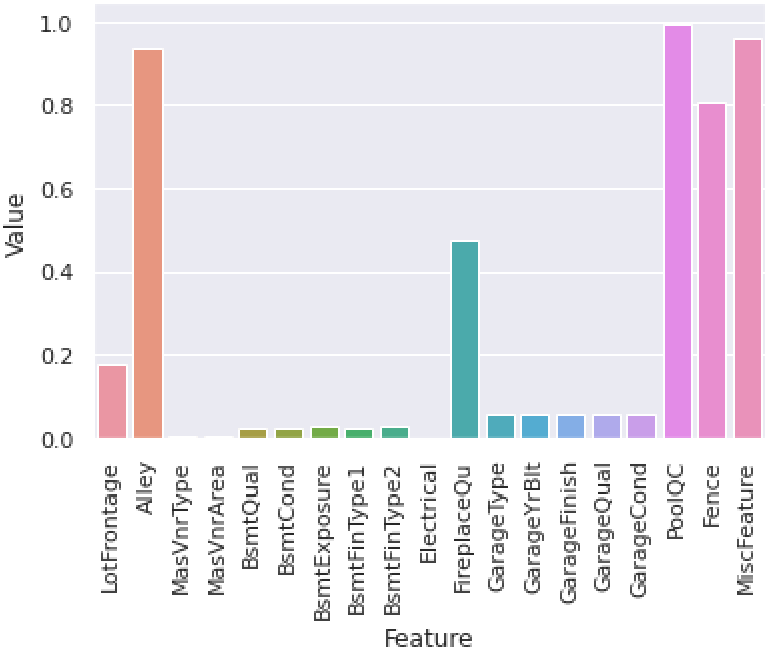
Missing Values

In [ ]:

```
data = {
    "Feature": df.isna().mean().index,
    "Value": df.isna().mean().values
}

missing = pd.DataFrame(data)
missing = missing[missing["Value"] > 0]
ax = sns.barplot(data=missing,
                 x="Feature",
                 y="Value")
plt.xticks(rotation=90)
```

Out[ ]:

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18]), <a list of 19 Text major ticklabel objects>)
```



In [ ]:

```
def drop_feature_with_miss(df):
  result = df.isna().mean()
  result = result[result >= 0.15]
  columns = result.index
  df.drop(columns, axis = 1, inplace = True)
```

In [ ]:

```
drop_feature_with_miss(df)
```

In [ ]:

```
def handle_missing(features):
    # the data description states that NA refers to typical ('Typ') values
    features['Functional'] = features['Functional'].fillna('Typ')
    # Replace the missing values in each of the columns below with their mode
    features['Electrical'] = features['Electrical'].fillna("SBrkr")
    features['KitchenQual'] = features['KitchenQual'].fillna("TA")
    features['Exterior1st'] = features['Exterior1st'].fillna(features['Exterior1st']
    features['Exterior2nd'] = features['Exterior2nd'].fillna(features['Exterior2nd']
    features['SaleType'] = features['SaleType'].fillna(features['SaleType'].mode()[0
    features['MSZoning'] = features.groupby('MSSubClass')['MSZoning'].transform(lamb

    # the data description stats that NA refers to "No Pool"
    features["PoolQC"] = features["PoolQC"].fillna("None")
    # Replacing the missing values with 0, since no garage = no cars in garage
    for col in ('GarageYrBlt', 'GarageArea', 'GarageCars'):
        features[col] = features[col].fillna(0)
    # Replacing the missing values with None
    for col in ['GarageType', 'GarageFinish', 'GarageQual', 'GarageCond']:
        features[col] = features[col].fillna('None')
    # NaN values for these categorical basement features, means there's no basement
    for col in ('BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType
        features[col] = features[col].fillna('None')

    # Group the by neighborhoods, and fill in missing value by the median LotFrontag
    features['LotFrontage'] = features.groupby('Neighborhood')['LotFrontage'].transf

    # We have no particular intuition around how to fill in the rest of the categori
    # So we replace their missing values with None
    objects = []
    for i in features.columns:
        if features[i].dtype == object:
```

```python
            objects.append(i)
    features.update(features[objects].fillna('None'))

    # And we do the same thing for numerical features, but this time with 0s
    numeric_dtypes = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    numeric = []
    for i in features.columns:
        if features[i].dtype in numeric_dtypes:
            numeric.append(i)
    features.update(features[numeric].fillna(0))
    return features

all_features = handle_missing(df)
```

In [ ]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1458 non-null   int64  
 1   MSSubClass     1458 non-null   int64  
 2   MSZoning       1458 non-null   object 
 3   LotFrontage    1458 non-null   float64
 4   LotArea        1458 non-null   int64  
 5   Street         1458 non-null   object 
 6   Alley          1458 non-null   object 
 7   LotShape       1458 non-null   object 
 8   LandContour    1458 non-null   object 
 9   Utilities      1458 non-null   object 
 10  LotConfig      1458 non-null   object 
 11  LandSlope      1458 non-null   object 
 12  Neighborhood   1458 non-null   object 
 13  Condition1     1458 non-null   object 
 14  Condition2     1458 non-null   object 
 15  BldgType       1458 non-null   object 
 16  HouseStyle     1458 non-null   object 
 17  OverallQual    1458 non-null   int64  
 18  OverallCond    1458 non-null   int64  
 19  YearBuilt      1458 non-null   int64  
 20  YearRemodAdd   1458 non-null   int64  
 21  RoofStyle      1458 non-null   object 
 22  RoofMatl       1458 non-null   object 
 23  Exterior1st    1458 non-null   object 
 24  Exterior2nd    1458 non-null   object 
 25  MasVnrType     1458 non-null   object 
 26  MasVnrArea     1458 non-null   float64
 27  ExterQual      1458 non-null   object 
 28  ExterCond      1458 non-null   object 
 29  Foundation     1458 non-null   object 
 30  BsmtQual       1458 non-null   object 
 31  BsmtCond       1458 non-null   object 
 32  BsmtExposure   1458 non-null   object 
 33  BsmtFinType1   1458 non-null   object 
 34  BsmtFinSF1     1458 non-null   int64  
 35  BsmtFinType2   1458 non-null   object 
 36  BsmtFinSF2     1458 non-null   int64  
 37  BsmtUnfSF      1458 non-null   int64  
 38  TotalBsmtSF    1458 non-null   int64  
 39  Heating        1458 non-null   object 
 40  HeatingQC      1458 non-null   object 
```

```
 41  CentralAir     1458 non-null   object 
 42  Electrical     1458 non-null   object 
 43  1stFlrSF       1458 non-null   int64  
 44  2ndFlrSF       1458 non-null   int64  
 45  LowQualFinSF   1458 non-null   int64  
 46  GrLivArea      1458 non-null   int64  
 47  BsmtFullBath   1458 non-null   int64  
 48  BsmtHalfBath   1458 non-null   int64  
 49  FullBath       1458 non-null   int64  
 50  HalfBath       1458 non-null   int64  
 51  BedroomAbvGr   1458 non-null   int64  
 52  KitchenAbvGr   1458 non-null   int64  
 53  KitchenQual    1458 non-null   object 
 54  TotRmsAbvGrd   1458 non-null   int64  
 55  Functional     1458 non-null   object 
 56  Fireplaces     1458 non-null   int64  
 57  FireplaceQu    1458 non-null   object 
 58  GarageType     1458 non-null   object 
 59  GarageYrBlt    1458 non-null   float64
 60  GarageFinish   1458 non-null   object 
 61  GarageCars     1458 non-null   int64  
 62  GarageArea     1458 non-null   int64  
 63  GarageQual     1458 non-null   object 
 64  GarageCond     1458 non-null   object 
 65  PavedDrive     1458 non-null   object 
 66  WoodDeckSF     1458 non-null   int64  
 67  OpenPorchSF    1458 non-null   int64  
 68  EnclosedPorch  1458 non-null   int64  
 69  3SsnPorch      1458 non-null   int64  
 70  ScreenPorch    1458 non-null   int64  
 71  PoolArea       1458 non-null   int64  
 72  PoolQC         1458 non-null   object 
 73  Fence          1458 non-null   object 
 74  MiscFeature    1458 non-null   object 
 75  MiscVal        1458 non-null   int64  
 76  MoSold         1458 non-null   int64  
 77  YrSold         1458 non-null   int64  
 78  SaleType       1458 non-null   object 
 79  SaleCondition  1458 non-null   object 
 80  SalePrice      1458 non-null   float64
dtypes: float64(4), int64(34), object(43)
memory usage: 922.8+ KB
```

In [ ]:

```
all_features.head()
```

Out[ ]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utiliti
0	1	60	RL	65.0	8450	Pave	None	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	None	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	None	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	None	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	None	IR1	Lvl	AllPu

5 rows × 81 columns

In [ ]:

```
from scipy.stats import skew, norm
from scipy.special import boxcox1p
```

```
from scipy.stats import boxcox_normmax

skew_features = all_features[numeric].apply(lambda x: skew(x)).sort_values(ascending

high_skew = skew_features[skew_features > 0.5]
skew_index = high_skew.index
```

In [ ]:

```
for i in skew_index:
    all_features[i] = boxcox1p(all_features[i], boxcox_normmax(all_features[i] + 1))
```

```
/usr/local/lib/python3.7/dist-packages/scipy/stats/stats.py:4023: PearsonRConstantIn
putWarning: An input array is constant; the correlation coefficient is not defined.
  warnings.warn(PearsonRConstantInputWarning())
/usr/local/lib/python3.7/dist-packages/scipy/stats/stats.py:4053: PearsonRNearConsta
ntInputWarning: An input array is nearly constant; the computed correlation coeffici
ent may be inaccurate.
  warnings.warn(PearsonRNearConstantInputWarning())
```

In [ ]:

```
all_features = pd.get_dummies(all_features).reset_index(drop=True)
all_features.shape
```

Out[ ]:

```
(1458, 303)
```

In [ ]:

```
X = all_features.drop("SalePrice", axis=1)
y = all_features["SalePrice"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)
```

In [ ]:

```
# codigo sem a validação cruzada
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

rf.fit(X_train, y_train)
lm.fit(X_train, y_train)
lasso.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_pred_lm = lm.predict(X_test)
y_pred_lasso = lasso.predict(X_test)

print("MSE RF: ", mean_squared_error(y_test, y_pred_rf))
print("MSE LM: ", mean_squared_error(y_test, y_pred_lm))
print("MSE LASSO: ", mean_squared_error(y_test, y_pred_lasso))

print("R2 RF: ", r2_score(y_test, y_pred_rf))
print("R2 LM: ", r2_score(y_test, y_pred_lm))
print("R2 LASSO: ", r2_score(y_test, y_pred_lasso))

print("RMSE RF: ", mean_squared_error(y_test, y_pred_rf, squared=False))
print("RMSE LM: ", mean_squared_error(y_test, y_pred_lm, squared=False))
print("RMSE LASSO: ", mean_squared_error(y_test, y_pred_lasso, squared=False))
```

```
MSE RF:  0.01926306985189282
```

```
MSE LM:  0.016165139194202354
MSE LASSO:  0.034859234653039084
R2 RF:  0.8773058061444857
R2 LM:  0.8970377651514384
R2 LASSO:  0.7779675966987903
RMSE RF:  0.13879146173988088
RMSE LM:  0.1271422006817656
RMSE LASSO:  0.18670627909376558
```

In [ ]:

```python
#X = all_features.drop("SalePrice", axis=1)
#y = all_features["SalePrice"]
#X_train, X_test, y_train, y_test = train_test_split(
#    X, y, test_size=0.33, random_state=42)

data = all_features.drop("SalePrice", axis=1)
data["target"] = all_features["SalePrice"]

lm = LinearRegression()

data2 = train_test_model(lm, data, 2, "linearModel")
```

In [ ]:

```python
rf = RandomForestRegressor()

data2.update(train_test_model(rf, data, 2, "randomForest"))
```

In [ ]:

```python
lasso = Lasso()

data2.update(train_test_model(lasso, data, 2, "lasso"))
```

In [ ]:

```python
## So treinar os modelos a partir daqui
```

================ Dataset 3 ================

https://www.kaggle.com/datasets/shree1992/housedata

In [ ]:

```python
from zipfile import ZipFile

# specifying the zip file name
file_name = "/content/drive/MyDrive/experimental/archive.zip"

# opening the zip file in READ mode
with ZipFile(file_name, 'r') as zip:
    # reading  the data
    df = pd.read_csv(zip.open("data.csv"))

df.head()
```

Out[ ]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
0	2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0	0	

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condit
1	2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0	4	
2	2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0	0	
3	2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0	0	
4	2014-05-02 00:00:00	550000.0	4.0	2.50	1940	10500	1.0	0	0	

In [ ]:

```
df.drop(["street", "statezip", "country"], axis=1, inplace=True)
```

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 15 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   date           4600 non-null   object
 1   price          4600 non-null   float64
 2   bedrooms       4600 non-null   float64
 3   bathrooms      4600 non-null   float64
 4   sqft_living    4600 non-null   int64
 5   sqft_lot       4600 non-null   int64
 6   floors         4600 non-null   float64
 7   waterfront     4600 non-null   int64
 8   view           4600 non-null   int64
 9   condition      4600 non-null   int64
 10  sqft_above     4600 non-null   int64
 11  sqft_basement  4600 non-null   int64
 12  yr_built       4600 non-null   int64
 13  yr_renovated   4600 non-null   int64
 14  city           4600 non-null   object
dtypes: float64(4), int64(9), object(2)
memory usage: 539.2+ KB
```

In [ ]:

```
profile = ProfileReport(df, title="Pandas Profiling Report")
```

In [ ]:

```
profile.to_notebook_iframe()
```

Overview

Dataset statistics

Number of variables	15
Number of observations	4600
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	539.2 KiB
Average record size in memory	120.0 B

Variable types

Categorical	5
Numeric	10

Alerts

`date` has a high cardinality: 70 distinct values	**High cardinality**
`price` is highly correlated with `sqft_living` and 1 other fields (sqft_living, sqft_above)	**High correlation**
`bedrooms` is highly correlated with `bathrooms` and 2 other fields	**High correlation**

In [ ]:

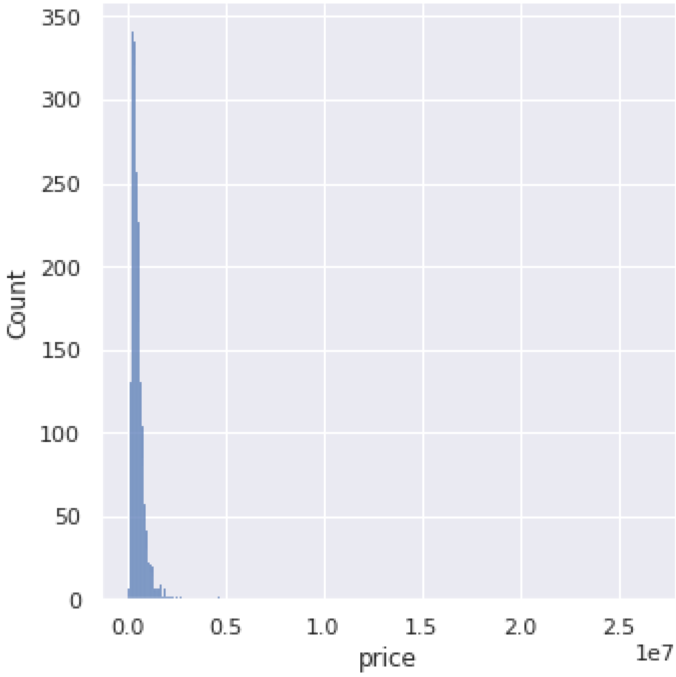
```
df.drop(df[df["price"] == 0].index, inplace=True)
```

In [ ]:

```
sns.displot(df["price"])
```

Out[ ]:

```
<seaborn.axisgrid.FacetGrid at 0x7ff2e05d3e50>
```



In [ ]:

```
df["price"].describe()
```

Out[ ]:

```
count    4.551000e+03
mean     5.579059e+05
std      5.639299e+05
min      7.800000e+03
25%      3.262643e+05
50%      4.650000e+05
75%      6.575000e+05
max      2.659000e+07
Name: price, dtype: float64
```

In [ ]:

```
from scipy.stats.mstats_basic import kurtosis
print("Skewness:", df["price"].skew())
print("Peakdness: ", df["price"].kurt())
```

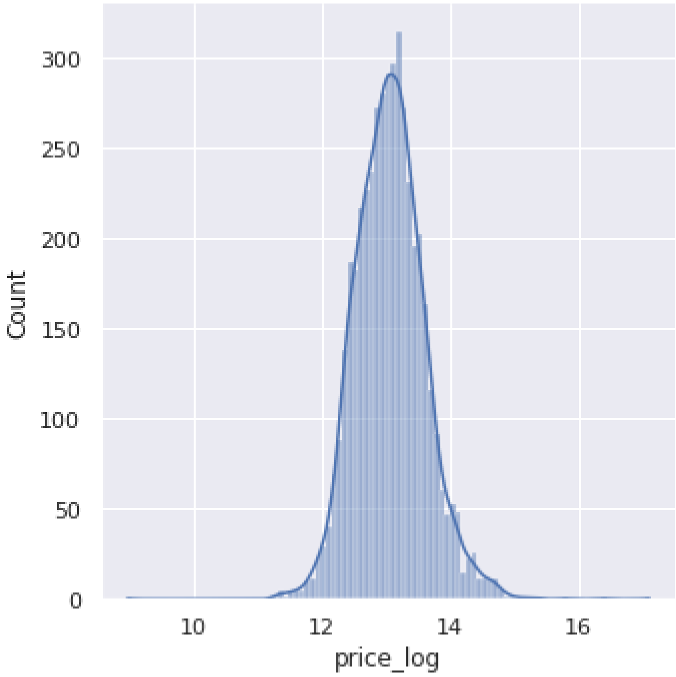
```
Skewness: 25.023817262008482
Peakdness:  1053.865419055905
```

In [ ]:

```
df["price_log"] = np.log(df["price"])
sns.displot(df["price_log"],
            kde=True)
```

Out[ ]:

```
<seaborn.axisgrid.FacetGrid at 0x7ff2e2423450>
```



In [ ]:

```
from scipy.stats import skew

print("Skewness:", skew(df["price_log"]))
print("Peakdness: ", df["price_log"].kurt())
```

```
Skewness: 0.3298726126818522
Peakdness:  2.0847763184794865
```

In [ ]:

```
from scipy.stats import shapiro

shapiro(df["price_log"])
```

Out[ ]:

```
ShapiroResult(statistic=0.9847530126571655, pvalue=9.043211621511537e-22)
```

In [ ]:

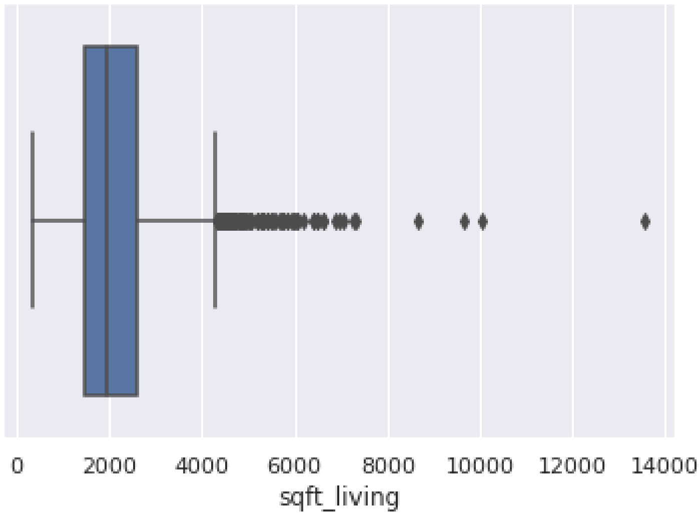
```
def plot_some_graphs(df):
  fig, ax = plt.subplots(2, 2, sharey='row')
  sns.scatterplot(data=df,
                  y="price_log",
                  x="bedrooms",
                  ax=ax[0, 0])

  sns.scatterplot(data=df,
                  y="price_log",
                  x="bathrooms",
                  ax=ax[0, 1])


  sns.scatterplot(data=df,
                  y="price_log",
                  x="sqft_living",
                  ax=ax[1, 1])



  sns.scatterplot(data=df,
                  y="price_log",
                  x="yr_built",
                  ax=ax[1, 0])
```

In [ ]:

```
sns.boxplot(df["sqft_living"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
s the following variable as a keyword arg: x. From version 0.12, the only valid posi
tional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  FutureWarning
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f49027c2f90>



In [ ]:

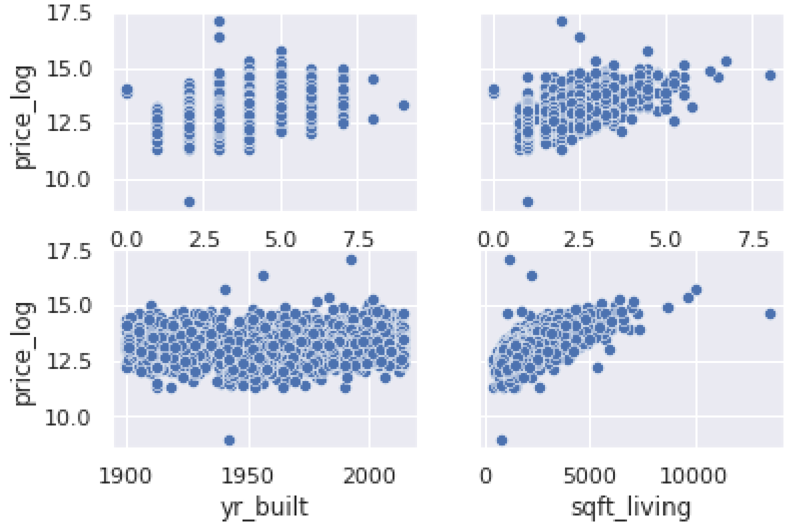
```
df.corr()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
price	1.000000	0.210228	0.341126	0.445494	0.051347	0.152758	0.150083	0.24
bedrooms	0.210228	1.000000	0.547612	0.596053	0.071138	0.176219	-0.005521	0.11
bathrooms	0.341126	0.547612	1.000000	0.757213	0.109331	0.489548	0.063310	0.20
sqft_living	0.445494	0.596053	0.757213	1.000000	0.213268	0.343513	0.107758	0.30
sqft_lot	0.051347	0.071138	0.109331	0.213268	1.000000	0.004245	0.017408	0.07
floors	0.152758	0.176219	0.489548	0.343513	0.004245	1.000000	0.015804	0.03
waterfront	0.150083	-0.005521	0.063310	0.107758	0.017408	0.015804	1.000000	0.34
view	0.242587	0.115080	0.205536	0.309343	0.072527	0.031980	0.347572	1.00
condition	0.038892	0.023018	-0.120765	-0.062529	0.000929	-0.273786	0.006112	0.06
sqft_above	0.380661	0.485672	0.687208	0.875657	0.219193	0.522215	0.072502	0.17
sqft_basement	0.217782	0.335103	0.295832	0.449671	0.035894	-0.255042	0.088880	0.31
yr_built	0.021757	0.141498	0.464239	0.284733	0.049163	0.466691	-0.032017	-0.06
yr_renovated	-0.029034	-0.062219	-0.218160	-0.121589	-0.021068	-0.235969	0.015821	0.02
price_log	0.677507	0.355346	0.548583	0.671307	0.085856	0.305319	0.141863	0.32

In [ ]:

```
plot_some_graphs(df)
```




```
In [ ]: df.corr()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
price	1.000000	0.210228	0.341126	0.445494	0.051347	0.152758	0.150083	0.24
bedrooms	0.210228	1.000000	0.547612	0.596053	0.071138	0.176219	-0.005521	0.11
bathrooms	0.341126	0.547612	1.000000	0.757213	0.109331	0.489548	0.063310	0.20
sqft_living	0.445494	0.596053	0.757213	1.000000	0.213268	0.343513	0.107758	0.30
sqft_lot	0.051347	0.071138	0.109331	0.213268	1.000000	0.004245	0.017408	0.07
floors	0.152758	0.176219	0.489548	0.343513	0.004245	1.000000	0.015804	0.03
waterfront	0.150083	-0.005521	0.063310	0.107758	0.017408	0.015804	1.000000	0.34
view	0.242587	0.115080	0.205536	0.309343	0.072527	0.031980	0.347572	1.00
condition	0.038892	0.023018	-0.120765	-0.062529	0.000929	-0.273786	0.006112	0.06
sqft_above	0.380661	0.485672	0.687208	0.875657	0.219193	0.522215	0.072502	0.17
sqft_basement	0.217782	0.335103	0.295832	0.449671	0.035894	-0.255042	0.088880	0.31
yr_built	0.021757	0.141498	0.464239	0.284733	0.049163	0.466691	-0.032017	-0.06
yr_renovated	-0.029034	-0.062219	-0.218160	-0.121589	-0.021068	-0.235969	0.015821	0.02
price_log	0.677507	0.355346	0.548583	0.671307	0.085856	0.305319	0.141863	0.32

```
In [ ]: df = df[df["sqft_living"] <= 10000]
        df.corr()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
price	1.000000	0.206737	0.336112	0.433339	0.045333	0.151128	0.122973	0.23
bedrooms	0.206737	1.000000	0.544925	0.597606	0.064364	0.173971	-0.010437	0.11
bathrooms	0.336112	0.544925	1.000000	0.755027	0.096846	0.488370	0.056641	0.19
sqft_living	0.433339	0.597606	0.755027	1.000000	0.196791	0.342972	0.089191	0.30
sqft_lot	0.045333	0.064364	0.096846	0.196791	1.000000	-0.000833	0.016250	0.06

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
floors	0.151128	0.173971	0.488370	0.342972	-0.000833	1.000000	0.013648	0.02
waterfront	0.122973	-0.010437	0.056641	0.089191	0.016250	0.013648	1.000000	0.34
view	0.237948	0.110459	0.197937	0.300235	0.064079	0.028652	0.348365	1.00
condition	0.041688	0.023913	-0.120105	-0.061008	0.002229	-0.273530	0.008031	0.06
sqft_above	0.368167	0.482941	0.682348	0.872211	0.206729	0.523225	0.055856	0.16
sqft_basement	0.206203	0.330021	0.284004	0.434215	0.020833	-0.263756	0.079129	0.30
yr_built	0.024130	0.141398	0.466848	0.291015	0.047973	0.466856	-0.029711	-0.06
yr_renovated	-0.032080	-0.062116	-0.219246	-0.124589	-0.019909	-0.235986	0.012737	0.02
price_log	0.676021	0.352888	0.546424	0.672815	0.080863	0.303959	0.131126	0.32

In [ ]:

```
df["sqft_living_log"] = np.log(df["sqft_living"])
```

In [ ]:

```
df.corr()
```

Out[ ]:

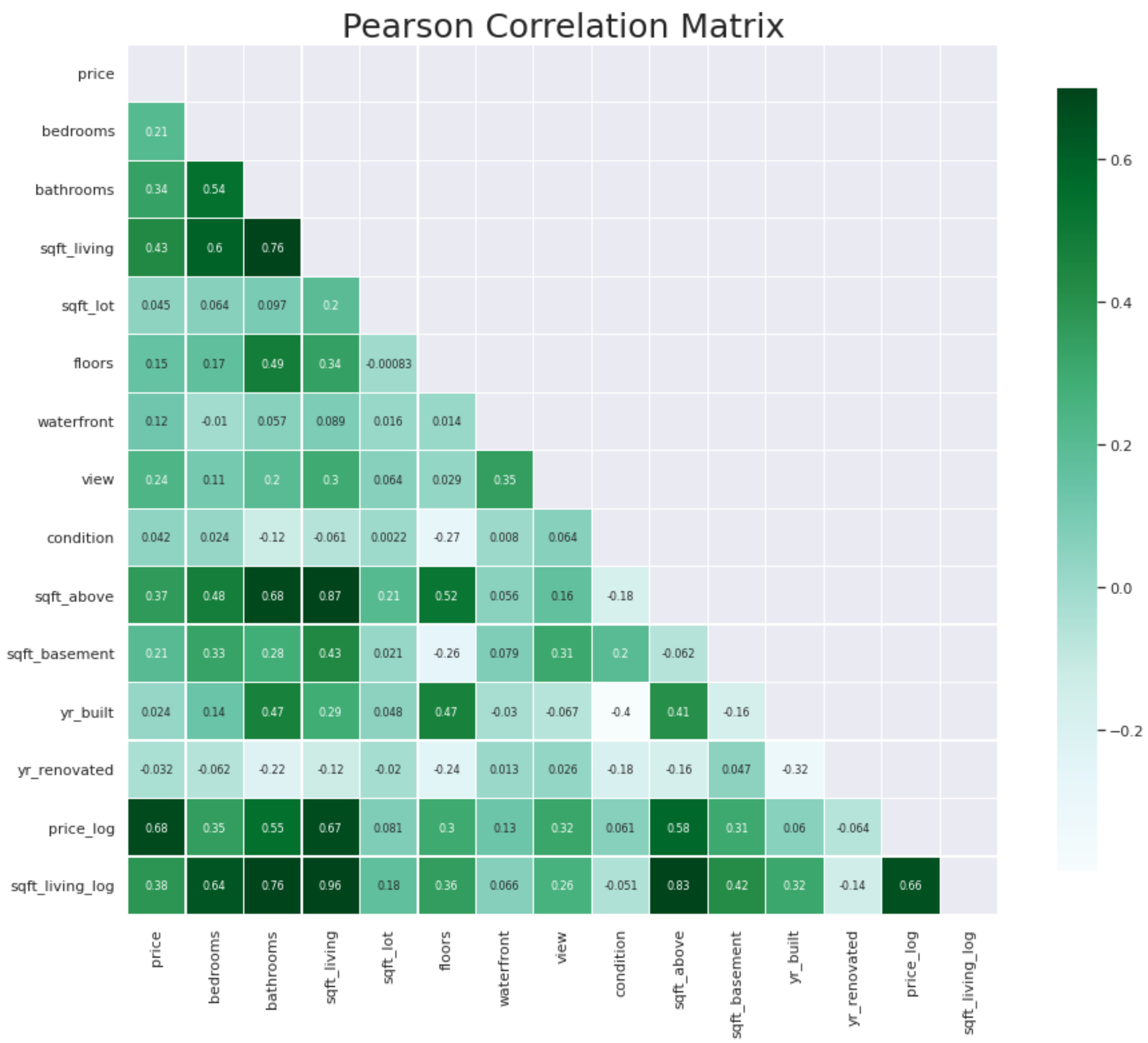
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
price	1.000000	0.206737	0.336112	0.433339	0.045333	0.151128	0.122973	0.23
bedrooms	0.206737	1.000000	0.544925	0.597606	0.064364	0.173971	-0.010437	0.11
bathrooms	0.336112	0.544925	1.000000	0.755027	0.096846	0.488370	0.056641	0.19
sqft_living	0.433339	0.597606	0.755027	1.000000	0.196791	0.342972	0.089191	0.30
sqft_lot	0.045333	0.064364	0.096846	0.196791	1.000000	-0.000833	0.016250	0.06
floors	0.151128	0.173971	0.488370	0.342972	-0.000833	1.000000	0.013648	0.02
waterfront	0.122973	-0.010437	0.056641	0.089191	0.016250	0.013648	1.000000	0.34
view	0.237948	0.110459	0.197937	0.300235	0.064079	0.028652	0.348365	1.00
condition	0.041688	0.023913	-0.120105	-0.061008	0.002229	-0.273530	0.008031	0.06
sqft_above	0.368167	0.482941	0.682348	0.872211	0.206729	0.523225	0.055856	0.16
sqft_basement	0.206203	0.330021	0.284004	0.434215	0.020833	-0.263756	0.079129	0.30
yr_built	0.024130	0.141398	0.466848	0.291015	0.047973	0.466856	-0.029711	-0.06
yr_renovated	-0.032080	-0.062116	-0.219246	-0.124589	-0.019909	-0.235986	0.012737	0.02
price_log	0.676021	0.352888	0.546424	0.672815	0.080863	0.303959	0.131126	0.32
sqft_living_log	0.384688	0.640976	0.759764	0.955694	0.175095	0.355169	0.065952	0.25

In [ ]:

```
# Thanks to: https://www.kaggle.com/burhanykiyakoglu/predicting-house-prices
mask = np.zeros_like(df.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(16, 12))
plt.title('Pearson Correlation Matrix',fontsize=25)
```

```
sns.heatmap(df.corr(),linewidths=0.25,vmax=0.7,square=True,cmap="BuGn", #"BuGn_r" to
            linecolor='w',annot=True,annot_kws={"size":8},mask=mask,cbar_kws={"shrin
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: DeprecationWarning:
`np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use
`bool` by itself. Doing this will not modify any behavior and is safe. If you specif
ically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/r
elease/1.20.0-notes.html#deprecations
```



In [ ]:

```
# sqft living e above dizem quase a mesma coisa
df.drop("sqft_above", axis=1, inplace=True)
```

In [ ]:

```
df["yr_renovated"] = df["yr_renovated"].apply(lambda x: 0 if x == 0 else 1)
```

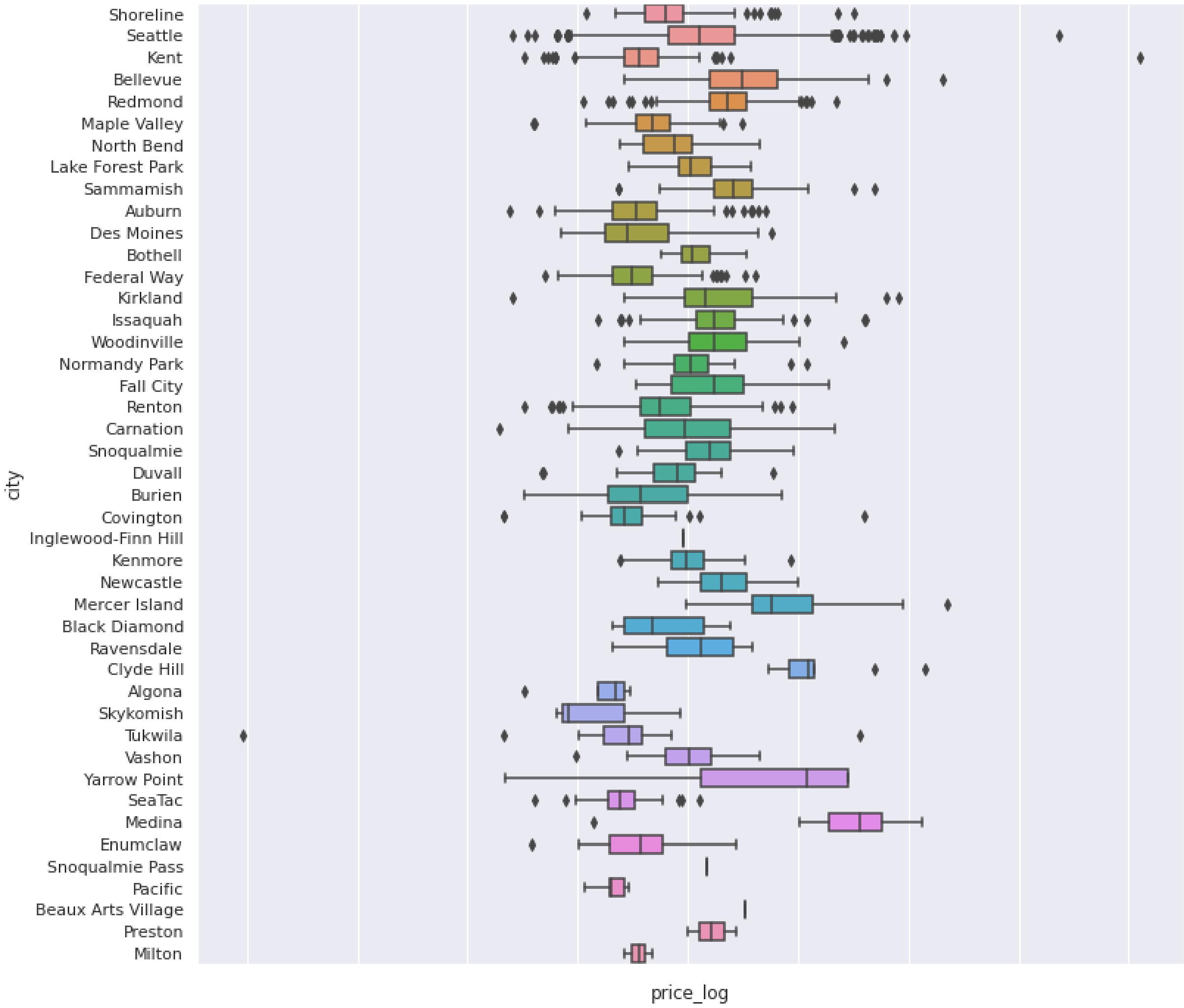
In [ ]:

```
plt.figure(figsize = (12, 12))
ax = sns.boxplot(data=df,
            x="price_log",
            y="city")

ax.set_xticklabels(ax.get_xticklabels(),rotation=90)
```

Out[ ]:

```
[Text(0, 0, ''),
 Text(0, 0, ''),
```

```
Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, ''),
 Text(0, 0, '')]
```

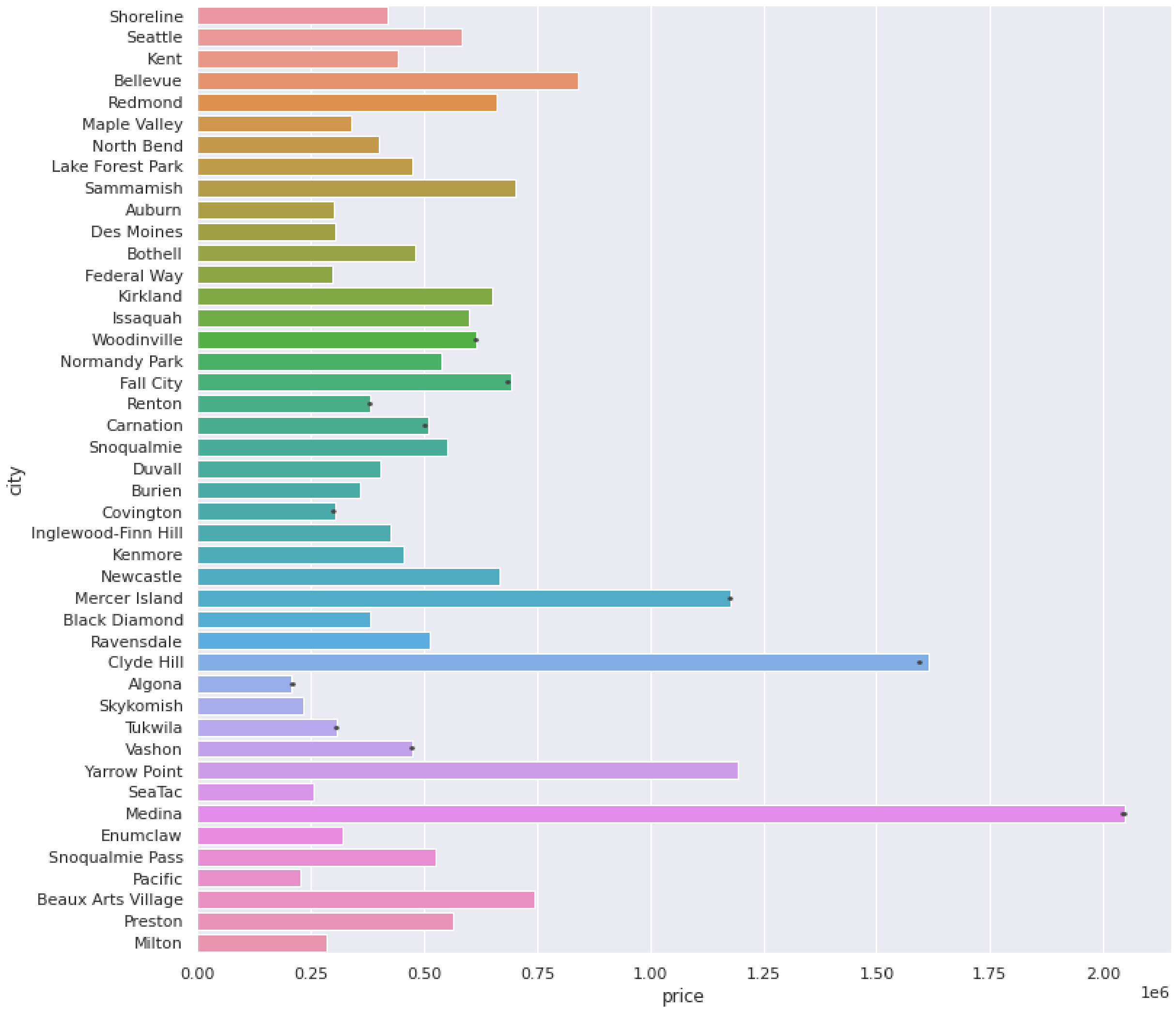


In [ ]:

```
plt.figure(figsize = (12, 12))
sns.barplot(data = df,
            y = "city",
            x = "price",
            ci = .95)

ax.set_xticklabels(ax.get_xticklabels(),
                   rotation=90)
```

Out[ ]:

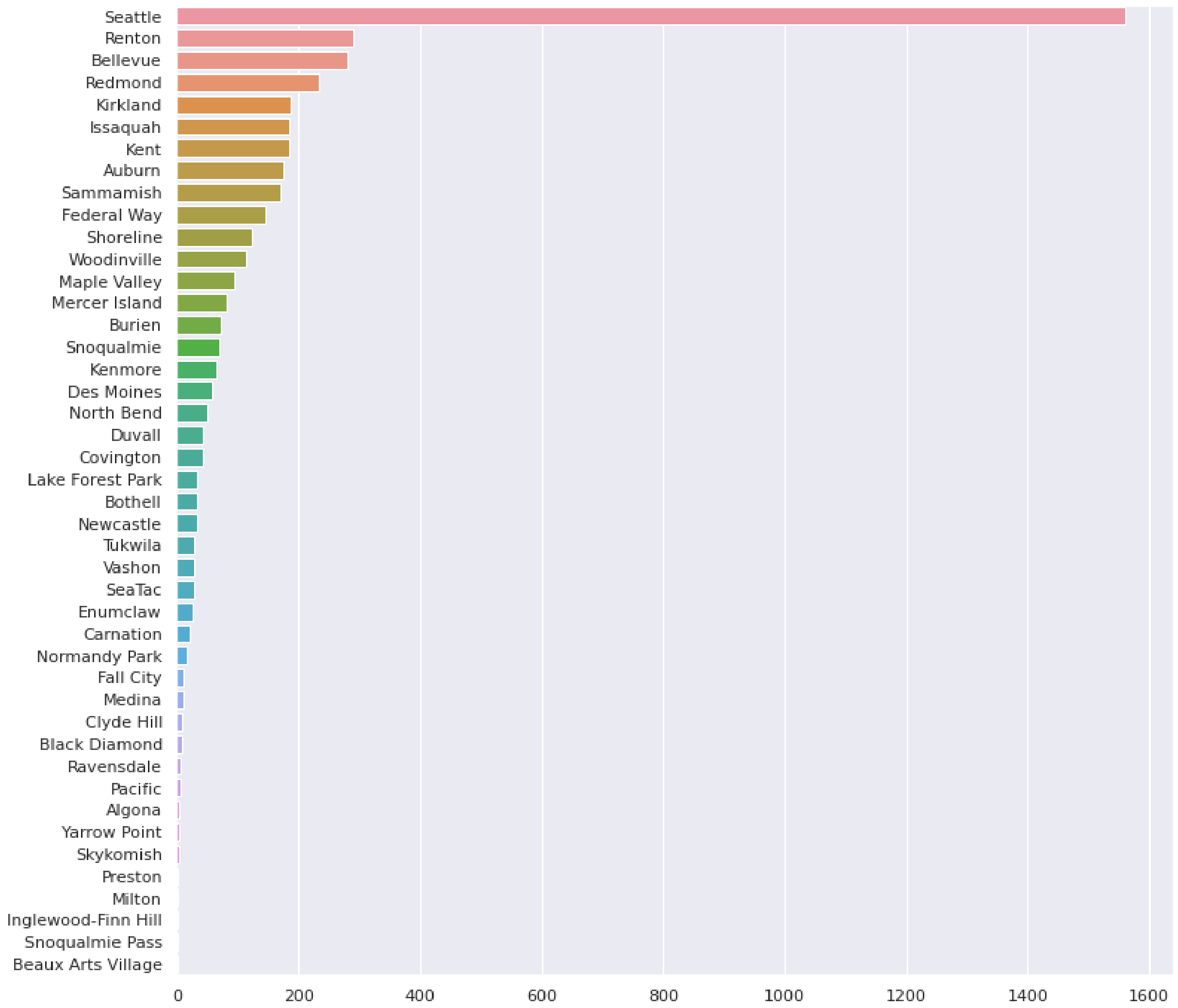
```
[Text(8.0, 0, ''),
 Text(9.0, 0, ''),
 Text(10.0, 0, ''),
 Text(11.0, 0, ''),
 Text(12.0, 0, ''),
 Text(13.0, 0, ''),
 Text(14.0, 0, ''),
 Text(15.0, 0, ''),
 Text(16.0, 0, ''),
 Text(17.0, 0, ''),
 Text(18.0, 0, '')]
```



In [ ]:

```
plt.figure(figsize = (12, 12))
sns.barplot(x = df["city"].value_counts().values,
            y = df["city"].value_counts().index)
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f48fd3f8d50>



In [ ]:

```
df.corr()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	
price	1.000000	0.206737	0.336112	0.433339	0.045333	0.151128	0.122973	0.23
bedrooms	0.206737	1.000000	0.544925	0.597606	0.064364	0.173971	-0.010437	0.11
bathrooms	0.336112	0.544925	1.000000	0.755027	0.096846	0.488370	0.056641	0.19
sqft_living	0.433339	0.597606	0.755027	1.000000	0.196791	0.342972	0.089191	0.30
sqft_lot	0.045333	0.064364	0.096846	0.196791	1.000000	-0.000833	0.016250	0.06
floors	0.151128	0.173971	0.488370	0.342972	-0.000833	1.000000	0.013648	0.02
waterfront	0.122973	-0.010437	0.056641	0.089191	0.016250	0.013648	1.000000	0.34
view	0.237948	0.110459	0.197937	0.300235	0.064079	0.028652	0.348365	1.00
condition	0.041688	0.023913	-0.120105	-0.061008	0.002229	-0.273530	0.008031	0.06
sqft_basement	0.206203	0.330021	0.284004	0.434215	0.020833	-0.263756	0.079129	0.30
yr_built	0.024130	0.141398	0.466848	0.291015	0.047973	0.466856	-0.029711	-0.06
yr_renovated	-0.031865	-0.061797	-0.218292	-0.124057	-0.020370	-0.234395	0.012627	0.02
price_log	0.676021	0.352888	0.546424	0.672815	0.080863	0.303959	0.131126	0.32
sqft_living_log	0.384688	0.640976	0.759764	0.955694	0.175095	0.355169	0.065952	0.25

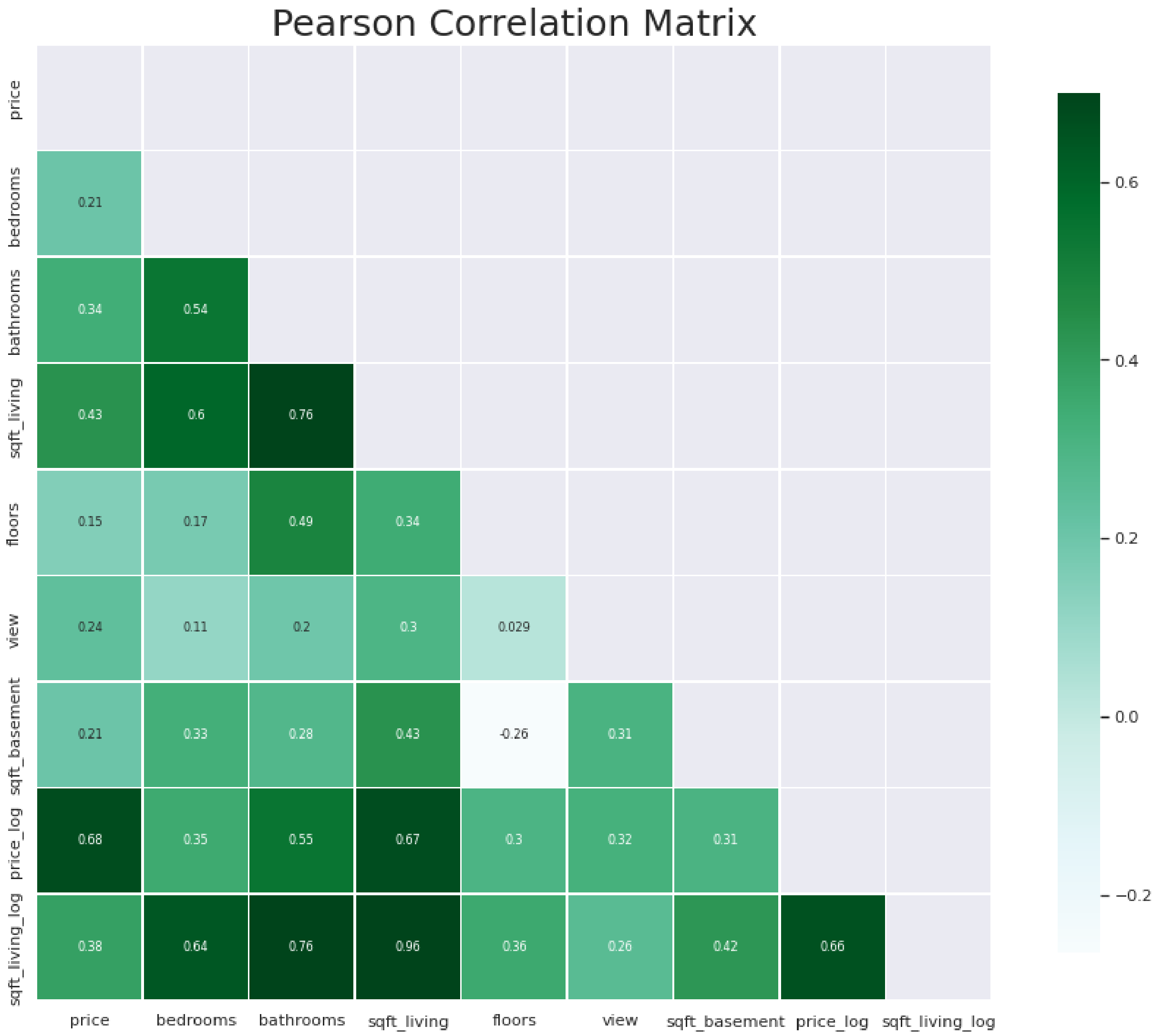
In [ ]:

```
df.drop(["yr_built", "waterfront", "yr_renovated", "sqft_lot", "condition", "date"],
```

In [ ]:

```
mask = np.zeros_like(df.corr(), dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(16, 12))
plt.title('Pearson Correlation Matrix',fontsize=25)

sns.heatmap(df.corr(),linewidths=0.25,vmax=0.7,square=True,cmap="BuGn", #"BuGn_r" to
            linecolor='w',annot=True,annot_kws={"size":8},mask=mask,cbar_kws={"shrin
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: DeprecationWarning:
`np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use
`bool` by itself. Doing this will not modify any behavior and is safe. If you specif
ically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/r
elease/1.20.0-notes.html#deprecations
  """Entry point for launching an IPython kernel.
```



In [ ]:

```
df = pd.get_dummies(df, drop_first=True)
df.head()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	floors	view	sqft_basement	price_log	sqft_living
0	313000.0	3.0	1.50	1340	1.5	0	0	12.653958	7.20(

	price	bedrooms	bathrooms	sqft_living	floors	view	sqft_basement	price_log	sqft_living
1	2384000.0	5.0	2.50	3650	2.0	4	280	14.684290	8.202
2	342000.0	3.0	2.00	1930	1.0	0	0	12.742566	7.565
3	420000.0	3.0	2.25	2000	1.0	0	1000	12.948010	7.600
4	550000.0	4.0	2.50	1940	1.0	0	800	13.217674	7.570

5 rows × 52 columns

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4549 entries, 0 to 4599
Data columns (total 52 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   price                      4549 non-null   float64
 1   bedrooms                   4549 non-null   float64
 2   bathrooms                  4549 non-null   float64
 3   sqft_living                4549 non-null   int64  
 4   floors                     4549 non-null   float64
 5   view                       4549 non-null   int64  
 6   sqft_basement              4549 non-null   int64  
 7   price_log                  4549 non-null   float64
 8   sqft_living_log            4549 non-null   float64
 9   city_Auburn                4549 non-null   uint8  
 10  city_Beaux Arts Village    4549 non-null   uint8  
 11  city_Bellevue              4549 non-null   uint8  
 12  city_Black Diamond         4549 non-null   uint8  
 13  city_Bothell               4549 non-null   uint8  
 14  city_Burien                4549 non-null   uint8  
 15  city_Carnation             4549 non-null   uint8  
 16  city_Clyde Hill            4549 non-null   uint8  
 17  city_Covington             4549 non-null   uint8  
 18  city_Des Moines            4549 non-null   uint8  
 19  city_Duvall                4549 non-null   uint8  
 20  city_Enumclaw              4549 non-null   uint8  
 21  city_Fall City             4549 non-null   uint8  
 22  city_Federal Way           4549 non-null   uint8  
 23  city_Inglewood-Finn Hill   4549 non-null   uint8  
 24  city_Issaquah              4549 non-null   uint8  
 25  city_Kenmore               4549 non-null   uint8  
 26  city_Kent                  4549 non-null   uint8  
 27  city_Kirkland              4549 non-null   uint8  
 28  city_Lake Forest Park      4549 non-null   uint8  
 29  city_Maple Valley          4549 non-null   uint8  
 30  city_Medina                4549 non-null   uint8  
 31  city_Mercer Island         4549 non-null   uint8  
 32  city_Milton                4549 non-null   uint8  
 33  city_Newcastle             4549 non-null   uint8  
 34  city_Normandy Park         4549 non-null   uint8  
 35  city_North Bend            4549 non-null   uint8  
 36  city_Pacific               4549 non-null   uint8  
 37  city_Preston               4549 non-null   uint8  
 38  city_Ravensdale            4549 non-null   uint8  
 39  city_Redmond               4549 non-null   uint8  
 40  city_Renton                4549 non-null   uint8  
```

```
 41  city_Sammamish           4549 non-null   uint8
 42  city_SeaTac              4549 non-null   uint8
 43  city_Seattle             4549 non-null   uint8
 44  city_Shoreline           4549 non-null   uint8
 45  city_Skykomish           4549 non-null   uint8
 46  city_Snoqualmie          4549 non-null   uint8
 47  city_Snoqualmie Pass     4549 non-null   uint8
 48  city_Tukwila             4549 non-null   uint8
 49  city_Vashon              4549 non-null   uint8
 50  city_Woodinville         4549 non-null   uint8
 51  city_Yarrow Point        4549 non-null   uint8
dtypes: float64(6), int64(3), uint8(43)
memory usage: 675.5 KB
```

In [ ]:

```
# codigo sem a validação cruzada
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

X =  df.drop(["price", "price_log"], axis=1)
y =  df["price_log"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

rf.fit(X_train, y_train)
lm.fit(X_train, y_train)
lasso.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_pred_lm = lm.predict(X_test)
y_pred_lasso = lasso.predict(X_test)

print("MSE RF: ", mean_squared_error(y_test, y_pred_rf))
print("MSE LM: ", mean_squared_error(y_test, y_pred_lm))
print("MSE LASSO: ", mean_squared_error(y_test, y_pred_lasso))

print("R2 RF: ", r2_score(y_test, y_pred_rf))
print("R2 LM: ", r2_score(y_test, y_pred_lm))
print("R2 LASSO: ", r2_score(y_test, y_pred_lasso))

print("RMSE RF: ", mean_squared_error(y_test, y_pred_rf, squared=False))
print("RMSE LM: ", mean_squared_error(y_test, y_pred_lm, squared=False))
print("RMSE LASSO: ", mean_squared_error(y_test, y_pred_lasso, squared=False))
```

```
MSE RF:  0.09546576352989107
MSE LM:  0.08191361517924213
MSE LASSO:  0.15053179657864088
R2 RF:  0.6667426117004311
R2 LM:  0.7140512320706174
R2 LASSO:  0.47451493049513493
RMSE RF:  0.30897534453397907
RMSE LM:  0.2862055470797904
RMSE LASSO:  0.38798427362283755
```

In [ ]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
```

```python
rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

data = df.drop(["price", "price_log"], axis=1)
data["target"] = df["price_log"]

data3 = train_test_model(lm, data, 3, "linearModel")
data3.update(train_test_model(rf, data, 3, "randomForest"))
data3.update(train_test_model(lasso, data, 3, "lasso"))
```

In [ ]:

```python
data3
```

Out[ ]:

```
{'lasso3_1': 0.13465403689561722,
 'lasso3_2': 0.1476062364938255,
 'lasso3_3': 0.135640650670338,
 'lasso3_4': 0.13779134769203485,
 'lasso3_5': 0.24667661136732294,
 'linearModel3_1': 0.05866627307553877,
 'linearModel3_2': 0.07400731721979265,
 'linearModel3_3': 0.05755393687845289,
 'linearModel3_4': 0.058586358853223025,
 'linearModel3_5': 0.17815043486319804,
 'randomForest3_1': 0.07277932303563518,
 'randomForest3_2': 0.0906450154879114,
 'randomForest3_3': 0.0738784013388832,
 'randomForest3_4': 0.0768020837708036,
 'randomForest3_5': 0.17805419597776698}
```

In [ ]:

```python
data1.update(data3)
```

In [ ]:

```python
data1
```

Out[ ]:

```
{'lasso1_1': 0.3109808467574476,
 'lasso1_2': 0.3516004718101653,
 'lasso1_3': 0.482183225146634,
 'lasso1_4': 0.707694131563812,
 'lasso1_5': 0.31954255398438325,
 'lasso2_1': 0.03262755292988901,
 'lasso2_2': 0.03523533357828243,
 'lasso2_3': 0.036041304080416316,
 'lasso2_4': 0.039269738888971326,
 'lasso2_5': 0.03443652162793467,
 'lasso3_1': 0.13465403689561722,
 'lasso3_2': 0.1476062364938255,
 'lasso3_3': 0.135640650670338,
 'lasso3_4': 0.13779134769203485,
 'lasso3_5': 0.24667661136732294,
 'linearModel1_1': 0.26057262002426623,
 'linearModel1_2': 0.32360692100888855,
 'linearModel1_3': 0.26789677324267563,
 'linearModel1_4': 0.33518885055800735,
 'linearModel1_5': 0.3215892438602057,
 'linearModel2_1': 0.014190740159076124,
 'linearModel2_2': 0.016344615376627642,
 'linearModel2_3': 0.019174802837470615,
 'linearModel2_4': 0.012127678277354274,
 'linearModel2_5': 0.014054599165485 1,
 'linearModel3_1': 0.05866627307553877,
 'linearModel3_2': 0.07400731721979265,
```

```
'linearModel3_3': 0.05755393687845289,
'linearModel3_4': 0.058586358853223025,
'linearModel3_5': 0.17815043486319804,
'randomForest1_1': 0.17708090175036023,
'randomForest1_2': 0.1778795651543115,
'randomForest1_3': 0.23681970741927452,
'randomForest1_4': 0.35695374099579,
'randomForest1_5': 0.2586996399949596,
'randomForest2_1': 0.018562538060529928,
'randomForest2_2': 0.01973511575259254,
'randomForest2_3': 0.02084398963821763,
'randomForest2_4': 0.017929240807915494,
'randomForest2_5': 0.02001366282592511,
'randomForest3_1': 0.07277932303563518,
'randomForest3_2': 0.0906450154879114,
'randomForest3_3': 0.0738784013388832,
'randomForest3_4': 0.0768020837708036,
'randomForest3_5': 0.17805419597776698}
```

Dataset 4 - https://www.kaggle.com/datasets/anmolkumar/house-price-prediction-challenge?select=test.csv

In [ ]:

```
df_train = pd.read_csv("/content/drive/MyDrive/experimental/train_india.csv")
df_test =  pd.read_csv("/content/drive/MyDrive/experimental/train_india.csv")
df_train.head()
```

Out[ ]:

	POSTED_BY	UNDER_CONSTRUCTION	RERA	BHK_NO.	BHK_OR_RK	SQUARE_FT	READY_TO_MOV
0	Owner	0	0	2	BHK	1300.236407	
1	Dealer	0	0	2	BHK	1275.000000	
2	Owner	0	0	2	BHK	933.159722	
3	Owner	0	1	2	BHK	929.921143	
4	Dealer	1	0	2	BHK	999.009247	

In [ ]:

```
df_train.drop("ADDRESS", axis=1, inplace=True)
df_test.drop("ADDRESS", axis=1, inplace=True)
```

In [ ]:

```
df_train["TARGET(PRICE_IN_LACS)"] = np.log(df_train["TARGET(PRICE_IN_LACS)"])
df_test["TARGET(PRICE_IN_LACS)"] = np.log(df_test["TARGET(PRICE_IN_LACS)"])
```

In [ ]:

```
df_train = pd.get_dummies(df_train)
df_test = pd.get_dummies(df_test)
```

In [ ]:

```
# codigo sem a validação cruzada
from sklearn.ensemble import RandomForestRegressor
```

```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

X_train, X_test = df_train.drop("TARGET(PRICE_IN_LACS)", axis=1), df_test.drop("TARG
y_train, y_test = df_train["TARGET(PRICE_IN_LACS)"], df_test["TARGET(PRICE_IN_LACS)"

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

rf.fit(X_train, y_train)
lm.fit(X_train, y_train)
lasso.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_pred_lm = lm.predict(X_test)
y_pred_lasso = lasso.predict(X_test)

print("MSE RF: ", mean_squared_error(y_test, y_pred_rf))
print("MSE LM: ", mean_squared_error(y_test, y_pred_lm))
print("MSE LASSO: ", mean_squared_error(y_test, y_pred_lasso))

print("R2 RF: ", r2_score(y_test, y_pred_rf))
print("R2 LM: ", r2_score(y_test, y_pred_lm))
print("R2 LASSO: ", r2_score(y_test, y_pred_lasso))

print("RMSE RF: ", mean_squared_error(y_test, y_pred_rf, squared=False))
print("RMSE LM: ", mean_squared_error(y_test, y_pred_lm, squared=False))
print("RMSE LASSO: ", mean_squared_error(y_test, y_pred_lasso, squared=False))
```

```
MSE RF:  0.01795063618680436
MSE LM:  0.4875613271974304
MSE LASSO:  0.8056270183418669
R2 RF:  0.9778100814341294
R2 LM:  0.39729455637166544
R2 LASSO:  0.004113406041146073
RMSE RF:  0.13397998427677307
RMSE LM:  0.6982559181256042
RMSE LASSO:  0.8975672778916726
```

Dataset 5 - https://www.kaggle.com/datasets/amaanafif/cl house-price

In [ ]:

```
df = pd.read_csv("/content/drive/MyDrive/experimental/clean_data.csv")
df.head()
```

Out[ ]:

	price	area	status	bhk	bathroom	age	location	builder
0	37.49	872	Ready to move	2	NaN	1.0	Sembakkam	MP Developers
1	93.54	1346	Under Construction	3	2.0	NaN	Selaiyur	DAC Promoters
2	151.00	2225	Under Construction	3	NaN	0.0	Mogappair	Casagrand Builder Private Limited
3	49.00	1028	Ready to move	2	2.0	3.0	Ambattur	Dugar Housing Builders

	price	area	status	bhk	bathroom	age	location	builder
4	42.28	588	Under Construction	2	1.0	0.0	Pallavaram	Radiance Realty Developers India Ltd

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2620 entries, 0 to 2619
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   price     2620 non-null   float64
 1   area      2620 non-null   int64
 2   status    2620 non-null   object
 3   bhk       2620 non-null   int64
 4   bathroom  1403 non-null   float64
 5   age       1729 non-null   float64
 6   location  2620 non-null   object
 7   builder   2620 non-null   object
dtypes: float64(3), int64(2), object(3)
memory usage: 163.9+ KB
```

In [ ]:

```
df["bathroom"].unique()
```

Out[ ]:

```
array([nan,  2.,  1.,  3.,  4.,  5.,  6.,  7.])
```

In [ ]:

```
df["bathroom"].fillna(0, inplace=True)
```

In [ ]:

```
df["age"].fillna(df["age"].mean(), inplace=True)
```

In [ ]:

```
df.drop(["location", "builder"], axis=1, inplace=True)
```

In [ ]:

```
df["price"] = np.log(df["price"])
```

In [ ]:

```
df = pd.get_dummies(df, drop_first=True)
```

In [ ]:

```
df.head()
```

Out[ ]:

	price	area	bhk	bathroom	age	status_Under Construction
0	3.624074	872	2	0.0	1.000000	0
1	4.538389	1346	3	2.0	1.355119	1
2	5.017280	2225	3	0.0	0.000000	1
3	3.891820	1028	2	2.0	3.000000	0
4	3.744314	588	2	1.0	0.000000	1

In [ ]:

```
# codigo sem a validação cruzada
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error, r2_score

X = df.drop("price", axis=1)
y = df["price"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)

rf = RandomForestRegressor()
lm = LinearRegression()
lasso = Lasso()

rf.fit(X_train, y_train)
lm.fit(X_train, y_train)
lasso.fit(X_train, y_train)

y_pred_rf = rf.predict(X_test)
y_pred_lm = lm.predict(X_test)
y_pred_lasso = lasso.predict(X_test)

print("MSE RF: ", mean_squared_error(y_test, y_pred_rf))
print("MSE LM: ", mean_squared_error(y_test, y_pred_lm))
print("MSE LASSO: ", mean_squared_error(y_test, y_pred_lasso))

print("R2 RF: ", r2_score(y_test, y_pred_rf))
print("R2 LM: ", r2_score(y_test, y_pred_lm))
print("R2 LASSO: ", r2_score(y_test, y_pred_lasso))

print("RMSE RF: ", mean_squared_error(y_test, y_pred_rf, squared=False))
print("RMSE LM: ", mean_squared_error(y_test, y_pred_lm, squared=False))
print("RMSE LASSO: ", mean_squared_error(y_test, y_pred_lasso, squared=False))
```

```
MSE RF:  0.10326491207273183
MSE LM:  0.15544723368727498
MSE LASSO:  0.1681107524853939
R2 RF:  0.7936998760474089
R2 LM:  0.6894513060236235
R2 LASSO:  0.664152436879302
RMSE RF:  0.321348583430411
RMSE LM:  0.39426797192680385
RMSE LASSO:  0.41001311257738315
```

In [ ]:

```python
model = []
value = []
for i in data1.keys():
  model.append(i)
  value.append(data1[i])
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-12-4d4017c17d79> in <module>()
      1 model = []
      2 value = []
----> 3 for i in data1.keys():
      4   model.append(i)
      5   value.append(data1[i])

NameError: name 'data1' is not defined
```

In [ ]:

```python
data = {
```

```
        "model": model,
        "MSE": value
    }

data_df = pd.DataFrame(data)
data_df["dataset"] = data_df["model"].apply(lambda x: x[-3:])
data_df["model"] = data_df["model"].apply(lambda x: x[:-3])

data_df.head()
```

Out[ ]:

	model	MSE	dataset
0	linearModel	0.260573	1_1
1	linearModel	0.323607	1_2
2	linearModel	0.267897	1_3
3	linearModel	0.335189	1_4
4	linearModel	0.321589	1_5

In [ ]:

```
data_df.to_csv("resultados.csv", index=None)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-3-ff2da36091fb> in <module>()
----> 1 data_df.to_csv("resultados.csv", index=None)

NameError: name 'data_df' is not defined
```

In [ ]:

```
data = {
    "rf_1":  0.09773409840389369,
    "lm_1":  0.08191361517924213,
    "lasso_1":  0.15053179657864088,
    "rf_2":  0.019822085618431597,
    "lm_2":  0.016165139194202354,
    "lasso_2":  0.034859234653039084,
    "rf_3":  0.1446016071407616,
    "lm_3":  0.21942260490186888,
    "lasso_3":  0.4028687329520718,
    "rf_4":  0.01853176337613036,
    "lm_4":  0.4875613271974304,
    "lasso_4":  0.8056270183418669,
    "rf_5":  0.10301816980122472,
    "lm_5":  0.15544723368727498,
    "lasso_5":  0.1681107524853939
}

data = {
    "rf_1":  0.8322846779365841,
    "lm_1":   0.7452897365815508,
    "lasso_1":  0.5323417059096036,
    "rf_2":  0.8773058061444857,
    "lm_2":  0.8970377651514384,
    "lasso_2":  0.7779675966987903,
    "rf_3":  0.6667426117004311,
    "lm_3":  0.7140512320706174,
    "lasso_3":  0.47451493049513493,
    "rf_4":  0.9778100814341294,
    "lm_4":  0.39729455637166544,
    "lasso_4":  0.004113406041146073,
```

```
    "rf_5":  0.7936998760474089,
    "lm_5":  0.6894513060236235,
    "lasso_5":  0.664152436879302
}



keys = data.keys()
values = data.values()
data = {
    "dataset": keys,
    "R2": values
}
data_df = pd.DataFrame(data=data)
data_df.head()
```

Out[ ]:

	dataset	R2
0	rf_1	0.832285
1	lm_1	0.745290
2	lasso_1	0.532342
3	rf_2	0.877306
4	lm_2	0.897038

In [ ]:

```
data_df["model"] = data_df["dataset"].str.split("_", expand=True)[0]
data_df["dataset"] = data_df["dataset"].str.split("_", expand=True)[1]
```

In [ ]:

```
data_df.to_csv("resultados_r2.csv", index=None)
```

In [ ]:

```

```