Untitled

January 24, 2025

0.1 Housing Prices Competition for Kaggle Learn Users

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.

With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

Goal It is your job to predict the sales price for each house. For each Id in the test set, you must predict the value of the SalePrice variable.

Metric Submissions are evaluated on Root-Mean-Squared-Error (RMSE) between the logarithm of the predicted value and the logarithm of the observed sales price. (Taking logs means that errors in predicting expensive houses and cheap houses will affect the result equally.)

[52]:
```
#Importando o os pacotes
import pandas as pd
import numpy as np
!pip install scikit-learn
!pip install matplotlib
```

```
Requirement already satisfied: scikit-learn in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages
(1.3.2)
Requirement already satisfied: numpy<2.0,>=1.17.3 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
scikit-learn) (1.24.4)
Requirement already satisfied: scipy>=1.5.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
scikit-learn) (1.10.1)
Requirement already satisfied: joblib>=1.1.1 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
```

```
scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
scikit-learn) (3.5.0)
Collecting matplotlib
  Downloading matplotlib-3.7.5-cp38-cp38-win_amd64.whl.metadata (5.8 kB)
Collecting contourpy>=1.0.1 (from matplotlib)
  Downloading contourpy-1.1.1-cp38-cp38-win_amd64.whl.metadata (5.9 kB)
Collecting cycler>=0.10 (from matplotlib)
  Downloading cycler-0.12.1-py3-none-any.whl.metadata (3.8 kB)
Collecting fonttools>=4.22.0 (from matplotlib)
  Downloading fonttools-4.55.5-cp38-cp38-win_amd64.whl.metadata (169 kB)
Collecting kiwisolver>=1.0.1 (from matplotlib)
  Downloading kiwisolver-1.4.7-cp38-cp38-win_amd64.whl.metadata (6.4 kB)
Requirement already satisfied: numpy<2,>=1.20 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
matplotlib) (1.24.4)
Requirement already satisfied: packaging>=20.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
matplotlib) (10.4.0)
Collecting pyparsing>=2.3.1 (from matplotlib)
  Downloading pyparsing-3.1.4-py3-none-any.whl.metadata (5.1 kB)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
matplotlib) (2.8.2)
Requirement already satisfied: importlib-resources>=3.2.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
matplotlib) (6.1.1)
Requirement already satisfied: zipp>=3.1.0 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
importlib-resources>=3.2.0->matplotlib) (3.17.0)
Requirement already satisfied: six>=1.5 in
c:\users\vinicius\appdata\local\programs\python\python38\lib\site-packages (from
python-dateutil>=2.7->matplotlib) (1.16.0)
Downloading matplotlib-3.7.5-cp38-cp38-win_amd64.whl (7.5 MB)
   ---------------------------------------- 0.0/7.5 MB ? eta -:--:--
   ---- ----------------------------------- 0.8/7.5 MB 3.7 MB/s eta 0:00:02
   ------------ --------------------------- 2.4/7.5 MB 5.8 MB/s eta 0:00:01
   -------------------- ------------------- 3.9/7.5 MB 6.5 MB/s eta 0:00:01
   ------------------------------ --------- 5.8/7.5 MB 6.8 MB/s eta 0:00:01
   ---------------------------------------  7.3/7.5 MB 6.9 MB/s eta 0:00:01
   ---------------------------------------- 7.5/7.5 MB 6.4 MB/s eta 0:00:00
Downloading contourpy-1.1.1-cp38-cp38-win_amd64.whl (477 kB)
Downloading cycler-0.12.1-py3-none-any.whl (8.3 kB)
Downloading fonttools-4.55.5-cp38-cp38-win_amd64.whl (1.5 MB)
```

```
   ---------------------------------------- 0.0/1.5 MB ? eta -:--:--
   ---------------------------------- ------ 1.3/1.5 MB 7.4 MB/s eta 0:00:01
   ---------------------------------------- 1.5/1.5 MB 5.1 MB/s eta 0:00:00
Downloading kiwisolver-1.4.7-cp38-cp38-win_amd64.whl (55 kB)
Downloading pyparsing-3.1.4-py3-none-any.whl (104 kB)
Installing collected packages: pyparsing, kiwisolver, fonttools, cycler,
contourpy, matplotlib
Successfully installed contourpy-1.1.1 cycler-0.12.1 fonttools-4.55.5
kiwisolver-1.4.7 matplotlib-3.7.5 pyparsing-3.1.4
```

[2]:
```
#Importando o dataset de treino
data = pd.read_csv("C:/Users/Vinicius/Desktop/Kaggle/Housing Prices/train.csv")
```

[3]:
```
#Visualizando os dados
data.head(5)
```

[3]:

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

	LandContour	Utilities	…	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	\
0	Lvl	AllPub	…	0	NaN	NaN	NaN	0	2	
1	Lvl	AllPub	…	0	NaN	NaN	NaN	0	5	
2	Lvl	AllPub	…	0	NaN	NaN	NaN	0	9	
3	Lvl	AllPub	…	0	NaN	NaN	NaN	0	2	
4	Lvl	AllPub	…	0	NaN	NaN	NaN	0	12	

	YrSold	SaleType	SaleCondition	SalePrice
0	2008	WD	Normal	208500
1	2007	WD	Normal	181500
2	2008	WD	Normal	223500
3	2006	WD	Abnorml	140000
4	2008	WD	Normal	250000

[5 rows x 81 columns]

[4]:
```
#Retornando o shape dos dados
data.shape
```

[4]: (1460, 81)

[5]:
```
# Vendo as informações
data.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     588 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
```

[6]:
```
# Visualizando os 20 primeiros -  quantidade de valores vazios
(data.isnull().sum()/data.shape[0]).sort_values(ascending=False).head(20)
```

[6]:
```
PoolQC          0.995205
MiscFeature     0.963014
Alley           0.937671
Fence           0.807534
```

```
MasVnrType      0.597260
FireplaceQu     0.472603
LotFrontage     0.177397
GarageYrBlt     0.055479
GarageCond      0.055479
GarageType      0.055479
GarageFinish    0.055479
GarageQual      0.055479
BsmtFinType2    0.026027
BsmtExposure    0.026027
BsmtQual        0.025342
BsmtCond        0.025342
BsmtFinType1    0.025342
MasVnrArea      0.005479
Electrical      0.000685
Id              0.000000
dtype: float64
```

[7]:
```
# Podemos eliminar as colunas com mais de 20% de valores vazios
eliminar = data.columns[(data.isnull().sum()/data.shape[0]) >  0.2]
eliminar
```

[7]:
```
Index(['Alley', 'MasVnrType', 'FireplaceQu', 'PoolQC', 'Fence', 'MiscFeature'],
dtype='object')
```

[8]:
```
# Eliminando essas colunas
base = data.drop(eliminar,axis=1)
```

[9]:
```
#Visualizando quantidade de valores vazios
(base.isnull().sum()/base.shape[0]).sort_values(ascending=False).head(20)
```

[9]:
```
LotFrontage     0.177397
GarageYrBlt     0.055479
GarageCond      0.055479
GarageType      0.055479
GarageFinish    0.055479
GarageQual      0.055479
BsmtFinType2    0.026027
BsmtExposure    0.026027
BsmtFinType1    0.025342
BsmtCond        0.025342
BsmtQual        0.025342
MasVnrArea      0.005479
Electrical      0.000685
WoodDeckSF      0.000000
PavedDrive      0.000000
LowQualFinSF    0.000000
```

```
GrLivArea       0.000000
BsmtFullBath    0.000000
BsmtHalfBath    0.000000
FullBath        0.000000
dtype: float64
```

- Vamos eliminar as colunas de texto
- Precisamos escolher tratar os valores vazios
- Vamos escolher alguns algoritmos para testar e um método de avaliação de erro

[10]:
```
#Selecionando apenas colunas numéricas
colunas = base.columns[base.dtypes != 'object']
colunas
```

[10]:
```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
       'MiscVal', 'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

[11]:
```
# Criar uma nova base com esses valores
base2 = base.loc[:,colunas]
base2.head(3)
```

[11]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	…	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	MoSold	YrSold	SalePrice
0	1	60	65.0	8450	7	5	2003	2003	196.0	706	…	0	61	0	0	0	0	0	2	2008	208500
1	2	20	80.0	9600	6	8	1976	1976	0.0	978	…	298	0	0	0	0	0	0	5	2007	181500
2	3	60	68.0	11250	7	5	2001	2002	162.0	486	…	0	42	0	0	0	0	0	9	2008	223500

```
[3 rows x 38 columns]
```

[12]:
```
#Verificando os valores vazios
base2.isnull().sum().sort_values(ascending=False).head(3)
```

[12]:
```
LotFrontage    259
GarageYrBlt     81
MasVnrArea       8
dtype: int64
```

[13]:
```
base2 = base2.fillna(-1)
```

1 Criando o meu modelo

- Precisa separar em treino e teste

Conforme: https://scikit-learn.org/1.6/modules/generated/sklearn.model_selection.train_test_split.html

[22]:
```
#Selecionando o X e o Y
X = base2.drop('SalePrice',axis=1)
y = base2.SalePrice
```

[30]:
```
#Importando o train_test_split
from sklearn.model_selection import train_test_split
```

[31]:
```
#Separando essa base em treino e teste
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)
```

2 O próximo passo é selecionar os algoritmos que vou utilizar. Com algoritmos menos robustos.

- Regressão Linear;
  - https://scikit-learn.org/1.5/modules/generated/sklearn.linear_model.LinearRegression.html
- Árvore de Regressão;
  - https://scikit-learn.org/1.5/modules/tree.html
- KNNeigboardsRegressor;
  - https://scikit-learn.org/1.5/modules/generated/sklearn.neighbors.KNeighborsClassifier.html

[32]:
```
#Importando a regressão Linear
from sklearn.linear_model import LinearRegression
```

[33]:
```
#Criando a regressão e fazendo o fit coom os dados de treino
reg_rl = LinearRegression().fit(X_train, y_train)
```

[34]:
```
#Fazendo a previsão para os dados de teste
y_rl = reg_rl.predict(X_test)
```

[35]:
```
#Importando  o pacote da árvore de decisão
from sklearn import tree
```

[36]:
```
#Criando o regressor e fazendo o fit com os dados de treino
reg_ar = tree.DecisionTreeRegressor(random_state=42).fit(X_train, y_train)
```

[37]:
```
#Fazendo a previsão
y_ar = reg_ar.predict(X_test)
```

[38]:
```
#Importando o KNN
from sklearn.neighbors import KNeighborsClassifier
```

[39]:
```
#Criando o regressor e fazendo o fit com os dados do treino
reg_knn = KNeighborsClassifier(n_neighbors=3).fit(X_train, y_train)
```

[40]:
```
y_knn = reg_knn.predict(X_test)
```

#Agora deve-se avaliar esses dados, utilizando o erro absoluto e o quadrático. - Erro médio Absoluto -https://scikit-learn.org/1.5/modules/generated/sklearn.metrics.mean_absolute_error.html - Erro quadrático médio -https://scikit-learn.org/1.5/modules/generated/sklearn.metrics.mean_squared_error.html

[41]:
```
#Importando o Erro médio absoluto
from sklearn.metrics import mean_absolute_error
```

[42]:
```
# Importando o erro quadrático médio
from sklearn.metrics import mean_squared_error
```

[43]:
```
#Avaliando o erro da regressão linear
print(mean_absolute_error(y_test,y_rl))
print(mean_squared_error(y_test,y_rl))
```

```
23802.62054087979
1538459666.3792715
```

[44]:
```
#Avaliando o erro da árvore de decisão
print(mean_absolute_error(y_test,y_ar))
print(mean_squared_error(y_test,y_ar))
```

```
26693.82572614108
1682730719.020747
```

[45]:
```
#Avaliando o erro do knn
print(mean_absolute_error(y_test,y_knn))
print(mean_squared_error(y_test,y_knn))
```

```
43864.85062240664
4510231790.157677
```

3 Visualização dos Gráficos

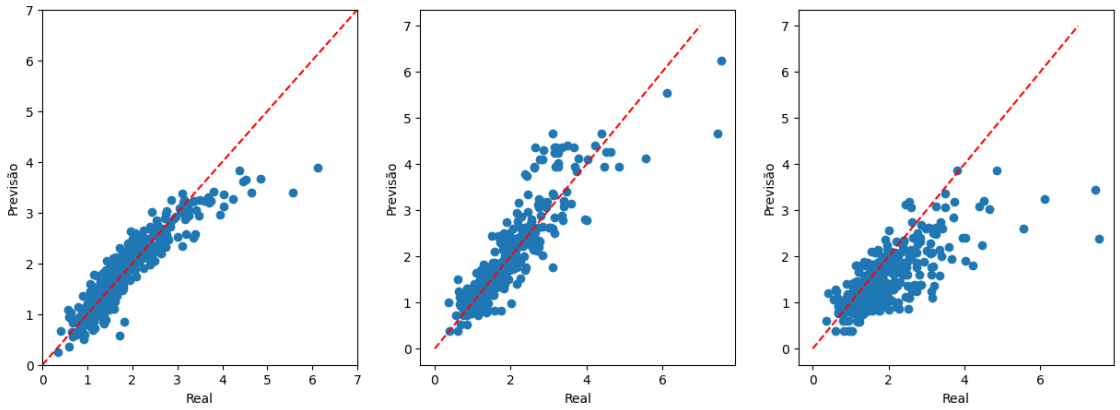
[53]:
```
#Importando a biblioteca
import matplotlib.pyplot as plt
```

[54]:
```
#Criando o gráfico
fig, ax = plt.subplots(ncols=3, figsize=(15,5))

ax[0].scatter(y_test/100000, y_rl/100000)
ax[0].plot([0,7], [0,7], '--r')
ax[1].scatter(y_test/100000,y_ar/100000)
ax[1].plot([0,7],[0,7],'--r')
ax[2].scatter(y_test/100000,y_knn/100000)
ax[2].plot([0,7],[0,7],'--r')

ax[0].set(xlim=(0,7),ylim=(0,7))
ax[0].set_xlabel('Real')
ax[0].set_ylabel('Previsão')
ax[1].set_xlabel('Real')
ax[1].set_ylabel('Previsão')
ax[2].set_xlabel('Real')
ax[2].set_ylabel('Previsão')

plt.show()
```



- Vou utilizar a Regressão Linear por apresentar o algoritmo com o menor erro quadrático médio, a mesma métrica avaliada pelo Kaggle de classificar os modelos

4 Fazendo a previsão de teste da competição

- Agora vou repetir os mesmos tratamentos que fiz na base de treino

  -OBS: Não posso excluir linhas

[72]:
```
#Baixando o dataset de teste
teste = pd.read_csv("C:/Users/Vinicius/Desktop/Kaggle/Housing Prices/test.csv")
```

[73]:
```
#Eliminando as mesmas colunas da base de treino
teste = teste.drop(eliminar, axis=1)
```

[74]:
```
# Verificando as colunas numéricas
colunas2 = teste.columns[teste.dtypes != 'object']
colunas2
```

[74]:
```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea',
       'MiscVal', 'MoSold', 'YrSold'],
      dtype='object')
```

[75]:
```
#Mantendo também apenas as colunas numéricas
teste = teste.loc[:,colunas2]
```

[76]:
```
teste.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 37 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1459 non-null   int64
 1   MSSubClass     1459 non-null   int64
 2   LotFrontage    1232 non-null   float64
 3   LotArea        1459 non-null   int64
 4   OverallQual    1459 non-null   int64
 5   OverallCond    1459 non-null   int64
 6   YearBuilt      1459 non-null   int64
 7   YearRemodAdd   1459 non-null   int64
 8   MasVnrArea     1444 non-null   float64
 9   BsmtFinSF1     1458 non-null   float64
 10  BsmtFinSF2     1458 non-null   float64
 11  BsmtUnfSF      1458 non-null   float64
 12  TotalBsmtSF    1458 non-null   float64
 13  1stFlrSF       1459 non-null   int64
 14  2ndFlrSF       1459 non-null   int64
 15  LowQualFinSF   1459 non-null   int64
 16  GrLivArea      1459 non-null   int64
 17  BsmtFullBath   1457 non-null   float64
```

```
 18  BsmtHalfBath   1457 non-null   float64
 19  FullBath       1459 non-null   int64
 20  HalfBath       1459 non-null   int64
 21  BedroomAbvGr   1459 non-null   int64
 22  KitchenAbvGr   1459 non-null   int64
 23  TotRmsAbvGrd   1459 non-null   int64
 24  Fireplaces     1459 non-null   int64
 25  GarageYrBlt    1381 non-null   float64
 26  GarageCars     1458 non-null   float64
 27  GarageArea     1458 non-null   float64
 28  WoodDeckSF     1459 non-null   int64
 29  OpenPorchSF    1459 non-null   int64
 30  EnclosedPorch  1459 non-null   int64
 31  3SsnPorch      1459 non-null   int64
 32  ScreenPorch    1459 non-null   int64
 33  PoolArea       1459 non-null   int64
 34  MiscVal        1459 non-null   int64
 35  MoSold         1459 non-null   int64
 36  YrSold         1459 non-null   int64
dtypes: float64(11), int64(26)
memory usage: 421.9 KB
```

[78]:
```
#Visualizando quantidade de valores vazios
teste.isnull().sum().sort_values(ascending=False).head(10)
```

[78]:
```
LotFrontage     227
GarageYrBlt      78
MasVnrArea       15
BsmtHalfBath      2
BsmtFullBath      2
BsmtFinSF2        1
GarageCars        1
GarageArea        1
TotalBsmtSF       1
BsmtUnfSF         1
dtype: int64
```

[80]:
```
#Substituindo os valores vazios por -1
teste = teste.fillna(-1)
```

5 Agora vou usar o modelo e ajustar os dados para usar no Kaggle

[82]:
```
# Vou usar a regressão linear para fazer a previsão
y_pred = reg_rl.predict(teste)
```

[83]:
```
# Adicionando essa coluna de previsão na base
teste['SalePrice'] = y_pred
```

[93]:
```
#Extrair somente o Id e o SalePrice
resultado = teste[['Id','SalePrice']]
resultado.head(3)
```

[93]:

	Id	SalePrice
0	1461	121717.547491
1	1462	136419.150857
2	1463	169185.099092

[97]:
```
#Posso então exportar essa base
resultado.to_csv('resultado.csv',index=False)
```

[ ]:
```

```